

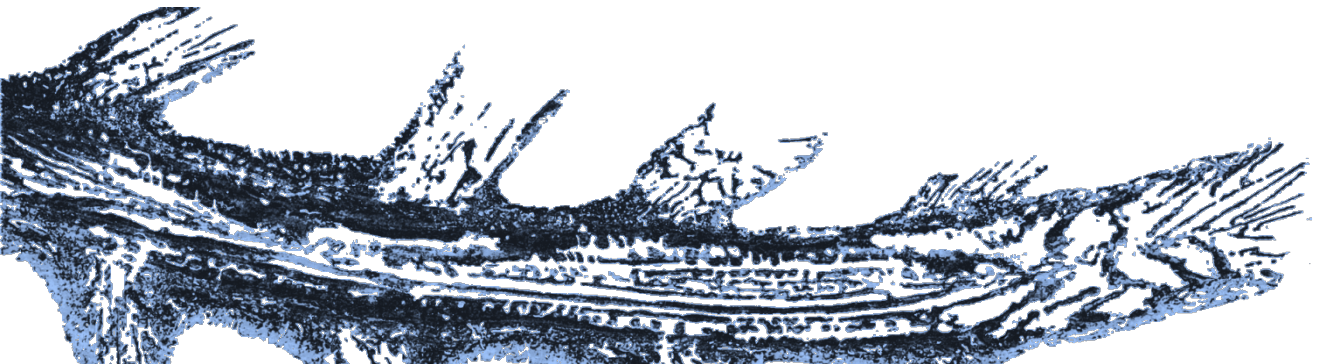
L'imagerie LIBS hyper « mega » spectrale couplée à l'IA : un fort potentiel analytique !

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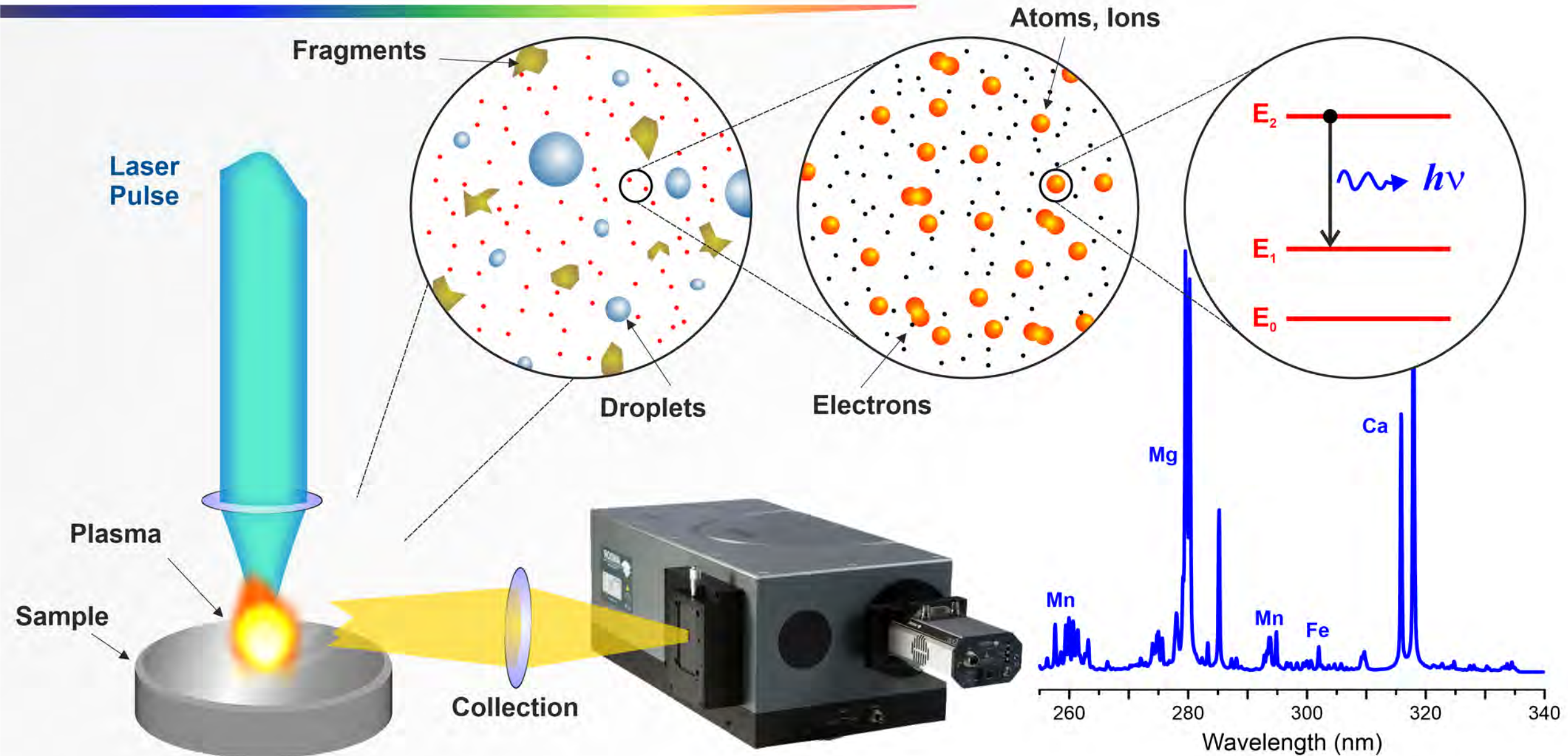
²*Ablatom SAS, 10 Rue Ada Byron, 69622 Villeurbanne, France*



GDR Groupement
de recherche
EMILI Étude des milieux ionisés
Plasmas froids créés par décharge
et laser

Laser-Induced Breakdown Spectroscopy (LIBS)

Principle



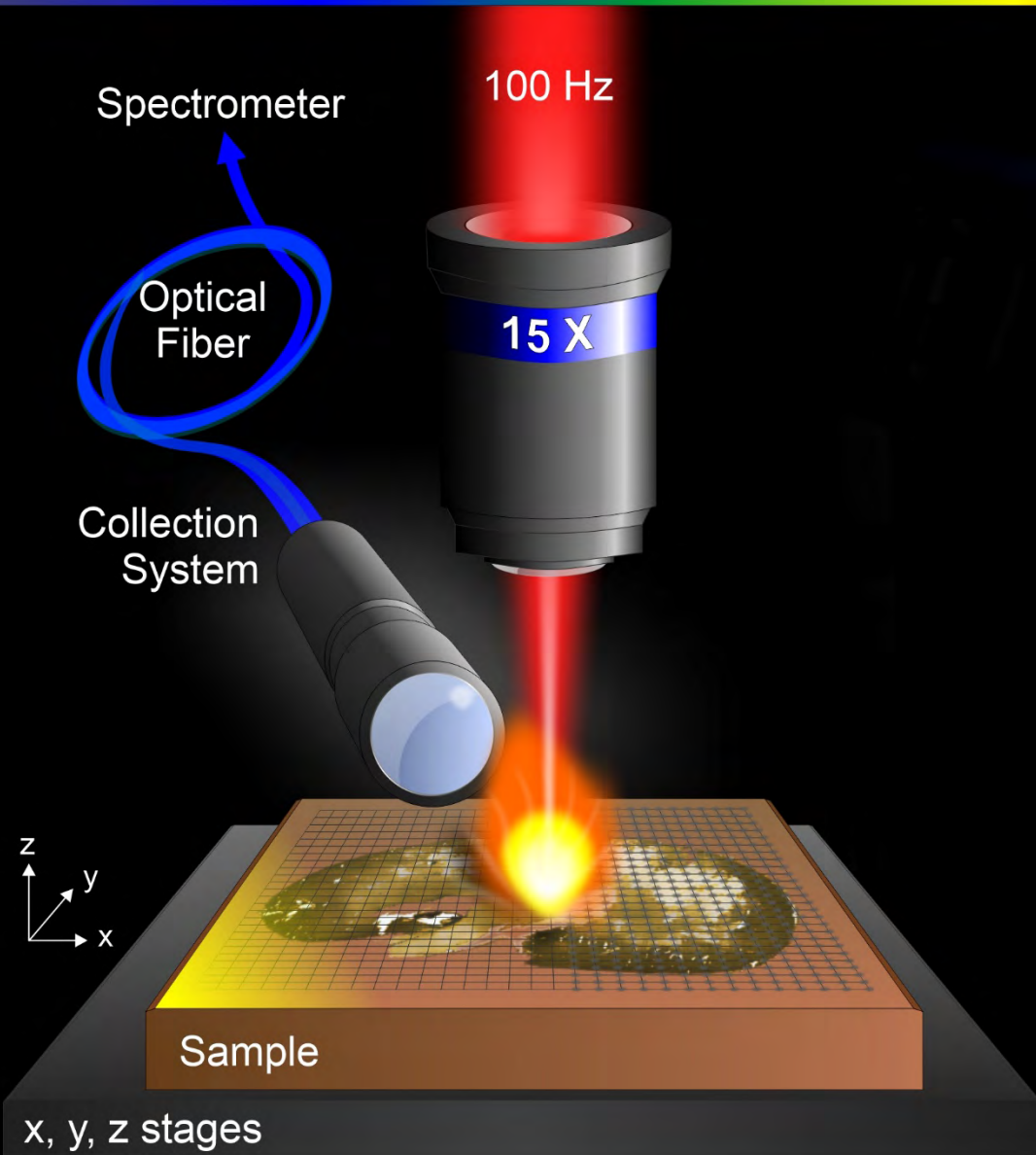
Outline

1. LIBS-based imaging
Principle & Instrumentation
2. Specificities and Data Processing
The good and not so good
3. Application of the ANN
Archeological Mortar Characterization
4. Perspectives



LIBS-based imaging

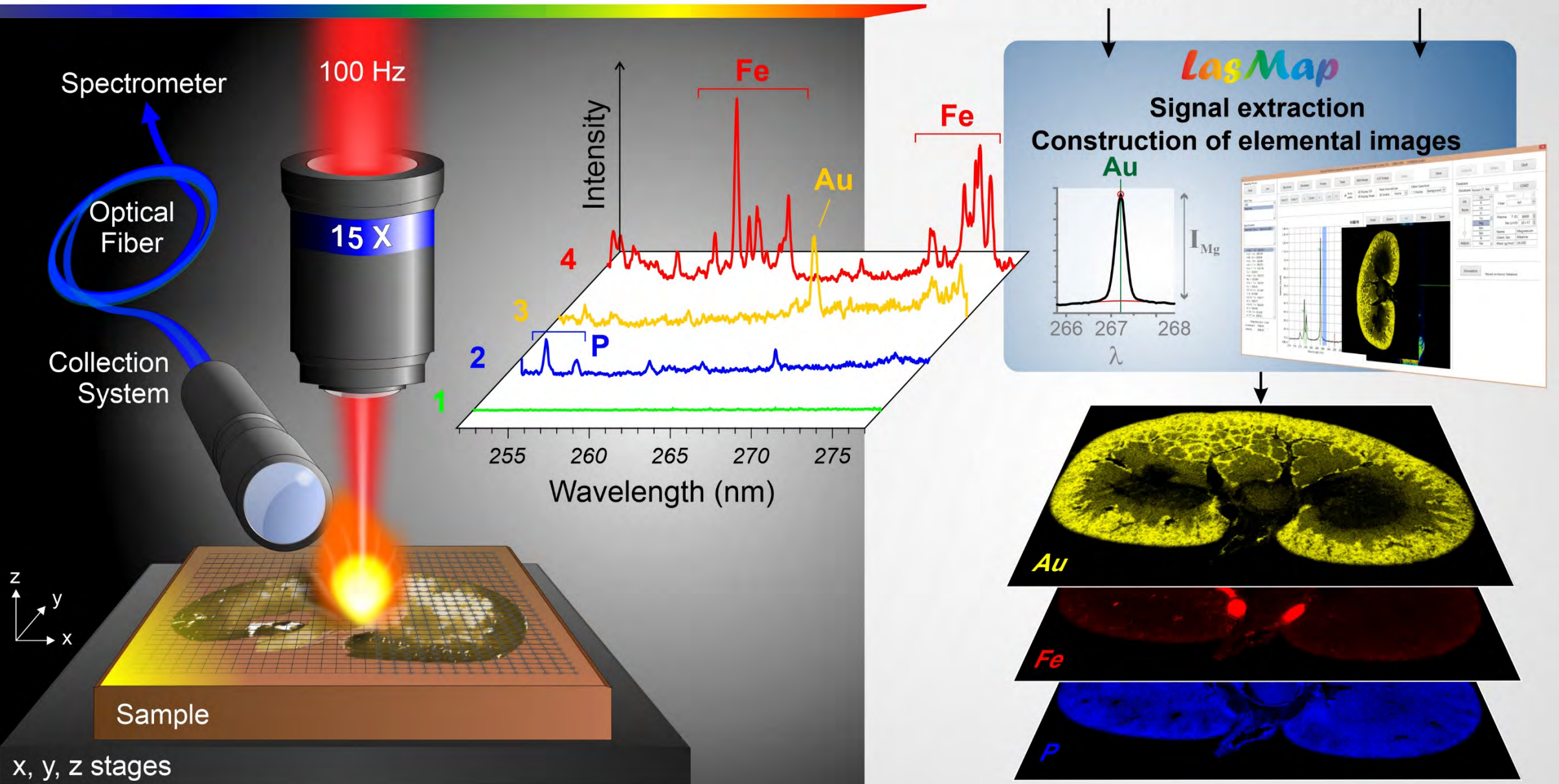
Principle



L. Jolivet, M. Leprince, S. Moncayo, L. Sorbier, et al. SAB 2019 (Review)
V. Gardette, V. Motto-Ros, C. Alvarez-Llomas, et al. Anal. Chem. 2023 (Review)

LIBS-based imaging

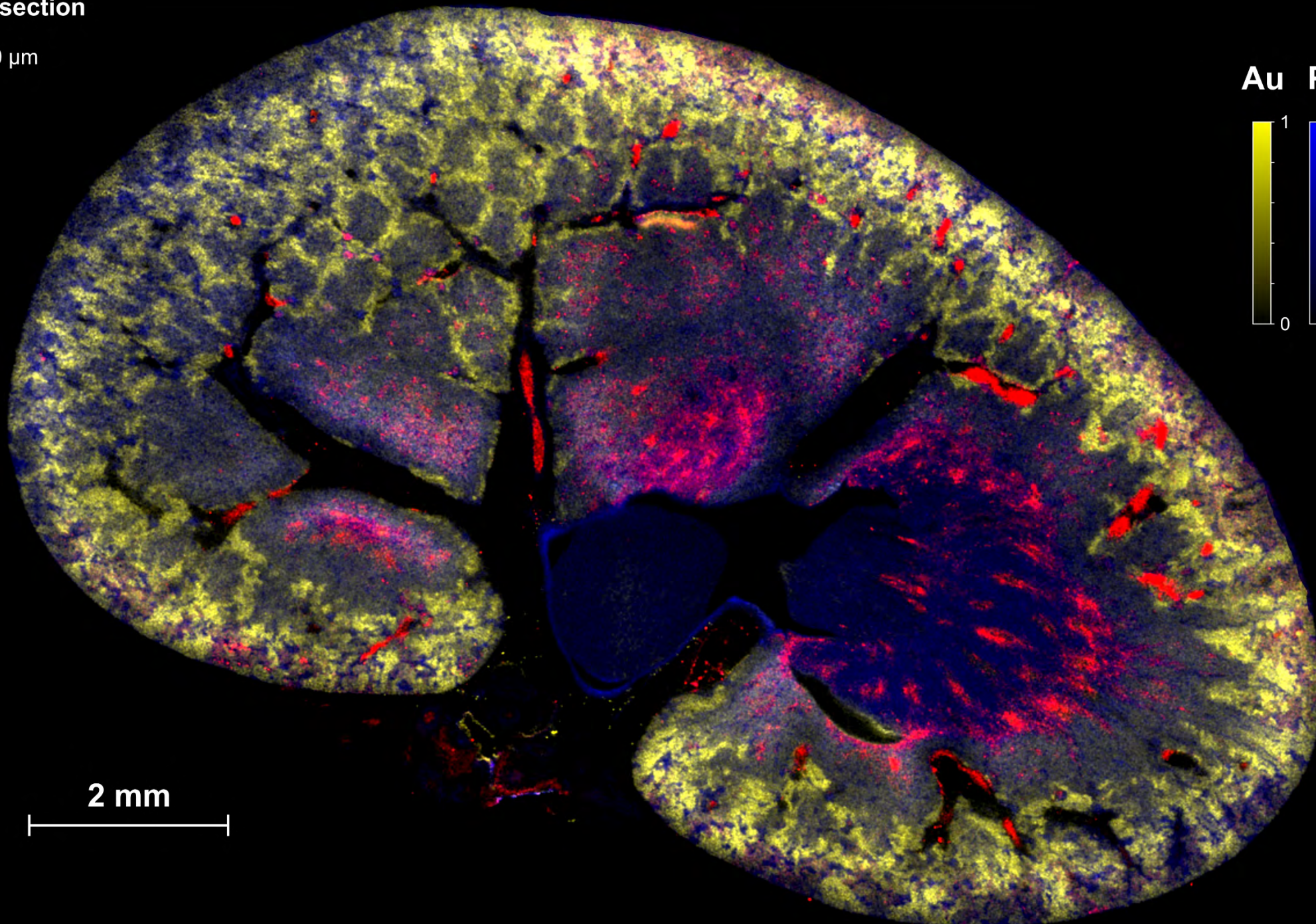
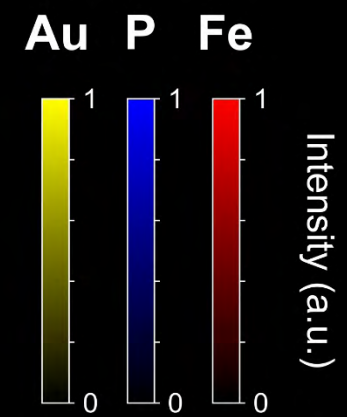
Principle



Rat kidney section

2 megapixels

Resolution: 10 μm

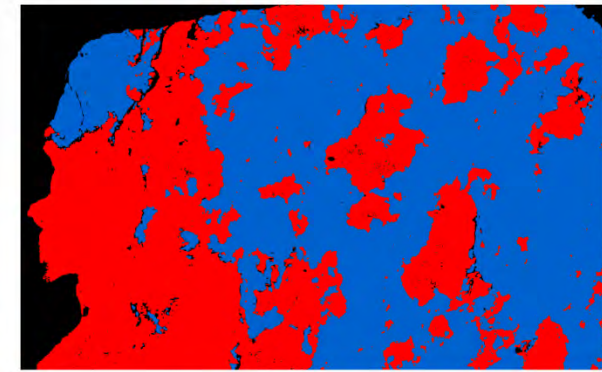
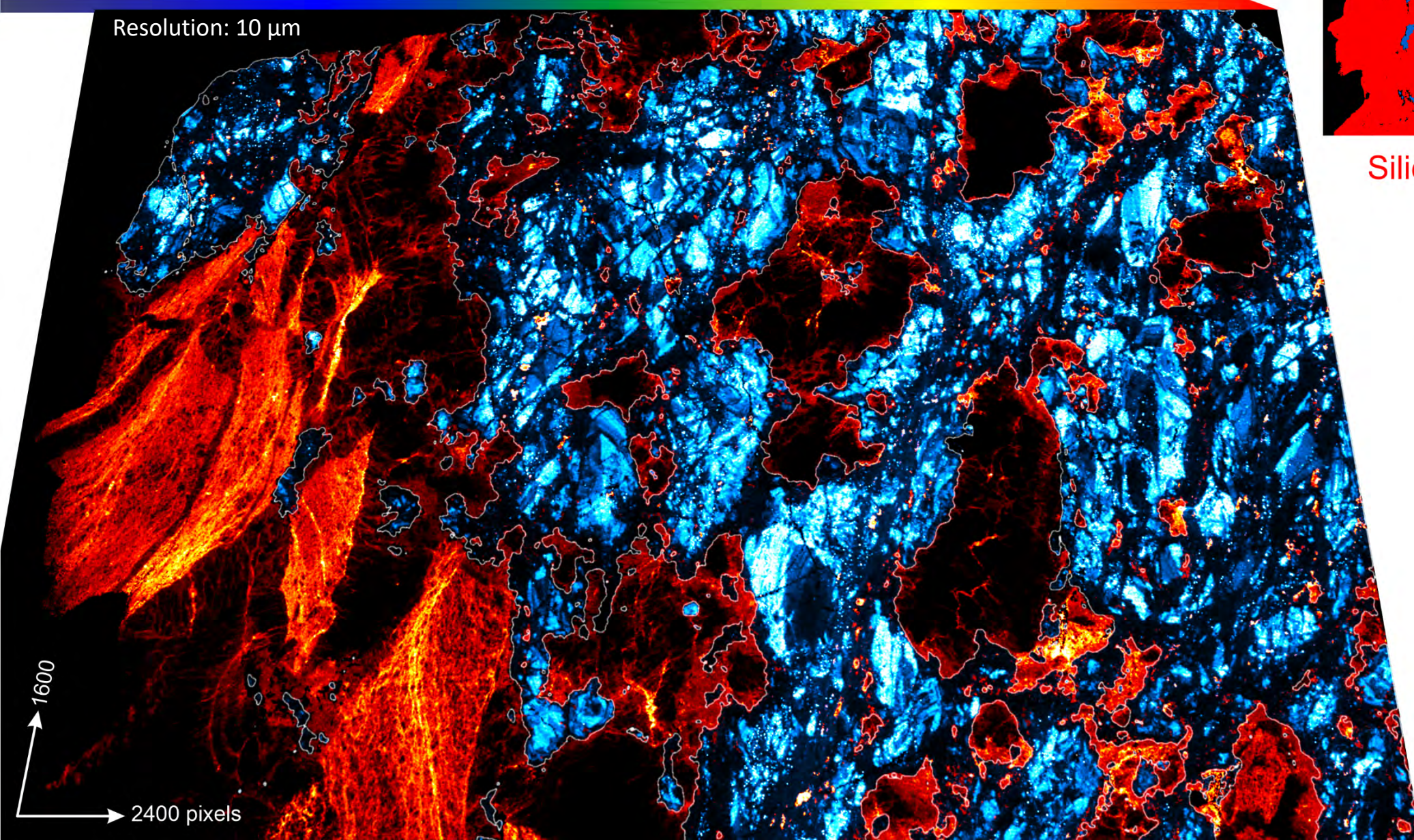


2 mm

LIBS imaging

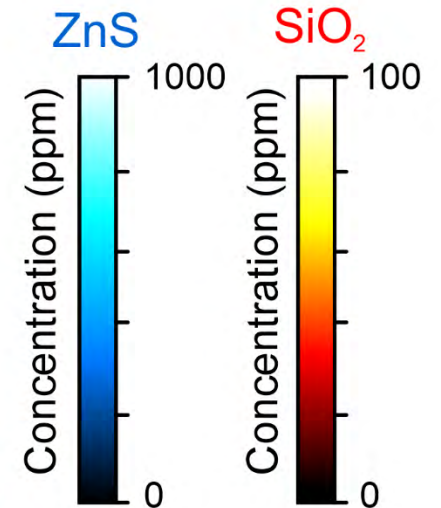
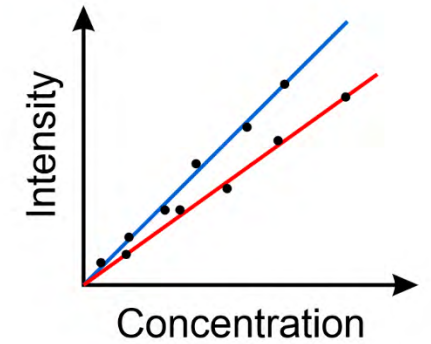
An example with a mine ore: Ge

A. Cugerone *et al.* *Geology* 48 (2019)



Silicate

Sphalerite



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Issues with Data Processing

Generalities

Emission Spectroscopy

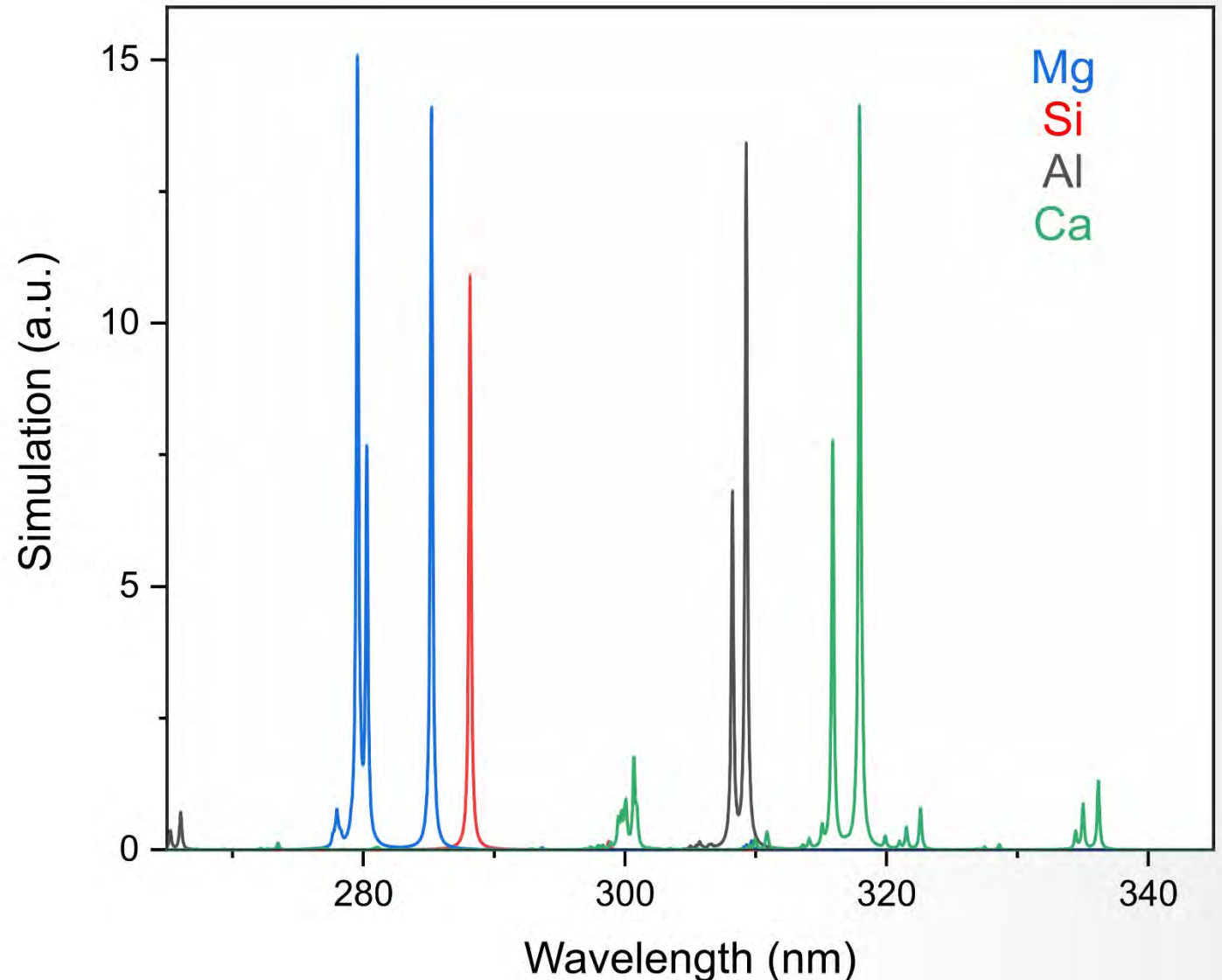
Complex spectral structure

Some elements have a very dense emission spectrum with thousands of lines (Ti, Fe, etc...)

High sample heterogeneity

By principle the aim in LIBS imaging is to reveal the heterogeneity of elements

Kurucz simulation $T_e = 9000\text{K}$, $N_e = 5.10^{17} / \text{cm}^3$



Issues with Data Processing

Generalities

Emission Spectroscopy

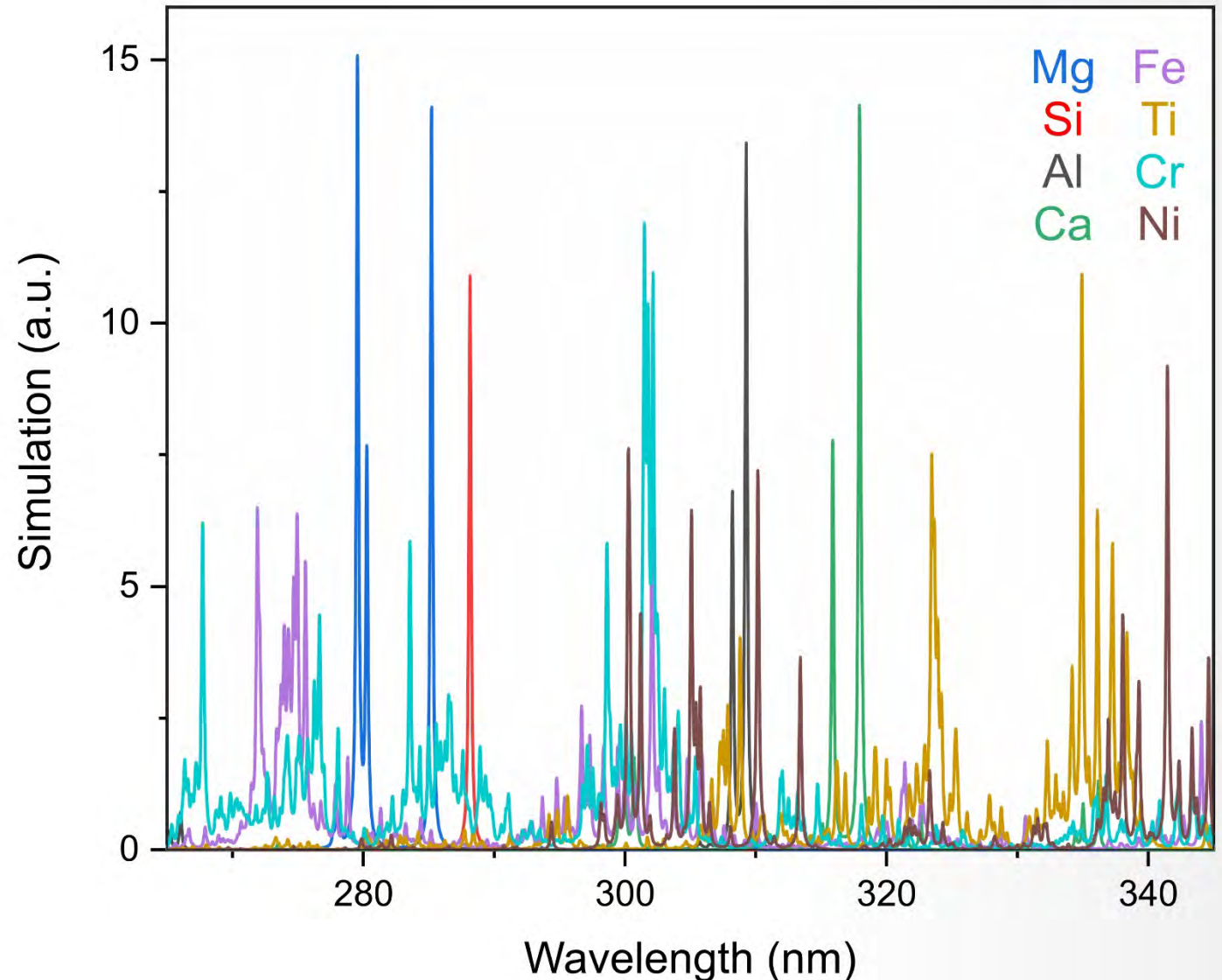
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Issues with Data Processing

Generalities

Emission Spectroscopy

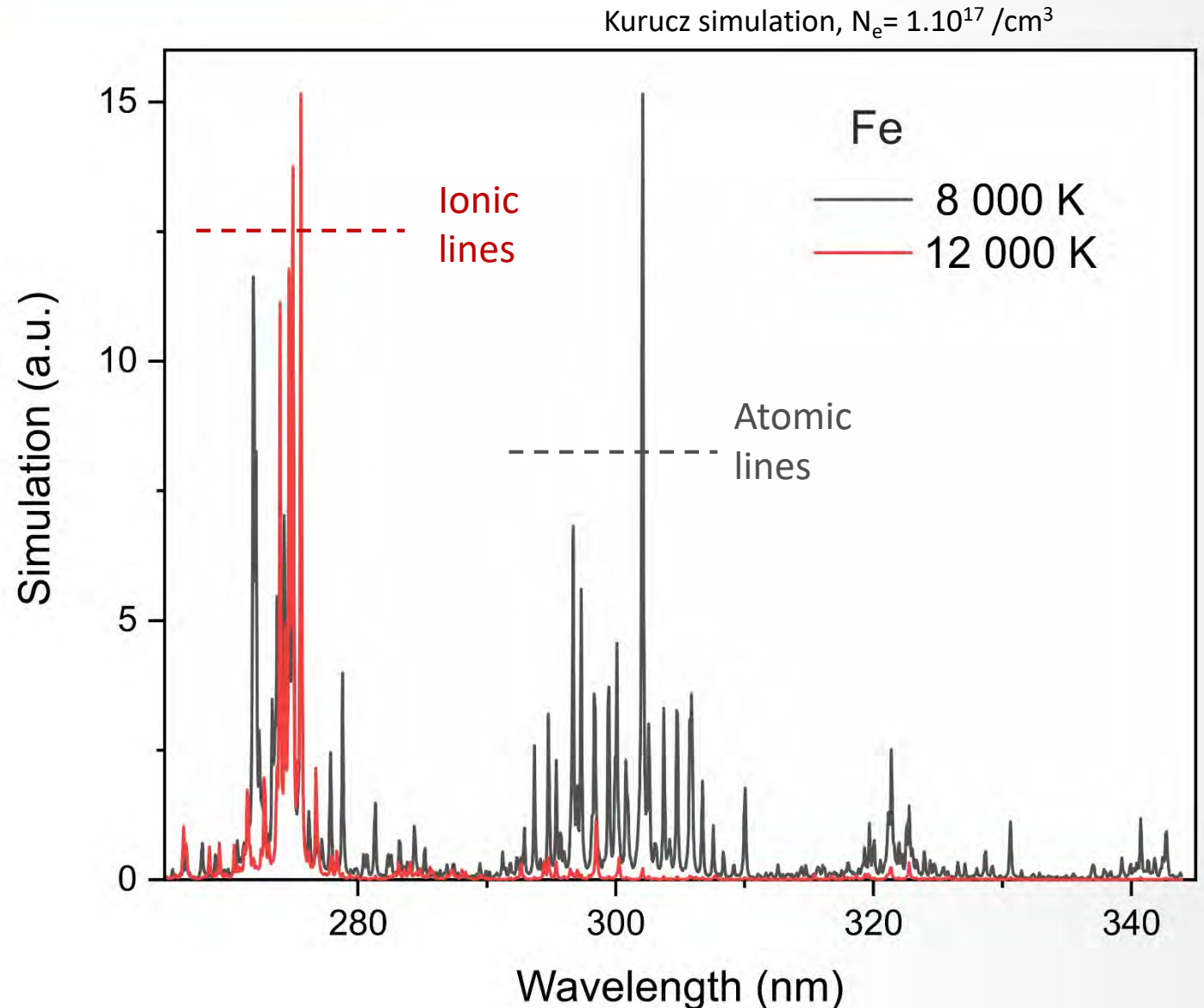
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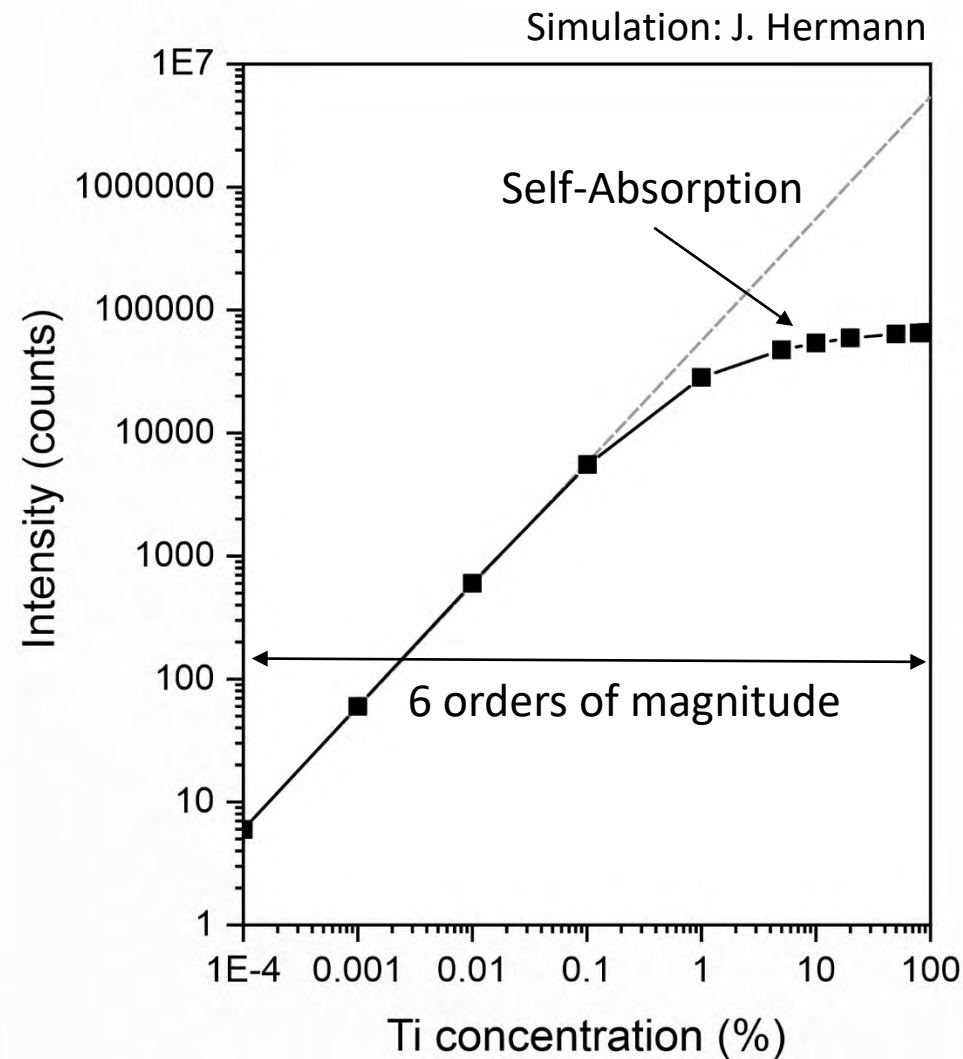
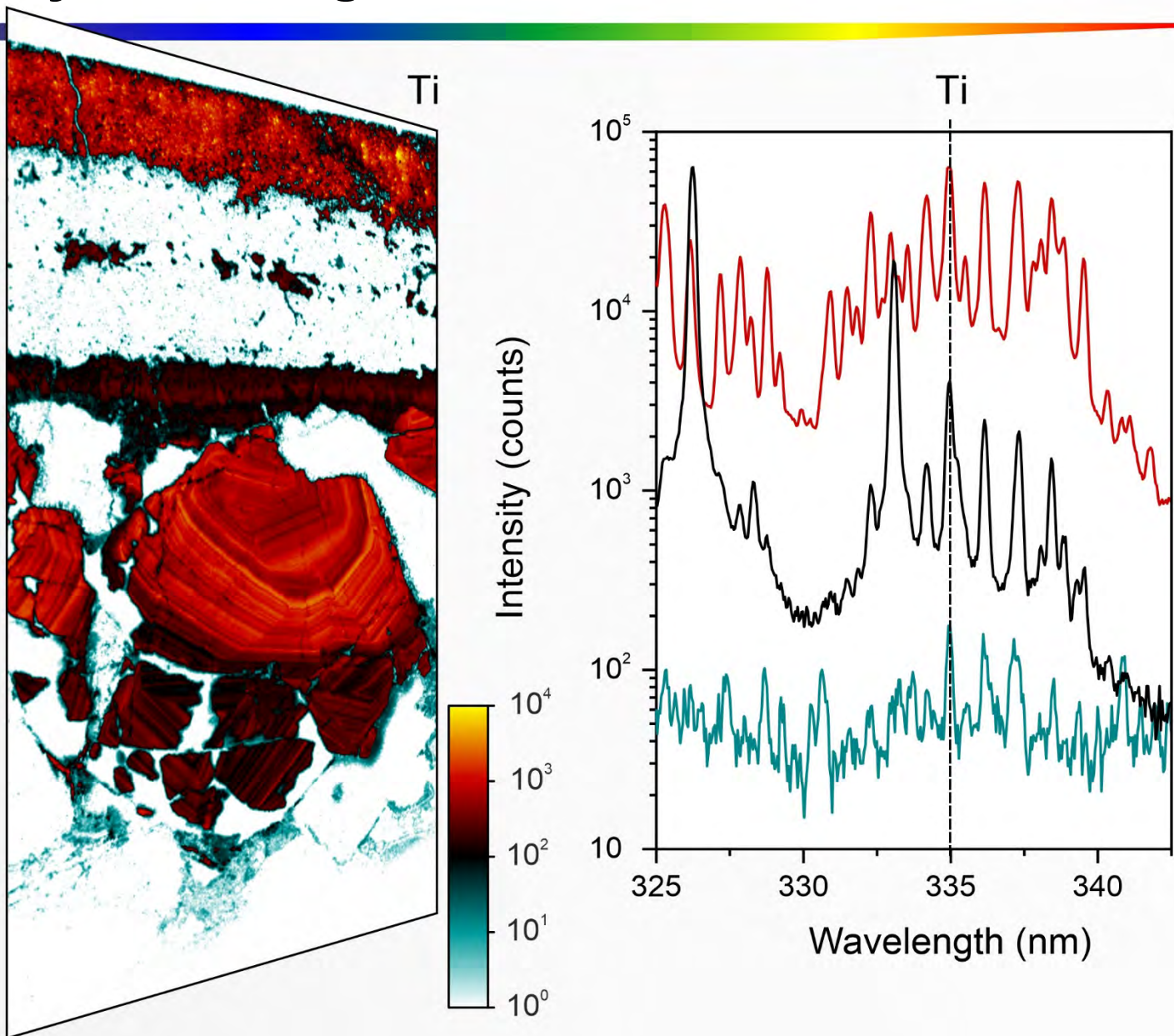
By principle the aim in LIBS imaging is to reveal the heterogeneity of elements

Dependence on plasma parameters



Issues with Data Processing

Dynamic range in “concentration”



Issues with Data Processing

To resume



Large Spectral Dataset

> millions of spectra

Up to 3 spectrometers (i.e. ~ 6000 wavelength channels)

Complexity of the Emission Spectra

Complex structure in wavelength (line interferences)

High dynamic range in intensity

Non linearity

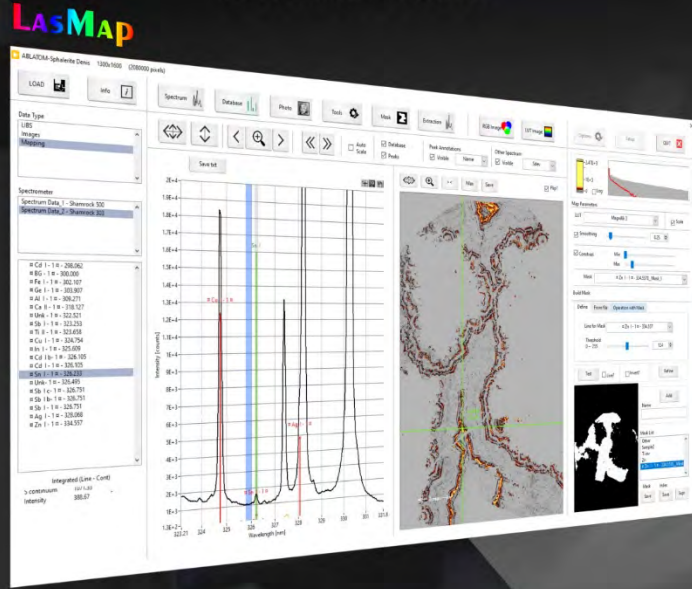
Plasma variability

Single shot analysis

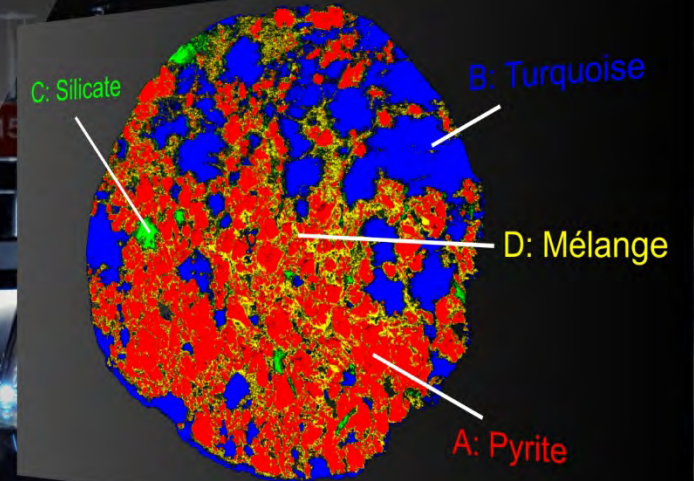
All the more
challenging as the
sample is complex

Data Processing

Méthodes Univariées



Méthodes Multivariées

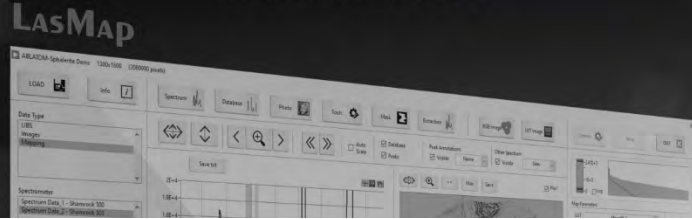


Vers un traitement automatisé?

- A. Nardecchia *et al.*, Anal. Chim. Act. (2021)
- A. Nardecchia *et al.*, Anal. Chim. Act. (2021)
- A. Nardecchia *et al.*, Anal. Chim. Act. (2020)
- V. Motto-Ros *et al.*, SAB (2019)
- S. Moncayo *et al.*, JAAS (2018)

Data Processing

Méthodes
Univariées



MITI

étape 1



**Caractérisation du mortier
archéologique**

Septembre 2021 - 36 Mois



UMR 5138
Archéologie et Archéométrie



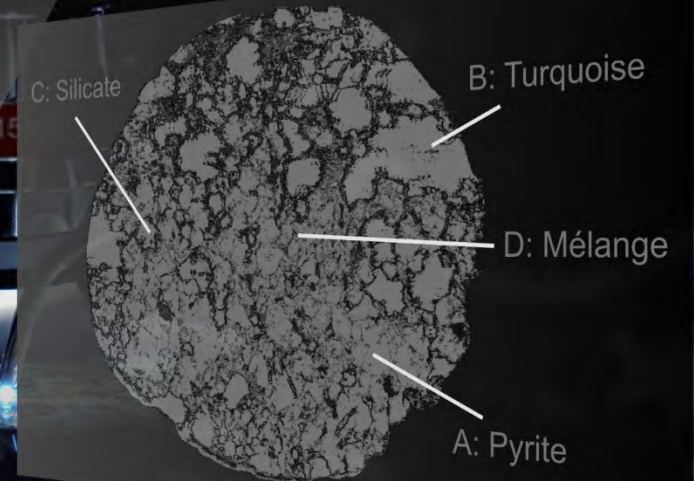
INSTITUT LUMIÈRE MATIÈRE

Intelligence
Artificielle



Vers un traitement
automatisé?

Méthodes
Multivariées



diAg-EM

étape 2



**Diagnostic médical par intelligence
artificielle appliquée à la microscopie LIBS
élémentaire**


Novembre 2020 - 42 Mois



EPIGENETICS
CHRONIC DISEASES
CANCER

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JAAS

ROYAL SOCIETY OF CHEMISTRY

PAPER

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View Journal

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Cite this: DOI: 10.1039/d2ja00389a

Artificial neural network for high-throughput spectral data processing in LIBS imaging: application to archaeological mortar†

N. Herreyre,^{ab} A. Cormier,^a S. Hermelin,^a C. Oberlin,^b A. Schmitt,^b V. Thirion-Merle,^b A. Borlenghi,^b D. Prigent,^c C. Coquidé,^{bd} A. Valois,^d C. Dujardin,^a P. Dugourd,^a L. Duponchel,^e C. Comby-Zerbino^{*a} and V. Motto-Ros^{id,*a}

With the development of micro-LIBS imaging, the ever-increasing size of datasets (sometimes >1 million spectra) makes the processing of spectral data difficult and time consuming. Advanced statistical methods have become necessary to process these data, but most of them still require strong expertise and are not adapted to fast data treatment or a high throughput analysis. To address these issues, we evaluate, in the present work, the use of an artificial neural network (ANN) for LIBS imaging spectral data processing for the identification of different mineral phases in archaeological lime mortar. Common in ancient architecture, this building material is a complex mixture of lime with one or more aggregates, some components of which are of the same chemical nature (e.g. calcium carbonates). In this study, we trained an artificial neural network (ANN) for automatic detection of different phases in these complex samples. The training of such a predictive model was made possible by building a LIBS dataset of more than 1300 reference spectra, obtained from various selected materials that may be present in mortars. The ANN parameters (pre-treatment of data, number of neurons and of iterations) were optimized to ensure the best recognition of mortar components, while avoiding overtraining. The results demonstrate a fast and accurate identification of each component. The use of an ANN appears to be a strong means to provide an efficient, fast and automated LIBS characterization of archaeological mortar, a concept that could later be generalized to other samples and other scientific fields and methods.

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DOI: 10.1039/d2ja00389a
rsc.li/jaas

x3

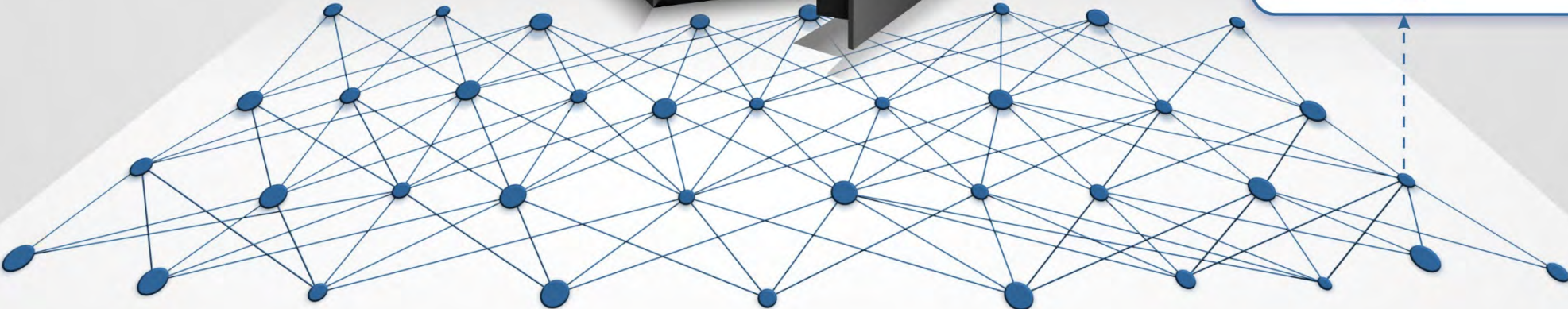
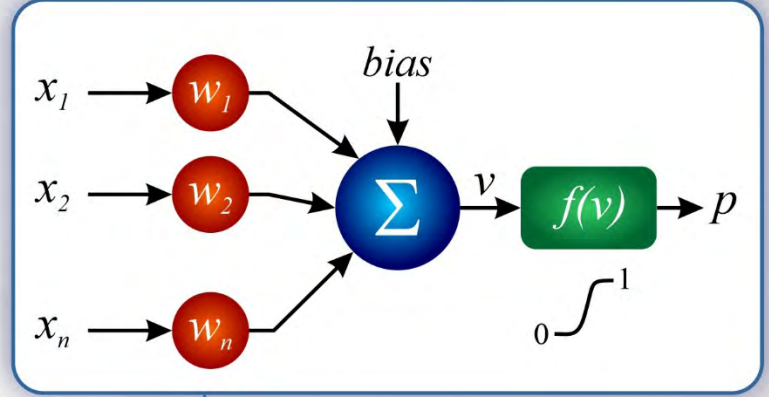
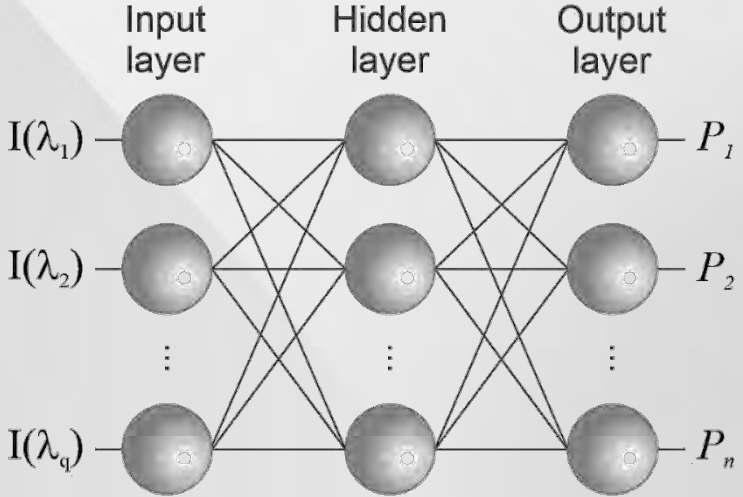
1. Characterization of the aggregates
2. Carbon extraction

anr[®]

Need of a real time processing to identify minerals
→ accurate discrimination between the carbonates

Artificial Neural Network

Through an automated processing?



Methodology

Key point

~ 1400 reference spectra
For 8 categories

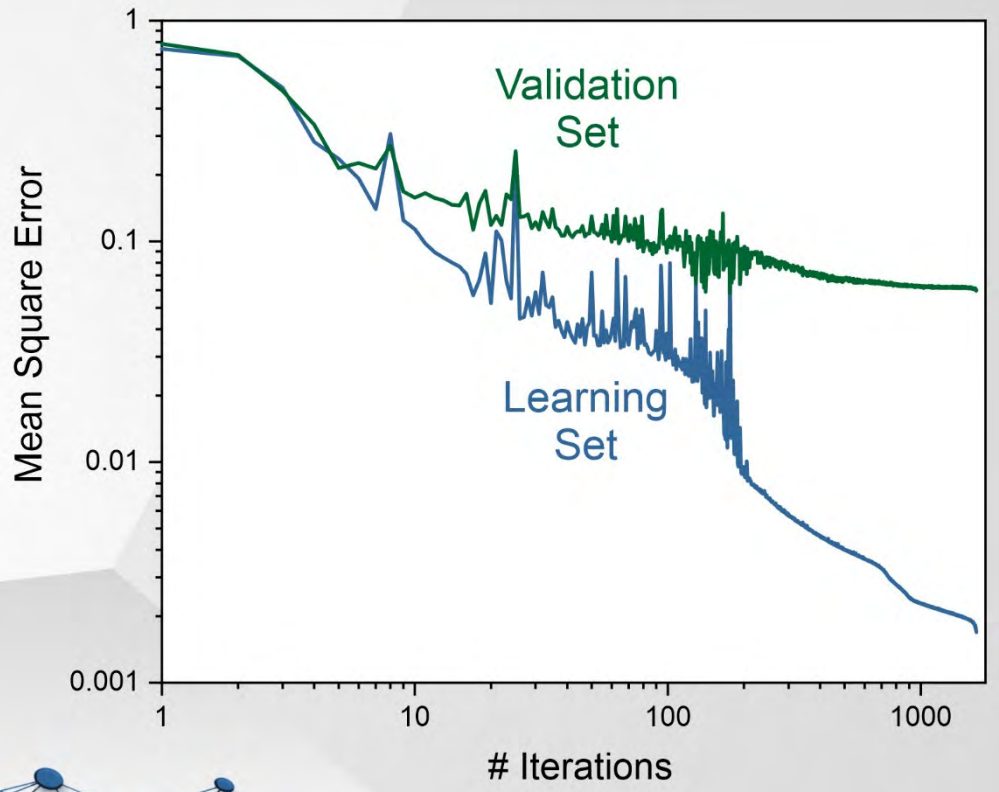
3 steps

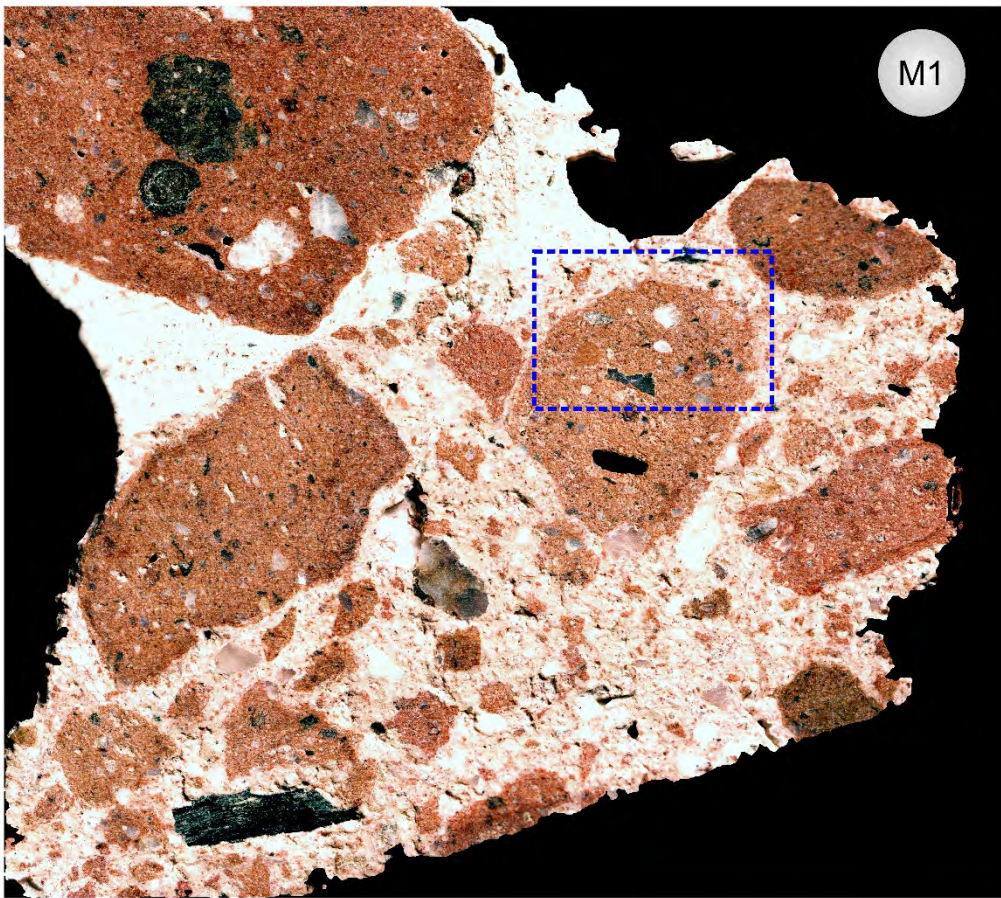
- Learning
- Validation
- Step



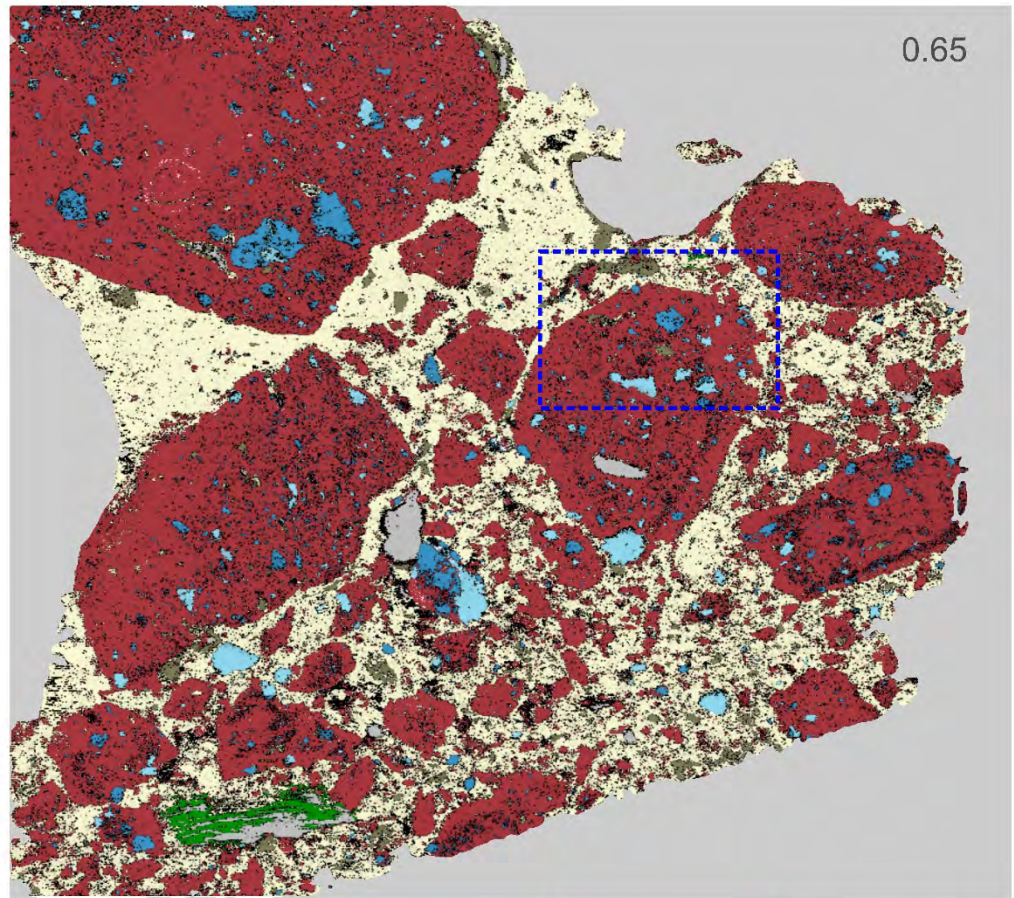
Artificial Neural Network

Through an automated processing?

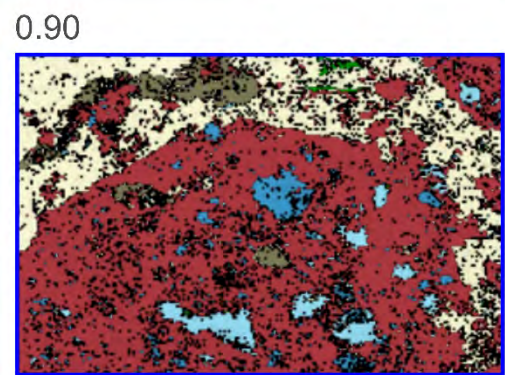
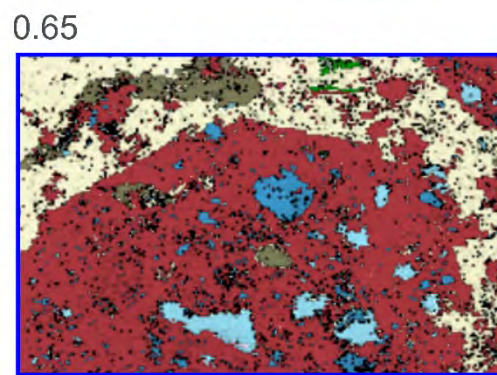
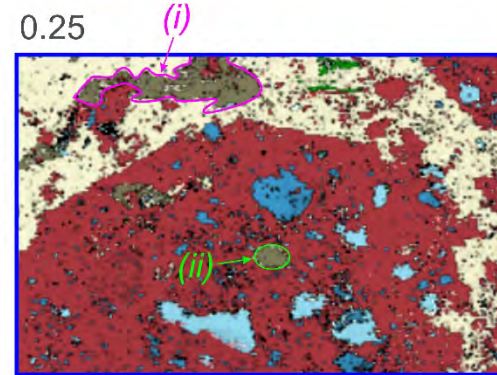




M1



0.65



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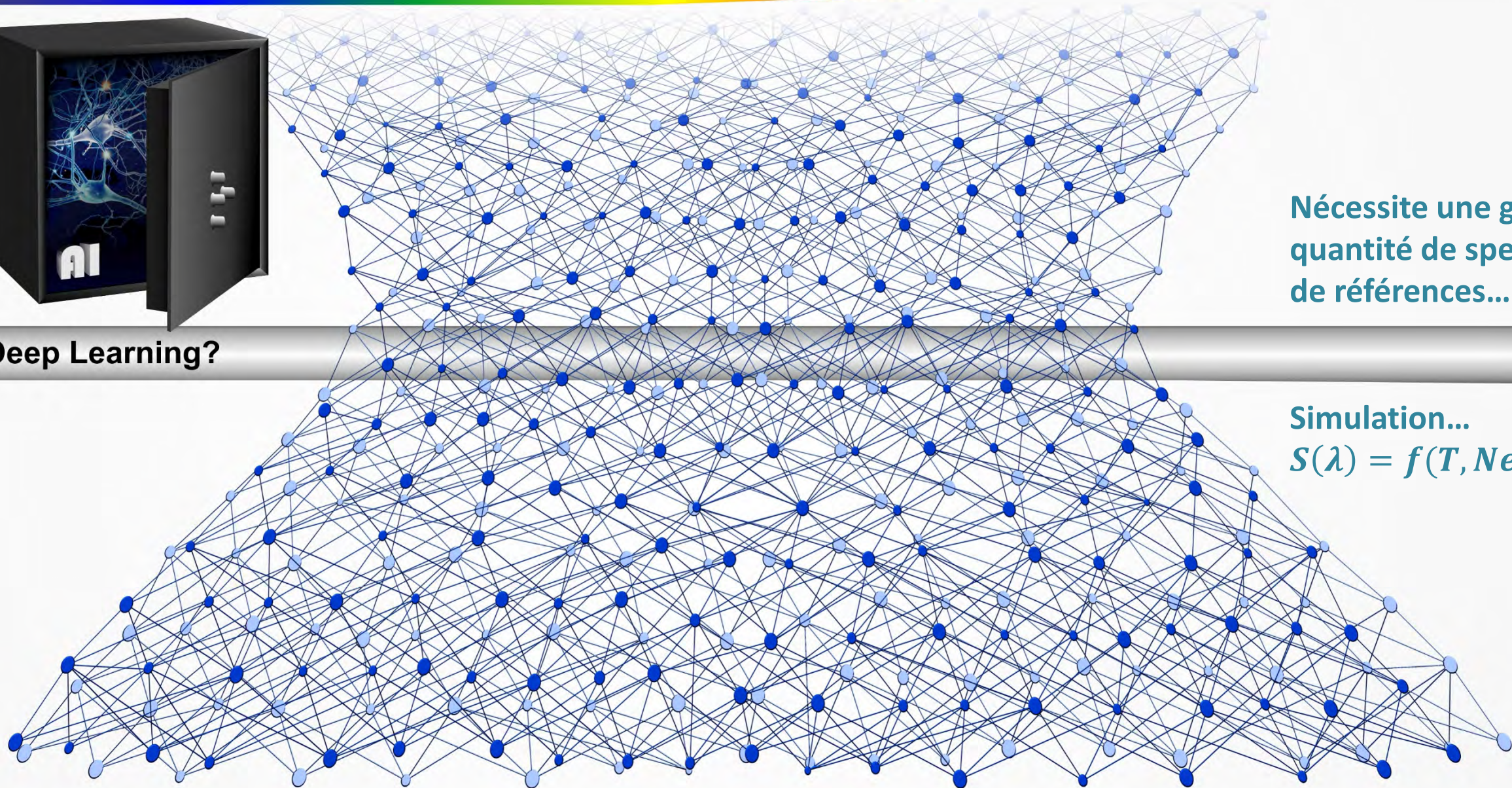


Deep learning in LIBS imaging

A dream?



Deep Learning?



Nécessite une grande quantité de spectres de références...

Simulation...
 $S(\lambda) = f(T, Ne, C_x)$

Deep learning in LIBS imaging

Spectra simulation

Assuming a uniform plasma in LTE
(Local Thermodynamic Equilibrium):

Boltzmann equation: Population density of the emitters

$$I_{\alpha}^z = f \frac{hc}{\lambda_{\alpha}^z} \frac{A_{\alpha}^z g_{\alpha}^z}{U^z(T)} N_{\alpha}^z \exp\left[-\frac{E_{\alpha}^z}{kT}\right]$$

$z=0$ (neutral)
 $z=1$ (singly ionised)

Saha equation: Ionization states

$$\frac{N_{\alpha}^1}{N_{\alpha}^0} = \frac{2}{Ne} \frac{U_{\alpha}^1(T)}{U_{\alpha}^0(T)} \left(\frac{mkT}{2\pi\hbar^2}\right)^{3/2} \exp\left[-\frac{E_{ion}^1 - \Delta E}{kT}\right]$$

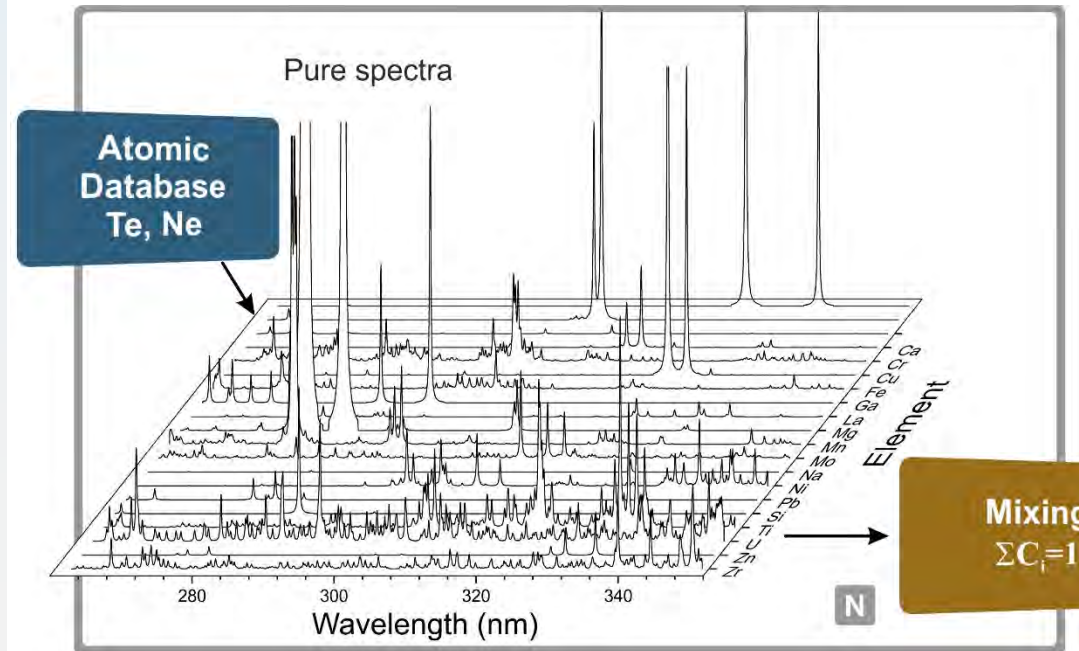
Spectral radiance (self-absorption)

$$B_{\lambda} = B_{\lambda}^0 (1 - e^{-\tau(\lambda)})$$

$\tau(\lambda)$ Optical thickness

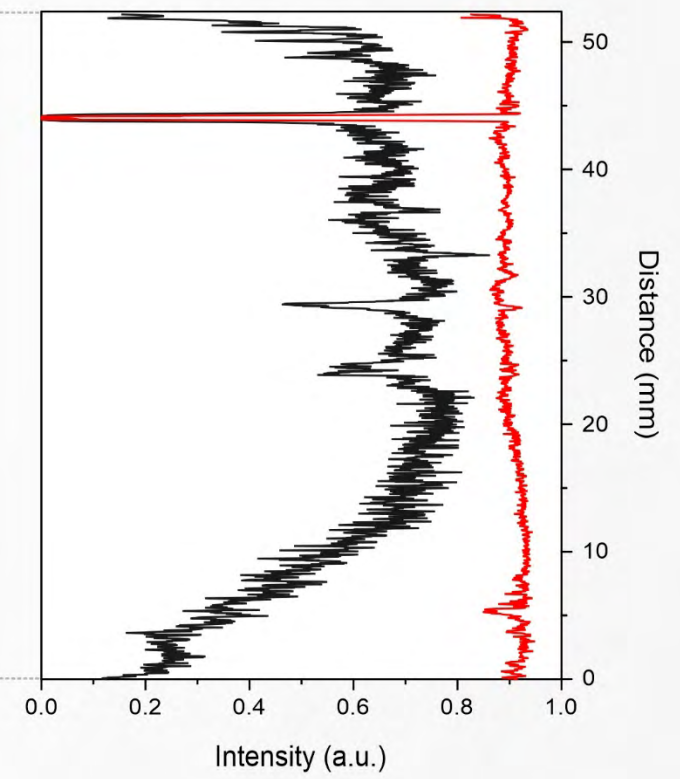
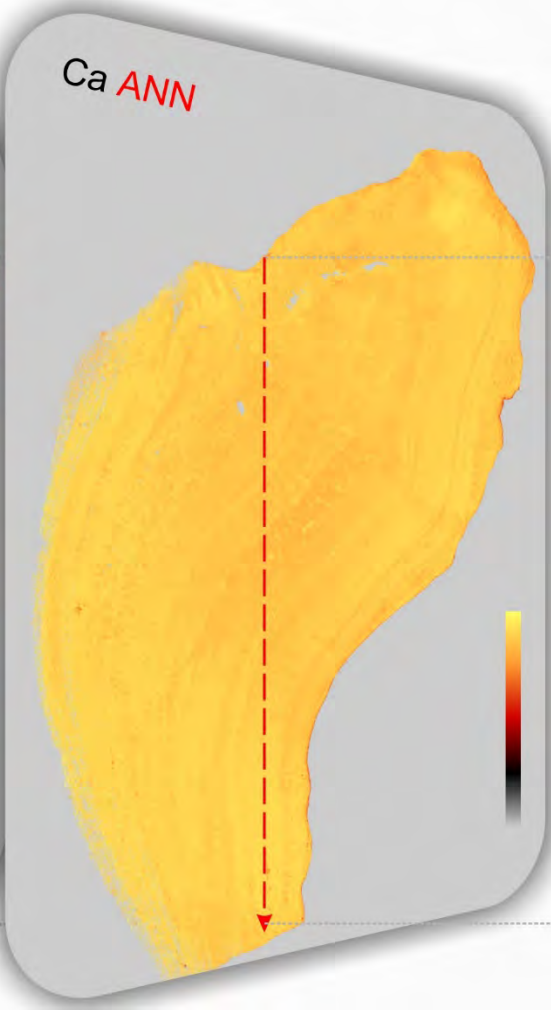
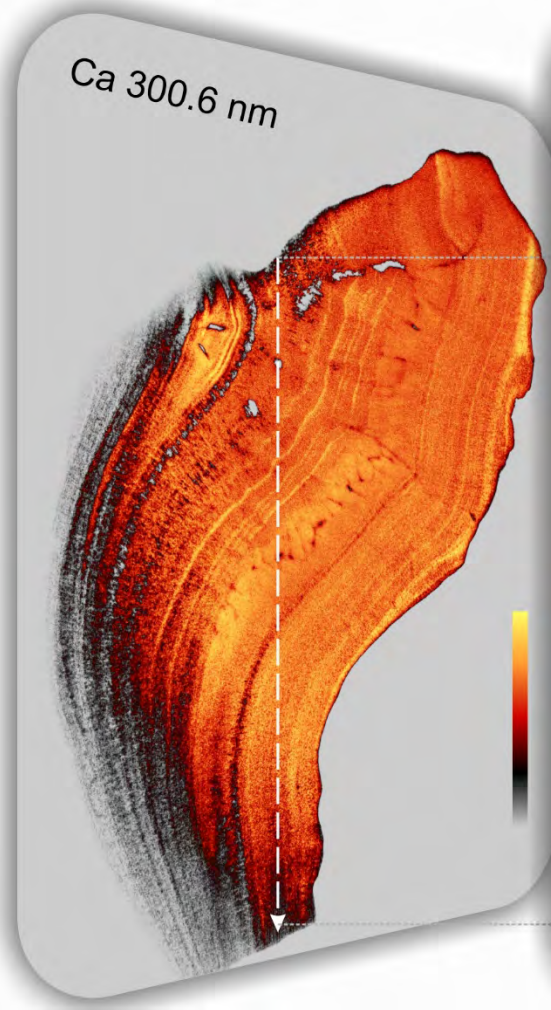
Collaborations
Jörg Hermann
Ludovic Duponchel

Simulation of pure elemental
emissions for various T and Ne



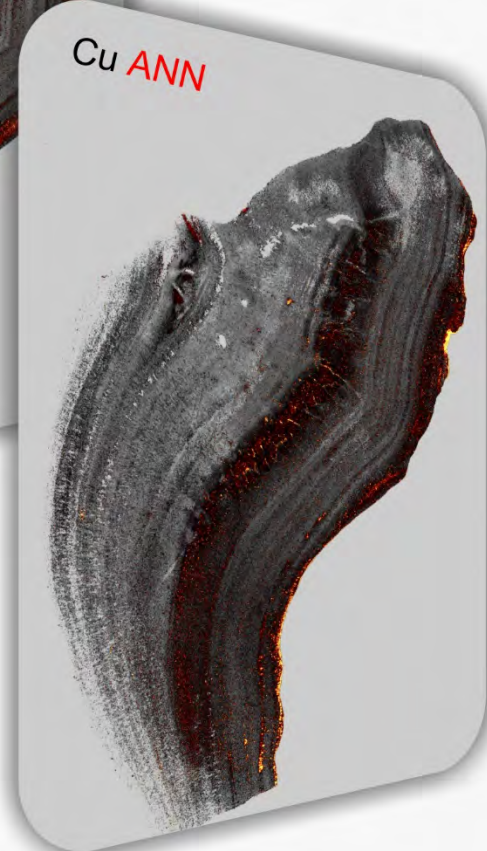
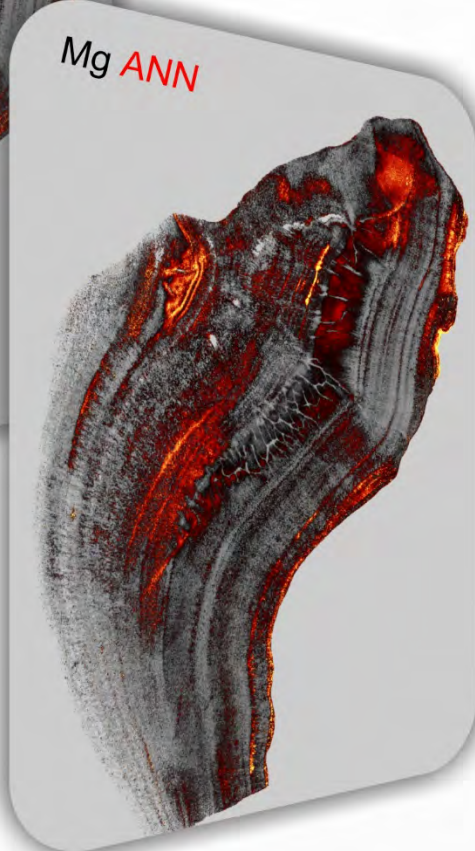
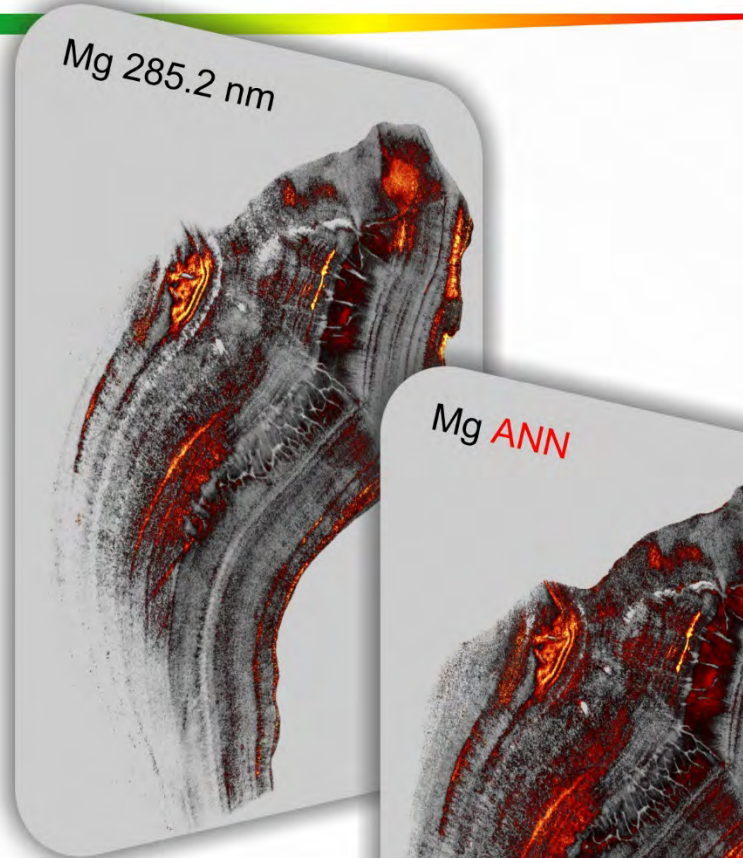
Deep learning in LIBS imaging

A dream?



Deep learning in LIBS imaging

A dream?





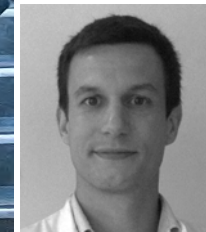
S Hermelin



C Dujardin



D. Devismes



B. Busser



L. Sancey



F. Pelascini



L. Duponchel



C Fabre

Vincent, César, Lana, Jordan, Nicolas, Adrian, Sarah & Clothilde



LIBS collaborations: M. Baudalet, B. Bousquet, J.O. Caceres, V. Detalle, A. Di-Giacomo, F. Doucet, M. Gaft, J. Hermann

F. Le Cras, W. Berthou, M. Aramendia Marzo, M. Rezano, P. Veber, G. Panczer, O. Tillement, K. Leddoux, V. Bonneterre, M. Catinon, G. Alombert, J. Cauzid, R. Chapoulie, J. Charles, A. Detappe,, B. Franko, C. P. Lienmann, F. Lux, J. Martín-Chivelet, N. Pinel, S. Roux, A.M. Sfarghiu, F. Surma, L. Sorbier, Manuel Munoz, Alexandre Curgerone, etc...

Thanks for your attention!

