

Unveiling “The Scream” by Edvard Munch: Iterative Fuzzy C-means Analysis Of Macro-XRF Mapping



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SAPIENZA
UNIVERSITÀ DI ROMA



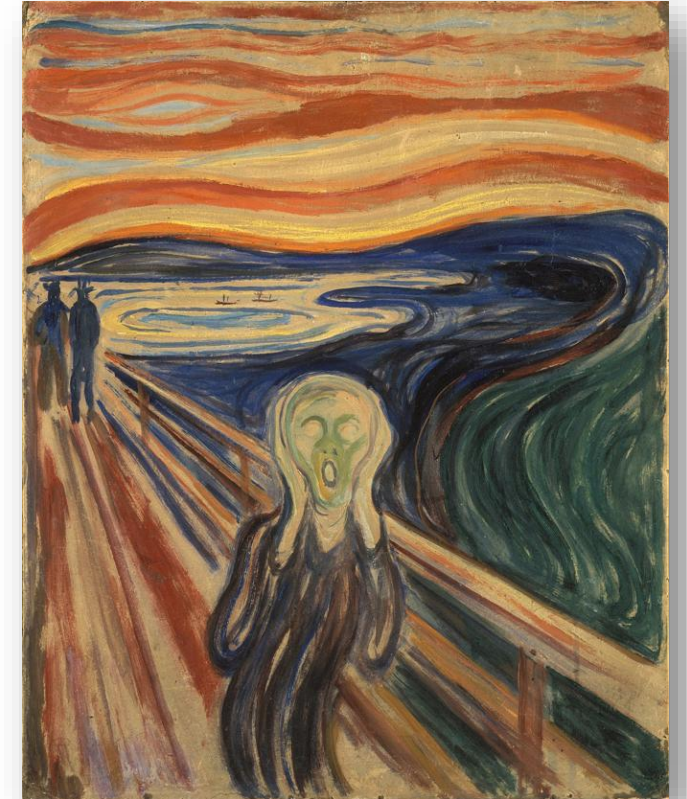
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DIPARTIMENTO DI CHIMICA,
BIOLOGIA E BIOTECNOLOGIE



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Rio de Janeiro
Campus Paracambi

Outline

1. Data description and preliminary analysis
2. Algorithm:
FCM
3. Procedure and settings:
Two-stage FCM-based analysis
4. Results
5. Conclusion and future perspectives



MA-XRF investigations



MA-XRF:

Widely used non-invasive and non-destructive technique available in situ

IN CULTURAL HERITAGE

- Elemental analysis and mapping of works of art materials
- Information about dates, artist techniques, restoration interventions, clues of fakes

MA-XRF investigations



MA-XRF Scanner:

CRONO by XGLaB (Bruker Nano Analytics)

- **Source:** X-ray tube with Rh anode, max 50KV 200 μ A, 1 or 2mm pinhole collimator
- **Detector:** silicon drift detector Energy resolution 130eV at MnKa, 4096 channels
- **Scanning system:** Scan Area 60x45cm, Max Speed: 30 mm/s; Z range: 7.5 cm

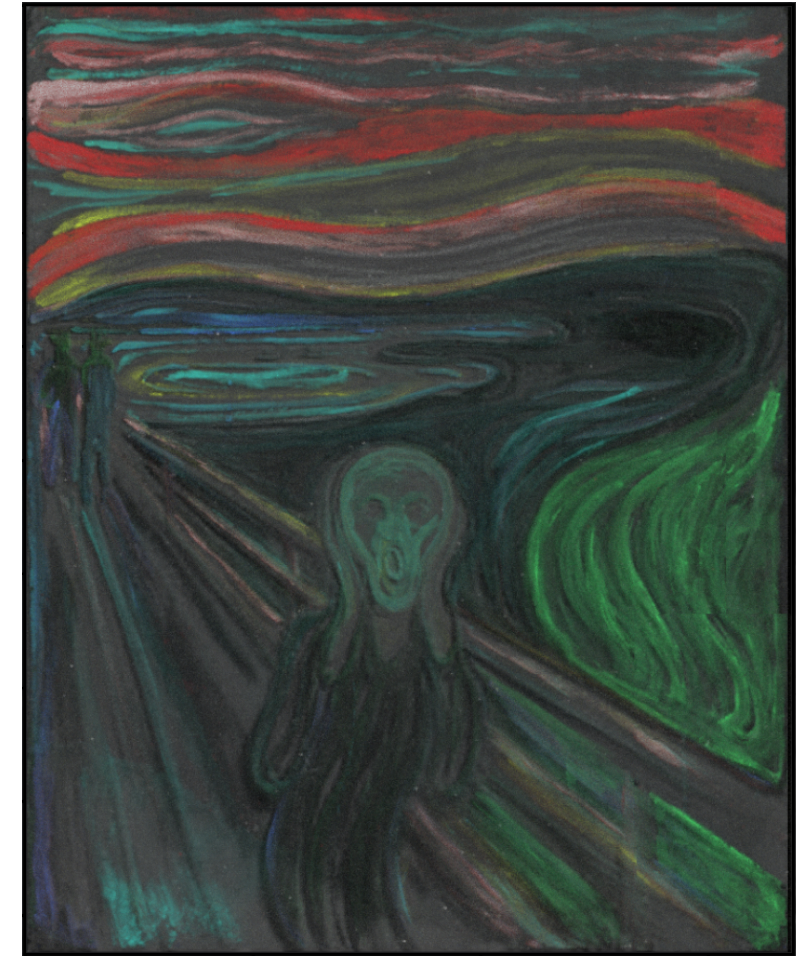
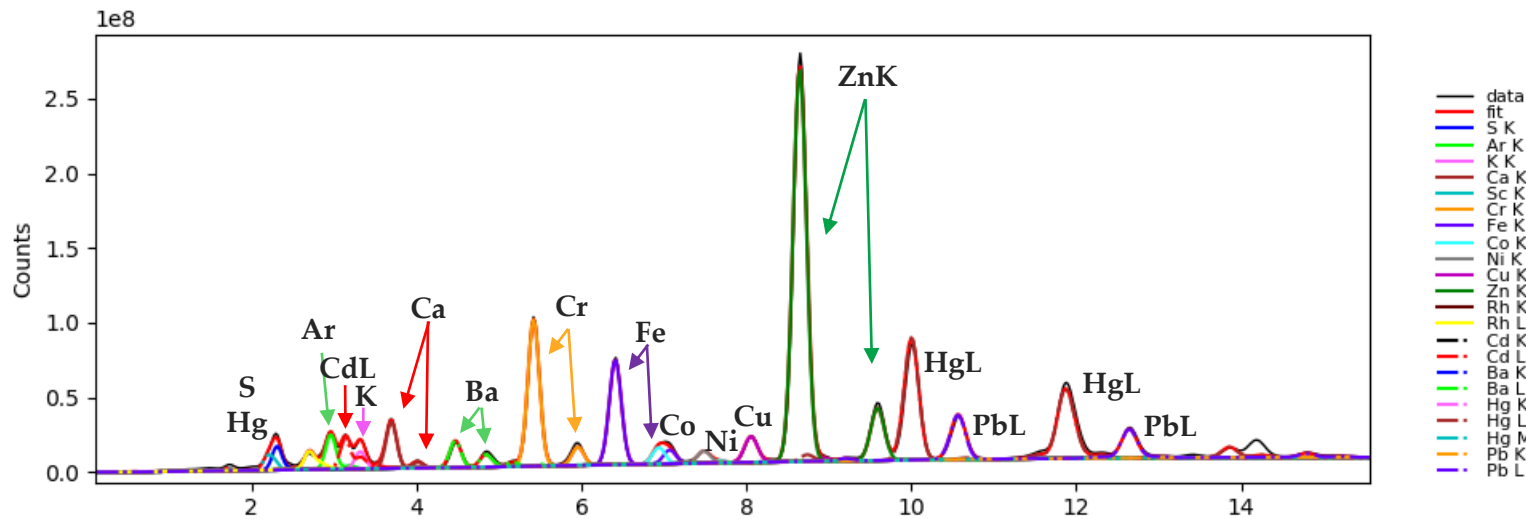
MUNCH acquisition set-up:

- Four data-taking sessions to cover the entire painting
- **Source:** 50KV, 200 μ A, 1mm collimator
- **Scanning parameters:** linear speed 20 mm/s, 40ms per spectrum

Complete Map

835 x 675 pixels/spectra binned from 4096 to 2048 channels to improve the signal-to-noise ratio

Preliminary analysis of the MA-XRF datacube



Softwares: PyMCA [1], DataMuncher [2]

- [1] M. Cotte et al., *Watching Kinetic Studies as Chemical Maps Using Open-Source Software*, *Anal. Chem.* 88 (2016) 6154–6160;
- [2] M. Alfeld, K. Janssens, *Strategies for processing mega-pixel x-ray fluorescence hyperspectral data: A case study on a version of Caravaggio's painting, Supper at Emmaus*. *J. Anal. At. Spectrom* 30, 777–789 (2015);

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LIMITS:

Not able to provide sufficient information about the mixtures of the identified pigments and the manifold paint layering

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Iterative and nonlinear process:
blind FCM + supervised analysis

Fuzzy C-Means (FCM) algorithm

- Unsupervised clustering technique
- Points can belong to multiple clusters with varying degrees of membership [3]

[3] J.C. Bezdek, "Pattern Recognition with Fuzzy Objective Function Algorithms", Plenum Press, New York, 1981.

Fuzzy C-Means (FCM) algorithm

- Unsupervised clustering technique
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IN THE CONTEXT OF SPECTRAL IMAGES:

- identification of structures in the data
- segmentation of the image into regions with similar spectral properties

[3] J.C. Bezdek, "Pattern Recognition with Fuzzy Objective Function Algorithms", Plenum Press, New York, 1981.

Fuzzy C-Means (FCM) algorithm

Minimization of the **objective function**:

$$J_m = \sum_{i=1}^D \sum_{j=1}^N \mu_{ij}^m \|x_i - c_j\|^2$$

where:

- D **number of data points**, N **number of clusters**
- x_i **i th data point**, c_j **center of the j th cluster**
- m **fuzzy partition matrix exponent**, μ_{ij} **degree of membership** of x_i in the j th cluster

The algorithm stops when: **maximum number of iterations** max_{iter} reached

OR the variation of the objective function less than **predefined threshold** Δ_j

Fuzzy C-Means (FCM) algorithm

INPUT: number of clusters N , fuzzy exponent m , maximum number of iterations max_{iter} , threshold Δ_J

1. Initialization of the membership values, μ_{ij} .
2. **While** the maximum number of iteration max_{iter} is not reached
and the variation of the objective function J_m is not less than the threshold Δ_J :

2.1. Computation of cluster centers:

$$c_j = \frac{\sum_{i=1}^D \mu_{ij}^m x_i}{\sum_{i=1}^D \mu_{ij}^m} ;$$

2.2. Updating of μ_{ij} :

$$\mu_{ij} = \frac{1}{\sum_{k=1}^N \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} ;$$

2.3. Evaluation of the objective function J_m and its variation.

OUTPUT: Soft partition P

Conversion of the soft partition to a hard partition according to a **maximum membership rule**.

Two-stage FCM-based analysis

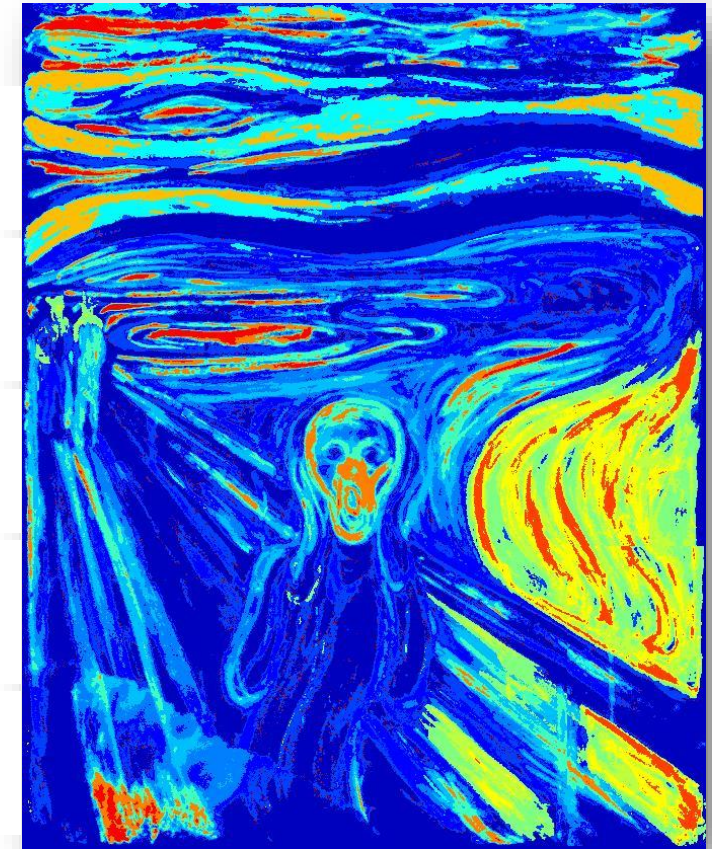
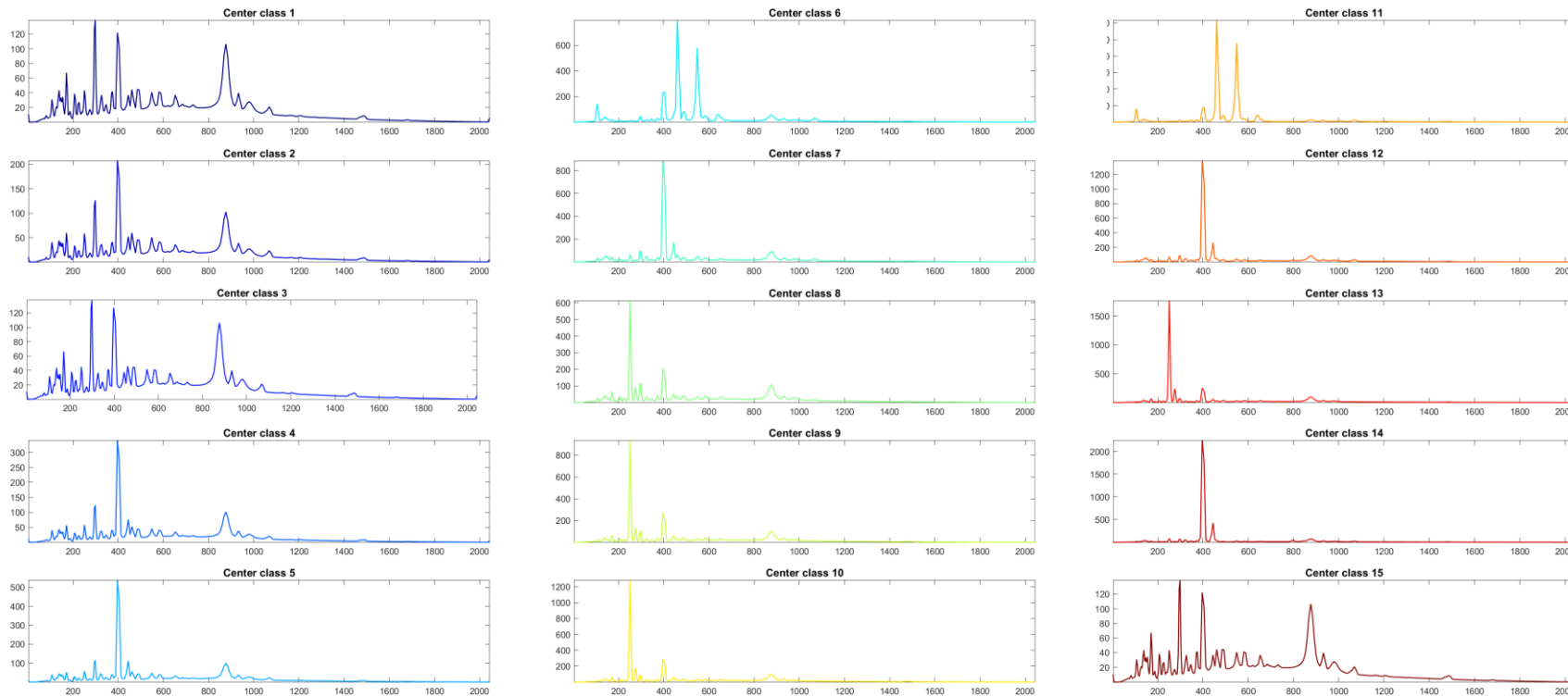
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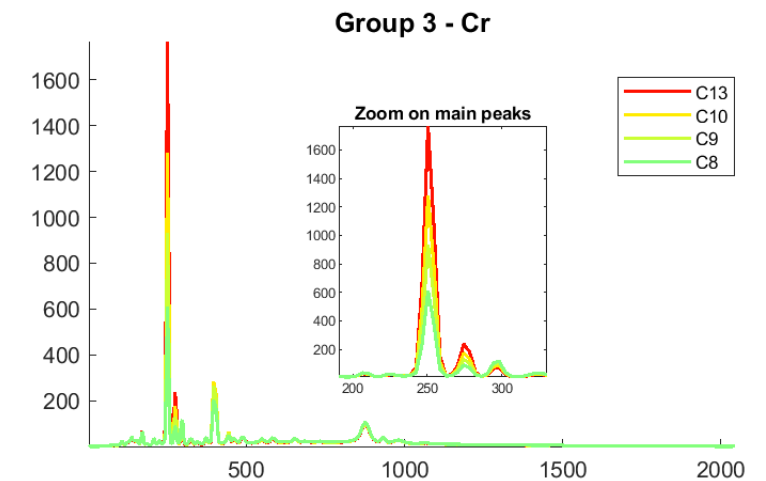
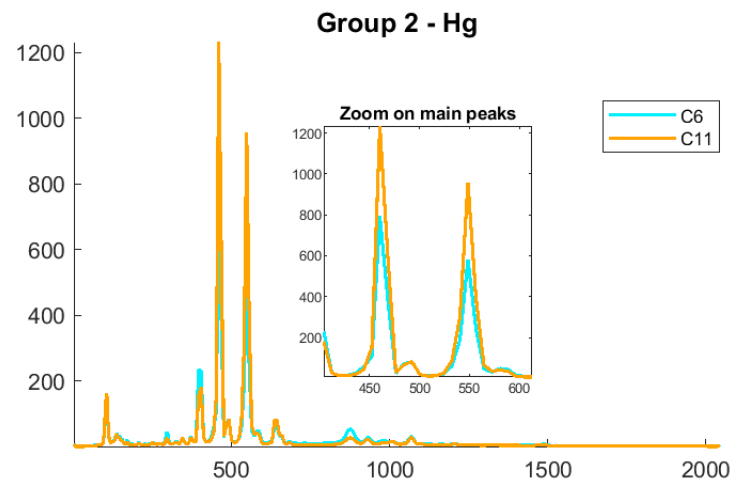
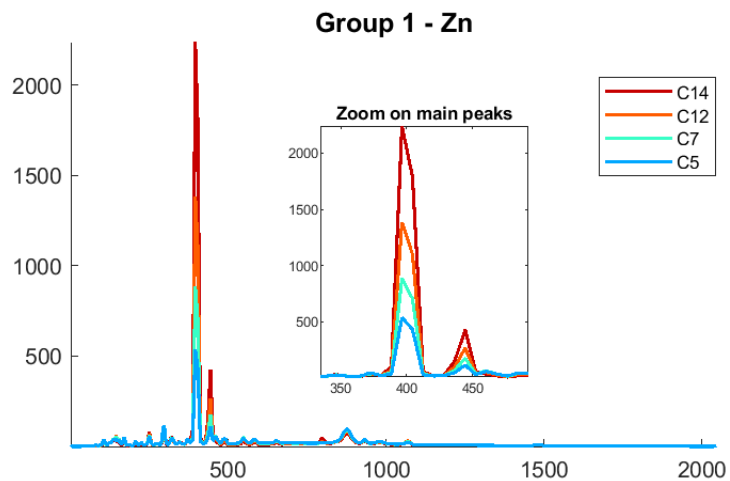
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1. Partition of data in classes $C_i, i = 1, \dots, n$ using FCM;
2. Identification of classes of interest, and grouping according to the dominant peaks of the spectrum of the class center c_i .

Classes sharing the same dominant element are assigned to the same group



Two-stage FCM-based analysis

SECOND STAGE: *iterative process*

3. For each group G_j , $j = 1, \dots, K$, and each class C_i in G_j :
 - While** predominant elements are detected and classes C_i are separated from FCM:
 - 3.1. Removal of predominant element peaks from pixels in C_i ;

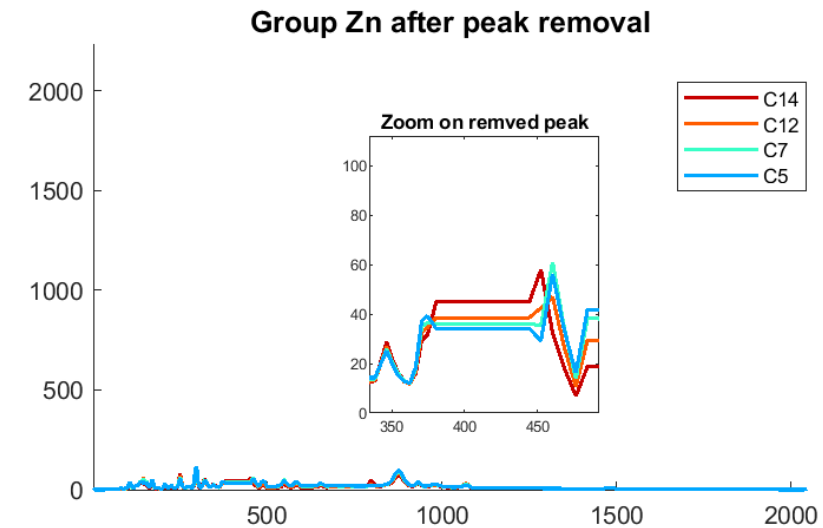
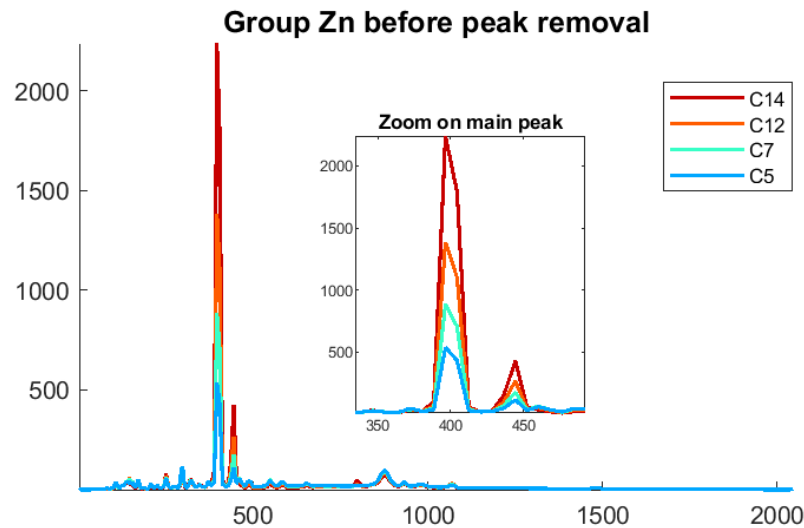
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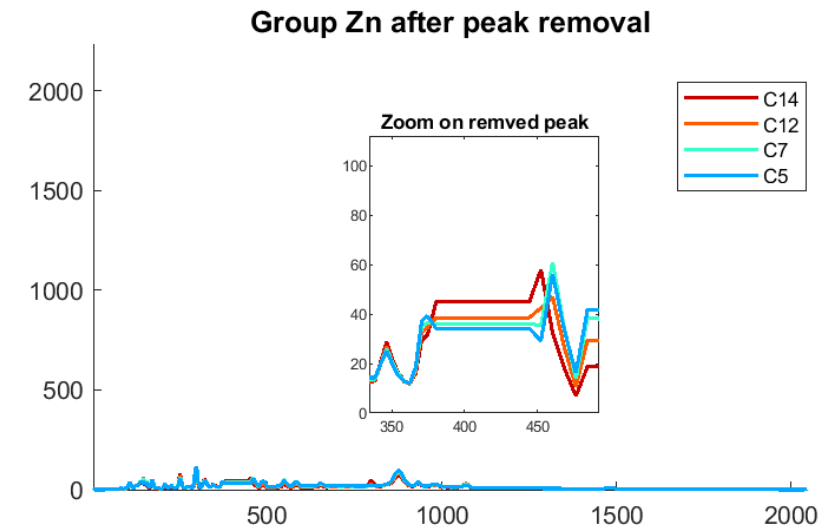
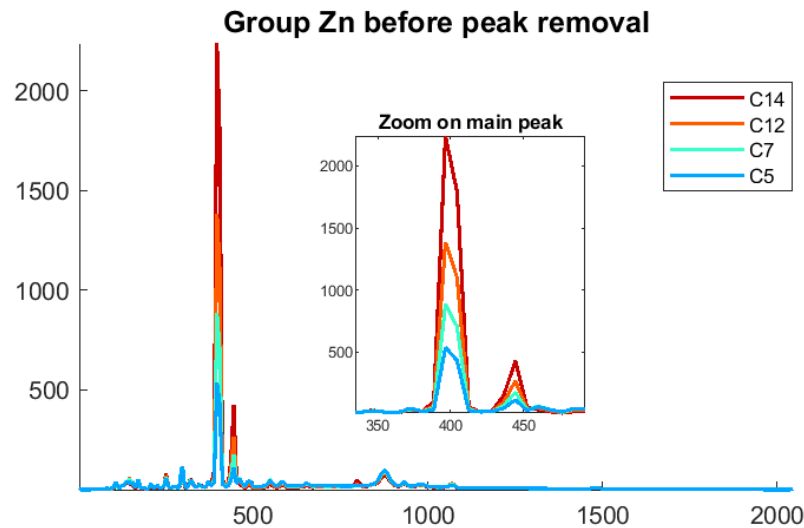
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3.2. Performing of FCM on C_i .

Experimental settings

DATA AVERAGING: moving average filters

- 4 channels before 8 keV ($\sim$ first 380 channels)
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CLASS MERGING

SECOND STAGE: small number of pixels in each class C_i , with low variability

—→ merging operation based on the distance between the centers of the classes

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ALGORITHM SETTINGS

- Standard setting for the FCM parameters
- 15 classes used as FCM input at first stage

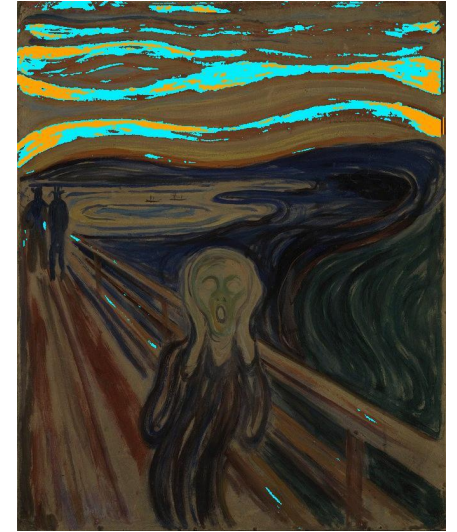
Results - first stage



Group 1 - Zinc



Group 2 - Mercury



Group 3 - Chrome

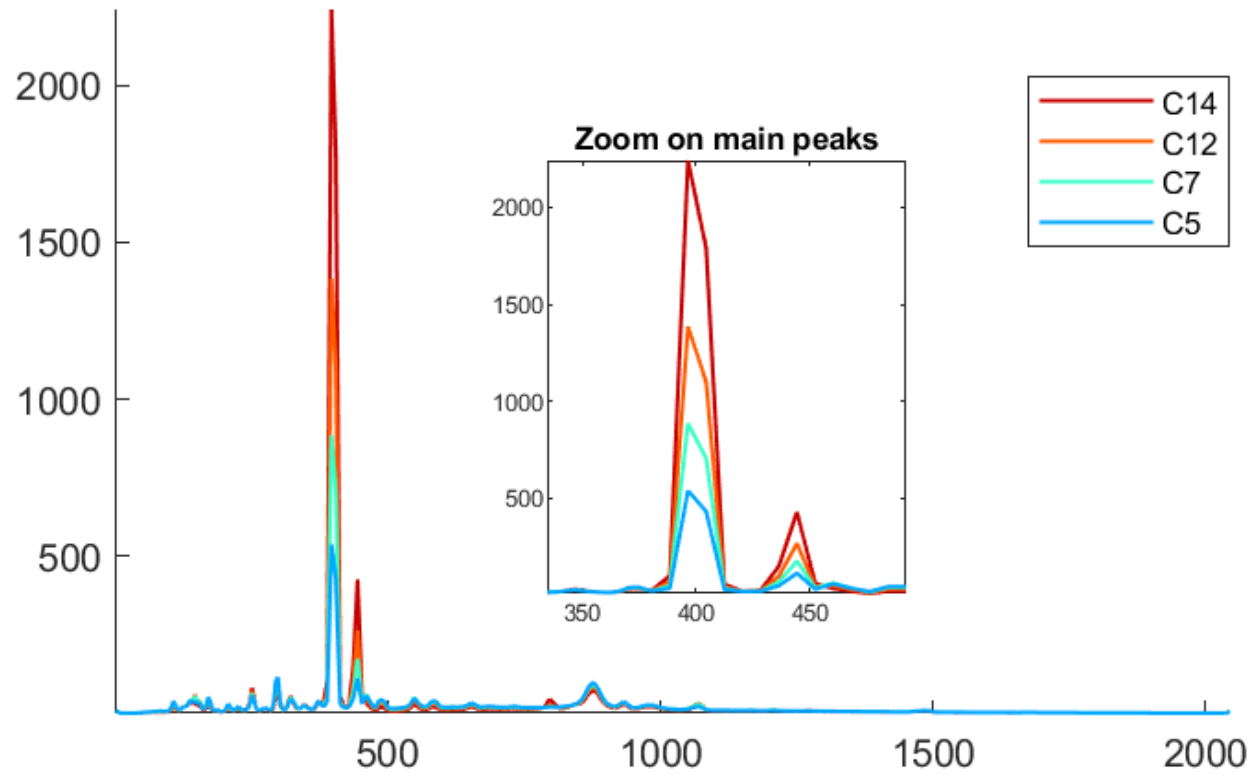


Group 4 - Low signals



Results - first stage

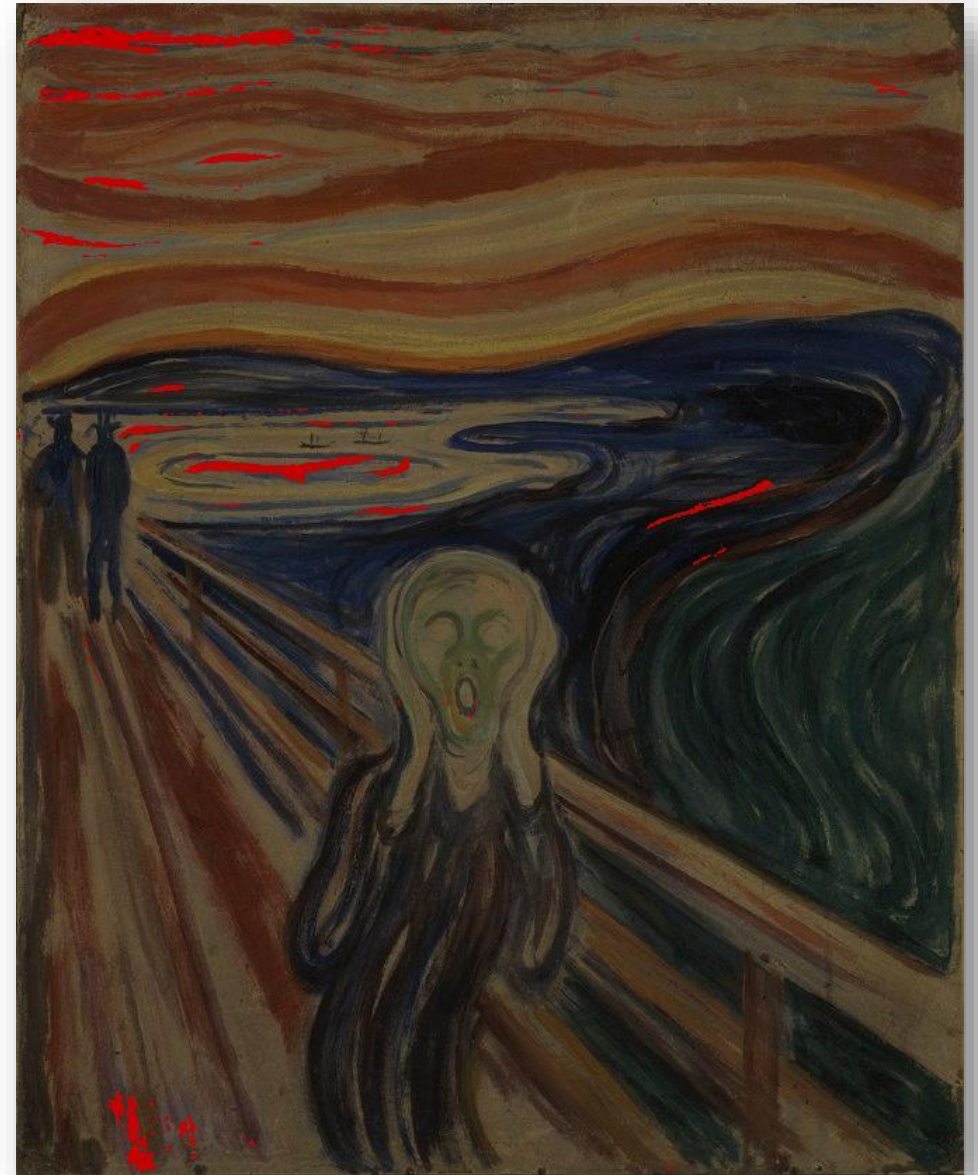
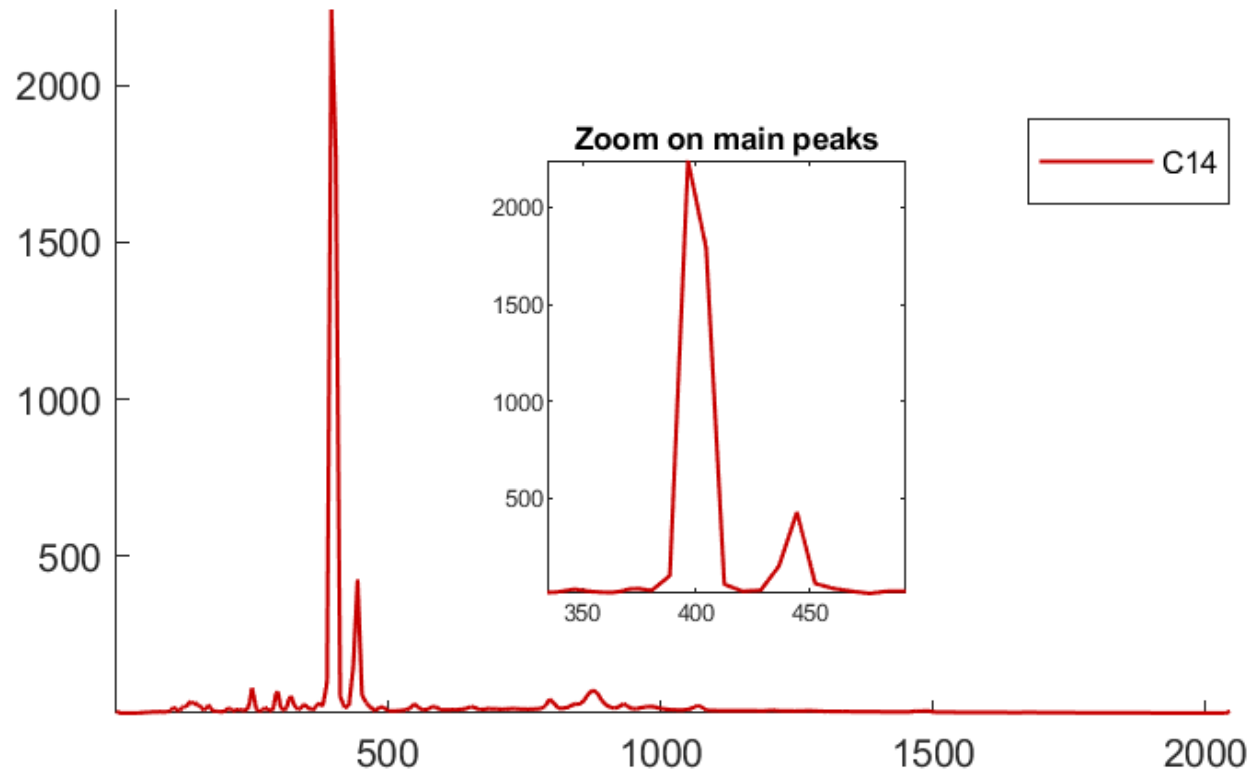
Group 1 - Zinc



Results - first stage

Group 1 - Zinc

Zn +++

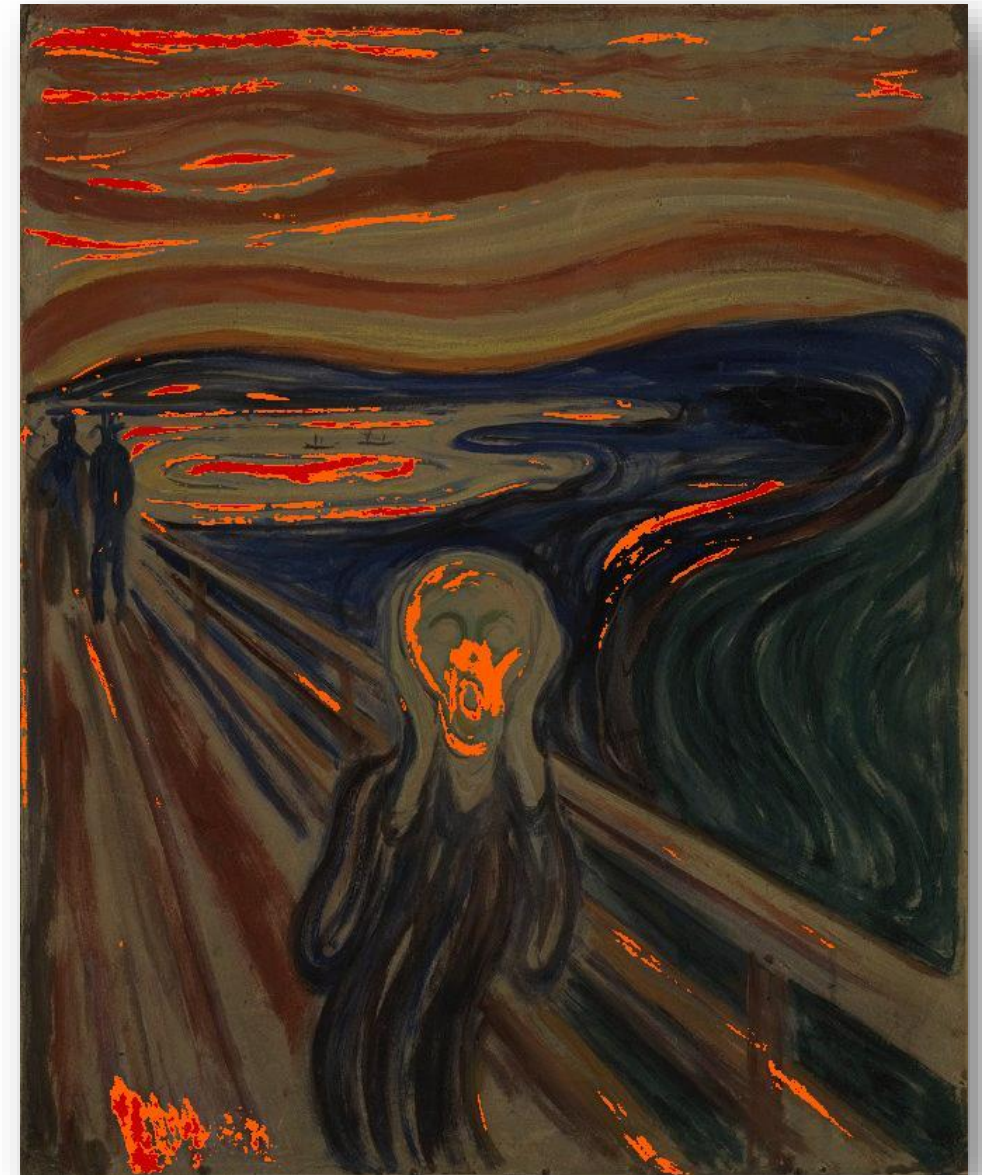
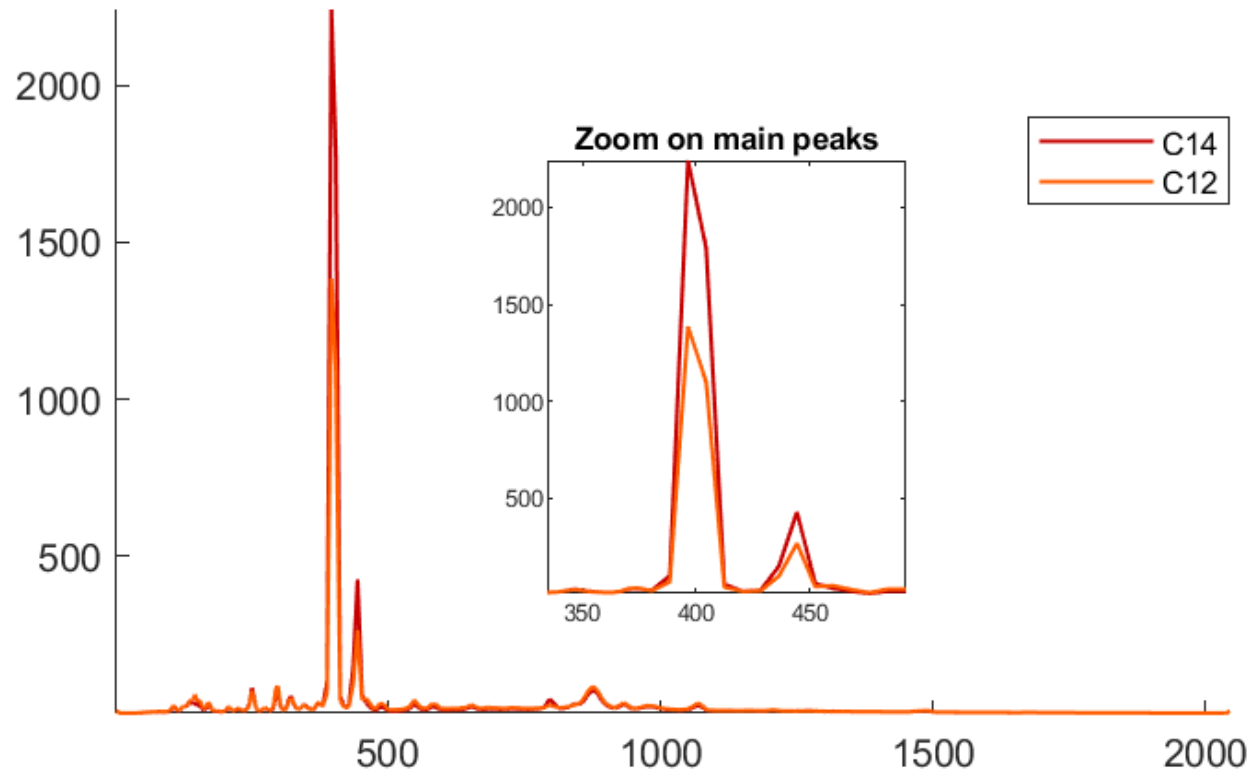


Results - first stage

Group 1 - Zinc

Zn +++

Zn ++



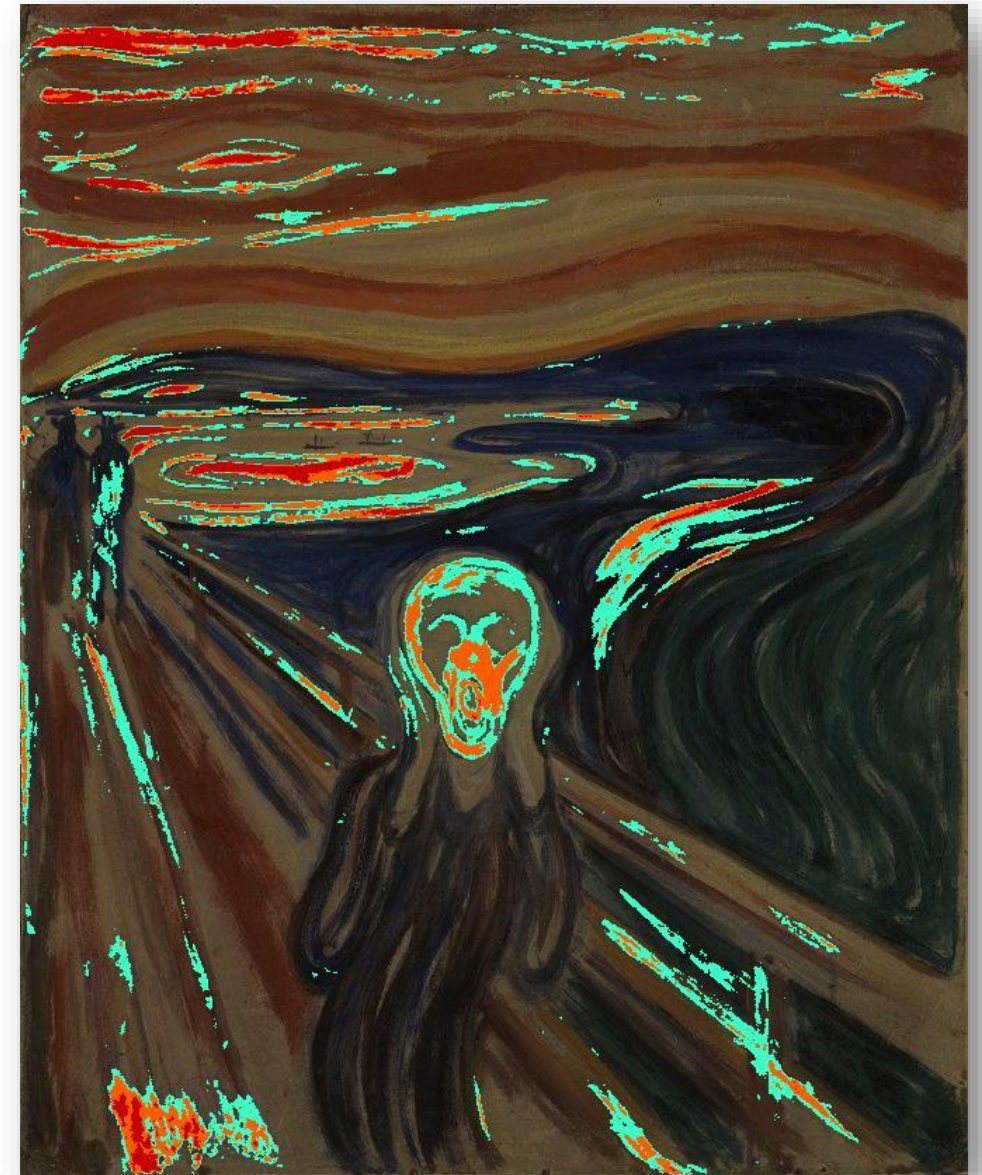
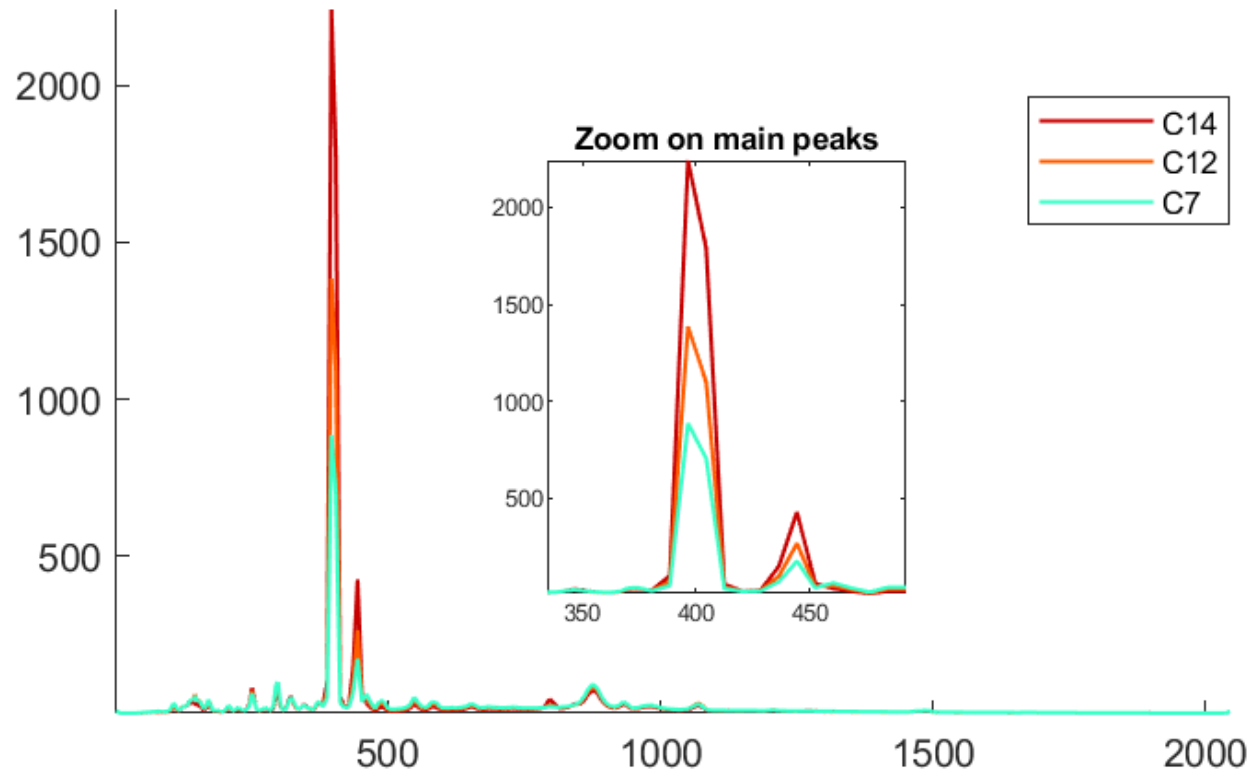
Results - first stage

Group 1 - Zinc

Zn +++

Zn ++

Zn +



Results - first stage

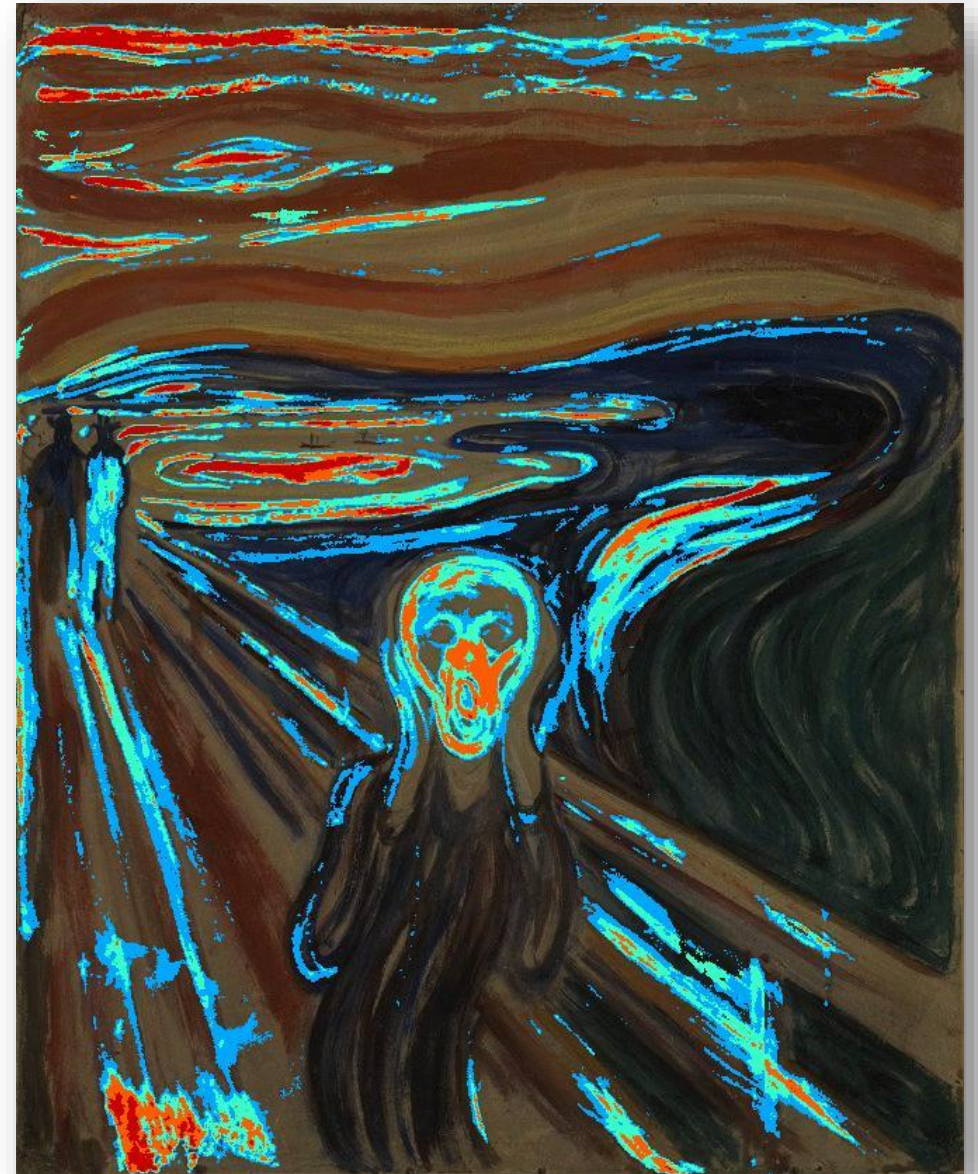
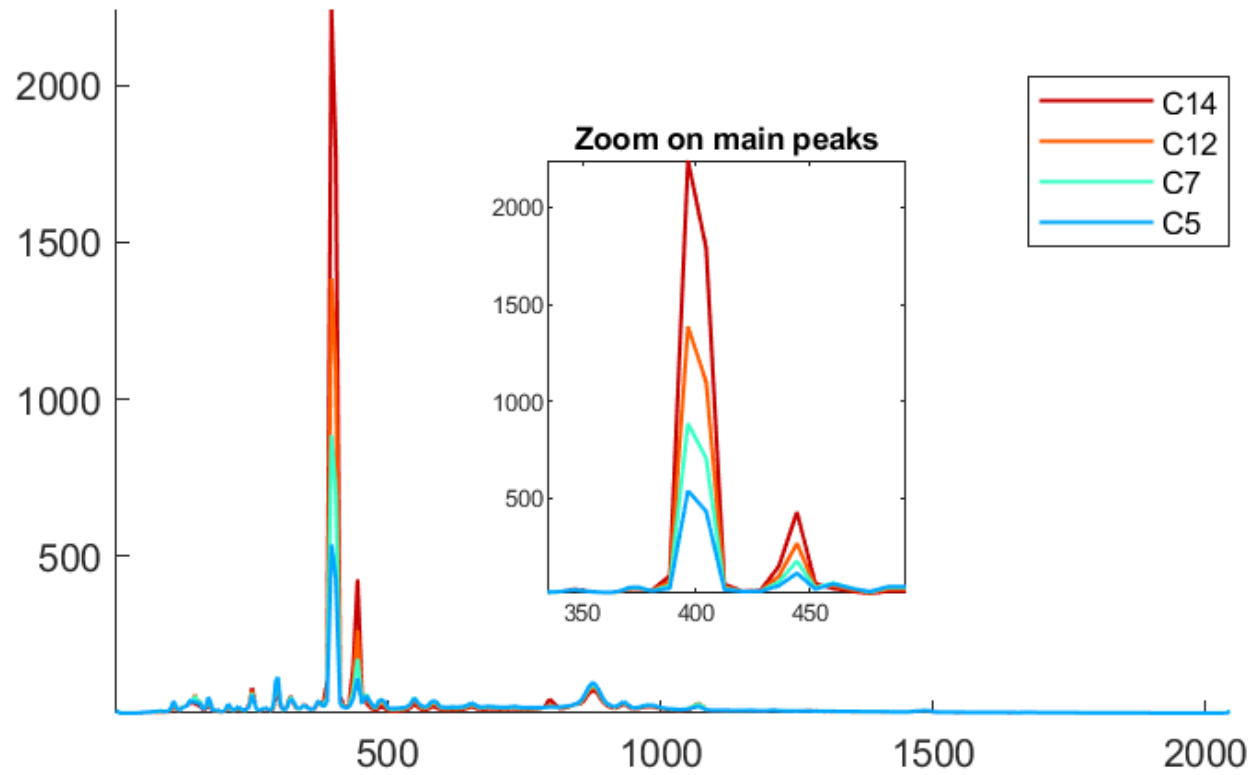
Group 1 - Zinc

Zn +++

Zn ++

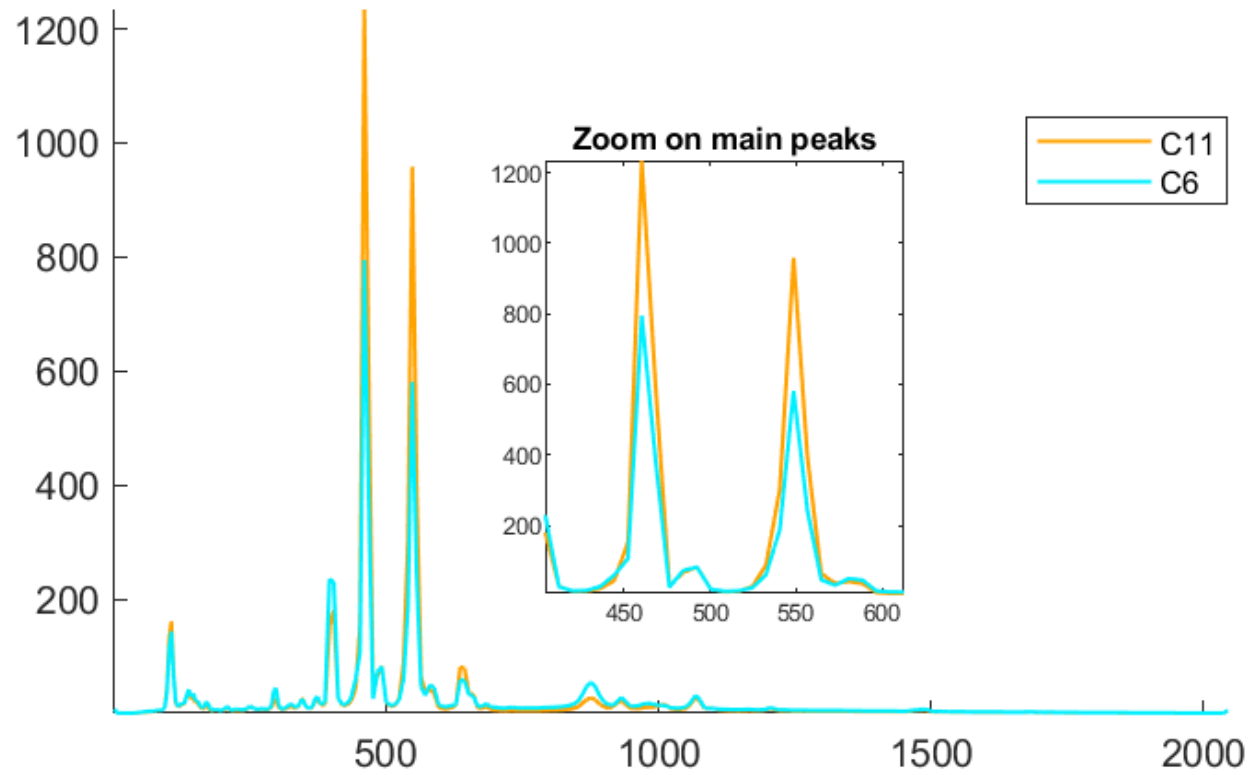
Zn +

Zn



Results - first stage

Group 2 - Mercury

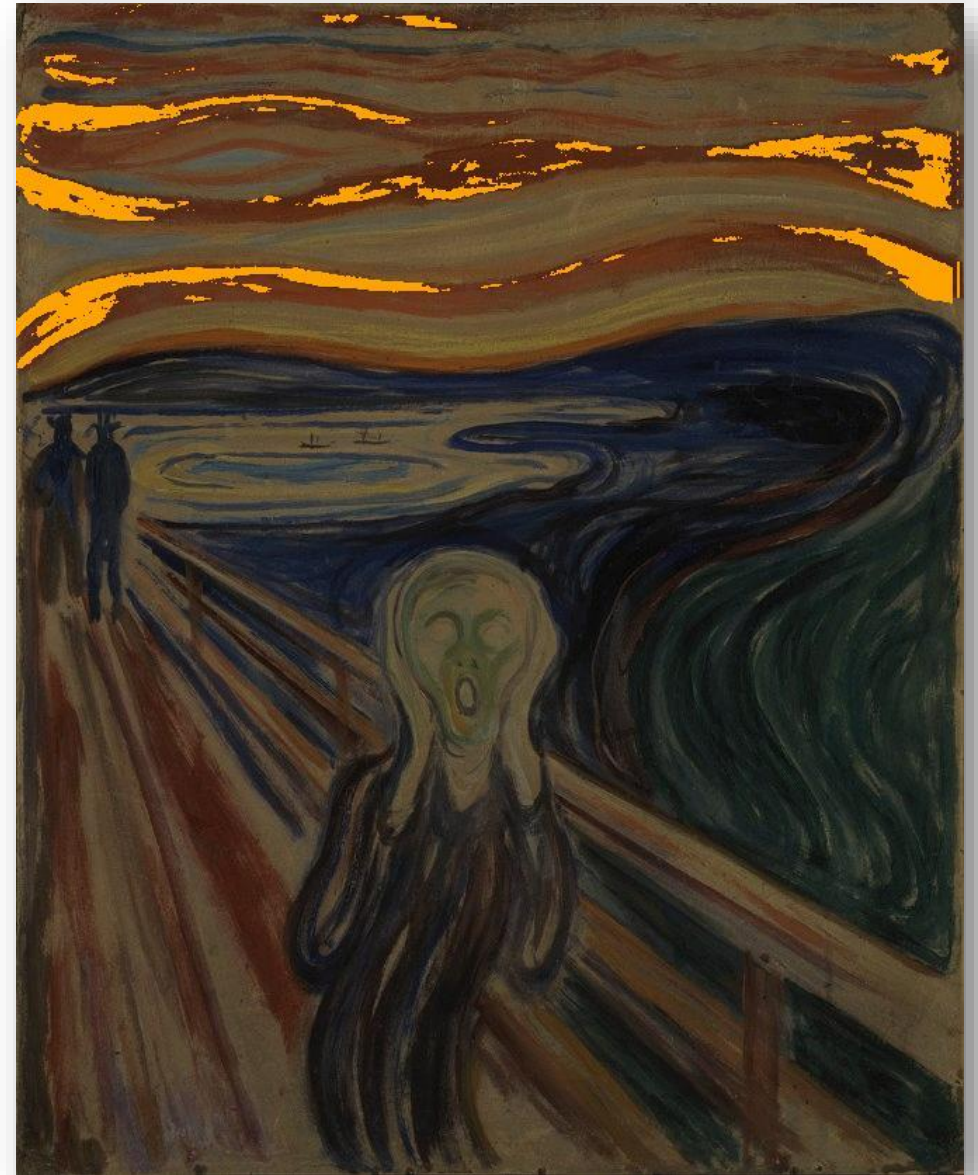
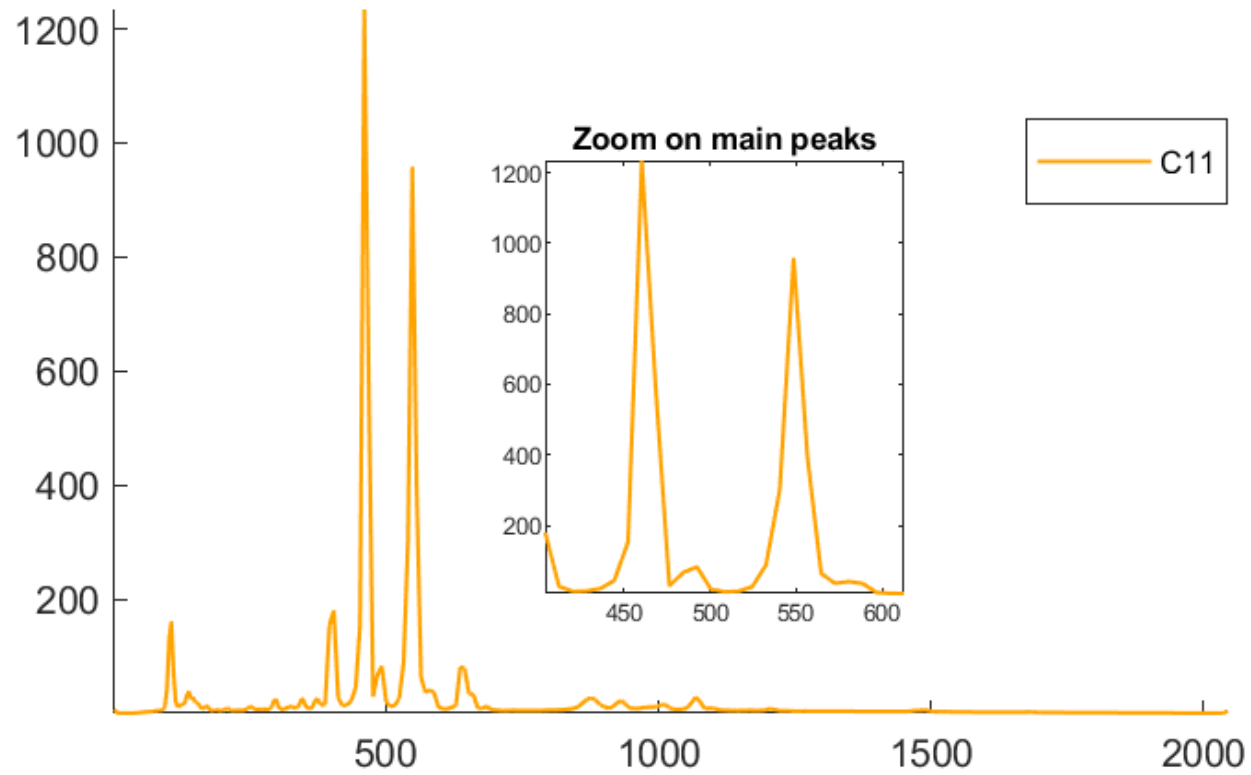


Results - first stage

Hg +



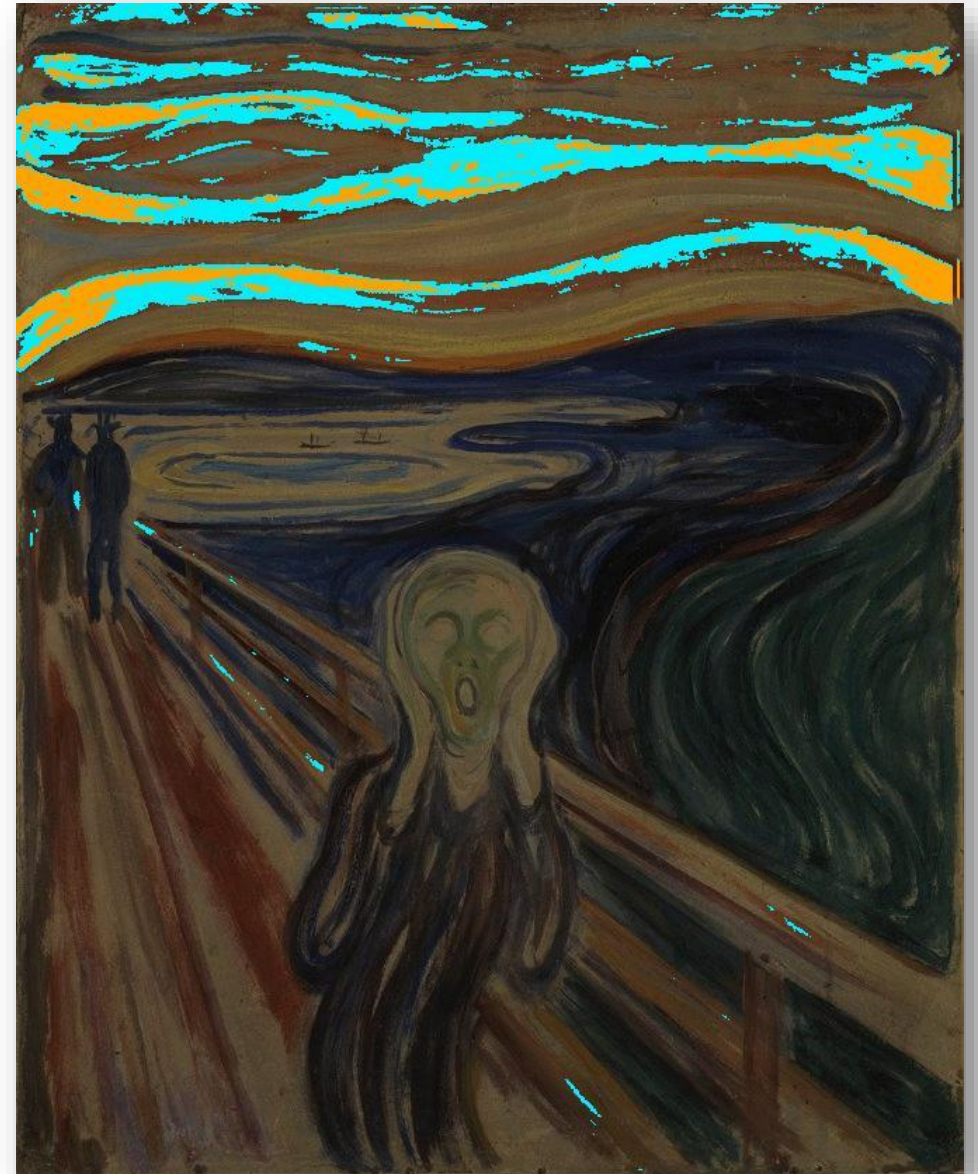
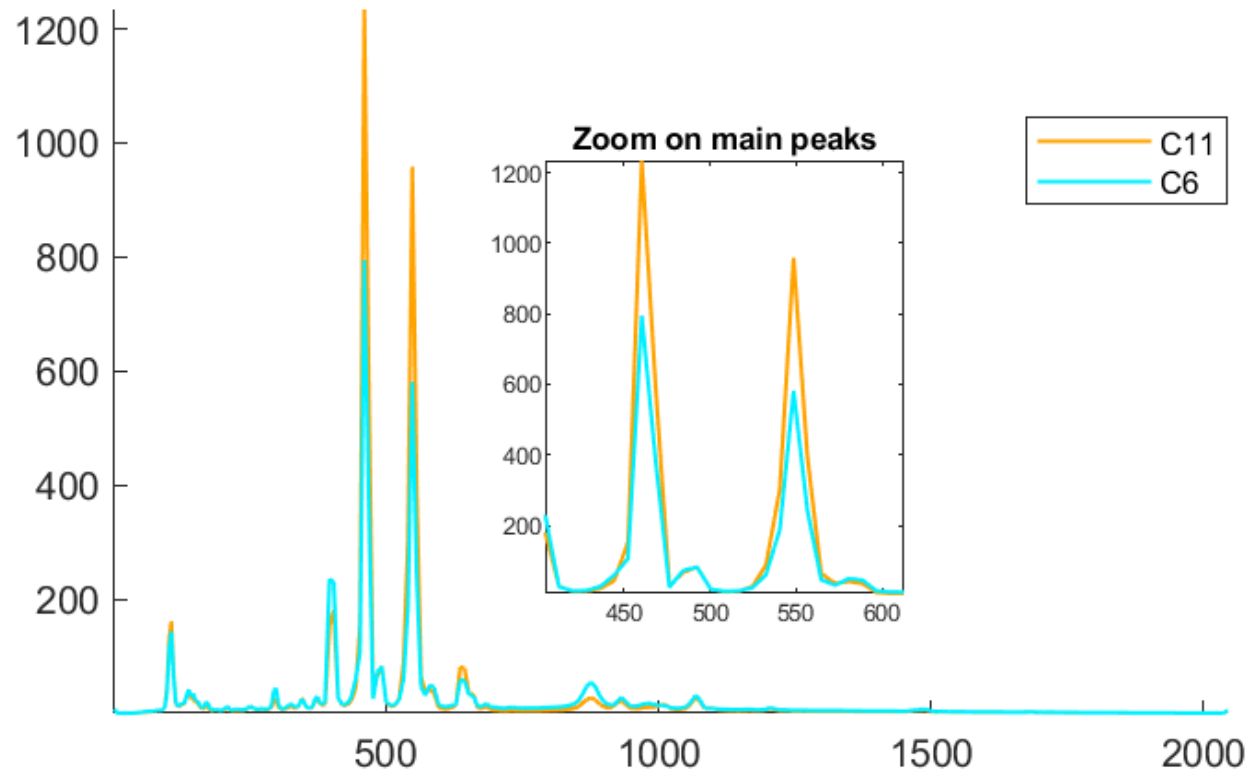
Group 2 - Mercury



Results - first stage

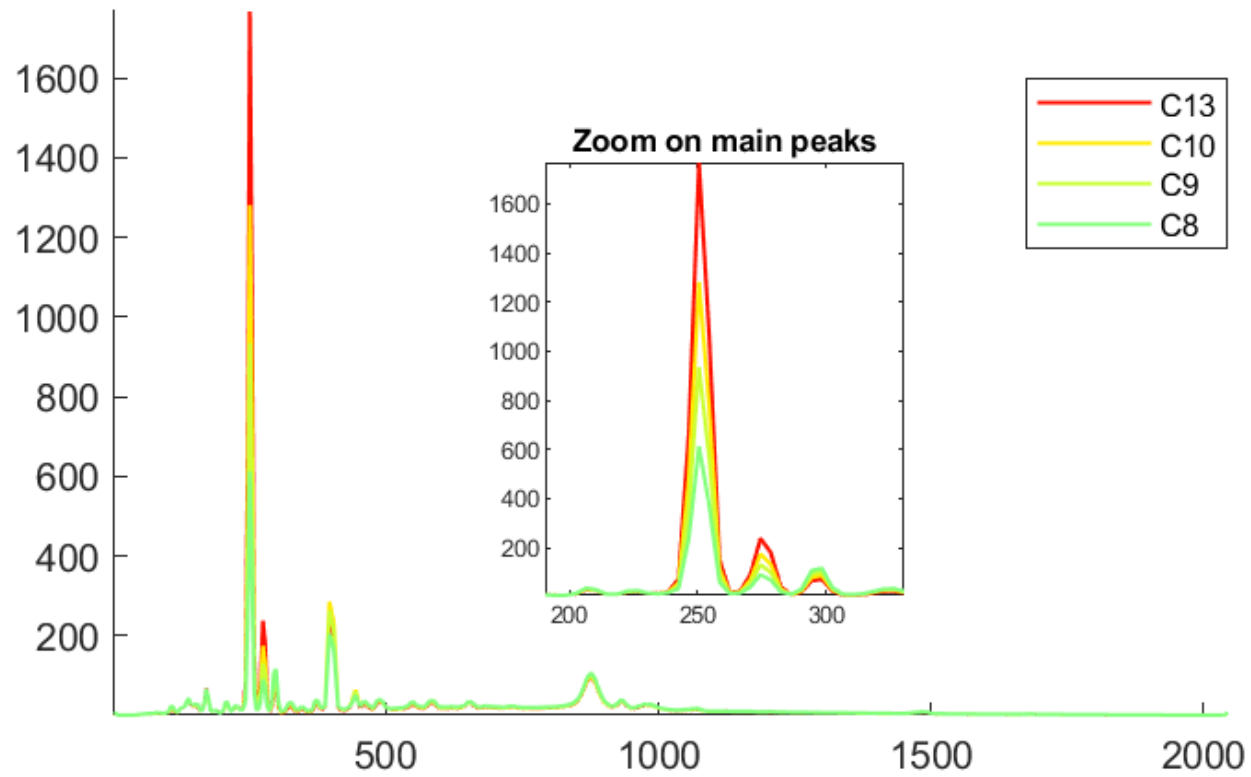
Group 2 - Mercury

Hg +
Hg



Results - first stage

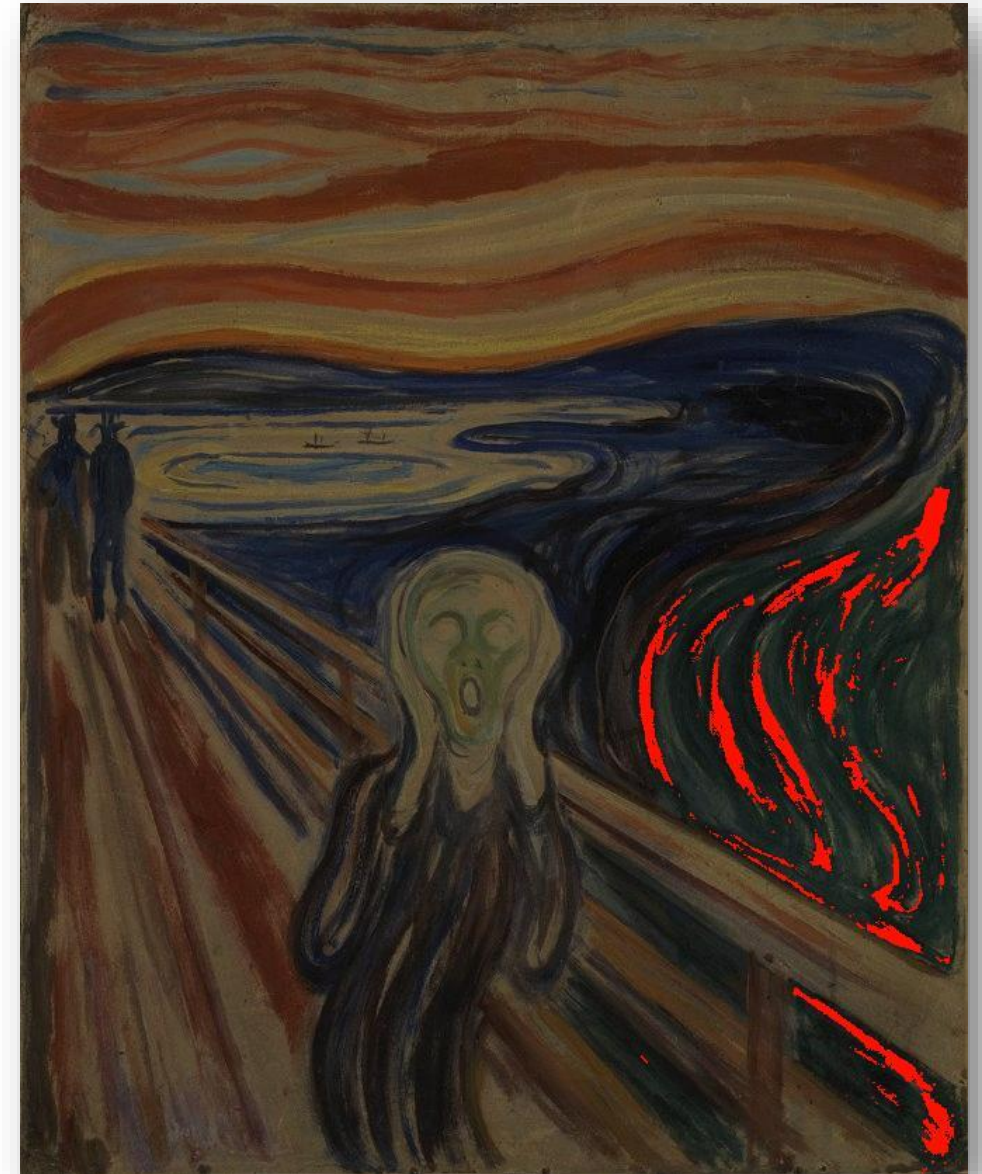
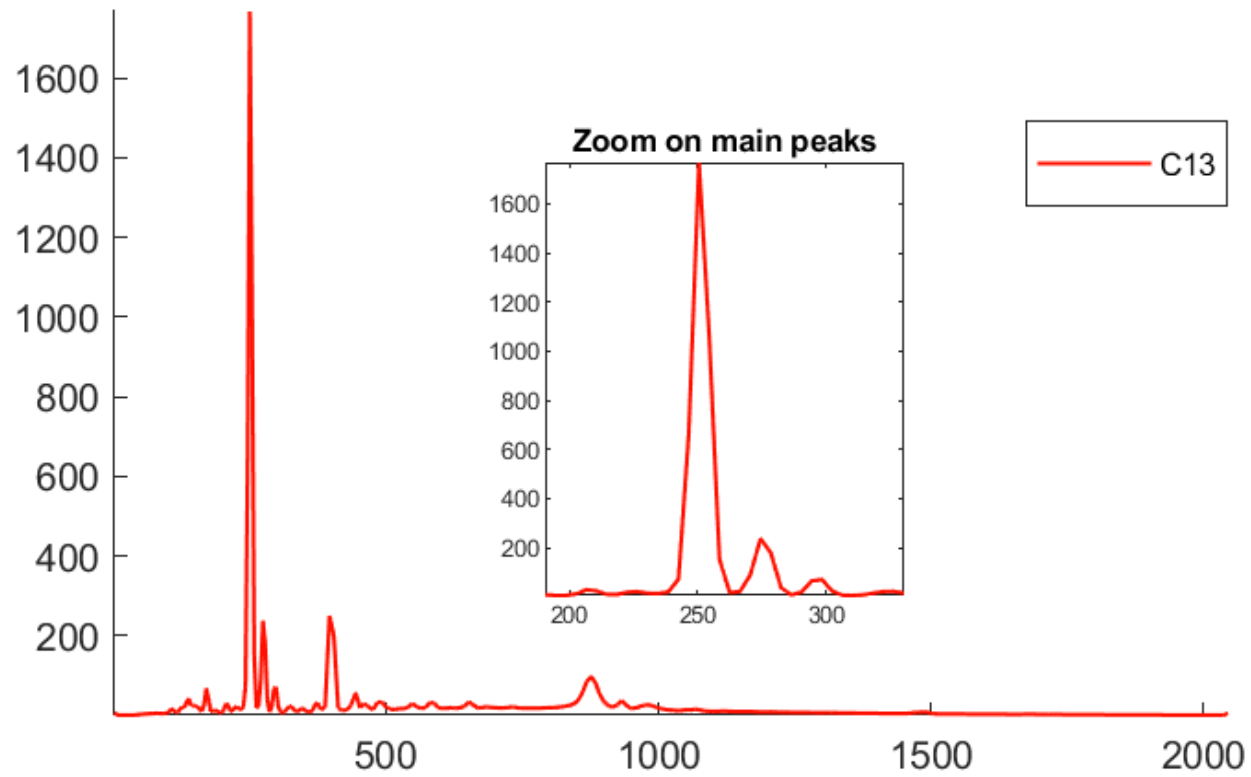
Group 3 - Chrome



Results - first stage

Group 3 - Chrome

Cr +++

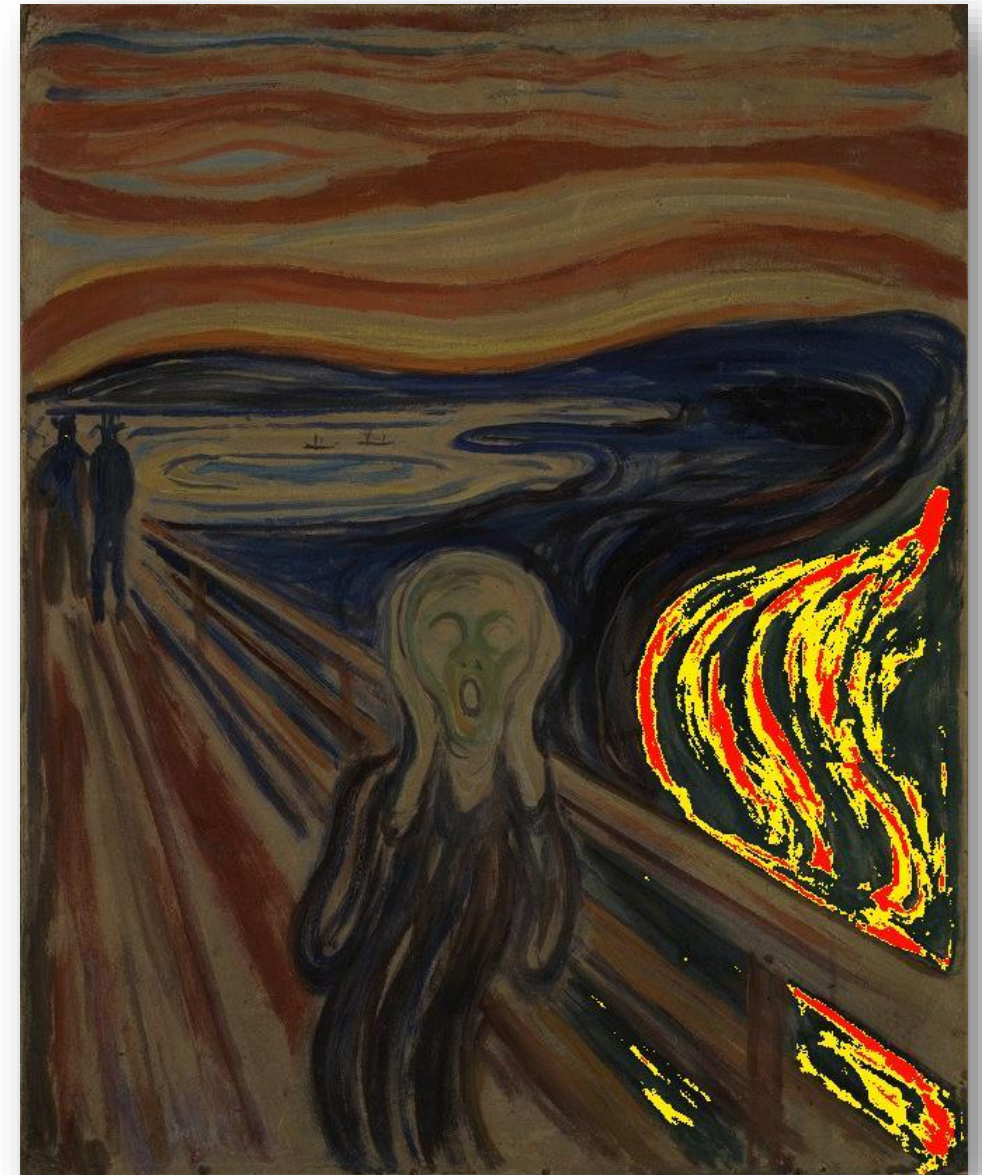
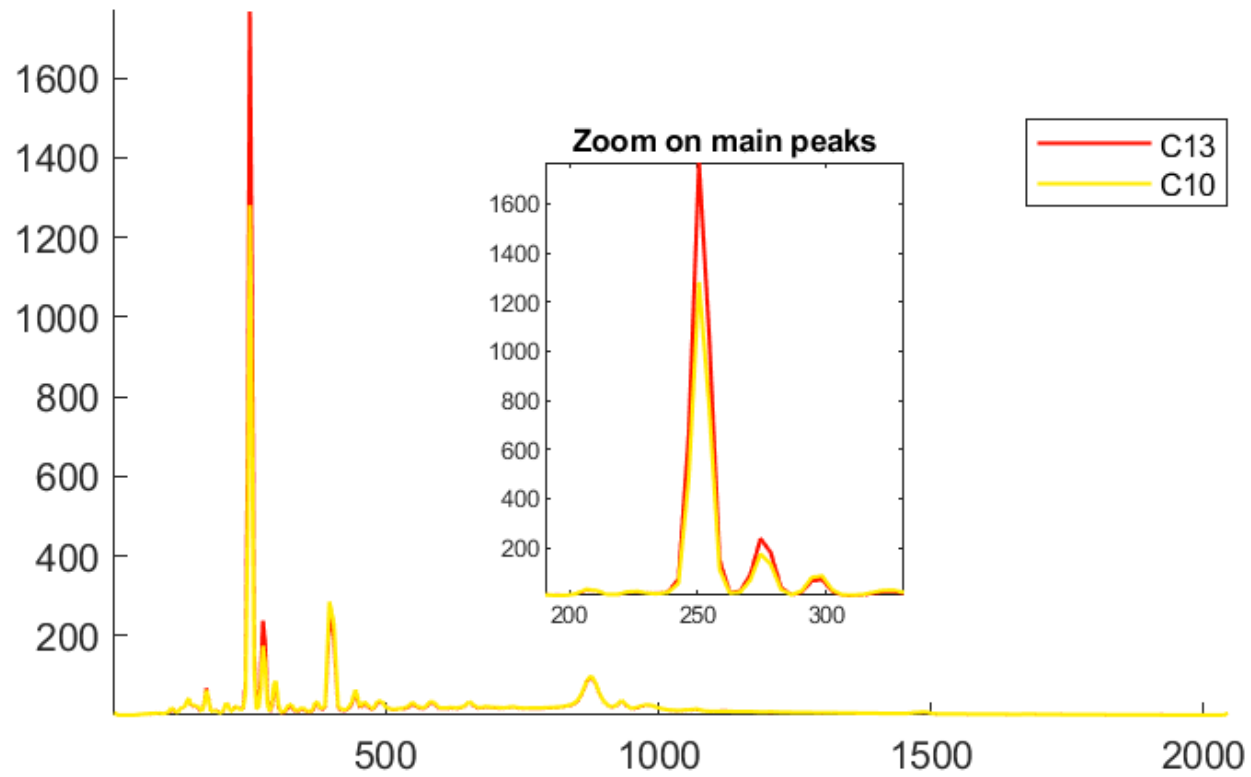


Results - first stage

Group 3 - Chrome

Cr +++

Cr ++



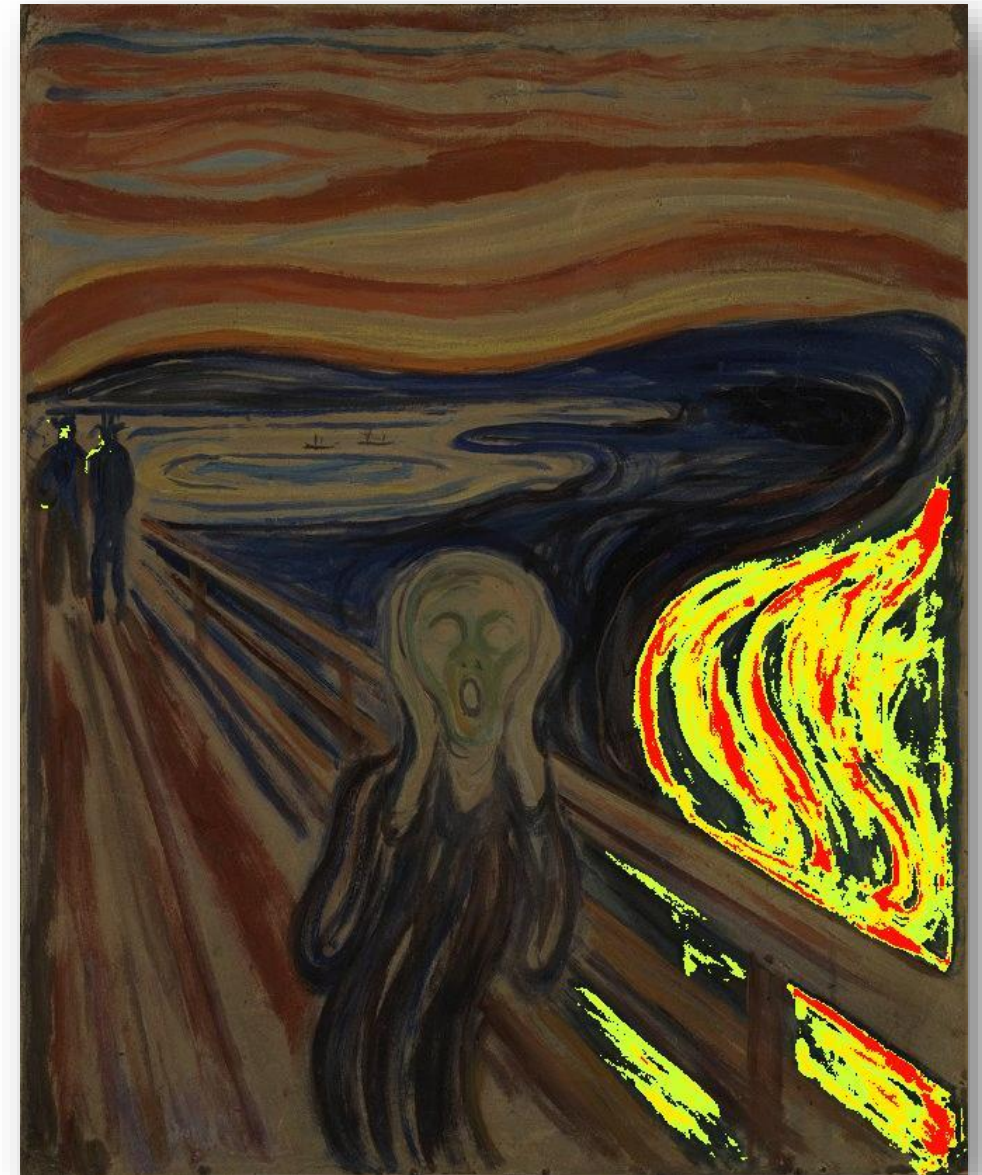
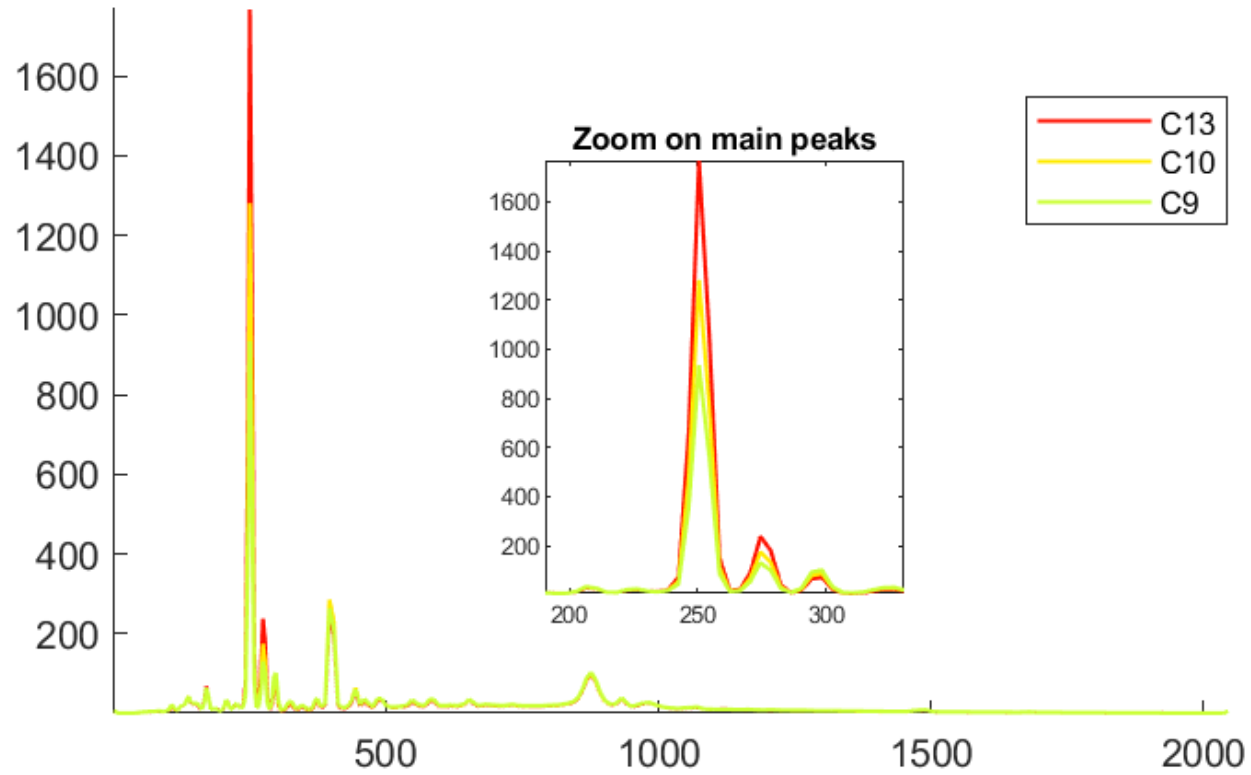
Results - first stage

Group 3 - Chrome

Cr +++

Cr ++

Cr +



Results - first stage

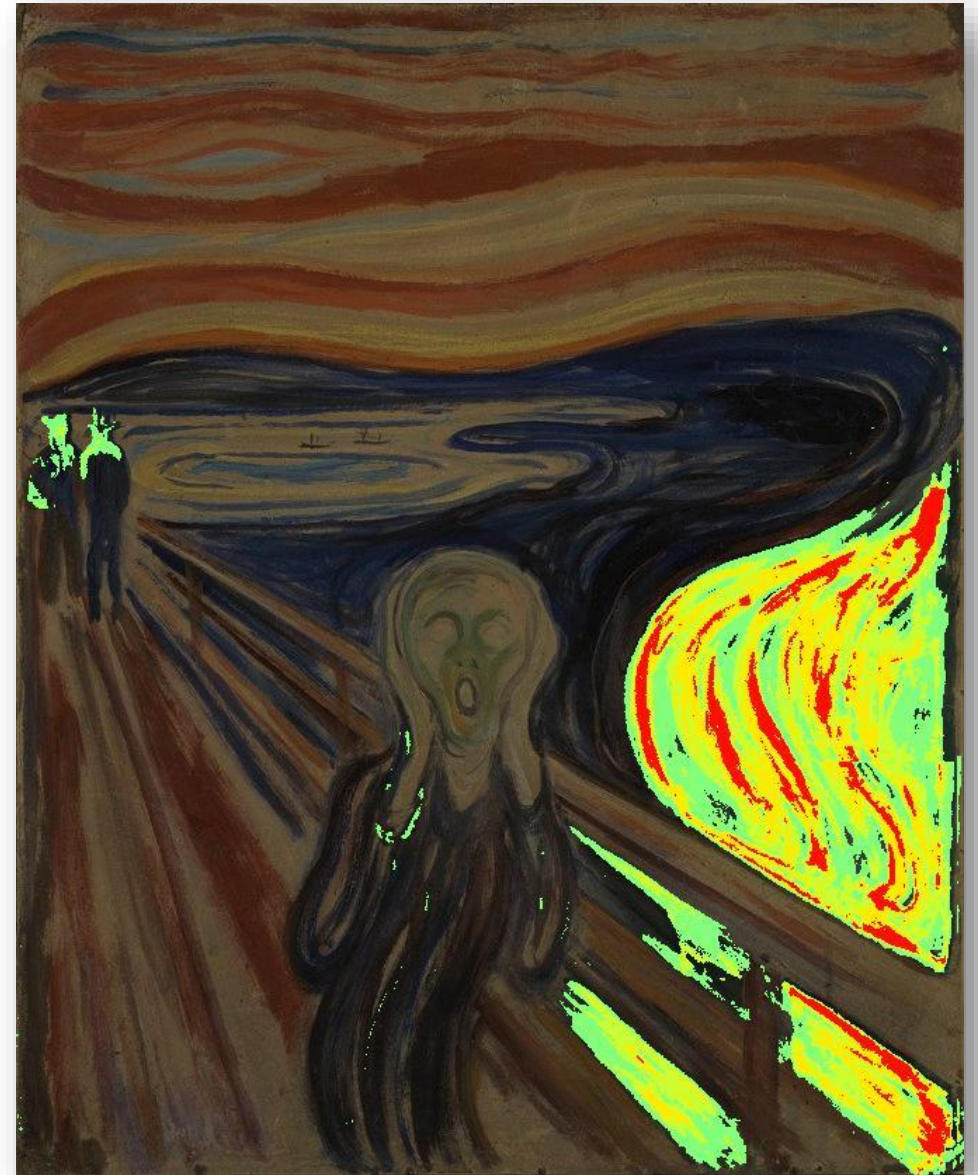
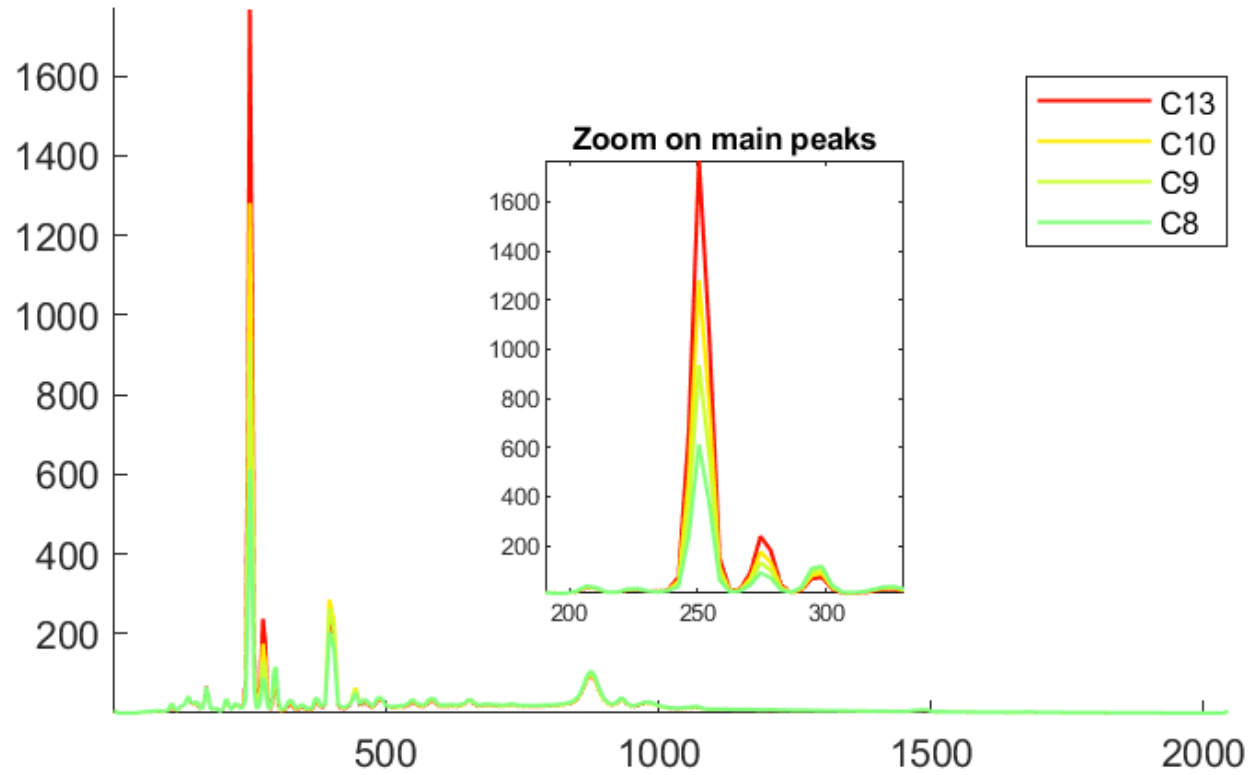
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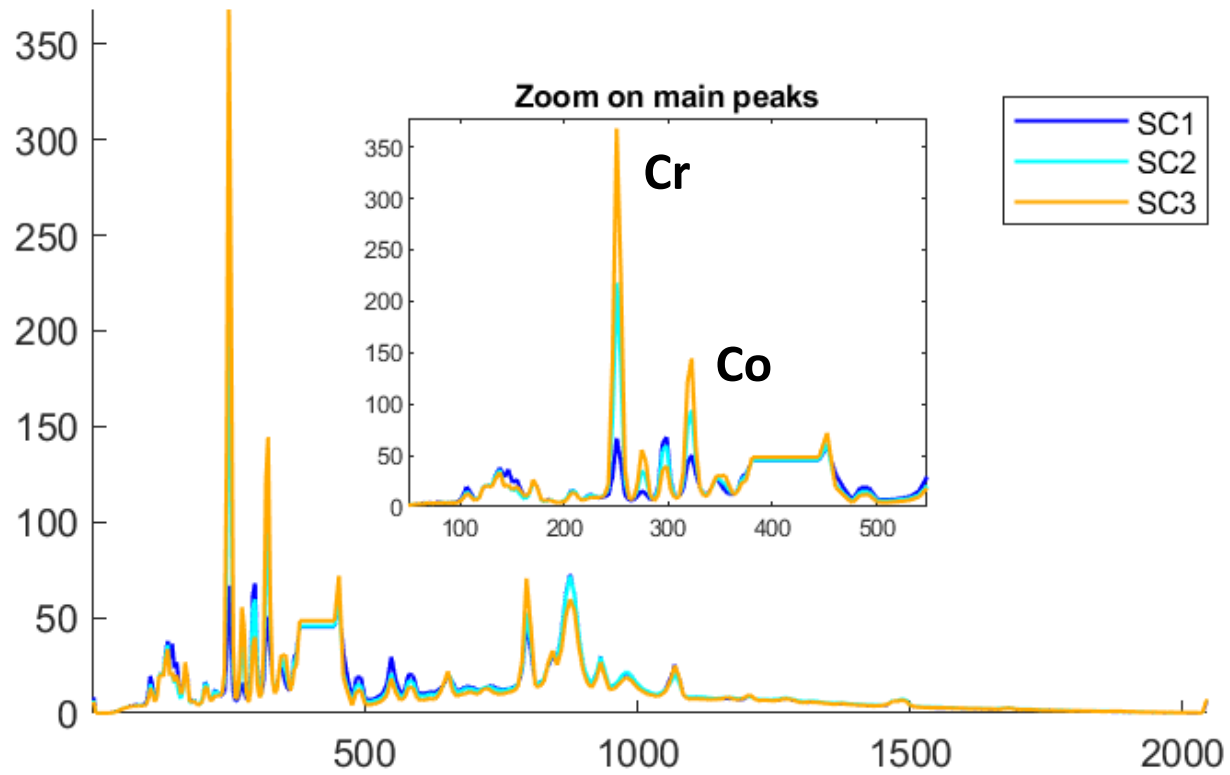
Cr +

Cr



Results - second stage

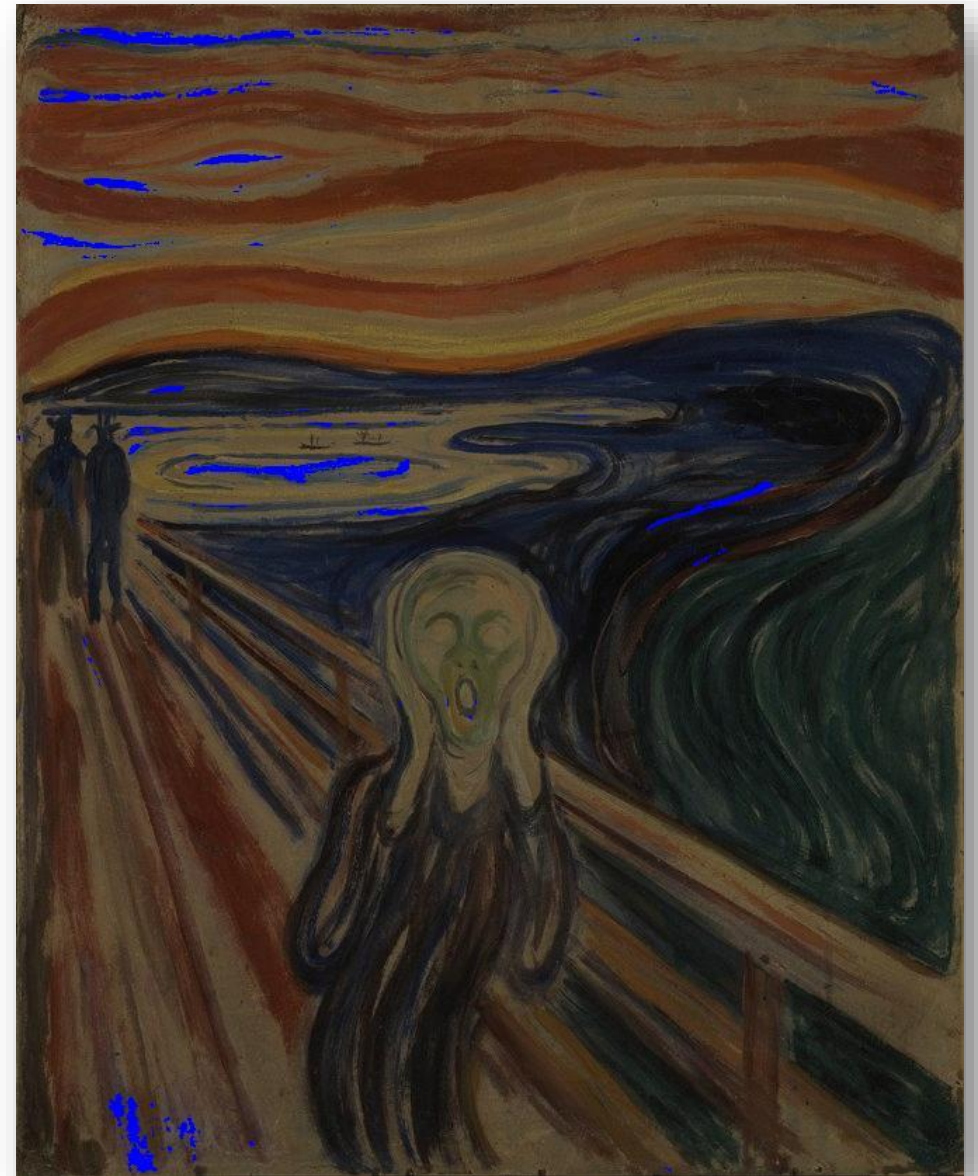
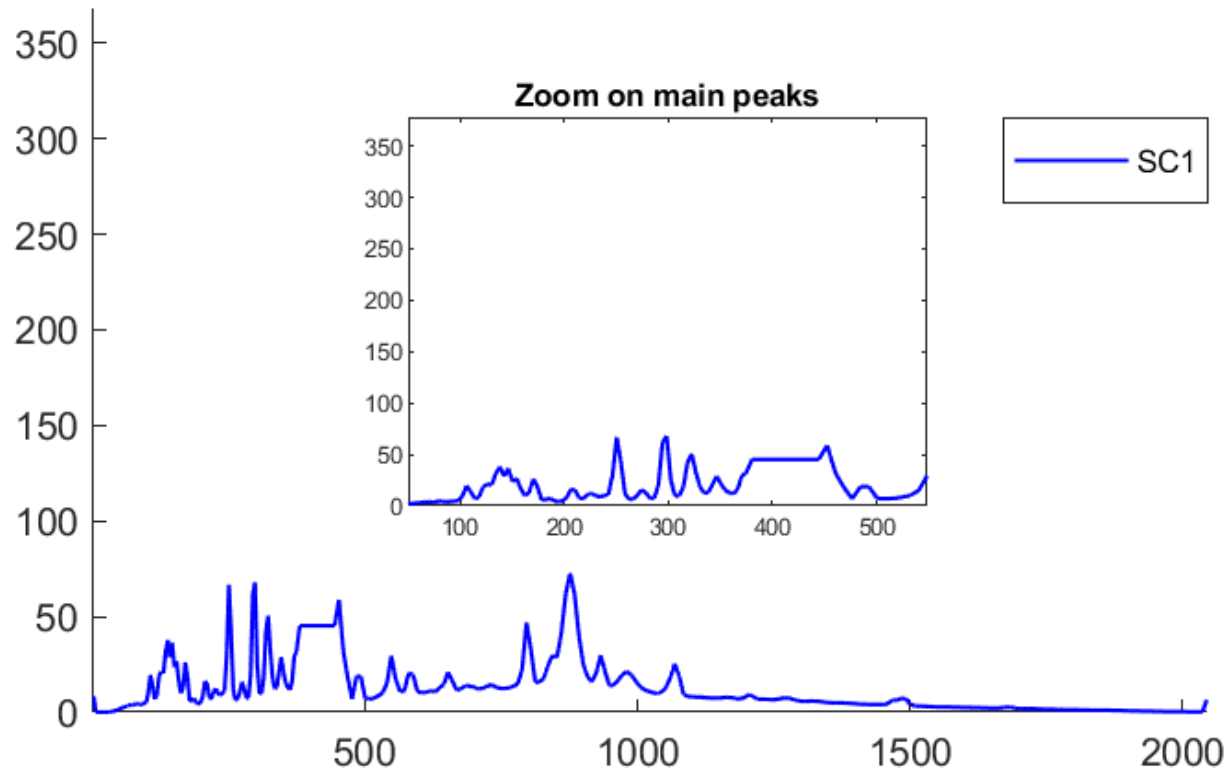
Subclasses of class 14



“pure” Zn

Results - second stage

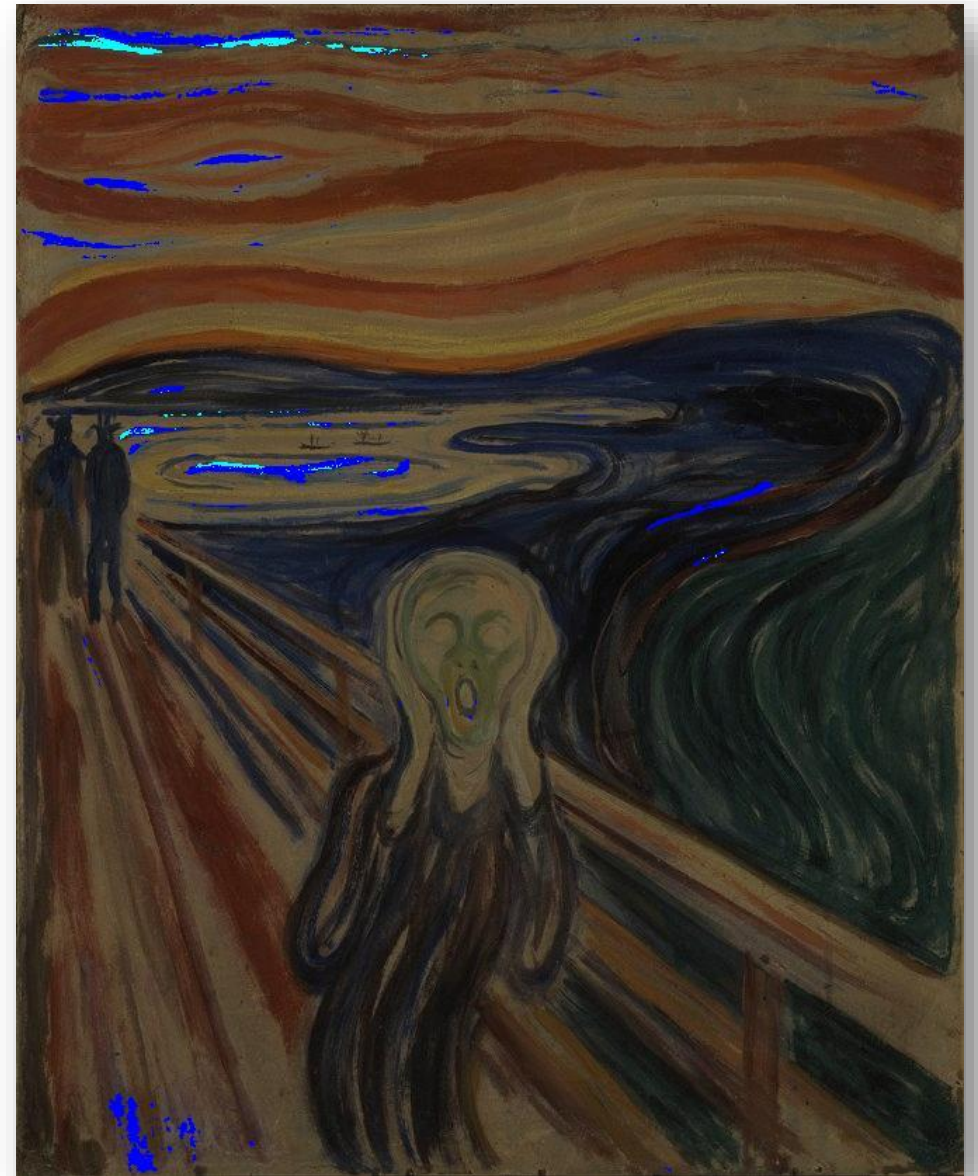
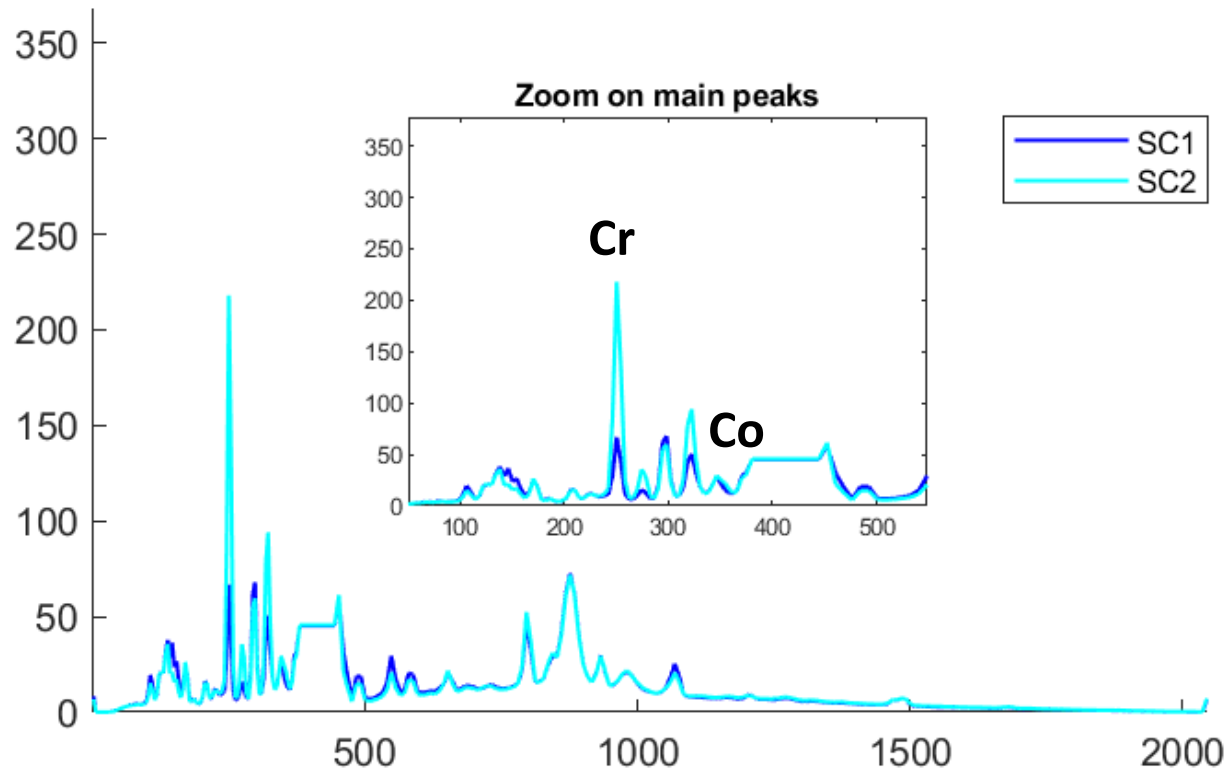
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Results - second stage

“pure” Zn
Zn - Cr - Co

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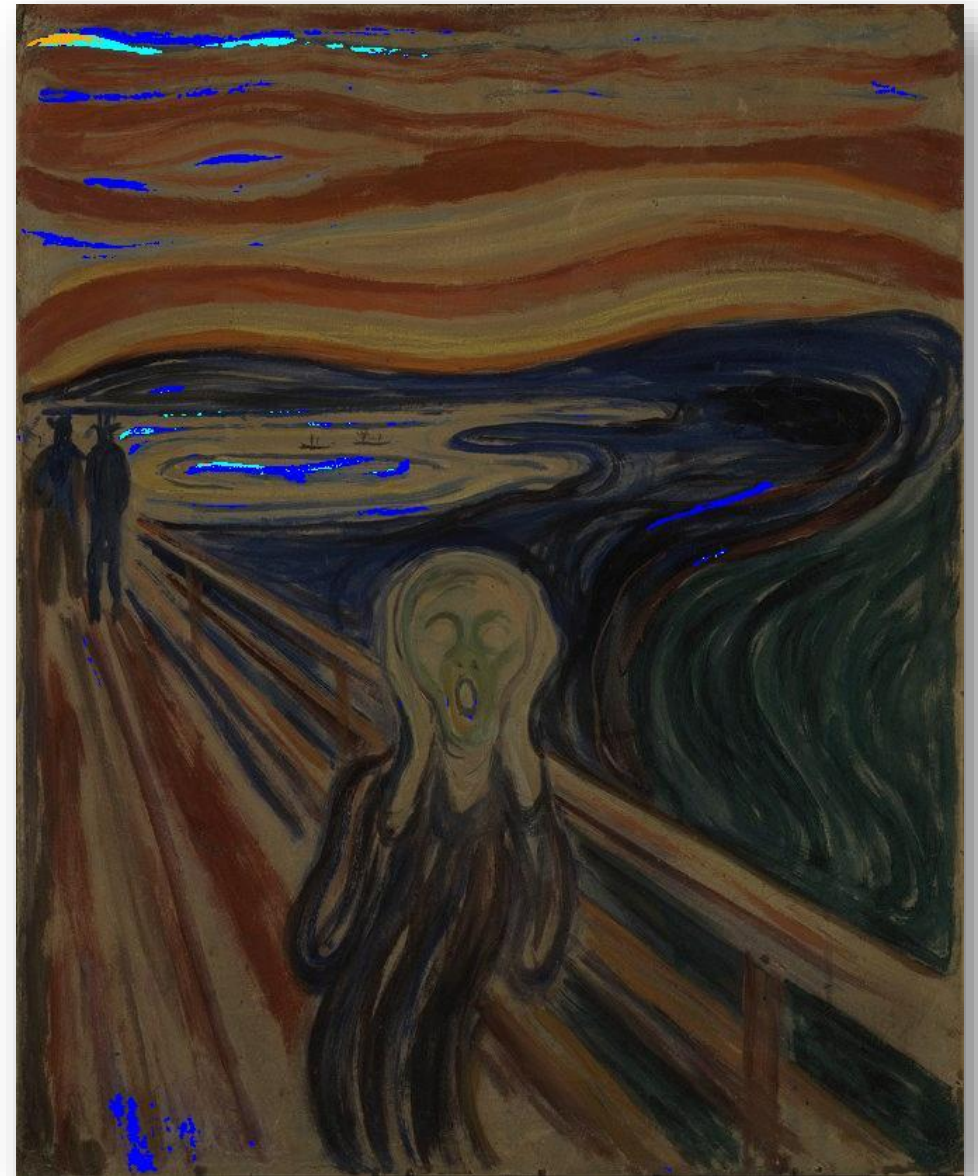
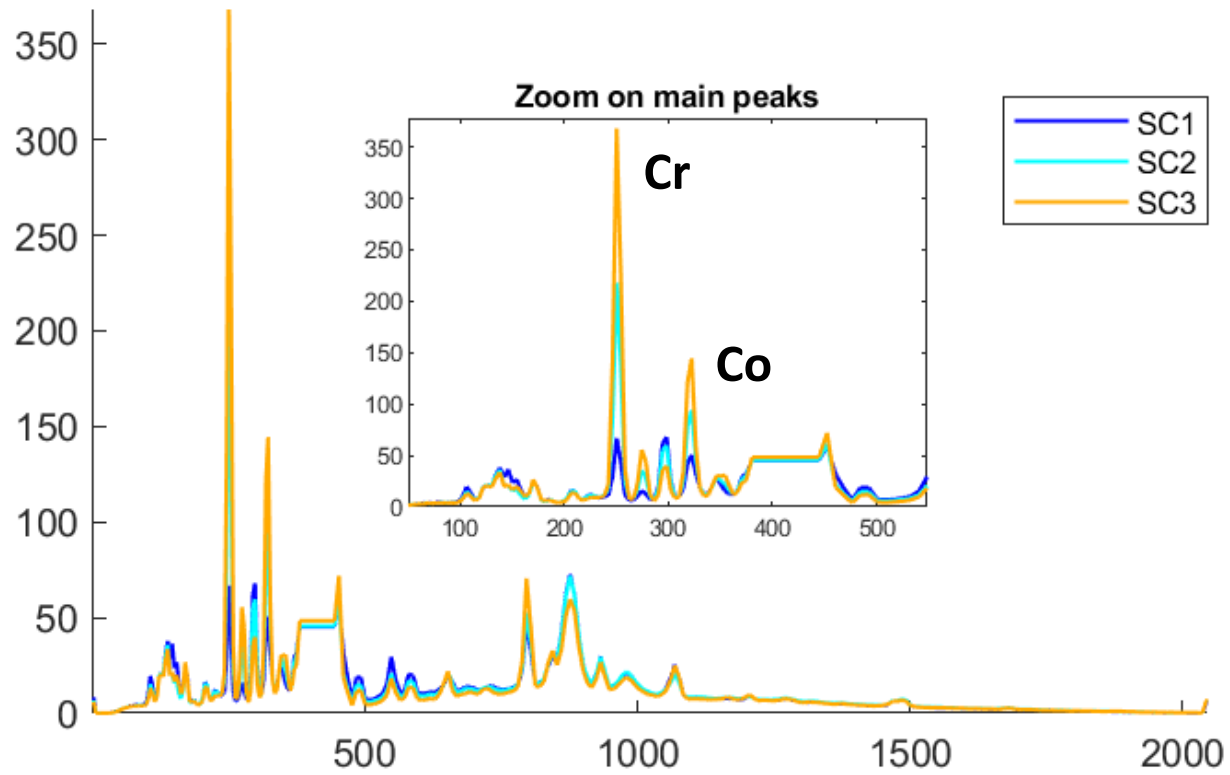
Results - second stage

“pure” Zn

Zn - Cr - Co

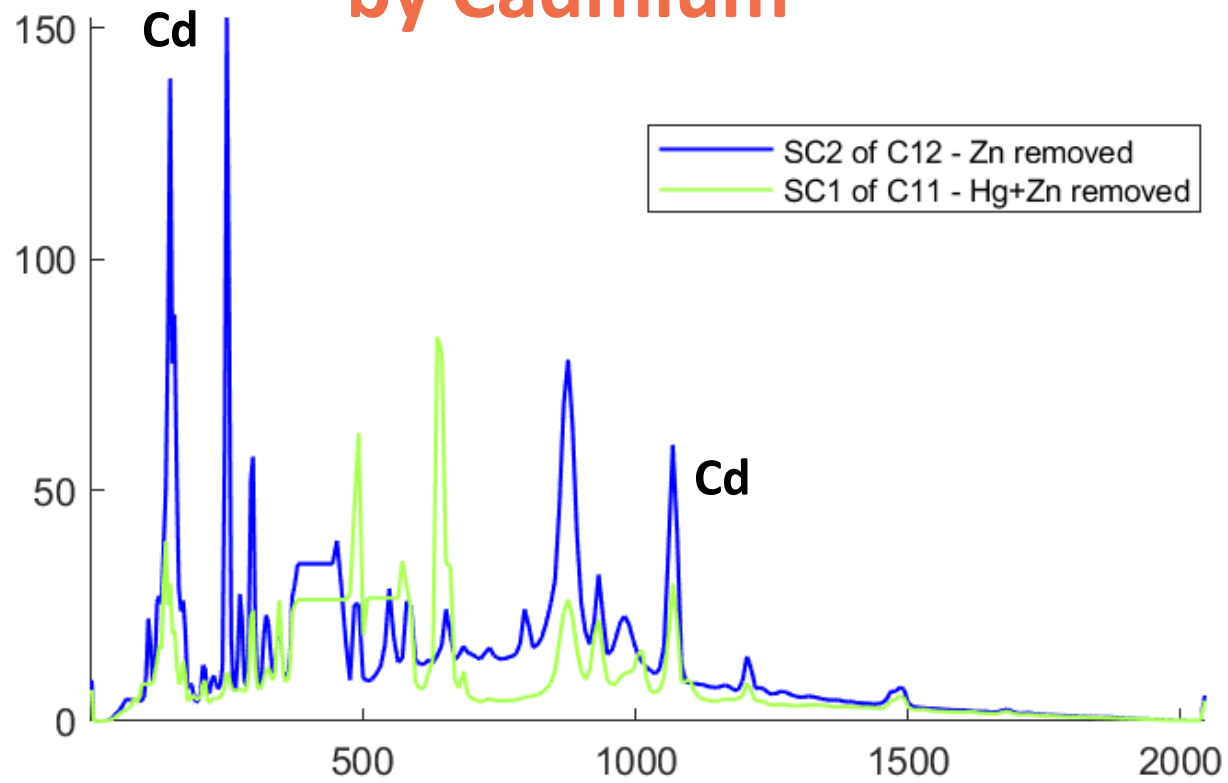
Zn - Cr - Co +

Subclasses of class 14



Results - second stage

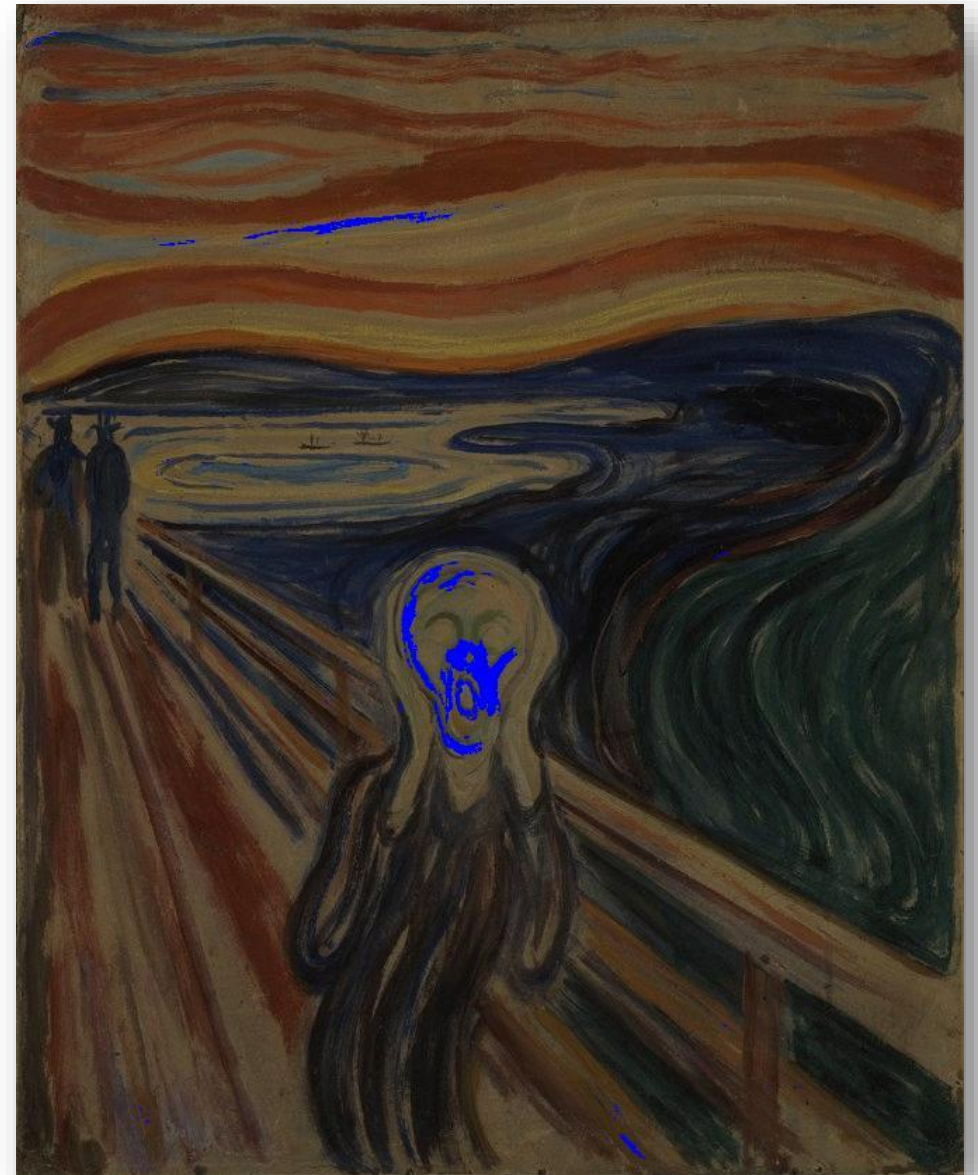
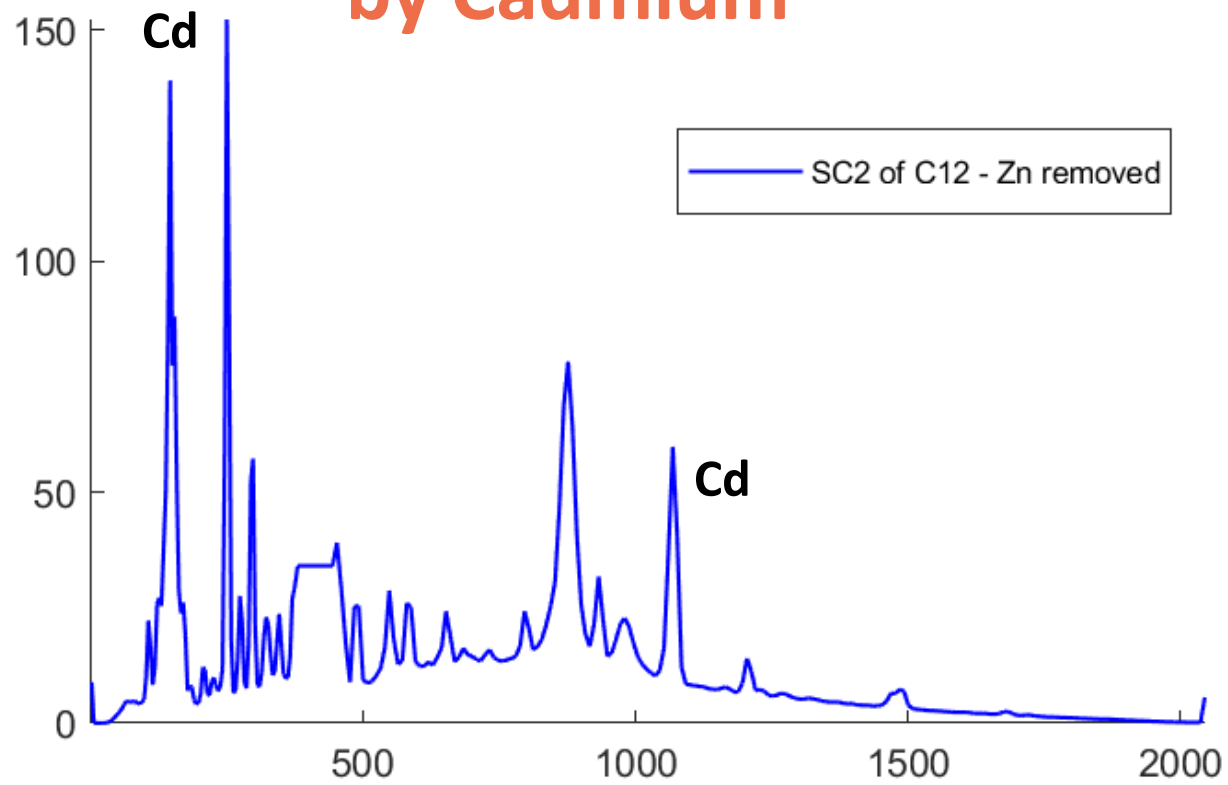
Subclasses weighted by Cadmium



Zn - Cd

Results - second stage

Subclasses weighted
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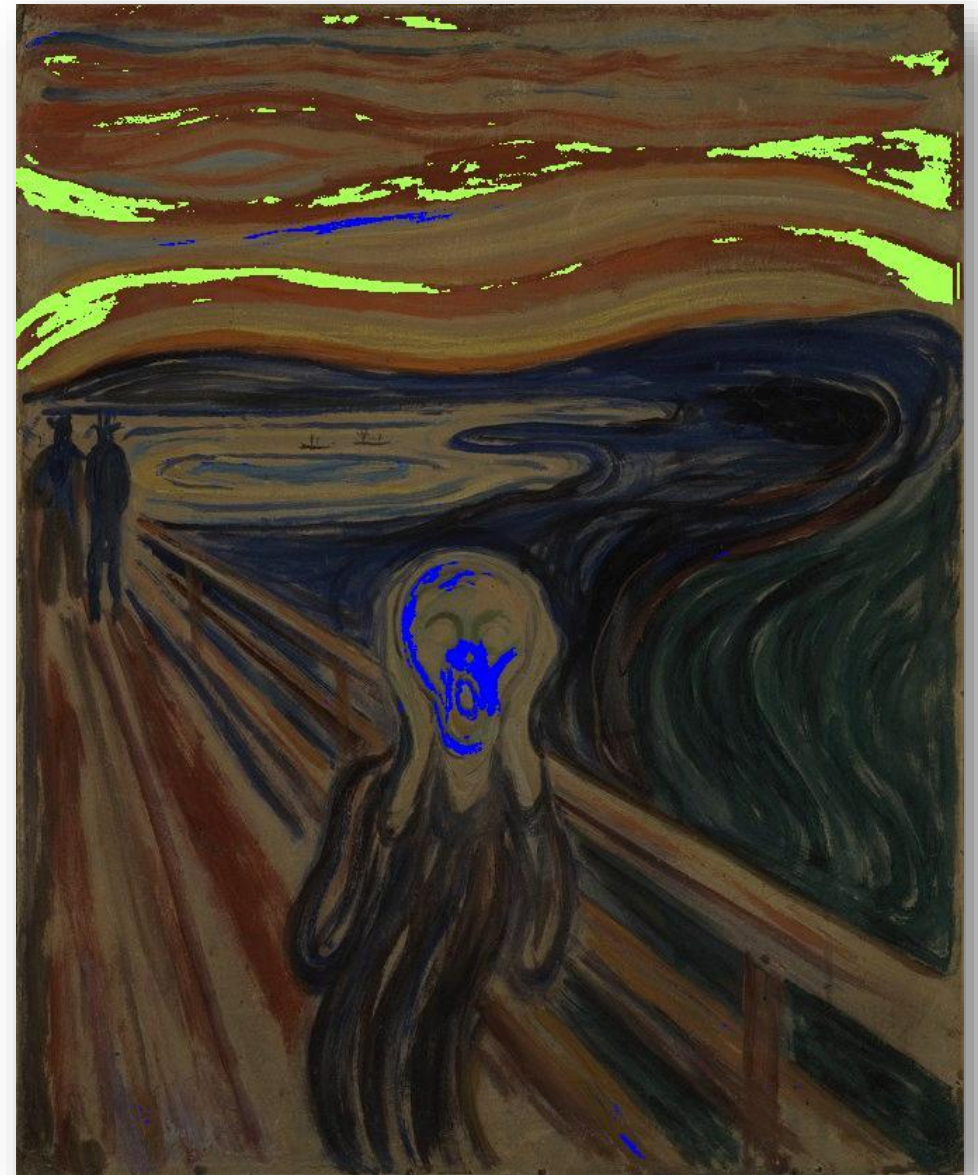
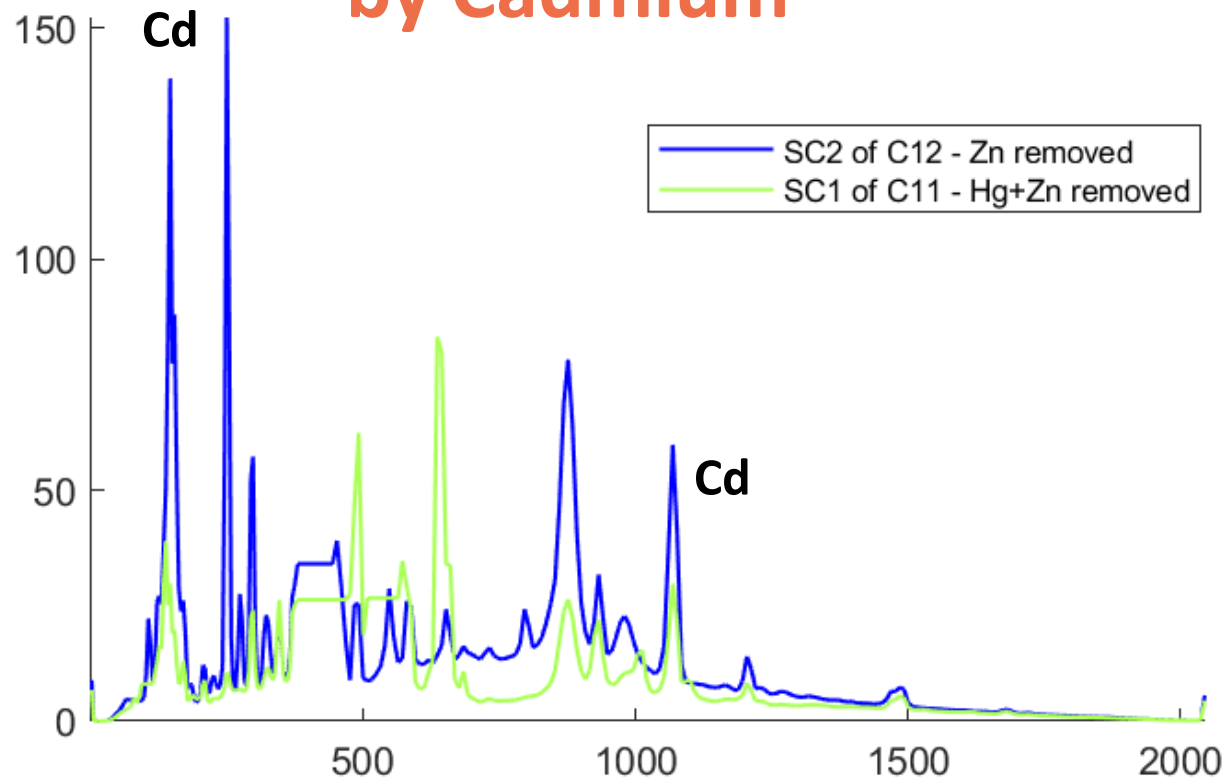


Results - second stage

Zn - Cd

Hg - Zn - Cd

Subclasses weighted
by Cadmium



Conclusions

FIRST STAGE OF FCM-BASED ANALYSIS:

Classification of the elements' distribution into four main groups:

Zn – Hg – Cr – low signals

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ADVANTAGES:

- Highlighting of important details
- Clarification of paint mixtures and of relations among main pigments
- Correlation between main and minor elements

Future perspectives

AUTOMATIZATION of grouping operation

- For each class C_i , identify p_i position of the main peak;
- Let $p_j, j = 1, \dots, K$, be the distinct positions identified; include in the group G_j all classes whose main peak falls at position p_j .

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→ More robustness w.r.t. the initial choice of the number of clusters

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FURTHER REFINEMENT

- More appropriate similarity metrics or nonlinear operators
- Employing a soft clustering approach
 - > more sensitivity
 - > increased capability of emphasizing relationship between non-predominant elements

Thank you
for your attention!