Extraction of Main Dynamics in Platform Metrics

Evelyn Trautmann

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Lovoo

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- $\approx 3.5\,TB$ analysis data per month

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- platform monitoring means keeping track of various metrics
- some effects are visible only in sub-dimensions like single countries, or device types
- dimension reduction without losing important details

Clustering

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- similarity defines (inverse) distance measure
- find clusters of closely related points

Toy Example - Gaming App

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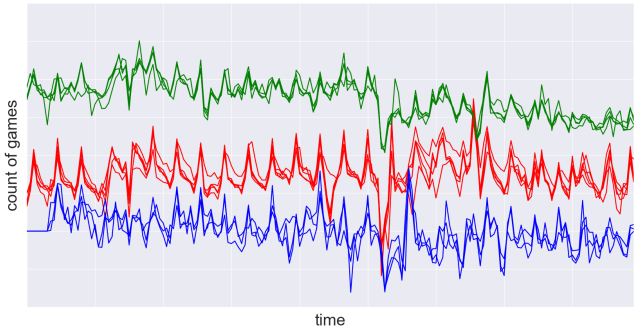
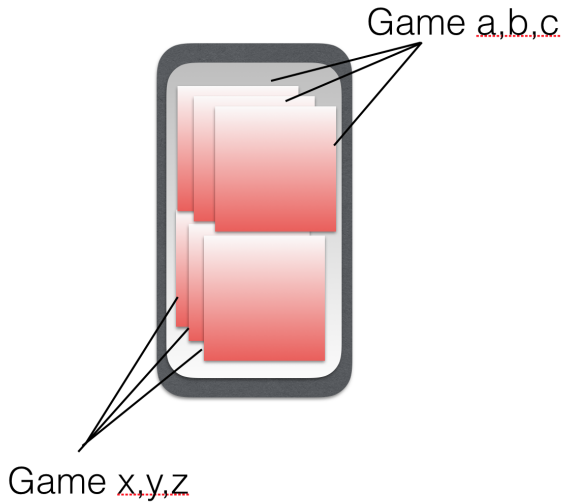
metric 0 game a: count of games played by paying users
metric 1 game a: count of games played by non paying users
metric 2 game b: count of games played by paying users
metric 3 game b: count of games played by non paying users
...





Similarity Function

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- correlation based similarity
- handle negative correlations

Similarity Graph

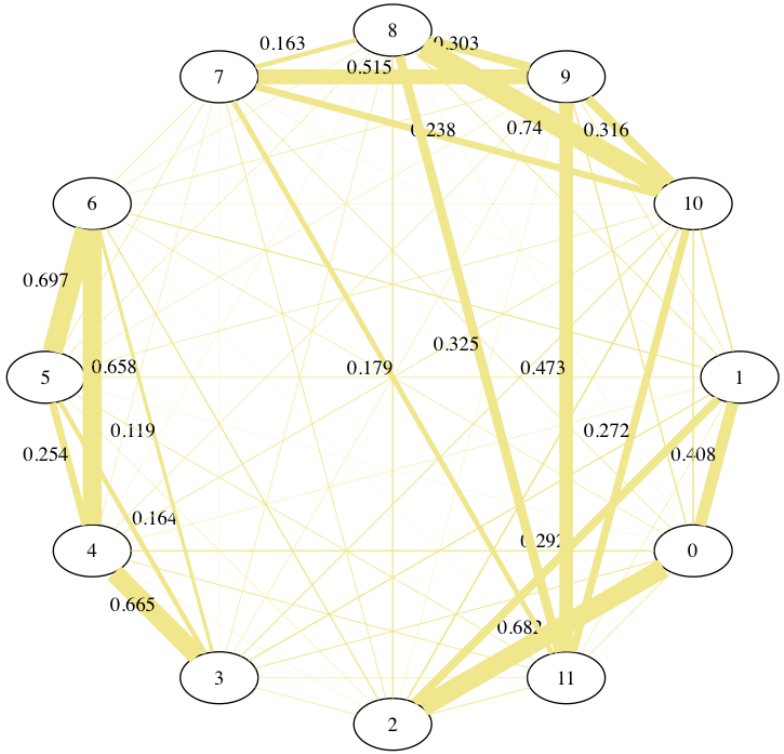
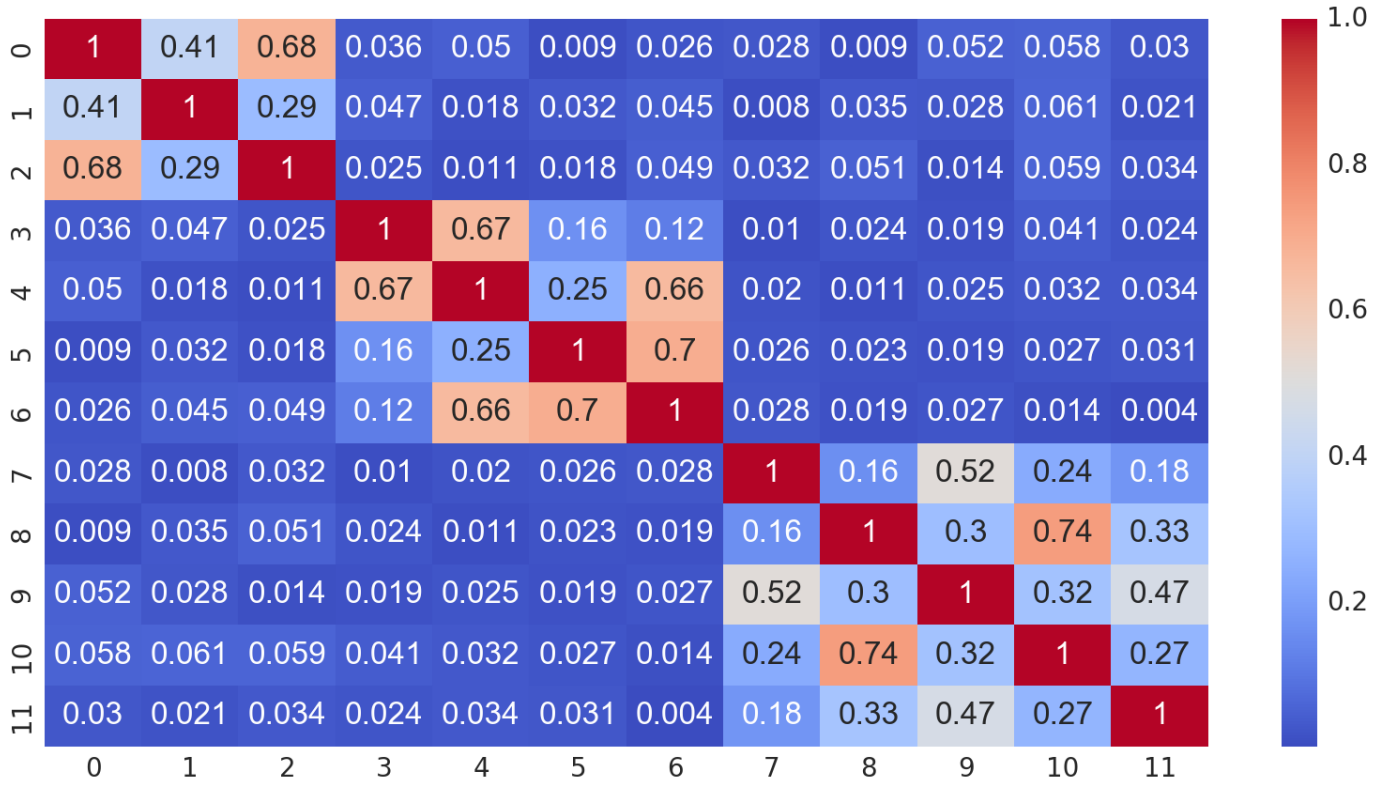


Figure: Similarity Graph

Matrix Representation



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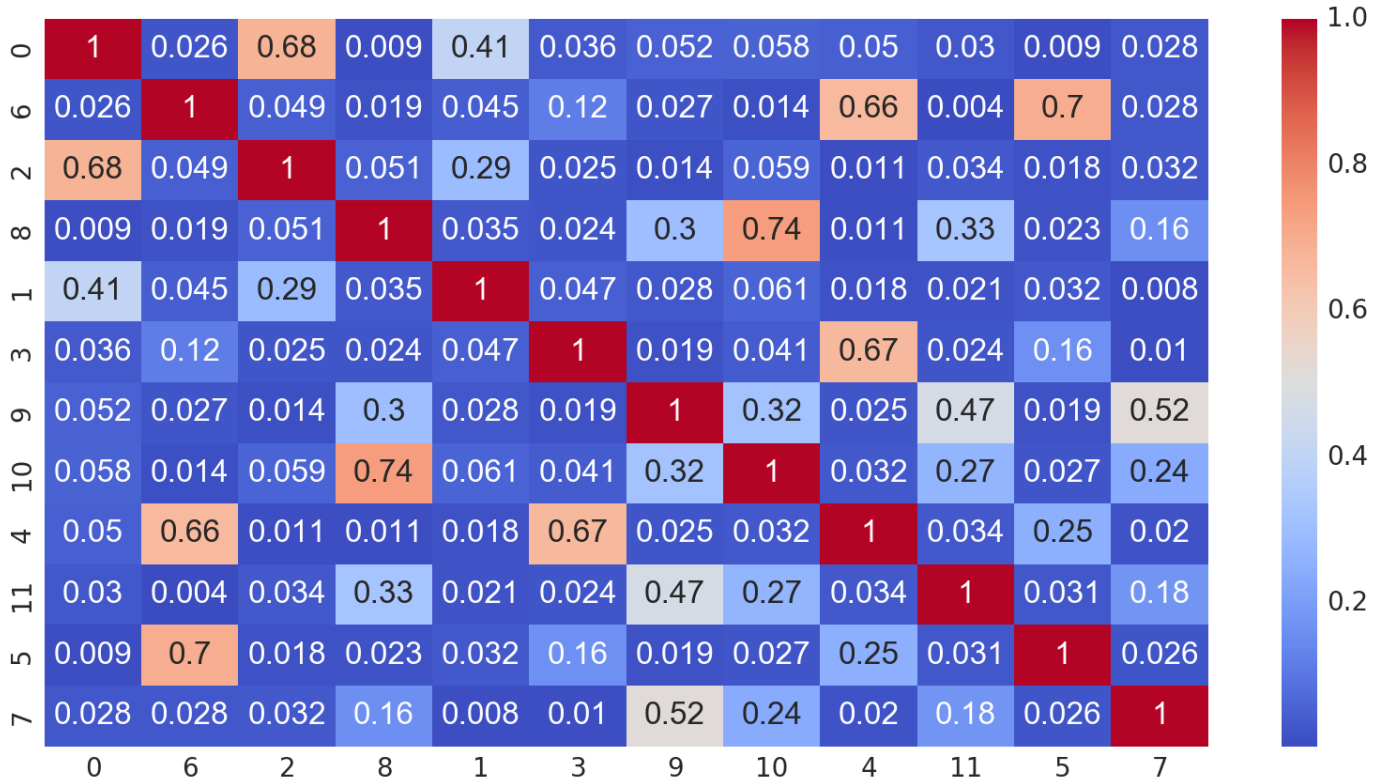
Matrix Representation



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- Graph Laplacian with similarities as off-diagonal entries

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- negative row sums on diagonal

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- block matrices have multiple largest eigenvalues and piecewise constant eigenvectors

Spectral Clustering [vL07]

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1: **procedure** SpectralClustering(X, k)
2: compute similarity matrix with pairwise similarities
3: Transform to Graph Laplacian L
4: $v_1, ..., v_k = eig(L, k)$ ▷ first k eigenvectors
5: $U = V^T$ ▷ k n-dimensional → n k-dimensional vectors
6: $clusterAssignment = kmeans(U, k)$
7: **return** *clusterAssignment*
8: **end procedure**

`https://github.com/metterlein/spectral_clustering`

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- possible approach:
  - PCA explained variance

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- combination of metrics and dimensions generates around 300 timeseries in our example.

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- aggregation per day
- normalization $X = \frac{1}{\sigma}(X - \mu)$, with μ mean value and σ standard deviation
- rolling mean of 7 days to smooth weekly periodicity

Real Data Example [PVG+11]

Real Data Example.ipynb

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- small number of interpretable cluster representatives help keeping track of main platform dynamics
- by cluster assignments can be discovered unexpected relations between several metrics

References I

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, *Scikit-learn: Machine learning in Python*, Journal of Machine Learning Research **12** (2011), 2825–2830.

Ulrike von Luxburg, *A tutorial on spectral clustering*, CoRR **abs/0711.0189** (2007).

Thank You!

Questions?

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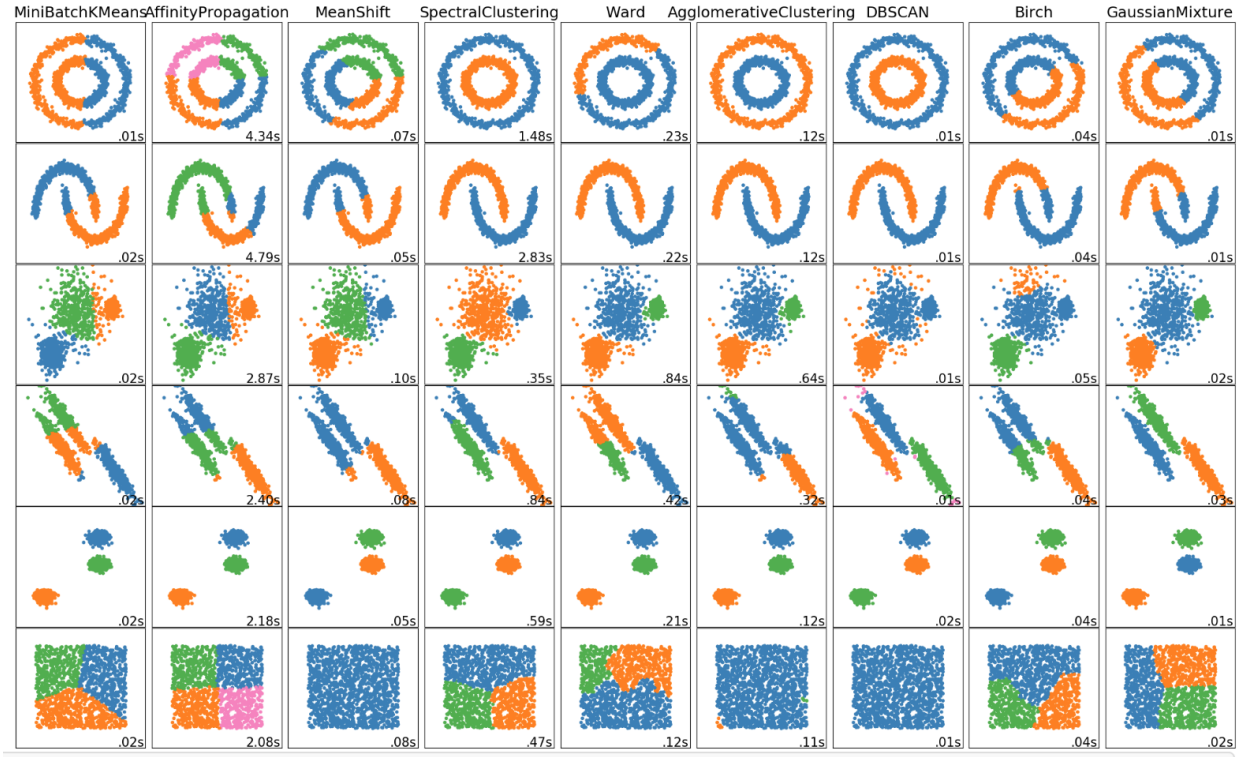
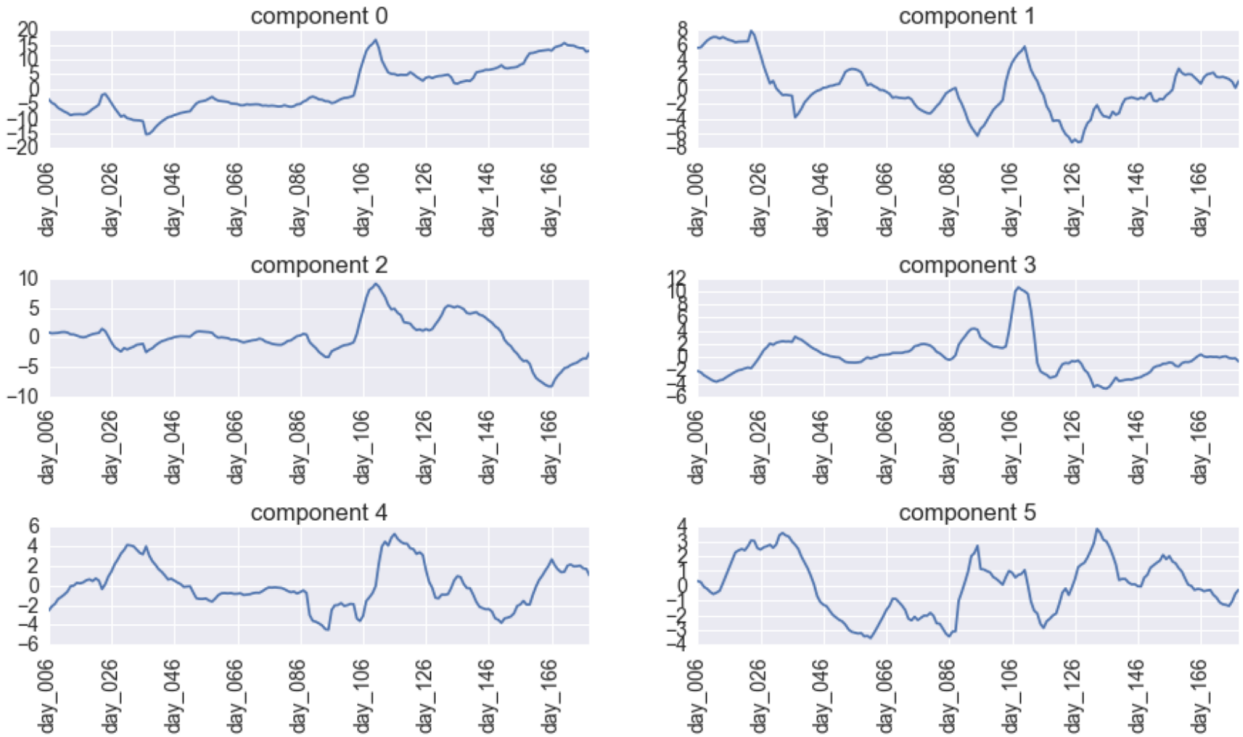
https://github.com/metterlein/spectral_clustering

Clustering Methods

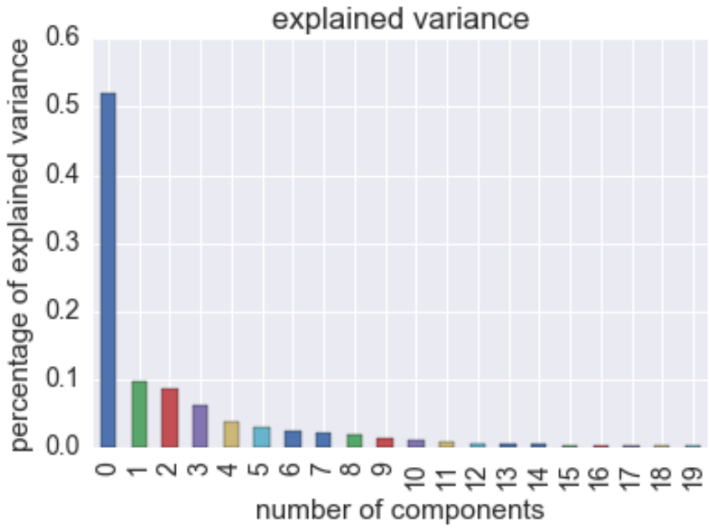
[PVG+11]



PCA

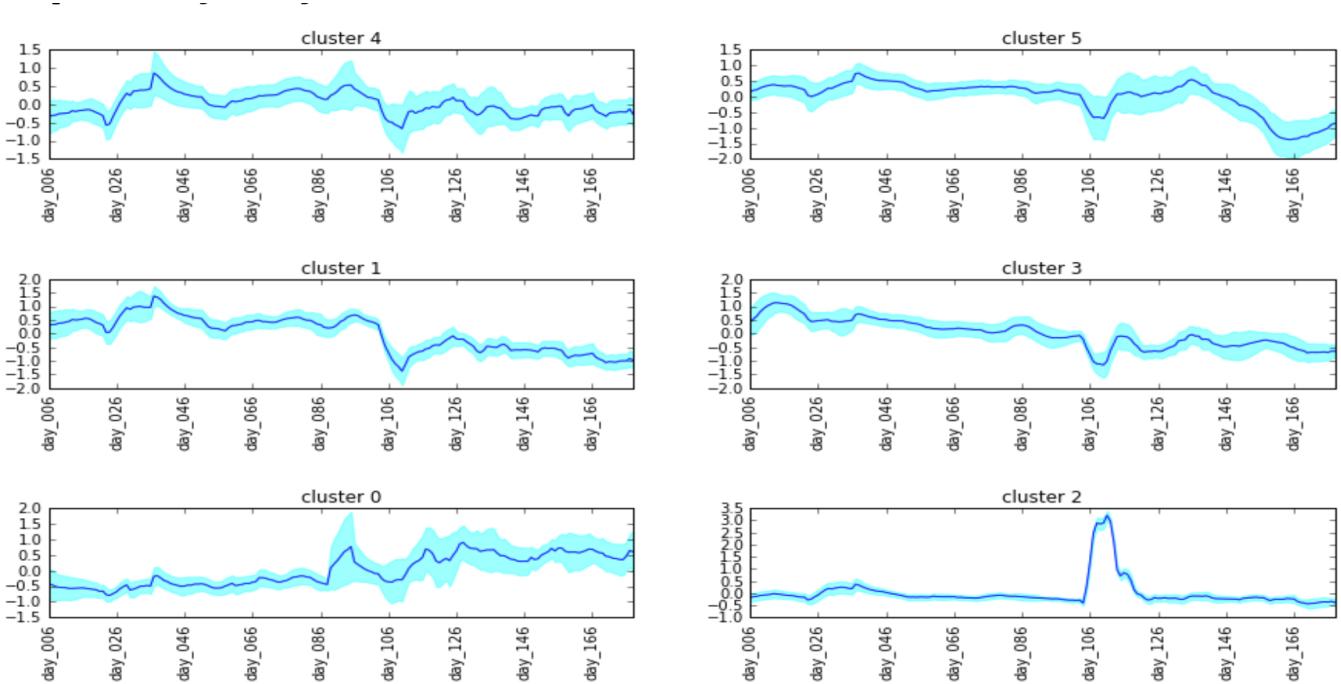

component 0
component 1
component 2
component 3
component 4
component 5
day_006
day_026
day_046
day_066
day_086
day_106
day_126
day_146
day_166

PCA


explained variance
percentage of explained variance
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19
number of components

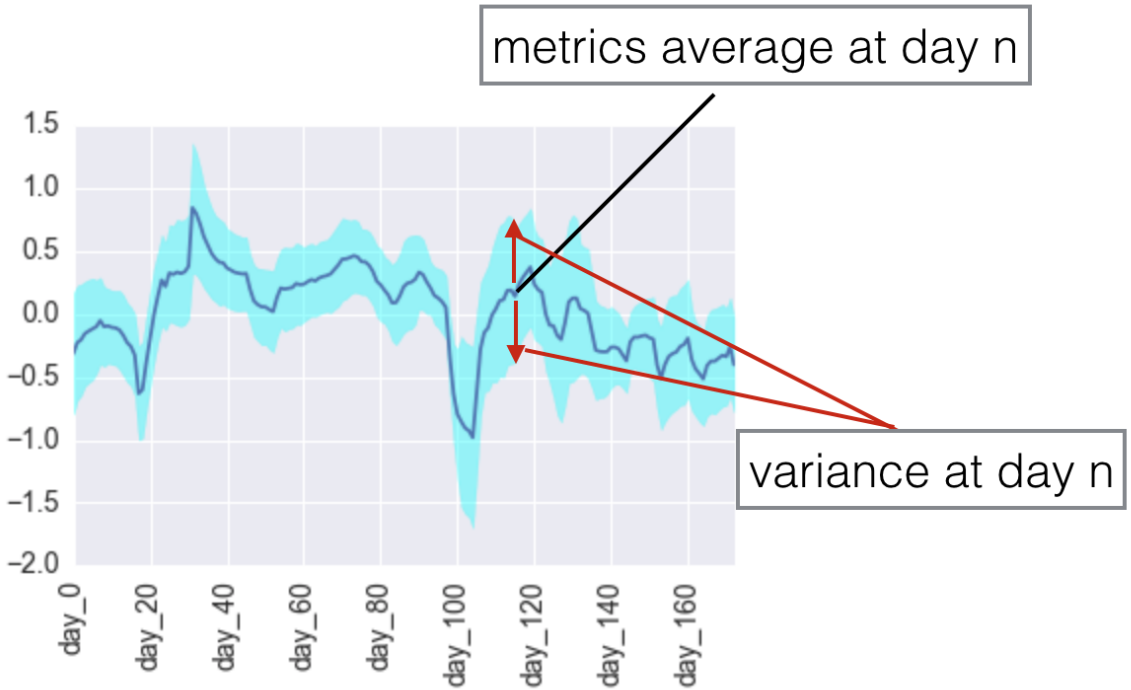
Extract Platform Dynamics by means of Cluster Centers

- compute average timeseries per cluster
- illustrate average cluster timeseries with variance corridor
- visualize metrics types and subdimensions entering respective clusters



Measure Clustering Quality

- compute variance for each timepoint over all cluster members
- optimal clustering minimizes variance for each cluster



Outlook

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- investigate cluster assignment change over time

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- hierarchical approach: clustering sub-blocks

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- add time shifted series to recognize Granger causalities