

$$\begin{aligned}
& \prod_{\ell=1}^M \left[p(\mathbf{v}^{\ell,1}, \dots, \mathbf{v}^{\ell,n^\ell} \mid \boldsymbol{\mu}_1, \dots, \boldsymbol{\mu}_N, N) \right] p(\boldsymbol{\mu}_1, \dots, \boldsymbol{\mu}_N \mid N) p(N) \\
&= \prod_{\ell=1}^M \left[\sum_{\mathbf{a}^\ell \in A(n^\ell, N)} \left(\underbrace{\prod_{k=1}^{n^\ell} p(\mathbf{v}^{\ell,k} \mid \boldsymbol{\mu}_{a_k^\ell})}_{\textcircled{4}} \right) \underbrace{p(\bar{V}(\mathbf{a}^\ell) \mid \boldsymbol{\mu}_1, \dots, \boldsymbol{\mu}_N, N)}_{\textcircled{3}} \right] \underbrace{p(\boldsymbol{\mu}_1, \dots, \boldsymbol{\mu}_N \mid N)}_{\textcircled{2}} \underbrace{p(N)}_{\textcircled{1}}
\end{aligned} \tag{2}$$

Figure 2: Joint likelihood of M vowel systems under our deep generative probability model for continuous-space vowel inventories. Here language ℓ has an observed inventory of pronunciations $\{\mathbf{v}^{\ell,k} : 1 \leq k \leq n^\ell\}$, and $a_k^\ell \in [1, N]$ denotes a phone that might be responsible for the pronunciation $\mathbf{v}^{\ell,k}$. Thus, \mathbf{a}^ℓ denotes some way to jointly label all n^ℓ pronunciations with distinct phones. We must sum over all $\binom{N}{n^\ell}$ such labelings $\mathbf{a}^\ell \in A(n^\ell, N)$ since the true labeling is not observed. In other words, we sum over all ways \mathbf{a}^ℓ of completing the data for language ℓ . Within each summand, the product of factors 3 and 4 is the probability of the completed data, i.e., the joint probability of generating the inventory $\bar{V}(\mathbf{a}^\ell)$ of phones used in the labeling and their associated pronunciations. Factor 3 considers the prior probability of $\bar{V}(\mathbf{a}^\ell)$ under the DPP, and factor 4 is a likelihood term that considers the probability of the associated pronunciations.