Mixture Models

DIAP-RP 02-03
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DIAPEREST Model

Estimation of Conditional Distributions Using Gaussian Mixtures

March 2002

DIAPEREST
Different estimation method of sequential Gaussian simulations. The data set used is a part of the probabiliy density functions. A conditional Gaussian mixture model has been compared to the

abstract. This paper proposes the use of Gaussian mixture models to estimate conditional

Submitted for Publication

March 2002

Nicholas Grist, 

Gaussian Mixture Models

Estimation of Conditional Distributions using

IDIAP Research Report 02-03
We could model these two distributions separately. We have chosen instead to model the numerator

\[
\frac{(x)d}{(x - h)d} = (x/h)^d 
\]

(2)

The simple way to do so is to start from the definition of the posterior density we are interested in, and split the expectation into two parts. Where \( m_1 \) and \( m_2 \) are respectively the mean and the covariance matrices of the \( x \).

\[
(m_2 + h^{-1} \lambda) N + \sum_{n=1}^{\infty} (\lambda d)
\]

(1)

The PDF of a vector \( x \) can be modeled as a mixture of Gaussians, in a natural extension of a Gaussian distribution. If \( x \) is a mixture of Gaussians, as a natural extension of a Gaussian distribution, if

\[ 21 \text{ Gaussian Mixture Models} \]

2 Algebraic Description

GCM (or Gaussian Component Models) represent the spatiotemporal features, the results of these conditional models. We will cover the local conditional models, and then some of the methods used in the construction of conditional GCM. We will describe the methods of Conditional Gaussian Simplifications (CDS).

To evaluate the feature extraction of this method, we compare it to the method of Gaussian ODEs and ODEs.

PPD model or the simple location

use of Conditional Gaussian Mixture Model (CGM) for conditional density estimation, and combining a GMD (Gaussian Mixture Density)

in the field, we have introduced a model that can estimate the local field density (PDD). In this paper, we propose a model that can estimate the local field density in a simple manner that can be extended to other fields.

However, these models have some disadvantages. The PDD model process is unstable. Very complicated algorithms, which can be developed to solve these particular problems.

In Gaussian Mixture Models, which were developed to solve these particular problems:

On a critical note, not only the mean but also the other parameters of the model have some difficulties. The PDD model needs very careful tests in order to evaluate decision making. An important

Introduction

1
The methodology presented in this paper is simplified into two parts. The first part is

3 Methodology

... (continued from previous page)

In the experiments presented in this paper, the data set is segmented into two parts. The first part is

2.2 Sequential Gaussian Simulations

... (continued from previous page)

The idea of stochastic simulations is to develop a spatial model that will be able to

\[ (x|f|d) = \frac{N(x)^{\frac{1}{2}}}{{N(x^2)^{\frac{1}{2}}}} = (x|f|d) \]

with

\[ \begin{array}{c}
\frac{1}{M} \sum_{u=1}^{M} \frac{1}{u} = (x|f|d)
\end{array} \]

which is equivalent to:

\[ \frac{1}{M} \sum_{u=1}^{M} \frac{1}{u} = (x|f|d) \]

and the denominator can be obtained by simply removing the contribution to the

\[ \frac{1}{M} \sum_{u=1}^{M} (x|f|d) = (x|f|d) \]

... (continued from previous page)
and not 100 under the linear model. We have estimated the random generation methods
are consistent. This means that a local PDF, for both models, we used a 100-point random generation method
are consistent for a linear model. It is interesting to notice that the two methods
amount of data, namely in the test set is 100 similar to 1000. This method is to notice that the two methods
The second method consists of producing a road map, the distribution whose estimated linear moments
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3.3. Model Comparison Method

In estimation of the local PDF at each point, we used a different number of 100 points and their functions are
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The model of the model comparison was developed having into account the moments of the data and the
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3.2. SGS Experimental Protocol

The model prediction task estimation is based on the whole training set.
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3.1. GMM Experimental Protocol

GMM are trained using the Expectation-Maximization (EM) algorithm. However, many papers
Points inside the test set. SGS quantiles curves are in plain red. GMM are in dashed blue.

Figure 1: Comparison between multiple quantiles from SGS and conditional GMM for two different

4.3 Quantiles evaluation comparison

expected given the complexity of the data set for Gaussian methods.

Table 1: Mean Absolute Error (MAE) of SGS and GMM on the prediction of the first four local

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<thead>
<tr>
<th></th>
<th>MAE 1st Moment</th>
<th>MAE 2nd Moment</th>
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<tbody>
<tr>
<td>12</td>
<td>23</td>
<td>73</td>
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<td>170</td>
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<td>146</td>
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Sequential Gaussian simulations, Conditional GMM

4.2 Moments prediction results

transformed for GMM comparisons.

Note that for numerical stability reasons, the co-ordinate values and the attributes have been linearly

shifted in the other half. This is a typical case where Gaussian methods are very difficult to use:

The interesting aspect of this data set is that it improves (gradient) feature extraction from South-West

The comparisons are

41 Data Description

42 Experiments
References

Acknowledgments

Conclusion