# Discovering, Visualizing and Targeting Customer Segments

Dr. Anestis Fachantidis



# The Ever Increasing Personalization

# Personalization is the top priority of the Marketers today. According to Forrester:

- In email only 7% of consumers agree with the statement "Email offers are usually well timed with my needs" (down from 9% in 2014). Meanwhile, marketers ranked "improving the customer experience" first in their list of priorities for the year. [1]
- Only 30% of customers today feel that they are getting their desired level of personalization

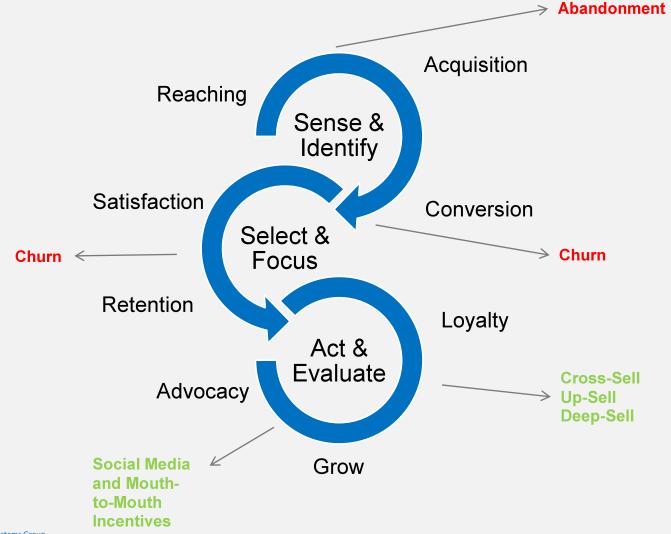
# Machine Learning (ML) is the key enabling technology for personalization

 Discovering and exploiting the connection of attributes (customer characteristics) to specific output variables (customer behavior) could (almost) work as a ML definition

[1] "The Contextual Marketing Imperative: The Evolution Of Personalization From Push Messaging To One-To-One Personal Customer Experiences," Forrester 2015.



# The Customer Success Journey



# **Customer Segmentation**

# **Customer Segmentation**

Dividing a company's customer base into smaller, distinct and internally homogeneous groups of customers based on a set of customer characteristics

Example of customer characteristics – the classic RFM model:

- Recency
- Frequency
- Monetary

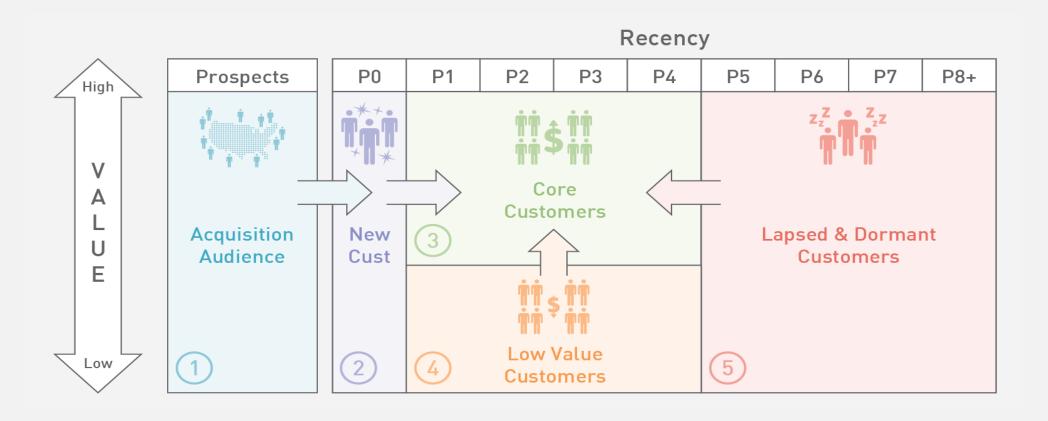
A finer customer model (more customer characteristics **or** more detailed ones) will enable the formation of *micro-segments* 

Marketers create targeting strategies tailor-made for each customer segment



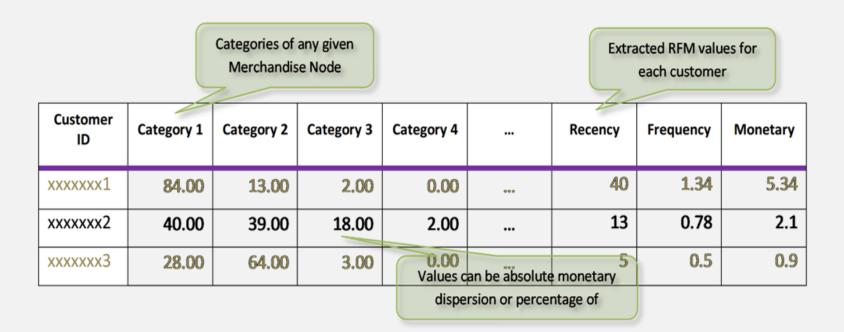


# The Business Perspective



source: wiland.com

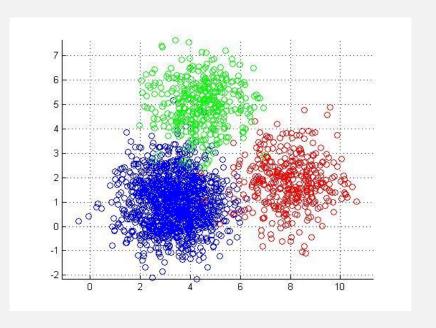
# The Data Perspective

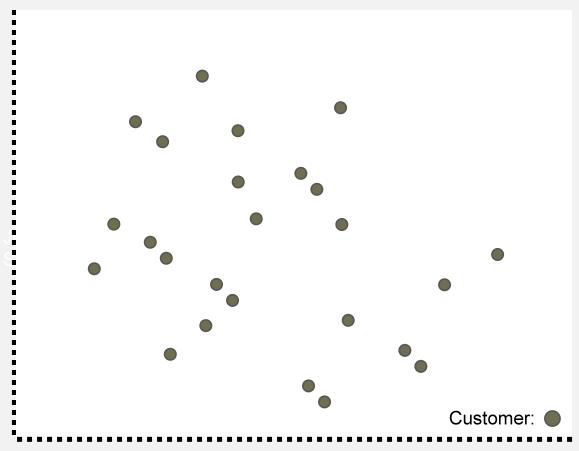


# Linking Business & Data Perspectives

#### The Machine Learning Advantage:

- Non-automated segmentation requires extensive and costly experimentation
- Data-driven automated analysis can be far more reliable and efficient
- Clustering algorithms (from unsupervised machine learning) can discover the natural-underlying groupings of customers
- Over 100 clustering algorithms in literature. Three well known families are:
  - Centroid-based (e.g. K-Means)
  - Hierarchical (named after their linkage criterion)
  - Density based (e.g. DBSCAN)

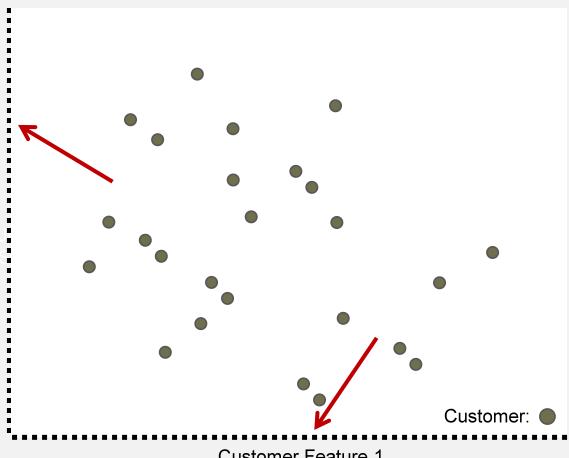




# Key Considerations:

- Knowledge Representation & Feature Engineering
- 2. Defining similarity
- 3. Algorithm Selection
- 4. Evaluation strategy

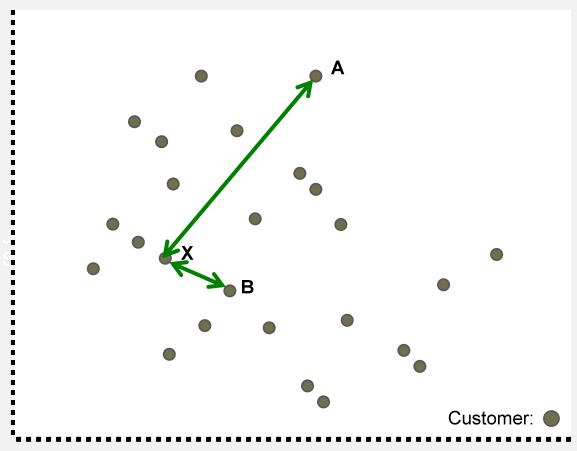
**Customer Feature 1** 



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#### **Key Considerations:**

- 1. Knowledge Representation & **Feature Engineering**
- 2. Defining similarity
- 3. Algorithm Selection
- 4. Evaluation strategy
- What do these features represent? (customer value?)
- How will they be produced? (aggregations, summaries, etc.)
- What types of features? (qualitative/quantitative etc)



**Customer Feature 1** 

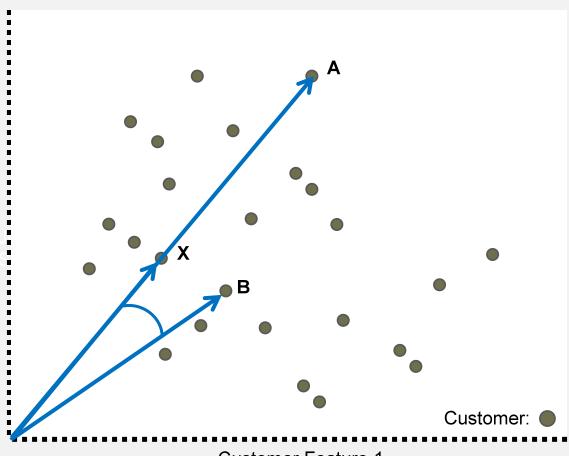
# Intelligent Systems Group Computer Science Department Aristotle University

#### **Key Considerations:**

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Different distance measures will express different types of similarity between customers. Example:

- Euclidean distance, usually for real-valued data (customer value), X is closer to B
- Cosine distance, suitable for count data (customer basket),
   X is closer to A



**Customer Feature 1** 

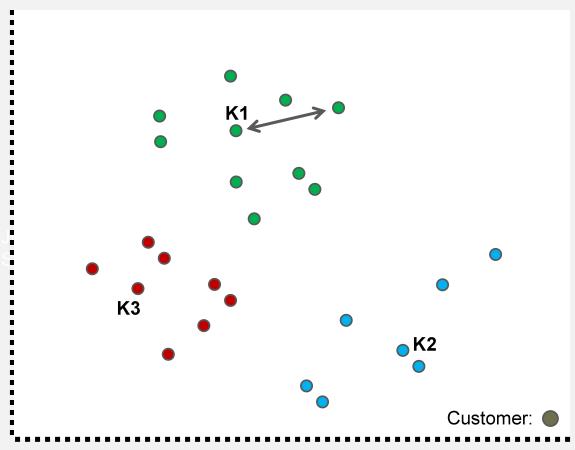
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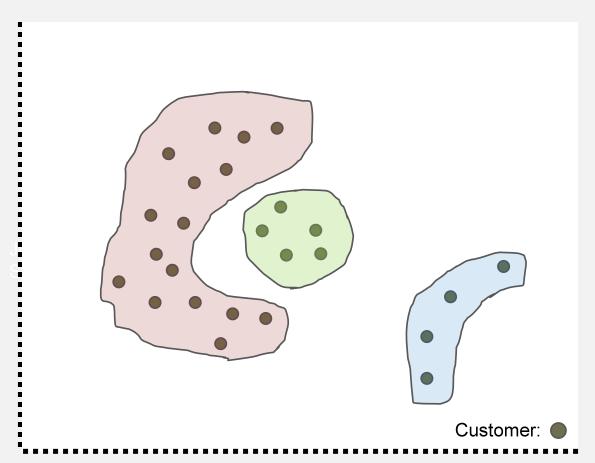
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#### **Centroid-Based Clustering**

(e.g., K-Means)

- Set number of cluster representatives (# of clusters)
- An optimization process of continually setting new cluster centers (customer archetypes) and forming clusters with the data points (customers) closer to them





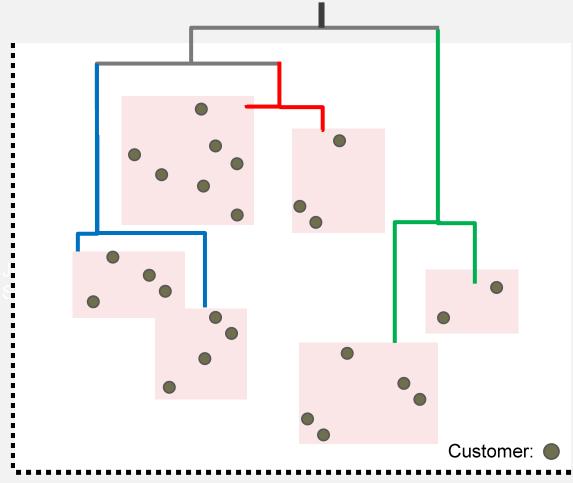
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**Density-Based Clustering** (e.g., DBSCAN)

Clusters are defined as areas of higher density than the remainder of the data set.



**Customer Feature 1** 

#### **Key Considerations:**

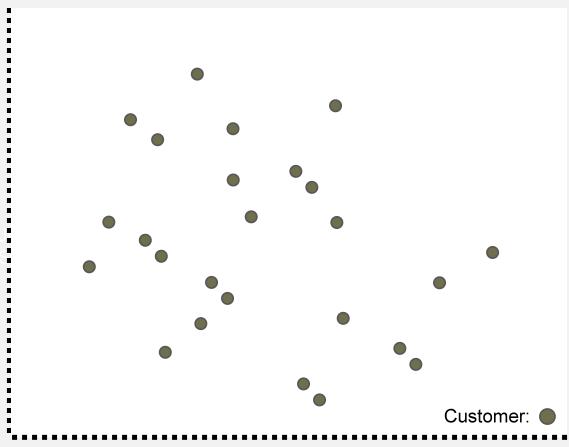
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#### **Hierarchical Clustering**

Given a distance level, different but nested cluster structures can be formed, resulting to a cluster hierarchy

- Computationally expensive
- Significant flexibility for business use / natural microsegments



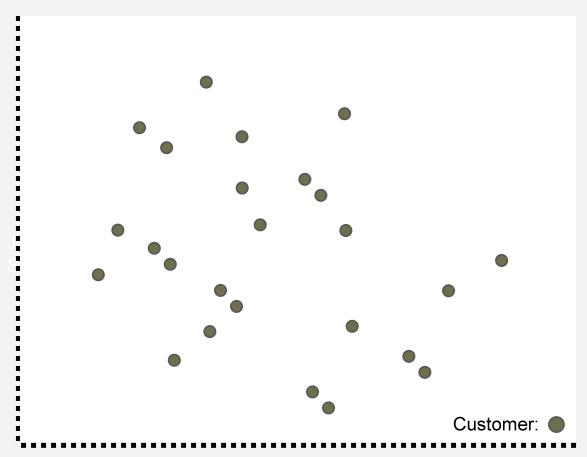


**Customer Feature 1** 

#### **Key Considerations:**

- Knowledge Representation & Feature Engineering
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- 4. Evaluation strategy
- Internal evaluation: measures such as the silhouette and gap scores
- External business
   evaluation: does a customer
   segment responds
   homogeneously to the same
   marketing actions?





**Customer Feature 1** 

#### **Key Considerations:**

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#### **Extra considerations:**

- 1. Need for robust models
- Big Data → high computational complexity

# **Personalized Campaigns**

# The Minimalistic Campaign Model

#### A campaign *unit* consists of:

#### **Audience**

- Segment (or micro-segment)
- Manually defined (threshold-based query) or automatically discovered (clustering) or both

#### Content

Auto-generated or manually curated – includes an offer or not

#### Context

Location or time-zone (e.g., at home, specific time-zone or event trigger)

#### Channel

e.g., Mobile app, or user account or SMS

#### Evaluation criteria & time period

- KPIs such as R/F/M improvements at a time period (e.g. 1 week)
- Transitions from "poor" to "rich" micro-segments

# A Working Example from the Betting Industry

#### Let's create a campaign!

This campaign will focus on the following:

#### Content

A 10% discount offer for a betting amount above 50 €

#### Audience

Age : any

Game : Football or Basketball

- Medium-High Value Customers (Healthy)
- No churn customers in this example (assumption)

#### Context

Customers connected on the mobile app

#### Channel

Push notification in mobile app account

#### Duration of the campaign

1 Week

There will be **two variations** of this campaign altering one of these characteristics and forming **Campaign Unit A** and **Campaign Unit B** 



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And then with their value:

- Red hat → Likely to churn
- Green hat → Healthy



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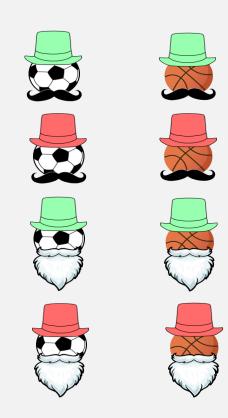
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#### And then with their age:

- Black moustache → 30-45
- White beard → 45-60+



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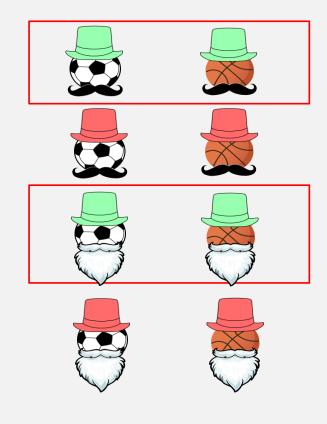
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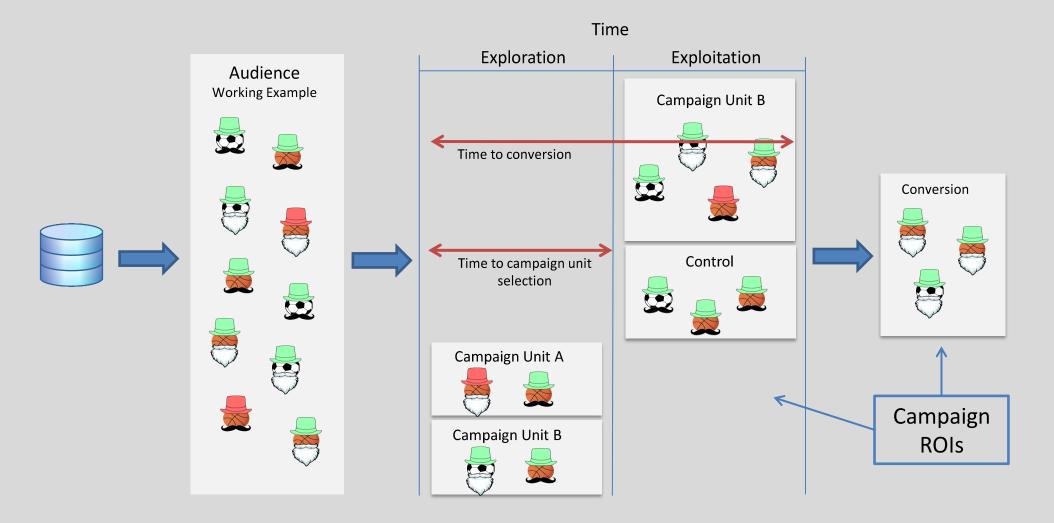
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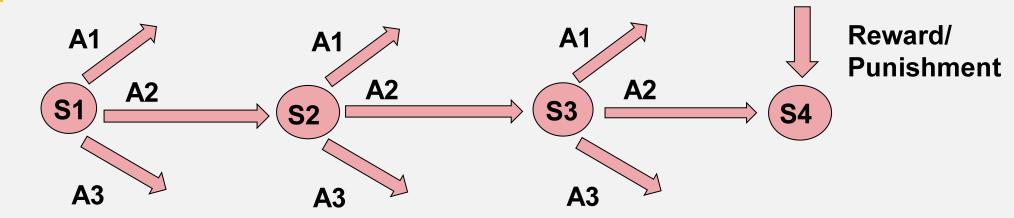
Our campaign example focuses on these personas



# A/B Testing



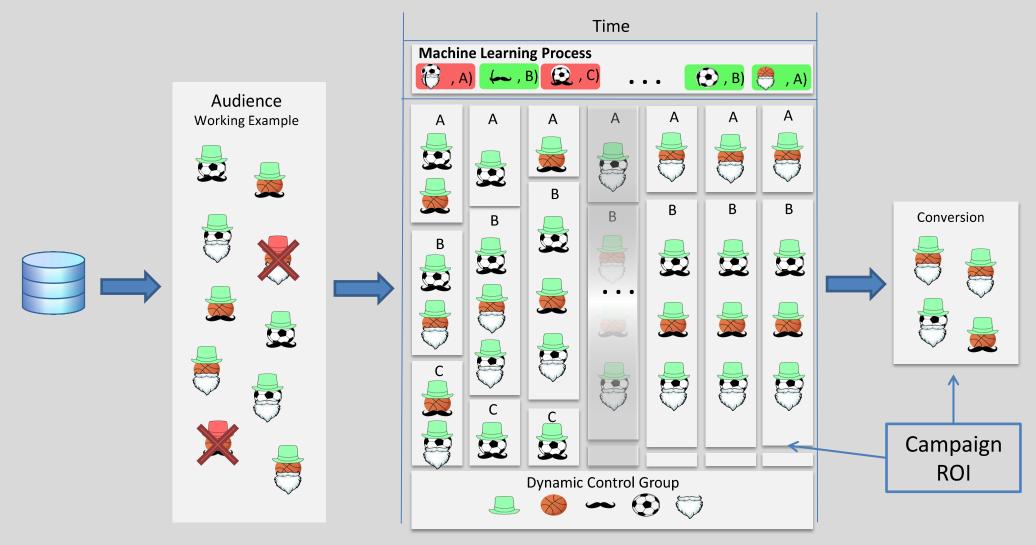
# Reinforcement Learning: The Basics



- Problems with **limited feedback** on the sequence of actions (i.e., customer interactions) we should follow to achieve a goal (no dataset of examples)
- The only feedback is a scalar evaluation of our actions (A) called reward (could be some customer behavior KPI)
- The current status of the customer is described from feature values and forms the state (S)
- Reinforcement learning algorithms learn an action policy that maximizes the long-term, cumulative reward.



# The Reinforcement Learning Approach



# Segmento

Example of an integrated customer segmentation & targeting solution

# segmento

#### **Discover and Target Valuable Customer Segments**

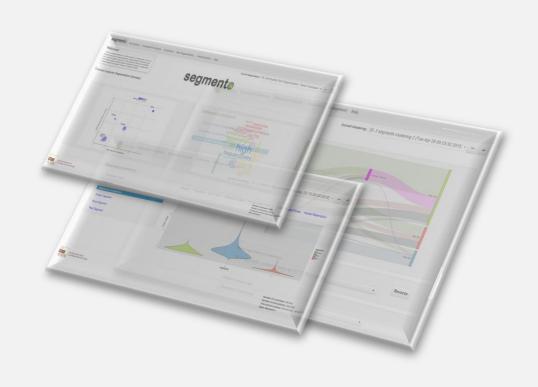
An integrated, data-driven customer segmentation **solution** 

Automatically **discover** customer segments with common and distinct needs, preferences or value

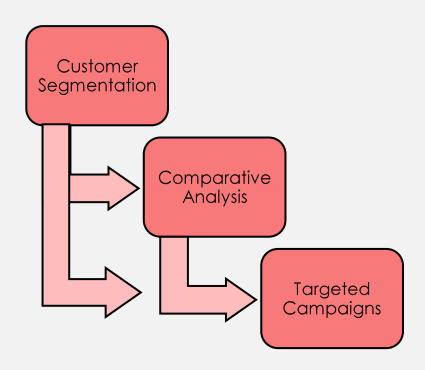
**Learn** what each segment represents with detailed descriptives and unique visualizations

**Observe** the progress of the discovered segments over time

Design and evaluate targeted marketing campaigns



## Solution Overview





Or

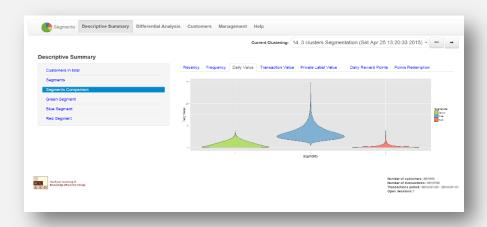
Microsoft Excel Report

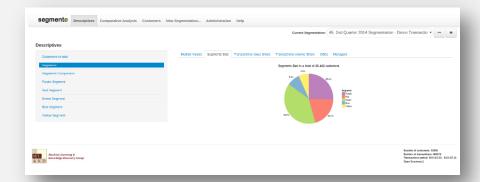
# **Customer Segmentation**

Users freely select among a big variety of segmentation criteria (clustering features)

Create and save multiple customizable segmentation scenarios

State-of-the-art visualizations for each aspect of a segment's profile and the customer base in total





# **Customer Segmentation**



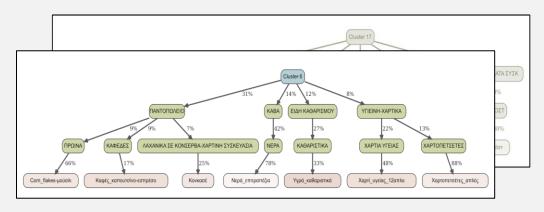
Create segments based on quantitative data (i.e., betting preferences, type of game, teams, betting style etc.)

Example of two segments generated from 592,218 transactions and 31,675 customers in one fiscal year and four geographical locations

Segmento identified 20 customer segments

Positive and statistically significant differentiations compared to the rest of the customer base

Cluster	Category Desription	Avg. Difference	Freq. C.I. Lower	Freq. C.I. Upper
5	Μπισκότα_αλμυρά_κράκερ	+18.84%	0.54	0.61
5	Μπισκότα_γεμιστά	+15.24%	0.79	0.89
5	Ξηροί_καρποί_συσκ/νοι	+101.97%	1.39	1.68
5	Παξιμαδάκια_σνάκ	+11.71%	0.25	0.32
5	Πατατάκια	+191.06%	2.36	2.64
5	Σνακ_διάφορα	+376.11%	4.14	4.46
17	Γάλα_μακράς_διάρκειας	+129.73%	12.00	14.00
17	Μουστάρδες	+13.31%	0.33	0.33
17	Πάνα_απλή	+87.55%	1.00	1.33
17	Παιδικές_κρέμες	+55.19%	0.33	1.00
17	Σαμπουάν	+16.45%	0.67	0.67
17	Σνακ_διάφορα	+42.10%	1.00	1.33
17	Ψωμιά_τόστ	+41.77%	1.33	2.00



# **Comparative Analysis**

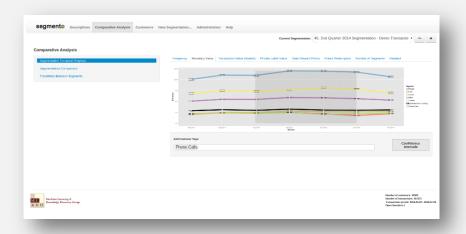
Watch each segment progress over time, for each KPI

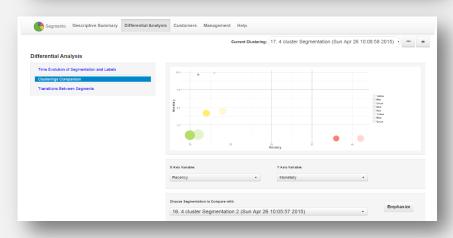
Information-rich plots and tables describe the effect of time over the segment's performance

Compare segments between different segmentations

Transitions between segments for different segmentation periods

Estimate per-day profit/loss for each customer transition



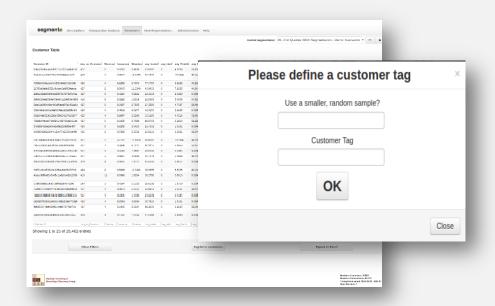


# Targeted Campaigns

Identify suitable segments for a new targeted campaign

Over 20 customer filters for finer and more focused customer selection

Export campaign customers directly to company's DB or even to an MS Excel file

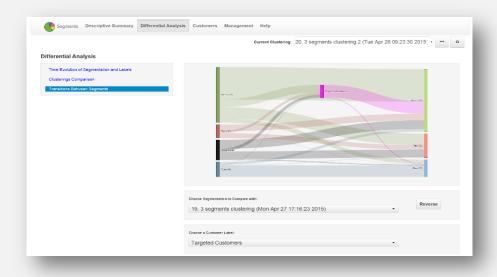


# Targeted Campaigns

Evaluate campaign impact for specific customer segments

Trace customers' transitions between segments

Evaluate campaign ROI





## Thank You

Although this talk was not personalized...

... I would like to personally thank each one of you for attending