

Relative distance comparisons with confidence judgements

Supplementary material

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1 Proof of Theorem 4.1

We first derive the formula for the expected value of the estimator, and then show how it can be upper bounded by assuming the constraint on s_i given in the theorem. In the following, we shorten $d_{u_j v_j}$ as d_j .

The estimator for d_j is defined as:

$$(1.1) \quad d_j = \prod_{i \in S} 2(1 - p_i) \prod_{i \in L} \frac{1}{2(1 - p_i)}.$$

Since we have assumed the noise terms to be independent, we have

$$E[d_j] = \prod_{i \in S} E[2(1 - p_i)] \prod_{i \in L} E\left[\frac{1}{2(1 - p_i)}\right].$$

Also, we assume $p_i = p_i^* + \varepsilon_i$. Of these, only ε_i is a random variable, others are constants. Since $\varepsilon_i \sim \text{Unif}(-s, s)$, we have $E[\varepsilon_i] = 0$. Thus, by linearity of expectation we have $E[2(1 - p_i)] = 2(1 - E[p_i]) = 2(1 - (p_i^* + E[\varepsilon_i])) = 2(1 - p_i^*)$. For the second part, we have

$$\begin{aligned} E\left[\frac{1}{2(1 - p_i)}\right] &= \int_{-s}^s 2(1 - (p_i^* + \varepsilon_i)) \frac{1}{2s} d\varepsilon_i \\ &= \frac{1}{4s} \log\left(\frac{1 - p_i^* + s}{1 - p_i^* - s}\right), \end{aligned}$$

which yields

$$E[d_j] = \prod_{i \in S} 2(1 - p_i^*) \prod_{i \in L} \frac{1}{4s} \log\left(\frac{1 - p_i^* + s}{1 - p_i^* - s}\right).$$

Now consider the inequality $E[d_j] \leq \alpha d_j^*$. Since the product $\prod_{i \in S} 2(1 - p_i^*)$ (that corresponds to the short pairs) appears in both the expression for $E[d_j]$ and d_j^* , it can be divided out leaving us with

$$\prod_{i \in L} \frac{1}{4s} \log\left(\frac{1 - p_i^* + s}{1 - p_i^* - s}\right) \leq \alpha \prod_{i \in L} \frac{1}{2(1 - p_i^*)},$$

which can be rearranged as

$$\prod_{i \in L} \underbrace{\frac{1}{4s} \log\left(\frac{1 - p_i^* + s}{1 - p_i^* - s}\right)}_{f(p_i^*)} 2(1 - p_i^*) \leq \alpha.$$

We then derive an upper bound for $f(p_i^*)$ by using the bound $\log x \leq x - 1$ to obtain

$$\frac{1}{4s} \log\left(\frac{1 - p_i^* + s}{1 - p_i^* - s}\right) \leq \frac{1}{2(1 - p_i^* - s)},$$

meaning

$$f(p_i^*) \leq \frac{1 - p_i^*}{1 - p_i^* - s}.$$

This yields

$$\prod_{i \in L} f(p_i^*) \leq \prod_{i \in L} \frac{1 - p_i^*}{1 - p_i^* - s} \leq \prod_{i=1}^j \frac{1 - p_i^*}{1 - p_i^* - s} \leq \alpha,$$

where the 2nd inequality follows from $\frac{1 - p_i^*}{1 - p_i^* - s} \geq 1$, and the fact that $|L| \leq j$. Now, the rightmost inequality above holds when for all i

$$\frac{1 - p_i^*}{1 - p_i^* - s} \leq \alpha^{1/j}.$$

Allowing s to depend on i , and solving the above for s_i gives

$$s_i \leq -\left(1 - \frac{1}{\alpha^{1/j}}\right) p_i^* + \left(1 - \frac{1}{\alpha^{1/j}}\right),$$

which is the bound for s_i required in the theorem.

2 Proof of Theorem 4.2

Again, we shorten $d_{u_j v_j}$ as d_j . We use Chebyshev's inequality to determine a similar relationship between s and p_i as in Theorem 4.1, so that the probability of the estimates being "far" from their expected value (not the "true" d_j^*) is bounded by q .

$$\begin{aligned} Pr(|d_j - E[d_j]| \geq aE[d_j]) &\leq \frac{Var[d_j]}{a^2 E[d_j]^2} \\ &= \frac{1}{a^2} \left(\frac{E[d_j^2]}{E[d_j]^2} - 1 \right) \leq q. \end{aligned}$$

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$$\begin{aligned}
\frac{E[d_j^2]}{E[d_j]^2} &= \frac{\prod_{i \in S} E[4(1-p_i)^2]}{\prod_{i \in S} 4(1-p_i^*)^2} \frac{\prod_{i \in L} E[\frac{1}{4(1-p_i)^2}]}{\prod_{i \in L} (\frac{1}{4s} \log(\frac{1-p_i^*+s}{1-p_i^*-s}))^2} \\
&= \prod_{i \in S} \left(1 + \frac{s}{\sqrt{3}(1-p_i^*)}\right) \prod_{i \in L} \frac{2s^{(\frac{1}{(1-p_i^*-s)} - \frac{1}{(1-p_i^*+s)})}}{\log(\frac{1-p_i^*+s}{1-p_i^*-s})^2} \\
&\leq \prod_{i \in S} \left(1 + \frac{s}{\sqrt{3}(1-p_i^*)}\right) \prod_{i \in L} \left(1 + \frac{s}{\sqrt{3}(1-p_i^*)}\right) \\
&\leq \prod_{i=1}^j \left(1 + \frac{s}{\sqrt{3}(1-p_i^*)}\right).
\end{aligned}$$

(It can be shown that the first inequality above holds when we constrain s_i using the same bound as in Theorem 4.1 with any $\alpha \in [1, 23.75]$. We consider this to be a reasonable range of αs , as normally one would prefer the bias to be small. This means that if the amount of noise is sensible, the inequality holds.)

Substituting the above upper bound into Chebyshev RHS:

$$\frac{1}{a^2} \left(\prod_{i=1}^j \left(1 + \frac{s}{\sqrt{3}(1-p_i^*)}\right) - 1 \right) \leq q$$

which is equivalent to

$$\prod_{i=1}^j \left(1 + \frac{s}{\sqrt{3}(1-p_i^*)}\right) \leq a^2 q + 1$$

Again we allow $s = s_i$ to depend on p_i^* . The above holds when

$$\left(1 + \frac{s_i}{\sqrt{3}(1-p_i^*)}\right) \leq (a^2 q + 1)^{1/j} = \gamma,$$

which holds when

$$s_i \leq -\sqrt{3}(\gamma - 1)p_i^* + \sqrt{3}(\gamma - 1).$$