Kernel PCA for SNe photometric classification

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1. The problem

Ironically...

We have too much data!

Type Ia SN surveys are not able to provide complete spectroscopic follow up

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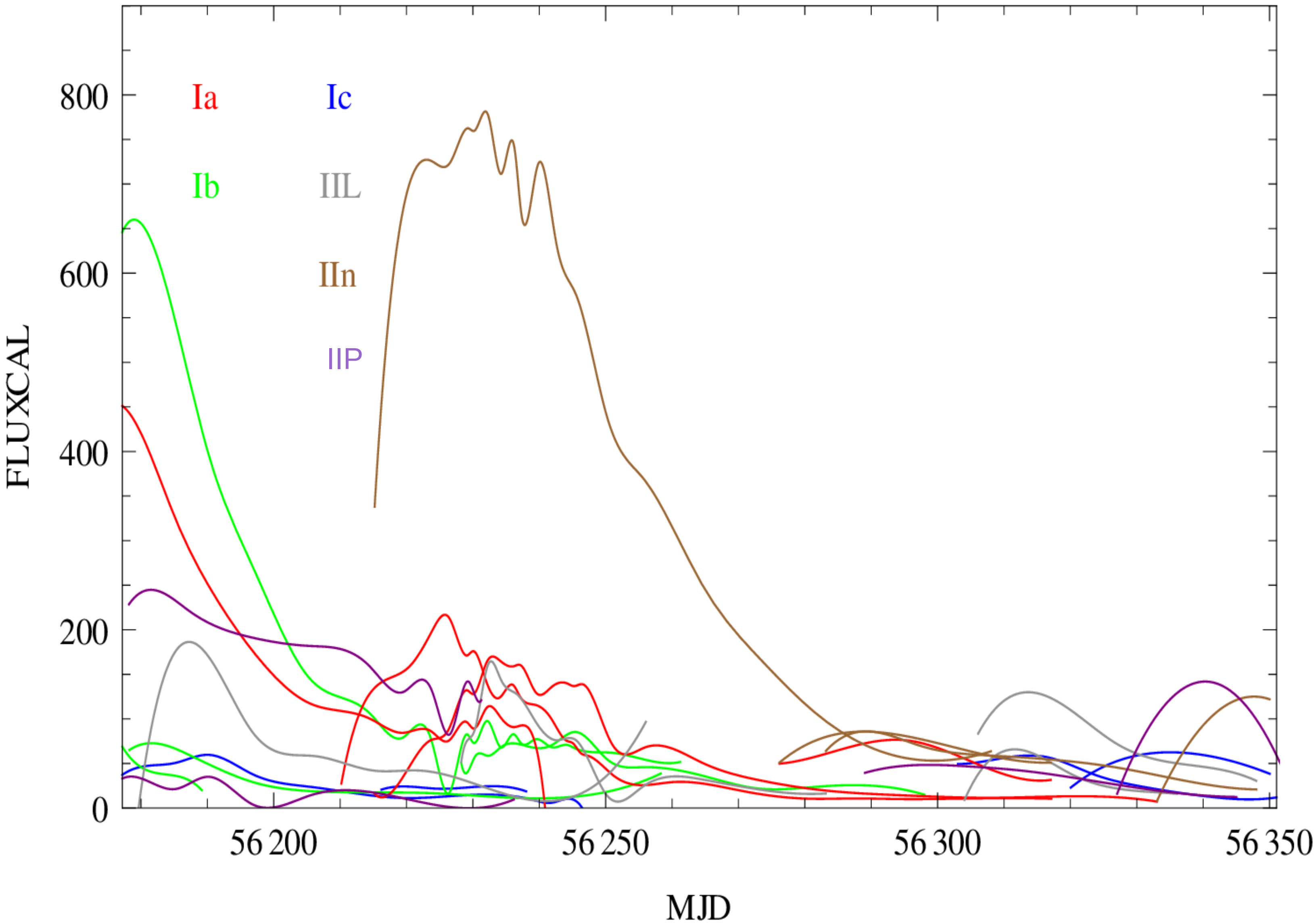
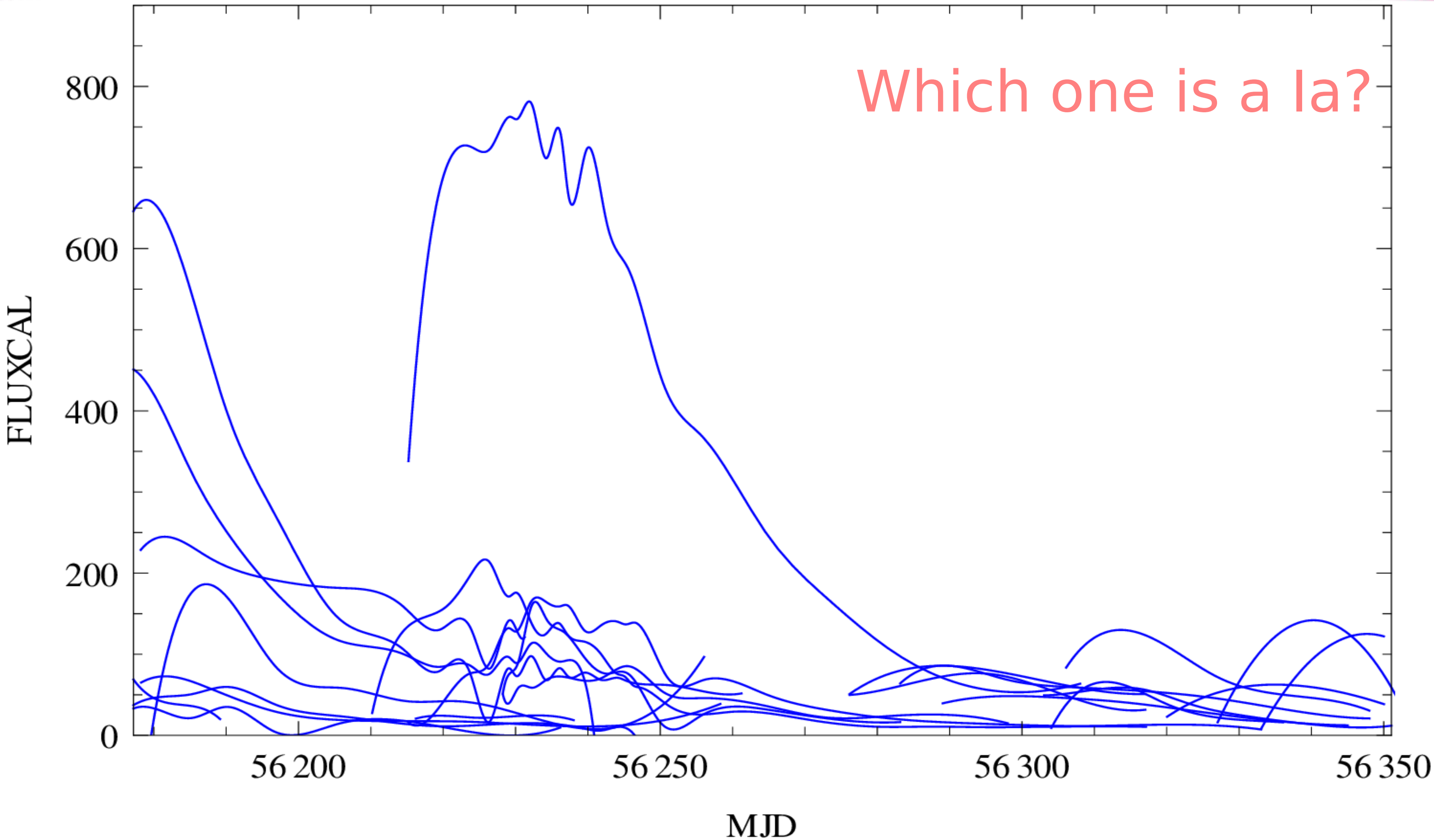
1. The problem



1. The problem



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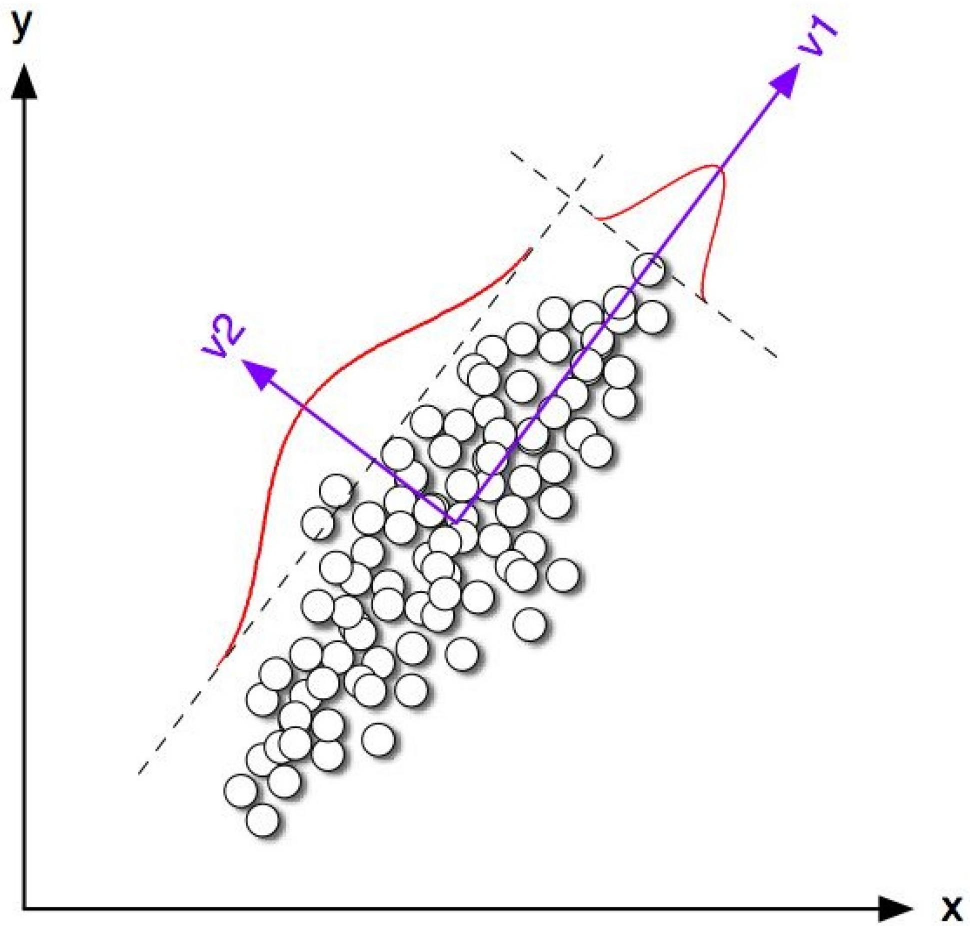
2. Principal Component Analysis (PCA)

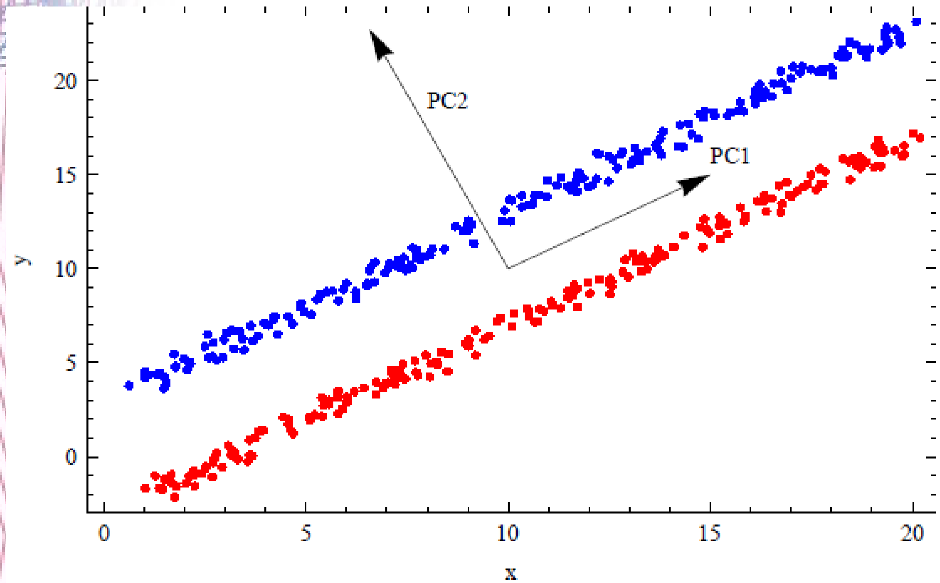


http://web.media.mit.edu/~tristan/phd/dissertation/figures/PCA.jpg

Dimensionality reduction technique

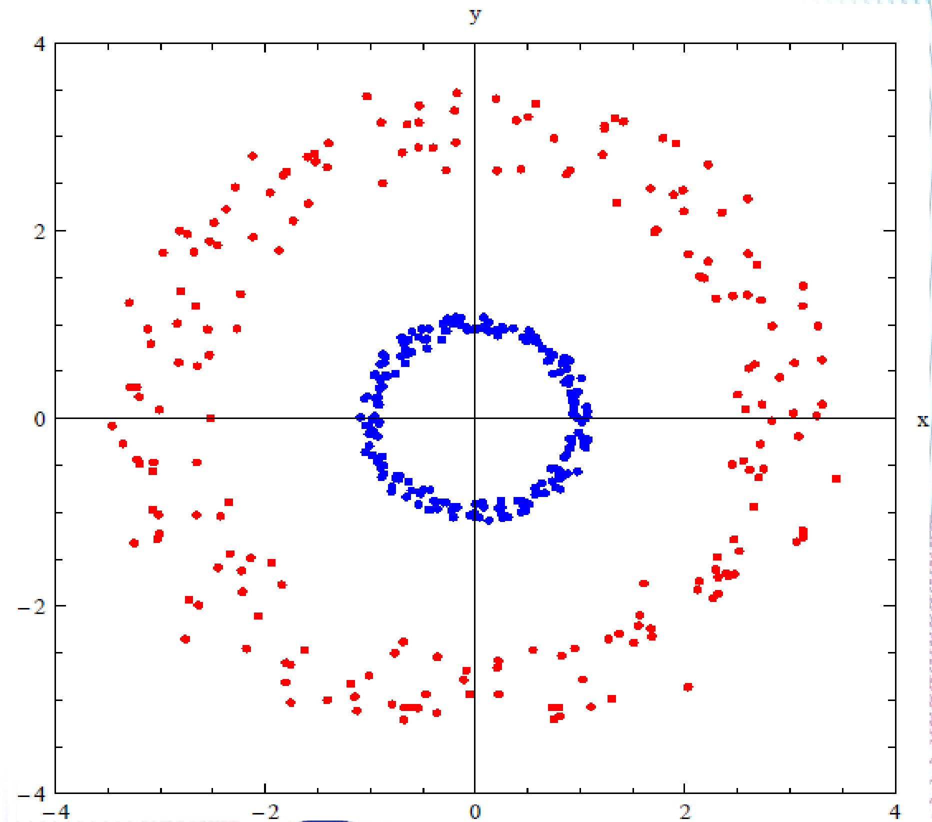
Look for directions that maximizes variance

2. PCA limitations

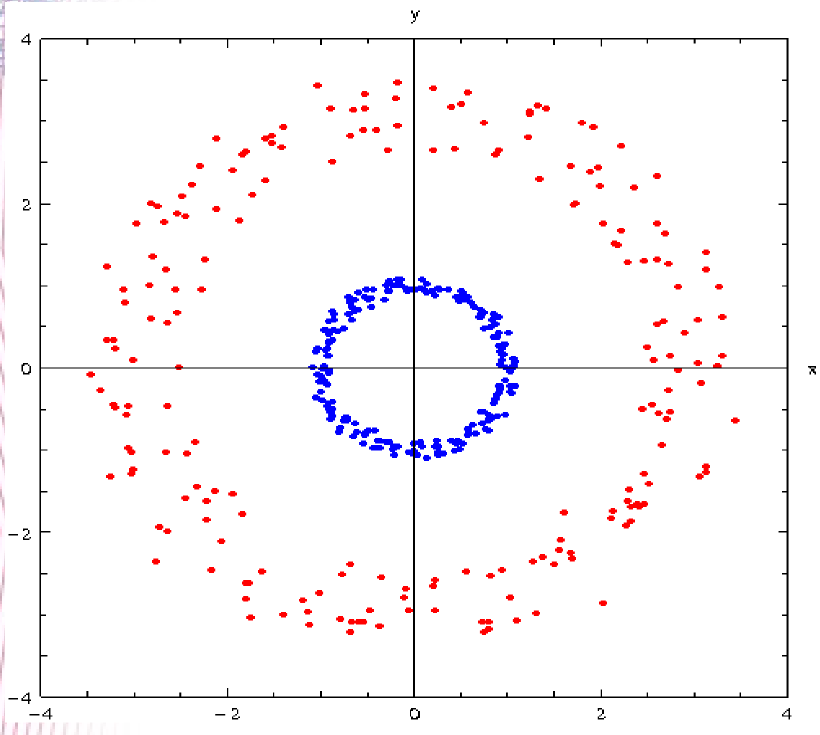


Is not designed to capture non-linear structure

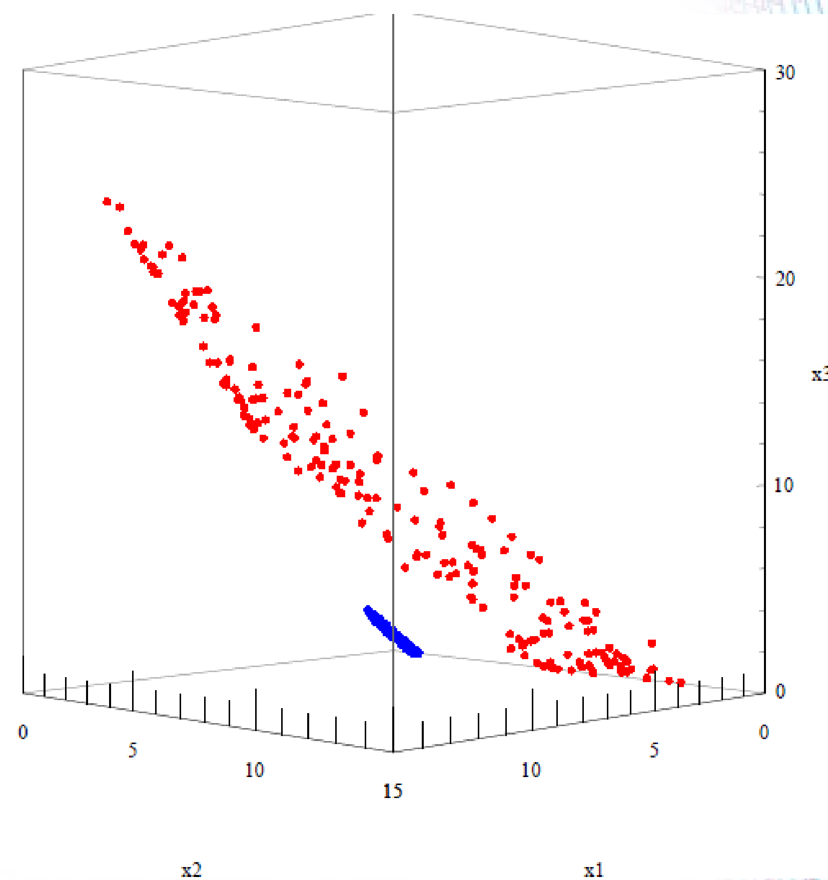
Does not care about labels



2. PCA extensions



$$(x, y) \quad \rightarrow \quad z = \sqrt{x^2 + y^2}$$



Sometimes, going to higher dimensions might solve the problem

2.The kernel trick

In the linear case, with

$\boldsymbol{x}_i \quad \rightarrow i-th$ data vector,

$$K_{ij} = \boldsymbol{x}_i^T \boldsymbol{x}_j$$

$\alpha_k \rightarrow k-th$ eigenvalue

$\boldsymbol{v_k} \rightarrow k-th$ eigenvector

$$\boldsymbol{v}_k^T \boldsymbol{n} = \sum_{i=1}^{N} \alpha_k K(\boldsymbol{x_i}, \boldsymbol{n})$$

where $\boldsymbol{n}$ is the data to be projected and

$$K(\boldsymbol{x}_i, \boldsymbol{n}) = \boldsymbol{x}_i^T \boldsymbol{n}$$

In the kernel approach,

$\Phi : \mathbb{R} \rightarrow \mathbb{F}$

$\boldsymbol{x} \rightarrow \Phi(\boldsymbol{x})$

$$K_F(\boldsymbol{x}_i, \boldsymbol{x}_j) = \Phi(\boldsymbol{x}_i) \cdot \Phi(\boldsymbol{x}_j)$$

$$\boldsymbol{v}_\Phi^l \cdot \Phi(\boldsymbol{n}) = \sum_{i=1}^{N} \alpha_{\Phi_i}^l K_F(\boldsymbol{x}_i, \boldsymbol{n})$$

First natural choice - Gaussian kernel

$$k(\mathrm{x}_i, \mathrm{x}_j) = \exp\left[\frac{\|\mathrm{x}_i - \mathrm{x}_j\|^2}{2\sigma^2}\right]$$

2.The kernel trick

In the linear case, with

$\boldsymbol{x}_i \quad \rightarrow i-th$ data vector,

In the kernel approach,

$\Phi : \mathbb{R} \rightarrow \mathbb{F}$

It is not necesary to know the mapping!

where n is the data

to be projected and

$$K(\boldsymbol{x}_i, \boldsymbol{n}) = \boldsymbol{x}_i^T \boldsymbol{n}$$

First natural choice - Gaussian kernel

$$k(\mathrm{x}_i, \mathrm{x}_j) = \exp\left[\frac{\|\mathrm{x}_i - \mathrm{x}_j\|^2}{2\sigma^2}\right]$$

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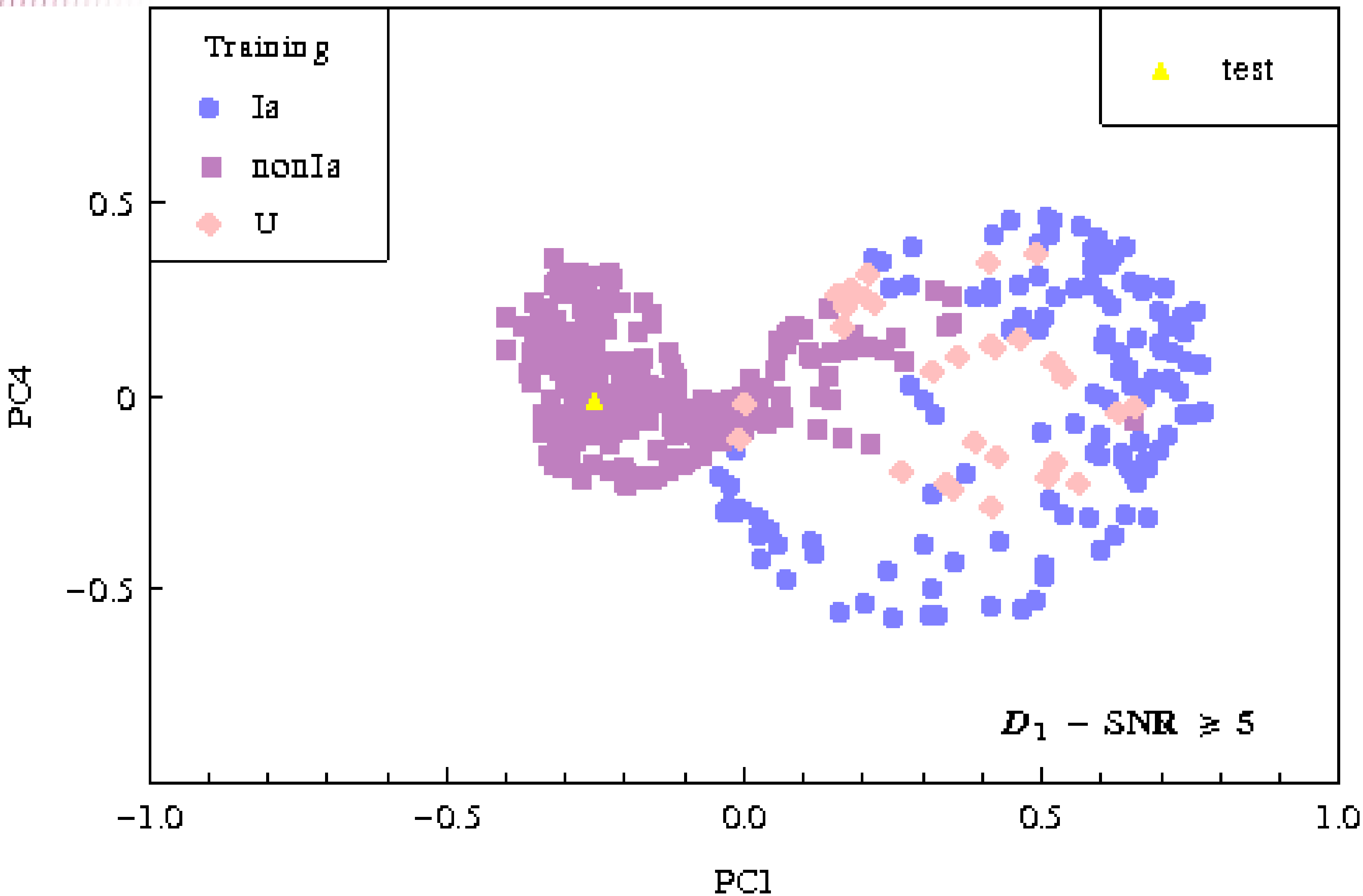
3. kPCA applied to SNe classification

Classification



THE
Nearest
Neighbor

(1NN)

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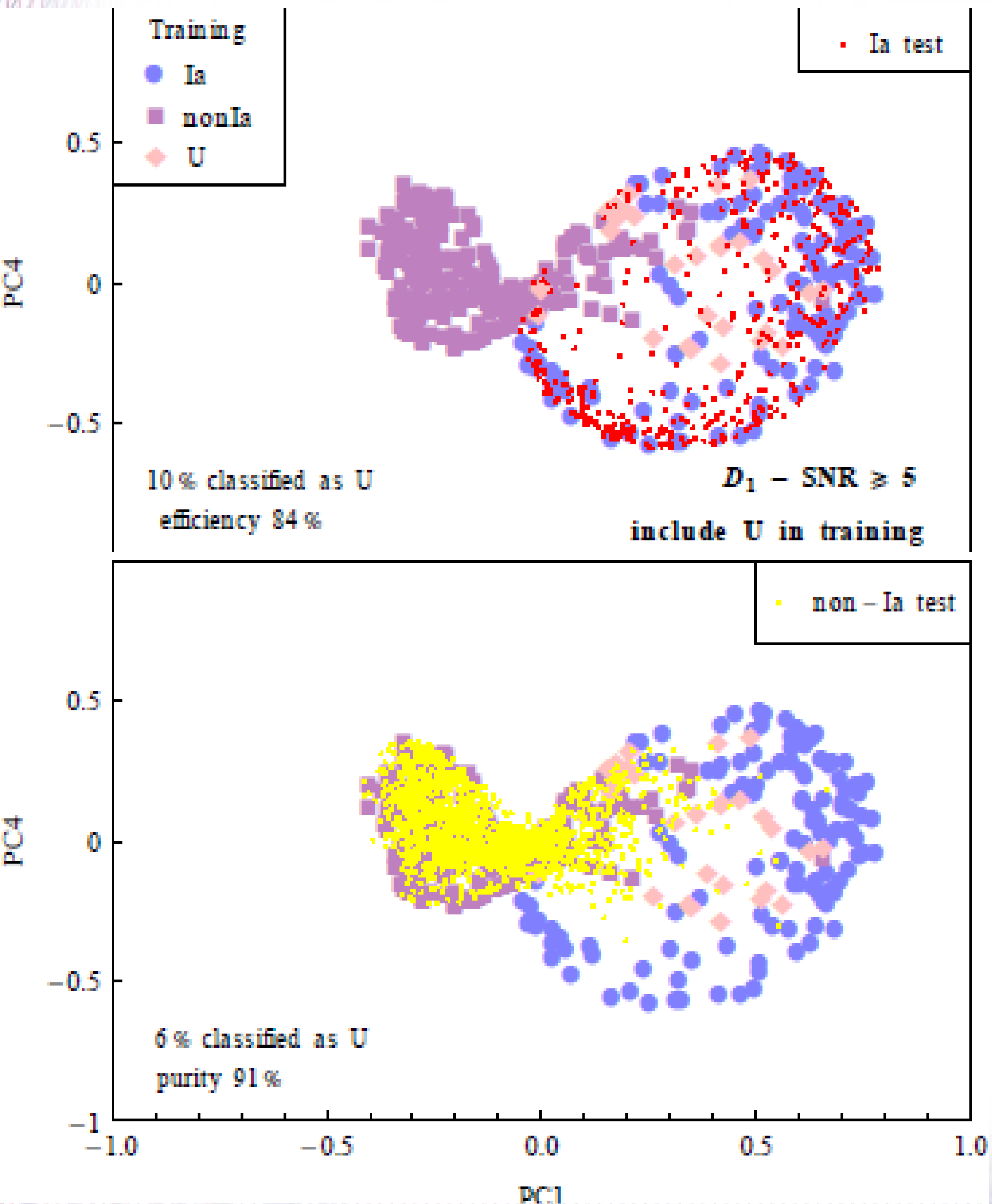
3. kPCA applied to SNe classification



Post-SNPCC sample
After selection cuts

FoM ~0.60

SC ~91%

<u>Selection cuts:</u>
{-3,+24} in r-band
At least 3 obs with SNR>5
in each band

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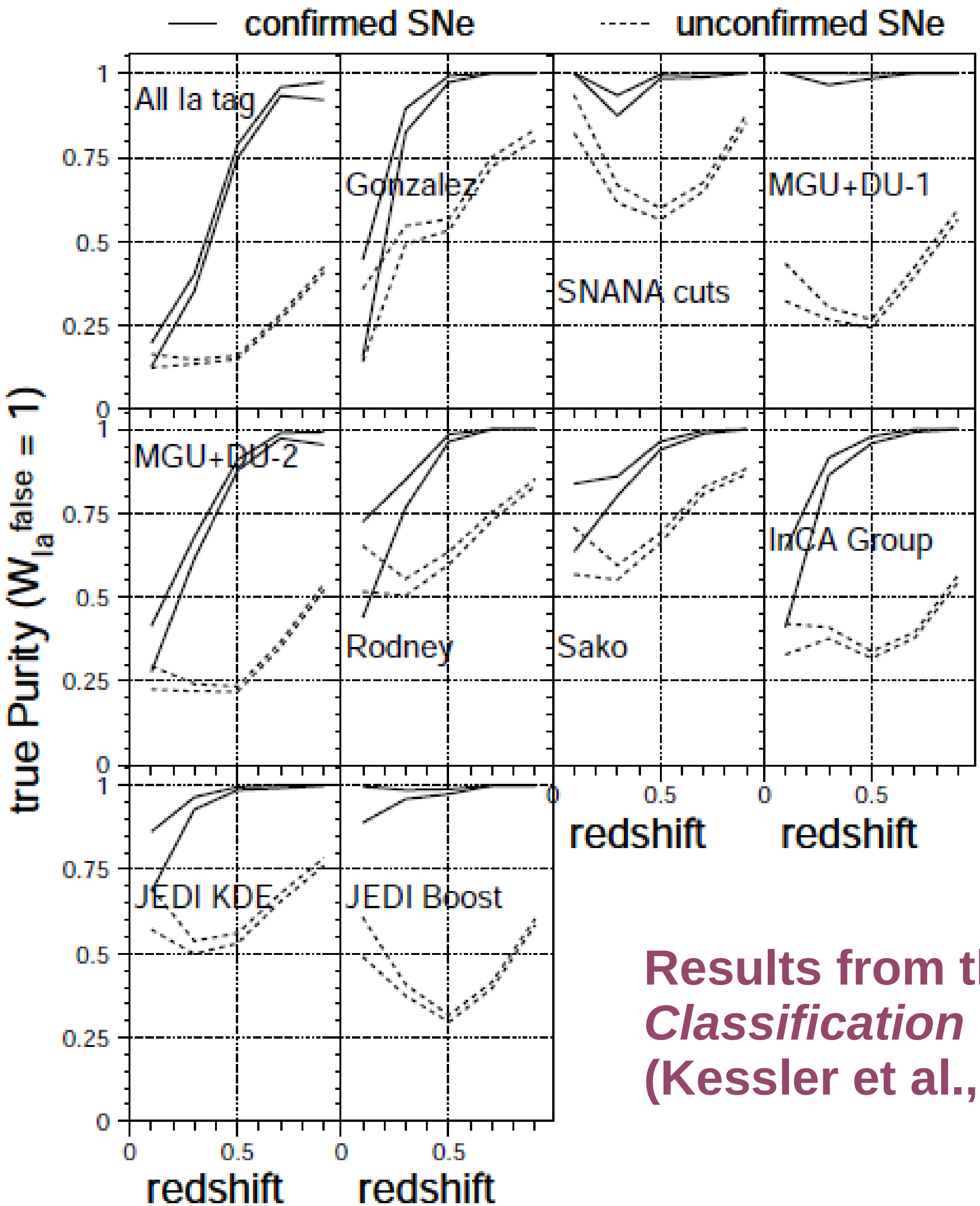
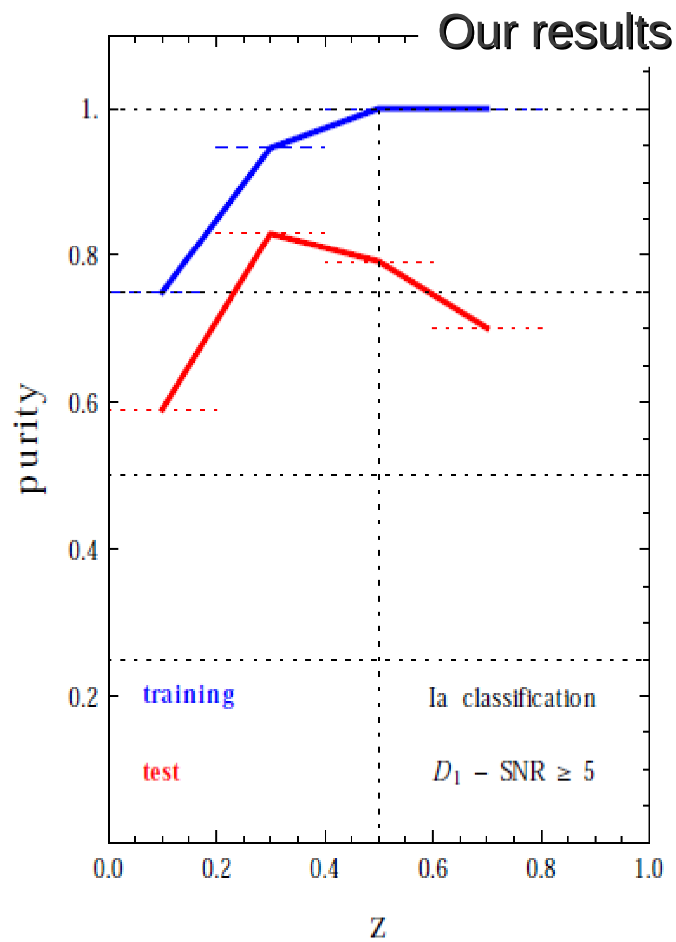
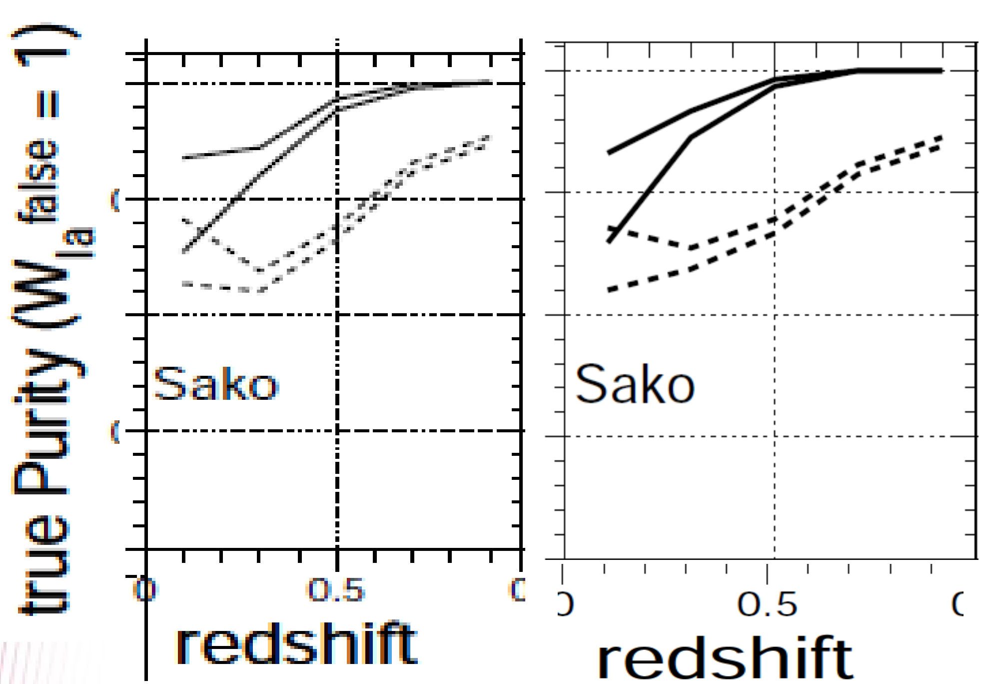
3. kPCA applied to SNe classification





Results from the *Supernova Photometric Classification Challenge* (Kessler et al., 2010)

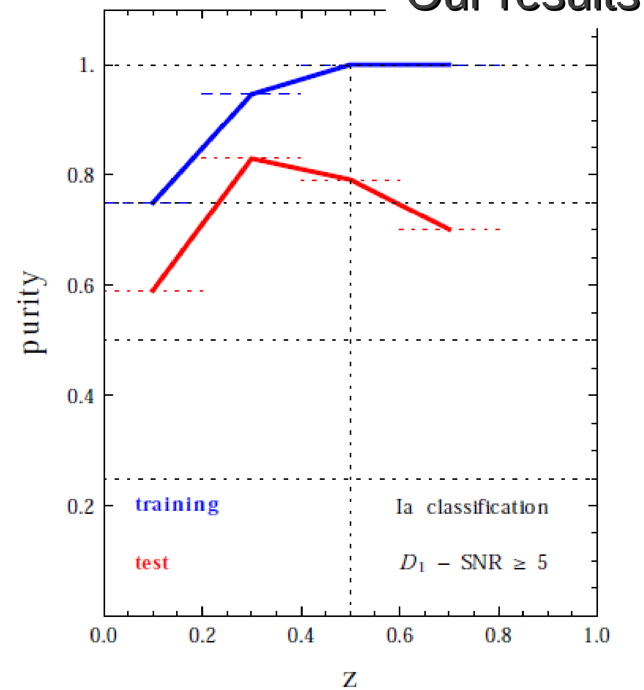
3. kPCA applied to SNe classification



No hostZ

hostZ

Our results



average purity: 75%

Same result as winner SNPCC (76%), without using host redshift information

Results from the *Supernova Photometric Classification Challenge* (Kessler et al., 2010)

Better result in intermediate redshift

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4. Conclusions

1. SNe photometric classification is not a future issue..
   it is already here!

2. kPCA is a powerfull tool, mainly if we are interested in a high quality purity in intermediate redshifts.

3. There is no need of enviromental, redshift or astrophysical hypothesis

4. Great potential in detecting previously non-observed objects: Application to PISN search

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