

# Flow Matching and Dynamic Optimal Transport

**Exercise 1 .** Starting from a coupling  $(X_0, X_1)$ , we define the linear interpolation  $X_t = tX_1 + (1-t)X_0$ . We remind that the velocity field defined in flow matching writes

$$v_t(x) = \mathbb{E}[X_1 - X_0 | X_t = x] = \frac{1}{1-t} \mathbb{E}[X_1 - X_t | X_t = x] = \frac{1}{1-t} (\mathbb{E}[X_1 | X_t = x] - x). \quad (1)$$

Let  $A \in \mathbb{R}^{d \times d}$  be invertible,  $b \in \mathbb{R}^d$  and  $c \in \mathbb{R}_+^*$ . Show the following properties:

- (i) The velocity  $v_t^{A,b}$  defined from the coupling  $(AX_0 + b, AX_1 + b)$  is given by

$$v_t^{A,b}(x) = Av_t(A^{-1}(x - b)).$$

- (ii) The velocity  $v_t^b$  from the coupling  $(X_0, X_1 + b)$  is given by  $v_t^b(x) = v_t(x - tb) + b$ .

- (iii) The velocity  $v_t^c$  defined from the coupling  $(X_0, cX_1)$  is given by

$$v_t^c = \frac{c}{1-t+tc} v_r \left( \frac{x}{1-t+tc} \right) + \frac{c-1}{1-t+tc} x, \quad \text{with } r = \frac{tc}{1-t+tc}.$$

**Exercise 2 .** Assume that  $\alpha$  is an absolutely continuous probability measure with respect to the Lebesgue measure, and  $\beta$  is a probability measure on  $\mathbb{R}^d$ . Write  $T^*$  the optimal transport map between  $\alpha$  and  $\beta$  for the squared Euclidean cost. Can we say something on what  $T^*$  becomes in the cases considered in Exercise 1?

**Exercise 3 .** Assume that  $\alpha$  and  $\beta$  are probability measures on  $\mathbb{R}$ . Let  $(X_0, X_1)$  be a coupling between  $\alpha$  and  $\beta$  such that the velocity field  $v_t(x) = \mathbb{E}[X_1 - X_0 | X_t = x]$  has a unique flow on  $[0, 1]$ . Show that the flow  $\varphi_t$  associated to  $v_t$  is such that  $\varphi_1$  is an optimal transport map between  $\alpha$  and  $\beta$ .

**Exercise 4 .** Assume that  $(X_0, X_1) \sim \mathcal{N}(0, \Sigma)$  with  $\Sigma = \begin{pmatrix} \Sigma_0 & \Sigma_{10} \\ \Sigma_{01} & \Sigma_1 \end{pmatrix}$ , for positive definite  $\Sigma_0$  and  $\Sigma_1$ . Remind that if  $(Z, T)$  is a Gaussian vector, then  $\mathbb{E}[Z|T] = \mathbb{E}[Z] + \text{Cov}(Z, T)\text{Cov}(T, T)^{-1}(T - \mathbb{E}[T])$ .

- (i) Show that the velocity field  $v_t(x) := \mathbb{E}[X_1 - X_0 | X_t = x]$  is given by

$$v_t(x) = \frac{1}{1-t} ((1-t)\Sigma_{01} + t\Sigma_1)\Sigma_t^{-1} - \text{Id} \, x, \quad (2)$$

where  $\Sigma_t = \text{Cov}(X_t) = (1-t)^2\Sigma_0 + (1-t)t(\Sigma_{01} + \Sigma_{10}) + t^2\Sigma_1$ .

- (ii) Let  $\Sigma_{01} = \Sigma_{10} = 0$  and assume that  $\Sigma_0$  and  $\Sigma_1$  can be jointly diagonalized. Show that the flow  $\varphi_t$  associated to  $v_t$  is such that  $\varphi_1$  is an optimal transport map between  $\alpha$  and  $\beta$ .

**Exercise 5 .**

Assume that  $(X_0, X_1) \sim \sum_{k=1}^K \pi_k \mathcal{N}(m^k, \Sigma^k)$  with  $m^k = \begin{pmatrix} m_0^k \\ m_1^k \end{pmatrix}$  and  $\Sigma^k = \begin{pmatrix} \Sigma_0^k & \Sigma_{10}^k \\ \Sigma_{01}^k & \Sigma_1^k \end{pmatrix}$  for positive definite  $\Sigma_0^k$  and  $\Sigma_1^k$ . Write  $v_t^k$  the velocity field (2) for the covariance matrix  $\Sigma^k$  and write  $w_t^k(x) = v_t^k(x - tm_1^k - (1-t)m_0^k) + m_1^k - m_0^k$ . Show that the velocity field  $v_t(x) := \mathbb{E}[X_1 - X_0 | X_t = x]$  is given by

$$v_t(x) = \sum_{k=1}^K \alpha^k(x) w_t^k(x), \quad (3)$$

where  $\alpha^k(x) = \frac{\pi_k p_t^k(x)}{\sum_{j=1}^K \pi_j p_t^j(x)}$ , with  $p_t^j$  is the Gaussian density of  $\mathcal{N}(m_t^j, \Sigma_t^j)$  with  $m_t^j = tm_1^j + (1-t)m_0^j$  and  $\Sigma_t^j = t^2\Sigma_1^j + (1-t)^2\Sigma_0^j + t(1-t)(\Sigma_{10}^j + \Sigma_{01}^j)$ . What happens if  $X_0$  is a standard centered Gaussian and  $X_1$  follows a discrete distribution of  $K$  equal Dirac masses?