# 第3章：参数估计(续)

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# 上次课主要内容回顾

- 离散变量贝叶斯决策
- 复合模式分类

- 最大似然参数估计
- 贝叶斯估计

高斯分布的情况

Parameter space vs
feature space

二者的区别和联系

# 提 纲

- 第3章
  - 特征维数问题
  - 期望最大法
  - 隐马尔可夫模型

# 特征维数问题

- 统计模式分类
  - 特征空间划分
  - 贝叶斯决策：最小风险规则，MAP
- 增加特征有什么好处
  - 判别性：类别间有差异的特征有助于分类
- 带来什么问题
  - 计算
  - 存储
  - 泛化性能，Overfitting

# 分类错误率与特征的关系

- 二类高斯分布
  - $p(\mathbf{x}|\omega_j)$~$N(\mu_j,\Sigma)$, $j$=1,2, 等协方差矩阵
  - Bayes error rate

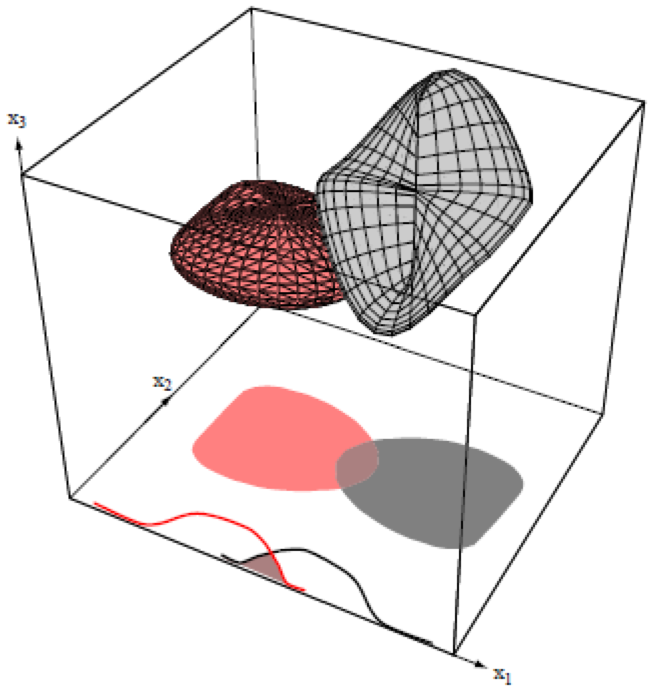
$$P(e)=\frac{1}{\sqrt{2\pi}}\int_{r/2}^{\infty}e^{-u^2/2}\,du \qquad r^2=(\boldsymbol{\mu}_1-\boldsymbol{\mu}_2)^t\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu}_1-\boldsymbol{\mu}_2)$$

$$\begin{aligned}P(error) &= P(\mathbf{x}\in\mathcal{R}_2,\omega_1)+P(\mathbf{x}\in\mathcal{R}_1,\omega_2)\\ &= P(\mathbf{x}\in\mathcal{R}_2|\omega_1)P(\omega_1)+P(\mathbf{x}\in\mathcal{R}_1|\omega_2)P(\omega_2)\\ &= \int_{\mathcal{R}_2}p(\mathbf{x}|\omega_1)P(\omega_1)\,d\mathbf{x}+\int_{\mathcal{R}_1}p(\mathbf{x}|\omega_2)P(\omega_2)\,d\mathbf{x}.\end{aligned}$$

  - Conditionally independent case $\Sigma=diag(\sigma_1^2,...,\sigma_d^2)$
    - 每一维二类均值之间距离反映区分度，决定错误率
    - 特征增加有助于减小错误率($r^2$增大)

$$r^2=\sum_{i=1}^{d}\left(\frac{\mu_{i1}-\mu_{i2}}{\sigma_i}\right)^2$$

- 特征维数决定可分性的例子
  - 3D空间完全可分
  - 2D和1D投影空间有重叠




然而，增加特征也可能导致分类性能更差，因为有模型估计误差(wrong model)

# 计算复杂度

- 最大似然估计
  - 高斯分布，*d*维特征，*n*个样本
  - 参数估计的复杂度，主要由Σ决定

$$g(\mathbf{x}) = -\frac{1}{2}(\mathbf{x} - \overset{\overset{O(dn)}{\uparrow}}{\hat{\boldsymbol{\mu}}})^t \overbrace{\widehat{\boldsymbol{\Sigma}}^{-1}}^{O(nd^2)} (\mathbf{x} - \hat{\boldsymbol{\mu}}) - \overbrace{\frac{d}{2}\ln 2\pi}^{O(1)} - \overbrace{\frac{1}{2}\ln|\widehat{\boldsymbol{\Sigma}}|}^{O(d^2 n)} + \overbrace{\ln P(\omega)}^{O(n)}$$

$$\widehat{\boldsymbol{\Sigma}} = \frac{1}{n}\sum_{k=1}^{n}(\mathbf{x}_k - \mathbf{m}_n)(\mathbf{x}_k - \mathbf{m}_n)^t$$

- 参数存储复杂度

$$c(d + d(d+1)/2)$$

- 分类复杂度？

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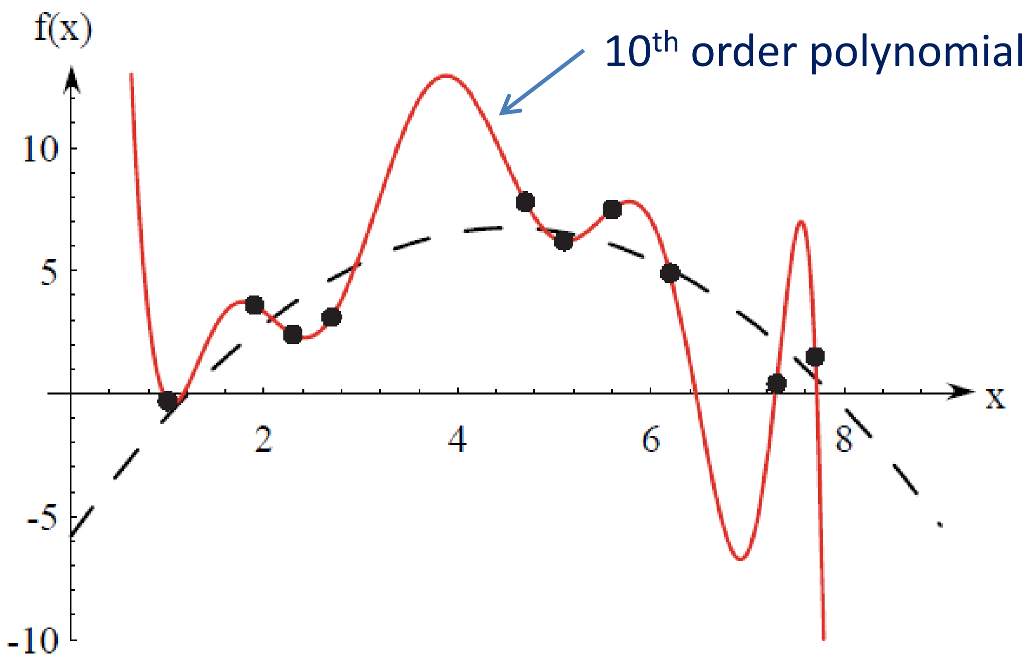
# 过拟合(Overfitting)

- Overfitting
  - 特征维数高、训练样本少导致模型参数估计不准确
    - 比如协方差矩阵需要样本数在*d*以上
- 克服办法
  - 特征降维：特征提取(变换)、特征选择
  - 参数共享/平滑
    - 共享协方差矩阵$\Sigma_0$
    - Shrinkage (a.k.a. Regularized Discriminant Analysis)

$$\Sigma_i(\alpha) = \frac{(1-\alpha)n_i\Sigma_i + \alpha n\Sigma}{(1-\alpha)n_i + \alpha n}$$

$$\Sigma(\beta) = (1-\beta)\Sigma + \beta\mathbf{I}$$

- 过拟合的例子




$$f(x) = ax^2 + bx + c + \epsilon \text{ where } p(\epsilon) \sim N(0, \sigma^2)$$

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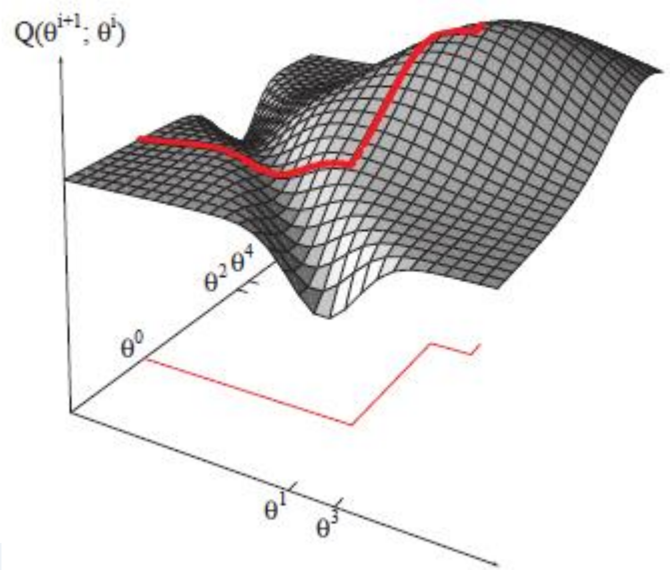
# 期望-最大法(EM)

- 数据缺失情况下的参数估计
  - Good features, missing/bad features $\mathbf{x}_k = \{\mathbf{x}_{kg}, \mathbf{x}_{kb}\}$

$$\mathcal{D} = \{\mathbf{x}_1, ..., \mathbf{x}_n\} = \mathcal{D}_g \cup \mathcal{D}_b$$

  - 已知参数θ^i情况下估计新参数θ
    - 对缺失数据求期望(marginalize)

max $Q(\theta;\ \theta^i) = \mathcal{E}_{\mathcal{D}_b}[\ln p(\mathcal{D}_g, \mathcal{D}_b;\ \theta)|\mathcal{D}_g;\ \theta^i]$



- Expectation-Maximization (EM)

**Algorithm 1** (Expectation-Maximization)

$$
\begin{array}{l}
\underline{\textbf{begin}}\ \underline{\textbf{initialize}}\ \theta^0, T, i = 0 \\
\qquad \underline{\textbf{do}}\ i \leftarrow i + 1 \\
\qquad\qquad \textbf{E step}: \text{compute } Q(\boldsymbol{\theta};\ \boldsymbol{\theta}^i) \\
\qquad\qquad \textbf{M step}: \boldsymbol{\theta}^{i+1} \leftarrow \arg\max_{\theta} Q(\boldsymbol{\theta};\ \boldsymbol{\theta}^i) \\
\qquad \underline{\textbf{until}}\ Q(\boldsymbol{\theta}^{i+1};\ \boldsymbol{\theta}^i) - Q(\boldsymbol{\theta}^i;\ \boldsymbol{\theta}^{i-1}) \leq T \\
\quad \underline{\textbf{return}}\ \hat{\theta} \leftarrow \theta^{i+1} \\
\underline{\textbf{end}}
\end{array}
$$

The EM algorithm guarantees that the log-likelihood of good data increases monotonically.

- Example: EM for a 2D Gaussian

$$\mathcal{D} = \{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4\} = \left\{\binom{0}{2}, \binom{1}{0}, \binom{2}{2}, \binom{*}{4}\right\}$$

parameters $\boldsymbol{\theta} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \sigma_1^2 \\ \sigma_2^2 \end{pmatrix}$ initially $\boldsymbol{\theta}^0 = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 1 \end{pmatrix}$

$$\begin{aligned}
Q(\boldsymbol{\theta};\ \boldsymbol{\theta}^0) &= \mathcal{E}_{x_{41}}[\ln p(\mathbf{x}_g, \mathbf{x}_b;\ \boldsymbol{\theta}|\boldsymbol{\theta}^0;\ \mathcal{D}_g)] \\
&= \int_{-\infty}^{\infty} \left[\sum_{k=1}^{3} \ln p(\mathbf{x}_k|\boldsymbol{\theta}) + \ln p(\mathbf{x}_4|\boldsymbol{\theta})\right] p(x_{41}|\boldsymbol{\theta}^0;\ x_{42}=4)\ dx_{41} \\
&= \sum_{k=1}^{3} [\ln p(\mathbf{x}_k|\boldsymbol{\theta})] + \int_{-\infty}^{\infty} \ln p\left(\left.\binom{x_{41}}{4}\right|\boldsymbol{\theta}\right) \frac{p\left(\binom{x_{41}}{4}|\boldsymbol{\theta}^0\right)}{\underbrace{\left(\int_{-\infty}^{\infty} p\left(\left.\binom{x'_{41}}{4}\right|\boldsymbol{\theta}^0\right) dx'_{41}\right)}_{\equiv K}} dx_{41}
\end{aligned}$$

$$\begin{aligned}
Q(\boldsymbol{\theta};\ \boldsymbol{\theta}^0) &= \sum_{k=1}^{3} [\ln p(\mathbf{x}_k|\boldsymbol{\theta})] + \frac{1}{K} \int_{-\infty}^{\infty} \ln p\left(\left.\binom{x_{41}}{4}\right|\boldsymbol{\theta}\right) \frac{1}{2\pi \left|\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}\right|} \exp\left[-\frac{1}{2}(x_{41}^2 + 4^2)\right] dx_{41} \\
&= \sum_{k=1}^{3} [\ln p(\mathbf{x}_k|\boldsymbol{\theta})] - \frac{1+\mu_1^2}{2\sigma_1^2} - \frac{(4-\mu_2)^2}{2\sigma_2^2} - \ln\ (2\pi\sigma_1\sigma_2).
\end{aligned}$$

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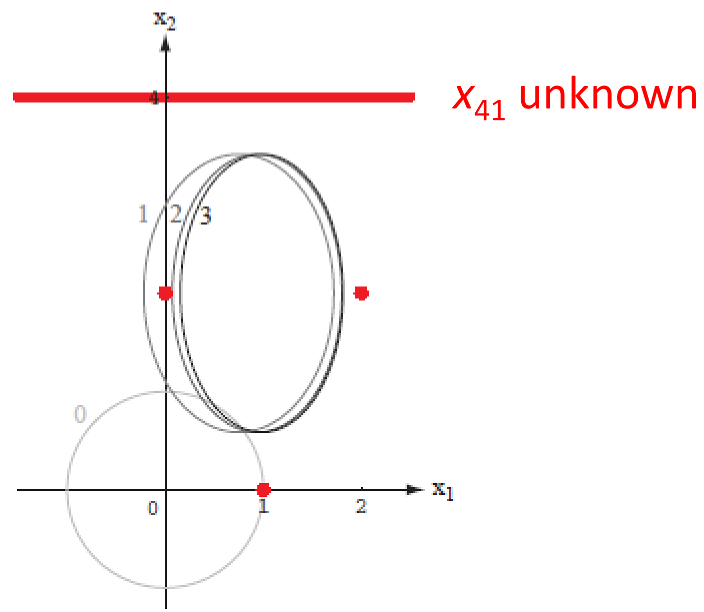
$$\max \sum_{k=1}^{3} [\ln p(\mathbf{x}_k|\boldsymbol{\theta})] - \frac{1+\mu_1^2}{2\sigma_1^2} - \frac{(4-\mu_2)^2}{2\sigma_2^2} - \ln\,(2\pi\sigma_1\sigma_2)$$

$$\boldsymbol{\theta}^1 = \begin{pmatrix} 0.75 \\ 2.0 \\ 0.938 \\ 2.0 \end{pmatrix}$$

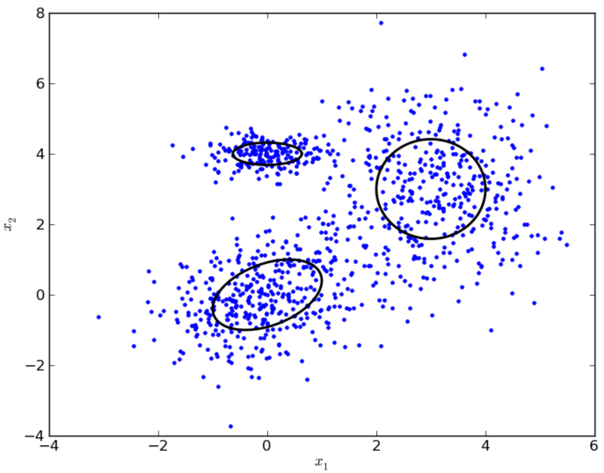
After 3 iterations $\boldsymbol{\mu} = \binom{1.0}{2.0}$, and $\boldsymbol{\Sigma} = \begin{pmatrix} 0.667 & 0 \\ 0 & 2.0 \end{pmatrix}$



- EM for Gaussian mixture
  - 参数型概率密度函数，可以表示复杂的分布

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \, p(\mathbf{x} \mid \theta_k)$$

$$\text{subject to } \sum_{k=1}^{K} \pi_k = 1$$




- Gaussian component

$$p(\mathbf{x} \mid \theta_k) = \mathcal{N}(\mathbf{x} \mid \mu_k, \Sigma_k)$$

  - 参数估计：Maximum Likelihood (ML)

$$\max LL = \log \prod_{n=1}^{N} p(\mathbf{x}_n) = \sum_{n=1}^{N} \log \sum_{k=1}^{K} \pi_k \, p(\mathbf{x}_n \mid \theta_k)$$

$$\nabla_{\pi_k} LL = 0, \quad \nabla_{\mu_k} LL = 0, \quad \nabla_{\Sigma_k} LL = 0$$

不能解析求解

- EM Algorithm for Gaussian mixture
  - Incomplete data X, complete data {X,Z}

$$z_{nk} \in \{0,1\}, \quad k = 1, \ldots, K$$

  - Expectation of complete data log-likelihood

$$Q(\Theta, \Theta^{old}) = \sum_{\mathbf{Z}} \log p(\mathbf{X}, \mathbf{Z} \mid \Theta) \, p(\mathbf{Z} \mid \mathbf{X}, \Theta^{old})$$

1. Choose an initial set of parameters for $\Theta^{old}$
2. E-step: Evaluate p(Z|X, $\Theta^{old}$)
3. M-step: Update parameters

$$\Theta^{new} = \arg\max_{\Theta} Q(\Theta, \Theta^{old})$$

4. If convergence condition is not satisfied

$$\Theta^{old} \leftarrow \Theta^{new}$$

5. Return to E-step

(C.M. Bishop, *Pattern Recognition and Machine Learning*, 2006)

- EM Algorithm for Gaussian mixture

E-step $$p(\mathbf{X},\mathbf{Z}\mid\Theta)=\prod_{n=1}^{N}\prod_{k=1}^{K}\pi_k^{z_{nk}}\mathcal{N}(\mathbf{x}_n\mid\mu_k,\Sigma_k)^{z_{nk}}$$

$$Q(\Theta,\Theta^{old})=\mathrm{E}_{\mathbf{Z}}[\log p(\mathbf{X},\mathbf{Z}\mid\Theta)]=\sum_{n=1}^{N}\sum_{k=1}^{K}\gamma(z_{nk})\{\log\pi_k+\log\mathcal{N}(\mathbf{x}\mid\mu_k,\Sigma_k)\}$$

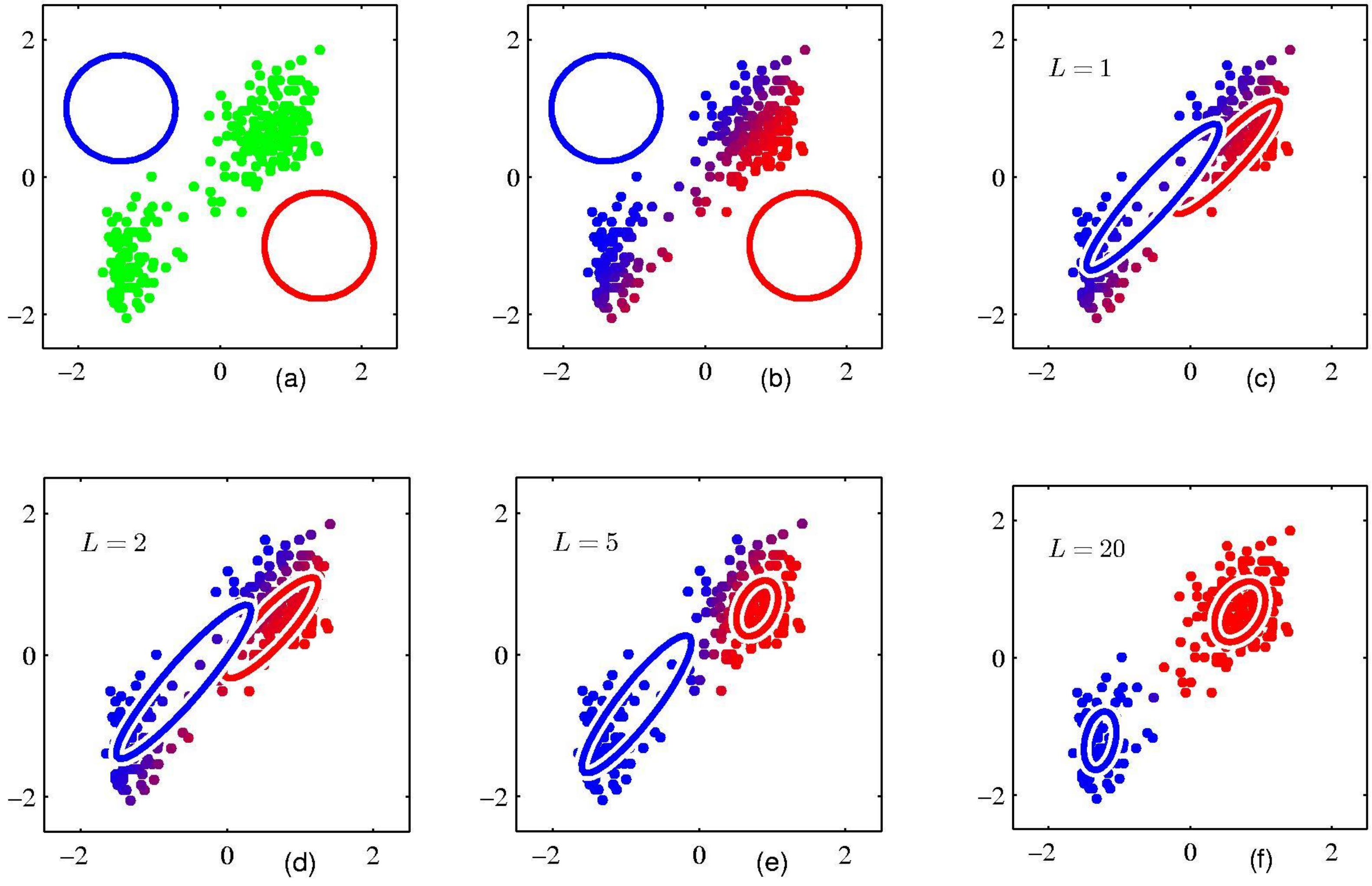
$$\gamma(z_{nk})=P(z_{nk}=1\mid\mathbf{x}_n)=\frac{\pi_k N(\mathbf{x}_n\mid\mu_k,\Sigma_k)}{\sum_{j=1}^{K}\pi_j N(\mathbf{x}_n\mid\mu_j,\Sigma_j)}$$

M-step $$\nabla_{\pi_k}Q=0,\quad \nabla_{\mu_k}Q=0,\quad \nabla_{\Sigma_k}Q=0$$

$$\begin{cases}\mu_k^{new}=\dfrac{1}{N_k}\sum_{n=1}^{N}\gamma(z_{nk})\mathbf{x}_n\\ \Sigma_k^{new}=\dfrac{1}{N_k}\sum_{n=1}^{N}\gamma(z_{nk})(\mathbf{x}_n-\mu_k^{new})(\mathbf{x}_n-\mu_k^{new})^T\\ \pi_k^{new}=\dfrac{N_k}{N}\end{cases}$$

$$N_k=\sum_{n=1}^{N}\gamma(z_{nk})$$

An example, from (C.M. Bishop, *Pattern Recognition and Machine Learning*, 2006. Figure 9.8)



# Break

# 隐马尔可夫模型


- Sequential (Temporal) Pattern
  - Variable length
  - Distortion
  - Ambiguous boundary between primitives (symbols)
- Bayesian Classification
  - Sequence of patterns (observations) $\mathbf{O} = O_1 O_2 \cdots O_T$
  - Sequence class (states) $\mathbf{q} = q_1 q_2 \cdots q_T$
  - Posterior probability $$P(\mathbf{q} \mid \mathbf{O}) = \frac{p(\mathbf{O} \mid \mathbf{q}) P(\mathbf{q})}{p(\mathbf{O})}$$
- Hidden Markov Model (HMM)
  - Model $p(\mathbf{O} \mid \mathbf{q})$, $p(\mathbf{O}, \mathbf{q})$

# Markov Chain

- Sequence of States (classes)

$$P(q_1 q_2 \cdots q_T) = P(q_1)P(q_2 | q_1)P(q_3 | q_1 q_2)\cdots P(q_T | q_1 \cdots q_{T-1})$$

$$q_t \in \{S_1, \ldots S_N\}$$

  - First-Order Markov

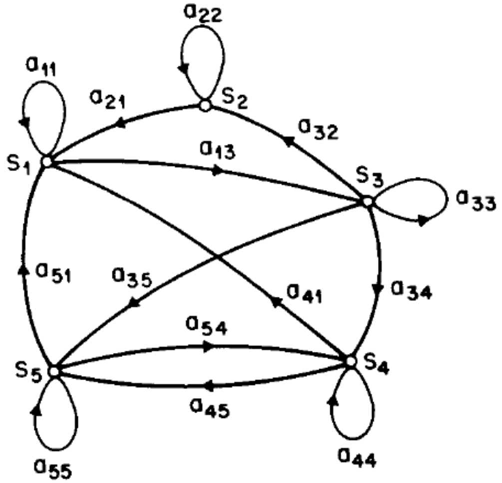
$$P(q_t = S_j \,|\, q_{t-1} = S_i, q_{t-2} = S_k, \cdots) = P(q_t = S_j \,|\, q_{t-1} = S_i)$$

$$P(q_1 q_2 \cdots q_T) =$$
$$P(q_1)P(q_2 | q_1)P(q_3 | q_2)\cdots P(q_T | q_{T-1})$$

State transition probabilities

$$a_{ij} = P(q_t = S_j \,|\, q_{t-1} = S_i), \quad 1 \le i, j \le N$$

$$\sum_{j=1}^{N} a_{ij} = 1$$




L.R. Rabiner, A tutorial on hidden Markov models and selected applications in speech recognition, *Proc. IEEE*, 77(2): 257-286, 1989.

– State duration (self-transition)

$$O=\{\underset{1}{S_i},\ \underset{2}{S_i},\ \underset{3}{S_i},\ \cdots,\ \underset{d}{S_i},\ \underset{d+1}{S_j} \neq S_i\}$$

$$P(O \mid \text{Model}, q_1 = S_i) = (a_{ii})^{d-1}(1-a_{ii}) = p_i(d)$$

– Expected duration of specific state

$$\bar{d}_i = \sum_{d=1}^{\infty} d\ p_i(d)$$

$$= \sum_{d=1}^{\infty} d(a_{ii})^{d-1}(1\text{-}a_{ii}) = \frac{1}{1-a_{ii}}$$

- Example: Transition of Weather

**State 1: rain or (snow)**

**State 2: cloudy**

**State 3: sunny**

$$\mathbf{A} = \{a_{ij}\} = \begin{bmatrix} 0.4 & 0.3 & 0.3 \\ 0.2 & 0.6 & 0.2 \\ 0.1 & 0.1 & 0.8 \end{bmatrix}$$

Expected number of days for sunny and cloudy?

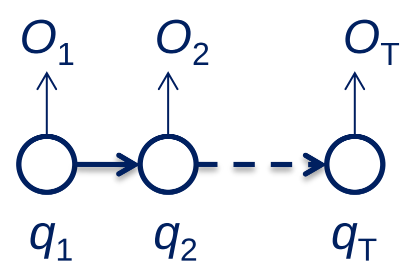
# Hidden Markov Model (HMM)

- Markov Chain: States are Observable
- Hidden States: An Example
  - Imagine you are in a un-windowed room, cannot see the weather outside. Instead, you can guess the weather from the temperature and humidity in room
    - Observations: temperature, humidity
    - Hidden states: weather
  - Hidden Markov Model (HMM): Doubly embedded stochastic process

    $P(O_1,O_2,\ldots,O_T)$

    $P(q_1,q_2,\ldots,q_T)$

    - Infer states from observations



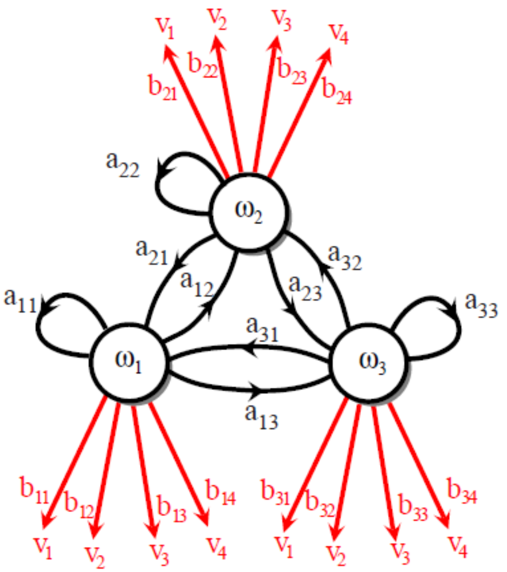

$q_i \in \{S_1,S_2,\ldots,S_N\}$

- Elements of an HMM $\boldsymbol{\lambda} = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi})$
  - $N$: number of states in the model, $S=\{S_1,S_2,\ldots,S_N\}$
  - $M$: number of observation symbols, $V=\{v_1,v_2,\ldots,v_M\}$
  - State transition probability distribution $A=\{a_{ij}\}$

$$a_{ij} = P(q_{t+1} = S_j \mid q_t = S_i), \quad 1 \le i, j \le N$$

  - Observation symbol (emission) probability distribution $B=\{b_j(k)\}$ $\quad b_j(k) = P(v_k \text{ at } t \mid q_t = S_j), \; 1 \le j \le N, \; 1 \le k \le M$
  - Initial state distribution $\boldsymbol{\pi} = \{\pi_i\}$

$$\pi_i = P(q_1 = S_i), \; 1 \le i \le N$$



- Three Basic Problems of HMM
  - Problem 1 (Evaluation):

    How to efficiently compute the probability of observation sequence $P(O|\lambda)$
  - Problem 2 (Decoding):

    How to choose the best state sequence responding to an observation sequence
  - Problem 3 (Training):

    How to estimate the model parameters

# Evaluation Problem

- Given model $\boldsymbol{\lambda} = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi})$ and observation sequence $O=O_1O_2\ldots O_T$, compute $P(O \mid \boldsymbol{\lambda})$
  - Direct computation

$$\boxed{\begin{aligned} P(O \mid \boldsymbol{\lambda}) &= \sum_{all\ Q} P(O \mid Q, \boldsymbol{\lambda}) P(Q \mid \boldsymbol{\lambda}) \\ &= \sum_{q_1, q_2, \ldots, q_T} \pi_{q_1} b_{q_1}(O_1) a_{q_1 q_2} b_{q_2}(O_2) \cdots a_{q_{T-1} q_T} b_{q_T}(O_\mathbf{T}) \end{aligned}}$$

Conditional independence

$$P(O \mid Q, \boldsymbol{\lambda}) = \prod_{t=1}^{T} P(O_t \mid q_t, \boldsymbol{\lambda}) = b_{q_1}(O_1) b_{q_2}(O_2) \cdots b_{q_T}(O_\mathbf{T})$$

$$P(Q \mid \boldsymbol{\lambda}) = \pi_{q_1} a_{q_1 q_2} a_{q_2 q_3} \cdots a_{q_{T-1} q_T}$$

Markov chain of states

  - Complexity: O(2$TN^T$)!

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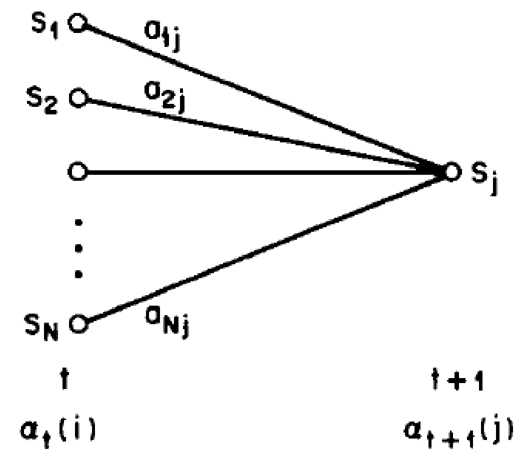
- Evaluation: Forward Procedure
  - Define forward variable $\boxed{\alpha_t(i) = P(O_1 O_2 \cdots O_t, q_t = S_i \mid \lambda)}$
  - Initialization $\alpha_1(i) = \pi_i b_i(O_1), \; 1 \le i \le N$
  - Induction

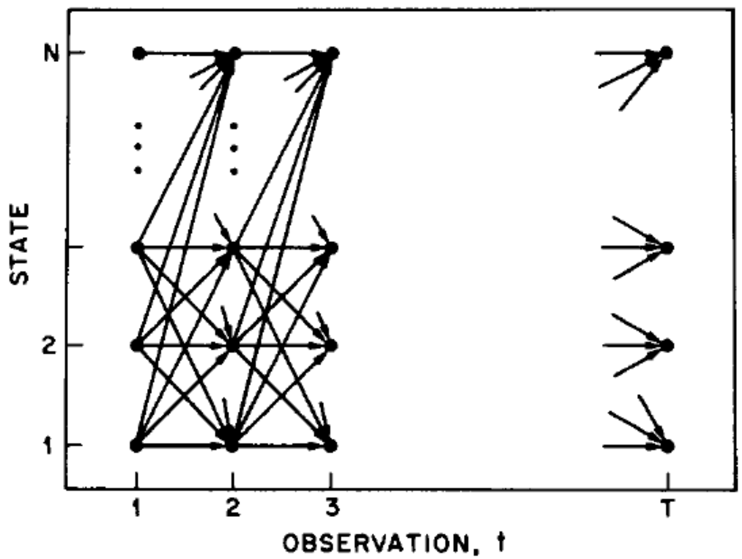
$$\boxed{\begin{gathered}\alpha_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha_t(i) a_{ij}\right] b_j(O_{t+1}), \\ 1 \le t \le T-1, \qquad 1 \le j \le N.\end{gathered}}$$




  - Termination

$$P(O \mid \lambda) = \sum_{i=1}^{N} \alpha_T(i)$$

  - Complexity: O($TN^2$)



- Evaluation: Backward Procedure
  - Define backward variable

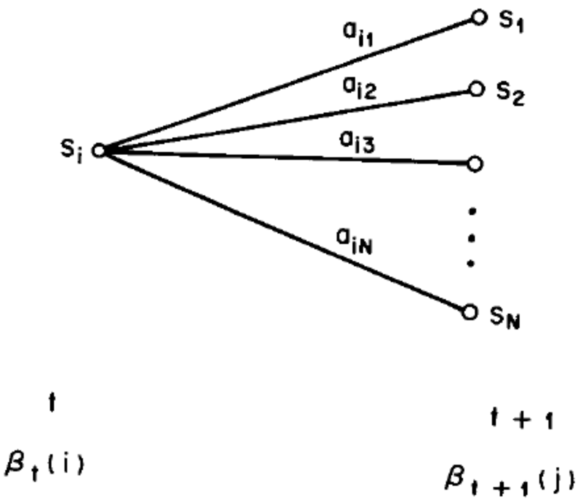
$$\beta_t(i) = P(O_{t+1}, \cdots, O_T \mid q_t = S_i, \lambda)$$

  - Initialization

$$\beta_T(i) = 1, \quad 1 \le i \le N$$

  - Induction

$$\boxed{\begin{gathered}\beta_t(i) = \sum_{j=1}^{N} a_{ij} b_j(O_{t+1}) \beta_{t+1}(j), \\ 1 \le t \le T-1, \quad 1 \le i \le N\end{gathered}}$$




  - Termination

$$P(O \mid \lambda) = \sum_{i=1}^{N} \pi_i b_i(O_1) \beta_1(i) = \sum_{i=1}^{N} \alpha_1(i) \beta_1(i)$$

  - Complexity?

# Decoding Problem

- This is Pattern Recognition
- Optimal Sequence of States

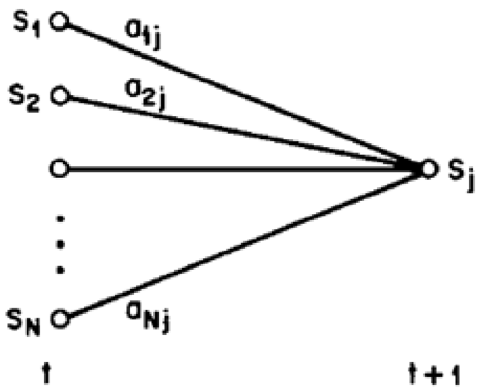
$$\max_{q_1 q_2 \cdots q_T} P(q_1 q_2 \cdots q_T \mid O, \boldsymbol{\lambda}) = \max_{q_1 q_2 \cdots q_T} P(q_1 q_2 \cdots q_T, O \mid \boldsymbol{\lambda})$$

- Viterbi Algorithm (DP)
  - Define variable

$$\delta_t(i) = \max_{q_1, q_2, \cdots, q_{t-1}} P(q_1 q_2 \cdots q_t = i, O_1 O_2 \cdots O_t / \boldsymbol{\lambda})$$

  - DP

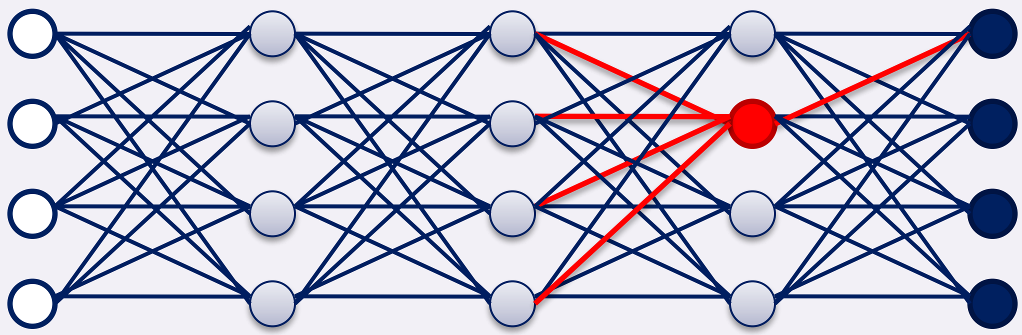
$$\delta_{t+1}(j) = \left[ \max_i \delta_t(i) a_{ij} \right] \cdot b_j(O_{t+1})$$




  - Initialization

$$\delta_1(i) = \pi_i b_i(O_1), \quad 1 \le i \le N$$
$$\psi_1(i) = 0.$$

- Appendix: Dynamic Programming (DP) Principle (Bellman Principle of Optimality)
  - The best path through a particular, intermediate place is the best way from start to it, followed by the best way from it to the goal.
  - Implication: from multiple ways reaching an intermediate place, only retain the best one
  - Often used in sequence matching and HMMs



$$\delta_t(i)=\max_{q_1,q_2,\ldots,q_{t-1}} P(q_1q_2\cdots q_t=i, O_1O_2\cdots O_t \mid \lambda)$$

- Viterbi Algorithm (Cont.)
  - Recursion

$$\boxed{\begin{aligned}&\delta_t(j)=\left[\max_{1\le i\le N}\delta_{t\text{-}1}(i)a_{ij}\right]b_j(O_t),\\&\psi_t(j)=\arg\max_{1\le i\le N}\delta_{t\text{-}1}(i)a_{ij},\\&\quad 2\le t\le T,\quad 1\le j\le N\end{aligned}}$$

  - Termination

$$P^*=\max_{1\le i\le N}\delta_T(i)$$

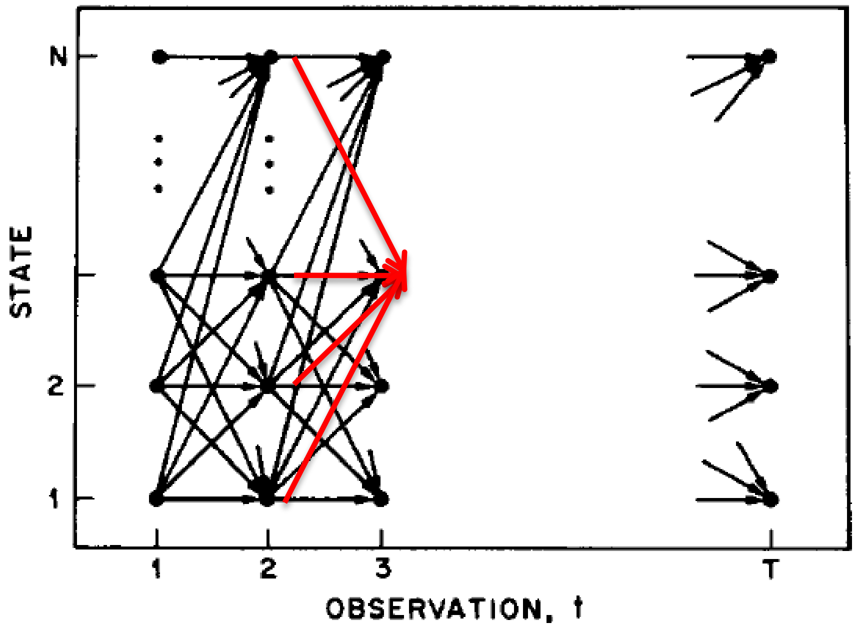
$$q_T^{\ *}=\arg\max_{1\le i\le N}\delta_T(i)$$

  - Backtracking

$$q_t^*=\psi_{t+1}(q_{t+1}^*),$$

$$1\le t\le T-1$$

  - Complexity: O($TN^2$)



# Training Problem

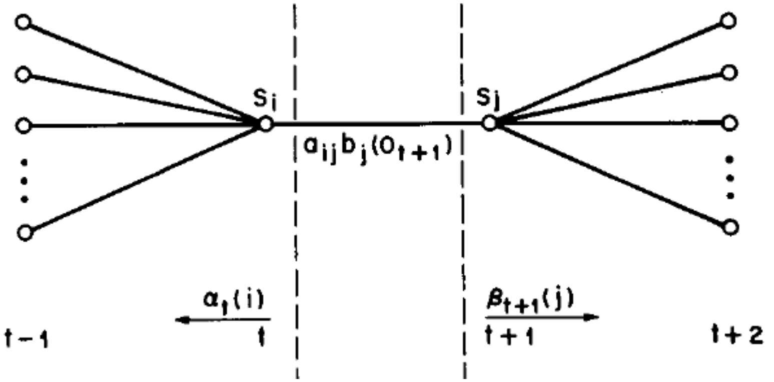
- Maximum Likelihood (ML) $\max_{A,B,\pi} P(O \mid \lambda)$
- Baum-Welch Algorithm (EM)

$$\max_{\bar{\lambda}} Q(\lambda, \bar{\lambda}) = \sum_{Q} \log P(Q, O \mid \bar{\lambda}) P(Q, O \mid \lambda)$$

– Define variable $\boxed{\xi_t(i,j) = P(q_t = S_i, q_{t+1} = S_j \mid O, \boldsymbol{\lambda})}$

$$\xi_t(i,j) = \frac{\alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{P(O \mid \boldsymbol{\lambda})} = \frac{\alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}$$

$P(O, q_t = S_i, q_{t+1} = S_j \mid \lambda)$




– Define probability

$$\gamma_t(i) = P(q_t = S_i \mid O, \boldsymbol{\lambda}) = \frac{\alpha_t(i)\beta_t(i)}{P(O \mid \boldsymbol{\lambda})} = \frac{\alpha_t(i)\beta_t(i)}{\sum_{i=1}^{N} \alpha_t(i)\beta_t(i)} = \sum_{j=1}^{N} \xi_t(i,j)$$

- Baum-Welch Algorithm (Cont.)
  - Reestimation formulas

$$\bar{\pi}_i = \text{expected frequency (number of times) in state } S_i \text{ at time (t=1)} = \gamma_1(i)$$

$$\bar{a}_{ij} = \frac{\text{expected number of transitions from state } S_i \text{ to state } S_j}{\text{expected number of transitions from state } S_i}$$

$$= \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)} = \frac{\sum_{t=1}^{T-1} \alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{\sum_{t=1}^{T-1} \alpha_t(i) \beta_t(i)}$$

$$\bar{b}_j(k) = \frac{\text{expected number of times in state } j \text{ and observing symbol } v_k}{\text{expected number of times in state } j}$$

$$= \frac{\sum_{t=1,\ \text{s.t. } O_t = v_k}^{T-1} \gamma_t(j)}{\sum_{t=1}^{T-1} \gamma_t(j)} = \frac{\sum_{t=1,\ \text{s.t. } O_t = v_k}^{T} \alpha_t(j) \beta_t(j)}{\sum_{t=1}^{T} \alpha_t(j) \beta_t(j)}$$

# Continuous Density HMM

- Handling Continuous Observations
  - Continuous features: vector $\boldsymbol{O}_T$
  - Discretization: vector quantization (VQ)
    - Each vector replaced with its closest codevector, which is viewed as a symbol
    - Small codebook: distortion
    - Large codebook: large data required in emission probability estimation
  - Continuous emission density: Gaussian mixture (GM)

$$b_j(O) = \sum_{m=1}^{M} c_{jm} \mathcal{N}(O; \mu_{jm}, U_{jm}), \quad 1 \le j \le N$$

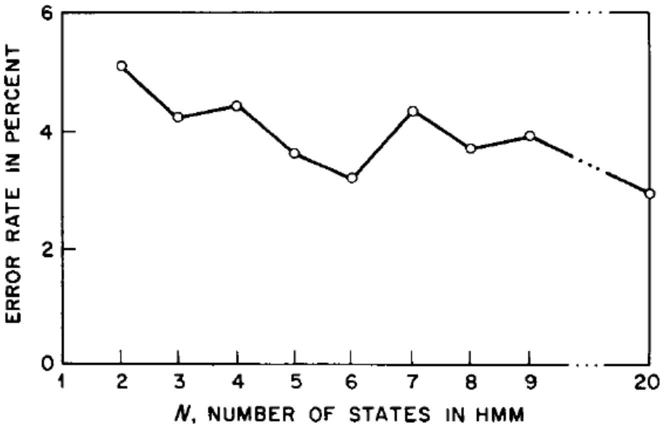
- Parameter Estimation of Continuous HMM (omitted)

# Application to Speech Recognition

- Isolated Word Recognition
  - Given HMM $\lambda^v$ for each word in the vocabulary
  - Input observation sequence ***O***, Bayes decision (assuming equal prior probabilities)

$$v^* = \arg\max_{1\le v\le V} P(\boldsymbol{\lambda}^v \mid O) = \arg\max_{1\le v\le V} P(O \mid \boldsymbol{\lambda}^v)$$

  - Acoustic features ($\boldsymbol{O}_t$) (details omitted)
  - Vector quantization (discrete observation symbols)
  - Choice of model parameters
    - Number of states: empirical, correspond roughly to the number of sounds (phonemes) in a word, maybe equal for all word models
    - Number of components in GM

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# Extensions of HMM

- Hybrid HMM/Neural
  - HMM: parametric $b_j(O_t)=p(O_t|q_t=S_j)$, conditional independence
  - Neural: discriminative emission probability $p(q_t=S_j|O_t)$
    - Neural network outputs approximate posterior probabilities
  - Replace $p(\mathbf{x}_t|q_t)$ with $p(q_t|\mathbf{x}_t)/p(q_t)$

$$\frac{p(\mathbf{x}_t \mid q_t)}{p(\mathbf{x}_t)} = \frac{p(q_t \mid \mathbf{x}_t)}{P(q_t)}$$

  - ANN may input multiple frames to learn the correlation

- Latest: deep neural networks

# 讨 论

- 特征维数与过拟合
  – 克服过拟合的方法?
- 期望最大法(EM)
  – 对数似然度对缺失数据的期望
  – EM for Gaussian mixture
- 隐马尔可夫模型(HMM)
  – Three basic problems
  – Viterbi Algorithm
  – Extensions

# 下次课内容

- 第4章 非参数法
  - 密度估计
  - Parzen窗方法
  - K近邻估计
  - 最近邻规则
  - 距离度量
  - Reduced Coulomb Energy Network
  - Approximation by Series Expansion