# An Inequality for Logarithms and Applications in Information Theory 

S. S. Dragomir<br>School of Communications and Informatics<br>Victoria University of Technology<br>P.O. Box 14428, Melbourne City MC, Victoria 8001, Australia<br>sever@matilda.vut.edu.au<br>N. M. Dragomir<br>Department of Mathematics<br>University of Transkei, Private Bag X1, UNITRA<br>Umtata, 5117, South Africa<br>K. Pranesh<br>Department of Statistics<br>University of Transkei, Private Bag X1, UNITRA<br>Umtata, 5117, South Africa

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#### Abstract

A new analytic inequality for logarithms which provides a converse to arithmetic meangeometric mean inequality and its applications in information theory are given. © 1999 Elsevier Science Ltd. All rights reserved.


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## 1. INTRODUCTION

The present paper continues the investigations started in [1], where the main result is the following.

Theorem 1.1. Let $\xi_{k} \in(0, \infty), p_{k}>0, k=1, \ldots, n$ with $\sum_{k=1}^{n} p_{k}=1$ and $b>1$. Then

$$
\begin{align*}
0 & \leq \log _{b}\left(\sum_{k=1}^{n} p_{k} \xi_{k}\right)-\sum_{k=1}^{n} p_{k} \log _{b} \xi_{k} \\
& \leq \frac{1}{2 \ln b} \sum_{k, i=1}^{n} \frac{p_{k} p_{i}}{\xi_{k} \xi_{i}}\left(\xi_{i}-\xi_{k}\right)^{2} . \tag{1.1}
\end{align*}
$$

The equality holds in both inequalities simultaneously if and only if $\xi_{1}=\cdots=\xi_{n}$.

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## 2. A NEW ANALYTIC INEQUALITY FOR LOGARITHMS

We shall start to the following analytic inequality for logarithms which provides a different bound than the inequality of (1.1).
Theorem 2.1. Let $\xi_{k} \in[1, \infty)$ and $p_{k}>0$ with $\sum_{k=1}^{n} p_{k}=1$ and $b>1$. Then we have

$$
\begin{align*}
0 & \leq \log _{b}\left(\sum_{k=1}^{n} p_{k} \xi_{k}\right)-\sum_{k=1}^{n} p_{k} \log _{b} \xi_{k} \\
& \leq \frac{1}{4 \ln b} \sum_{i, j=1}^{n} p_{i} p_{j}\left(\xi_{i}-\xi_{j}\right)^{2} . \tag{2.1}
\end{align*}
$$

The equality holds in both inequalities simultaneously if and only if $\xi_{1}=\cdots=\xi_{n}$.
Proof. We shall use the well-known Jensen's discrete inequality for convex mappings which states that

$$
\begin{equation*}
f\left(\sum_{i=1}^{n} p_{i} x_{i}\right) \leq \sum_{i=1}^{n} p_{i} f\left(x_{i}\right), \tag{2.2}
\end{equation*}
$$

for all $p_{i}>0, \sum_{i=1}^{n} p_{i}=1, f$ a convex mapping on a given interval $I$ and $x_{i} \in I(i=1, \ldots, n)$.
Now, let consider the mapping $f:[1, \infty) \rightarrow \mathbf{R}, f(x)=x^{2} / 2+\ln x$. Then

$$
f^{\prime}(x)=x+\frac{1}{x}=\frac{x^{2}+1}{x}, \quad \text { for all } x \in[1, \infty)
$$

and

$$
f^{\prime \prime}(x)=1-\frac{1}{x^{2}}=\frac{x^{2}-1}{x^{2}}, \quad \text { for all } x \in[1, \infty)
$$

i.e., $f$ is a strictly convex mapping on $[1, \infty)$.

Applying Jensen's discrete inequality for convex mappings, we have

$$
\begin{equation*}
\frac{1}{2}\left(\sum_{i=1}^{n} p_{i} \xi_{i}\right)^{2}+\ln \left(\sum_{i=1}^{n} p_{i} \xi_{i}\right) \leq \frac{1}{2} \sum_{i=1}^{n} p_{i} \xi_{i}^{2}+\sum_{i=1}^{n} p_{i} \ln \xi_{i} \tag{2.3}
\end{equation*}
$$

which is equivalent to

$$
\ln \left(\sum_{i=1}^{n} p_{i} \xi_{i}\right)-\sum_{i=1}^{n} p_{i} \ln \xi_{i} \leq \frac{1}{2}\left[\sum_{i=1}^{n} p_{i} \xi_{i}^{2}-\left(\sum_{i=1}^{n} p_{i} \xi_{i}\right)^{2}\right]
$$

But

$$
\begin{aligned}
\sum_{i, j=1}^{n} p_{i} p_{j}\left(\xi_{i}-\xi_{j}\right)^{2} & =\sum_{i, j=1}^{n} p_{i} p_{j}\left[\xi_{i}^{2}+\xi_{j}^{2}-2 \xi_{i} \xi_{j}\right] \\
& =2\left[\sum_{i=1}^{n} p_{i} \sum_{i=1}^{n} p_{i} \xi_{i}^{2}-\left(\sum_{i=1}^{n} p_{i} \xi_{i}\right)^{2}\right]=2\left[\sum_{i=1}^{n} p_{i} \xi_{i}^{2}-\left(\sum_{i=1}^{n} p_{i} \xi_{i}\right)^{2}\right]
\end{aligned}
$$

and then the above inequality becomes

$$
\begin{equation*}
\ln \left(\sum_{i=1}^{n} p_{i} \xi_{i}\right)-\sum_{i=1}^{n} p_{i} \ln \xi_{i} \leq \frac{1}{4} \sum_{i, j=1}^{n} p_{i} p_{j}\left(\xi_{i}-\xi_{j}\right)^{2} . \tag{2.4}
\end{equation*}
$$

Now, as $\log _{b} x=(\ln x / \ln b)$, inequality (2.4) is equivalent to the desired inequality (2.1). The case of equality follows by the strict convexity of $f$ and we omit the details.

Remark 2.1. Define

$$
B_{1}:=\frac{1}{2 \ln b} \sum_{i, j=1}^{n} \frac{p_{i} p_{j}}{\xi_{i} \xi_{j}}\left(\xi_{i}-\xi_{j}\right)^{2}, \quad \text { (as in Theorem 1.1) }
$$

and

$$
B_{2}:=\frac{1}{4 \ln b} \sum_{i, j=1}^{n} p_{i} p_{j}\left(\xi_{i}-\xi_{j}\right)^{2}, \quad \text { (as in Theorem 2.1) }
$$

and compute the difference

$$
\begin{aligned}
B_{1}-B_{2} & =\frac{1}{2 \ln b} \sum_{i, j=1}^{n} p_{i} p_{j}\left(\xi_{i}-\xi_{j}\right)^{2}\left[\frac{1}{\xi_{i} \xi_{j}}-\frac{1}{2}\right] \\
& =\frac{1}{4 \ln b} \sum_{i, j=1}^{n} \frac{p_{i} p_{j}\left(\xi_{i}-\xi_{j}\right)^{2}}{\xi_{i} \xi_{j}}\left(2-\xi_{i} \xi_{j}\right)
\end{aligned}
$$

Consequently, if $\xi_{i} \in[1, \infty)$ so that $\xi_{i} \xi_{j} \leq 2$, for all $i, j \in\{1, \ldots, n\}$, then the bound $B_{2}$ provided by Theorem 2.1 is better than the bound $B_{1}$ provided by Theorem 1.1. If $\xi_{i} \in[1, \infty)$ so that $\xi_{i} \xi_{j} \geq 2$, for all $i, j \in\{1, \ldots, n\}$, then Theorem 1.1 provides a better result than Theorem 2.1.

We give now some applications of the above results for arithmetic mean-geometric mean inequality.

Recall that for $q_{i}>0$ with $Q_{n}:=\sum_{i=1}^{n} q_{i}$, the arithmetic mean of $x_{i}$ with the weights $q_{i}, i \in$ $\{1, \ldots, n\}$ is

$$
\begin{equation*}
A_{n}(\bar{q}, \bar{x}):=\frac{1}{Q_{n}} \sum_{i=1}^{n} q_{i} x_{i} \tag{A}
\end{equation*}
$$

and the geometric mean of $x_{i}$ with the weights $q_{i}, i \in\{1, \ldots, n\}$, is

$$
\begin{equation*}
G_{n}(\bar{q}, \bar{x}):=\left(\prod_{i=1}^{n} x_{i}^{q_{i}}\right)^{1 / Q_{n}} \tag{G}
\end{equation*}
$$

It is well known that the following inequality so-called arithmetic mean-geometric mean inequality, holds

$$
\begin{equation*}
A_{n}(\bar{q}, \bar{x}) \geq G_{n}(\bar{q}, \bar{x}) \tag{2.5}
\end{equation*}
$$

with equality if and only if $x_{1}=\cdots=x_{n}$.
Now, using Theorem 1.1, we can state the following proposition containing a counterpart of the arithmetic mean-geometric mean inequality (2.5).
Proposition 2.2. With the above assumptions for $\bar{q}$ and $\bar{x}$, we have

$$
\begin{equation*}
1 \leq \frac{A_{n}(\bar{q}, \bar{x})}{G_{n}(\bar{q}, \bar{x})} \leq \exp _{b}\left[\frac{1}{2 Q_{n}^{2} \ln b} \sum_{i, j=1}^{n} \frac{q_{i} q_{j}}{x_{i} x_{j}}\left(x_{i}-x_{j}\right)^{2}\right] \tag{2.6}
\end{equation*}
$$

where $\exp _{b}(x)=b^{x},(b>1)$. The equality holds in both inequalities simultaneously if and only if $x_{1}=\cdots=x_{n}$.

Also, using Theorem 2.1, we have another converse inequality for (2.5).
Proposition 2.3. Let $\bar{q}$ be as above and $\bar{x} \in \mathbf{R}^{n}$ with $x_{i} \geq 1, i=1, \ldots, n$. Then we have the inequality

$$
\begin{equation*}
1 \leq \frac{A_{n}(\bar{q}, \bar{x})}{G_{n}(\bar{q}, \bar{x})} \leq \exp _{b}\left[\frac{1}{4 Q_{n}^{2} \ln b} \sum_{i, j=1}^{n} \frac{q_{i} q_{j}}{x_{i} x_{j}}\left(x_{i}-x_{j}\right)^{2}\right], \tag{2.7}
\end{equation*}
$$

where $b>1$. The equality holds in both inequalities simultaneously if and only if $x_{1}=\cdots=x_{n}$. Remark 2.2. As in the previous remark, if $1 \leq x_{i} x_{j} \leq 2$ then bound (2.7) is better than (2.6). If $x_{i} x_{j} \geq 2$, then (2.6) is better than (2.7).

## 3. APPLICATIONS FOR THE ENTROPY MAPPING

Let us consider now, the b-entropy mapping of the discrete random variable $X$ with $n$ possible outcomes and having the probability distribution $p=\left(p_{i}\right), i=\{1, \ldots, n\}$,

$$
H_{b}(X)=\sum_{i=1}^{n} p_{i} \log _{b}\left(\frac{1}{p_{i}}\right)
$$

We know (see [1]) that the following converse inequality holds:

$$
\begin{equation*}
0 \leq \log _{b} n-H_{b}(X) \leq \frac{1}{2 \ln b} \sum_{i, j=1}^{n}\left(p_{i}-p_{j}\right)^{2} \tag{3.1}
\end{equation*}
$$

with equality if and only if $p_{i}=1 / n$, for all $i \in\{1, \ldots, n\}$.
The following similar result also holds.
Theorem 3.1. Let $X$ be as above. Then we have

$$
\begin{equation*}
0 \leq \log _{b} n-H_{b}(X) \leq \frac{1}{4 \ln b} \sum_{i, j=1}^{n} \frac{\left(p_{i}-p_{j}\right)^{2}}{p_{i} p_{j}} \tag{3.2}
\end{equation*}
$$

The equality holds if and only if $p_{i}=1 / n$, for all $i \in\{1, \ldots, n\}$.
Proof. As $p_{i} \in(0,1]$, then $\xi_{i}=1 / p_{i} \in[1, \infty)$ and we can apply Theorem 2.1 to get

$$
\begin{align*}
0 & \leq \log _{b} n-H_{b}(X) \leq \frac{1}{4 \ln b} \sum_{i, j=1}^{n} p_{i} p_{j}\left(\frac{1}{p_{i}}-\frac{1}{p_{j}}\right)^{2} \\
& =\frac{1}{4 \ln b} \sum_{i, j=1}^{n} \frac{\left(p_{i}-p_{j}\right)^{2}}{p_{i} p_{j}} \tag{3.3}
\end{align*}
$$

The equality holds iff $\xi_{i}=\xi_{j}$, for all $i, j \in\{1, \ldots, n\}$ which is equivalent to $p_{i}=p_{j}$, for all $i, j \in\{1, \ldots, n\}$, i.e., $p_{i}=1 / n$, for all $i \in\{1, \ldots, n\}$.

The following corollary is important in applications as it provides a sufficient condition on the probability $p$ so that $\log _{b} n-H_{b}(X)$ is small enough.
Corollary 3.2. Let $X$ be as above and $\varepsilon>0$. If the probabilities $p_{i}, i=1, \ldots, n$, satisfy the conditions

$$
\begin{equation*}
\frac{1}{2}[2+k-\sqrt{k(k+4)}] \leq \frac{p_{i}}{p_{j}} \leq \frac{1}{2}[2+k+\sqrt{k(k+4)}], \tag{3.4}
\end{equation*}
$$

for all $1 \leq i<j \leq n$, where

$$
k=\frac{4 \varepsilon \ln b}{n(n-1)}, \quad(n \geq 2)
$$

then we have the estimation

$$
\begin{equation*}
0 \leq \log _{b} n-H_{b}(X) \leq \varepsilon \tag{3.5}
\end{equation*}
$$

Proof. Observe that

$$
\frac{1}{4 \ln b} \sum_{i, j=1}^{n} \frac{\left(p_{i}-p_{j}\right)^{2}}{p_{i} p_{j}}=\frac{1}{2 \ln b} \sum_{1 \leq i<j \leq n} \frac{\left(p_{i}-p_{j}\right)^{2}}{p_{i} p_{j}}
$$

Suppose that

$$
\frac{\left(p_{i}-p_{j}\right)^{2}}{p_{i} p_{j}} \leq k, \quad \text { for } 1 \leq i<j \leq n
$$

Then

$$
p_{i}^{2}-(2+k) p_{i} p_{j}+p_{j}^{2} \leq 0, \quad \text { for } 1 \leq i<j \leq n .
$$

Denoting $t=p_{i} / p_{j}$, the above inequality is equivalent to $t^{2}-(2+k) t+1 \leq 0$, i.e., $t \in\left[t_{1}, t_{2}\right]$, where

$$
t_{1}=\frac{2+k-\sqrt{k(k+4)}}{2} \text { and } t_{2}=\frac{2+k+\sqrt{k(k+4)}}{2}
$$

If we choose $k=(4 \varepsilon \ln b / n(n-1))$, then by (3.3) we have

$$
\begin{aligned}
0 & \leq \log _{b} n-H_{b}(X) \leq \frac{1}{4 \ln b} \sum_{i, j=1}^{n} \frac{\left(p_{i}-p_{j}\right)^{2}}{p_{i} p_{j}} \\
& =\frac{1}{2 \ln b} \sum_{1 \leq i<j \leq n} \frac{\left(p_{i}-p_{j}\right)^{2}}{p_{i} p_{j}} \\
& \leq \frac{1}{2 \ln b} \sum_{1 \leq i<j \leq n} k=\frac{n(n-1)}{4 \ln b} \cdot \frac{4 \varepsilon \ln b}{n(n-1)}=\varepsilon,
\end{aligned}
$$

and the corollary is proved.
Now, consider the bounds

$$
\left.M_{1}:=\frac{1}{2 \ln b} \sum_{i, j=1}^{n}\left(p_{i}-p_{j}\right)^{2}, \quad \text { (given by }(3.1)\right)
$$

and

$$
M_{2}:=\frac{1}{4 \ln b} \sum_{i, j=1}^{n} \frac{\left(p_{i}-p_{j}\right)^{2}}{p_{i} p_{j}}, \quad \text { (given by (3.3)). }
$$

We give an example for which $M_{1}$ is less than $M_{2}$ and another example for which $M_{2}$ is less than $M_{1}$ which will suggest that we can use both of them to estimate the above difference $\log _{b} n-H_{b}(X)$.
Example 3.1. Consider the probability distribution

$$
\begin{array}{lll}
p_{1}=0.3475, & p_{2}=0.2398, & p_{3}=0.1654, \\
p_{4}=0.1142, & p_{5}=0.0788, & p_{6}=0.0544 .
\end{array}
$$

In this case,

$$
\overline{M_{1}}=6.5119, \quad \bar{M}_{2}=12.1166,
$$

where

$$
\bar{M}_{1}:=\frac{1}{2} \sum_{i, j=1}^{n}\left(p_{i}-p_{j}\right)^{2}, \quad \bar{M}_{2}:=\frac{1}{4} \sum_{i, j=1}^{n} \frac{\left(p_{i}-p_{j}\right)^{2}}{p_{i} p_{j}}, \quad \text { and } \quad n=6 .
$$

Example 3.2. Consider the probability distribution

$$
\begin{array}{lll}
p_{1}=0.2468, & p_{2}=0.2072, & p_{3}=0.1740, \\
p_{4}=0.1461, & p_{5}=0.1227, & p_{6}=0.1031 .
\end{array}
$$

In this case,

$$
\bar{M}_{1}=5.2095, \quad \bar{M}_{2}=2.3706
$$

## 4. BOUNDS FOR JOINT ENTROPY

Consider the joint entropy of two random variable $X$ and $Y[2$, p. 25]

$$
H_{b}(X, Y):=\sum_{x, y} p(x, y) \log _{b} \frac{1}{p(x, y)}
$$

where the joint probability $p(x, y)=P\{X=x, Y=y\}$.
In [3], Dragomir and Goh have proved the following result using Theorem 1.1.
Theorem 4.1. With the above assumptions, we have that

$$
\begin{equation*}
0 \leq \log _{b}(r s)-H_{b}(X, Y) \leq \frac{1}{2 \ln b} \sum_{x, y} \sum_{u, v}(p(x, y)-p(u, v))^{2}, \tag{4.1}
\end{equation*}
$$

where the range of $X$ contains $r$ elements and the range of $Y$ contains $s$ elements. Equality holds in both inequalities simultaneously if and only if $p(x, y)=p(u, v)$, for all $(x, y),(u, v)$.

The following corollary is useful in practice.
Corollary 4.2. With the above assumptions and if

$$
\max _{(x, y),(u, v)}|p(x, y)-p(u, v)| \leq \sqrt{\frac{2 \varepsilon \ln b}{r s}}, \quad \varepsilon>0
$$

then we have the estimation

$$
0 \leq \log _{b}(r, s)-H_{b}(X, Y) \leq \varepsilon .
$$

Now, using the second converse inequality embodied in Theorem 2.1, we are able to prove another upper bound for the difference $\log _{b}(r s)-H_{b}(X, Y)$.

Theorem 4.3. With the above assumptions, we have

$$
\begin{equation*}
0 \leq \log _{b}(r s)-H_{b}(X, Y) \leq \frac{1}{4 \ln b} \sum_{x, y} \sum_{u, v} \frac{(p(x, y)-p(u, v))^{2}}{p(x, y) p(u, v)} \tag{4.2}
\end{equation*}
$$

where the range of $X$ and $Y$ are as above. Equality holds in both inequalities simultaneously iff $p(x, y)=p(u, v)$, for all $(x, y)$ and $(u, v)$.
Proof. Using Theorem 2.1, we have for $p_{i}=p(x, y)$ and $\xi_{i}=(1 / p(x, y))$,

$$
\begin{aligned}
0 & \leq \log _{b}\left(\sum_{x, y} p(x, y) \cdot \frac{1}{p(x, y)}\right)-\sum_{x, y} p(x, y) \log _{b} \frac{1}{p(x, y)} \\
& \leq \frac{1}{4 \ln b} \sum_{x, y} \sum_{u, v} p(x, y) p(u, v)\left(\frac{1}{p(x, y)}-\frac{1}{p(u, v)}\right)^{2} \\
& =\frac{1}{4 \ln b} \sum_{x, y} \sum_{u, v} \frac{(p(x, y)-p(u, v))^{2}}{p(x, y) p(u, v)},
\end{aligned}
$$

which is clearly equal to the desired result. The case of equality is obvious by Theorem 2.1.
The following corollary is important in practical applications.

Corollary 4.4. Let $X$ and $Y$ be as above and $\varepsilon>0$. Denote $P=\max p(x, y)$ and $p=$ $\min p(x, y)$. If

$$
\begin{equation*}
\frac{P}{p} \leq 1+k+\sqrt{k(k+2)}, \tag{4.3}
\end{equation*}
$$

where

$$
k:=\frac{2 \varepsilon \ln b}{(r s)^{2}}
$$

then we have the bound

$$
0 \leq \log _{b}(r s)-H_{b}(X, Y) \leq \varepsilon
$$

Proof. At the beginning, let us consider the inequality

$$
\frac{(a-b)^{2}}{2 a b} \leq k, \quad \text { for } a, b>0, \text { and } k \geq 0 .
$$

This inequality is clearly equivalent to

$$
a^{2}-2(1+k) a b+b^{2} \leq 0
$$

or denoting $t:=a / b$, to

$$
t^{2}-2(1+k) t+1 \leq 0
$$

i.e.,

$$
1+k-\sqrt{k(k+2)} \leq t \leq 1+k+\sqrt{k(k+2)} .
$$

Now, let suppose that

$$
\begin{equation*}
1+k-\sqrt{k(k+2)} \leq \frac{p(x, y)}{p(u, v)} \leq 1+k+\sqrt{k(k+2)} \tag{4.4}
\end{equation*}
$$

for all $(x, y)$ and $(u, v)$ and $k:=\left(2 \varepsilon \ln b /(r s)^{2}\right)$. Then by (4.2), we have

$$
\begin{aligned}
0 & \leq \log _{b}(r s)-H_{b}(X, Y) \leq \frac{1}{4 \ln b} \sum_{x, y} \sum_{u, v} \frac{(p(x, y)-p(u, v))^{2}}{p(x, y) p(u, v)} \\
& \leq \frac{1}{2 \ln b} \cdot(r s)^{2} k=\frac{(r s)^{2}}{2 \ln b} \cdot \frac{2 \varepsilon \ln b}{(r s)^{2}}=\varepsilon .
\end{aligned}
$$

Now, let observe that inequality (4.4) is equivalent to

$$
1+k-\sqrt{k(k+2)} \leq \frac{p}{P} \leq \frac{P}{p} \leq 1+k+\sqrt{k}(k+2)
$$

But $p / P \geq 1+k-\sqrt{k(k+2)}$ is equivalent to

$$
\frac{P}{p} \leq \frac{1}{1+k-\sqrt{k(k+2)}}=k+1+\sqrt{k(k+2)}
$$

and the corollary is proved.

## REFERENCES

1. S.S. Dragomir and C.J. Goh, A counterpart of Jensen's discrete inequality for differentiable convex mapping and application in information theory, Mathl. Comput. Modelling 24 (2), 1-4, (1996).
2. S. Roman, Coding and Information Theory, Springer-Verlag, New York.
3. S.S. Dragomir and C.J. Goh, Further counterparts of some inequalities in information theory, (submitted).

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