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

Visualizing High-Dimensional Chemical Abundance Space in GALAH DR2

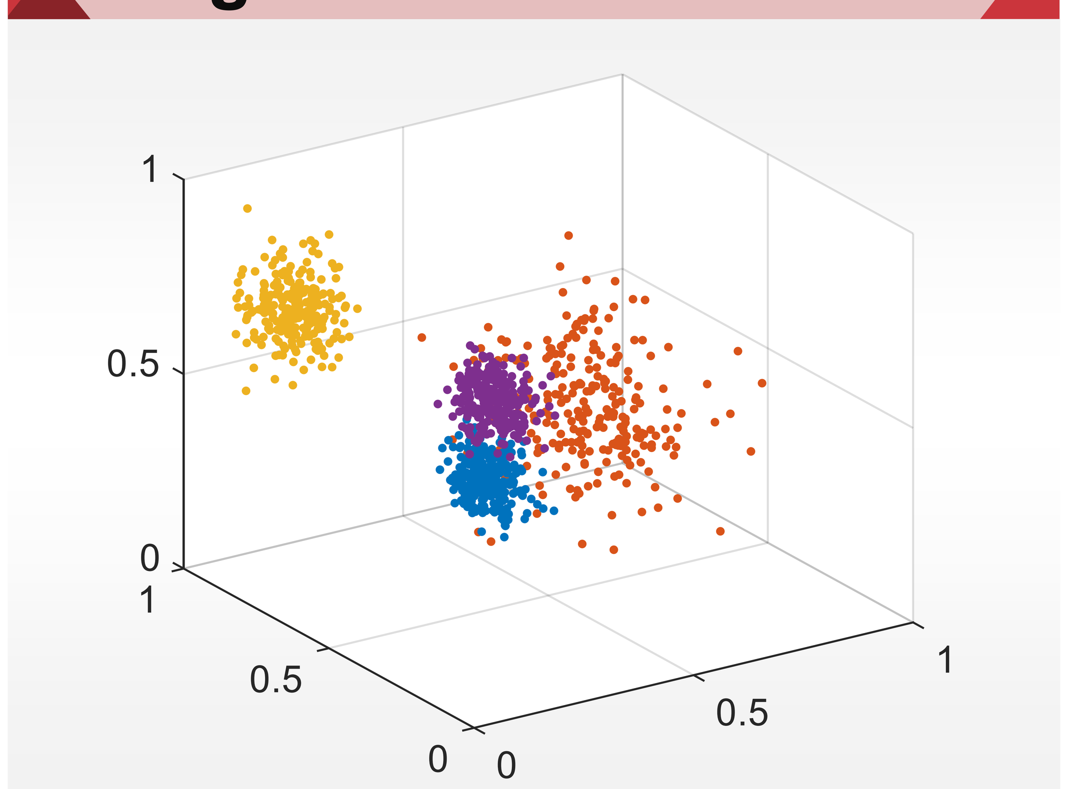
Youngjoo Kim[1, 2] Scott C. Trager[2] Alexandru C. Telea[1] Jos B. T. M. Roerdink[1]

[1]Bernoulli Institute for Mathematics, Computer Science and Artificial Intelligence, University of Groningen

[2]Kapteyn Astronomical Institute, University of Groningen

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

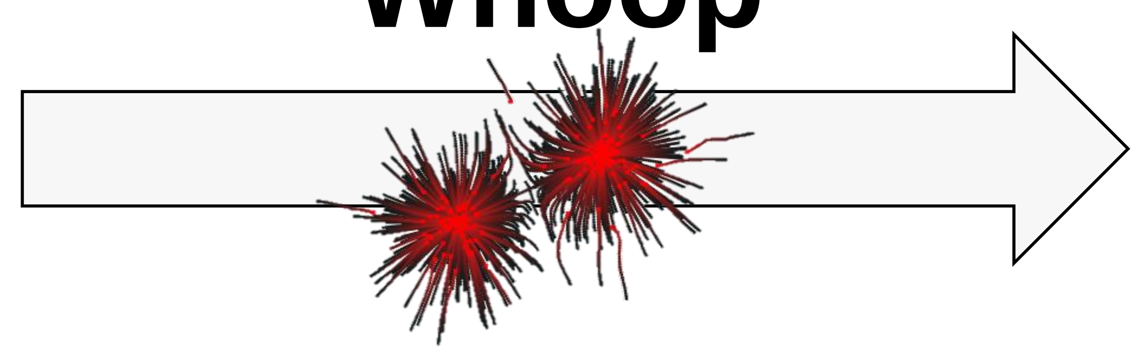
High-Dimensional Data



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

Filter high-dimensional data

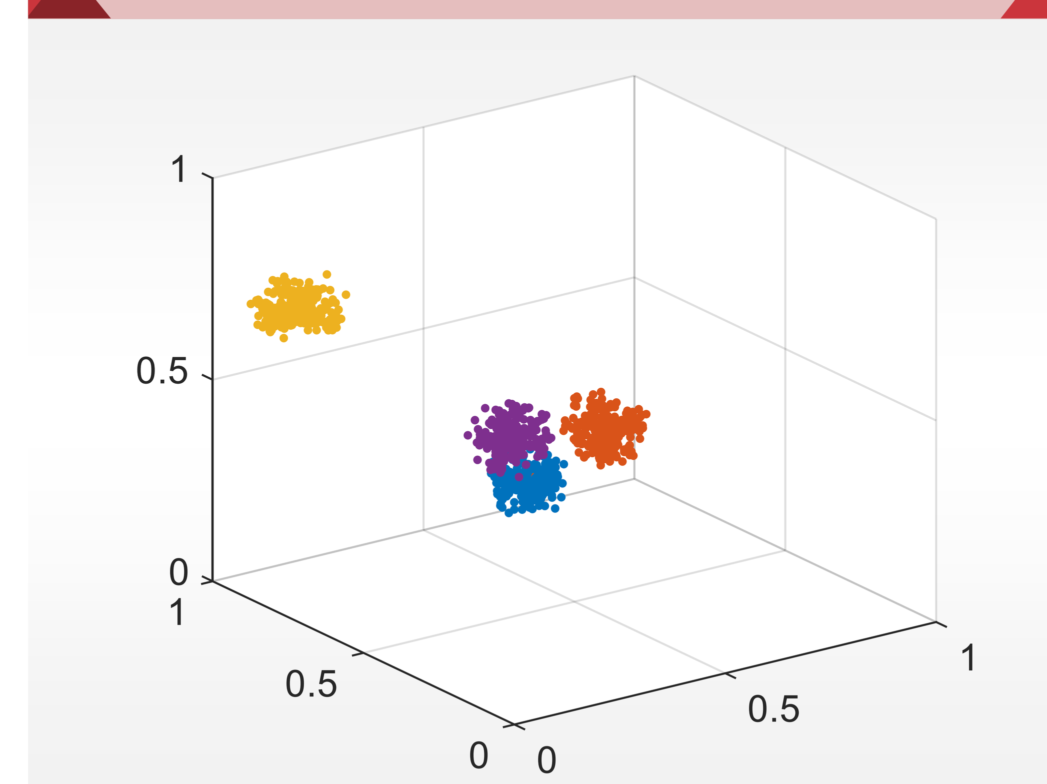
“Whoop”



Local Gradient Clustering (LGC)

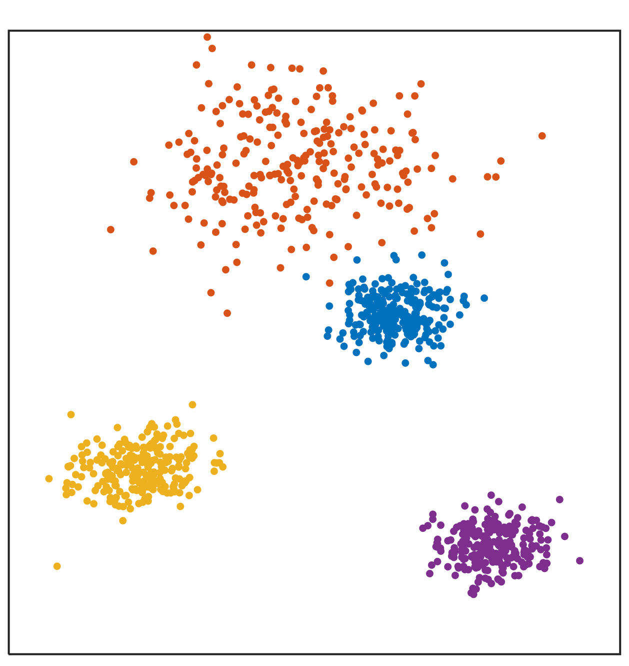
Shift points along the gradient of the kernel density estimator

Filtered Data

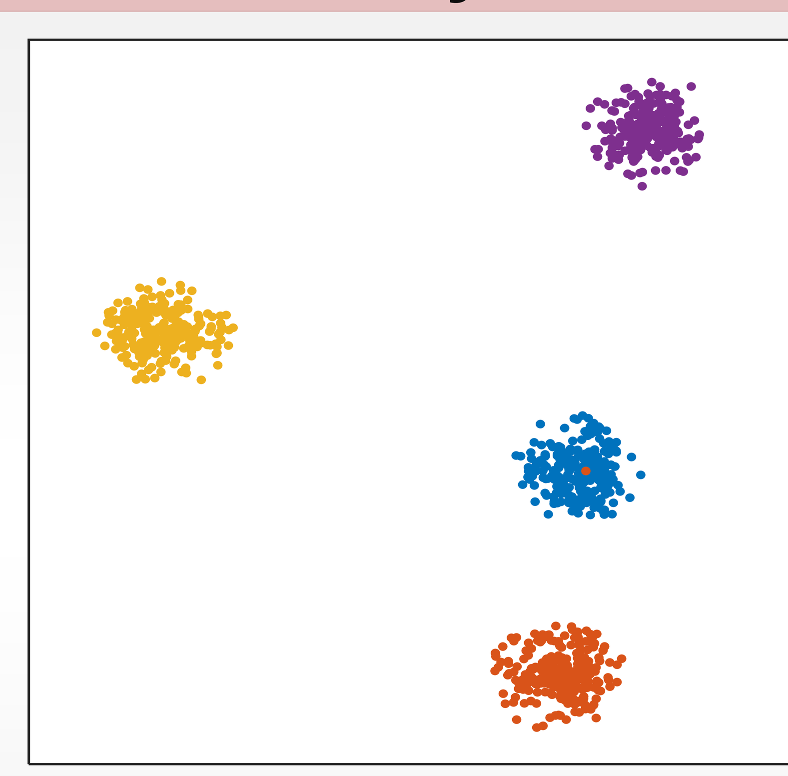


Clusters are separated in 3D

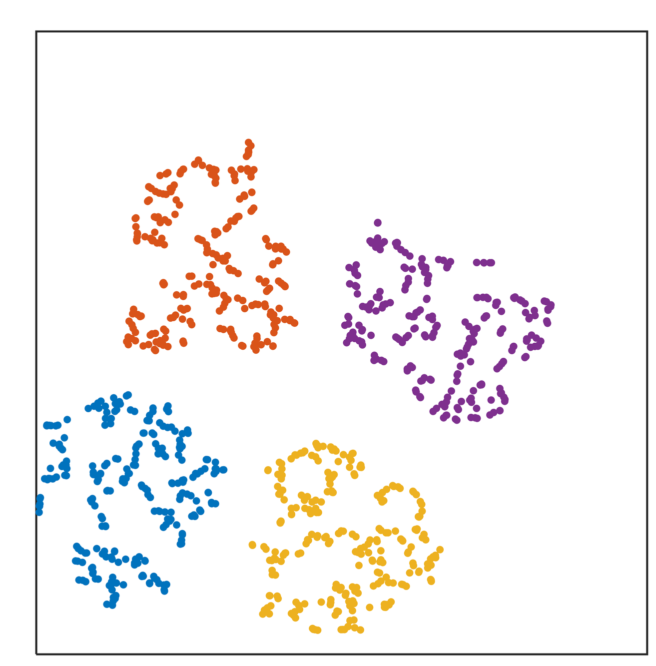
Dimensionality Reduction



VS.



VS.



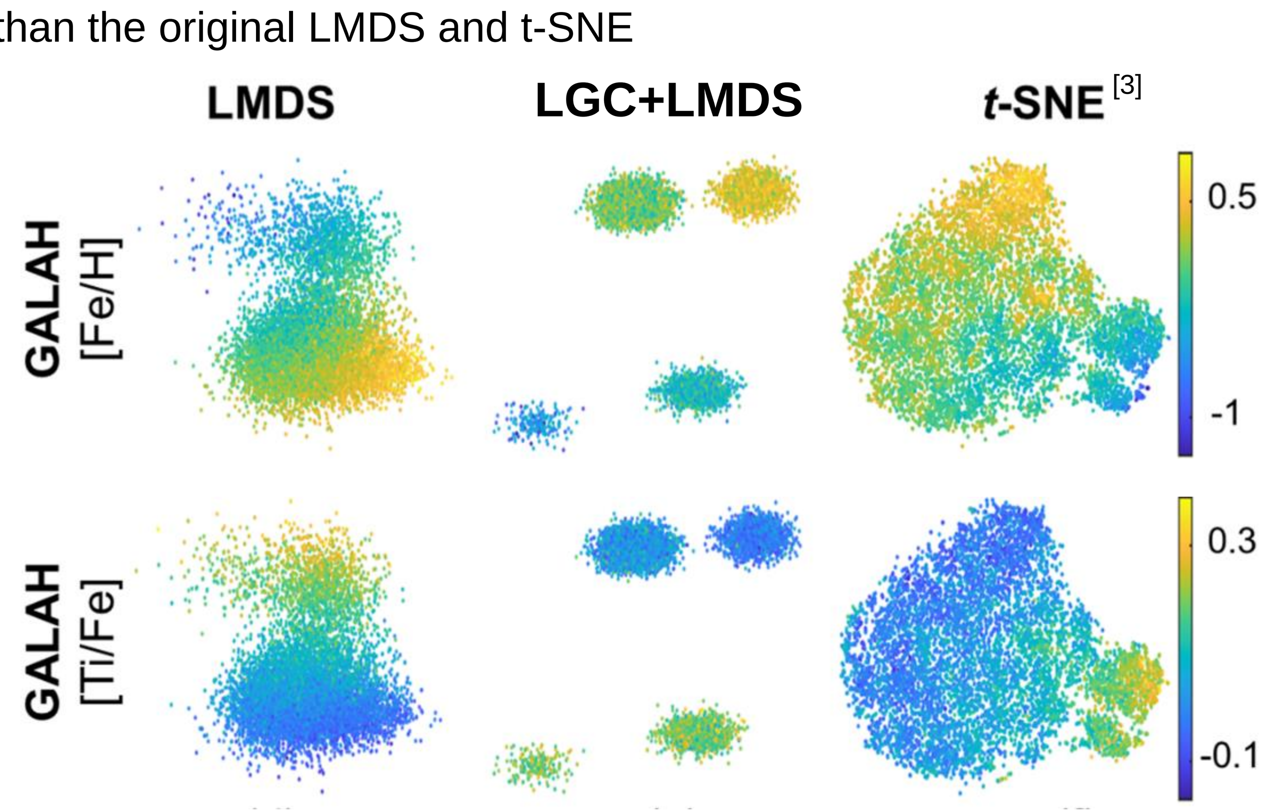
Landmark Multidimensional Scaling (LMDS [1]):
Clusters are **not well separated**.
Method is **fast**.

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 abundance-space than the original LMDS and t-SNE



References

[1] V. De Silva and J. B. Tenenbaum, “Sparse multidimensional scaling using landmark points,” Technical report, Stanford University, Vol. 120, 2004.

[2] L. V. D. Maaten and G. Hinton, “Visualizing data using t-SNE,” Journal of machine learning research, No. 9, pp. 2579-2605, 2008.

[3] F. Anders *et al.,* “Dissecting stellar chemical abundance space with t-sne,” Astronomy & Astrophysics, Vol. 619, No. A125, 2018.

[4] S. Buder et al., “The GALAH Survey: Second data release,” Monthly Notices of the Royal Astronomical Society, Vol. 478, 2018.

[5] Gaia Collaboration. “The Gaia mission,” Astronomy & Astrophysics, Vol. 595, No. A1, 2016.

[6] Gaia Collaboration. “Gaia Data Release 2-Summary of the contents and survey properties,” Astronomy & Astrophysics, Vol. 616, No. A1, 2018.

[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, Vol. 14, No.1, pp. 153-158, 1969.

[9] K. Fukunaga and L. Hostetler, "The estimation of the gradient of a density function, with applications in pattern recognition," IEEE Transactions on information theory, Vol. 21, No. 1, pp. 32-40, 1975.

Summary

Key idea

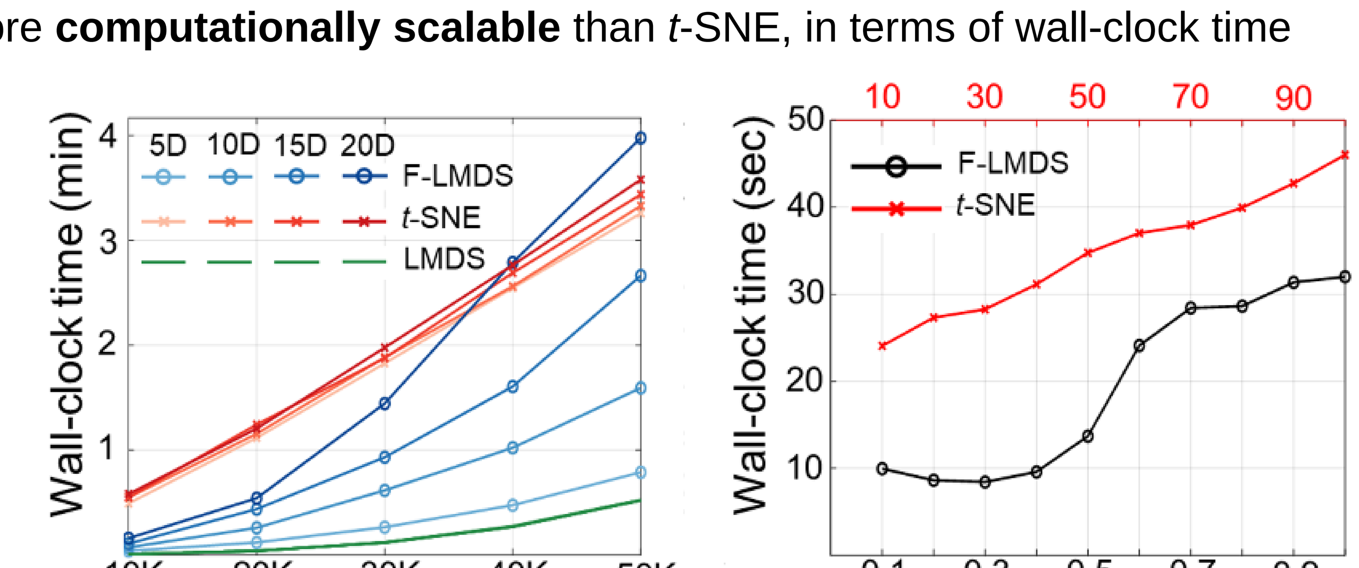
Filter the high-dimensional data so that potential clusters are well separated even after dimensionality reduction

Method

I. Estimate density using Epanechnikov kernel [7-8]
II. 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

Contact: lyoungjookiml@gmail.com