



Swiss Federal Institute of Technology Zurich

Seminar for  
Statistics

Department of Mathematics

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Bachelor Thesis

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Submission Date: placeholder

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## **Abstract**

The intent of this work is to compare The EM algorithm to a MLE approach in the case of multivariate normal mixture models using the Cholesky decomposition. The EM algorithm is widely used in statistics and is proven to converge, however in pathological cases convergence slows down considerably. MLE doesn't have this particular error, but is computationally costly. The Cholesky decomposition cuts down the necessary parameters almost in half....

methods(not done)

results(not done)

## Contents

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# Chapter 1

## Introduction to normal mixture models

here intro to normal mixtures

A good and thorough introductory book is the work of McLachlan and Peel 2000 and the reader is encouraged to study that to learn in depth about normal mixtures. We will here give a short explanation about normal mixtures to fix notation and nomenclature.

**Definition 1.0.0.1.** *asdf*

explain in scetch EM algo

explain idea to use parameter optimizer instead, EM has pathological insufficiencies, like 'getting stuck' for many iterations. we hope we need less iterations, and as consequence less time. 'special' idea: using cholesky decomp.

### 1.1 choice of notation

describe difference in notation between ceuleux & govaert and our covariance matrix decomposition.

explanation for the volume, shape and orientation descriptors

make clear that the models can not be translated one to one to ldlt model

make nice table(maybe sideways to account for parameter list)

Model	$\Sigma_k$	C&G	volume	shape	orientation	parameters	count	$LDL^\top$	parameters	count
EII	$\alpha I$		equal	equal	-	$\alpha$	1	same as C&G		
VII	$\alpha_k I$		variable	equal	-	$\alpha_k$	$K$			
E EI	$\alpha \Lambda$		equal	equal	coordinate axes	$\alpha, \lambda_i$	$1 + p$			
V EI	$\alpha_k \Lambda$		variable	equal	coordinate axes	$\alpha_k, \lambda_i$	$K + p$			
E VI	$\alpha \Lambda_k$		equal	variable	coordinate axes	$\alpha, \lambda_{i,k}$	$1 + pK$			
V VI	$\alpha_k \Lambda_k$		variable	variable	coordinate axes	$\alpha_k, \lambda_{i,k}$	$K + pK$			
EEE	$\alpha Q \Lambda Q^\top$		equal	equal	equal	$\alpha, \lambda_i, q_{i,j}$	$1 + p + p^2$	don't exist		
E VE	$\alpha Q \Lambda_k Q^\top$		equal	variable	equal	$\alpha, \lambda_{i,k}, q_{i,j}$	$1 + pK + p^2$			
V EE	$\alpha_k Q \Lambda Q^\top$		variable	equal	equal	$\alpha_k, \lambda_i, q_{i,j}$	$K + p + p^2$			
V VE	$\alpha_k Q \Lambda_k Q^\top$		variable	variable	equal	$\alpha_k, \lambda_{i,k}, q_{i,j}$	$K + pK + p^2$			
E EV	$\alpha Q_k \Lambda Q_k^\top$		equal	equal	variable	$\alpha, \lambda_i, q_{i,j,k}$	$1 + p + Kp^2$			
V EV	$\alpha_k Q_k \Lambda Q_k^\top$		variable	equal	variable	$\alpha_k, \lambda_i, q_{i,j,k}$	$K + p + Kp^2$			
EVV	$\alpha Q_k \Lambda_k Q_k^\top$		equal	variable	variable	$\alpha, \lambda_i, q_{i,j,k}$	$1 + pK + Kp^2$	$\alpha L_k D_k L_k^\top$	$\lambda, d_{i,k}, l_{i,j,k} \quad j > i$	$1 + pK + K \frac{p(p-1)}{2}$
VVV	$\alpha_k Q_k \Lambda_k Q_k^\top$		variable	variable	variable	$\alpha_k, \lambda_i, q_{i,j,k}$	$K + pK + Kp^2$	$\alpha_k L_k D_k L_k^\top$	$\lambda_k, d_{i,k}, l_{i,j,k} \quad j > i$	$K + pK + K \frac{p(p-1)}{2}$



## Chapter 2

# placeholder

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# Bibliography

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- Hampel, F. R. (1985). The breakdown points of the mean combined with some rejection rules. *Technometrics* 27(2), 95–107.
- Stahel, W. and S. Weisberg (1991). *Directions in Robust Statistics and Diagnostics*, 2 vol. N. Y.: Springer-Verlag.



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