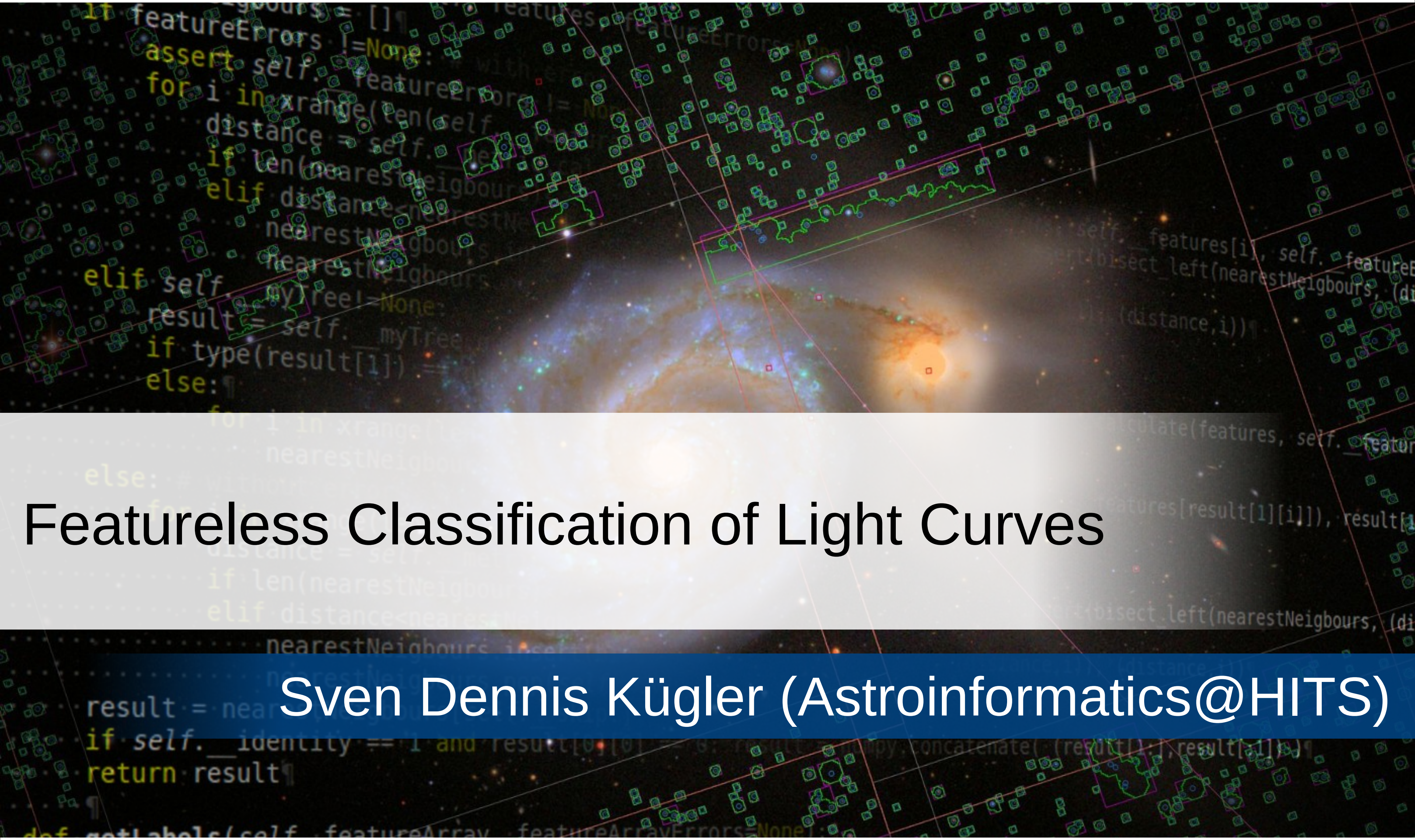
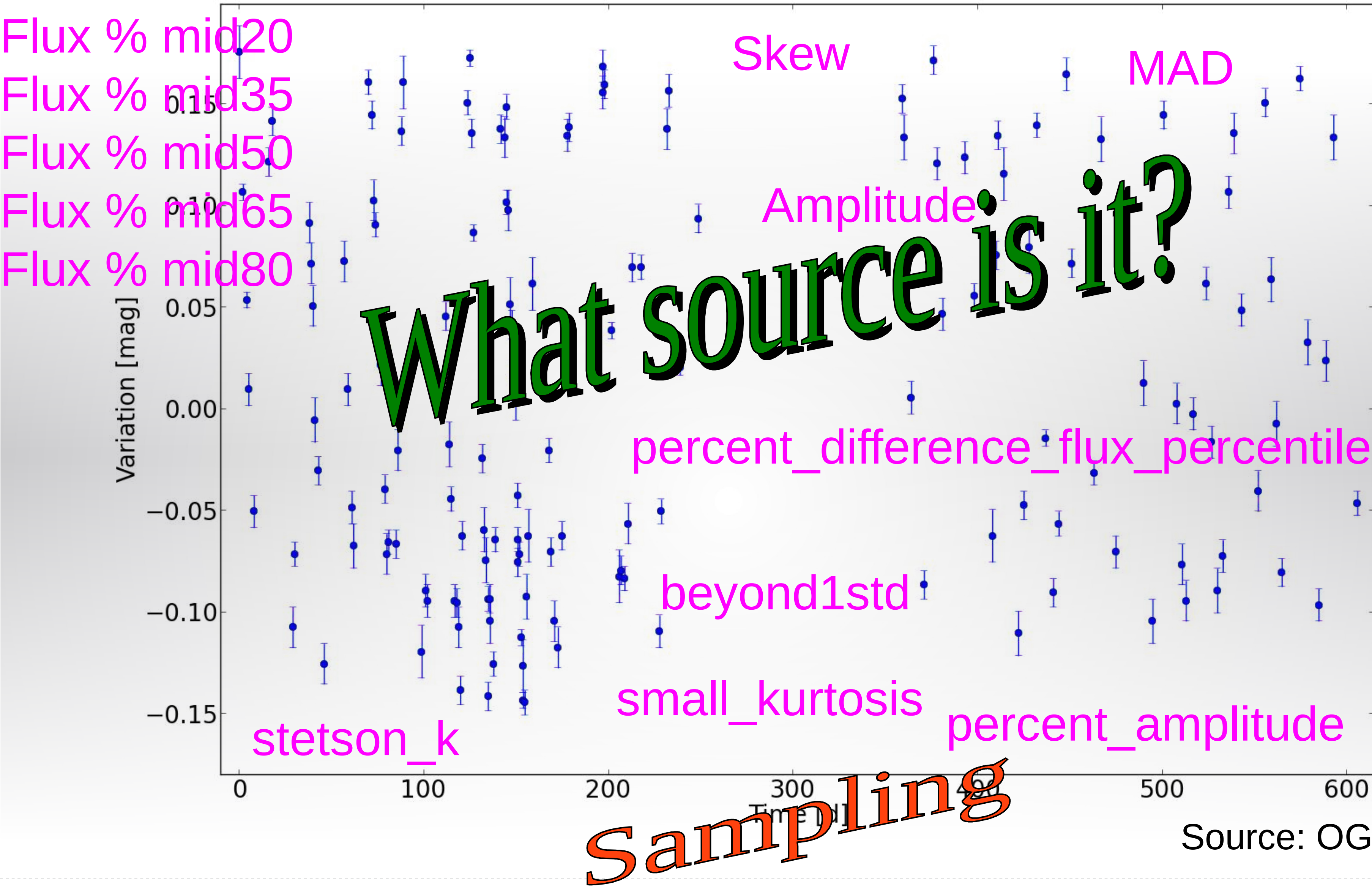


Featureless Classification of Light Curves

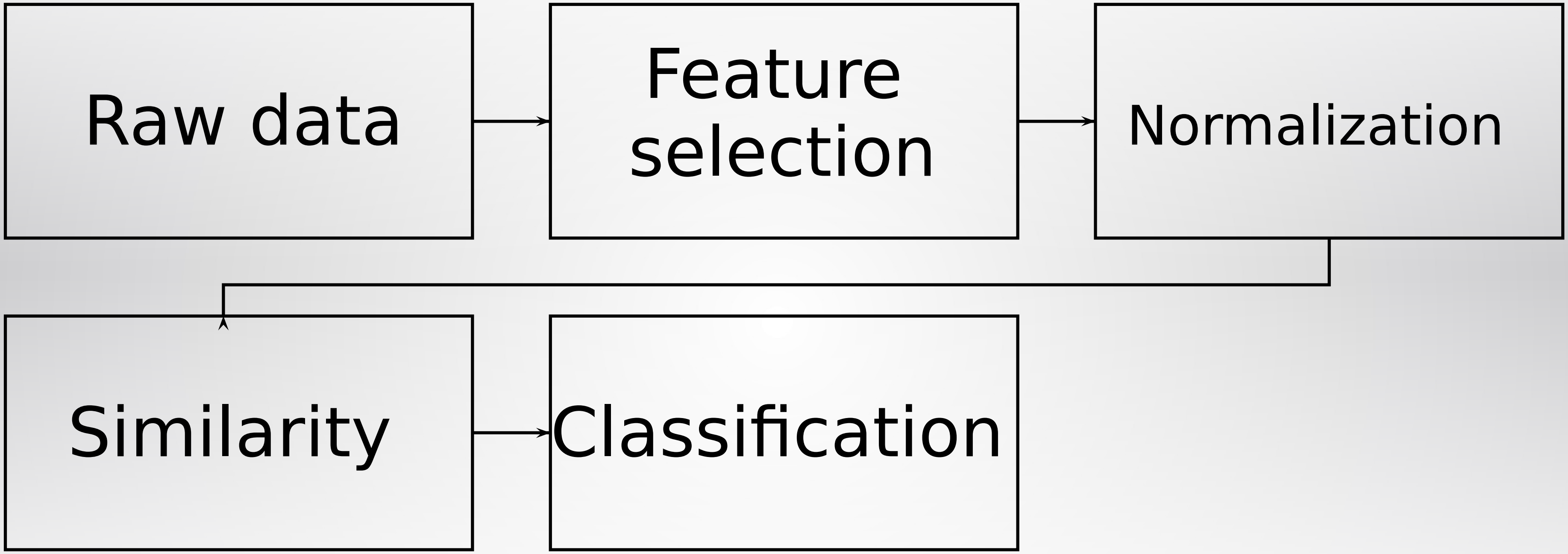
Sven Dennis Kügler (Astroinformatics@HITS)

Feature-based representation



Source: OGLE

Feature-based representation



Feature-based representation

Problem:

– Creation & selection of features is arbitrary

– Features are strongly biased

– Features do not allow meaningful use of unsupervized tasks

– Uncertainty cannot be taken into account

↓

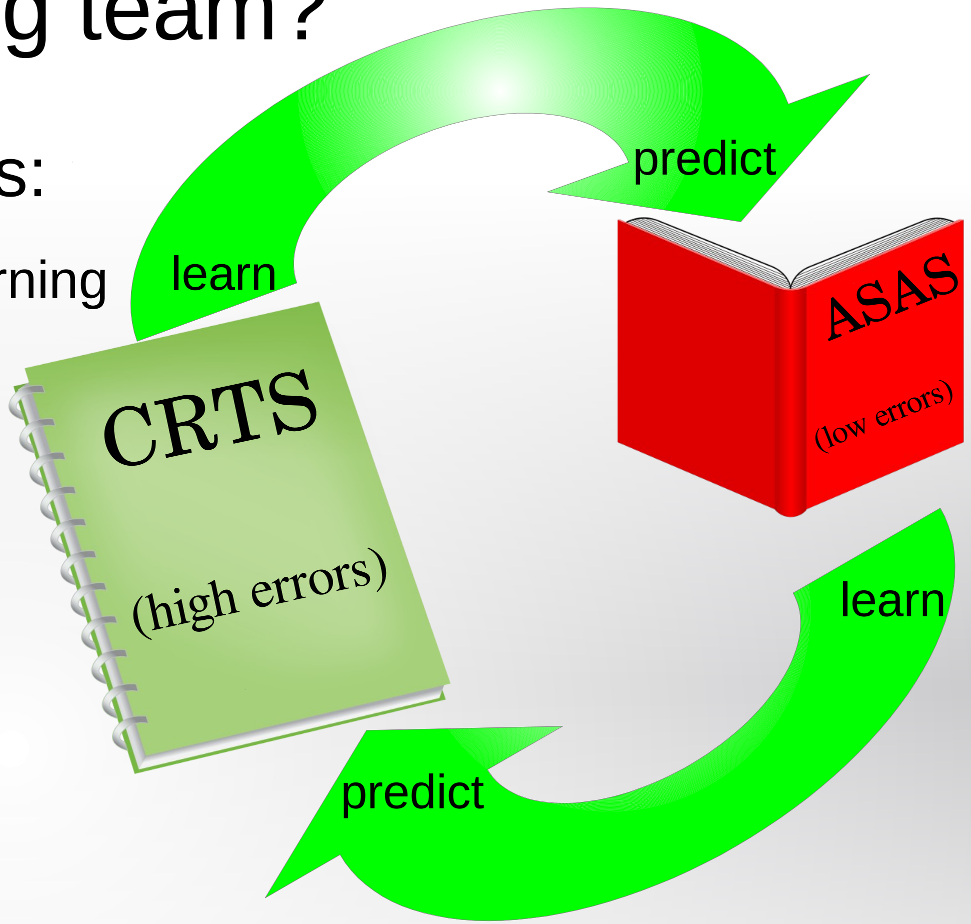
works well for classification of similarly bright objects in individual surveys

But nothing else

Never change a winning team?

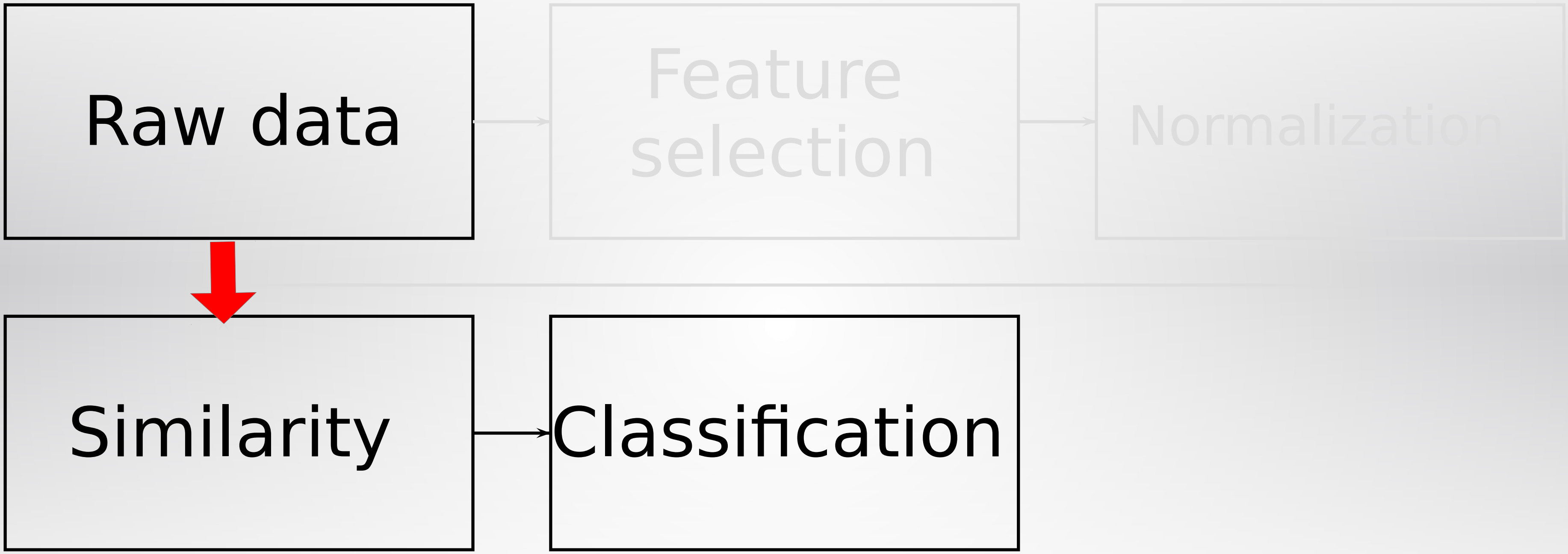
Prospects for new approaches:

- (semi-supervised) transfer learning
- Avoiding in-survey biases
- Detection of outliers
- Unsupervized methodology

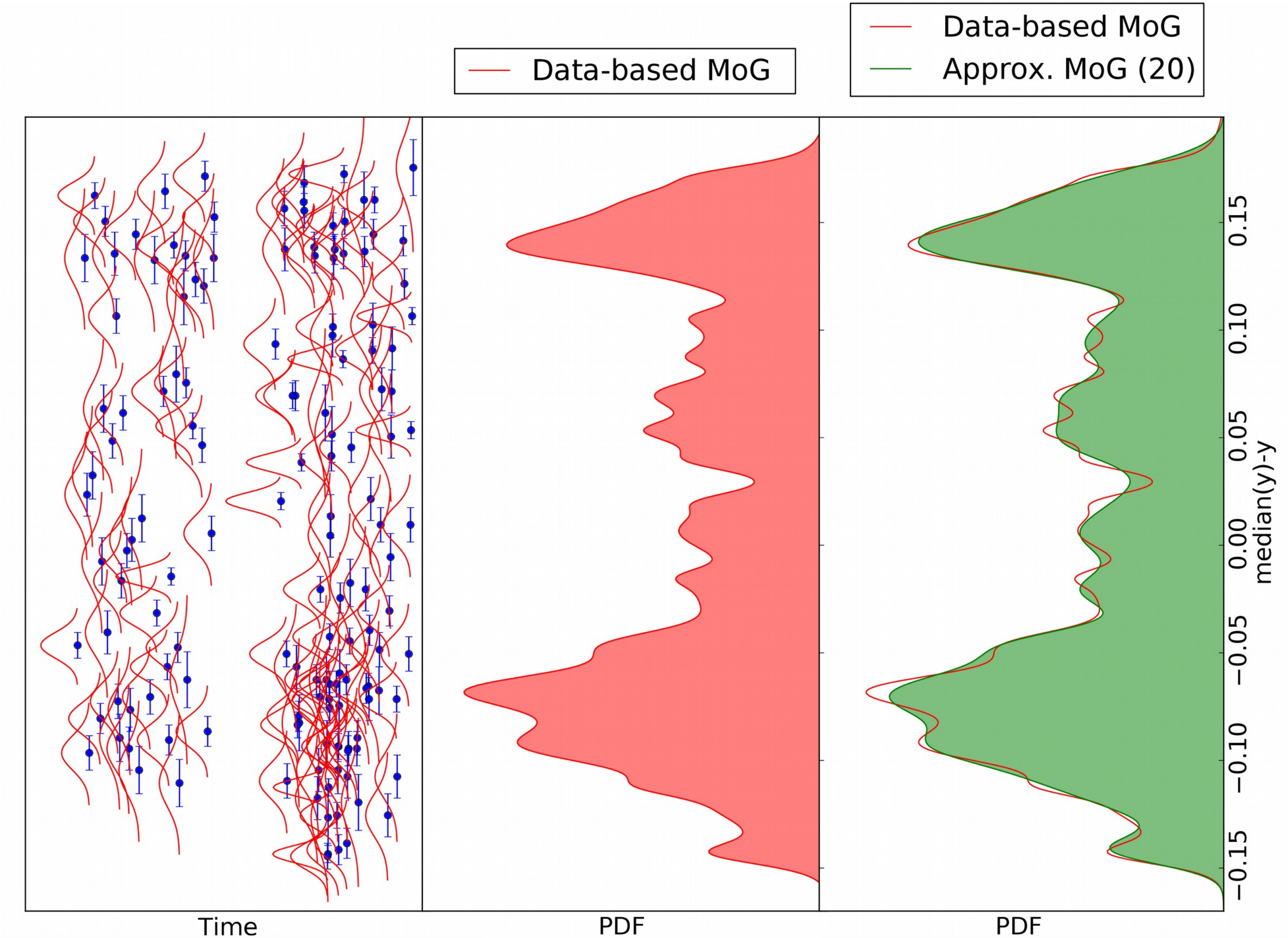


Avoiding black-box-like selections allows to obtain "real" understanding of data

Density-based representation



Density-based representation



Kügler et al., 2015, MNRAS

Density-based representation

Judging distances between two densities:

L2 norm

$$\int_{-\infty}^{+\infty} (|p(x)-q(x)|)^2 dx$$

Bhattacharyya

$$-\ln\left(\int_{-\infty}^{+\infty} \sqrt{p(x)q(x)}\,dx\right)$$

Kullback-Leibler-Divergence

$$\int_{-\infty}^{+\infty} p(x)\log\left(\frac{p(x)}{q(x)}\right)dx+\int_{-\infty}^{+\infty} q(x)\log\left(\frac{q(x)}{p(x)}\right)dx$$

Numerical experiments

7-class-classification experiment (ASAS)

	kNN	ν-SVM	RF
Features (raw)	74.22 ± 1.24 k=11	78.02 ± 0.68 $\nu = 0.19$, $\delta = 0.53$	79.98 ± 1.16 $T = 400$
Features (norm.)	77.60 ± 0.76 k=17	80.47 ± 1.21 $\nu = 0.17$, $\delta = 0.10$	79.99 ± 1.55 $T = 400$
L2	79.57 ± 0.80 k=19	82.08 ± 0.89 $\nu = 0.01$, $\delta = 0.56$	– –
KLD	78.96 ± 1.87 k=23	75.56 ± 0.94 $\nu = 0.26$, $\delta = 0.34$	– –
BHA	79.73 ± 0.83 k=29	81.11 ± 0.90 $\nu = 0.20$, $\delta = 0.14$	– –

Kügler et al., 2015, MNRAS

Numerical experiments

7-class-classification experiment (ASAS)

Feature-based

	MIRA	ED	RRL	EC	ESD	DSCT	DCEP-FU
MIRA	94.5	0.5	3.8	0.7	0.0	0.0	0.4
ED	0.8	90.5	0.0	3.6	4.7	0.2	0.1
RRL	9.3	0.7	75.1	7.6	0.1	3.7	3.5
EC	1.5	1.4	1.4	90.1	2.5	2.4	0.5
ESD	2.0	19.1	0.3	19.8	52.6	5.2	0.9
DSCT	3.4	3.7	11.3	35.0	7.2	35.5	3.9
DCEP-FU	7.9	3.9	24.2	20.0	3.8	8.2	32.0

Density-based

	MIRA	ED	RRL	EC	ESD	DSCT	DCEP-FU
MIRA	93.7	0.3	4.6	0.7	0.0	0.1	0.6
ED	0.1	91.4	0.1	2.8	4.8	0.5	0.2
RRL	9.3	0.2	79.5	2.9	0.1	3.2	4.8
EC	0.6	0.8	1.0	90.9	3.0	2.5	1.1
ESD	0.4	20.3	0.2	19.0	55.3	3.2	1.5
DSCT	0.7	4.2	14.5	25.8	3.2	43.6	8.0
DCEP-FU	5.9	2.6	24.7	15.5	2.6	11.8	37.0

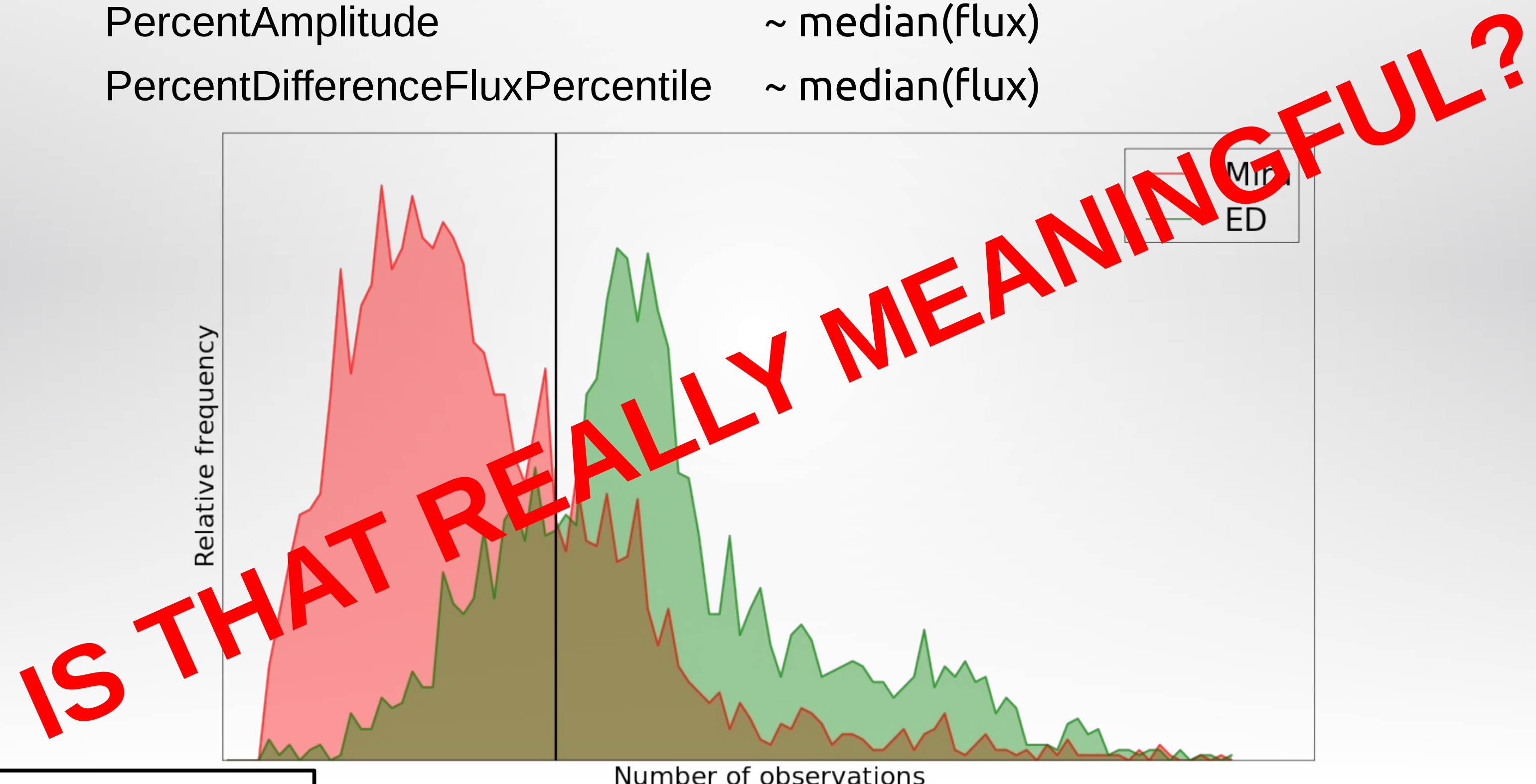
Kügler et al., 2015, MNRAS

Numerical experiments

7-class-classification experiment (ASAS)

3 features cannot be encoded in density-representation:

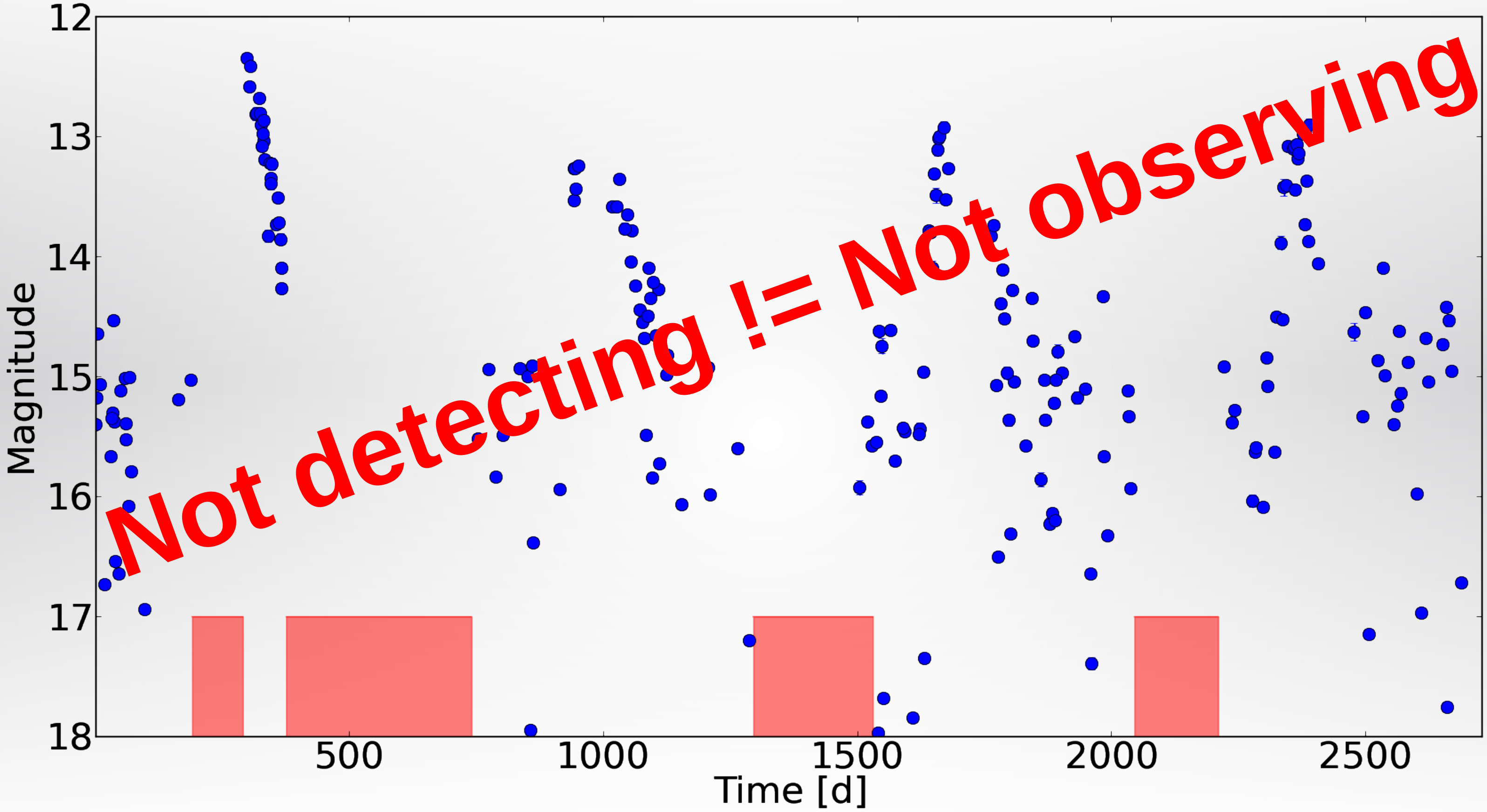
StetsonK	~ 1/(number of observations)
PercentAmplitude	~ median(flux)
PercentDifferenceFluxPercentile	~ median(flux)



Kügler et al., 2015, MNRAS

Numerical experiments

7-class-classification experiment (ASAS)

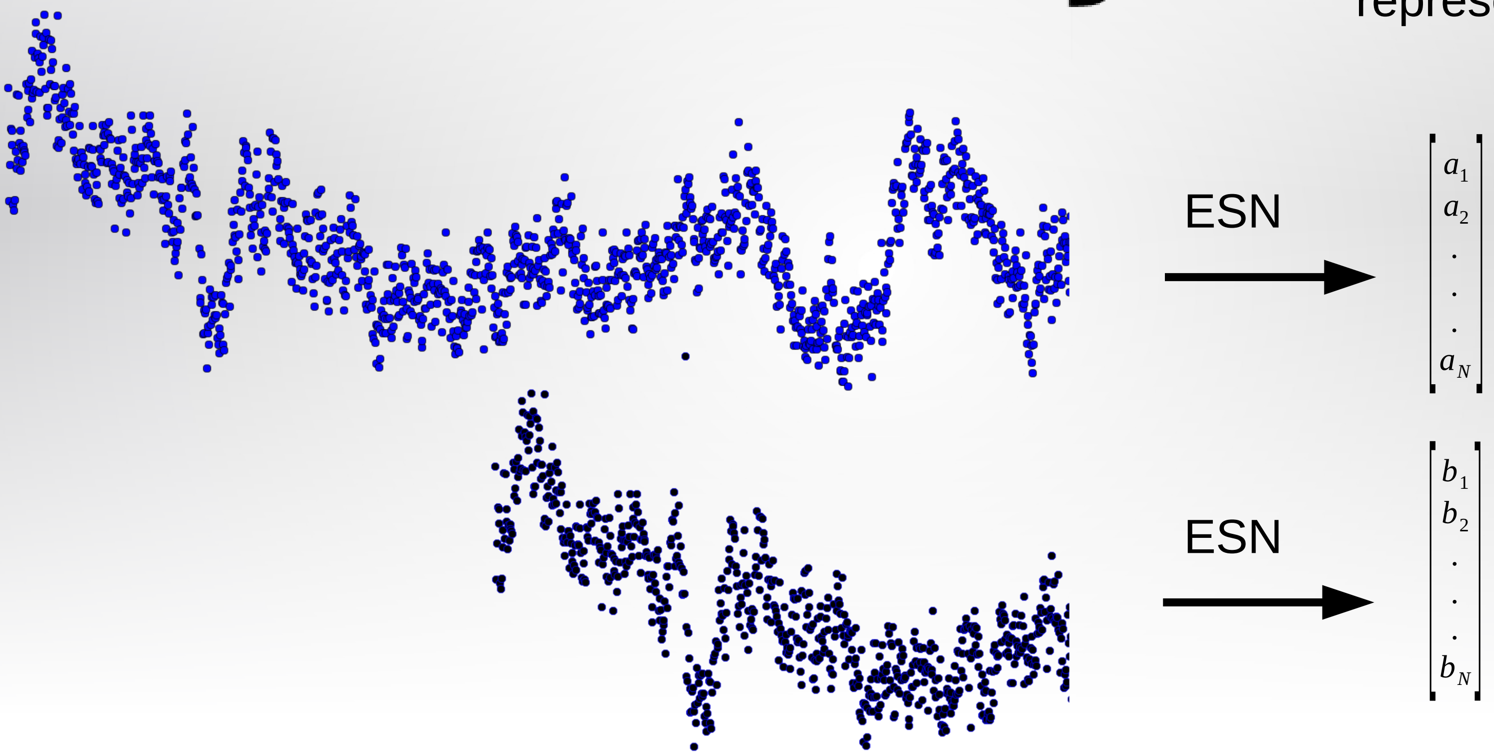


Analysis of Regular Time Series

Problem:

- Time series generally of variable length
- Respect of sequential behavior
- Invariance against time shifts required

Conversion to a **vector** representation



Analysis of Regular Time Series

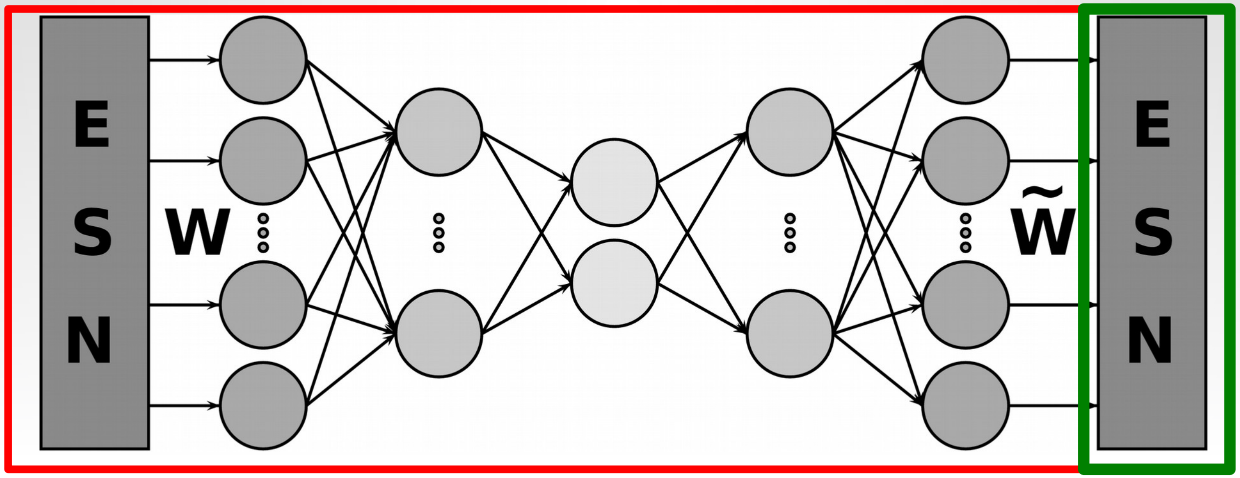
These **vector representations** can be visualized.

However

- Visualization algorithms: optimal de- & compression of representation
- Scientifically more interesting: reconstruction error on the data

We propose coupling

Regular visualization



Returns a valid model

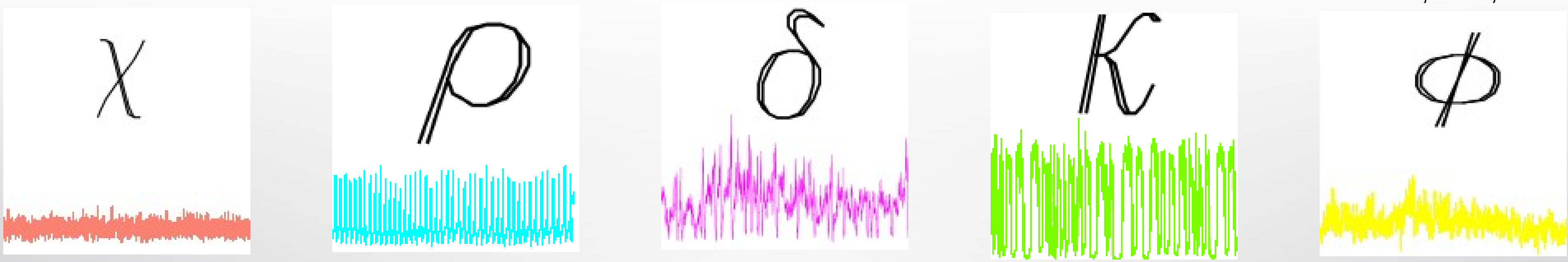
↓

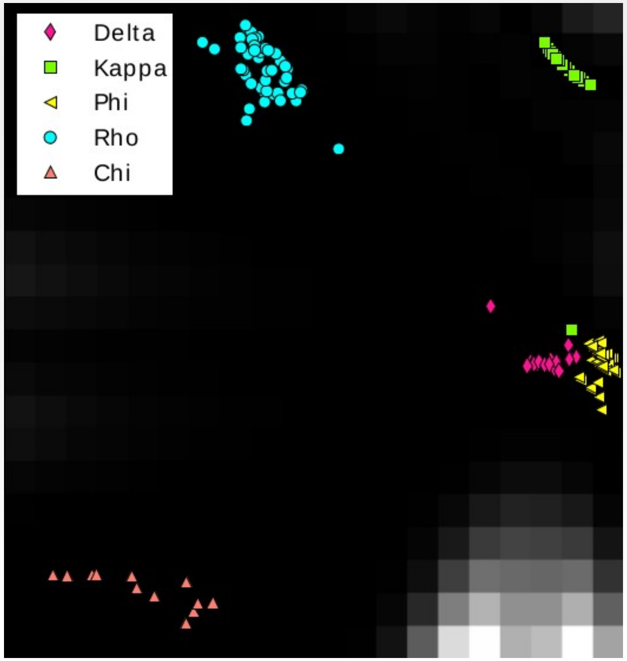
reconstruction of data

Results

Application to different states of an X-ray binary (RXTE)

Credit: Harikrishnan et al., RAA, 2012

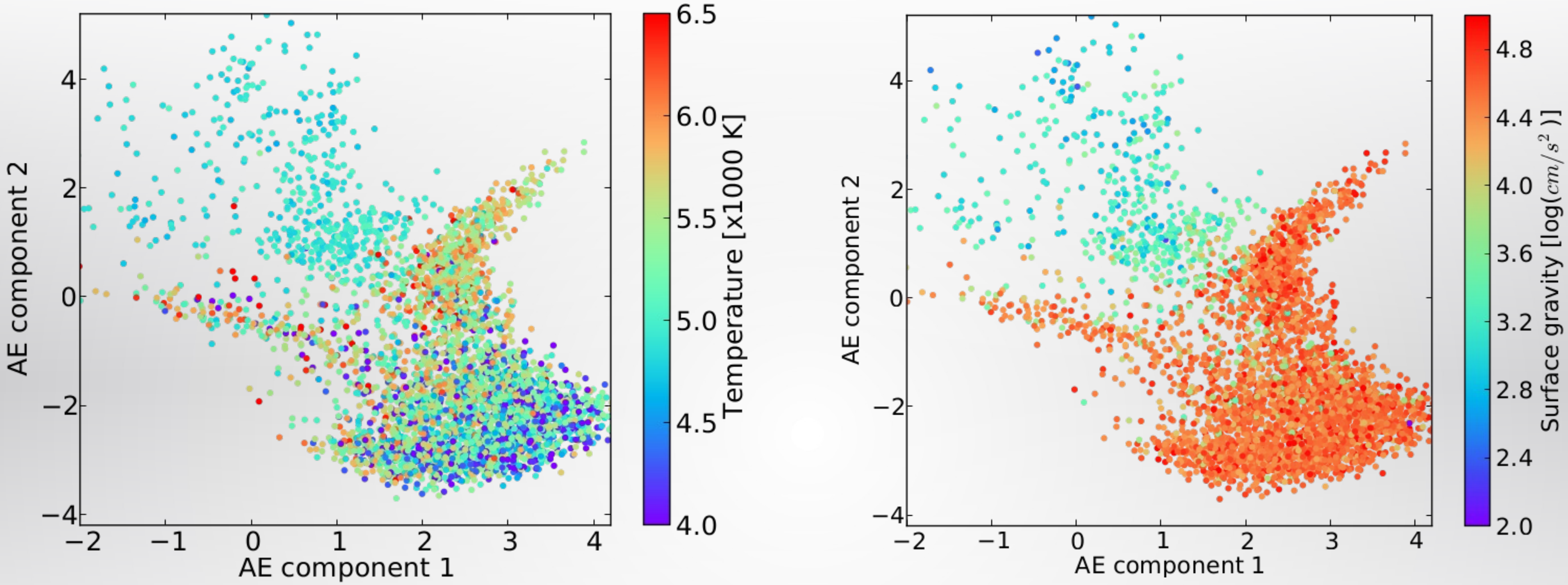




Gianniotis et al., 2015
submitted to Neurocomputing

Results

Application to Kepler Light Curves



Kügler et al., 2015
submitted to MNRAS

Summary

Irregularly sampled time series

Method

density-based representation

capturing all uncertainties

Inclusion of non-detections

Avoiding survey specific biases

Results

Comparable Performance to features

Omitting arbitrary feature selection

Allowing for unsupervised methodology

Exploring transfer learning scheme

Regularly sampled time series

Method

ESN as vector representation

Respecting sequential nature

Coupling visualization to ESN

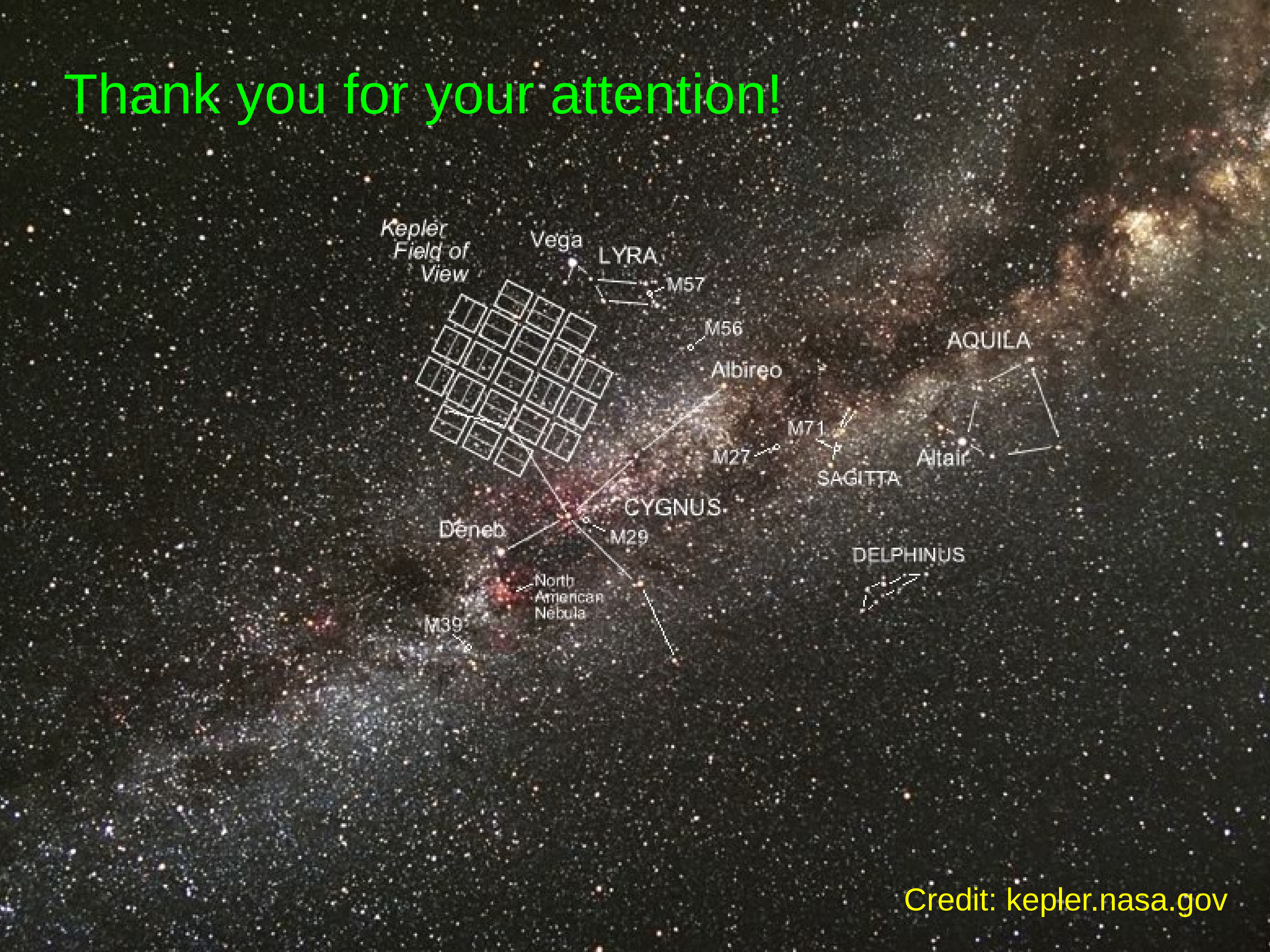
Results

Visualization according to latent dynamics

Recovery of physical properties

No comparable method exists

Thank you for your attention!



Credit: kepler.nasa.gov