# Machine Learning - Lecture 2

## Probability Density Estimation

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Many slides adapted from B. Schiele



## Announcements

- Course webpage
  - http://www.vision.rwth-aachen.de/teaching/
  - Slides will be made available on the webpage
- L2P electronic repository
  - Exercises and supplementary materials will be posted on the L2P
- Please subscribe to the lecture on the Campus system!
  - Important to get email announcements and L2P access!



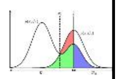
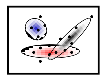
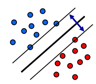
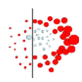
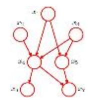
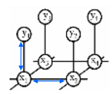
## Announcements

- Exercise sheet 1 is now available on L2P
  - Bayes decision theory
  - Maximum Likelihood
  - Kernel density estimation / k-NN
  - ⇒ *Submit your results to Ishrat/Michael until evening of 29.04.*
- Work in teams (of up to 3 people) is encouraged
  - Who is not part of an exercise team yet?



## Course Outline

- Fundamentals (2 weeks)
  - Bayes Decision Theory
  - Probability Density Estimation
- Discriminative Approaches (5 weeks)
  - Linear Discriminant Functions
  - Support Vector Machines
  - Ensemble Methods & Boosting
  - Randomized Trees, Forests & Ferns
- Generative Models (4 weeks)
  - Bayesian Networks
  - Markov Random Fields



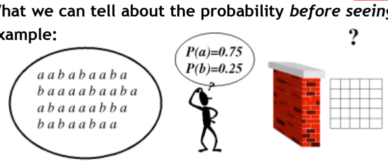
## Topics of This Lecture

- Bayes Decision Theory
  - Basic concepts
  - Minimizing the misclassification rate
  - Minimizing the expected loss
  - Discriminant functions
- Probability Density Estimation
  - General concepts
  - Gaussian distribution
- Parametric Methods
  - Maximum Likelihood approach
  - Bayesian vs. Frequentist views on probability
  - Bayesian Learning



## Recap: Bayes Decision Theory Concepts

- Concept 1: Priors (a priori probabilities) $p(C_k)$
  - What we can tell about the probability *before seeing the data*.
  - Example:



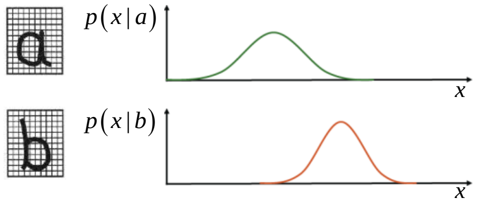

$$C_1 = a \qquad p(C_1) = 0.75$$
$$C_2 = b \qquad p(C_2) = 0.25$$

- In general: $\sum_k p(C_k) = 1$

Slide credit: Bernt Schiele

## Recap: Bayes Decision Theory Concepts

- Concept 2: **Conditional probabilities** $p(x|C_k)$
  - Let $x$ be a feature vector.
  - $x$ measures/describes certain properties of the input.
    - E.g. number of black pixels, aspect ratio, …
  - $p(x|C_k)$ describes its likelihood for class $C_k$.



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## Bayes Decision Theory Concepts

- Concept 3: **Posterior probabilities** $p(C_k|x)$
  - We are typically interested in the *a posteriori* probability, i.e. the probability of class $C_k$ given the measurement vector $x$.
- Bayes' Theorem:

$$p(C_k|x) = \frac{p(x|C_k)\,p(C_k)}{p(x)} = \frac{p(x|C_k)\,p(C_k)}{\sum_i p(x|C_i)\,p(C_i)}$$

- Interpretation

$$Posterior = \frac{Likelihood \times Prior}{Normalization\ Factor}$$



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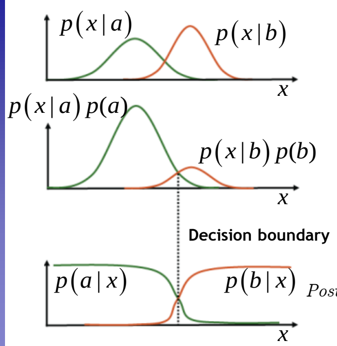
## Bayes Decision Theory




*Likelihood*

*Likelihood* × *Prior*

$$Posterior = \frac{Likelihood \times Prior}{NormalizationFactor}$$



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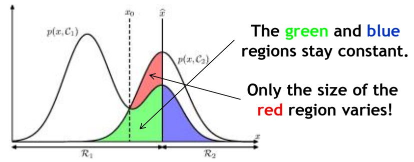
## Bayesian Decision Theory

- Goal: **Minimize the probability of a misclassification**




$$\begin{aligned} p(\text{mistake}) &= p(\mathbf{x} \in \mathcal{R}_1, \mathcal{C}_2) + p(\mathbf{x} \in \mathcal{R}_2, \mathcal{C}_1) \\ &= \int_{\mathcal{R}_1} p(\mathbf{x}, \mathcal{C}_2)\,\mathrm{d}\mathbf{x} + \int_{\mathcal{R}_2} p(\mathbf{x}, \mathcal{C}_1)\,\mathrm{d}\mathbf{x}. \\ &= \int_{\mathcal{R}_1} p(\mathcal{C}_2|\mathbf{x})p(\mathbf{x})d\mathbf{x} + \int_{\mathcal{R}_2} p(\mathcal{C}_1|\mathbf{x})p(\mathbf{x})d\mathbf{x} \end{aligned}$$



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## Bayes Decision Theory

- Optimal decision rule
  - Decide for $C_1$ if

$$p(\mathcal{C}_1|x) > p(\mathcal{C}_2|x)$$

  - This is equivalent to

$$p(x|\mathcal{C}_1)p(\mathcal{C}_1) > p(x|\mathcal{C}_2)p(\mathcal{C}_2)$$

  - Which is again equivalent to (Likelihood-Ratio test)

$$\frac{p(x|\mathcal{C}_1)}{p(x|\mathcal{C}_2)} > \underbrace{\frac{p(\mathcal{C}_2)}{p(\mathcal{C}_1)}}_{\text{Decision threshold } \theta}$$



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## Generalization to More Than 2 Classes

- Decide for class $k$ whenever it has the greatest posterior probability of all classes:

$$p(\mathcal{C}_k|x) > p(\mathcal{C}_j|x) \quad \forall j \neq k$$

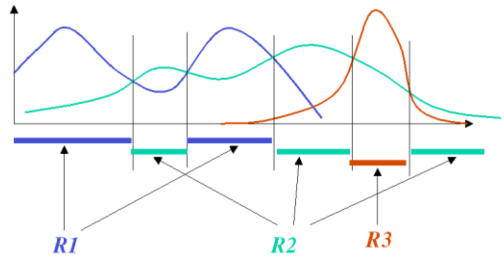
$$p(x|\mathcal{C}_k)p(\mathcal{C}_k) > p(x|\mathcal{C}_j)p(\mathcal{C}_j) \quad \forall j \neq k$$

- Likelihood-ratio test

$$\frac{p(x|\mathcal{C}_k)}{p(x|\mathcal{C}_j)} > \frac{p(\mathcal{C}_j)}{p(\mathcal{C}_k)} \quad \forall j \neq k$$

## Bayes Decision Theory

- Decision regions: $\mathcal{R}_1$, $\mathcal{R}_2$, $\mathcal{R}_3$, …








## Classifying with Loss Functions

- Generalization to decisions with a loss function
  - Differentiate between the possible decisions and the possible true classes.
  - Example: medical diagnosis
    - Decisions: diagnosis is *sick* or *healthy* (or: *further examination necessary*)
    - Classes: patient is *sick* or *healthy*
  - The cost may be asymmetric:

$$loss(decision = healthy|patient = sick) >>$$
$$loss(decision = sick|patient = healthy)$$





## Classifying with Loss Functions

- In general, we can formalize this by introducing a loss matrix $L_{kj}$

$$L_{kj} = loss\ for\ decision\ \mathcal{C}_j\ if\ truth\ is\ \mathcal{C}_k.$$

- Example: cancer diagnosis

Decision

$$L_{cancer\ diagnosis} = \begin{array}{c|cc} \text{Truth} & \text{cancer} & \text{normal} \\ \hline \text{cancer} & 0 & 1000 \\ \text{normal} & 1 & 0 \end{array}$$



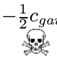


## Classifying with Loss Functions

- Loss functions may be different for different actors.
  - Example: ("invest", "don't invest")

$$L_{stocktrader}(subprime) = \begin{pmatrix} -\frac{1}{2}c_{gain} & 0 \\ 0 & 0 \end{pmatrix}$$

$$L_{bank}(subprime) = \begin{pmatrix} -\frac{1}{2}c_{gain} & 0 \\ & 0 \end{pmatrix}$$



⇒ Different loss functions may lead to different Bayes optimal strategies.





## Minimizing the Expected Loss

- Optimal solution is the one that minimizes the loss.
  - But: loss function depends on the true class, which is unknown.
- Solution: Minimize the expected loss

$$\mathbb{E}[L] = \sum_k \sum_j \int_{\mathcal{R}_j} L_{kj} p(\mathbf{x}, \mathcal{C}_k)\,\mathrm{d}\mathbf{x}$$

- This can be done by choosing the regions $\mathcal{R}_j$ such that

$$\mathbb{E}[L] = \sum_k L_{kj} p(\mathcal{C}_k|\mathbf{x})$$

which is easy to do once we know the posterior class probabilities $p(\mathcal{C}_k|\mathbf{x})$.





## Minimizing the Expected Loss

- Example:
  - 2 Classes: $C_1$, $C_2$
  - 2 Decision: $\alpha_1$, $\alpha_2$
  - Loss function: $L(\alpha_j|\mathcal{C}_k) = L_{kj}$
  - Expected loss (= risk $R$) for the two decisions:

$$\mathbb{E}_{\alpha_1}[L] = R(\alpha_1|\mathbf{x}) = L_{11} p(\mathcal{C}_1|\mathbf{x}) + L_{21} p(\mathcal{C}_2|\mathbf{x})$$
$$\mathbb{E}_{\alpha_2}[L] = R(\alpha_2|\mathbf{x}) = L_{12} p(\mathcal{C}_1|\mathbf{x}) + L_{22} p(\mathcal{C}_2|\mathbf{x})$$

- Goal: Decide such that expected loss is minimized
  - I.e. decide $\alpha_1$ if $R(\alpha_2|\mathbf{x}) > R(\alpha_1|\mathbf{x})$

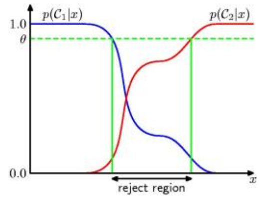
## Minimizing the Expected Loss

$$
\begin{aligned}
R(\alpha_2|\mathbf{x}) &> R(\alpha_1|\mathbf{x}) \\
L_{12}p(\mathcal{C}_1|\mathbf{x}) + L_{22}p(\mathcal{C}_2|\mathbf{x}) &> L_{11}p(\mathcal{C}_1|\mathbf{x}) + L_{21}p(\mathcal{C}_2|\mathbf{x}) \\
(L_{12} - L_{11})p(\mathcal{C}_1|\mathbf{x}) &> (L_{21} - L_{22})p(\mathcal{C}_2|\mathbf{x}) \\
\frac{(L_{12} - L_{11})}{(L_{21} - L_{22})} &> \frac{p(\mathcal{C}_2|\mathbf{x})}{p(\mathcal{C}_1|\mathbf{x})} = \frac{p(\mathbf{x}|\mathcal{C}_2)p(\mathcal{C}_2)}{p(\mathbf{x}|\mathcal{C}_1)p(\mathcal{C}_1)} \\
\frac{p(\mathbf{x}|\mathcal{C}_1)}{p(\mathbf{x}|\mathcal{C}_2)} &> \frac{(L_{21} - L_{22})}{(L_{12} - L_{11})}\frac{p(\mathcal{C}_2)}{p(\mathcal{C}_1)}
\end{aligned}
$$

⇒ Adapted decision rule taking into account the loss.



## The Reject Option




- Classification errors arise from regions where the largest posterior probability $p(\mathcal{C}_k|\mathbf{x})$ is significantly less than 1.
  - These are the regions where we are relatively uncertain about class membership.
  - For some applications, it may be better to reject the automatic decision entirely in such a case and e.g. consult a human expert.



## Discriminant Functions

- Formulate classification in terms of comparisons
  - Discriminant functions

$$y_1(x), \ldots, y_K(x)$$

  - Classify $x$ as class $C_k$ if

$$y_k(x) > y_j(x) \quad \forall j \neq k$$

- Examples (Bayes Decision Theory)

$$
\begin{aligned}
y_k(x) &= p(\mathcal{C}_k|x) \\
y_k(x) &= p(x|\mathcal{C}_k)p(\mathcal{C}_k) \\
y_k(x) &= \log p(x|\mathcal{C}_k) + \log p(\mathcal{C}_k)
\end{aligned}
$$



## Different Views on the Decision Problem

- $y_k(x) \propto p(x|\mathcal{C}_k)p(\mathcal{C}_k)$
  - First determine the class-conditional densities for each class individually and separately infer the prior class probabilities.
  - Then use Bayes' theorem to determine class membership.
  - ⇒ *Generative methods*
- $y_k(x) = p(\mathcal{C}_k|x)$
  - First solve the inference problem of determining the posterior class probabilities.
  - Then use decision theory to assign each new $x$ to its class.
  - ⇒ *Discriminative methods*
- Alternative
  - Directly find a discriminant function $y_k(x)$ which maps each input $x$ directly onto a class label.



## Topics of This Lecture





## Probability Density Estimation

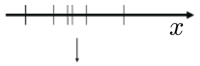
- Up to now
  - Bayes optimal classification
  - Based on the probabilities $p(\mathbf{x}|\mathcal{C}_k)p(\mathcal{C}_k)$
- How can we estimate (=learn) those probability densities?
  - Supervised training case: data and class labels are known.
  - Estimate the probability density for each class $\mathcal{C}_k$ separately:

$$p(\mathbf{x}|\mathcal{C}_k)$$

  - (For simplicity of notation, we will drop the class label $\mathcal{C}_k$ in the following.)

## Probability Density Estimation

- Data: $x_1$, $x_2$, $x_3$, $x_4$, …




- Estimate: $p(x)$


- Methods
  - Parametric representations
  - Non-parametric representations
  - Mixture models (next lecture)

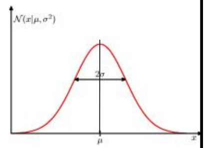




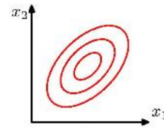
## The Gaussian (or Normal) Distribution

- One-dimensional case
  - Mean $\mu$
  - Variance $\sigma^2$

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




- Multi-dimensional case
  - Mean $\mu$
  - Covariance $\Sigma$



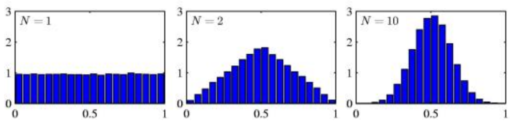

$$\mathcal{N}(\mathbf{x}|\boldsymbol{\mu},\boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{D/2}|\boldsymbol{\Sigma}|^{1/2}}\exp\left\{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right\}$$





## Gaussian Distribution - Properties

- Central Limit Theorem
  - "The distribution of the sum of $N$ i.i.d. random variables becomes increasingly Gaussian as $N$ grows."
  - In practice, the convergence to a Gaussian can be very rapid.
  - This makes the Gaussian interesting for many applications.
- Example: $N$ uniform [0,1] random variables.

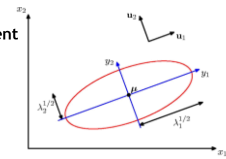







## Gaussian Distribution - Properties

- Quadratic Form
  - $\mathcal{N}$ depends on $\mathbf{x}$ through the exponent
    $$\Delta^2 = (\mathbf{x}-\boldsymbol{\mu})^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})$$
  - Here, $\Delta$ is often called the Mahalanobis distance from $\mu$ to $\mathbf{x}$.




- Shape of the Gaussian
  - $\Sigma$ is a real, symmetric matrix.
  - We can therefore decompose it into its eigenvectors
    $$\boldsymbol{\Sigma} = \sum_{i=1}^{D}\lambda_i\mathbf{u}_i\mathbf{u}_i^{\mathrm{T}} \qquad \boldsymbol{\Sigma}^{-1} = \sum_{i=1}^{D}\frac{1}{\lambda_i}\mathbf{u}_i\mathbf{u}_i^{\mathrm{T}}$$
    and thus obtain $\Delta^2 = \sum_{i=1}^{D}\frac{y_i^2}{\lambda_i}$ with $y_i = \mathbf{u}_i^{\mathrm{T}}(\mathbf{x}-\boldsymbol{\mu})$.

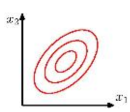
  ⇒ Constant density on ellipsoids with main directions along the eigenvectors $\mathbf{u}_i$ and scaling factors $\sqrt{\lambda_i}$.



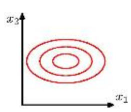


## Gaussian Distribution - Properties

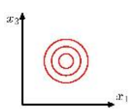
- Special cases
  - Full covariance matrix
    $$\boldsymbol{\Sigma} = [\sigma_{ij}]$$
    ⇒ General ellipsoid shape




  - Diagonal covariance matrix
    $$\boldsymbol{\Sigma} = diag\{\sigma_i\}$$
    ⇒ Axis-aligned ellipsoid




  - Uniform variance
    $$\boldsymbol{\Sigma} = \sigma^2\mathbf{I}$$
    ⇒ Hypersphere

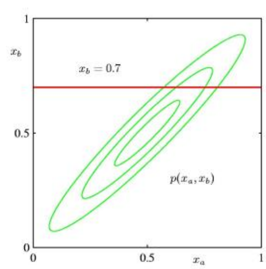


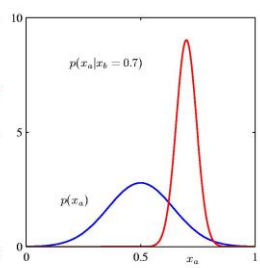





## Gaussian Distribution - Properties

- The marginals of a Gaussian are again Gaussians:



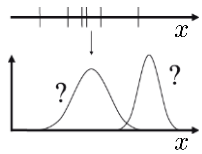
## Topics of This Lecture

- Bayes Decision Theory
  - Basic concepts
  - Minimizing the misclassification rate
  - Minimizing the expected loss
  - Discriminant functions
- Probability Density Estimation
  - General concepts
  - Gaussian distribution
- **Parametric Methods**
  - Maximum Likelihood approach
  - Bayesian vs. Frequentist views on probability
  - Bayesian Learning



## Parametric Methods

- Given
  - Data $X = \{x_1, x_2, \ldots, x_N\}$
  - Parametric form of the distribution with parameters $\theta$
  - E.g. for Gaussian distrib.: $\theta = (\mu, \sigma)$




- Learning
  - Estimation of the parameters $\theta$
- Likelihood of $\theta$
  - Probability that the data $X$ have indeed been generated from a probability density with parameters $\theta$

$$L(\theta) = p(X|\theta)$$

Slide adapted from Bernt Schiele



## Maximum Likelihood Approach

- Computation of the likelihood
  - Single data point: $p(x_n|\theta)$
  - Assumption: all data points are independent

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

  - Log-likelihood

$$E(\theta) = -\ln L(\theta) = -\sum_{n=1}^{N} \ln p(x_n|\theta)$$

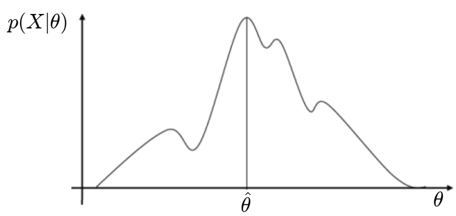
  - Estimation of the parameters $\theta$ (Learning)
    - Maximize the likelihood
    - Minimize the negative log-likelihood

Slide credit: Bernt Schiele



## Maximum Likelihood Approach

- Likelihood: $L(\theta) = p(X|\theta) = \prod_{n=1}^{N} p(x_n|\theta)$
- We want to obtain $\hat{\theta}$ such that $L(\hat{\theta})$ is maximized.

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## Maximum Likelihood Approach

- Minimizing the log-likelihood
  - How do we minimize a function?
  - ⇒ Take the derivative and set it to zero.

$$\frac{\partial}{\partial\theta}E(\theta) = -\frac{\partial}{\partial\theta}\sum_{n=1}^{N} \ln p(x_n|\theta) = -\sum_{n=1}^{N} \frac{\frac{\partial}{\partial\theta}p(x_n|\theta)}{p(x_n|\theta)} \stackrel{!}{=} 0$$

- Log-likelihood for Normal distribution (1D case)

$$\begin{aligned} E(\theta) &= -\sum_{n=1}^{N} \ln p(x_n|\mu,\sigma) \\ &= -\sum_{n=1}^{N} \ln\left(\frac{1}{\sqrt{2\pi}\sigma}\exp\left\{-\frac{||x_n-\mu||^2}{2\sigma^2}\right\}\right) \end{aligned}$$



## Maximum Likelihood Approach

- Minimizing the log-likelihood

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

$$\begin{aligned} \frac{\partial}{\partial\mu}E(\mu,\sigma) &= -\sum_{n=1}^{N} \frac{\frac{\partial}{\partial\mu}p(x_n|\mu,\sigma)}{p(x_n|\mu,\sigma)} \\ &= -\sum_{n=1}^{N} -\frac{2(x_n-\mu)}{2\sigma^2} \\ &= \frac{1}{\sigma^2}\sum_{n=1}^{N}(x_n-\mu) \\ &= \frac{1}{\sigma^2}\left(\sum_{n=1}^{N} x_n - N\mu\right) \end{aligned}$$

$$\frac{\partial}{\partial\mu}E(\mu,\sigma) \stackrel{!}{=} 0 \quad \Leftrightarrow \quad \hat{\mu} = \frac{1}{N}\sum_{n=1}^{N} x_n$$

## Maximum Likelihood Approach

- We thus obtain

$$\hat{\mu} = \frac{1}{N}\sum_{n=1}^{N} x_n \qquad \text{"sample mean"}$$

- In a similar fashion, we get

$$\hat{\sigma}^2 = \frac{1}{N}\sum_{n=1}^{N} (x_n - \hat{\mu})^2 \qquad \text{"sample variance"}$$

- $\hat{\theta} = (\hat{\mu}, \hat{\sigma})$ is the Maximum Likelihood estimate for the parameters of a Gaussian distribution.
- This is a very important result.
- Unfortunately, it is wrong…



## Maximum Likelihood Approach

- Or not wrong, but rather biased…
- Assume the samples $x_1, x_2, \ldots, x_N$ come from a true Gaussian distribution with mean $\mu$ and variance $\sigma^2$
  - We can now compute the expectations of the ML estimates with respect to the data set values. It can be shown that

$$\mathbb{E}(\mu_{\mathrm{ML}}) = \mu$$

$$\mathbb{E}(\sigma^2_{\mathrm{ML}}) = \left(\frac{N-1}{N}\right)\sigma^2$$

⇒ The ML estimate will underestimate the true variance.

- Corrected estimate:

$$\tilde{\sigma}^2 = \frac{N}{N-1}\sigma^2_{\mathrm{ML}} = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \hat{\mu})^2$$

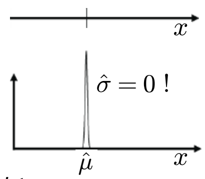


## Maximum Likelihood - Limitations

- Maximum Likelihood has several significant limitations
  - It systematically underestimates the variance of the distribution!
  - E.g. consider the case

$$N = 1, X = \{x_1\}$$

⇒ Maximum-likelihood estimate:




  - We say ML *overfits to the observed data.*
  - We will still often use ML, but it is important to know about this effect.



## Deeper Reason

- Maximum Likelihood is a Frequentist concept
  - In the Frequentist view, probabilities are the frequencies of random, repeatable events.
  - These frequencies are fixed, but can be estimated more precisely when more data is available.
- This is in contrast to the Bayesian interpretation
  - In the Bayesian view, probabilities quantify the uncertainty about certain states or events.
  - This uncertainty can be revised in the light of new evidence.
- Bayesians and Frequentists do not like each other too well…



## Bayesian vs. Frequentist View

- To see the difference…
  - Suppose we want to estimate the uncertainty whether the Arctic ice cap will have disappeared by the end of the century.
  - This question makes no sense in a Frequentist view, since the event cannot be repeated numerous times.
  - In the Bayesian view, we generally have a prior, e.g. from calculations how fast the polar ice is melting.
  - If we now get fresh evidence, e.g. from a new satellite, we may revise our opinion and update the uncertainty from the prior.

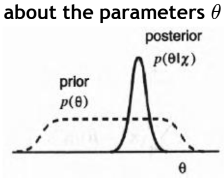
$$\textit{Posterior} \propto \textit{Likelihood} \times \textit{Prior}$$

  - This generally allows to get better uncertainty estimates for many situations.
- Main Frequentist criticism
  - The prior has to come from somewhere and if it is wrong, the result will be worse.



## Bayesian Approach to Parameter Learning

- Conceptual shift
  - Maximum Likelihood views the true parameter vector $\theta$ to be unknown, but fixed.
  - In Bayesian learning, we consider $\theta$ to be a random variable.
- This allows us to use knowledge about the parameters $\theta$
  - i.e. to use a prior for $\theta$
  - Training data then converts this prior distribution on $\theta$ into a posterior probability density.




  - The prior thus encodes knowledge we have about the type of distribution we expect to see for $\theta$.

## Bayesian Learning Approach

- **Bayesian view:**
  - Consider the parameter vector $\theta$ as a random variable.
  - When estimating the parameters, what we compute is

$$p(x|X) = \int p(x, \theta|X) d\theta$$

Assumption: given $\theta$, this doesn't depend on X anymore

$$p(x, \theta|X) = p(x|\theta, \cancel{X}) p(\theta|X)$$

$$p(x|X) = \int \underbrace{p(x|\theta)}p(\theta|X) d\theta$$

This is entirely determined by the parameter $\theta$ (i.e. by the parametric form of the pdf).

Slide adapted from Bernt Schiele

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## Bayesian Learning Approach

$$p(x|X) = \int p(x|\theta)\underbrace{p(\theta|X)} d\theta$$

$$p(\theta|X) = \frac{p(X|\theta)p(\theta)}{p(X)} = \frac{p(\theta)}{p(X)}L(\theta)$$

$$p(X) = \int p(X|\theta)p(\theta)d\theta = \int L(\theta)p(\theta)d\theta$$

- Inserting this above, we obtain

$$p(x|X) = \int \frac{p(x|\theta)L(\theta)p(\theta)}{p(X)} d\theta = \int \frac{p(x|\theta)L(\theta)p(\theta)}{\int L(\theta)p(\theta)d\theta} d\theta$$

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## Bayesian Learning Approach

- Discussion

Likelihood of the parametric form $\theta$ given the data set $X$.

Estimate for $x$ based on parametric form $\theta$

Prior for the parameters $\theta$

$$p(x|X) = \int \frac{p(x|\theta)L(\theta)p(\theta)}{\underbrace{\int L(\theta)p(\theta)d\theta}} d\theta$$

Normalization: integrate over all possible values of $\theta$

  - If we now plug in a (suitable) prior $p(\theta)$, we can estimate $p(x|X)$ from the data set $X$.

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## Bayesian Density Estimation

- Discussion

$$p(x|X) = \int p(x|\theta)p(\theta|X)d\theta = \int \frac{p(x|\theta)L(\theta)p(\theta)}{\int L(\theta)p(\theta)d\theta} d\theta$$

  - The probability $p(\theta|X)$ makes the dependency of the estimate on the data explicit.
  - If $p(\theta|X)$ is very small everywhere, but is large for one $\hat{\theta}$, then

$$p(x|X) \approx p(x|\hat{\theta})$$

$\Rightarrow$ The more uncertain we are about $\theta$, the more we average over all parameter values.

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## Bayesian Density Estimation

- **Problem**
  - In the general case, the integration over $\theta$ is not possible (or only possible stochastically).
- **Example where an analytical solution is possible**
  - Normal distribution for the data, $\sigma^2$ assumed known and fixed.
  - Estimate the distribution of the mean:

$$p(\mu|X) = \frac{p(X|\mu)p(\mu)}{p(X)}$$

  - Prior: We assume a Gaussian prior over $\mu$,

$$p(\mu) = \mathcal{N}\left(\mu|\mu_0, \sigma_0^2\right).$$

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## Bayesian Learning Approach

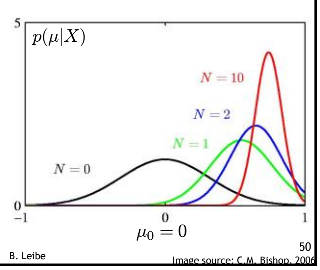
- **Sample mean:** $\bar{x} = \frac{1}{N}\sum_{n=1}^{N} x_n$
- **Bayes estimate:**

$$\mu_N = \frac{\sigma^2\mu_0 + N\sigma_0^2\bar{x}}{\sigma^2 + N\sigma_0^2}$$

$$\frac{1}{\sigma_N^2} = \frac{1}{\sigma_0^2} + \frac{N}{\sigma^2}$$

- **Note:**

| | $N = 0$ | $N \to \infty$ |
|---|---|---|
| $\mu_N$ | $\mu_0$ | $\mu_{\mathrm{ML}}$ |
| $\sigma_N^2$ | $\sigma_0^2$ | 0 |




Slide adapted from Bernt Schiele

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Image source: C.M. Bishop, 2006



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## Summary: ML vs. Bayesian Learning

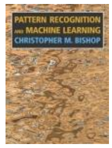
- Maximum Likelihood
  - Simple approach, often analytically possible.
  - Problem: estimation is biased, tends to overfit to the data.
    - ⇒ Often needs some correction or regularization.
  - But:
    - Approximation gets accurate for $N \to \infty$.
- Bayesian Learning
  - General approach, avoids the estimation bias through a prior.
  - Problems:
    - Need to choose a suitable prior (not always obvious).
    - Integral over $\theta$ often not analytically feasible anymore.
  - But:
    - Efficient stochastic sampling techniques available (see Lecture 15).

*(In this lecture, we'll use both concepts wherever appropriate)*



## References and Further Reading

- More information in Bishop's book
  - Gaussian distribution and ML: Ch. 1.2.4 and 2.3.1-2.3.4.
  - Bayesian Learning: Ch. 1.2.3 and 2.3.6.
  - Nonparametric methods: Ch. 2.5.
- Additional information can be found in Duda & Hart
  - ML estimation: Ch. 3.2
  - Bayesian Learning: Ch. 3.3-3.5
  - Nonparametric methods: Ch. 4.1-4.5

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