

Supplementaries

Total loss function for multiDGD

$$-\log p(x, z, \phi, \theta) = \sum_{\text{mod}} \text{Loss}_{\text{recon}}^{\text{mod}} + \text{Loss}_{\text{rep}}^{\text{basal}} + \sum_{\text{cov}} \text{Loss}_{\text{rep}}^{\text{cov}} + \text{Loss}_{\text{prior}}$$

The softball priors

The composition of the Dirichlet prior loss is given as follow:

$$\begin{aligned} \text{Loss}_{\text{prior}}^{\text{basal}} &= -\log p(\phi) = -\log p(\mu, w, -\log \Sigma) \\ &= -\log(p(\mu) p(w) p(-\log \Sigma)) \end{aligned}$$

$$p(\mu) = \prod_k p_{\text{Softball}}(\mu_k | \text{scale, sharpness})$$

$$p(w) = \prod_k \text{Dir}(\mu_k | \alpha)$$

$$p(-\log \Sigma) = \prod_k \prod_l \mathcal{N}\left(-\log \Sigma_{k,l} | -\log 0.2 \times \frac{\text{scale}}{K}, 1\right)$$

Figures

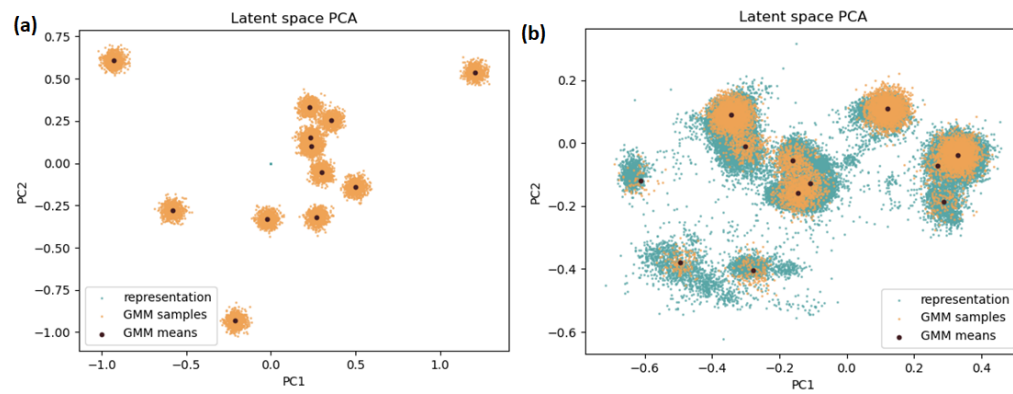


Figure 1: Latent space visualization. (a) Initialized latent space. (b) Latent space learnt after training.

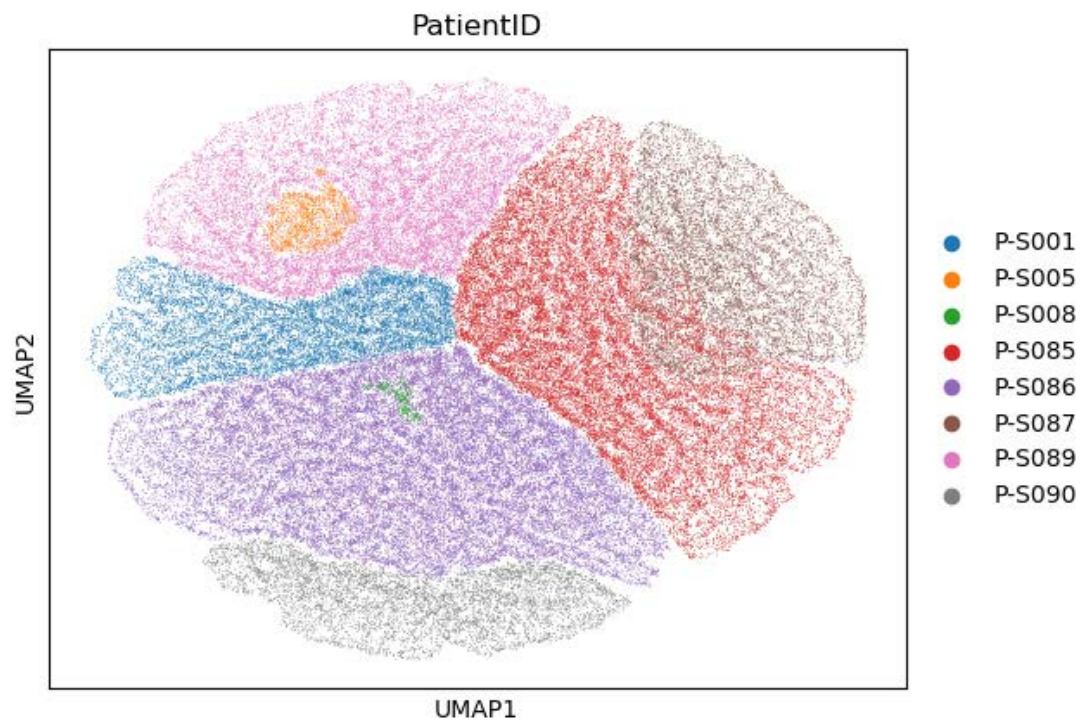


Figure 2: Latent space learnt for covariate in multiDGD

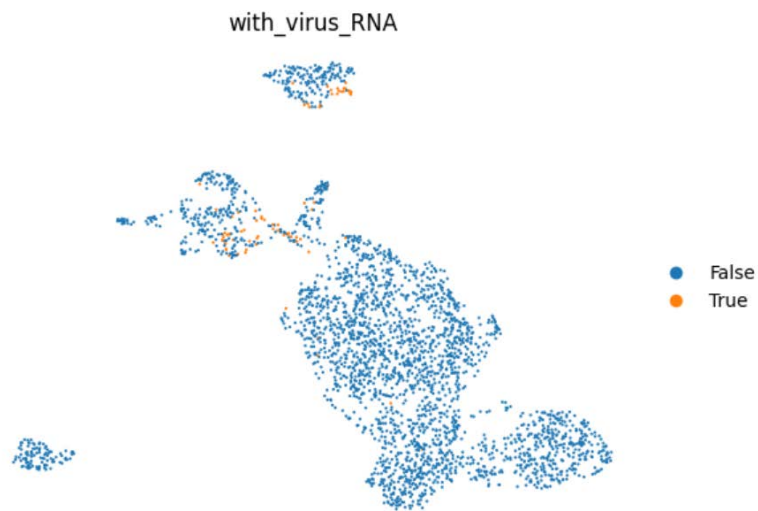


Figure 3: Testing the model’s ability to identify cell’s phenotypes like infection status in low-dimensional space

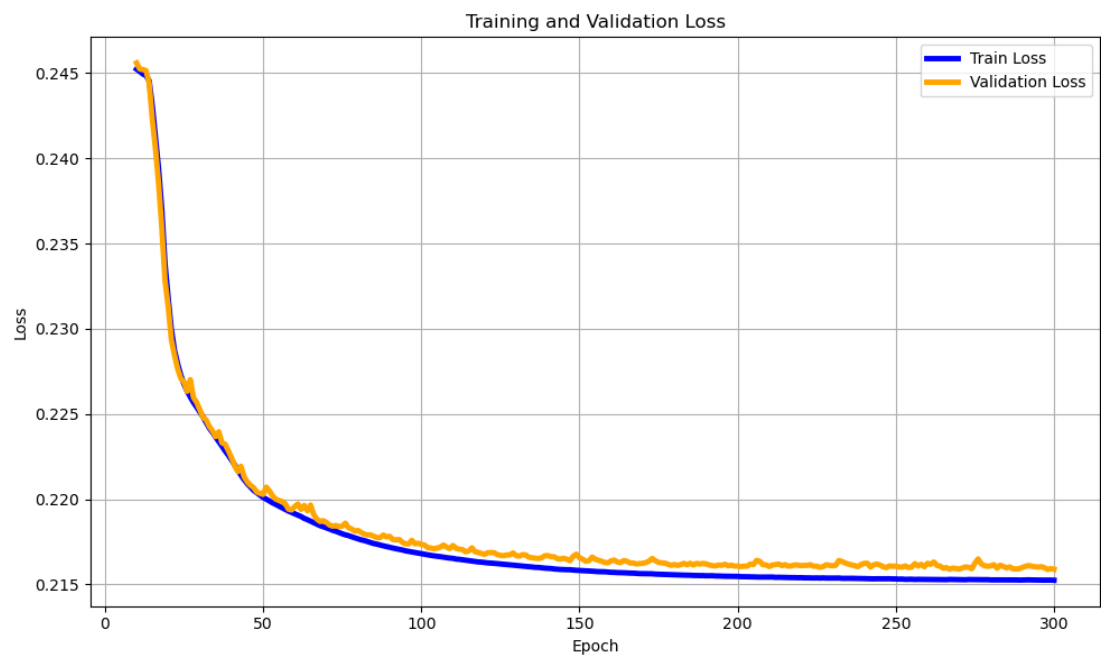


Figure 4: Training progress of the scDGD model

Tables

Table 1: DGD Hyperparameters Search

Parameter	Search
Learning rate decay	$1e-4$, $1e-3$
Dirichlet $\alpha(\alpha)$	1,2,5
Hidden layers	20,50,100
Dropout	0.1, 0.2
Standard deviation (GMM)	0.1,0.2,0.5
Batch size	200~800