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

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

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

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

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

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

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:

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

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}.

2.1 Notation

$|\cdot|$ denotes set cardinality.

3 Theory

In this section we determine the value of $C_k(\iota)$, leading to 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,

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

We obtain this result by first reducing the problem to the case of densities with uniform marginals, then doing the optimization over the reduced space.

3.1 Reduction

Let $p(x, y)$ be a density supported on $\mathcal{X} \times \mathcal{Y}$, where $\mathcal{X}$ is a subset of $\mathbb{R}^{d_1}$ and $\mathcal{Y}$ is a subset of $\mathbb{R}^{d_2}$, and such that $p(x)$ is uniform on $\mathcal{X}$ and $p(y)$ is uniform on $\mathcal{Y}$.

Now let $\mathcal{P}^{unif}$ denote the set of such distributions: in other words, $\mathcal{P}^{unif}$ is the space of joint densities in Euclidean space with uniform marginals over the marginal supports. In this section, we prove that

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

thus reducing the problem of optimizing over the space of all densities to the problem of optimizing over densities with uniform marginals.

Also define $\mathcal{P}^{bounded}$ to be the space of all densities $p(x, y)$ with finite-volume support. Since uniform distributions can only be defined over sets of finite volume, we have

$$\mathcal{P}^{unif} \subset \mathcal{P}^{bounded} \subset \mathcal{P}.$$

Therefore, it is necessary to first show that

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

This is accomplished via the following lemma.

Lemma 3.2 *(Truncation). Let $p(x,y)$ be a density on $\mathbb{R}^{d_x} \times \mathbb{R}^{d_y}$. For all $\epsilon > 0$, there exists a subset $\mathcal{X} \subset \mathbb{R}^{d_x}$ with finite volume with respect to d_x-dimensional Lesbegue measure, and a subset $\mathcal{Y} \subset \mathbb{R}^{d_y}$ with finite volume with respect to d_y-dimensional Lesbegue measure, such that defining*

$$\tilde{p}(x,y) = \frac{I\{(x,y) \in \mathcal{X} \times \mathcal{Y}\}}{\int_{\mathcal{X} \times \mathcal{Y}} p(x,y) dx dy} p(x,y),$$

we have

$$|I[p] - I[\tilde{p}]| < \epsilon$$

and

$$|ABA_k[p] - ABA_k[\tilde{p}]| < \epsilon.$$

Proof. Recall the definition of the Shannon entropy H:

$$\mathrm{H}[p(x)] = -\int p(x) \log p(x) dx.$$

It is a well-known in information theory that

$$\mathrm{I}[p(x,y)] = \mathrm{H}[p(x)] + \mathrm{H}[p(y)] - \mathrm{H}[p(x,y)].$$

There exists a sequence $(\mathcal{X}_i, \mathcal{Y}_i)_{i=1}^\infty$ where $(\mathcal{X}_i)_{i=1}^\infty$ is an increasing sequence of finite-volume subsets of $\mathbb{R}^{d_x}$ and $(\mathcal{Y}_i)_{i=1}^\infty$ is an increasing sequence of finite-volume subsets of $\mathbb{R}^{d_y}$, and $\lim_{i \to \infty} \mathcal{X}_i = \mathbb{R}^{d_x}$, $\lim_{i \to \infty} \mathcal{Y}_j$. Define

$$\tilde{p}_i(x,y) = \frac{I\{(x,y) \in \mathcal{X}_i \times \mathcal{Y}_i\}}{\int_{\mathcal{X}_i \times \mathcal{Y}_i} p(x,y) dx dy} p(x,y)$$

Note that $\tilde{p}_i$ gives the conditional distribution of (X,Y) conditional on $(X,Y) \in \mathcal{X}_i \times \mathcal{Y}_i$. Furthermore, it is convenient to define $\tilde{p}_\infty = p$. We can find some i_1, such that for all $i \geq i_1$, we have

$$\left| \int_{x \notin \mathcal{X}_i} p(x) \log p(x) dx \right| < \frac{\epsilon}{6}$$

$$\left| \int_{y \notin \mathcal{Y}_i} p(y) \log p(y) dy \right| < \frac{\epsilon}{6}$$

$$\left| \int_{(x,y) \notin \mathcal{X}_i \times \mathcal{Y}_i} p(x,y) \log p(x,y) dx dy \right| < \frac{\epsilon}{6}$$

and also such that

$$-\log \left[\int_{x,y \in \mathcal{X}_i \times \mathcal{Y}_i} p(x,y) dx dy \right] < \frac{\epsilon}{2}$$

Then, it follows that

$$|\mathrm{I}[p] - \mathrm{I}[\tilde{p}_i]| < \epsilon$$

for all $i \geq i_1$.

Now we turn to the analysis of average Bayes error. Let f_i denote the Bayes k-class classifier for $\tilde{p}_i(x,y)$ and f_∞ the Bayes k-class classifier for $p(x,y)$: recall that by definition,

$$\mathrm{ABA}_k[\tilde{p}_i] = \Pr_{\tilde{p}_i}[f_i(X_1, ..., X_k, Y) = Z]$$

Define

$$\epsilon_i = \Pr_p[(X_1, ..., X_k, Y) \notin \mathcal{X}_i^k \times \mathcal{Y}_i];$$

by continuity of probability we have $\lim_i \epsilon_i \to 0$. We claim that

$$|\mathrm{ABA}_k[\tilde{p}_i] - \mathrm{ABA}_k[p]| \leq \epsilon_i.$$

Given the claim, the proof is completed by finding $i > i_1$ such that $\epsilon_i < \epsilon$, and defining $\mathcal{X} = \mathcal{X}_i$, $\mathcal{Y} = \mathcal{Y}_i$.

Consider using f_i to obtain a classification rule for $p(x,y)$: define

$$\tilde{f}_i = \begin{cases} f_i(x_1, ..., x_k, y) & \text{when } (x_1, ..., x_k, y) \in \mathcal{X}_i^k \times \mathcal{Y} \\ 0 & \text{otherwise.} \end{cases}$$

We have

$$
\begin{aligned}
\mathrm{ABA}_k[p] =& \sup_f \Pr_p[f(X_1, ..., X_k, Y) = Z] \\
\geq& \\
=&(1 - \epsilon_i) \Pr_p[f_i(X_1, ..., X_k, Y) = Z | (X_1, ..., X_k, Y) \in \mathcal{X}_i^k \times \mathcal{Y}_i] \\
&+ \epsilon_i \Pr_p[f_i(X_1, ..., X_k, Y) = Z | (X_1, ..., X_k, Y) \notin \mathcal{X}_i^k \times \mathcal{Y}_i] \\
=&(1 - \epsilon_i) \Pr_{\tilde{p}}[f_i(X_1, ..., X_k, Y) = Z] + \epsilon_i 0 \\
=&(1 - \epsilon_i)\mathrm{ABA}_k[\tilde{p}_i] \geq \mathrm{ABA}_k[\tilde{p}_i] - \epsilon_i.
\end{aligned}
$$

In other words, when $\tilde{p}_i$ is close to p, the Bayes classification rule for $\tilde{p}_i$ obtains close to the Bayes rate when the data is generated under p.

Now consider the reverse scenario of using f_p to perform classification under $\tilde{p}_i$. This is equivalent to generating data under $p(x, y)$, performing classification using f, then only evaluating classification accuracy conditional on $(X_1, ..., X_k, Y) \in \mathcal{X}_i^k \times \mathcal{Y}_i$. Therefore,

$$
\begin{aligned}
\mathrm{ABA}_k[\tilde{p}_i] =& \sup_f \Pr_{\tilde{p}_i}[f(X_1, ..., X_k, Y) = Z] \\
\geq& \Pr_{\tilde{p}_i}[f_p(X_1, ..., X_k, Y) = Z] \\
=& \Pr_p[f_p(X_1, ..., X_k, Y) = Z | (X_1, ..., X_k, Y) \in \mathcal{X}_i^k \times \mathcal{Y}_i] \\
=& \frac{1}{1 - \epsilon_i} \Pr_p[I\{(X_1, ..., X_k, Y) \in \mathcal{X}_i^k \times \mathcal{Y}_i\} \text{ and } f_p(X_1, ..., X_k, Y) = Z] \\
\geq& \frac{1}{1 - \epsilon_i} \left(1 - \Pr_p[I\{(X_1, ..., X_k, Y) \notin \mathcal{X}_i^k \times \mathcal{Y}_i\}] - \Pr_p[f_p(X_1, ..., X_k, Y) \neq Z]\right) \\
=& \frac{\mathrm{ABA}_k[p] - \epsilon_i}{1 - \epsilon_i} \geq \mathrm{ABA}_k[p] - \epsilon_i.
\end{aligned}
$$

In other words, when $\tilde{p}_i$ is close to p, the Bayes classification rule for p obtains close to the Bayes rate when the data is generated under $\tilde{p}_i$.

Combining the two directions gives $|\mathrm{ABA}_k[\tilde{p}_i] - \mathrm{ABA}_k[p]| \leq \epsilon_i$, as claimed.
□

One can go from bounded-volume sets to uniform distributions by adding auxillary variables. To illustrate the intution, consider a density $p(x)$ on a set of bounded volume, $\mathcal{X}$. Introduce a variable W such that conditional on $X = x$, we have w uniform on $[0, p(x)]$. It follows that the joint density $p(x, w) = 1$ and is supported on a set $\mathcal{X}' = \mathcal{X} \times [0, \infty]$. Furthermore, $\mathcal{X}'$ is of bounded volume (in fact, of volume 1) since

$$\int_{\mathcal{X}'} dx = \int_{\mathcal{X}'} p(x, w) dx = 1.$$

Therefore, to accomplish the reduction from $\mathcal{P}$ to $\mathcal{P}^{unif}$, we start with a density $p(x, y) \in \mathcal{P}$, and using Lemma 3.2, find a suitable finite-volume truncation $\tilde{p}(x, y)$. Finally, we introduce auxillary variables w and z so that the expanded joint distribution $p(x, w, y, z)$ has uniform marginals $p(x, w)$ and $p(y, z)$. However, we still need to check that the introduction of auxillary variables preserves the mutual information and average Bayes error; this is the content of the next lemma.

Lemma 3.3 *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,*

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

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,

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

□

Combining these lemmas gives the needed reduction, given by the following theorem.

Theorem 3.4 *(Reduction.)*

$$\inf_{p\in\mathcal{P}:I[p(x,y)]\le\iota} ABA_k[p(x,y)] = \inf_{p\in\mathcal{P}^{unif}:I[p(x,y)]\le\iota} ABA_k[p(x,y)].$$

The proof is trivial given the previous two lemmas.

3.2 Optimization

Having reduced the problem to an optimization over $\mathcal{P}^{unif}$, in this section we use variational calculus to find the global optimum to the optimization problem

$$\text{maximize}_{p\in\mathcal{P}^{unif}:\mathrm{I}[p(x,y)]\le\iota}\mathrm{ABA}_k[p(x,y)]$$

The proof depends on the following lemmas.

Lemma 3.5 *Let $f(t)$ be an increasing function from $[a,b]\to\mathbb{R}$, where $a<b$, and let $g(t)$ be a bounded continuous function from $[a,b]\to\mathbb{R}$. 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 3.6 *Let $f(t)$ be a measurable function from $[a,b] \to \mathbb{R}$, 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 3.7 *Define an exponential family on $[0,1]$ by the density function*

$$q_\beta(t) = \exp[\beta t^{k-1} - \log Z(\beta)]$$

where

$$Z(\beta) = \int_0^1 \exp[\beta t^{k-1}] dt.$$

Then, the negative entropy

$$I(\beta) = \int_0^1 q_\beta(t) \log q_\beta(t) dt$$

is decreasing in β on the interval $(-\infty, 0]$. and increasing on the interval $[0, \infty)$.

Furthermore, for any $\iota \in (0, \infty)$, there exist two solutions to $I(\beta) = \iota$: one positive and one negative.

Lemma 3.8 *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 3.9 *The map*

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

is concave in $\iota > 0$.

Proof of Lemma 3.5. (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 the property that for all $t \in A^\pm$, ther 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 $i = 1, ...,$ 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 3.6. (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. It follows from definition that for any $B \in B_0$, that f is not constant on any proper superinterval $B' \supset B$.

Meanwhile, let $\mathcal{B}_1$ be a countable partition of B_1 into intervals.

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.

Since $t \in [a, b]$ belongs to either B_0 or B_1, letting $\mathcal{B} = \mathcal{B}_0 \cup \mathcal{B}_1$ yields the desired partition of $[a, b]$. $\square$.

Proof of Lemma 3.7.

Define $\beta(\mu)$ as the solution to

$$\mu = \int_0^1 t q_\beta(t) dt.$$

By [Wainwright and Jordan 2008], the function $\beta(\mu)$ is well-defined. Furthermore, since the sufficient statistic t^{k-1} is increasing in t, it follows that $\beta(\mu)$ is increasing.

Define the negative entropy as a function of μ,

$$N(\mu) = \int_0^1 q_{\beta(\mu)}(t) \log q_{\beta(\mu)}(t) dt.$$

By Theorem 3.4 of [Wainwright and Jordan 2008], $N(\mu)$ is convex in μ. We claim that the derivative of $N(\mu) = 0$ at $\mu = \frac{1}{2}$. This implies that $N(\mu)$ is decreasing in μ for $\mu \leq \frac{1}{2}$ and increasing for $\mu \geq \frac{1}{2}$. Since $I(\beta(\mu)) = N(\mu)$, β is increasing in μ, and $\beta(\frac{1}{2}) = 0$, this implies that $I(\beta)$ is decreasing in β for $\beta \leq 0$ and increasing for $\beta \geq 0$.

We will now prove the claim. Write

$$\frac{d}{d\mu} N(\mu)\bigg|_{\mu=1/2} = \frac{d}{d\beta} I(\beta(\mu))\bigg|_{\beta=0} \frac{d\beta}{d\mu}\bigg|_{\mu=1/2}.$$

We have

$$\frac{d}{d\beta} I(\beta) = \beta \int q_\beta t^{k-1} dt - \log Z(\beta).$$

Meanwhile, $Z(0) = 1$ so $\log Z(0) = 0$. Therefore,

$$\frac{d}{d\beta} I(\beta)\bigg|_{\beta=0} = 0.$$

This implies that $\frac{d}{d\mu} N(\mu)|_{\mu=1/2} = 0$, as needed.

For the final statement of the lemma, note that $I(0) = 0$ since q_0 is the uniform distribution. Meanwhile, since q_β tends to a point mass as either $\beta \to \infty$ or $\beta \to -\infty$, we have

$$\lim_{\beta\to\infty} I(\beta) = \lim_{\beta\to-\infty} I(\beta) = \infty.$$

And, as we can check that $I(\beta)$ is continuous in β, this means that

$$I((-\infty,0]) = I([0,\infty)) = [0,\infty)$$

by the mean-value theorem. Combining this fact with the monotonicity of $I(\beta)$ restricted to either the positive and negative half-line yields the fact that for any $\iota > 0$, there exists $\beta_1 < 0 < \beta_2$ such that $I(\beta_1) = I(\beta_2) = \iota$. $\Box$.

Proof of Lemma 3.8. (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 $\mathcal{Q}_\iota$ denote the collection of quantile functions of distributions in P_ι. Then, $\mathcal{Q}_\iota$ consists of monotonic functions $Q : [0,1] \to [0,\infty]$ 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

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

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

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

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

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

The global minimizer Q^* is also necessarily a stationary point: that is, for any perturbation function $\xi : [0, 1] \to \mathbb{R}$ such that $Q^* + \xi \in \mathcal{Q}$, we have $\mathcal{L}[Q^*] \leq \mathcal{L}[Q^* + \xi]$. For sufficiently small ξ, we have

$$\mathcal{L}[Q + \xi] \approx \mathcal{L}[Q] + \int_0^1 \xi(t)(-t^{k-1} + \lambda + \nu + \nu \log Q(t))dt. \tag{2}$$

Define

$$\nabla \mathcal{L}_{Q^*}(t) = -t^{k-1} + \lambda + \nu + \nu \log Q(t). \tag{3}$$

The function $\nabla \mathcal{L}_{Q^*}(t)$ is a *functional derivative* of the Lagrangian. Note that if we were able to show that $\nabla \mathcal{L}_{Q^*}(t) = 0$, this immediately yields

$$Q^*(t) = \exp[-1 - \lambda \nu^{-1} + \nu^{-1} t^{k-1}]. \tag{4}$$

At this point, we know that the right-hand side of (4) gives a stationary point of $\mathcal{L}$, but we cannot be sure that it gives the global minimzer. The reason is because the optimization occurs on a constrained space. We will show that (4) indeed gives the global minimizer Q^*, but we do so by showing that the set of points t where $\nabla \mathcal{L}_{Q^*}(t) \neq 0$ is of zero measure. Since sets of zero measure don't affect the integrals defining the optimization problem (1), we conclude there exists a global optimal solution with $\nabla \mathcal{L}_{Q^*}(t) = 0$ everywhere, which is therefore given explicitly by (4) for some $\lambda \in \mathbb{R}$, $\nu \geq 0$.

We will need the following result: that for $\iota > 0$, any solution to (1) satisfies $\phi_k[Q] < 1$. This follows from the fact that

$$E[Q] - \phi_k[Q] = \int_0^1 (1 - t^{k-1}) Q(t) dt,$$

where the term $(1 - t^{k-1})$ is negative, except for the one point $t = 1$. Therefore, in order for $\phi_k[Q] = 1 = E[Q]$, we must have $Q(t) = 0$ for $t < 1$. However, this yields a contradiction since $Q(t) = 0$ for $t < 1$ implies that $E[Q] = 0$, a violation of the hard constraint $E[Q] = 1$.

Let us establish that $\nu > 0$: in other words, the constraint $I[Q] = \iota$ is tight. Suppose to the contrary, that for some $\iota > 0$, the global optimum Q^* minimizes a Lagrangian with $\nu = 0$. Let $\phi^* = \phi_k[Q^*] < 1$. However, if we define $Q_\kappa(t) = I\{t \geq 1 - \frac{1}{\kappa}\}\kappa$, we have $E[Q_\kappa] = 1$, and also for some sufficiently large $\kappa > 0$, $\phi_k[Q_\kappa] > \phi^*$. But since the Lagrangian lacks a term corresponding to $I[Q]$, we conclude that $\mathcal{L}[Q_\kappa] < \mathcal{L}[Q^*]$, a contradiction.

The rest of the proof proceeds as follows. We will use Lemmas 3.5 and 3.6 to define a decomposition $A = D_0 \cup D_1 \cup D_2$, where D_2 is of measure zero. First, we show that assuming the existence of $t \in D_0$ yields a contradiction, and hence $D_0 = \emptyset$. Then, again using argument from contradiction we establish that $D_1 = \emptyset$. Finally, since D_2 is a set of zero measure, this allows us to conclude that the $Q^*(t) = 0$ on all but a set of zero measure.

We will now apply the Lemmas to obtain the necessary ingredients for constructing the sets D_i. Since $\nabla \mathcal{L}_{Q^*}(t)$ is a difference between an increasing function and a continuous stricly increasing function, we can apply Lemma 3.5 to conclude that there exists a countable partition $\mathcal{A}$ of the set $A : \{t \in [0,1] : \nabla \mathcal{L}_{Q^*}(t) \neq 0\}$ into intervals such that for all $J \in \mathcal{A}$, $|\text{Sign}(\nabla Q^*(J))| = 1$ and $\inf J < \sup I$. Applying Lemma 3.6 we get a countable partition $\mathcal{B} = \mathcal{B}_0 \cup \mathcal{B}_1$ of $[0,1]$ so that each element $J \in \mathcal{B}_0$ is an interval such that $\nabla \mathcal{L}_{Q^*}(t)$ is constant on J, and furthermore is not properly contained in any interval with the same property, and each element $J \in \mathcal{B}_1$ is an interval, such that J contains no positive-length subinterval where $\nabla \mathcal{L}_{Q^*}(t)$ is constant. Also define B_i as the union of the sets in $\mathcal{B}_i$ for $i = 0, 1$.

Note that B_0 is necessarily a subset of A. That is because if $\nabla \mathcal{L}_{Q^*}(t) = 0$ on any interval J, then that $Q^*(t)$ is necessarily not constant on the interval.

We will construct a new countable partition of A, called $\mathcal{D}$. The partition $\mathcal{D}$ is constructed by taking the union of three families of intervals,

$$\mathcal{D} = \mathcal{D}_0 \cup \mathcal{D}_1 \cup \mathcal{D}_2.$$

Define D_i to be the union of intervals in $\mathcal{D}_i$ for $i = 0, 1, 2$.

Define $\mathcal{D}_0 = \mathcal{B}_0$, Define a countable partition $\mathcal{D}_1$ by

$$\mathcal{D}_1 = \{J \cap L : J \in \mathcal{A}, L \in \mathcal{B}_1, \text{ and } |L| > 1\},$$

in order words, $\mathcal{D}_1$ consists of positive-length intervals where $\nabla Q^*(t)$ is entirely positive or negative and is not constant. Define

$$\mathcal{D}_2 = \{J \in \mathcal{B}_1 : J \subset A \text{ and } |J| = 1\},$$

i.e. $\mathcal{D}_2$ consists of isolated points in A.

One verifies that $\mathcal{D}$ is indeed a partition of A by checking that $D_0 = B_0$, $D_1 \cup D_2 = B_1 \cap A$, so that $D_0 \cup D_2 \cup D_2 = A$: it is also easy to check that elements of $\mathcal{D}$ are disjoint. Furthermore, as we mentioned earlier, the set D_2 is indeed of zero measure, since it consists of countably many isolated points.

Now we will show that the existence of $t \in D_0$ implies a contradiction. Take $t \in D$ for $D \in \mathcal{D}_0$, and 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 $\nabla\mathcal{L}_{Q^*}(t)$ 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 $\nabla\mathcal{L}_{Q^*}(t)$ cannot be strictly negative on D either. From this pertubation argument, we conclude that $\nabla\mathcal{L}_{Q^*}(t) = 0$. Since this argument applies for all $t \in D_0$, we conclude that $D_0 = \emptyset$: therefore, on the set $[0, 1] \setminus (D_1 \cup D_2)$, we have $\nabla\mathcal{L}_{Q^*}(t) = 0$.

The following observation is needed for the next stage of the proof. If we look at the function $Q^*(t)$, then up so sets of neglible measure, it is given by the expression (4) on the set $[0, 1] \setminus D_1$, and it is piecewise constant in-between. But since (4) gives a strictly increasing function, and since Q^* is increasing, this implies that Q^* is discontinuous at the boundary of D_1.

Now we are prepared to show that $\nabla\mathcal{L}_{Q^*}(t) = 0$ for $t \in D_1$. Take $t \in D$ for $D \in \mathcal{D}_1$, and let $a = \inf D$ and $b = \sup D$. From the previous argument, there is a discontinuity at both a and b, so that $\lim_{u \to a^-} Q(u) < Q(t) < \lim_{u \to b^+} Q(u)$. Therefore, for any $\xi(t)$ which is increasing on D and zero elsewhere, there exists $\epsilon > 0$ such that $\nabla Q^* + \epsilon\xi \in \mathcal{Q}$. It remains to find such a perturbation ξ such that $\mathcal{L}[Q + \epsilon\xi] < \mathcal{L}[Q]$.

Also, since by definition $\nabla \mathcal{L}_{Q^*}(t)$ is constant on D, follows from(3) that ∇Q^* is strictly decreasing, and thus either

- Case 1: $\nabla \mathcal{L}_{Q^*}(t) \geq 0$ on D,
- Case 2: $\nabla \mathcal{L}_{Q^*}(t) \leq 0$ on D, or
- Case 3: $\nabla \mathcal{L}_{Q^*}(t) \geq 0$ for all $t \in D \cap [a, t_0]$ and $\nabla \mathcal{L}_{Q^*}(t) \leq 0$ for all $t \in D \cap [t_0, b]$.

Depending on the case, we construct a suitable perturbation ξ:

- Case 1: Construct $\xi(t) = -I\{t \in D\}$.
- Case 2: Construct $\xi(t) = I\{t \in D\}$
- Case 2: Construct

$$\xi(t) = \begin{cases} -1 & \text{for } t \in D \cap [a, t_0], \\ 0 & \text{otherwise.} \end{cases}$$

In all three cases, given the corresponding construction for $\xi(t)$ we get

$$\int_0^1 \xi(t) \nabla \mathcal{L}_{Q^*}(t) dt < 0.$$

Therefore, from (2), there exists some $\epsilon > 0$ such that $\mathcal{L}[Q + \epsilon\xi] < \mathcal{L}[Q]$, a contradiction. Again, since the contradiction applies for all $t \in D_1$, we conclude that $D_1 = \emptyset$.

By now we have established that a global optimum for (1) exists, and is given by (4) for some $\lambda \in \mathbb{R}$, $\nu > 0$. It remains to determine the values of λ and ν.

Reparameterize $\alpha = \exp[-1 - \lambda\nu^{-1}]$ and $\beta = \nu^{-1}$. Therefore,

$$Q^*(t) = \alpha \exp[\beta t^{k-1}]$$

for $\alpha > 0$, $\beta > 0$. There is a one-to-one mapping from $(\alpha, \beta) \in (0, \infty)^2$ to $(\lambda, \nu) \in \mathbb{R} \times (0, \infty)$.

Now, from the constraint

$$1 = E[Q^*] = \int_0^1 \alpha \exp[\beta t^{k-1}] dt.$$

we conclude that

$$\alpha = \frac{1}{\int_0^1 \exp[\beta t^{k-1}] dt.}$$

Therefore, we have reduced the set of possible solutions Q^* to a one-parameter family,

$$Q^*(t) = \frac{\exp[\beta t^{k-1}]}{Z(\beta)}.$$

where

$$Z(\beta) = \int_0^1 \exp[\beta t^{k-1}] dt.$$

Next, note that

$$I[Q^*] = \int_0^1 Q^*(t) \log Q^*(t) = \beta \mu_\beta - \log Z(\beta),$$

as a function of β, is completely characterized by Lemma 3.7. Let us define c_ι as the unique positive solution to the equation

$$c_\iota \mu_{c_\iota} - \log Z(c_\iota) = \iota$$

given by Lemma 3.7. We therefore have

$$Q^*(t) = \frac{\exp[c_\iota t^{k-1}]}{\int_0^1 \exp[c_\iota t^{k-1}]},$$

as needed. □

Proof of Lemma 3.9. It is equivalent to show that the inverse function

$$C_k^{-1}(p) = \inf_{G: E[G]=1, \phi_k[G]=p} I[G]$$

is convex. Let $p_1, p_2 \in [0, 1]$. From lemma 3.8, we can find measures G_1, G_2 on $[0, \infty)$ which minimize $I[G_i]$ subject to $E[G_i] = 1$ and $\phi_k[G_i] = p_i$. Define the measure

$$H = \frac{G_1 + G_2}{2}.$$

Since ϕ_k is a linear functional,

$$\phi_k[H] = \frac{\phi_k[G_1] + \phi_k[G_2]}{2} = \frac{p_1 + p_2}{2}.$$

But since I is a convex functional,

$$I[H] \leq \frac{I[G_1] + I[G_2]}{2}.$$

Therefore,

$$C_k^{-1}\left(\frac{p_1 + p_2}{2}\right) \leq I[H] = \frac{I[G_1] + I[G_2]}{2} = \frac{C_k^{-1}(p_1) + C_k^{-1}(p_2)}{2}.$$

$\square$.

Proof of theorem 3.1

Using Theorem 3.4, we have

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

Define $f(\iota) = \int_0^1 Q_{c_\iota}(t) t^{k-1} dt$: our goal is to establish that $C_k(\iota) = f(\iota)$. Note that $f(\iota)$ is the same function which appears in Lemma 3.9 and the same bound as established in Lemma 3.8.

Define the 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.

One can verify that $\mathrm{I}[p_\iota] = \iota$, and

$$\mathrm{ABA}_k[p] = \int_0^1 Q_{c_\iota}(t) t^{k-1} dt.$$

This establishes that

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

It remains to show that for all $p \in \mathcal{P}^{unif}$ with $\mathrm{I}[p] \leq \iota$, that $\mathrm{ABA}_k[p] \leq \mathrm{ABA}_k[p_\iota]$.

Take $p \in \mathcal{P}^{unif}$ such that $\mathrm{I}[p] \leq \iota$. Letting $X_1, ..., X_k \sim \mathrm{Unif}[0,1]$, and $Y \sim \mathrm{Unif}[0,1]$ define $Z_i(y) = p(y|X_i)$. We have $\mathbf{E}(Z(y)) = 1$ and,

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

while

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

Letting G_y be the distribution of $Z(y)$, we have

$$E[G_y] = 1$$

$$\mathrm{I}[p(x,y)] = \mathbf{E}(I[G_Y])$$
$$\mathrm{ABA}_k[p(x,y)] = \mathbf{E}(\psi_k[G_Y])$$

where the expectation is taken over $Y \sim \mathrm{Unif}[0,1]$ and where $E[G]$, $I[G]$, and $\psi_k[G]$ are defined as in Lemma 3.8.

Define the random variable $J = I[G_Y]$. We have

$$\begin{aligned}
\mathrm{ABA}_k[p(x,y)] &= \mathbf{E}(\psi_k[G_Y]) \\
&= \int_0^1 \psi_k[G_y] dy \\
&\leq \int_0^1 \left(\sup_{G: I[G] \leq I[G_y]} \psi_k[G] \right) dy \\
&= \int_0^1 f(I[G_y]) dy = \mathbf{E}[f(J)].
\end{aligned}$$

Now, since f is concave by Lemma 3.9, we can apply Jensen's inequality to conclude that

$$\mathrm{ABA}_k[p(x,y)] = \mathbf{E}[f(J)] \leq f(\mathbf{E}[J]) = f(\iota),$$

which completes the proof. □

Appendix

3.3 Computation

Noting that Q_β in theorem 3.1 defines an exponential family on $[0,1]$, we obtain the following result:

$$C_k(\iota) = \sup_{\beta:\mathrm{I}^{(k)}(\beta)=\iota} \mathrm{ABA}^{(k)}(\beta)$$

where

$$\mathrm{I}^{(k)}(\beta) = \beta\dot{\Lambda}^{(k)}(\beta) - \Lambda^{(k)}(\beta)$$

and

$$\mathrm{ABA}^{(k)}(\beta) = \dot{(\Lambda)}^{(k)}(\beta)$$

for

$$\Lambda^{(k)}(\beta) = \log\int_0^1 \exp[\beta t^{k-1}]dt.$$

Therefore, computing $C_k(\iota)$ depends in turn on computing $\Lambda^{(k)}(\beta)$ and its first derivative.

The following result provides a rapidly converging power series for $\Lambda^{(k)}(\beta)$ and also a limiting result which facilitates large-k approximation.

Theorem 3.10

$$\Lambda^{(k)}(\beta) = \log\sum_{j=0}^{\infty}\frac{\beta^j}{j!(j+\frac{1}{k-1})} - \log(k-1)$$

and therefore,

$$\lim_{k\to\infty}(k-1)(\exp(\Lambda^{(k)})-1) = W(\beta),$$

where

$$W(\beta) = \sum_{j=1}^{\infty}\frac{\beta^j}{j!j}.$$

Proof. Write

$$
\begin{aligned}
(k-1)(e^{\Lambda^{(k)}(\beta)}-1) &= (k-1)(\int_0^1 \exp(\beta t^{k-1})dt - 1) \\
&= (k-1)\left(\int_0^1 \sum_{j=0}^{\infty} \frac{\beta^j t^{j(k-1)}}{j!} dt - 1\right) \\
&= (k-1)\left(\sum_{j=0}^{\infty} \int_0^1 \frac{\beta^j t^{j(k-1)}}{j!} dt - 1\right) \\
&= (k-1)\left(\sum_{j=0}^{\infty} \frac{\beta^j}{j!(j(k-1)+1)} dt - 1\right) \\
&= \left(\sum_{j=0}^{\infty} \frac{\beta^j}{j!(j+\frac{1}{k-1})} dt - (k-1)\right) \\
&= \sum_{j=1}^{\infty} \frac{\beta^j}{j!(j+\frac{1}{k-1})} dt.
\end{aligned}
$$

Taking the limit as $k \to \infty$ yields the stated formula for $W(\beta)$. $\square$