Dimensionality Reduction

Principal Component Analysis (PCA)

t-Stochastic Neighbor Embedding (t-SNE)

Uniform Manifold Approximation and Projection (UMAP)

Quick review

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What sorts of things are we now good at?

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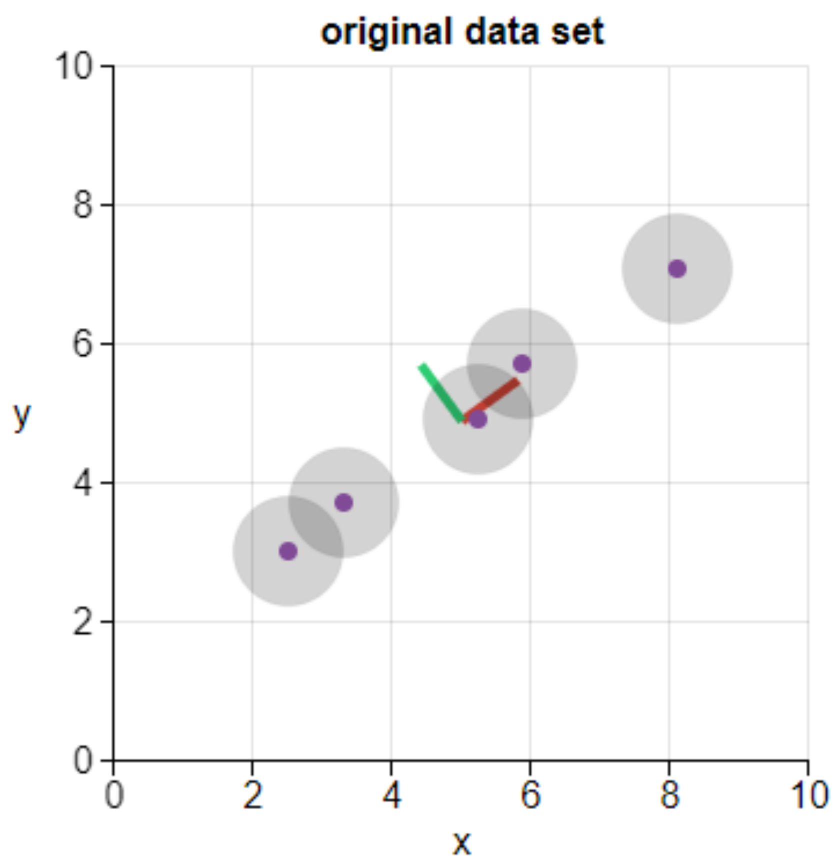
https://setosa.io/ev/principal-component-analysis/



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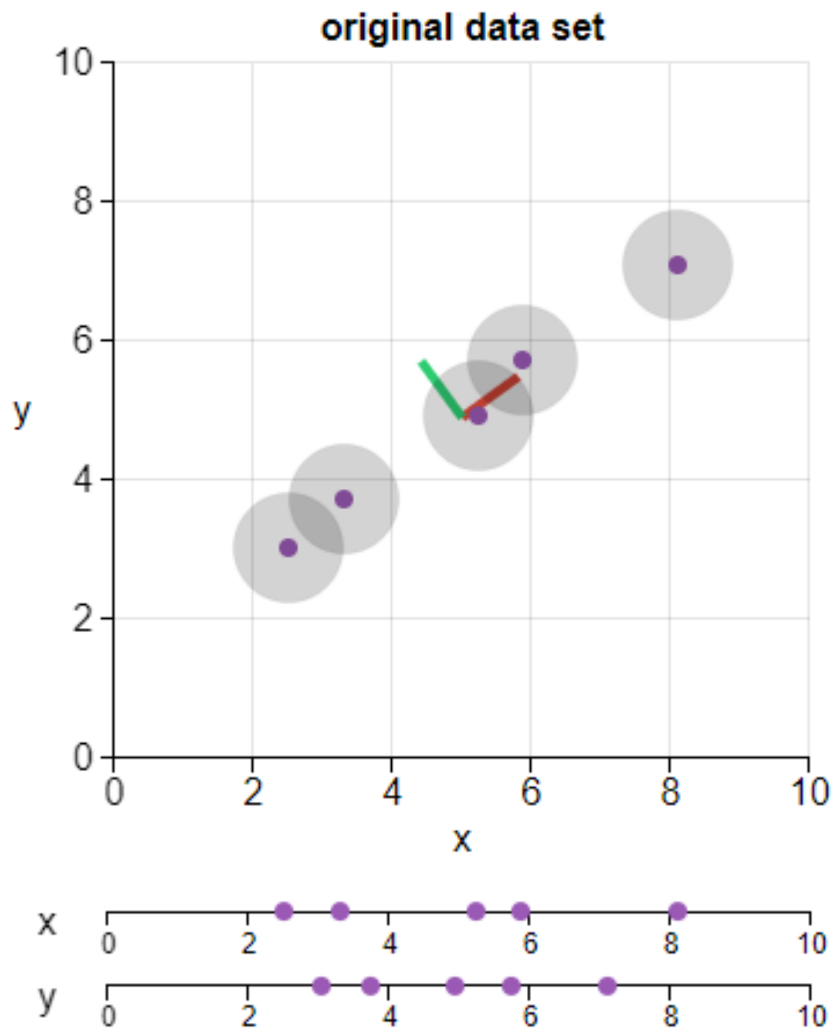

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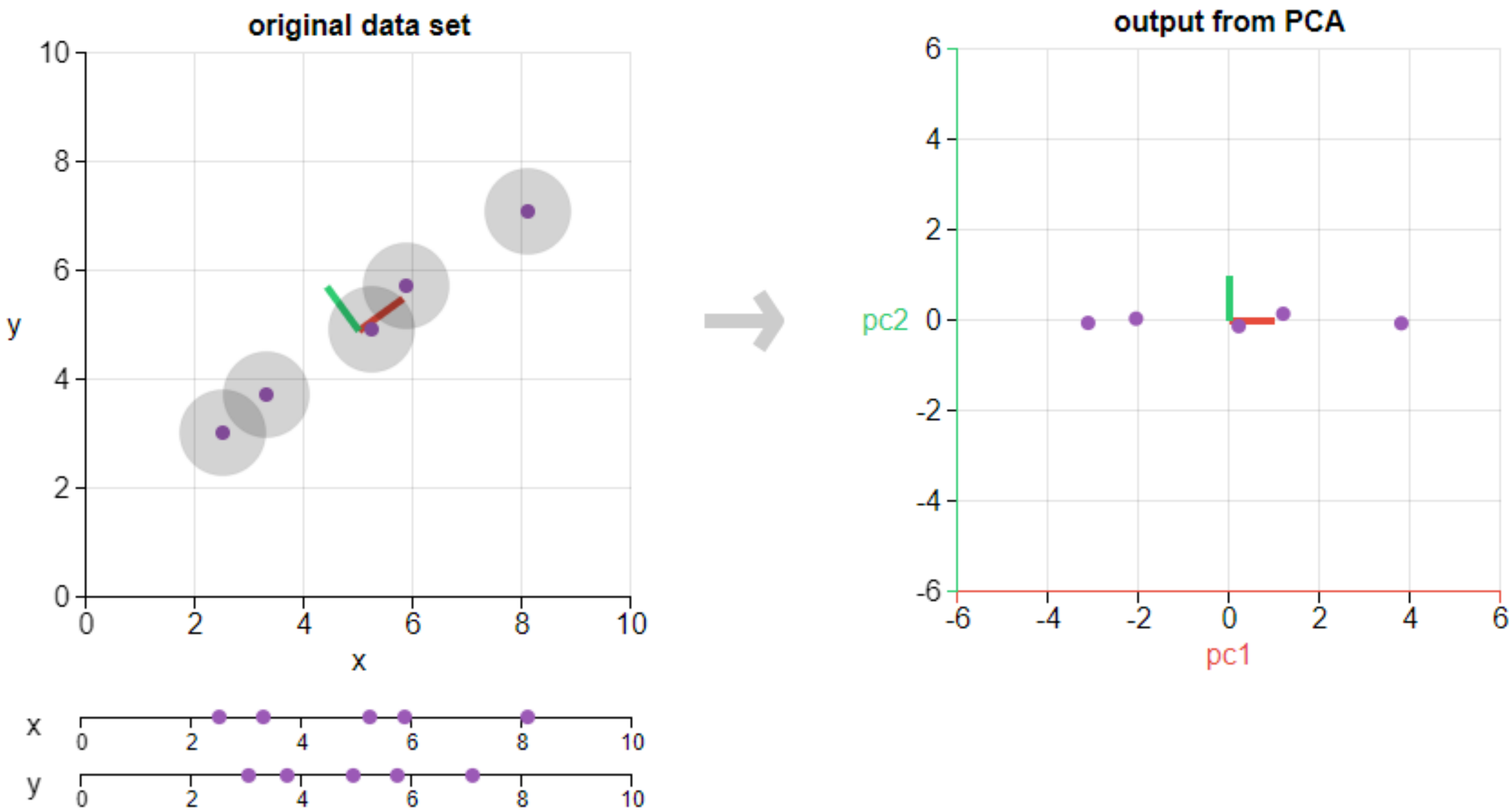

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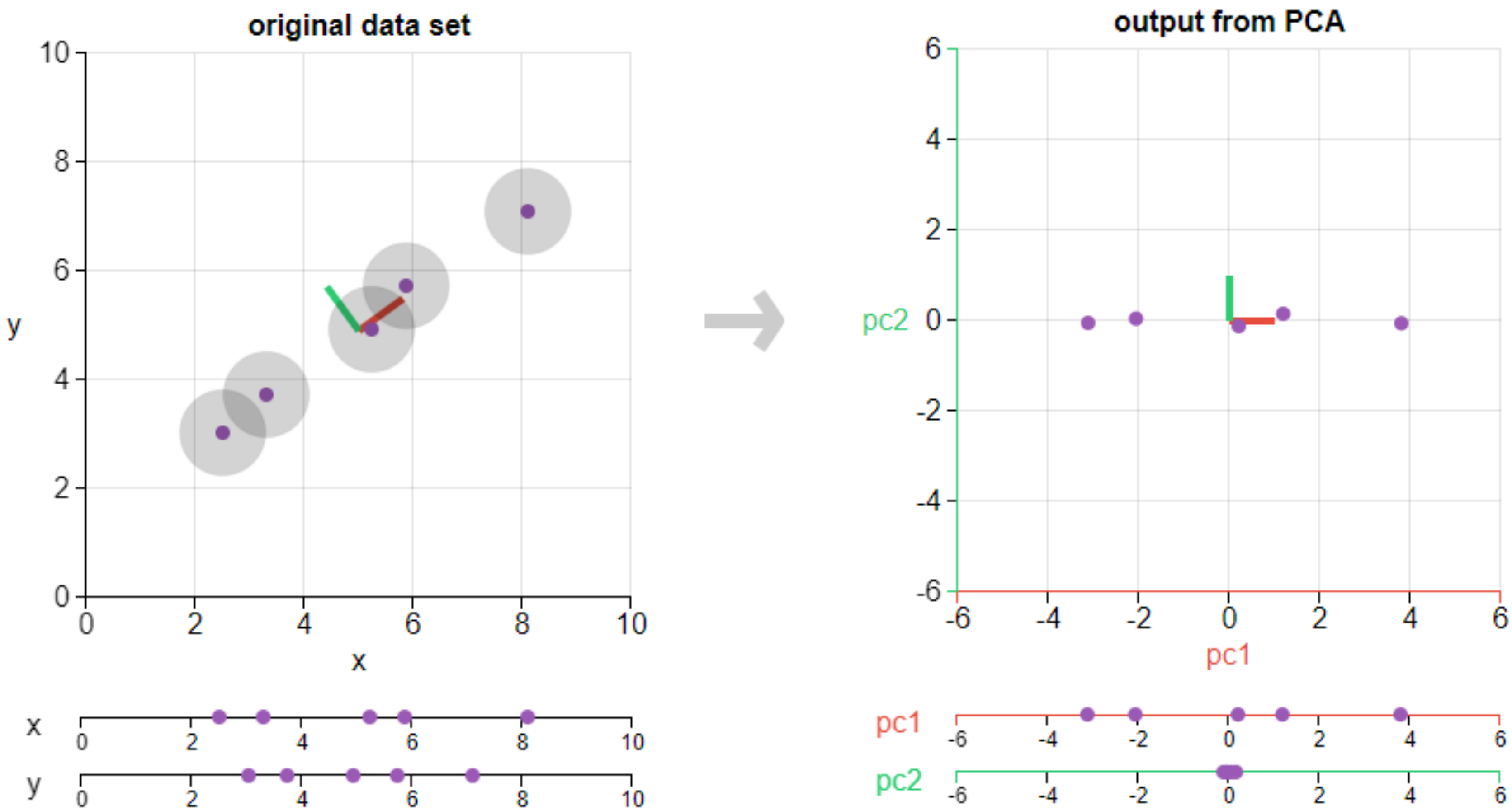
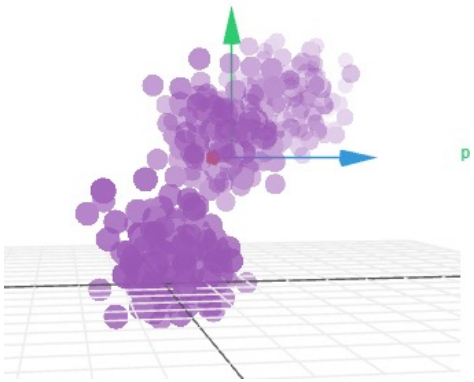


PCA in 3D

https://setosa.io/ev/principal-component-analysis/



COSMIC DAWN CENTER
DAWN

PCA in 3D

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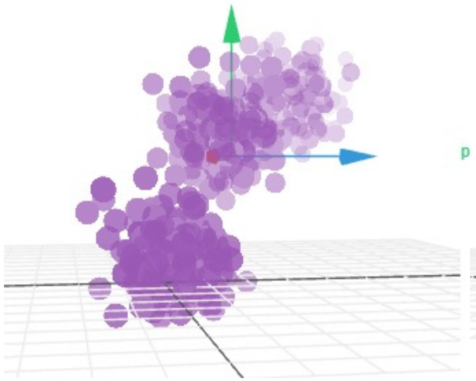

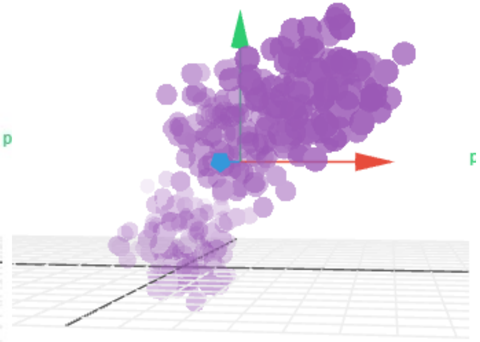

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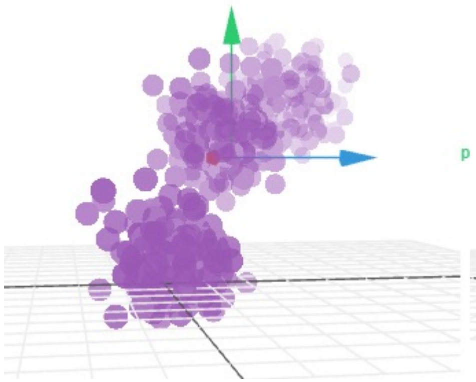

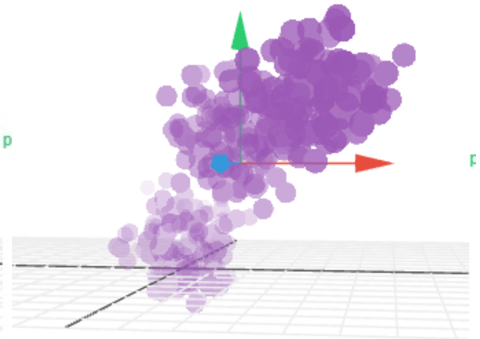

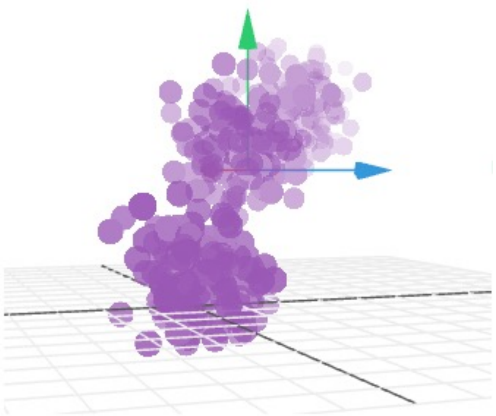

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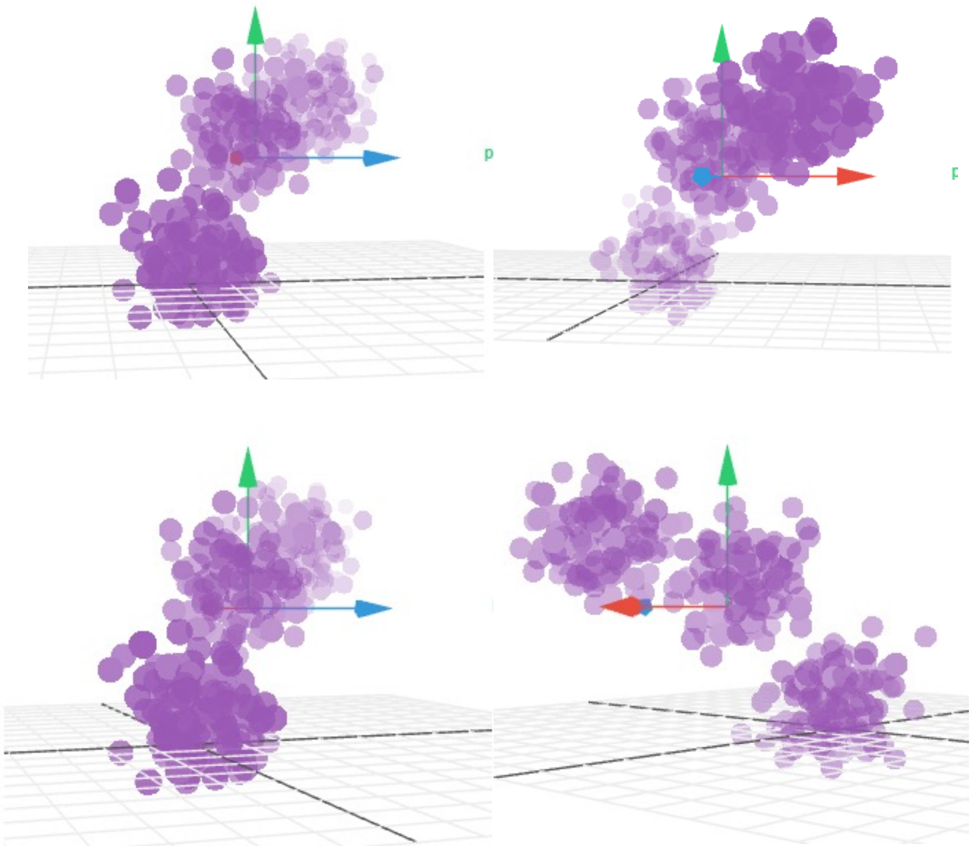

COSMIC DAWN CENTER

DAWN

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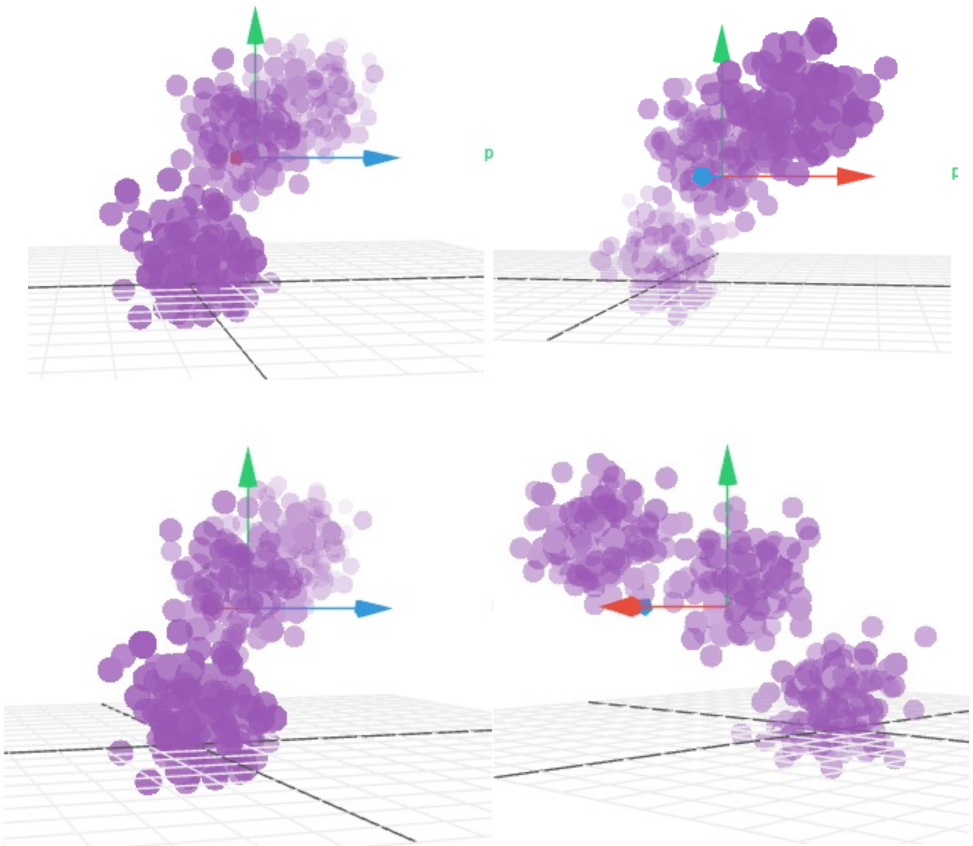

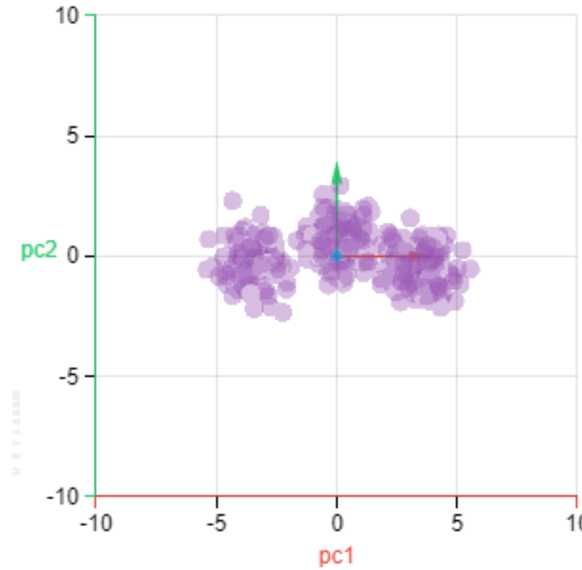

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DAWN

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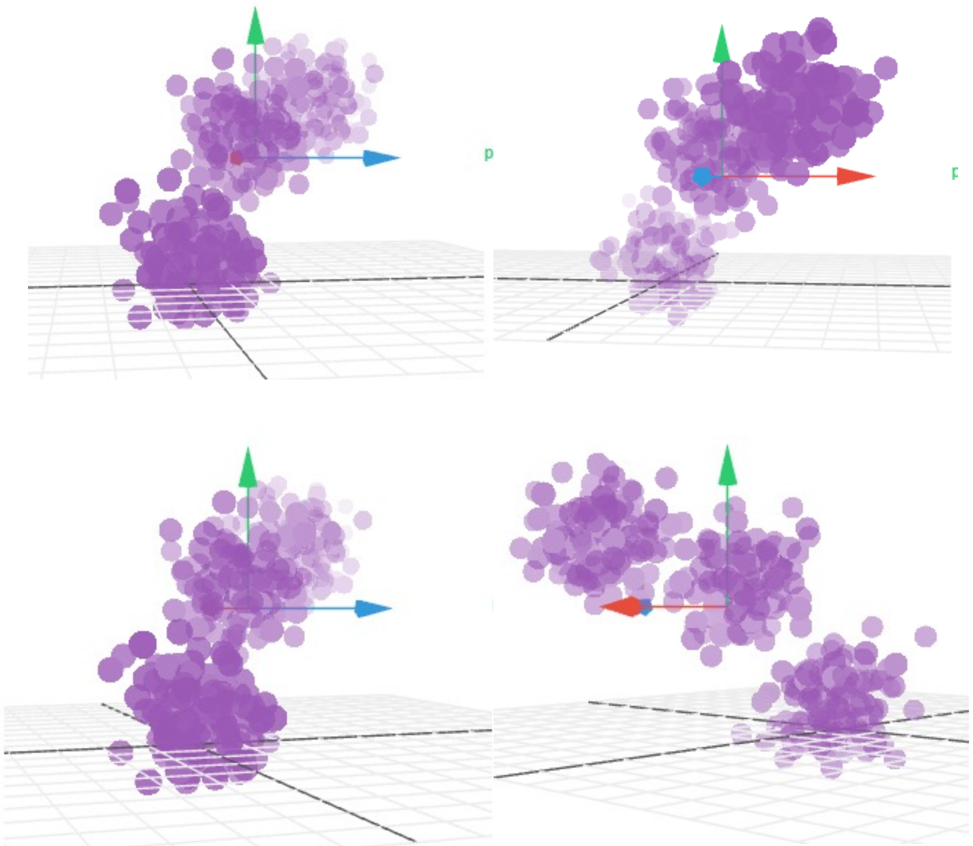

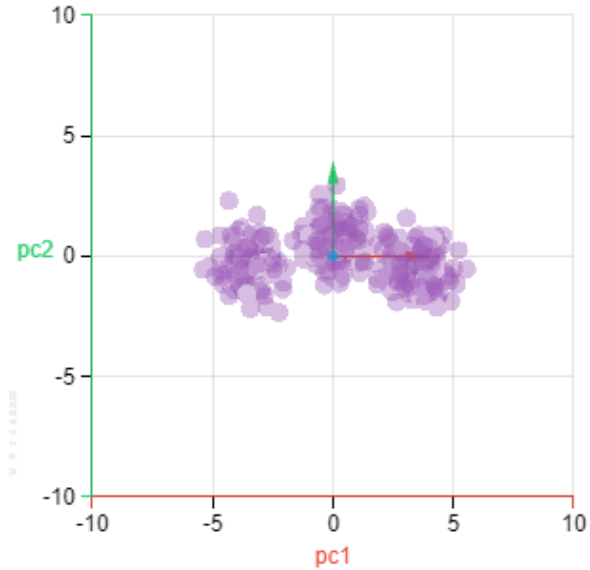

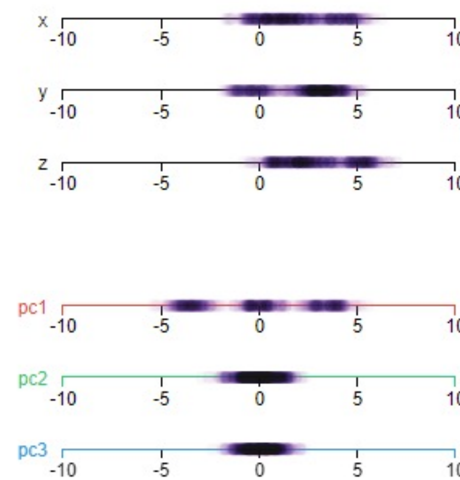

PCA in 17D

https://setosa.io/ev/principal-component-analysis/

	England	N Ireland	Scotland	Wales
Alcoholic drinks	375	135	458	475
Beverages	57	47	53	73
Carcase meat	245	267	242	227
Cereals	1472	1494	1462	1582
Cheese	105	66	103	103
Confectionery	54	41	62	64
Fats and oils	193	209	184	235
Fish	147	93	122	160
Fresh fruit	1102	674	957	1137
Fresh potatoes	720	1033	566	874
Fresh Veg	253	143	171	265
Other meat	685	586	750	803
Other Veg	488	355	418	570
Processed potatoes	198	187	220	203
Processed Veg	360	334	337	365
Soft drinks	1374	1506	1572	1256
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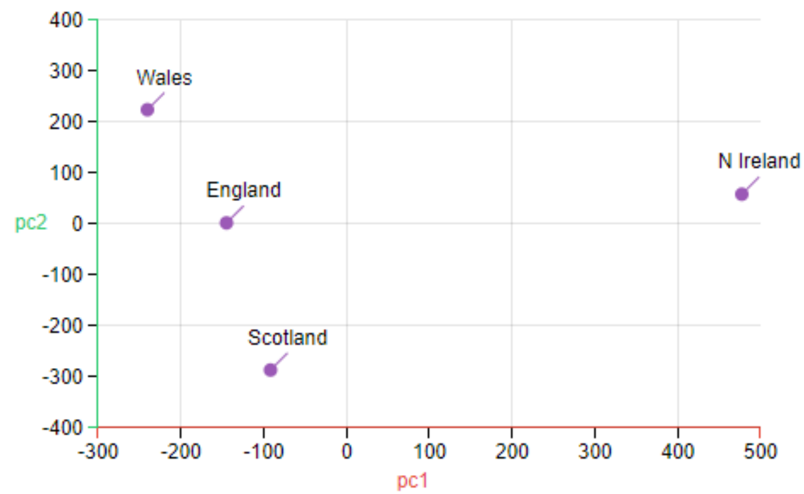

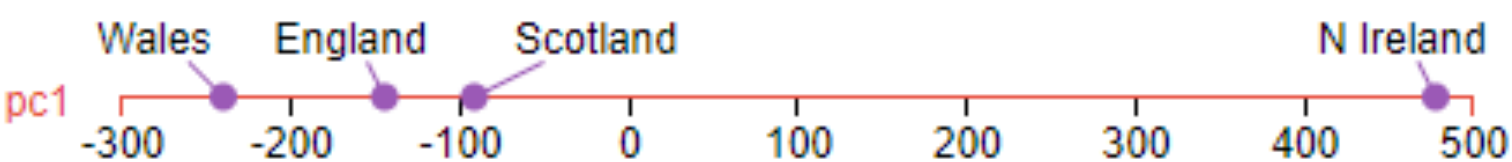

COSMIC DAWN CENTER
DAWN

OK, so how can we find the right basis?

1. Standardization

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2. Compute covariance matrix

$$\begin{bmatrix} Cov(x,x) & Cov(x,y) & Cov(x,z) \\ Cov(y,x) & Cov(y,y) & Cov(y,z) \\ Cov(z,x) & Cov(z,y) & Cov(z,z) \end{bmatrix}$$

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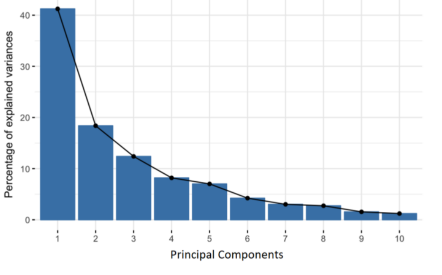
3. Compute eigenvectors and eigenvalues



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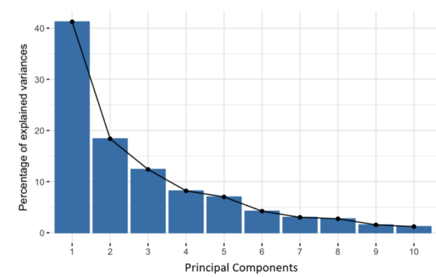
3. Compute eigenvectors and eigenvalues

4. Discard vectors that are not important enough



Example: Handwritten Digits

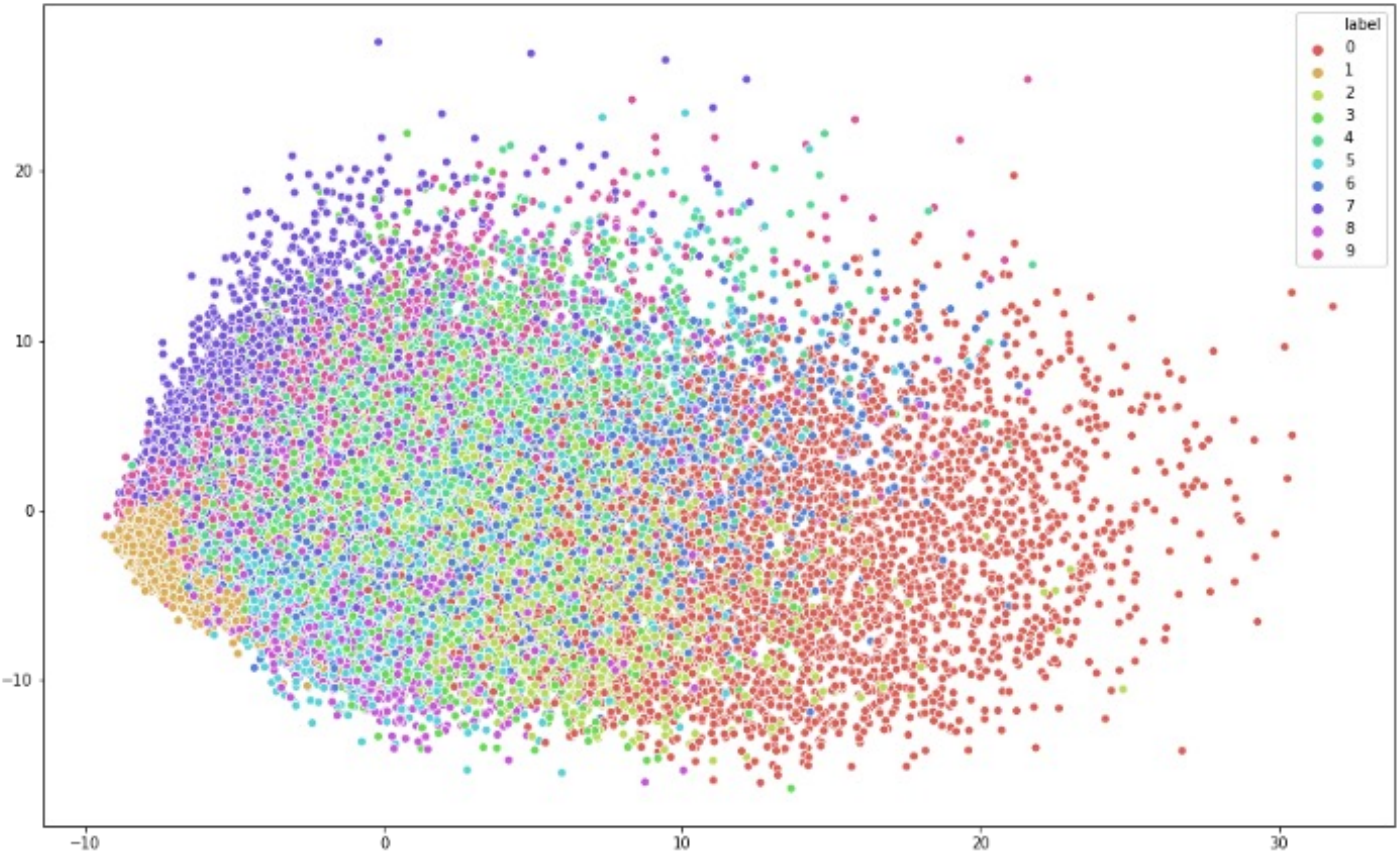
MNIST dataset

COSMIC DAWN CENTER

DAWN

Group "similar" things together

Principal Component Analysis

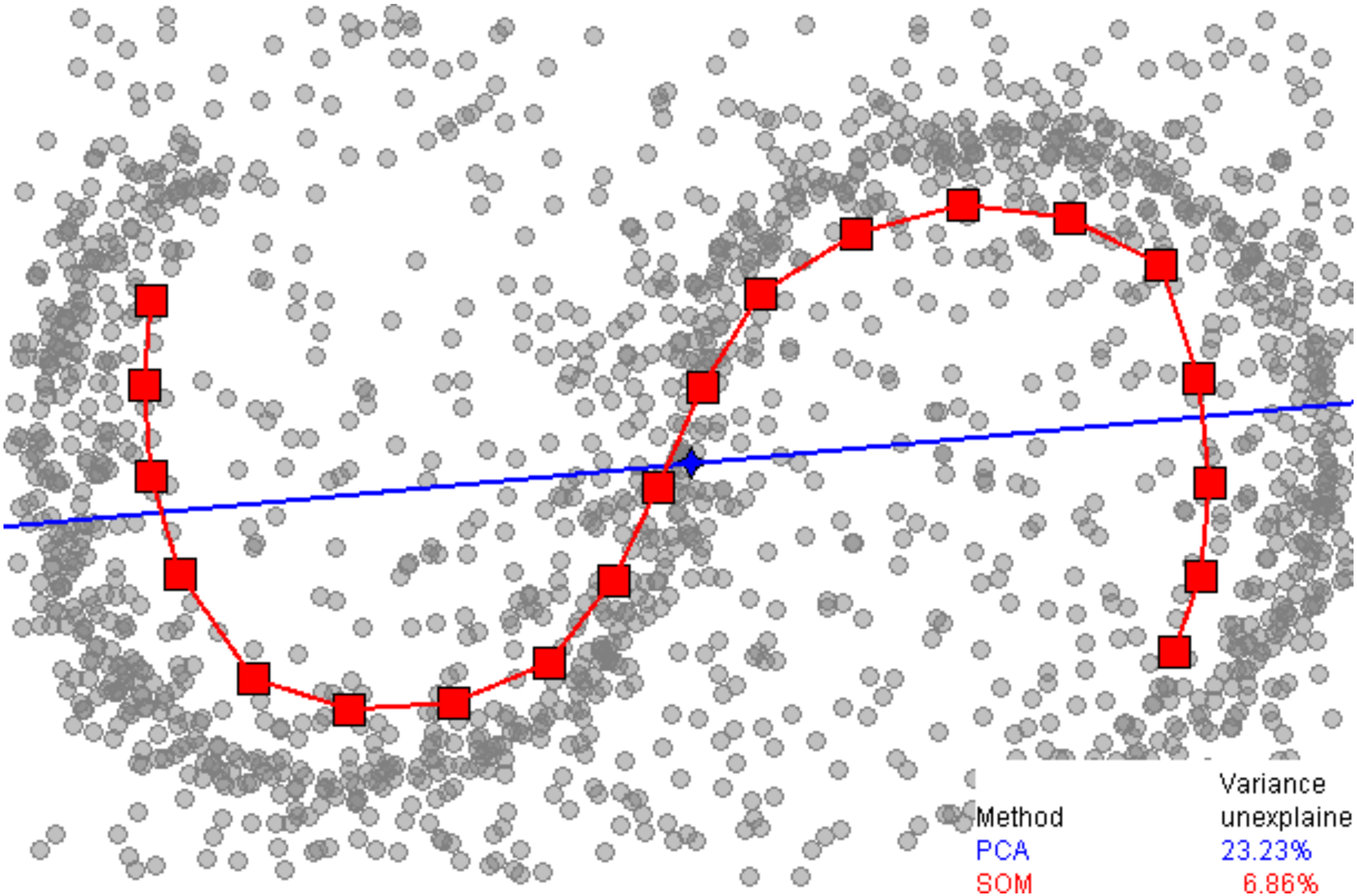


Example: Handwritten Digits

MNIST dataset

Some things aren't linear!

Wikimedia Commons



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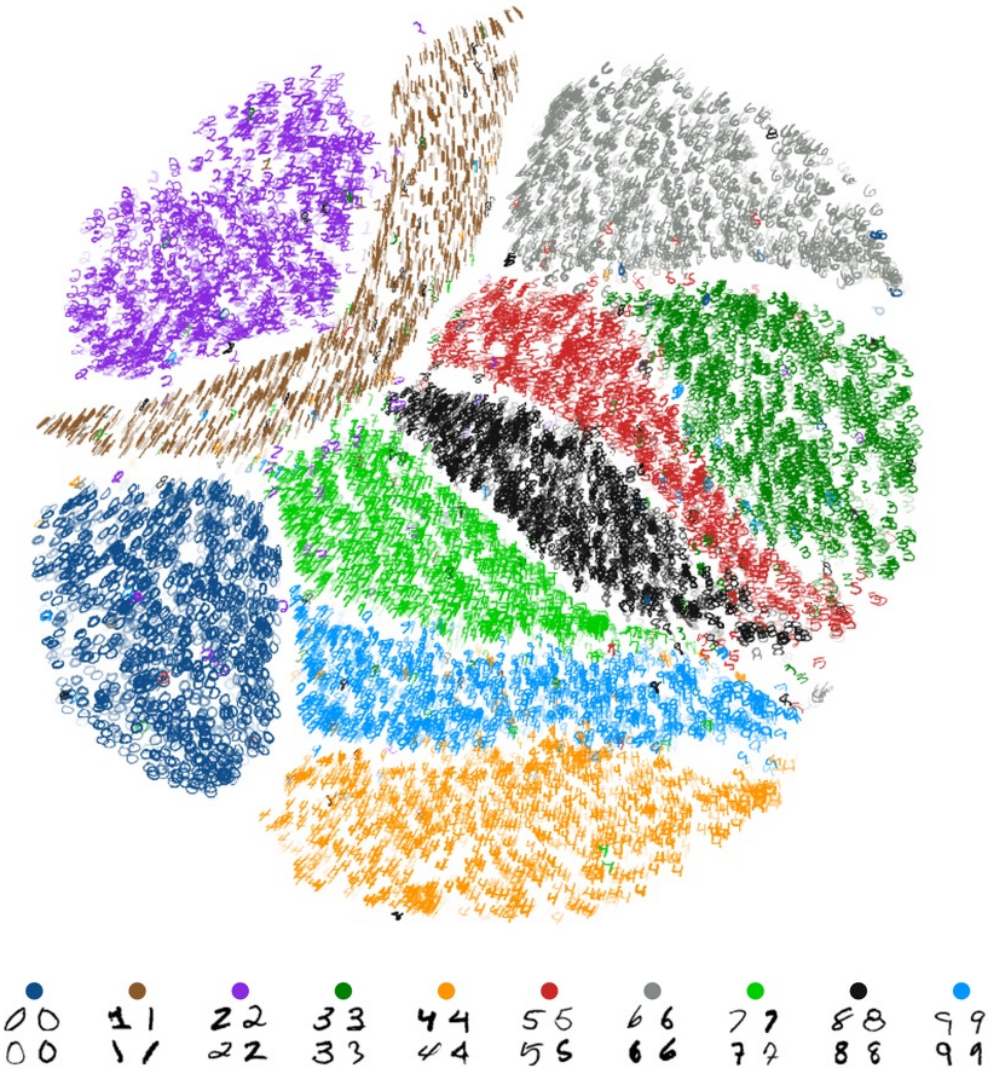
DAWN

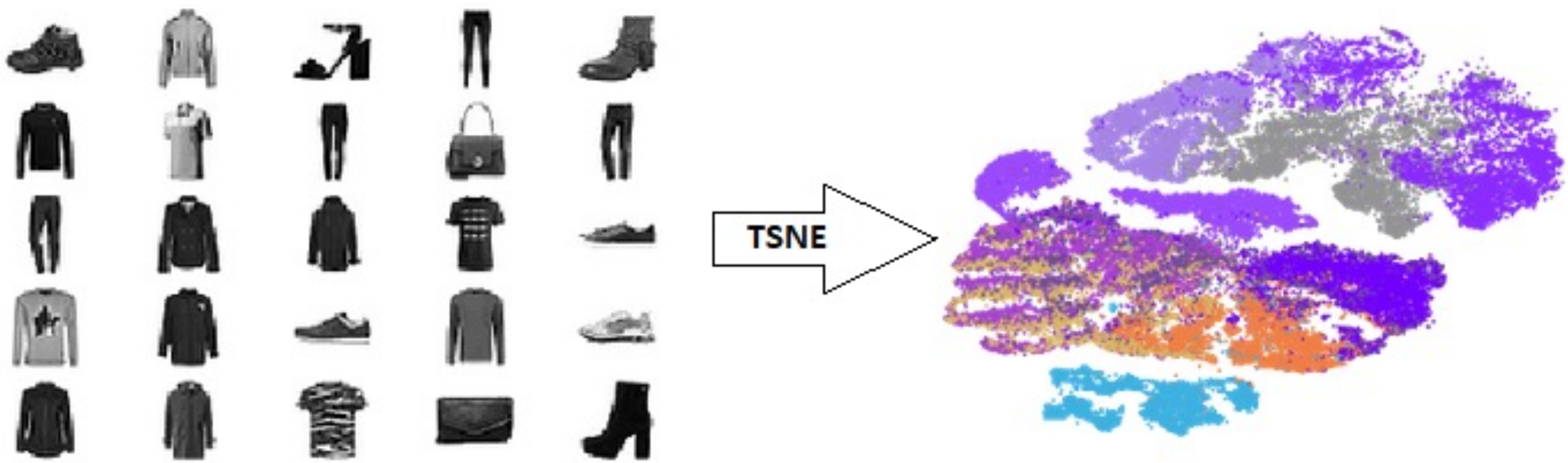
Group "similar" things together

Pezzotti 2019



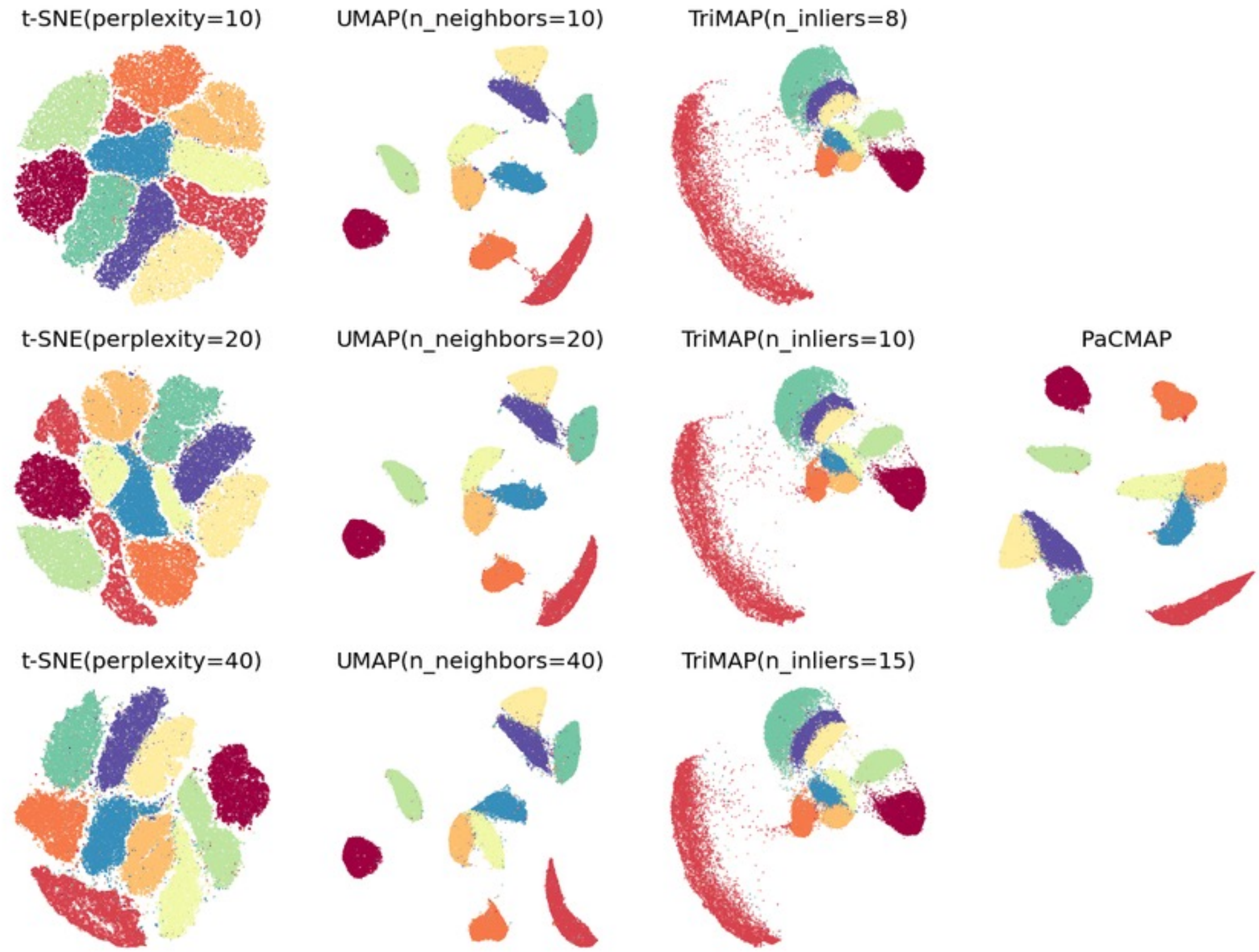
Group “similar” things together

“Fashion MNIST” datasets, t-SNE



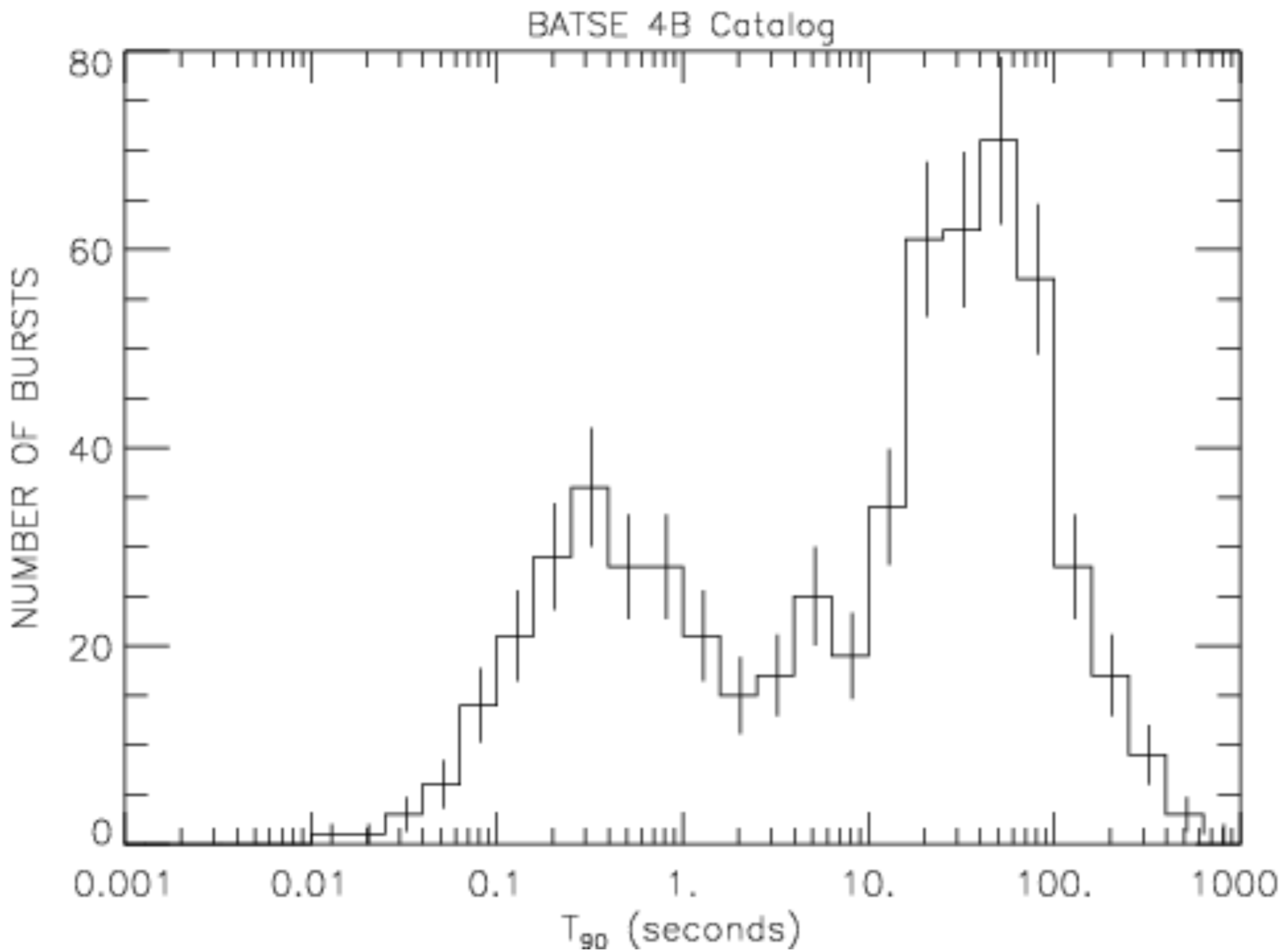
Group “similar” things together

Wang et al. 2020



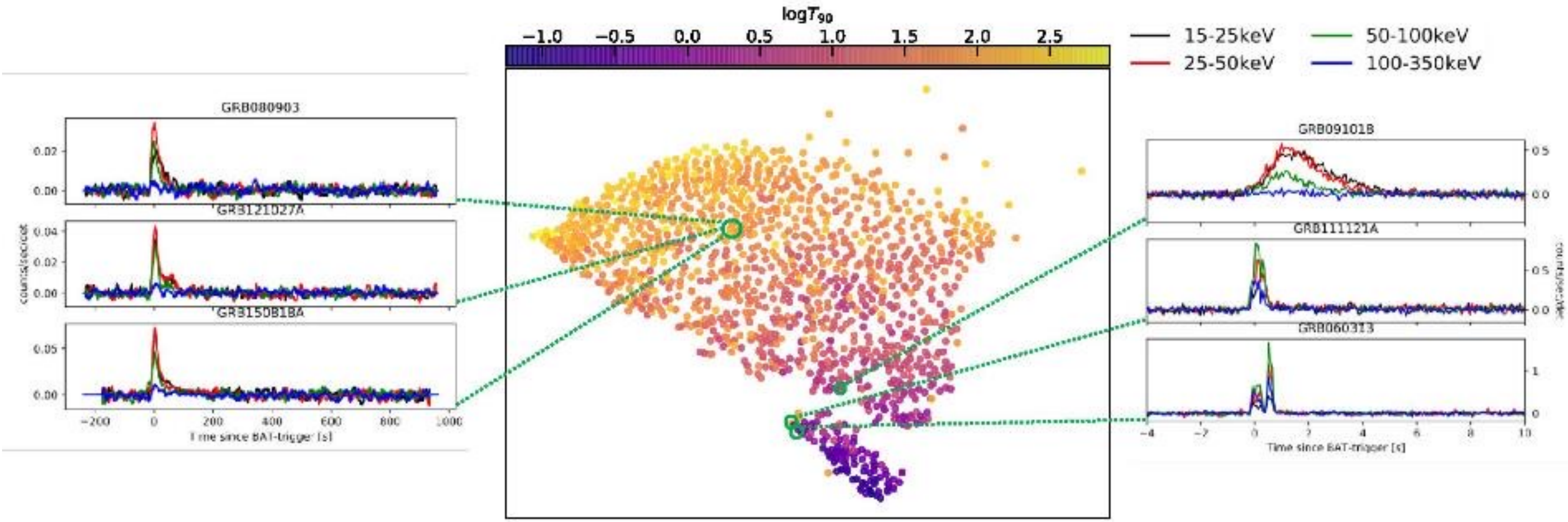
Example: Separate Short and Long GRBs

R. Mallozzi, updated Aug 2018 at https://gammaray.msfc.nasa.gov/batse/grb/duration/



t-SNE map for *Swift* light curves

Kragh Jespersen et al. 2020



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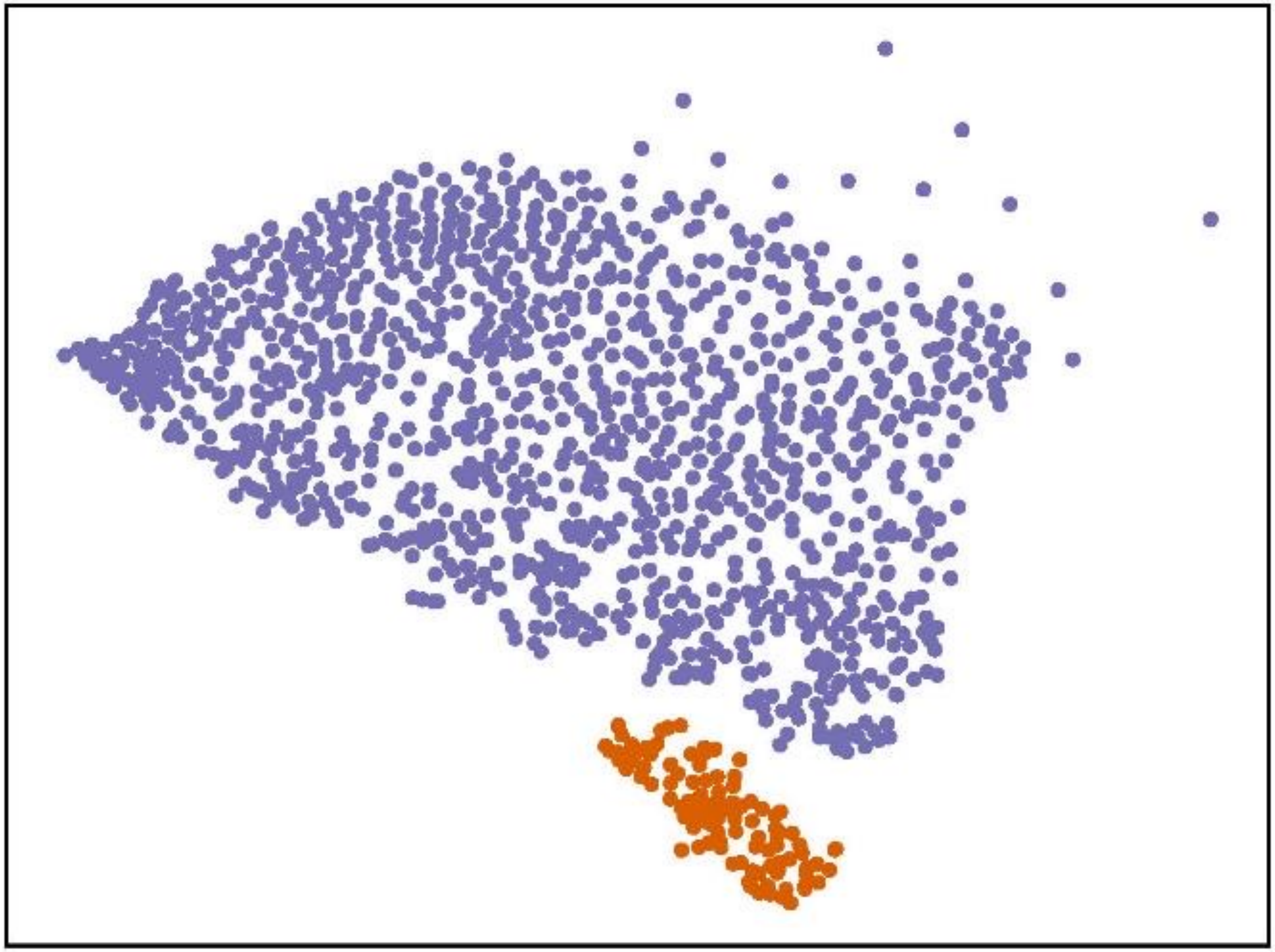

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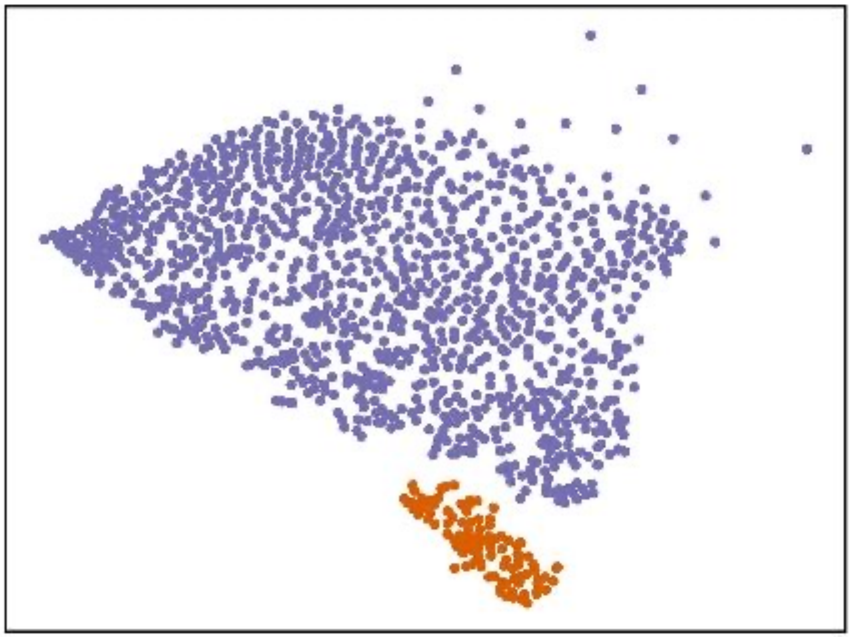
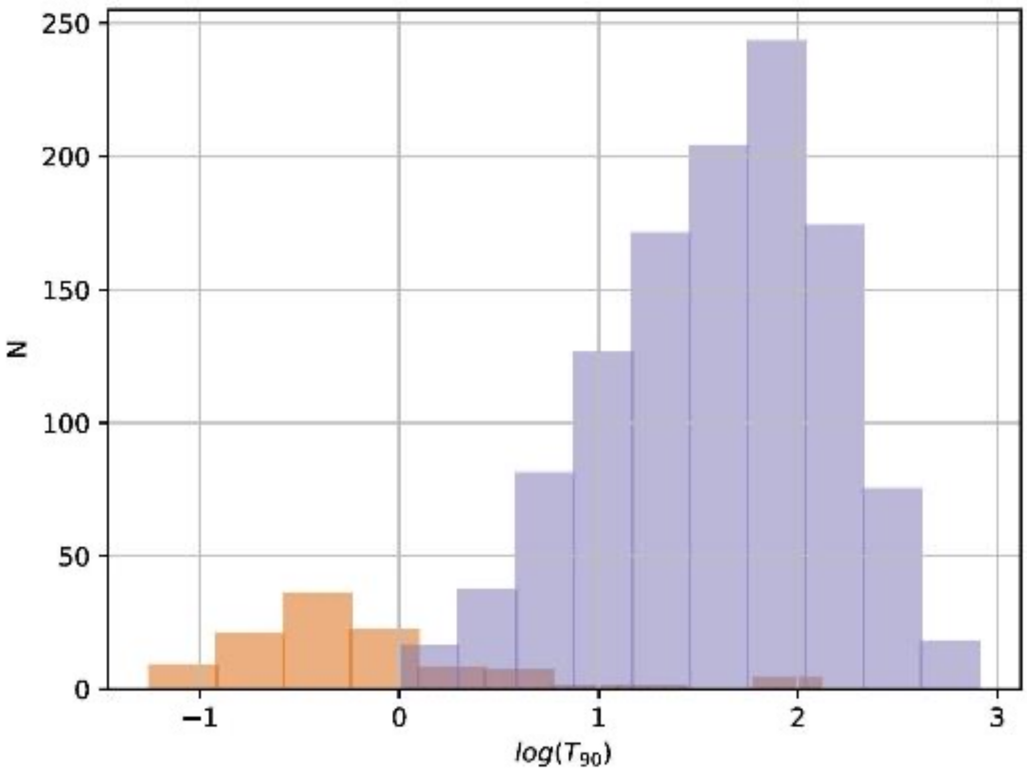
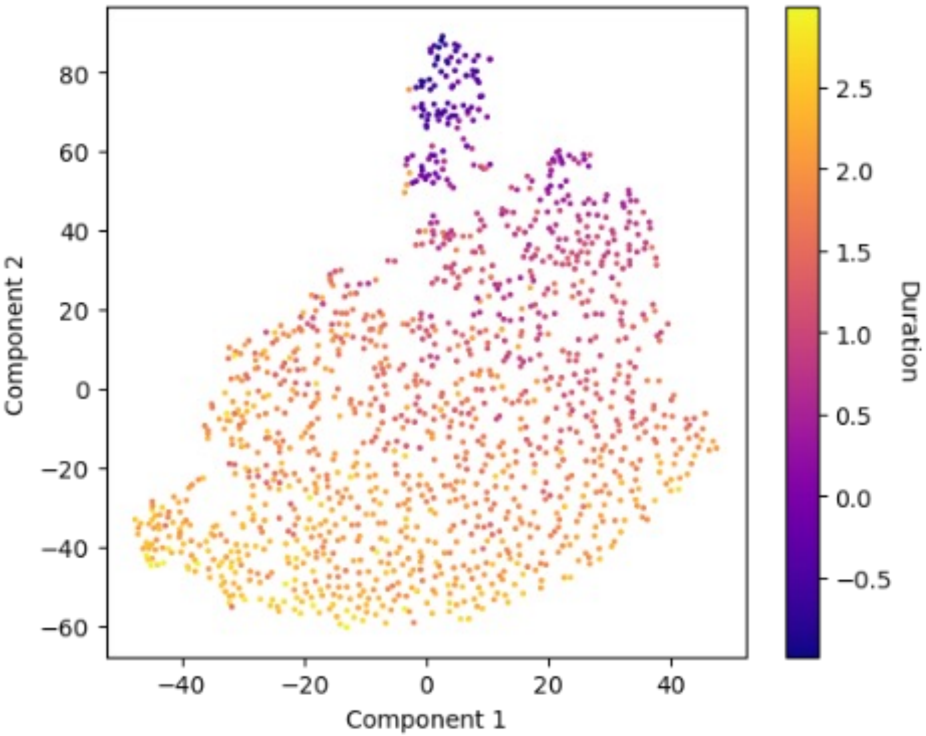
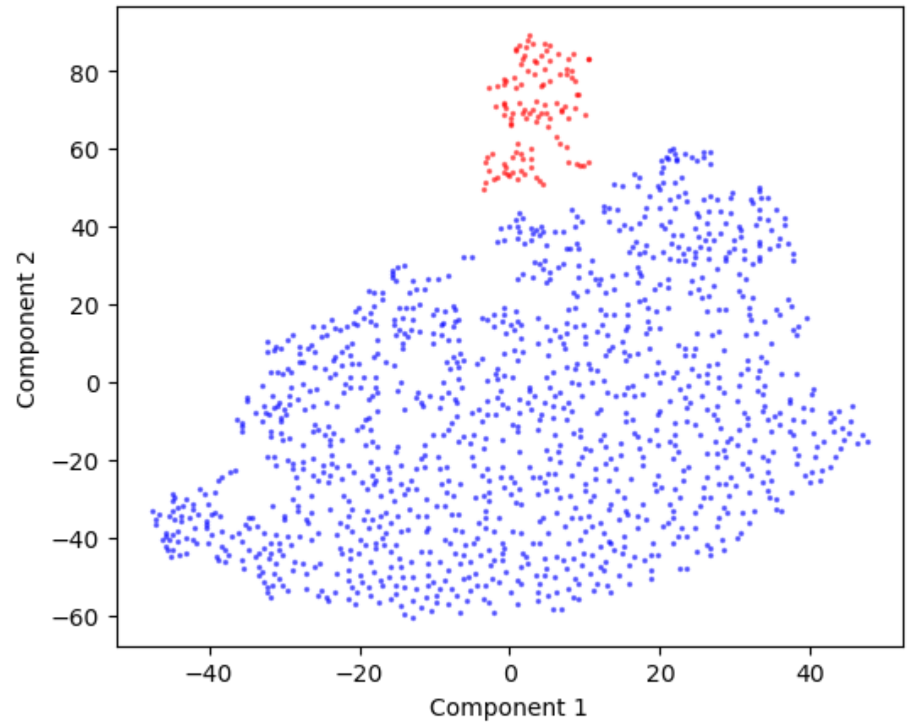




COSMIC DAWN CENTER
DAWN

Embeddings, colored by duration





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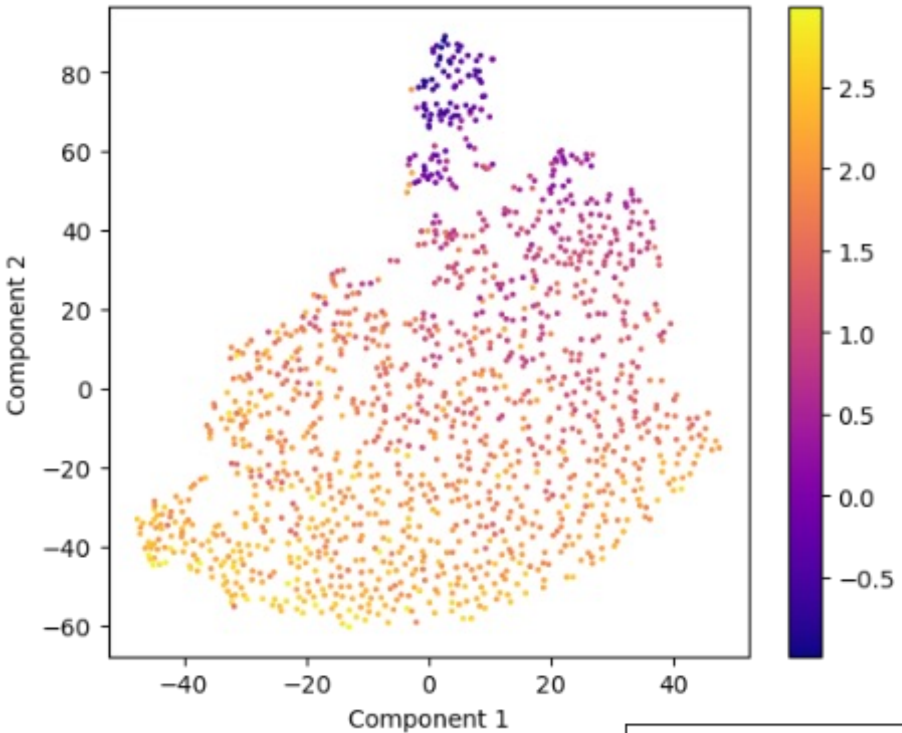

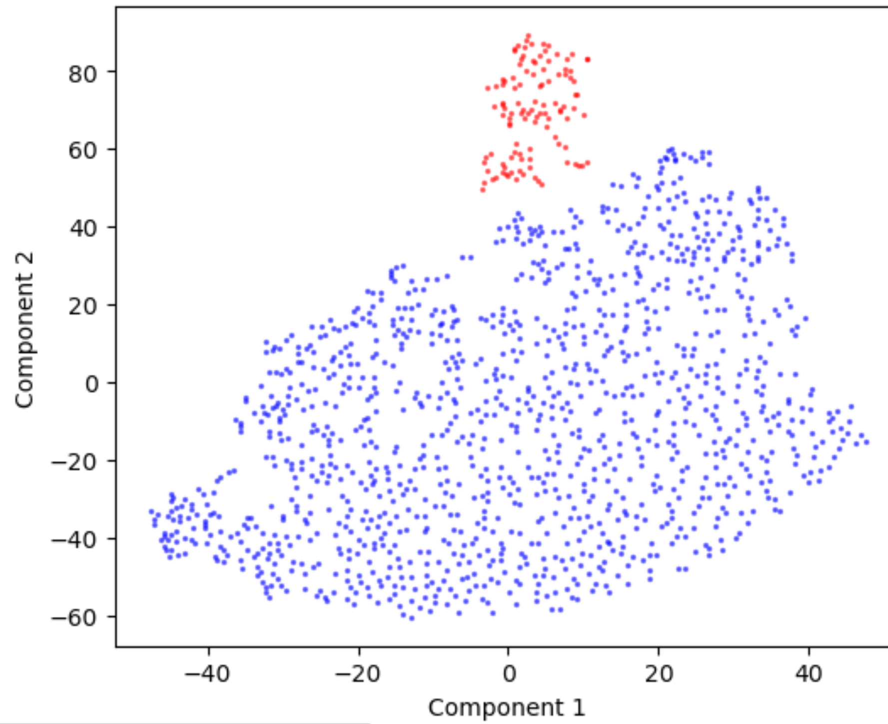

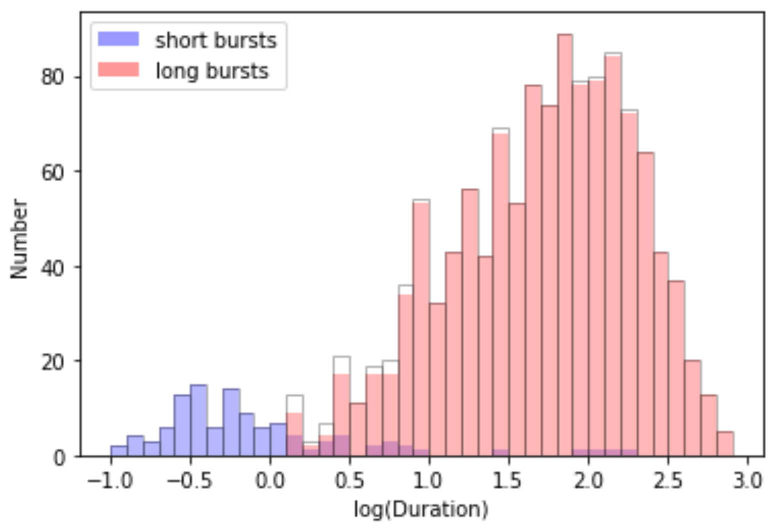

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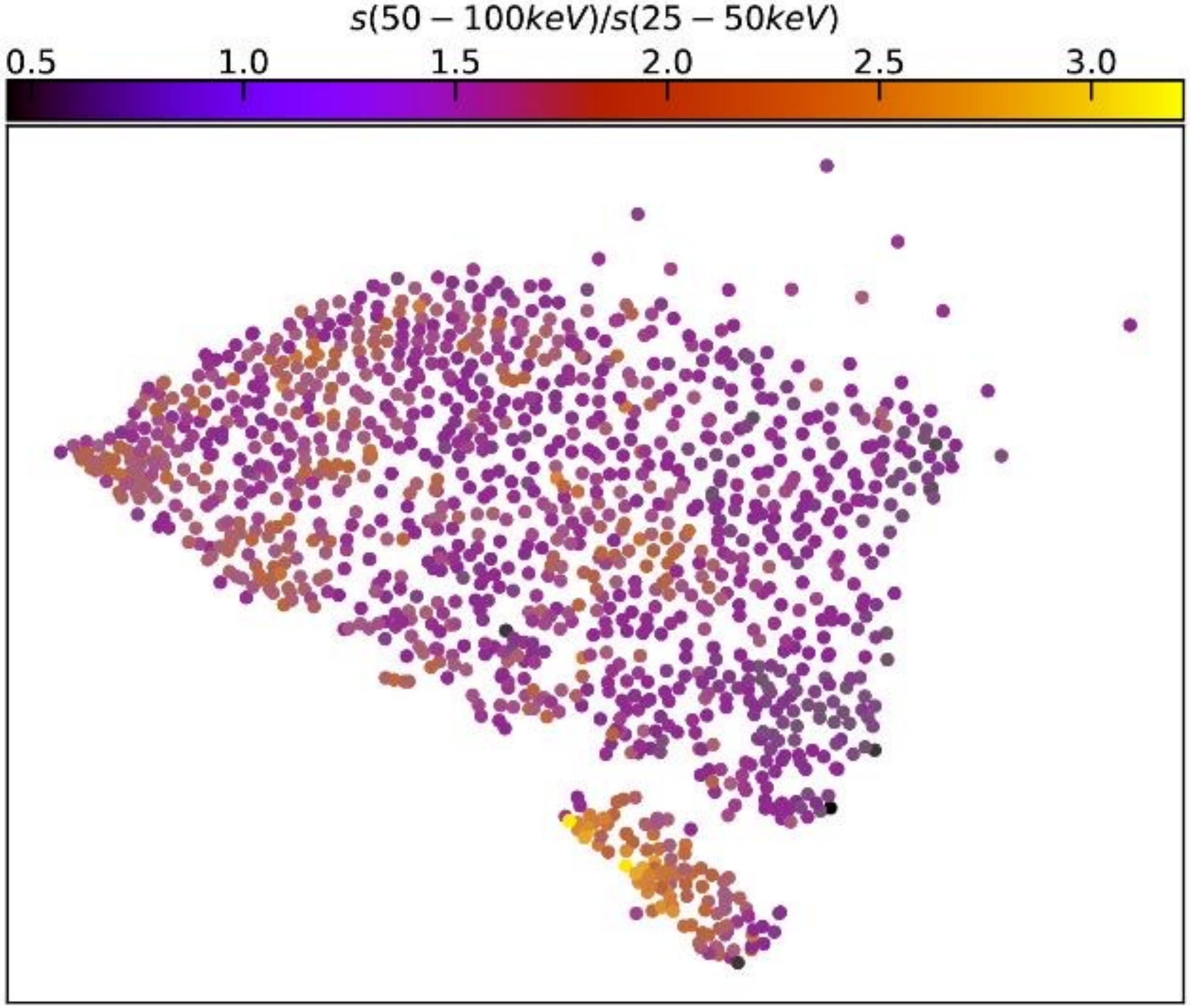
DAWN

Wednesday May 3, 2023

Hardness distribution

Kragh Jespersen et al. 2020



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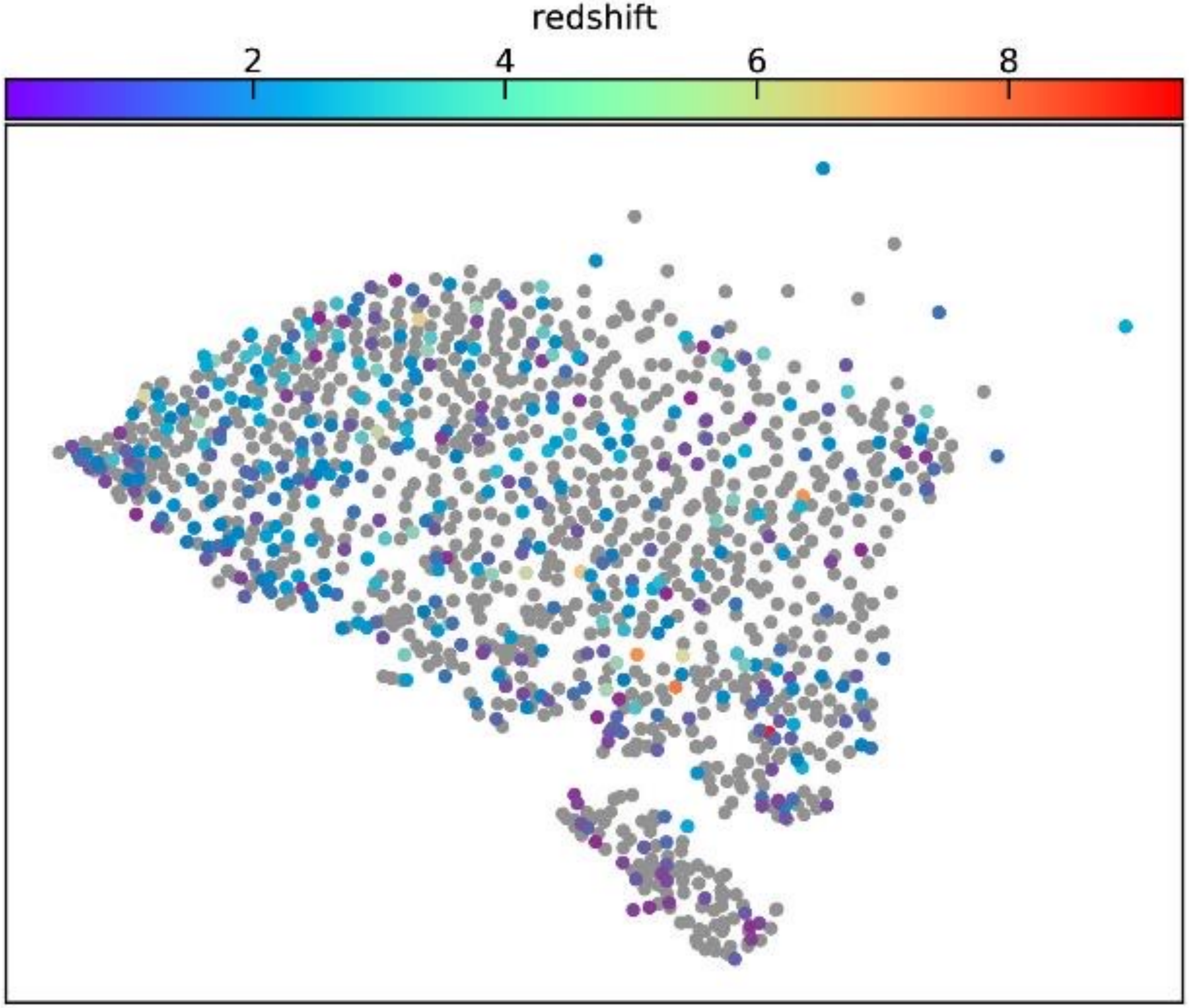
Redshift distribution

Kragh Jespersen et al. 2020



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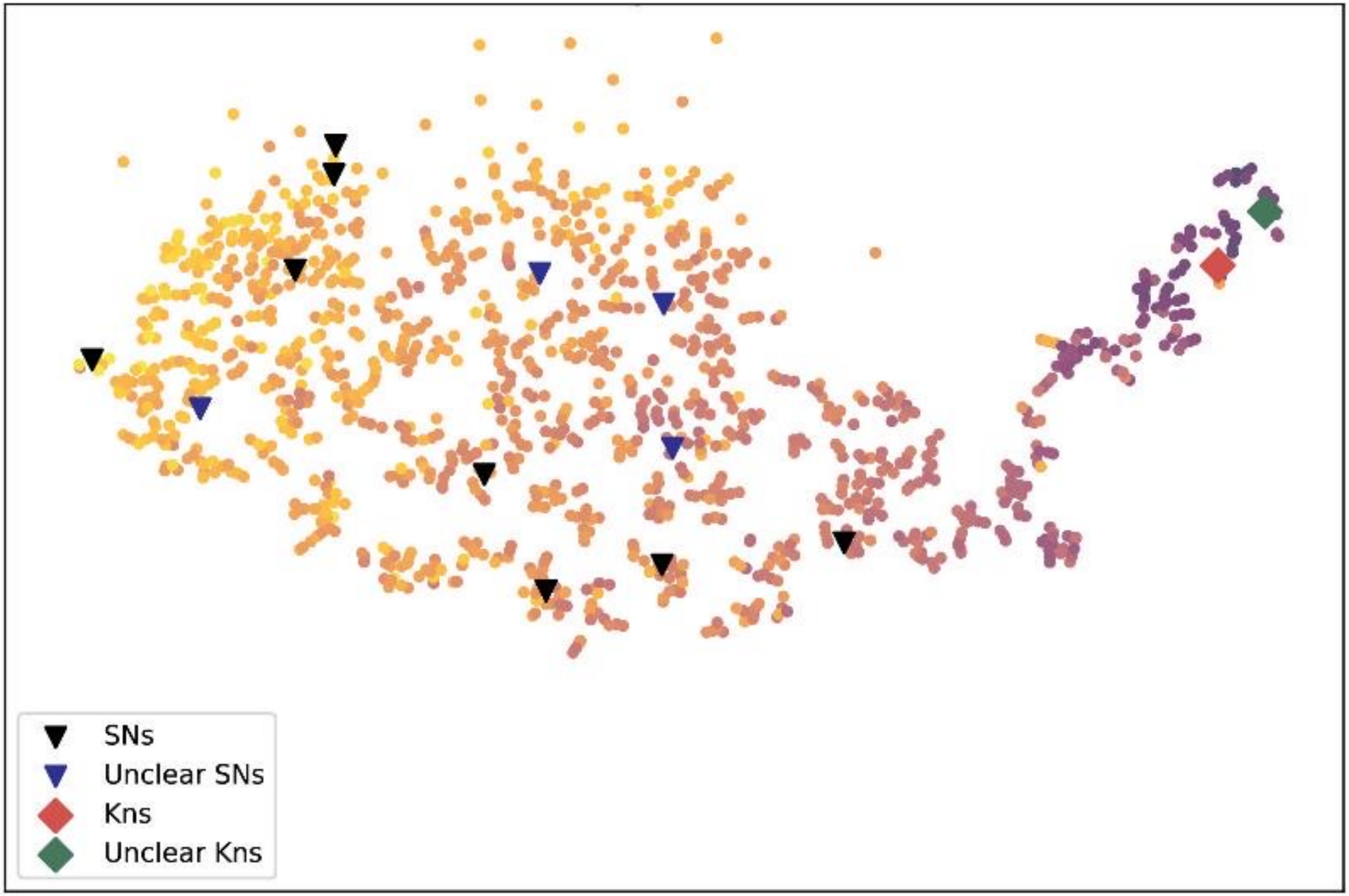
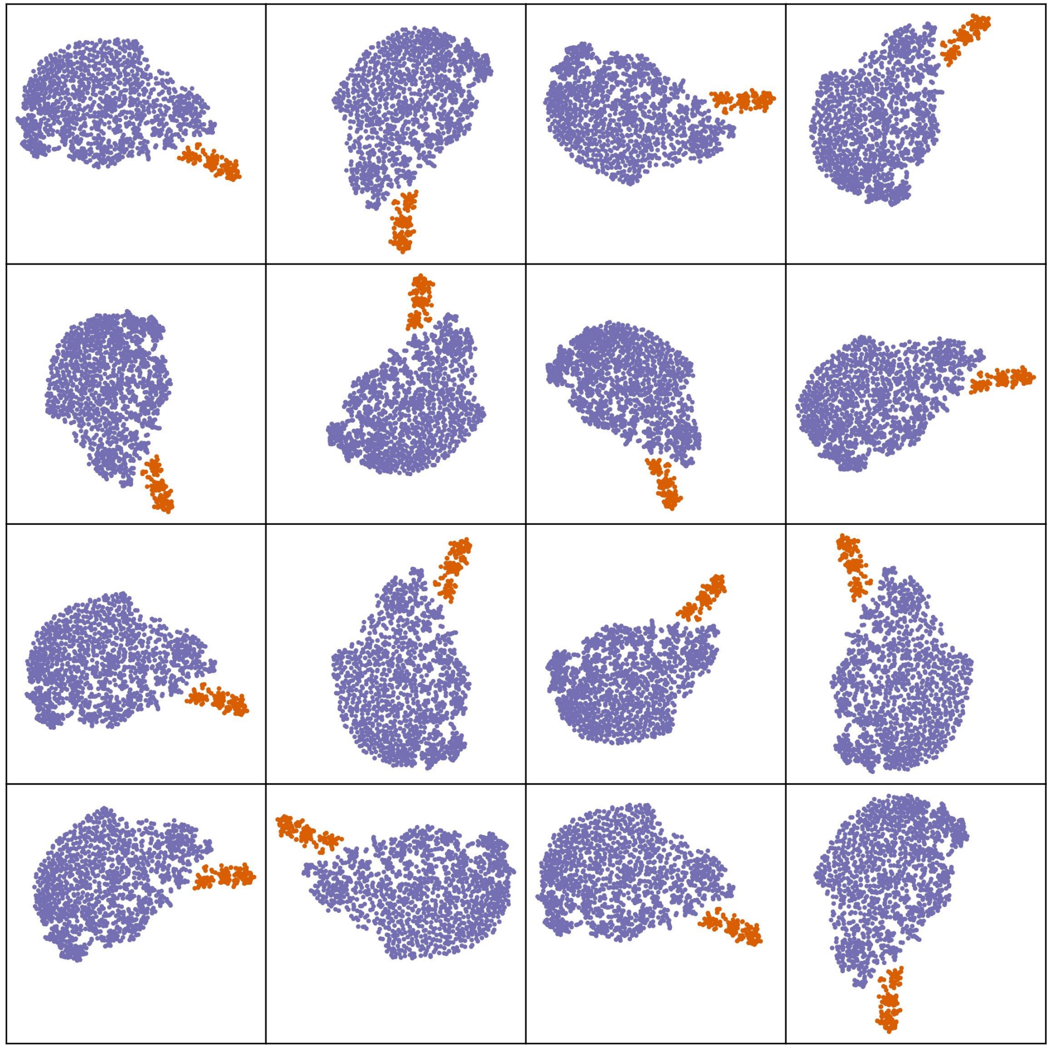
Possible subgroupings?

Kragh Jespersen et al. 2020



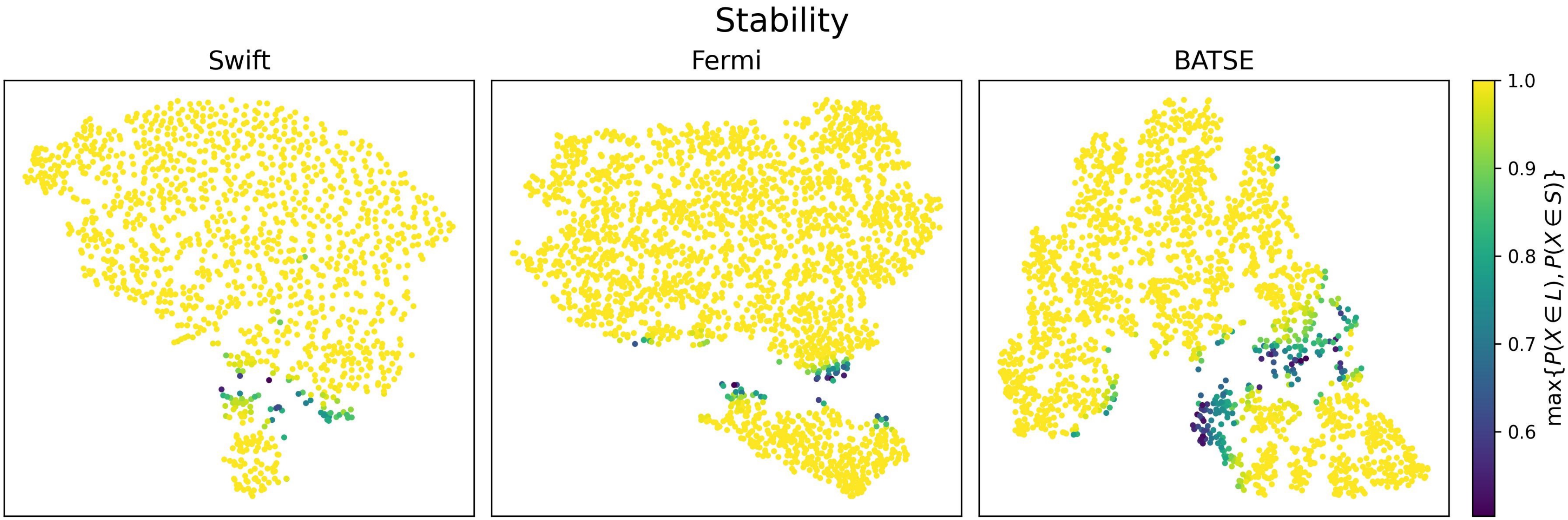
Structure is durable, not location!

Steinhardt, Mann, Rusakov, and Kragh Jespersen 2023



Objects can "jump"

Steinhardt, Mann, Rusakov, and Kragh Jespersen 2023



Example: Photometry

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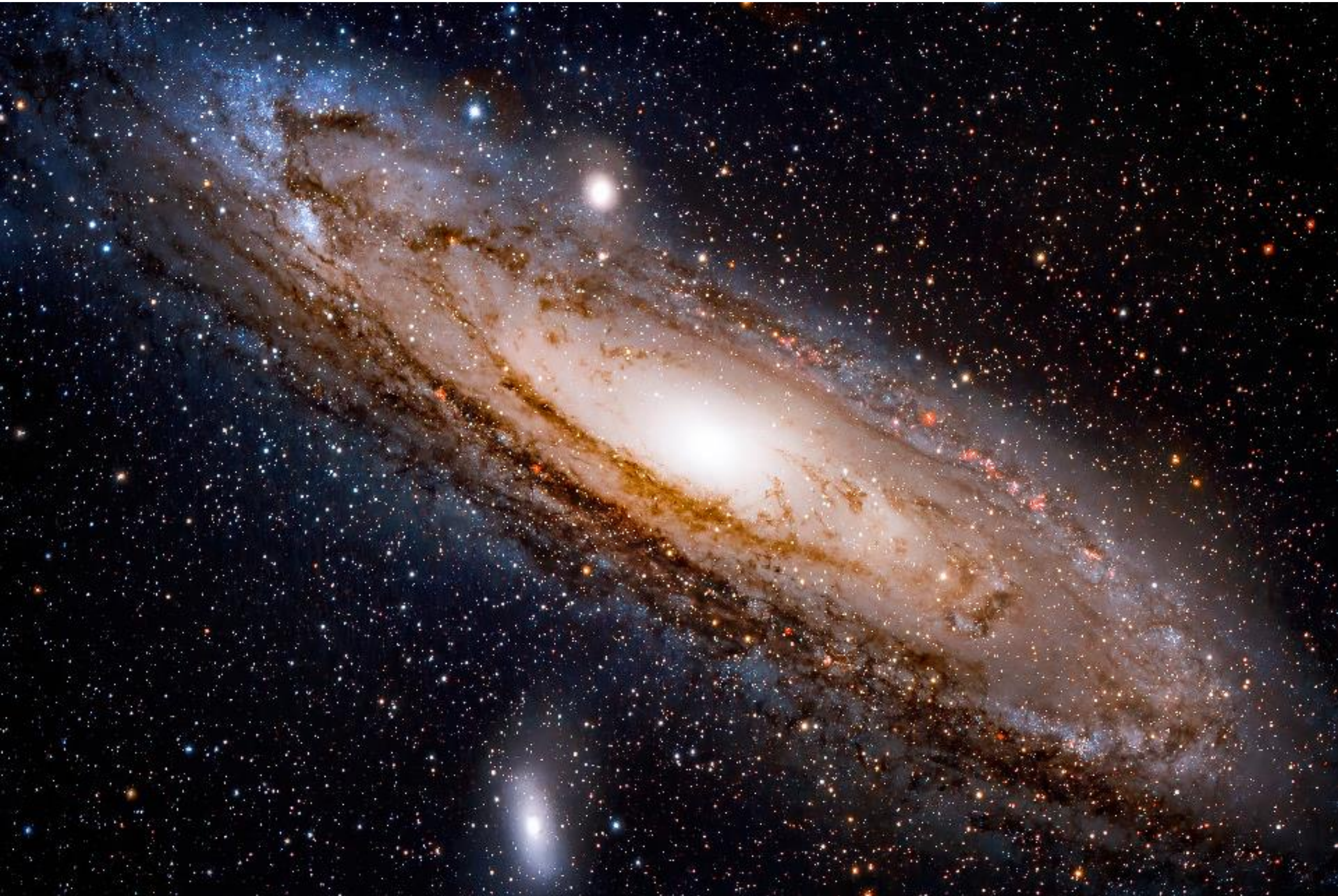
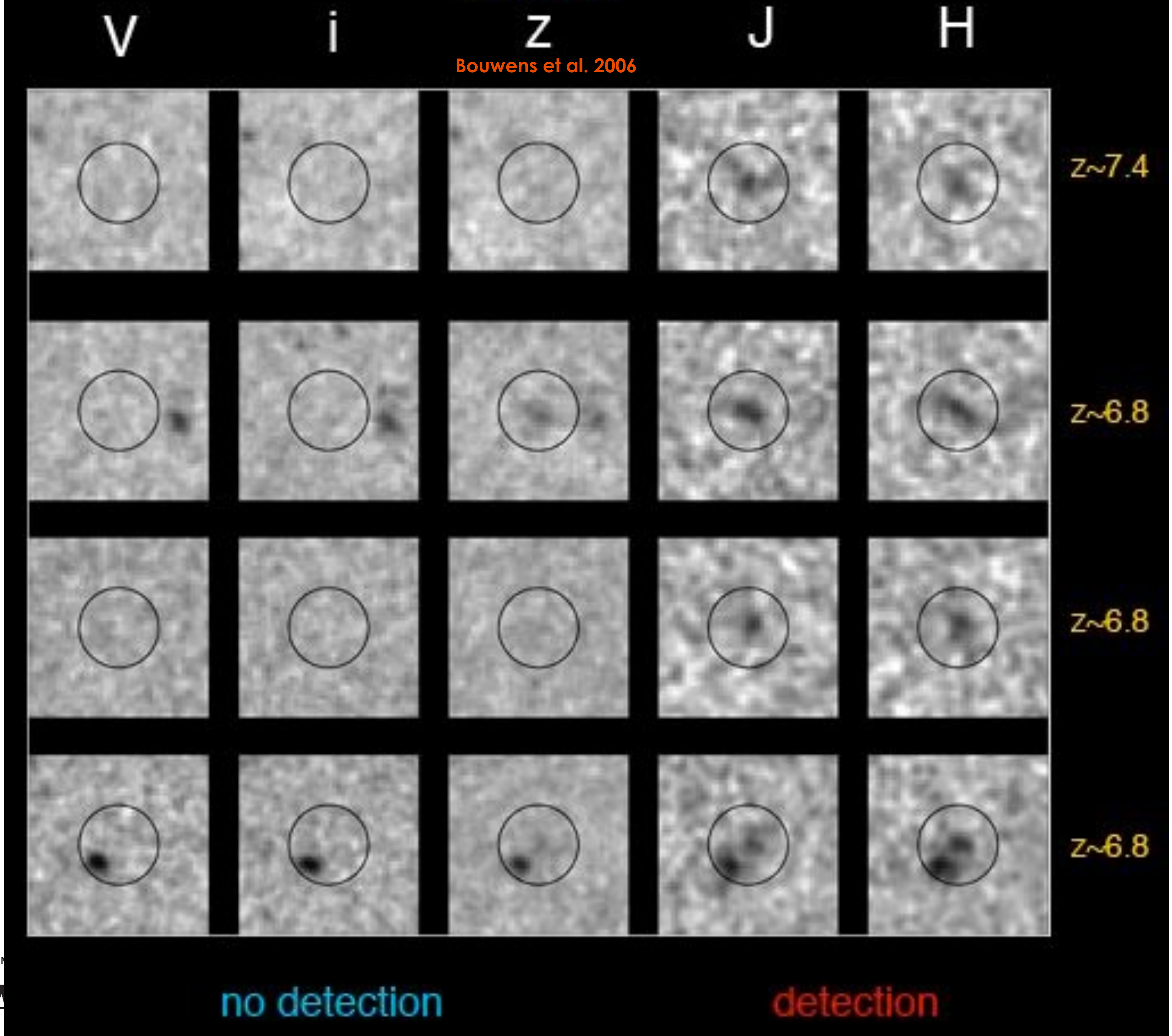
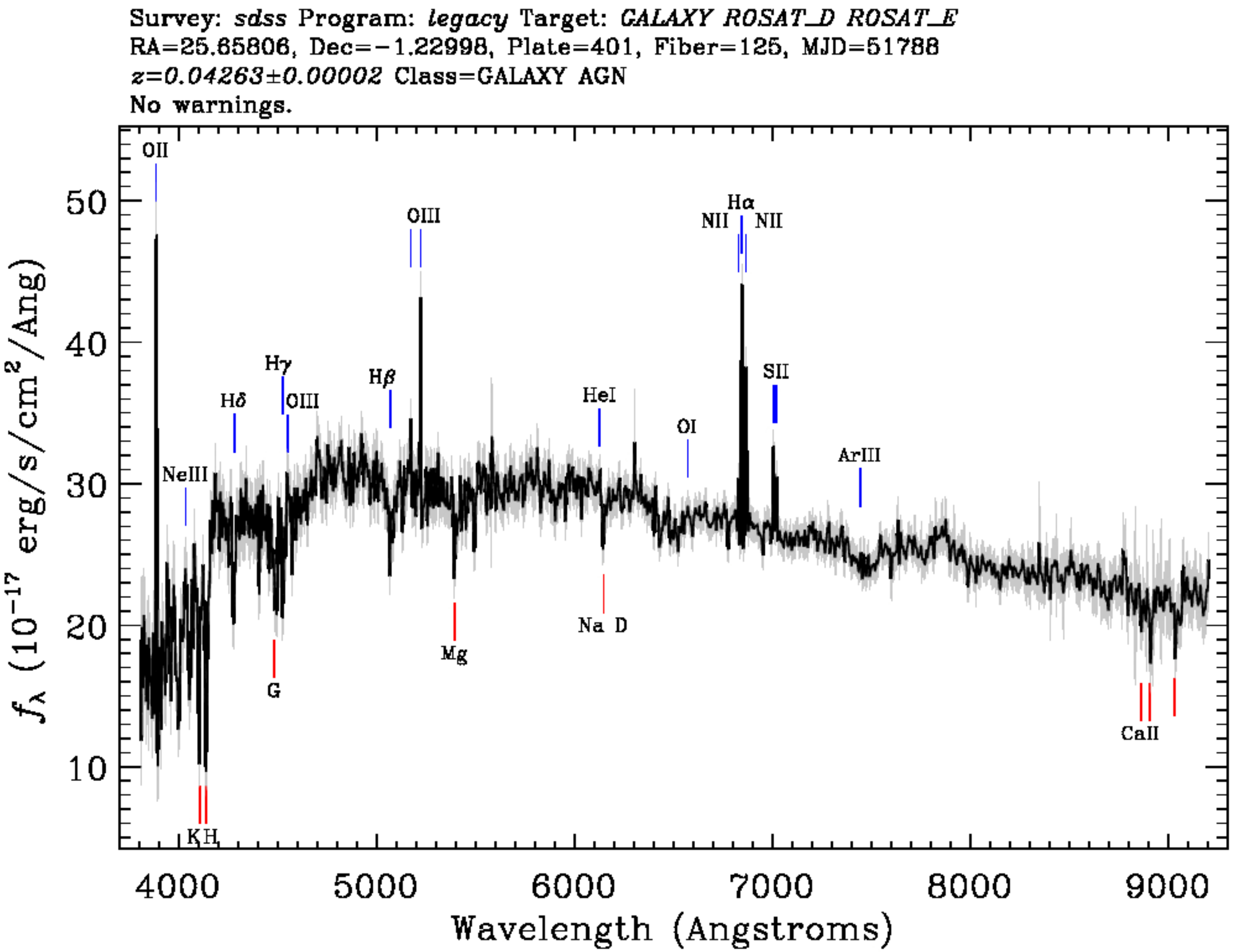



V
i
z
J
H
Bouwens et al. 2006
z~7.4
z~6.8
z~6.8
z~6.8
no detection
detection

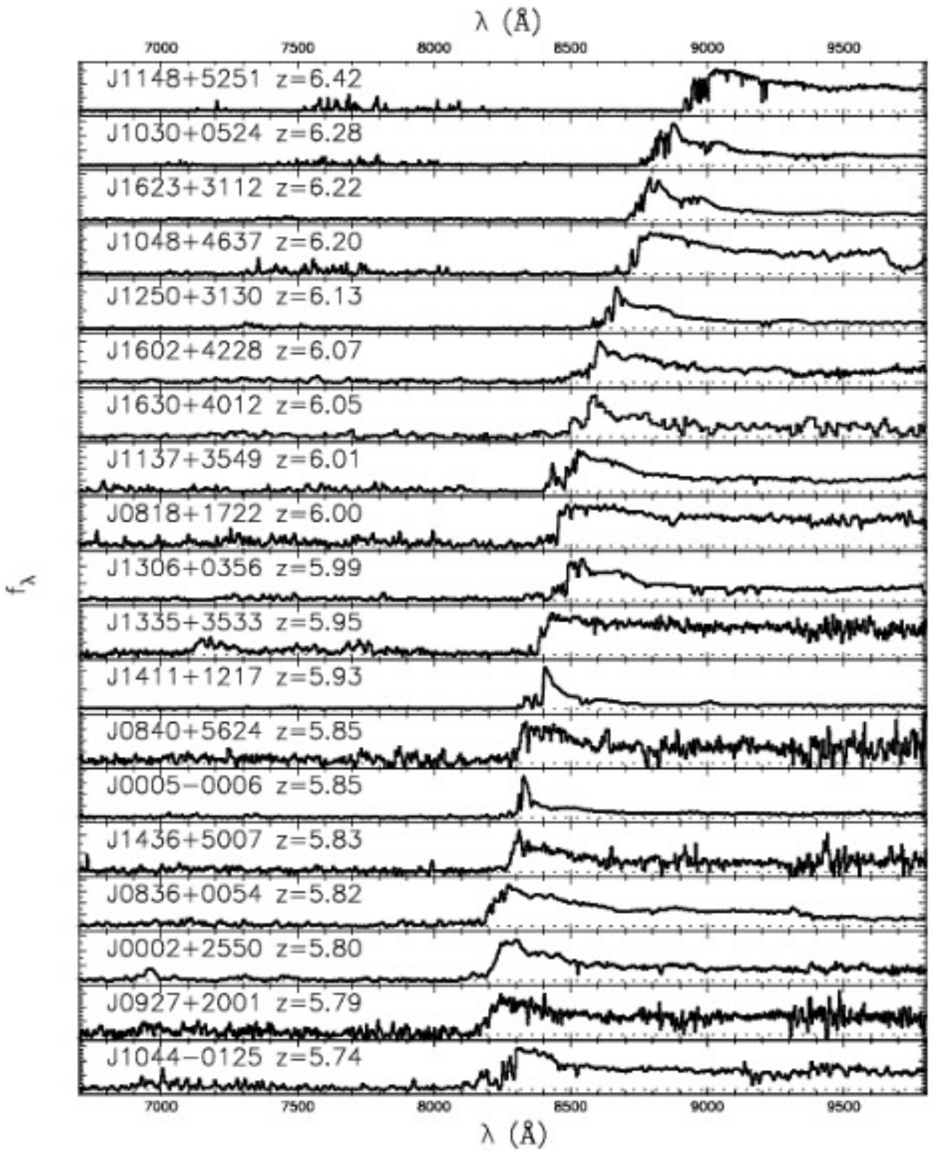
Example: Galaxy spectra

SDSS/Galaxy Zoo



Spectra have similar features!

Zaroubi et al. 2013



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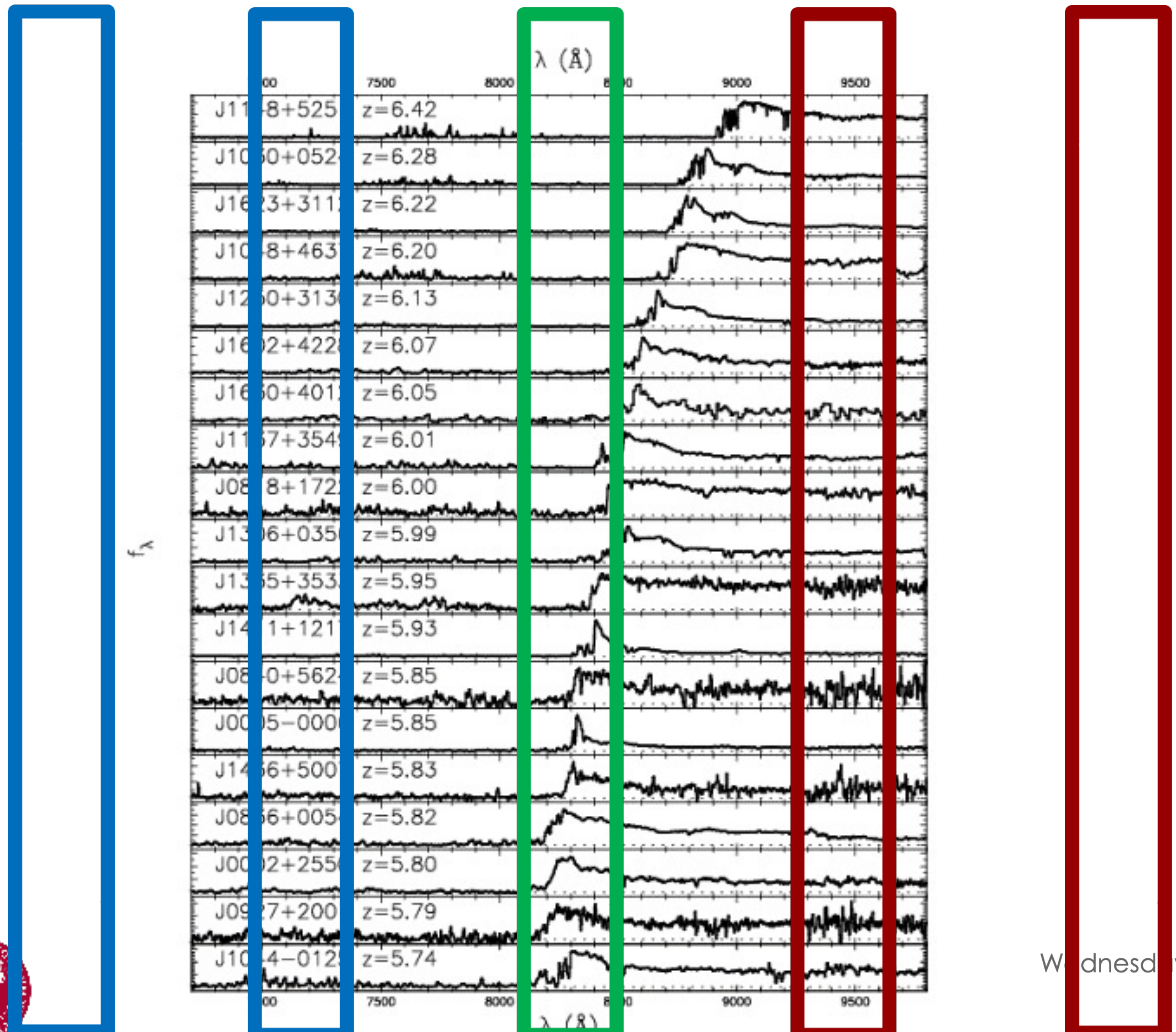
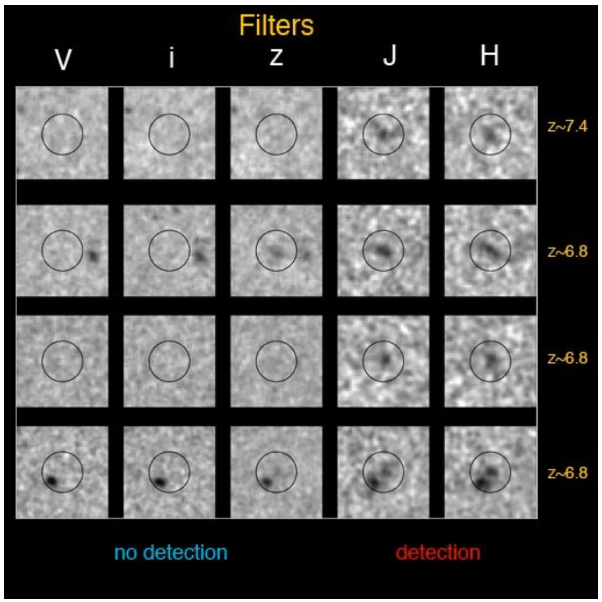
Maybe limited information is enough

Zaroubi et al. 2013



Our goal:



"V band"
"i band"
"z band"
"J band"
"H band"

etc.

(Stellar) Mass
Star formation rate
Star formation history
Distance/Redshift
Age

etc.

Two Fundamental Assumptions for Photometry

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1. If an object is sufficiently well-measured, there is a surjective (one-to-one or many-to-one, but not one-to-many) mapping from photometric fluxes to astrophysical properties

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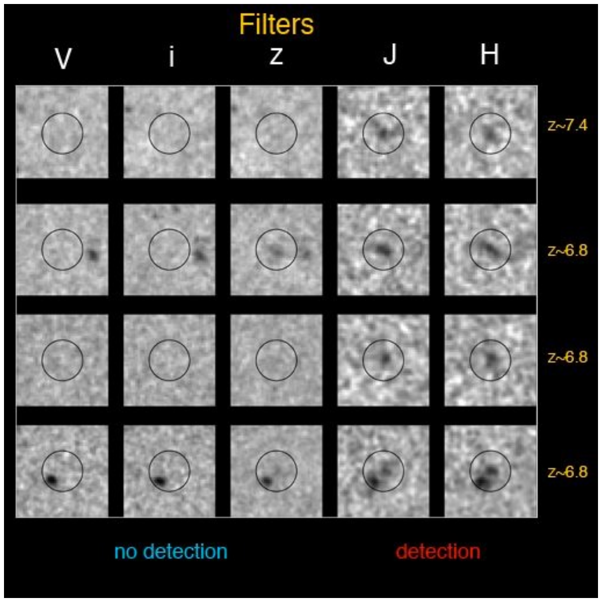

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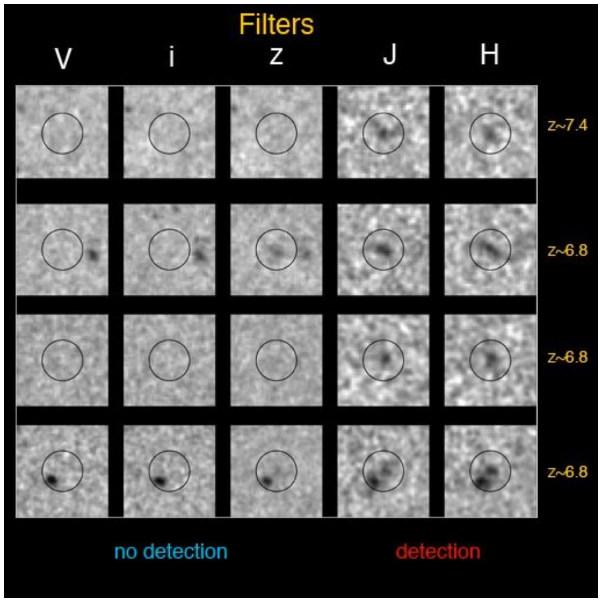

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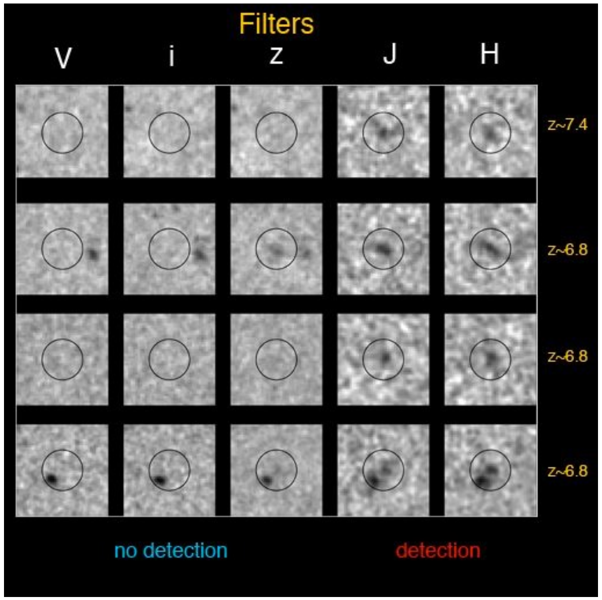

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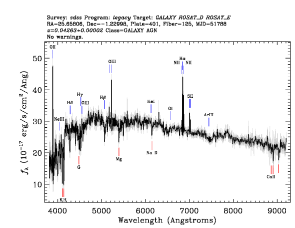
Choose a few good examples



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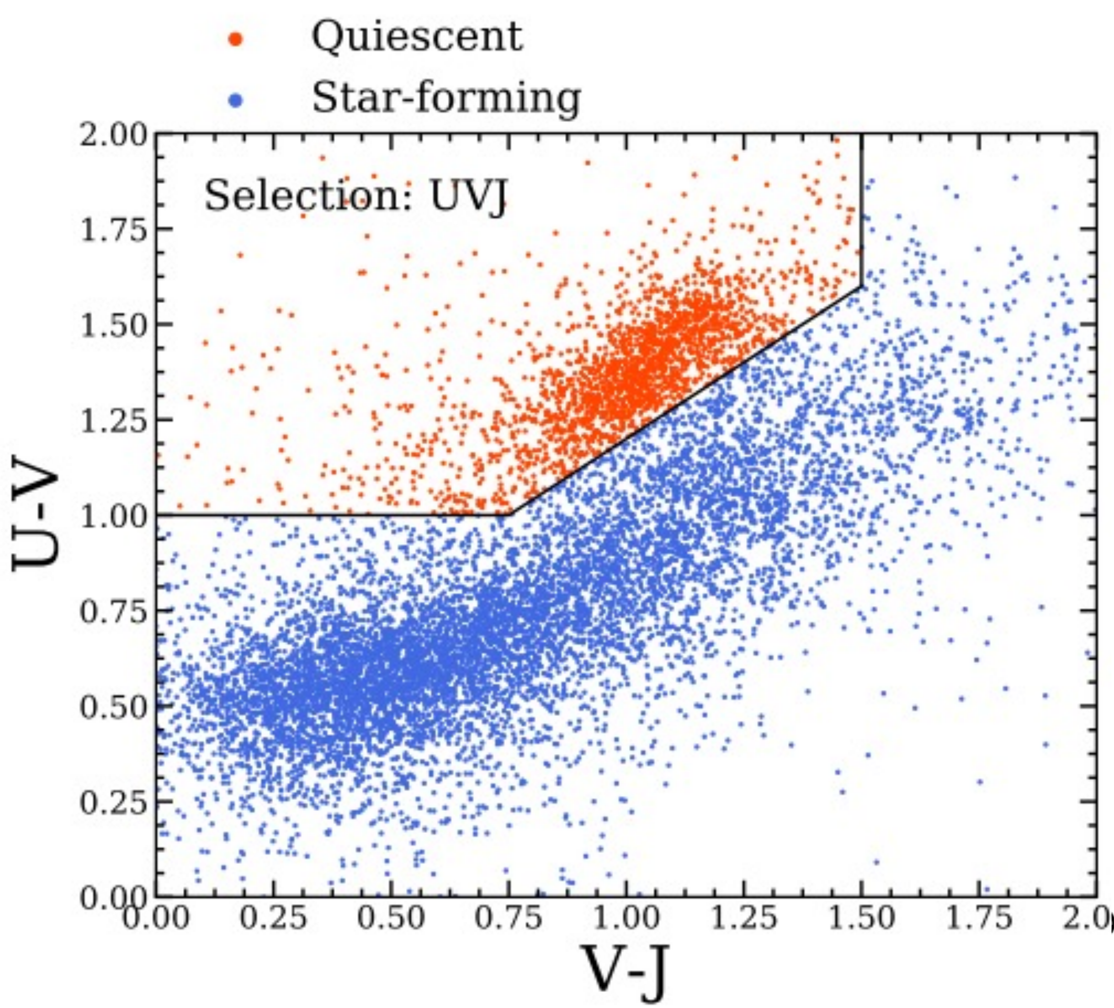
COSMIC DAWN CENTER
DAWN

Approach 1: Color space map using two colors (three bands)

COSMOS2015 catalog, objects at z≈1



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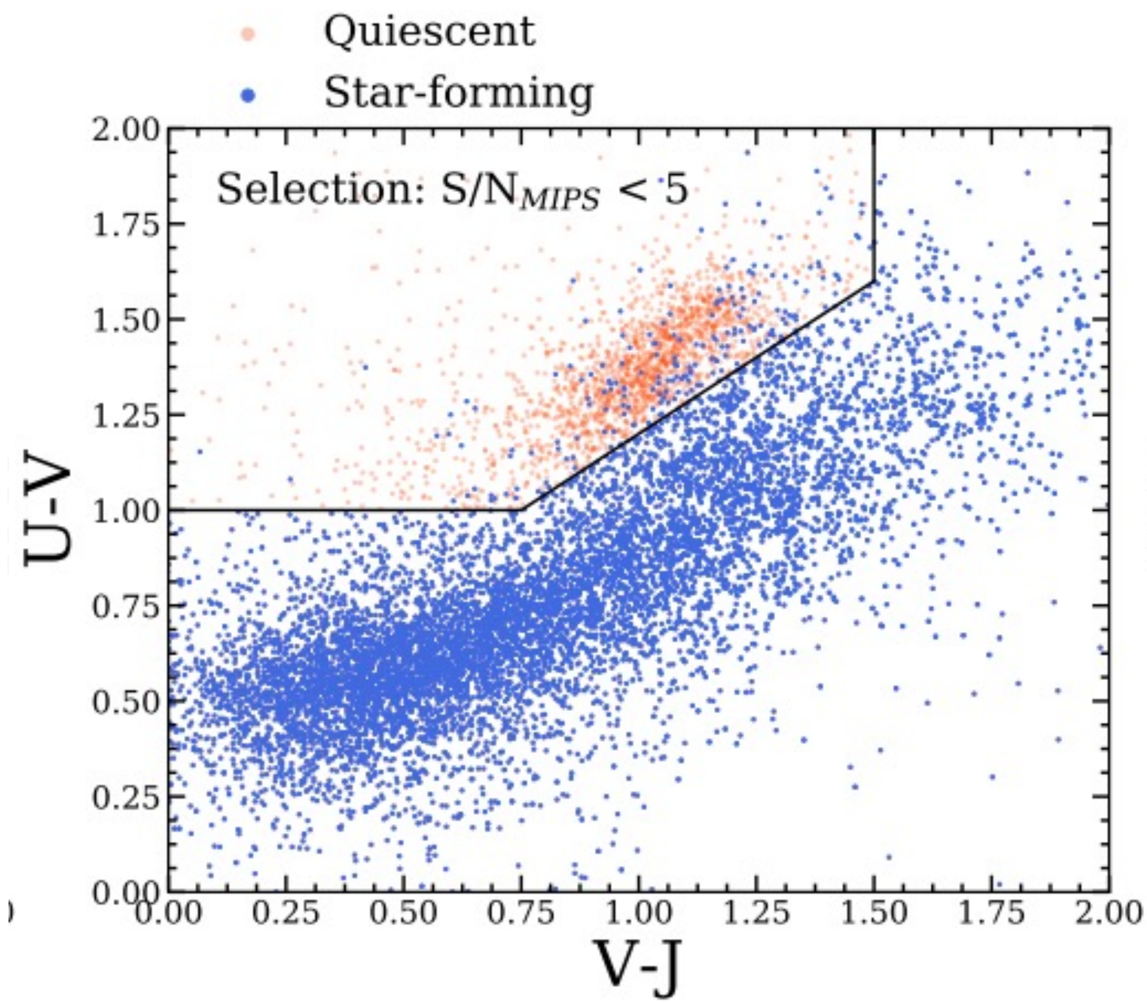

COSMIC DAWN CENTER
DAWN

Approach 2: Color space map using all bands

~~Two~~ Three Fundamental Assumptions for Photometry

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3. We can map objects from the full, n-dimensional space with all bands to a smaller one with many neighbors, and the other two assumptions will continue to hold.

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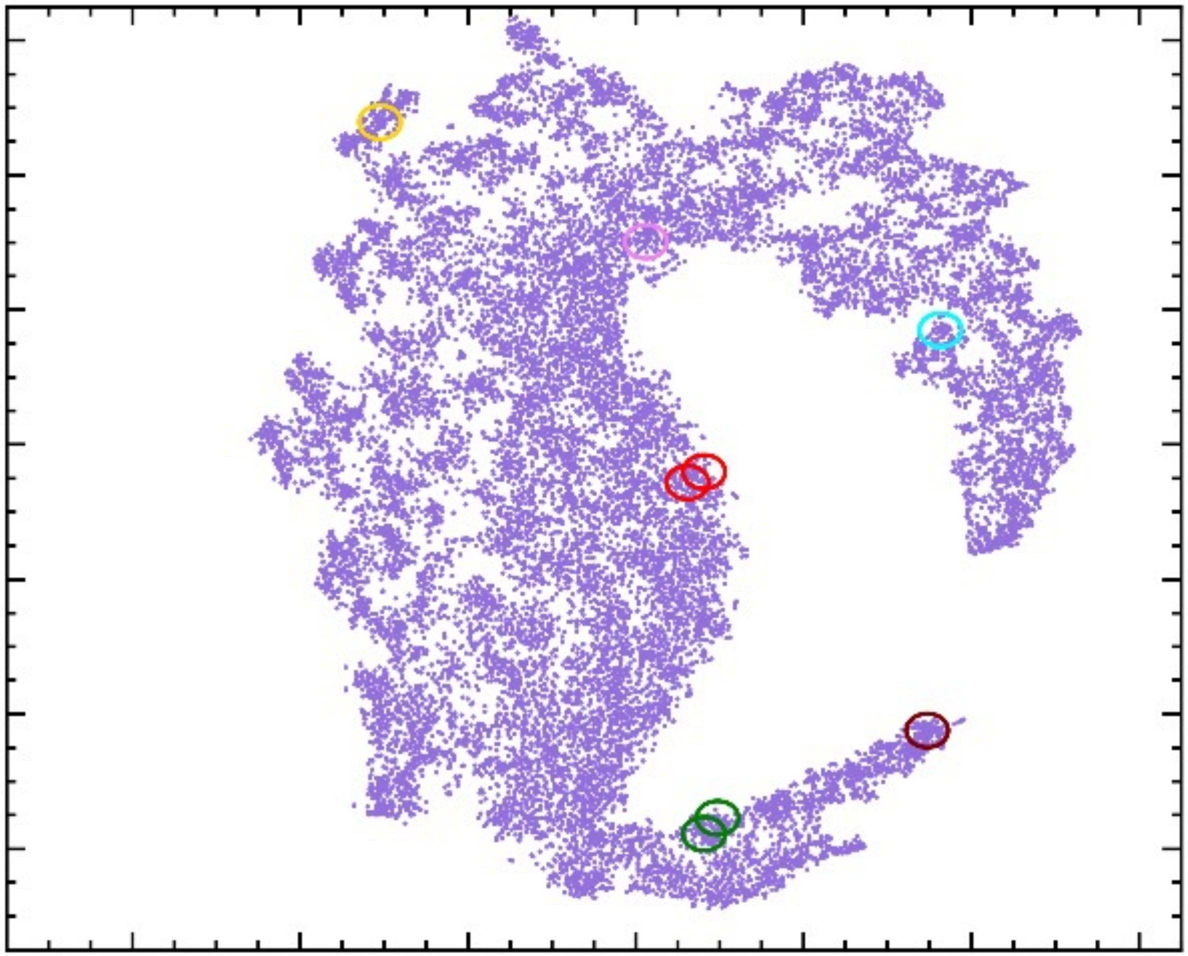
Can we somehow decide what information is "important" even without labels?

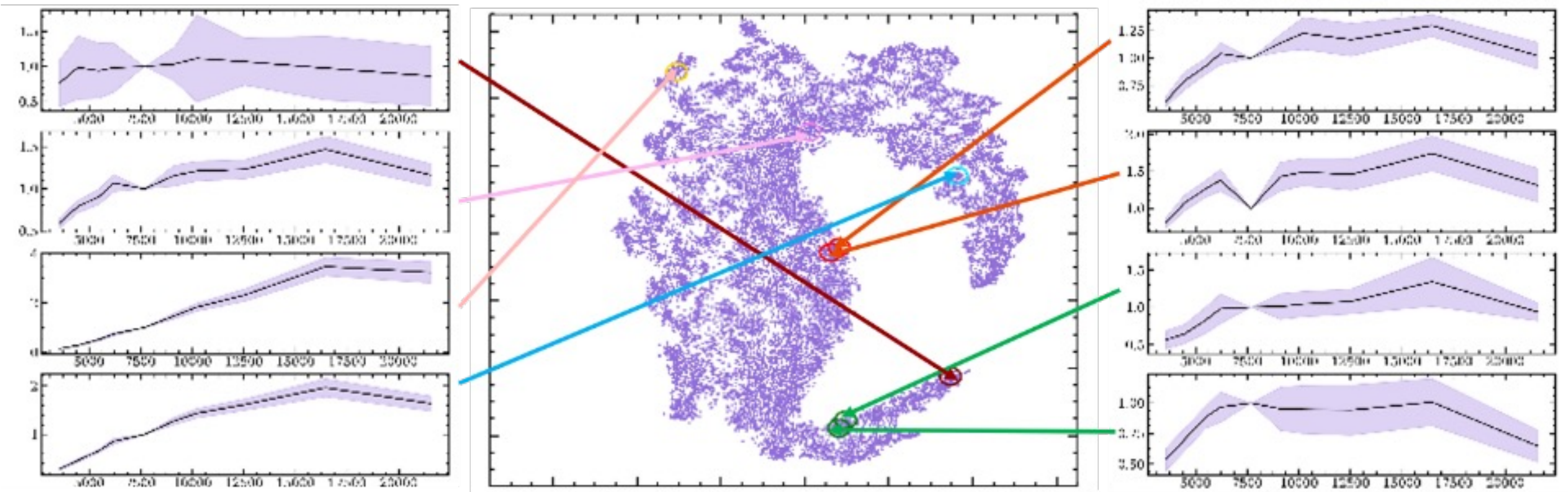
Approach 2: First, make a t-SNE map reducing to two dimensions

COSMOS2015 catalog, objects at z≈1



Approach 2: Similar galaxies are nearby

COSMOS2015 catalog, objects at z≈1

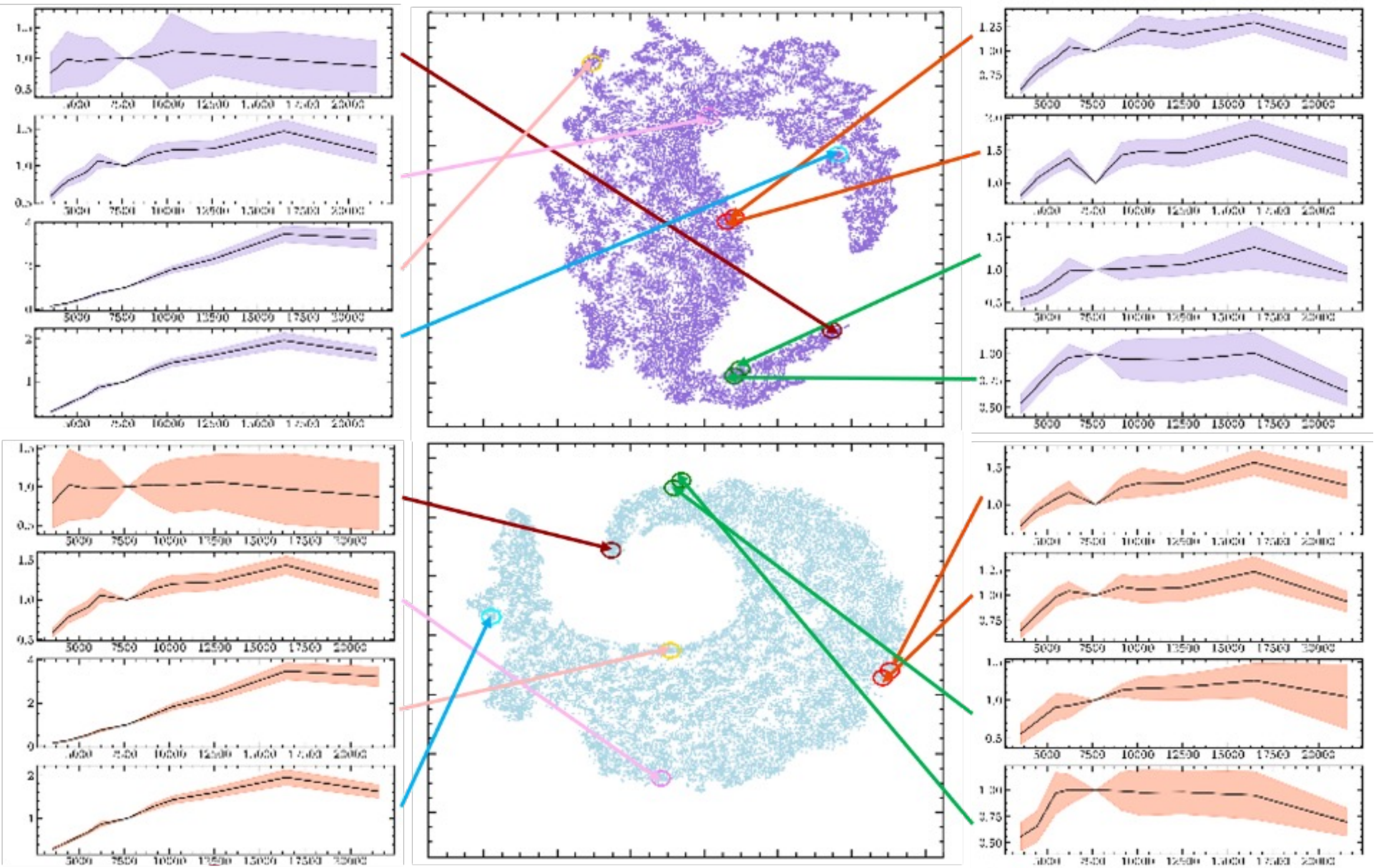


COSMIC DAWN CENTER

DAWN

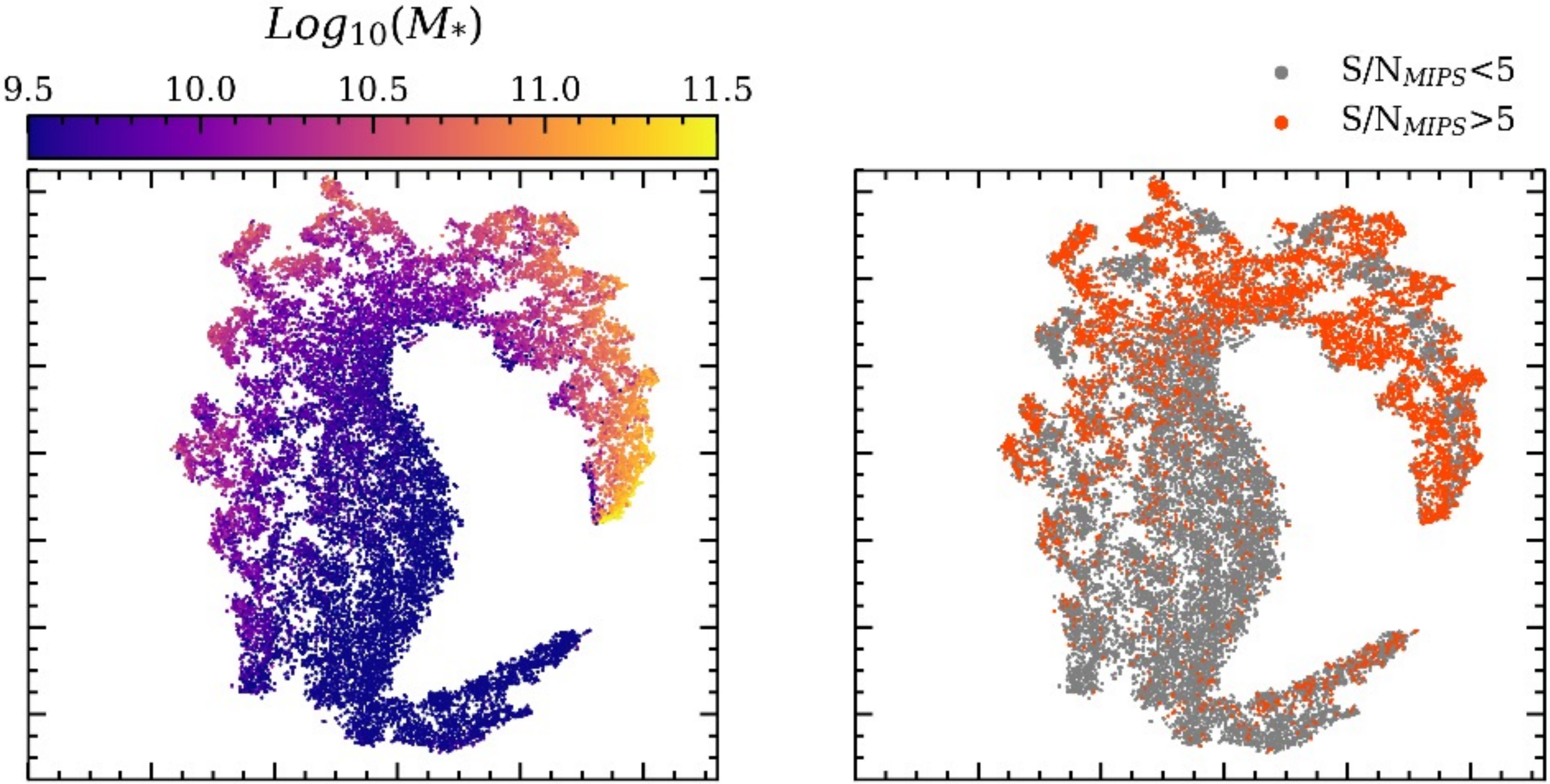
Approach 2: Similar galaxies are nearby

WARNING: positions are neither fixed nor meaningful. Topology is meaningful.



Approach 2: Arranging by photometry also calculates other useful things!

COSMOS2015 catalog, objects at z≈1



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