CHAPTER 12:

LOCAL MODELS
Divide the input space into local regions and learn simple (constant/linear) models in each patch

- **Unsupervised**: Competitive, online clustering
- **Supervised**: Radial-basis functions, mixture of experts
Competitive Learning

\[ E(\{m_i\}_{i=1}^k|X) = \sum_t \sum_i b_i^t \|x^t - m_i\| \]

\[ b_i^t = \begin{cases} 
1 & \text{if } \|x^t - m_i\| = \min_j \|x^t - m_j\| \\
0 & \text{otherwise}
\end{cases} \]

Batch \( k \)-means: \( m_i = \frac{\sum_t b_i^t x^t}{\sum_t b_i^t} \)

Online \( k \)-means:
\[ \Delta m_{ij} = -\eta \frac{\partial E^t}{\partial m_{ij}} = \eta b_i^t (x_j^t - m_{ij}) \]
Initialize $m_i, i = 1, \ldots, k$, for example, to $k$ random $x^t$
Repeat
    For all $x^t \in X$ in random order
    \[
        i \leftarrow \arg \min_j \|x^t - m_j\|
    \]
    \[
        m_i \leftarrow m_i + \eta(x^t - m_j)
    \]
Until $m_i$ converge

**Winner-take-all network**
Adaptive Resonance Theory

- Incremental; add a new cluster if not covered; defined by vigilance, $\rho$

$$b_i^t = \|x^t - m_i\| = -\min_{i=1}^k \|x^t - m_i\|$$

$$\begin{align*}
    \begin{cases} 
    m_{k+1} \leftarrow x^t & \text{if } b_i > \rho \\
    \Delta m_i = \eta(x^t - m_i) & \text{otherwise}
    \end{cases}
\end{align*}$$

(Carpenter and Grossberg, 1988)
Self-Organizing Maps

- Units have a **neighborhood** defined; \( m_i \) is “between” \( m_{i-1} \) and \( m_{i+1} \), and are all updated together.

- One-dim map:

\[
\Delta m_i = \eta e(l,i)(x^t - m_i)
\]
\[
e(l,i) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{(l-i)^2}{2\sigma^2}\right]
\]

(Kohonen, 1990)
Radial-Basis Functions

- Locally-tuned units:

\[ p_h^t = \exp \left[ -\frac{\|x^t - m_h\|^2}{2s^2_h} \right] \]

\[ y^t = \sum_{h=1}^{H} w_h p_h^t + w_0 \]
Local vs Distributed Representation

Local representation in the space of \( (p_1, p_2, p_3) \)
- \( x^a : (1.0, 0.0, 0.0) \)
- \( x^b : (0.0, 0.0, 1.0) \)
- \( x^c : (1.0, 1.0, 0.0) \)

Distributed representation in the space of \( (h_1, h_2) \)
- \( x^a : (1.0, 1.0) \)
- \( x^b : (0.0, 1.0) \)
- \( x^c : (1.0, 0.0) \)
Training RBF

- Hybrid learning:
  - First layer centers and spreads:
    Unsupervised $k$-means
  - Second layer weights:
    Supervised gradient-descent

- Fully supervised
  (Broomhead and Lowe, 1988; Moody and Darken, 1989)
Regression

\[ E(\{m_h, s_h, w_{ih}\}_{i,h} | \chi) = \frac{1}{2} \sum_t \sum_i (r_i^t - y_i^t)^2 \]

\[ y_i^t = \sum_{h=1}^{H} w_{ih} p_h^t + w_{i0} \]

\[ \Delta w_{ih} = \eta \sum_t (r_i^t - y_i^t) p_h^t \]

\[ \Delta m_{hj} = \eta \sum_t \left[ \sum_i (r_i^t - y_i^t) w_{ih} \right] p_h^t \left( x_j^t - m_{hj} \right) \frac{s_h^2}{s_h^2} \]

\[ \Delta s_h = \eta \sum_t \left[ \sum_i (r_i^t - y_i^t) w_{ih} \right] p_h^t \left\| x^t - m_h \right\|^2 \frac{s_h^3}{s_h^3} \]
Classification

\[ E(\{m_h, s_h, w_{ih}\}_{i,h} \mid \chi) = -\sum_t \sum_i r^t_i \log y^t_i \]

\[ y^t_i = \frac{\exp\left[\sum_h w_{ih}p^t_h + w_{i0}\right]}{\sum_k \exp\left[\sum_h w_{kh}p^t_h + w_{k0}\right]} \]
Rules and Exceptions

\[ y^t = \sum_{h=1}^{H} w_h \rho^t_h + v^T x^t + v_0 \]

Exceptions

Default rule
Rule-Based Knowledge

IF \((x_1 \approx a) \text{ AND } (x_2 \approx b)\) OR \((x_3 \approx c)\) THEN \(y = 0.1\)

\[
p_1 = \exp\left[ -\frac{(x_1 - a)^2}{2s_1^2} \right] \cdot \exp\left[ -\frac{(x_2 - b)^2}{2s_2^2} \right] \quad \text{with } w_1 = 0.1
\]

\[
p_2 = \exp\left[ -\frac{(x_3 - c)^2}{2s_3^2} \right] \quad \text{with } w_2 = 0.1
\]

- Incorporation of prior knowledge (before training)
- Rule extraction (after training) (Tresp et al., 1997)
- Fuzzy membership functions and fuzzy rules
Normalized Basis Functions

\[ g_h^t = \frac{p_h^t}{\sum_{l=1}^{H} p_l^t} \]

\[ = \frac{\exp\left[-\|x^t - m_h\|^2 / 2s_h^2\right]}{\sum_l \exp\left[-\|x^t - m_l\|^2 / 2s_l^2\right]} \]

\[ y_i^t = \sum_{h=1}^{H} w_{ih} g_h^t \]

\[ \Delta w_{ih} = \eta \sum_t (r_i^t - y_i^t) g_h^t \]

\[ \Delta m_{hj} = \eta \sum_t \sum_i (r_i^t - y_i^t)(w_{ih} - y_i^t) g_h^t \frac{(x_j^t - m_{hj})}{s_h^2} \]
Competitive Basis Functions

- Mixture model: \( p(r^t | x^t) = \sum_{h=1}^{H} p(h | x^t) p(r^t | h, x^t) \)

\[
p(h | x^t) = \frac{p(x^t | h)p(h)}{\sum_i p(x^t | l)p(l)}
\]

\[
g^t_h = \frac{a_h \exp[-\|x^t - m_h\|^2 / 2s_h^2]}{\sum_i a_i \exp[-\|x^t - m_i\|^2 / 2s_i^2]}
\]
Regression

\[ p(r^t \mid x^t) = \prod_i \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{(r_i^t - y_i^t)^2}{2\sigma^2}\right] \]

\[ \mathcal{L}(\{m_h, s_h, w_{ih}\}_{i,h} \mid X) = \sum_t \log \sum_h g^t_h \exp\left[-\frac{1}{2} \sum_i (r_i^t - y_{ih})^2\right] \]

\[ y_{ih} = w_{ih} \text{ is the constant fit} \]

\[ \Delta w_{ih} = \eta \sum_t (r_i^t - y_{ih}^t) f_h^t \quad \Delta m_{hj} = \eta \sum_t (f_h^t - g_h^t) \frac{(x_j^t - m_{hj})}{s_h^2} \]

\[ f_h^t = \frac{g_h^t \exp\left[-(1/2)\sum_i (r_i^t - y_{ih})^2\right]}{\sum_l g_l^t \exp\left[-(1/2)\sum_i (r_i^t - y_{il})^2\right]} \]

\[ p(h \mid r, x) = \frac{p(h \mid x)p(r \mid h, x)}{\sum_l p(l \mid x)p(r \mid l, x)} \]
Classification

\[
\mathcal{L}(\{\mathbf{m}_h, s_h, w_{ih}\}_{i,h} | \mathcal{X}) = \sum_t \log \sum_h g_h^t \prod_i (y_{ih}^t)^{r_i^t}
\]

\[
= \sum_t \log \sum_h g_h^t \exp \left[ \sum_i r_i^t \log y_{ih}^t \right]
\]

\[
y_{ih}^t = \frac{\exp \mathbf{w}_{ih}}{\sum_k \exp \mathbf{w}_{kh}}
\]

\[
f_h^t = \frac{g_h^t \exp \left[ \sum_i r_i^t \log y_{ih}^t \right]}{\sum_l g_i^t \exp \left[ \sum_i r_i^t \log y_{il}^t \right]}
\]
EM for RBF (Supervised EM)

- E-step:
  \[ f_h^t \equiv p(r \mid h, x^t) \]

- M-step:
  \[ m_h = \frac{\sum_t f_h^t x^t}{\sum_t f_h^t} \]
  \[ s_h = \frac{\sum_t f_h^t (x^t - m_h)(x^t - m_h)^T}{\sum_t f_h^t} \]
  \[ w_{ih} = \frac{\sum_t f_h^t r_i^t}{\sum_t f_h^t} \]
Learning Vector Quantization

- $H$ units per class prelabeled (Kohonen, 1990)
- Given $x$, $m_i$ is the closest:

\[
\begin{align*}
\Delta m_i &= \eta (x^t - m_i) \quad \text{if label}(x^t) = \text{label}(m_i) \\
\Delta m_i &= -\eta (x^t - m_i) \quad \text{otherwise}
\end{align*}
\]
Mixture of Experts

- In RBF, each local fit is a constant, $w_{ih}$, second layer weight.
- In MoE, each local fit is a linear function of $x$, a local expert:
  \[ y_i = w_{ih}^T x \]

(Jacobs et al., 1991)
MoE as Models Combined

- Radial gating:
  
  \[ g_h^t = \frac{\exp\left[-\|x^t - m_h\|^2 / 2s_h^2\right]}{\sum_i \exp\left[-\|x^t - m_i\|^2 / 2s_i^2\right]} \]

- Softmax gating:
  
  \[ g_h^t = \frac{\exp[m_h^T \! x^t]}{\sum_i \exp[m_i^T \! x^t]} \]
Cooperative MoE

\[ E\left(\{m_h, s_h, w_{ih}\}_{i,h} \mid X\right) = \frac{1}{2} \sum_t \sum_i (r_i^t - y_i^t)^2 \]

\[ \Delta v_{ih} = \eta \sum_t (r_i^t - y_i^t) g_h^t x^t \]

\[ \Delta m_{hj} = \eta \sum_t (r_i^t - y_{ih}) (w_{ih}^t - y_i^t) g_h^t x_j^t \]

- Regression
Competitive MoE: Regression

\[ L(\{m_h, s_h, w_{ih}\}_{i, h} | \mathbf{X}) = \sum_t \log \sum_h g_h^t \exp \left[ -\frac{1}{2} \sum_i (r_i^t - y_{ih}^t)^2 \right] \]

\[ y_{ih}^t = w_{ih} = v_{ih} x_t \]

\[ \Delta v_{ih} = \eta \sum_t (r_i^t - y_{ih}^t) f_h^t x_t \]

\[ \Delta m_h = \eta \sum_t (f_h^t - g_h^t) x_t \]
Competitive MoE: Classification

\[ \mathcal{L}(\{m_h, s_h, w_{ih}\}_{i,h} | \mathbf{X}) = \sum_k \log \left( \sum_h \prod_i g_h^{t_i} \right) \]

\[ = \sum_k \log \left( \sum_h \prod_i g_h^{t_i} \exp \left[ \sum_i r_i^{t_i} \log y_{ih}^{t_i} \right] \right) \]

\[ y_{ih}^{t_i} = \frac{\exp w_{ih}^{t_i}}{\sum_k \exp w_{kh}^{t_i}} = \frac{\exp v_{ih}^{t_i} \mathbf{x}_t}{\sum_k \exp v_{kh}^{t_i} \mathbf{x}_t} \]
Hierarchical Mixture of Experts

- Tree of MoE where each MoE is an expert in a higher-level MoE

- **Soft decision tree**: Takes a weighted (gating) average of all leaves (experts), as opposed to using a single path and a single leaf

- Can be trained using EM (Jordan and Jacobs, 1994)