

4. Machine Learning and Binaural Hearing

1. Binaural Features
2. Mapping Sounds onto Their Directions
3. Collecting Training Data
4. The Binaural Manifold
5. Localization with a Look-up Table
6. Linear Regression
7. **Piecewise Linear Regression**
8. Predicting the Direction of Speech
9. Principles of Sound Separation
10. Separation & Localization Method

Regression

- Reversed **Linear regression**, $\mathbf{x} \in \mathbb{R}^2$, $\mathbf{y} \in \mathbb{R}^D$:

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{b}, \quad \mathbf{A} \in \mathbb{R}^{D \times 2}, \mathbf{b} \in \mathbb{R}^D$$

- **Piecewise linear regression** (there are K possible mappings):

$$\mathbf{y} = \sum_{k=1}^K \mathbb{I}(z = k)(\mathbf{A}_k \mathbf{x} + \mathbf{b}_k + \mathbf{e}_k)$$

- $\mathbb{I}(z)$ is called an **indicator function**, that selects the k -th affine transformation $\mathbf{A}_k, \mathbf{b}_k$.
- $\mathbf{e}_k \in \mathbb{R}^D$ is an error vector accounting for the piecewise linear approximation.

Probabilistic Setting

- The joint input-output probability is decomposed:

$$p(\mathbf{y}, \mathbf{x}) = \sum_{k=1}^K p(\mathbf{y}|\mathbf{x}, Z = k)p(\mathbf{x}|Z = k)p(Z = k)$$

- Assuming Gaussian (normal) distributions we have:

$$p(\mathbf{y}|\mathbf{x}, Z = k) = \mathcal{N}(\mathbf{y}; \mathbf{A}_k \mathbf{x} + \mathbf{b}_k, \mathbf{\Sigma})$$

$$p(\mathbf{x}|Z = k) = \mathcal{N}(\mathbf{x}; \mathbf{c}_k, \mathbf{\Gamma}_k)$$

$$p(Z = k) = \pi_k$$

Gaussian Mixture Model

- This formulation belongs to Gaussian Mixture Models (GMM).
- The model parameters are:

$$\theta = \{\mathbf{c}_k, \boldsymbol{\Gamma}_k, \pi_k, \mathbf{A}_k, \mathbf{b}_k, \boldsymbol{\Sigma}_k\}_{k=1}^K$$

- The parameters can be estimated via an expectation-maximization (EM) algorithm:

1. Initialize the model parameters $\theta^{(0)} = \{\mathbf{c}_k^{(0)}, \boldsymbol{\Gamma}_k^{(0)}, \pi_k^{(0)}, \mathbf{A}_k^{(0)}, \mathbf{b}_k^{(0)}, \boldsymbol{\Sigma}_k^{(0)}\}_{k=1}^K$,
2. Evaluate the posterior probabilities $r_{kn}^{(i)} = p(Z_n = k | \mathbf{x}_n, \mathbf{y}_n; \theta^{(i-1)})$,
3. Maximize the **complete-data expected log-likelihood**:

$$\theta^{(i)} = \underset{\theta}{\operatorname{argmax}} \mathbb{E}[\log p(\mathbf{X}, \mathbf{Y}, Z | \theta; \theta^{(i-1)})].$$

4. Iterate steps 2 & 3 until convergence.

Posterior Probabilities (I)

- The optimal parameters $\hat{\theta}$ thus obtained allow to estimate the probability of \mathbf{y} given \mathbf{x} :

$$p(\mathbf{y}|\mathbf{x}; \hat{\theta}) = \sum_{k=1}^K \frac{\pi_k \mathcal{N}(\mathbf{x}; \hat{\mathbf{c}}_k, \hat{\mathbf{\Gamma}}_k)}{\sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{x}; \hat{\mathbf{c}}_j, \hat{\mathbf{\Gamma}}_j)} \mathcal{N}(\mathbf{y}; \hat{\mathbf{A}}_k \mathbf{x} + \hat{\mathbf{b}}_k, \hat{\mathbf{\Sigma}}_k).$$

Posterior Probabilities (II)

- More interesting, one can also evaluate the posterior probability of the sound direction, \mathbf{x} , given an ILPD vector, \mathbf{y} :

$$\begin{aligned} p(\mathbf{x}|\mathbf{y}; \tilde{\theta}) &= \sum_{k=1}^K \frac{\pi_k \mathcal{N}(\mathbf{y}; \tilde{\mathbf{c}}_k, \tilde{\mathbf{\Gamma}}_k)}{\underbrace{\sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{y}; \tilde{\mathbf{c}}_j, \tilde{\mathbf{\Gamma}}_j)}_{\tilde{v}_k(\text{proportion})}} \mathcal{N}(\mathbf{x}; \underbrace{\tilde{\mathbf{A}}_k \mathbf{y} + \tilde{\mathbf{b}}_k}_{\tilde{\boldsymbol{\mu}}_k(\text{mean})}, \tilde{\boldsymbol{\Sigma}}_k) \\ &= \sum_{k=1}^K \tilde{v}_k \mathcal{N}(\mathbf{x}; \tilde{\boldsymbol{\mu}}_k, \tilde{\boldsymbol{\Sigma}}_k) \end{aligned}$$

- The parameters $\tilde{\theta}$ are closed-form expressions of $\hat{\theta}$.¹

¹<https://hal.inria.fr/hal-00863468/en>

Session Summary

- Probabilistic treatment of regression
- Gaussian mixture model for regression
- Parameter estimation
- Bayes inversion