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# Generalizations of maximal inequalities to arbitrary selection rules

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## ARTICLE INFO

### Article history:

Received 29 August 2017  
 Received in revised form 2 January 2018  
 Accepted 5 January 2018  
 Available online xxxx

MSC:  
 60E15  
 60G70

### Keywords:

Entropy  
 Maximal inequality  
 Orlicz function  
 Convex duality  
 Generalized Holder's inequality

## ABSTRACT

We present a generalization of the maximal inequalities that upper bound the expectation of the maximum of  $n$  jointly distributed random variables. We control the expectation of a randomly selected random variable from  $n$  jointly distributed random variables, and present bounds that are at least as tight as the classical maximal inequalities, and much tighter when the distribution of selection index is near deterministic. A new family of information theoretic measures was introduced in the process, which may be of independent interest.

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## 1. Introduction

Throughout this paper, we consider  $n$  random variables  $Z_i$ ,  $1 \leq i \leq n$  such that  $\mathbb{E}[Z_i] = 0$ , where  $n$  is a finite positive integer. The zero mean condition can be satisfied via the operation  $Z'_i = Z_i - \mathbb{E}[Z_i]$  upon assuming that all  $Z_i$ 's are integrable. The following two maximal inequalities are well known in the literature and serve as the motivational results for this work.

**Lemma 1.** Let  $\psi \geq 0$  be a convex function defined on the interval  $[0, b)$  where  $0 < b \leq \infty$ . Assume that  $\psi(0) = 0$ . Set, for every  $t \geq 0$ ,

$$\psi^*(t) = \sup_{\lambda \in (0, b)} (\lambda t - \psi(\lambda)). \quad (1)$$

Suppose that  $\ln \mathbb{E}[e^{\lambda Z_i}] \leq \psi(\lambda)$  for all  $\lambda \in [0, b)$ ,  $1 \leq i \leq n$ . Then,

$$\mathbb{E}[\max_i Z_i] \leq \psi^{*-1}(\ln n), \quad (2)$$

where  $\psi^{*-1}(y)$  is defined as

$$\psi^{*-1}(y) = \inf\{t \geq 0 : \psi^*(t) > y\}. \quad (3)$$

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To introduce the second inequality, we say a function  $\psi$  is an Orlicz function if  $\psi : [0, \infty) \mapsto [0, \infty]$  is a convex function vanishing at zero and is also not identically 0 or  $\infty$  on  $(0, \infty)$ . We define the Luxemburg  $\psi$  norm of a random variable  $X$  as

$$\|X\|_{\psi} = \inf \left\{ \sigma > 0 : \mathbb{E} \left[ \psi \left( \frac{|X|}{\sigma} \right) \right] \leq 1 \right\}. \quad (4)$$

**Lemma 2** (Pollard, 2005). Let  $\psi$  be an Orlicz function. Suppose  $\|Z_i\|_{\psi} \leq \sigma$ ,  $1 \leq i \leq n$ . Then,

$$\mathbb{E}[\max_i Z_i] \leq \sigma \cdot \psi^{-1}(n), \quad (5)$$

where  $\psi^{-1}(y)$  is defined as  $\psi^{-1}(y) = \inf\{t \geq 0 : \psi(t) > y\}$ .

This paper concerns with the question of generalizing Lemmas 1 and 2 to arbitrary selection rules. Concretely, suppose  $T \in \{1, 2, \dots, n\}$  is a random variable jointly distributed with  $Z_1, Z_2, \dots, Z_n$ . We would like to upper bound  $\mathbb{E}[Z_T]$ , which subsumes the maximal inequality  $T = \operatorname{argmax}_i Z_i$  as a special case. Naturally, since

$$\mathbb{E}[Z_T] \leq \mathbb{E}[\max_i Z_i], \quad (6)$$

we would like to obtain bounds that are at least as strong as Lemmas 1 and 2, but dependent on the joint distribution of  $T, Z_1, Z_2, \dots, Z_n$ . In particular, the upper bound should be zero if  $T$  is deterministic since we have already assumed that  $\mathbb{E}[Z_i] = 0$  for all  $1 \leq i \leq n$ .

A generalization of Lemma 1 was achieved in Jiao et al. (2017) using the Donsker–Varadhan variational representation of the relative entropy, which is a generalization of the sub-Gaussian case in Russo and Zou (0000). Denote the entropy of a discrete random variable  $T$  as

$$H(T) = \sum_t P_T(t) \ln \frac{1}{P_T(t)}, \quad (7)$$

and the mutual information  $I(X; Y)$  between  $X$  and  $Y$  as

$$I(X; Y) = \begin{cases} \int \ln \frac{dP_{XY}}{d(P_X P_Y)} dP_{XY} & \text{if } P_{XY} \ll P_X P_Y \\ \infty & \text{otherwise.} \end{cases} \quad (8)$$

The following was shown in Jiao et al. (2017).

**Lemma 3.** Let  $\psi \geq 0$  be a convex function defined on the interval  $[0, b)$  where  $0 < b \leq \infty$ . Assume that  $\psi(0) = 0$ . Set, for every  $t \geq 0$ ,

$$\psi^*(t) = \sup_{\lambda \in (0, b)} (\lambda t - \psi(\lambda)). \quad (9)$$

Suppose that  $\ln \mathbb{E}[e^{\lambda Z_i}] \leq \psi(\lambda)$  for all  $\lambda \in [0, b)$ ,  $1 \leq i \leq n$ , and  $\mathbb{E}[Z_i] = 0$ ,  $1 \leq i \leq n$ . Then,

$$\mathbb{E}[Z_T] \leq \psi^{*-1}(I(T; \mathbf{Z})) \quad (10)$$

$$\leq \psi^{*-1}(H(T)) \quad (11)$$

where  $\psi^{*-1}(y)$  is defined as

$$\psi^{*-1}(y) = \inf\{t \geq 0 : \psi^*(t) > y\}. \quad (12)$$

and  $\mathbf{Z} = (Z_1, Z_2, \dots, Z_n)$ .

Lemma 3 is clearly stronger than Lemma 1 since  $I(T; \mathbf{Z}) \leq H(T) \leq \ln n$ . It is also interesting to observe that the soft bound is maximized when  $T$  follows a uniform distribution, and it is zero when  $T$  is deterministic.

Similar attempts were made to generalize Lemma 2 in Jiao et al. (2017). However, it was not satisfactory since that even in the case of  $\psi(x) = x^p$ ,  $p \geq 1$ ,  $x \geq 0$ , the generalization bound obtained in Jiao et al. (2017) may be infinity when  $1 \leq p < 2$ , while Lemma 2 shows that it is universally bounded by  $\sigma \cdot n^{1/p}$  for every  $p \geq 1$ .

Our main contribution in this paper is the generalization of Lemma 2 to arbitrary selection rules. Our generalization satisfies the following properties:

1. It is at least as strong as Lemma 2: in other words, it can be shown that the worst case joint distribution of  $T$  and  $\mathbf{Z}$  would not incur an upper bound larger than  $\sigma \cdot \psi^{-1}(n)$ , which is the upper bound in Lemma 2.
2. It admits a closed form expression for the  $p$ -norm case, i.e., the case where  $\psi(x) = x^p$ ,  $p \geq 1$ ,  $x \geq 0$ . In other words, it defines another information theoretic measure paralleling the Shannon entropy  $H(T)$  in Lemma 3. Concretely, for

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