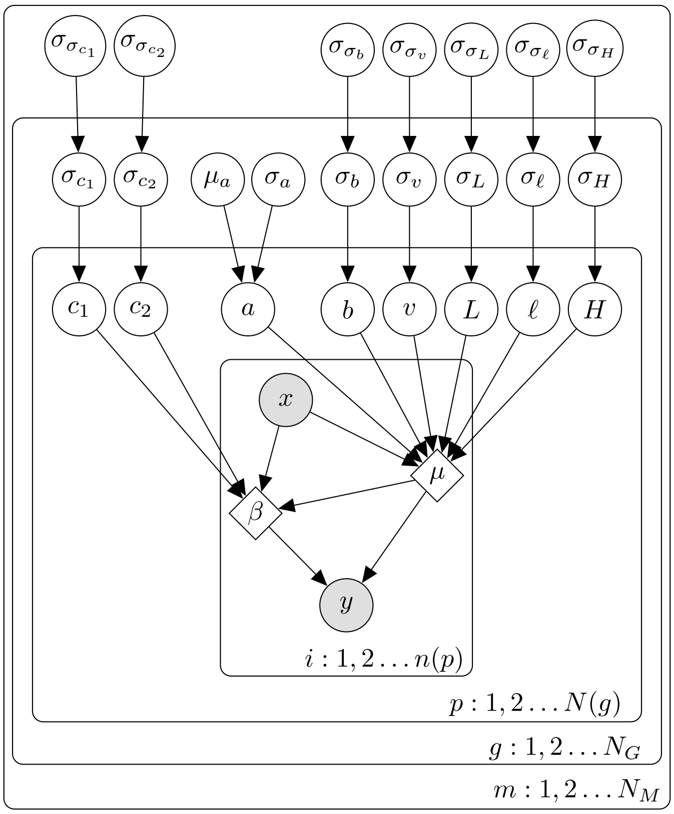
More often than not, y_i^p is not a scalar but an $M-$ dimensional vector $y_i^p = (y_i^{p,0} \dots y_i^{p,M})$ of MEP sizes $y_i^{p,m} \in \mathbb{R}^+$ recorded from m^{th} muscle, for a total of M muscles. hbmep extends the default model to accommodate $M-$ dimensional MEP sizes by assuming that the MEP sizes $y_i^{p,m}$ are independent given the stimulus intensity x_i^p and muscle specific parameters θ_p^m.

$$y_i^{p,m} \mid x_i^p, \theta_{p,m}, \gamma \sim P(y_i^{p,m} \mid x_i^p, \theta_{p,m}, \gamma_m) \tag{4.3.4}$$
$$\theta_{p,m} \mid \gamma \sim P(\theta_{p,m} \mid \gamma_m) \tag{4.3.5}$$
$$\gamma_m \sim P(\gamma_m) \tag{4.3.6}$$

Fig. 4.3.4 shows how the group model from section 4.3.2 extends to handle multiple muscles.



$$y \mid x, \Omega \sim (1-q_y)\cdot \mathcal{G}\left(\mu\beta, \beta\right) + q_y \cdot \mathcal{HN}\left(\sigma_{\text{outlier}}\right) \tag{4.3.7}$$

$$q_y \sim \text{Bern}\left(p_{\text{outlier}}\right) \tag{4.3.8}$$

$$p_{\text{outlier}} \sim \text{Unif}\left(0, C_{p_{\text{outlier}}}\right) \tag{4.3.9}$$

$$\sigma_{\text{outlier}} \sim \mathcal{HN}\left(C_{\sigma_{\text{outlier}}}\right) \tag{4.3.10}$$

where $C_{p_{\text{outlier}}}, C_{\sigma_{\text{outlier}}} > 0$ are constants and $C_{p_{\text{outlier}}} < 1$ is chosen to be very small, usually in the range $0.01 - 0.02$. Intuitively, this means we expect there to be roughly $1\% - 2\%$ outliers which will be captured by the HalfNormal distribution.