

Solving Wordle using Information Theory: Tasks 1-6

Andy Arrigony Pérez, Maryam Abuissa, Daniel Flores García

March 2023

1 Task 1

Consider $I[T; G] = H(T) - H(T|G)$. But note that $H(T) = H(T|G)$ because T and G are independent. So $I[T; G] = 0$.

2 Task 2

Consider $I[T; G|P] = H(T|P) - H(T|G, P)$. But note that $H(T|P) > H(T|G, P)$, intuitively because knowing both the guess and the pattern leads to less uncertainty about T than knowing just the pattern.

3 Task 3

If we know both the guess and the target, we can deduce the pattern. Hence, $H[P|G, T] = 0$.

4 Task 4

Consider: $I[T; P|G] = H(T|G) - H(T|P, G)$. But note that $H(T|G) = H(T) - I[T; G] = H(T)$, which does not depend on π . Thus, we need to minimize the subtractive term $H(T|P, G)$ (since it *does* depend on π) in order to maximize $I[T; P|G]$.

5 Task 5

Let R be the alphabet of P . Consider:

$$H[T|G, P] = \sum_{t \in W} \sum_{g \in W} \sum_{r \in R} p(t, g, r) \log\left(\frac{1}{p(t|g, r)}\right) = \sum_{t \in W} \sum_{g \in W} \sum_{r \in R} p(r|t, g) p(t, g) \log\left(\frac{1}{p(t|g, r)}\right)$$

But note that $\exists r' \in R$ s.t. $p(r'|t, g) = 1$ and therefore $p(r^*|t, g) = 0 \forall r^* \in R$ s.t. $r^* \neq r'$. Therefore:

$$= \sum_{t \in W} \sum_{g \in W} p(t, g) \log\left(\frac{1}{p(t|g, r')}$$

Moreover, by uniformity of T , $p(t|g, r') = \frac{1}{|W'(g, t)|}$, where $W'(g, t)$ is a pruned alphabet. Moreover, changing the summation order:

$$= \sum_{g \in W} \sum_{t \in W} p(t, g) \log(|W'(g, t)|) = \sum_{g \in W} \sum_{t \in W} p(t) p(g) \log(|W'(g, t)|) = \frac{1}{|W|} \sum_{g \in W} \pi(g) \sum_{t \in W} \log(|W'(g, t)|)$$

And letting $\alpha_g = \sum_{t \in W} \log(|W'(g, t)|)$:

$$= \frac{1}{|W|} \sum_{g \in W} \pi(g) \alpha_g$$

6 Task 6

Suppose there are multiple guesses $g_1, g_2, \dots, g_k \in W$ with the same minimum value for $\alpha_{g_1} = \alpha_{g_2} = \dots = \alpha_{g_k}$. Then, let π be a distribution s.t. $\sum_{i=1}^k \pi(g_i) = 1$ and $\pi(g_i) \geq 0$. Note that $\pi(g_j) = 0 \ \forall g_j \in W$ s.t. $g_j \neq g_i$. Additionally, let $\alpha_\phi = \alpha_{g_i}$ for any $i \in [1, \dots, k]$. Consider:

$$\begin{aligned} \frac{1}{|W|} \sum_{g \in W} \pi(g) \alpha_g &= \frac{1}{|W|} \sum_{i=1}^k \pi(g_i) \alpha_\phi = \frac{\alpha_\phi}{|W|} \sum_{i=1}^k \pi(g_i) \\ &= \frac{\alpha_\phi}{|W|} \end{aligned}$$

Now, to show that π is optimal, we show that for an arbitrary distribution π^* , $\frac{1}{|W|} \sum_{g \in W} \pi^*(g) \alpha_g \geq \frac{1}{|W|} \sum_{g \in W} \pi(g) \alpha_g$. Let g_j be a guess such that $g_j \neq g_i \ \forall i \in [1, \dots, k], \forall j \in [1, \dots, t]$. Consider:

$$\frac{1}{|W|} \sum_{g \in W} \pi^*(g) = \frac{1}{|W|} \left(\sum_{i=1}^k \pi^*(g_i) \alpha_\phi + \sum_{j=1}^t \pi^*(g_j) \alpha_j \right)$$

But note that:

$$\sum_{j=1}^t \pi^*(g_j) \alpha_j = \sum_{j=1}^t \pi^*(g_j) (\alpha_\phi + \beta_j)$$

for some $\beta_j \geq 0$, because α_ϕ is minimum and ≥ 0 . So:

$$= \sum_{j=1}^t \pi^*(g_j) \alpha_\phi + \sum_{j=1}^t \pi^*(g_j) \beta_j$$

Plugging this into the earlier expression:

$$\begin{aligned} \frac{1}{|W|} \left(\sum_{i=1}^k \pi^*(g_i) \alpha_\phi + \sum_{j=1}^t \pi^*(g_j) \alpha_j \right) &= \frac{1}{|W|} \left(\sum_{i=1}^k \pi^*(g_i) \alpha_\phi + \sum_{j=1}^t \pi^*(g_j) \alpha_\phi + \sum_{j=1}^t \pi^*(g_j) \beta_j \right) \\ &= \frac{1}{|W|} \left(\alpha_\phi \left(\sum_{i=1}^k \pi^*(g_i) + \sum_{j=1}^t \pi^*(g_j) \right) + \sum_{j=1}^t \pi^*(g_j) \beta_j \right) = \frac{1}{|W|} \left(\alpha_\phi + \sum_{j=1}^t \pi^*(g_j) \beta_j \right) \end{aligned}$$

Because $\sum_{j=1}^t \pi^*(g_j) \geq 0$:

$$\geq \frac{\alpha_\phi}{|W|}$$