UNSUPERVISED
METHODS TO GROUP
USERS' CONSUMPTION
BEHAVIOUR TO
ENHANCE
PERSONALIZE SERVICE
DEGRADATION
POLICIES

PROJECT MODULE 1

ROBERTO CASALUCE – MACIEJ ZUZIAK



OVERVIEW



ONE DATASET
CONTAINING 1249
STATISTICAL UNITS



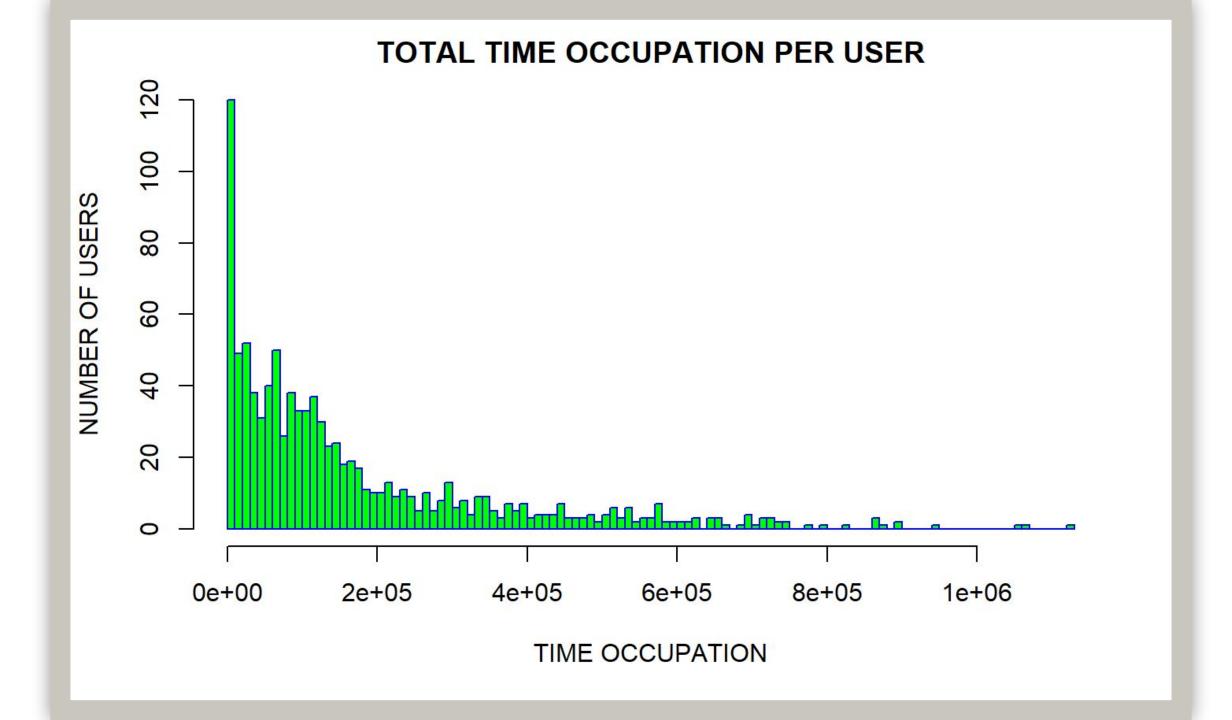
114 DIFFERENT
FEATURES (ONLINE
PLATFORMS AND
MOBILE APPLICATIONS)

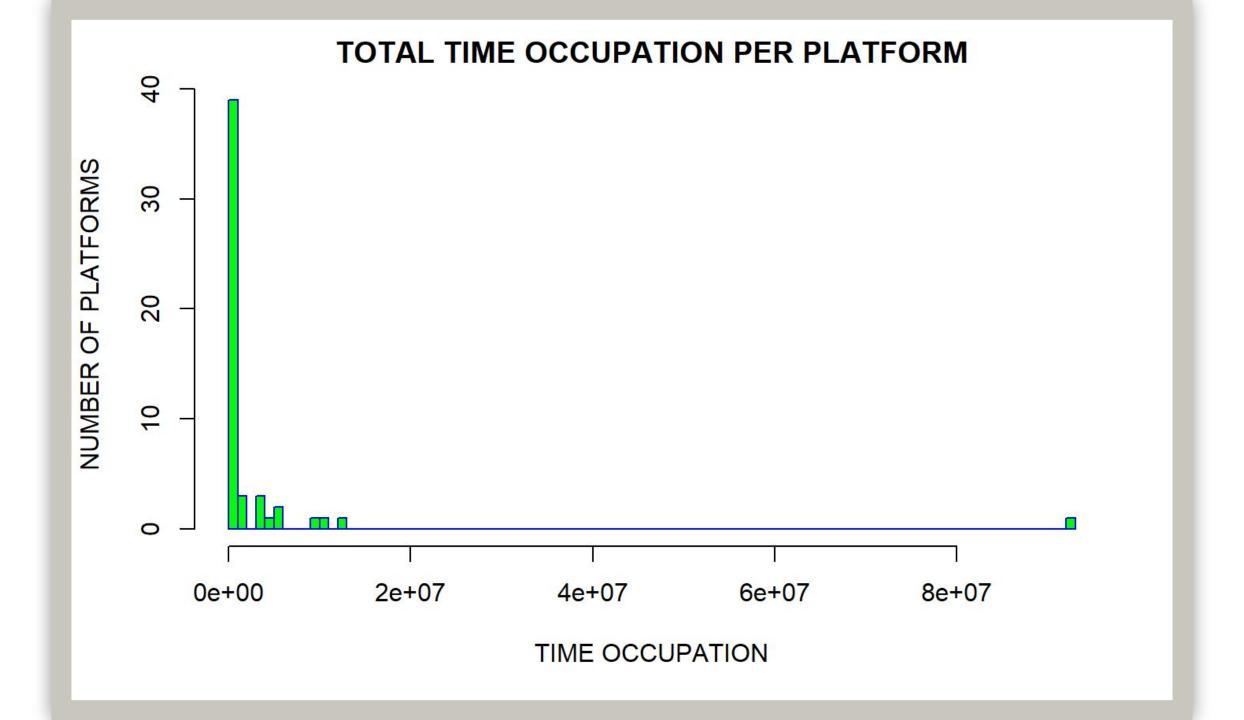


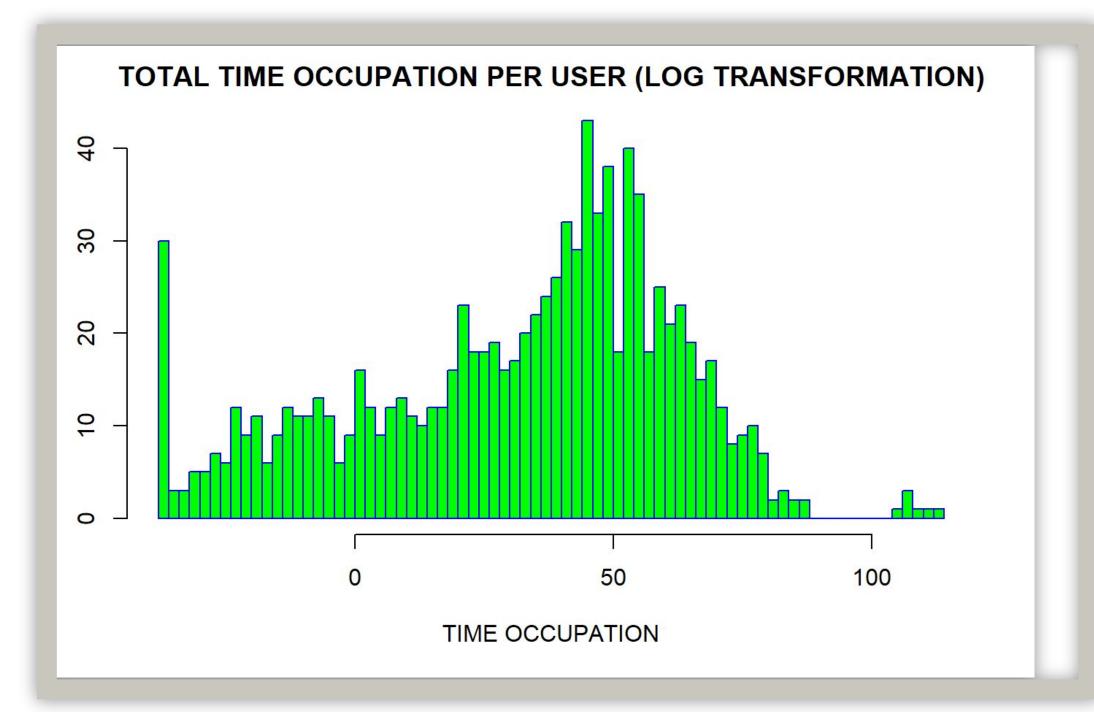
TIME EXPRESSED IN SECOND, DATA CONSUMPTION IN BYTES



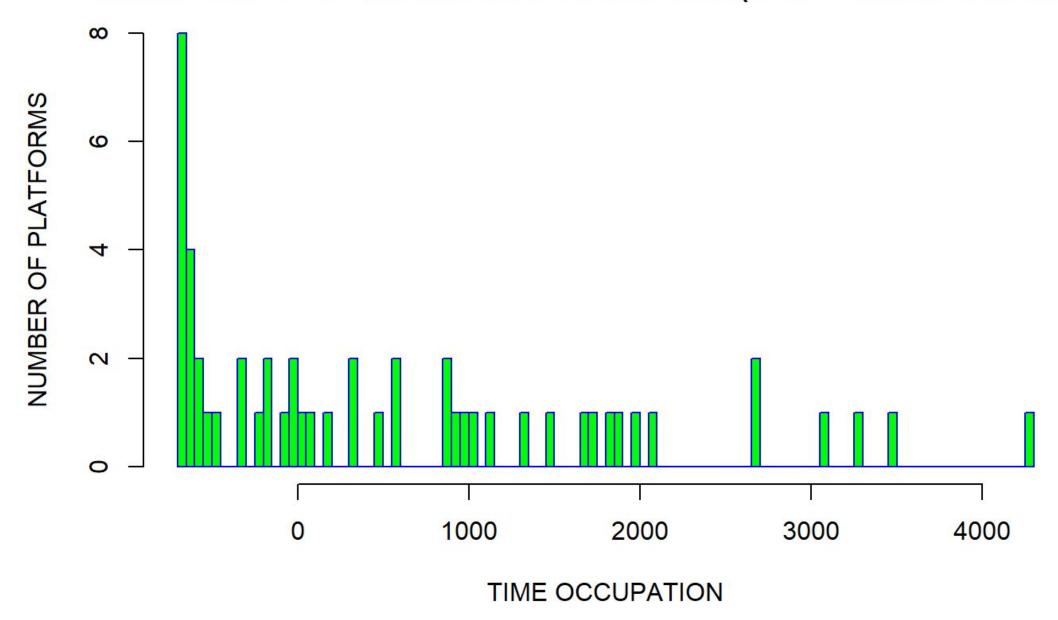
TASK IS TO IDENTIFY THE EXISTENCE OF CONSUMER GROUPS





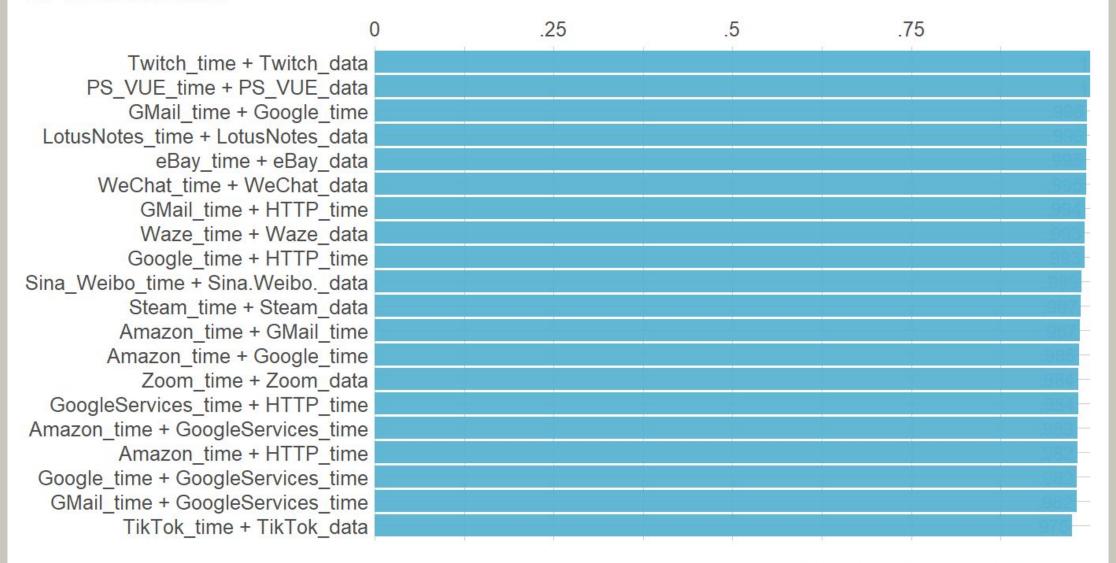


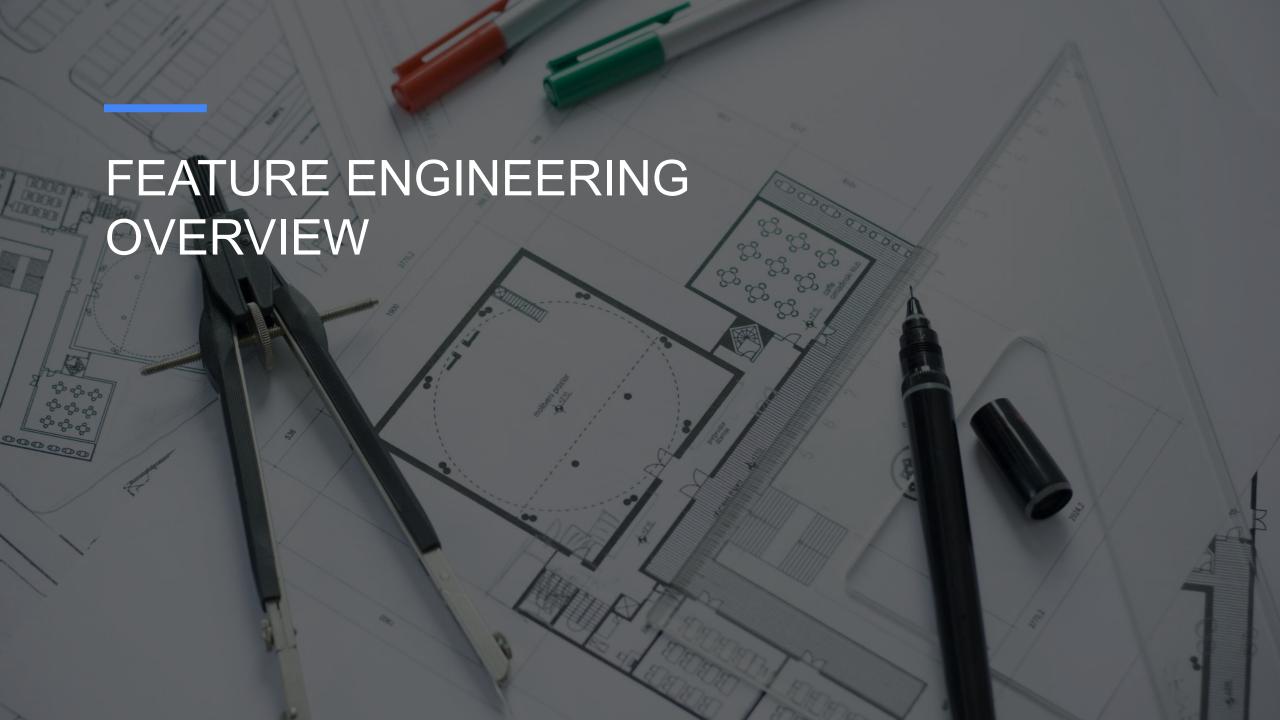
TOTAL TIME OCCUPATION PER PLATFORM (LOG TRANSFORMATION)



Ranked Cross-Correlations

20 most relevant





WE HAVE...

01

DELETED FEATURES RELATED TO DATA USAGE 02

DELETED FEATURES
THAT CONTAINED
LESS THAN TWO
USERS' ENTRIES

03

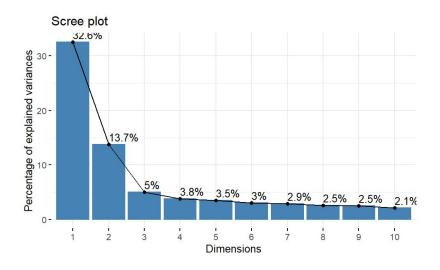
DELETED
DUPLICATED
ENTRIES

04

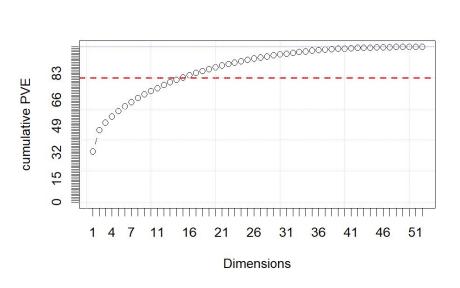
PERFORMED LOG TRANSFORMATION DESCRIBED BEFORE

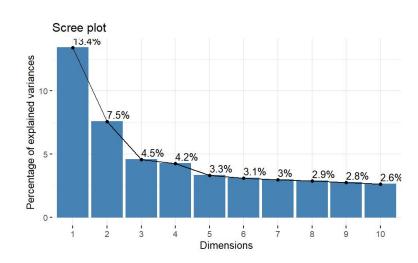


PCA

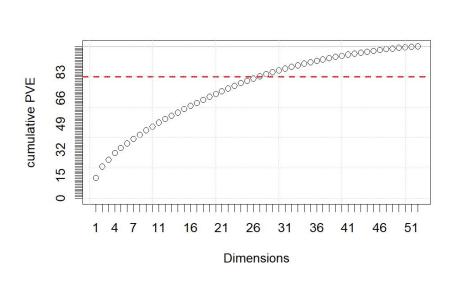


Log transformed data

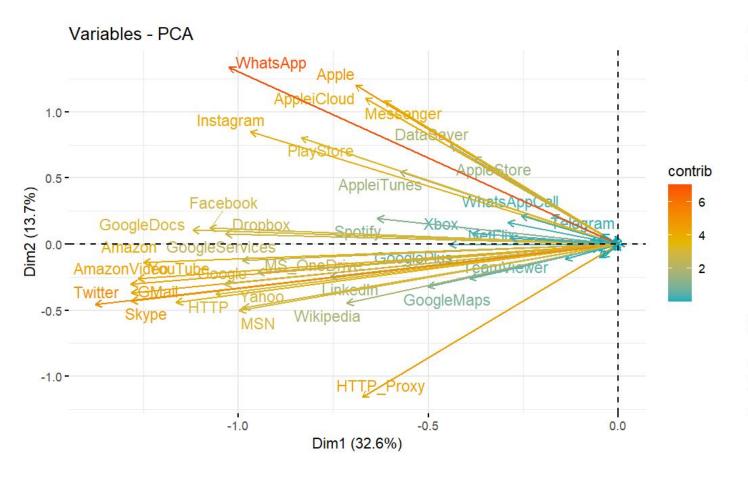


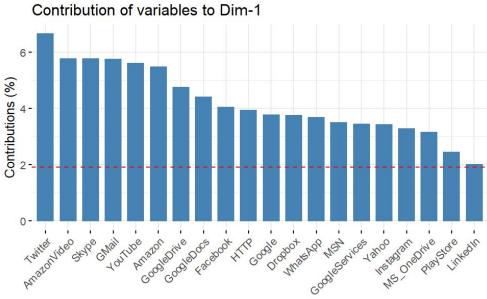


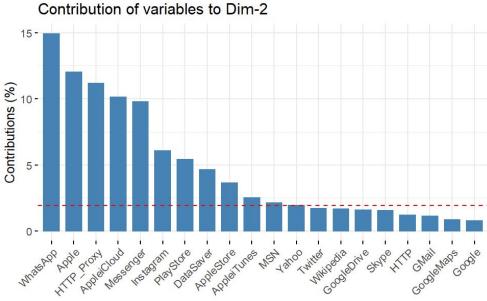
Scaled data



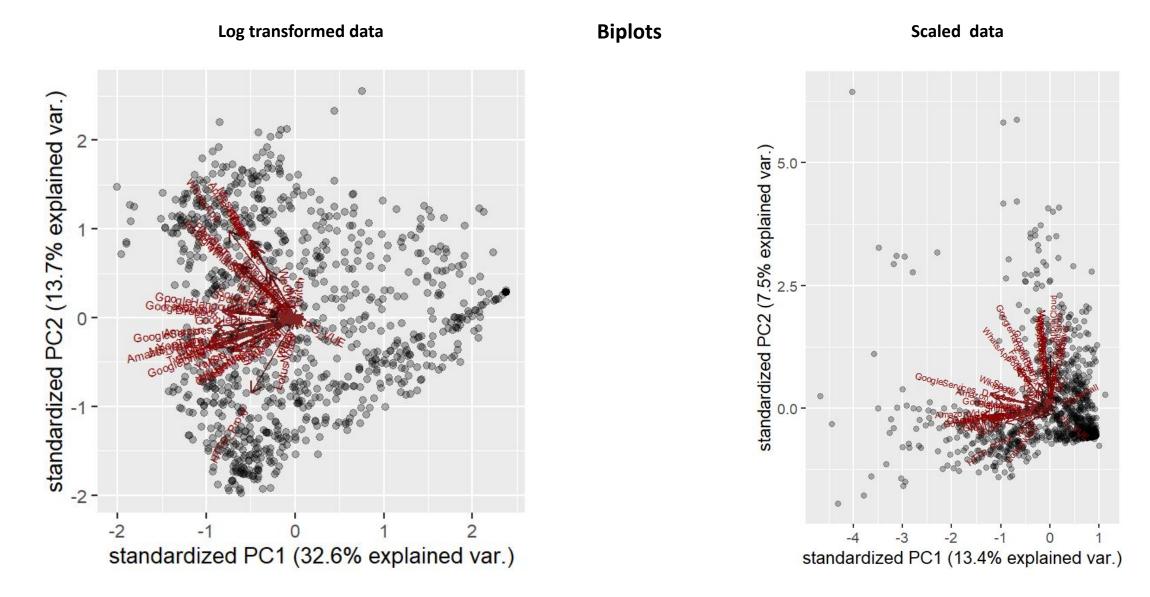
PCA







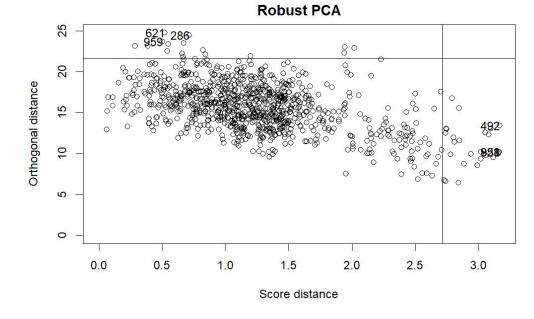
PCA



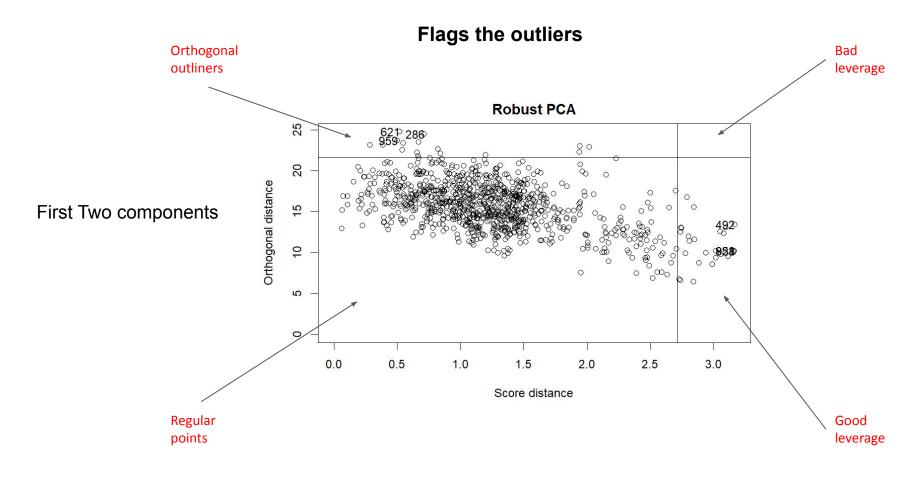
Robust PCA

Flags the outliers

First Two components

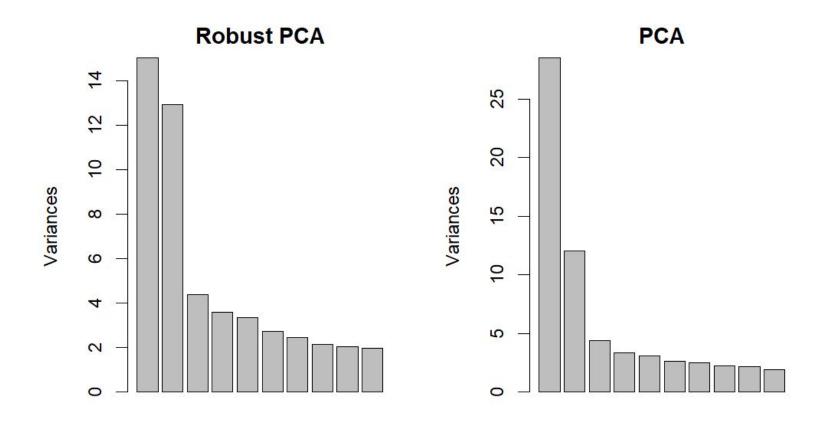


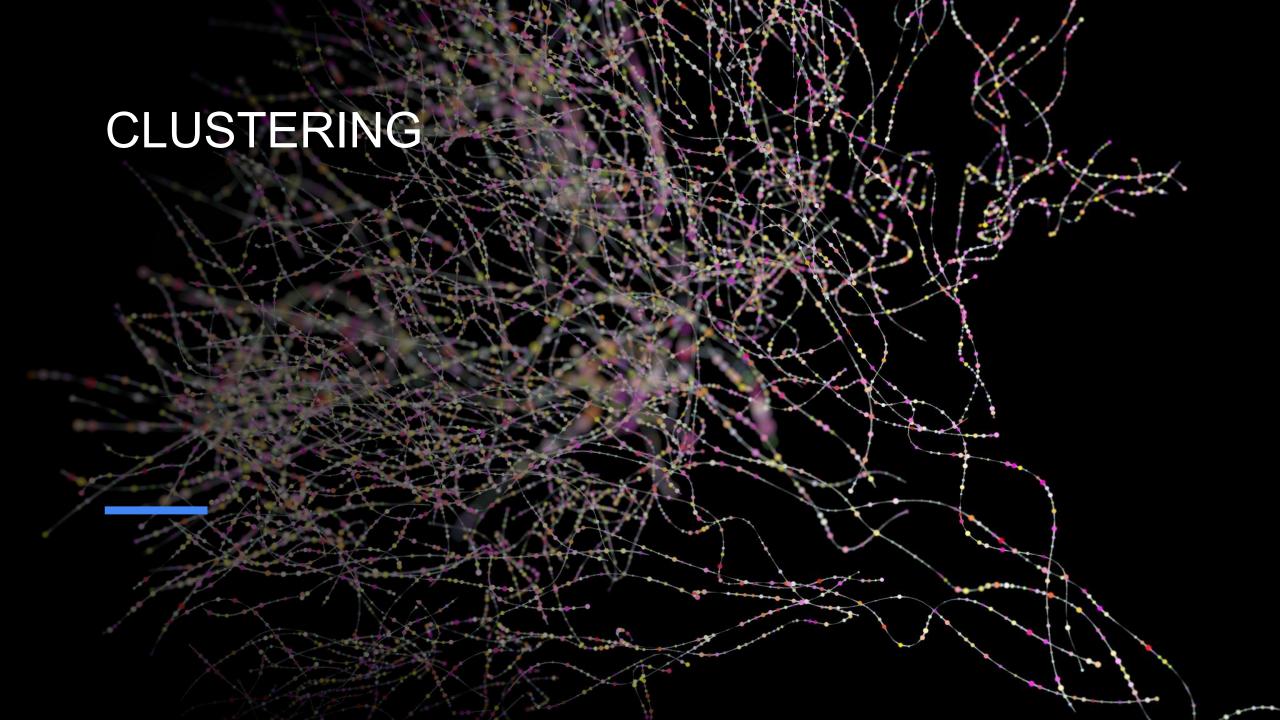
Robust PCA



(Chen et al., 2020)

Variances Robust and Classic PCA



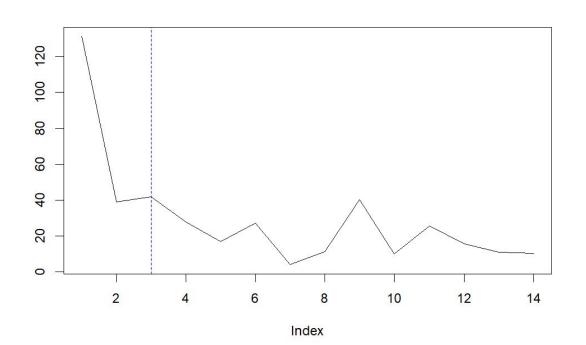


Clustering method selection

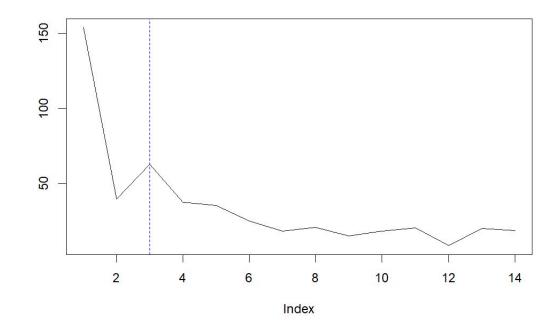
From a previous work (Rojas et al., 2020): 3/4 clusters - **Low**, **Medium**, **High and Very High**

Hartigan Index

Agglomerative Hierarchical clustering method



Kmeans clustering method



Evaluating Clustering methods (Brock et al., 2008)

Cluster **stability** measure:

- The average proportion of non-overlap (APN)
- The average distance (AD)
- The average distance between means (ADM)
- The figure of merit (FOM)

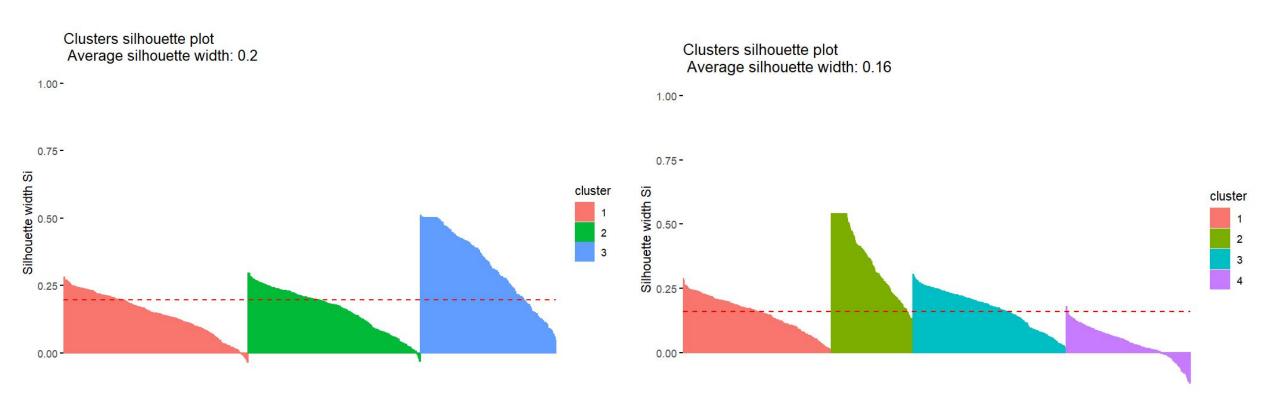
APN	0.009	kmeans	3
AD	10.2	kmeans	4
ADM	0.095	kmeans	3
FOM	0.93	kmeans	4

Connectivity	139.75	hierarchical	3
Dunn	0.26	hierarchical	3
Silhouette	0.20	kmeans	3

Internal measures for cluster validation

Evaluating a Clustering Solution

Silhouette widths kmeans

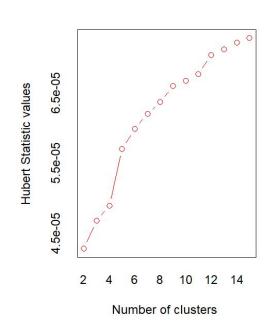


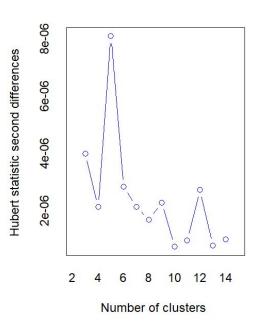
Evaluating a Clustering Solution

Hubert index kmeans

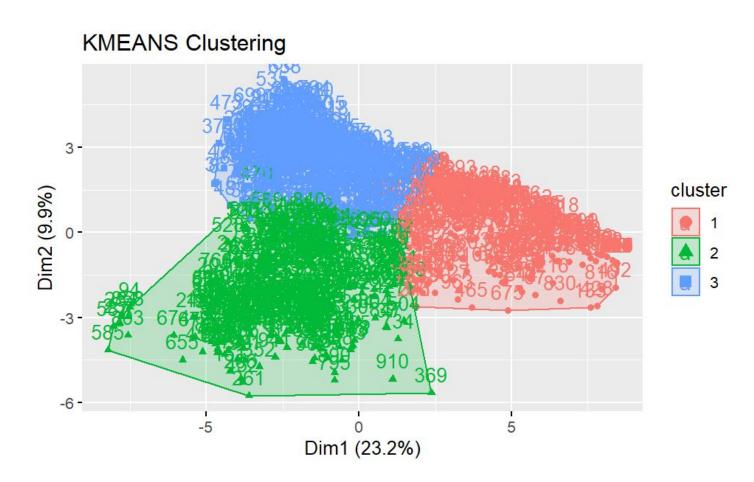
According to the majority rule, the best number of clusters is 3

- * 11 proposed 3 as the best number of clusters
- * 1 proposed 4 as the best number of clusters
- * 9 proposed 2 as the best number of clusters





Kmeans 3 clusters



Size Clusters				
1	2	3		
266	343	364		

Reference

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