Extracting relevant Metrics with Spectral Clustering

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PyData Berlin

6-8 July, 2018

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Introduction

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- 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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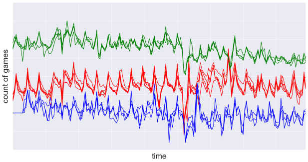
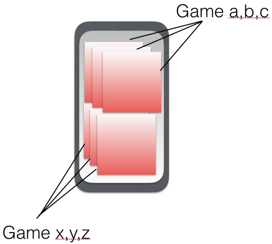
- metrics considered as points in a vector space
- similarity defines (inverse) distance measure
- find clusters of closely related points

Toy Example - Gaming App

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 Graph

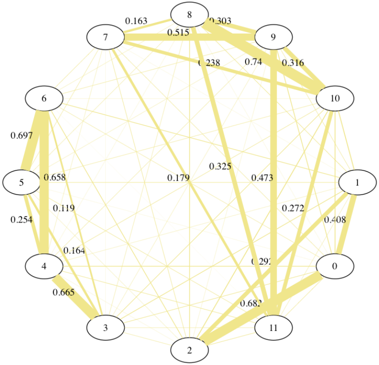


Figure: Similarity Graph

Matrix Representation

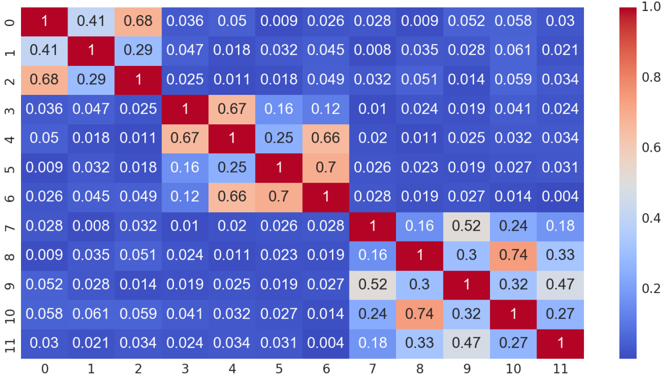


Figure: Matrix Representation

Matrix Representation

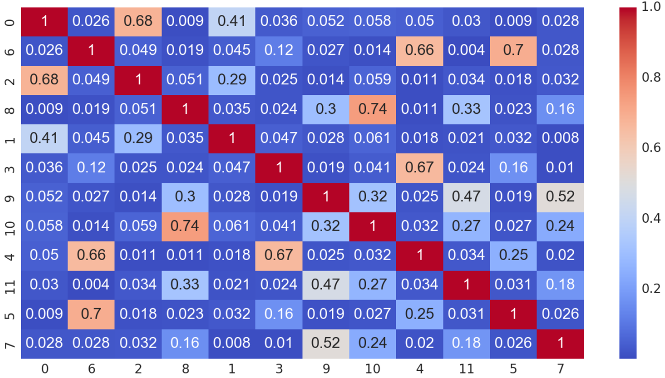


Figure: Matrix Representation

Toy Example

Toy Example.ipynb
https://github.com/metterlein/spectral_clustering.

Spectral Clustering

procedure $\textsc{SpectralClustering}(X, k)$

compute similarity matrix with pairwise similarities

Transform to Graph Laplacian L

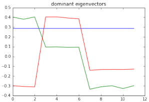
$v_1, ..., v_k = eig(L, k)$ ▷ first k eigenvectors

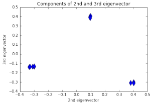
$U = V^T$ ▷ k n-dimensional → n k-dimensional vectors

$clusterAssignment = kmeans(U, k)$

return *clusterAssignment*

end procedure[vL07]





Similarity Function

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- handle negative correlations

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- possible approach:
  - PCA explained variance

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- each metric is divided in several dimensions like country, gender, etc
- combination of metrics and dimensions generates around 300 timeseries in our example.

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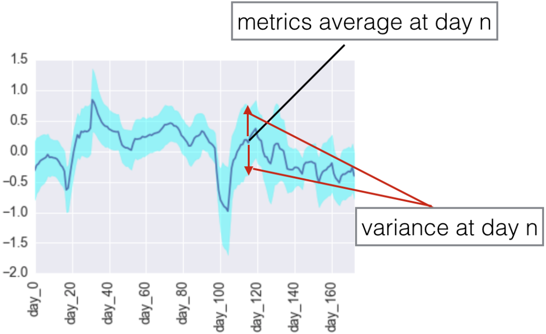
- rolling mean of 7 days to smooth weekly periodicity

Measure Clustering Quality

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



Real Data Example

Real Data Example.ipynb

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Conclusion

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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

Outlook

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- investigate cluster assignment change over time
- hierarchical approach: clustering sub-blocks
- add time shifted series to recognize Granger causalities

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.
- Evelyn Trautmann, *Spectral clustering demo*, `https://github.com/metterlein/spectral_clustering`, 2018.
- Ulrike von Luxburg, *A tutorial on spectral clustering*, CoRR **abs/0711.0189** (2007).

Thank You!

Questions?

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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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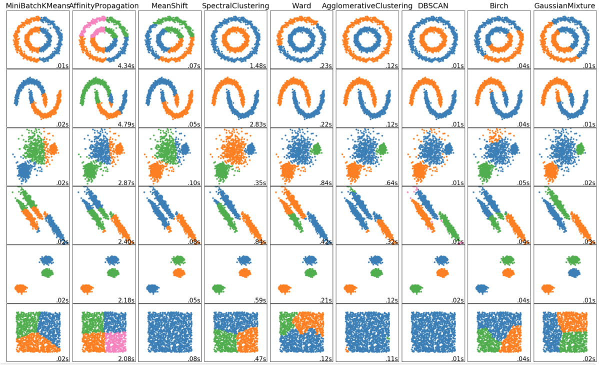
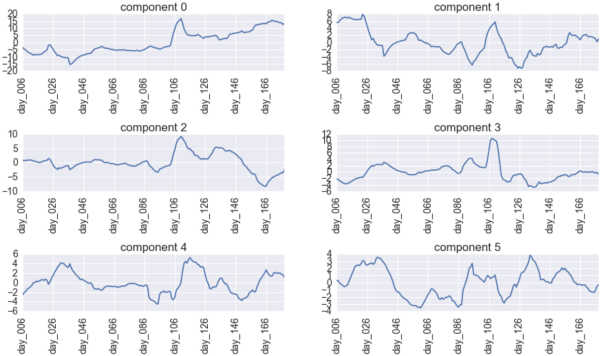
- matrix exponential is a stochastic matrix
- results from Markov chain theory applicable

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
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day_146
day_166

PCA

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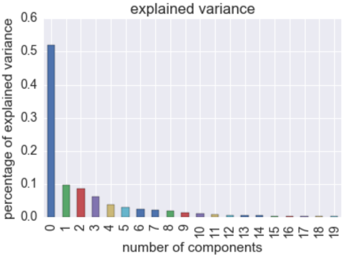
explained variance
percentage of explained variance
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19
number of components

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