

# On The Negative Inter-Dependencies of the Multivariate Hypergeometric Distribution

Szymon Snoeck

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## 1 Introduction

The multivariate hypergeometric distribution naturally arises in algorithm analysis and discrete math. Often, one is trying to prove large-deviation bounds or bounds on the expectation of a multivariate hypergeometric random variable,  $(m_1, \dots, m_k)$ . This is naturally complicated by the inter-dependencies between  $m_1, \dots, m_k$ . Towards a resolution, this note shows that the expectation of a multivariate hypergeometric distribution can be upper bounded by suitably chosen independent binomials. In particular, this result can be extended to a bound on the moment generating function and in turn provide large deviation bounds.

## 2 Setup and Main Result

Suppose one has an urn containing balls, each labeled with a number from 1 to  $k \in \mathbb{N}$ , and  $m \in \mathbb{N}$  balls are selected uniformly, without replacement. Let  $V$  of size  $n \in \mathbb{N}$  denote the set of all balls in urn. For  $i \in [k]$ , define  $S_i$  as the set of balls with label  $i \in [k]$ . If  $S$  of size  $m$  is the set of balls picked then  $|S \cap S_1|, \dots, |S \cap S_k|$ —the number of balls picked of each label—form a multivariate hypergeometric distribution. Now it is shown that  $|S \cap S_1|, \dots, |S \cap S_k|$  have a strong negative inter-dependence in that their expectation with respect to a wide range of functions is upper bounded by the same expectation over a multinomial or independent binomial distribution.

**Theorem 1.** *Fix a partition  $S_1, \dots, S_k$  of  $V$  and any  $m \in \mathbb{N}$ . Let  $b_1, \dots, b_k$  be independent binomial random variables such that  $b_i \sim \text{bin}(m, |S_i|/n)$ . Then for any  $g : \mathbb{R} \rightarrow \mathbb{R}_{>0}$  that is log convex and increasing, the following holds:*

$$\mathbb{E}_{S \sim \text{Unif}\{S' \subseteq V : |S'|=m\}}[g(|S \cap S_1|) \cdots g(|S \cap S_k|)] \leq \mathbb{E}[g(b_1)] \cdots \mathbb{E}[g(b_k)].$$

**Corollary 1.** *Fix a partition  $S_1, \dots, S_k$  of  $V$  and any  $m \in \mathbb{N}$ . Let  $b_1, \dots, b_k$  be a multinomial random variable with  $m$  trials such that  $b_i \sim \text{bin}(m, |S_i|/n)$ . Then*

for any  $f : \mathbb{R}^k \rightarrow \mathbb{R}$  that is convex, the following holds:

$$\mathbb{E}_{S \sim \text{Unif}\{S' \subseteq V : |S'|=m\}}[f(|S \cap S_1|, \dots, |S \cap S_k|)] \leq \mathbb{E}[f(b_1, \dots, b_k)].$$

*Proof of Theorem 1.* This argument was inspired by techniques introduced by Luh and Pippenger [2014]. Consider creating two sequences  $C, \tilde{C}$  through the following random process: starting with  $C = \tilde{C} = \emptyset$ , sample  $v$  uniformly from  $V$  and append  $v$  to  $\tilde{C}$ . If  $v$  is not already in  $C$  then add it to the end of  $C$ . Repeat until all  $v \in V$  have been sampled (this process terminates with probability 1). After the process is done the sequences are:  $C = (c_1, c_2, \dots, c_n)$  and  $\tilde{C} = (\tilde{c}_1, \tilde{c}_2, \dots)$ .

At this point it will be useful to define  $\sigma : [\tilde{C}] \rightarrow [n]$  such that  $\sigma(j)$  is the smallest index  $i \in [n]$  such that  $c_i = \tilde{c}_j$  which exists by construction. Moreover, it is easy to see that  $\sigma(j) \leq j$  for all  $j \in [\tilde{C}]$ .

For all  $i \in [k], j \in [n]$ , define the following random variables:  $x_{ij} \equiv \mathbb{1}[c_j \in S_i]$  and  $\tilde{x}_{ij} \equiv \mathbb{1}[\tilde{c}_j \in S_i]$ . Thus,  $S \equiv \{c_1, \dots, c_m\}$  is a uniformly sampled  $m$ -sized subset of  $V$ , and for all  $i \in [m]$ ,  $|S \cap S_i| = \sum_{j \in [m]} x_{ij}$ . Furthermore, for  $i \in [k]$ ,  $b_i \equiv \sum_{j \in [m]} \tilde{x}_{ij}$  is distributed like a binomial with  $m$  trials and probability of success  $|S_i|/m$ .

To finish the proof, it is shown that for all  $i \in [m]$ ,  $\mathbb{E}[b_i \mid |S \cap S_1|, \dots, |S \cap S_k|] = |S \cap S_i|$ . Since  $C$  is a uniformly, randomly chosen ordering of the  $v \in V$ , for any  $j, j' \in [m]$ , we have that:

$$\mathbb{E}[x_{ij} \mid |S \cap S_1| = s_1, \dots, |S \cap S_k| = s_k] = \mathbb{E}[x_{ij'} \mid |S \cap S_1| = s_1, \dots, |S \cap S_k| = s_k].$$

Thus, for any  $j \in [m]$ ,  $\mathbb{E}[x_{ij} \mid |S \cap S_1| = s_1, \dots, |S \cap S_k| = s_k] = s_i/m$  since  $s_i = \sum_{j \in [m]} \mathbb{E}[x_{ij} \mid |S \cap S_1| = s_1, \dots, |S \cap S_k| = s_k]$ . This gives us that:

$$\begin{aligned} \mathbb{E}[b_i \mid |S \cap S_1| = s_1, \dots, |S \cap S_k| = s_k] &= \sum_{j \in [m]} \mathbb{E}[\tilde{x}_{ij} \mid |S \cap S_1| = s_1, \dots, |S \cap S_k| = s_k] \\ &= \sum_{j \in [m]} \mathbb{E}[x_{i\sigma(j)} \mid |S \cap S_1| = s_1, \dots, |S \cap S_k| = s_k] \\ &= \sum_{j \in [m]} s_i/m = s_i. \end{aligned}$$

Hence  $\mathbb{E}[b_i \mid |S \cap S_1|, \dots, |S \cap S_k|] = |S \cap S_i|$ . Since  $g$  is log convex, the function  $f : \mathbb{R}^k \rightarrow \mathbb{R}_{>0}$  defined as  $f(a_1, \dots, a_k) = g(a_1) \cdots g(a_k) = \exp(\sum_{i \in [k]} \log(g(a_i)))$  is convex as well. By multivariate Jensen's inequality, we get:

$$\begin{aligned} \mathbb{E}[f(|S \cap S_1|, \dots, |S \cap S_k|)] &= \mathbb{E}[f(\mathbb{E}[b_1 \mid |S \cap S_1|, \dots, |S \cap S_k|], \dots, \mathbb{E}[b_k \mid |S \cap S_1|, \dots, |S \cap S_k|])] \\ &\leq \mathbb{E}[f(b_1, \dots, b_k) \mid |S \cap S_1|, \dots, |S \cap S_k|] \\ &= \mathbb{E}[f(b_1, \dots, b_k)] = \mathbb{E}[g(b_1) \cdots g(b_k)]. \end{aligned}$$

Note that  $b_1, \dots, b_k$  form a multinomial distribution so the above proves Corollary 1. To finish the proof we apply a result by Dubhashi and Ranjan [1996] which proved that for  $g$  increasing the following holds:

$$\mathbb{E}[g(b_1) \cdots g(b_k)] \leq \mathbb{E}[g(b_1)] \cdots \mathbb{E}[g(b_k)].$$

□

## References

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