TimeCluster:
Dimension Reduction Applied to Temporal Data for Visual Analytics

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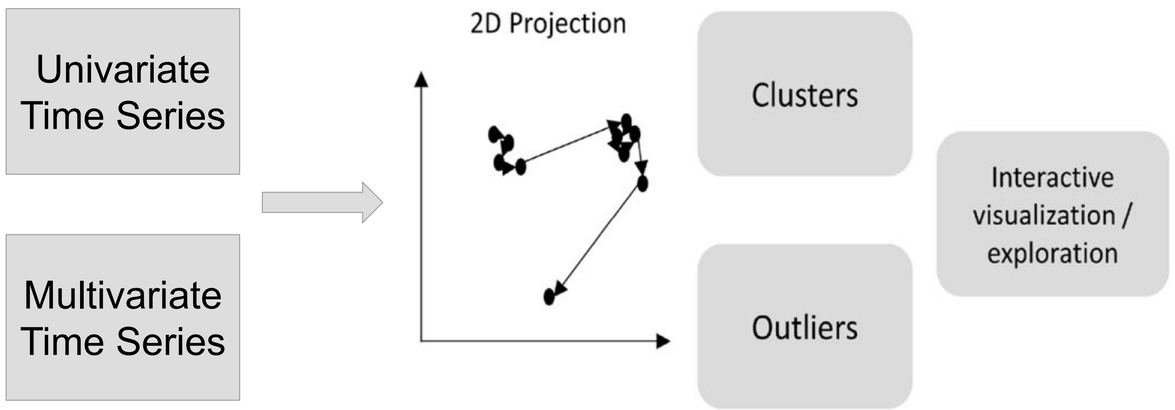
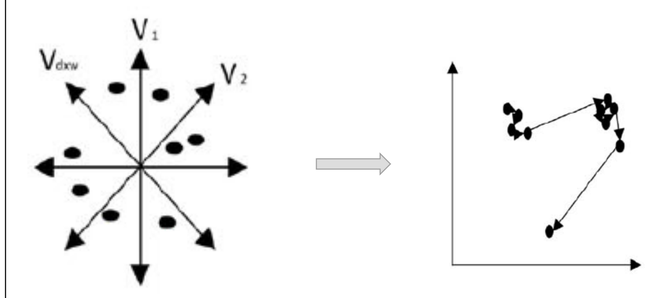
Poster by Saul Navarrete-Martinez and Quinn Porath-Yeager

Introduction

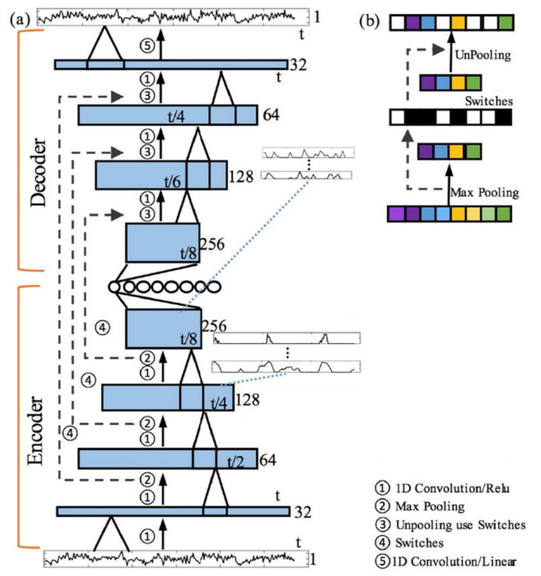
Problem



Dimensionality Reduction Methods



PCA, t-SNE or UMAP

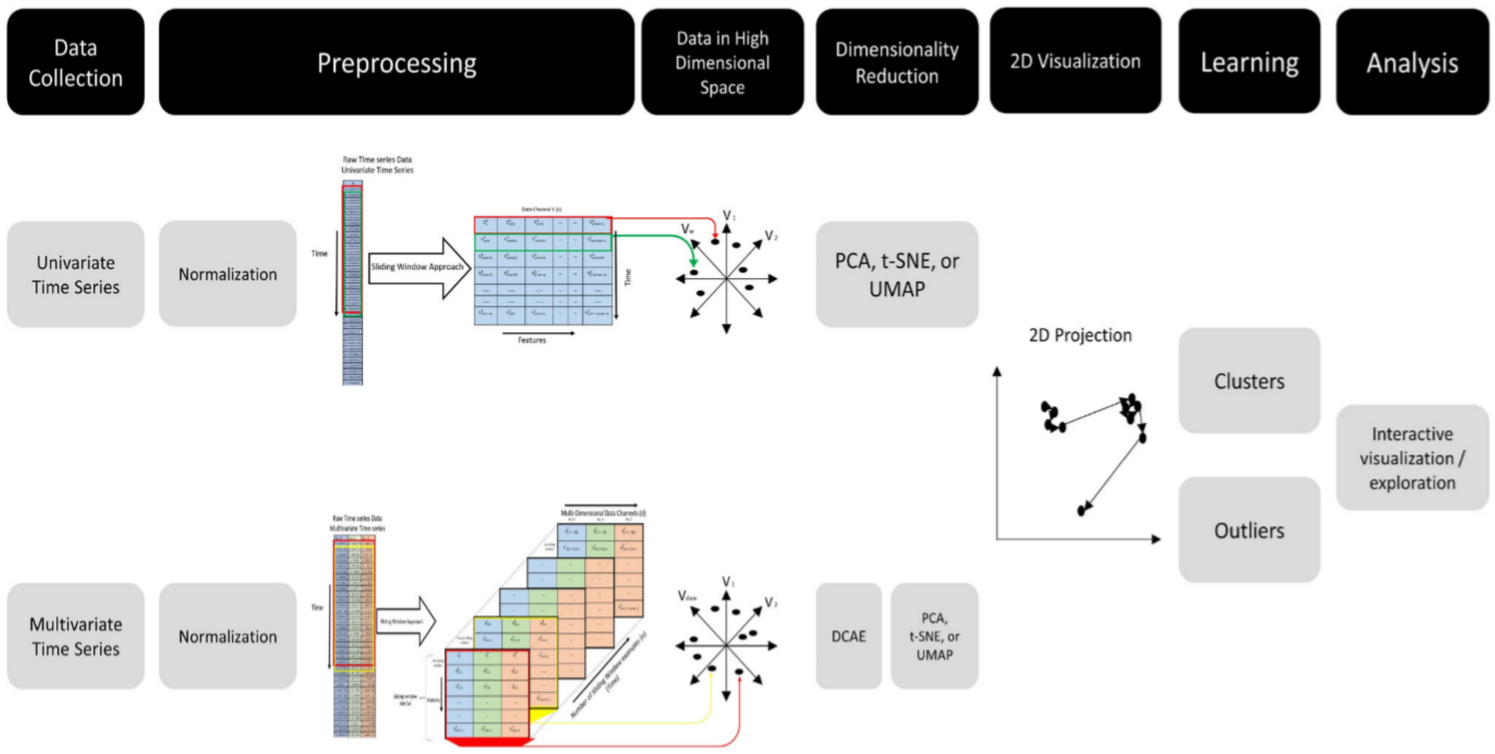


Deep **C**onvolutional **A**uto-**E**ncoder (**DCAE**)

Overview of the Methodology

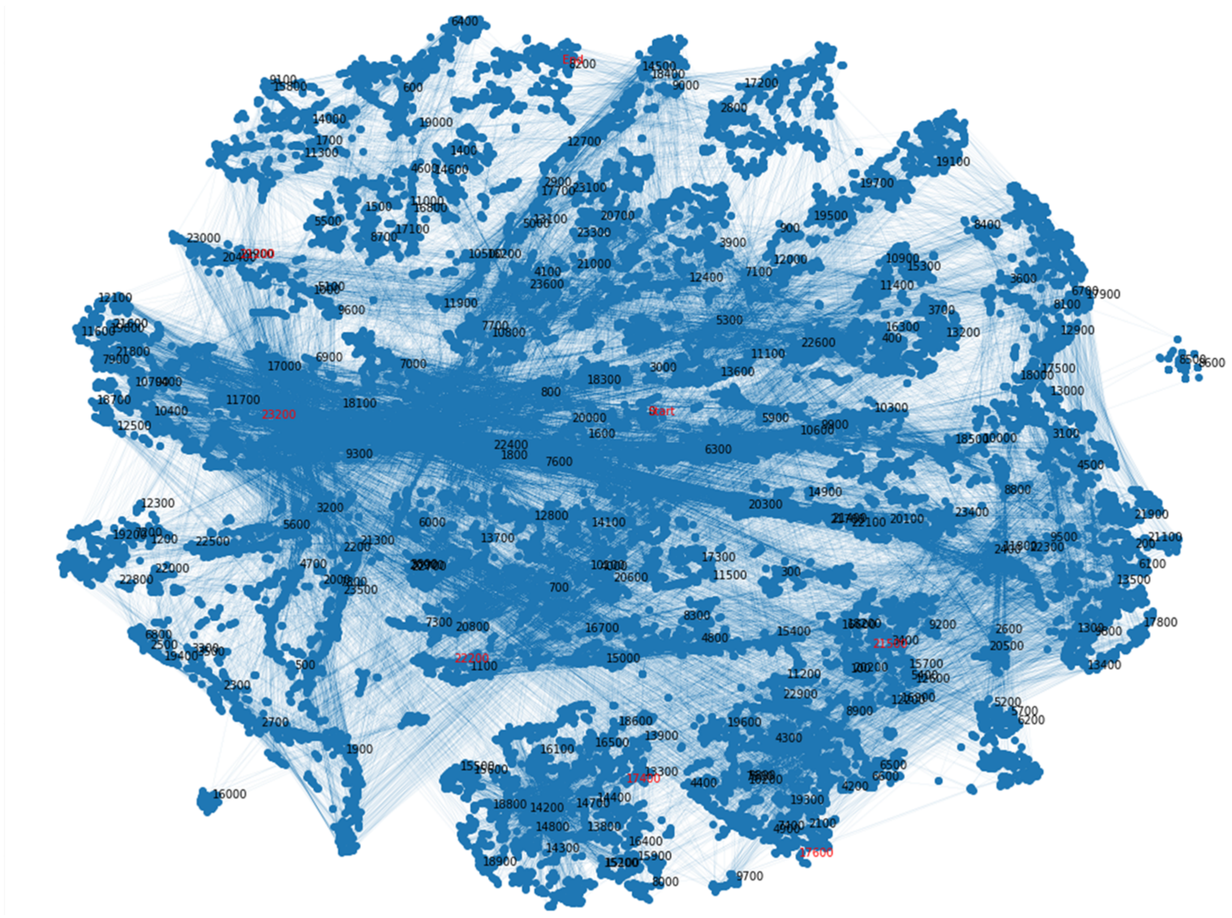
The methodology is designed for **detecting**, **exploring** and **interpreting** outlier patterns (anomalous) and repeated patterns (clusters) in large time-series data.

1. **Preprocessing**
2. **Dimensionality reduction (DR)**
   - **2.1 PCA, t-SNE or UMAP**
   - **2.2 DCAE**



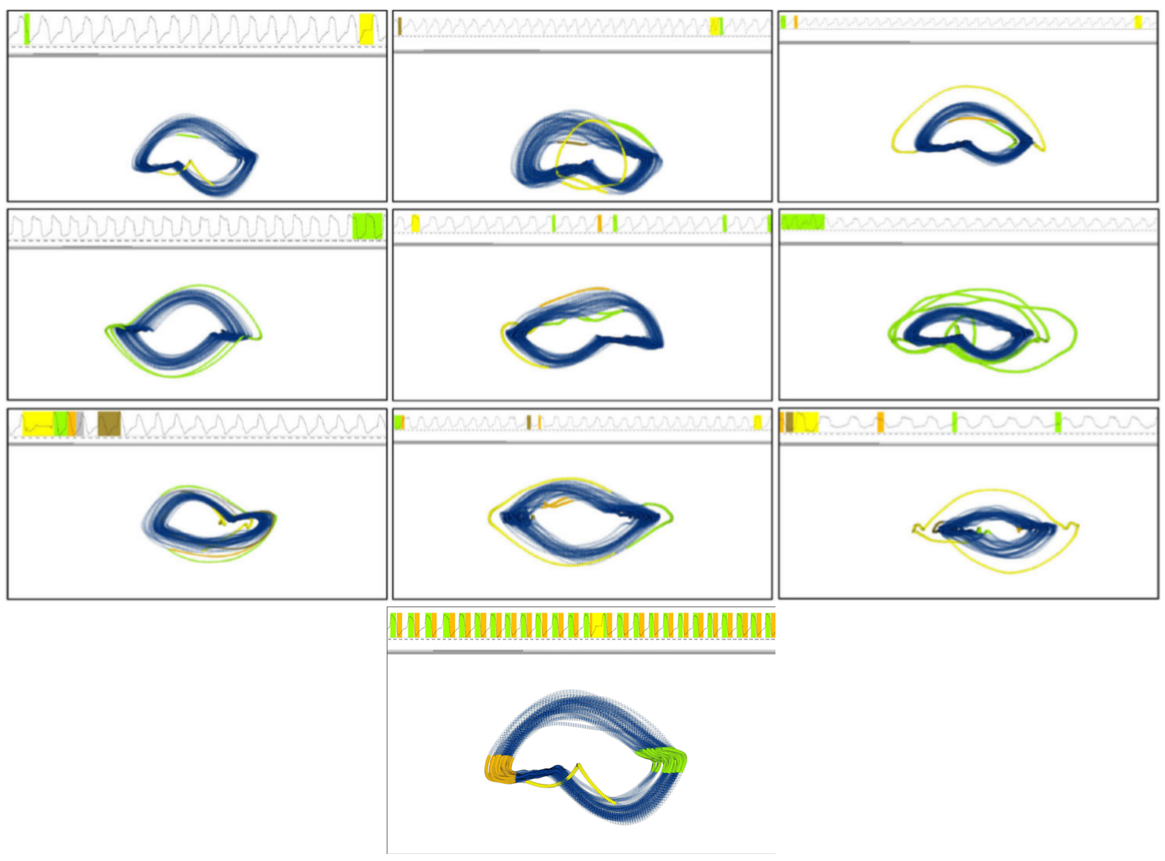
Household Power Consumption

Visualization of data collected from the Individual Household Electric Power Consumption Data Set. The data was taken from 2007 alone.



Breathing Patterns

Nine breathing patterns for nine different participants where the abnormal patterns could be easily evidenced through the connected scatter plot after applying the proposed approach (PCA).



References:
[1] Ali, M., Jones, M. W., Xie, X., & Williams, M. (2019). TimeCluster: dimension reduction applied to temporal data for visual analytics. The Visual Computer, 35(6-8), 1013-1026.
[2] Maaten, L. V. D., & Hinton, G. (2008). Visualizing data using t-SNE. Journal of machine learning research.
[3] Huang, H., Hu, X., Zhao, Y., Makkie, M., Dong, Q., Zhao, S., & Liu, T. (2017). Modeling task fMRI data via deep convolutional autoencoder. *IEEE transactions on medical imaging*, *37*(7), 1551-1561.