Inference of average Bayes accuracy

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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.

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

$$\text{ABA}_k[p(x, y)] = \sup_f \Pr[f(X_1, ..., X_k, Y) = Z]$$

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

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

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

$$\text{ABA}_k = \frac{1}{k} \int \left[\prod_{i=1}^{k} p(x_i)dx_i \right] \int dy \max_i p(y|x_i),$$

as stated in the following theorem.

Theorem 1.1 *For a joint distribution $p(x,y)$, define*

$$ABA_k[p(x,y)] = \sup_f \Pr[f(x_1,...,x_k,y) = Z]$$

where $X_1,...,X_K$ are iid from $p(x)$, Z is uniform from $1,..,k$, and $Y \sim p(y|X_Z)$, and the supremum is taken over all functions $f : \mathcal{X}^k \times \mathcal{Y} \to \{1,...,k\}$. Then,

$$ABA_k = \frac{1}{k}\int \left[\prod_{i=1}^k p(x_i)dx_i\right] \int dy \max_i p(y|x_i).$$

Proof. First, we claim that the supremum is attained by choosing

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

To show this claim, write

$$\sup_f \Pr[f(X_1,...,X_k,Y) = Z] = \sup_f \frac{1}{k}\int p_X(x_1)\dots p_X(x_k)p(y|x_{f(x_1,...,x_k,y)})dx_1\dots dx_k dy$$

We see that maximizing $\Pr[f(X_1,...,X_k,Y) = Z]$ over functions f additively decomposes into infinitely many subproblems, where in each subproblem we are given $\{x_1,...,x_k,y\} \in \mathcal{X}^k \times \mathcal{Y}$, and our goal is to choose $f(x_1,...,x_k,y)$ from the set $\{1,...,k\}$ in order to maximize the quantity $p(y|x_{f(x_1,...,x_k,y)})$. In each subproblem, the maximum is attained by setting $f(x_1,...,x_k,y) = \text{argmax}_z p(y|x_z)$–and the resulting function f attains the supremum to the functional optimization problem. This proves the claim.

We therefore have

$$p(y|x_{f(x_1,...,x_k,y)}) = \max_{i=1}^k p(y|x_i).$$

Therefore, we can write

$$\begin{aligned}
\text{ABA}_k[p(x,y)] &= \sup_f \Pr[f(X_1,...,X_k,Y) = Z] \\
&= \frac{1}{k}\int p_X(x_1)\dots p_X(x_k)p(y|x_{f(x_1,...,x_k,y)})dx_1\dots dx_k dy. \\
&= \frac{1}{k}\int p_X(x_1)\dots p_X(x_k)\max_{i=1}^k p(y|x_i)dx_1\dots dx_k dy.
\end{aligned}$$

2 Variability of Bayes Accuracy

We have

$$\mathrm{ABA}_k = \mathbf{E}[\mathrm{BA}(X_1, ..., X_k)]$$

where the expectation is over the independent sampling of $X_1, ..., X_k$ from $p(x)$.

Therefore, $\mathrm{BA}_k = \mathrm{BA}(X_1, ..., X_k)$ is already an unbiased estimator of ABA_k. However, to get confidence intervals for ABA_k, we also need to know the variability.

We have the following upper bound on the variability.

Theorem 2.1 *Given joint density $p(x, y)$, for $X_1, ..., X_k \overset{iid}{\sim} p(x)$, we have*

$$Var[BA(X_1, ..., X_k)] \leq \frac{1}{4k}.$$

Proof. According to the Efron-Stein lemma,

$$\mathrm{Var}[\mathrm{BA}(X_1, ..., X_k)] \leq \sum_{i=1}^{k} \mathbf{E}[\mathrm{Var}[\mathrm{BA}|X_1, ..., X_{i-1}, X_{i+1}, ..., X_k]].$$

which is the same as

$$\mathrm{Var}[\mathrm{BA}(X_1, ..., X_k)] \leq k\mathbf{E}[\mathrm{Var}[\mathrm{BA}|X_1, ..., X_{k-1}]].$$

The term $\mathrm{Var}[\mathrm{BA}|X_1, ..., X_{k-1}]$ is the variance of $\mathrm{BA}(X_1, ..., X_k)$ conditional on fixing the first $k-1$ curves $p(y|x_1), ..., p(y|x_{k-1})$ and allowing the final curve $p(y|X_k)$ to vary randomly.

Note the following trivial results

$$-p(y|x_k) + \max_{i=1}^{k} p(y|x_i) \leq \max_{i=1}^{k-1} p(y|x_i) \leq \max_{i=1}^{k} p(y|x_i).$$

This implies

$$\mathrm{BA}(X_1, ..., X_k) - \frac{1}{k} \leq \frac{k-1}{k}\mathrm{BA}(X_1, ..., X_{k-1}) \leq \mathrm{BA}(X_1, ..., X_k).$$

i.e. conditional on $(X_1, ..., X_{k-1})$, BA_k is supported on an interval of size $1/k$. Therefore,

$$\mathrm{Var}[\mathrm{BA}|X_1, ..., X_{k-1}] \leq \frac{1}{4k^2}$$

since $\frac{1}{4c^2}$ is the maximal variance for any r.v. with support of length c. $\square$

In the next section we report on some empirical results which suggest that the constant in the bound can be greatly improved.

3 Empirical results

In this section we search over a class of distributions $p(x, y)$ in an attempt to find a distribution which achieves close to the maximum variability.

The theoretical upper bound is

$$\mathrm{sd}(\mathrm{BA}_k) \leq \frac{1}{2\sqrt{k}}.$$

We compare the theoretical bound with the largest sd found for any distribution.

k	2	3	4	5	6	7	8
$\frac{1}{2\sqrt{k}}$	0.353	0.289	0.250	0.223	0.204	0.189	0.177
Worst-case sd	0.25	0.194	0.167	0.150	0.136	0.126	0.118

3.1 Methodology

We search over discrete distributions where $Y \in \{1, ..., d\}$ and $X = (X_1, ..., X_d)$ lies in the space of all d-permutations. The pmf $p(x, y)$ is defined as

$$p(x, y) = \frac{1}{d!} v_{x_y}$$

where

$$0 \leq v_1 \leq v_2 \leq ... \leq v_d$$

and

$$\sum_i v_i = 1.$$

Define the random vector $M^{(k)}$ by

$$M_i^{(k)} = \max_{j=1}^{k} X_i^{(j)}$$

where $X^{(1)}, ..., X^{(k)}$ are indenpendent random permuations for $i = 1, .., d$. Then define the random vector $C^{(k)}$ by

$$C_i^{(k)} = \sum_{j=1}^{d} I\{M_j^{(k)} = i\}.$$

For this class of distributions, the variance is given by

$$\mathrm{Var}(BA_k) = v' \Gamma^{(d,k)} v$$

where $\Gamma^{(d,k)}$ is the $d \times d$ covariance matrix with entries

$$\Gamma_{ij}^{(d,k)} = \mathrm{Cov}(C_i^{(k)}, C_j^{(k)}).$$

Therefore, having computed $\Gamma^{(d,k)}$, one can find distributions which solve the constrained optimization problem:

$$\text{maximize}_{v_1,\ldots,v_d} v'\Gamma^{(d,k)} v \text{ subject to } 0 \le v_1 \le v_2 \le \ldots \le v_d \text{ and } \sum_{i=1}^{d} v_i = 1 \tag{1}$$

3.2 Empirical worst-case distributions

An empirical result is as follows: for all (d,k) examined, maximizers of (1) take the form

$$v = (0, \ldots, 0, 1). \tag{2}$$

While the problem (1) is non-convex, to show that (2) is the global maximizer, it suffices to examine the matrix $\Gamma^{(d,k)}$.

The following properties have been seen to hold for small (d,k), but there may be counterexamples. (In the following, we omit the superscript in $\Gamma^{(d,k)}$.)

P1. For all j, $\max_{i>j} \Gamma_{ij} = \Gamma_{dj}$.

P2. For all i,

$$\alpha^2 \Gamma_{ii} + 2\alpha(1-\alpha)\Gamma_{di} + (1-\alpha)^2 \Gamma_{dd}$$

where $\alpha \in [0, \frac{1}{d-i}]$ is maximized by $\alpha = 0$. Equivalently,

$$\max\left\{\frac{\Gamma_{ii} + 2(i-1)\Gamma_{di}}{2i-1}, \Gamma_{di}\right\} \le \Gamma_{dd}.$$

If P1 and P2 hold, then it follows that (2) maximizes (1), as stated in the following theorem.

Theorem 3.1 *Consider the optimization problem*

$$\textit{maximize}_{v_1,\ldots,v_d} v'\Gamma^{(d,k)} v \textit{ subject to } 0 \le v_1 \le v_2 \le \ldots \le v_d \textit{ and } \sum_{i=1}^{d} v_i = 1$$

If properties P1 and P2 hold for Γ, then the solution is

$$v = (0, \ldots, 0, 1).$$

Proof.

Let S_i be the set of all feasible vectors v such that $v_1 = ... = v_{d-i} = 0$ for $i = 1, ..., d$. Let $v^{(i)}$ be the element of S_i which maximizes $v'\Gamma v$ over S_i.

It is clear that $v^{(1)} = (0, ..., 0, 1)$. Now we proceed to show by induction that if $v^{(i)} = (0, ..., 0, 1)$, then also $v^{(i+1)} = (0, ..., 0, 1)$.

Suppose $v^{(i)} = (0, ..., 0, 1)$. Now, any element $v \in S^{(i+1)}$ can be written

$$v = (0, ..., 0, \alpha, (1-\alpha)w)$$

where $w \in S_i$, for $\alpha \in [0, 1/i]$. Therefore, we have

$$\begin{aligned} v'\Gamma v &= \alpha^2\Gamma_{ii} + 2\alpha(1-\alpha)(\Gamma_{i+1,i}, ..., \Gamma_{di})'w + (1-\alpha)^2 w'\Gamma_{(i+1)\cdots d,(i+1)\cdots d} \\ &\leq \alpha^2\Gamma_{ii} + 2\alpha(1-\alpha)(\Gamma_{i+1,i}, ..., \Gamma_{di})'w + (1-\alpha)^2\Gamma_{dd} \\ &\leq \alpha^2\Gamma_{ii} + 2\alpha(1-\alpha)\Gamma_{di} + (1-\alpha)^2\Gamma_{dd}. \\ &\leq \Gamma_{dd} \text{ by property P2.} \end{aligned}$$

But

$$v'\Gamma v \leq \Gamma_{dd} = (0, ..., 0, 1)'\Gamma(0, ..., 0, 1)$$

implies that

$$v^{(i+1)} = (0, ..., 0, 1).$$

$\square$.