



# Probing the QSOs distribution within the Virtual Observatory

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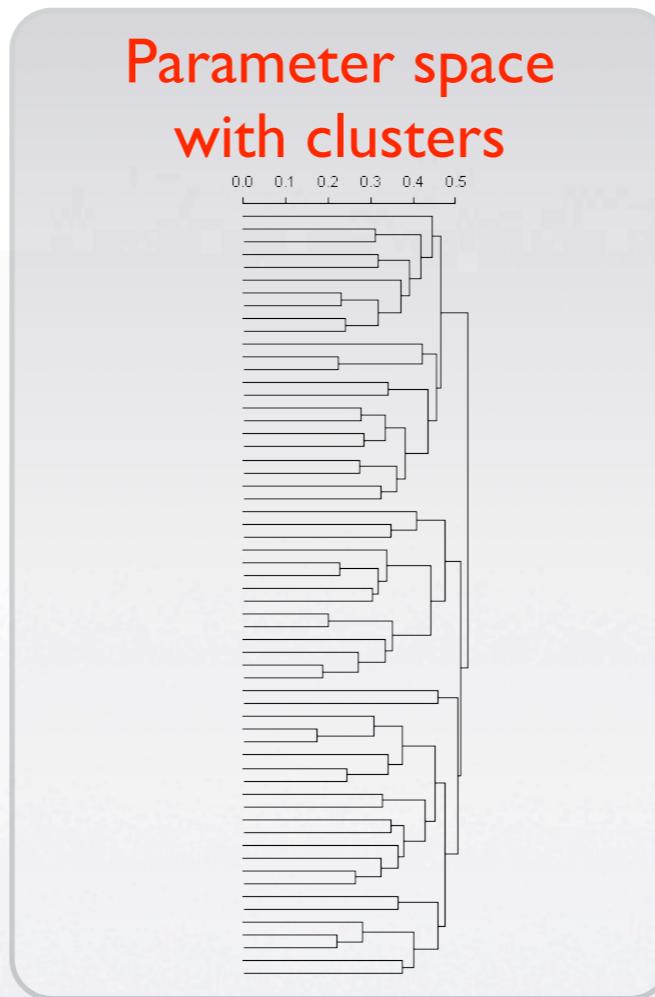
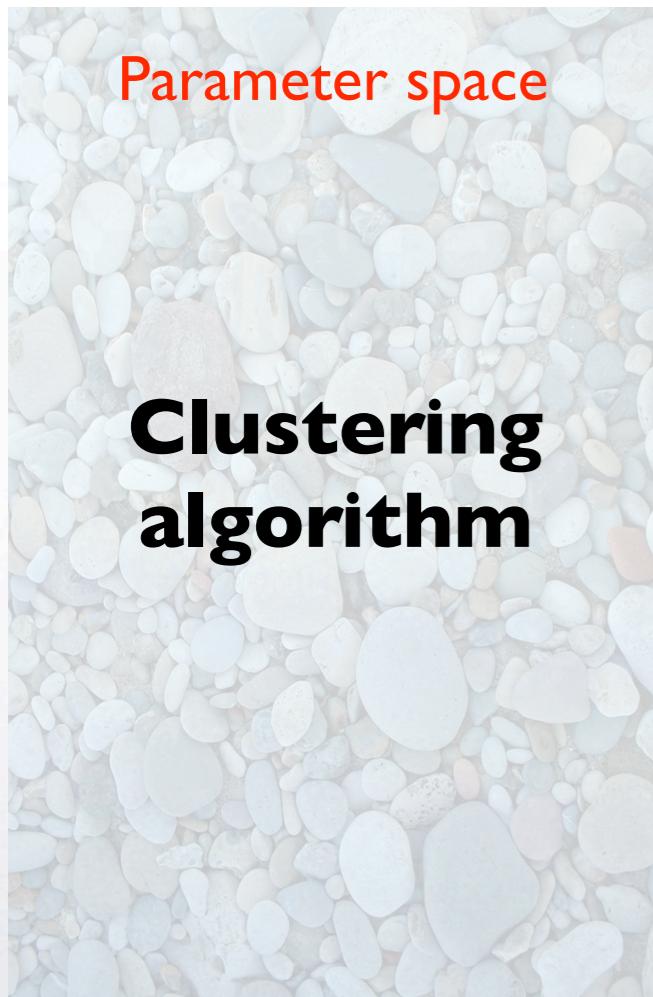
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**AAS 213<sup>th</sup> Meeting - 1/6/09**



# Candidate QSOs



Raw distribution of points in the parameter space (PS).

Clusters in the PS

Labelled clusters in the PS

(D'Abrusco et al., sub. to MNRAS)



**Start**

spectroscopic  
data

**PPS**

**NEC**

Selection of  
best  
clusterization

Photometric  
data

i-th generation of clustering

Successful  
cluster?

No

Yes

Characterization  
in parameter  
space

Selection of  
photometric  
objects

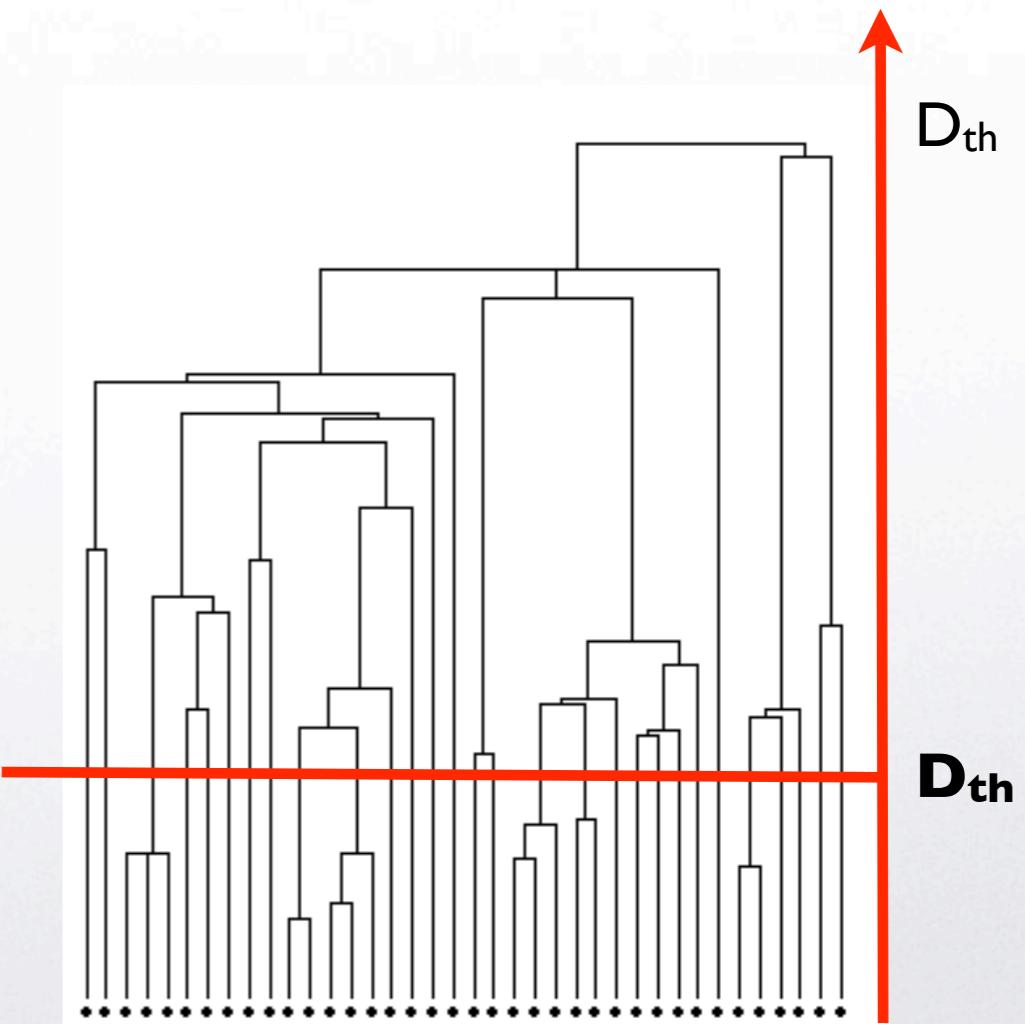
Mahalanobis'  
distance

**End**

candidate  
quasars

# Candidates QSOs selection

The selection of candidates from photometric catalogues of stellar sources exploits the determined clustering in the PS and a specific distance (Mahalanobis' distance).





# Photometric redshifts

Multicolour photometry maps physical parameters:

$$\begin{array}{l} \text{luminosity } L \\ \text{redshift } z \\ \text{spectral type } T \end{array} \xrightarrow{f} \text{observed fluxes}$$

If the relation can be inverted then:

$$u,g,r,i,z,H,J,K,\dots \xrightarrow{f^{-1}} z, L, T$$

The function  $f^{-1}$  can be approximated by regression in the photometric parameter space using the NNs trained on a set of sources for which the  $z_{\text{spec}}$  are available.



# The ingredients for $z_{\text{phot}}$

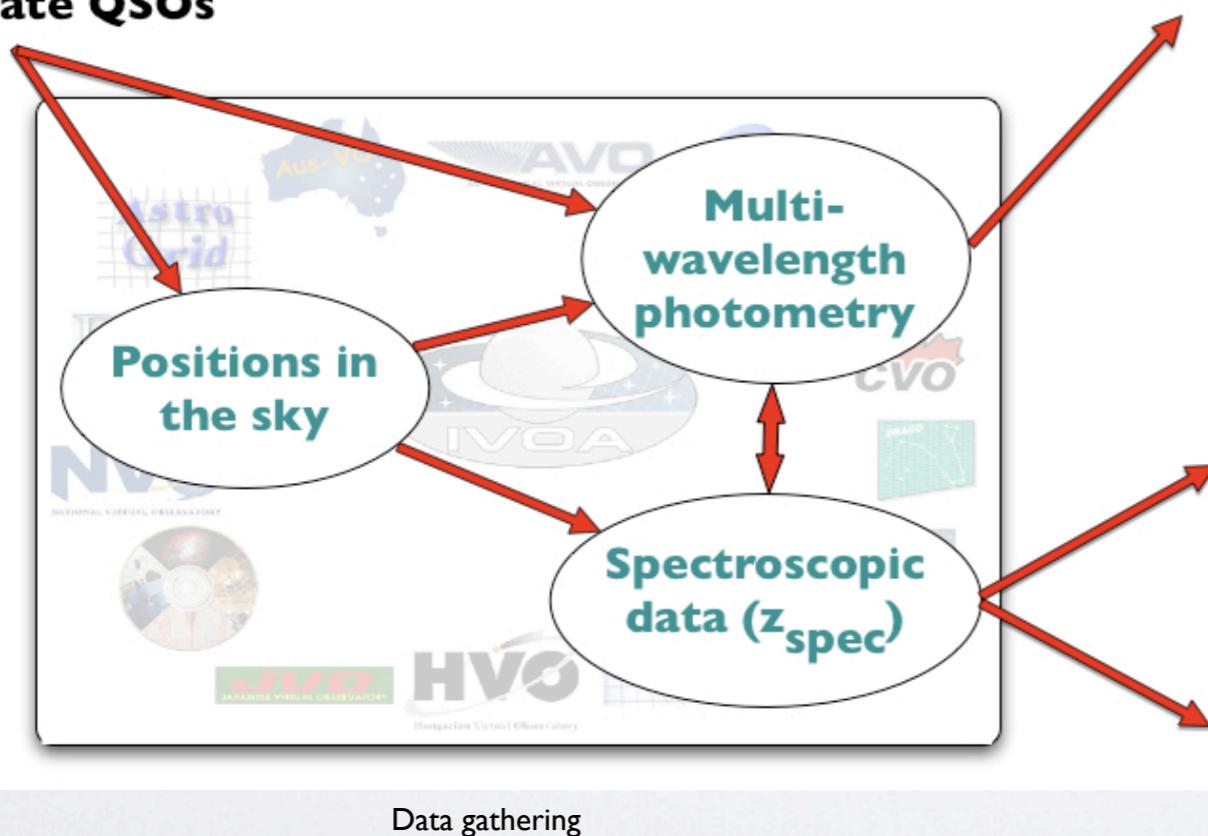
Generalization of the approach described in D'Abrusco et al., 2007 for machine learning-based QSOs  $z_{\text{phot}}$  reconstruction.

- ▶ VO capability of gathering and crossmatching multiwavelength data.
- ▶ Unsupervised fuzzy clustering algorithm (k-means).
- ▶ Neural Networks (MLP architecture).
- ▶ A criterion: maximization of  $z_{\text{phot}}$  accuracy.

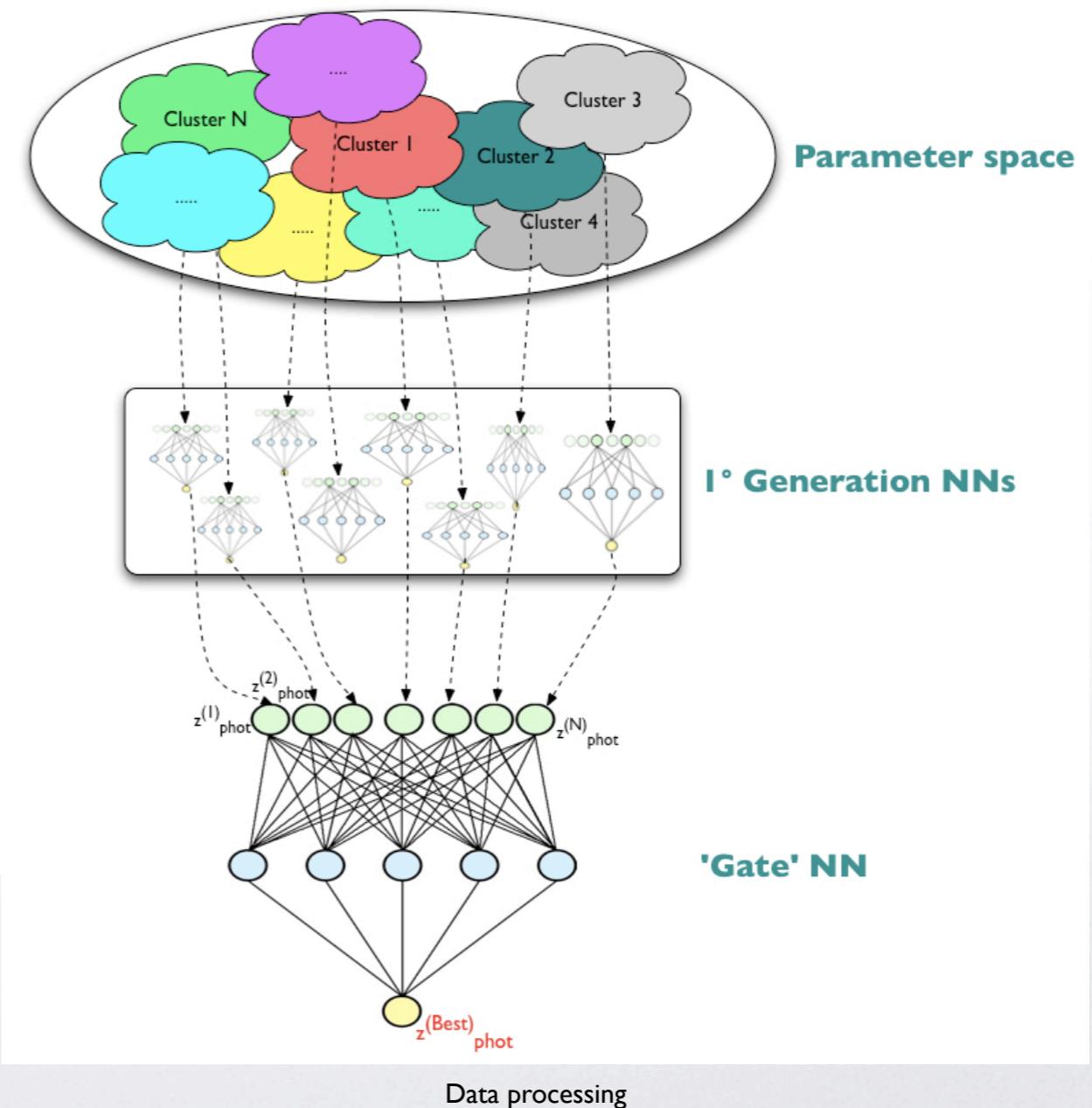


# The recipe for zphot

Candidate QSOs

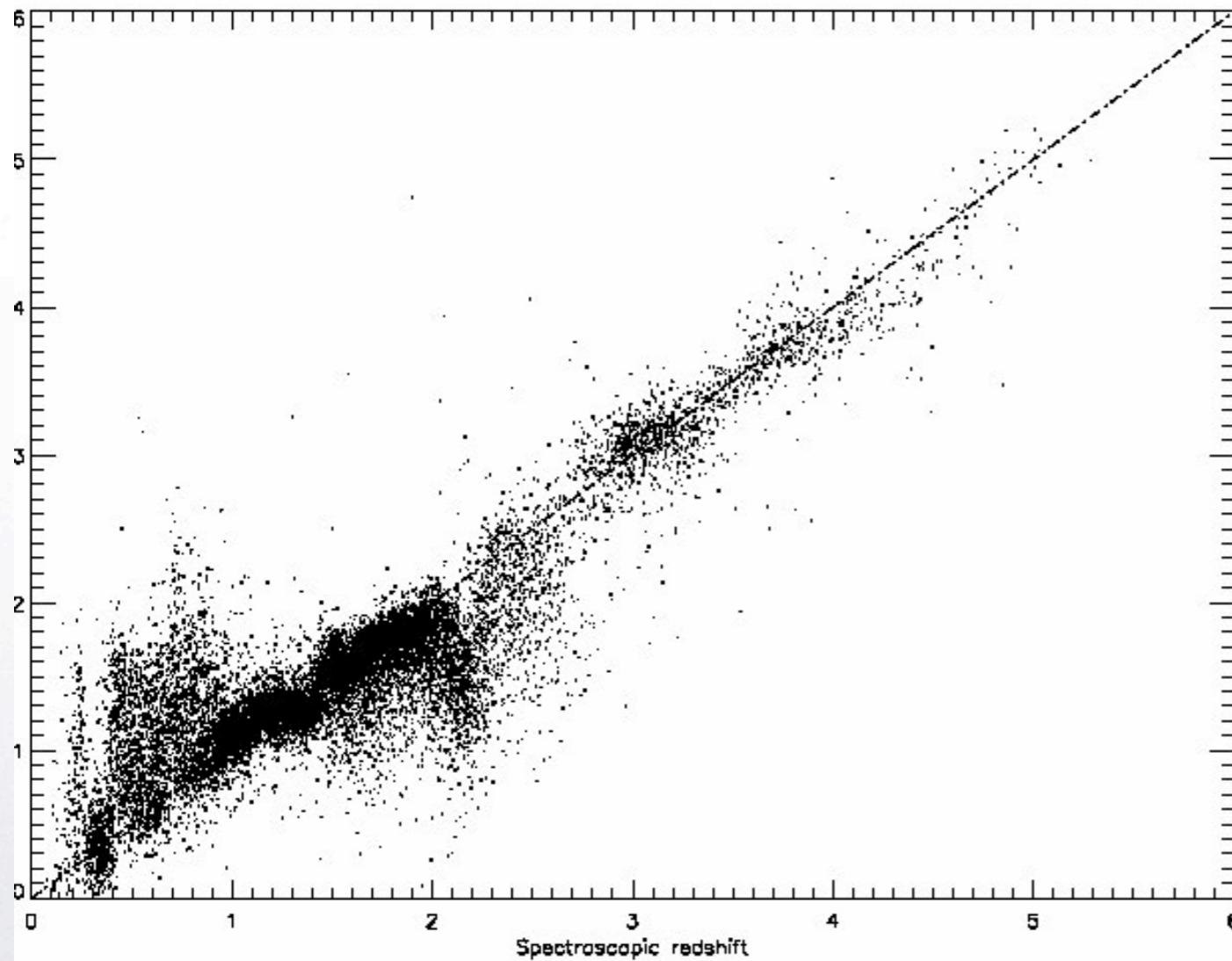


Data gathering



Data processing

# Optical candidates

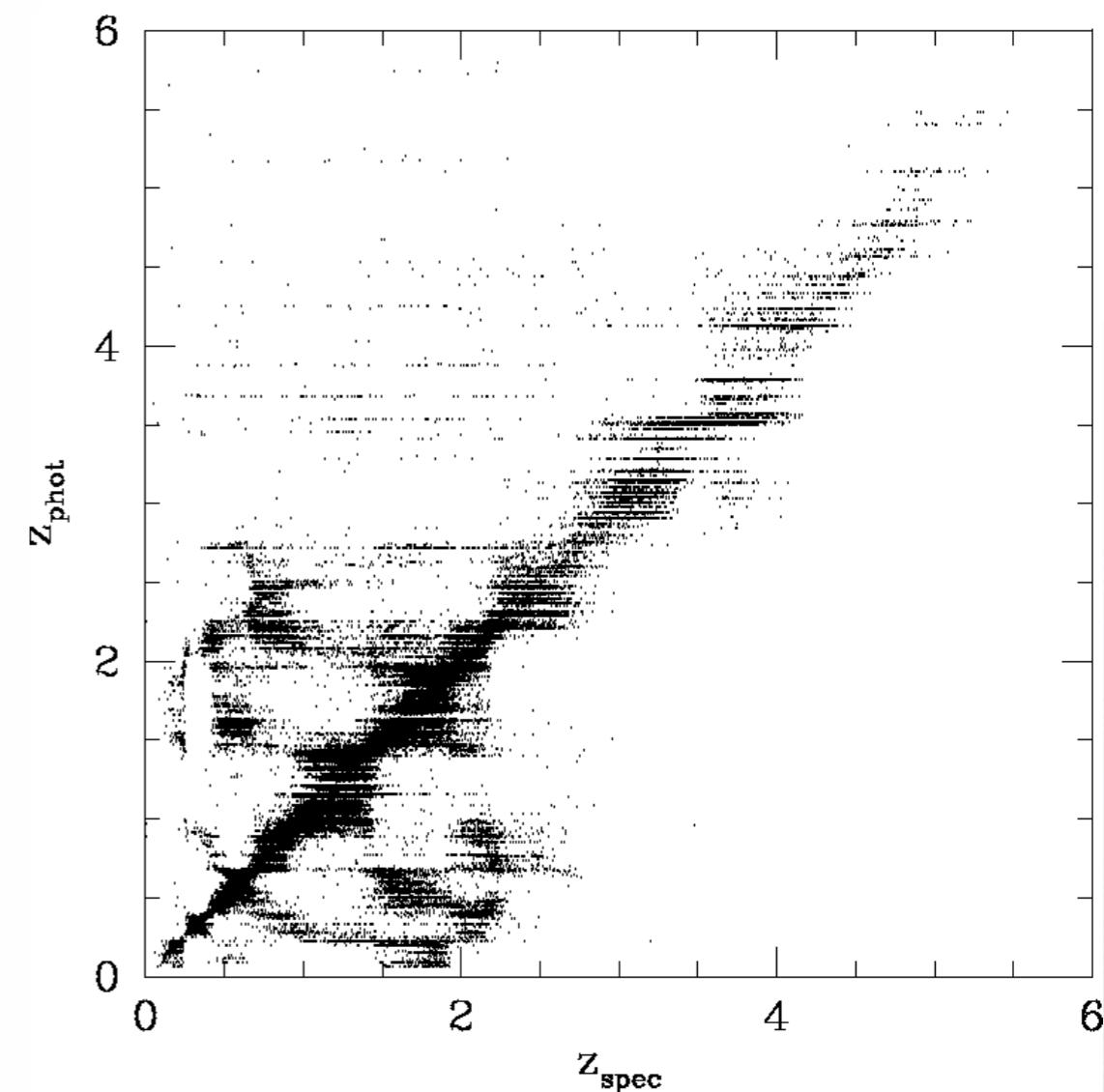
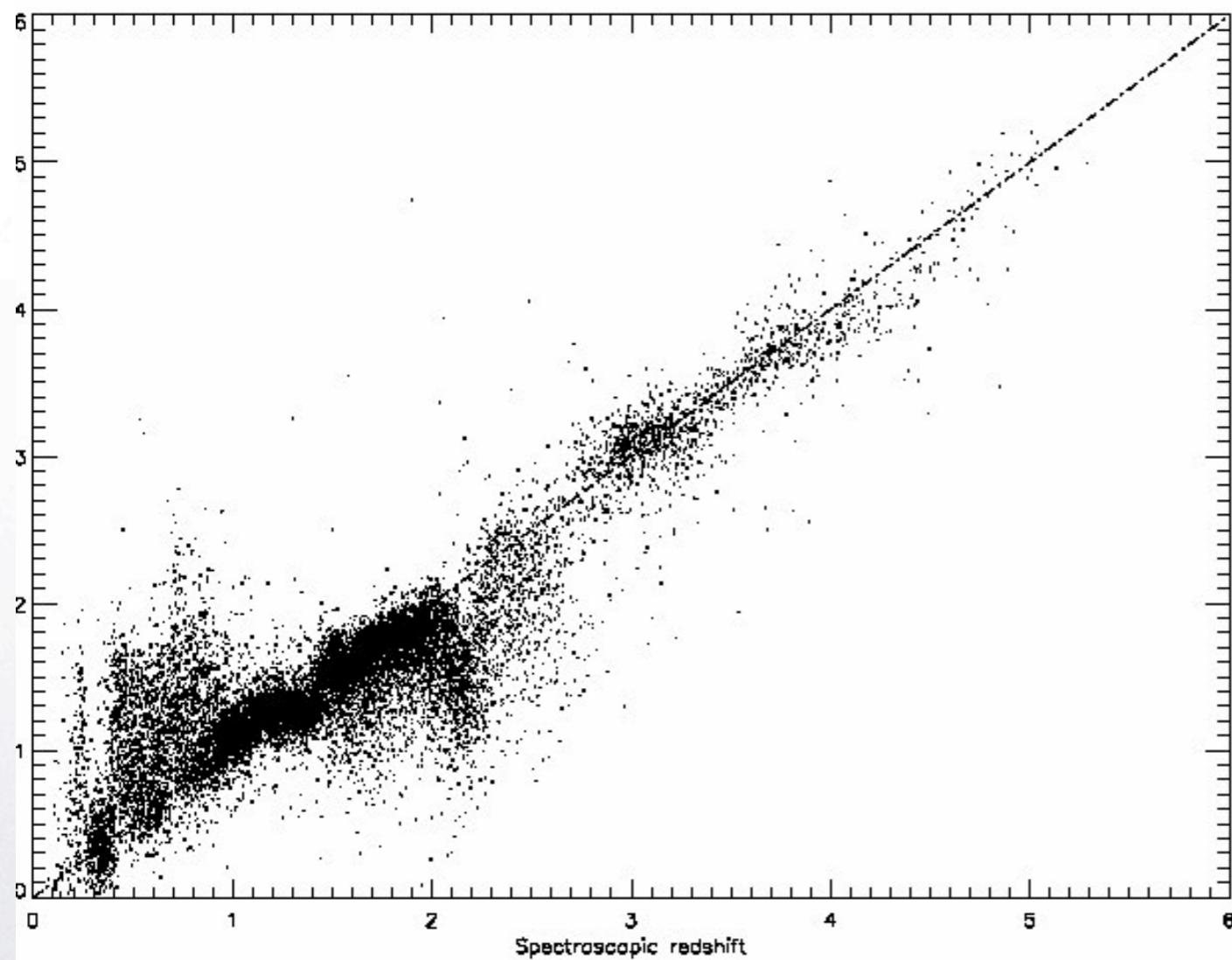


$z_{\text{spec}}$  vs  $z_{\text{phot}}$  scatter plot for QSOs candidates (D'Abrusco et al. 2009  $\cap$  Richards et al. 2008) using optical colours (SDSS).

- Optical colours ( $u-g, g-r, r-i, i-z$ )
- $z_{\text{spec}}$  from SDSS-DR6
- Optimal number of clusters: 4
- Robust sigma  $\sigma_{\text{rob}} = 0.27$
- Outliers < 5%

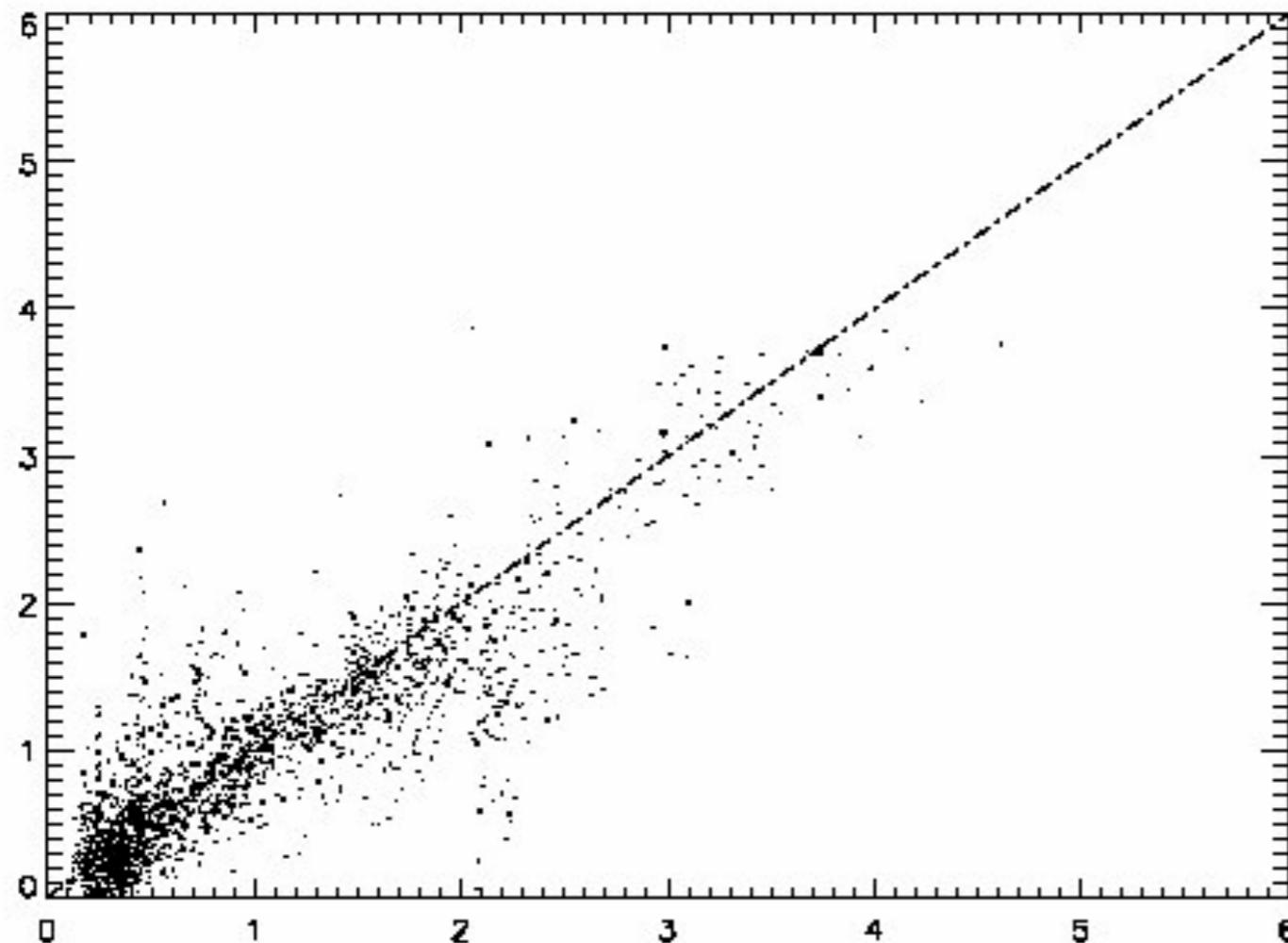


# Optical candidates



$Z_{\text{spec}}$  vs  $Z_{\text{phot}}$  scatter plot for QSOs candidates (D'Abrusco et al. 2009  $\cap$  Richards et al. 2008) using optical colours (SDSS).

# Optical + NIR candidates



$z_{\text{spec}}$  vs  $z_{\text{phot}}$  scatter plot for QSOs candidates (D'Abrusco et al. 2009) using optical (SDSS) and near infrared colours (UKIDSS).

- Optical + NI colours ( $u-g, g-r, r-i, i-z, Y-J, J-H, H-K$ )
- $z_{\text{spec}}$  from SDSS-DR6
- Optimal number of clusters: 6
- Robust sigma  $\sigma_{\text{rob}} = 0.21$
- Outliers < 3 %



# Conclusions

- ▶ Working on uncertainty of  $z_{\text{phot}}$  estimates.
- ▶ Applications: LF and CF of candidate QSOs.
- ▶ This method achieves better results than those found in the literature for QSOs  $z_{\text{phot}}$ .
- ▶ QSOs extraction and  $z_{\text{phot}}$  estimation methods are strictly complementary and data-mining/VO oriented.
- ▶ Web application: **<http://dame.na.infn.it>**