Extraction of Main Dynamics in Platform Metrics

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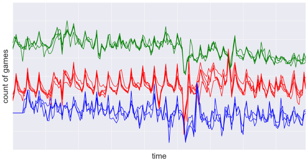
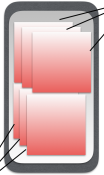
- similarity defines (inverse) distance measure
- find clusters of closely related points

Toy Example - Gaming App

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

...





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- correlation based similarity
- handle negative correlations

Similarity Graph

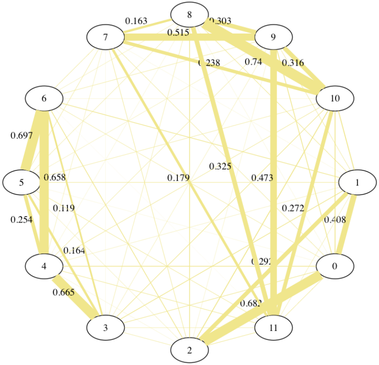

Figure: Similarity Graph

Matrix Representation

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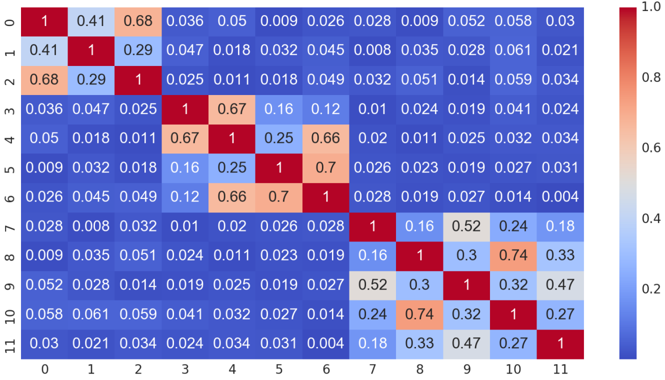

Figure: Matrix Representation

Matrix Representation

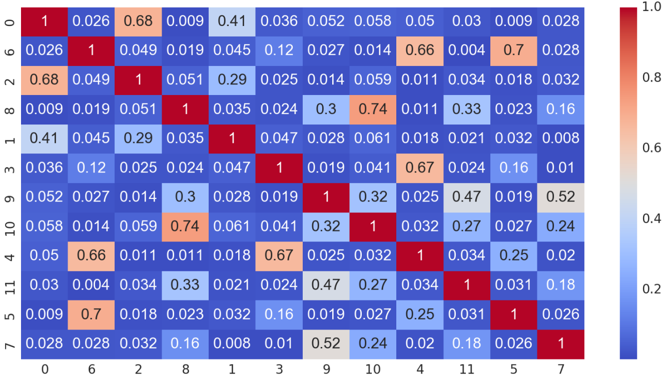

Figure: Matrix Representation

Graph Laplacian

- Graph Laplacian with similarities as off-diagonal entries

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- negative row sums on diagonal

$$L = \begin{cases} l_{ij} \geq 0, \text{for } i \neq j \\ l_{ii} = -\sum_{k \neq i} l_{ik}, \text{for } i = j. \end{cases}$$

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- and the respective eigenvalue is constant
- block matrices have multiple largest eigenvalues and piecewise constant eigenvectors

Spectral Clustering [vL07]

```
procedure 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
```

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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- 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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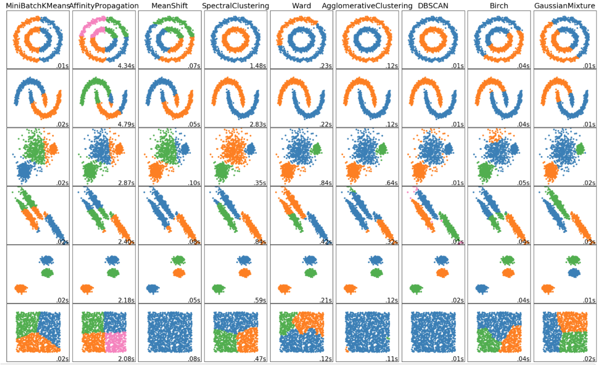
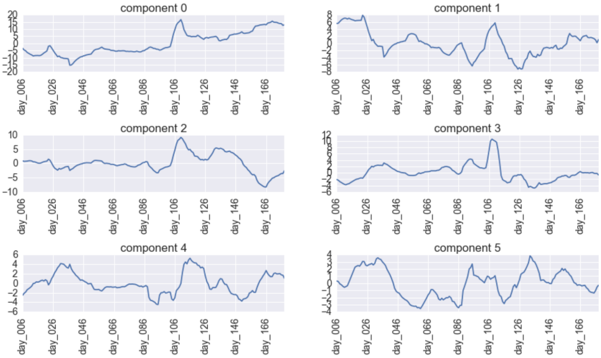
Clustering Methods

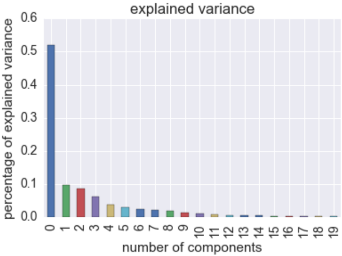
[PVG+11]



PCA

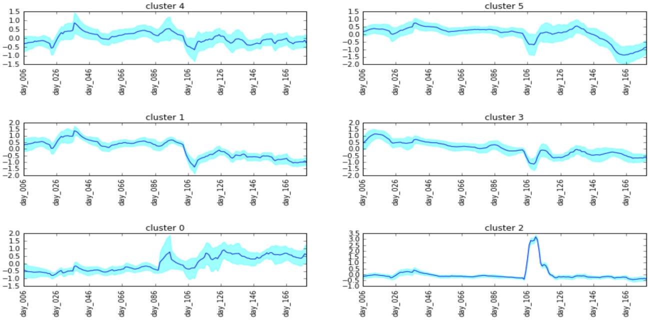

component 0
component 1
component 2
component 3
component 4
component 5
day_006
day_026
day_046
day_066
day_086
day_106
day_126
day_146
day_166

PCA


explained variance
percentage of explained variance
0.6
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

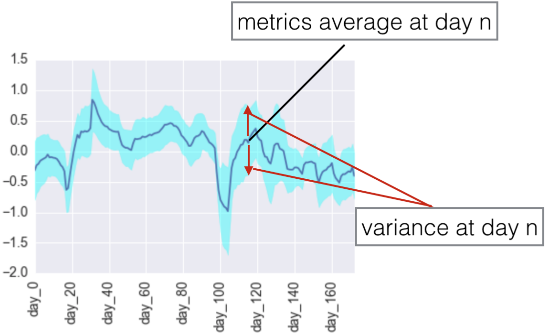
Extract Platform Dynamics by means of Cluster Centers

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



Measure Clustering Quality

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



Outlook

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- hierarchical approach: clustering sub-blocks

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- hierarchical approach: clustering sub-blocks
- add time shifted series to recognize Granger causalities