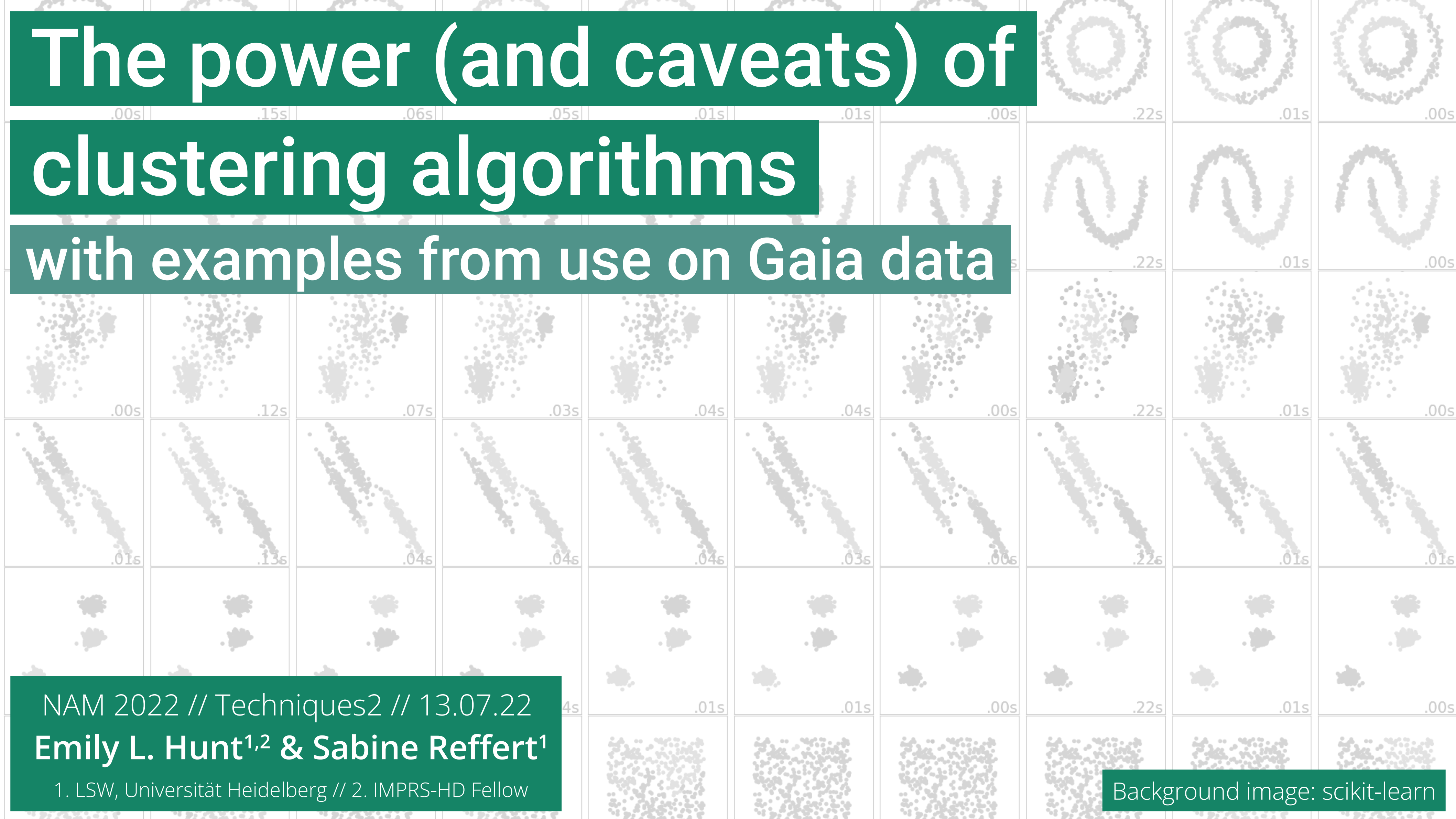


The power (and caveats) of clustering algorithms

with examples from use on Gaia data

NAM 2022 // Techniques2 // 13.07.22

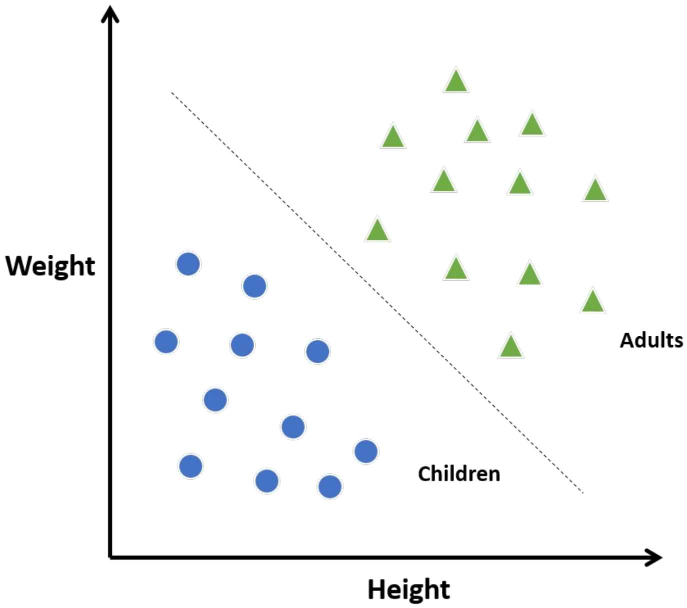
Emily L. Hunt[1,2] & Sabine Reffert[1]

1. LSW, Universität Heidelberg // 2. IMPRS-HD Fellow

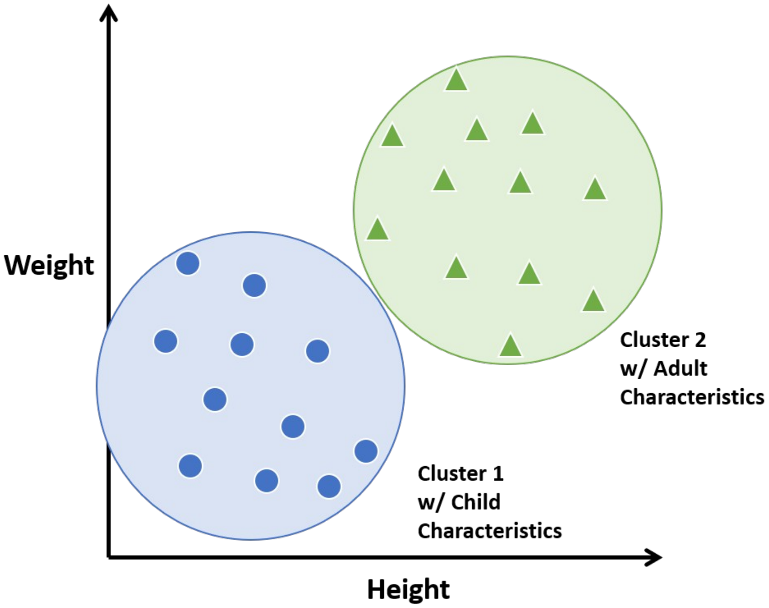
Background image: scikit-learn

what is *unsupervised* ML?

Classification in supervised ML is about making a **decision boundary** between different regions



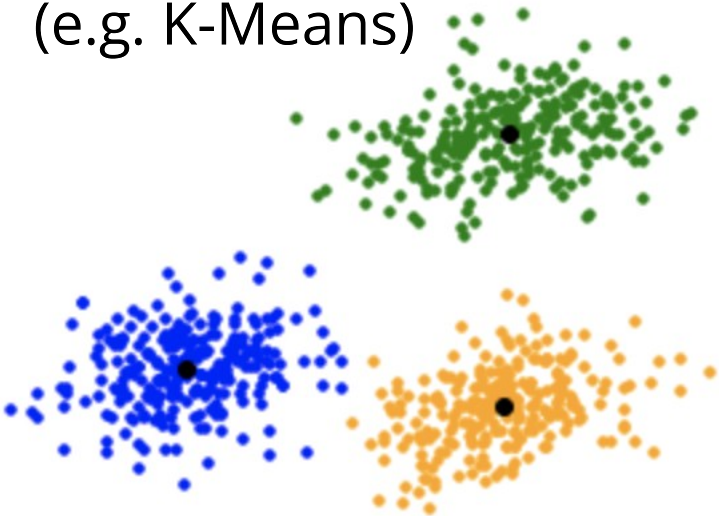
Clustering algorithms (a type of unsupervised ML) do this using **properties of the data itself**



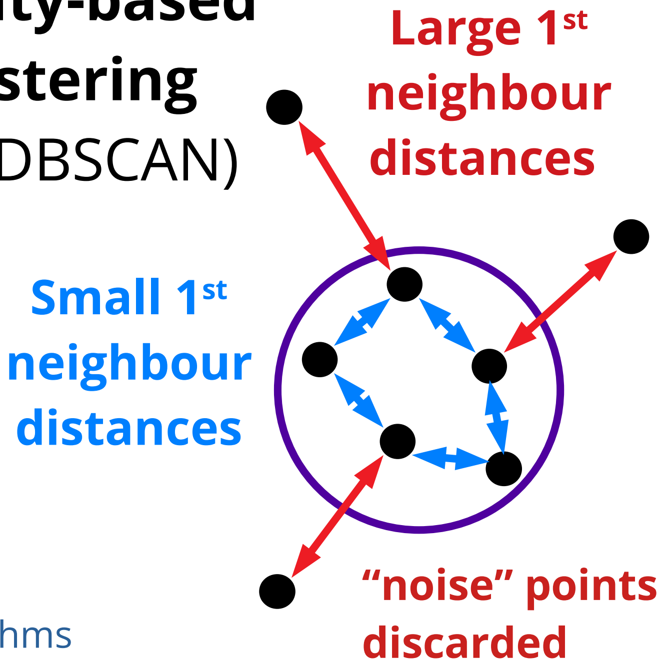
the many, many algorithms...

There are many different types, each suited to different problems

Partitioning
(e.g. K-Means)



Density-based clustering
(e.g. DBSCAN)



Link: Overview of various algorithms

play around with this in a notebook!

github.com/emilyhunt/nam_2022_talk

(also includes these slides)

4. The clustering algorithms

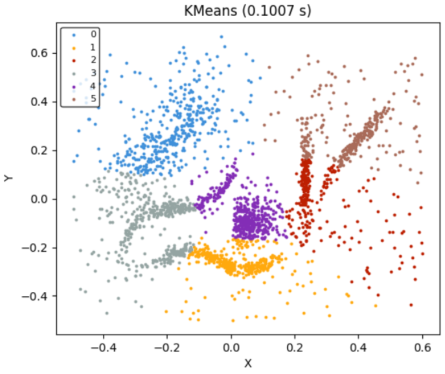
Let's try various algorithms! Feel free to play around with the parameters.

4.1. K-Means

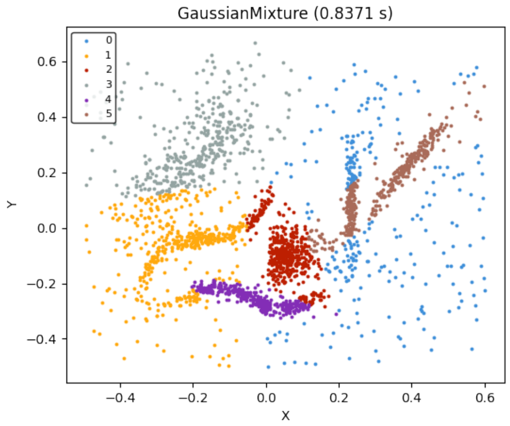
The archetypal (and most simple) clustering algorithm...

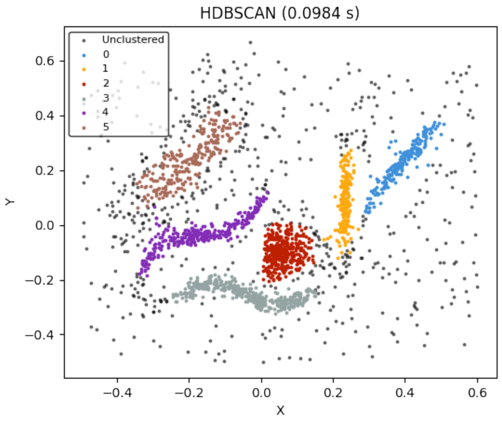
[118]:
```
run_clustering_algorithm(data, sklearn.cluster.KMeans, n_clusters=6, savename='KMeans')
```

```
Running clustering algorithm!
  clustering took 0.1007 seconds
Plotting results!
```



Basic algorithm; some things are roughly separated, but not so well.





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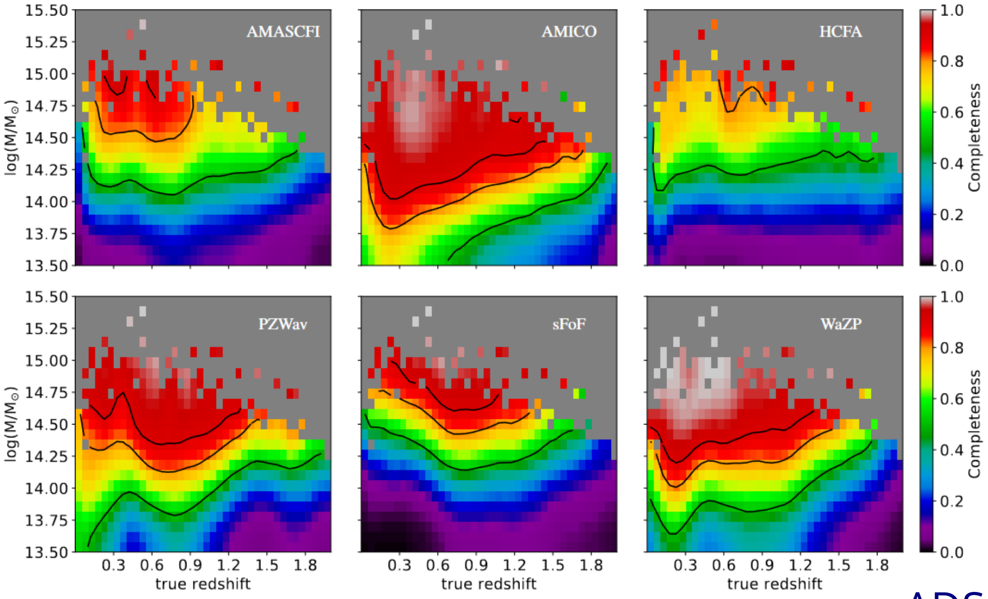

ADS

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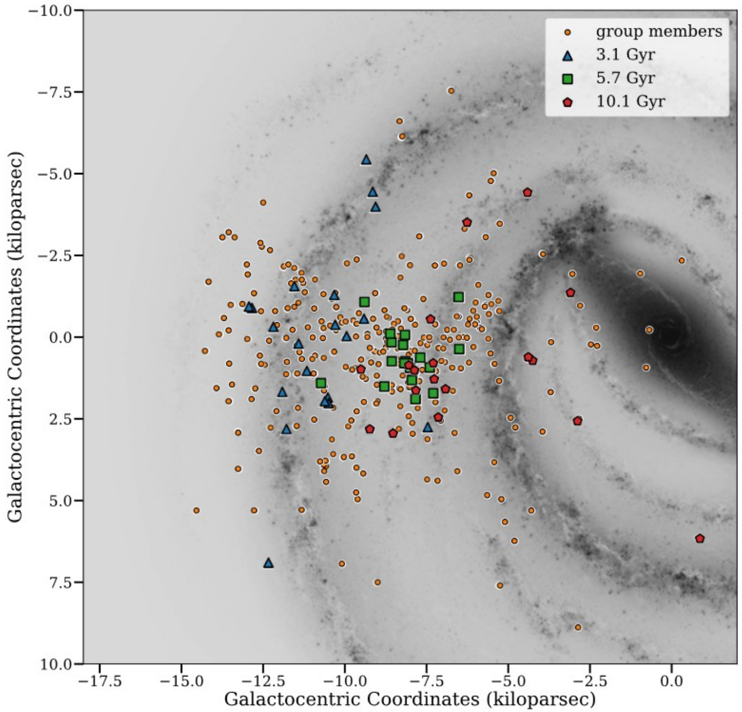

ADS

our problem: open clusters of stars.

The Pleiades, age: ~100 Myr

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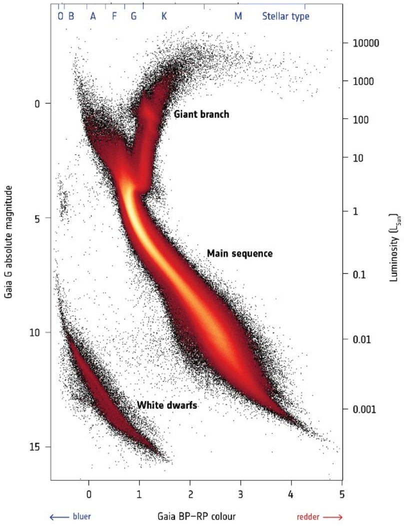
Highly useful to stellar & galactic science!



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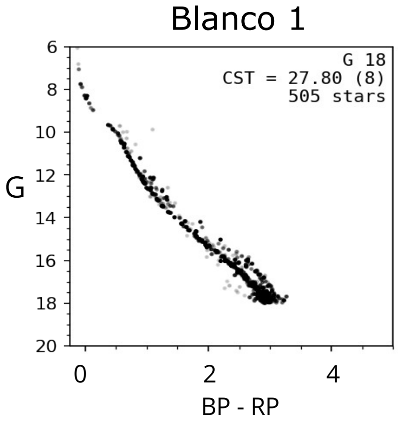

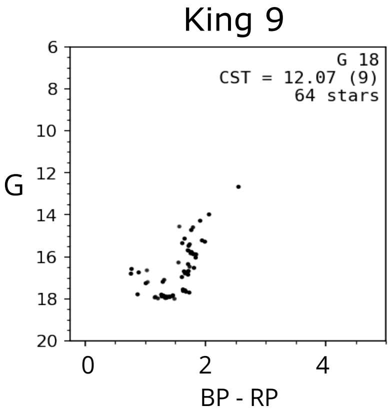

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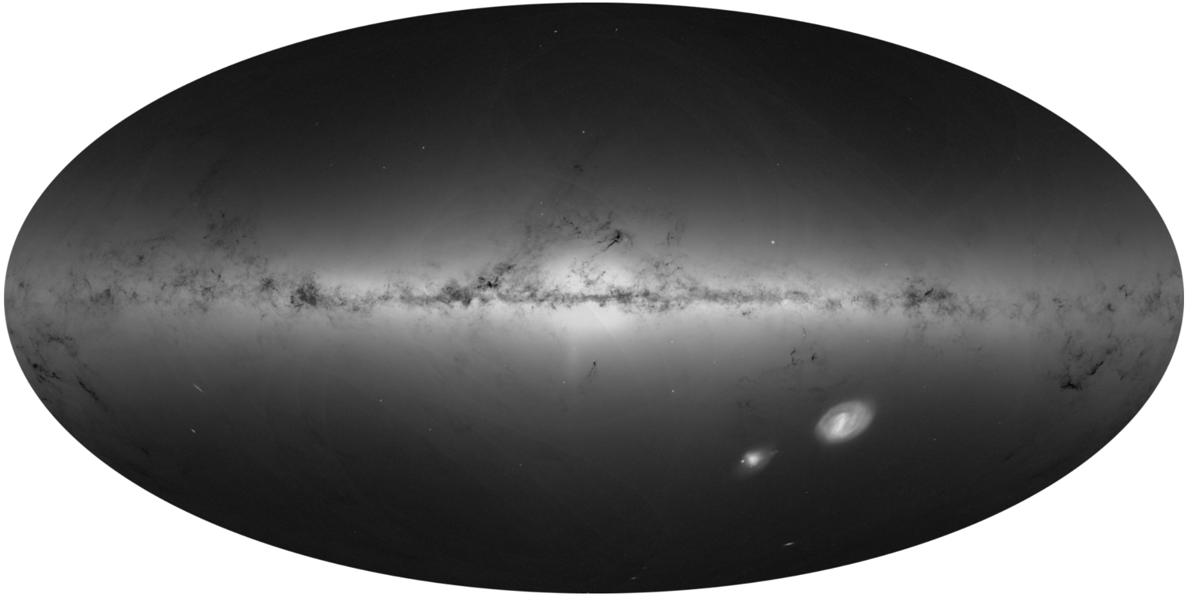

Gaia source density skymap. Credit: ESA

Some challenges:

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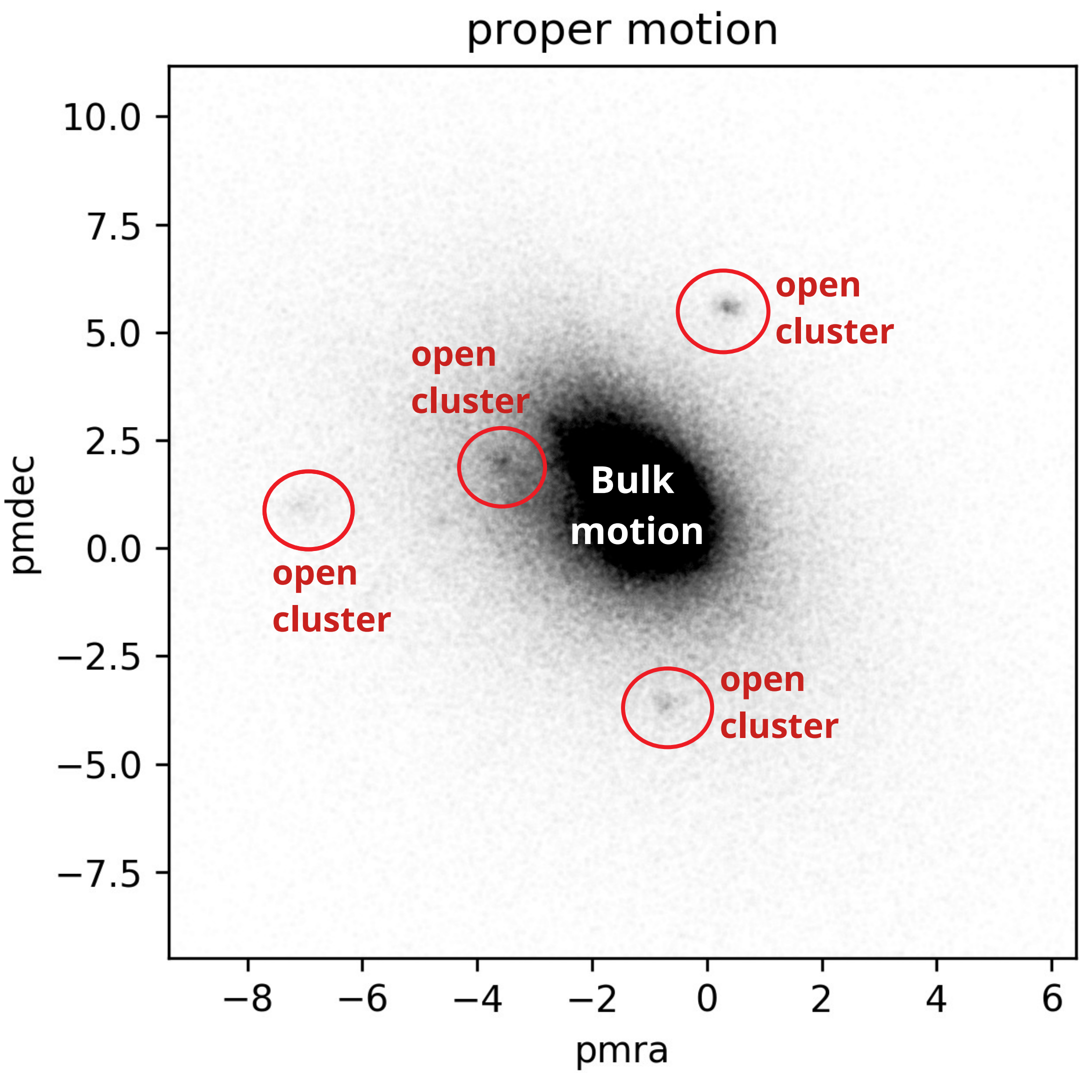

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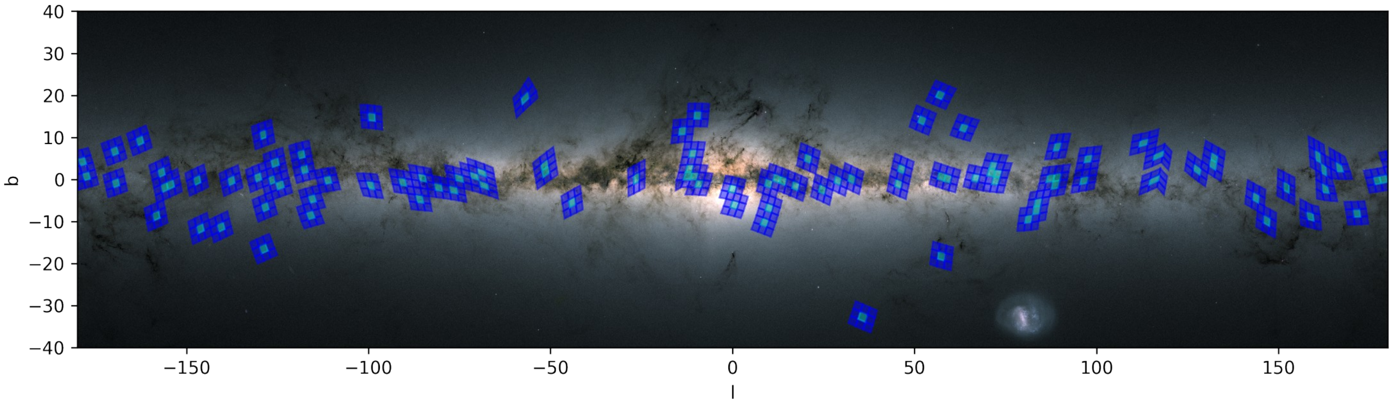

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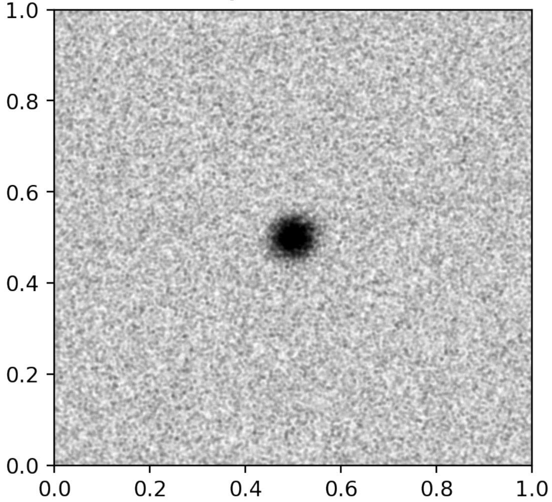
← **Main literature approach**

← **My favourite**

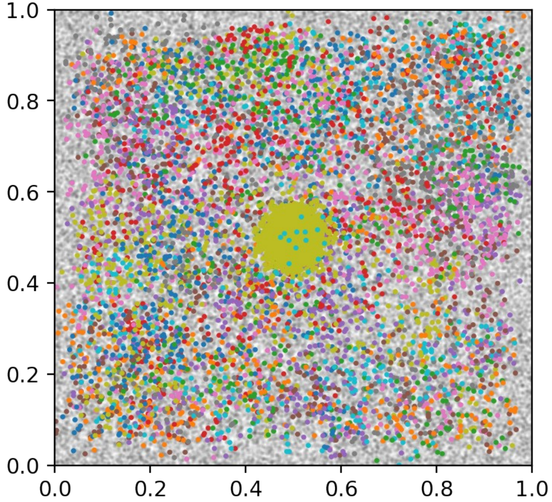
let's talk about false positives.

The **most sensitive** clustering methods can also produce **the most false positives**. Care **must** be taken when using "off-the-shelf" methods

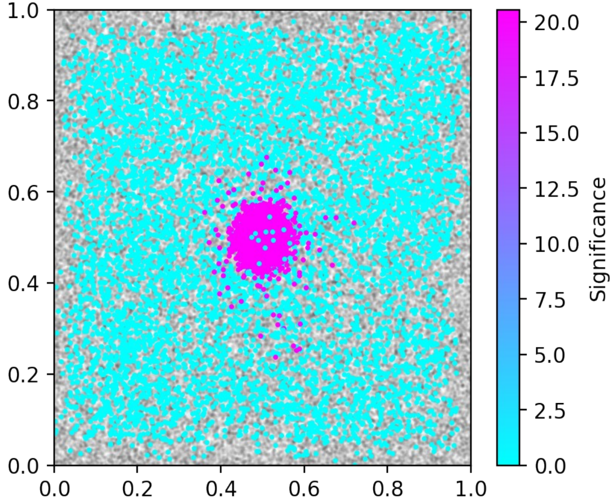
100,000 uniformly distributed 5D points + a 5000 point Gaussian



HDBSCAN, m_{clSize}=20… 151 clusters?!



Density test → only the real cluster is significant



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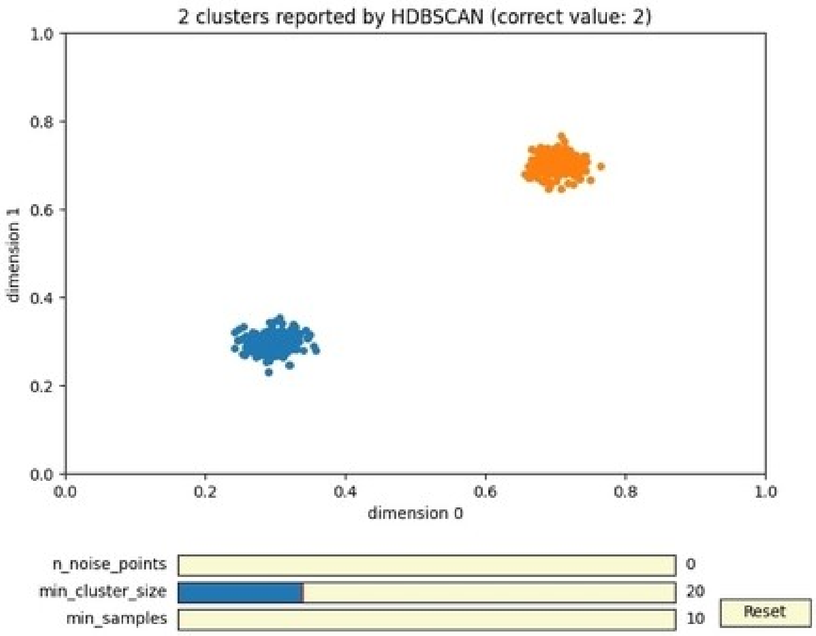

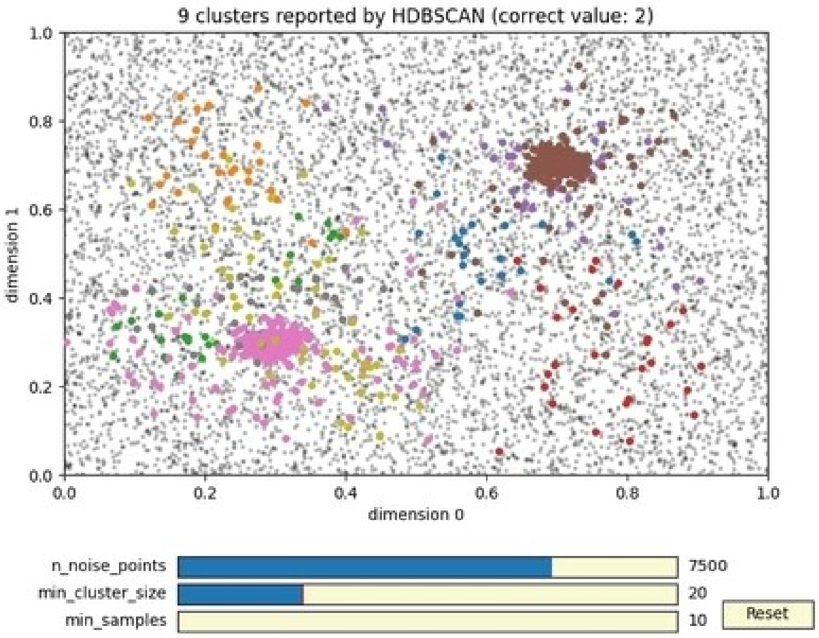

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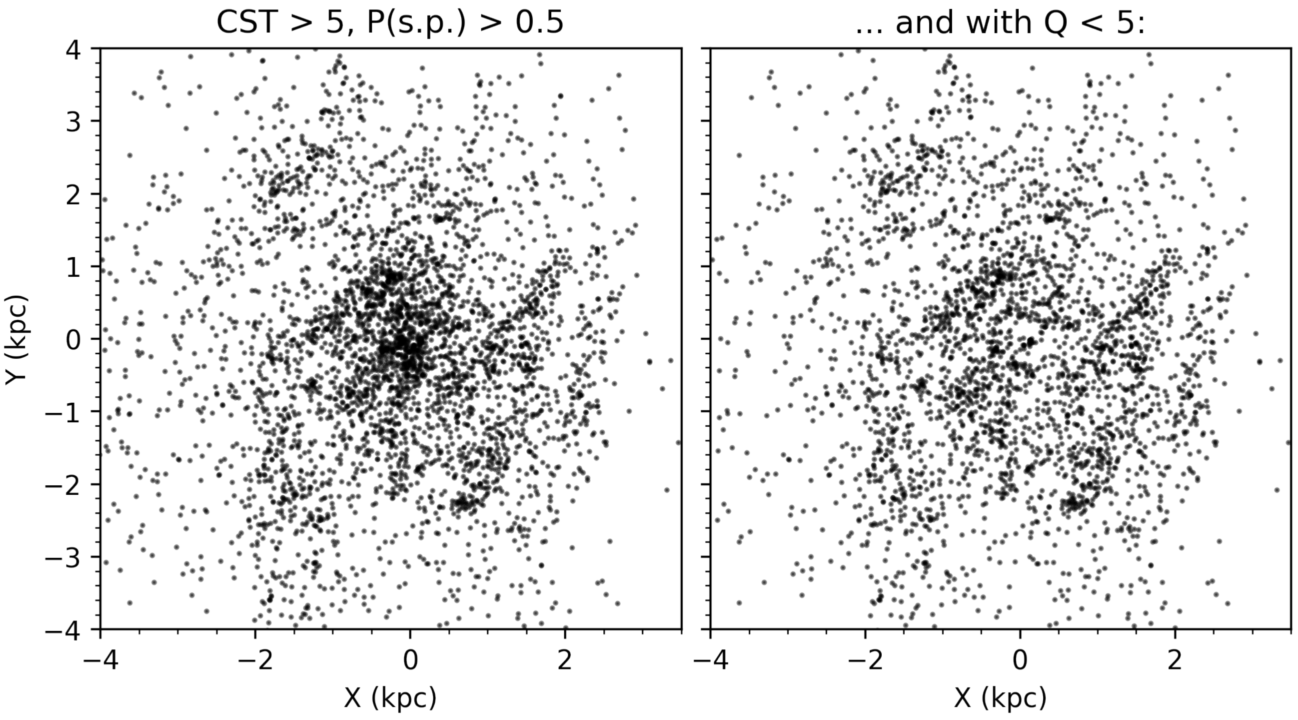

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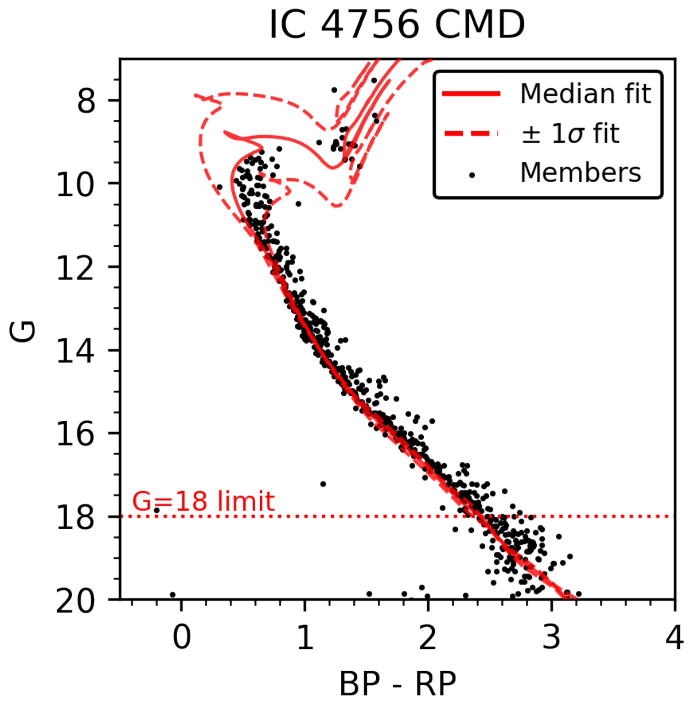

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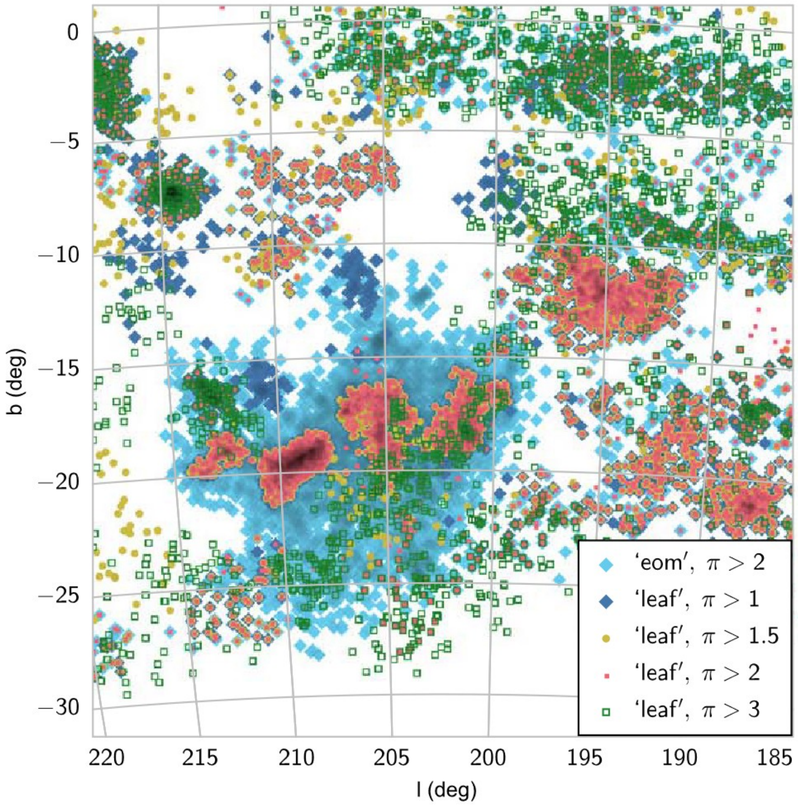

where next for clustering algorithms?

- Clustering algorithms are **fantastic** tools for astronomy
- Many off-the-shelf algorithms available (e.g. scikit-learn)
- BUT: they aren't designed for astronomy problems, and can run into weird issues

In the future: astro <u>must</u> collaborate with computer scientists, mathematicians etc. to develop algorithms

datasets to come...

Gaia DR5 (~2030): 2 billion stars

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+ many, many other uses across astronomy for clustering algorithms

emilydoesastro.com
@emilydoesastro

Check out the slides on GitHub:

Direct link:
github.com/emilyhunt/nam_2022_talk

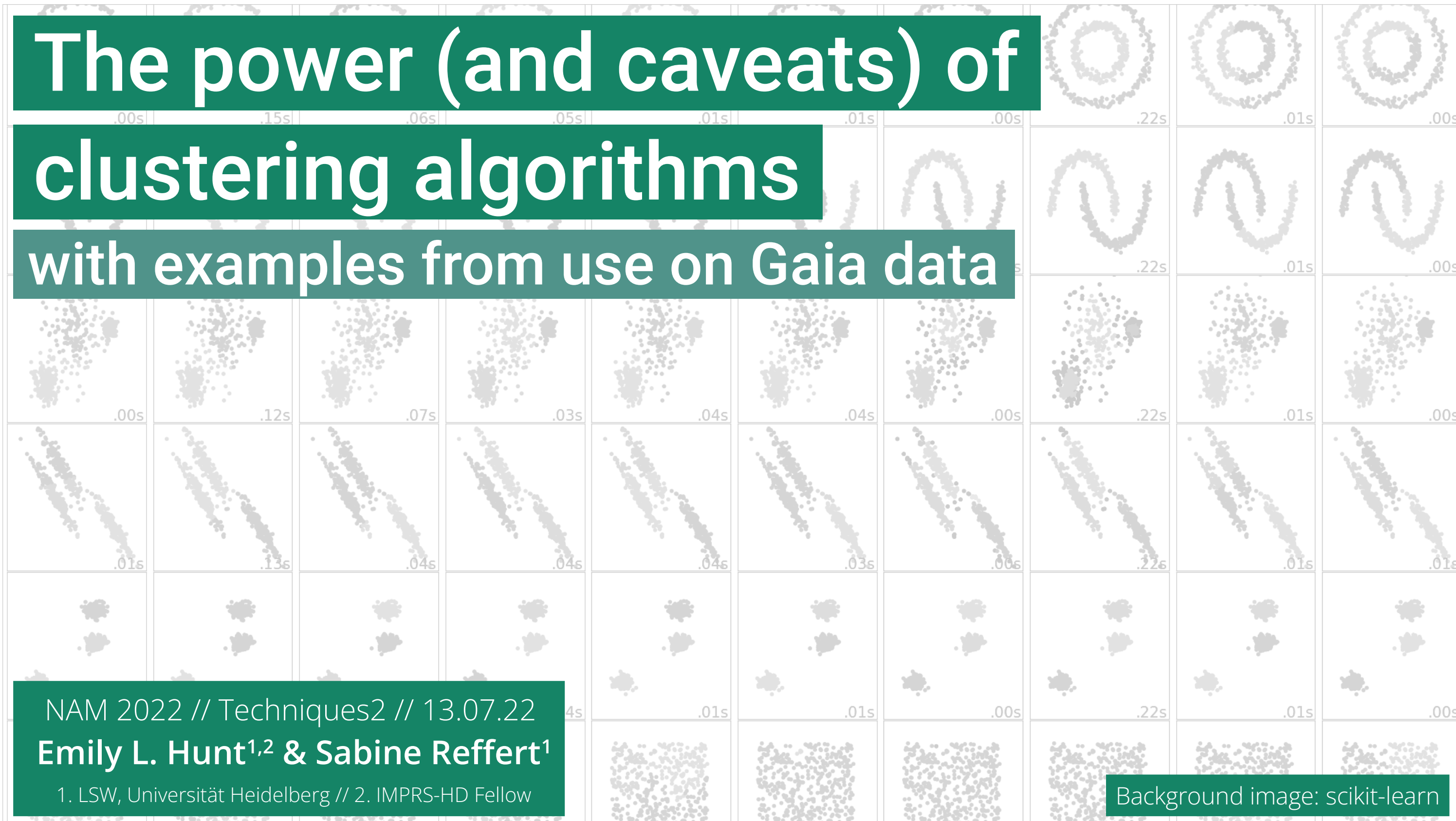
Key Takeaways:

→ Clustering algorithms are great

→ Many off-the-shelf solutions available

→ BUT: be careful! They can be wrong (and not tell you)

Background image: scikit-learn



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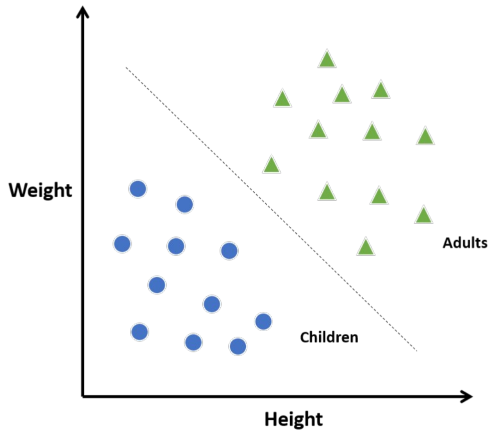

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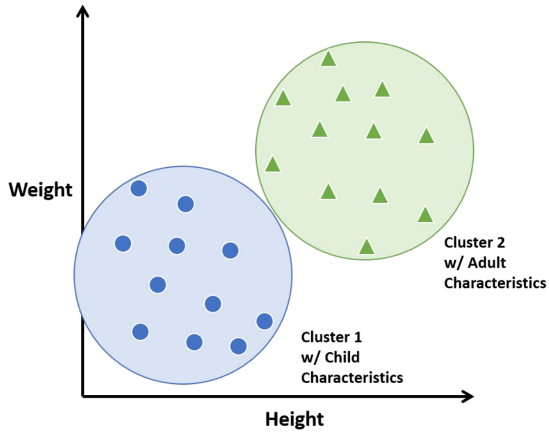

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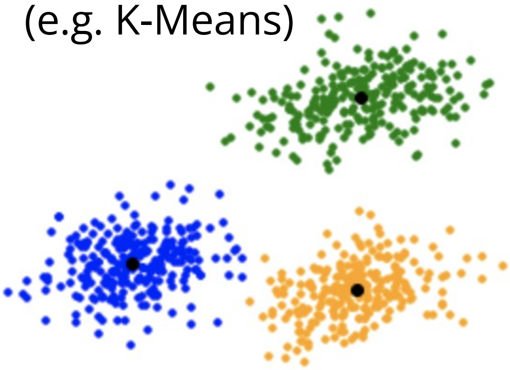

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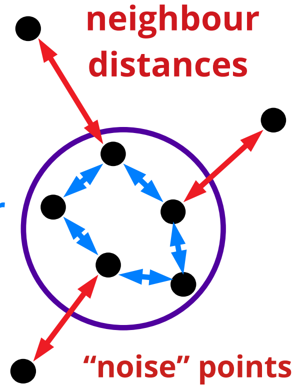

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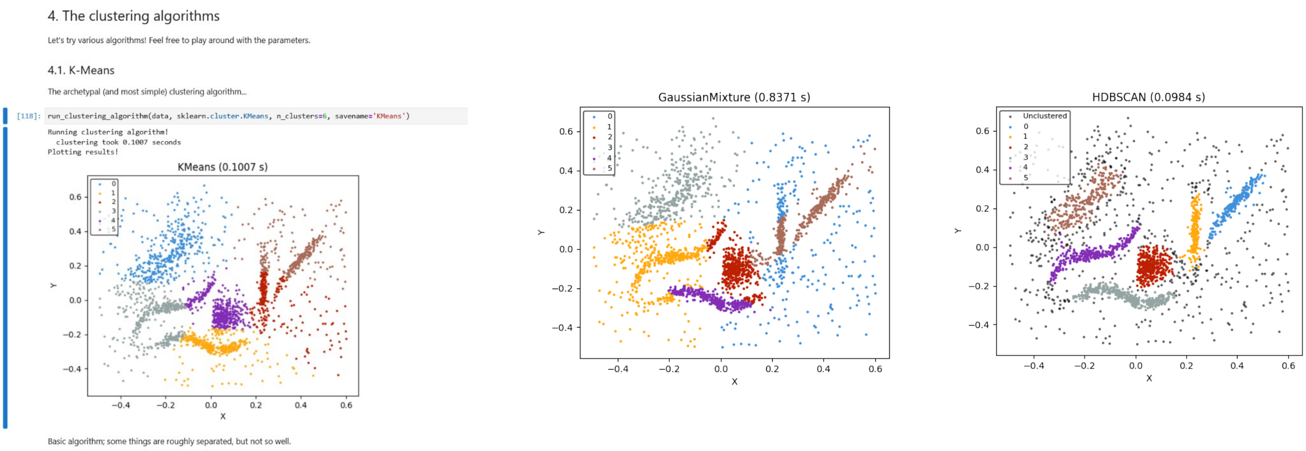

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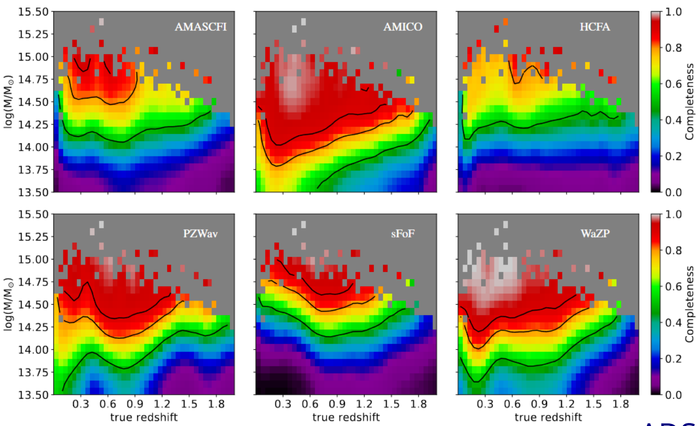

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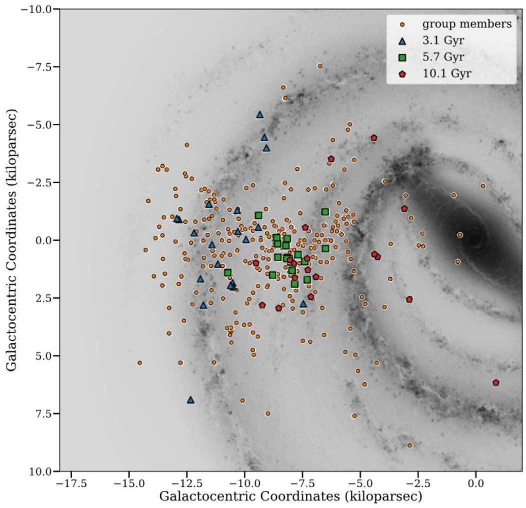

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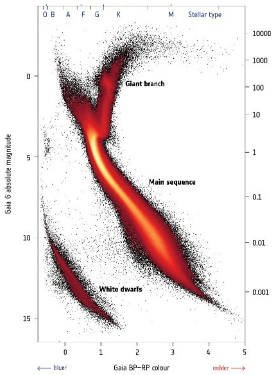

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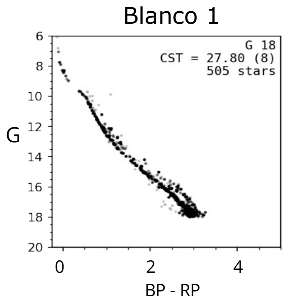

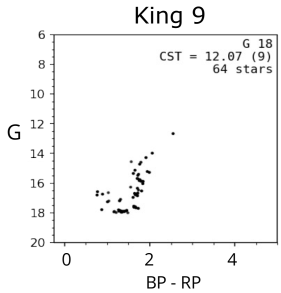

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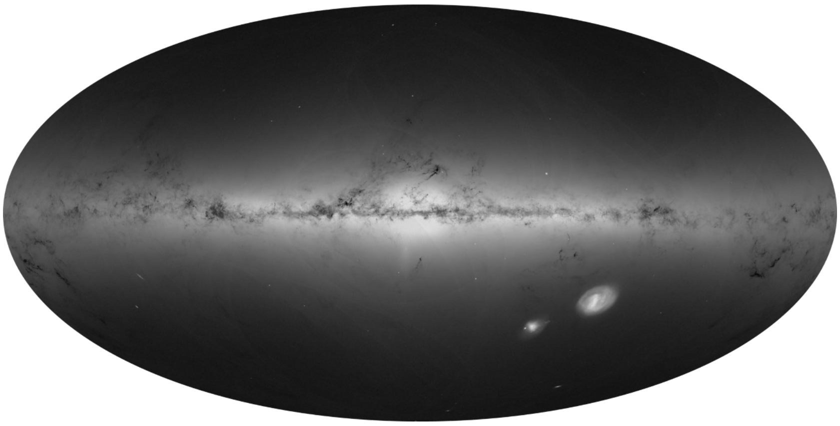

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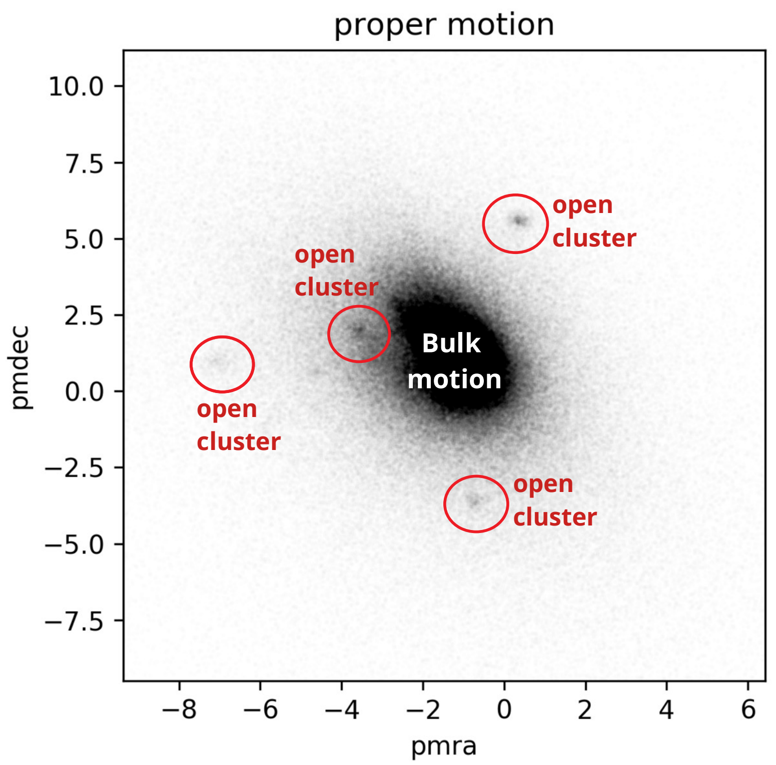

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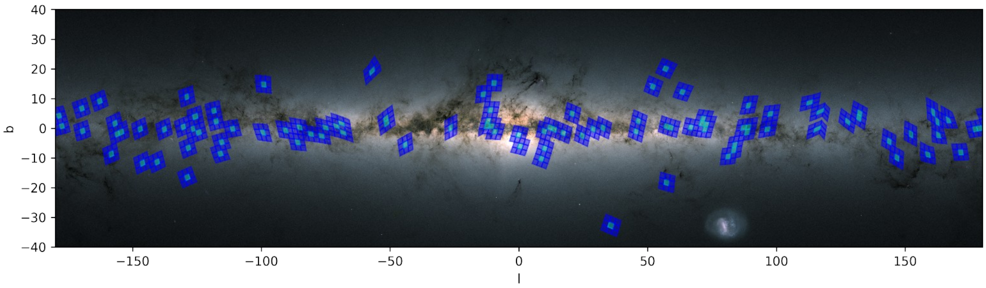

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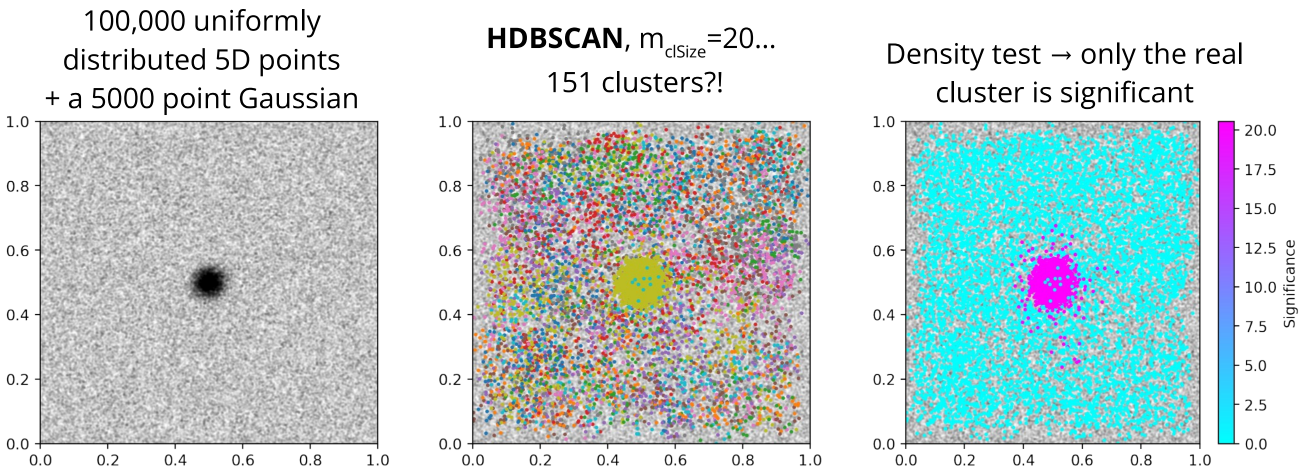

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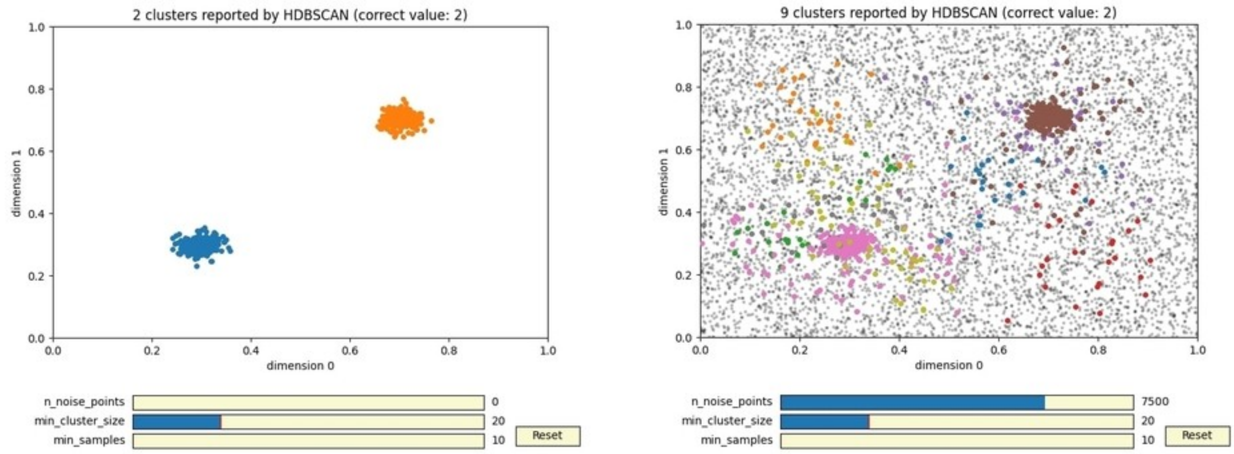

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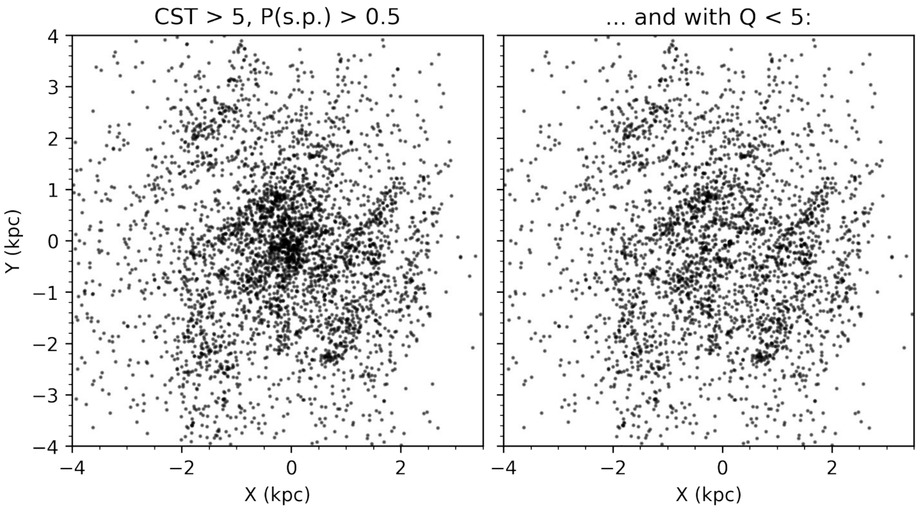

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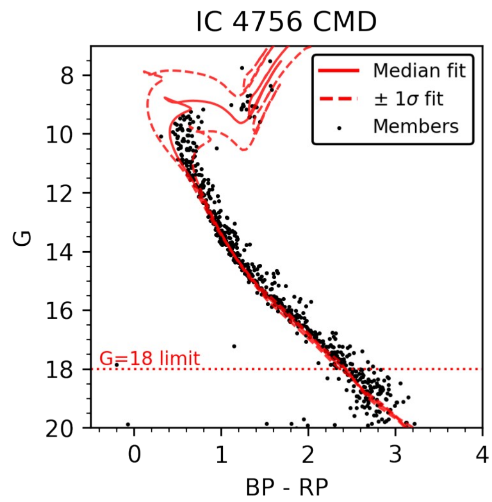

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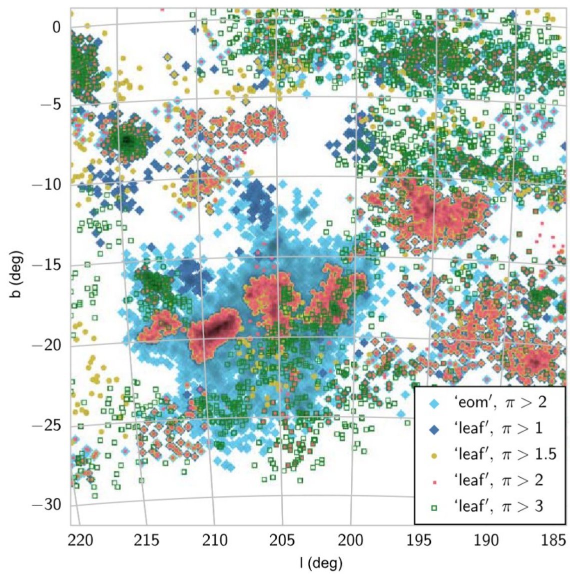

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