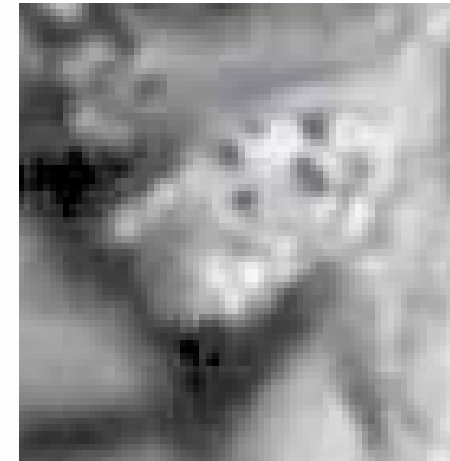
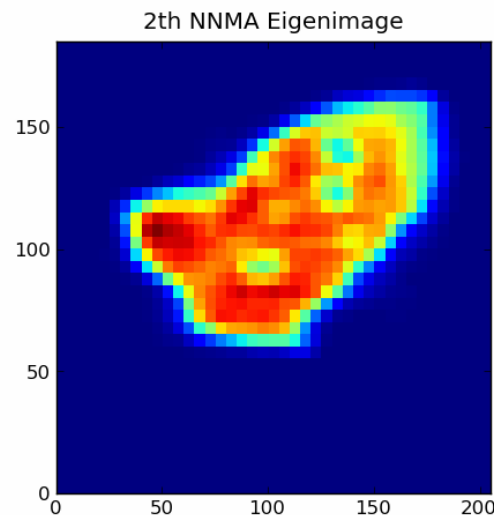
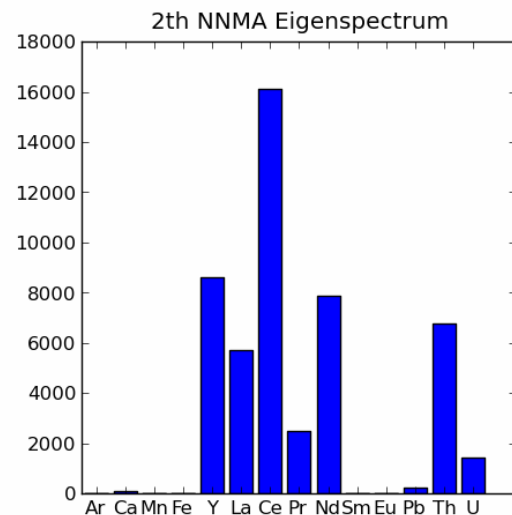


# NNMA in fluorescence analysis

Why Non-Negativity is so positive for data analysis,  
and what we should consider to get there.



Gerd Wellenreuther

HDF5 workshop

Grenoble, 11.-13. January 2010

# Outline

- > My personal starting point: Elemental maps
- > Motivation
- > Factor analysis of a monazite-mineral in the presence of other crystalline phases
  - PCA: Introduction + results
  - Non-Negative Matrix Approximation (NNMA)
- > Conclusion
- > Outlook / Ideas



Picture of monazite-minerals  
(stolen from Wikipedia)

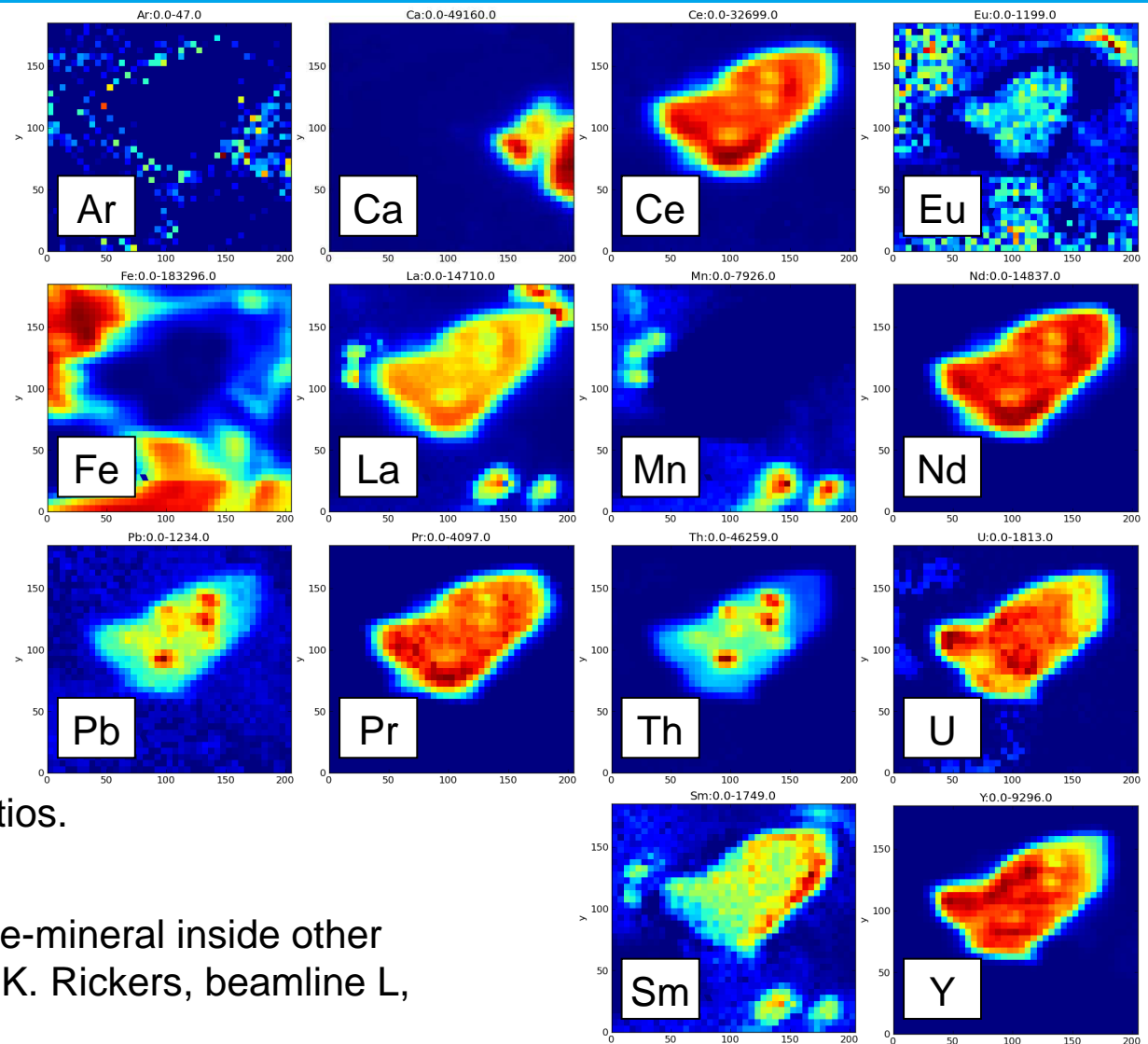
# Starting point: Elemental maps



Above: microscope image taken with beamline microscope

Scientific question:  
Image age of mineral by examination of U : Th : Pb – ratios.

Right: Fitted data from monazite-mineral inside other crystalline phases (courtesy of K. Rickers, beamline L, HASYLAB).



# Motivation

Deliver more than “just” elemental maps to the users:

- > Samples consist of parts/clearly distinct contributions:
    - Spectroscopic data should nicely factorize (I think)
  - > Go beyond elemental distributions:
    - Chemical fingerprints of parts of the sample
  - > 2d-mapping projects the 3d-sample:
    - Previously well separated parts can overlap
- Use statistical methods, e.g. **factor analysis!**



# Factor analysis / multivariate analysis

- > Given: Spectroscopic data **D** (n\_pixels, n\_spectrum)
- > Find factorisation into **maps M** (n\_pixels, n\_factors) and **spectra S** (n\_factors, n\_spectrum)

$$\mathbf{D} \approx \mathbf{M} * \mathbf{S}$$

- > Goals:
  - **Dimensional reduction** (n\_factors << n\_spectrum)
  - **Identify underlying factors**  
(good methods should be meaningful/interpretable)
- > It does not ...
  - ... know anything about chemistry (bad) or your sample (not biased → good)
  - ... take into account knowledge about adjacent pixels, detector physics etc.



# Why PCA is unfit for the photon counting community

PCA (Principal Component Analysis):

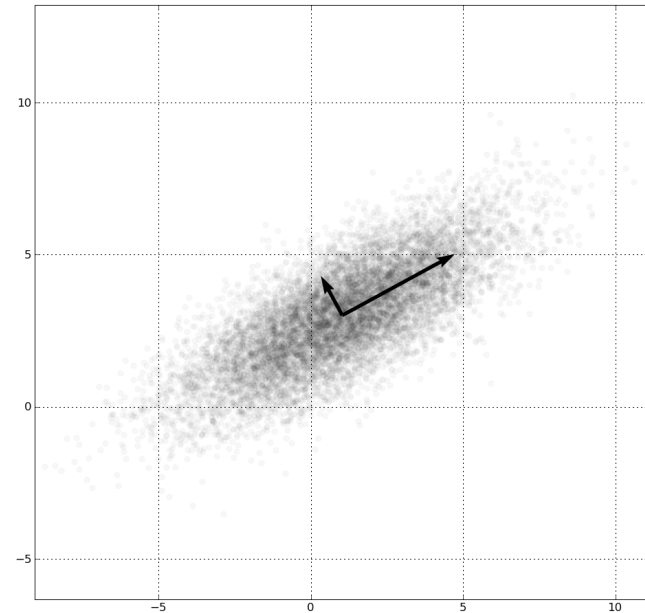
> Most used factor analysis, **quick + unique**

> Does a **principal axis transformation** of the **covariance** matrix

> Assumption: **Variance = Information**  
(not true in general, definitely broken e.g. in trace and ultra-trace analysis)

→ Resulting spectra are **orthogonal**  
(→ in the presence of pure A a compound like AB will be demixed)

→ Spectra and maps contain **negative values**  
(→ what is to be gained from negative concentrations or negative photons is unclear at best)

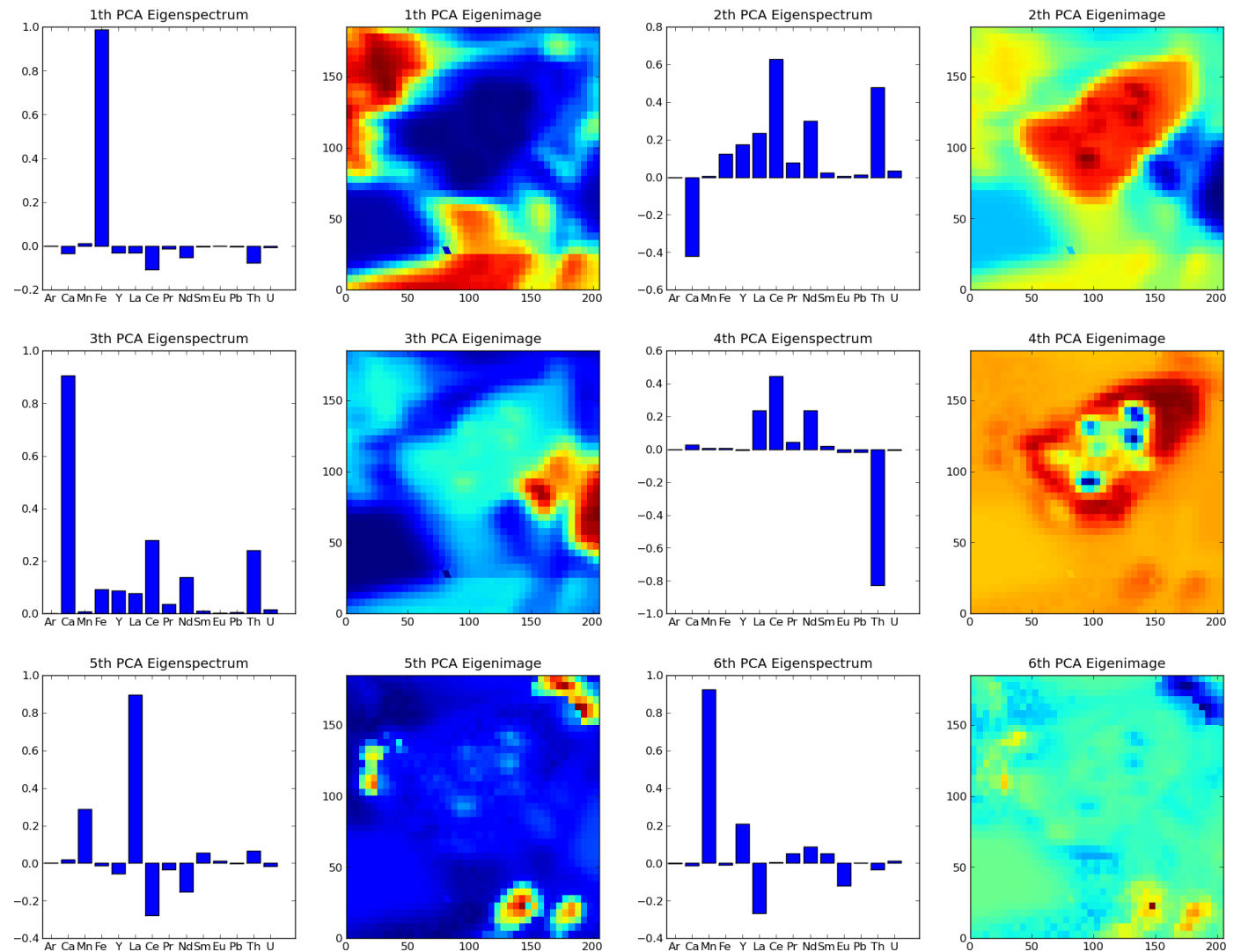


# Example: Monazite PCAed

Eigenspectra  
can be **partly  
negative** →  
anti-correlation

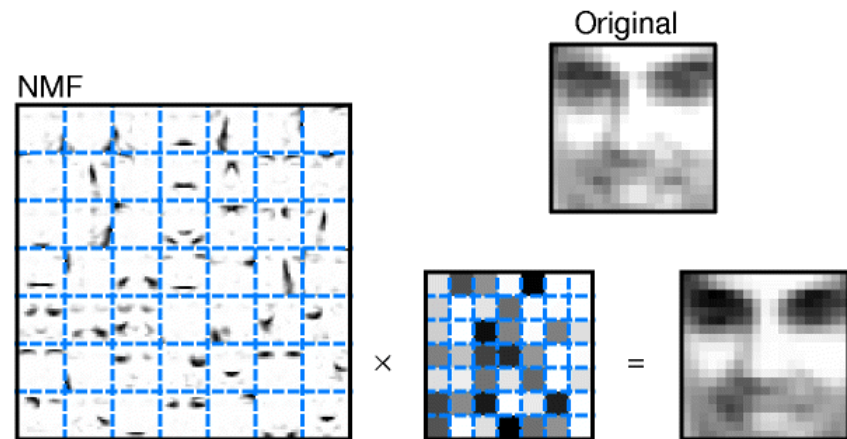
→ PCA uses  
cancellation  
effects.

We need a  
factor analysis  
which is **not  
enforcing  
orthogonality** of  
spectra, but  
**non-negativity!**



# Non-negative matrix approximation

- > “Here we demonstrate an algorithm for **non-negative matrix factorization** that is able to learn **parts** of faces and semantic features of text.
- > This is in contrast to other methods, such as **principal components analysis** and vector quantization, that **learn holistic**, not parts-based, representations.
- > Non-negative matrix factorization is distinguished from the other methods by its use of **non-negativity constraints**.
- > These constraints lead to a **parts-based representation because they allow only additive, not subtractive, combinations**.“



„Learning the parts of objects by non-negative matrix factorization”,  
by Lee & Seung, *Nature* 401, 788-791 (21 October 1999)

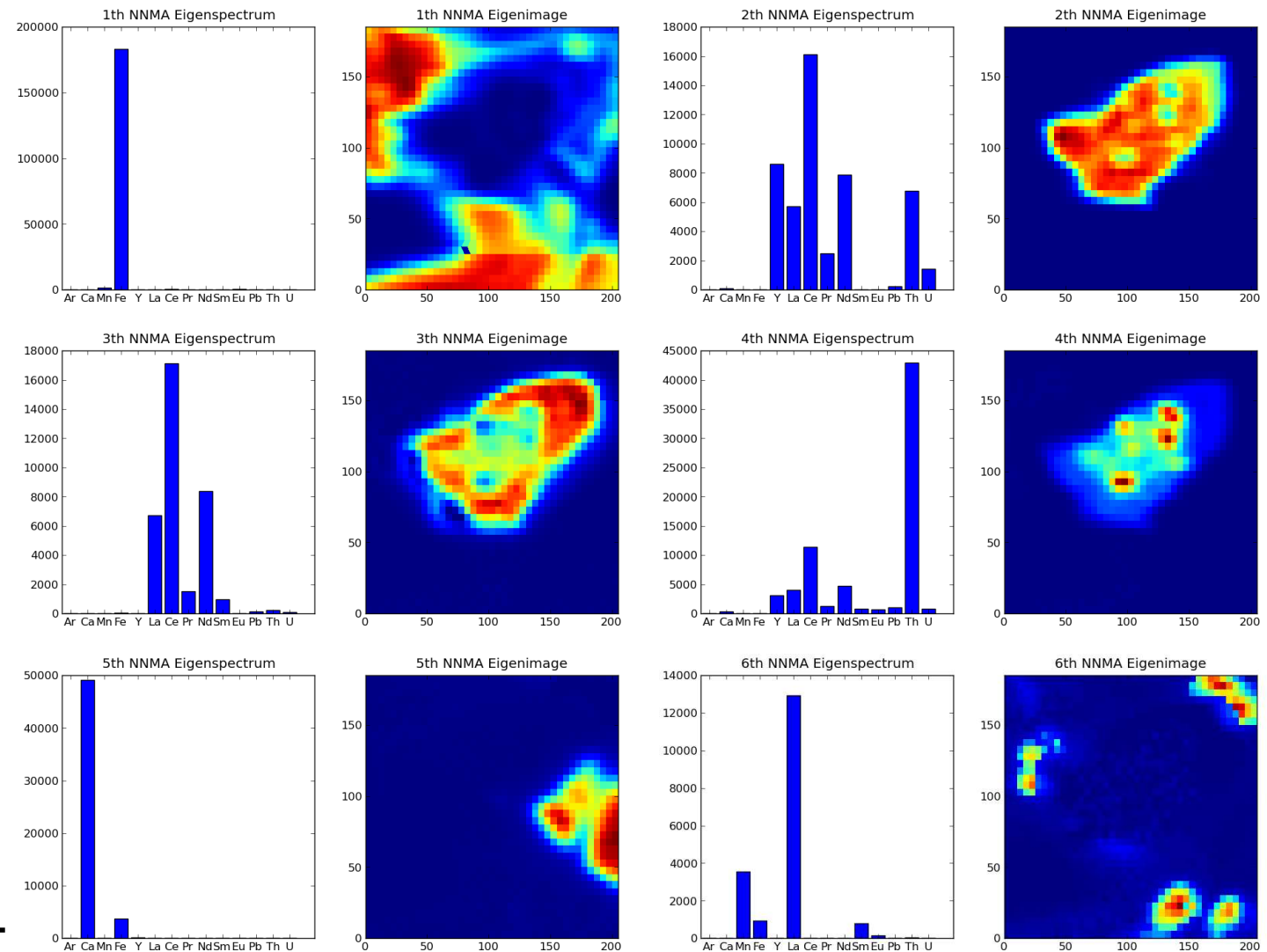


# Example: Monazite NNMAed

## Current interpretation:

1. Biotite
2. Monazit
3. Overgrowth at the monazit rim
4. Thorianite (ThO<sub>2</sub>)
5. Anorthite
6. Something exotic – most probably two phases

**99.4% of data properly modelled,  
~ each 0.6% under- and over-estimated**



# First conclusion

## Advantages of NNMA

- > Non-negativity restrain: Tries to **divide the data into similar parts**
- > Does **not enforce orthogonality** of Eigenspectra  
(→ no unnecessary demixing of entirely proper compounds)

## Disadvantages

- > Only **approximation** – needs significantly **longer!**
- > You either need to **guess the number of Eigenspectra**,  
or you have to test several numbers.
- > Solution is by definition **not** guaranteed to be **unique**  
→ check a couple of NNMA-runs from different starting position

**→ Can all be healed using more PC-power!**

(estimated order for a real large dataset: ~ hours on a normal computer)



# Things one should exploit

- > If possible, **reduce the data first!** This could remove a lot of real noise.  
(going from full spectral data → elementals maps or PCA-filtered data  
should yield at least a factor of 100-1000 in time)
- > Number of factors: **Start with few factors**, add factors until satisfied.
- > Starting position: **Use quick algorithms first!** Then refine.  
(maybe Non-negative ICA? Rather quick NNMA-algos like RRI?)
- > **Initially reduce resolution** to approach minimum quicker.  
(can be done iteratively in any dimension)
- > Especially trace elements: **Treat all elements on the same level →**  
apply weighting scheme before NNMA, reverse afterwards  
(e.g. Poisson weighting, work by Paul Kotula & Michael Keenan)



# Acknowledgements

- > **Karen Rickers**  
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- > **Uwe Schmitt**  
for writing the python implementation  
of a whole bunch of different NNMA-algorithms
- > **Armando Solé**  
for implementing Uwes NNMA-module  
along PCA in PyMca

