As in the previous case, the confusion matrix must be normalized, but in this case to contain the conditional probabilities $P(w_j \mid \mathcal{C}_k)$, where w_j is the j-th component of the GMM in use and $\mathcal{C}_k$ is the k-th target class.

This way, $P(\mathcal{C}_k \mid x)$, the *a posteriori* probability that the current period corresponds to target class $\mathcal{C}_k$ when x has been observed, will be computed as follows according to the Bayes' rule:

$$P(\mathcal{C}_k \mid x) = \frac{\pi(\mathcal{C}_k) \cdot p(x \mid \mathcal{C}_k)}{\sum_c \pi(\mathcal{C}_c) \cdot p(x \mid \mathcal{C}_c)}$$

where

- $\pi(\mathcal{C}_k)$ is the *a priori* probability of the target class $\mathcal{C}_k$, and
- $p(x \mid \mathcal{C}_k)$ is the *conditional probability density* of generating x during the period in which the state of the patient corresponds to target class $\mathcal{C}_k$.

The *conditional probability density* $P(x \mid \mathcal{C}_k)$ is computed as follows:

$$p(x \mid \mathcal{C}_k) = \sum_{j=1}^{J} \pi(w_j) \cdot p(x \mid w_j) \cdot P(w_j \mid \mathcal{C}_k)$$

where

- J is the number of components in the GMM in use,
- $\pi(w_j)$ is the weight of Gaussian w_j in the mixture,
- $p(x \mid w_j) = \mathcal{N}(x \mid \mu_j, \Sigma_j)$ and
- $P(w_j \mid \mathcal{C}_k)$ is the conditional probability of observing samples generated by the Gaussian component w_j during a period corresponding to target class $\mathcal{C}_k$.