Dictionary learning methods and single-channel source separation

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November 29, 2012

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Acknowledgements

Ministere de la Recherche

European Research Council

Willow team

Sierra team
TSI Telecom ParisTech

Acknowledgements II

Host institutions :

Interuniversity Attraction Pole

Pole INMA

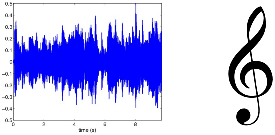
Current collaborators :

Pierre-Antoine Absil

François Glineur

Nicolas Gillis

From raw signals to intelligible information

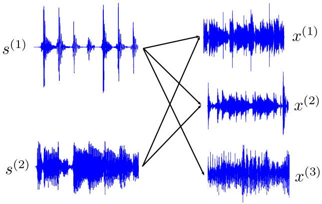


(a) Transcription of polyphonic signals

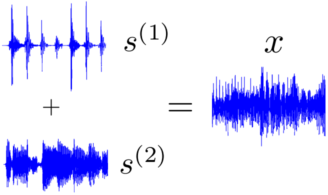
```
Susie kchrr
I'm in the
subway
pffrrrrt
Meet me at
?x%r square
at 9 in front
of pfffrrt
```

(b) Speech recognition in complex environments

What is source separation ?



(c) Overdetermined



(d) Underdetermined

How do we define a source ?

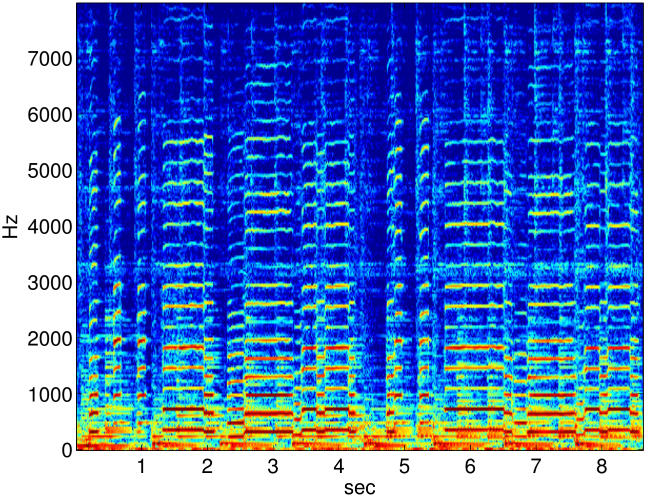
Different sources may sound similar.

How do sources interact ?

Outline

Time-frequency representations

$$
\begin{array}{ccccc}
x \in \mathbb{R}^T & \rightarrow & X \in \mathbb{C}^{F \times N} & \rightarrow & V_{fn} = |X_{fn}|^2 \,, \\
s^{(g)} & \rightarrow & S^{(g)} & \rightarrow & V_{fn}^{(g)} = |S_{fn}^{(g)}|^2 \,.
\end{array}
$$



Nonnegative Matrix Factorization

Reduce the number of unknowns to explain redundancy in the data :

$$V = \underbrace{(W^{(1)} H^{(1)})}_{\hat{V}^{(2)}} + \underbrace{(W^{(2)} H^{(2)})}_{\hat{V}^{(1)}}\,.$$

$W \in \mathbb{R}_+^{F \times K}$ is a dictionary with K basis elements ($K < F$).
$H \in \mathbb{R}_+^{K \times N}$ is a matrix of activation coefficients.
Enforce (pointwise) nonnegativity of the input :

$$W^{(g)} \geq 0, H^{(g)} \geq 0 \Rightarrow \hat{V}^{(g)} \geq 0\,.$$

1) W fixed, H unknown : nonnegative linear model.
2) (W, H) unknown : nonnegative matrix factorization.

(Paatero & Tapper, 1994; Smaragdis & Brown, 2003)

Itakura-Saito NMF

$$\begin{array}{cc} \min_{W,H} & \sum_{fn} d_{IS}(V_{fn}, (WH)_{fn}) \\ \text{s.t.} & W \geq 0, H \geq 0 \end{array}$$

$d_{IS}(x, y) = \frac{x}{y} - \log(\frac{x}{y}) - 1.$
$d_{IS}(x, y) \geq 0.$
$d_{IS}(x, y) = 0 \Rightarrow x = y.$
$d_{IS}(\lambda x, \lambda y) = d_{IS}(x, y)$

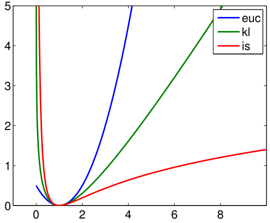


Figure: Plot of $d_{IS}(1, x)$ alongside Kullback-Leibler and Euclidean distance.

Probabilistic interpretation of Itakura-Saito NMF

$V_{\cdot n} \in \mathbb{R}_+^F$ observed power spectrum at time n.

$$V_{fn} = \left| \sum_g S_{fn}^{(g)} \right|^2 \qquad S_{fn}^{(g)} \sim \mathcal{N}_c(0, \mathrm{diag}(\sum_k W_{fk}^{(g)} H_{kn}^{(g)}))\,.$$

(Févotte et al., 2009)

- Phase of spectrograms is assumed uninformative.
- Reconstruct $S^{(g)}$ from $\hat{V}^{(g)}$ and X in a principled way.

$$S_{fn}^{(1)} = \frac{\hat{V}_{fn}^{(1)}}{\hat{V}_{fn}^{(1)} + \hat{V}_{fn}^{(2)}} X_{fn} \qquad \text{keep the same phase as the mixture}$$

- Select the number of components, cheaper than cross-validation.

(Tan & Févotte, 2009; Hoffmann et al., 2010; Lefèvre et al., 2011)

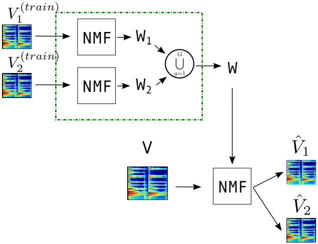
Finding a dictionary

What dictionary should we use ?

1) Ask a physicist to design the dictionary for you.
2) Use a large collection of samples from source 1 and source 2.

Storing all samples from source 1 and source 2 into memory is inconvenient and violates the assumption $K < F$.

Supervised dictionary learning



Having at hand a collection of true source signals decouples learning in two separate problems.

$$
\begin{array}{ll}
\text{Find} & (W, H) \\
s.t. & V^{(g)} = W^{(g)} H^{(g)} \\
 & W \geq 0, H \geq 0
\end{array}
$$

- Combine dictionaries at test time to compute activation coefficients.

Structure

$$\min_H \quad \sum_{fn} \| V_{fn} - (WH)_{fn} \|^2 + \lambda \Psi(H) \, .$$

Few fewer basis elements are used at the same time :
$\Psi(H) = \{$number of nonzero coordinates of $H\}$.

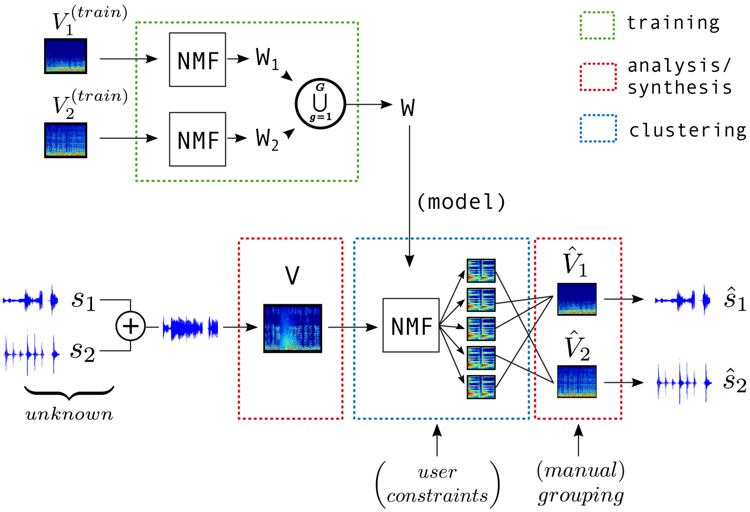
Choice of Ψ reflects assumed structure : temporal continuity at 200ms scale, phonems in speech, etc.

This thesis : Ψ models independence between sources as a group of basis elements.

Assuming simple interactions, we can make weaker assumptions on the dictionary.

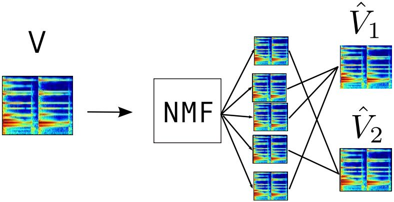
(Hoyer, 2004; Virtanen, 2007; Mysore et al., 2010)

Overview



$V_1^{(train)}$
$V_2^{(train)}$
NMF
NMF
W_1
W_2
$\bigcup_{g=1}^{G}$
W
(model)
training
analysis/
synthesis
clustering
s_1
s_2
unknown
V
NMF
$\hat{V}_1$
$\hat{V}_2$
$\hat{s}_1$
$\hat{s}_2$
(user constraints)
(manual) grouping

Unsupervised learning



If no training data is available to learn $W^{(g)}$ separately, then

$$\begin{array}{ll} \text{Find} & (W, H) \\ s.t. & W^{(1)}H^{(1)} + W^{(2)}H^{(2)} = WH = V\,. \end{array}$$

Not ill-posed any more, but there are still several global optima (nonconvex problem).

Trial and error : find a dictionary that reconstructs the input while enforcing specified structure.

NMF with time-frequency annotations

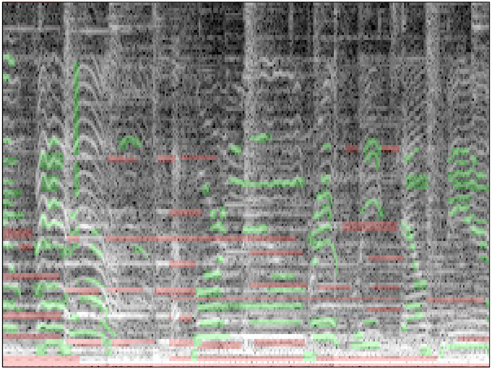


Figure: Example of user annotations in a ten seconds' audio track: green voice. red accompaniment.

NMF with time-frequency annotations

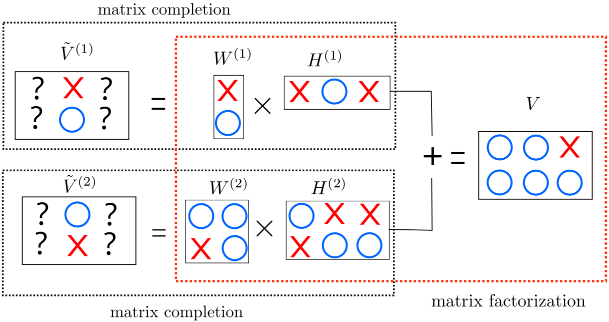


Figure: Semi-supervised NMF consists in solving G matrix completion problems, coupled by a matrix factorization problem.

Robustness to error via relaxation of the constraints (tuning parameter)
Allow "soft" annotations : $M_{fn}^{(g)} \in [0, 1]$.
Discard $M_{fn}^{(g)} = 0.5$.

Towards automatic annotations

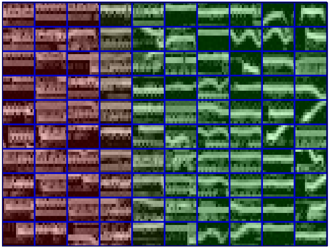


Figure: Time-frequency patches
(green) voice (red) accompaniment

Nearest neighbour.

Quantized nearest-neighbour.

Random Forest.

Experimental results

	% annotated	% correct
track 1	0.23	0.91
track 2	0.10	0.89
track 3	0.29	0.91
track 4	0.17	0.81
track 5	0.22	0.95

Table: Evaluation of user annotations on the SISEC database.

Experimental results

	Track1	
true	accomp	voice
ideal(20%)	15.65	10.34
user(20%)	8.74	3.18
auto	2.44	2.35
baseline	8.20	0.86
lazy	5.07	-5.11

Table: Time-frequency annotations : listening tests

ideal : annotations computed from ground truth (upper-bound).
baseline : NMF with optimally permuted components[1].
auto : automatic annotations.
user : user annotations.
lazy : use $\frac{1}{2}x$ as estimate of each source.

[1]Supposing expert correctly finds best permutation among 10^{18} possibilites ...

New : a convex re-formulation

$$\begin{array}{ll} \min & \|\bar{V} - \sum_{g=1}^{G} V^{(g)}\|_F^2 + \lambda \sum_{g=1}^{G} \|V^{(g)}\|_\star \\ \text{subject to} & M_{fn}^{(g)} V_{fn}^{(g)} = M_{fn}^{(g)} \bar{V}_{fn}^{(g)} \\ & V^{(1)} \geq 0, V^{(2)} \geq 0\,. \end{array} \tag{1}$$

Convex ! So not dependent on initial guess.

Tune the number of components with a continuous parameter λ.

Low-rank (+ nonnegative) solutions of linear underdetermined system of equations.

Nonnegativity constraints are weaker : only source estimates, not dictionary.

New : a convex re-formulation

	SDR	SIR	SAR
nmf	5.9706	13.1744	7.2764
lownuc	7.5785	13.609	9.1102

Table: Average results on 5 audio tracks using 20% of annotations.

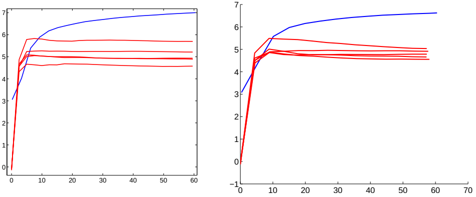


Figure: Source separation quality vs allowed cpu time. (Blue) our method. (Red) NMF.

Convex ! So not dependent on initial guess.

Bottlenecks in NMF

Batch algorithm requires computing and storing matrix-matrix products of the same size as the data set.

Online learning : can't afford to store past data and re-compute activation coefficients.

Large scale learning : $N \to +\infty$, train set is too large to store into memory.

1) Divide-and-conquer strategies (Cao et al., 2007; Mackey et al., 2011).
2) Stochastic updates (Robbins & Monro, 1951).
3) Incremental updates (Neal & Hinton, 1998; Mairal et al., 2010).

On-the-fly updates of the auxiliary function

Batch algorithm works on majorization-minimization

$$\sum_{fn} d_{IS}(V_{fn}, (WH)_{fn}) \leq \sum_{fk} \frac{A_{fk}}{W_{fk}} + B_{fk} W_{fk} \, .$$

H optimized using current estimate $\underline{W}$.

$$\begin{aligned} A_{fk} \leftarrow & \quad \underline{W}_{fk}^2 \textstyle\sum_{n=1}^N V_{fn} (\underline{W} H)_{fn}^{-2} H_{kn} \, , \\ B_{fk} \leftarrow & \qquad \textstyle\sum_{n=1}^N (\underline{W} H)_{fn}^{-1} H_{kn} , \, , \end{aligned}$$

Matrix products in $O(FKN)$ in time and memory.

On-the-fly updates of the auxiliary function

Batch algorithm works on majorization-minimization

$$\sum_{fn} d_{IS}(V_{fn}, (WH)_{fn}) \leq \sum_{fk} \frac{A_{fk}}{W_{fk}} + B_{fk} W_{fk} \, .$$

Draw v at random from V. h optimized using $\underline{W}$.

$$\begin{aligned} A_{fk} &\leftarrow A_{fk} + \underline{W}_{fk}^2 v_f (\underline{W} h)_f^{-2} h_k \, , \\ B_{fk} &\leftarrow B_{fk} + (\underline{W} h)_f^{-1} h_k , \end{aligned}$$

Matrix-vector products in $O(FK)$ in time and memory.

After N draws, same overall number of operations $O(FKN)$.

Memory requirements reduced to $O(FK)$.

How much faster ?

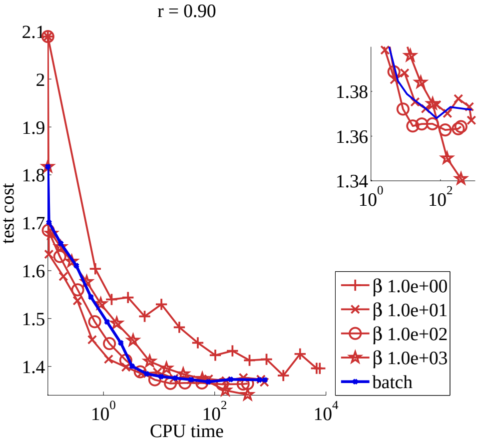


Figure: $N \simeq 10^3$ (30 seconds' excerpt)

How much faster ?

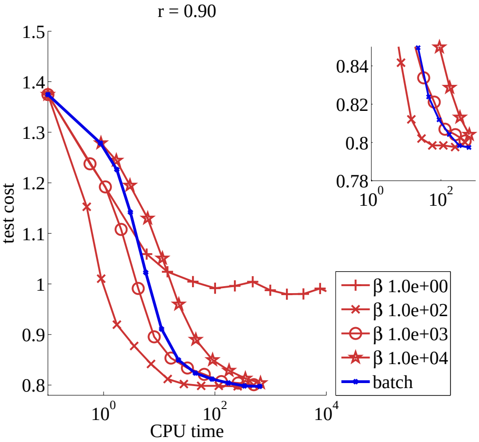


Figure: $N \simeq 10^4$ (4 minutes' audio track)

How much faster ?

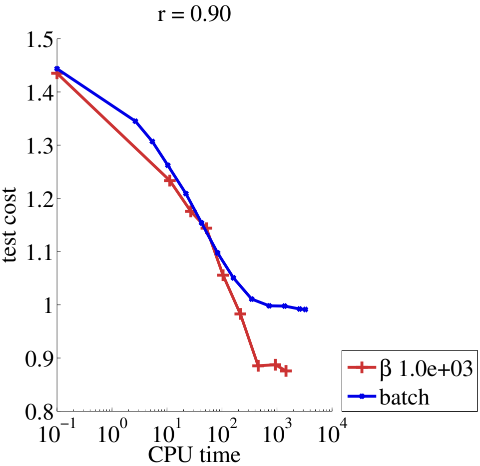


Figure: $N \simeq 10^5$ (1 hour 20 minutes' album)

Conclusion

Machine learning

- "Sensible" solutions to an otherwise underdetermined problem.
- User input gives ideas to design structure.
- Structured decompositions enhance user input.
- Stochastic optimization opens the door to large scale data analysis.

Audio source separation

- Dictionary learning does not replace expert knowledge, it enhances it.
- Audio analysis on larger units : CD, audio collections, and beyond.

Perpectives

Nonnegative decoding in a finite number of iterations.

Automatic annotations using harmonic structure of sound signals (multipitch).

Find other ways to exploit sparsity of time-frequency images.

Audio collections are naturally structured in graphs : we should use that !

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