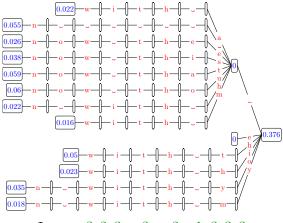
## A. Pruning a hierarchical decomposition

To provide further intuition for how our method behaves, we have included the hierarchical decomposition for one of the test examples from our experiments:



Input: ? ? ? n ? w ? t h ? ? ?

This is the hierarchical decomposition used to infer the missing characters for the phrase ...???n?w?th???....

The decomposition doesn't waste resources representing the first 3 unknown characters, and maintains plausible hypotheses for the hidden characters such as ...with a..., ...now thee..., and ...now this.... Each blue decimal number indicates a region in the decomposition together with the local probability mass assigned to that region.

## B. Pruning a hierarchical decomposition

In our inference algorithm for choosing a good hierarchical decomposition B, we had two major steps: refining the decomposition, and pruning it back down to a given size k. In this appendix, we will provide a dynamic programming algorithm for computing an optimal pruning B of A, assuming that  $Fit(a, C_B(a))$ depends only on a. Let  $\hat{p}_{\theta_A}$  be the approximating distribution corresponding to A, and  $\hat{p}_{\theta_B}$  be the approximating distribution corresponding to B. Our goal is to minimize KL  $(p^* \parallel \hat{p}_{\theta_B})$ ; we will make the assumption that A and  $\theta_A$  are chosen well enough that  $\hat{p}_{\theta_A}$ is already close to  $p^*$ , and thus that  $\mathrm{KL}\left(\hat{f}_{\theta_A} \ \middle\| \ \hat{f}_{\theta_B}\right)$ is a good surrogate for  $\mathrm{KL}\,(p^*\parallel\hat{p}_{\theta_B})$ . We will also ignore normalization constants and instead consider the divergence KL  $(\hat{f}_{\theta_A} \parallel \hat{f}_{\theta_B})$  between the unnormalized distributions  $\hat{f}_{\theta_A}$  and  $\hat{f}_{\theta_B}$ . Formally, we will solve the following problem:

Given a hierarchical decomposition A, and assuming that  $\operatorname{Fit}(a, \mathcal{C}_B(a))$  depends only on a, find the subset  $B \subseteq A$  of vertices of size k such that  $\operatorname{KL}\left(\hat{f}_{\theta_A} \parallel \hat{f}_{\theta_B}\right)$  is minimized.

For a hierarchical decomposition A and a subset B of A, let  $\alpha_B(a)$  denote the smallest  $b \in B$  such that  $a \subseteq b$ . By equation (4), we have

$$KL\left(\hat{f}_{\theta_A} \parallel \hat{f}_{\theta_B}\right) = \sum_{a \in A} KL_{a^{\circ}} \left(\hat{f}_{\theta_A} \parallel \hat{f}_{\theta_B}\right)$$
(19)

$$= \sum_{a \in A} \mathrm{KL}_{a^{\circ}} \left( \hat{f}_{\theta_a} \parallel \hat{f}_{\theta_{\alpha_B(a)}} \right) \quad (20)$$

$$= \sum_{a \in A} K_{a^{\circ}}(a \| \alpha_B(a)), \tag{21}$$

where 
$$K_c(a||b) \stackrel{\text{def}}{=} \sum_{x \in c} \hat{f}_{\theta_a}(x) \log \left( \frac{\hat{f}_{\theta_a}(x)}{\hat{f}_{\theta_b}(x)} \right)$$
. It is here that we make use of the assumption that

is here that we make use of the assumption that  $\operatorname{Fit}(\alpha_B(a), \mathcal{C}_B(\alpha_B(a)))$  depends only on a; otherwise,  $K_{a^{\circ}}(a||\alpha_B(a))$  would depend on the particular value of  $\mathcal{C}_B(\alpha_B(a))$ .

In the remainder of this appendix, we will write out a succession of recursive formulas for computing  $\mathrm{KL}\left(\hat{f}_{\theta_A} \parallel \hat{f}_{\theta_B}\right)$ , expanding the state space each time until we eventually have a recursion for optimizing  $\mathrm{KL}\left(\hat{f}_{\theta_A} \parallel \hat{f}_{\theta_B}\right)$  over all subsets  $B\subseteq A$  of size k.

Computing  $\mathrm{KL}\left(\hat{f}_{\theta_A} \parallel \hat{f}_{\theta_B}\right)$  for fixed B. To make the expression in (21) more amenable to dynamic programming, we will write it out recursively. For  $a \subseteq p$ , define D(a,p) to be the contribution of the descendants of a (including a) to  $\mathrm{KL}\left(\hat{f}_{\theta_A} \parallel \hat{f}_{\theta_B}\right)$  assuming that  $\alpha_B(a) = p$ . More formally, we define D(a,p) recursively as

$$D(a,p) \stackrel{\text{def}}{=} \begin{cases} K_{a^{\circ}}(a||a) + \sum_{b \in \mathcal{C}_A(a)} D(b,a) & : \quad a \in B \\ K_{a^{\circ}}(a||p) + \sum_{b \in \mathcal{C}_A(a)} D(b,p) & : \quad a \notin B \end{cases}$$

$$(22)$$

(Note that  $K_{a^{\circ}}(a||a)$  is equal to 0; we have left it in the recursion to expose the symmetry in the two cases.)

With this definition, one can verify that D(X,X) expands out to (21) and hence is equal to  $\mathrm{KL}\left(\hat{f}_{\theta_A} \ \middle|\ \hat{f}_{\theta_B}\right)$ . (Recall that X is the entire state space and is always an element of A.)

**Optimizing over** B. Equation (22) gives us a recursive formula for  $\mathrm{KL}\left(\hat{f}_{\theta_A} \parallel \hat{f}_{\theta_B}\right)$  when B is fixed. However, the only dependence on B is in deciding between the two cases in the recursion, so it is easy to ex-

tend the recursion to simultaneously choose B. In particular, define the three-variable function D(a, p, m) to be the minimum value of D(a, p) if there are m elements in B that are contained in a (including, possibly, a itself). We then have the recursion

$$D(a, p, m)$$

$$\stackrel{\text{def}}{=} \min \left\{ \begin{array}{l} K_{a^{\circ}}(a \| a) + \min_{\sum m_b = m - 1} \left[ \sum_{b \in \mathcal{C}_A(a)} D(b, a, m_b) \right], \\ K_{a^{\circ}}(a \| p) + \min_{\sum m_b = m} \left[ \sum_{b \in \mathcal{C}_A(a)} D(b, p, m_b) \right]. \end{array} \right.$$

The first case corresponds to including a in B, in which case we have m-1 remaining elements of B to distribute among the descendants of a. The second case corresponds to excluding a from B, in which case we have m elements of B to distribute. Now D(X, X, k) is the minimum value of D(X, X) across all subsets B of size k, which is the quantity we are after.

Computing the minimum tractably. We are almost done, but we need an efficient way to compute the minimum over all  $m_j$  that sum to m. To do this, number the children of a as  $b_1, b_2, \ldots$ , and define the four-variable function D(a, p, m, j), which, intuitively, tracks the minimum value of D(a, p) if there are m elements in B left to be distributed among children  $b_j, b_{j+1}, \ldots$  and their subtrees. More formally, define D(a, p, m, j) via

$$D(a, p, m, j)$$

$$\stackrel{\text{def}}{=} \begin{cases} \min \{ D(a, a, m - 1, 0), D(a, p, m, 0) \} : j = -1 \\ \min_{0 \le m' \le m} \{ D(b_j, p, m', -1) \\ + D(a, p, m - m', j + 1) \} \\ K_{a^{\circ}}(a||p)$$

$$: j = |\mathcal{C}_A(a)|.$$

The three cases can be thought of as follows:

- D(a, p, m, -1) decides whether or not to include a in B
- D(a, p, m, j) decides how many elements of B to include among the descendants of  $b_j$
- $D(a, p, m, |\mathcal{C}_A(a)|)$  computes the local contribution of a to  $\mathrm{KL}\left(\hat{f}_{\theta_A} \mid\mid \hat{f}_{\theta_B}\right)$ .

Overall, then, D(X, X, k, -1) is equal to the minimum value of  $\mathrm{KL}\left(\hat{f}_{\theta_A} \parallel \hat{f}_{\theta_B}\right)$  over all  $B \subseteq A$  with |B| = k.

**Runtime.** Suppose that the decomposition A has depth d. Then there are O(|A|d) triples (p, a, j), so the size of the state space is O(|A|dk). Furthermore, the first case of the recursion can be computed in O(1) time, the second case in O(k) time, and the final case in O(1) time (on average across all a). Therefore, the runtime is  $O(|A|dk^2)$ .