

A dynamic naive Bayes classifier (DNBC) is an extension of the popular probabilistic graphical model called hidden Markov model. Output variables are assumed to be statistically independent, which helps us in case of the curse of dimensionality occurring in high-dimensional space. Moreover, output variables that come from different probability distributions can be learned easier.

This thesis aims to create a parallel implementation of DNBC that can be easily executed on a computational cluster. For that reason, the algorithm will be implemented in the Scala language on top of Apache Spark.

1. Study DNBC and its possibilities of parallelism.
2. Implement DNBC that is applicable for both discrete and continuous output variables.
3. Parallelize the implementation on top of Apache Spark.
4. Evaluate the parallel implementation and compare it with the sequential implementation in terms of parallel scalability.





**FACULTY  
OF INFORMATION  
TECHNOLOGY  
CTU IN PRAGUE**

Bachelor's thesis

# **Paralelní implementace dynamického naivního Bayesovského klasifikátoru**

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April 2, 2018



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## Abstrakt

V několika větách shrňte obsah a přínos této práce v češtině. Po přečtení abstraktu by se čtenář měl mít čtenář dost informací pro rozhodnutí, zda chce Vaši práci číst.

**Klíčová slova**    Nahraďte seznamem klíčových slov v češtině oddělených čárkou.

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## Abstract

Sem doplňte ekvivalent abstraktu Vaší práce v angličtině.

**Keywords**    Nahraďte seznamem klíčových slov v angličtině oddělených čárkou.





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# Introduction





## Cíl práce



# Mathematical background

## 2.1 Probability density function

Probability density function (PDF) of a continuous random variable determines a likelihood that a given value occurs. Furthermore, 2.1 gives a probability of value being in interval  $[a, b]$ .

$$P(a \leq x \leq b) = \int_a^b \text{PDF}(x)dx \quad (2.1)$$

To satisfy the property that  $P(-\inf < x < \inf) = 1$ , the following has to hold:

$$\int_{-\inf}^{\inf} \text{PDF}(x)dx = 1. \quad (2.2)$$

## 2.2 Gaussian distribution

Gaussian (normal) distribution is defined by a probability density function

$$\text{PDF}_{\mathcal{N}(\mu, \sigma^2)}(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}. \quad (2.3)$$

The distribution is defined by two parameters - mean  $\mu$  and variance  $\sigma^2$ . Figure 2.1 provides a visualization of the probability density function.

Normal distribution is one of the most widespread distribution found in nature [2]. Imagine  $n$  independent identically distributed (i.i.d.) random variables. For large  $n > 30$ , both sum and average of the variables converge to normal distribution. This phenomenon occurs because of the Central Limit Theorem. See book *Introduction to Probability* [3] for a proof.



Figure 2.1: Visualization of Gaussian PDF with parameters  $\mu = 10$  and  $\sigma^2 = 3^2$ .

### 2.3 Gaussian mixture distribution

Combining multiple Gaussian distributions together results in Gaussian mixture distribution. The PDF is given by 2.4, where  $n$  is number of components.

$$\text{PDF}_{\mathcal{N}^*(\theta)}(x) = \sum_{i=1}^n w_i \text{PDF}_{\mathcal{N}(\mu_i, \sigma_i^2)}(x), \quad (2.4)$$

where  $w_i$  is a weight of particular component. The following conditions have to hold:

$$w_i \geq 0, 1 \leq i \leq n, \quad (2.5)$$

$$\sum_{i=1}^n w_i = 1. \quad (2.6)$$



Figure 2.2: Visualization of a mixture with three components with parameters  $\mu_1 = 5, \mu_2 = 10, \mu_3 = 15$  and  $\sigma_{1,2,3}^2 = 2^2$ . Weights are  $w_{1,2,3} = \frac{1}{3}$ . Author: Smason79 [1].



# Analysis

## 3.1 Markov chain

### 3.1.1 Introduction

Markov chain describes possible sequences of events in which a probability of being at a state at given time depends only on value of previous state.

### 3.1.2 Description

A Markov chain is defined by

- set of states  $S = \{S_1, S_2, \dots, S_N\}$ ,
- transition matrix  $A \in \mathbf{R}^{N \times N}$ ,
- initial probability vector  $\pi \in \mathbf{R}^N$ .

Where  $a_{ij}, 1 \leq i, j \leq N$  is a probability of transitioning from state  $S_i$  into state  $S_j$ .  $\pi_i$  is a probability that the initial state is  $S_i$ .

Suppose a sequence of states  $y_1, y_2, \dots, y_T$ , where  $T \geq 2$ . At time  $t$ , where  $1 \leq t \leq T - 1$ , there is a probability  $P(y_{t+1} = S_j | y_t = S_i)$ . This probability is described by  $a_{ij}$ .

### 3.1.3 Markov property

Markov chain satisfies a Markov property. This property says that  $P(y_{t+1} = S_i | y_1 = s_1, y_2 = s_2, \dots, y_t = s_t) = P(y_{t+1} = S_i | y_t = s_t)$ . In another words, being at state  $S_i$  at time  $t + 1$  only conditionally depends on being at state  $s_t$  at time  $t$ . Further history doesn't influence the probability.



Figure 3.1: Visualization of a Markov chain with three states.

### 3.1.4 Example

As an example, consider a Markov chain (MC) with three states:  $S_1 = \text{sunny}$ ,  $S_2 = \text{rainy}$  and  $S_3 = \text{cloudy}$ . This MC models how weather changes on every day. Suppose the following transition matrix:

$$A = \begin{bmatrix} 0.6 & 0.1 & 0.3 \\ 0.1 & 0.7 & 0.2 \\ 0.3 & 0.3 & 0.4 \end{bmatrix}. \quad (3.1)$$

If the weather is sunny, tomorrow will be most likely sunny as well. With probability 0.3 it will be cloudy. Rainy weather is very unlikely tomorrow. Consider the following initial probability vector:

$$\pi = \begin{bmatrix} 0.3 \\ 0.2 \\ 0.5 \end{bmatrix}. \quad (3.2)$$

The most likely weather on first day of measurement is cloudy.



### 3.1.5 Limitations

The previous example only takes into account weather at time  $t$  to predict weather at time  $t + 1$ . In reality, there are multiple factors that influence what the weather will be like. According to the example, if a weather is sunny now, it is unlikely it will start raining. If we, however, take into account humidity, we can improve the prediction. If we know that humidity is high, even though it was sunny, we can predict it started raining. Hidden Markov Model addresses this issue.

## 3.2 Hidden Markov Model

### 3.2.1 Introduction

Hidden Markov Model (HMM) is an extension of Markov chain. The states are now called hidden states and every hidden state has an associated observed state.

### 3.2.2 Description

HMM is defined by: (based on paper by Lawrence Rabiner [4])

- set of hidden states  $S = \{S_1, S_2, \dots, S_N\}$ ,
- set of observed states  $X$ ,
- transition matrix  $A \in \mathbf{R}^{N \times N}$ ,
- observation probability functions  $B = \{b_1(o), b_2(o), \dots, b_N(o)\}$ ,
- initial probability vector  $\pi \in \mathbf{R}^N$ .

The values of the  $X$  can be either discrete or continuous. The values of  $S$  are assumed to be discrete. The observation probability function  $b_i(o)$  describes a probability  $P(x_t = o | y_t = S_i)$ .  $b_i(o)$  is also called an emission function.

Imagine a walk through a HMM graph. At time point  $t$ , there is a hidden state  $y_t$  and an observed state  $x_t$ . Value of the observed state conditionally depends on value of the hidden state. The dependency is described by emission function  $b_i(o)$ .

If  $t \neq 1$  and  $T > 1$ , there is a hidden state  $y_t$  that conditionally depends on value of previous hidden state  $y_{t-1}$ . The dependency is described by transition  $a_{ij}$ .

If  $t = 1$ , there is a hidden state  $y_1$  that conditionally depends on initial transition  $\pi_i$ .



Figure 3.2: Visualization of a walk through a Hidden Markov Model. At each time point, there is a hidden state  $y_t$  and an observed state  $x_t$ .

### 3.2.3 Operations

There are two most important operations that can be performed on HMM. Learning and inference.

#### 3.2.3.1 Learning

Learning is used to calculate the model parameters  $\{\pi, A, B\} = \lambda$ . It is desired to estimate the parameters such that  $\prod_{j=1}^M P(\mathbf{x}_j | \lambda)$  is maximized. Where  $M \in \mathbf{N}$  is a number of sequences to be learned.  $\mathbf{x}_j$  is a  $j$ -th sequence of observed states. In another words, it is desired to maximize the product of probabilities that given sequence of observed states was generated by given model.

#### 3.2.3.2 Inference

Inference returns the most likely sequence of hidden states, given a sequence of observed states.

#### 3.2.3.3 Scoring?

### 3.2.4 Learning

#### 3.2.4.1 Maximum likelihood estimation

This method uses maximum likelihood estimation (MLE) to compute model parameters. MLE is a technique for finding parameters of a probabilistic model that best describe behavior of a random variable. The method aims to maximize the likelihood of all the learning data.

Formally  $\operatorname{argmax}_{\theta \in \Theta} \prod_{j=1}^M L(x_j, \theta)$ , where:

- $M$  is number of data points,
- $x_j$  is a  $j$ -th data point,
- $L$  is a likelihood function (defined further),

- $\theta$  describes model parameters,
- $\Theta$  is a set of all model parameters.

Let's examine how one can view parameters of HMM as probabilistic functions of random variables.

**Initial transition function** The initial probability vector  $\pi$  can be viewed as a probability function  $\pi_i$ , assigning a probability to every hidden state  $S_i \in S$ . This is a function of discrete random variable.

**Transition function** Every row of  $A$  defines a probability function  $a_{ij}$  with parameter  $j$ . The function describes a probability of transitioning into state  $S_j$  from state  $S_i$ .  $a_{ij}$  is a function of discrete random variable.

**Emission function** The observation probability functions  $b_i(o)$  are functions of either discrete or continuous random variable that takes on values in set of observed states  $X$ . For purposes of this thesis, it is assumed that continuous variables have Gaussian or Gaussian mixture distribution.

**Discrete random variables** Here I present a straightforward way of defining the  $L$  likelihood function in case of discrete random variables.  $L(x, \theta) = x_{cnt}/M$ , where  $x_{cnt}$  is the number of times  $x$  occurs in learning data. The number of data points is  $M$ . Since the likelihood function does not depend on parameter  $\theta$ , there is no expression to optimize.

There is a reason I did not choose any standard discrete probability distribution to define  $L$ . The random variable does not have to be  $\mathbf{Z}$ , nor  $\mathbf{N}$ . In fact it can be any abstract object, such as an animal. A type, where comparison between two objects doesn't make sense. Therefore, it wouldn't make sense to assign non zero probability to values that are not specified in learning phase.

As an example, consider the following data: {dog, bird, dog, cat, bird, dog}. Figure 3.4 shows a likelihood function  $L$  associated with the data.

**Continuous random variables** This work considers two kinds of distributions for continuous random variables: Gaussian distribution and Gaussian mixture distribution.

**Gaussian distribution** Normal distribution is defined by  $\theta = \{\mu, \sigma^2\}$ . The goal is to find parameter  $\theta \in \Theta$ , such that the product in 3.3 is maximized.

$$\prod_{j=1}^M L(x_j, \theta) \tag{3.3}$$

### 3. ANALYSIS

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Figure 3.3: Frequency of data in discrete data set.



Figure 3.4: Likelihood function  $L$  of data in discrete data set. Probability is zero at undefined states.

In case of Gaussian distribution, the likelihood function  $L$  is defined by

$$L(x, \theta) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}. \quad (3.4)$$

Taking derivative of 3.3 with respect to  $\mu$  equal to 0 yields

$$\sum_{j=1}^M x_j - M\mu = 0. \quad (3.5)$$

Maximum likelihood estimate of  $\mu$  is therefore

$$\mu_{\text{est}} = \bar{X}_M. \quad (3.6)$$

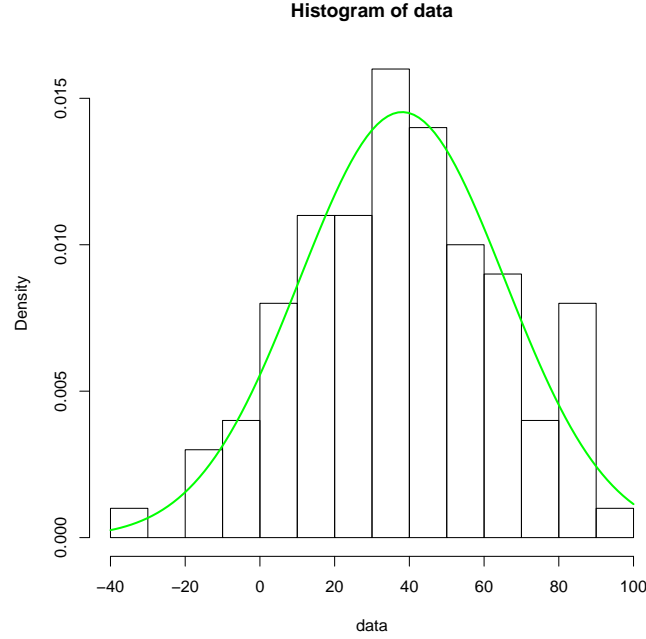


Figure 3.5: Histogram of randomly generated data from normal distribution  $\mathcal{N}(40, 32^2)$ . The green curve is a plot of normal distribution with the maximum likelihood estimate of  $\theta$  parameters.

Derivative of 3.3 with respect to  $\sigma^2$  equal to zero results in MLE of  $\sigma^2$  to be

$$\sigma_{\text{est}}^2 = \frac{1}{M} \sum_{j=1}^M (X_j - \bar{X}_M)^2. \quad (3.7)$$

Figure 3.5 shows an example of MLE on normally distributed random variable.

#### Gaussian mixture distribution TODO: not a MLE!

Given  $K$  components, there are  $K$  component parameters  $\theta_1, \theta_2, \dots, \theta_K$  and  $K$  weights  $w_1, w_2, \dots, w_K$  to estimate. Here I provide description of Expectation-Maximization algorithm based on lecture notes by Padhraic Smyth [5]. This algorithm provides an estimate of the aforementioned parameters.

Let's define a membership weight  $w_{jk}$ , of data point  $x_j$  in component  $k$  as

$$w_{jk} = \frac{\alpha_k \text{PDF}_{\mathcal{N}(\theta_k)}(x_j)}{\sum_{i=1}^K \alpha_i \text{PDF}_{\mathcal{N}(\theta_i)}(x_j)}, \quad (3.8)$$

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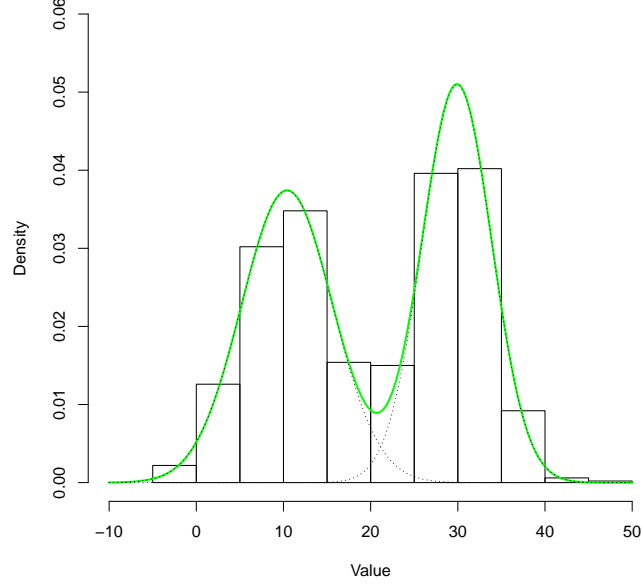


Figure 3.6: Histogram of randomly generated data from two normal distributions  $\mathcal{N}(10, 5^2)$  and  $\mathcal{N}(30, 4^2)$ . The green curve is the best estimate, found using EM algorithm, of underlying normal mixture distribution. Dotted curves are estimates of individual Gaussian mixture components.

where  $\alpha_k$  is a probability that a randomly selected  $x_j$  was generated by component  $k$ .  $w_{jk}$  can be thought of as a level of certainty that  $x_j$  was generated by component  $k$ .  $\sum_{k=1}^K w_{jk} = 1$  holds.

Likelihood of all data points given gaussian mixture parameters is defined as

$$l = \sum_{j=1}^M \sum_{k=1}^K \alpha_k \text{PDF}_{\mathcal{N}(\theta_k)}(x_j). \quad (3.9)$$

EM is an iterative algorithm, typically iterating until convergence is detected. Each iteration consists of two parts. An E-step and an M-step.

In the E-step, weight  $w_{jk}$  is computed for each data point  $x_j$  and component  $k$ .

Define  $W_k = \sum_{j=1}^M w_{jk}$ , the weight of all data points in component  $k$ . In the M-step, new model parameters are calculated as follows:

$$\alpha_k^{\text{new}} = \frac{W_k}{M}, \quad (3.10)$$

$$\mu_k^{\text{new}} = \frac{\sum_{j=1}^M w_{jk} x_j}{W_k}, \quad (3.11)$$

$$\sigma_k^{2\text{new}} = \frac{\sum_{j=1}^M w_{jk} (x_j - \mu_k^{\text{new}})^2}{W_k}. \quad (3.12)$$

Where  $\mu_k^{\text{new}}$  resembles standard equation for estimating mean, and  $\sigma_k^{2\text{new}}$  is similar to an equation for estimating variance. The differences are in weighting.

Before the iterations begin, an initial guess of model parameters is necessary. This can be chosen randomly or through a heuristic. One issue with the EM algorithm is that it does not guarantee to find a global optimum.

Termination of the algorithm is determined by checking that the likelihood 3.9 of all data points hasn't improved enough in between iterations. In another words

$$l_{\text{cur}} - l_{\text{prev}} < \text{tol}. \quad (3.13)$$

### 3.2.5 Inference

Given a sequence of observed states, what is the most likely associated sequence of hidden states? Viterbi algorithm answers this question. Let's define  $\alpha_t(i)$  to be the maximum probability of sequence of hidden and observed states up to time point  $t$ :

$$\alpha_t(i) = \max_{y_1, y_2, \dots, y_{t-1}} P(y_1, y_2, \dots, y_{t-1}, y_t = S_i, x_1, x_2, \dots, x_t | \lambda), \quad (3.14)$$

where  $\lambda$  are parameters of HMM model.

**Initialization** At time point  $t = 1$ , the probability of being at hidden state  $S_i$  is simply the initial probability of being at that state and a probability of being at observed state  $x_1$  given hidden state  $S_i$ . In another words:

$$\alpha_1(i) = \pi_i b_i(x_1). \quad (3.15)$$

**Recursion** Taking into account the structure of HMM, the equation 3.14 can be rewritten recursively as

$$\alpha_t(j) = [\max_i \alpha_{t-1}(i) a_{ij}] b_j(x_t). \quad (3.16)$$

Hidden state at particular time point  $t$  is determined by

$$s_t = S_{\arg\max_i \alpha_t(i)}. \quad (3.17)$$

**Complexity** At each time point  $t$  and hidden state index  $j$ , the equation 3.16 loops through every hidden state index  $i$ . There are  $N$  hidden states. In addition, the recursion continues for every time point  $t$ . There are  $T$  time points. Thus the overall complexity is  $N^2T$ .

#### 3.2.6 Example

Suppose an extension of an example mentioned in Markov chain chapter. i.e. there are three hidden states of weather:  $S_1 = \text{sunny}$ ,  $S_2 = \text{rainy}$  and  $S_3 = \text{cloudy}$ . Lets introduce a continuous observed random variable describing humidity level. It is easy to imagine that on sunny day, the humidity will be low. The set of hidden states is assumed to be discrete. typically lower than on a rainy day. This observable variable can help in predicting future weather.

#### 3.2.7 Limitations

There is only one observed variable, which may not be sufficient for successful prediction in real-life applications. One could increase the dimensionality of the observed variable. That would, however, lead to a problem called curse of dimensionality. As we would increase the dimensionality of observed variable, the learning time would increase greatly up to the point where it would no longer be tractable. Dynamic naive Bayesian classifier addresses this issue.

### 3.3 Bayesian network

Bayesian network is a probabilistic graphical model consisting of nodes and edges. The model is a directed acyclic graph (DAG). Every node describes a random variable which can be either discrete or continuous. Edges describe a conditional dependency among the nodes (variables).

As an example, consider a Bayesian network in figure 3.7. Every node represents a discrete random variable with two possible states - *true* and *false*. It can be imagined that dehydration can cause red skin, but it can also influence presence of cancer. In addition, red skin may signal a lack of water intake, or the skin may be red because of cancer cells. Every node defines a conditional probability table (CPT) given nodes it depends on.

### 3.4 Naive Bayesian classifier

Naive Bayesian classifier is a classifier (model that assigns class labels to given inputs) where features (random variables) are assumed to be conditionally independent from each other.

Imagine we would like to classify a class  $C_k$  given feature vector  $\mathbf{x}$ :

$$P(C_k|x_1, x_2, \dots, x_n). \quad (3.18)$$



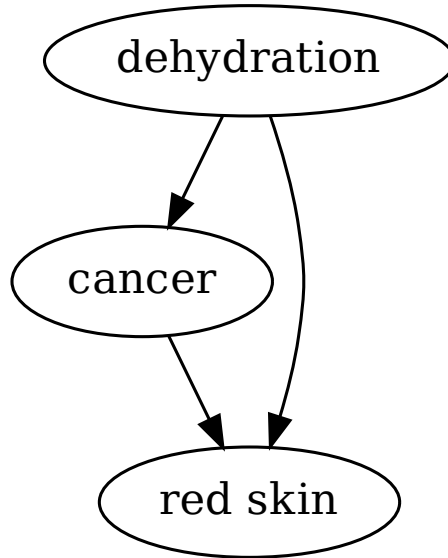


Figure 3.7: Visualization of a Bayesian network with three states.

dehydration	
true	false
0.1	0.9

Table 3.1: CPT for *dehydration*.

input		cancer	
dehydration		true	false
true		0.1	0.9
false		0.01	0.99

Table 3.2: CPT for *cancer*.

input		red skin	
cancer	dehydration	true	false
true	true	0.4	0.6
true	false	0.3	0.7
false	true	0.4	0.6
false	false	0.1	0.9

Table 3.3: CPT for *red skin*.

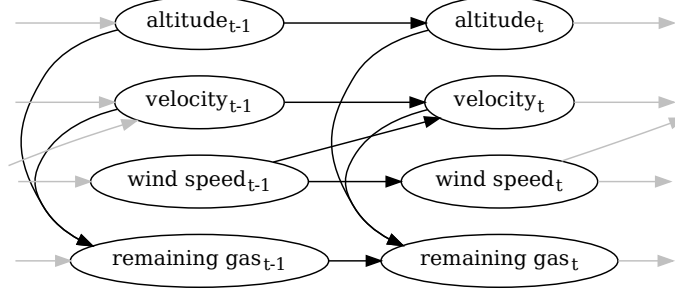


Figure 3.8: Visualization of a Dynamic Bayesian network with four variables at time  $t$ .

Using Bayes' theorem, the conditional probability can be rewritten as

$$P(C_k|\mathbf{x}) = \frac{P(C_k, \mathbf{x})}{P(\mathbf{x})} = \frac{P(C_k)P(\mathbf{x}|C_k)}{P(\mathbf{x})}. \quad (3.19)$$

Because the features are assumed to be conditionally independent from each other, the probability in numerator can be rewritten as

$$P(\mathbf{x}|C_k) = P(x_1|C_k)P(x_2|C_k) \cdots P(x_n|C_k). \quad (3.20)$$

Because of the independence assumption, learning of the classifier can be performed effectively, as mentioned in article by K. M. Leung [6].

### 3.5 Dynamic Bayesian network

Dynamic Bayesian network is a Bayesian network which accounts for time. At each time point  $t$ , the values of random variables can be computed based on values of associated random variables in time  $t - 1$ .

Consider figure 3.8 as an example. It can be imagined that velocity of an airplane at time  $t$  conditionally depends on velocity at time  $t - 1$  as well as on wind speed at time  $t - 1$ . Remaining gas at time  $t$  conditionally depends on remaining gas at  $t - 1$  and it is also influenced by altitude and velocity at current time  $t$ .

### 3.6 Dynamic naive Bayesian classifier

#### 3.6.1 Introduction

Dynamic naive Bayesian classifier (DNBC) is an extension of Hidden Markov Model (HMM). The difference is that there may be a number of observed

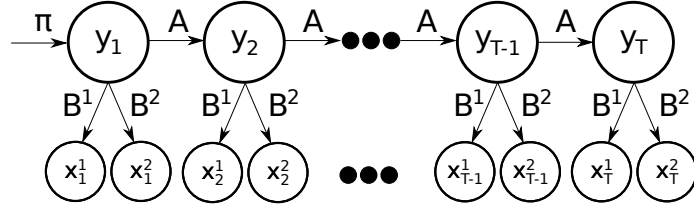


Figure 3.9: Visualization of a Dynamic naive Bayesian classifier with two observed variables. At each time point, there is a hidden state  $y_t$  and two observed states:  $x_t^1$  and  $x_t^2$ .

variables. In contrast, HMM is defined for only one observed variable. DNBC is dynamic, because it classifies sequences with variables at every time  $t$ . It is also naive, because the output variables are assumed to be conditionally independent from each other. Figure 3.9 demonstrates a walk through a model with 2 observed variables.

### 3.6.2 Description

DNBC is defined by

- number of observed variables  $M$ ,
- set of hidden states  $S = \{S_1, S_2, \dots, S_N\}$ ,
- sets of observed states  $X^j, j \in [1, M]$
- transition matrix  $A \in \mathbf{R}^{N \times N}$ ,
- observation probability functions  $B^j = \{b_1^j(o), b_2^j(o), \dots, b_N^j(o)\}, j \in [1, M]$ ,
- initial probability vector  $\pi \in \mathbf{R}^N$ .

The values of particular set of observed states  $X^j$  can be either discrete or continuous. The values of  $S$  are assumed to be discrete. The observation probability function  $b_i^j(o)$  describes a probability  $P(x_t^j = o | y_t = S_i)$ .  $b_i^j(o)$  is called an emission function.

Imagine a walk through DNBC graph. At time point  $t$ , there is a hidden state  $y_t$  and  $M$  observed states  $x_t^j$  where  $j \in [1, M]$ . Value of every observed state conditionally depends on value of the hidden state. The dependency is described by emission function  $b_i^j(o)$ .

An important property of DNBC is that the observed variables are assumed to be independent from each other. Therefore, DNBC does not define any conditional dependency function between two observed variables.

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If  $t \neq 1$  and  $T > 1$ , there is a hidden state  $y_t$  that conditionally depends on value of previous hidden state  $y_{t-1}$ . The dependency is described by transition  $a_{ij}$ .

If  $t = 1$ , there is a hidden state  $y_1$  that conditionally depends on initial transition  $\pi_i$ .

#### 3.6.3 Operations

There are two most important operations that can be performed on DNBC. Learning and inference.

##### 3.6.3.1 Learning

Learning is used to calculate the model parameters  $\{\pi, A, B^1, B^2, \dots, B^M\} = \lambda$ . It is desired to estimate the parameters such that  $\prod_{j=1}^M P(\mathbf{x}_j|\lambda)$  is maximized. Where  $M \in \mathbf{N}$  is a number of sequences to be learned.  $\mathbf{x}_j$  is a  $j$ -th sequence of observed states. In another words, it is desired to maximize the product of probabilities that given sequence of observed states was generated by given model.

##### 3.6.3.2 Inference

Inference returns the most likely sequence of hidden states, given sequences of observed states. Each sequence of observed states corresponds to particular observed variable. Each sequence thus has the same number of elements.

#### 3.6.4 Learning

##### 3.6.4.1 Maximum likelihood estimation

This learning approach is similar to one described in case of HMM. The only difference is that there are multiple emission functions  $b_i^j(o)$  where  $j \in [1, M]$  and  $M$  is the number of observed variables. Therefore, there is now  $M \times N$  continuous distributions to be learned. Each distribution is assumed to be Gaussian or Gaussian mixture.

##### 3.6.5 Inference

Inference algorithm is again Viterbi. It is simply extended to support multiple observed variables. Let  $\mathbf{x}_t^j$  be a sequence of observed states of variable  $j$  up to time point  $t$ .

$$\mathbf{x}_t^j = x_1^j, x_2^j, \dots, x_t^j. \quad (3.21)$$

Let's define  $a_t(i)$  to be the maximum probability of sequence of hidden and sets of observed states up to time point  $t$ :

$$a_t(i) = \max_{y_1, y_2, \dots, y_{t-1}} P(y_1, y_2, \dots, y_{t-1}, y_t = S_i, \mathbf{x}_t^1, \mathbf{x}_t^2, \dots, \mathbf{x}_t^M | \lambda), \quad (3.22)$$

where  $\lambda$  are parameters of DNBC model.

**Initialization** At time point  $t = 1$ , the probability of being at hidden state  $S_i$  is equal to the initial probability of being at that state and probabilities of being at observed state  $x_1^j$  given hidden state  $S_i$ . In another words:

$$\alpha_1(i) = \pi_i \prod_{j=1}^M b_i^j(x_1^j). \quad (3.23)$$

**Recursion** Taking into account the structure of DNBC, the equation 3.22 can be rewritten recursively as

$$\alpha_t(j) = [\max_i \alpha_{t-1}(i) a_{ij}] \prod_{k=1}^M b_j^k(x_t^k). \quad (3.24)$$

Hidden state at particular time point  $t$  is determined by

$$s_t = S_{\arg\max_i \alpha_t(i)}. \quad (3.25)$$

**Complexity** At each time point  $t$  and hidden state index  $j$ , the equation 3.24 loops through every hidden state index  $i$  and every observed variable index  $k$ . There are  $N$  hidden states and  $M$  observed variables. In addition, the recursion continues for every time point  $t$ . There are  $T$  time points. Thus the overall time complexity is  $N(N + M)T$ .

### 3.6.6 Example

Consider a problem of weather prediction. Let's define a set of hidden states to be  $S = \{S_1 = \text{sunny}, S_2 = \text{rainy}, S_3 = \text{cloudy}\}$ . Let's consider the following observed variables: temperature, humidity and windiness. At every time  $t$ , the hidden state conditionally depends on hidden state at time  $t - 1$ . The three hidden variables at time  $t$  conditionally depend on hidden state  $t$ . These variables can help in predicting the hidden state.

### 3.6.7 Limitations

The observed variables are assumed to be conditionally independent from each other. While this assumption enables the use of algorithms with relatively low time complexity, it also limits the ability to describe more complicated

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relations among random variables. For example, the observed variables may be correlated in reality.

# Návrh





## CHAPTER 5

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# Realizace



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## Conclusion



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## Seznam použitých zkratek

**GUI** Graphical user interface

**XML** Extensible markup language





## Obsah přiloženého CD

	readme.txt .....	stručný popis obsahu CD
	exe .....	adresář se spustitelnou formou implementace
	src	
	impl.....	zdrojové kódy implementace
	thesis .....	zdrojová forma práce ve formátu L <sup>A</sup> T <sub>E</sub> X
	text .....	text práce
	thesis.pdf .....	text práce ve formátu PDF
	thesis.ps .....	text práce ve formátu PS