Automatic Media Data Rating Based on Class Probability Output Networks

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Abstract — *This paper presents a novel method of classifying media data whether they include X-rated contents or not. In our work, the classification of media data is performed using the class probability output network (CPON) which estimates the conditional class probability. Consequently, the classification of media data can be done using the degree of confidence for the class membership, not just using the discriminant value which is usually used in many classification problems. Furthermore, the accuracy of the estimated conditional class probability can be measured in the suggested CPON and this gives a good guideline for the final decision of classification. To demonstrate the effectiveness of the suggested method, the simulation for automatic media rating of the data sampled from multimedia data streams in the Internet was performed. We showed that the suggested CPON-based method provides the better performance than other classifiers using discriminant functions* [1].

Index Terms — Media Data Rating, Multimedia Data, Support Vector Machine, Class Probability Output Network.

I. Introduction

In recent years, the advances in broadband access have made possible the incursion of a multitude of services and technologies that we never thought possible just a couple of decades ago. These changes can be easily reflected in our daily life, in a way that we communicate and do business. Unfortunately, not all the material accessible through Internet is recommended to all users. This is the case of offensive and pornographic websites. For parents, keeping children away from accessing such contents has been a priority concern. A similar issue has been a concern for companies, having to reduce the work time invested in such websites by their employees. In order to restrict the access of such materials, parental control technologies of filtering such contents has been proposed and implemented with some success [1]. But once the filtering takes place, the following problem arises: which websites must be filtered? Two basic approaches have been used to address this problem: URL and content-based blocking. In the first approach, the website is filtered if it is in a block list. The obvious problem is keeping up-to-date such lists, given the rapid growth and name changes such websites undergo [2]. On the other hand, content-based blocking aims to detect the offensive material on the website in question. This can be done by analyzing texts, images and videos [3]-[7]. In this context, the automatic media data rating in the Internet is a necessary tool for a web filtering system. For this purpose of classifying media data whether they include X-rated contents or not, a novel method is suggested using the conditional class probability estimated from the class probability output network (CPON) [8].

There are various ways of implementing pattern classifiers. The most popular way is to use a discriminant function whose values are supposed to indicate the degree of confidence for the classification. In these classifiers, the decision of classification is made by selecting the class that has the greatest discriminant value. For example, support vector machines (SVMs) provide the optimal structure of discriminant function using the structural risk minimization (SRM) principle [9]. However, in general, the output of SVM is not necessarily related with the conditional class probability. Rather, the output of SVM just discriminates whether the pattern belongs to the class or not. In this context, the more natural way of representing the degree of confidence for the classification is using the posterior probability for the decision. For the posterior probability, we can use the Bayes theorem to implement pattern classifiers. For these classifiers, we need to acquire the information of data distribution; however, in many real applications, we do not have a prior knowledge of data distribution and this makes hard to implement Bayes classifiers. One way to solve this problem is using the nonparametric estimation; that is, the form of the probability distribution itself is determined from the data. For example, the Parzen window approach [10] can be applied to construct the probability density function of the data by locating the window function at each datum. In the case of relevance vector machine [11], the functional form is similar with that of SVM, but it provides probabilistic classification with much smaller number of support vectors. However, one of difficulties in these methods is that we need more time complexity for the training of these models compared to the SVM method. Furthermore, in many classification problems, the classifiers using discriminant functions are better than the classifiers using class probability estimates from the viewpoint of classification performances. In this context, we consider the post processing of the pattern

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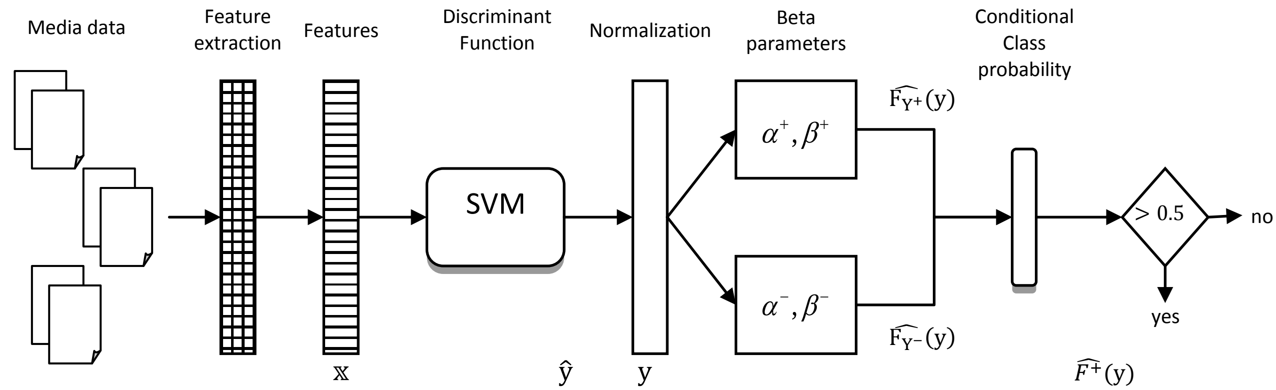

Fig. 1. Automatic Media Data Rating System

classifiers using discriminant functions in such a way that the output of classifier represents the posterior probability of soft decision while the classifier preserves the sparsity of kernel functions. As a result, we may expect better classification performances compared to the canonical classifiers using discriminant functions alone. In this context, we suggested a new method of class probability output network (CPON) in which the posterior probability of class membership is estimated using the beta distribution parameters. The good features of beta distribution are that any symmetric or nonsymmetric unimodal distribution within a finite range of data is well fitted to the beta distribution using two parameters α and β, and that these parameters are easily estimated from the mean and variance of data. Here, for each class, we can estimate the beta cumulative distribution function (CDF) using the parameters α and β. On the other hand, other density functions of exponential families such as Gaussian, Laplacian, Exponential, Gamma, etc., have long tails in the positive side or both the positive and negative sides of data values, and they are not so flexible as compared to the beta distribution. One of characteristics in this statistical estimation is that the beta CDF values for the classifier's output data become uniformly distributed if the beta distribution parameters are well fitted to the real distribution of the classifier's output. From this point of view, we checked the uniformity of the distribution of the beta CDF values for the classifier's output samples using the Kolmogorov-Smirnov (K-S) test [12]. This K-S test is also used to select the beta distribution parameters as well as the shape parameters of kernel functions describing the discriminant function. After the CDF for the classifier's output is estimated using the beta distribution, we can determine the posterior probability of class membership using the CDF values for each class. Then, the final decision for the class can be determined by identifying the class which has the maximum posterior probability of class membership. Furthermore, the accuracy of the CPON output can be described by the confidence interval for the conditional class probability. As a result, the suggested CPON method is able to provide consistent improvement of classification performances for the classifiers using discriminant functions alone.

In this paper, the suggested CPON method is applied to automatic media data rating to check whether they include X-rated contents or not. For this problem, the media data features are extracted and the SVM is trained using the data with these features. In this training, the beta parameters as well as the kernel parameters are adjusted in such a way that the classifier's output follows a beta distribution as much as possible. As a result, the suggested CPON method is able to provide a statistically meaningful performance improvement over other methods including the SVM. These results imply that the CPON-based classification of media data is very effective compared with other methods and provides a good guideline for the final decision of classification using the estimated conditional class probability.

This paper is organized as follows: in Section 2, the flow of automatic media data rating system is explained; Section 3 contains a detailed description of the proposed CPON method; in Section 4, the simulation for media data rating using the proposed CPON method is performed and compared with other classification methods; and finally, in Section 5, the conclusion of our work is presented.

II. Automatic Media Data Rating System

In our problem of media data classification, the media data are obtained from the web-pages or the web-hard service of the Internet. From the media data, we obtained voice and image data sets. Here, each voice data set is composed of 10 second-length audio clips that are extracted from dramas, movies, sports, adult videos and so on, and each image dataset is made from a wide variety of the media genre; for example, landscape, portrait, bikini girls, topless girls, sexual intercourse, etc. Then, after obtaining the data set, the voice or image features are extracted as the input of classifier. In the case of audio features, the mel-frequency cepstrum coefficients (MFCCs) [13] or audio spectrum features [14] are used whereas in the case of image features, the MPEG-7 visual descriptors [15] and the skin color detection algorithm [16] are used.

The schematic diagram of the whole structure is illustrated in Figure 1. Here, the automatic media data rating system is constructed as follows: 1) for the given media data, features for the pattern classifier are extracted, 2) the discriminant value (such as the output of SVM) is then calculated for the given media data features, 3) the output of discriminant value is normalized by the value between 0 and 1, 4) the beta CDF values for the positive and negative classes are calculated, 5) the conditional class probability for the given media data is calculated using the beta CDF values, 6) and then, the final decision for the media data classification is made. This method provides an accurate estimation of conditional class probabilities since in this training of classifiers, the beta distribution parameters as well as the kernel parameters are adjusted in such a way that the classifier's output distributions become closer to the ideal beta distributions. Furthermore, the suggested CPON method is able to provide the degree of uncertainty for the final decision of classification by estimating the confidence intervals for the conditional class probabilities.

III. Construction of Class Probability Output Networks for Image Data Classification

In many classification problems, it is desirable that the output of a classifier represents the conditional class probability. For the conditional class probability, the distribution of classifier's output can be well approximated by the beta distribution under the assumption that the output of classifier lies within a finite range and the distribution of classifier's output is unimodal; that is, the distribution has one modal value with the greatest frequency. This assumption is quite reasonable for many cases of classification problems with the proper selection of kernel parameters of a classifier. Here, we consider the following discriminant function $\hat{y}$ as the classifier's output for the input pattern $\mathbb{x}$:

$$\hat{y}(\mathbb{x}) = \sum_{i=1}^{m} w_i \phi_i(\mathbb{x}|\theta), \tag{1}$$

where m represents the number of kernels and w_i, ϕ_i, and θ represent the ith weight, the ith kernel function, and the kernel parameter, respectively. Furthermore, the beta distribution represents the conjugate prior of the binomial distribution; that is, in our case, the conditional class probability in binary classification problems. In this context, we consider the following beta probability density function (PDF) of a random variable Y as the normalized classifier's output:

$$f_Y(y|\alpha,\beta) = \frac{1}{B(\alpha,\beta)} y^{\alpha-1}(1-y)^{\beta-1}, \; 0 \le y \le 1, \tag{2}$$

where α and β represents the parameters of beta distribution, and $B(\alpha,\beta)$ represents a beta function defined by

$$B(\alpha,\beta) = \int_0^1 y^{\alpha-1}(1-y)^{\beta-1} dy. \tag{3}$$

Here, we assume that the classifier's output value; that is, $\hat{y}$ is normalized between 0 and 1. One of the advantages of the beta distribution is that the beta distribution parameters can be easily guessed from the mean $E[Y]$ and variance $Var(Y)$ as follows:

$$\alpha = E[Y]\left(\frac{E[Y](1-E[Y])}{Var(Y)} - 1\right) \tag{4}$$

and

$$\beta = (1-E[Y])\left(\frac{E[Y](1-E[Y])}{Var(Y)} - 1\right). \tag{5}$$

Although this moment matching (MM) method is simple, these estimators usually don't provide accurate estimations especially for smaller number of data. In such cases, the maximum likelihood estimation (MLE) or the minimum variance of CDF values [8] will produce a more accurate estimation. If the data distribution follows a beta distribution and the optimal beta parameters are obtained, the ideal CDF values of the data $u = F_Y(y)$ follow an uniform distribution; that is,

$$f_U(u) = \frac{f_Y(y)}{\left|\frac{dF_Y}{dy}\right|} = \frac{f_Y(y)}{|f_Y(y)|} = 1. \tag{6}$$

To check whether the data distribution fits with the proposed beta distribution, the Kolmogorov-Smirinov (K-S) test of data distribution can be considered as follows:

- First, determine the distance D_n between the empirical and ideal CDF values:

$$D_n = \sup_u |F_U^*(u) - F_U(u)|, \tag{7}$$

where $F_U^*(u)$ and $F_U(u)$ represent the empirical and theoretical CDFs of $u = F_Y(y)$; that is, the CDF values of the normalized output of a classifier. In this case, $F_U(u) = u$ since the data $u = F_Y(y)$ follow an uniform distribution if the data y follows the presumed (or ideal) beta distribution.

- Determine the p-value of testing the hypothesis of beta distribution:

$$\text{p-value} = P\left(D_n \ge \frac{t}{\sqrt{n}}\right) = 1 - H(t), \tag{8}$$

where $t = \sqrt{n} d_n$ (the value of a random variable D_n) and the CDF of the K-S statistic $H(t)$ is given by

$$H(t) = \frac{\sqrt{2\pi}}{t} \sum_{i=1}^{\infty} e^{-(2i-1)^2\pi^2/(8t^2)}. \tag{9}$$

- Make a decision of accepting the hypothesis of beta distribution H_0 using the p-value according to the level of significance δ:

accept H_0, if p-value$\ge\delta$; reject H_0, otherwise.

In this construction of CPON, we choose the SVM method to obtain the discriminant function since this classifier provides sparse representation of training patterns using the SRM principle. Then, the output of SVM is normalized between 0 and 1 using the linear scaling method. For the normalized classifier's output distributions, the positive and negative classes are approximated by the beta distribution parameters. In this training of classifiers, the beta distribution parameters as well as the kernel parameters are adjusted in such a way that the classifier's output distributions become closer to the ideal beta distributions. Here, we use the K-S test for the hypothesis that the distribution of normalized classifier's output follows a beta distribution. If the hypothesis of beta distribution is accepted, it implies that the estimates of beta parameters are good enough to represent the distribution of classifier's output. However, in some cases, this hypothesis is rejected due to the inaccurate estimation of the distribution of classifier's output. In this case, the beta distribution parameters are further adjusted in such a way to minimize the variance of CDF values of the normalized classifier's output. For the detail description of this update rule of beta distribution parameters, refer to [8]. In this work, the CPON algorithm is applied to media data classification. Furthermore, to see the accuracy of the CPON output; that is, estimated conditional class probabilities, the confidence intervals of the CPON output are suggested for this method. These confidence intervals provide a good guideline whether we can trust the decision of classification or not. Here, the CPON algorithm for media data classification is described as follows:

<u>Media Data Classification Algorithm Based on the CPON</u>

Step 1. Given the data set D, divide it into training and validation sets D^{train} and D^{valid}.

Step 2. For a set of kernel parameters θ_i, $i=1, \ldots, k$, do the following procedure:

1) Train a classifier (such as a SVM) using the training set D^{train} and obtain the discriminant function $\hat{y}$ of a classifier.
2) From the classifier's output $\hat{y}$, determine the normalized classifier's output y between 0 and 1 using the linear scaling method.
3) For the normalized output of positive and negative data sets; that is, the data sets that belong to the positive $(+)$ and negative $(-)$ classes of D^{train}, estimate the beta parameters for each class using the MM or MLE method [17].
4) Determine the estimated CDF values for the data sets of positive and negative classes in the validation set D^{valid}; they are $u^+ = \widehat{F_{Y^+}}(y)$ and $u^- = \widehat{F_{Y^-}}(y)$.
5) For two sets of data in D^{valid}, determine the empirical CDFs; they are $F^*_{U^+}(u^+)$ and $F^*_{U^-}(u^-)$, and calculate the distances between empirical and ideal CDF values; they are D_n^+ and D_n^-.
6) For D_n^+ and D_n^-, determine the p-values of the K-S statistic; they are p_i^+ and p_i^-.

Step 3. Select the optimal kernel parameters which maximize the p-value of the K-S test; that is, determine θ_j such that

$$j = \arg\max_i p_i^+ p_i^-. \tag{10}$$

Step 4. For the trained classifier with the kernel parameter θ_j, perform the fine tuning of beta parameters using the data set D. For the detail description of the fine tuning of beta parameters, refer to [8].

After the CPON is trained, the classification for an unknown pattern can be determined by the beta distribution for each class. First, for the unknown pattern, the normalized output for the classifier is computed. Here, if the normalized value is greater than 1, we set that value as 1; on the other hand, if the value is less than 0, we set that value as 0. Then, the following conditional probability; that is, the output of CPON $F^+(y)$ is calculated:

$$\begin{aligned} F^+(y) &= P(+|Y^+ \leq y \text{ or } Y^- \geq y) \\ &= \frac{F_{Y^+}(y)}{F_{Y^+}(y) + 1 - F_{Y^-}(y)}. \end{aligned} \tag{11}$$

This output implies the p-value ratio of testing hypotheses of positive and negative classes; that is,

$$\begin{aligned} &F^+(y) \\ &= \frac{\text{p-value of testing } H^+}{\text{p-value of testing } H^+ + \text{p-value of testing } H^-}, \end{aligned} \tag{12}$$

where H^+ and H^- represent the hypotheses that the given instance belongs to the positive and negative classes, respectively. The final decision can be made using the conditional class probability for the given pattern; that is,

$$\text{class} = \begin{cases} \text{positive} & \text{if } F^+(y) > 0.5 \\ \text{negative} & \text{otherwise.} \end{cases} \tag{13}$$

In this way, we can make our decision of media data classification using the CPON output. However, in practice, we obtained the estimated conditional class probability such as

$$\widehat{F^+}(y) = \frac{\widehat{F_{Y^+}}(y)}{\widehat{F_{Y^+}}(y) + 1 - \widehat{F_{Y^-}}(y)}. \tag{14}$$

In this case, we can determine the degree of uncertainty for the decision of classification. This can be done by estimating the confidence intervals for the conditional class probabilities. These confidence intervals can be determined by using the K-S statistic:

- First, find the distance measures $D^{\pm}_{n,\alpha}$ for the positive and negative classes; they are

$$D^+_{n,\alpha} = \frac{K_\alpha}{\sqrt{n^+}} \text{ and } D^-_{n,\alpha} = \frac{K_\alpha}{\sqrt{n^-}}, \tag{15}$$

where K_α represents the value that satisfies $H(K_\alpha) = 1 - \alpha$, and n^+ and n^- represent the sample size of the positive and negative classes, respectively.

- Setting the variables $u^{\pm}$ as follows:

$$u^+ = \widehat{F_{Y^+}}(y) \text{ and } u^- = \widehat{F_{Y^-}}(y). \tag{16}$$

- Determine the confidence intervals for the CDFs of the positive and negative classes:

$$F^*_{U^+}(u^+) - D^+_{n,\alpha} \leq F_{Y^+}(y) \leq F^*_{U^+}(u^+) + D^+_{n,\alpha} \text{ and}$$
$$1 - F^*_{U^-}(u^-) - D^-_{n,\alpha} \leq 1 - F_{Y^-}(y) \leq 1 - F^*_{U^-}(u^-) + D^-_{n,\alpha}. \quad (17)$$

- Then, with a probability of $(1-\alpha)^2 \approx 1 - 2\alpha$, we can determine the confidence intervals for the conditional class probabilities of the positive and negative classes:

$$\frac{F^*_{U^+}(u^+) - D^+_{n,\alpha}}{F^*_{U^+}(u^+) - D^+_{n,\alpha} + 1 - F^*_{U^-}(u^-) + D^-_{n,\alpha}} \leq F^+(y) \leq \frac{F^*_{U^+}(u^+) + D^+_{n,\alpha}}{F^*_{U^+}(u^+) + D^+_{n,\alpha} + 1F^*_{U^-}(u^-) - D^-_{n,\alpha}} \text{ and}$$

$$\frac{1 - F^*_{U^-}(u^-) - D^-_{n,\alpha}}{F^*_{U^+}(u^+) + D^+_{n,\alpha} + 1 - F^*_{U^-}(u^-) - D^-_{n,\alpha}} \leq F^-(y) \leq \frac{1 - F^*_{U^-}(u^-) + D^-_{n,\alpha}}{F^*_{U^+}(u^+) - D^+_{n,\alpha} + 1 - F^*_{U^-}(u^-) + D^-_{n,\alpha}}. \quad (18)$$

These two confidence intervals contribute to determine the degree of uncertainty for the decision of classification: If these two confidence intervals are separated, we are quite sure that $F^+(y) > F^-(y)$. If not, there is a chance that the CPON output makes a wrong decision. In this case, we may need to use other information (or external knowledge) of data for the final decision of classification.

IV. SIMULATION FOR MEDIA DATA RATING

To show the effectiveness of the proposed method, we selected 6 different media data sets: they were audio and image data sets obtained from multimedia data streams as the benchmark data sets. These data sets are listed in Table I.

TABLE I
BENCHMARK DATA SETS FOR MEDIA DATA RATING

Data Set	*Type*	*Features*	*Train*	*Test*
1	Audio	630	2475	1951
2	Audio	22	2475	1953
3	Audio	48	2475	1953
4	Image	673	2000	2000
5	Image	11	2000	2000
6	Image (Body-Parts)	162	2407	2074

For audio data sets 1, 2, and 3, the ratio of X-rated to non-X-rated audio clips were around 1:1.8. In these audio data sets, X-rated audio clips were extracted from 3 types of videos; they were adult video, hidden or self camera film, and adult broadcast. These audio data sets also contained all ages admitted audio clips which were obtained from 7 types of video and audio tracks; they were soap operas, sports, current events and culture, entertainment, news, pop music, and instrumental music. In the case of image data sets 4 and 5, each data set was composed of 2,000 all ages admitted images and 2,000 X-rated images. All ages admitted images were obtained from the genres of landscape, still-life paintings, artifacts, animals, animation or cartoons, people wearing clothes, people wearing underwear, bikini girls, and images including many people. On the other hand, the X-rated image set consisted of 7 categories; they were images exposing one breast, images exposing two breasts, images exposing buttocks, images exposing the genital area, fully nude images, and sexual intercourse images. The image data set of body-parts (image data set 6) consisted of any part of body, especially the part of arousing sexual excitement. In this data set, two types of images, only face and non-face images were used. The component ratios of these two types of images were almost the same.

For these data sets, voice or image features were obtained. In the case of audio feature sets, features were produced from 10 second-length of audio clips. First, an audio clip was divided into 20 segments and each segment covered 500ms length. Then, 50% overlapping part in each of two adjacent segments were used to compute a feature of audio data. Here, for the audio data set 1, two-dimensional MFCCs [13] with 21 orders of quefrency coefficients and 15 orders of temporal variations, were used to determine the audio features. In the case of audio data set 2, auditory spectrum features [14] with 11 orders were used while in the case of audio data set 3, MFCCs with 24 orders were used to determine the audio features. In the case of image features, the MPEG-7 visual descriptors [15] and skin color detection algorithm [16] were used. For the image data sets 4 and 5, the MPEG-7 visual descriptors and the skin color ratios were used to determine the image features. From the MPEG-7, the color layout descriptors (CLDs), color structure descriptors (CSDs), scalable color descriptors (SCDs), homogeneous texture descriptors (HTDs), and edge histogram descriptors (EHDs) were considered. In the case of image data set 6, the image features using the CLDs and EHDs were obtained to capture the body part images.

For the purpose of comparing classification performances with the proposed CPON method, the SVM [9] and k nearest neighbor (kNN) classifiers [18] were considered. The SVM is a well-known and widely used method in a multitude of classification problems. For the simulation of SVM, we used the Matlab implementation of LIBSVM with Gaussian kernels [19]. The kNN is another well-known statistical classification method. Its algorithm is relatively simple compared with other methods: for the given instance, the distances between the instance and the k-nearest samples for the classes are compared, and the decision of classification is made. For the implementation of the proposed CPON method, the SVM were constructed initially and the beta parameters for the positive and negative classes were estimated. In the initial set up of SVM, the optimal kernel parameters and C parameter were searched using the randomly selected validation data which occupied 1/3 of the training data. Here, in the case of the proposed CPON, the selection was performed using the p-value of the K-S test while in the case of the SVM, the selection was performed using a classification performance such as accuracy. Then, the beta parameters were adjusted for the whole training data. Here, a similar approach with the SVM was used to determine the value of k in the k-NN method. The simulation for media data rating were run in a dual-processor Intel Xeon 3.2GHz (X2), running Linux kernel 2.6 and Matlab 7.9 (R2009b). The simulation experiments were run 10 times and the classification performances were averaged.

In order to find the efficiency of the proposed method, we used a series of standard performance measures: they are the accuracy, precision, recall and F_1 measures. The accuracy measure represents one minus the ratio of the wrong assignments over the total number of assignments, more formally

$$\text{accuracy} = 1 - \frac{|\text{FP}| + |\text{FN}|}{|\text{TP}| + |\text{FP}| + |\text{TN}| + |\text{FN}|}, \quad (19)$$

where TP, TN, FP, and FN represents the true positives, true negatives, false positives, and false negatives, respectively.

The precision measure represents the ratio of true positives over the total of positive assignments:

$$\text{p} = \frac{|\text{TP}|}{|\text{TP}| + |\text{FP}|}. \quad (20)$$

The recall measure is defined as the ratio of true positives over the total of correct assignments:

$$\text{r} = \frac{|\text{TP}|}{|\text{TP}| + |\text{FN}|}. \quad (21)$$

Finally the F_1 measure, which is a tradeoff between the precision and recall; that is,

$$F_1 = \frac{2pr}{p + r}. \quad (22)$$

The simulation results for the classification performances of these measures are listed in Tables II through V: The accuracy, precision, recall, and F_1 measures for classification performances are listed in Tables II, III, IV, and V, respectively.

TABLE II
ACCURACY RESULTS

Data Set	*kNN*	*SVM*	*CPON*
1	0.8900	0.9340	**0.9401**
2	0.7587	0.8800	**0.8938**
3	0.9130	0.9211	**0.9410**
4	0.6103	0.6551	**0.7005**
5	0.6668	0.7095	**0.7251**
6	0.7999	0.8025	**0.8399**

TABLE III
PRECISION RESULTS

Data Set	*kNN*	*SVM*	*CPON*
1	0.9122	0.9545	**0.9580**
2	0.6230	**0.8314**	0.8257
3	**0.9093**	0.8999	0.8979
4	0.6015	0.6701	**0.7939**
5	**0.7111**	0.6310	0.6933
6	0.8200	**0.8980**	0.8500

TABLE IV
RECALL RESULTS

Data Set	*kNN*	*SVM*	*CPON*
1	0.7942	0.8900	**0.8998**
2	0.6074	**0.8205**	0.8152
3	0.8600	**0.8650**	0.8599
4	0.5518	0.6125	**0.6800**
5	0.5958	0.6145	**0.6215**
6	0.7714	0.7807	**0.8121**

TABLE V
F_1 MEASURE RESULTS

Data Set	*kNN*	*SVM*	*CPON*
1	0.8773	0.9089	**0.9100**
2	0.6202	**0.8243**	0.8199
3	0.8611	0.8678	**0.8866**
4	0.5967	0.6400	**0.7243**
5	0.6049	0.6157	**0.6771**
6	0.7800	0.7995	**0.8400**

These simulation results for media data classification showed that 1) the CPON method provided the best accuracy measure compared with the kNN or SVM method as described in Table II, 2) for the precision measure, three classification methods gave mixed results for these data sets, suggesting the absence of a clear best classifier for the precision measure as described in Table III, 3) for the recall measure, the SVM and CPON methods outperformed the kNN method, while on average, the CPON method shows better results compared with the SVM method as described in Table IV, and 4) for the F_1 measure as the summary of precision and recall measures, the CPON method provided better performances than the SVM method except the case of data set 2. In fact, for the data sets 1 and 2, the classification performances of the SVM and CPON methods were almost equivalent from the statistical point of view while for the data sets 3 through 6, the CPON method provided better performances than the SVM method. These results may come from the fact that for the data sets 1 and 2, the data distributions were favorable to deal with SVM so that the performance improvement using the CPON was minor.

In summary, through the simulation for automatic media data rating, we have demonstrated that the proposed CPON method outperformed other classifiers such as the kNN and SVM using four standard measures of pattern classification.

These results are possible since the proposed CPON provides accurate estimates of conditional class probabilities by adjusting both the beta parameters and kernel parameters in such a way that the classifier's output distribution is close to the ideal data distribution (in our case, the beta distribution) as much as possible. These simulation results suggest that the proposed CPON can be considered as a valid alternative to other benchmarked classifiers such as the kNN and SVM.

V. Conclusion

We have presented a new way of automatic media rating method using the conditional class probability estimated from the CPON. In the proposed automatic media rating system, the features for the pattern classifier are extracted for the given media data and the discriminant value (such as the output of SVM) is then calculated. One distinct feature of the CPON method is the ability to estimate the posterior probability of class membership using the beta distribution parameters. For each class, the beta cumulative distribution function (CDF) is estimated. One of properties in this statistical estimation is that the CDF values for the classifier's output data become uniformly distributed if the beta distribution parameters are well fitted to the real distribution of the classifier's output. From this point of view, we checked the uniformity of the distribution of the CDF values for the classifier's output data using the Kolmogorov-Smirnov (K-S) statistic in order to select the beta distribution parameters as well as the shape parameters of the kernel functions that describe the discriminant function. As a result, the CPON provides accurate estimates of conditional class probabilities. Through the simulation for automatic media data rating, we showed that the proposed CPON-based method provides better performances than other classifiers using discriminant functions. Furthermore, in the CPON, the degree of uncertainty for the final decision of classification can be described by estimating the confidence intervals for the conditional class probabilities. The proposed CPON-based method can be easily applied to various types of classification problems that require a degree of confidence for the class membership.

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