

Space in Cyberspace: hidden patterns in astrophysical datasets

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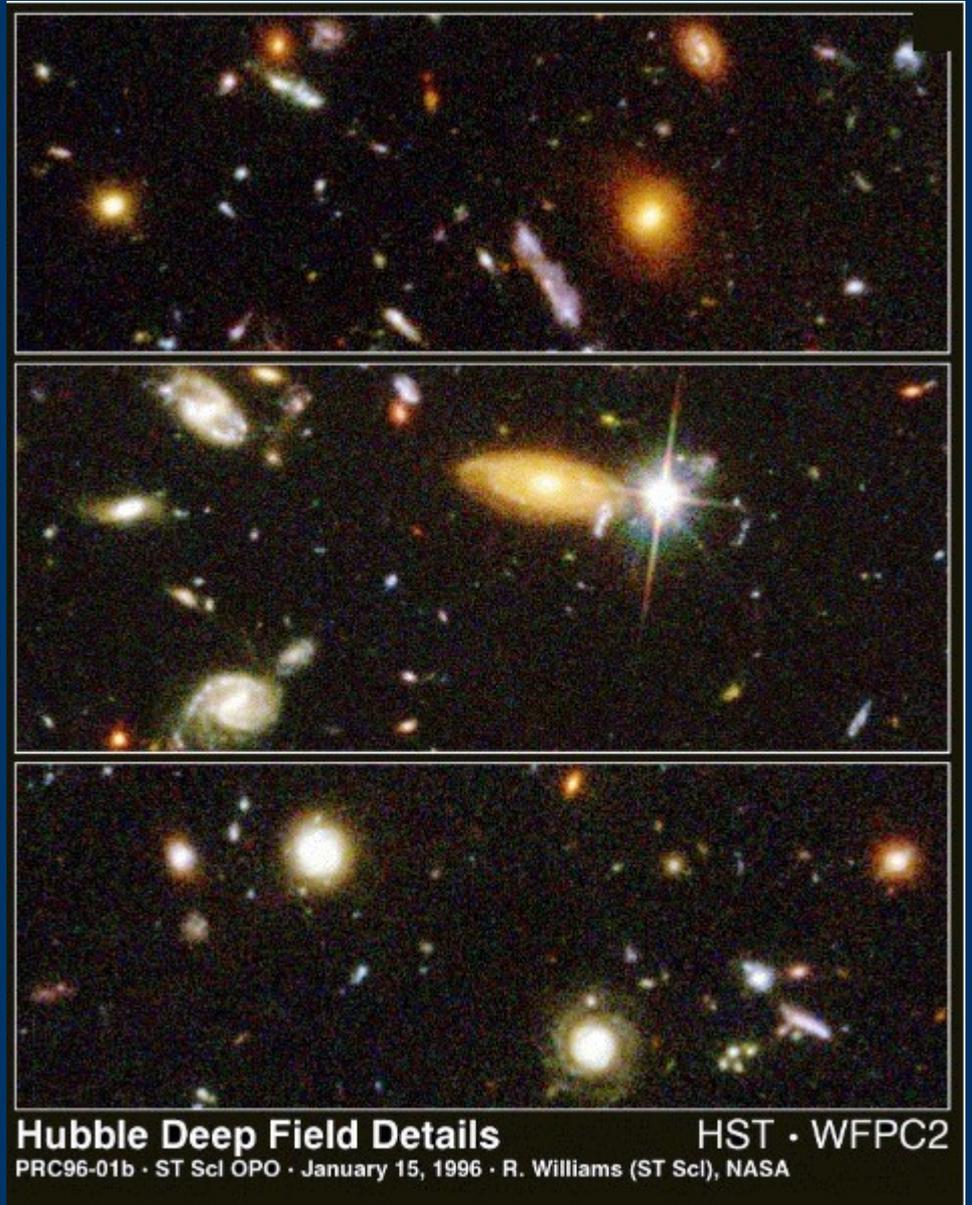
with M. Bilicki, M. Gromadzki, A. Pollo

30.06.2017

EWASS, Prague

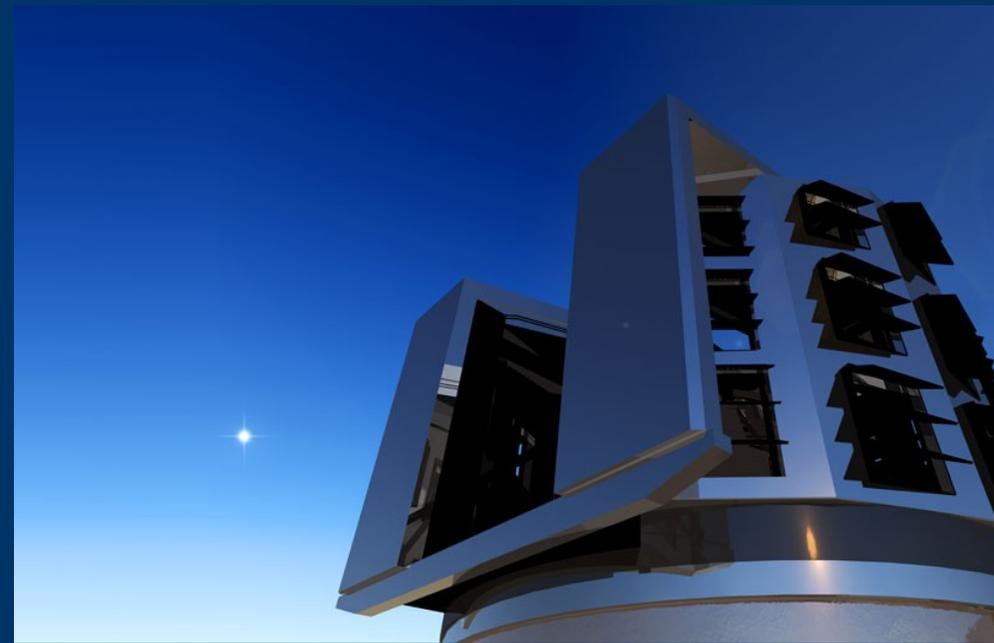
Digital Sky Surveys

- As large and as deep as possible
- Sky surveys designed to provide statistical samples of celestial objects.
- Spatial overview, completeness, homogeneous datasets;
- Base for general conclusions about objects;
- Rare and/or unusual objects;



Data avalanche

- SDSS: ~115 TB in total
- Zwicky Transient Facility (ZTF; start 2017)
1 PB of image data ~1 billion objects
- Large Synoptic Survey Telescope (LSST; first light ~2020); 30 TB PER NIGHT
- The Square Kilometer Array (SKA) ~4.6 Zetabytes
- **Need of automated tools to detect, characterize and classify gathered information**



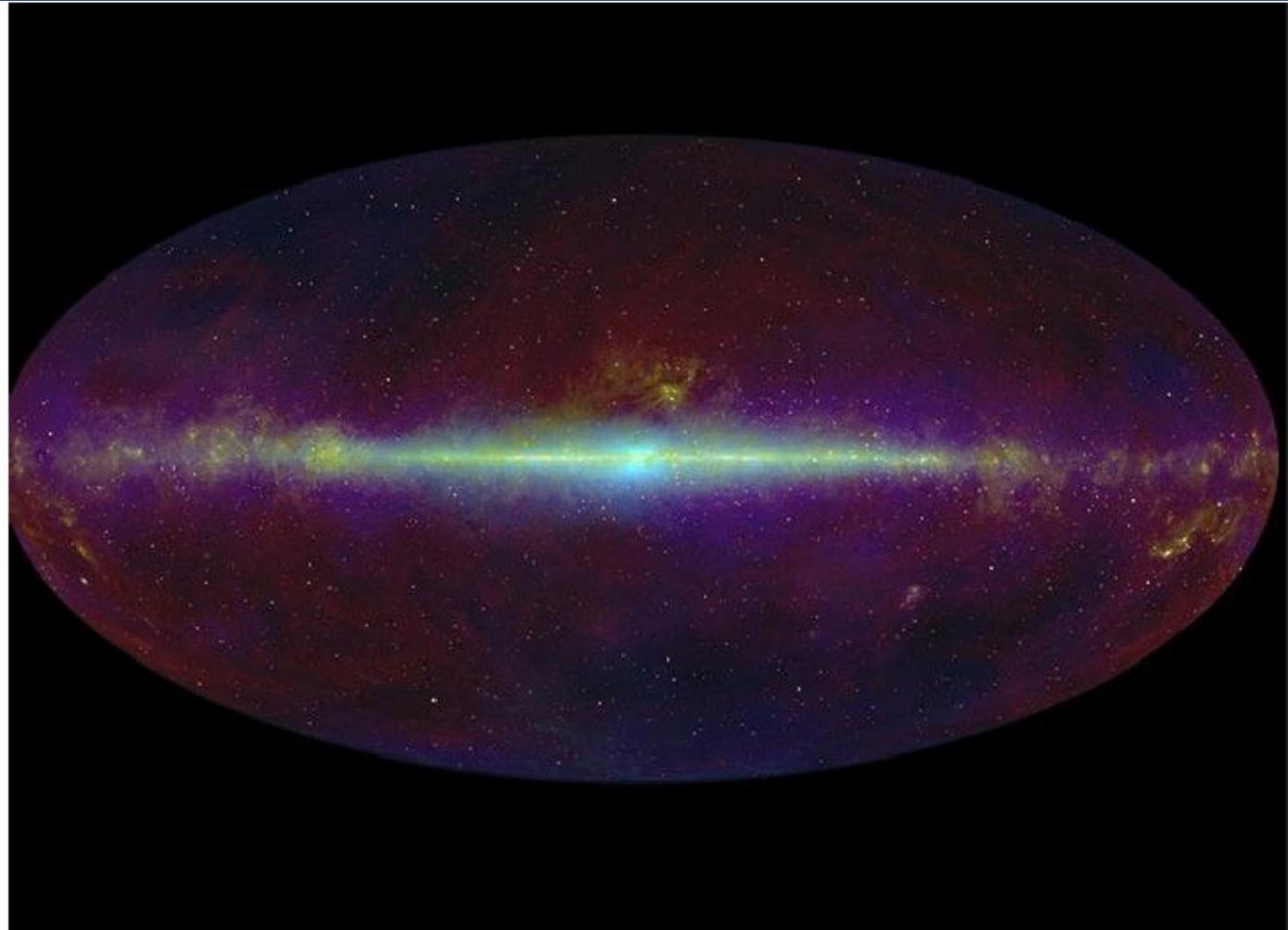
<https://www.lsst.org/lsst>

SKA; South Africa

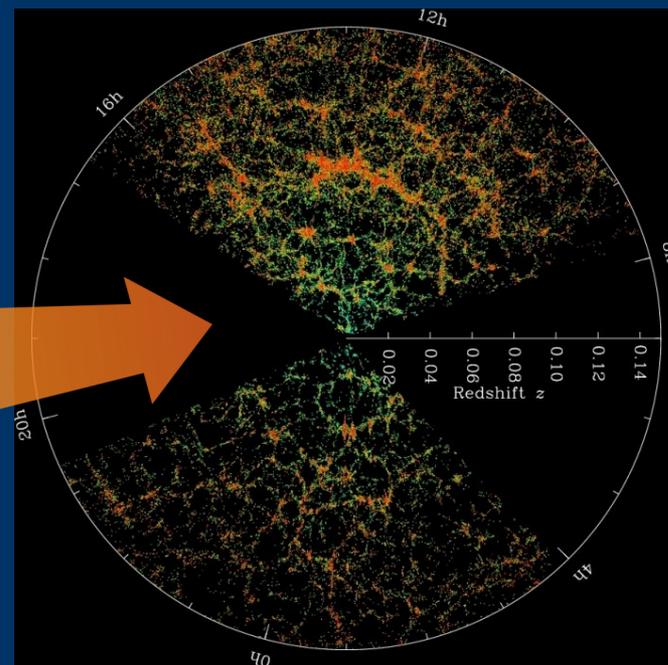
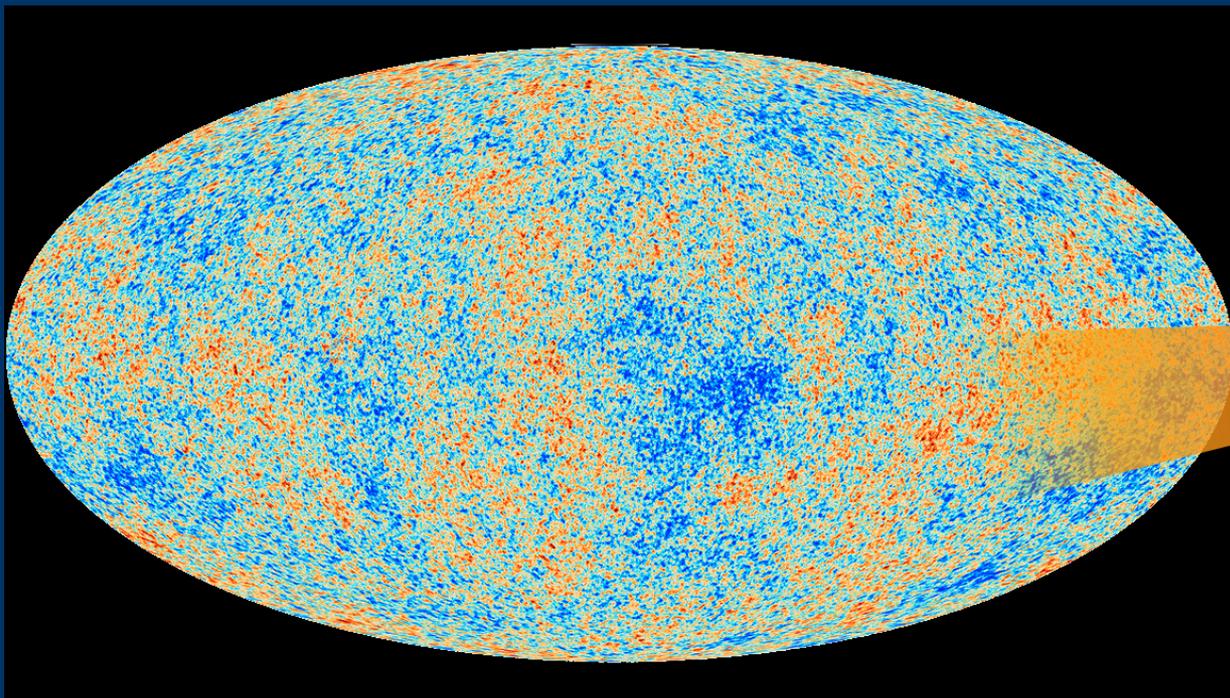


The deepest and widest so far: Wide-field Infrared Survey Explorer (WISE)

- All-Sky survey in IR
- Detected over 747 mln sources
(15 PB of data; tables + images)
- Publicly available (position, photometry in 4 bands (3.6-22 um))
- Low angular resolution (~6")
- No redshift information so far



Objectives



→ Create as complete and as deep catalogues of **stars, galaxies and quasars** as possible (with as little effort as possible) to get a better understanding of the formation and evolution of the Universe

→ **WISE: largest and deepest → perfect for testing efficient methods of fast and effective catalogue creation for further studies**

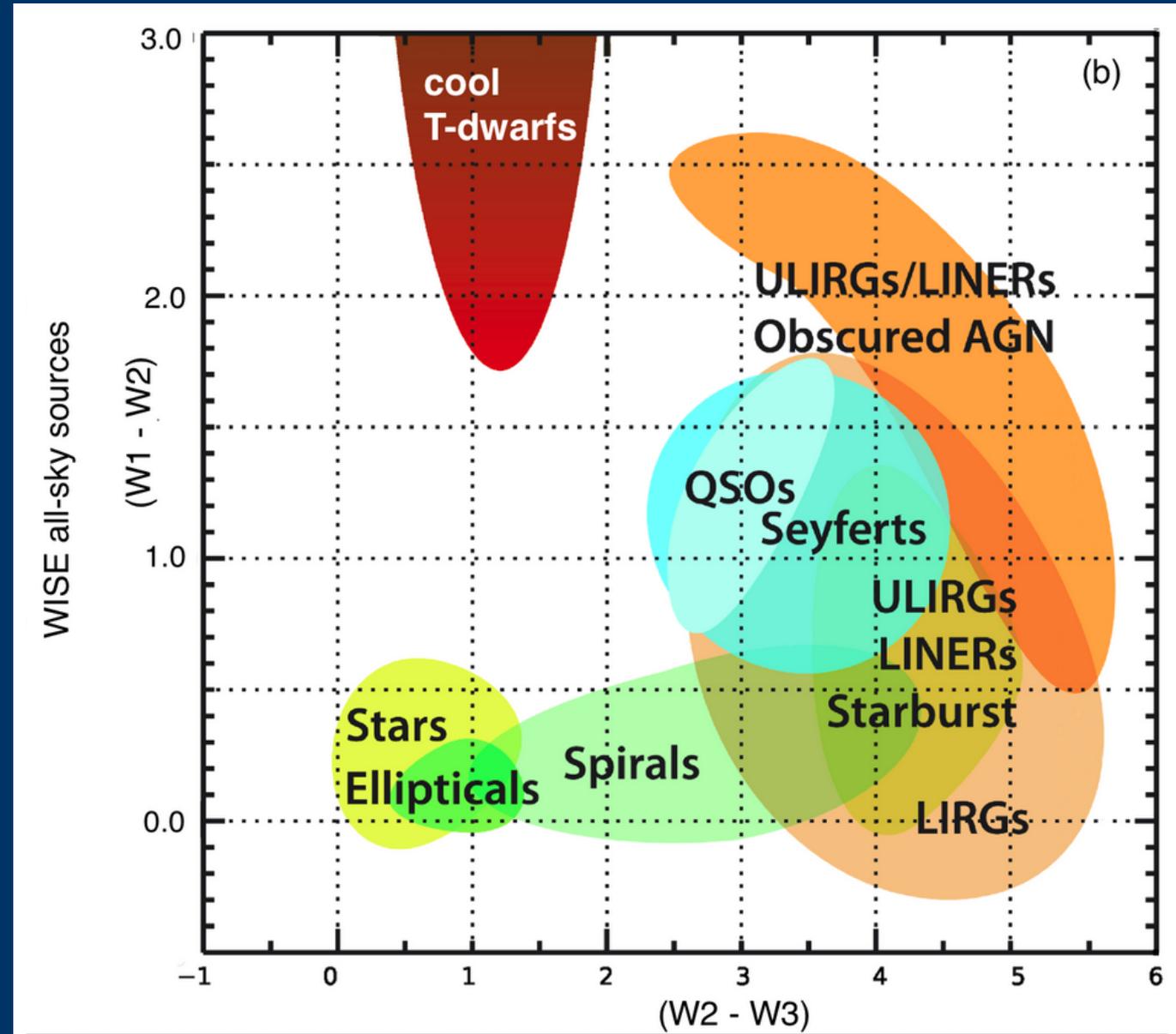
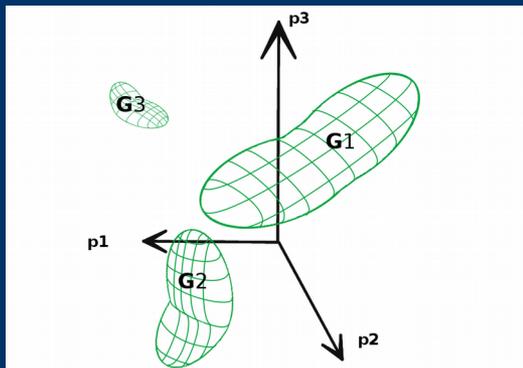
Exploration of parameter spaces

The usual approach to selection of desired sources: CC diagrams

BUT! With simple approach much information is lost/unseen by human eye

- A computer can be more precise and deal with a lot of data at once; not restricted to three dimensions

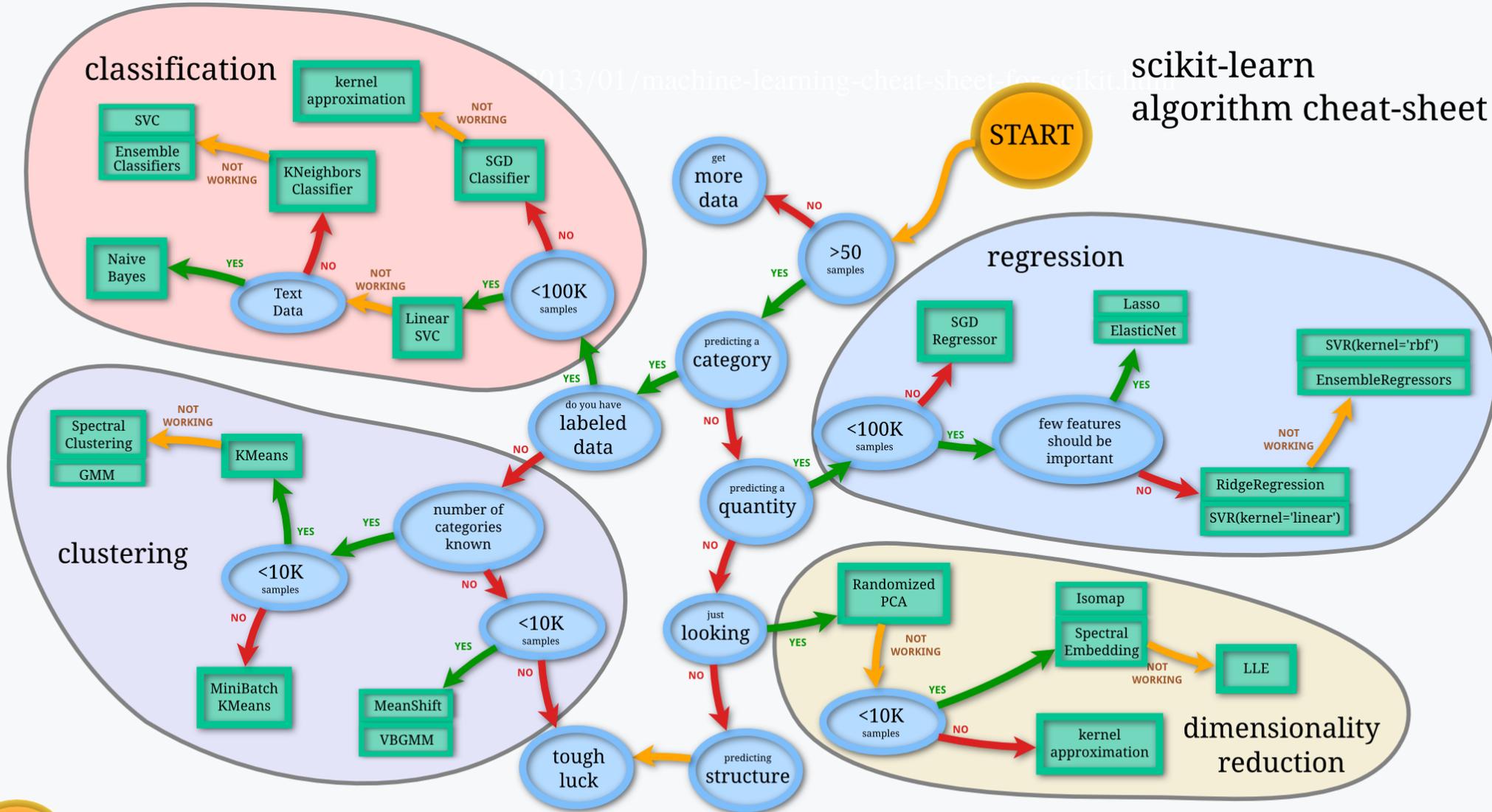
→ **Machine learning!**



Best algorithm?

2013/01/machine-learning-cheat-sheet-for-scikit-learn

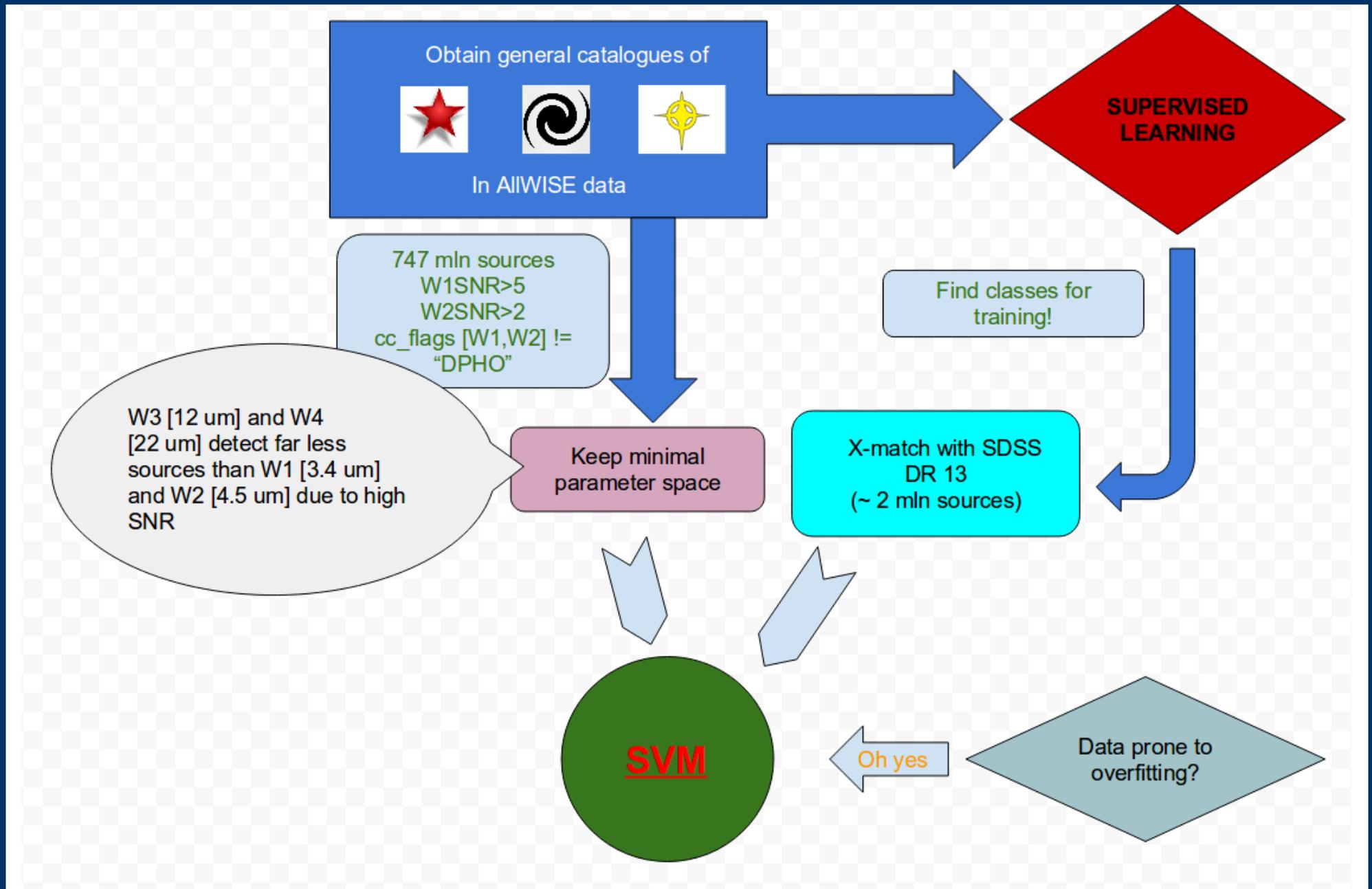
scikit-learn
algorithm cheat-sheet



Back



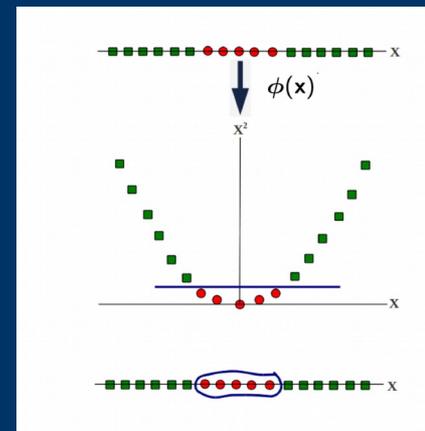
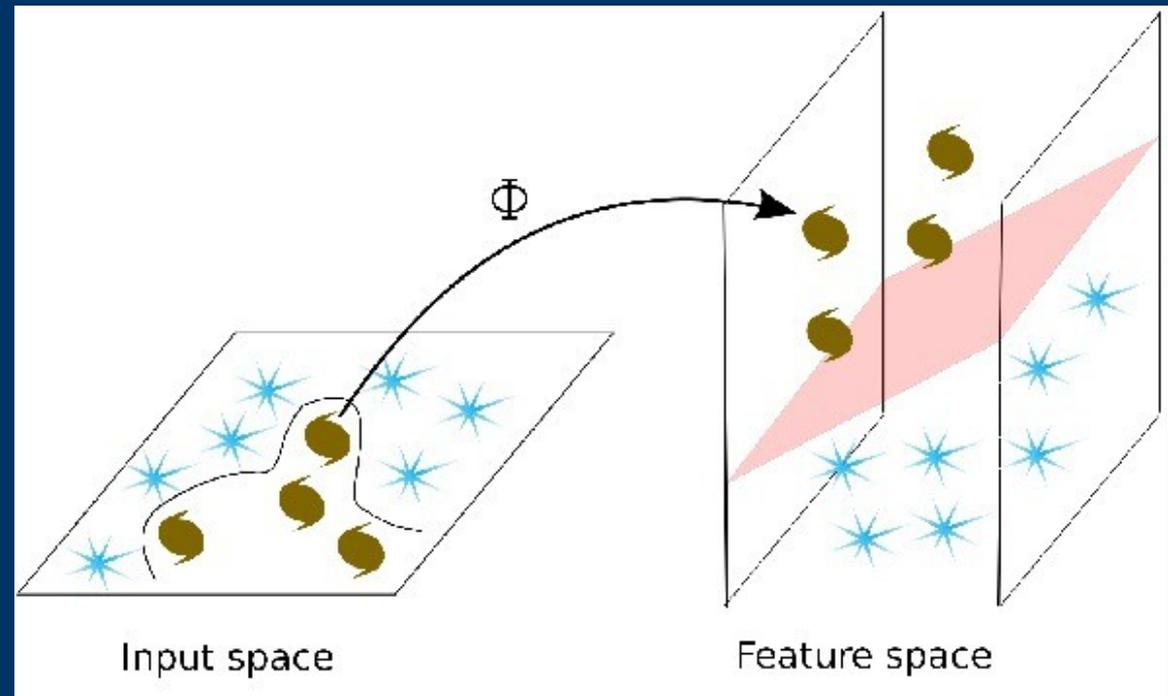
Best algorithm for WISE?



Support Vector Machines (SVM) : a supervised approach

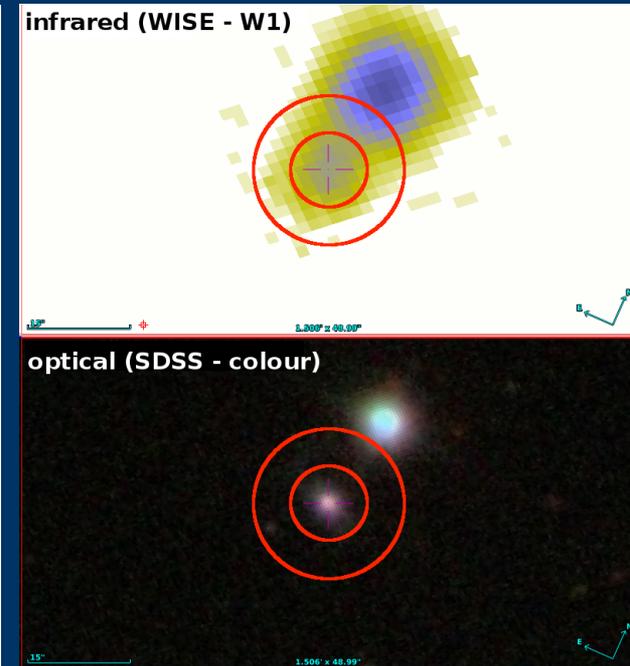
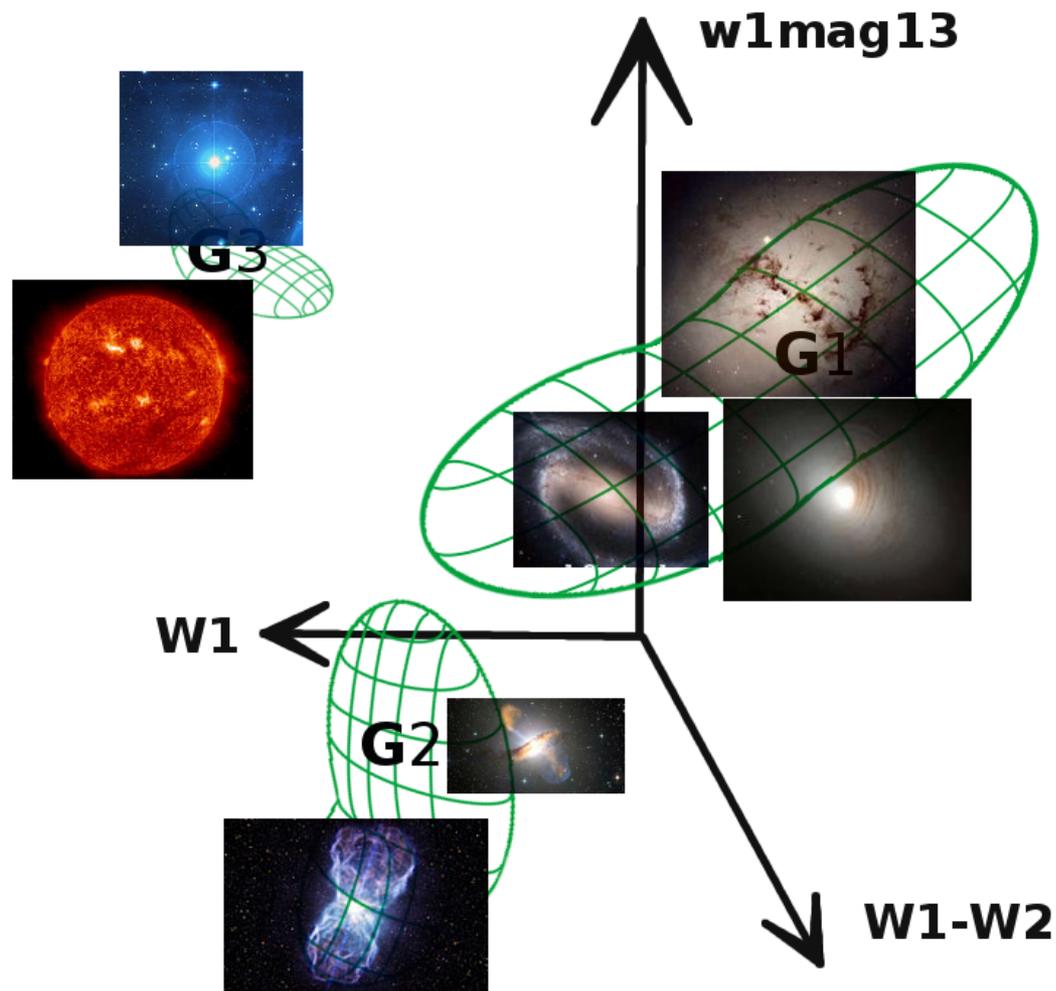
SVM: segregate data into 2 (or more) categories based on training examples

- Use **kernel functions** to map input data into higher dimensional feature space
- Find a hyperplane separating two classes in the feature space
- New data: class assigned based on their relative position from the boundary



WISE: first attempt at source classification

AllWISE x SDSS (α, δ) parameter space: W1, W1-W2, w1mag13



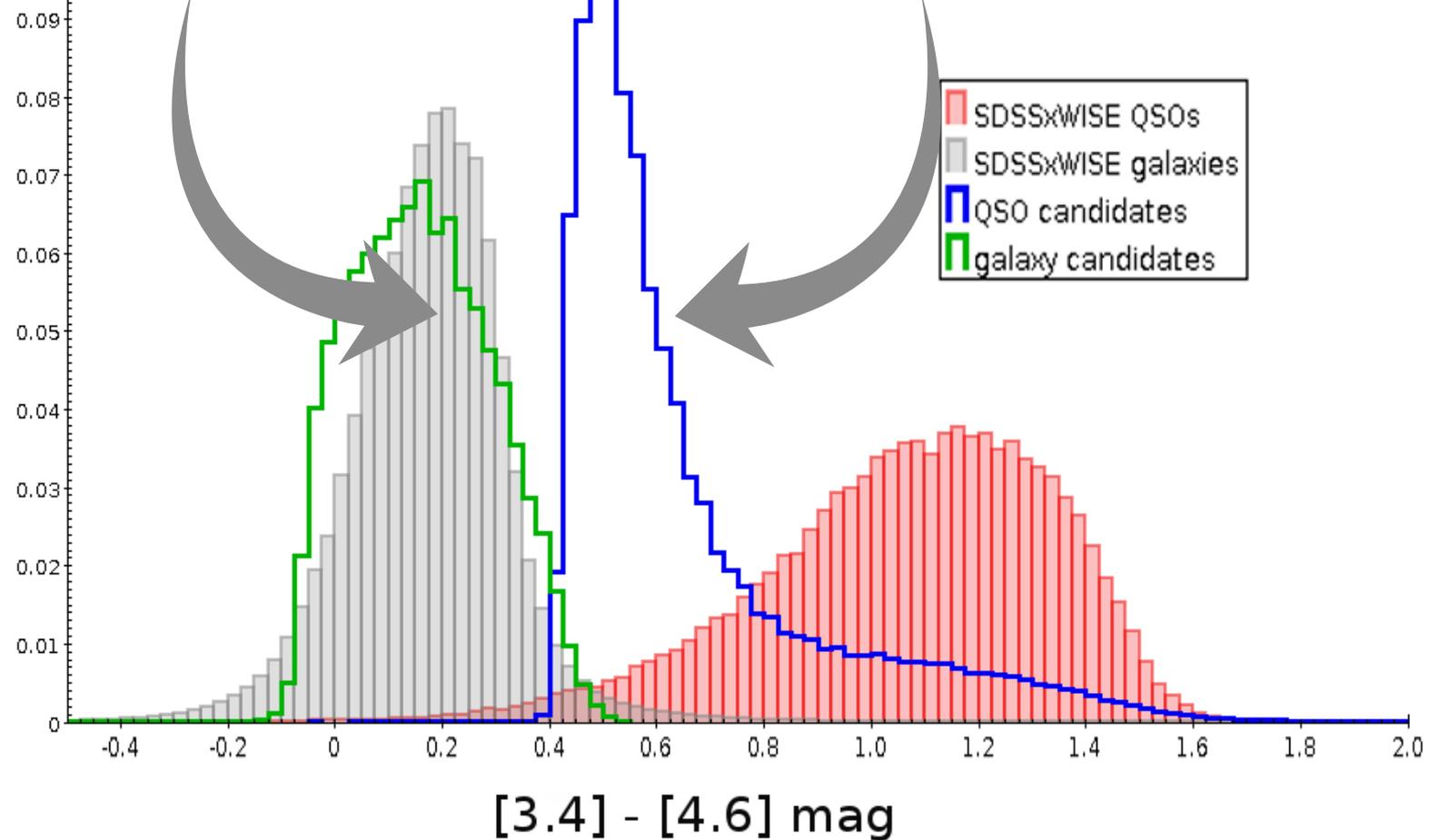
$$\begin{aligned} \text{W1mag13} &= \\ &= \text{w1mpro}(5'') - \text{w1mpro}(11'') \end{aligned}$$

Compactness
parameter

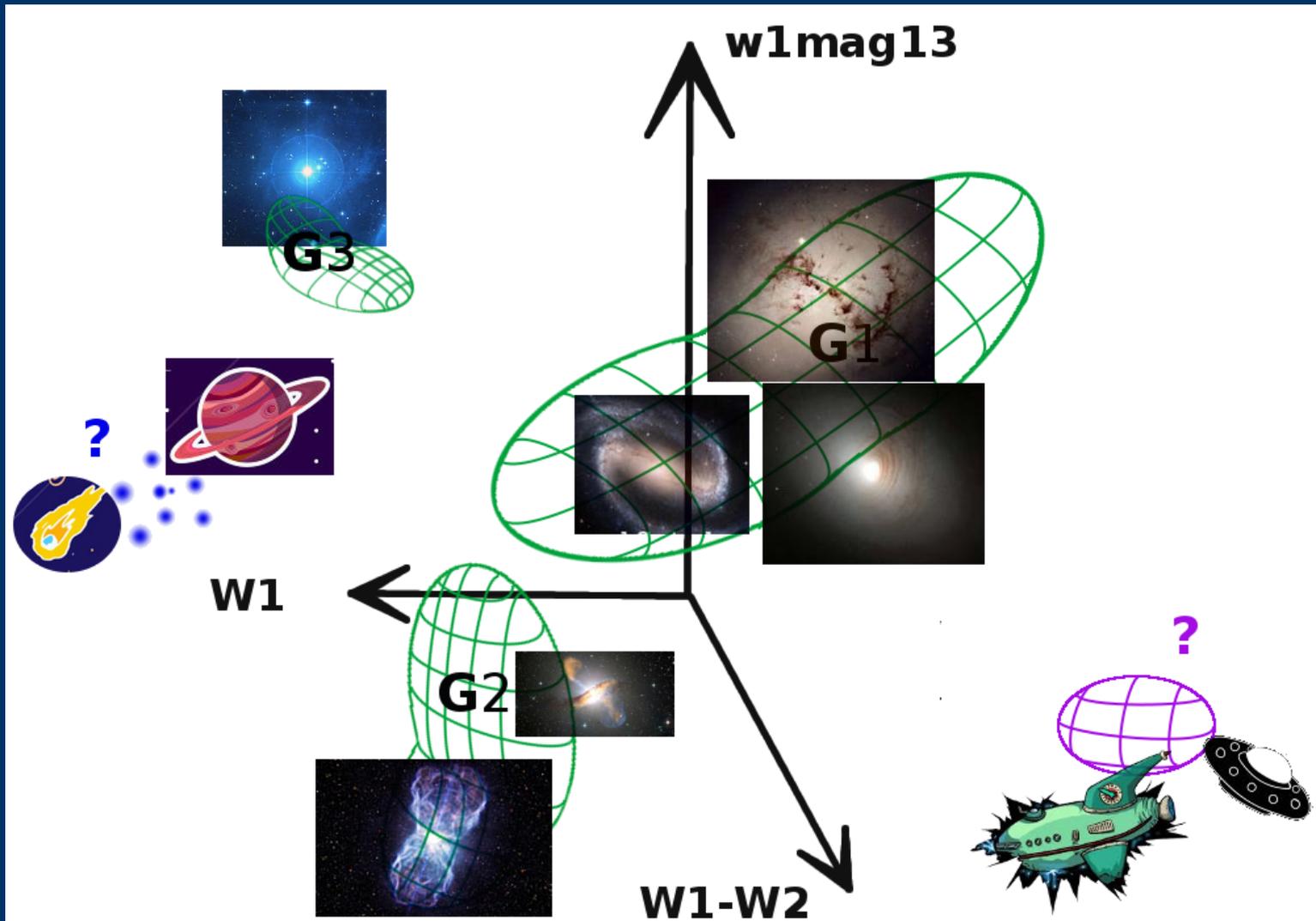
WISE: first attempt at source classification

Galaxies well recognized

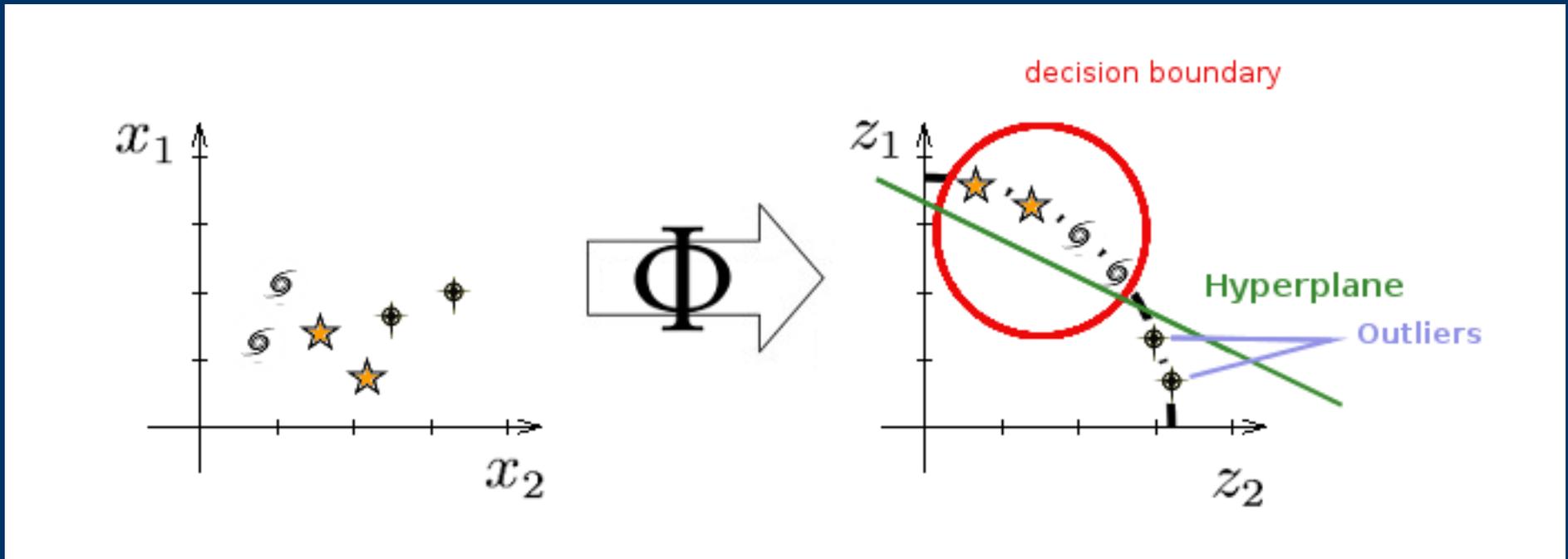
QSO not so much



WISE: what caused the algorithm to fail



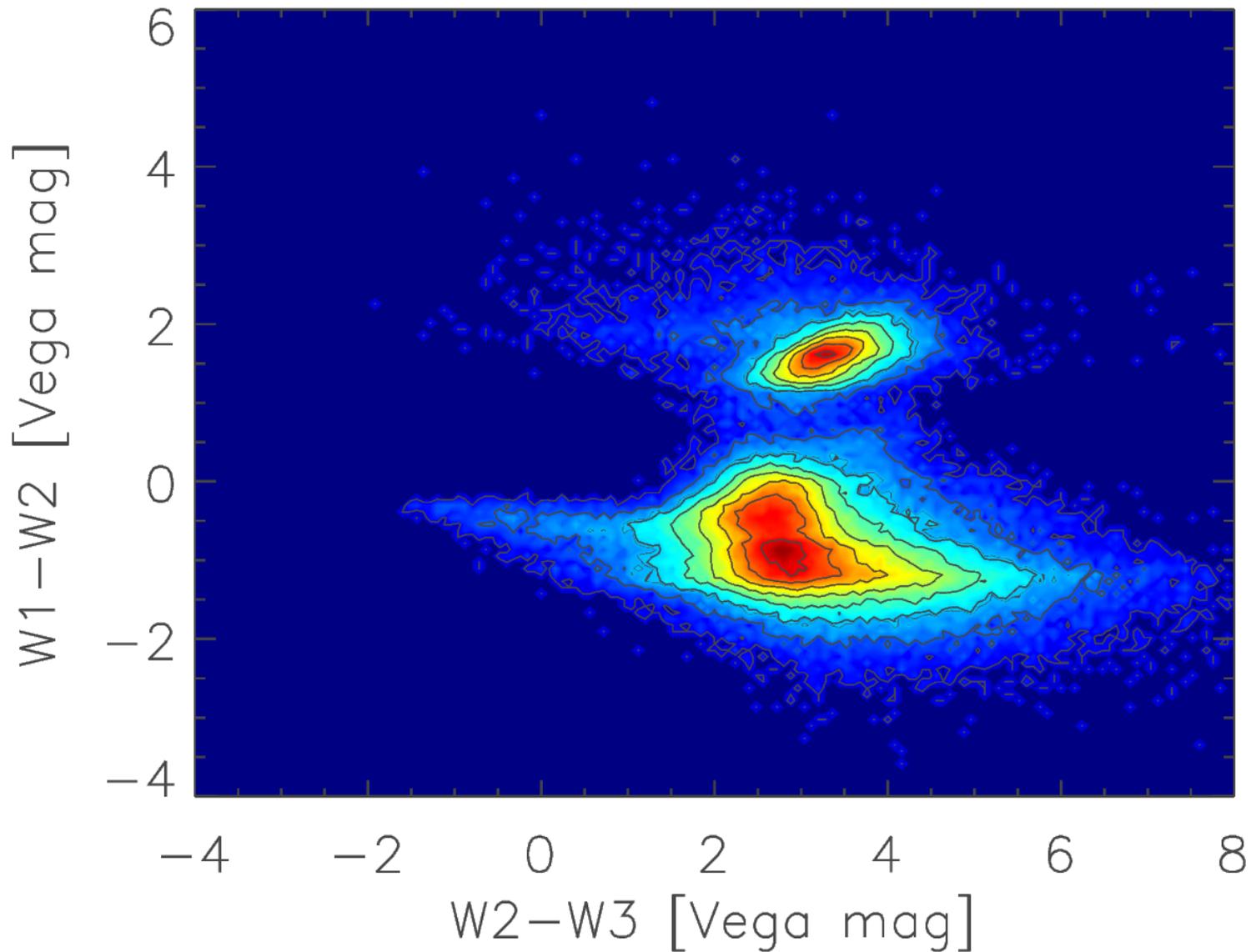
One-class SVM enhancement



- Create one 'known' class (mix of AllWISE x SDSS galaxies, stars, QSOs)
- Hypersurface hugging the expected sources
- Anything with 'unknown' patterns falls outside the hypersurface => anomalies

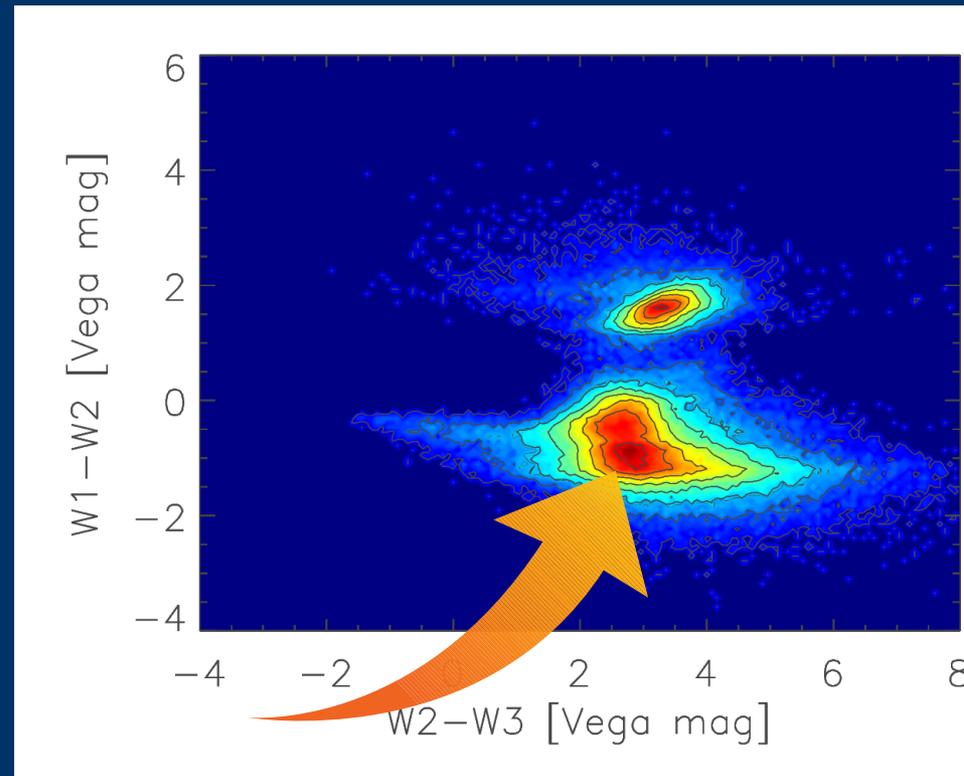
Results

~650,000 anomalous sources

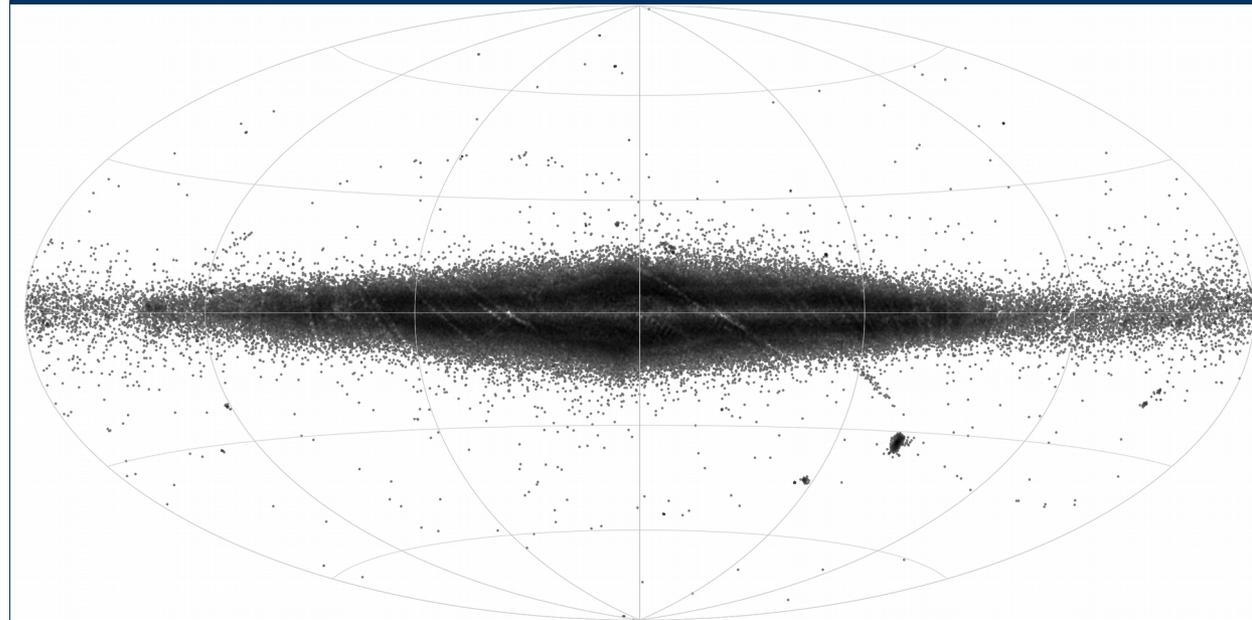
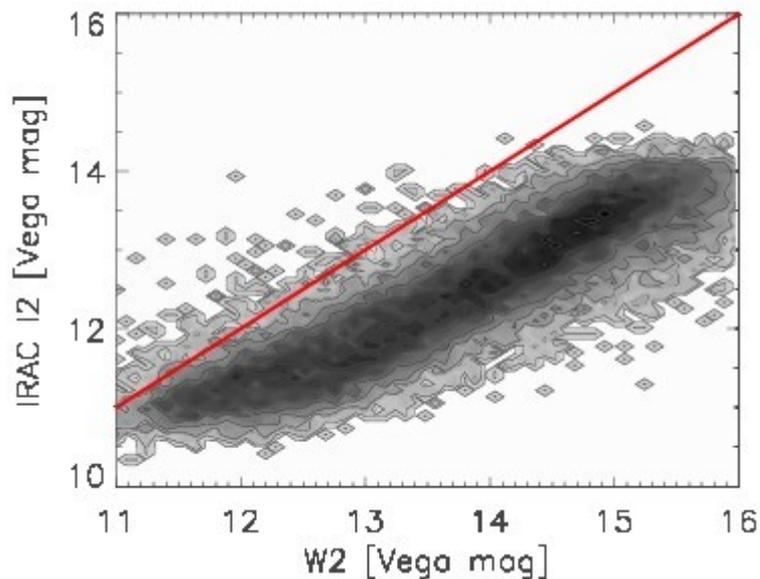


Spurious sources

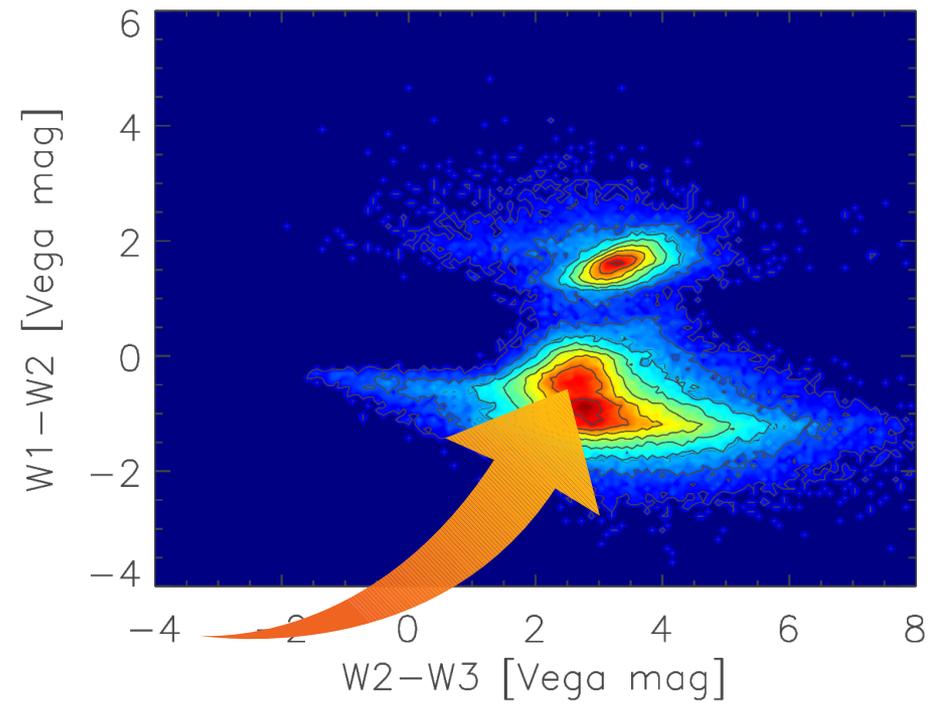
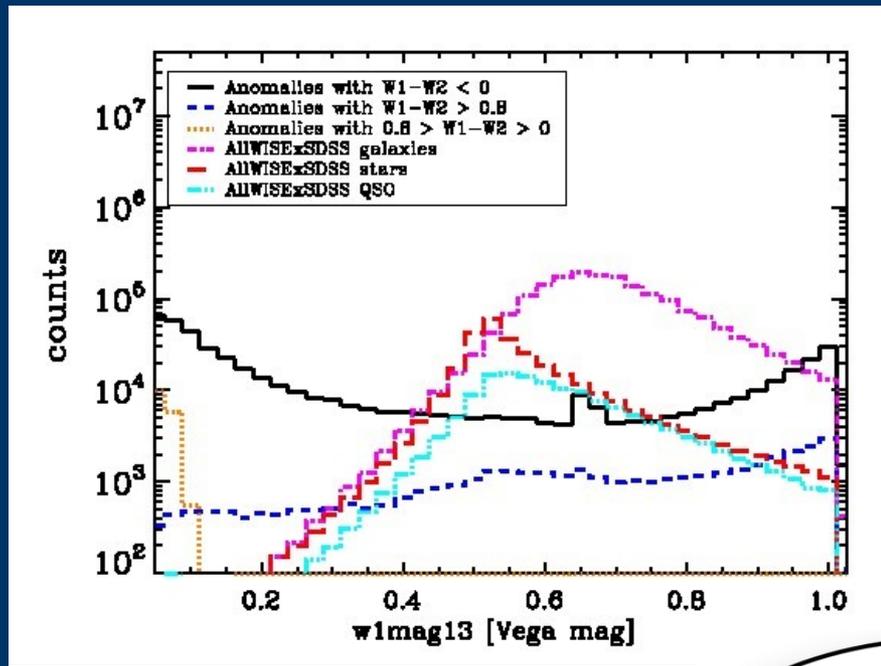
- $W1-W2 \sim -1$; 80%
- Spitzer GLIMPSE:
IRAC I1 [3.6 μm], IRAC I2 [4.5 μm]
- Low WISE resolution (6'')
in crowded fields => blends
- **OCSVM**: good tool for selecting hidden artefacts



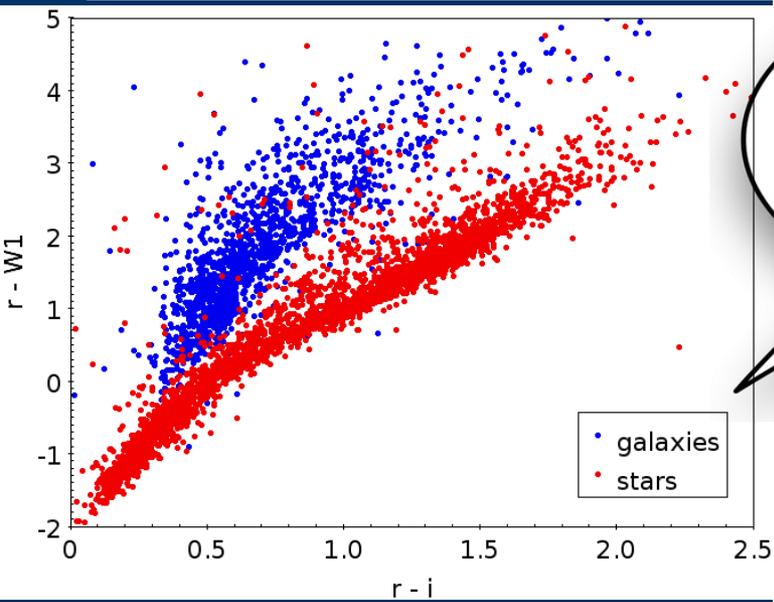
Solarz et al. 2017



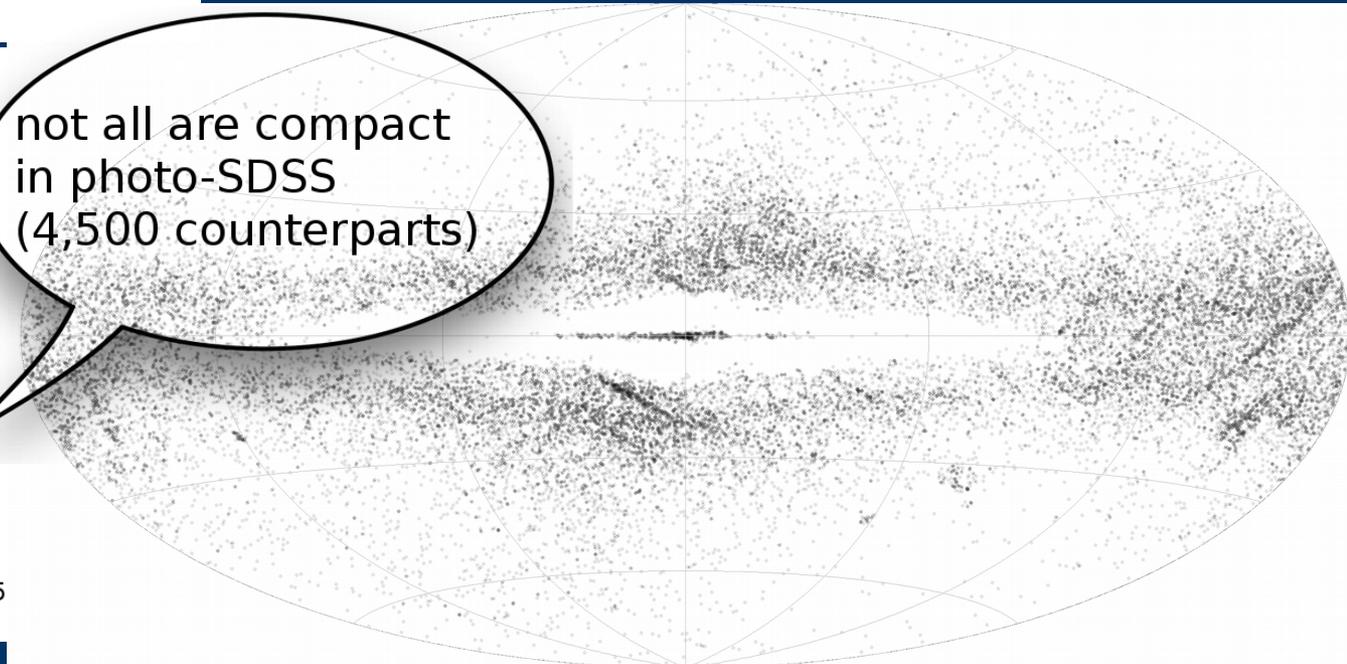
Mix of galaxies and stars?



Solarz et al. 2017

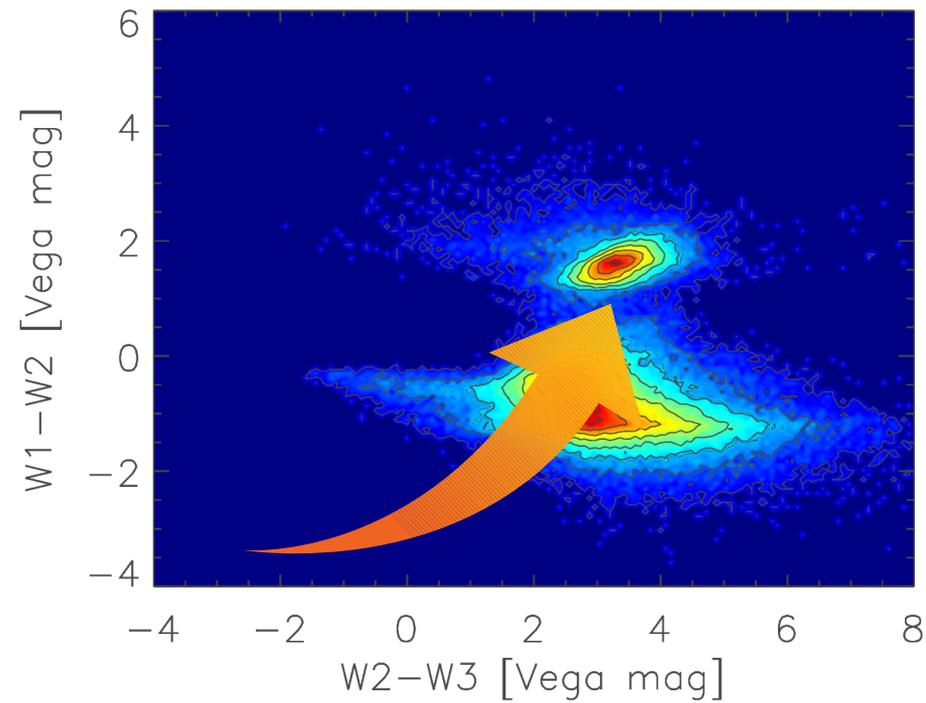


not all are compact
in photo-SDSS
(4,500 counterparts)

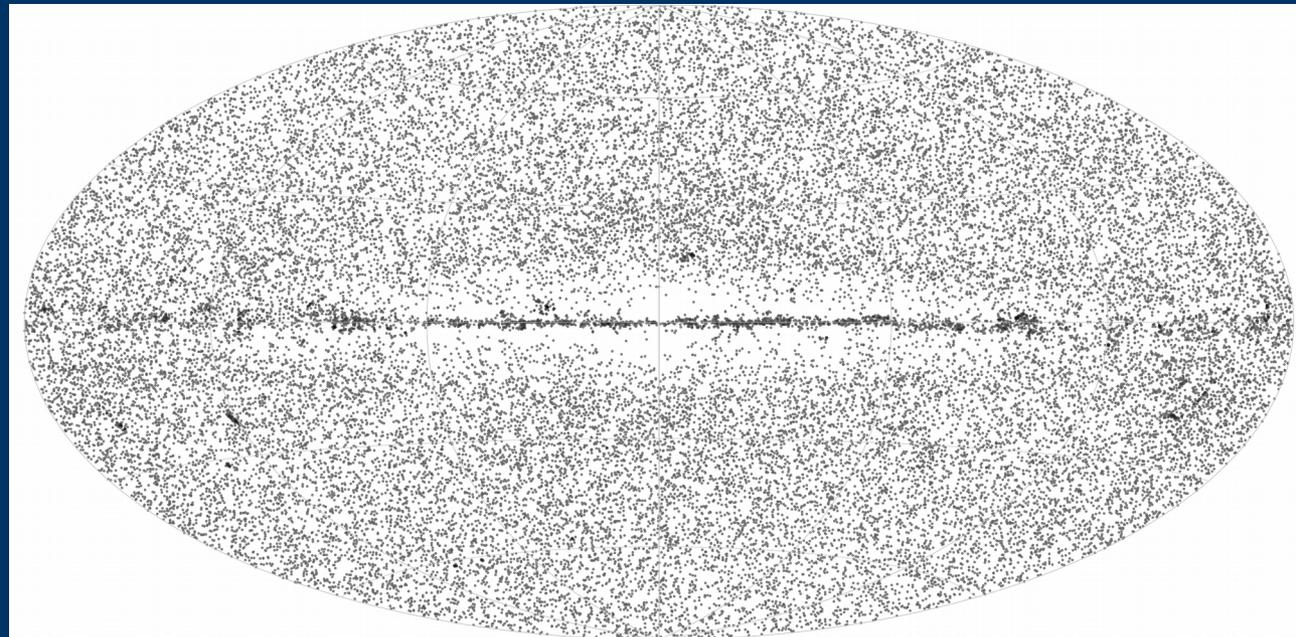
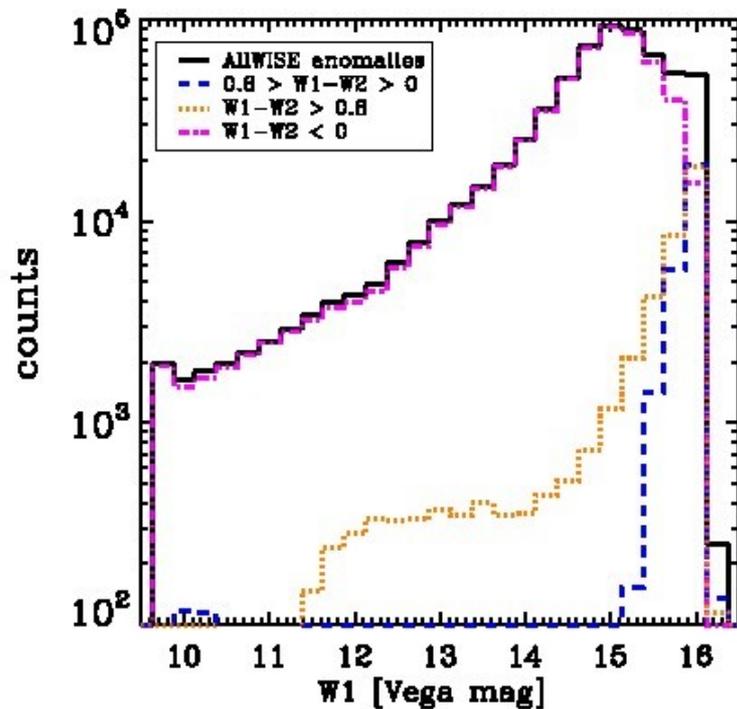


AGN candidates?

- 40,000 sources
- $W1 \sim 16$ [Vega mag], $W3$ [12 μm] ~ 10 [Vega mag]
- no starlight can be redshifted to this channel
- Warm dust emission/PAH emission lines
- From theoretical predictions: AGN colours (Jarrett et al. 2011)
- Galactic Plane: mostly blends;

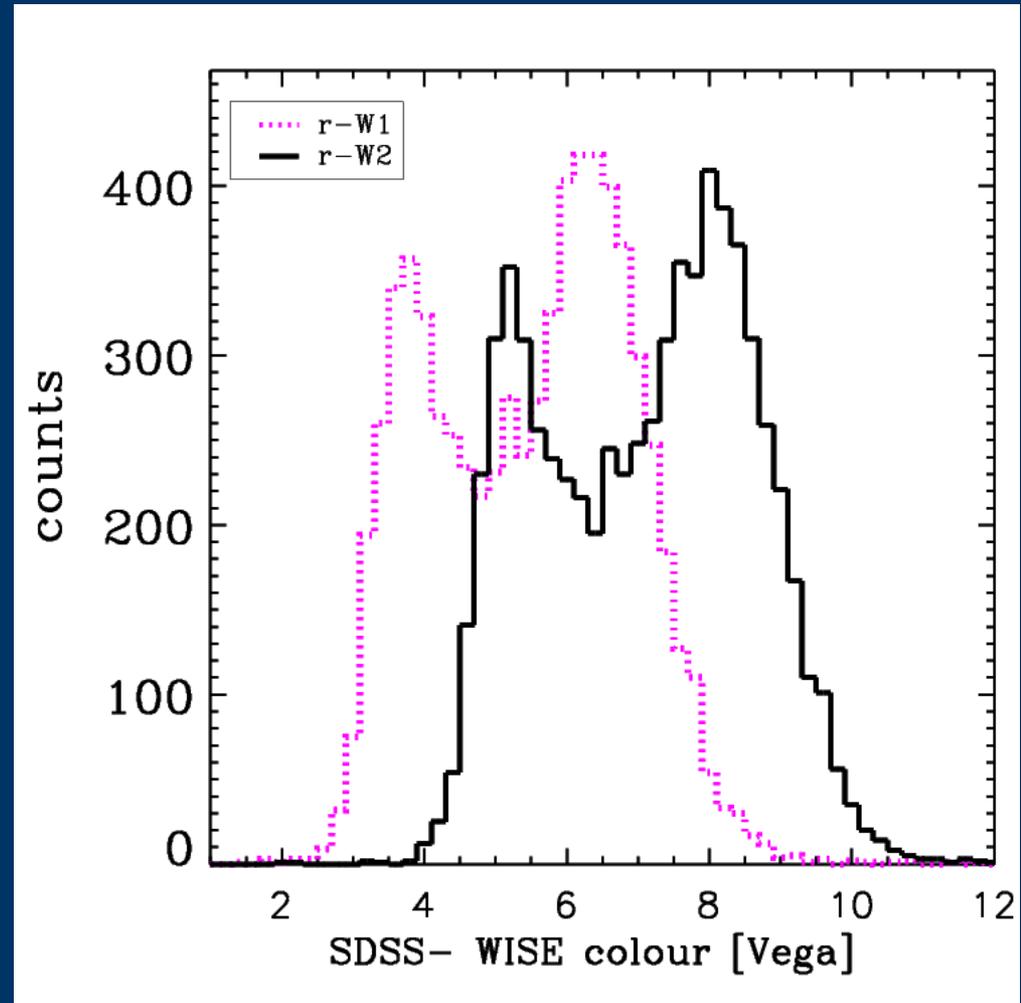


Solarz et al. 2017



Obscured/Unobscured AGNs

- 7000 found in photometric SDSS, but no spectrum
- => all sky extrapolation (to full depth of WISE): 40% with no optical counterpart
- Two populations of AGNs: obscured and unobscured
- No other counterparts in any publicly available catalogues
- To confirm:
 - Follow-up optical photometry needed (future SDSS releases?)
 - Spectroscopy would be best



Summary

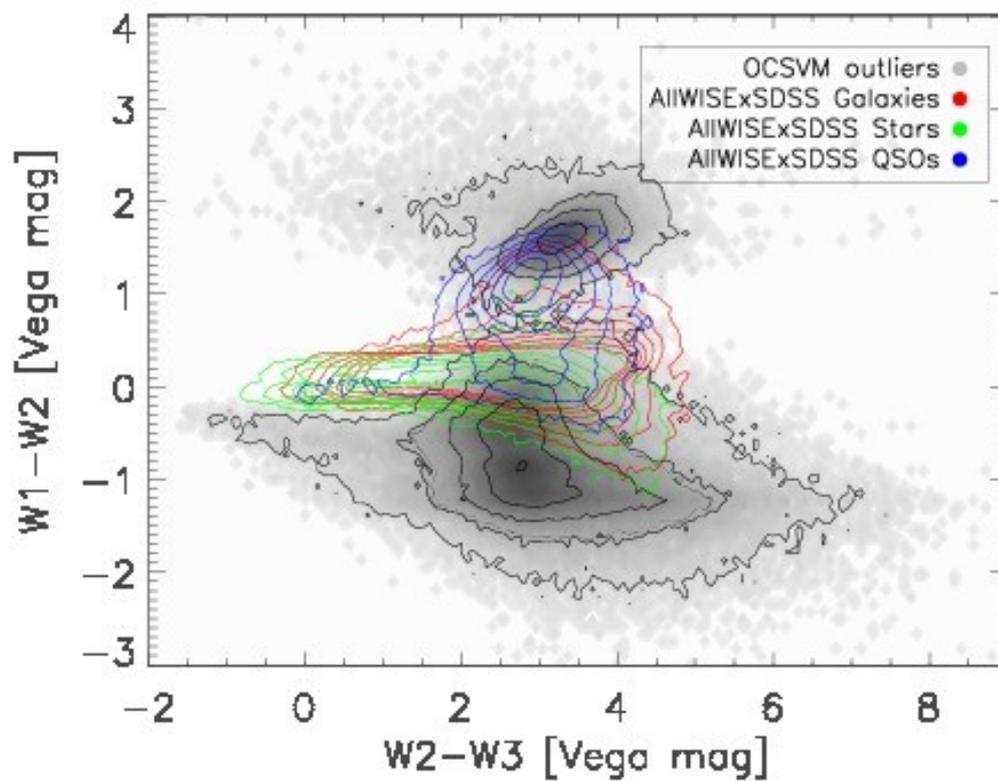
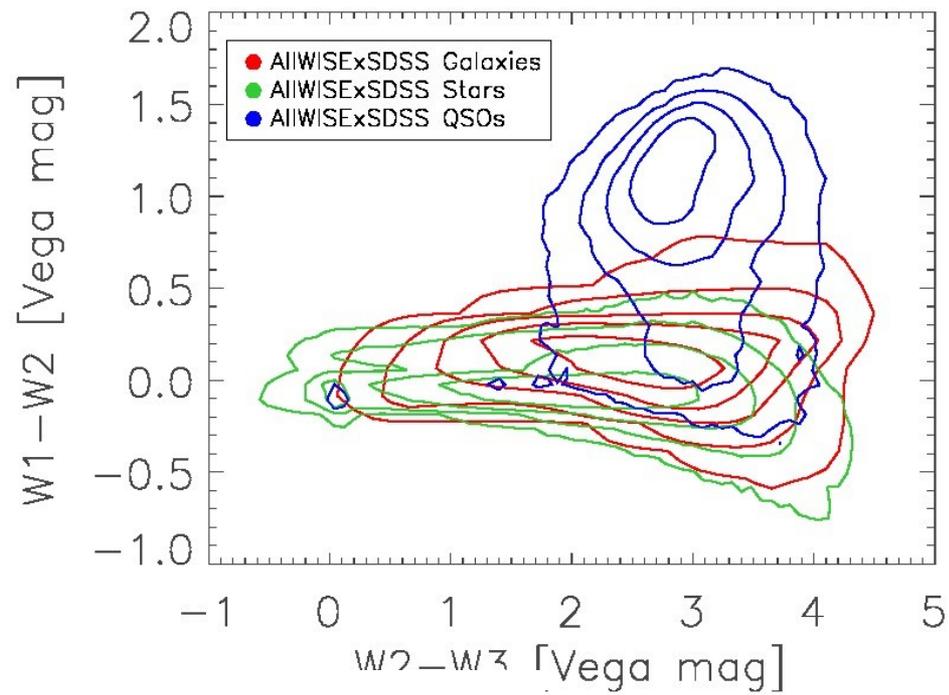
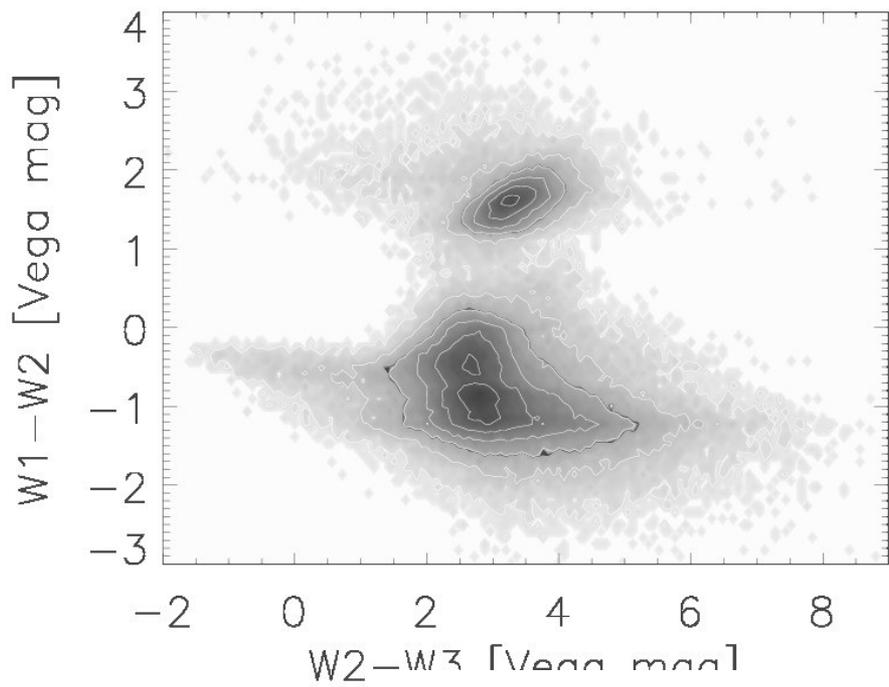


- We need to deal with unusual patterns in the data
 - i.e. search for ‘**unknown unknowns**’
 - Anomaly detection:
 - OCSVM => efficient selection of interesting and previously unclassified objects
 - cleaning the data of unexpected/unaccounted for artifacts
 - Verify nature of selected AGN candidates + correlation function calculations
-
- <http://www.R-project.org>
 - <https://cran.r-project.org/web/packages/doParallel/index.html>
 - <https://cran.r-project.org/web/packages/caret/index.html>

Special thanks to Mark Taylor for the TOPCAT (Taylor 2005) and STILTS (Taylor 2006) software

Backup slides

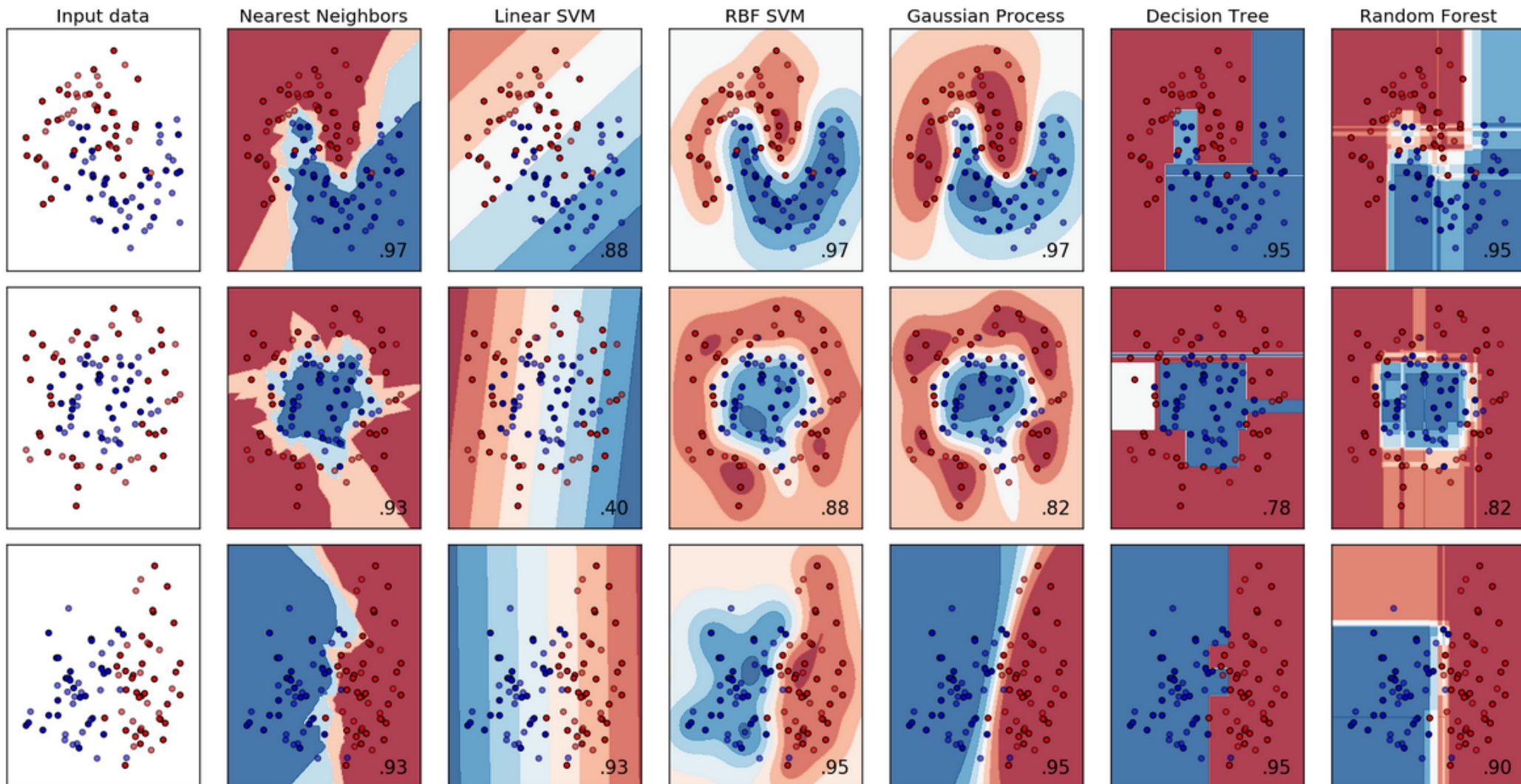




Why (OC) SVM?

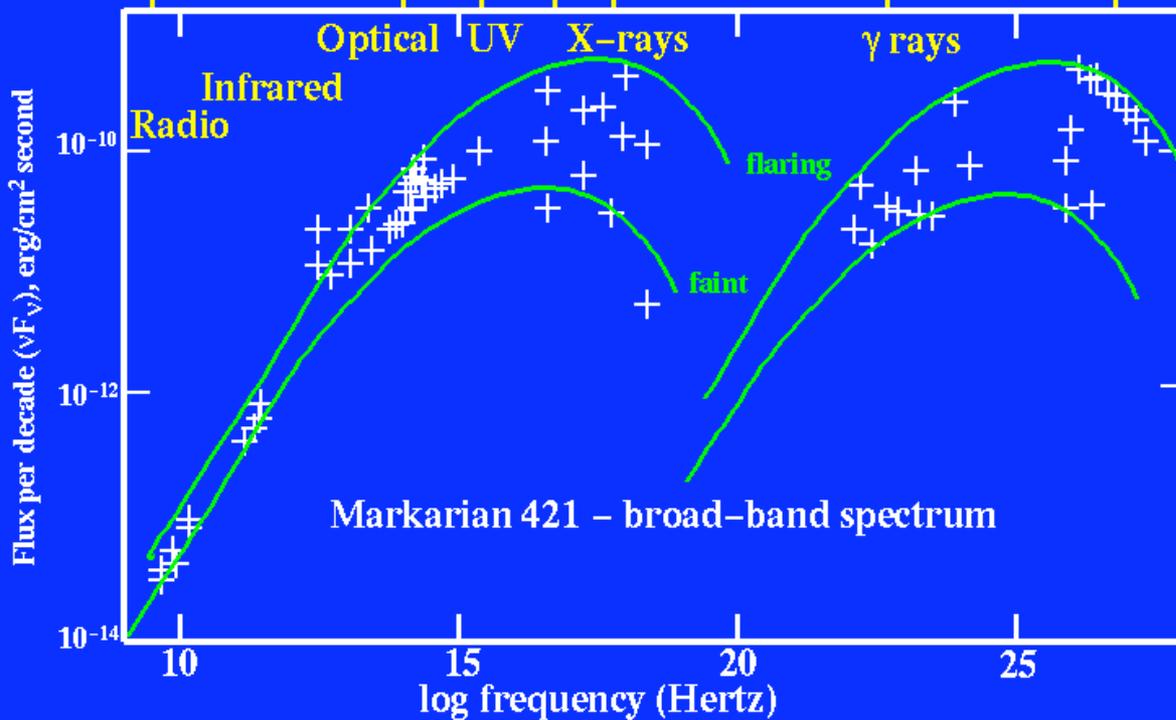
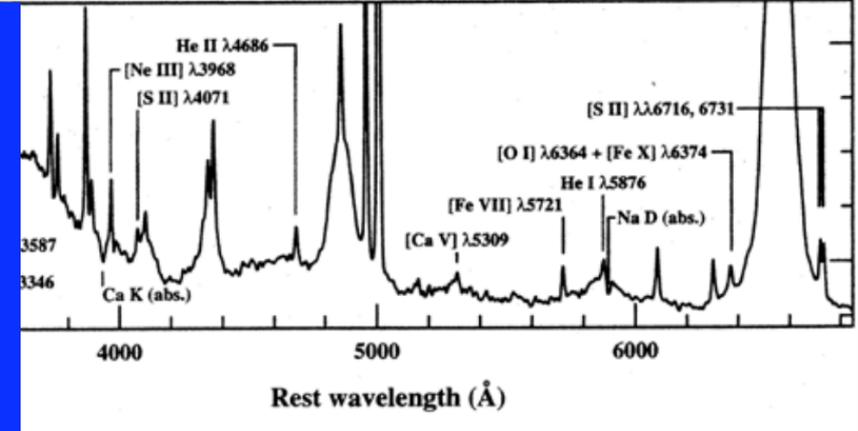
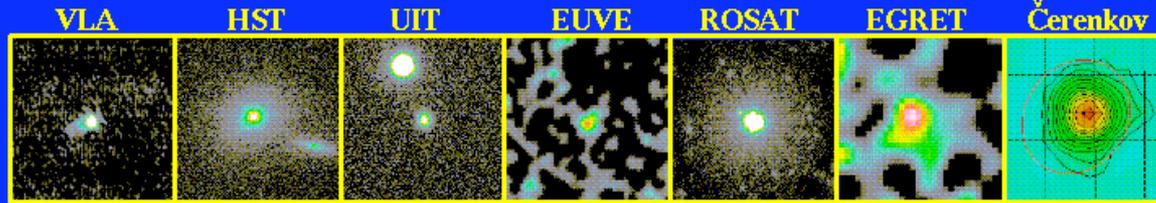
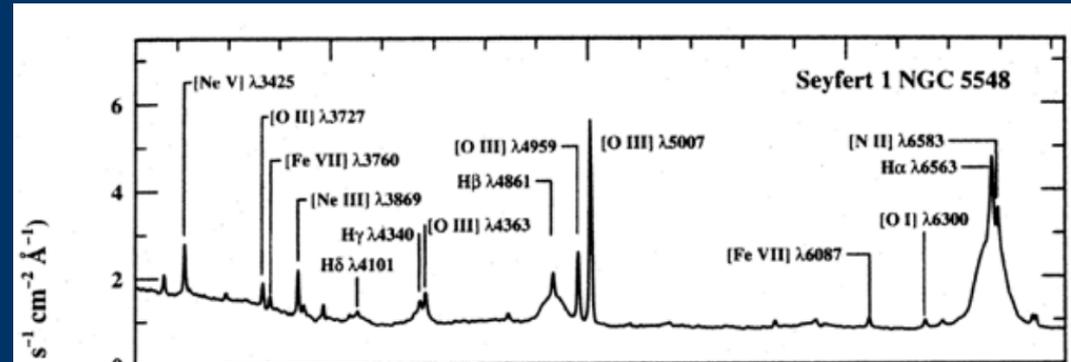
- Domain-based methods: location of the novelty boundary based on nearest points
- Do not make any assumptions about the data distribution
- distance-based methods, e.g. NN; clustering: require definition of the distance metrics, distance measures in many dimensions lose ability to differentiate between normal and outlying data points; lack the flexibility of parameter tuning => unsuitable for full automatisation
- Great review of different anomaly detection schemes:
Pimentel et al. 2014

Best algorithm?



Variety of AGN sources

- Seyfert galaxies (spirals)
- Quasars (Nuclear emission dominates)
- Blazars (violently variable)
- Radio galaxies (ellipticals)
- Etc.

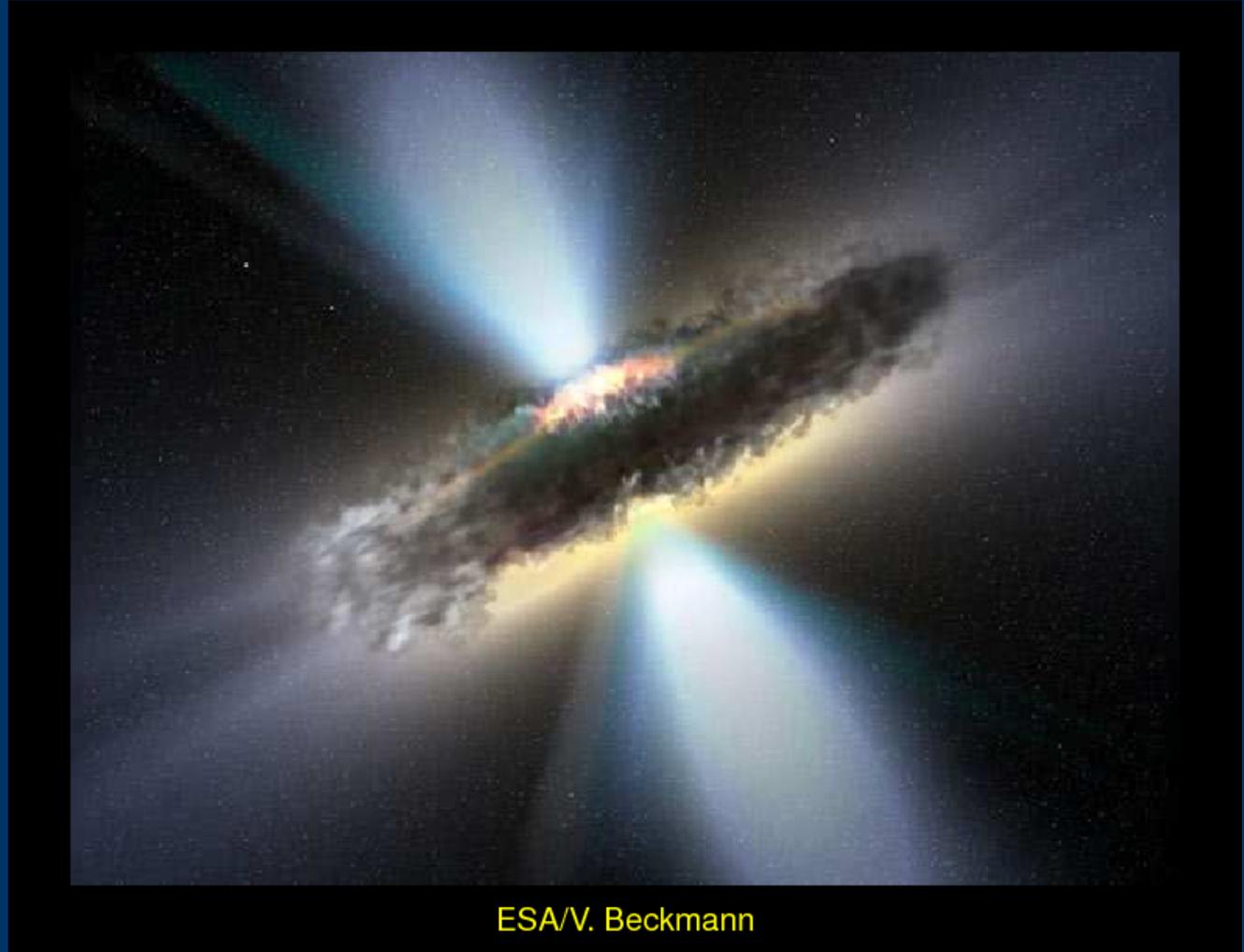


Obscured/unobscured AGNs : unified model

why such variety of
observed phenomena
→ different objects?

Unified models:

→ different classes of
AGN => different
orientations of
intrinsically similar
systems to the
observer's line of
sight.

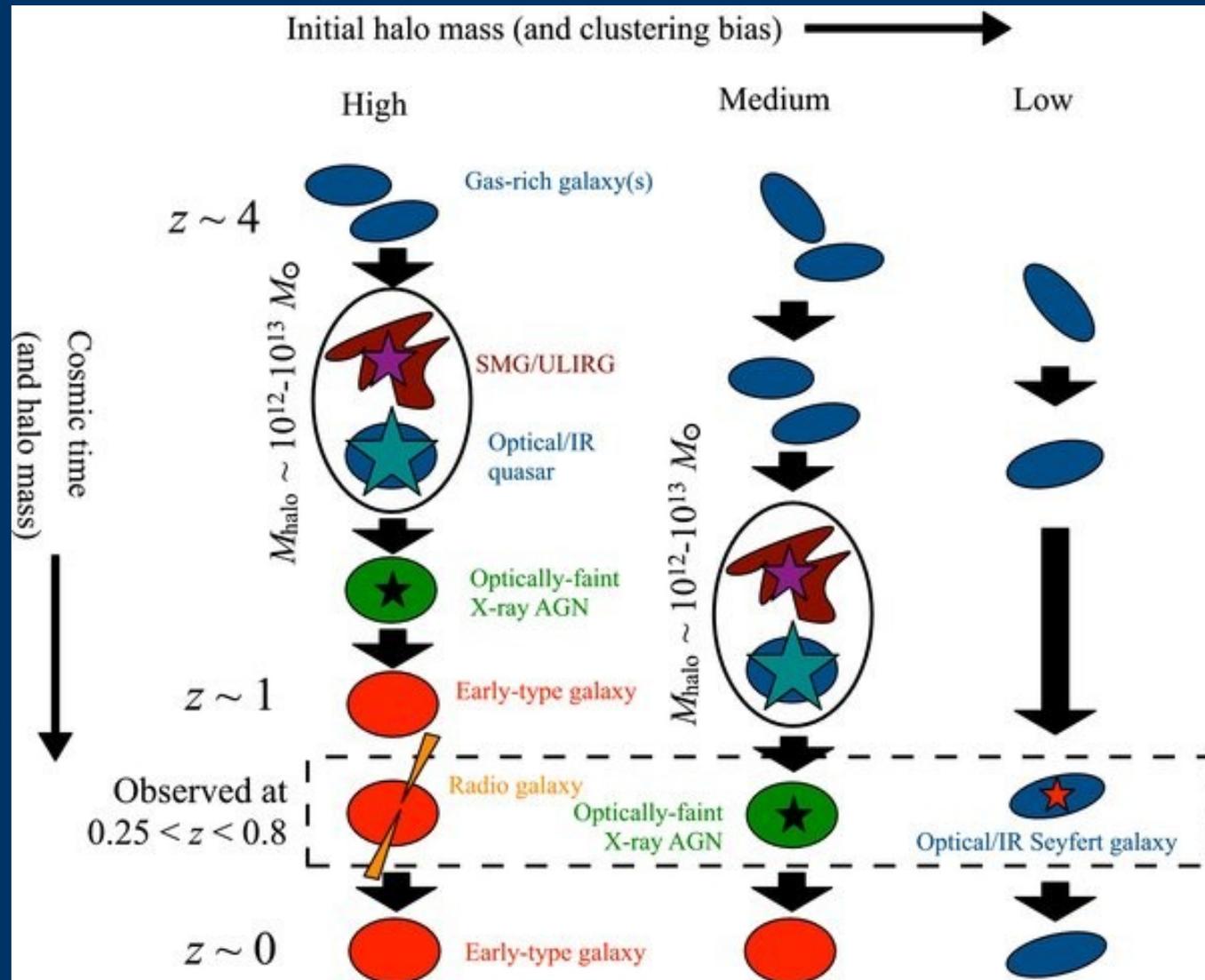


ESA/V. Beckmann

Obscured/unobscured AGNs : evolutionary differences

According to clustering measurements obscured/unobscured AGNs => separate populations evolving in different way

→ If we get photo/spec redshifts we can weigh in on this discussion



Hickox et al. 2011