

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

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

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

$$ABA_k[p(x, y)] = \sup_f \Pr[f(X_1, \dots, X_k, Y) = Z]$$

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

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

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*

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

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

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

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

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

To show this claim, write

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

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

We therefore have

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

Therefore, we can write

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

2 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 :

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

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

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

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

Conversely we have

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

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

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

regardless of ι .

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

2.1 Notation

$|\cdot|$ denotes set cardinality.

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. Let \mathcal{P}^{unif} denote the set of such distributions, and

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

We prove the following result:

Theorem 3.1 *For any $\iota > 0$, there exists $c_\iota \geq 0$ such that defining*

$$Q_c(t) = \frac{\exp[ct^{k-1}]}{\int_0^1 \exp[ct^{k-1}]},$$

we have

$$\int_0^1 Q_{c_\iota}(t) \log Q_{c_\iota}(t) dt = \iota.$$

Then,

$$C_k^{unif} = \int_0^1 Q_{c_\iota}(t) t^{k-1} dt.$$

The proof depends on the following lemmas.

Lemma 3.2 *Let $f(t)$ be an increasing function from $[a, b] \rightarrow \mathbb{R}$, where $a < b$, and let $g(t)$ be a bounded continuous function from $[a, b] \rightarrow \mathbb{R}$. Define the set*

$$A = \{t : f(t) \neq g(t)\}.$$

Then, we can write A as a countable union of intervals

$$A = \bigcup_{i=1}^{\infty} A_i$$

where A_i are mutually disjoint intervals, with $\inf A_i < \sup A_i$, and for each i , either $f(t) > g(t)$ for all $t \in A_i$ or $f(t) < g(t)$ for all $t \in A_i$.

Lemma 3.3 *Let $f(t)$ be a measurable function from $[a, b] \rightarrow \mathbb{R}$, where $a < b$. Then there exists sets \mathcal{B}_0 and \mathcal{B}_1 , satisfying the following properties:*

- $\mathcal{B} = \mathcal{B}_0 \cup \mathcal{B}_1$ is countable partition of $[a, b]$,
- $f(t)$ is constant on all $B \in \mathcal{B}_0$, but not constant on any proper super-interval $B' \supset B$, and
- $B \in \mathcal{B}_1$ contains no positive-length subinterval where $f(t)$ is constant.

Lemma 3.4 *For any measure G on $[0, \infty]$, let G^k denote the measure defined by*

$$G^k(A) = G(A)^k,$$

and define

$$E[G] = \int x dG(x).$$

$$I[G] = \int x \log x dG(x)$$

and

$$\psi_k[G] = \int x d(G^k)(x).$$

Then, defining Q_c and c_ι as in Theorem 1, we have

$$\sup_{G: E[G]=1, I[G] \leq \iota} \psi_k[G] = \int_0^1 Q_{c_\iota}(t) t^{k-1} dt.$$

Furthermore, the supremum is attained by a measure G that has cdf equal to Q_c^{-1} , and thus has a density g with respect to Lesbegue measure.

Lemma 3.5 *The map*

$$\iota \rightarrow \int_0^1 Q_{c_\iota}(t) t^{k-1} dt$$

is concave in $\iota > 0$.

Proof of Lemma 3.2. (This will appear in the appendix of the paper.)

The function $h(t) = f(t) - g(t)$ is measurable, since all increasing functions are measurable. Define $A^+ = \{t : f(t) > g(t)\}$ and $A^- = \{t : f(t) < g(t)\}$. Since A^+ and A^- are measurable subsets of \mathbb{R} , they both admit countable partitions consisting of open, closed, or half-open intervals. Let \mathcal{H}^+ be the

collection of all partitions of A^+ consisting of such intervals. There exists a least refined partition \mathcal{A}^+ within \mathcal{H}^+ . Define \mathcal{A}^- analogously, and let

$$\mathcal{A} = \mathcal{A}^+ \cup \mathcal{A}^-$$

and enumerate the elements

$$\mathcal{A} = \{A_i\}_{i=1}^\infty.$$

We claim that the partitions \mathcal{A}^+ and \mathcal{A}^- have the property that for all $t \in A^\pm$, the interval $I \in \mathcal{A}^\pm$ containing t has endpoints $l \leq u$ defined by

$$l = \inf_{x \in [a, b]} \{x : \text{Sign}(h([x, t])) = \{\text{Sign}(h(t))\}\}$$

and

$$u = \sup_{x \in [a, b]} \{x : \text{Sign}(h([t, x])) = \{\text{Sign}(h(t))\}\}.$$

We prove the claim for the partition \mathcal{A}^+ . Take $t \in A^+$ and define l and u as above. It is clear that $(l, u) \in A^+$, and furthermore, there is no $l' < l$ and $u' > u$ such that $(l', x) \in A^+$ or $(x, u') \in A^+$ for any $x \in I$. Let \mathcal{H} be any other partition of A^+ . Some disjoint union of intervals $H_i \in \mathcal{H}$ necessarily covers I for $i = 1, \dots$, and we can further require that none of the H_i are disjoint with I . Since each H_i has nonempty intersection with I , and I is an interval, this implies that $\cup_i H_i$ is also an interval. Let $l'' \leq u''$ be the endpoints of $\cup_i H_i$. Since $I \subseteq \cup_i H_i$, we have $l'' \leq l \leq u \leq u''$. However, since also $I \in A^+$, we must have $l \leq l'' \leq u'' \leq u$. This implies that $l'' = l$ and $u'' = u$. Since $\cup_i H_i = I$, and this holds for any $I \in \mathcal{A}^+$, we conclude that \mathcal{H} is a refinement of \mathcal{A}^+ . The proof of the claim for \mathcal{A}^- is similar.

It remains to show that there are not isolated points in \mathcal{A} , i.e. that for all $I \in \mathcal{A}$ with endpoints $l \leq u$, we have $l < u$. Take $I \in \mathcal{A}$ with endpoints $l \leq u$ and let $t = \frac{l+u}{2}$. By definition, we have $h(t) \neq 0$. Consider the two cases $h(t) > 0$ and $h(t) < 0$.

If $h(t) > 0$, then $t' = g^{-1}(h(t)) > t$, and for all $x \in [t, t']$ we have $h(x) > 0$. Therefore, it follows from definition that $[t, t'] \in I$, and since $l \leq t < t' \leq u$, this implies that $l < u$. The case $h(t) < 0$ is handled similarly. \square

Proof of Lemma 3.3. (This will appear in the appendix of the paper.) To construct the interval, define

$$l(t) = \inf\{x \in [0, 1] : f([x, t]) = \{f(t)\}\}$$

$$u(t) = \sup\{x \in [0, 1] : f([t, x]) = \{f(t)\}\},$$

Let B_0 be the set of all t such that $l(t) < u(t)$, and let B_1 be the set of all t such that $l(t) = t = u(t)$. For all $t \in B_0$, define

$$I(t) = (l(t), u(t)) \cup \{x \in \{l(t), u(t)\} : f(x) = f(t)\}.$$

Then we claim

$$\mathcal{B}_0 = \{I(t) : t \in B_0\}$$

is a countable partition of B_0 . The claim follows since the members of \mathcal{B}_0 are disjoint intervals of nonzero length, and B_0 has finite length. Meanwhile, let \mathcal{B}_1 be a countable partition of B_1 into intervals.

It follows from definition that for any $B \in B_0$, that f is not constant on any proper superinterval $B' \supset B$.

Next, we show that for all $I \in \mathcal{B}_1$, I does not contain a subinterval I' of nonzero length such that f is constant on I' . Suppose to the contrary, we could find such an interval I and subinterval I' . Then for any $t \in I'$, we have $t \in B_0$. However, this implies that $t \notin B_1$, a contradiction.

Therefore, letting $\mathcal{B} = \mathcal{B}_0 \cup \mathcal{B}_1$ yields the desired partition of $[a, b]$.

Proof of Lemma 3.4. (This will appear in the appendix of the paper.)

Consider the quantile function $Q(t) = \inf_{x \in [0, 1]} : G((-\infty, x]) \geq t$. $Q(t)$ must be a monotonically increasing function from $[0, 1]$ to $[0, \infty)$. Let \mathcal{Q} denote the collection of all such quantile functions.

We have

$$E[G] = \int_0^1 Q(t) dt$$

$$\psi_k[G] = \int_0^1 Q(t) x^{k-1} dt.$$

and

$$I[G] = \int_0^1 Q(t) \log Q(t) dt.$$

For any given ι , let P_ι denote the class of probability distributions G on $[0, \infty]$ such that $E[G] = 1$ and $I[G] \leq \iota$. From Markov's inequality, for any $G \in P_\iota$ we have

$$G([x, \infty]) \leq x^{-1}$$

for any $x \geq 0$, hence P_ι is tight. From tightness, we conclude that P_ι is closed under limits with respect to weak convergence. Hence, since ψ_k is a

continuous function, there exists a distribution $G^* \in P_\iota$ which attains the supremum

$$\sup_{G \in P_\iota} \psi_k[G].$$

Let \mathcal{Q}_ι denote the collection of quantile functions of distributions in P_ι . Then, \mathcal{Q}_ι consists of monotonic functions $Q : [0, 1] \rightarrow [0, \infty]$ which satisfy

$$E[Q] = \int_0^1 Q(t) dt = 1,$$

and

$$I[Q] = \int_0^1 Q(t) \log Q(t) dt \leq \iota.$$

Let \mathcal{Q} denote the collection of *all* quantile functions from measures on $[0, \infty]$. And letting Q^* be the quantile function for G^* , we have that Q^* attains the supremum

$$\sup_{Q \in \mathcal{Q}_\iota} \phi_k[Q] = \sup_{Q \in \mathcal{Q}_\iota} \int_0^1 Q(t) t^{k-1} dt.$$

Therefore, there exist Lagrange multipliers $\lambda \geq 0$ and $\nu \leq 0$ such that defining

$$\mathcal{L}[Q] = E[Q] + \lambda \phi_k[Q] + \nu I[Q] = \int_0^1 Q(t) (1 + \lambda \log Q(t) + \nu t^{k-1}) dt,$$

Q^* attains the infimum of $\mathcal{L}[Q]$ over *all* quantile functions,

$$\mathcal{L}[Q^*] = \inf_{Q \in \mathcal{Q}} \mathcal{L}[Q].$$

We now claim that for such λ and ν , we have

$$1 + \lambda + \lambda \log Q(t) + \nu t^{k-1} = 0.$$

Consider a perturbation function $\xi : [0, 1] \rightarrow \mathbb{R}$. We have

$$\mathcal{L}[Q + \xi] \approx \mathcal{L}[Q] + \int_0^1 \xi(t) (1 + \lambda + \lambda \log Q(t) + \nu t^{k-1}) dt$$

for small ξ . Define

$$\nabla Q^*(t) = (1 + \lambda + \lambda \log Q^*(t) + \nu t^{k-1}).$$

The function $\nabla Q^*(t)$ is a *functional derivative* of the Lagrangian. Note that if we were able to show that $\nabla Q^*(t) = 0$, as we might naively expect, this immediately yields

$$Q^*(t) = \exp[-\lambda^{-1} - 1 - \nu\lambda^{-1}t^{k-1}]. \quad (1)$$

However, the reason why we cannot simply assume $\nabla Q^*(t) = 0$ is because the optimization occurs on a constrained space. We will ultimately show that this is the case (up to sets of negligible measure), but some delicacy is needed.

First let us establish some properties of $\nabla Q^*(t)$. If we define $f(t) = 1 + \lambda + \lambda Q^*(t)$ and $g(t) = \nu t^{k-1}$, then f is increasing while g is continuous and strictly increasing. Therefore, as

$$\nabla Q^*(t) = f^+(t) - g(t),$$

we see that $\nabla Q^*(t)$ is a difference between two increasing functions. Therefore, we can apply Lemma 3.2 to conclude that there exists a countable partition \mathcal{A} of the set $A : \{t \in [0, 1] : \nabla Q^*(t) \neq 0\}$ into intervals such that for all $J \in \mathcal{A}$, $|\text{Sign}(\nabla Q^*(J))| = 1$ and $\inf J < \sup J$. Applying Lemma 3.3 we get a countable partition \mathcal{B} of $[0, 1]$ so that each element $J \in \mathcal{B}$ is an interval, and that either $\nabla Q^*(t)$ is constant on J , or J contains no positive-length subinterval where $\nabla Q^*(t)$ is constant.

Now let \mathcal{D} be the refinement of \mathcal{A} obtained by considering all intersections of sets in \mathcal{A} with sets in \mathcal{B} :

$$\mathcal{D} = \{J \cap L : J \in \mathcal{A}, L \in \mathcal{B}\}.$$

It follows that \mathcal{D} is a countable partition of the set A , that each element $D \in \mathcal{D}$ is an interval, with the two properties that that $\nabla Q^*(t)$ has the same sign throughout D , and also $Q^*(t)$ is either constant on D , or D contains no positive-length subinterval where $Q^*(t)$ is constant. Subdivide \mathcal{D} into three disjoint collections:

$$\mathcal{D}_1 = \{J \in \mathcal{D} : |J| = 0\}$$

$$\mathcal{D}_2 = \{J \in \mathcal{D} \setminus \mathcal{D}_1 : |Q^*(J)| = 1\}$$

$$\mathcal{D}_3 = \{J \in \mathcal{D} : \sup Q^*(J) > \inf Q^*(J)\}$$

That is, \mathcal{D}_1 is the set of zero-length intervals in \mathcal{D} , \mathcal{D}_2 is the set of positive-length intervals in \mathcal{D} where Q^* is constant, and \mathcal{D}_3 is the set of positive-length

intervals in \mathcal{D} where Q^* is not constant. Let D_i be the union of the sets in \mathcal{D}_i for $i = 1, 2, 3$.

The rest of the proof proceeds as follows. First, we show that for all $t \in D_3$, we have $\nabla Q^*(t) = 0$. Second, we show that for all $t \in D_2$, we have $\nabla Q^*(t) = 0$. Finally, since D_3 is a set of zero measure, this allows us to conclude that the $Q^*(t) = 0$ on all but a set of zero measure. Since sets of zero measure don't affect the integral, we conclude there exists a global optimal solution with $\nabla Q^*(t) = 0$.

Consider the case $t \in D$ for $D \in \mathcal{D}_3$. Let $a = \inf D$ and $b = \sup D$. Define

$$\xi^+ = I\{t \in D\}(Q(b) - Q(t))$$

and

$$\xi^- = I\{t \in D\}(Q(a) - Q(t)).$$

Observe that $Q + \epsilon\xi^+ \in \mathcal{Q}$ and $Q + \epsilon\xi^- \in \mathcal{Q}$ for any $\epsilon \in [0, 1]$. Now, if $\nabla Q^*(t)$ is strictly positive on D , then for some $\epsilon > 0$ we would have $\mathcal{L}[Q^* + \epsilon\xi^-] < \mathcal{L}[Q^*]$, a contradiction. A similar argument with ξ^+ shows that $\nabla Q^*(t)$ cannot be strictly negative on D either. From this perturbation argument, we conclude that $\nabla Q^*(t) = 0$. Since this argument applies for all $t \in D_3$, we know that $\nabla Q^*(D_3) = \{0\}$.

Without loss of generality, let a and b be the endpoints of the largest interval containing t such that $Q^*(t)$ is constant on (a, b) . Now, since $\nabla Q^*(t) \neq 0$ on a set of nonzero measure within $[a, b]$, it must be the case that there exists some $u \in [a, b]$ such that

$$\int_a^u \nabla Q^*(t) dt \neq 0.$$

If $\int_a^u \nabla Q^*(t) dt > 0$, then define $\xi^+(t) = -I\{t \in (a, u)\}$ (to be contd.)

Remark. More specifically, the supremum is attained by a distribution with density $p_\iota(x, y)$ where

$$p_\iota(x, y) = \begin{cases} g_\iota(y - x) & \text{for } x \geq y \\ g_\iota(1 + y - x) & \text{for } x < y \end{cases}$$

where

$$g_\iota(x) = \frac{d}{dx} G_\iota(x)$$

and G_ι is the inverse of Q_c .

In this case, letting $X_1, \dots, X_k \sim \text{Unif}[0, 1]$, and $Y \sim \text{Unif}[0, 1]$ define $Z_i(y) = p(y|X_i)$. We have $\mathbf{E}(Z(y)) = 1$ and,

$$I[p(x, y)] = \mathbf{E}(Z(Y) \log Z(Y))$$

while

$$\text{ABA}_k[p(x, y)] = k^{-1} \mathbf{E}(\max_i Z_i(Y)).$$

Letting g_y be the density of $Z(y)$, we have

$$I[p(x, y)] = \mathbf{E}(-H[g_Y])$$

and

$$\text{ABA}_k[p(x, y)] = \mathbf{E}(\psi_k[g_Y])$$

where

$$H[g] = - \int g(x) x \log x dx$$

and

$$\psi_k[g] = \int x g(x) G(x)^{k-1} dx$$

for $G(x) = \int_0^x g(t) dt$. Additionally g_y satisfies the constraint $\int x g(x) dx = 1$ since $\mathbf{E}[Z(y)] = 1$.

Define the set $D = \{(\alpha, \beta)\}$ as the set of possible values of $(-H[g], \psi_k[g])$ taken over all distributions g supported on $[0, \infty)$ with $\int x g(x) dx = 1$. Next, let $\mathcal{C}(D)$ denote the convex hull of D . It follows that $(I[p], \text{ABA}_k[p]) \in \mathcal{C}(D)$ since the pair is obtained via a convex average of points $(-H[g_y], \psi_k[g_y])$.

Define the upper envelope of D as the curve

$$d_k(\alpha) = \sup\{\beta : (\alpha, \beta) \in D\}.$$

We make the claim (to be shown in the following section) that $d_k(\alpha)$ is convex in α . As a result, the upper envelope of D is also the upper envelope of $\mathcal{C}(D)$. This in turn implies that $C_k^{unif}(\iota) = d_k(\iota)$. We establish these results, along with a open-form expression for C_k^{unif} , in the following section.

3.1 Variational methods

Consider the quantile function $Q(t) = G^{-1}(t)$. $Q(t)$ must be a continuous function from $[0, 1]$ to $[0, \infty)$. We can rewrite the moment constraint $\mathbf{E}[g] = 1$ as

$$\int_0^1 Q(t) dt = 1.$$

Meanwhile, $\beta = \psi_k[g]$ takes the form

$$\beta = \int_0^1 Q(t) x^{k-1} dt.$$

and $\alpha = -H[g]$ takes the form

$$\alpha = \int_0^1 Q(t) \log Q(t) dt.$$

To find the upper envelope, it will be useful to write the Langrangian

$$\begin{aligned} \mathcal{L}[g] &= \lambda \int_0^1 Q(t) dt + \mu \int_0^1 Q(t) x^{k-1} dt + \lambda \int_0^1 Q(t) \log Q(t) dt \\ &= \int_0^1 Q(t) (\lambda + \mu x^{k-1} + \nu \log Q(t)) dt. \end{aligned}$$

In order for a quantile function $Q(t)$ to be on the upper envelope, it must be a local maximum of $-H$ with respect to small perturbations. Therefore, consider the functional derivative

$$D[\xi] = \lim_{\epsilon \rightarrow 0} \frac{\mathcal{L}[g + \epsilon \xi] - \mathcal{L}[g]}{\epsilon}.$$

We have

$$D[\xi] = \int_0^1 \xi(t) (\lambda + \nu + \mu x^{k-1} + \nu \log Q(t)) dt.$$

Now consider the following three cases:

- $Q(t)$ is strictly monotonic, i.e. $Q'(t) > 0$.
- $Q(t)$ is differentiable but not strongly monotonic:
- $Q(t)$ is not strongly monotonic: there exist intervals $A_i = [a_i, b_i)$ such that $Q(t)$ is constant on A_i , and isolated points t_i where $Q'(t_i) = 0$.

Strictly monotonic case. Because Q is defined on a closed interval, strict monotonicity further implies the property of *strong monotonicity* where $\inf_{[0, 1]} Q'(t) > 0$. Therefore, for any differentiable perturbation $\xi(t)$ with $\sup |\xi'(t)| < \infty$, and further imposing that $\xi(0) \geq 0$ in the case that $Q(0) = 0$, there exists some $\epsilon > 0$ such that $(Q + \epsilon\xi)(t)$ is still a valid quantile function. Therefore, in order for $Q(t)$ to be a local maximum, we must have

$$0 = \lambda + \nu + \mu x^{k-1} + \nu \log Q(t)$$

for $t \in [0, 1]$. This implies that

$$Q(t) = c_0 e^{-c_1 x^{k-1}}$$

for some $c_0, c_1 \geq 0$.

Other cases. (TODO) We have to show that these cannot be local maxima.

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

$$\begin{aligned}
\mathbb{I}[p((x, w), (y, z))] &= \int dx dw dy dz \, p(x, y) p(w|x) p(z|w) \log \frac{p((x, w), (y, z))}{p(x, w) p(y, z)} \\
&= \int dx dw dy dz \, p(x, y) p(w|x) p(z|w) \log \frac{p(x, y) p(w|x) p(z|y)}{p(x) p(y) p(w|x) p(z|y)} \\
&= \int dx dw dy dz \, p(x, y) p(w|x) p(z|w) \log \frac{p(x, y)}{p(x) p(y)} \\
&= \int dx dy \, p(x, y) \log \frac{p(x, y)}{p(x) p(y)} = \mathbb{I}[p(x, y)].
\end{aligned}$$

Also,

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

□

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

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

where for discrete distributions, one defines

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

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

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

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