Source classification in large astronomical catalogs

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with

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AKARI team, VIPERS team, WISE team

We are now living in the epoch of large datasets – both photometric and spectroscopic.

A priori, we usually do not always know what we observe, and the available information is often very limited.

Machine learning for source classification:

Supervised → when we know a priori what sources we expect to find and we can use some datasets for training

→ classification (for separate groups) or regression (for smooth transition)

Unsupervised → clustering of sources into previously unknown and unexpected classes

In this talk, I will give a couple of examples of a successful application of both these approaches to the source classification in

AKARI (NIR to MIR satellite sky survey)

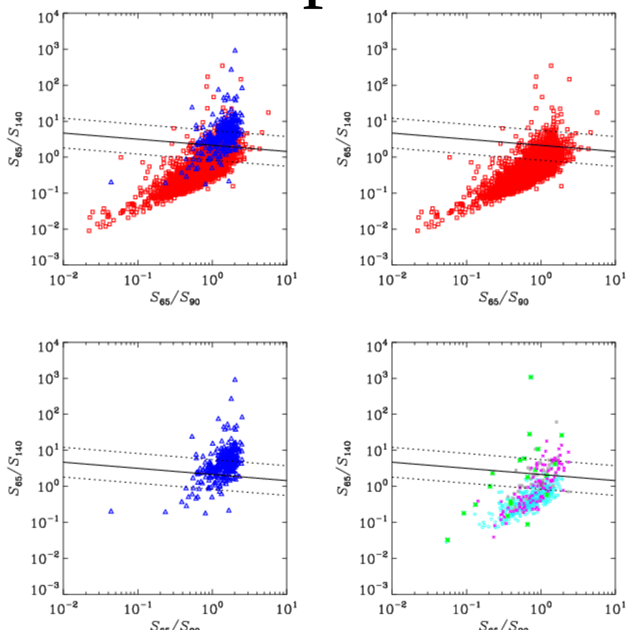
WISE (NIR to MIR satellite sky survey)

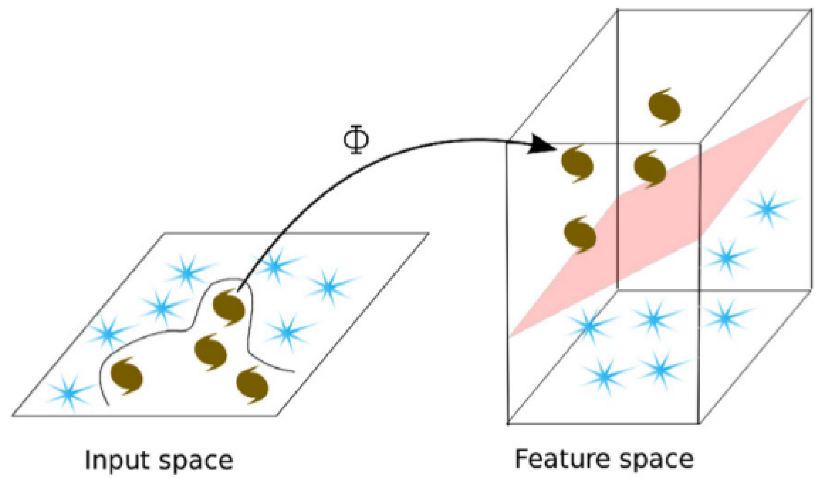
VIPERS (spectroscopic galaxy survey)

Our main – but not only - tool for classification (in this talk...): Suport Vector Machines

Basic idea: to move from classifications based on very limited number of parameters (like color-color plots or line-to-line ratio or sth. similar) to the feature space built from a larger number of parameters

Pollo et al. 2010

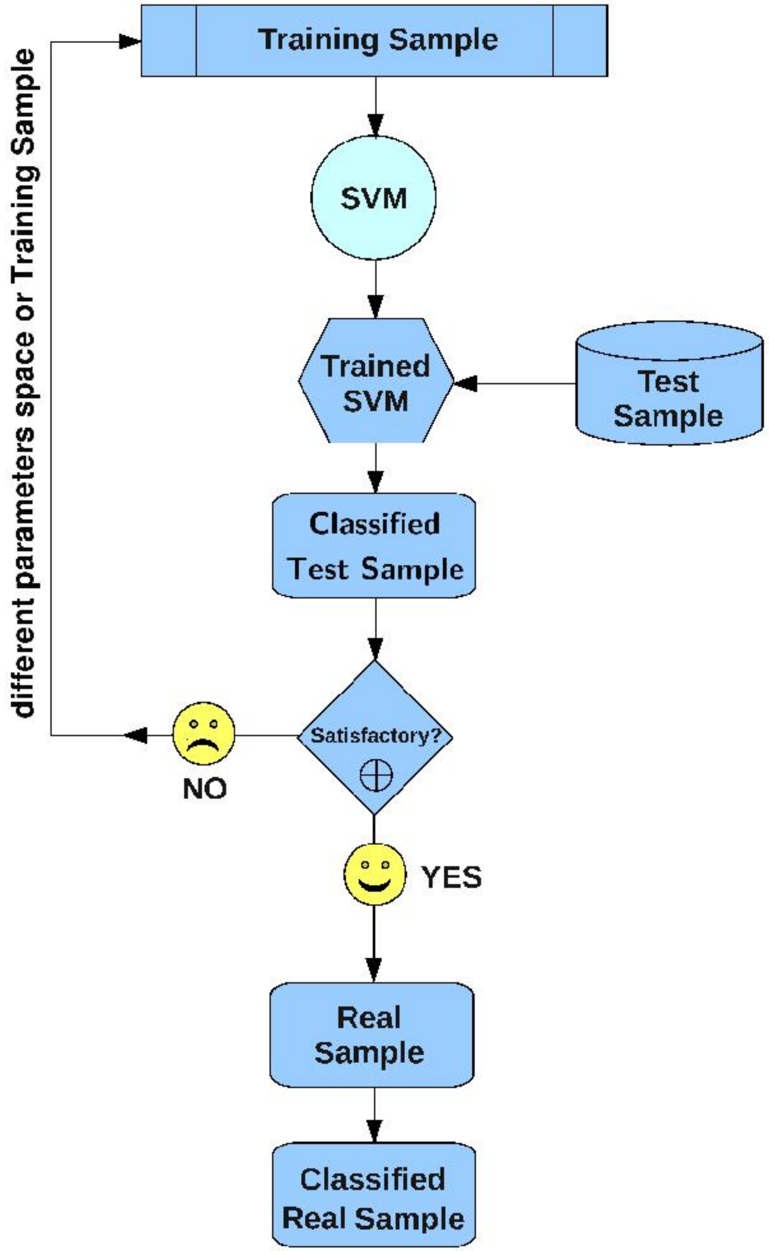


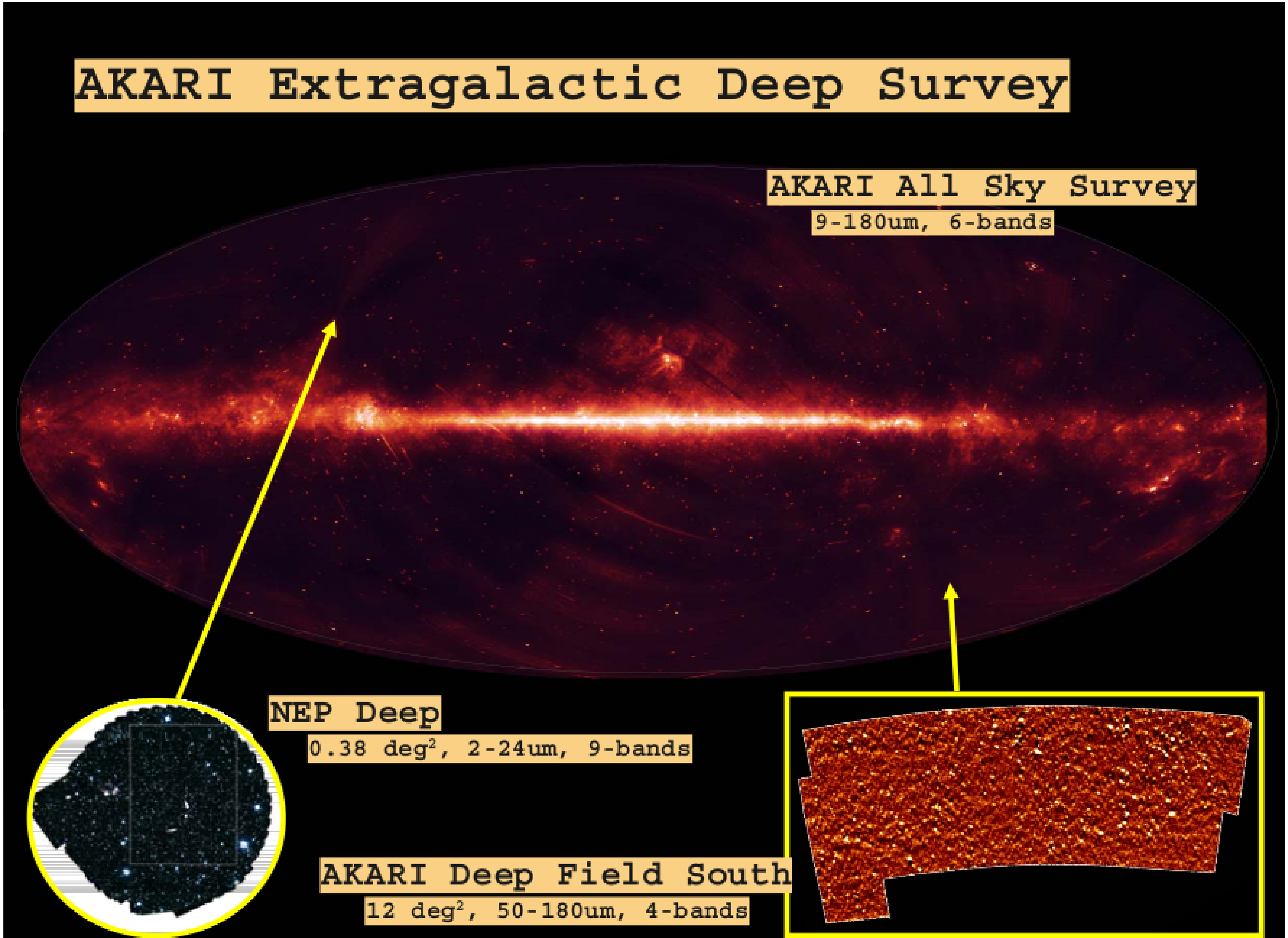


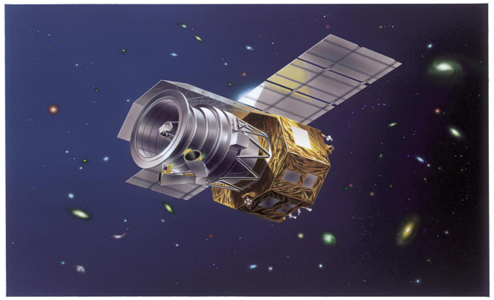
Malek et al. 2013

Objects poorly separated in the two parameter space can get well separated in a multi parameter space, and the problem is easier to linearize.

Malek et al. 2013



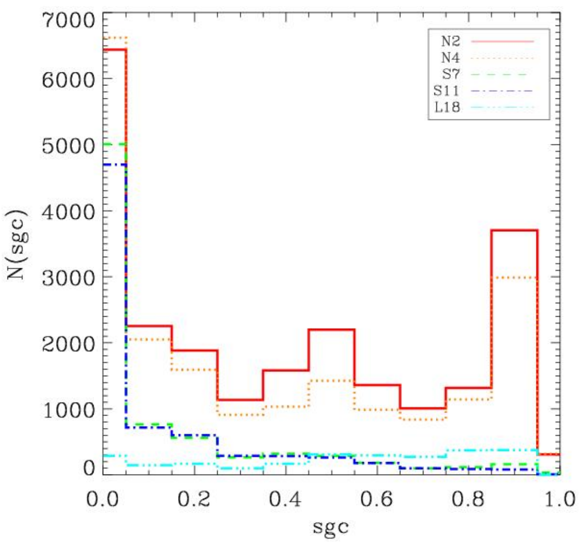

AKARI Extragalactic Deep Survey
AKARI All Sky Survey
9-180um, 6-bands
NEP Deep
0.38 deg^2, 2-24um, 9-bands
AKARI Deep Field South
12 deg^2, 50-180um, 4-bands

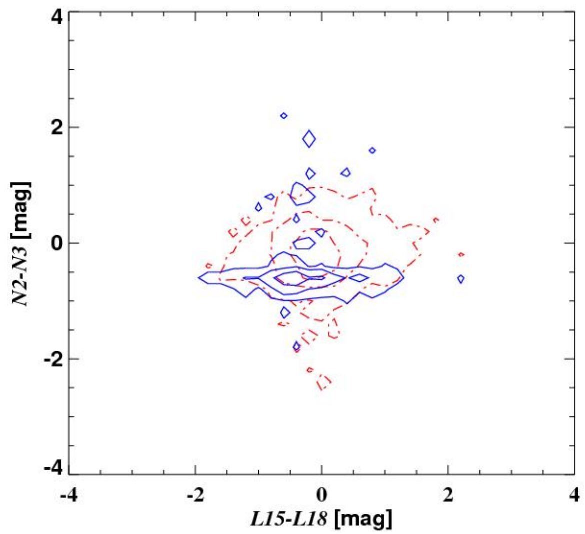


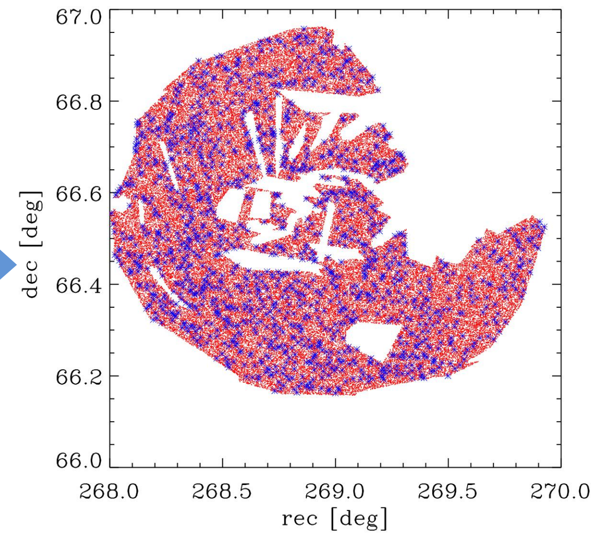
Source classification of tricky data: AKARI NEP deep field

0.38 sq. deg
deep observations in 9 bands 2-24 um
26 sources identified

What these sources are?
Stars, galaxies, AGNs?
Not obvious if you do not rely on comparison to optical data (which for the sake of completeness sometimes you do not want to do...







Solarz et al. 2012, 2015

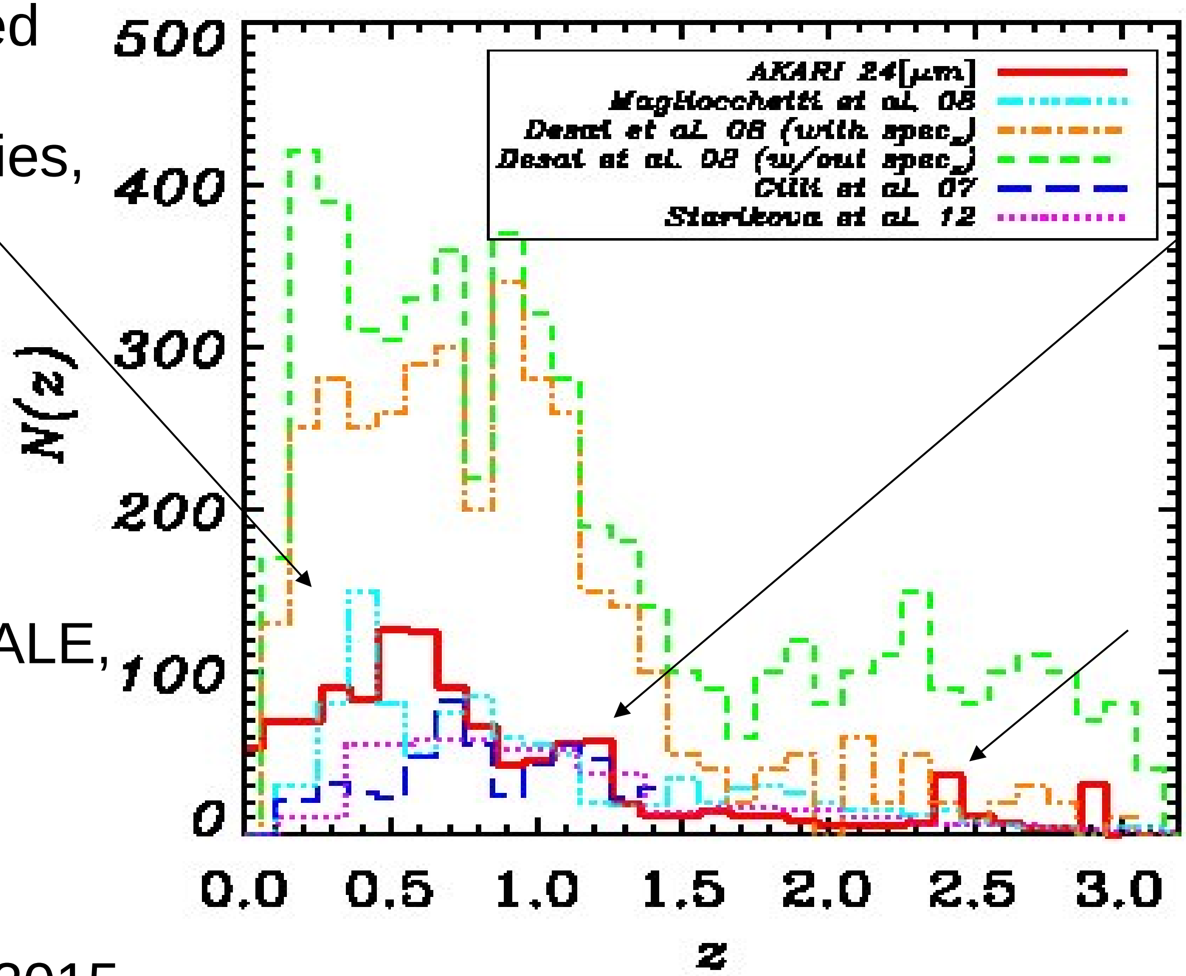
See a poster by Artem Poliszczuk for a continuation of these works

AKARI NEP: 24-um selected NEP galaxies

N(z) -> at least 3 different galaxy populations at different redshifts

Population centered at z ~0.6: dusty Star forming galaxies, Local LIRGs and ULIRGs

Photometric redshifts obtained with the aid of CIGALE, and calibrated with spectro-zs



Population centered at z~1.2: sources with 12.7 um PAH feature and/or 12.8 um NeII emission line

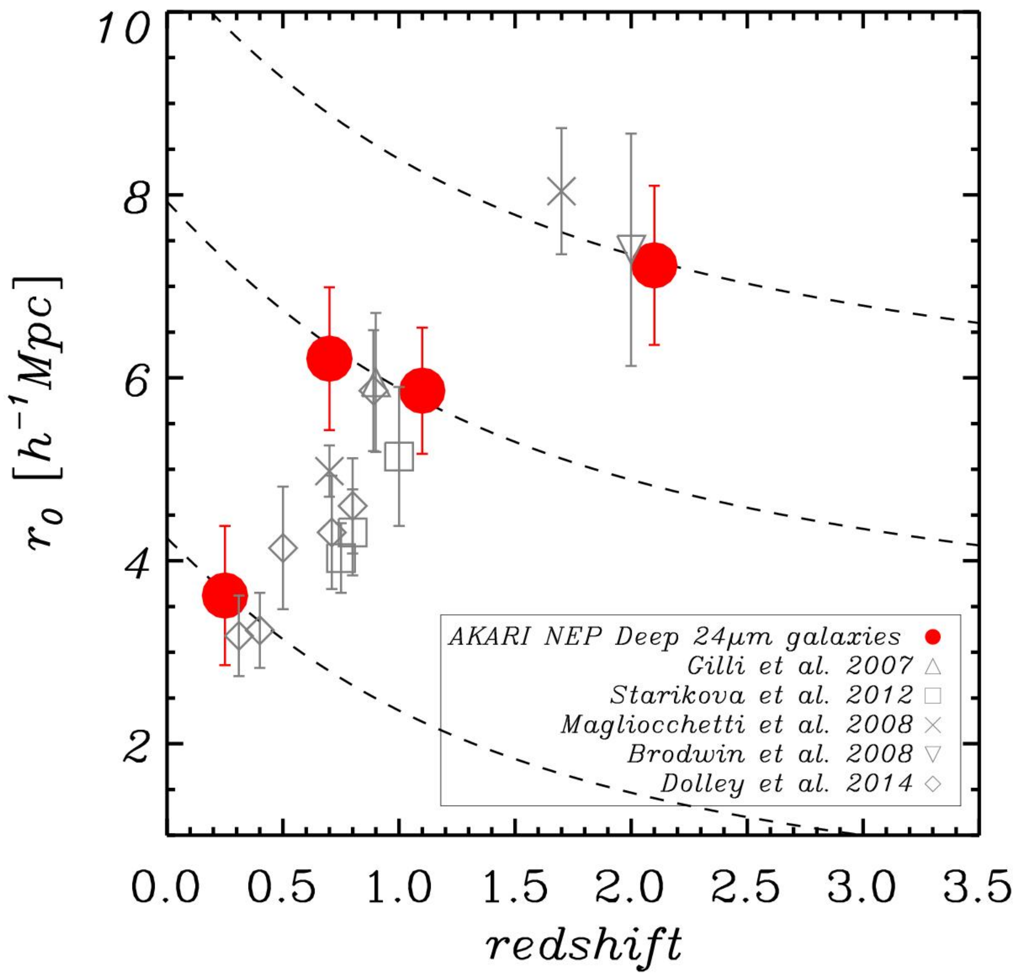
Population centered at z~2.4: sources dominated by AGNs and/or sources with 8 um PAH line

Solarz et al. 2012, 2015

AKARI: clustering of 24-um selected NEP galaxies:

All three populations at different redshifts: different but all strongly clustered

Differently related to underlying dark matter LSS -> evolution environmental dependence of evolution of these three populations.



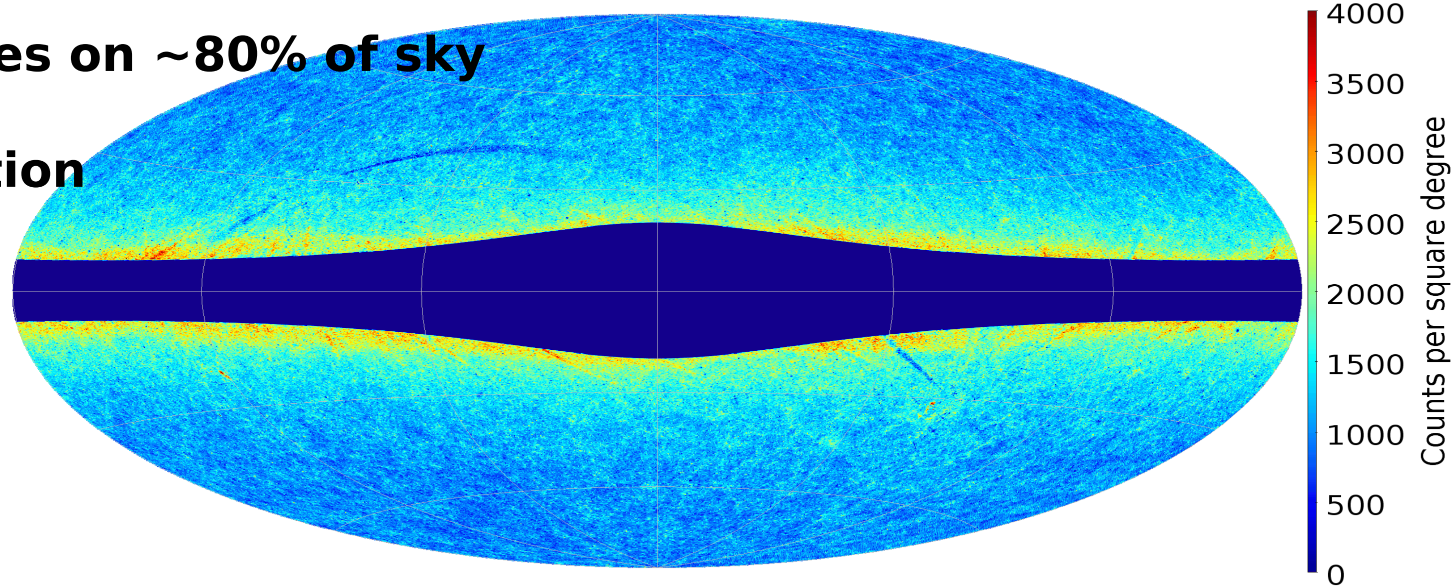
Solarz et al. 2015

Source classification of very large data: WISE

- 750 million sources
- four mid-infrared bands: 3.4, 4.6, 12, and 23 μm
- Great training grounds for all types of machine learning analyses

Star/galaxy/AGN separation in WISE

- We used the **support vector machines** algorithm trained on SDSS spectroscopic
- Current **results for W1<16** Vega (1 mag brighter than WISE flux limit) due to limitations of the training set (practically no SDSS galaxies at W1>16)
- **45 million galaxy candidates on ~80% of sky**
- Inevitable stellar **contamination at low latitudes** – blending due to 6” WISE beam



Kurcz et al. 2016

Star/galaxy/AGN separation in WISE

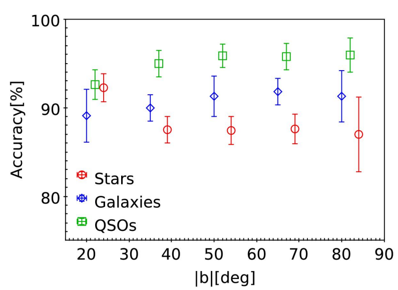
• We used the WISExSuperCOSMOS sample (Bilicki et al. 2014, 2016): flux-limited cross-matched sample at $|b| > 10^\circ$ with almost 48 million sources.

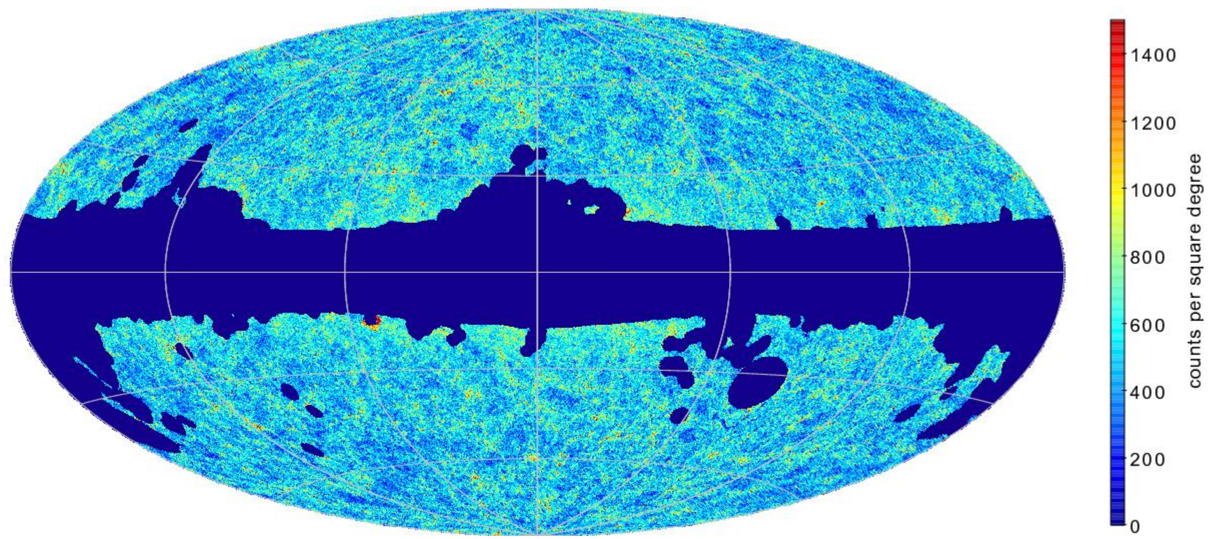
• **Result: 15 million galaxy candidates on ~68% of sky**

• Is this approach sufficient?

•**See Ola Solarz's talk tomorrow!**

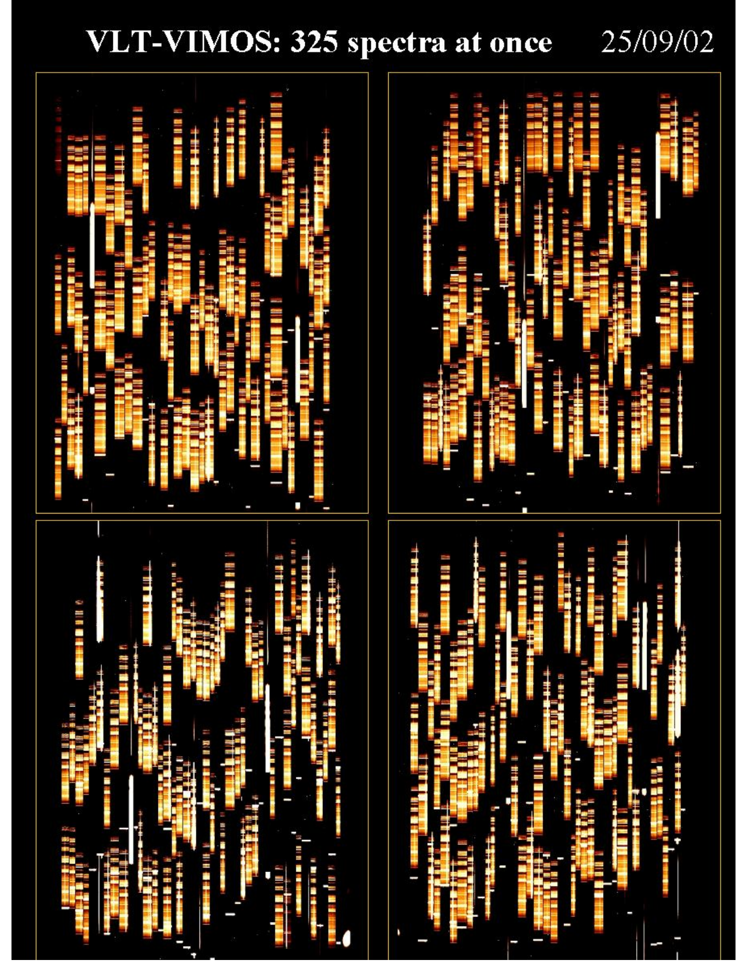
Krakowski et al. 2016



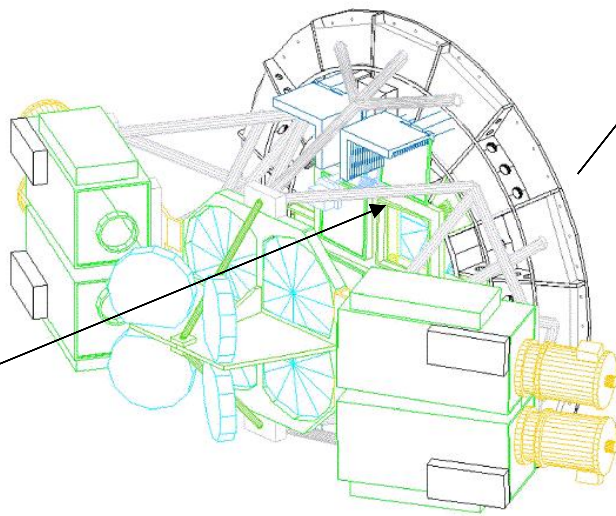


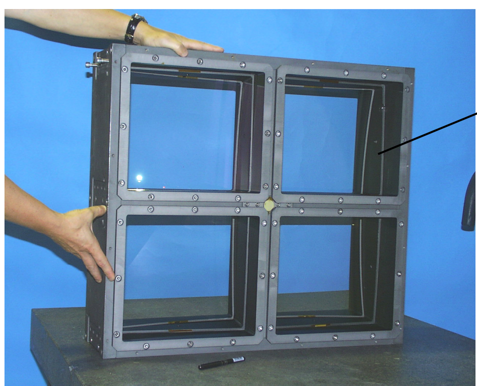
VIPERS

VIMOS PUBLIC EXTRAGALACTIC REDSHIFT SURVEY



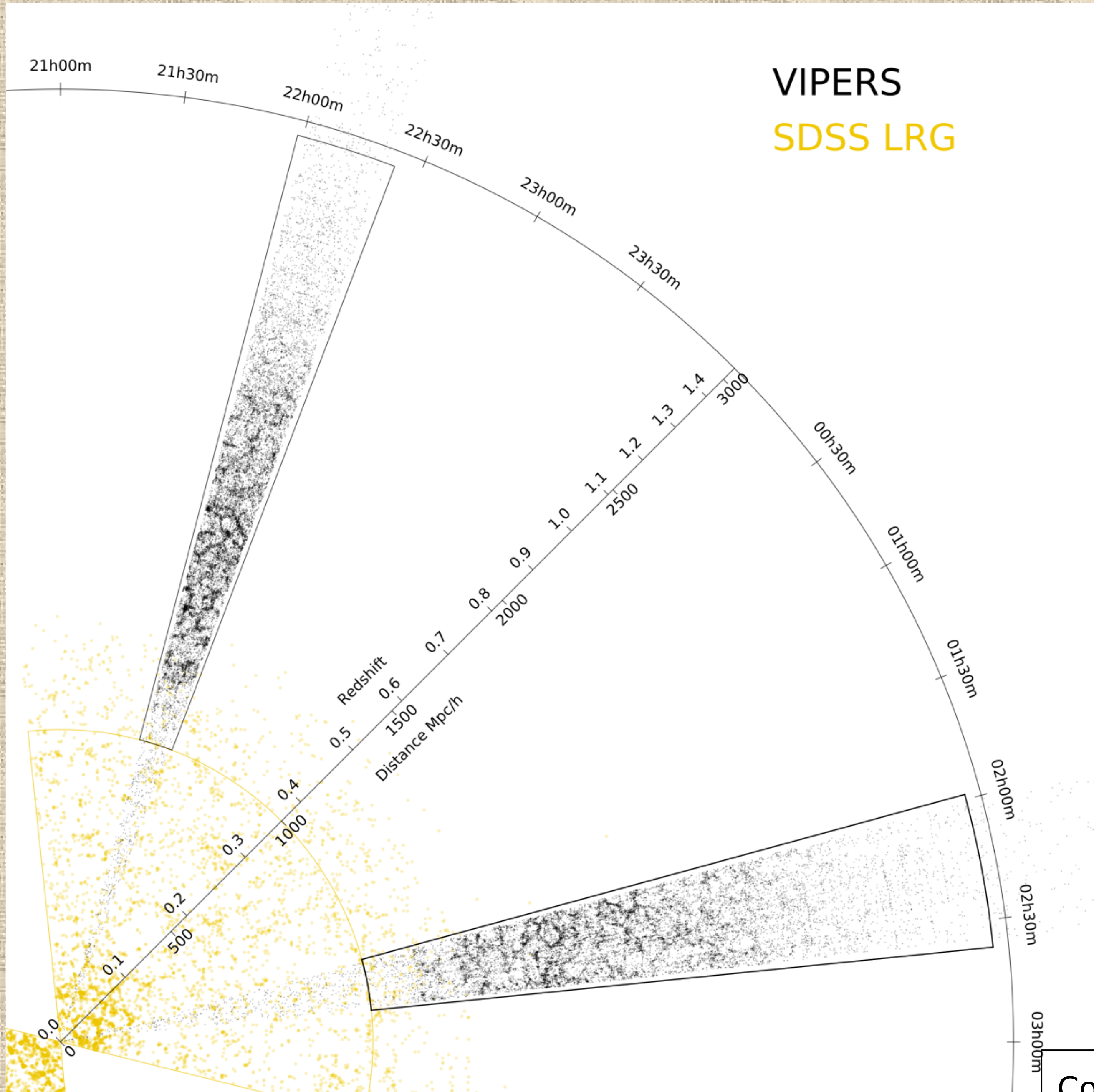
Large ESO Programme, started in 2008,
Data publicly released in the fall of 2016.
http://vipers.inaf.it/rel-pdr1.html



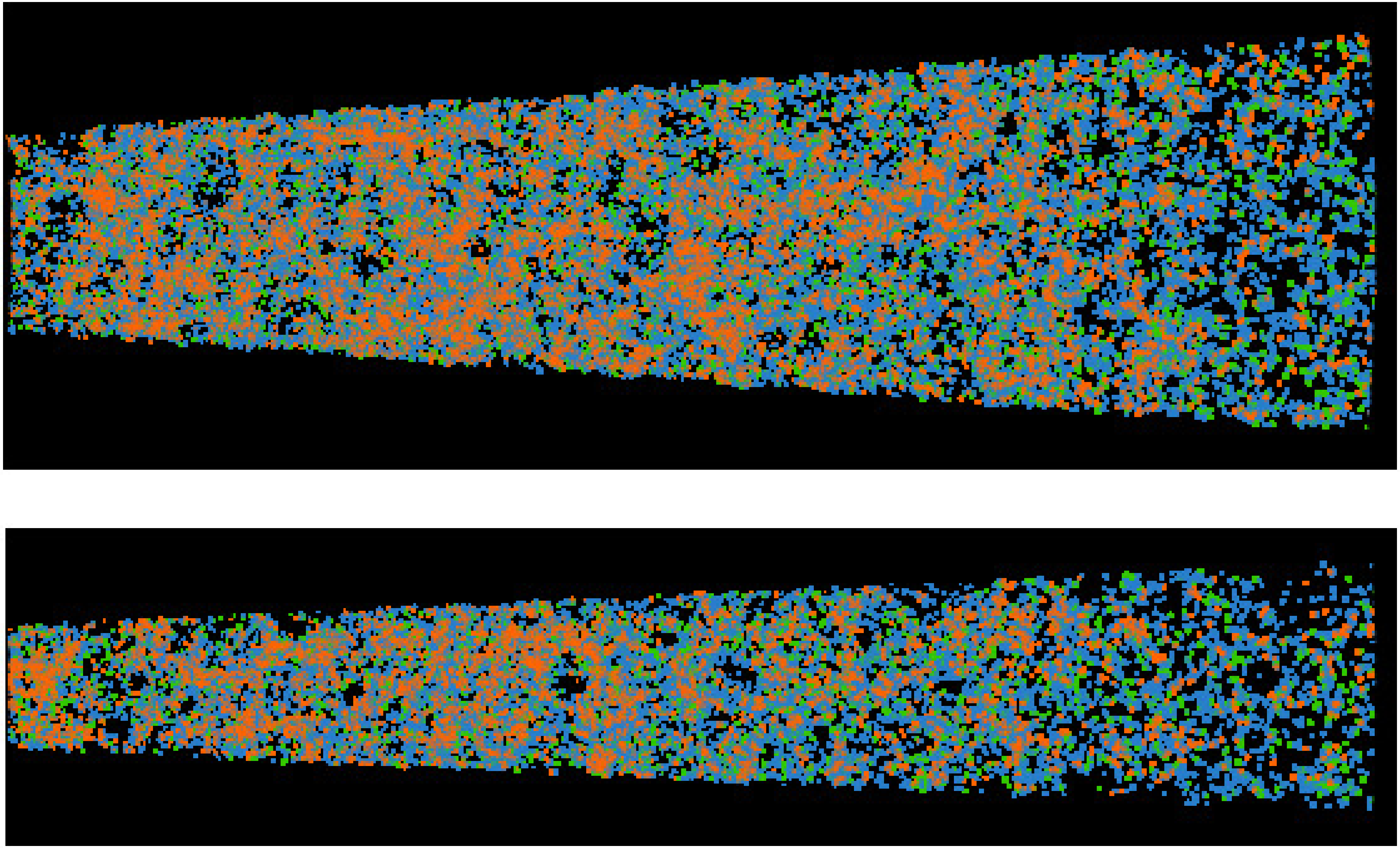


Goal: **100,000** spectra
of galaxies
at 0.5<z<1.2

Guzzo et al. 2014, 2017, Scodeggio et al. 2017



Courtesy Ben Granett



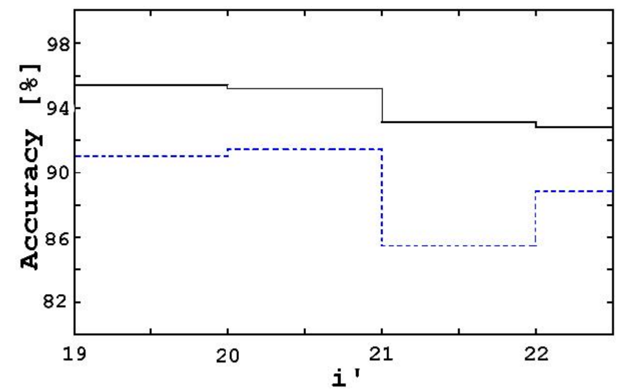
VIPERS: the case of rich data

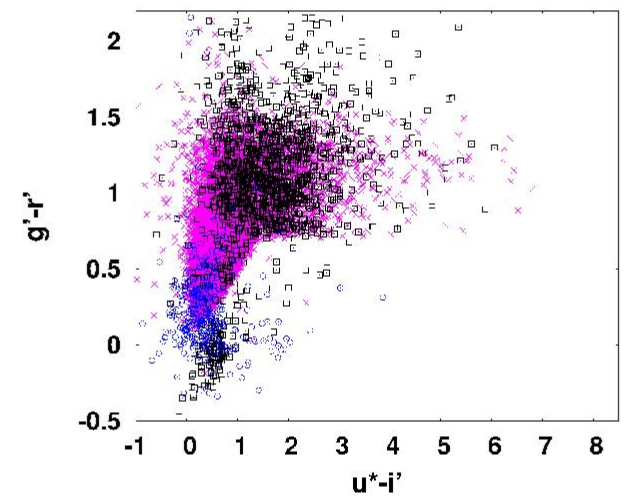
Question: based on the observed colors, but having a well defined training sample based on spectroscopic (VIPERS) data, how well can we pre-classify a sample into galaxies, stars and AGNs at $0.5<z<1.2$?

Malek, Solarz, Pollo et al. 2013

VIPERS-trained SVM classifier for AGNs, stars and galaxies at z>0.5

- Trained on almost 20,000 VIPERS sources with the best spectroscopic measurement
- Optical (based on 4 apparent magnitudes in u’, g’, r’ i’ bands) and NIR+optical classifiers trained
  - NIR measurement dramatically increases the classifier’s accuracy
- Classification pattern which is not obvious from color-color plots





Malek, Solarz, Pollo et al. 2013

Question: having such an unprecedented wealth of spectroscopic data, can we classify galaxies better than just traditional blue-red-green valley galaxies?

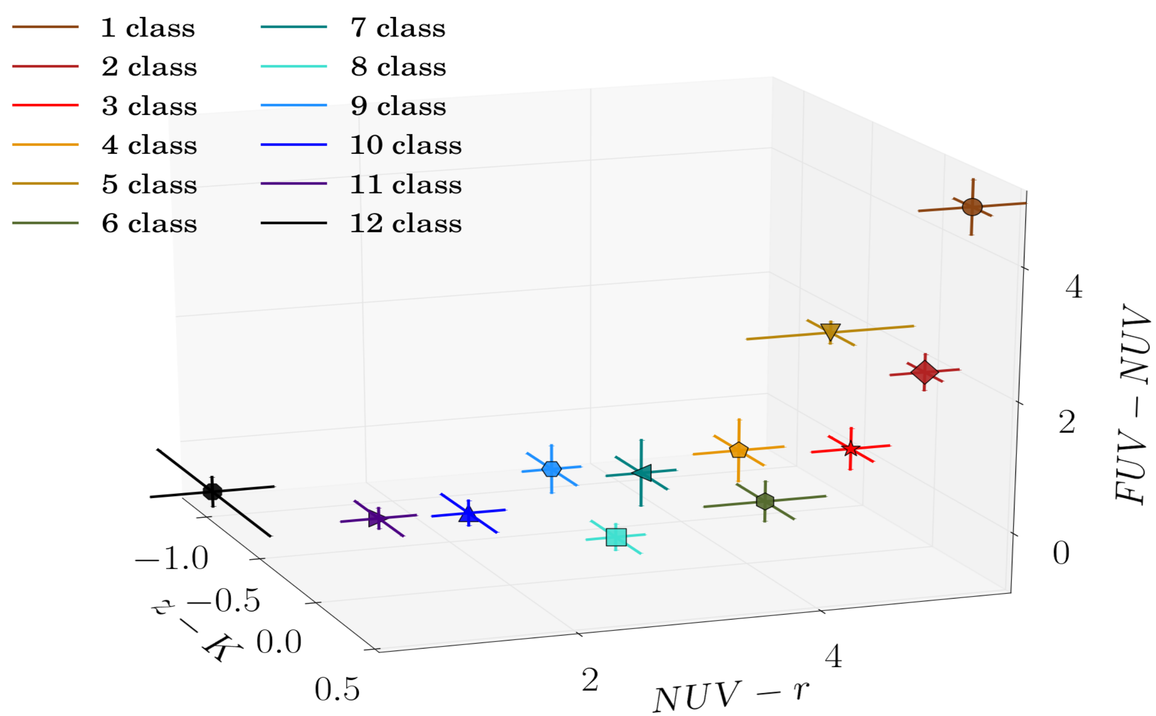
Method: unsupervised classification based on a feature space of absolute magnitudes + redshifts.

Siudek et al. (hopefully 2017)

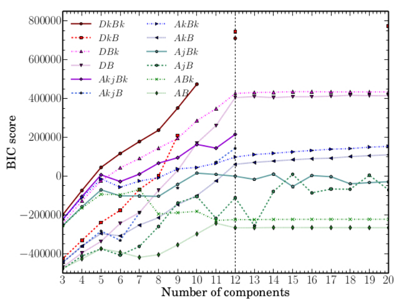
Unsupervised classification of galaxies at z>0.5

Unsupervised classification of VIPERS galaxies based on their distribution in a multidimensional absolute magnitude space
12 dimensions: absolute magnitudes + zspec

→ **blind separation** (no training sample or hints) into **12 classes**, which are well separated e.g. in the 3D diagram.



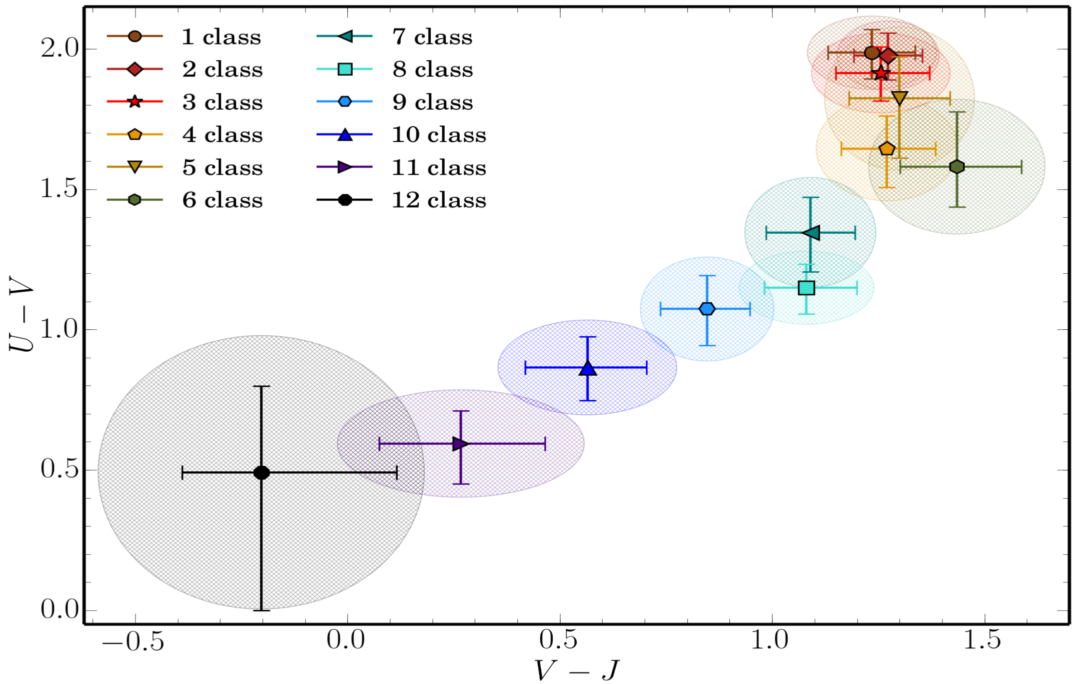
Method: Fisher expectation maximization algorithm (FEM) -

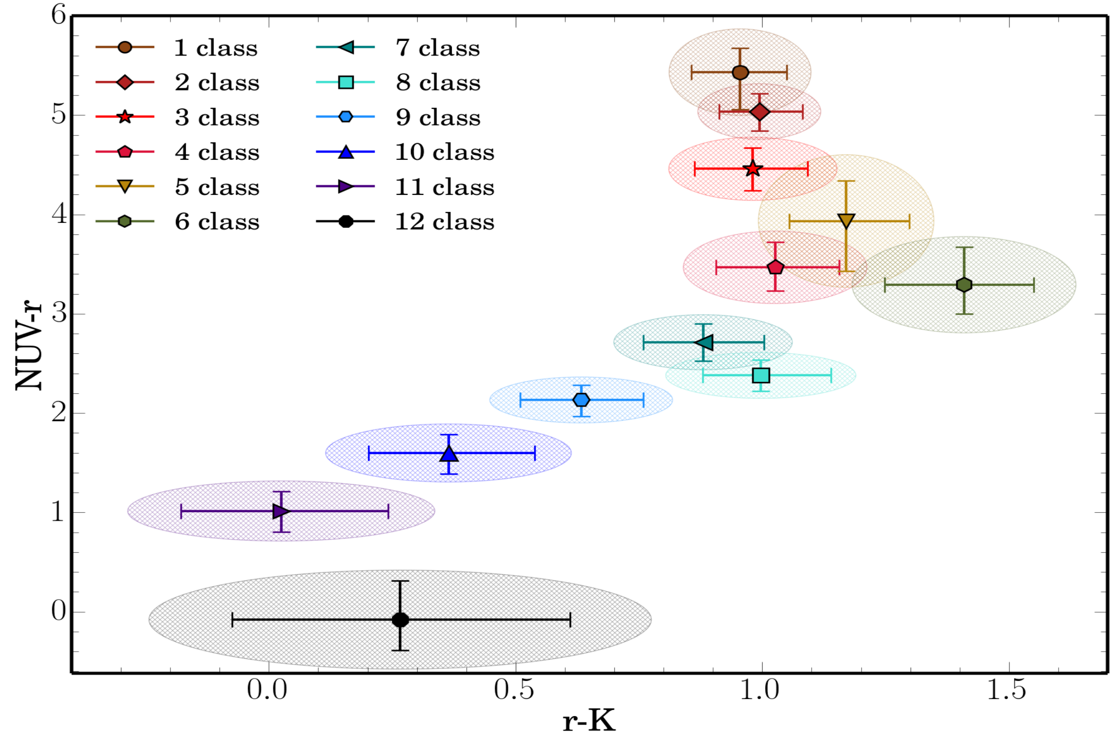


Choosing an optimal clustering model and number of groups based on the Bayesian Information Criterion (BIC).

Siudek et al. (hopefully 2017)

Unsupervised classification of galaxies at z>0.5

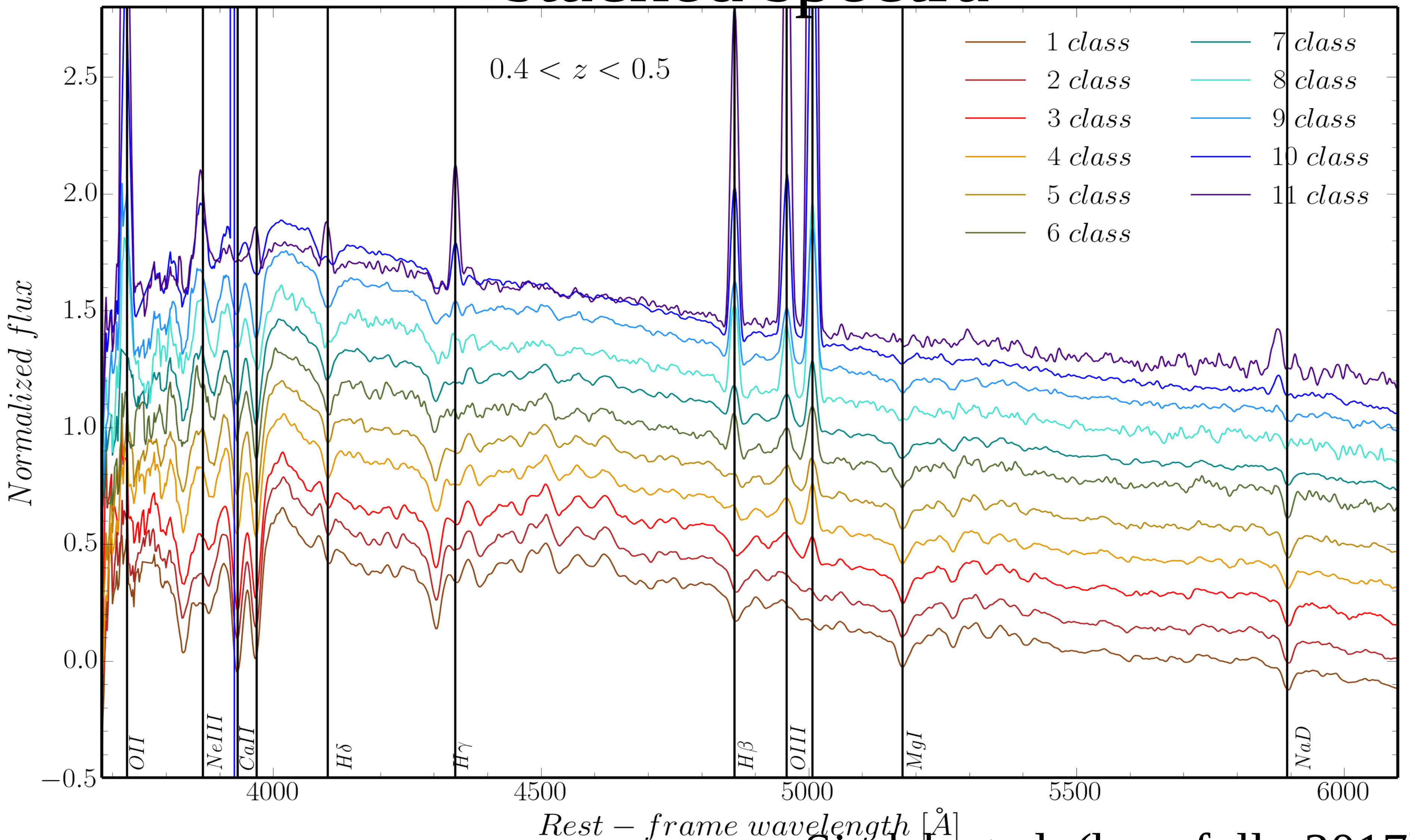




Multidimensional approach allows to achieve a better separation, while on the standard 2D color-color diagrams these classes overlap, e.g. red passive galaxies (classes 1, 2, and 3) are not distinguishable on UVJ diagram.

Siudek et al. (hopefully 2017)

Unsupervised classification stacked spectra



Siudek et al. (hopefully 2017)

Summary

- In the epoch of large astronomical datasets, we only started to exploit the possibilities of machine learning-based methods
- The existing datasets provide a very good training ground for future yet larger sky surveys of different type (LSST, Euclid, SKA…)
- ...but each time we need to adopt the method to the problem we want to address <u>and</u> to the properties of the data in question