

Détection et segmentation dans les images hyperspectrales astronomiques MUSE

Jean-Baptiste Courbot, Vincent Mazet
Emmanuel Monfrini, Christophe Collet

Outline

- 1 Introduction: the detection problem
- 2 Models
 - A. Hypothesis testing-based detection
 - B. Bayesian segmentation : Markov fields
 - C. Bayesian segmentation : Markov trees
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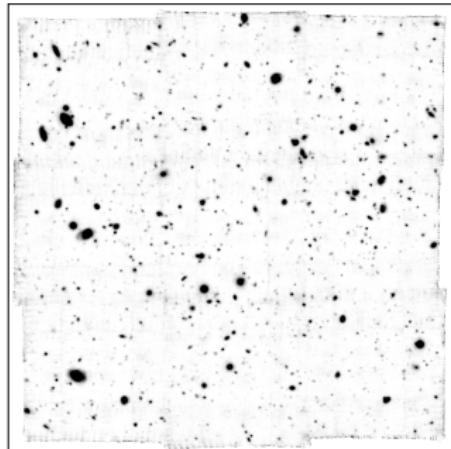
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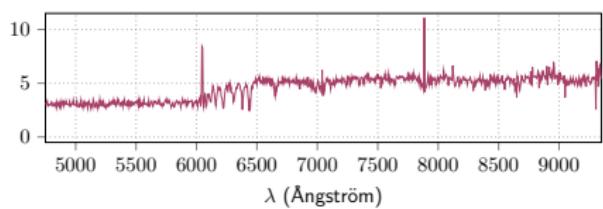
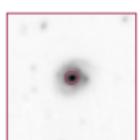
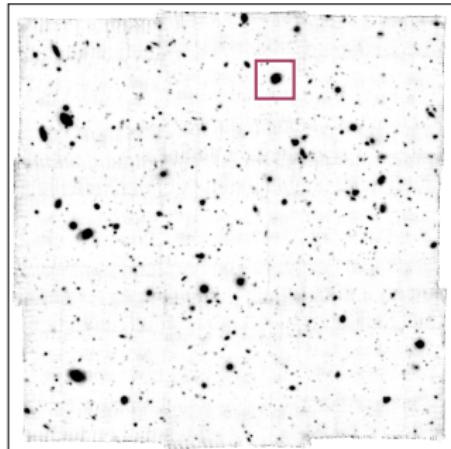
The MUSE hyperspectral imager



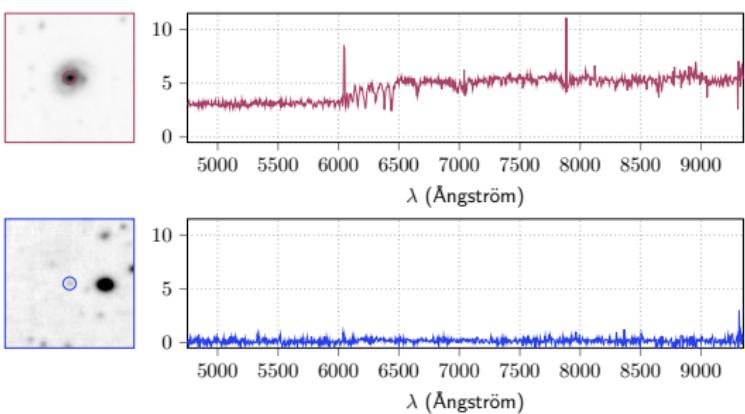
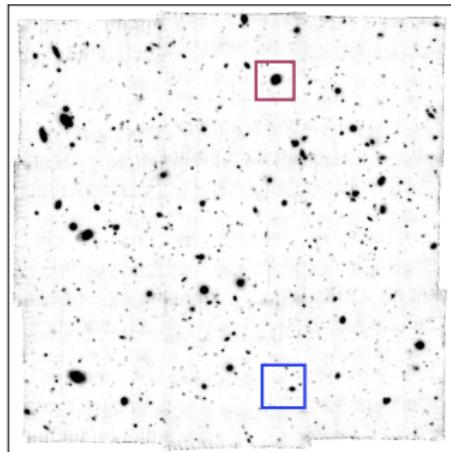
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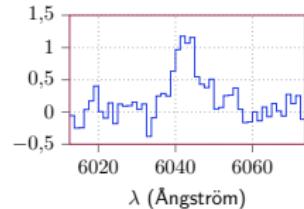
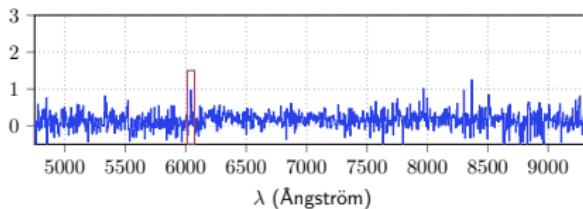
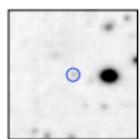
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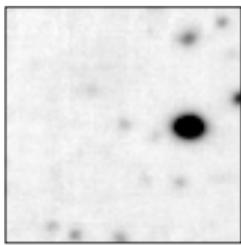
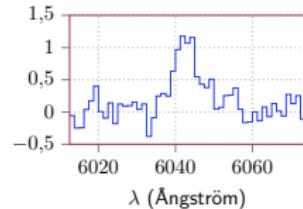
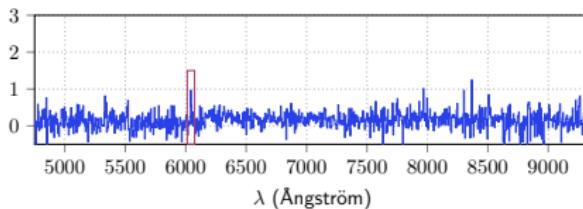
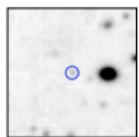
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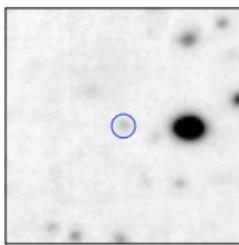
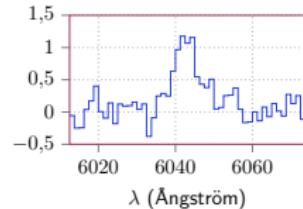
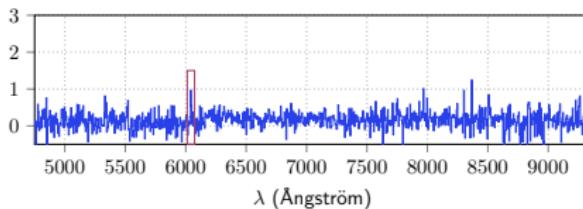
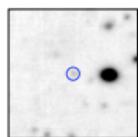
The detection problem



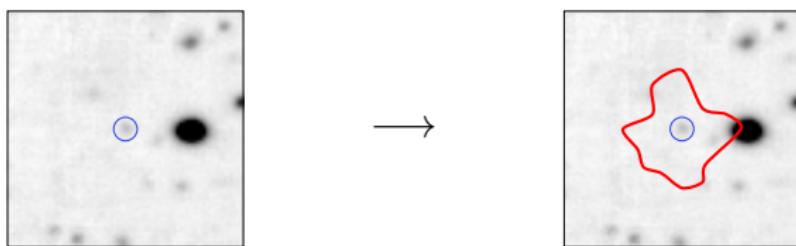
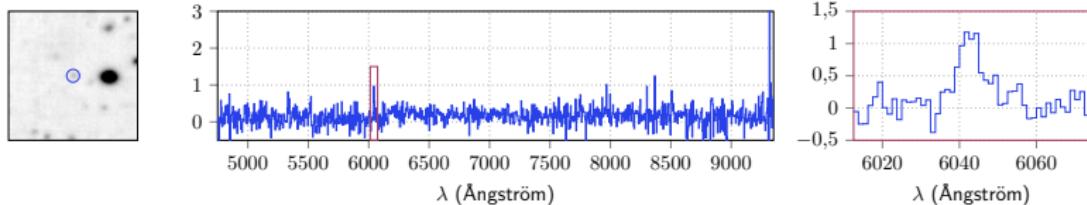
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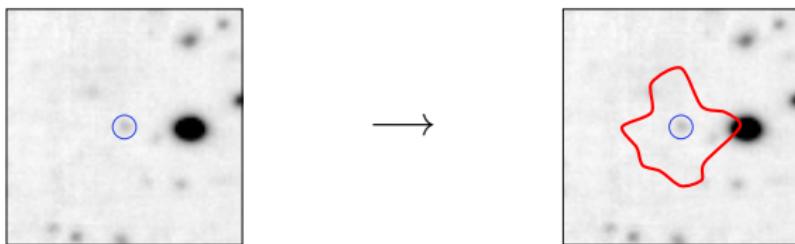
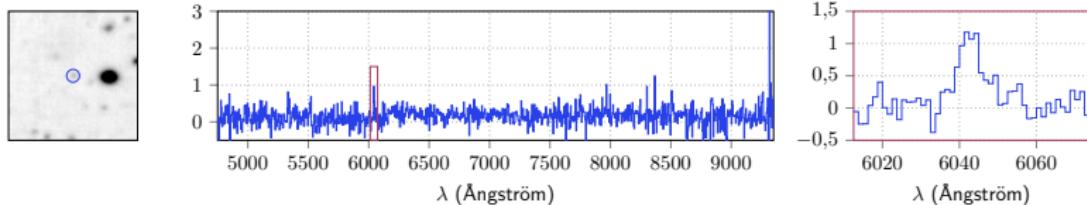


Image $y \longleftrightarrow$ Result \hat{x}

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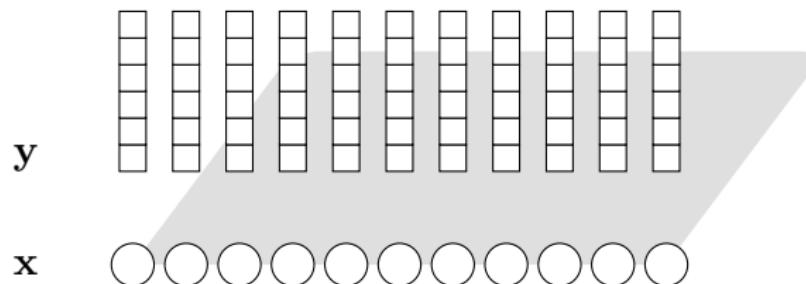
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A bit of modeling

How to solve the detection problem ?

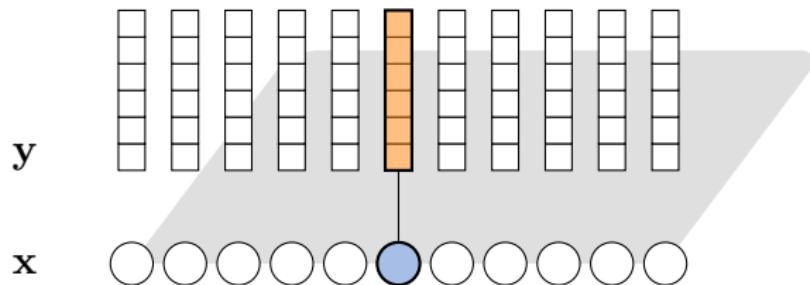
We need a model for x , y , and their relation.



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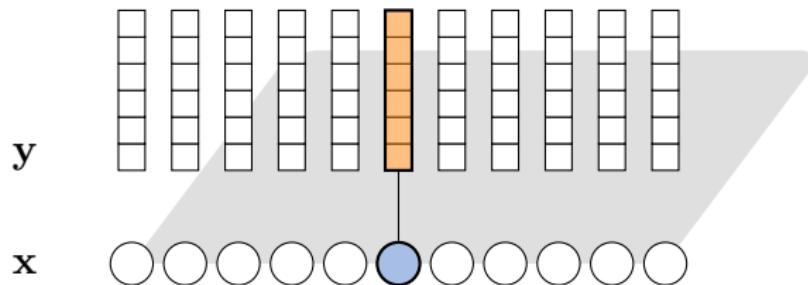
The first approach : hypothesis testing.

Given this spectrum, what is the more likely option ?

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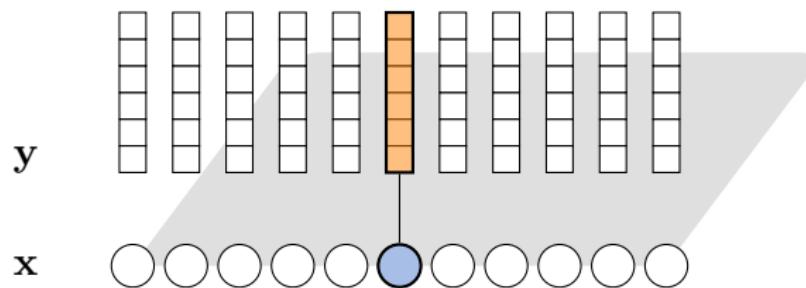
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Given this spectrum, what is the more likely option ?

Requirement: a model for $p(y|x)$

- ▶ noise model

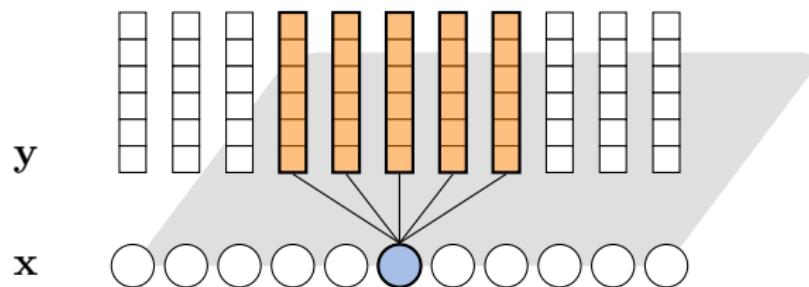
A bit of modeling (II)



The first approach: hypothesis testing **with convolution**.

(HT)

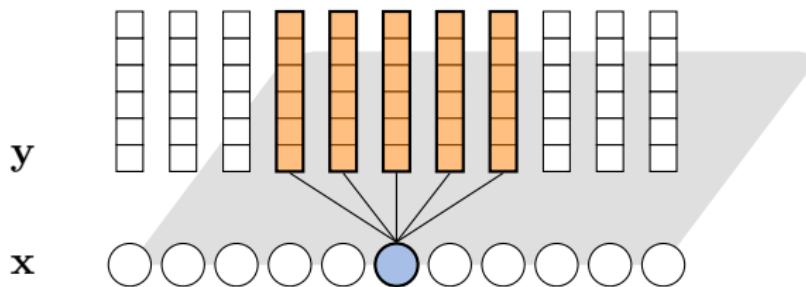
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The first approach: hypothesis testing **with convolution**.

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Given this spectra set, what is the more likely option ?

Requirement: a model for $p(y|x)$

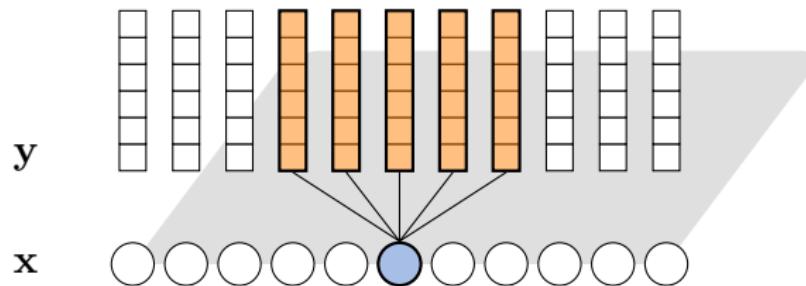
- ▶ noise
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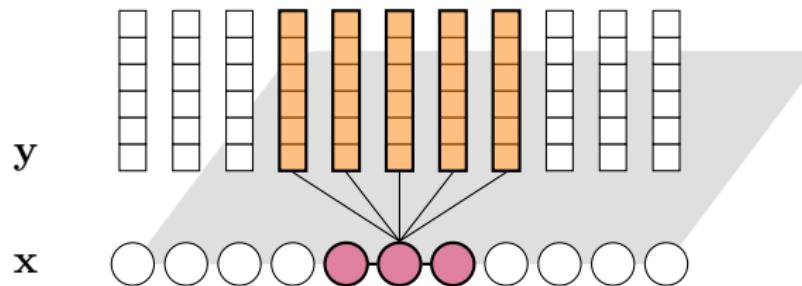
In HT, neighboring decisions are **independent**.
A prior is required to improve the results.



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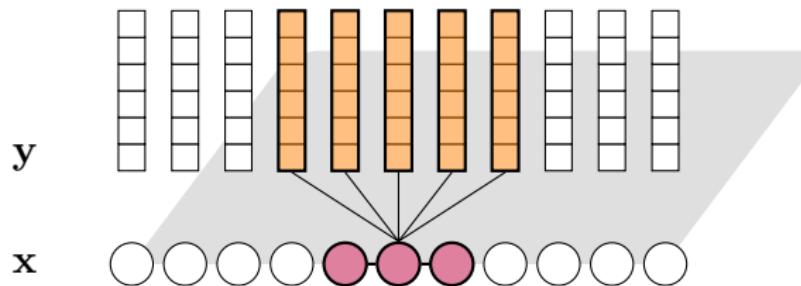
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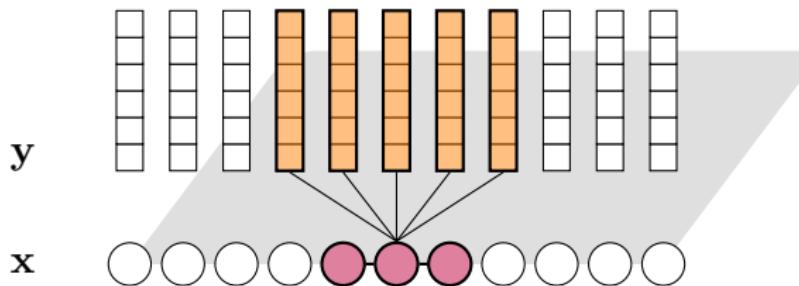
The second approach: pairwise Markov fields

(PMF)

A bit of modeling (III)

In HT, neighboring decisions are **independent**.

A prior is required to improve the results.



The second approach: pairwise Markov fields

(PMF)

Requires models for:

- ▶ $p(y|x)$: noise and convolution
- ▶ $p(x)$: Markov field \Rightarrow spatial smoothness

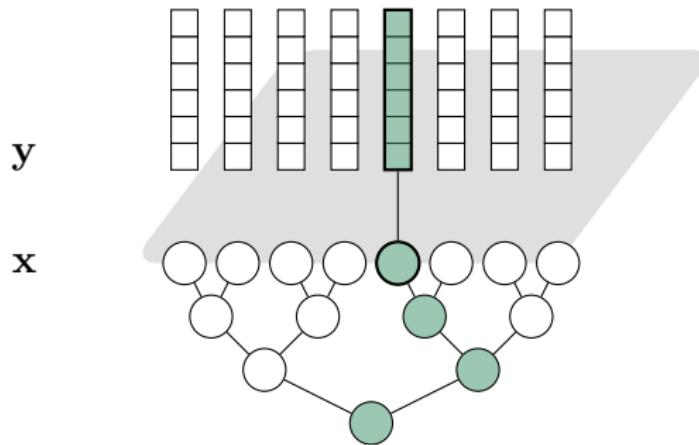
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A bit of modeling (IV)

What about large-scale interactions ?

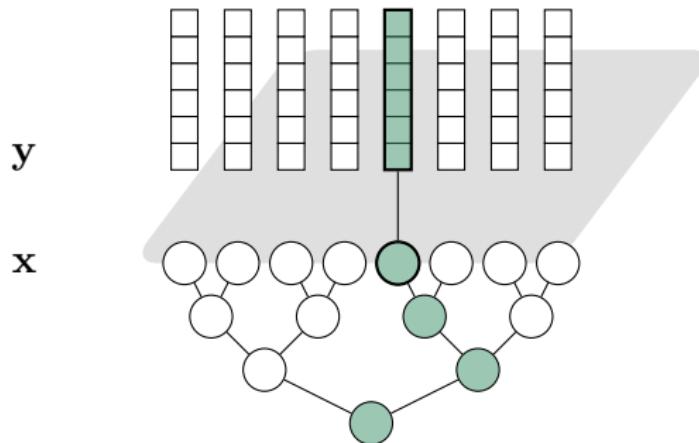
We need to change the kind of prior.



A bit of modeling (IV)

What about large-scale interactions ?

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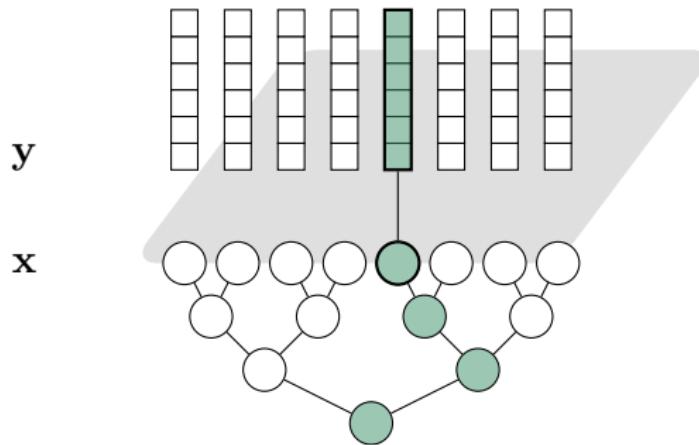
The third approach: Triplet Markov Trees

(TMT)

A bit of modeling (IV)

What about large-scale interactions ?

We need to change the kind of prior.



The third approach: Triplet Markov Trees

(TMT)

Requires models for:

- ▶ $p(y|x)$: noise and no convolution
- ▶ $p(x)$: Markov tree \implies hierarchical coherence

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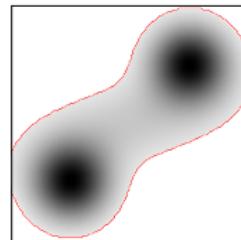
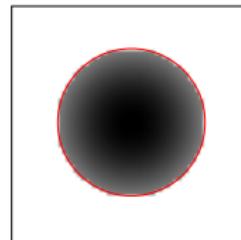
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Synthetic data

Experimental setting:

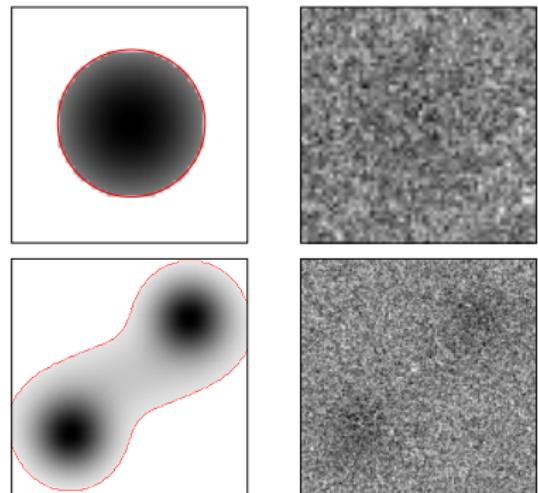
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- ▶ variable intensities



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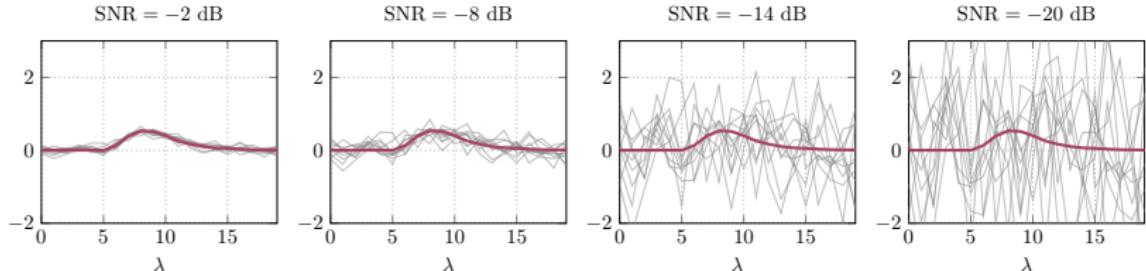
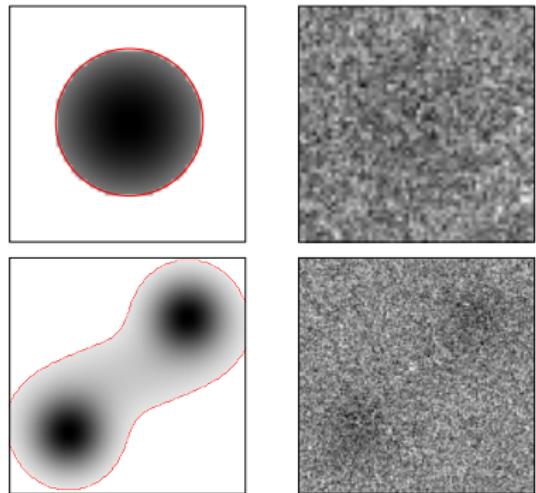
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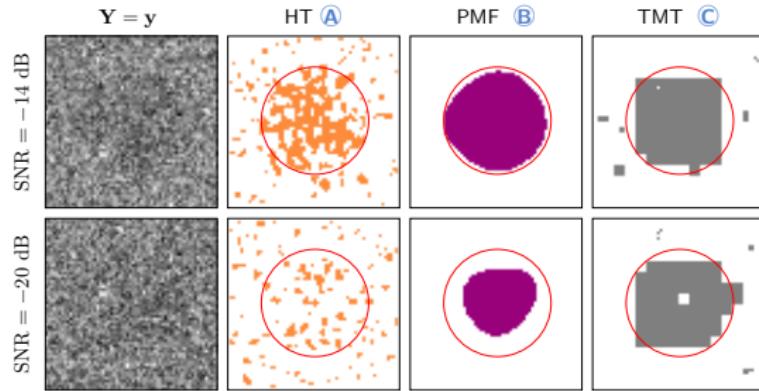
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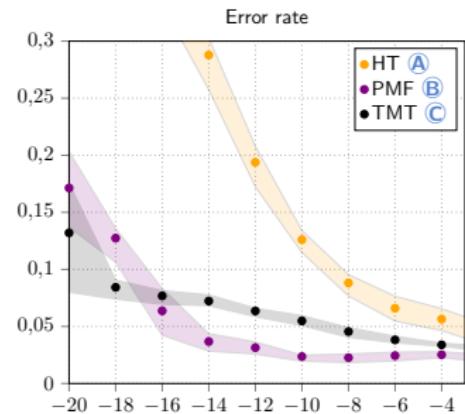
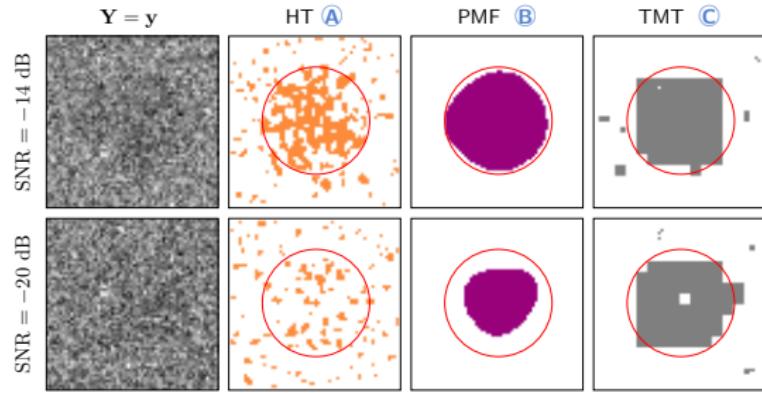
- ▶ “halo” and “filament”
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- ▶ $\text{SNR} \in [-20 \text{ dB}, 6 \text{ dB}]$



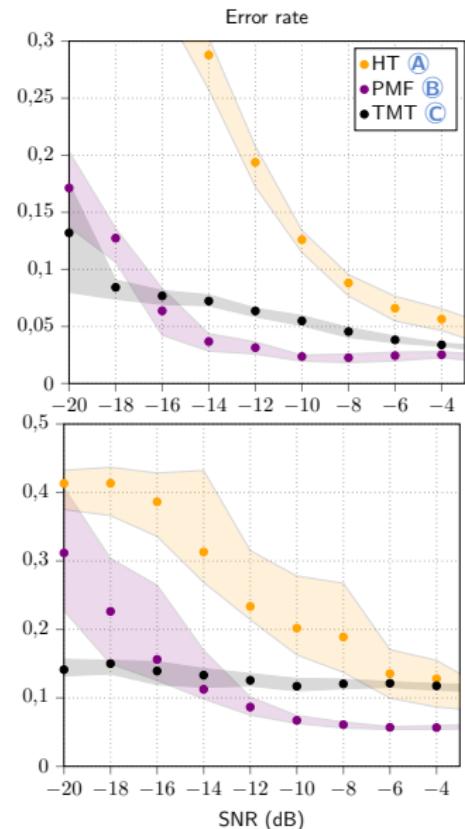
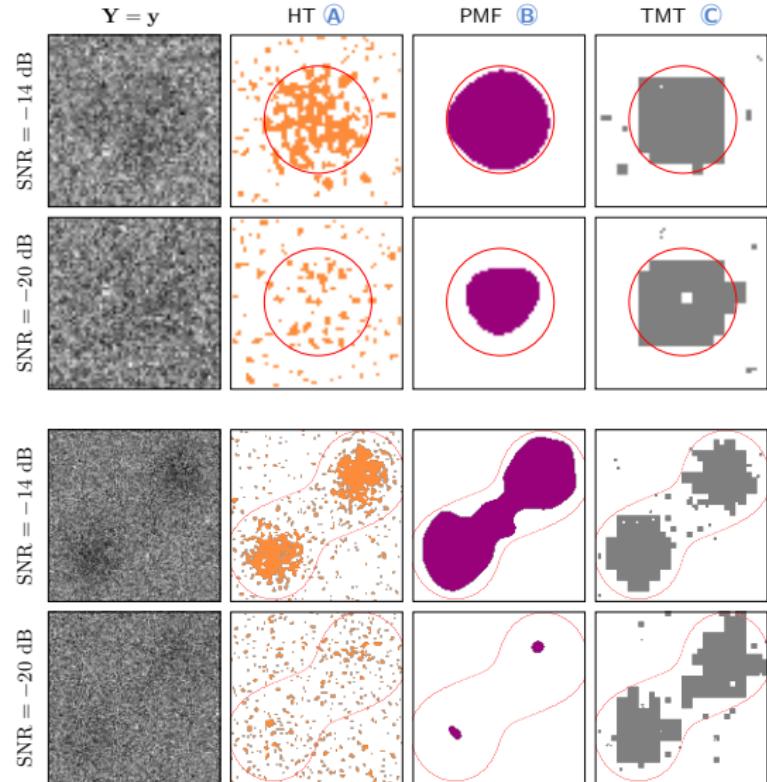
Results on synthetic images



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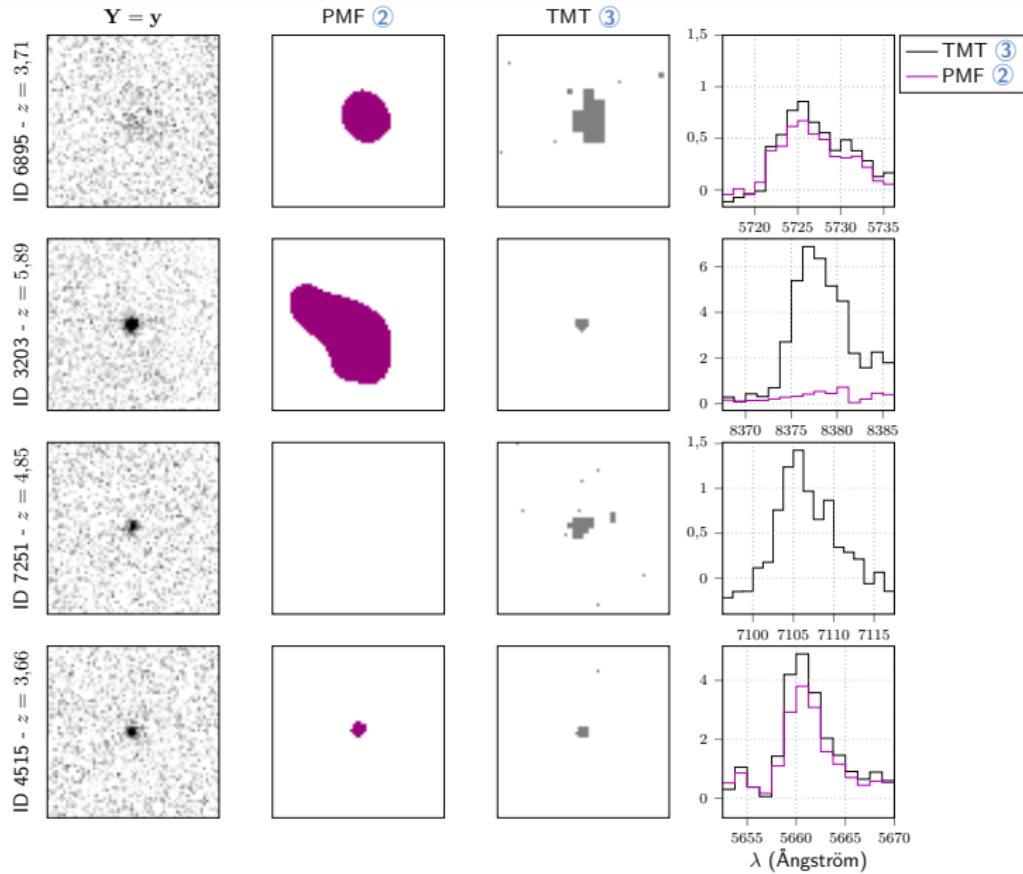
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Real images: a sample



A (simple) sample study

A simple study over MUSE UDF cubes.

242 isolated objects : no close neighbor, contamination, etc.

Criteria :

- ▶ spectral shape
- ▶ spatial extent

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59,5 %

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59,5 %

16,5 %

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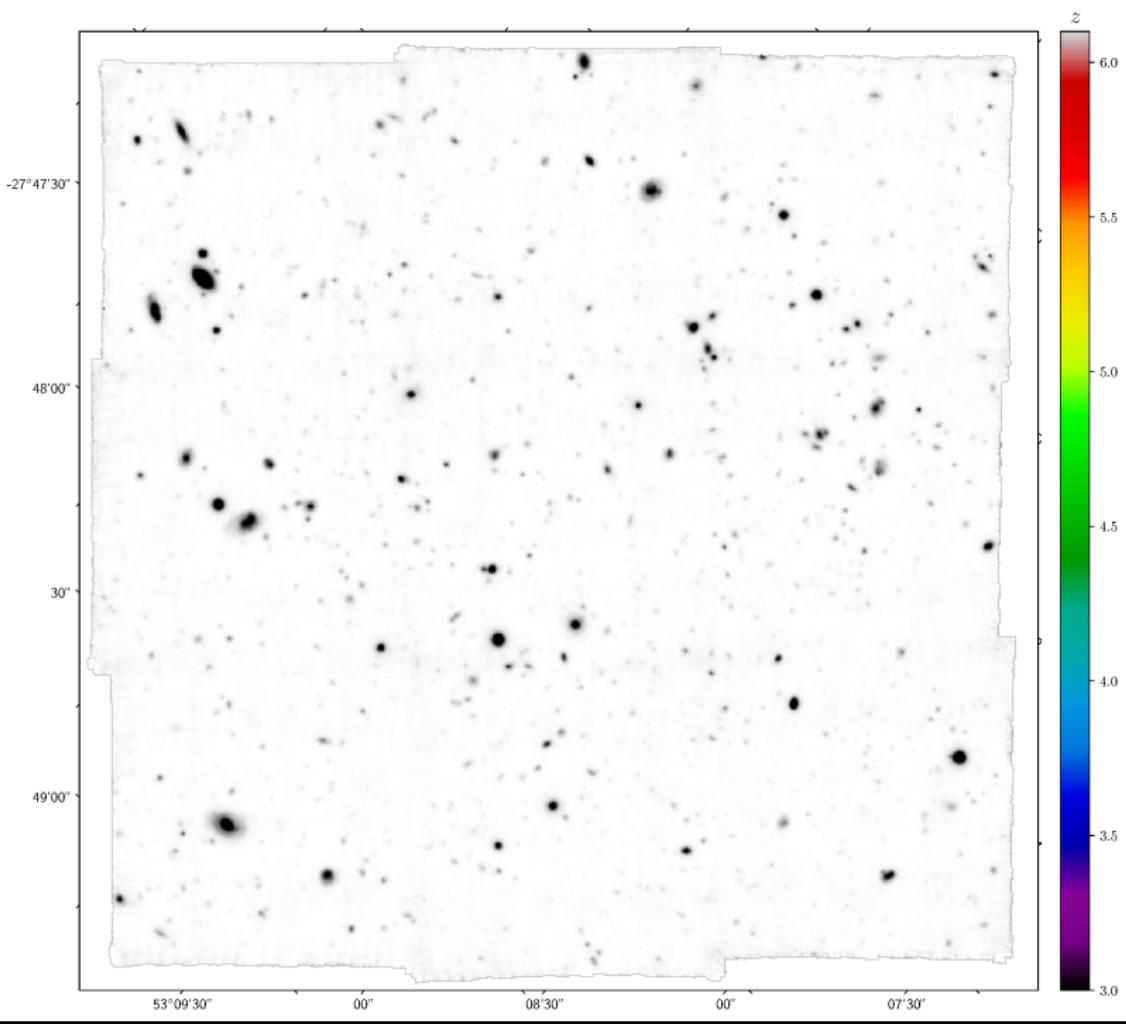
- ▶ PMF detection
- ▶ TMT additional detection
- ▶ small spatial extent
- ▶ no detection

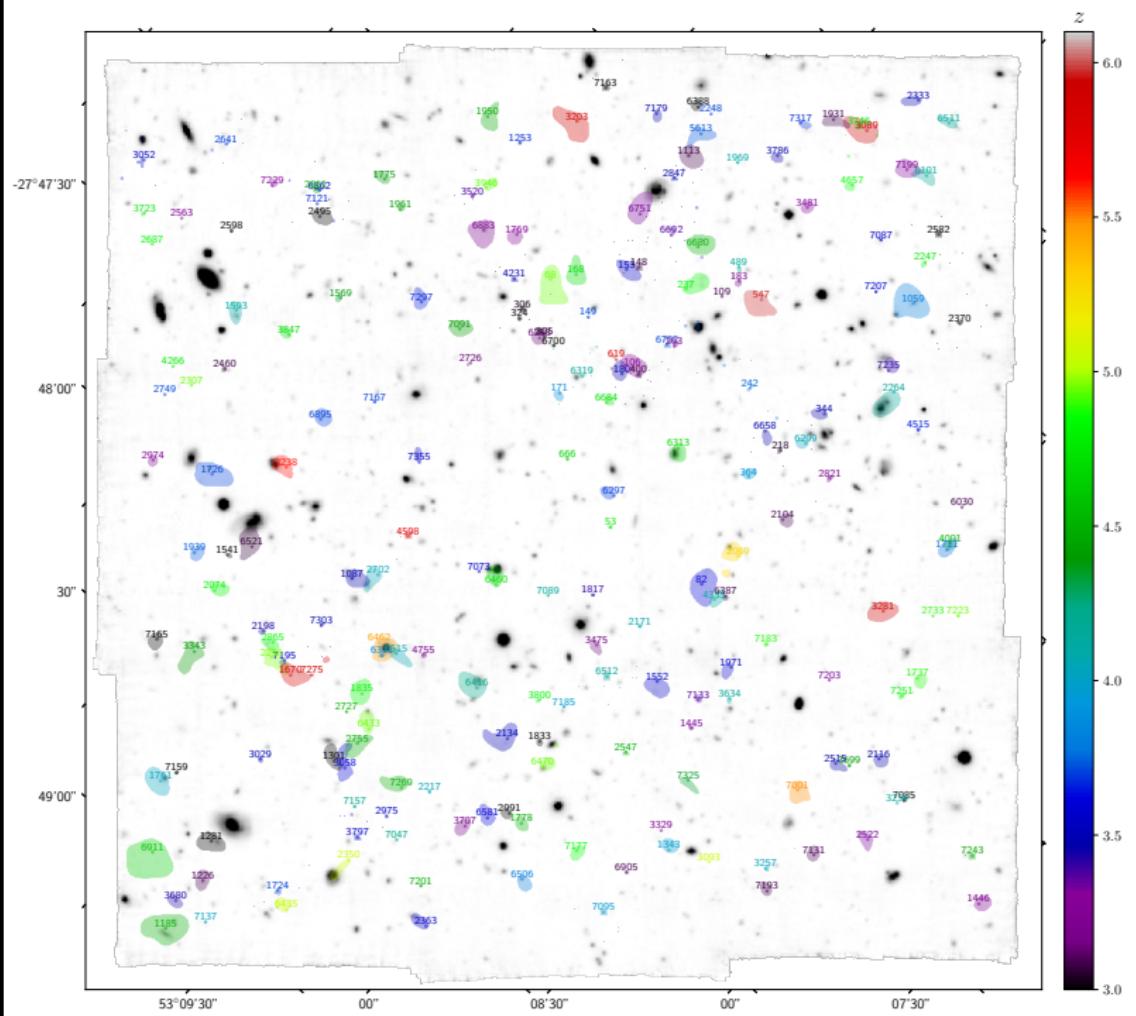
59,5 %

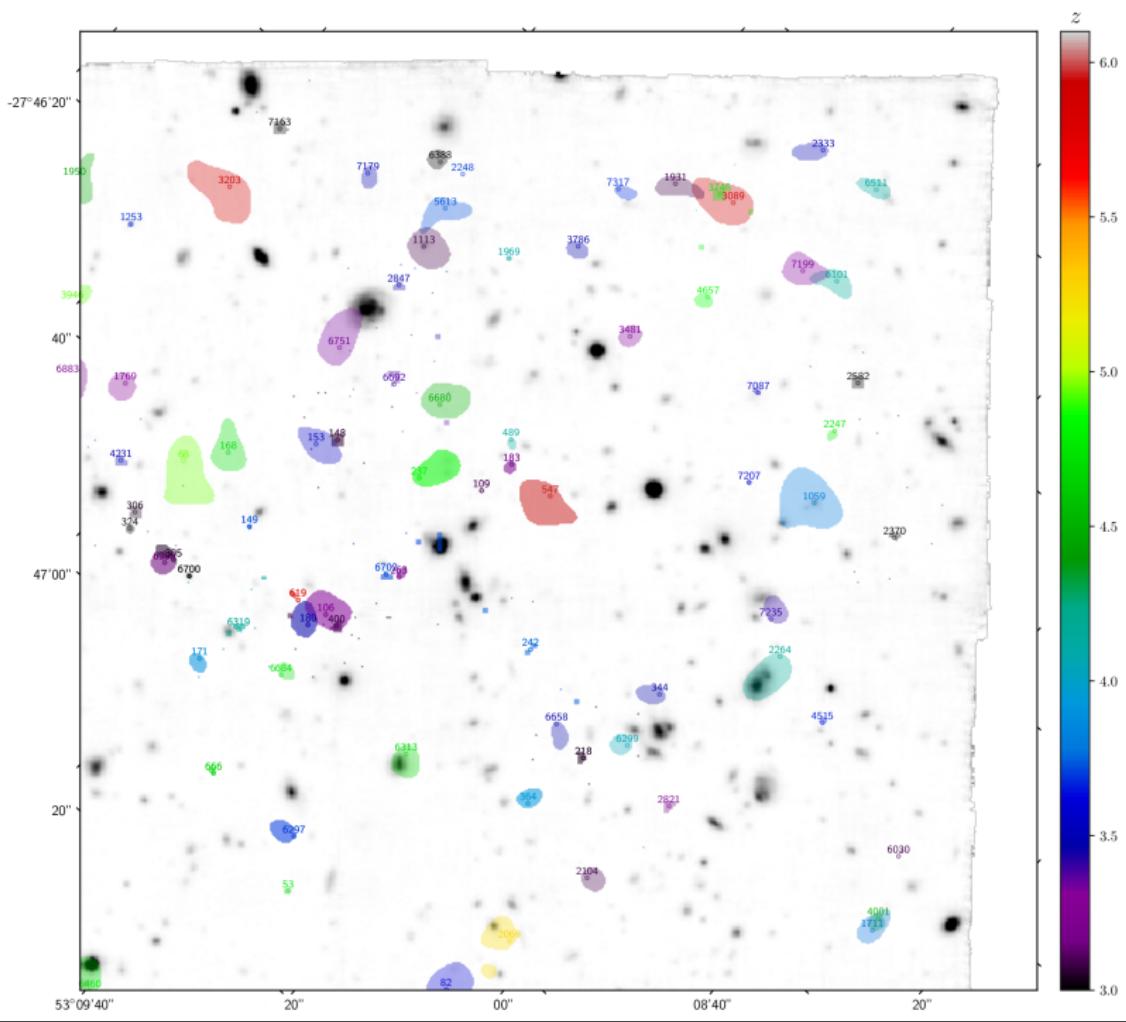
16,5 %

12 %

12 %







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- ▶ 3 detection models/methods
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