Upper bounds for average Bayes accuracy in terms of mutual information

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These are preliminary notes.

1 Introduction

Suppose X and Y are continuous random variables (or vectors) which have a joint distribution with density $p(x,y)$. Let $p(x) = \int p(x,y)dy$ and $p(y) = \int p(x,y)dx$ denote the respective marginal distributions, and $p(y|x) = p(x,y)/p(x)$ denote the conditional distribution.

Mutual information is defined

$$\mathrm{I}[p(x,y)] = \int p(x,y) \log \frac{p(x,y)}{p(x)p(y)} dxdy.$$

ABE_k, or k-class Average Bayes accuracy is defined as follows. Let $X_1, ..., X_K$ be iid from $p(x)$, and draw Z uniformly from $1, .., k$. Draw $Y \sim p(y|X_Z)$. Then, the average Bayes accuracy is defined as

$$\mathrm{ABA}_k[p(x,y)] = \sup_f \Pr[f(x_1, ..., x_k, y) = Z]$$

where the supremum is taken over all functions f. A function f which achieves the supremum is

$$f_{Bayes}(x_1, ..., x_k, y) = \mathrm{argmax}_{z \in \{1,...,k\}} p(y|x_z),$$

where an arbitrary rule can be employed to break ties. Such a function f_{Bayes} is called a *Bayes classification rule*. It follows that ABA_k is given explicitly by

$$\mathrm{ABA}_k = \frac{1}{k}\int \left[\prod_{i=1}^k p(x_i)dx_i\right] \int dy \frac{\sum_{i=1}^k p(y|x_i)^2}{\sum_{i=1}^k p(y|x_i)}.$$

2 Problem formulation

Let $\mathcal{P}$ denote the collection of all joint densities $p(x, y)$ on finite-dimensional Euclidean space. For $\iota \in [0, \infty)$ define $C_k(\iota)$ to be the largest k-class average Bayes error attained by any distribution $p(x, y)$ with mutual information not exceeding ι:

$$C_k(\iota) = \sup_{p \in \mathcal{P}: \mathrm{I}[p(x,y)] \leq \iota} \mathrm{ABA}_k[p(x, y)].$$

A priori, $C_k(\iota)$ exists since ABA_k is bounded between 0 and 1. Furthermore, C_k is nondecreasing since the domain of the supremum is monotonically increasing with ι.

It follows that for any density $p(x, y)$, we have

$$\mathrm{ABA}_k[p(x, y)] \leq C_k(\mathrm{I}[p(x, y)]).$$

Hence C_k provides an upper bound for average Bayes error in terms of mutual information.

Conversely we have

$$\mathrm{I}[p(x, y)] \geq C_k^{-1}(\mathrm{ABA}_k[p(x, y)])$$

so that C_k^{-1} provides a lower bound for mutual information in terms of average Bayes error.

On the other hand, there is no nontrivial *lower* bound for average Bayes error in terms of mutual information, nor upper bound for mutual information in terms of average Bayes error, since

$$\inf_{p \in \mathcal{P}: \mathrm{I}[p(x,y)] \leq \iota} \mathrm{ABA}_k[p(x, y)] = \frac{1}{k}.$$

regardless of ι.

The goal of this work is to attempt to compute or approximate the functions C_k and C_k^{-1}.

3 Special case

We work out the special case where $p(x, y)$ lies on the unit square, and $p(x)$ and $p(y)$ are both the uniform distribution. In this case, the mutual information $\mathrm{I}[p(x, y)]$ is equal to the joint entropy $\mathrm{H}[p(x, y)]$.

To be continued.

4 General case

We claim that the constants $C_k^{unif}(\iota)$ obtained for the special case also apply for the general case, i.e.

$$C_k(\iota) = C_k^{unif}(\iota).$$

We make use of the following Lemma:

Lemma. *Suppose X, Y, W, Z are continuous random variables, and that $W \perp Y|Z$, $Z \perp X|Y$, and $W \perp Z|(X, Y)$. Then,*

$$I[p(x, y)] = I[p((x, w), (y, z))]$$

and

$$ABA_k[p(x, y)] = ABA_k[p((x, w), (y, z))].$$

Proof. Due to conditional independence relationships, we have

$$p((x, w), (y, z)) = p(x, y)p(w|x)p(z|y).$$

It follows that

$$\begin{aligned}
\mathrm{I}[p((x, w), (y, z))] &= \int dxdwdydz\ p(x, y)p(w|x)p(z|w) \log \frac{p((x, w), (y, z))}{p(x, w)p(y, z)} \\
&= \int dxdwdydz\ p(x, y)p(w|x)p(z|w) \log \frac{p(x, y)p(w|x)p(z|y)}{p(x)p(y)p(w|x)p(z|y)} \\
&= \int dxdwdydz\ p(x, y)p(w|x)p(z|w) \log \frac{p(x, y)}{p(x)p(y)} \\
&= \int dxdy\ p(x, y) \log \frac{p(x, y)}{p(x)p(y)} = \mathrm{I}[p(x, y)].
\end{aligned}$$

Also,

$$\begin{aligned}
\mathrm{ABA}_k[p((x,w),(y,z))] &= \int \left[\prod_{i=1}^{k} p(x_i,w_i)dx_i dw_i\right] \int dydz \frac{\sum_{i=1}^{k} p(y,z|x_i,w_i)^2}{\sum_{i=1}^{k} p(y,z|x_i,w_i)} \\
&= \int \left[\prod_{i=1}^{k} p(x_i,w_i)dx_i dw_i\right] \int dy \frac{\sum_{i=1}^{k} p(y|x_i)^2}{\sum_{i=1}^{k} p(y|x_i)} \int p(z|y)dz \\
&= \int \left[\prod_{i=1}^{k} p(x_i)dx_i\right] \left[\prod_{i=1}^{k} \int dw_i p(w_i|x_i)\right] \int dy \frac{\sum_{i=1}^{k} p(y|x_i)^2}{\sum_{i=1}^{k} p(y|x_i)} \\
&= \int \left[\prod_{i=1}^{k} p(x_i)dx_i\right] \int dy \frac{\sum_{i=1}^{k} p(y|x_i)^2}{\sum_{i=1}^{k} p(y|x_i)} = \mathrm{ABA}_k[p(x,y)].
\end{aligned}$$

□

Next, we use the fact that for any $p(x,y)$ and $\epsilon > 0$, there exists a discrete distribution $p_\epsilon(\tilde{x},\tilde{y})$ such that

$$|\mathrm{I}[p(x,y)] - \mathrm{I}[p_\epsilon(\tilde{x},\tilde{y})]| < \epsilon,$$

where for discrete distributions, one defines

$$\mathrm{I}[p(x,y)] = \sum_x \sum_y p(x,y) \log \frac{p(x,y)}{p(x)p(y)}.$$

We require the additional condition that the marginals of the discrete distribution are close to uniform: that is, for some $\delta > 0$, we have

$$\sup_{x,x':p_\epsilon(x)>0 \text{ and } p_\epsilon(x')>0} \frac{p_\epsilon(x)}{p_\epsilon(x')} \leq 1+\delta.$$

and likewise

$$\sup_{y,y':p_\epsilon(y)>0 \text{ and } p_\epsilon(y')>0} \frac{p_\epsilon(y)}{p_\epsilon(y')} \leq 1+\delta.$$

To construct the discretization with the required properties, choose a regular rectangular grid Λ over the domain of $p(x,y)$ sufficiently fine so that partitioning X, Y into grid cells, we have

$$|\mathrm{I}[p(x,y)] - \mathrm{I}[\tilde{p}(\tilde{x},\tilde{y})]| < \epsilon.$$

[NOTE: to be written more clearly] Next, define