A Neural Network Approach to Visualising Astronomical Time Series

Nikos Gianniotis, Dennis Kügler, Kai Polsterer, Peter Tiňo

Astroinformatics Group @ Heidelberg Institute for Theoretical Studies HITS

Problem statement

We are working with datasets of time series, and what we would like to do is reduce the dimensionality of the time series.

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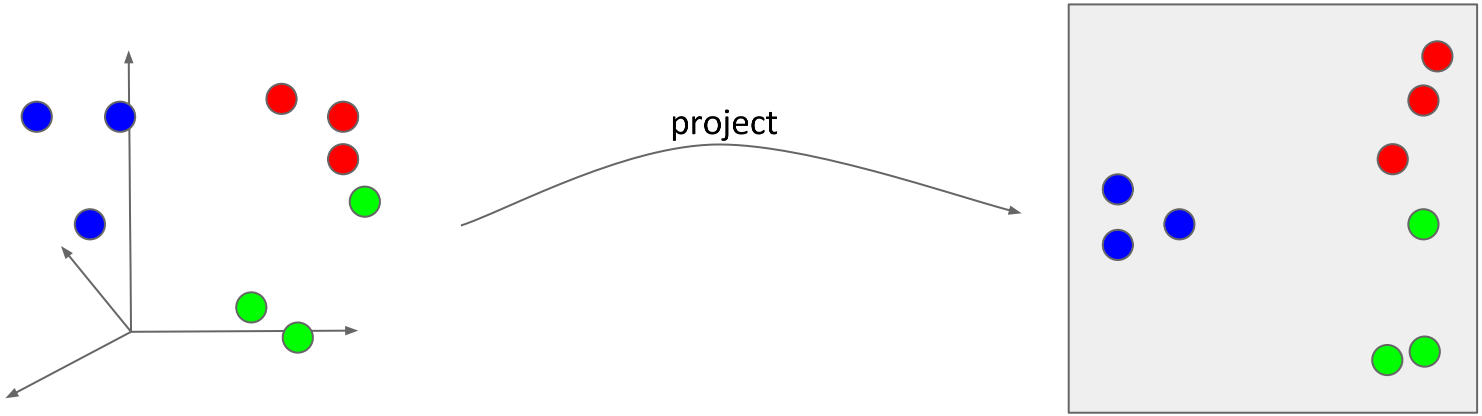

D-dimensional vector data **y**

2D projections **x**

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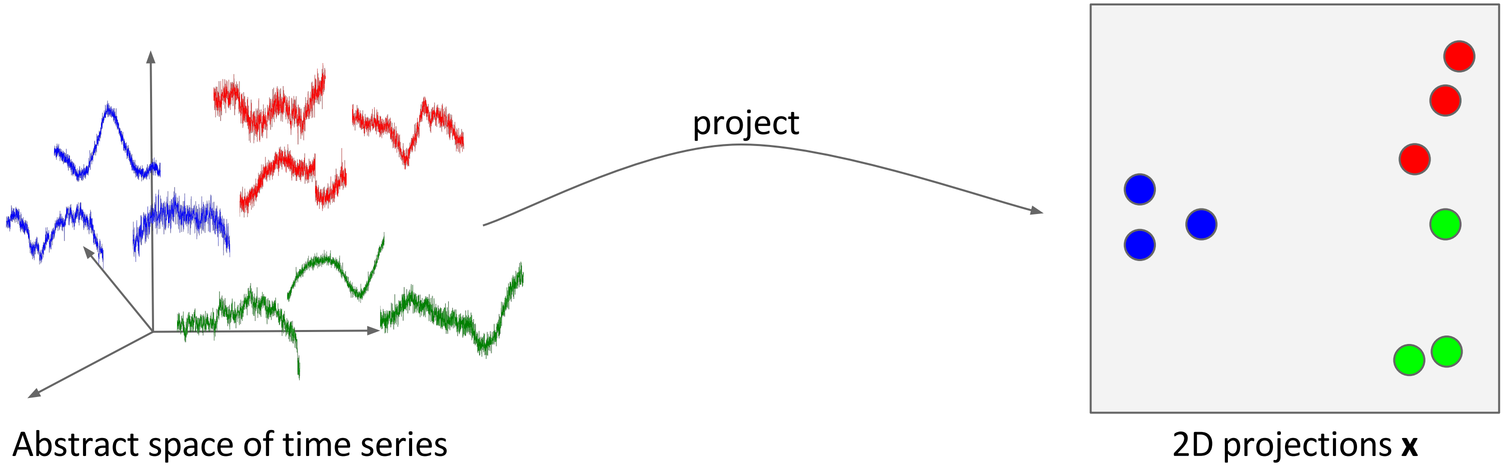
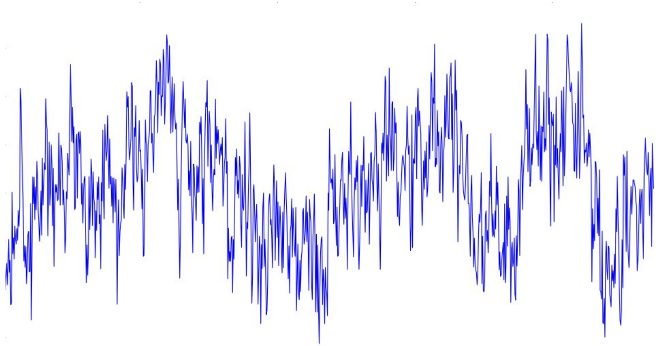
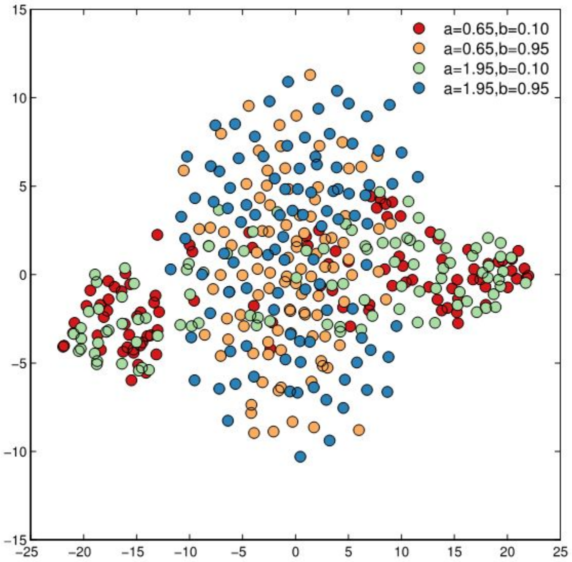


Is it serious?





Sequences from Gaussian process with correlation function given by

$$c(x_t, x_{t+1}) = (1 + |h|^{\alpha})^{-\frac{\alpha}{b}}$$

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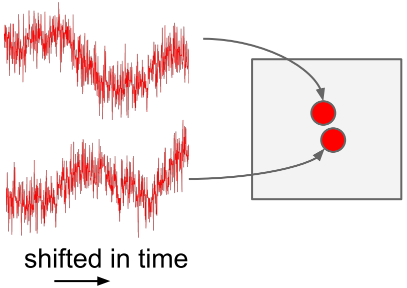
When projecting time series we must account for



translation invariance

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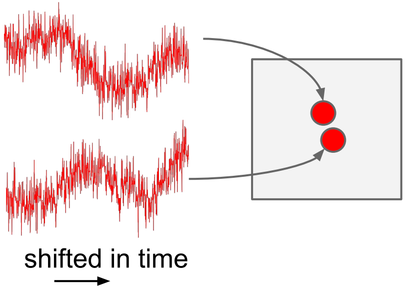

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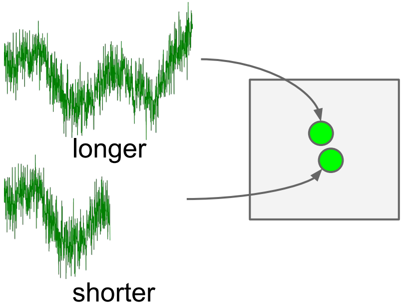

variable length

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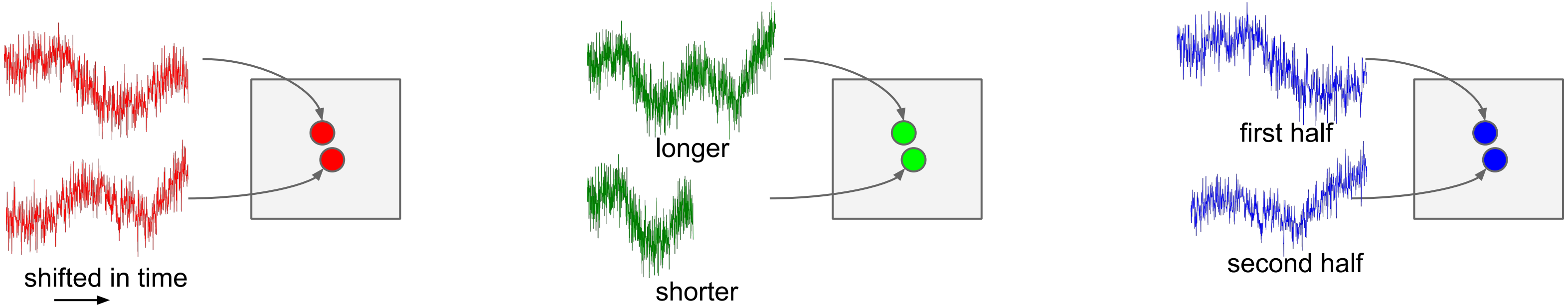

translation invariance **variable length** **partially observed**

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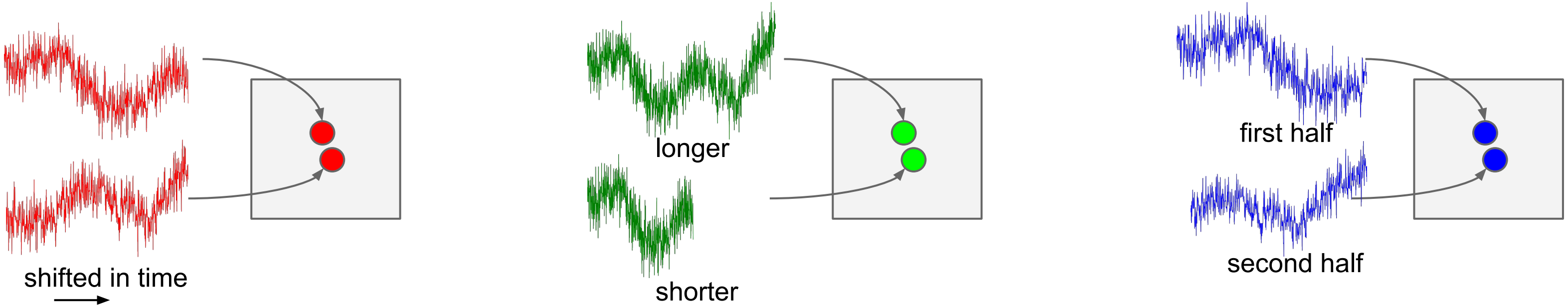


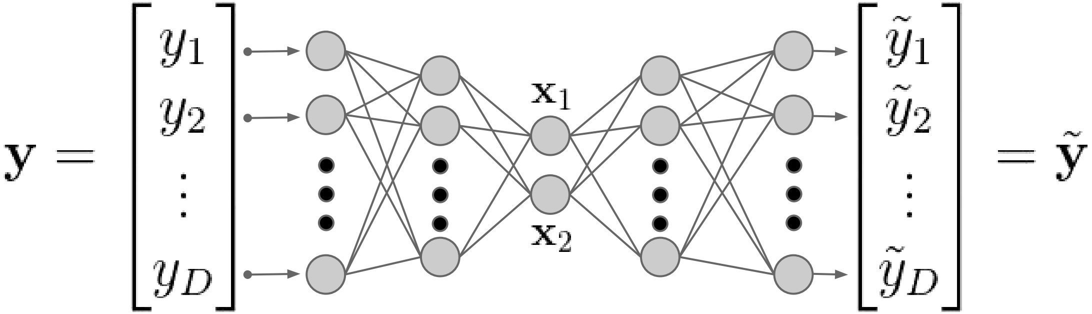
translation invariance **variable length** **partially observed**

Proposed solution

- come up with a new representation for time series
- reduce dimensionality of new representation via autoencoder

Sketch of autoencoder

Fan-in fan-out neural network



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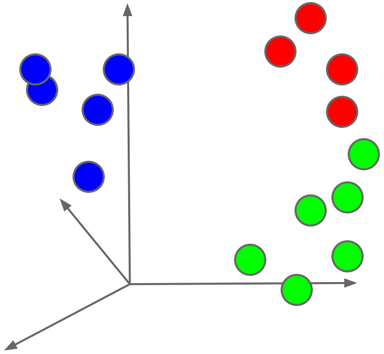

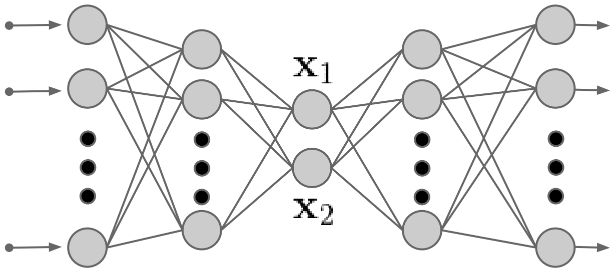

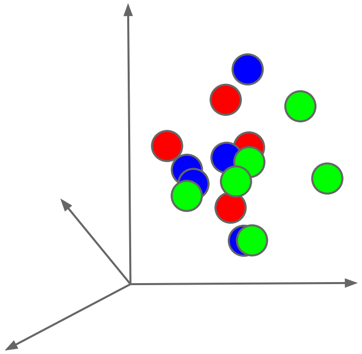

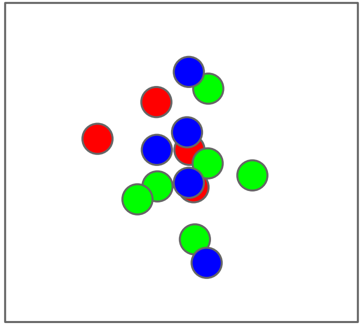

Train by minimising discrepancy

$$\|\mathbf{y} - \tilde{\mathbf{y}}\|^2$$

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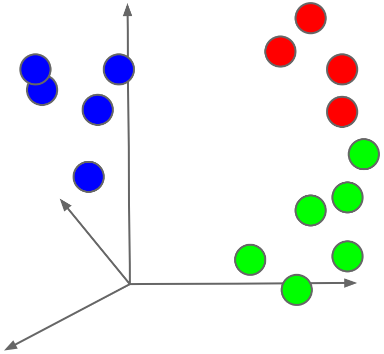

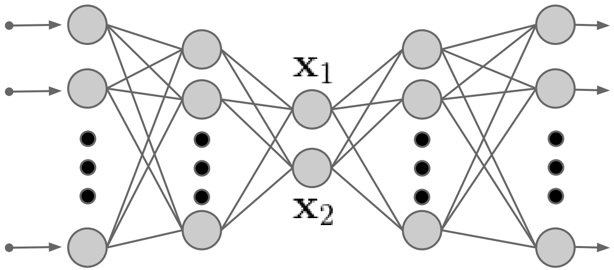

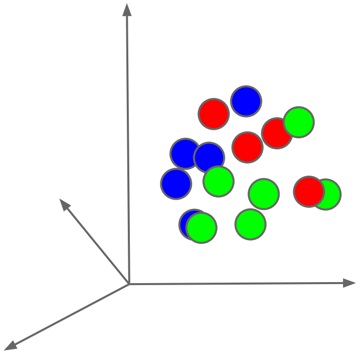

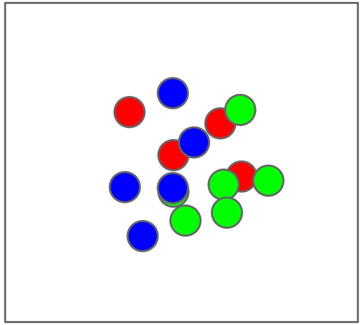

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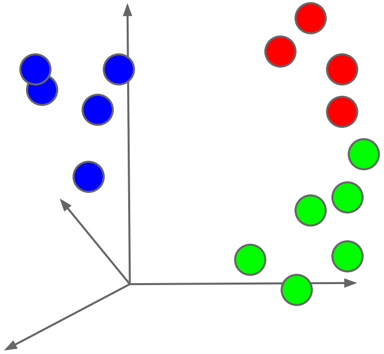

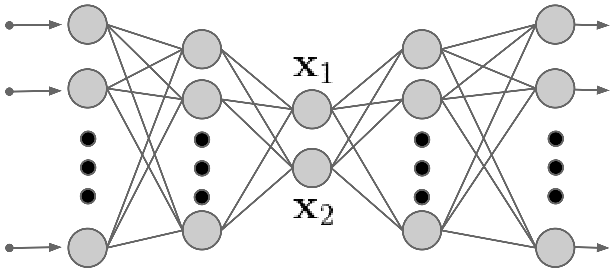

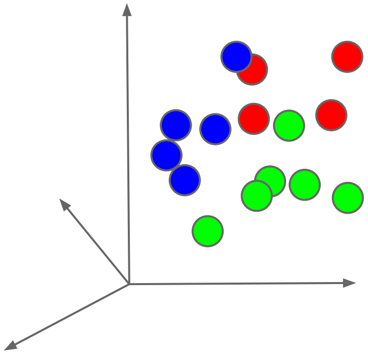

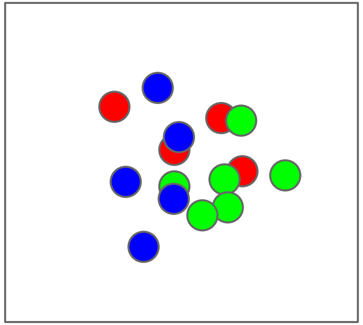

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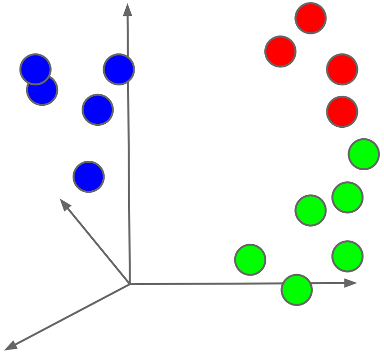

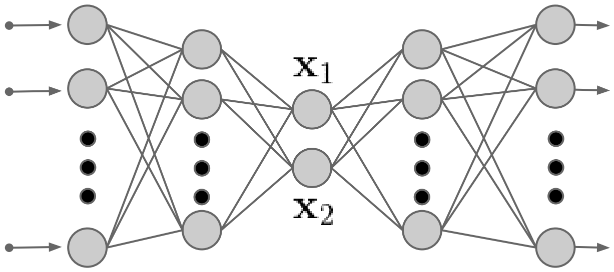

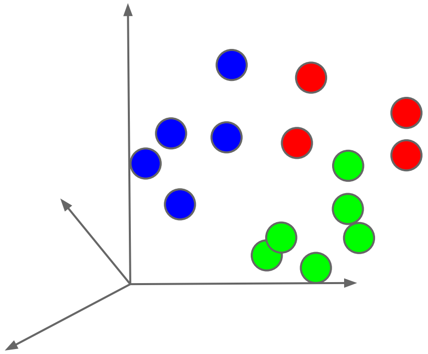

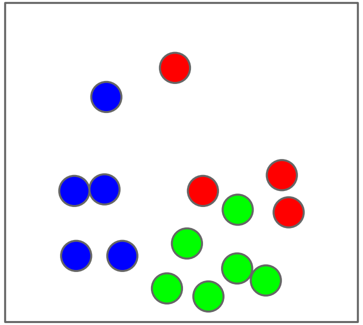

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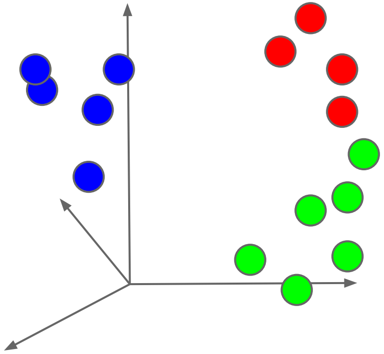

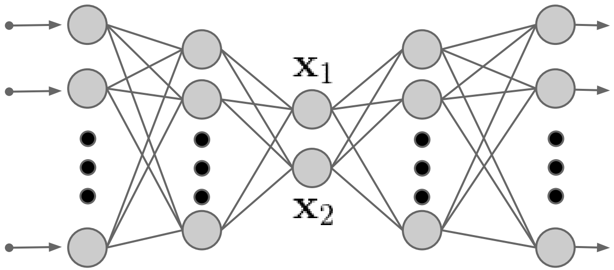

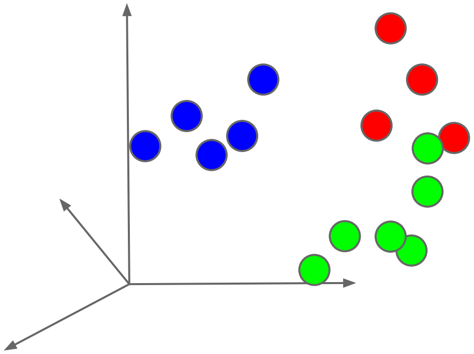

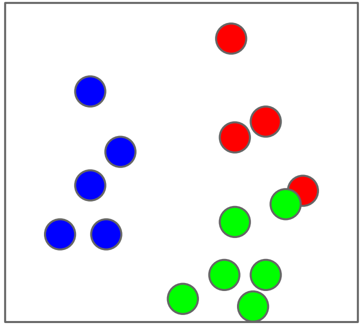

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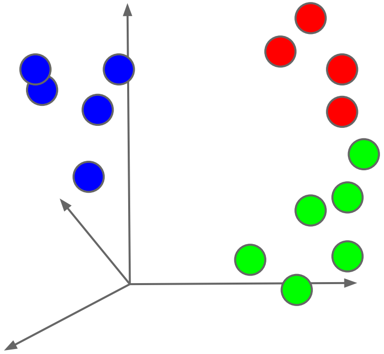

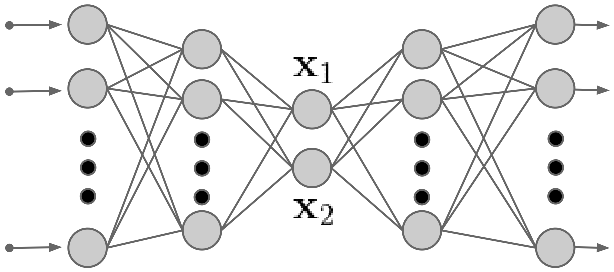

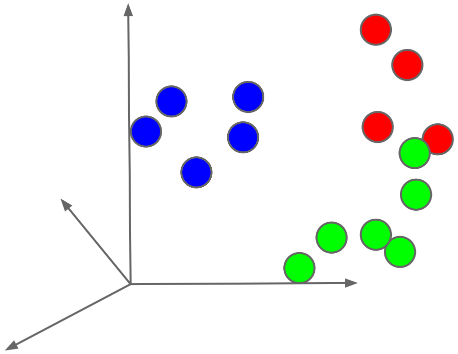

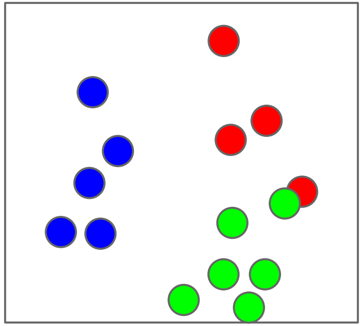

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New representation for time series

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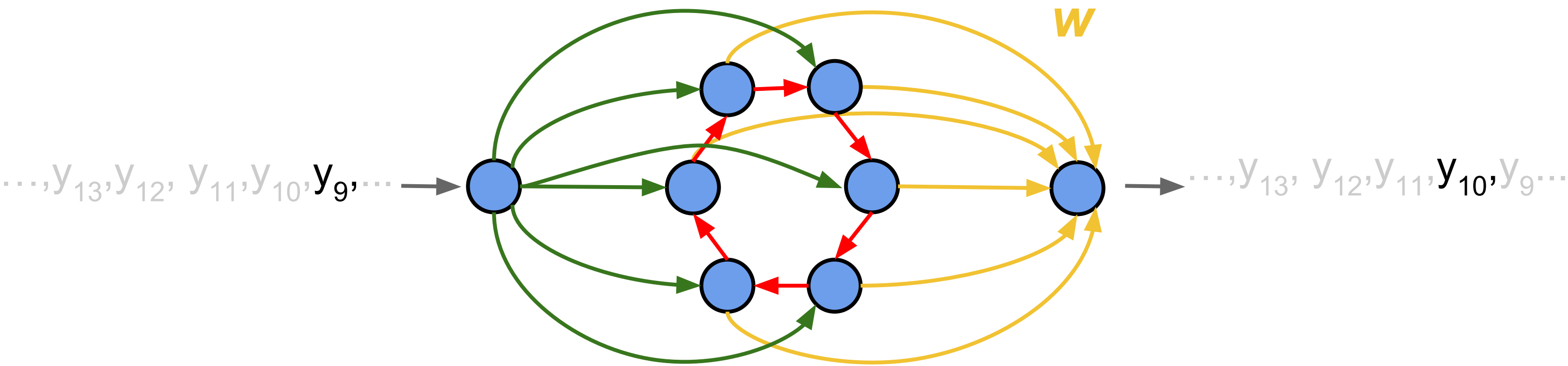
Use the echo state network (ESN) to represent time series as vectors *w*



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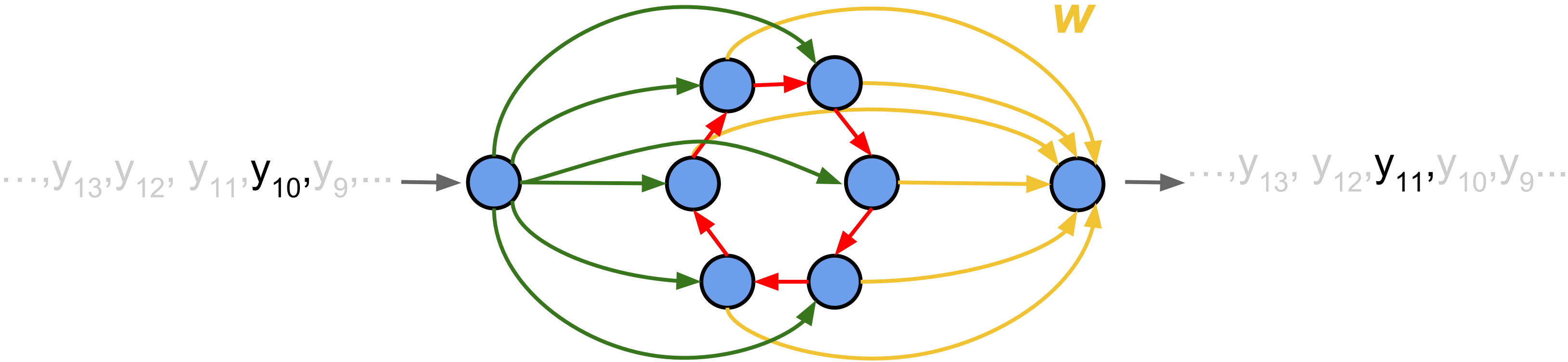

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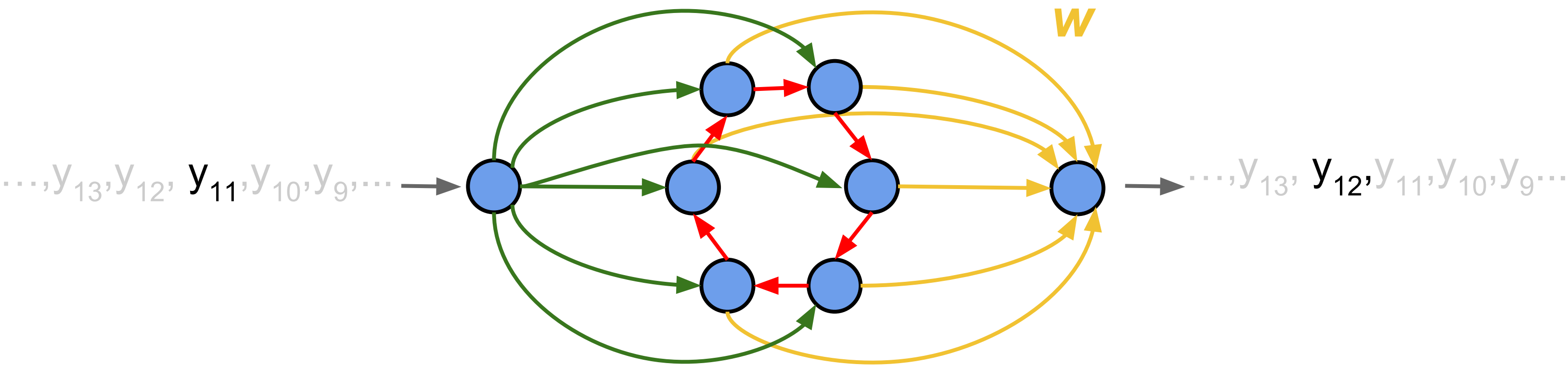

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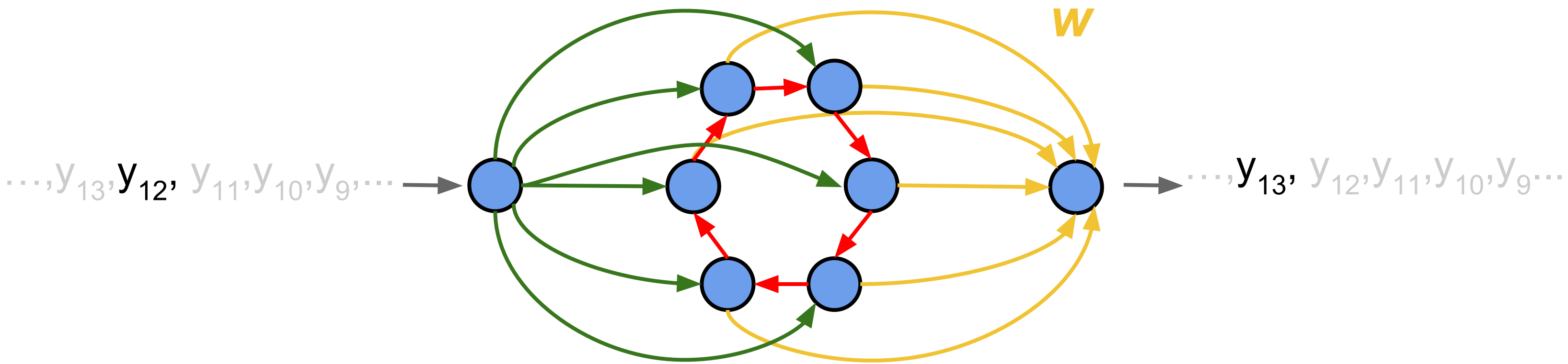

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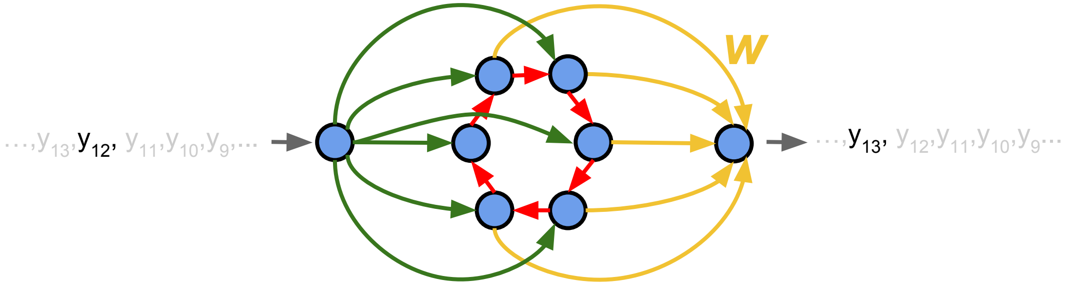

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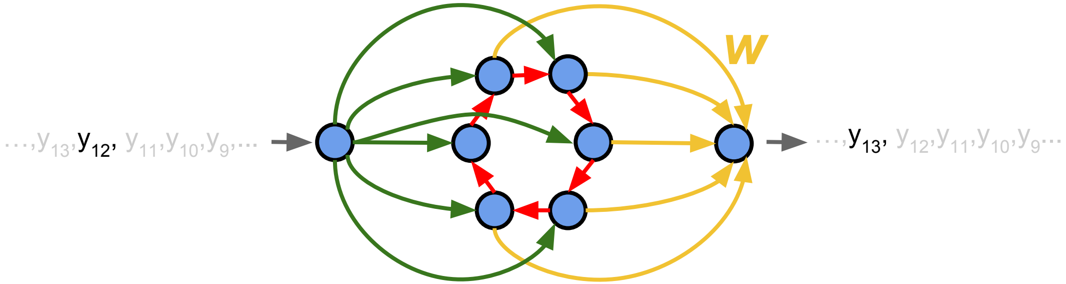

Measure *"one-step aheadedness"* via *g(y;w)*

Vector $\mathbf{w}$ captures temporal behaviour of $\mathbf{y}$

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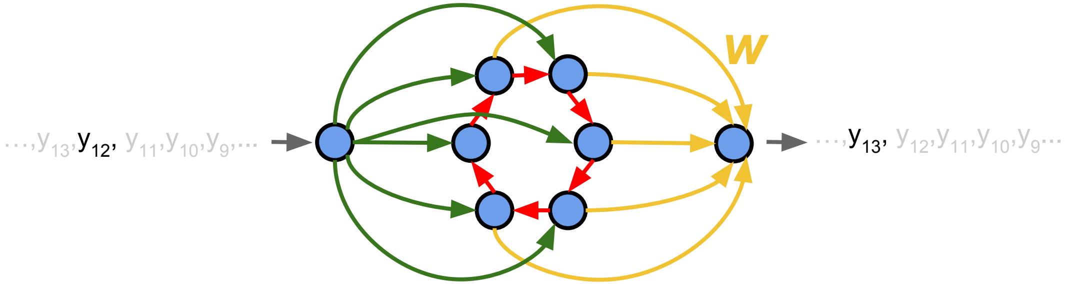

Measure *"one-step aheadedness"* via ***g(y;w)***

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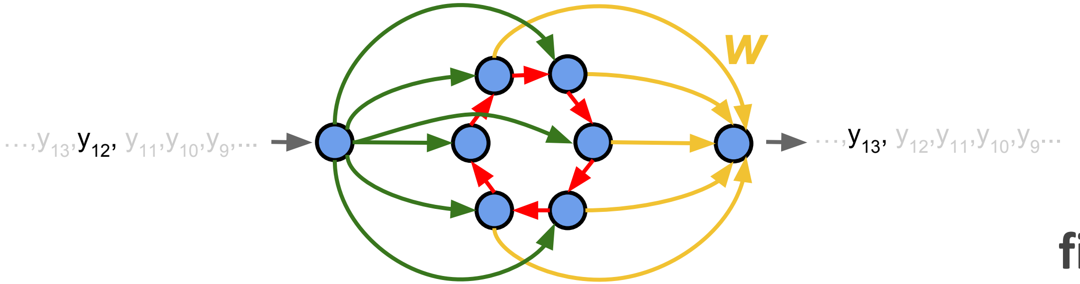
Fit an ESN model to each time series and obtain

$$
\begin{array}{ccc}
\mathbf{y}_1 & \rightarrow & \mathbf{w}_1 \\
\mathbf{y}_2 & \rightarrow & \mathbf{w}_2 \\
 & \vdots & \\
\mathbf{y}_N & \rightarrow & \mathbf{w}_N
\end{array}
$$

New representation for time series



fitted w invariant to shift, length, partial observation

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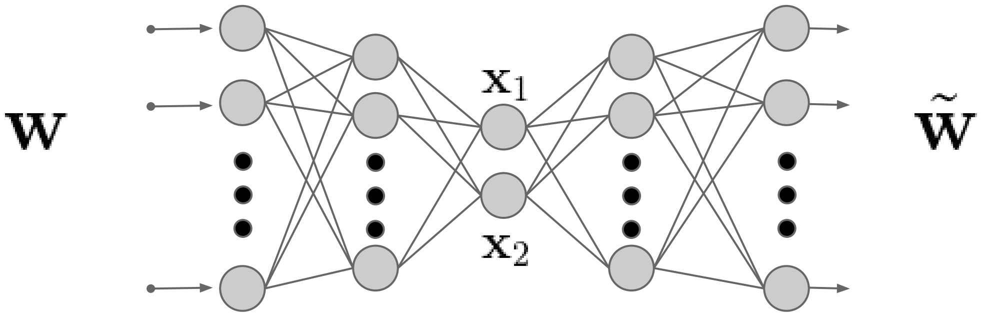
Autoencoding of new representation

Let us autoencode ***w*** instead of ***y***:



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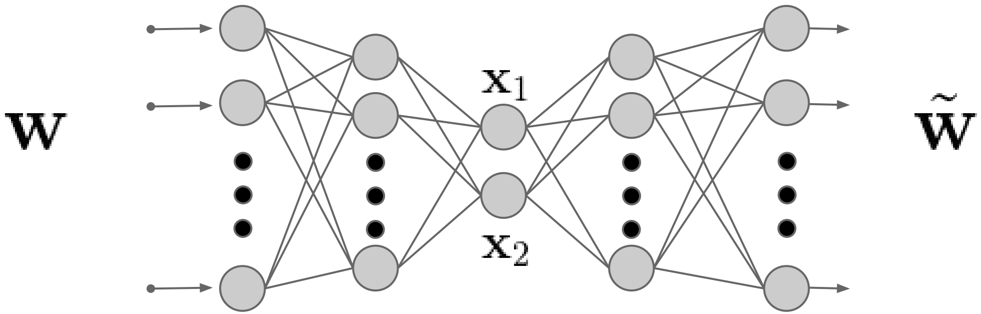

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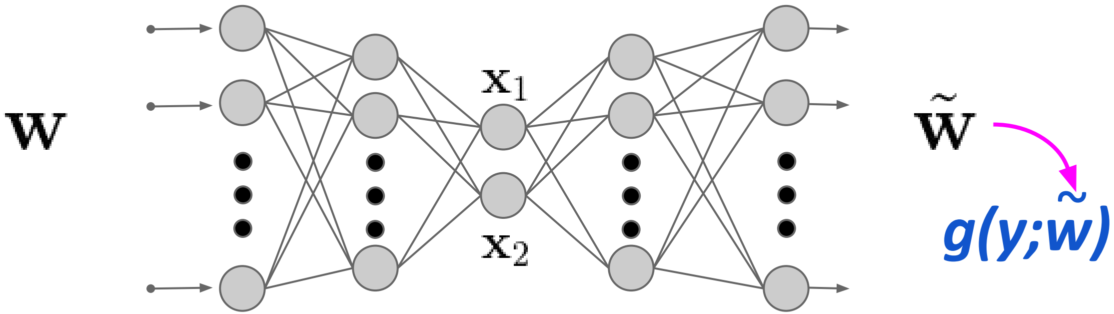
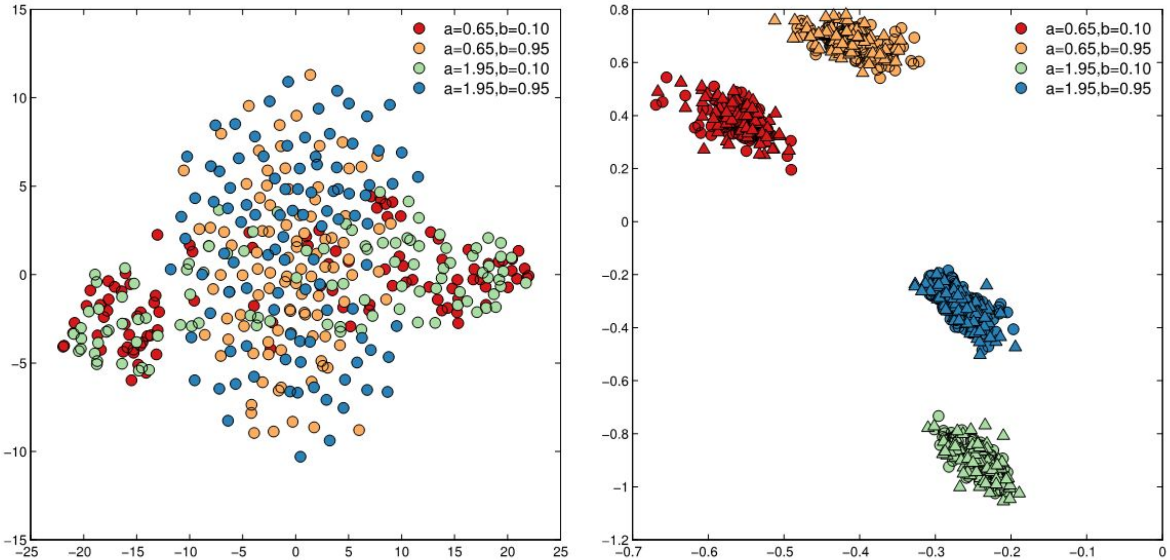


- Now we are compressing ESN weight vectors ***w***
- Don't measure reconstruction with ~~$||\mathbf{w} - \tilde{\mathbf{w}}||^2$~~
- Reconstruction: plug $\tilde{\mathbf{w}}$ into g and check how well it still predicts on ***y***

Revisit Cauchy series



before **proposed**

Sequences from stationary Gaussian process with correlation function given by

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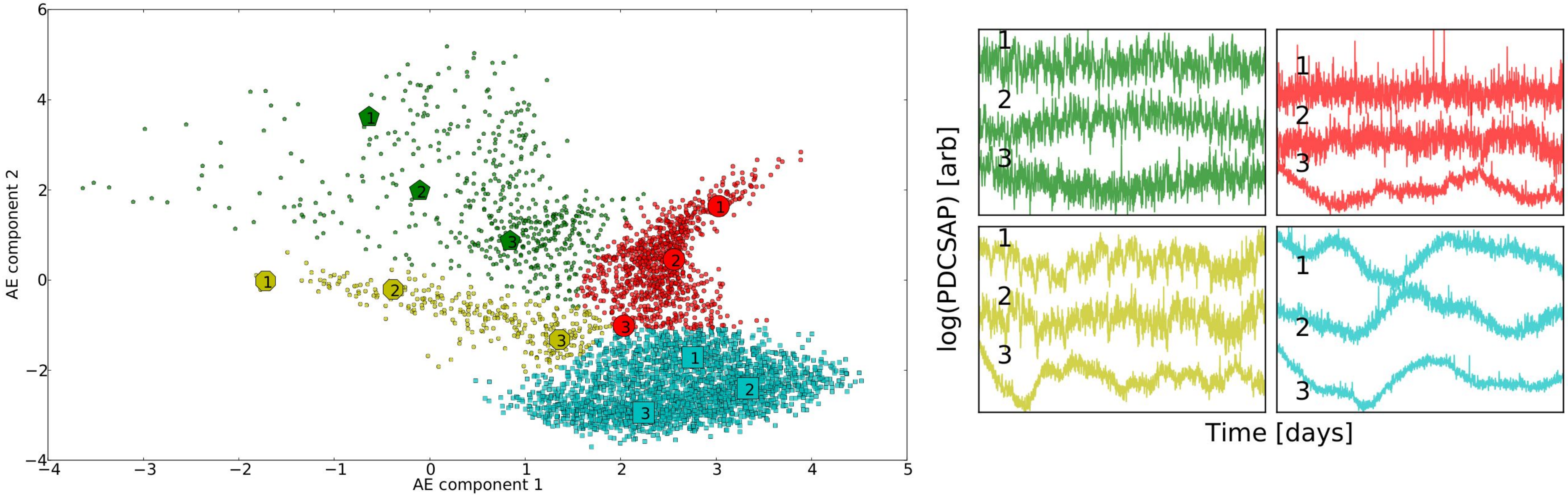
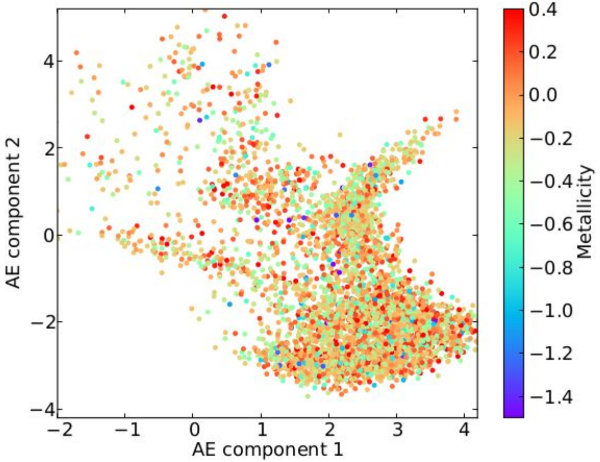
Real data - Kepler light curves (1)



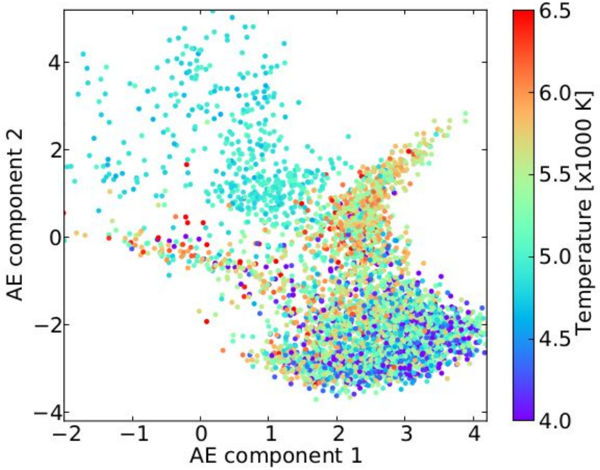
Data taken from online repository of Kepler mission

Real data - Kepler light curves (3)

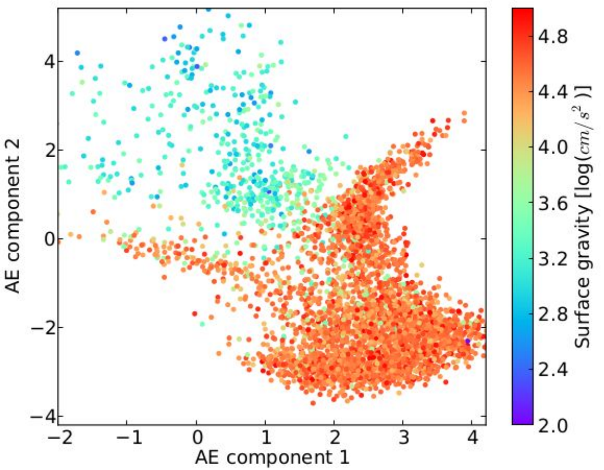
Physical properties



(a) Metallicity



(b) Temperature



(c) Surface gravity

Surface gravity correlates strongly with variability behaviour

Conclusion

- Time series are qualitatively different entities than vectors
- Latent regime must be accounted in dimensionality reduction
- Currently working on not regularly sampled time series
- For more information please refer to:

Model-Coupled Autoencoder for Time Series Visualisation, Neurocomputing

An Explorative Approach for Inspecting Kepler Data, MNRAS

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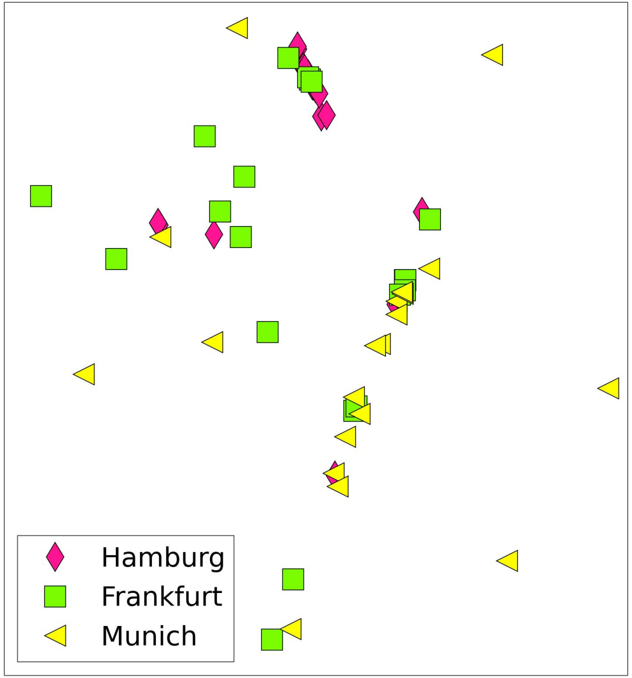
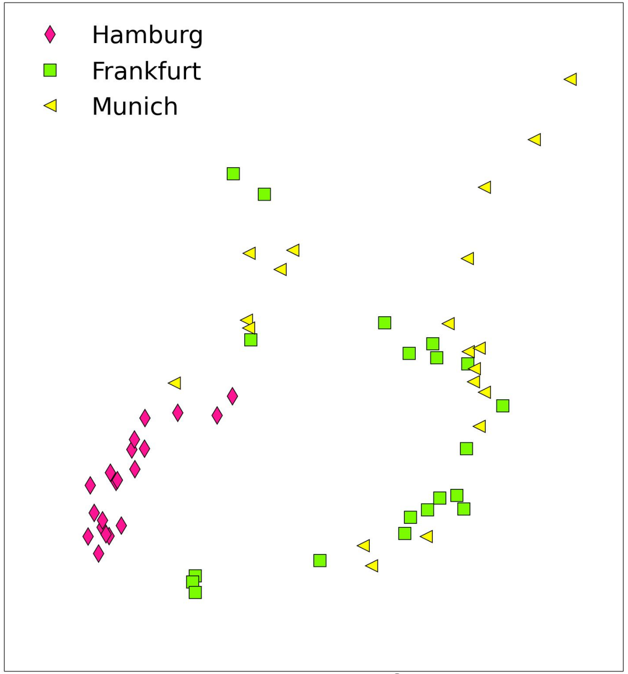
Thank you for your attention!

Real data - Wind speed data

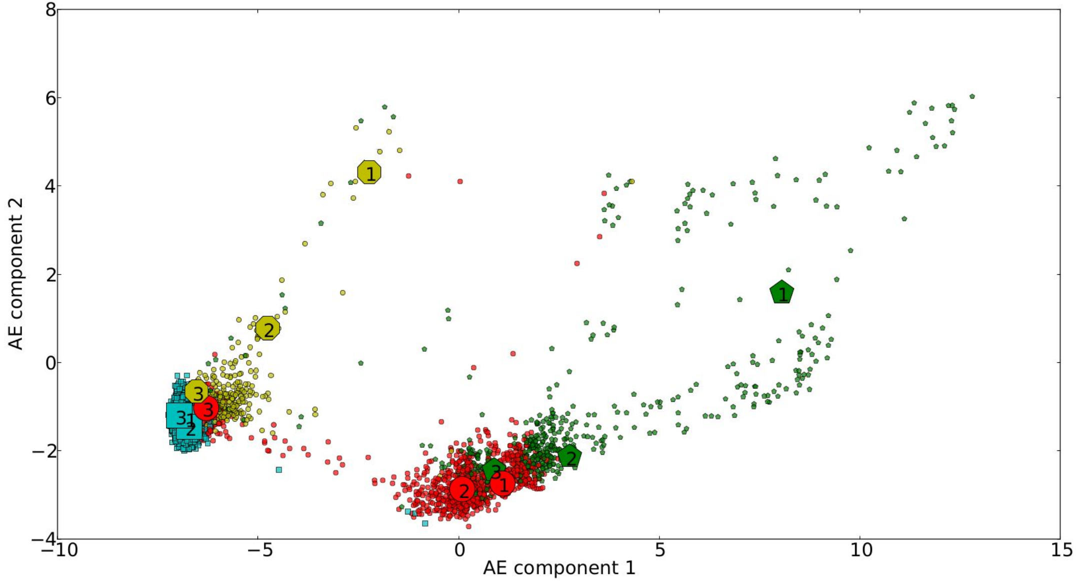


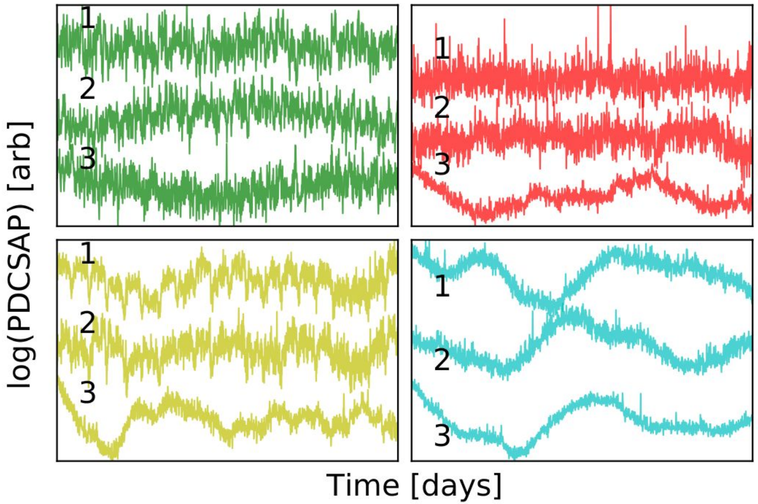


proposed

Data taken from 10 stations around Hamburg, Frankfurt and Munich
Courtesy of Deutscher Wetterdienst

Real data - Kepler light curves (2)





Time series autoencoded as vectors

Autoencoding of new representation

Let us a

Why is Euclidean distance on parameters meaningless?

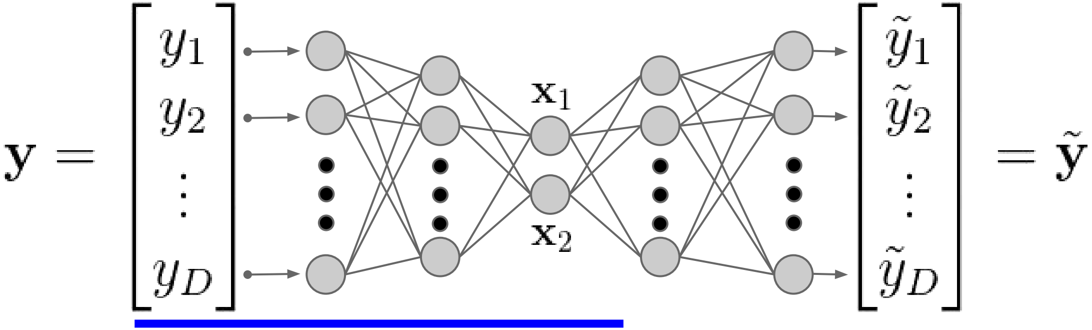
- some components w_i have no effect
- some components w_i more sensitive
- some components in different scale
- . . .

Bad idea!

- Now
- Don't measure reconstruction with $\left\| \mathbf{w} - \tilde{\mathbf{w}} \right\|^2$

Sketch of autoencoder

Fan-in fan-out architecture



$$f_{enc}(\mathbf{y}) : \mathbb{R}^D \rightarrow \mathbb{R}^2 \qquad f_{dec}(\mathbf{x}) : \mathbb{R}^2 \rightarrow \mathbb{R}^D$$