

Appendix

Details on Bound (24)

$$\begin{aligned}
 & \frac{1}{2} \mathbb{E}_{P_0} \left[\left(f(P_0) - \beta^T Z(\hat{P}_0) \right)^2 \right] \\
 &= \frac{1}{2} \psi^T \Sigma \psi + \mathbb{E}_{P_0} \left[\varsigma_0 Z(\hat{P}_0)^T \right] \psi + \frac{1}{2} \mathbb{E}_{P_0} [\varsigma_0^2] \\
 & \quad - \frac{1}{2} \psi^T \Sigma \psi - \mathbb{E}_{P_0} \left[\varsigma_0 Z(\hat{P}_0)^T \right] \Sigma^+ \Sigma \psi \\
 & \quad - \frac{1}{2} \mathbb{E}_{P_0} \left[\varsigma_0 Z(\hat{P}_0)^T \right] \Sigma^+ \mathbb{E}_{P_0} \left[\varsigma_0 Z(\hat{P}_0) \right] \\
 & \leq \frac{1}{2} \mathbb{E}_{P_0} [\varsigma_0^2] + \mathbb{E}_{P_0} \left[\varsigma_0 Z(\hat{P}_0)^T (\psi - \Sigma^+ \Sigma \psi) \right],
 \end{aligned}$$

since Σ^+ is PSD. Let $\Sigma = USU^{-1}$ be the eigen-decomposition of Σ ; i.e. S is diagonal matrix of decreasing eigenvalues and U is a real unitary matrix and $U^{-1} = U^T$. Then, $\Sigma^+ = US^+U^{-1}$, where S^+ is the diagonal matrix where $(S^+)_{ii} = 1/(S)_{ii}$ if $(S)_{ii} \neq 0$ and $(S^+)_{ii} = 0$ if $(S)_{ii} = 0$. Furthermore, let $r = \text{rank}(\Sigma)$, and I_r be the diagonal matrix with $(I_r)_{ii} = 1$ for $i \leq r$ and $(I_r)_{ii} = 0$ for $i > r$. Hence:

$$\begin{aligned}
 \|\Sigma^+ \Sigma \psi\|_2^2 &= \psi^T \Sigma \Sigma^+ \Sigma^+ \Sigma \psi \\
 &= \psi^T U S U^{-1} U S^+ U^{-1} U S^+ U^{-1} U S U^{-1} \psi \\
 &= \psi^T U I_r U^{-1} \psi \\
 &\leq \psi^T U I U^{-1} \psi \\
 &\leq \|\psi\|_2^2.
 \end{aligned}$$

Furthermore,

$$\|\psi\|_2 \leq \sum_{i=1}^{\infty} |\theta_i| \|Z(G_i)\|_2 \leq \sqrt{2}B.$$

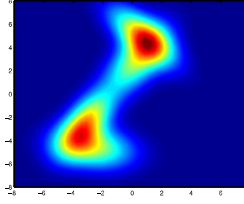
Hence,

$$\begin{aligned}
 & \frac{1}{2} \mathbb{E}_{P_0} \left[\left(f(P_0) - \beta^T Z(\hat{P}_0) \right)^2 \right] \\
 & \leq \frac{1}{2} \mathbb{E}_{P_0} [\varsigma_0^2] + \mathbb{E}_{P_0} \left[\varsigma_0 Z(\hat{P}_0)^T (\psi - \Sigma^+ \Sigma \psi) \right] \\
 & \leq \frac{1}{2} \mathbb{E}_{P_0} [\varsigma_0^2] + \mathbb{E}_{P_0} \left[|\varsigma_0| \|Z(\hat{P}_0)^T (\psi - \Sigma^+ \Sigma \psi)\| \right] \\
 & \leq \frac{1}{2} \mathbb{E}_{P_0} [\varsigma_0^2] + \mathbb{E}_{P_0} \left[|\varsigma_0| \|Z(\hat{P}_0)\|_2 \|\psi - \Sigma^+ \Sigma \psi\|_2 \right] \\
 & \leq \frac{1}{2} \mathbb{E}_{P_0} [\varsigma_0^2] + \sqrt{2} (\|\psi\|_2 + \|\Sigma^+ \Sigma \psi\|_2) \mathbb{E}_{P_0} [|\varsigma_0|] \\
 & \leq \frac{1}{2} \mathbb{E}_{P_0} [\varsigma_0^2] + \sqrt{2} (\|\psi\|_2 + \|\psi\|_2) \mathbb{E}_{P_0} [|\varsigma_0|] \\
 & \leq \frac{1}{2} \mathbb{E}_{P_0} [\varsigma_0^2] + \sqrt{2} (2\sqrt{2}B) \mathbb{E}_{P_0} [|\varsigma_0|] \\
 & \leq \frac{1}{2} \mathbb{E}_{P_0} [\varsigma_0^2] + 4B \sqrt{\mathbb{E}_{P_0} [\varsigma_0^2]},
 \end{aligned}$$

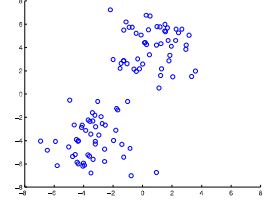
where the last line follows from Jensen's inequality.

GMM Figures

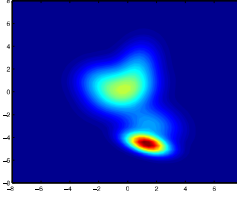
See Figure 5.



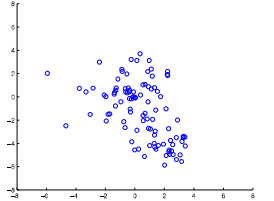
(a) $k = 4$ True Density



(b) $k = 4, n = 100$ Points



(c) $k = 5$ True Density



(d) $k = 5, n = 100$ Points

Figure 5: Typical GMMs generated in our datasets as well as their corresponding samples. One can see that it would be hard for even a human to predict the true number of components, yet the Double-Basis estimator does a good job.

Density Estimation Details

Let $M_t = \{\alpha : \kappa_\alpha(\nu, \gamma) \leq t\} = \{\alpha_1, \dots, \alpha_S\}$. First note that:

$$\begin{aligned}
 & \mathbb{E} [\|p_i - \tilde{p}_i\|_2^2] \\
 &= \mathbb{E} \left[\left\| \sum_{\alpha \in \mathbb{Z}} a_\alpha(P_i) \varphi_\alpha - \sum_{\alpha \in M_t} a_\alpha(\hat{P}_i) \varphi_\alpha \right\|_2^2 \right] \\
 &= \mathbb{E} \left[\int_{\Lambda^l} \left(\sum_{\alpha \in M_t} (a_\alpha(P_i) - a_\alpha(\hat{P}_i)) \varphi_\alpha(x) \right. \right. \\
 & \quad \left. \left. + \sum_{\alpha \in M_t^c} a_\alpha(P_i) \varphi_\alpha(x) \right)^2 dx \right] \\
 &= \mathbb{E} \left[\int_{\Lambda^l} \sum_{\alpha \in M_t} \sum_{\rho \in M_t} (a_\alpha(P_i) - a_\alpha(\hat{P}_i)) (a_\rho(P_i) - a_\rho(\hat{P}_i)) \right. \\
 & \quad \left. \varphi_\alpha(x) \varphi_\rho(x) dx \right] \\
 & \quad + 2 \mathbb{E} \left[\int_{\Lambda^l} \sum_{\alpha \in M_t} \sum_{\rho \in M_t^c} (a_\alpha(P_i) - a_\alpha(\hat{P}_i)) a_\rho(P_i) \right. \\
 & \quad \left. \varphi_\alpha(x) \varphi_\rho(x) dx \right]
 \end{aligned}$$

$$\begin{aligned}
 & + \mathbb{E} \left[\int_{\Lambda^l} \sum_{\alpha \in M_t^c} \sum_{\rho \in M_t^c} a_\alpha(P_i) a_\rho(P_i) \varphi_\alpha(x) \varphi_\rho(x) dx \right] \\
 = & \mathbb{E} \left[\sum_{\alpha \in M_t} (a_\alpha(P_i) - a_\alpha(\hat{P}_i))^2 \right] + \mathbb{E} \left[\sum_{\alpha \in M_t^c} a_\alpha^2(P_i) \right], \tag{27}
 \end{aligned}$$

where the last line follows from the orthonormality of $\{\varphi\}_{\alpha \in \mathbb{Z}}$. Furthermore, note that $\forall P_i \in \mathcal{I}$:

$$\begin{aligned}
 \sum_{\alpha \in M_t^c} a_\alpha^2(P_i) &= \frac{1}{t^2} \sum_{\alpha \in M_t^c} t^2 a_\alpha^2(P_i) \\
 &\leq \frac{1}{t^2} \sum_{\alpha \in \mathbb{Z}} \kappa_\alpha^2(\nu, \gamma) a_\alpha^2(P_i) \\
 &\leq \frac{A}{t^2}. \tag{28}
 \end{aligned}$$

Also,

$$\begin{aligned}
 \mathbb{E} \left[(a_\alpha(P_i) - a_\alpha(\hat{P}_i))^2 \right] &= \left(\mathbb{E} \left[a_\alpha(\hat{P}_i) \right] - a_\alpha(P_i) \right)^2 \\
 &\quad + \text{Var} \left[a_\alpha(\hat{P}_i) \right].
 \end{aligned}$$

Clearly, $a_\alpha(\hat{P}_i)$ is unbiased from (9). Also,

$$\begin{aligned}
 \text{Var} \left[a_\alpha(\hat{P}_i) \right] &= \frac{1}{n_i^2} \sum_{j=1}^{n_i} \text{Var} [\varphi_\alpha(X_{ij})] \\
 &\leq \frac{n_i \varphi_{\max}^2}{n_i^2} \\
 &= O(n_i^{-1}),
 \end{aligned}$$

where $\varphi_{\max} \equiv \max_{\alpha \in \mathbb{Z}^l} \|\varphi_\alpha\|_\infty$. Thus,

$$\mathbb{E} [\|p_i - \tilde{p}_i\|_2^2] \leq \frac{C_1 |M_t|}{n_i} + \frac{C_2}{t^2}.$$

First note that if we have a bound $\forall \alpha \in M_t$, $|\alpha_i| \leq c_i$ then $|M_t| \leq \prod_{i=1}^l (2c_i + 1)$, by a simple counting argument. Let $\lambda = \arg \min_i \nu_i^{2\gamma_i}$. For $\alpha \in M_t$ we have:

$$\sum_{i=1}^l |\alpha_i|^{2\gamma_i} \leq \frac{1}{\nu_\lambda^{2\gamma_\lambda}} \sum_{i=1}^l (\nu_i |\alpha_i|)^{2\gamma_i} = \frac{\kappa_\alpha^2(\nu, \gamma)}{\nu_\lambda^{2\gamma_\lambda}} \leq \frac{t^2}{\nu_\lambda^{2\gamma_\lambda}},$$

and

$$|\alpha_i|^{2\gamma_i} \leq \sum_{i=1}^l |\alpha_i|^{2\gamma_i} \leq t^2 \nu_\lambda^{-2\gamma_\lambda} \implies |\alpha_i| \leq \nu_\lambda^{-\frac{\gamma_\lambda}{\gamma_i}} t^{\frac{1}{\gamma_i}}.$$

Thus, $|M_t| \leq \prod_{i=1}^l (2\nu_\lambda^{-\frac{\gamma_\lambda}{\gamma_i}} t^{\frac{1}{\gamma_i}} + 1)$. Thus, $|M_t| = O(t^{\gamma^{-1}})$ where $\gamma^{-1} = \sum_{j=1}^l \gamma_j^{-1}$. Hence,

$$\frac{\partial}{\partial t} \left[\frac{C_1 t^{\gamma^{-1}}}{n_i} + \frac{C_2}{t^2} \right] = \frac{C_1' t^{\gamma^{-1}-1}}{n_i} - C_2' t^{-3} = 0 \implies$$

$$\begin{aligned}
 t &= C n^{\frac{1}{2+\gamma^{-1}}} \implies \\
 \mathbb{E} [\|p_i - \tilde{p}_i\|_2^2] &\leq \frac{C_1 |M_t|}{n_i} + \frac{C_2}{t^2} = O\left(n_i^{-\frac{2}{2+\gamma^{-1}}}\right).
 \end{aligned}$$

Furthermore, by (27) we may see that for $G_i \in \mathcal{I}$, if

$$\bar{g}_i = \sum_{\alpha \in \mathbb{Z}} a_\alpha(G_i) \varphi_\alpha,$$

then

$$\mathbb{E} [\|g_i - \bar{g}_i\|_2^2] = O\left(n_i^{-\frac{2}{2+\gamma^{-1}}}\right).$$