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# Visualizing hyperspectral data with linear and non-linear dimensionality reduction methods

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## Introduction

- **Hyperspectral (HS) data** is characterised as high dimensional with a large number of correlated dimensions leading to a **lower intrinsic dimensionality**
- **To visualize**, the HS data is transformed to a **lower dimensionality** explaining the data in terms of clusters
- The **shape of the data manifold** in the higher dimension largely determines the **effectiveness of the visualization method**
- In cases data **manifold** is **linear**, classical methods like principal component analysis (**PCA**) and multi-dimensional scaling (**MDS**) can perform well in preserving the structure
- However, when the points in high dimensional space lie very near or in **non-linear manifold**, methods like **PCA and MDS** fails to capture the structure
- This is because the aim of these methods is **to keep distant points as far as possible** and do not utilize information from **neighbouring data points** [1]
- In this case, **non-linear methods utilizing neighbourhood** information can perform better [2].

## Objective

- To test the potential of **linear and non-linear data visualisation** technique for visualizing near infrared HS data of tea products.
- Tested techniques: PCA, MDS, Isometric Mapping (ISOMAP) and t-distributed Stochastic Neighbour Embedding (t-SNE)

## Material and methods

- NIRS (950-1750 nm) hyperspectral data of six commercial tea samples (150 spectra each)
  - Green, Black, Orange, Pu-erh, White and Oolong
- Data was pre-processed with:
  - Standard Normal Variate
  - Savitzky-Golay smoothing

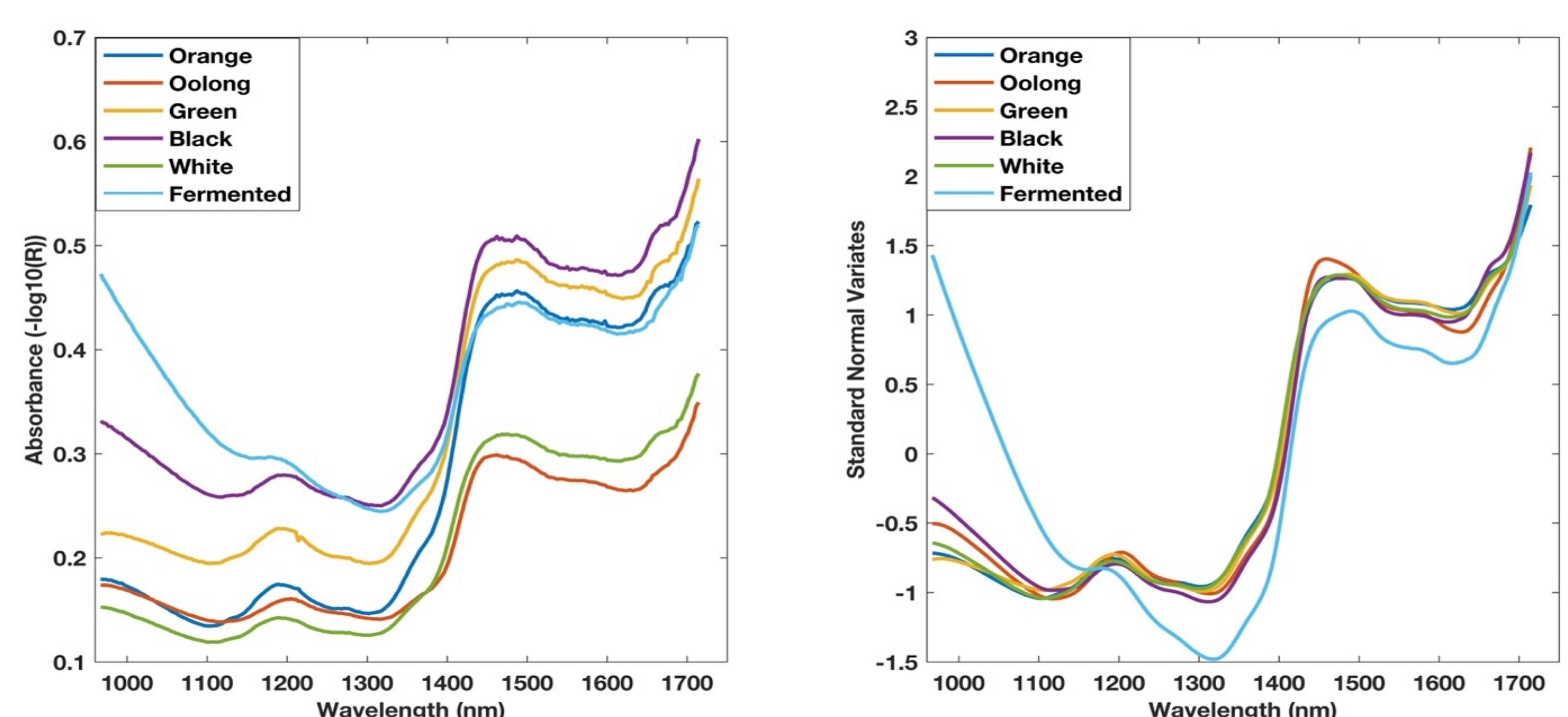


Figure 1: Mean absorbance profile of six different tea samples before and after pre-processing.

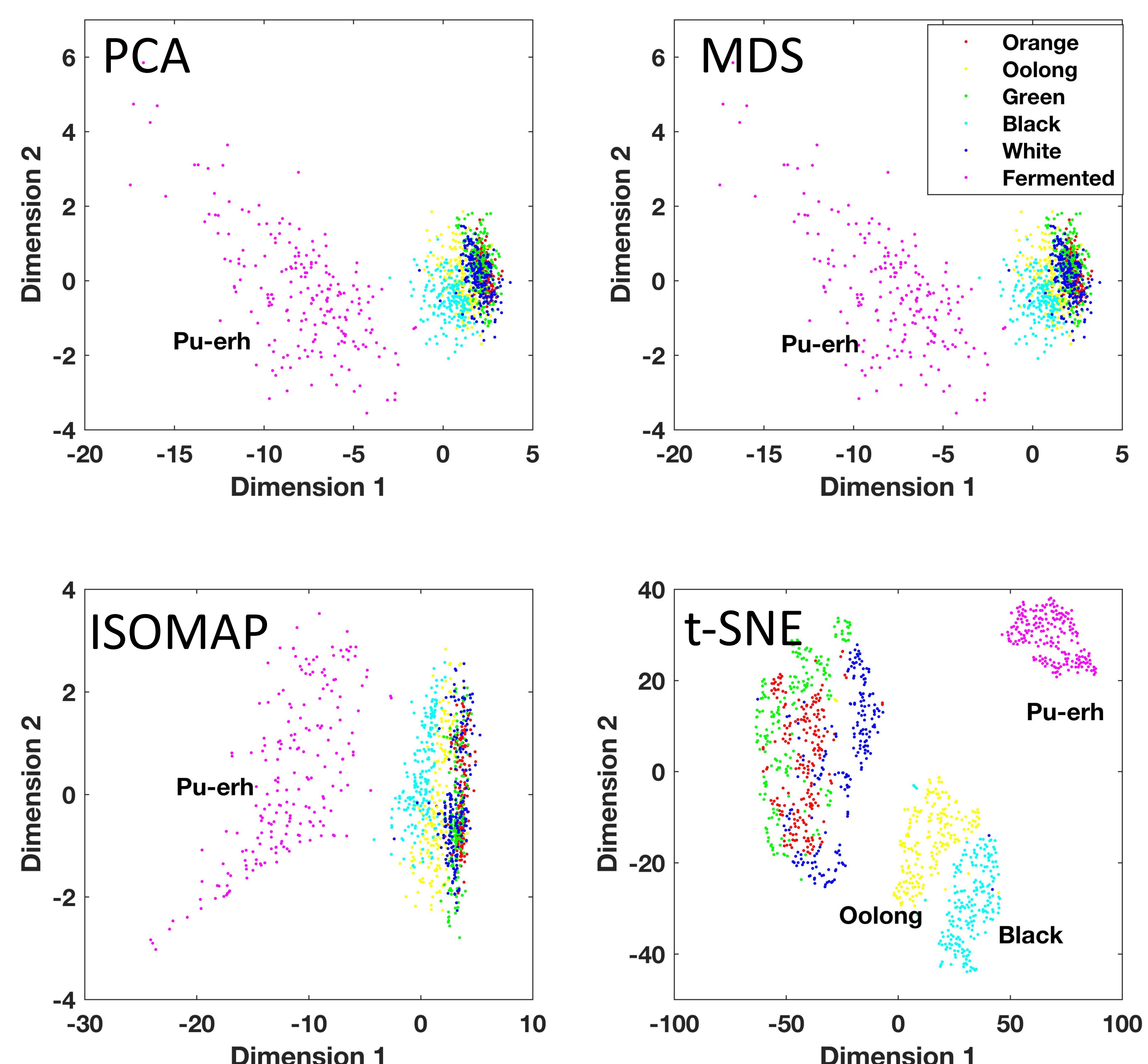
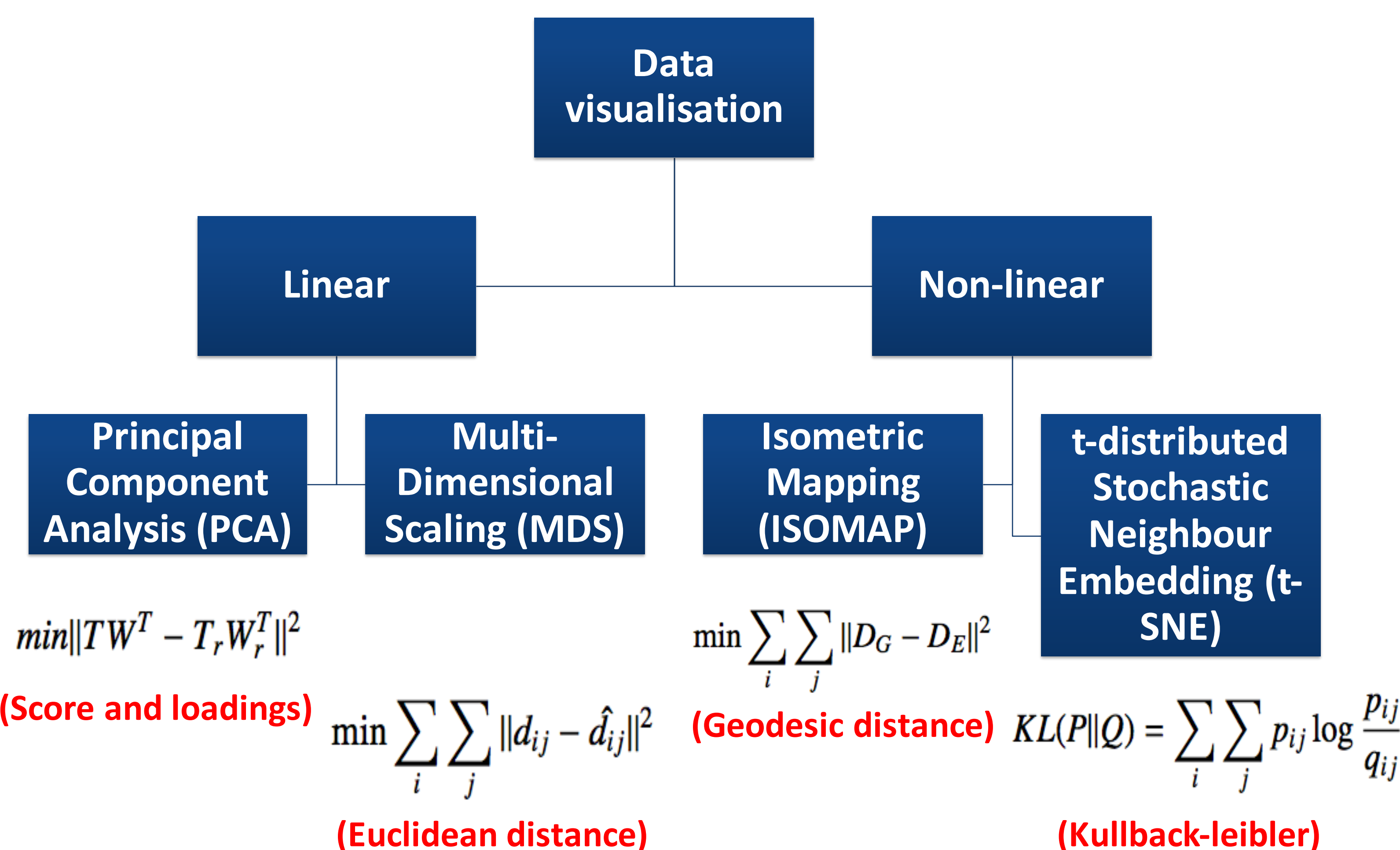


Figure 2: 2D scatter plots for 900 spectra corresponding to six commercial tea samples.

## Conclusions

- Oolong, green, yellow, white, black tea has very similar NIRS profile thus making it difficult for linear methods to separate them
- PCA, MDS and ISOMAP were able to separate the pu-erh tea from Oolong, green, yellow, white, black tea
- t-SNE provided the identification of three different clusters i.e. fermented tea products, oxidised tea products and minimal process tea products.

## References

- [1] Van Der Maaten, L., Postma, E. and Van den Herik, J., 2009. Dimensionality reduction: a comparative. *Journal of Machine Learning Research*, 10, pp.66-71.
- [2] Maaten, L.V.D. and Hinton, G., 2008. Visualizing data using t-SNE. *Journal of Machine Learning Research*, 9(Nov), pp.2579-2605.