Source Separation Using NMF

Ament and Aarti Bagu

Introductio

Pipeline

Data set Signal Processin

NMF Online Algorithm

Gradient Backtracking

Analysis/ Improvements

Parameters
Mini-hatch KMea

Mini-batch KMea

Conclusior

Source Separation Using NMF

Sebastian Ament and Aarti Bagul

December 16, 2015

Table of contents

Source Separation Using NMF

Ament and Aarti Bagu

Introductio

Data set
Signal Processin

NMF Online Algorithm

Analysis/ mprovements

Varying the Parameters Mini-batch KMeans

- Introduction
- 2 Pipeline
 - Data set
 - Signal Processing
 - NMF
 - Online Algorithm
 - Gradient Backtracking
- 3 Analysis/ Improvements
 - Varying the Parameters
 - Mini-batch KMeans
 - Smoothing
 - 4 Conclusion

Introduction

Source Separation Using NMF

Ament and Aarti Bagu

Introduction

Pipeline
Data set
Signal Processing
NMF
Online Algorithm
Gradient
Backtracking

Analysis/ Improvements Varying the Parameters Mini-batch KMeans

- Source Separation Estimating signal produced by single source from a mixture of sources
- Unsupervised learning
- eg: cocktail party problem, separating sounds of musical instruments
- Using Non-negative Matrix factorization and Ikatura-Saito divergence

Pipeline

Source Separation Using NMF

Sebastian Ament and Aarti Bagu

Introduction

Pipeline

Signal Process

NMF

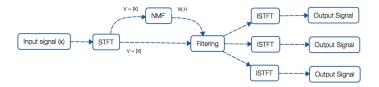
Online Algorith

Analysis/

Improvements

Mini-batch KMea

Canalusian



Data set

Source Separation Using NMF

Ament and Aarti Bagu

Introductio

Pipeline Data set Signal Process

NMF Online Algorithm Gradient

Analysis/ Improvements

Varying the Parameters Mini-batch KMear

- Piano recording of "Mary had a little lamb, 5 seconds long",
- Recording of 2 people talking at the same time, 20 seconds long
- 2 Jazz recordings with multiple instruments, 2 minutes long

Signal Processing

Source Separation Using NMF

Ament and Aarti Bagu

Introductio

Data set
Signal Processir
NMF
Online Algorithm

Analysis/ Improvements

Varying the Parameters Mini-batch KMea

- Input is a .wav soundfile
- Apply Short-Time Fourier Transform
- Sine window with a width of 256 samples and 128 samples overlap
- Compute magnitude squared of Fourier coefficients to get power spectrogram

Spectrogram

Source Separation Using NMF

Sebastian Ament and Aarti Bagu

Introductio

Data set

Signal Proces

NMF

Online Algorith

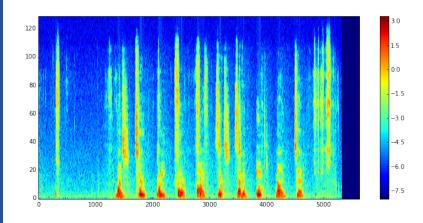
Analysis/

Improvements

Mini-batch KMea

Smoothing





Parameters
Mini-batch KMea

Conclusion

Non-negative matrix factorization:

$$V = WH$$

where $V \in \mathbb{R}_+^{F \times N}$, $W \in \mathbb{R}_+^{F \times K}$, and $H \in \mathbb{R}_+^{K \times N}$.

Itakura-Saito Divergence

$$d_{IS}(x,y) = \sum_{i} \frac{x_i}{y_i} - \log \frac{x_i}{y_i} - 1$$

We want to minimize

$$d(v, Wh) = \sum_{i} \frac{v_i}{(Wh)_i} - \log \frac{v_i}{(Wh)_i} - 1$$

Online Algorithm

Source Separation Using NMF

Sebastian Ament and Aarti Bagu

Introduction

Data set

Signal Procession

Online Algorithm

Gradient Backtracking

Analysis/ Improvements

Varying the Parameters

Mini-batch KMear

Conclusion

Online Algorithm for IS-NMF

Input Training set,
$$W^{(0)}$$
, $A^{(0)}$, $B^{(0)}$, ρ , β , η , ϵ repeat
$$t \leftarrow t+1$$
 draw point v_t from training set.
$$h_t \leftarrow \arg\min_h d_{IS}(\epsilon+v_t,\epsilon+Wh)$$

$$a^{(t)} \leftarrow (\frac{\epsilon+v_t}{(\epsilon+Wh_t)^2}h_t^T).W^2$$

$$b^{(t)} \leftarrow \frac{1}{(\epsilon+Wh_t)^2}h_t^T$$
 if $t \equiv 0[\beta]$
$$A^{(t)} \leftarrow A^{(t-\beta)} + \rho \sum_{s=t-\beta+1}^t a^{(s)}$$

$$B^{(t)} \leftarrow B^{(t-\beta)} + \rho \sum_{s=t-\beta+1}^t b^{(s)}$$

$$W^{(t)} \leftarrow \sqrt{\frac{A^{(t)}}{B^{(t)}}}$$
 for $k = 1...K$
$$s \leftarrow \sum_f W_{fk},$$

$$W_{fk} \leftarrow W_{fk}/s$$

$$A_{fk} \leftarrow A_{fk}/s,$$

$$B_{fk} \leftarrow B_{fk} \times s$$
 end for

Gradient Backtracking

Source Separation Using NMF

Sebastian Ament and Aarti Bagu

Introduction

Pipeline
Data set
Signal Processing
NMF
Online Algorithm
Gradient
Backtracking

Analysis/ Improvements

Varying the
Parameters

Parameters Mini-batch KMean Smoothing

Conclusion

• Gradient:

$$\nabla_h d_{IS}(v_t, Wh) = \frac{1}{Wh} \left(\vec{1} - \frac{1}{Wh} \right) \cdot W$$

For gradient descent with backtracking, we want:

$$\epsilon = \beta^{\it m} \eta$$

where, $m=\max$ number of backtracking steps, $\eta=$ the initial step size, $\beta=$ backtracking factor, and $\epsilon=$ the precision of the optimization.

This yields

$$m(\beta) = \frac{\log \epsilon - \log \eta}{\log \beta}$$

Gradient Backtracking

Source Separation Using NMF

Sebastian Ament and Aarti Bagu

Introduction

Pipeline
Data set
Signal Processing
NMF
Online Algorithm
Gradient
Backtracking

Analysis/ Improvements Varying the Parameters

Conclusion

β	m	t	$\mathbb{E}(\mathit{backsteps})$	$\mathbb{E}(s)$	max s
.1	16	3.5×10^{-4}	9	1.0×10^{-10}	1.0
.2	23	2.1×10^{-4}	11.5	9.1×10^{-10}	.5
.5	53	4.9×10^{-4}	26.5	1.4×10^{-9}	.2
.8	165	1.4×10^{-3}	82.5	1.9×10^{-9}	.125

s is computed backtracking constant and

 $\mathbb{E}(\cdot)$ is the empirical mean of " \cdot ".

 $\it m$ is the maximum number of backtracking steps

 β is the backtracking factor,

Analysis of parameters

Source Separation Using NMF

Ament and Aarti Bagu

Introductio

Data set
Signal Processir

Online Algorithm

Gradient

Analysis/ Improvements

Varying the Parameters Mini-batch KMean

Conclusion

Impact of β parameter on performance of NMF.

β	t[sec]	$d_{IS}(V,WH)$	
2 ⁶	3.9×10^{0}	3.8×10^{9}	
27	$7.6 imes 10^{0}$	7.4×10^{8}	
2 ⁸	$1.4 imes 10^1$	2.5×10^{6}	
2 ⁹	2.0×10^{1}	2.4×10^{6}	
2^{10}	3.9×10^{1}	2.2×10^{6}	
2^{11}	9.1×10^{1}	2.3×10^{6}	

t is the time until the stopping criterion is met, $d_{IS}(V, WH)$ the IS-divergence of the last iteration.

Mini-batch KMeans: Varying batch size

Source Separation Using NMF

Sebastian Ament and Aarti Bagu

Introduction

Pinelin

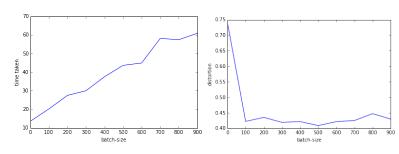
Data set Signal Processin

NMF

Gradient

Analysis/ Improvements

Mini-batch KMeans



Batch size v/s time

Batch size vs k-means objective

Mini-batch KMeans

Source Separation Using NMF

Sebastian Ament and Aarti Bagu

Introduction

D: 1:

Data set

Signal Process

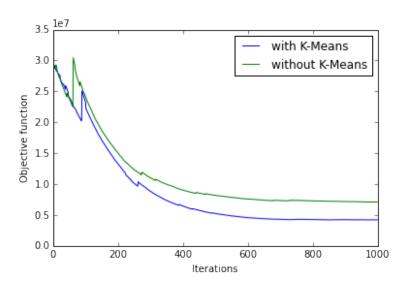
Online Algorith Gradient

Analysis/ Improvements

Varying the

Mini-batch KMeans

Conclusi



Smoothing

Source Separation Using NMF

Sebastian Ament and Aarti Bagu

Introductio

Pipeline
Data set
Signal Processing
NMF
Online Algorithm
Gradient

Analysis/ Improvements

Parameters
Mini-batch KMear
Smoothing

Conclusion

Smoothness term measures the deviation to the adjacent columns of $\cal H$

$$S_{\lambda,t}(h) = \lambda \left[d_{IS}(H_{\cdot(t-1)}, h) + d_{IS}(H_{\cdot(t+1)}, h) \right]$$

with corresponding gradient step

$$\nabla_h S_{\lambda,t}(h) = \lambda \left[\frac{1}{H_{\cdot(t-1)}} + \frac{1}{H_{\cdot(t+1)}} - 2\frac{1}{h} \right]$$

Our new minimization problem is given by

$$h_t = \arg\min_{h} \left[d_{IS}(v_t, Wh) + S_{\lambda,t}(h) \right]$$

Local Smoothing

Source Separation Using NMF

Sebastian Ament and Aarti Bagu

Introductio

Pipelin

Data set

NINE TOUCH

Online Algorith

Gradient

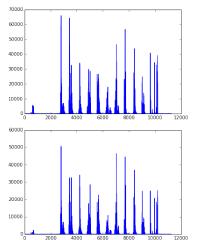
Analysis/

Improvements

Mini-batch I

Smoothing

Conclusion



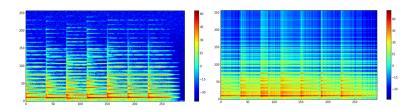
Without S

With S

One row of H

Approximated Spectrogram with K = 3

Source Separation Using NMF



- IS divergence after last iteration = 2×10^5
- While the reproduction of the spectrogram works to a satisfactory degree, meaningful source separation was not possible

Conclusion

Source Separation Using NMF

Sebastian Ament and Aarti Bagu

Introduction

Pipeline
Data set
Signal Processing
NMF
Online Algorithm
Gradient
Backtracking

Analysis/ Improvements Varying the Parameters Mini-batch KMeans

- Our implementation of the online IS-NMF exhibits higher performance compared to batch IS-NMF
- The initialization of W using k-means clustering of the input spectrogram speeds up the convergence of the NMF algorithm
- We proposed a new objective function for online IS-NMF, including a locally acting smoothness term
- This might be extended to a mini-batch version of the online algorithm, with a term that considers the smoothness of a whole batch instead of just one sample