INSEAD

The Business School for the World®

Prof. Anton Ovchinnikov

Prof. Spyros Zoumpoulis

DSB Classes 9-10, February 9, 2018

- Dimensionality Reduction. Clustering and Segmentation

Structure of the course

INSEAD
The Business School for the World®

- SESSIONS 1-2 (AO): Data analytics process; from Excel to R
  - Tutorial 1: Getting comfortable with R
- SESSIONS 3-4 (AO): Time Series Models
- SESSIONS 5-6 (AO): Intro to classification, logistic regression and machine learning
  - Tutorial 2: Midterm R help / classification
- SESSIONS 7-8 (SZ): Advanced Classification; From .R to Notebooks; Dimensionality reduction
- **SESSIONS 9-10 (SZ): Dimensionality Reduction; Clustering and Segmentation**
  - Tutorial 3: Q&A on R for three main modules
- SESSIONS 11-12 (SZ): Catch-up and wrap-up; Guest speaker
  - Tutorials 4, 5: Hands-on help on projects
- SESSIONS 13-14 (AO+SZ): Project presentations

Plan for the day
Learning objectives

INSEAD
The Business School for the World®

- Derived attributes and dimensionality reduction
  - Generate (a small number of) new manageable/interpretable attributes that capture most of the information in the data
- Clustering and segmentation
  - Group observations in a few segments so that data within any segment are similar while data across segments are different
- Work on business solution template for market segmentation (Assignment 3) for the Boats (A) case

Derived Attributes and Dimensionality Reduction

INSEAD
The Business School for the World®

- What is dimensionality reduction?
  - Generate (a small number of) new attributes that are (linear) combinations of the original ones, and capture most of the information in the original data
  - Often used as the first step in data analytics
- Why do dimensionality reduction?
  - Computational and statistical reasons: with thousands of features, very expensive and hard to estimate a good model
  - Managerial reason: the new attributes are interpretable and actionable
- The key idea of dimensionality reduction
  - Transform the original variables into a smaller set of **factors**
  - Understand and interpret the factors
  - Use the factors for subsequent analysis

Dimensionality Reduction: Key Questions

INSEAD
The Business School for the World®

1. How many factors do we need?
2. How would you name the factors? What do they mean?
3. How interpretable and actionable are the factors we found?

(A) Process for Dimensionality Reduction

INSEAD
The Business School for the World®

1. Confirm the data is metric
2. Scale the data
3. Check correlations
4. Choose number of factors
5. Interpret the factors
6. Save factor scores

Applying Dimensionality Reduction: Evaluation of MBA Applications

INSEAD
The Business School for the World®

Variables available:

1. GPA
2. GMAT score
3. Scholarships, fellowships won
4. Evidence of communications skills
5. Prior job experience
6. Organizational experience
7. Other extra curricular achievements

Which variables are correlated? What do these groups of variables capture?

Step 1: Confirm data is metric

INSEAD
The Business School for the World®

	Variables	GPA	GMAT	Fellow	Comm	Job.Ex	Organze	Extra
1	1	3	580	2	3.5	5	3.8	4
2	2	3.2	570	2	3.8	6	3.8	3.8
3	3	3.7	690	3	3.3	3	3.2	3.6
4	4	3.9	760	3	3.8	5	3.9	3.2
5	5	2.8	480	2	3.2	6	3.8	3.8
6	6	3.4	520	2.5	2.6	2	2.5	2.4
7	7	3.6	670	3	3.7	4	3.5	2.9
8	8	3.6	760	3	3.9	5	3.3	3.2

Step 2: Scale the data

INSEAD
The Business School for the World®

Before standardization

	Variables	min	X25.percent	median	mean	X75.percent	max	std
1	GPA	2.5	2.8	3.45	3.31	3.62	3.9	0.47
2	GMAT	380	480	575	583.5	682.5	760	119.44
3	Fellow	1	2	2.8	2.45	3	3.8	0.91
4	Comm	2	3.18	3.4	3.34	3.73	3.9	0.49
5	Job.Ex	2	3	5	4.25	5.25	6	1.52
6	Organze	1	3.05	3.4	3.2	3.8	3.9	0.73
7	Extra	2.4	2.88	3.4	3.3	3.8	4	0.52

Step 2: Scale the data

INSEAD
The Business School for the World®

Standardization….

```
ProjectDatafactor_scaled=apply(ProjectDataFactor,2, function(r) { #"2" applies the function over columns
 if (sd(r)!=0) {
  res=(r-mean(r))/sd(r)
  } else {
   res=0*r; res
   }
 })
```

Step 2: Scale the data

INSEAD
The Business School for the World®

After standardization

	Variables	min	X25.percent	median	mean	X75.percent	max	std
1	GPA	-1.72	-1.08	0.31	0	0.68	1.27	1
2	GMAT	-1.7	-0.87	-0.07	0	0.83	1.48	1
3	Fellow	-1.6	-0.5	0.39	0	0.61	1.49	1
4	Comm	-2.73	-0.33	0.13	0	0.8	1.16	1
5	Job.Ex	-1.48	-0.82	0.49	0	0.66	1.15	1
6	Organze	-2.99	-0.2	0.27	0	0.82	0.95	1
7	Extra	-1.75	-0.83	0.19	0	0.97	1.36	1

Step 3: Check correlations

INSEAD
The Business School for the World®

	GPA	GMAT	Fellow	Comm	Job.Ex	Organze	Extra
GPA	1.00	0.90	0.92	0.56	0.15	-0.03	0.01
GMAT	0.90	1.00	0.86	0.78	0.33	0.19	0.16
Fellow	0.92	0.86	1.00	0.59	0.18	0.01	0.02
Comm	0.56	0.78	0.59	1.00	0.60	0.47	0.39
Job.Ex	0.15	0.33	0.18	0.60	1.00	0.80	0.77
Organze	-0.03	0.19	0.01	0.47	0.80	1.00	0.61
Extra	0.01	0.16	0.02	0.39	0.77	0.61	1.00

Step 3: Check correlations

INSEAD

The Business School for the World®

	GPA	GMAT	Fellow	Comm	Job.Ex	Organze	Extra
GPA	1.00	0.90	0.92	0.56	0.15	-0.03	0.01
GMAT	0.90	1.00	0.86	0.78	0.33	0.19	0.16
Fellow	0.92	0.86	1.00	0.59	0.18	0.01	0.02
Comm	0.56	0.78	0.59	1.00	0.60	0.47	0.39
Job.Ex	0.15	0.33	0.18	0.60	1.00	0.80	0.77
Organze	-0.03	0.19	0.01	0.47	0.80	1.00	0.61
Extra	0.01	0.16	0.02	0.39	0.77	0.61	1.00

Step 4: Choose the number of factors

INSEAD
The Business School for the World®

We use Principal Component Analysis

Package: psych

```
UnRotated_Results<-principal(ProjectDataFactor, nfactors=ncol(ProjectDataFactor),
                              rotate="none”, score=TRUE)
```

- Factors are linear combinations of the original raw attributes…
- …so that they capture as much of the variability in the data as possible
- Factors are uncorrelated, and as many as the variables
- Each factor has an associated “eigenvalue” – which corresponds to the amount of variance captured by that factor
- First factor has the highest eigenvalue and explains most of the variance, then the second, …, and so on

Step 4: Choose the number of factors

INSEAD
The Business School for the World®

Package: FactoMineR

```
Variance_Explained_Table_results<-PCA(ProjectDataFactor, graph=FALSE)
Variance_Explained_Table<-Variance_Explained_Table_results$eig
```

	Eigenvalue	Pct of explained variance	Cumulative pct of explained variance
Component 1	3.74	53.48	53.48
Component 2	2.27	32.40	85.88
Component 3	0.42	6.07	91.95
Component 4	0.29	4.11	96.06
Component 5	0.14	1.99	98.05
Component 6	0.10	1.41	99.46
Component 7	0.04	0.54	100.00

```
> Variance_Explained_Table[1,1]/sum(Variance_Explained_Table[,1])
[1] 0.5347987
```

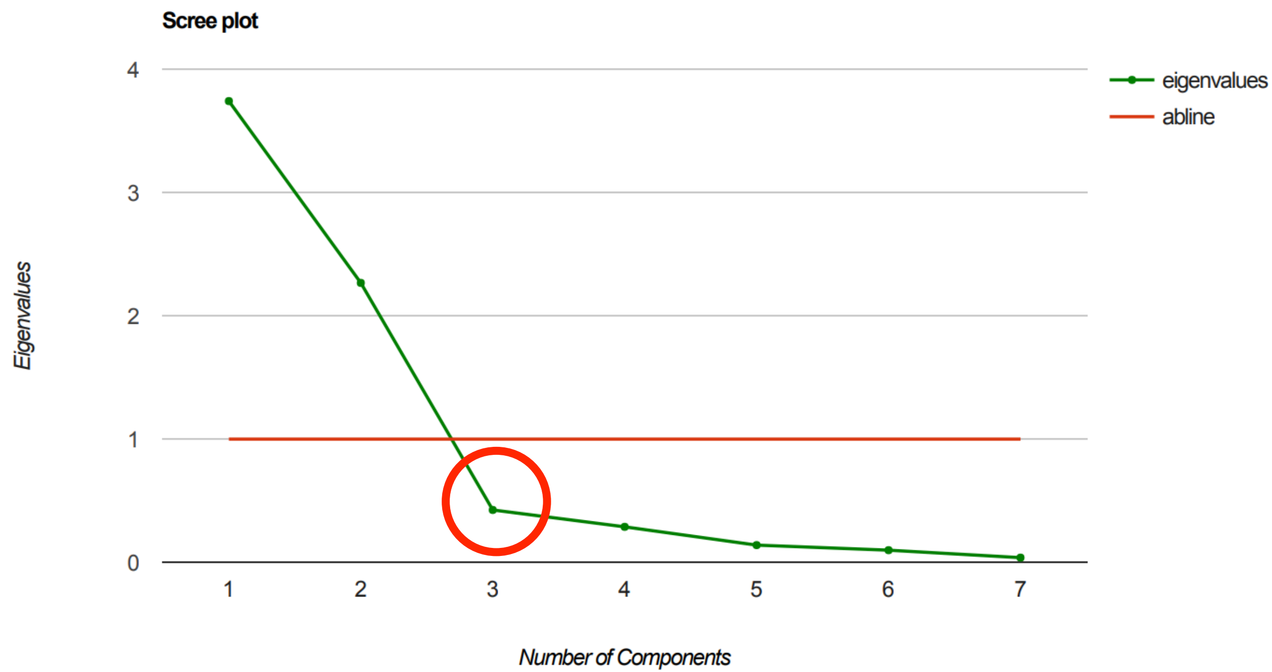
??

Step 4: Choose the number of factors

INSEAD
The Business School for the World®

We want to capture as much of the variance as possible, with as few factors as possible. How to choose the factors? Three criteria to use:

- Select all factors with eigenvalue > 1
- Select factors with highest eigenvalues up to exceeding a threshold (e.g. 65%) in cumulative % of explained variance
- Select factors up to the "elbow" of the scree plot



Step 5: Interpret the factors

To interpret the factors, we want them to use only a few, non-overlapping original attributes

- Factor "rotations" transform the estimated factors into new ones that satisfy that, while capturing the same information

Step 5: Interpret the factors

Package: psych

```
Rotated_Results<-principal(ProjectDataFactor, nfactors=max(factors_selected),
                           rotate="varimax", score=TRUE)
Rotated_Factors<-round(Rotated_Results$loadings,2)
```

	Component 1	Component 2
GPA	0.96	-0.05
GMAT	0.95	0.19
Fellow	0.95	-0.01
Comm	0.70	0.54
Job.Ex	0.19	0.93
Organze	0.01	0.89
Extra	0.01	0.86

To better visualize and interpret: suppress loadings with small values

```
Rotated_Factors_thres <- Rotated_Factors
Rotated_Factors_thres[abs(Rotated_Factors_thres) < 0.5]<-NA
```

	Component 1	Component 2
GPA	0.96	
GMAT	0.95	
Fellow	0.95	
Comm	0.70	0.54
Job.Ex		0.93
Organze		0.89
Extra		0.86

Step 5: Interpret the factors

INSEAD
The Business School for the World®

What factor loads “look good"? Three technical quality criteria:

1. For each factor (column) only a few loadings are large (in absolute value)
2. For each raw attribute (row) only a few loadings are large (in absolute value)
3. Any pair of factors (columns) should have different "patterns" of loading

Step 6: Save factor scores

INSEAD

The Business School for the World®

Replace the original data with a new dataset where each observation (row) is described using the derived factors

- For each row, estimate the **factor scores**: how the observation "scores" for each of the selected factors

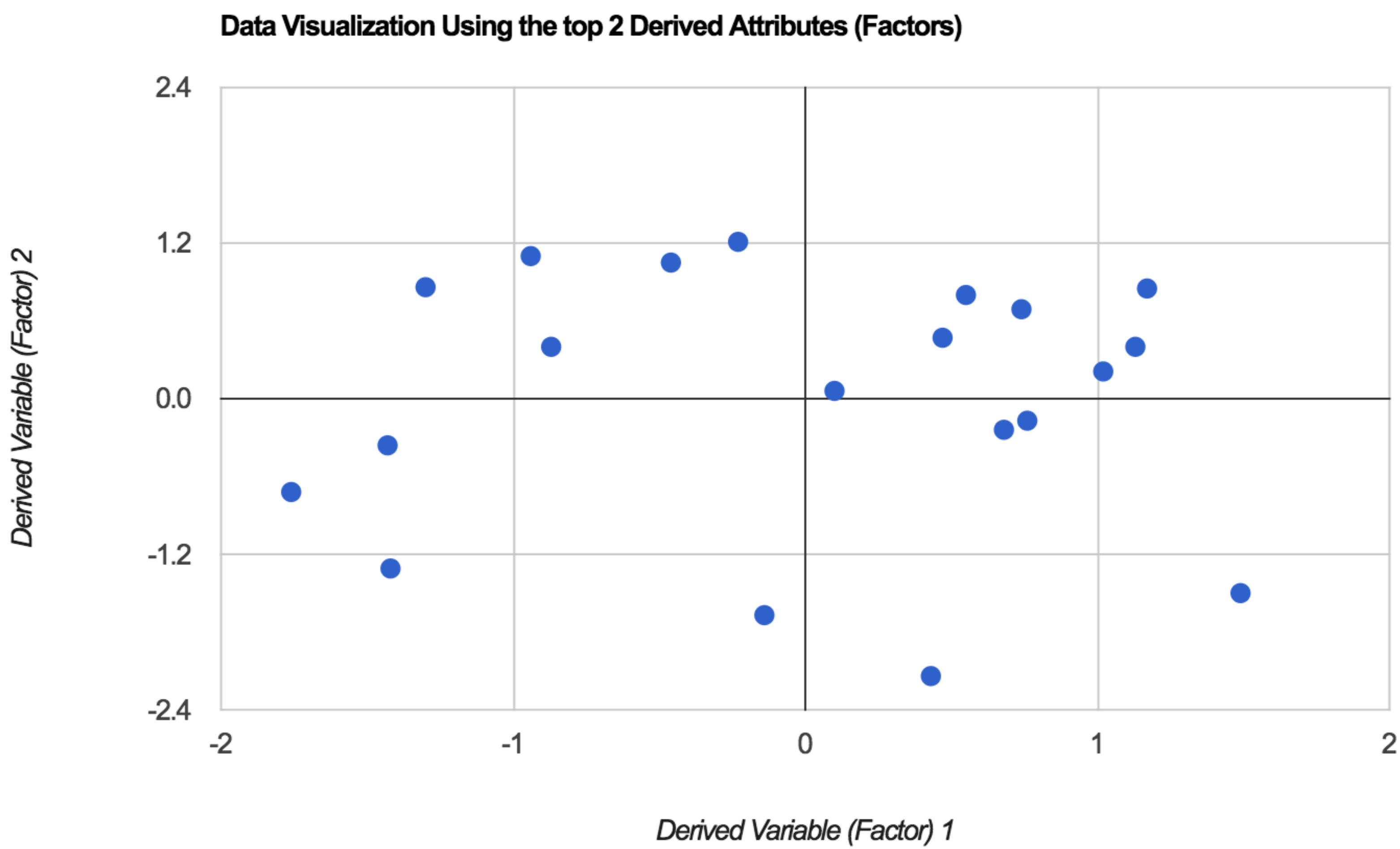
Package: psych

```
NEW_ProjectData <- round(Rotated_Results$scores[,1:factors_selected],2)
```

	Derived Variable (Factor) 1	Derived Variable (Factor) 2
observation 01	-0.46	1.05
observation 02	-0.23	1.21
observation 03	0.68	-0.24
observation 04	1.13	0.40
observation 05	-0.94	1.10
observation 06	-0.14	-1.67
observation 07	0.76	-0.17
observation 08	1.02	0.21
observation 09	-1.76	-0.72
observation 10	0.43	-2.14

Step 6: Save factor scores

Then continue the analysis (e.g., make decision, or do clustering, etc.) with the new attributes



Clustering and Segmentation

INSEAD
The Business School for the World®

- What is clustering and segmentation?
  - Processes and tools to organize data in a few segments, with data being as similar as possible within each segment, and as different as possible across segments

- Applications
  - Market segmentation
  - Co-moving asset classes
  - Geo-demographic segmentation
  - Recommender systems
  - Text mining

(A) Process for Clustering

INSEAD
The Business School for the World®

1. Confirm the data is metric
2. Scale the data
3. Select segmentation variables
4. Define similarity measure
5. Visualize pair-wise distances
6. Method and number of segments
7. Profile and interpret the segments
8. Robustness analysis

Step 3. Select segmentation variables

INSEAD
The Business School for the World®

Critically important decision for the solution

- Requires lots of contextual knowledge and creativity

Segmentation attributes vs. **profiling attributes**

For market research:

- Use attitudinal data for segmentation, so as to segment customers based on attitudes/needs
  - If ran dimensionality reduction before: segmentation attributes can be the original attributes with the highest absolute factor loading for each factor
- Use demographic and behavioral data for profiling the clusters found

Step 4. Define similarity measure

INSEAD
The Business School for the World®

Important: need to understand what makes two observations "similar" or "different"

There are infinitely many rigorous mathematical definitions of distance between two observations

Euclidean distance:

$$\|x - z\|_2 = \sqrt{(x_1 - z_1)^2 + \ldots (x_p - z_p)^2}$$

Manhattan distance:

$$\|x - z\|_1 = |x_1 - z_1| + \ldots + |x_p - z_p|$$

Step 4. Define similarity measure

INSEAD
The Business School for the World®

Using Euclidean distance:

	Obs.01	Obs.02	Obs.03	Obs.04	Obs.05	Obs.06	Obs.07	Obs.08	Obs.09	Obs.10
Obs.01	0									
Obs.02	4	0								
Obs.03	4	3	0							
Obs.04	4	4	4	0						
Obs.05	4	4	5	4	0					
Obs.06	4	3	3	4	4	0				
Obs.07	6	5	6	6	4	5	0			
Obs.08	4	3	4	4	4	4	5	0		
Obs.09	5	4	5	4	3	4	4	3	0	
Obs.10	8	6	7	7	8	5	7	7	7	0

Step 4. Define similarity measure

INSEAD
The Business School for the World®

Can also define distance manually

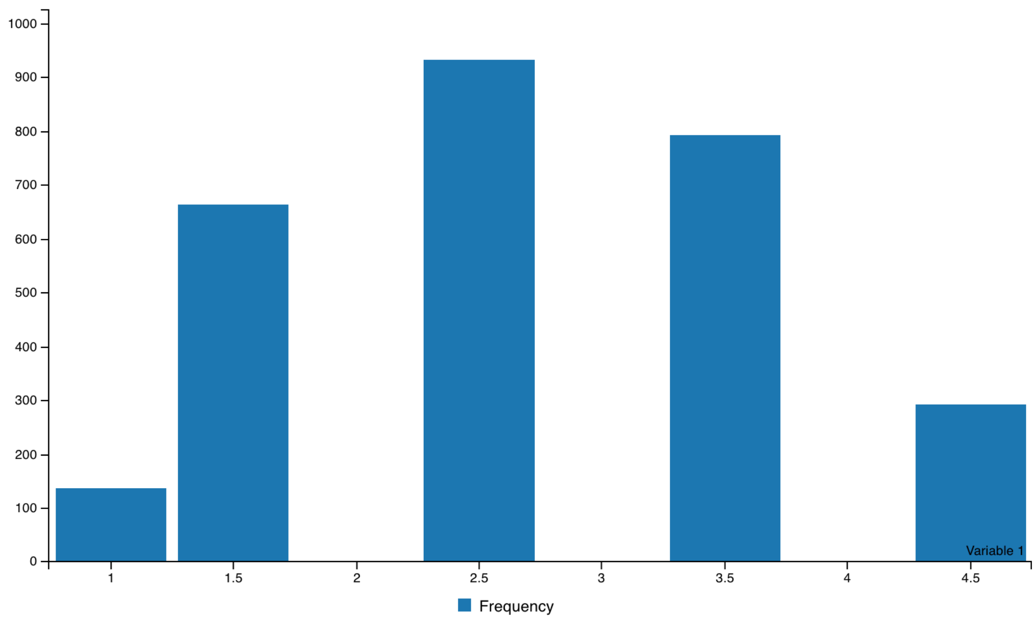
- Let's say that the management team believes that two customers are similar for an attitude if they do not differ in their ratings for that attitude by more than 2 points
- We can manually assign a distance of 1 for every question for which two customers gave an answer that differs by more than 2 points, and 0 otherwise

```
My_Distance_function<-function(x,y){ # x, y are vectors (answers of customers)
        sum(abs(x - y) > 2)
}
```

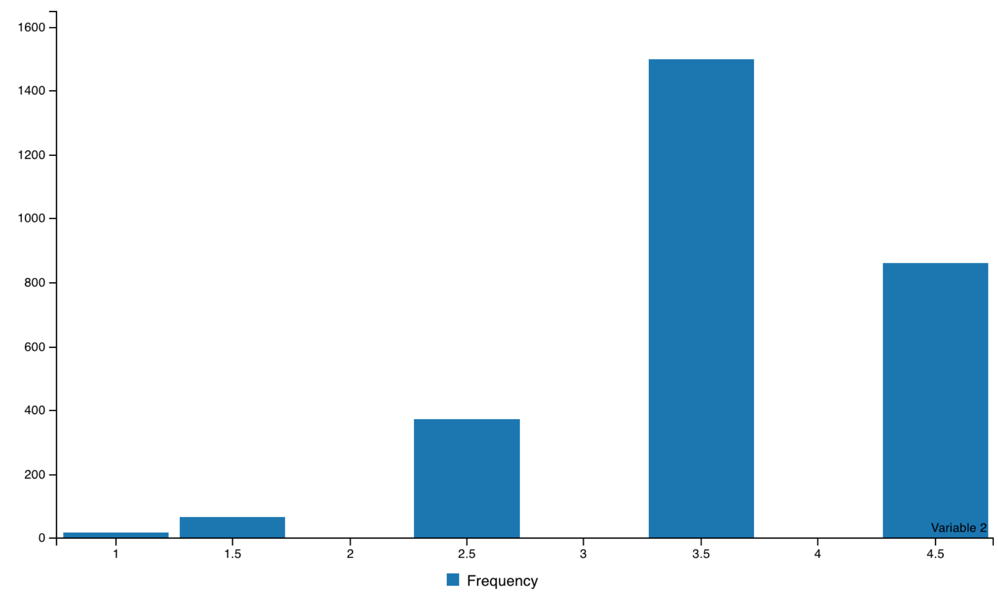
Step 5. Visualize pairwise distances

Visualize individual attributes…

Q1.27: Boating is the number one thing I do in my spare time



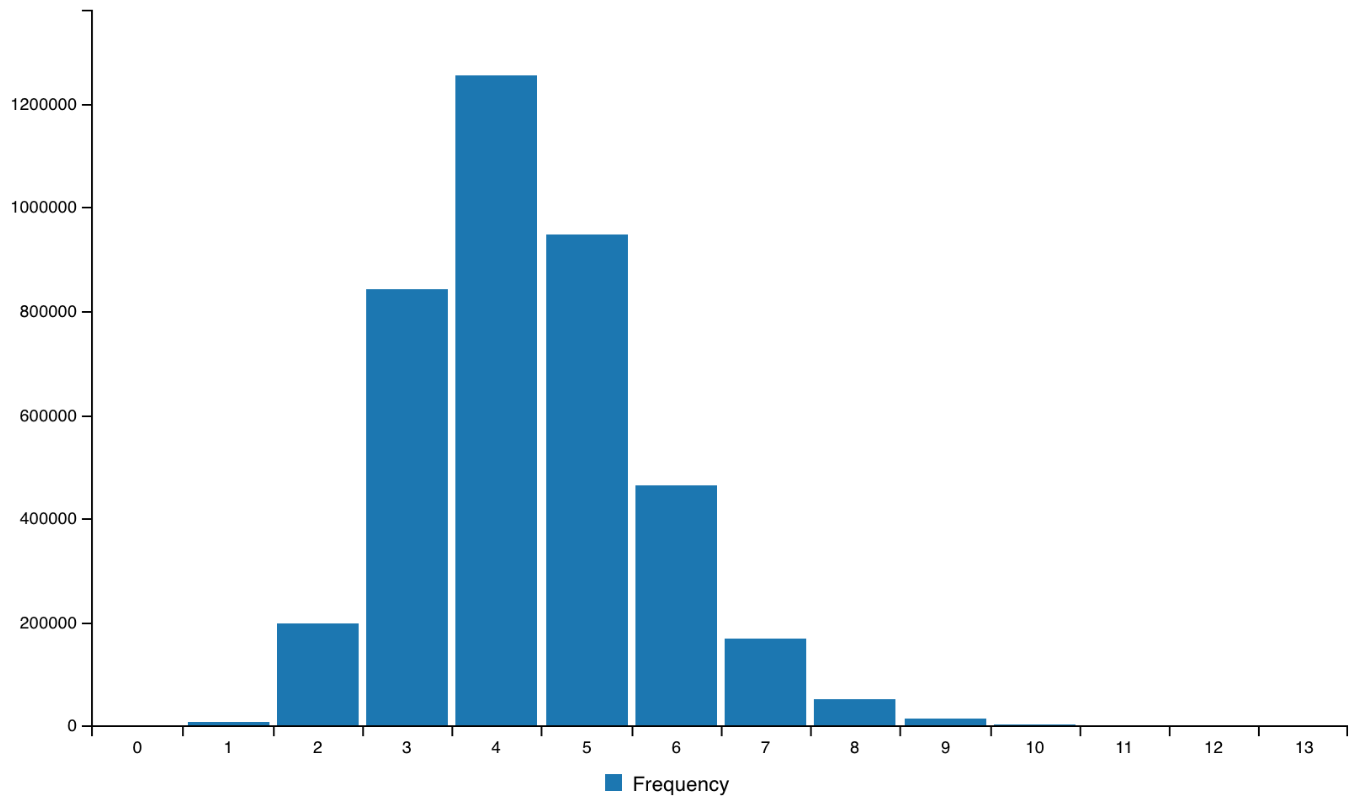
Q1.24: Boating gives me an outlet to socialize with family and/or friends



Step 5. Visualize pairwise distances

INSEAD
The Business School for the World®

… and pairwise distances



Step 6. Method and number of segments

INSEAD
The Business School for the World®

Many clustering methods. In practice, we want to use various approaches and select the solution that is robust, interpretable, actionable.

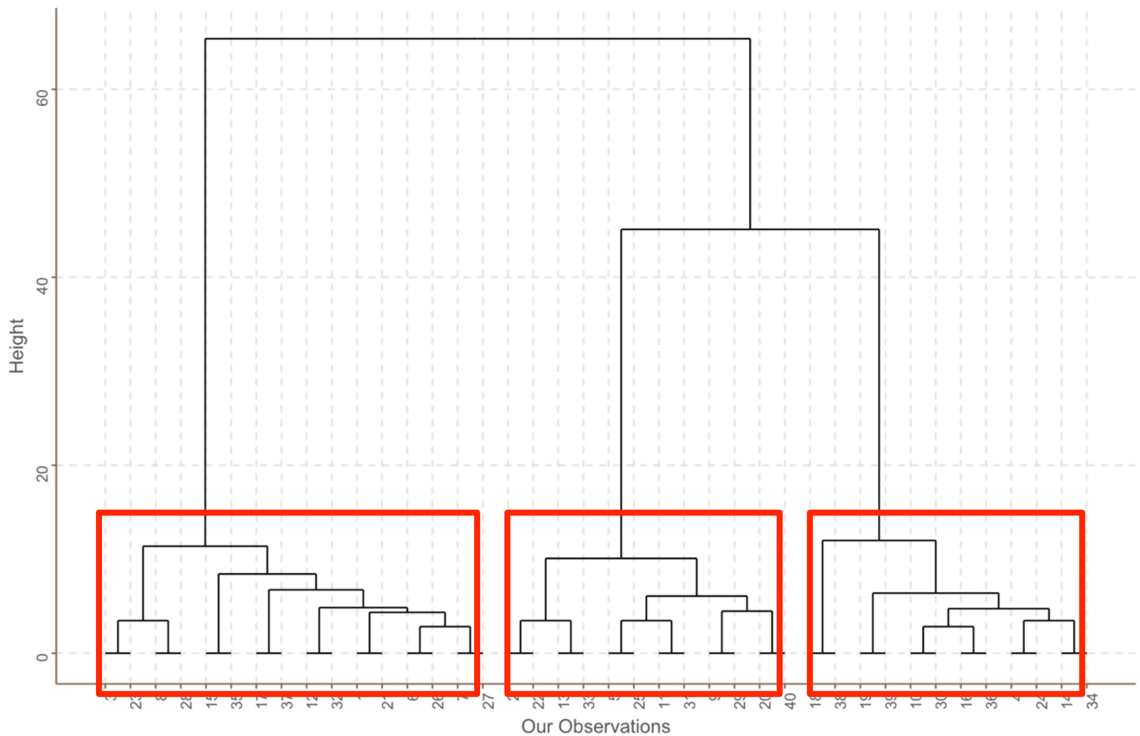
- Hierarchical clustering
- K-means

We can plug-and-play this "black box" in our analysis – with care

Step 6. Method and number of segments

INSEAD
The Business School for the World®

Hierarchical Clustering



"Dendrogram"

- Observations that are the closest to each other are grouped together
- Start with pairs
- Merge smaller groups into larger ones
- Eventually all our data are merged into one segment
- Heights of the branches of the tree indicate how different are the clusters merged at that level of the tree
- Then cut the tree so as to create the desired number of clusters

Step 6. Method and number of segments

INSEAD
The Business School for the World®

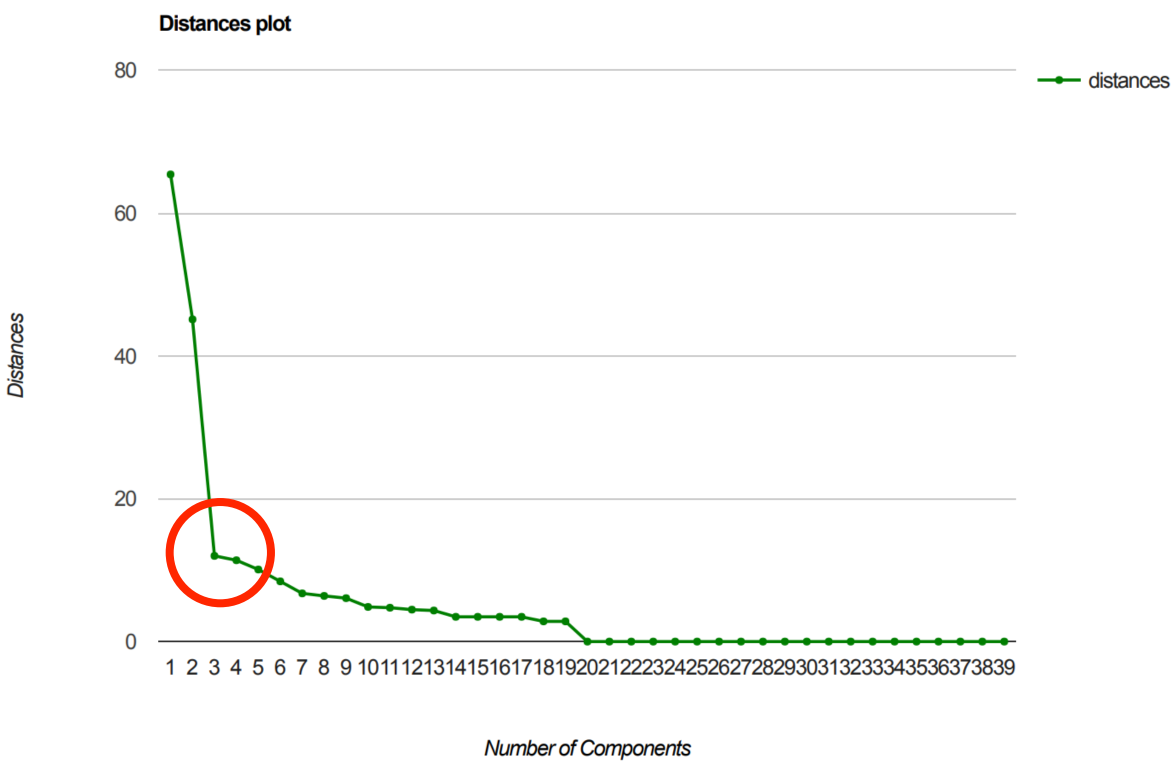
Hierarchical Clustering

```
ProjectData_segment <- ProjectData[,segmentation_attributes_used]
Hierarchical_Cluster_distances <- dist(ProjectData_segment, method="euclidean")
Hierarchical_Cluster <- hclust(Hierarchical_Cluster_distances, method="ward.D")
# Display dendrogram
iplot.dendrogram(Hierarchical_Cluster)
```

Step 6. Method and number of segments

INSEAD
The Business School for the World®

Hierarchical clustering: Choosing the number of clusters

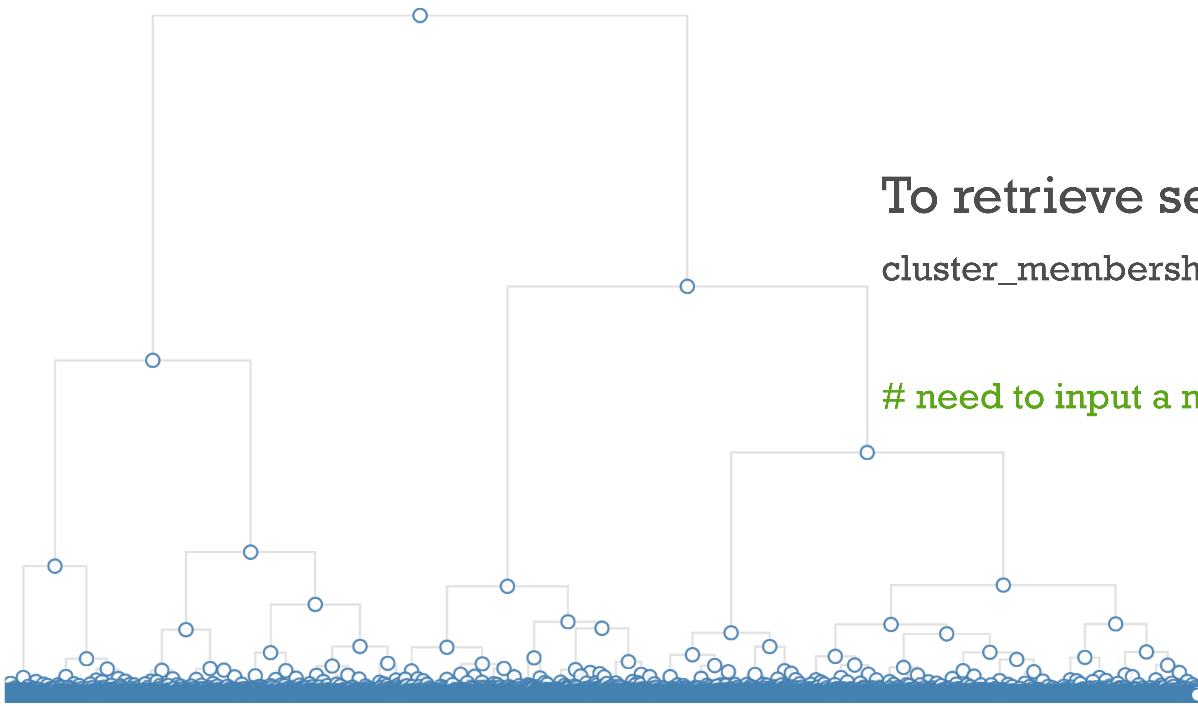


- Rule of thumb: set number of clusters as the "elbow" of the plot
- In practice: start with above rule, then explore different numbers of clusters
- Select final solution using also interpretability

Step 6. Method and number of segments

INSEAD
The Business School for the World®

Hierarchical clustering on Boats data



To retrieve segment membership:

```
cluster_memberships_hclust <- as.vector(cutree(HierarchicalCluster,
                                          k=numb_clusters_used))
# need to input a number of clusters for cutting the tree, not earlier
```

Observation Number	Cluster_Membership
1	1
2	2
3	1
4	3
5	4
6	1
7	4
8	2
9	4
10	3

Step 6. Method and number of segments

K-means clustering aims to partition the observations into k sets so as to minimize the sum of within-cluster variances

- In each iteration, every observation is assigned to the nearest mean
- K-means does not necessarily lead to the same solution every time you run it

```
kmeans_clusters <- kmeans(ProjectData_segment,centers = numb_clusters_used, iter.max = 2000,
                          algorithm="Lloyd")
# need to input a number of clusters as soon as clustering method is called
```

To retrieve segment membership:

```
kmeans_clusters$cluster
```

Observation Number	Cluster_Membership
1	5
2	5
3	5
4	5
5	5
6	5
7	5
8	5
9	5
10	3

Different methods may put observations in different clusters

Step 7. Profile and interpret the segments

INSEAD
The Business School for the World®

What are the resulting segments? We need to be able to understand and interpret the clustering solution

- Profile the segments using the profiling attributes

Average values within each segment and in total population

	Population	Seg.1	Seg.2	Seg.3	Seg.4	Seg.5	Seg.6	Seg.7
Q1.1	4.03	4.01	4.20	3.84	4.41	4.41	3.73	3.83
Q1.2	2.89	2.29	2.74	3.77	2.63	4.33	2.90	3.04
Q1.3	3.12	3.56	3.03	3.52	3.92	4.23	2.71	2.37

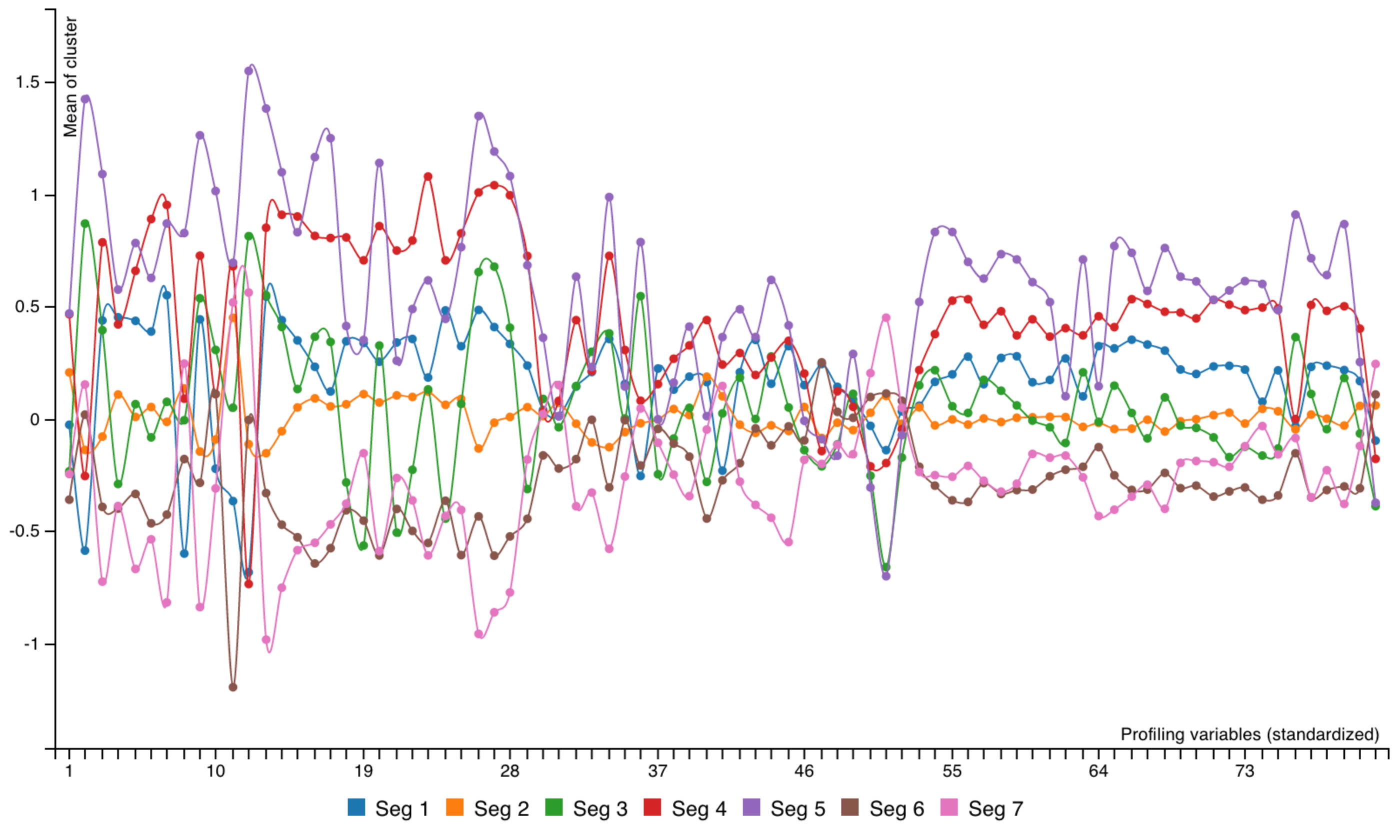
avg(segment)/avg(population) - 1

	Seg.1	Seg.2	Seg.3	Seg.4	Seg.5	Seg.6	Seg.7
Q1.1	0.01-	0.04	0.05-	0.09	0.10	0.07-	0.05-
Q1.2	0.21-	0.05-	0.30	0.09-	0.50	0.01	0.05
Q1.3	0.14	0.03-	0.13	0.26	0.36	0.13-	0.24-

Step 7. Profile and interpret the segments

INSEAD
The Business School for the World®

Snake plots for each cluster: means of (standardized) profiling variables



Step 8. Robustness analysis

INSEAD
The Business School for the World®

The segments found should be relatively robust to changes in the clustering methodology

- Large changes indicate that segmentation is not valid

Two basic tests for statistical robustness and stability of interpretation:

1. How much overlap is there between the clusters found using different approaches?
2. How similar are the profiles of the segments found?

Also try different

- subsets of the original data
- variations of the original segmentation attributes
- different distance metrics
- different numbers of clusters

Assignment 3 & Break-out Rooms

INSEAD
The Business School for the World®

- Assignment: Parts 1 and 2 of MarketSegmentationProcessInClass
- BORs: 319-329, 361A, 361E

Summary of Sessions 9-10

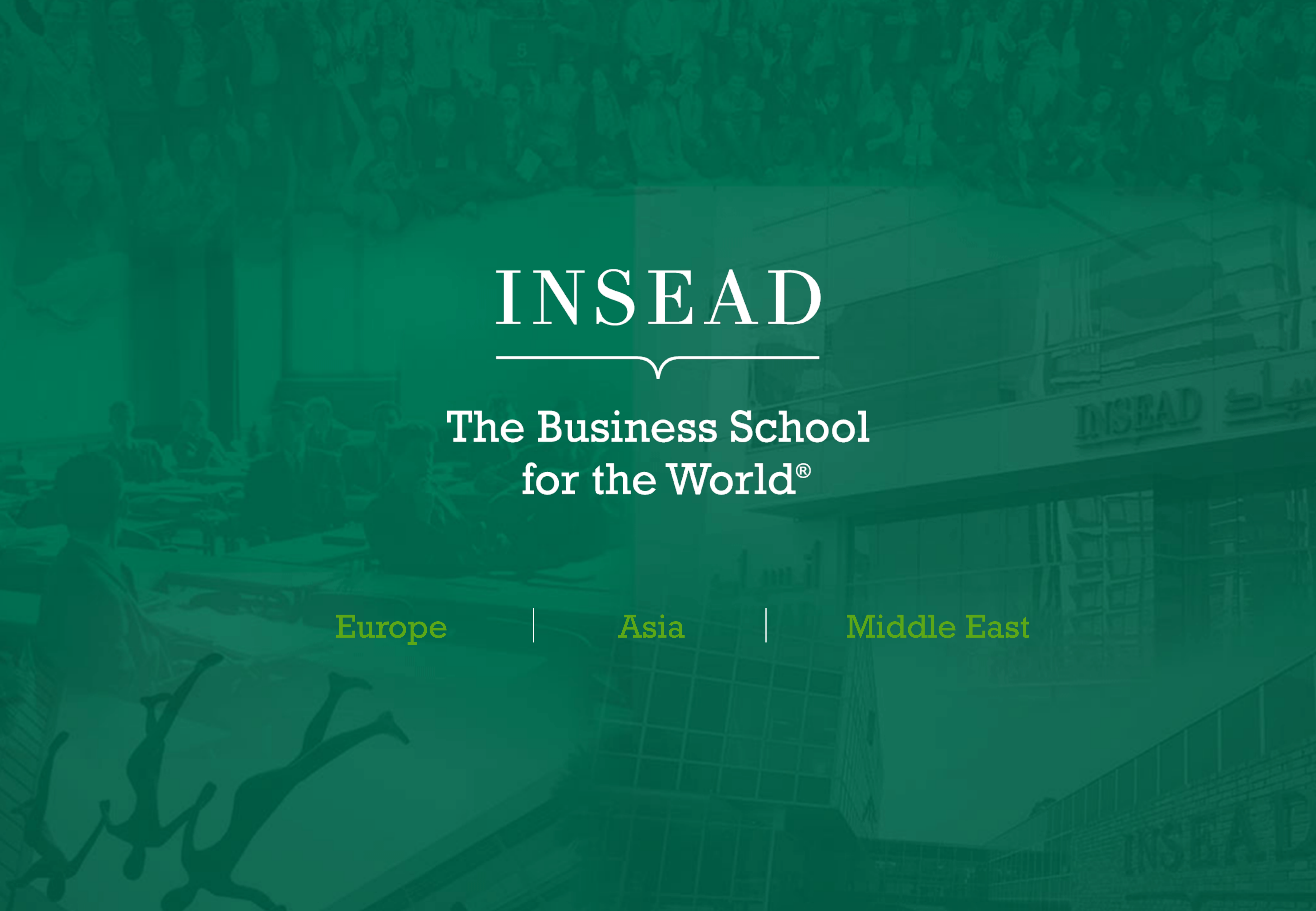
INSEAD
The Business School for the World®

- Derived attributes and dimensionality reduction
  - Principal Component Analysis, how to choose number of factors
  - Then continue analysis on the new attributes
- Clustering and segmentation
  - Create groups of similar observations
  - Hierarchical clustering, K-means clustering
- Template for market segmentation (Assignment 3) for the Boats (A) case

Next…

INSEAD
The Business School for the World®

- Tutorial 3 [Fri Feb 9, 7.15 pm, Amphi 102]
  - Walk through code chunks of market segmentation process
  - Help with Assignment 3
- Sessions 11-12 [Tue Feb 13, Amphi 105]
  - Catch up/wrap up
  - Guest speaker: advanced analytics leader in BCG's Financial Institutions and Insurance practices
- Assignment 3. Complete the market segmentation process + answers to questions of Parts 1 and 2
- Proposal for final project (due Feb 14)
- Final project (due Feb 20)


INSEAD
The Business School
for the World®
Europe
Asia
Middle East