Automatic Speech Recognition handout (2)

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Revision : 1.1

— Generative models and training algorithms —

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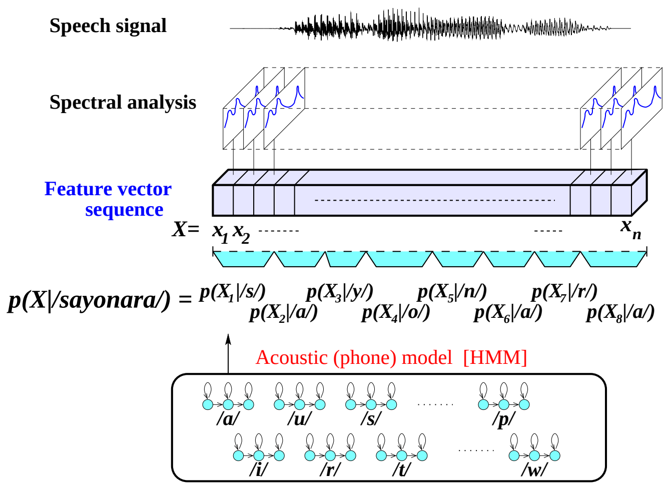
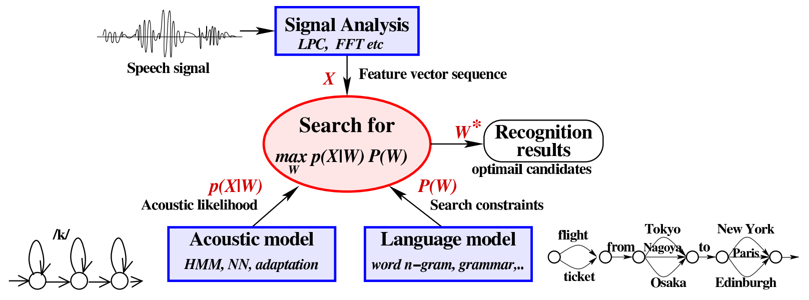
Speech Recognition recap


Speech signal
Spectral analysis
Feature vector sequence
X= x1 x2 ······ ····· xn
p(X|/sayonara/) = p(X1|/s/) p(X2|/a/) p(X3|/y/) p(X4|/o/) p(X5|/n/) p(X6|/a/) p(X7|/r/) p(X8|/a/)
Acoustic (phone) model [HMM]
/a/ /u/ /s/ ······· /p/
/i/ /r/ /t/ ······· /w/

Speech Recognition recap*(cont. 2)*



(after Sagayama, "Speech Translation Telephony",1994)

Bayes decision rule:

$$\begin{aligned}\boldsymbol{W}^* &= \arg\max_W P(W|X) = \arg\max_W \frac{p(X|W)P(W)}{p(X)}\\ &= \arg\max_W p(X|W)P(W)\end{aligned}$$

$X = (\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_T)$: feature vectors observed

$W = (w_1, w_2, \cdots, w_L)$: hypothesised words

How to calculate $p(X|/s/)$?

The conditional probability that we observe a feature sequence X for phone /s/ :

$$p(X|/s/) = p(\boldsymbol{x}_1, \cdots, \boldsymbol{x}_{T_1}|/s/), \quad \boldsymbol{x}_i = (x_{1i}, \cdots, x_{di})^t \in \mathcal{R}^d$$

We know

- **HMM can be employed to calculate this. (Viterbi algorithm, Forward / Backward algorithm)**
- **HMM should be trained beforehand with a set of *training samples*. (Baum-Welch algorithm (EM algorithm), Viterbi training)**

To investigate these algorithms in detail, let's start with assuming the simplest case: the length of the sequence is one ($T_1 = 1$), and the dimensionality of x is one ($d = 1$).

$$p(X|/s/) \longrightarrow p(x|/s/)$$

How to calculate $p(x|/s/)$?

$p(x|/s/)$: conditional probability
(conditional probability density function (pdf) of x)

- We learnt that a Gaussian / normal distribution function can be employed to approximate the pdf by:

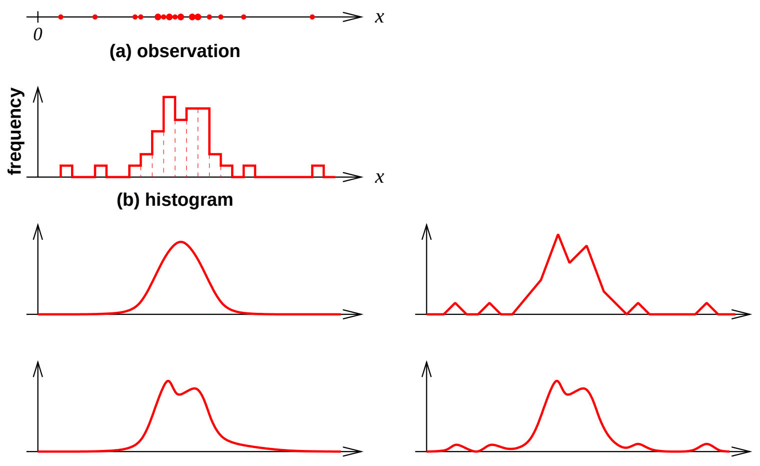
$$P(x|/s/) = \frac{1}{\sqrt{2\pi}\sigma_s} e^{-\frac{(x-\mu_s)^2}{2\sigma_s^2}}$$

- The function has only two parameters, μ_s and σ_s
- Given a set of training samples $\{x_1, \cdots, x_N\}$, we estimate μ_s and σ_s by

$$\hat{\mu}_s = \frac{1}{N}\sum_{i=1}^{N} x_i, \qquad \hat{\sigma}_s^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu_s)^2$$

But, how reliable are these estimates ?
how similar $p(x|\hat{\mu}_s, \hat{\sigma}_s)$ is to the true one ?

How to estimate $p(x|/s/)$?

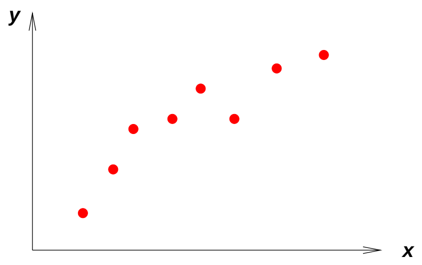


Why learning is so hard ?

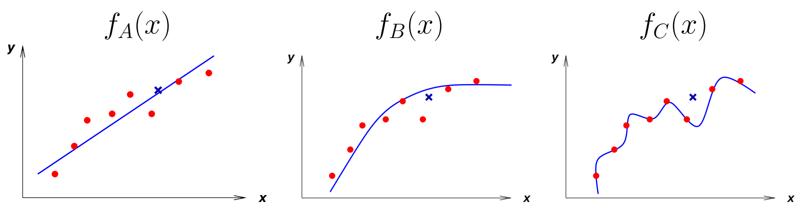
Who is this person ?

Why learning is so hard ? (cont. 2)

How does $y = f(x)$ look like ?



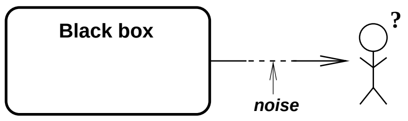
Why learning is so hard ? *(cont. 3)*



	$f_A(x)$	$f_B(x)$	$f_C(x)$
# of parameters	small	medium	large
Error on training samples	moderate	small	0 (zero)
Error on other samples	moderate ?	moderate/large ?	huge ?

Technical terms: robustness, generalisation, over-fitting

Why learning is so hard ? *(cont. 4)*



- **What we've observed are just samples from an unobservable system. Even worse, the samples might be distorted.**
- **With limited amount of samples, it is hard to estimate / identify the system completely, because more than one solution can exist and we do not know which is the best one.**
- **To find the best one, we need more knowledge about the system.**
- **Estimating the system from observation is regarded as an "inverse problem" or "ill-posed problem".**
- **To solve an inverse problem, we usually define an optimisation problem with some constraints (assumptions, models).**

Estimating pdf

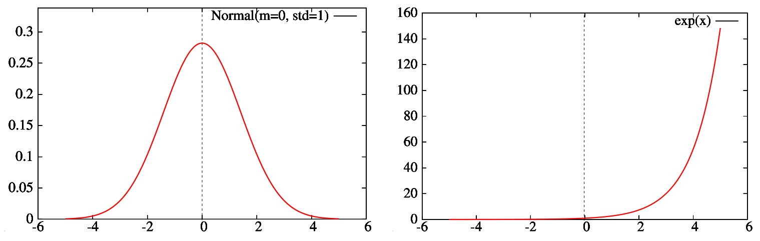
- **Non-parametric approach**
  - **histogram**
  - **kernel method, Parzen window**
  - **neural network**
- **Parametric approach**
  - **Gaussian / normal distribution**
  - **Gaussian mixture model**
  - **etc.**

Gaussian distribution

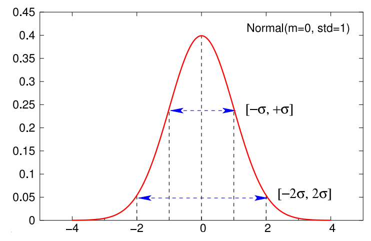
$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

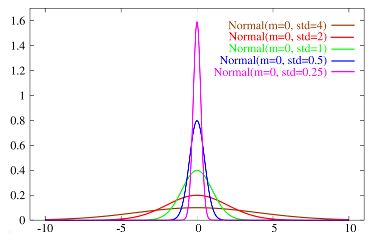
$$y = e^x$$

$$e = 2.7183\cdots$$



Gaussian distribution*(cont. 2)*





$$P(-\sigma < x < \sigma) \sim 0.683$$
$$P(-2\sigma < x < 2\sigma) \sim 0.954$$
$$P(-3\sigma < x < 3\sigma) \sim 0.997$$

Gaussian Distribution: 1-dim case

$$P(x|\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \quad \triangleq \quad \mathcal{N}(x;\mu,\sigma)$$

Given samples $\{x_1,\cdots,x_N\} = \{x_n\}_{n=1}^{N}$,
we know how to estimate (infer) the parameters μ,σ:

$$\hat{\mu} = \frac{1}{N}\sum_{n=1}^{N} x_n$$
$$\hat{\sigma}^2 = \frac{1}{N}\sum_{n=1}^{N}(x_n-\hat{\mu})^2 = \frac{1}{N}\sum_{n=1}^{N} x_n^2 - \left(\frac{1}{N}\sum_{n=1}^{N} x_n\right)^2$$

But,

- **Why we can say this is a right inference ?**
- **Are there any other inferences ?**

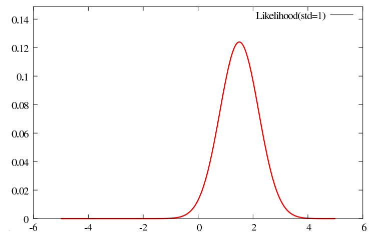
Maximum likelihood estimation

$$p(x|\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

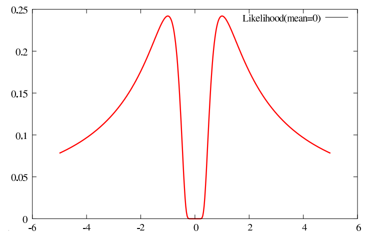
Interpretation of $p(x|\mu,\sigma)$

- **If μ,σ are fixed $\longrightarrow p(x|\mu,\sigma)$ is a function of x.**
  $p(x|\mu,\sigma)$: a probability density function.
- **If x is fixed $\longrightarrow p(x|\mu,\sigma)$ is a function of μ,σ.**
  $p(x|\mu,\sigma)$: a 'likelihood' function denoted as $L(\mu,\sigma;x)$

Maximum likelihood estimation*(cont. 2)*



likelihood as a function of μ



likelihood as a function of σ

$$L(\mu,\sigma;x) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

Maximum likelihood estimation *(cont. 3)*

ML estimation (MLE)

Assume $X = \{x_n\}_{n=1}^{N}$ are chosen independently (i.i.d.) [1]**.**
The probability of observing X is

$$\begin{aligned} p(x_1, \cdots, x_N|\mu,\sigma) &= p(x_1|\mu,\sigma)\cdots p(x_N|\mu,\sigma) = \prod_{n=1}^{N} p(x_n|\mu,\sigma) \\ &\triangleq L(\mu,\sigma|X) \end{aligned}$$

Find parameters $\mu,\ \sigma$ that maximise the likelihood:

$$\max_{\mu,\sigma} L(\mu,\sigma|X)$$

[1] i.i.d: independent identically-distributed, i.e. data points that are drawn independently from the same distribution.

Maximum likelihood estimation *(cont. 4)*

(Solution) **Take the derivative of $\log L(\mu,\sigma|X)$ and set it to zero.**

$$\begin{aligned} \ell(\mu,\sigma|X) &= \log L(\mu,\sigma|X) = \log \prod_{n=1}^{N} p(x_n|\mu,\sigma) = \sum_{n=1}^{N} \log p(x_n|\mu,\sigma) \\ &= -N\log(\sqrt{2\pi}\sigma) - \sum_{n=1}^{N} \frac{(x_n-\mu)^2}{2\sigma^2} \end{aligned}$$

$$\frac{\partial \ell}{\partial \mu} = -2\sum_{n=1}^{N} \frac{x_n-\mu}{2\sigma^2} = 0 \quad \Rightarrow \quad \mu = \frac{1}{N}\sum_{n=1}^{N} x_n$$

$$\frac{\partial \ell}{\partial \sigma} = -N\frac{1}{\sqrt{2\pi}\sigma} + \sum_{n=1}^{N} \frac{(x_n-\mu)2}{\sigma^3} = 0$$

$$\Rightarrow \quad \sigma^2 = \frac{1}{N}\sum_{n=1}^{N} (x_n-\mu)^2$$

Limitation of a Gaussian pdf

- **Gaussian distribution is assumed**
- **does not fit more complicated distributions (bimodal, etc.)**

Solutions

- **Transform features**
  (coordinate non-linear transformation)
- **Use other distribution functions**
  - **Poisson dist.**
  - **exponential dist.**
  - **gamma dist.**
  - **log-normal dist.**
- **Use a mixture of Gaussian distribution functions**
- **Use neural networks, kernel approaches**

Gaussian Mixture Model (GMM)

Idea **Approximate a "true" distribution by more than one Gaussian distribution.**

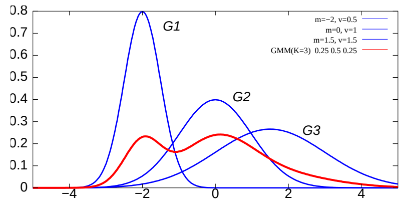
$$p(x|\Lambda) = \sum_{k=1}^{K} w_k\, p(x|\mu_k,\sigma_k) = \sum_{k=1}^{K} w_k\, \mathcal{N}(x;\mu_k,\sigma_k)$$

where $\Lambda = \{\lambda_k\}_{k=1}^{K} = \{\mu_k,\sigma_k\}_{k=1}^{K}$ $\cdots$ **a set of model parameters**
$\sum_{k=1}^{K} w_k = 1$

View as a generative-model

$$\begin{tikzcd} \boxed{\mathcal{N}(x;\mu_1,\sigma_1)} \arrow[dr] & & \\ \vdots & \boxed{\text{selector}} \arrow[r] & x \\ \boxed{\mathcal{N}(x;\mu_K,\sigma_K)} \arrow[ur] & \boxed{\{w_k\}_{k=1}^{N}} \arrow[u] & \end{tikzcd}$$

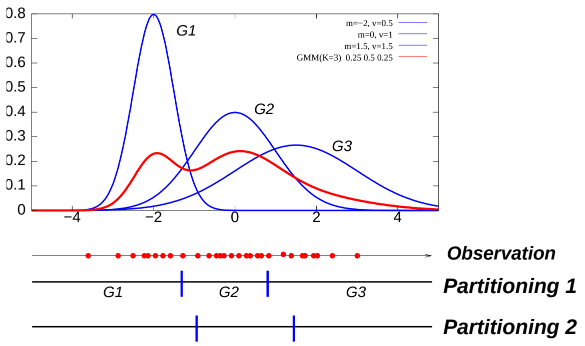
signal generators



Training GMM

Given a set of training samples $x_1, x_2, \cdots, x_N$,
assuming a mixture of K Gaussians,
we don't know from which Gaussian model each x_i came.

$\Rightarrow$ ML training can not be applied directly !



Training GMM *(cont. 2)*

Solution Assume each x_n has a label y_n showing from which model the data came.
i.e. y_n takes an index of Gaussian model $1, \cdots, K$.

observations	x_1	x_2	$\cdots$	x_N
labels (unseen)	y_1	y_2	$\cdots$	y_N

Then we would be able to use ML estimation recursively.

Approach A (hard k-means clustering) $\cdots$ assume each x_n belongs to an exact Gaussian y_n.

Approach B (soft k-means clustering) $\cdots$ assume each x_n belongs to Gaussian k with probability $P(y_n = k)$.
(y_n is treated as a random variable)

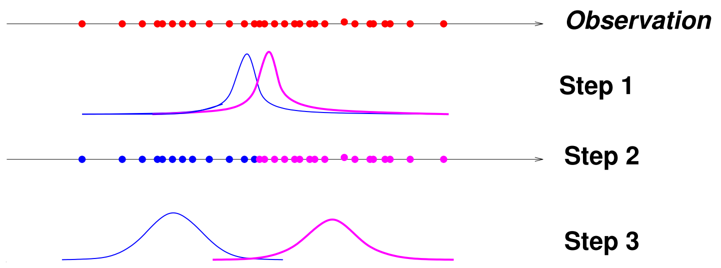
Training GMM by k-means clustering (hard version)

Step 1: Initialisation. Set model parameters Λ arbitrarily.

Step 2: Clustering: $y_n = \arg\max_k p(x_n|\lambda_k)$ for $k = 1, \ldots, N$

Step 3: Re-estimation: estimate model parameters Λ.

Step 4: Iteration: Repeat steps 2 and 3 until a predefined convergence criterion is satisfied. (estimate $\{w_k\}$ when exits.)



Training GMM by k-means clustering (soft version)

Problem of the hard k means clustering: non guarantee of ML.

The **EM algorithm** enables us to maximise the likelihood

$$L(\Lambda|X) = \prod_{n=1}^{N} p(x_n|\Lambda)$$

by iteratively maximising Q function with respect to $\Lambda^{(t+1)}$:

$$Q(\Lambda^{(t)}, \Lambda^{(t+1)}) = \sum_{Y} P(Y|X, \Lambda^{(t)}) \log p(X, Y|\Lambda^{(t+1)})$$

This is the expectation of log-likelihood from **complete data** (X, Y).
To maximise Q, we take the derivative of Q with respect to each parameter and set it to zero.

The Expectation-Maximisation Algorithm

The EM algorithm [Dempster, Laird, and Rubin, 1977]

Step 1: **Initialisation: Set $t = 0$, and choose an initial estimate $\Lambda^{(0)}$.**

Step 2: **E-Step: Compute $Q(\Lambda^{(t)}, \Lambda)$ based on current parameter $\Lambda^{(t)}$.**

Step 3: **M-Step: Compute $\Lambda^* = \arg\max_{\Lambda} Q(\Lambda^{(t)}, \Lambda)$ to maximise Q.**

Step 4: **Iteration: Set $\Lambda^{(t+1)} = \Lambda^*$ and $t \leftarrow t+1$, repeat from Step 2 until convergence.**

(Note)

- **The algorithm is a generalisation of MLE, when we have incomplete data (i.e. some data are unobservable (hidden)).**
- **The algorithm gives just a general idea, and actual implementation differs depending on the problems.**

EM algorithm for GMM

$$\begin{aligned}
Q(\Lambda^{(t)}, \Lambda^{(t+1)}) &= \sum_{n=1}^{N} Q_i(\Lambda^{(t)}, \Lambda^{(t+1)}) = \sum_{n=1}^{N} \sum_{y_n} P(y_n | x_n, \Lambda^{(t)}) \log p(x_n, y_n | \Lambda^{(t+1)}) \\
&= \sum_{n=1}^{N} \sum_{y_n} \frac{p(x_n, y_n | \Lambda^{(t)})}{p(x_n | \Lambda^{(t)})} \log p(x_n, y_n | \Lambda^{(t+1)}) \\
&= \sum_{k=1}^{K} \gamma_k \log w_k^{(t+1)} + \sum_{k=1}^{K} Q_\pi(\Lambda^{(t)}, \lambda_k^{(t+1)})
\end{aligned}$$

where

$$\gamma_k = \sum_{n=1}^{N} \gamma_k^n, \qquad \gamma_k^n = \frac{w_k^{(t)} p(x_n | \lambda_k^{(t)})}{p(x_n | \Lambda^{(t)})}$$

$$Q_\pi(\Lambda^{(t)}, \lambda_k^{(t+1)}) = \sum_{n=1}^{N} \gamma_k^n \log p(x_n | \lambda_k^{(t+1)})$$

$$w_k^{(t+1)} = \gamma_k \Big/ \sum_{k=1}^{K} \gamma_k = \gamma_k / N$$

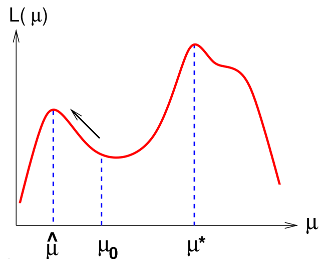
$$m_k^{(t+1)} = \sum_{n=1}^{N} \gamma_k^n x_n \Big/ \sum_{n=1}^{N} \gamma_k^n, \qquad \sigma_k^{(t+1)} = \sum_{n=1}^{N} \gamma_k^n (x - m_k^{(t)})^2 \Big/ \sum_{n=1}^{N} \gamma_k^n$$

Limitation of ML-trained GMM

- **Local optimum problem (the EM algorithm does not guarantee the global optimum)**
- **No mechanism for determining K (# of mixtures).**

Initial value problem of GMM

- **The EM iteration converges at a local maximum, which mighty be different from the global maximum.**
- **The performance of the algorithm highly relies on how appropriate initial value the algorithm starts from.**
- **As we increase the number of Gaussian mixture components, the chance we suffer the problem increases.**



Initial value problem of GMM *(cont. 2)*

Techniques to avoid the local maximum problem

Method-A: Use k-means clustering (hard) to find initial partitions of data, and calculate initial parameters of GMM.

Method-B: Increase the mixture number k of GMM gradually. (start from $k = 1$, and then $k \leftarrow k * 2$.)

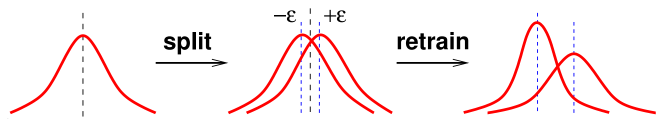


Fig. Mixture splitting

Remaining problems with GMM

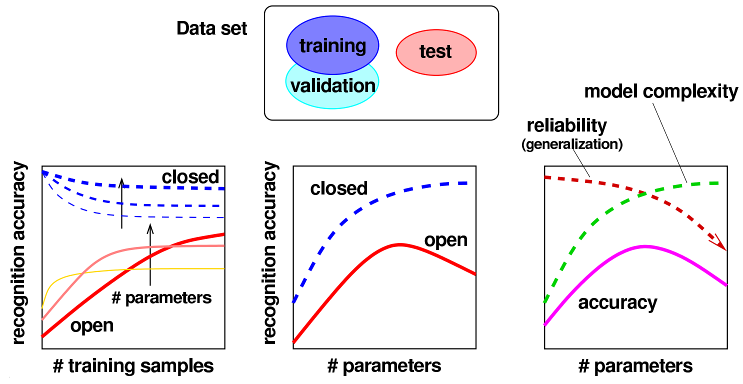
- Avoiding the local maximum problem is not enough
- There is another problem: **"over-fitting problem"**
  - the likelihood on training data increases, as k (# of mixtures) increases.
  - The ML training does not tell us what k is optimal.

Solutions

- use model selection technique such as
  - **AIC** (Akaike's information criterion)
  - **MDL** (minimum description length)

  $\rightarrow$ **"Occam's razor"**:
  "Entia non sunt multiplicanda praeter necessitatem"
  (accepts the simplest explanation that fits the data)
- use **validation data**

Remaining problems with GMM *(cont. 2)*



Maximum a posterior (MAP) estimation

X : a set of training data $\{x_n\}_{n=1}^{N}$
Λ : a set of parameters to estimate

ML estim. $\Lambda^* = \arg\max_{\Lambda} p(X|\Lambda)$

MAP estim. $\Lambda^* = \arg\max_{\Lambda} p(\Lambda|X) = \arg\max_{\Lambda} p(X|\Lambda)p(\Lambda)$

$p(\Lambda)$: a priori distribution over Λ
$p(\Lambda|X)$: a posteriors distribution after observing X

$$p(\Lambda|X) = \frac{p(X|\Lambda)p(\Lambda)}{p(X)} = \frac{p(X|\Lambda)p(\Lambda)}{\int p(X|\Lambda')p(\Lambda)'d\Lambda'}$$

- The object function takes the reliability of parameters, i.e. the a priori distribution, into account
- Regarded as a penalised (regularised) version of MLE
- How to define/calculate the **prior** $p(\Lambda)$?
  $\Rightarrow$ several approaches have been proposed

Bayesian estimation

p.d.f. estimation based on

- **point estimation**

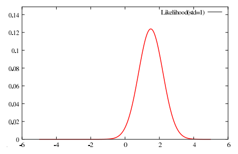
$$\hat{p}(\boldsymbol{x}|X) = p(\boldsymbol{x}|X,\Lambda^*), \quad \Lambda^* = \begin{cases} \max\limits_{\Lambda} p(X|\Lambda), & \textbf{MLE} \\ \max\limits_{\Lambda} p(X|\Lambda)p(\Lambda), & \textbf{MAP} \end{cases}$$

assuming parameter Λ is fixed but unknown.

- **interval estimation (Bayesian estimation)**

$$\hat{p}(\boldsymbol{x}|X) = \int p(\boldsymbol{x}|X,\Lambda)p(\Lambda|X)d\Lambda$$

where $p(\Lambda|X) = \dfrac{p(X|\Lambda)p(\Lambda)}{\int p(X|\Lambda)p(\Lambda)d\Lambda}$



assuming the parameters Λ are random variables with a prior distribution $p(\Lambda)$

Multivariate Gaussian pdf

One variable

data: $\boldsymbol{x}_n = (x_n)$

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i, \qquad \sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2$$

Two variables

$$\boldsymbol{x}_n = (x_{1n}, x_{2n})^t = \begin{pmatrix} x_{1n} \\ x_{2n} \end{pmatrix}, \quad \boldsymbol{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \quad \Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}$$

$$\mu_1 = \frac{1}{N}\sum_{i=1}^{N} x_{1n}, \quad \mu_2 = \frac{1}{N}\sum_{i=1}^{N} x_{2n}$$

$$\sigma_{11} = \frac{1}{N}\sum_{i=1}^{N}(x_{1i}-\mu_1)^2, \quad \sigma_{22} = \frac{1}{N}\sum_{i=1}^{N}(x_{2i}-\mu_2)^2$$

$$\sigma_{12} = \frac{1}{N}\sum_{i=1}^{N}(x_{1i}-\mu_1)(x_{2i}-\mu_2) = \sigma_{21}$$

Multivariate Gaussian pdf (cont. 2)

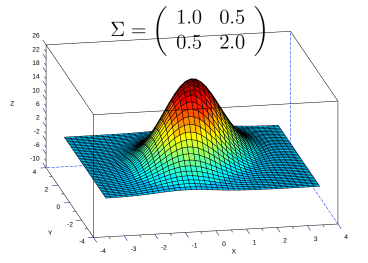
mean vector: $\boldsymbol{\mu} = (\mu_1, \mu_2)^t$

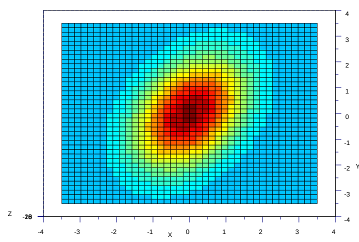
covariance matrix: $\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}$

$$p(\boldsymbol{x}|\boldsymbol{\mu},\Sigma) = \frac{1}{(2\pi)^{d/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^t\Sigma^{-1}(\boldsymbol{x}-\boldsymbol{\mu})\right)$$

where d denotes dimensions (here $d=2$).

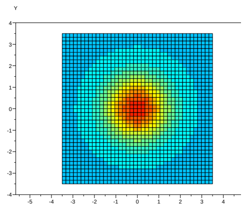
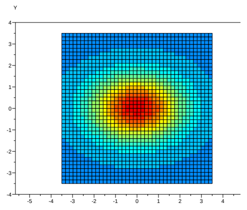
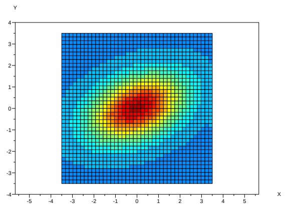
$\Sigma = \begin{pmatrix} 1.0 & 0.5 \\ 0.5 & 2.0 \end{pmatrix}$





Multivariate Gaussian pdf (cont. 3)

$\Sigma = \begin{pmatrix} 1.0 & 0.0 \\ 0.0 & 1.0 \end{pmatrix}$ $\Sigma = \begin{pmatrix} 2.0 & 0.0 \\ 0.0 & 1.0 \end{pmatrix}$ $\Sigma = \begin{pmatrix} 2.0 & 0.5 \\ 0.5 & 1.0 \end{pmatrix}$

x_1 **and** x_2 **are called uncorrelated if** $\sigma_{12} = 0$.

Gaussian pdf with diagonal covariances

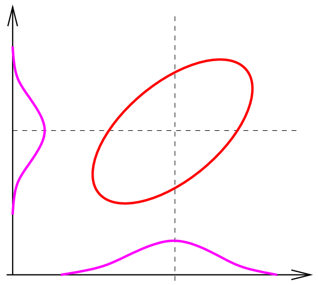
Gaussian pdf with a full-covariance

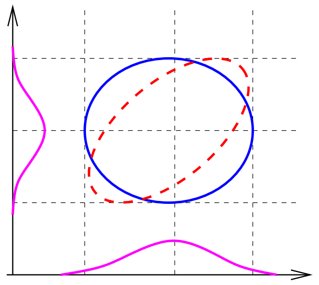
$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}$$

Gaussian pdf with diagonal-covariances

$$\Sigma = \begin{pmatrix} \sigma_{11} & 0 \\ 0 & \sigma_{22} \end{pmatrix}$$

$$p(\boldsymbol{x}|\boldsymbol{\mu},\Sigma) = p(x_1|\mu_1,\sigma_{11})\,p(x_2|\mu_2,\sigma_{22})$$



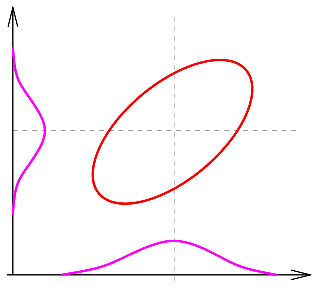


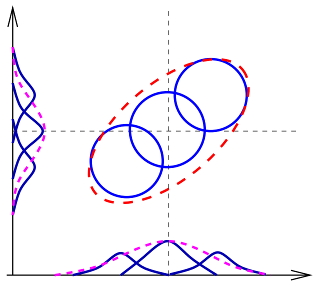
Gaussian pdf with diagonal covariances*(cont. 2)*

GMM with diag. covs. can model dependencies (correlations) !

Gaussian pdf with full-covariance

GMM pdf with diagonal-covariance





Gaussian pdf with diagonal covariances*(cont. 3)*

Question why we normally use GMM with diagonal covariances rather than the one with full covariances ?

Basic idea of estimating error rate

1. Prepare two subsets of the dataset:

training set	to train the recogniser
test(validation) set	to evaluate recognition performance

* these two subsets should be mutually exclusive (no overlap between them)

2. Train the recogniser using the training set.
3. Carry out a recognition experiment of the recogniser on the test set, and calculate the recognition error:

$$R_{\text{emp}} = \frac{\text{\# of misrecognised data}}{\text{\# of input data}} \quad \cdots \left(\begin{array}{l}\text{test set error, or} \\ \text{empirical error}\end{array} \right)$$

4. Repeat the recognition experiment with changing training and test sets to estimate the expectation of error:

   generalisation error: $R = E[R_{\text{emp}}]$

`http://en.wikipedia.org/wiki/Generalization_error`

k-fold Cross-Validation (CV)

Step 1 split the dataset randomly into k disjoint sets of equal size.

Step 2 train and test the recogniser k times: each time with choosing one set for validation and the remaining $k-1$ sets for training.

Step 3 Estimate the performance by taking the mean of the k errors.

k-fold CV	subsets
2-fold CV	Set2-0, Set2-1
5-fold CV	Set5-0, Set5-1, Set5-2, Set5-3, Set5-4

Similar techniques: leave-one-out, held-out, jacknife, bootstrap

References:

`http://en.wikipedia.org/wiki/Cross_validation`
`http://www.faqs.org/faqs/ai-faq/neural-nets/part3/section-12.html`

References

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  - **Christopher M. Bishop, “Pattern Recognition and Machine Learning”, ISBN 0387310738, Springer-Verlag, 2006.**
- **Web pages:**

  Normal (Gaussian) Distribution
  - **http://en.wikipedia.org/wiki/Normal_distribution**

  Maximum Likelihood Estimation (MLE)
  - **http://en.wikipedia.org/wiki/Maximum_likelihood**

  GMM
  - **http://en.wikipedia.org/wiki/Mixture_model**

  EM algorithm
  - **http://en.wikipedia.org/wiki/Expectation-maximization_algorithm**