The 29th Annual International Astronomical Data Analysis Software & Systems (ADASS) Conference

Visualizing High-Dimensional Chemical Abundance Space in GALAH DR2

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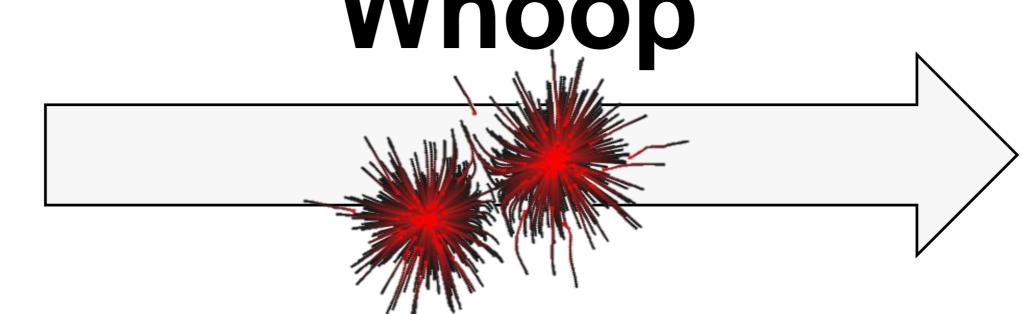
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Aim: Visualize high-dimensional data to find interesting patterns and underlying structures

High-Dimensional Data 0.5 0.5

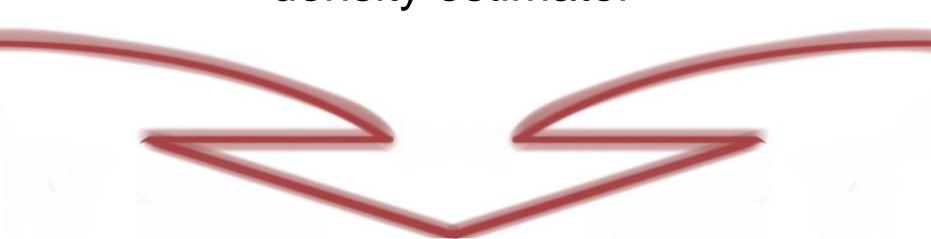
Gaussian random data with four clusters in 3D (also applicable to nD)

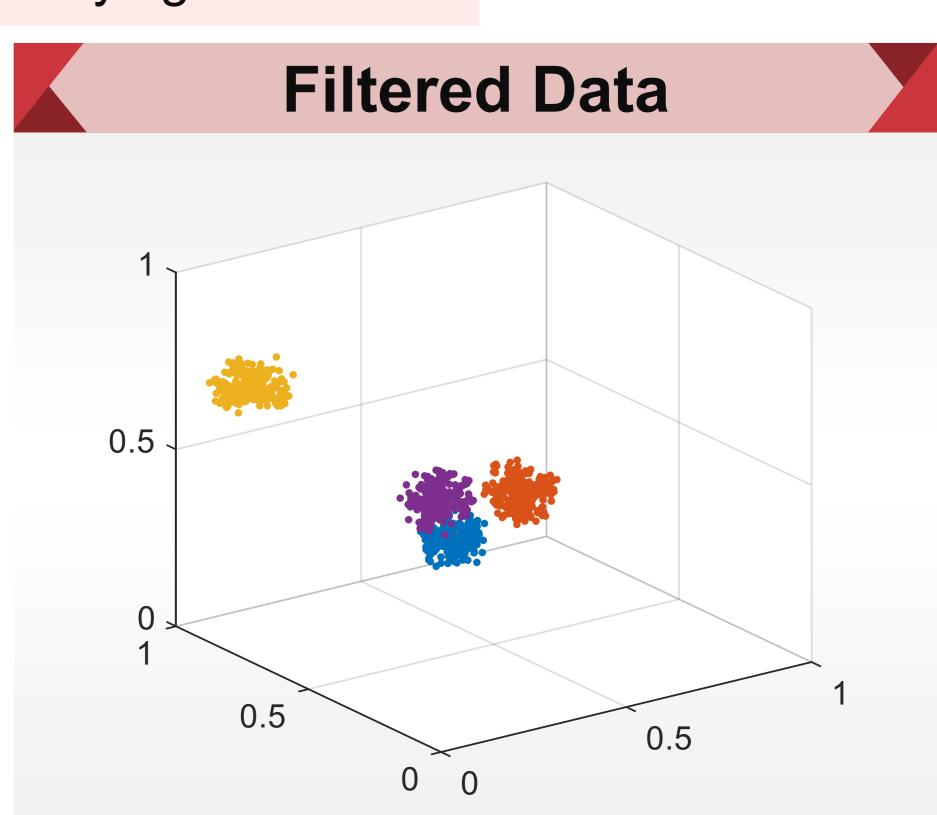
Filter high-dimensional data



Local Gradient Clustering (LGC)

Shift points along the gradient of the kernel density estimator





Clusters are separated in 3D

Landmark Multidimensional Scaling (LMDS [1]): Clusters are not well separated.

Method is fast.

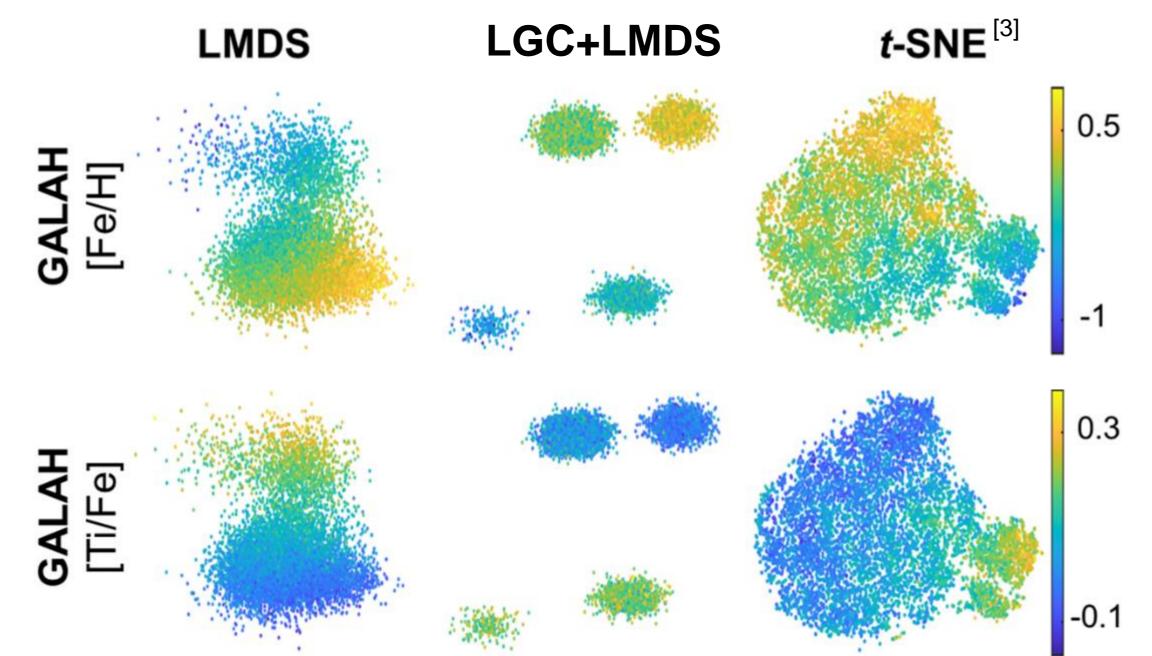
Dimensionality Reduction

Proposed method (LGC+LMDS): Clusters are well separated in the 2D projection. Method is fast.

t-Stochastic Neighbor Embedding (t-SNE [2]): Clusters are well separated. Method is slow.

GALAH DR2

- Dataset: 10K observations are randomly chosen from the second data release of GALactic Archaeology with HERMES survey (GALAH DR2) [4] cross-matched with Gaia DR2 [5-6]. 10-D data set that consists of the following 10 stellar abundances are used: [Fe/H], [Mg/Fe], [Al/Fe], [Si/Fe], [Ca/Fe], [Ti/Fe], [Cu/Fe], [Zn/Fe], [Y/Fe], and [Ba/Fe]
- Results: LGC+LMDS shows cleaner separation of substructures in the 2D abundancespace than the original LMDS and t-SNE



References

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[7] M. Muja and D. G. Lowe, "Fast Approximate Nearest Neighbors with Automatic Algorithm Configuration", International Conference on Computer Vision Theory and Applications (VISAPP'09), 2009. [8] V. A. Epanechnikov, "Non-parametric estimation of a multivariate probability density," Theory of Probability and its Applications,

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Key idea

Filter the high-dimensional data so that potential clusters are well separated even after dimensionality reduction

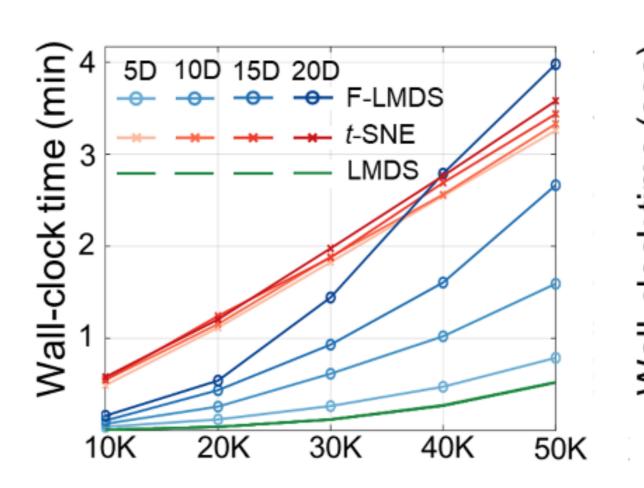
Summary

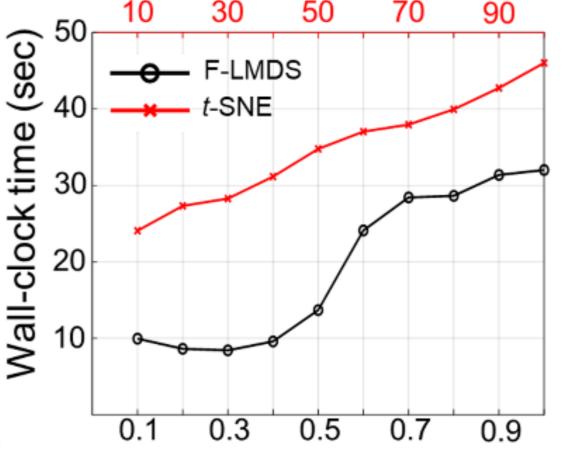
Method

- Estimate density using Epanechnikov kernel [7-8]
- Shift points upstream in kernel density gradient, resulting in cluster contraction [9]
- III. Perform LMDS [1]

Advantages

- Clusters are well separated after the projection by preprocessing the data with local-based gradient clustering
- Predictable outcome with one parameter
- More **computationally scalable** than *t*-SNE, in terms of wall-clock time





Future Work

A more sophisticated analysis of the different substructures gained from the LGC+LMDS results using GALAH DR2