

# Model inference

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Course of Machine Learning  
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## Purpose

Inferring a **probabilistic model** from a collection of observed data  $\mathbf{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ . A probabilistic model is a probability distribution over the data domain.

## Dataset

A dataset  $\mathbf{X}$  is a collection of  $N$  observed data, independent and identically distributed (iid): they can be seen as realizations of a single random variable.

## Problems considered

Inference objectives:

**Model selection** Selecting the probabilistic model  $\mathcal{M}$  best suited for a given data collection

**Estimation** Estimate the values of the set  $\boldsymbol{\theta} = (\theta_1, \dots, \theta_D)$  of parameters of a given model type (probability distribution), which best model the observed data  $\mathbf{X}$

**Prediction** Compute the probability  $p(x|\mathbf{X})$  of a new observation from the set of already observed data

## Context

Model space  $\mathcal{M}$ : a model  $m \in \mathcal{M}$  is a probability distribution  $p(\mathbf{x}|m)$  over data.

Let  $p(m)$  be any **prior distribution** of models

$$\sum_{m \in \mathcal{M}} p(m) = 1$$

The corresponding predictive distribution of data is

$$p(\mathbf{x}) = \sum_{m \in \mathcal{M}} p(\mathbf{x}|m)p(m)$$

After the observation of a dataset  $\mathbf{X}$ , the updated probabilities are

$$p(m|\mathbf{X}) = \frac{p(m)p(\mathbf{X}|m)}{p(\mathbf{X})} \propto p(m)p(\mathbf{X}|m) = p(m) \prod_{i=1}^n p(x_i|m)$$

and the predictive distribution is

$$p(\mathbf{x}|\mathbf{X}) = \sum_{m \in \mathcal{M}} p(\mathbf{x}|m)p(m|\mathbf{X})$$

## Parametric models

Models are defined as parametric probability distributions, with parameters  $\theta$  ranging on a **parameter space**  $\Theta$ .

A prior parameter distribution  $p(\theta|m)$  is defined for a model. The prior predictive distribution is then

$$p(\mathbf{x}|m) = \int_{\Theta} p(\mathbf{x}|\theta, m)p(\theta|m)d\theta$$

## Posterior parameter distribution

Given a model  $m \in \mathcal{M}$ , Bayes' formula makes it possible to infer the posterior distribution of parameters, given the dataset  $\mathbf{X}$

$$p(\theta|\mathbf{X}, m) = \frac{p(\theta|m)p(\mathbf{X}|\theta, m)}{p(\mathbf{X}|m)} \propto p(\theta|m)p(\mathbf{X}|\theta, m)$$

The posterior predictive distribution, given the model, is

$$p(\mathbf{x}|\mathbf{X}, m) = \int_{\Theta} p(\mathbf{x}|\theta, m)p(\theta|\mathbf{X}, m)d\theta$$

# Bayesian inference

According to the bayesian approach to inference, parameters are considered as random variables, whose distributions have to be inferred from observed data.

The approach relies on Bayes' classic result:

## Theorem (Bayes)

*Let  $\mathbf{X}, \mathbf{Y}$  be a pair of (sets of) random variables. Then,*

$$p(\mathbf{Y}|\mathbf{X}) = \frac{p(\mathbf{X}|\mathbf{Y})p(\mathbf{Y})}{p(\mathbf{X})} = \frac{p(\mathbf{X}|\mathbf{Y})p(\mathbf{Y})}{\int_{\mathbf{Z}} p(\mathbf{X}, \mathbf{Z})d\mathbf{Z}}$$

where

- $p(\mathbf{Y})$  is the **prior probability** of  $\mathbf{Y}$  (with respect to the observation of  $\mathbf{X}$ )
- $p(\mathbf{Y}|\mathbf{X})$  is the **posterior probability** of  $\mathbf{Y}$
- $p(\mathbf{X}|\mathbf{Y})$  is the **likelihood** of  $\mathbf{X}$  w.r.t.  $\mathbf{Y}$
- $p(\mathbf{X})$  is the **evidence** of  $\mathbf{X}$

# Point estimate of parameters

## Motivation

Given a model  $m$ , the bayesian approach is aimed to derive the posterior distribution of the set of parameters  $\theta$ . This requires computing

$$p(\theta|\mathbf{X}) = \frac{p(\mathbf{X}|\theta)p(\theta)}{p(\mathbf{X})} = \frac{p(\mathbf{X}|\theta)p(\theta)}{\int_{\Theta} p(\mathbf{X}|\theta)p(\theta)d\theta}$$

and

$$p(x|\mathbf{X}) = \int_{\theta} p(x|\theta)p(\theta|\mathbf{X})d\theta$$

This is usually impossible to be done efficiently.

## Idea

Only an estimate of the "best" value  $\hat{\theta}$  in  $\theta$  (according to some measure) is performed. The posterior predictive distribution can then be approximated as follows

$$\begin{aligned} p(\mathbf{x}|\mathbf{X}) &= \int_{\theta} p(\mathbf{x}|\theta)p(\theta|\mathbf{X})d\theta \approx \int_{\theta} p(\mathbf{x}|\hat{\theta})p(\theta|\mathbf{X})d\theta \\ &= p(\mathbf{x}|\hat{\theta}) \int_{\theta} p(\theta|\mathbf{X})d\theta = p(\mathbf{x}|\hat{\theta}) \end{aligned}$$



# Maximum likelihood estimate

## Approach

**Frequentist** point of view: parameters are deterministic variables, whose value is unknown and must be estimated.

Determine the parameter value that maximize the likelihood

$$L(\boldsymbol{\theta}|\mathbf{X}) = p(\mathbf{X}|\boldsymbol{\theta}) = \prod_{i=1}^N p(\mathbf{x}_i|\boldsymbol{\theta})$$

## Log-likelihood

$$l(\boldsymbol{\theta}|\mathbf{X}) = \ln L(\boldsymbol{\theta}|\mathbf{X}) = \sum_{i=1}^N \ln p(\mathbf{x}_i|\boldsymbol{\theta})$$

is usually preferable.

The maximum occurs at the same point:  $\operatorname{argmax}_{\boldsymbol{\theta}} l(\boldsymbol{\theta}|\mathbf{X}) = \operatorname{argmax}_{\boldsymbol{\theta}} L(\boldsymbol{\theta}|\mathbf{X})$

## Estimate

$$\hat{\boldsymbol{\theta}}_{ML} = \operatorname{argmax}_{\boldsymbol{\theta}} L(\boldsymbol{\theta}|\mathbf{X}) = \operatorname{argmax}_{\boldsymbol{\theta}} \sum_{i=1}^N \ln p(\mathbf{x}_i|\boldsymbol{\theta})$$

# Maximum likelihood estimate

## Solution

Solve the system

$$\frac{\partial l(\boldsymbol{\theta}|\mathbf{X})}{\partial \theta_i} = 0 \quad i = 1, \dots, D$$

more concisely,

$$\nabla_{\boldsymbol{\theta}} l(\boldsymbol{\theta}|\mathbf{X}) = \mathbf{0}$$

## Prediction

Probability of a new observation  $\mathbf{x}$ :

$$\begin{aligned} p(\mathbf{x}|\mathbf{X}) &= \int_{\boldsymbol{\theta}} p(\mathbf{x}|\boldsymbol{\theta})p(\boldsymbol{\theta}|\mathbf{X})d\boldsymbol{\theta} \approx \int_{\boldsymbol{\theta}} p(\mathbf{x}|\hat{\boldsymbol{\theta}}_{ML})p(\boldsymbol{\theta}|\mathbf{X})d\boldsymbol{\theta} \\ &= p(\mathbf{x}|\hat{\boldsymbol{\theta}}_{ML}) \int_{\boldsymbol{\theta}} p(\boldsymbol{\theta}|\mathbf{X})d\boldsymbol{\theta} = p(\mathbf{x}|\hat{\boldsymbol{\theta}}_{ML}) \end{aligned}$$

## Example

Collection  $\mathbf{X}$  of  $n$  binary events, modeled through a Bernoulli distribution with unknown parameter  $\phi$

$$p(x|\phi) = \phi^x (1 - \phi)^{1-x}$$

Likelihood

$$L(\phi|\mathbf{X}) = \prod_{i=1}^N \phi^{x_i} (1 - \phi)^{1-x_i}$$

Log-likelihood

$$l(\phi|\mathbf{X}) = \sum_{i=1}^N (x_i \ln \phi + (1 - x_i) \ln(1 - \phi)) = N_1 \ln \phi + N_0 \ln(1 - \phi)$$

where  $N_0$  ( $N_1$ ) is the number of events  $x \in \mathbf{X}$  equal to 0 (1)

$$\frac{\partial l(\phi|\mathbf{X})}{\partial \phi} = \frac{N_1}{\phi} - \frac{N_0}{1 - \phi} = 0 \quad \implies \quad \hat{\phi}_{ML} = \frac{N_1}{N_0 + N_1} = \frac{N_1}{N}$$

## Overfitting

Maximizing the likelihood of the observed dataset tends to result into an estimate too sensitive to the dataset values, hence into **overfitting**. The obtained estimates are suitable to model observed data, but may be too specialized to be used to model different datasets.

## Penalty functions

An additional function  $P(\boldsymbol{\theta})$  can be introduced with the aim to limit overfitting and the overall complexity of the model. This results in the following function to maximize

$$C(\boldsymbol{\theta}|\mathbf{X}) = l(\boldsymbol{\theta}|\mathbf{X}) - P(\boldsymbol{\theta})$$

as a common case,  $P(\boldsymbol{\theta}) = \frac{\gamma}{2} \|\boldsymbol{\theta}\|^2$ , with  $\gamma$  a **tuning** parameter.

# Maximum a posteriori estimate

## Idea

Inference through maximum a posteriori (MAP) is similar to ML, but  $\theta$  is now considered as a random variable, whose distribution has to be derived from observations, also taking into account previous knowledge (prior distribution). The parameter value maximizing

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

is computed.

## Estimate

$$\begin{aligned}\hat{\theta}_{MAP} &= \operatorname{argmax}_{\theta} p(\theta|\mathbf{X}) = \operatorname{argmax}_{\theta} p(\mathbf{X}|\theta)p(\theta) \\ &= \operatorname{argmax}_{\theta} L(\theta|\mathbf{X})p(\theta) = \operatorname{argmax}_{\theta} (l(\theta|\mathbf{X}) + \ln p(\theta)) \\ &= \operatorname{argmax}_{\theta} \left( \sum_{i=1}^N \ln p(\mathbf{x}_i|\theta) + \ln p(\theta) \right)\end{aligned}$$

## Hypothesis

Assume  $\boldsymbol{\theta}$  is distributed around the origin as a multivariate gaussian with uniform variance and null covariance. That is,

$$p(\boldsymbol{\theta}) \sim \mathcal{N}(\boldsymbol{\theta}|\mathbf{0}, \sigma^2) = \frac{1}{(2\pi)^{d/2}\sigma^d} \exp\left(-\frac{1}{2} \frac{\|\boldsymbol{\theta}\|^2}{\sigma^2}\right) \propto \exp\left(-\frac{\|\boldsymbol{\theta}\|^2}{2\sigma^2}\right)$$

## Inference

From the hypothesis,

$$\begin{aligned}\hat{\boldsymbol{\theta}}_{MAP} &= \underset{\boldsymbol{\theta}}{\operatorname{argmax}} p(\boldsymbol{\theta}|\mathbf{X}) = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} (l(\boldsymbol{\theta}|\mathbf{X}) + \ln p(\boldsymbol{\theta})) \\ &= \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \left( l(\boldsymbol{\theta}|\mathbf{X}) + \ln \exp\left(-\frac{\|\boldsymbol{\theta}\|^2}{2\sigma^2}\right) \right) = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \left( l(\boldsymbol{\theta}|\mathbf{X}) - \frac{\|\boldsymbol{\theta}\|^2}{2\sigma^2} \right)\end{aligned}$$

which is equal to the penalty function introduced before, if  $\gamma = \frac{1}{\sigma^2}$

## Example

Collection  $\mathbf{X}$  of  $n$  binary events, modeled as a Bernoulli distribution with unknown parameter  $\phi$ . Initial knowledge of  $\phi$  is modeled as a Beta distribution:

$$p(\phi|\alpha, \beta) = \text{Beta}(\phi|\alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \phi^{\alpha-1} (1 - \phi)^{\beta-1}$$

Log-likelihood

$$l(\phi|\mathbf{X}) = \sum_{i=1}^N (x_i \ln \phi + (1 - x_i) \ln(1 - \phi)) = N_1 \ln \phi + N_0 \ln(1 - \phi)$$

$$\frac{\partial}{\partial \phi} l(\phi|\mathbf{X}) + \ln \text{Beta}(\phi|\alpha, \beta) = \frac{N_1}{\phi} - \frac{N_0}{1 - \phi} + \frac{\alpha - 1}{\phi} - \frac{\beta - 1}{1 - \phi} = 0 \quad \Rightarrow$$

$$\hat{\phi}_{MAP} = \frac{N_1 + \alpha - 1}{N_0 + N_1 + \alpha + \beta - 2} = \frac{N_1 + \alpha - 1}{N + \alpha + \beta - 2}$$

## Gamma function

The function

$$\Gamma(x) = \int_0^{\infty} t^{x-1} e^{-t} dt$$

is an extension of the factorial to the real numbers field: hence, for any integer  $x$ ,

$$\Gamma(x) = (x-1)!$$

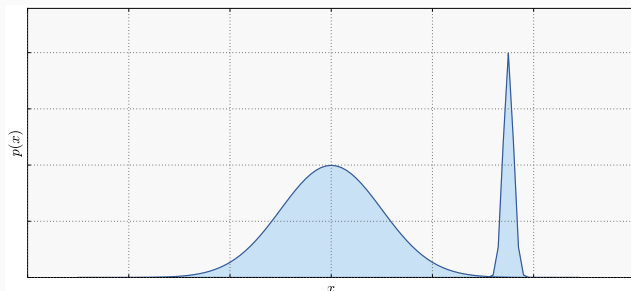


## Mode and mean

Once the posterior distribution

$$p(\theta|\mathbf{X}) = \frac{p(\mathbf{X}|\theta)p(\theta)}{p(\mathbf{X})} = \frac{p(\mathbf{X}|\theta)p(\theta)}{\int_{\theta} p(\mathbf{X}|\theta)d\theta}$$

is available, MAP estimate computes the most probable value (mode)  $\theta_{MAP}$  of the distribution. This may lead to inaccurate estimates, as in the figure below:



## Mode and mean

A better estimation can be obtained by applying a fully bayesian approach and referring to the whole posterior distribution, for example by deriving the expectation of  $\theta$  w.r.t.  $p(\theta|\mathbf{X})$ ,

$$\theta^* = E_{p(\theta|\mathbf{X})}[\theta] = \int_{\theta} \theta p(\theta|\mathbf{X}) d\theta$$

## Example

Collection  $\mathbf{X}$  of  $n$  binary events, modeled as a Bernoulli distribution with unknown parameter  $\phi$ . Initial knowledge of  $\phi$  is modeled as a Beta distribution:

$$p(\phi|\alpha, \beta) = \text{Beta}(\phi|\alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \phi^{\alpha-1} (1 - \phi)^{\beta-1}$$

Posterior distribution

$$\begin{aligned} p(\phi|\mathbf{X}, \alpha, \beta) &= \frac{\prod_{i=1}^N \phi^{x_i} (1 - \phi)^{1-x_i} p(\phi|\alpha, \beta)}{p(\mathbf{X})} \\ &= \frac{\phi^{N_1} (1 - \phi)^{N_0} \phi^{\alpha-1} (1 - \phi)^{\beta-1}}{\frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)} p(\mathbf{X})} = \frac{\phi^{N_1+\alpha-1} (1 - \phi)^{N_0+\beta-1}}{Z} \end{aligned}$$

since  $\int_{-\infty}^{+\infty} p(\phi|\mathbf{X}, \alpha, \beta) d\phi = 1$ ,  $Z$  must be equal to the normalizing coefficient of the distribution  $\text{Beta}(\phi|\alpha + N_1, \beta + N_0)$ . Hence,

$$p(\phi|\mathbf{X}, \alpha, \beta) = \text{Beta}(\phi|\alpha + N_1, \beta + N_0)$$

Example: learning in the dirichlet-multinomial model

A **language model** is a (categorical) probability distribution on a vocabulary of terms (possibly, all words which occur in a large collection of documents).

## Use

A language model can be applied to predict the next term occurring in a text. The probability of occurrence of a term is related to its information content and is at the basis of a number of information retrieval techniques.

## Hypothesis

It is assumed that the probability of occurrence of a term is independent from the preceding terms in a text (**bag of words** model).

## Generative model

Given a language model, it is possible to sample from the distribution to generate random documents statistically equivalent to the documents in the collection used to derive the model.

- Let  $\mathcal{T} = \{t_1, \dots, t_n\}$  be the set of terms occurring in a given collection  $\mathcal{C}$  of documents, after **stop word** (common, non informative terms) removal and **stemming** (reduction of words to their basic form).
- For each  $i = 1, \dots, n$  let  $m_i$  be the multiplicity (number of occurrences) of term  $t_i$  in  $\mathcal{C}$
- A language model can be derived as a categorical distribution associated to a vector  $\hat{\phi} = (\hat{\phi}_1, \dots, \hat{\phi}_n)^T$  of probabilities: that is,

$$0 \leq \hat{\phi}_i \leq 1 \quad i = 1, \dots, n \qquad \sum_{i=1}^n \hat{\phi}_i = 1$$

where  $\hat{\phi}_j = p(t_j|\mathcal{C})$

Applying maximum likelihood to derive term probabilities in the language model results into setting

$$\hat{\phi}_j = p(t_j|\mathcal{C}) = \frac{m_j}{\sum_{k=1}^n m_k} = \frac{m_j}{N}$$

where  $N = \sum_{i=1}^n m_i$  is the overall number of occurrences in  $\mathcal{C}$  after stopword removal.

## Smoothing

According to this estimate, a term  $t$  which never occurred in  $\mathcal{C}$  has zero probability to be observed (black swan paradox). Due to overfitting the model to the observed data, typical of ML estimation.

Solution: assign small, non zero, probability to events (terms) not observed up to now. This is called **smoothing**.

We may apply the dirichlet-multinomial model:

- this implies defining a Dirichlet prior  $\text{Dir}(\phi|\alpha)$ , with  $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_n)$  that is,

$$p(\phi_1, \dots, \phi_n | \alpha) = \frac{1}{\Delta(\alpha_1, \dots, \alpha_n)} \prod_{i=1}^n \phi_i^{\alpha_i - 1}$$

- the posterior distribution of  $\phi$  after  $\mathcal{C}$  has been observed is then  $\text{Dir}(\phi|\alpha')$ , where

$$\alpha' = (\alpha_1 + m_1, \alpha_2 + m_2, \dots, \alpha_n + m_n)$$

that is,

$$p(\phi_1, \dots, \phi_n | \alpha') = \frac{1}{\Delta(\alpha_1 + m_1, \dots, \alpha_n + m_n)} \prod_{i=1}^n \phi_i^{\alpha_i + m_i - 1}$$



## Bayesian learning of a language model

The language model  $\hat{\phi}$  corresponds to the predictive posterior distribution

$$\begin{aligned}\hat{\phi}_j &= p(t_j | \mathcal{C}, \boldsymbol{\alpha}) = \int p(t_j | \phi) p(\phi | \mathcal{C}, \boldsymbol{\alpha}) d\phi \\ &= \int \phi_j \text{Dir}(\phi | \boldsymbol{\alpha}') d\phi = E[\phi_j]\end{aligned}$$

where  $E[\phi_j]$  is taken w.r.t. the distribution  $\text{Dir}(\phi | \boldsymbol{\alpha}')$ . Then,

$$\hat{\phi}_j = \frac{\alpha'_j}{\sum_{k=1}^n \alpha'_k} = \frac{\alpha_j + m_j}{\sum_{k=1}^n (\alpha_k + m_k)} = \frac{\alpha_j + m_j}{\alpha_0 + N}$$

The  $\alpha_j$  term makes it impossible to obtain zero probabilities (**Dirichlet smoothing**).

Non informative prior:  $\alpha_i = \alpha$  for all  $i$ , which results into

$$p(t_j | \mathcal{C}, \boldsymbol{\alpha}) = \frac{m_j + \alpha}{\alpha V + N}$$

where  $V$  is the vocabulary size.

A language model can be applied to derive document classifiers into two or more classes.

- given two classes  $C_1, C_2$ , assume that, for any document  $d$ , the probabilities  $p(C_1|d)$  and  $p(C_2|d)$  are known: then,  $d$  can be assigned to the class with higher probability
- how to derive  $p(C_k|d)$  for any document, given a collection  $\mathcal{C}_1$  of documents known to belong to  $C_1$  and a similar collection  $\mathcal{C}_2$  for  $C_2$ ?  
Apply Bayes' rule:

$$p(C_k|d) \propto p(d|C_k)p(C_k)$$

the evidence  $p(d)$  is the same for both classes, and can be ignored.

- we have still the problem of computing  $p(C_k)$  and  $p(d|C_k)$  from  $\mathcal{C}_1$  and  $\mathcal{C}_2$

## Computing $p(C_k)$

The prior probabilities  $p(C_k)$  ( $k = 1, 2$ ) can be easily estimated from  $\mathcal{C}_1, \mathcal{C}_2$ : for example, by applying ML, we obtain

$$p(C_k) = \frac{|\mathcal{C}_1|}{|\mathcal{C}_1| + |\mathcal{C}_2|}$$

## Computing $p(d|C_k)$

For what concerns the likelihoods  $p(d|C_k)$  ( $k = 1, 2$ ), we observe that  $d$  can be seen, according to the bag of words assumption, as a multiset of  $n_d$  terms

$$d = \{\bar{t}_1, \bar{t}_2, \dots, \bar{t}_{n_d}\}$$

By applying the product rule, it results

$$\begin{aligned} p(d|C_k) &= p(\bar{t}_1, \dots, \bar{t}_{n_d}|C_k) \\ &= p(\bar{t}_1|C_k)p(\bar{t}_2|\bar{t}_1, C_k) \cdots p(\bar{t}_{n_d}|\bar{t}_1, \dots, \bar{t}_{n_d-1}, C_k) \end{aligned}$$

## The naive Bayes assumption

Computing  $p(d|C_k)$  is much easier if we assume that terms are pairwise conditionally independent, given the class  $C_k$ , that is, for  $i, j = 1 \dots, n_d$  and  $k = 1, 2$ ,

$$p(\bar{t}_i, \bar{t}_j | C_k) = p(\bar{t}_i | C_k) p(\bar{t}_j | C_k)$$

as, a consequence,

$$p(d|C_k) = \prod_{j=1}^{n_d} p(\bar{t}_j | C_k)$$

## Language models and NB classifiers

The probabilities  $p(\bar{t}_j | C_k)$  are available for all terms if language models have been derived for  $C_1$  and  $C_2$ , respectively from documents in  $\mathcal{C}_1$  and  $\mathcal{C}_2$ .

# Feature selection by mutual information

## Feature selection

The set of probabilities in a language model can be exploited to identify the most relevant terms for classification, that is terms whose presence or absence in a document best characterizes the class of the document.

## Mutual information

To measure relevance, we can apply the set of mutual informations  $\{I_1, \dots, I_n\}$

$$\begin{aligned} I_j &= \sum_{k=1,2} p(t_j, C_k) \log \frac{p(t_j, C_k)}{p(t_j)p(C_k)} \\ &= \sum_{k=1,2} p(C_k|t_j)p(t_j) \log \frac{p(C_k|t_j)}{p(C_k)} = p(t_j)KL(p(C_k|t_j)||p(C_k)) \end{aligned}$$

here,  $KL$  is a measure of the amount of information on class distributions provided by the presence of  $t_j$ . This amount is weighted by the probability of occurrence of  $t_j$ .

## Mutual information

Since  $p(t_j, C_k) = p(C_k|t_j)p(t_j) = p(t_j|C_k)p(C_k)$ ,  $I_j$  can be estimated as

$$\begin{aligned} I_j &= p(t_j|C_1)p(C_1) \log \frac{p(t_j|C_1)}{p(t_j)} + p(t_j|C_2)p(C_2) \log \frac{p(t_j|C_2)}{p(t_j)} \\ &= \phi_{j1}\pi_1 \log \frac{\phi_{j1}}{\phi_{j1}\pi_1 + \phi_{j2}\pi_2} + \phi_{j2}\pi_2 \log \frac{\phi_{j2}}{\phi_{j1}\pi_1 + \phi_{j2}\pi_2} \end{aligned}$$

where  $\phi_{jk}$  is the estimated probability of  $t_j$  in documents of class  $C_k$  and  $\pi_k$  is the estimated probability of a document of class  $C_k$  in the collection.

A selection of the most significant terms can be performed by selecting the set of terms with highest mutual information  $I_j$ .