

## Erratum

The Horizontal No Free Lunch theorem takes  $\tilde{T}$ , the set of possible targets to be a partition of the search space  $\Omega$ . However, in the case of multiple queries, they are treated as a single query to a larger search space  $\Omega_Q$ . Any distribution of targets on the original search space will produce overlapping targets on  $\Omega_Q$ . This prevents considering the set of possible targets as a partition of the search space  $\Omega_Q$ . As such the horizontal no free lunch theorem does not properly handle multiple queries.

**Theorem 1.** *Given a uniform distribution over targets of cardinality  $k$ , and baseline uniform distribution, the average active information will be non-positive*

*Proof.* The average active information formula in its general form is

$$E[I_+] = E \left[ -\log \frac{\phi(T)}{\psi(T)} \right] = E \left[ \log \frac{\psi(T)}{\phi(T)} \right] \quad (1)$$

where  $T$  the random variable taking the domain of the powerset of  $\Omega$ ,  $\phi(T)$  is the fixed probability of the baseline uniform search algorithm succeeding given a specific target and  $\psi(T)$  is the fixed probability of the search algorithm being considered succeeding given a specific target.

By Jensen's inequality

$$E \left[ \log \frac{\psi(T)}{\phi(T)} \right] \leq \log E \left[ \frac{\psi(T)}{\phi(T)} \right] \quad (2)$$

Any given target can be represented by a function producing 1 for every point  $\omega$  in the target, and 0 otherwise. All functions with the same number of targets will be closed under permutation. The algorithms succeed if they pick a point in the target, which is equivalent running single query and getting a 1. The No Free Lunch theorem holds for any distribution which is closed under permutation, and thus all algorithms will have on average, the same probability of success.

$$E[\psi(T)] = E[\phi(T)] = \frac{k}{|\Omega|} \quad (3)$$

We note that  $\phi(T)$  is a constant, performing the same regardless of the identity of the target. It is a baseline uniform search, and thus will select every target with the same probability. Therefore,

$$E \left[ \frac{\psi(T)}{\phi(T)} \right] = \frac{E[\psi(T)]}{\phi(T)} = \frac{\phi(T)}{\phi(T)} = 1 \quad (4)$$

This effectively restates the No Free Lunch theorem, the expected performance of two search algorithms does not differ. Using equation 2:

$$E[I_+] = E \left[ \log \frac{\psi(T)}{\phi(T)} \right] \leq \log E \left[ \frac{\psi(T)}{\phi(T)} \right] = \log \frac{E[\psi(T)]}{\phi(T)} = \log 1 = 0 \quad (5)$$

Therefore the expected active information is always non-positive.

Additionally, equality only occurs if

$$\frac{\psi(T)}{\phi(T)} \quad (6)$$

is the same for all values of  $T$ . This will only occur if both algorithms succeed and fail with the same probability for every target. □

**Corollary 1.** *Given a distribution over all targets, such that targets of the same cardinality have the same probability: the average active information will be non-positive*

$$E \left[ \log \frac{\psi(T)}{\phi(T)} \right] \leq 0 \quad (7)$$

*Proof.* We can express the average active information as

$$E \left[ \log \frac{\psi(T)}{\phi(T)} \right] = \sum_{k=0}^{k=|\Omega|} \Pr [|T| = k] E \left[ \log \frac{\psi(T)}{\phi(T)} \middle| |T| = k \right] \quad (8)$$

Since the probabilities for sets of the same size are the same, Theorem 1 applies to the inner expected value. The expression then takes the weighted average of non-positive values and thus will be non-positive.  $\square$

**Theorem 2.** *For every distribution of targets there is some baseline search for which the active information will always be non-positive.*

$$E[I_+] = E \left[ -\log \frac{\phi(T)}{\psi(T)} \right] \leq 0 \quad (9)$$

for some  $\phi$ .

*Proof.* We can rewrite the average active information as:

$$E[I_+] = E \left[ -\log \frac{\phi(T)}{\psi(T)} \right] = E [-\log \phi(T)] - E [-\log \psi(T)] \quad (10)$$

For every possible distribution over targets, there exists an algorithm,  $\phi$ , that maximizes  $E [-\log \phi(T)]$ .  $E [-\log \phi(T)] \geq E [-\log \psi(T)]$  since  $\phi$  maximizes the expectation, and thus,  $E [-\log \phi(T)] - E [-\log \psi(T)] \geq 0$ .  $\square$

The Horizontal No Free Lunch Theorem does hold in all cases; however, determining the baseline may be non-trivial.

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