

Search for neutrinos from AGN using a data-driven source selection

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FOR ASTROPARTICLE
PHYSICS

ecap

Sebastian Schindler

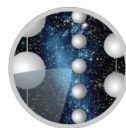
25th June 2024

MMS Annual Meeting 2024

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ICECUBE
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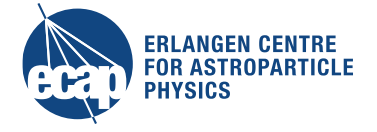


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FAU

Friedrich-Alexander-Universität
Naturwissenschaftliche Fakultät

Neutrinos from Active Galactic Nuclei



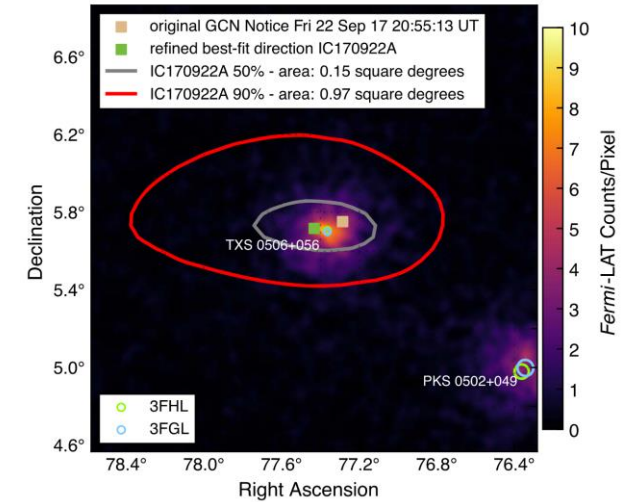
TXS 0506+056

significance: $\sim 3 \sigma$

type: **Blazar**

Multimessenger observations of a flaring blazar coincident with high-energy neutrino IceCube-170922A

The IceCube Collaboration, *Fermi*-LAT, MAGIC, *AGILE*, ASAS-SN, HAWC, H.E.S.S., *INTEGRAL*, Kanata, Kiso, Kapteyn, Liverpool Telescope, Subaru, *Swift*/*NuSTAR*, VERITAS, and VLA/17B-403 teams*†



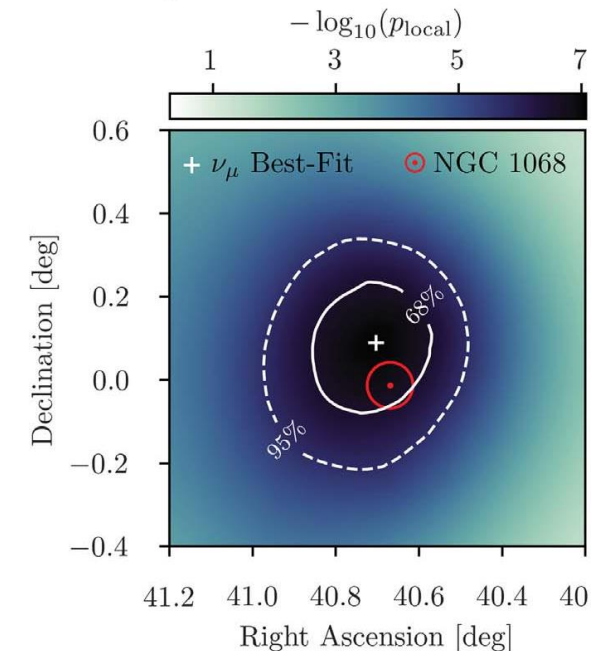
NGC 1068

significance: 4.2σ

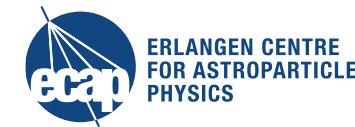
type: **Seyfert 2 galaxy**

Evidence for neutrino emission from the nearby active galaxy NGC 1068

IceCube Collaboration*†



Neutrinos from Active Galactic Nuclei



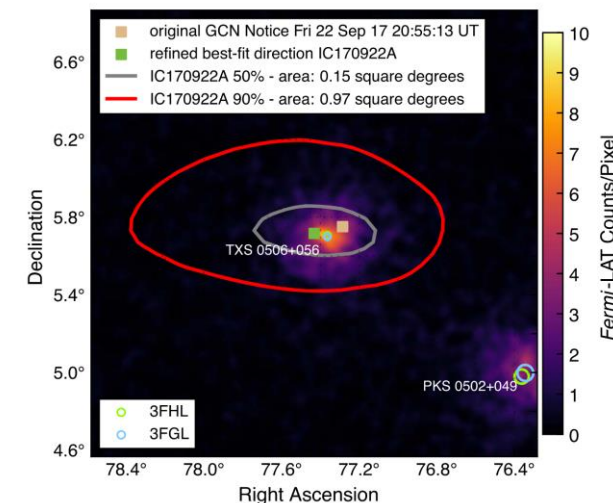
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Active Galactic Nuclei

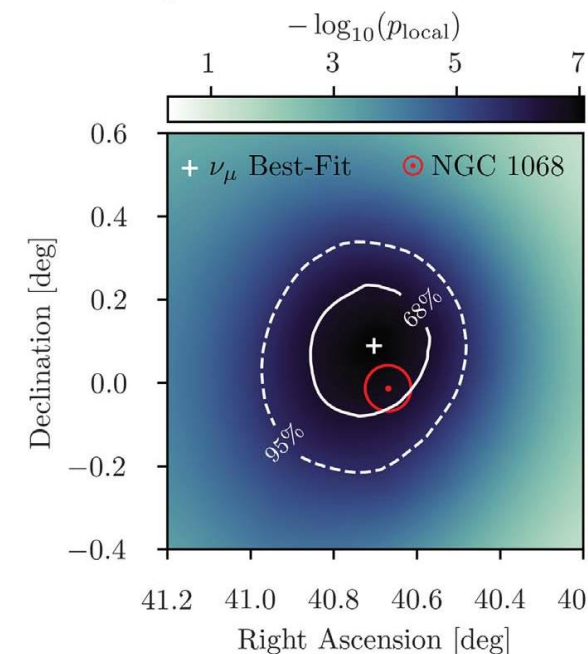
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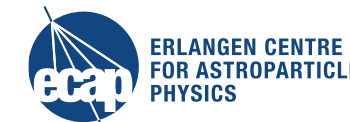
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→ so... stacking search with AGN ???

Neutrinos from Active Galactic Nuclei



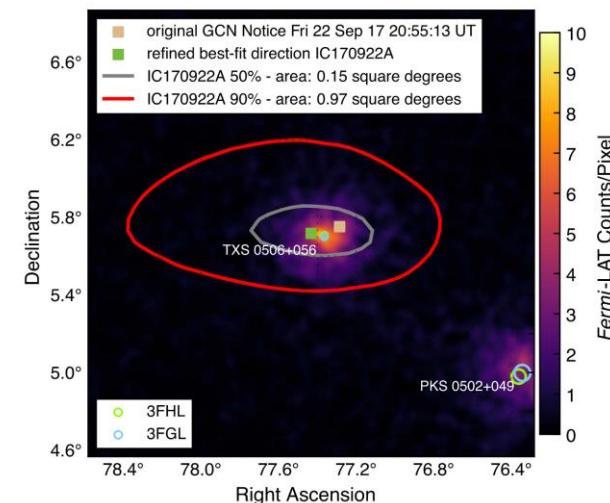
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Active Galactic Nuclei

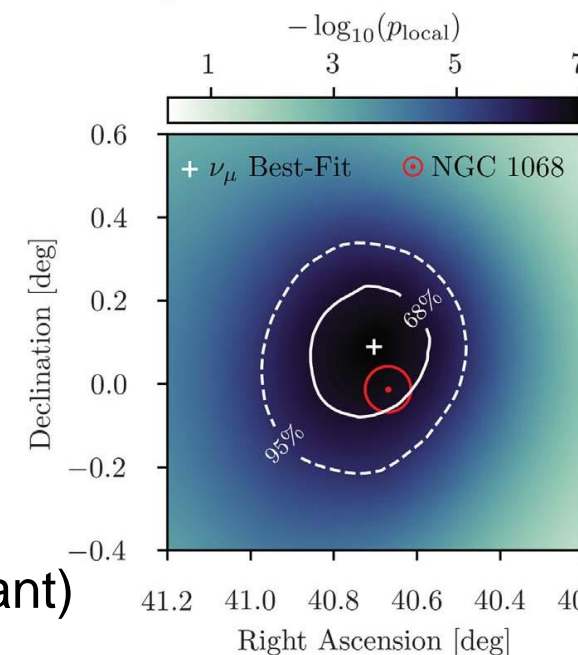
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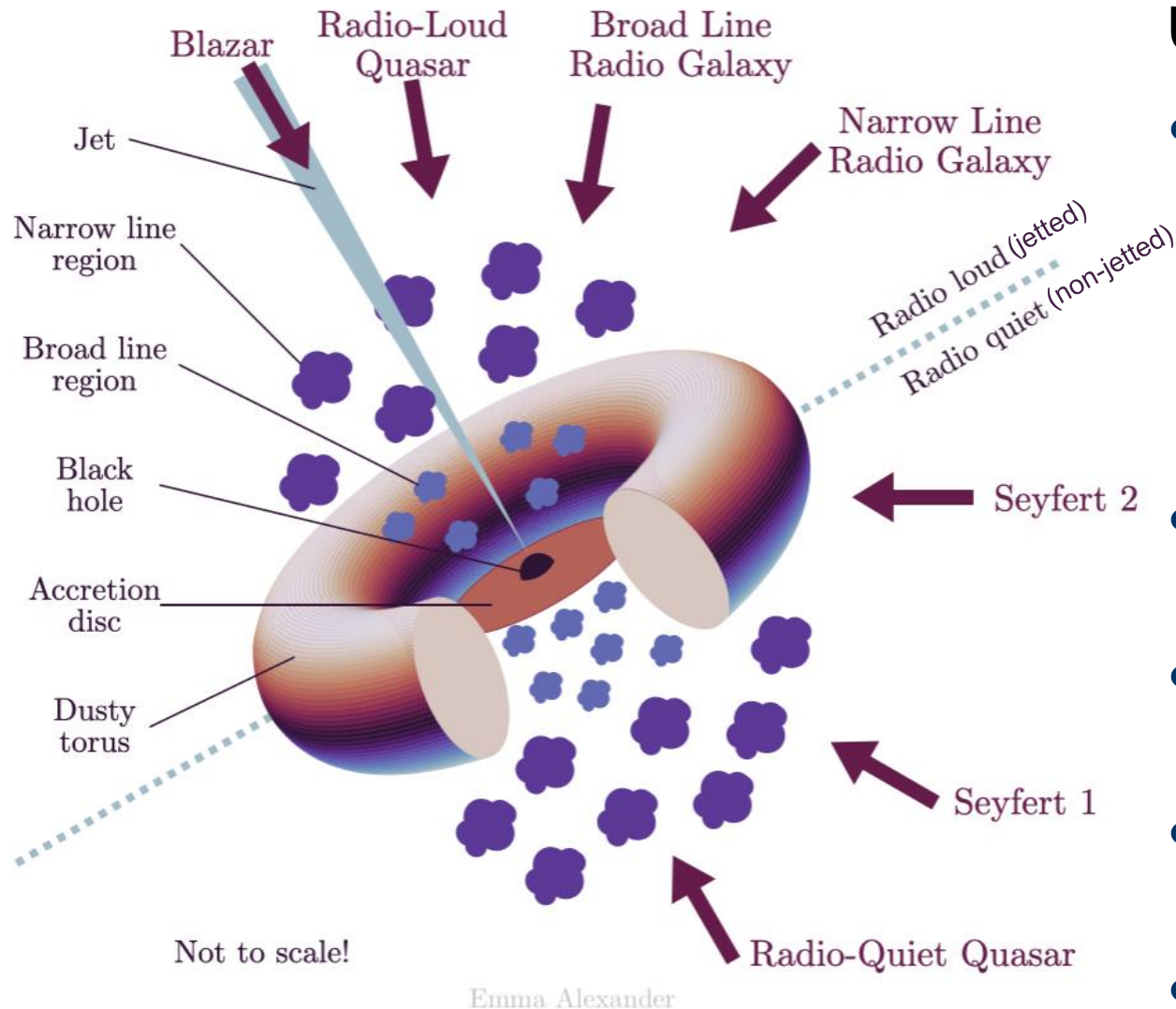


but which subset?

→ so... stacking search with AGN ???

(stack signal from (not-too-large) number of sources to become significant)

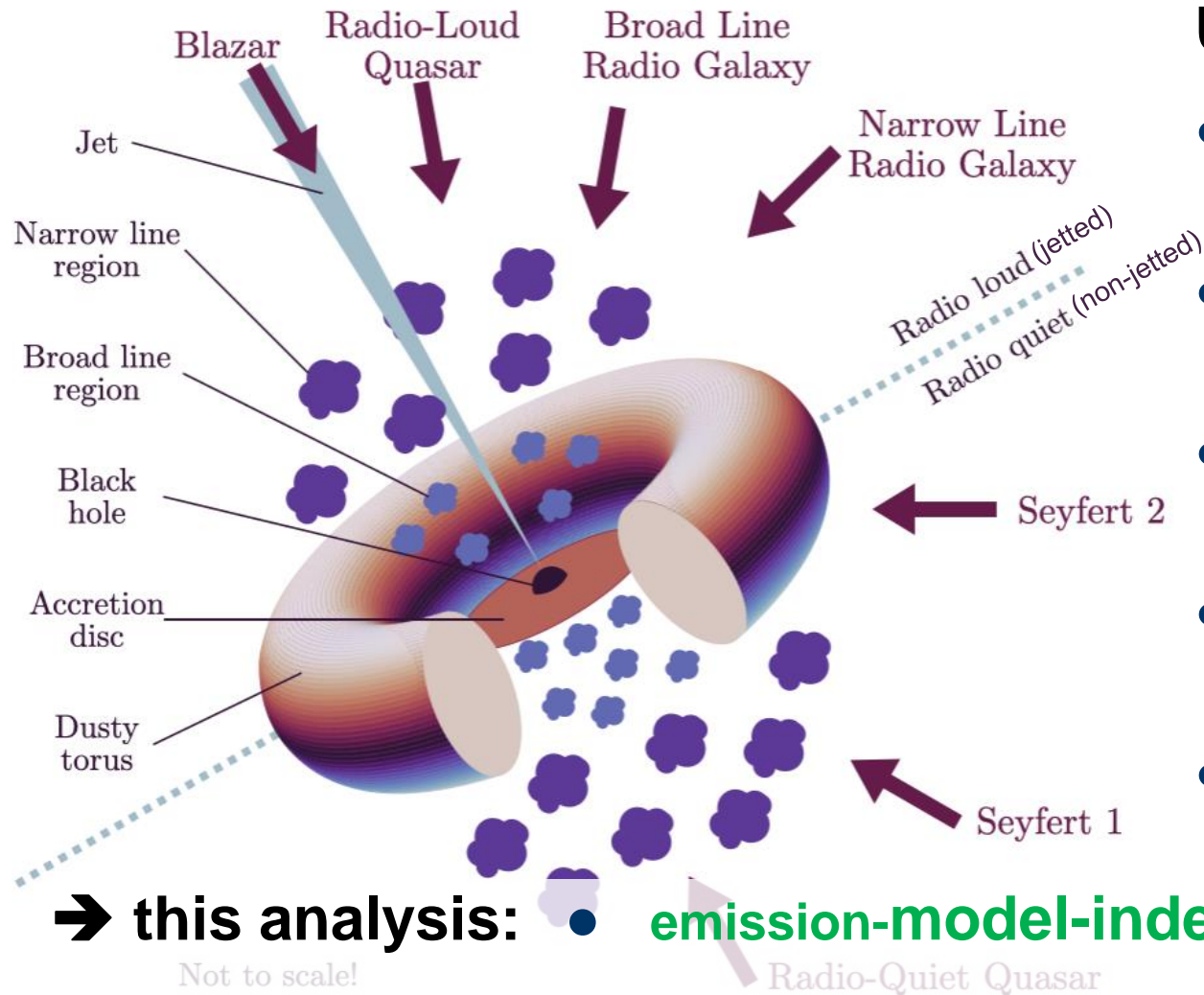
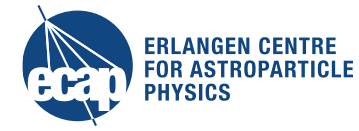
Classification of AGN as a problem



Unified Model of AGN (Urry, Padovani 1995)

- many observationally diverse extragalactic objects
 - e.g. small/large radio flux
 - spectral lines large/small or broad/narrow
 - variability in time yes/no etc. pp. ...
- explained as one type of object, appearing differently due to orientation to observer
- Type 1 vs Type 2 = **black hole** in center is obscured vs unobscured by a **dusty torus**
- **sub-classification** remains quite historical → not necessarily optimal for neutrino search!
- **neutrino emission** via several processes

Classification of AGN as a problem



Unified Model of AGN (Urry, Padovani 1995)

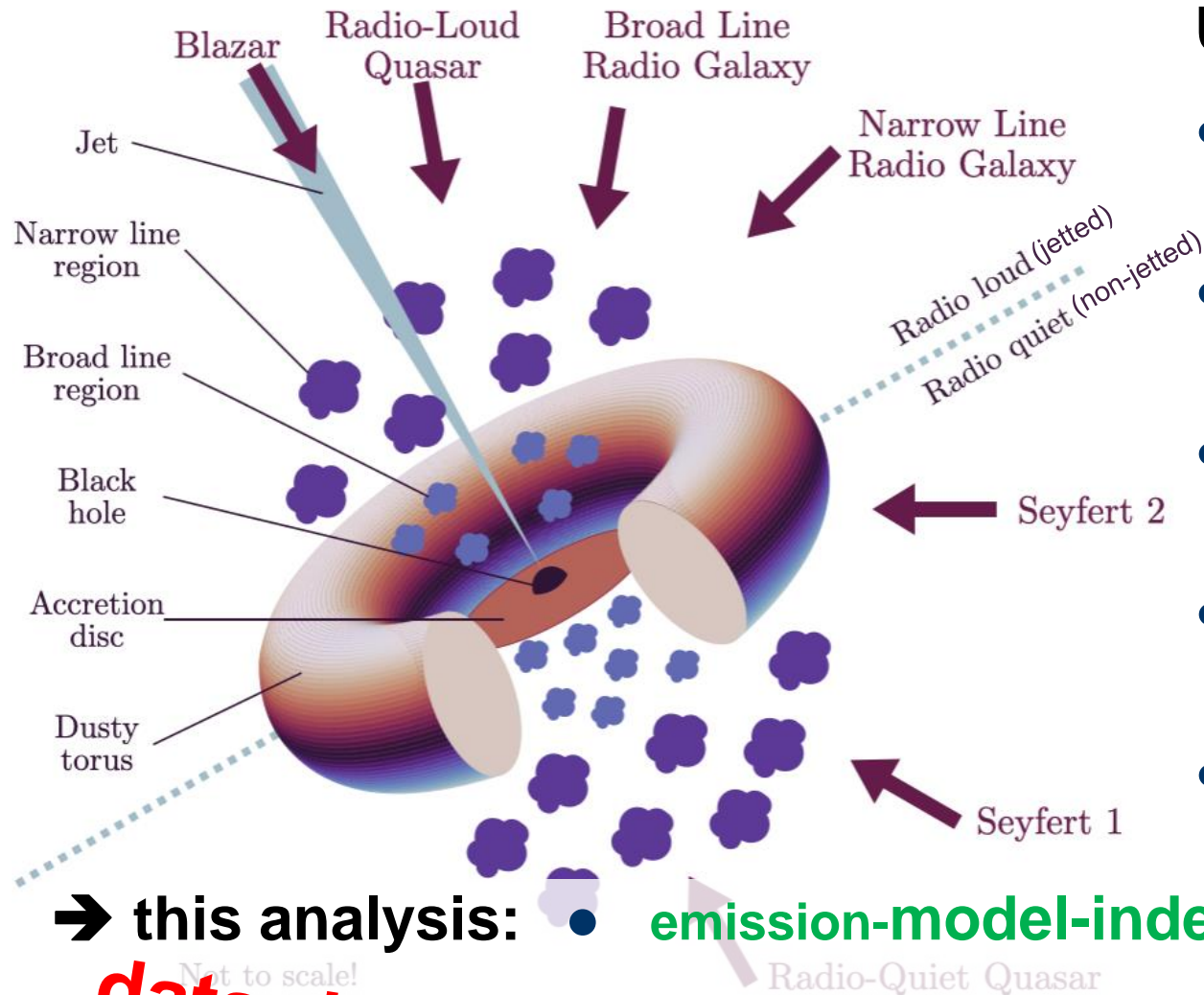
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→ this analysis:

- **emission-model-independent** search
- **independently from existing AGN classification scheme**

Not to scale!

Classification of AGN as a problem



Unified Model of AGN (Urry, Padovani 1995)

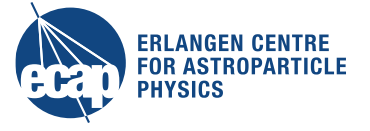
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→ this analysis:

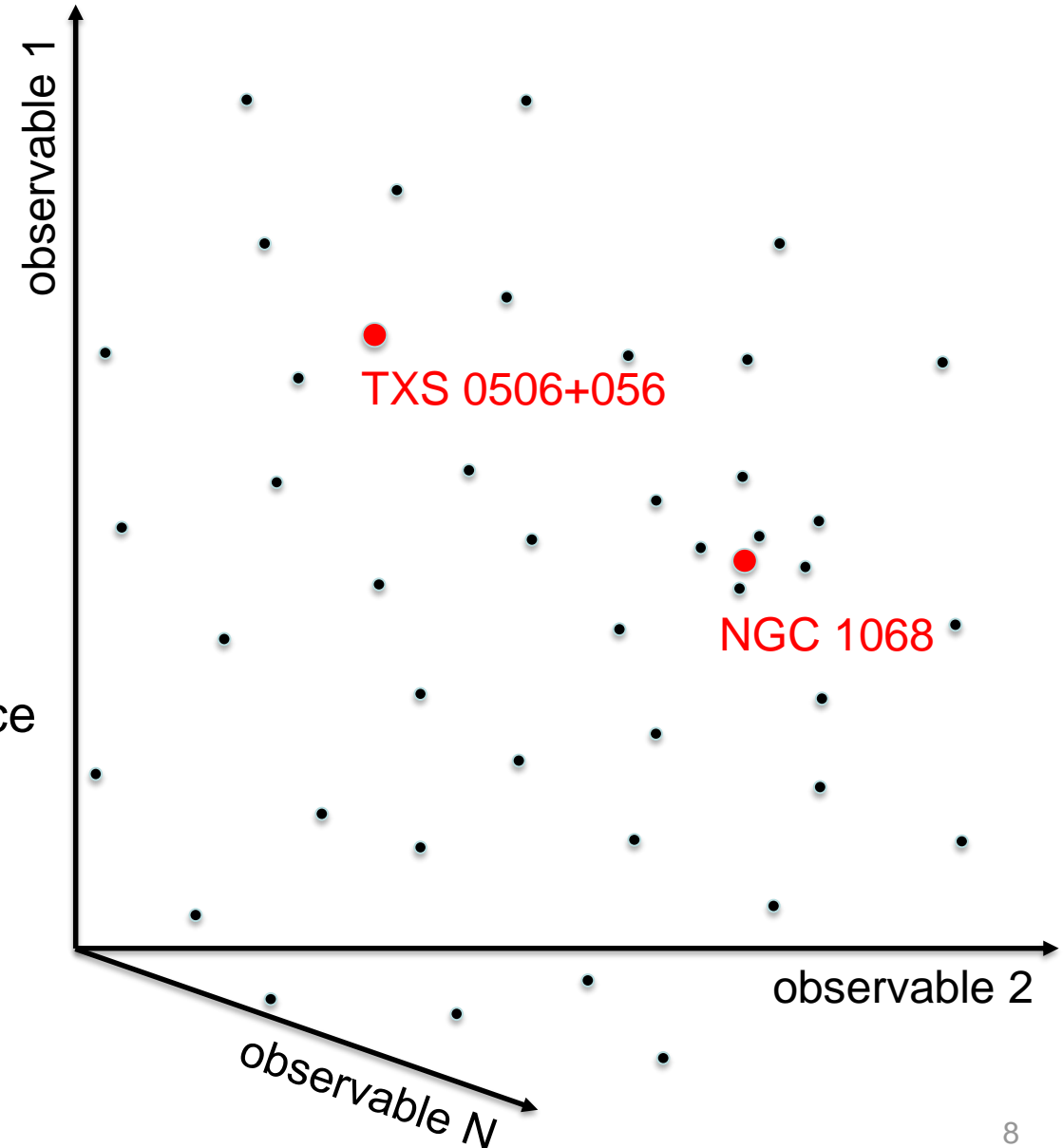
data-driven!

- **emission-model-independent** search
- independently from existing **AGN classification scheme**

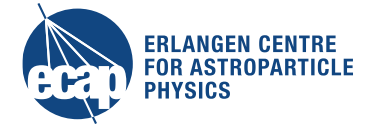
Phase space of AGN observables



- **many different observable quantities** from AGN:
 - flux in some waveband: radio, x-ray, γ -ray etc.
 - strength, broadness, shape etc. of spectral line X, Y, Z etc.
 - polarization etc.
- **each observable is a continuum** (axis in space)
 - many observables span a high-dimensional space
- **populate space** with many observed AGN
 - probably not homogeneously distributed



Phase space of AGN observables



distance in phase space

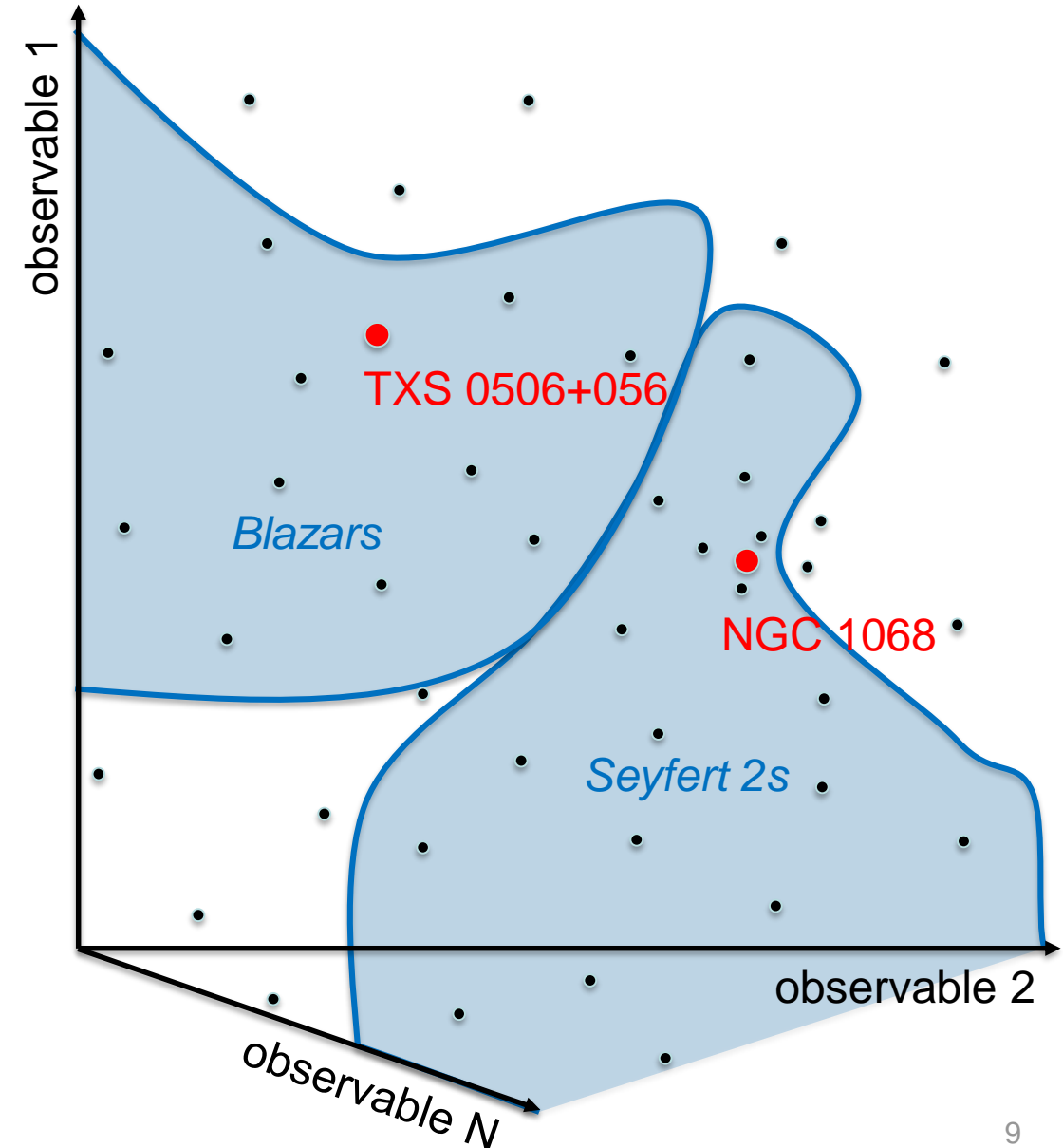


measure for similarity of AGN

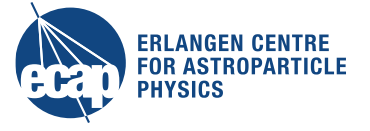
clusterings / distinguishable groups



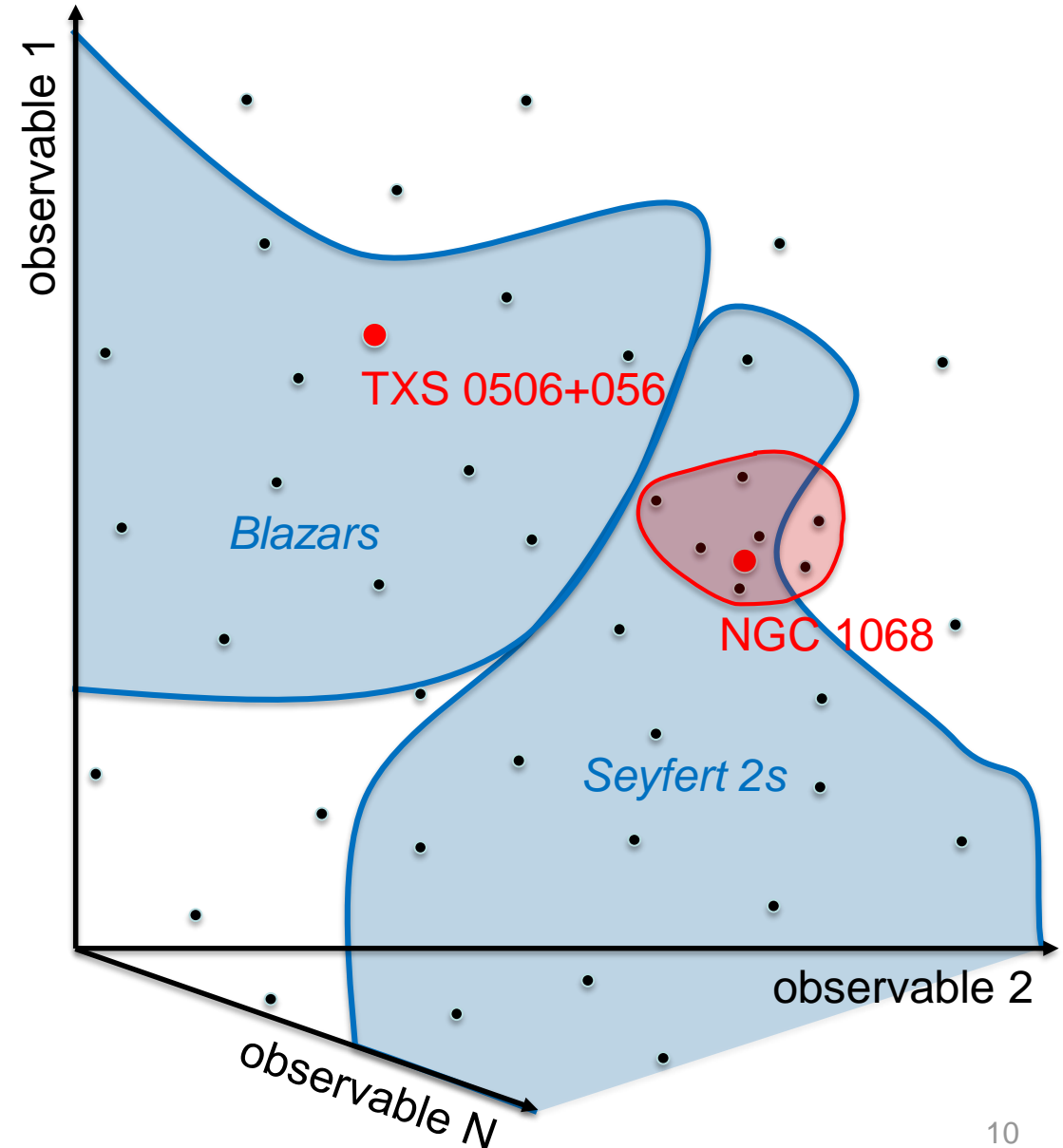
common features,
indication for sub-classes?



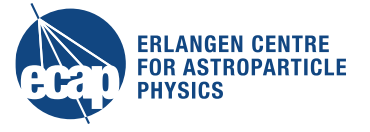
Phase space of AGN observables



- use **interesting clusters of AGN** as source list for stacking search
 - interesting clusters?
e.g. inclusion of **existing candidate** in cluster
→ “which smallest cluster includes NGC 1068?”
- stack sources that are **intrinsically similar to existing candidates**
(e.g. TXS 0506+056 & NGC 1068)

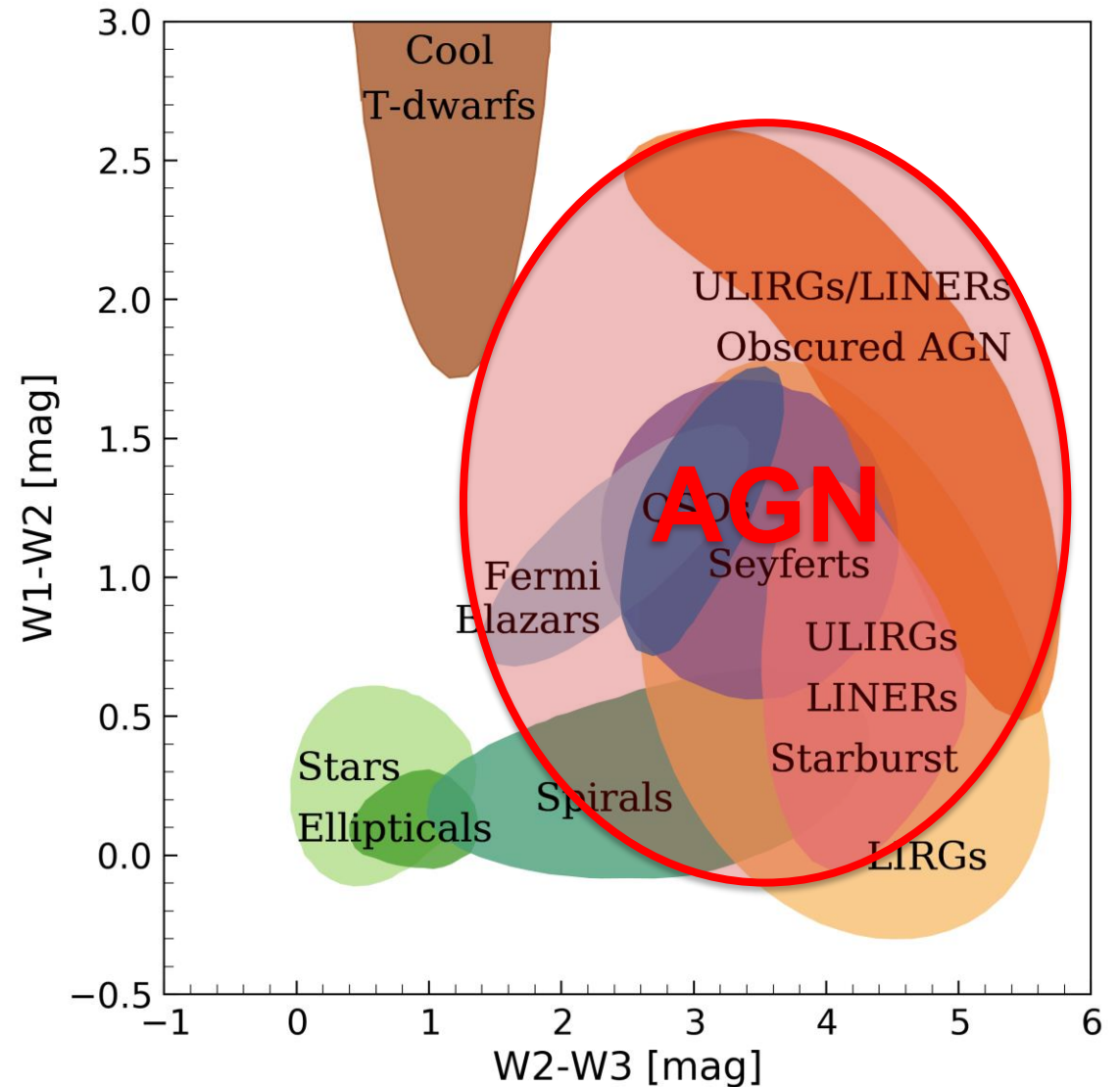


IR color-color diagrams

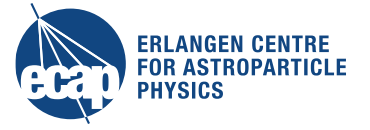


AllWISE: magnitude in 4 infrared bands
(W1, ..., W4)

- differences of bands („colors“)
= slope of spectrum
- color-color diagrams: shown to have good discrimination power between classes of objects
Nikutta et al. <https://doi.org/10.1093/mnras/stu1087>
- e.g. selection of AGN possible with cuts in this 2D space

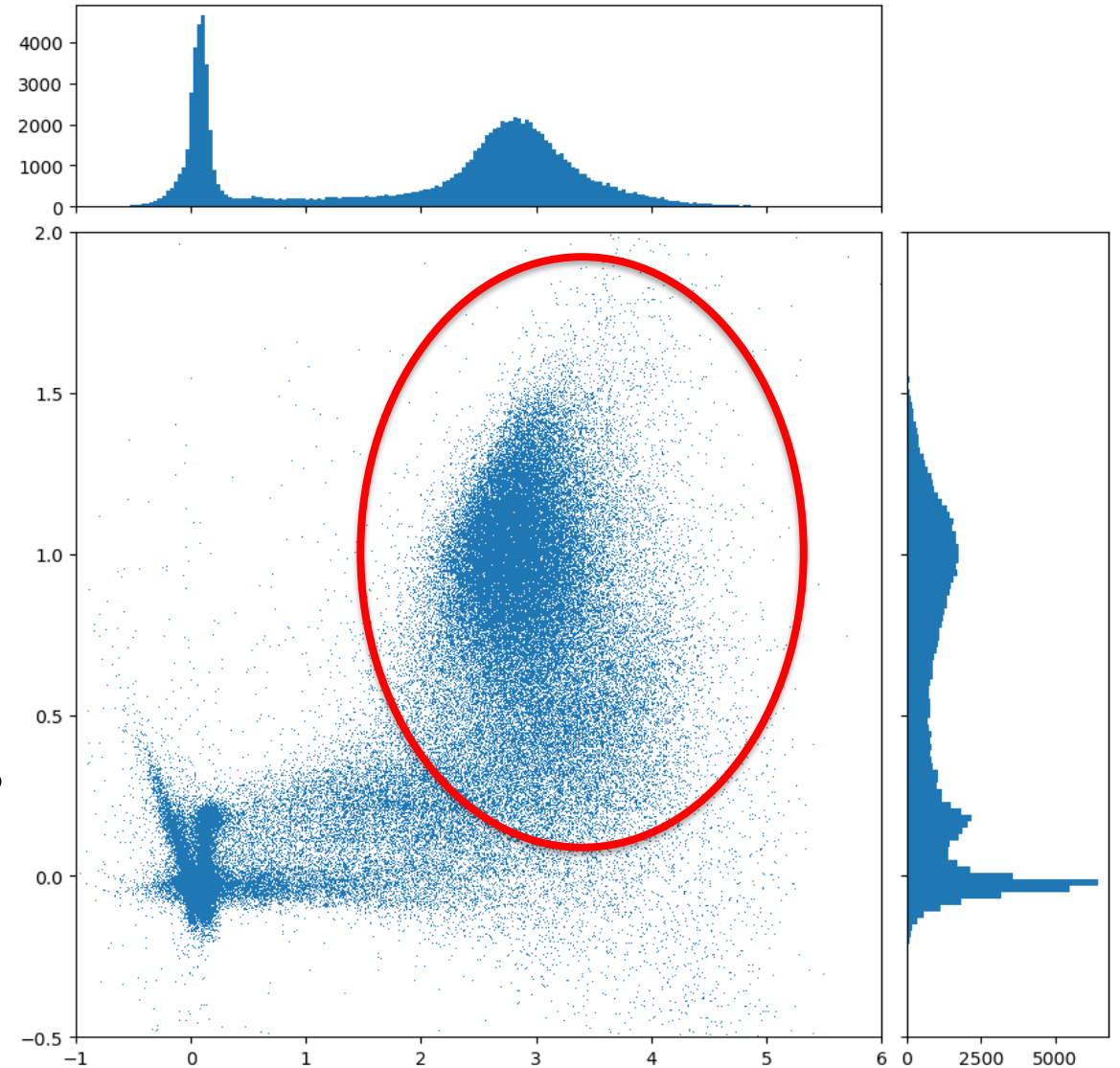


IR color-color diagrams



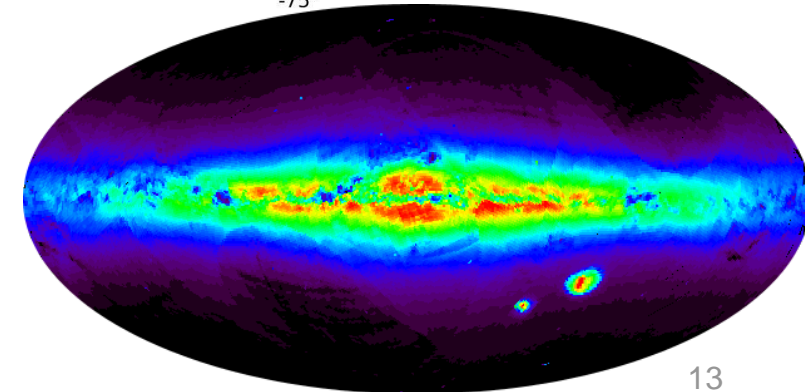
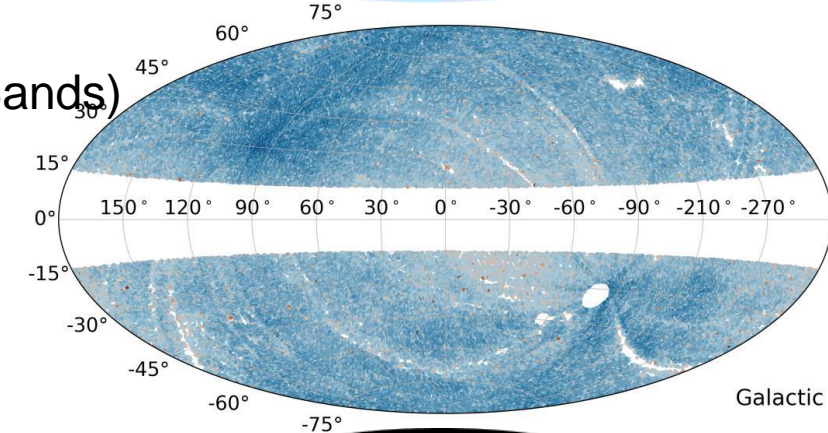
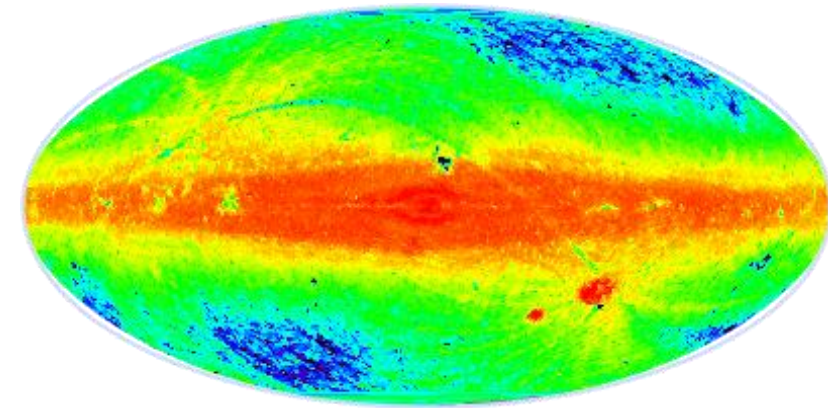
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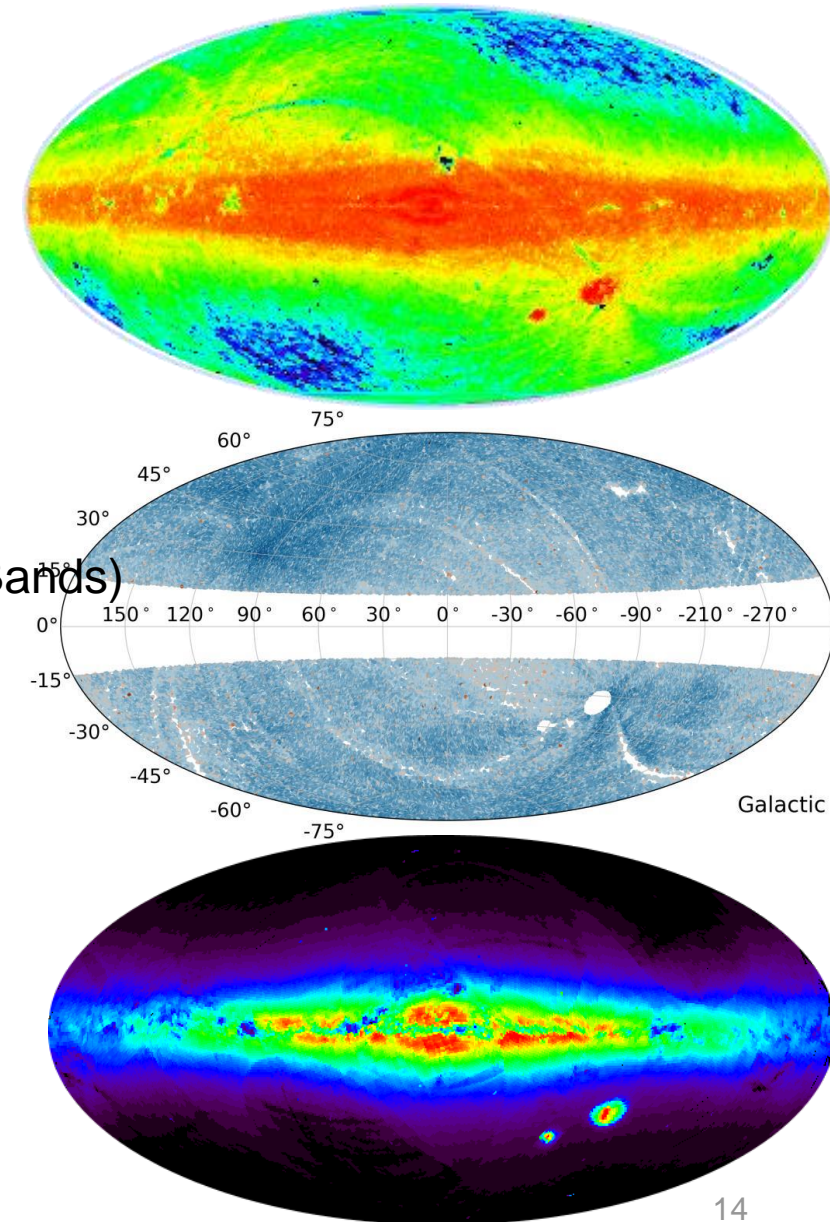
add more observables:

- infrared: **AllWISE** (*Wide-field Infrared Survey Explorer*, 2010, 4 bands at a few μm)
- x-ray: **2RXS** (*ROSAT All-sky Survey*, 1990, 0.1 – 2.4 keV)
+ **XMMSL2** (*XMM-Newton Slew 2 Survey*, 2017, 0.2 – 12 keV)
- optical: **Gaia + SDSS** (*Sloan Digital Sky Survey*, mean flux + u g r i z Bands)



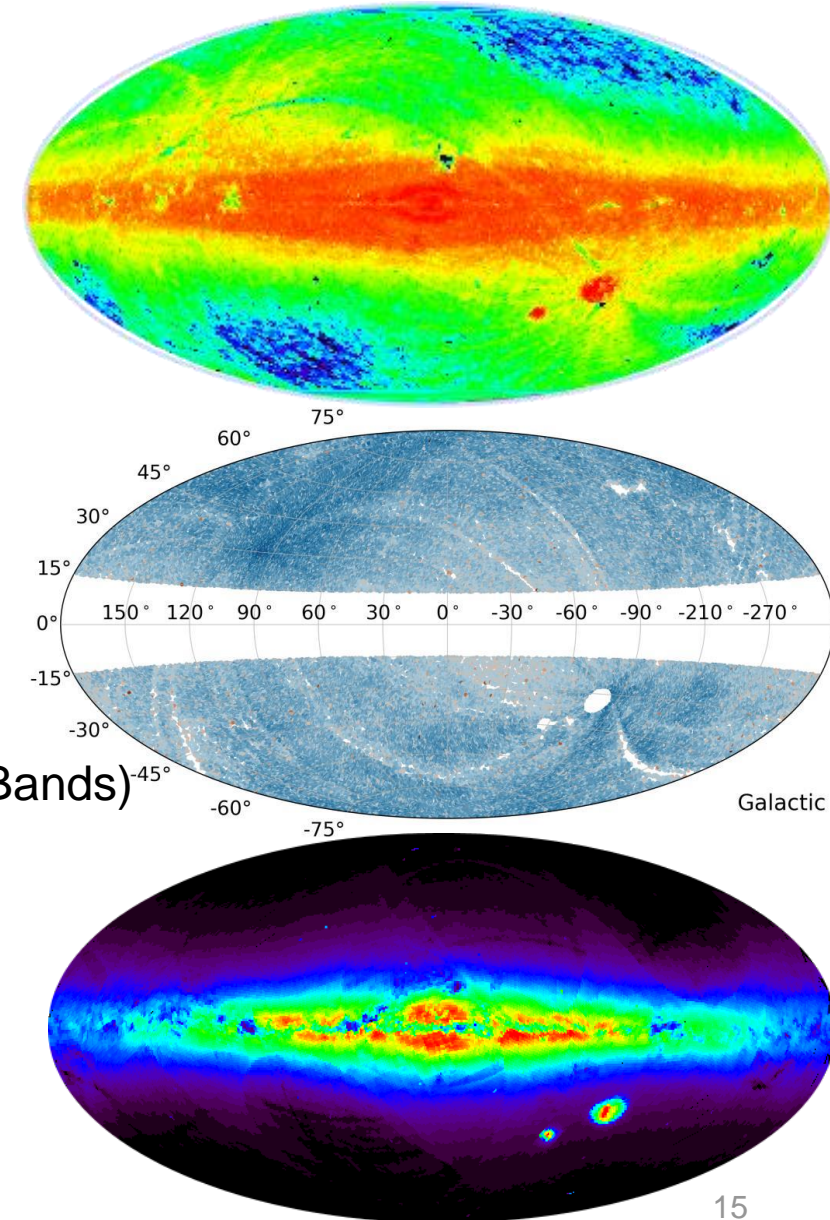
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→ all-sky, millions of AGN candidates
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→ all-sky, ~ 100,000 sources <https://www.mpe.mpg.de/ROSAT/2RXS>
correlated catalog of 2RXS and AllWISE by Salvato et al. 2017
<https://doi.org/10.1093/mnras/stx2651>
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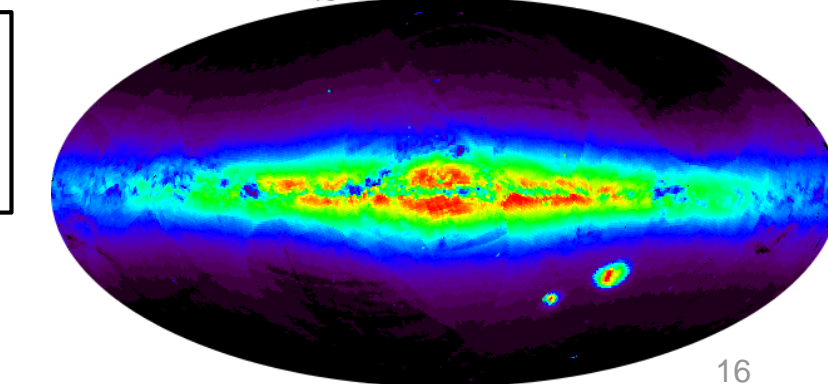
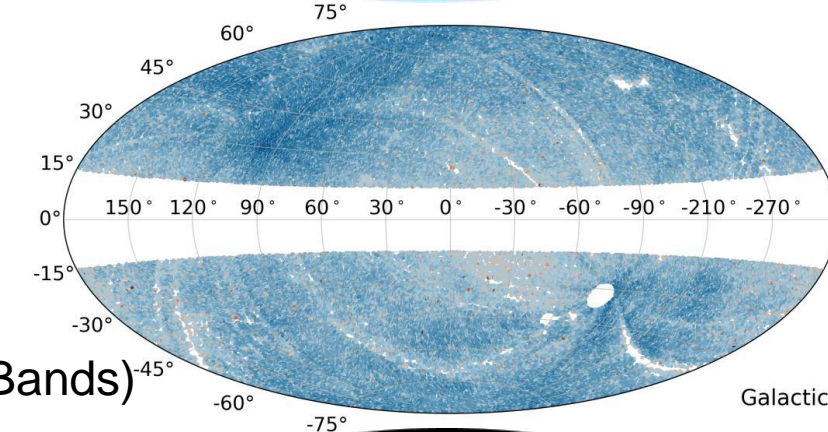
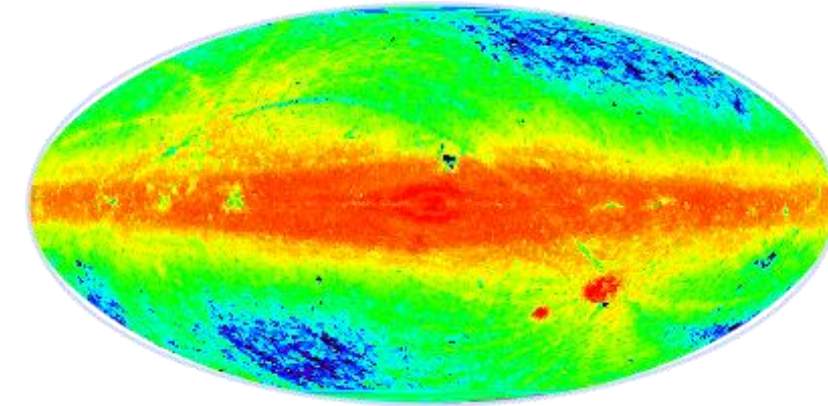
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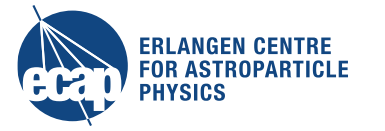
→ photometric data: 18 observables

- 4 infrared bands
- x-ray flux
- optical mean flux + 5 optical bands
- + 7 differences of fluxes (e.g. W1-W2, u-g)

combined catalogs from
Mechbal et al. (pre-print)
[arXiv:2303.18076](https://arxiv.org/abs/2303.18076)



18-dim. AGN data



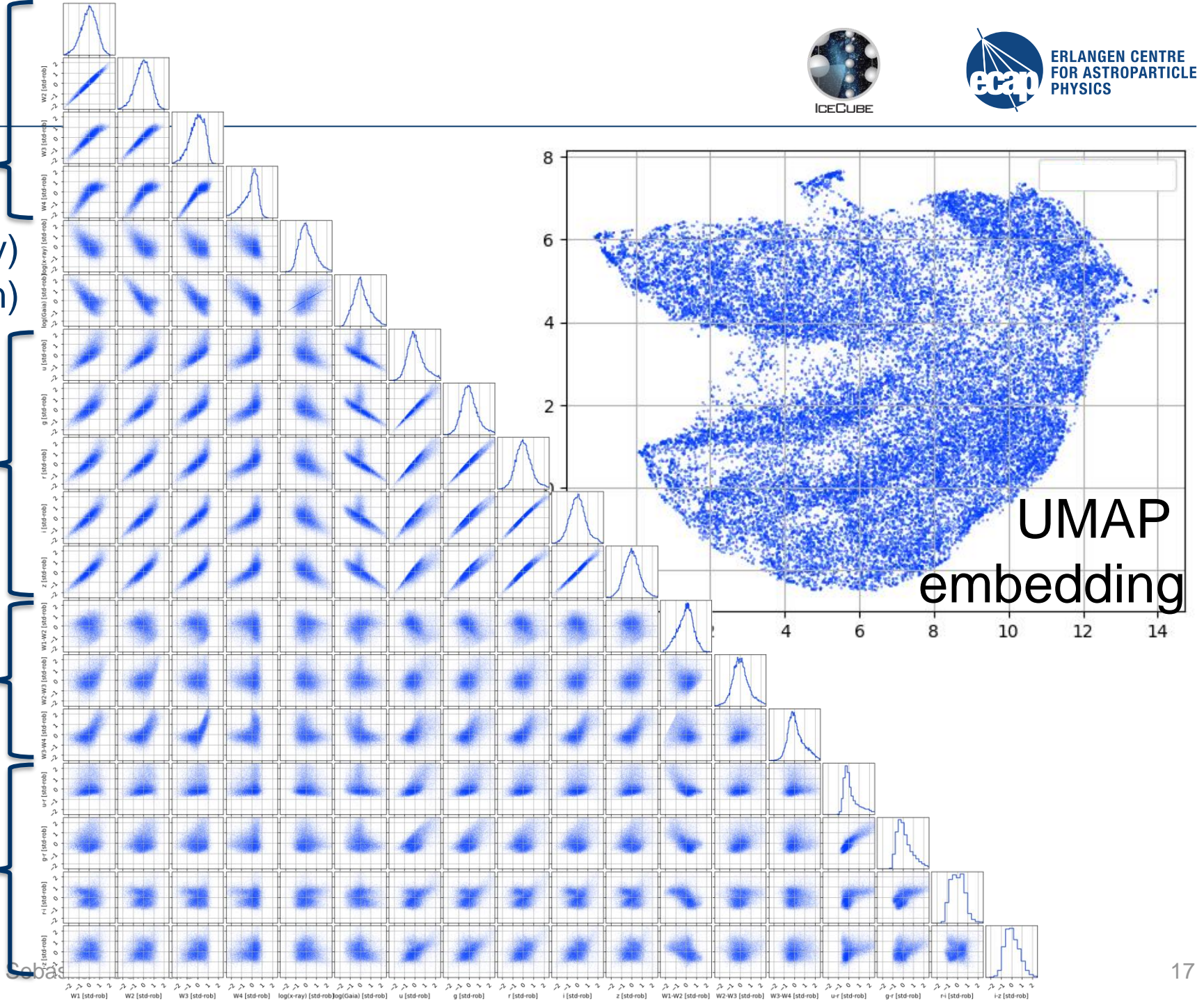
infrared (W1, ..., W4)

log(x-ray)
log(optical mean)

optical bands (u, g, r, i, z)

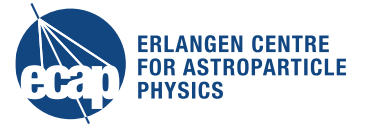
infrared differences

optical differences

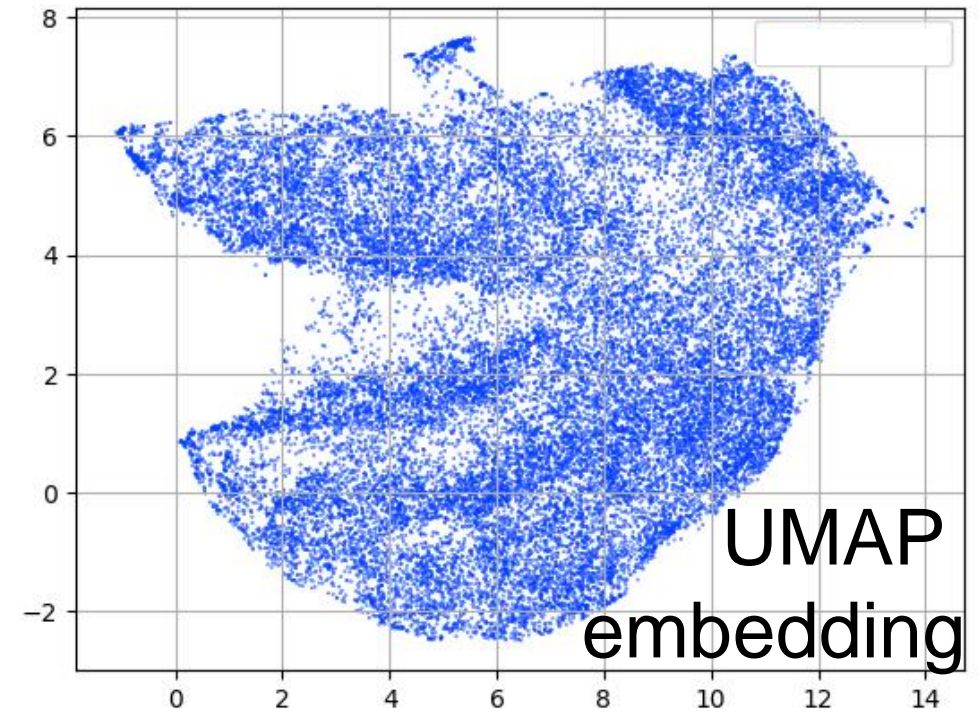


UMAP embedding

18-dim. AGN data



- rather homogeneous, connected distribution in most observables
→ no to-the-eye obvious distinguishable classes
- but high-dimensional = cannot see all hidden details even in corner plot
illustrative example:
 - sphere inside a spherical shell
 - 2D projections cannot depict problem entirely
- UMAP embedding:
 - difficult to interpret, however:
 - some structure: lower & upper part, upper-right part? → investigate!

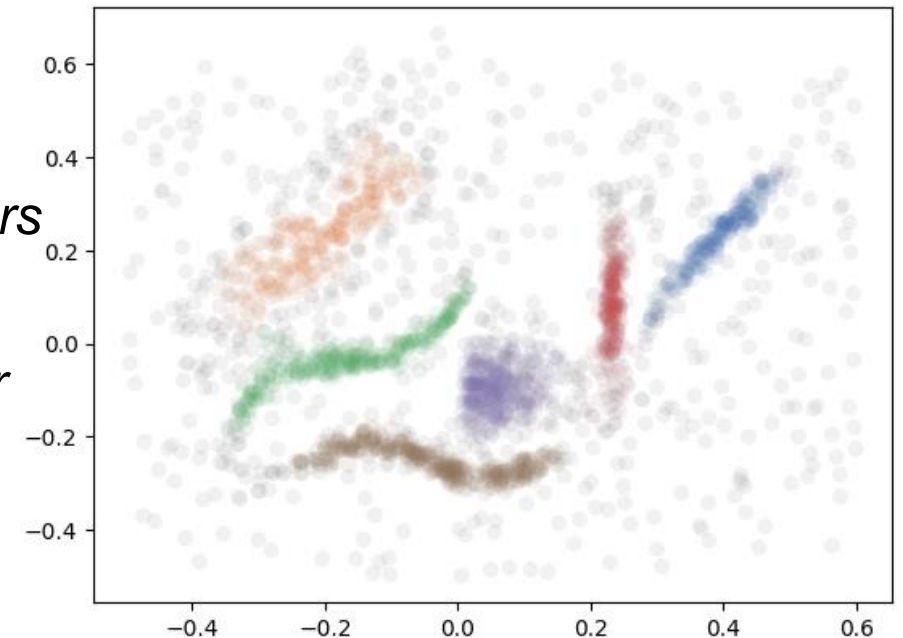


HDBSCAN: state-of-the-art algorithm for searching for clusters in arbitrary data

(*Hierarchical Density-Based Spatial Clustering of Applications with Noise*

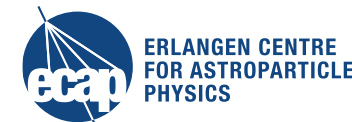
Campello, Moulavi, Sander https://doi.org/10.1007/978-3-642-37456-2_14)

- high dimensionality of data possible
- explorative: no required knowledge of number of clusters, arbitrary cluster shape
→ *but tends to produce some small additional clusters that seem like noise*
- fast (few seconds for 30k points in 18 dimensions)
- two main parameters to tune
→ *but not very easy to interpret these hyperparameters*
- has notion of unclustered data
→ *but often just leaves points around a central cluster unclustered, which is not that helpful*



Clustering applied

(one particular choice of hyperparameters)



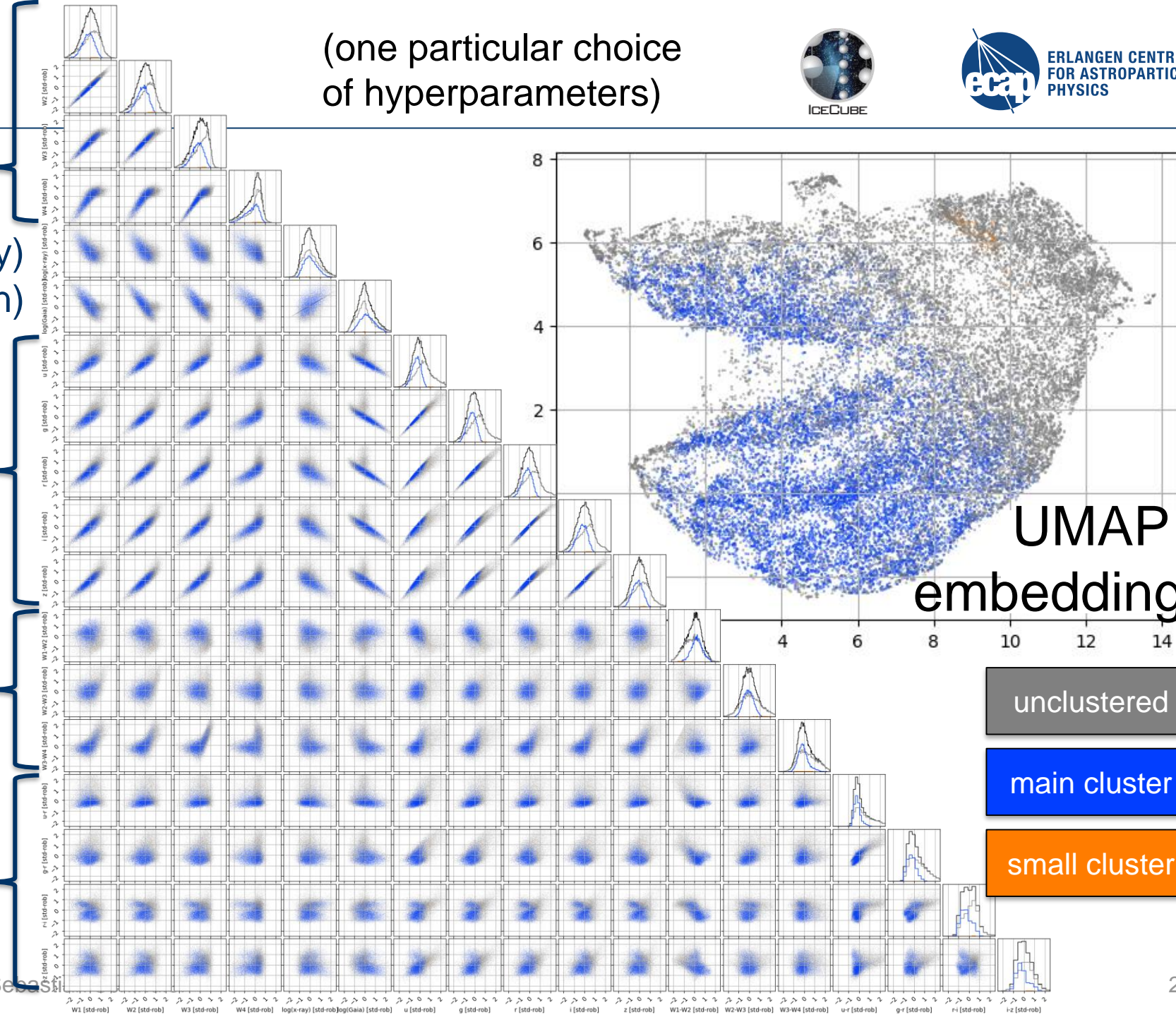
infrared (W1, ..., W4)

log(x-ray)
log(optical mean)

optical bands (u, g, r, i, z)

infrared differences

optical differences

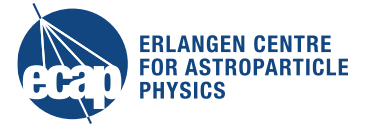


UMAP embedding

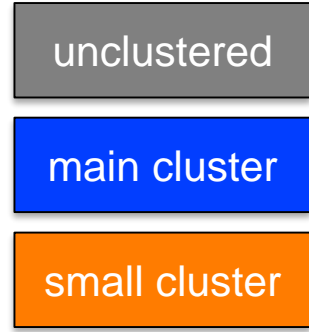
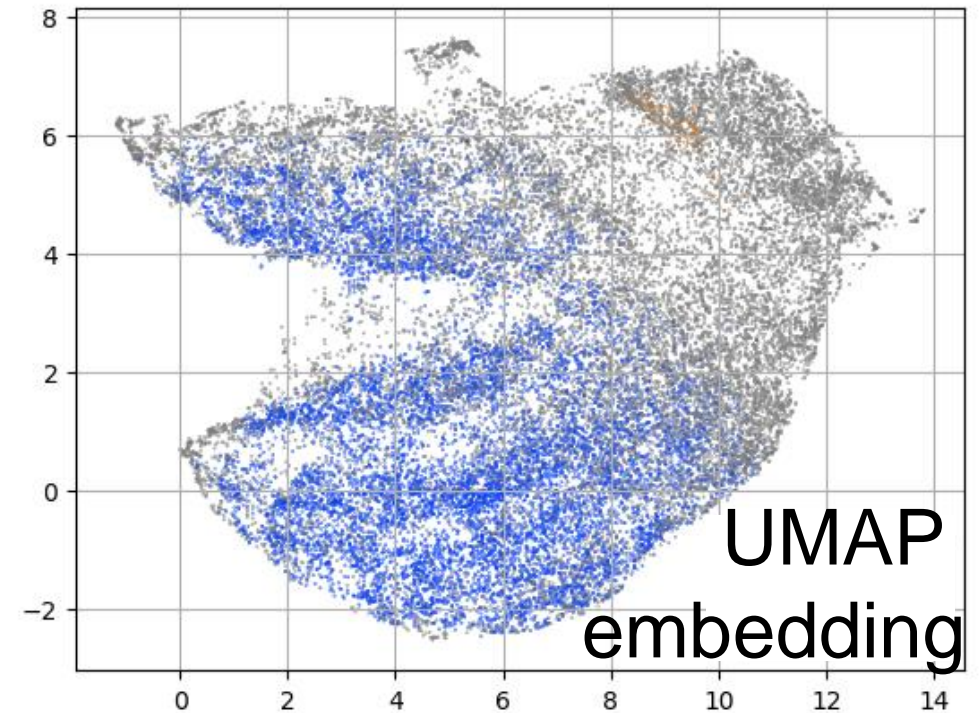
- unclustered
- main cluster
- small cluster

Clustering applied

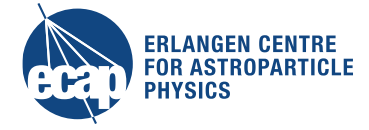
(one particular choice of hyperparameters)



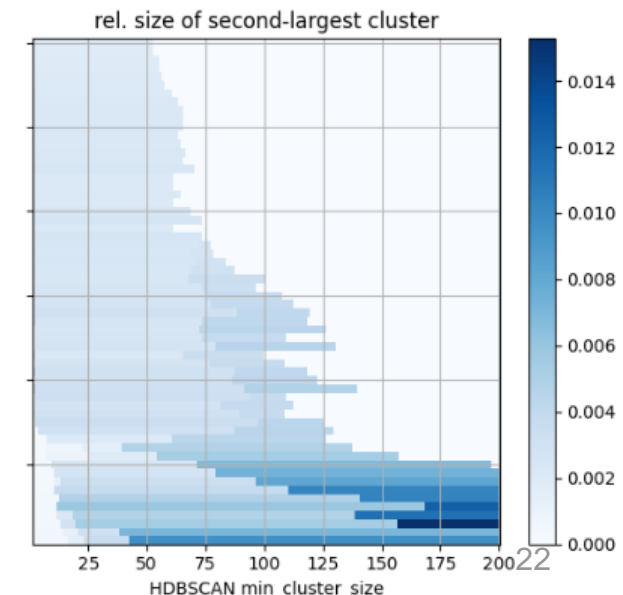
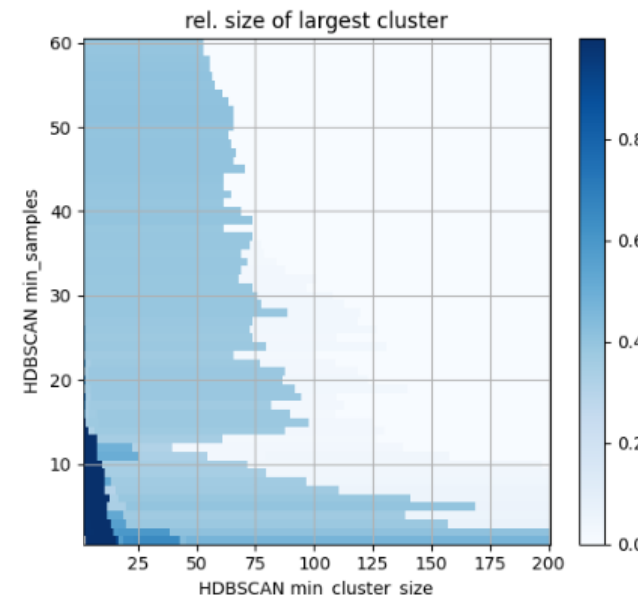
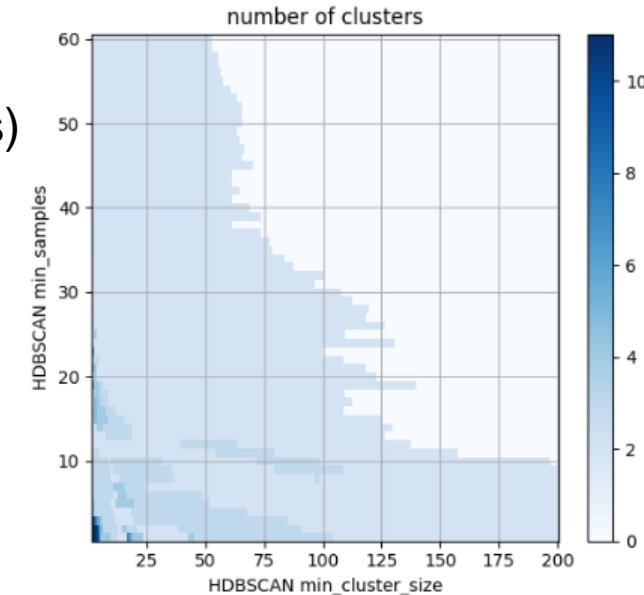
- one continuous, regularly shaped main cluster in most dense area
- many points around it remain unclustered (few micro clusters)
- hyperparameter choice does not change much
- UMAP embedding: clustering does not follow the visible structure...



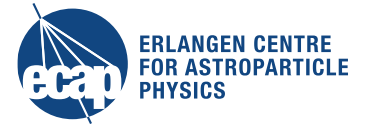
Hyperparameter scan



- hyperparameter choice for cluster algorithm is not obvious
→ scan hyperparameter space (i.e. run HDBSCAN for all combinations)
- look at summary quantities
 - number of clusters found
 - relative size of largest & second-largest cluster (fraction of points in this cluster)
- what choice is sensible?
→ introduce artificial clusters to test hyperparameter choice
 - introduce obvious clusters into the data
 - only hyperparameters that can identify those should be used



What to make of this?



naïve and hopeful idea does not really work:

- not that much structure in the phase space
- algorithm does not seem to find interesting non-obvious clusters

→ fault of HDBSCAN? use different cluster algorithm?



other Ansatz:

- compile list of interesting sources and mark them in the phase space
- (should not be a problem with blindness, as no neutrino data yet involved)

→ can we see something around the sources by eye?



fall-back option:

- use all sources in a pre-defined radius around very interesting sources (like NGC 1068)
- maybe radius such that ~ 100 sources are contained

Summary

- look for source list for stacking search based on similarity to known candidate sources
- high-dimensional dataset: about 30k AGN in 18 observables
- search for structures/clusters using HDBSCAN and UMAP
- not successfull currently → possibly pursue different Ansatz

Different idea

- instead of many different observables, use wealth of data in **optical only**
- optical spectra: treat each bin as one dimension (~ 1000 dimensions)
- apply UMAP (or other dimensionality reduction), then search for clusters again

Thank you for your attention

Questions?

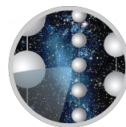
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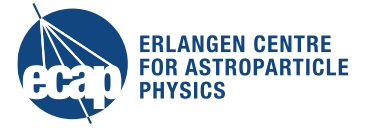


Backup

1. **build extensive catalog** of AGN with many different observables
 - a) decide on observables to use (flux in certain waveband, spectral lines etc.)
 - b) combine astronomical catalogs
 - c) populate phase space
2. **cluster search** in observable space to select AGN closest to candidates
 - a) run cluster search algorithm
 - b) select interesting clusters based on location of candidate sources
3. perform **stacking analysis** with AGN within selected clusters



Testing with a supervised-learning classifier



- can classify AGN as...
 - Type 1: unobscured disk, broad lines
 - Type 2: obscured disk, narrow lines
- Mechbal et al. pre-print [arXiv:2303.18076](https://arxiv.org/abs/2303.18076):

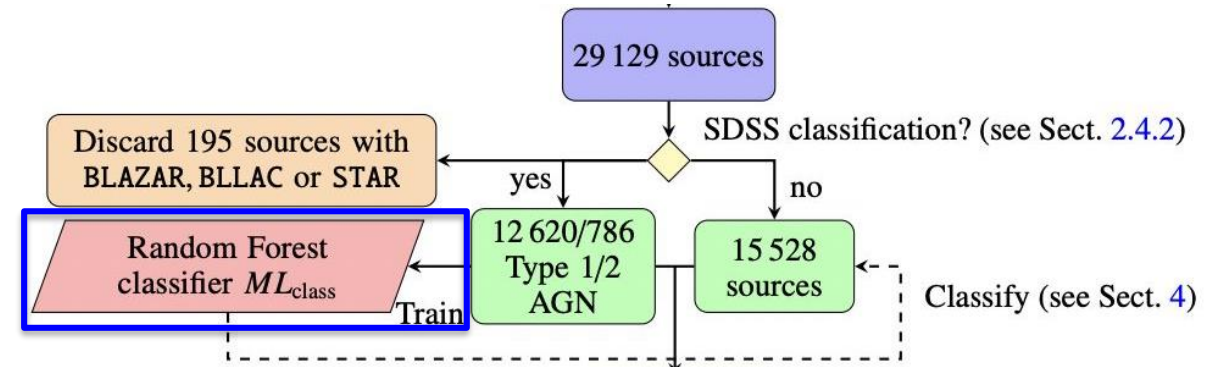
classification exists for $\sim 1/2$ of AGNs in dataset
(from SDSS catalog by visual inspection)

→ **train machine-learning classifier**

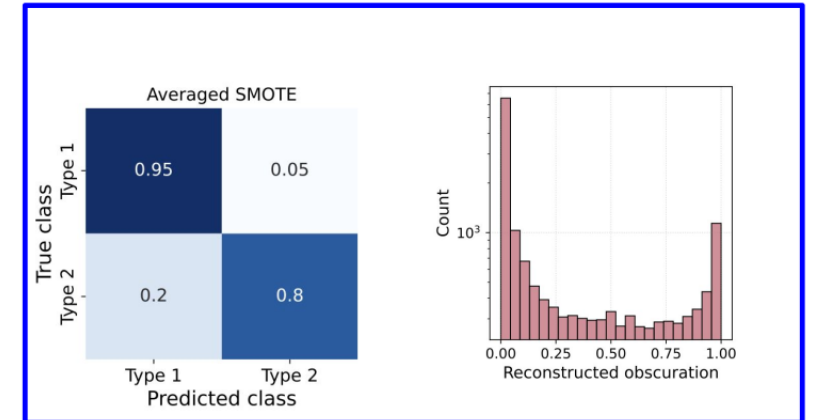
- photometric data of AGNs as input
- supervised learning with labels from existing classification
- apply to other $1/2$ of AGNs

→ also possible with **unsupervised clustering?**

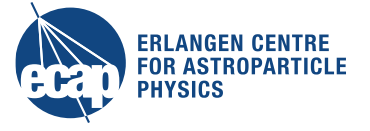
- classification problem is binary (Type 1 or 2)
- ... so there should be two clusters in the data



Classification task



Classifier (Mechbal et al.)



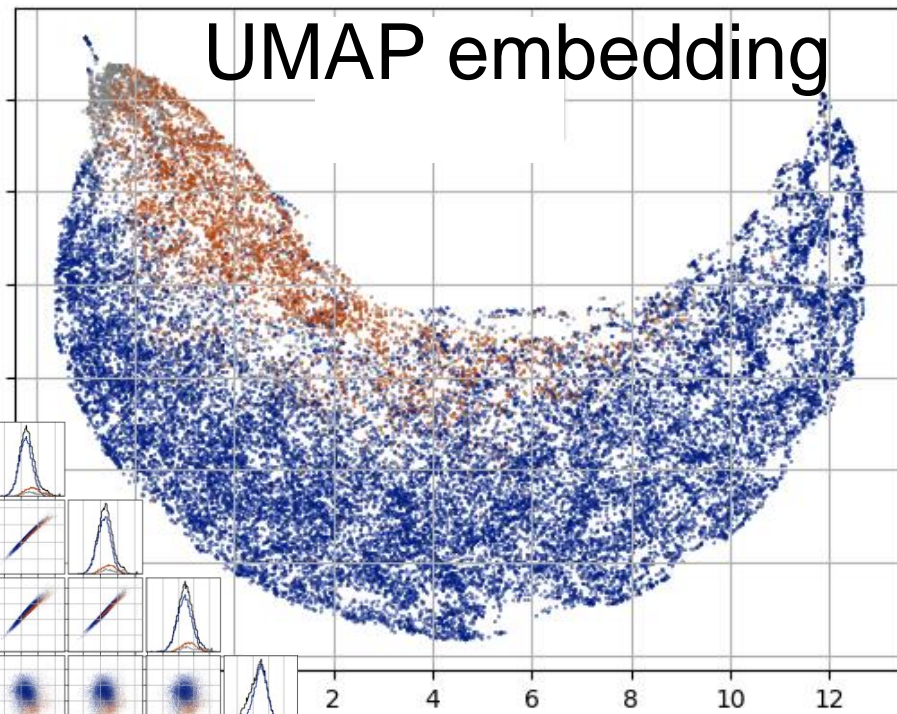
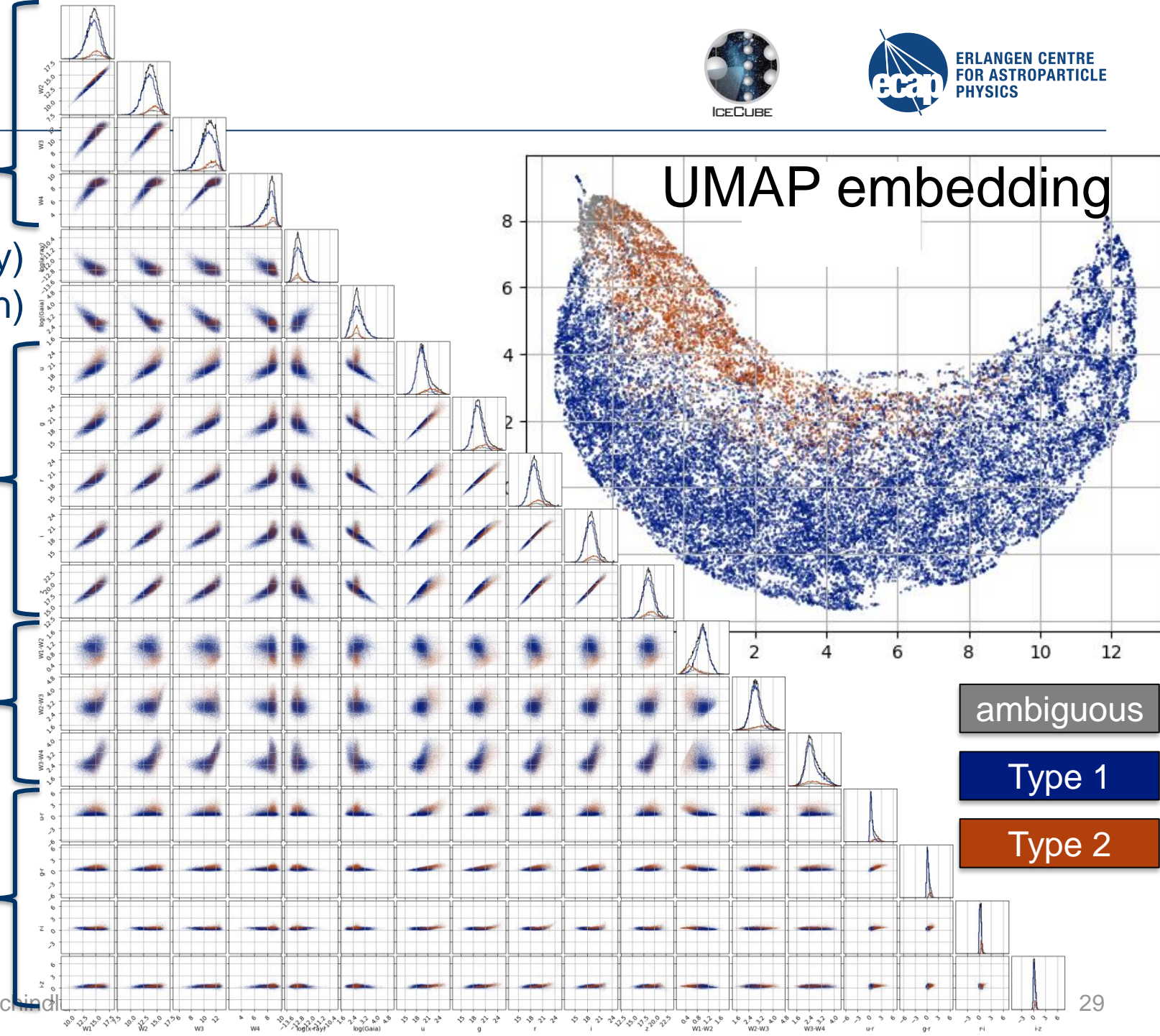
infrared (W1, ..., W4)

log(x-ray)
log(optical mean)

optical bands (u, g, r, i, z)

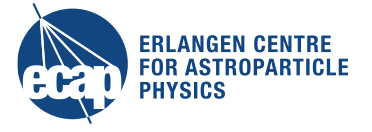
infrared differences

optical differences

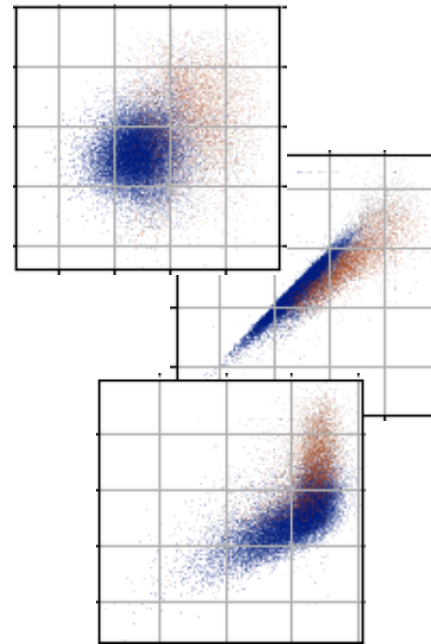
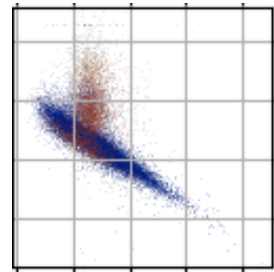


ambiguous
Type 1
Type 2

Classifier (Mechbal et al.)



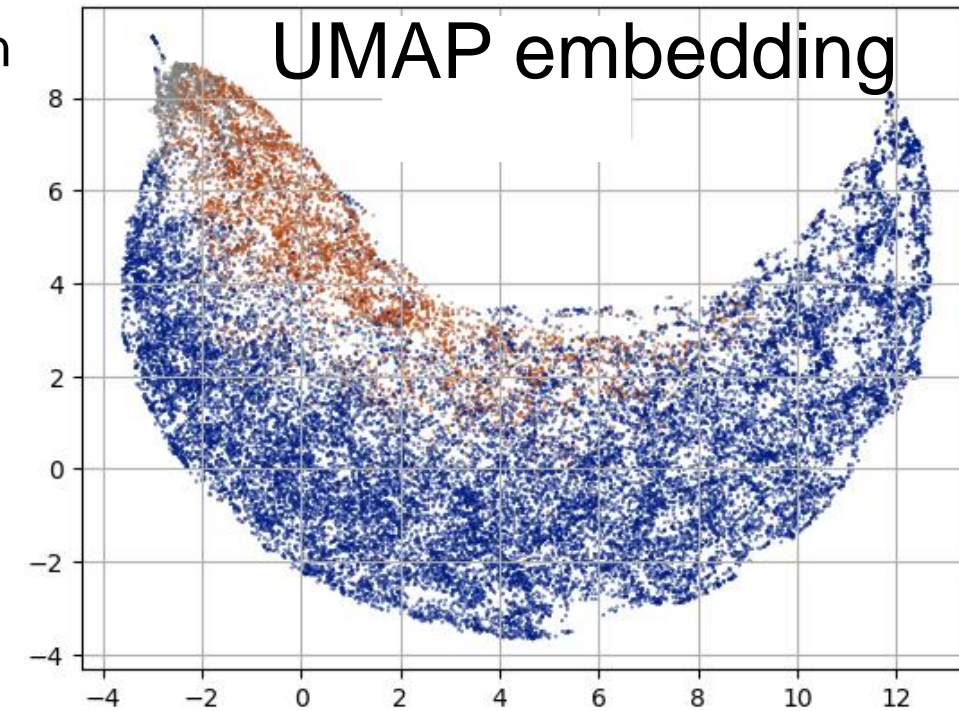
- separation between Type 1 / 2 somewhat similar to clustering
 - Type 1 more in dense center area
 - Type 2 more at the fringes
 - also the case in UMAP



- some smaller features can be mapped to Type 1 / 2

→ for **comparison with clustering**, associate...

- unclustered with Type 2
- main cluster with Type 1



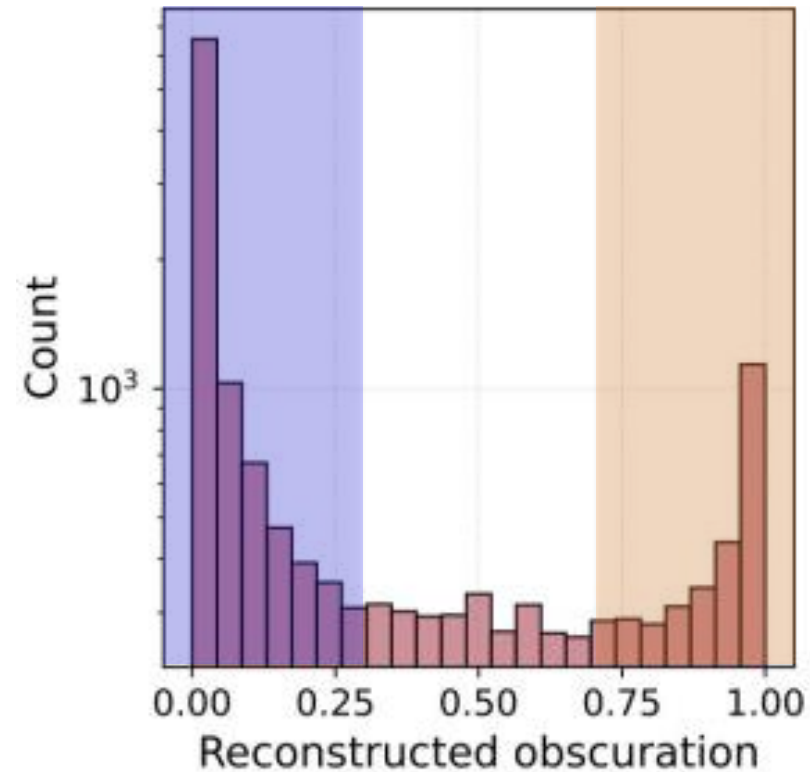
ambiguous

Type 1

Type 2

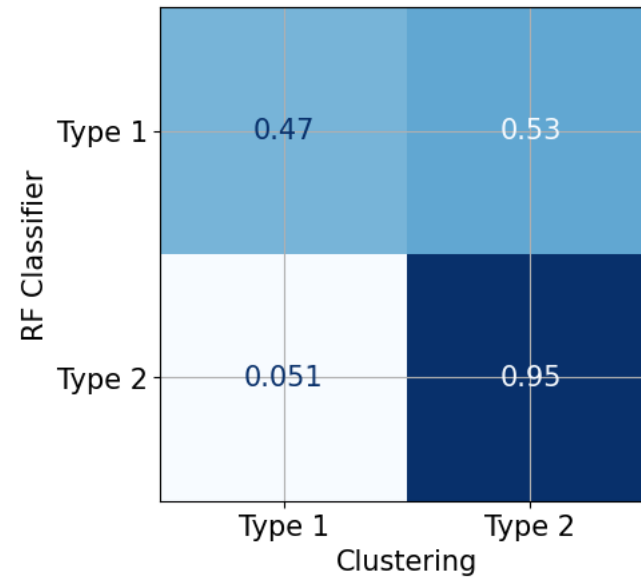
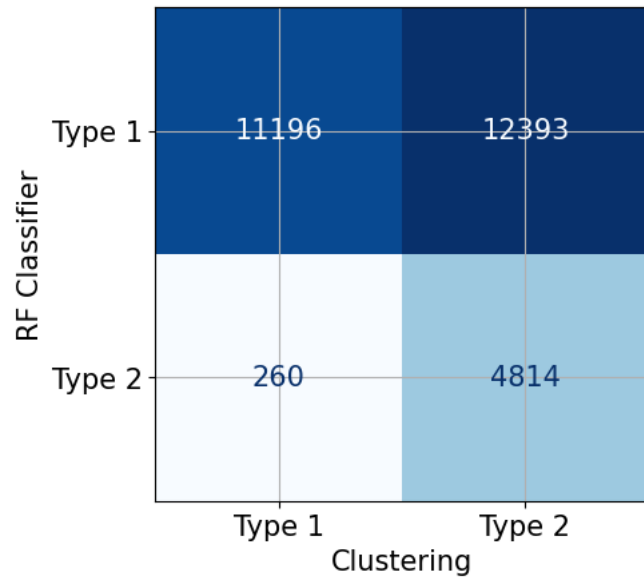
obscuration score μ

- $\mu < 0.3 \rightarrow$ Type 1
- $\mu > 0.7 \rightarrow$ Type 2
- $0.3 < \mu < 0.7 \rightarrow$ ambiguous type



current work in progress:

compare cluster result (prediction) to classifier (as truth):



→ clusterer...

- finds most Type 2 (95 %)
- but is just guessing for Type 1 (47 %)

however:
Type 1 more numerous!