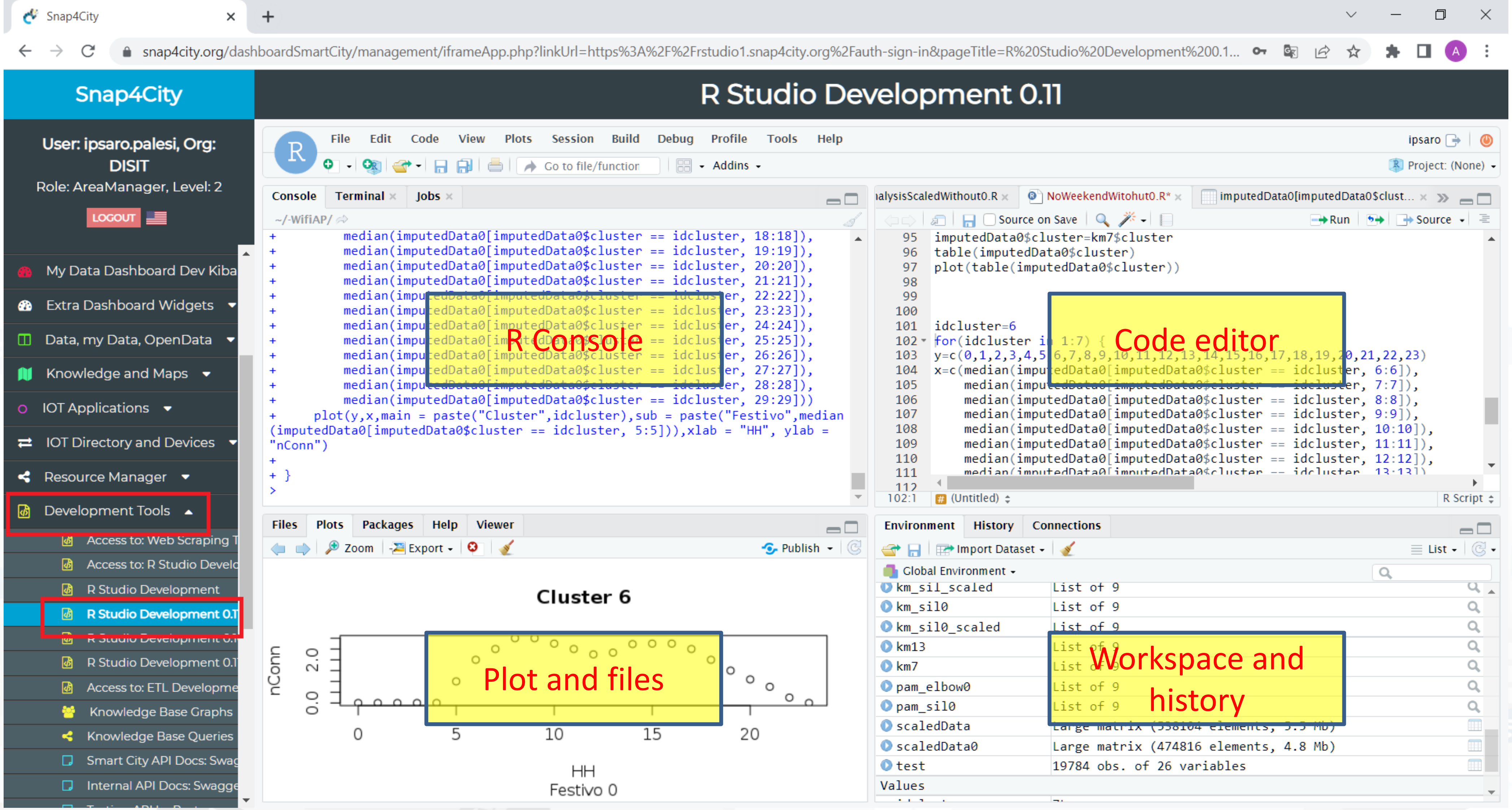
TOP

Fashion Retail Recommendations
Feedback Pilot

Rstudio


R Studio Development 0.11
R Console
Code editor
Plot and files
Workspace and history

R code

- Installing and loading R packages

install.packages("cluster")

From GitHub

install.packages("devtools")

devtools::install_github("kassambara/factoextra")

- Getting help with functions in R

?kmeans

- Importing your data into R

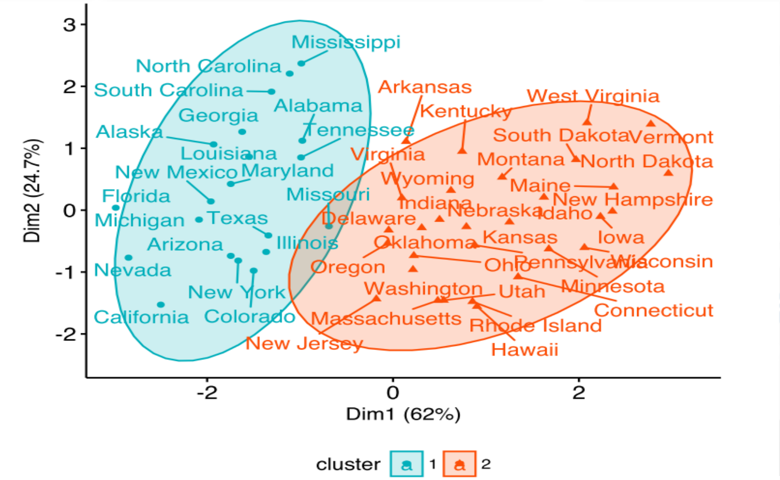
 # .csv file: Read comma (",") separated values

my_data <- read.csv(file.choose())

Clustering

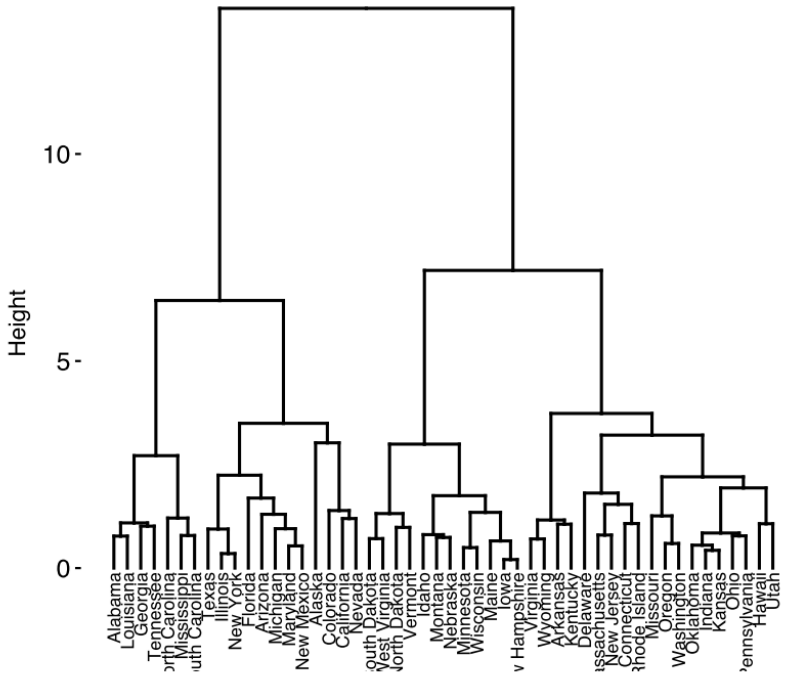
Partitioning

- K-Means Clustering
- K-Medoids
- CLARA - Clustering Large Applications



Hierarchical

- Agglomerative Clustering

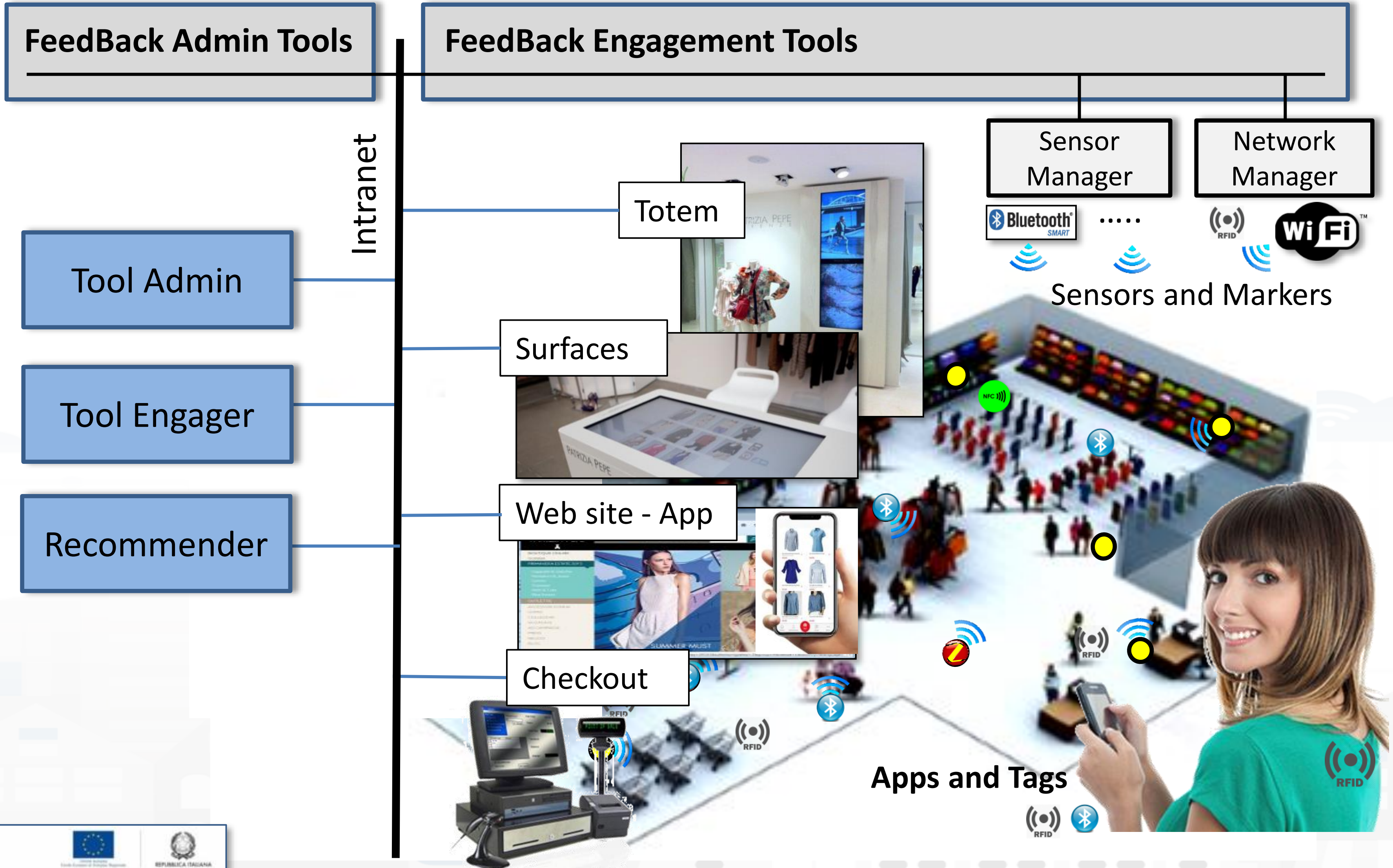


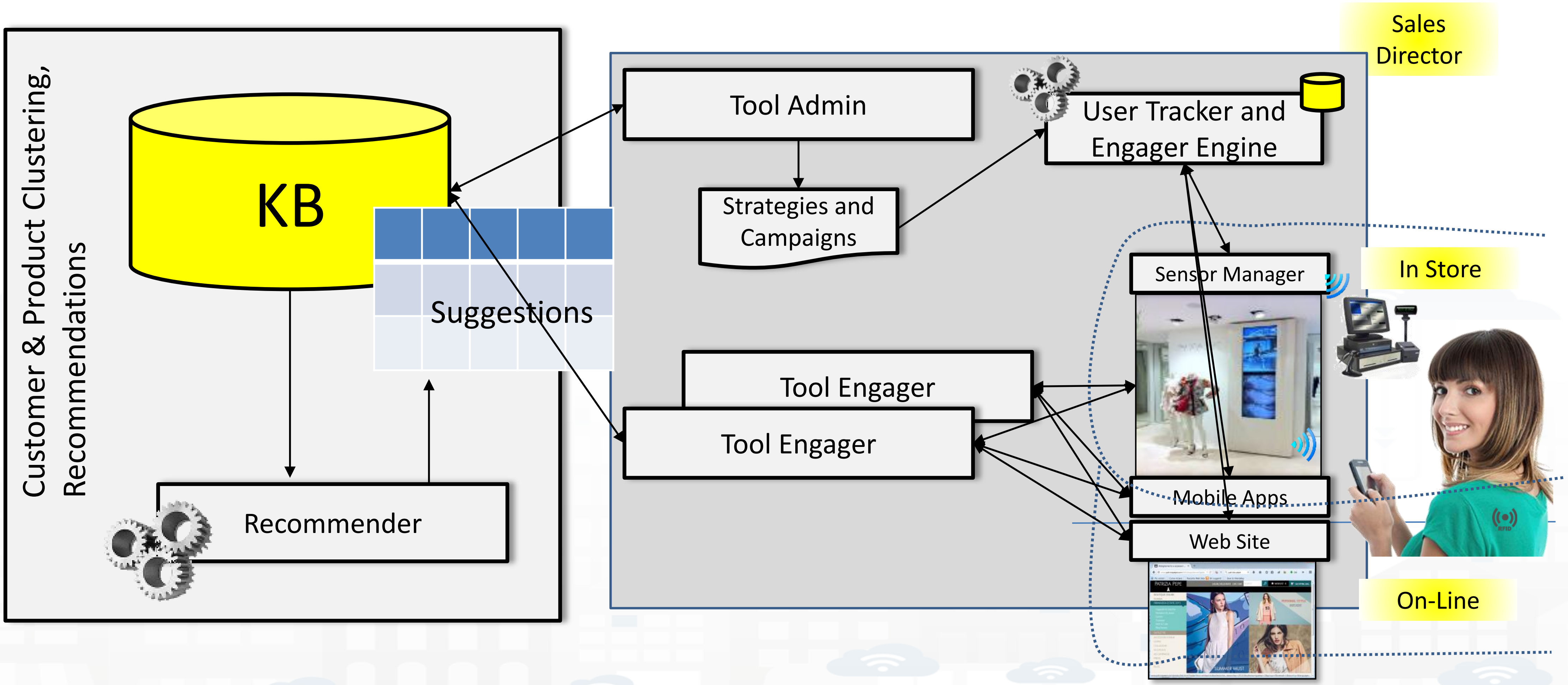
Smart Retail

- **Feedback Project:**
  - Flexible Advanced Engagement Exploiting User Profiles and Product/Production Knowledge
  - VAR, PatriziaPepe (Tessilform), DISIT, Effective Knowledge, SICE
  - Keywords: retail, GDO, …
- **Goals and drivers:**
  - adaptive user engagement, customer experience
  - Advanced user profiling, user behaviour analysis
  - IOT and instrumentation
  - Predictive models for engagement
  - Integrated in city customer experience
- **Aiming to solve current State of the Art issues:**
  - Cold start problems in generating recommendations for new users, also addressing seasonality of products and items
  - GDPR compliance

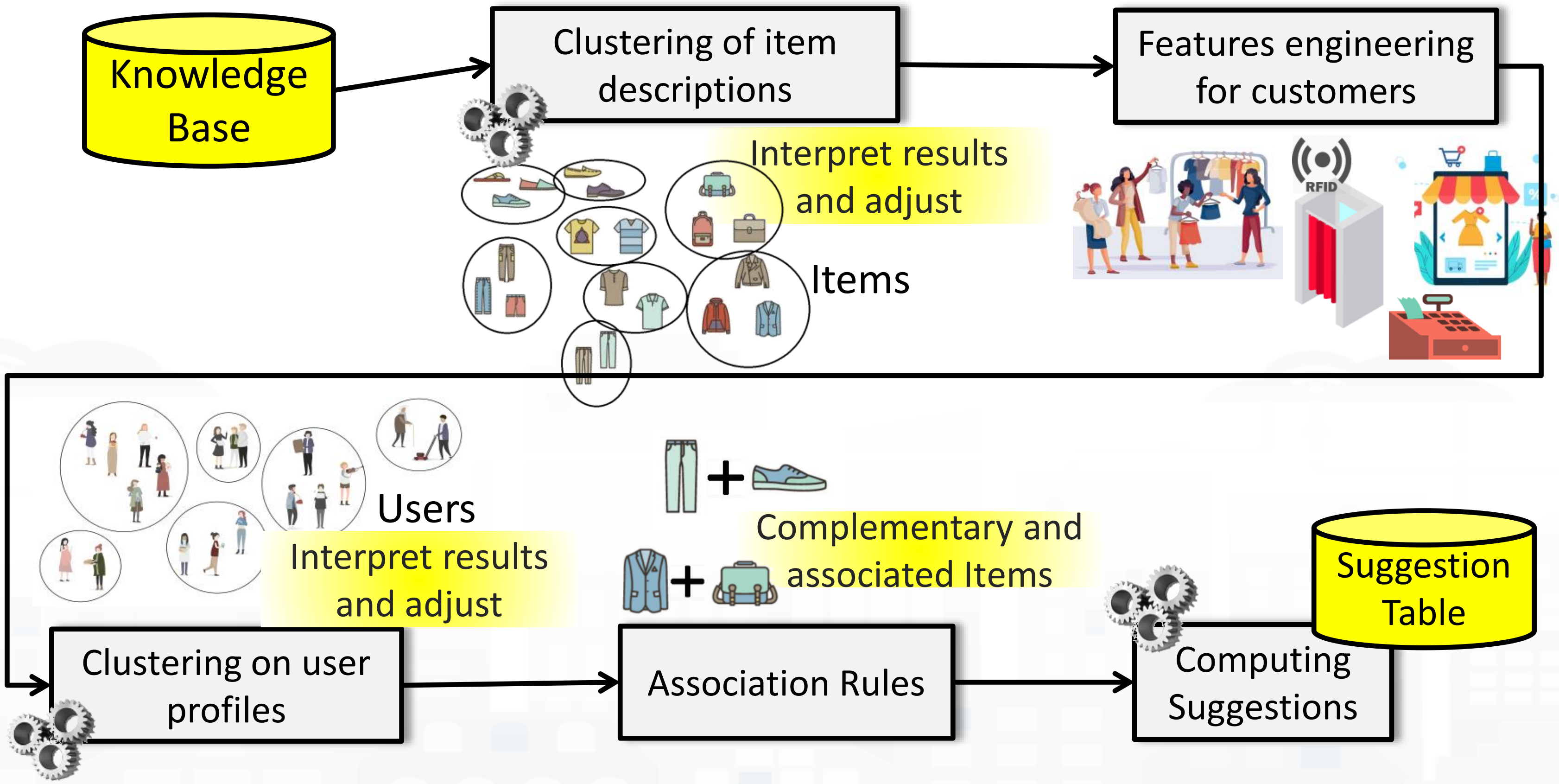
feedback

Scenario


FeedBack Admin Tools
FeedBack Engagement Tools
Intranet
Tool Admin
Tool Engager
Recommender
Totem
Surfaces
Web site - App
Checkout
Sensor Manager
Network Manager
Bluetooth SMART
.....
RFID
Wi Fi
Sensors and Markers
Apps and Tags
RFID


Customer & Product Clustering, Recommendations
KB
Suggestions
Recommender
Tool Admin
Strategies and Campaigns
User Tracker and Engager Engine
Tool Engager
Tool Engager
Sensor Manager
Mobile Apps
Web Site
Sales Director
In Store
On-Line

Workflow



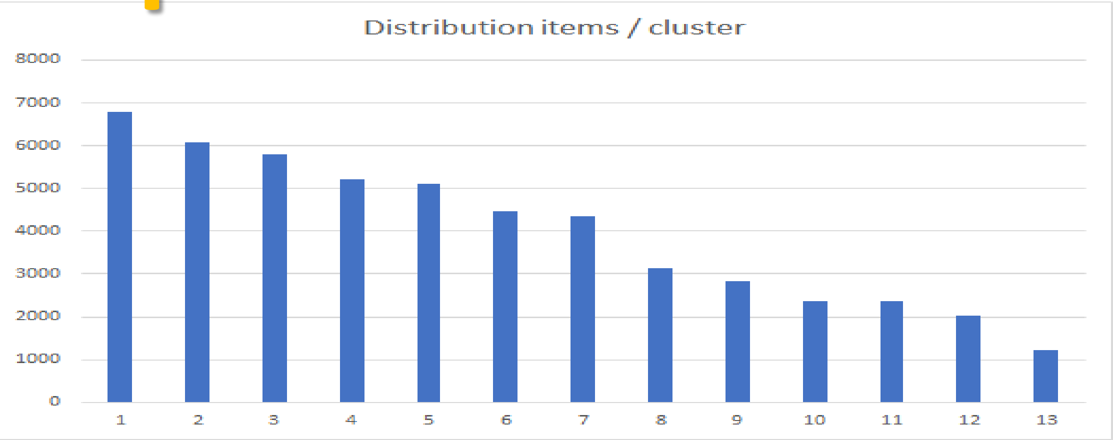
Knowledge Base
Clustering of item descriptions
Features engineering for customers
Interpret results and adjust
Items
RFID
Users
Interpret results and adjust
Complementary and associated Items
Suggestion Table
Clustering on user profiles
Association Rules
Computing Suggestions

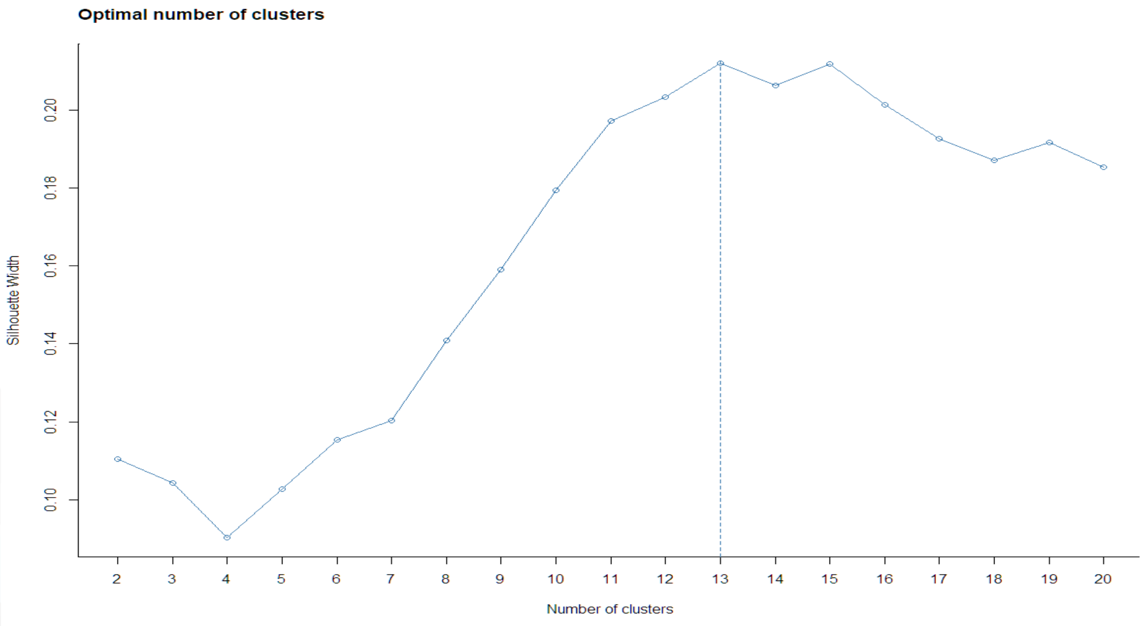
Clustering of Item Descriptions: Features

Field ID	Item Description	Example
TYPE	Type	“1A0145”, “1A0333”,…
CONFIGURATION	Configuration	“DRESS” ,“JACKET”,…
PATTERN	Color	“White”, “Red”, “Navy blue”, …
MODEL	Alphanumeric code model	“1A0145”, “1A0333”, …
PACKAGING_TYPE	Type packaging	"Packaging Basic PE", "Packaging Basic-Contin, …
PRODUCTION_CATEGORY	Production category	"Accessories", "Clothing", "Jeans", ……
MERCHANDISE_MCR_TYPE	Merchandise type	“Basic, Preview”, “Women”, “Main Women”, ……
MERCHANDISE_TYPOLOGY	Merchandise typology	“Preview Women SS”, “Main Women AI”, “Women PE”, ……
MERCHANDISE_MCR_FAMILY	Merchandise family	“Coat”, “Bag”, “Dress”, ……
MERCHANDISE_GROUP	Merchandise group	“Jewelry”, “Dress”, “Shirt”, ……
GENDER	Gender	“Accessories Women”, “Child”, “Women”, ……
BRAND	Brand	“VA”, “GM”, “PW”, ……
STYLE_GROUP	Style	“P”, “C”, ……
BIRTH_SEASON	Season	“20201”, “20062”, “20071”, ……
PERIODICITY	Periodicity	“C”, “S”, ……
IS_CLOTHING_ITEM	Marking if the item belongs to a clothing category	1,0 (yes/no)
5 X NRM_CAT_LVL	Code normalized business classification level 1….5	“Shopping”, “Dress”, “Jacket”, ……
NET_SOLD_PRICE	Price	1580.00
IN_STOCK	Whether an item is available or not	1,0 (yes/no)
132 X Hashtag tasche, abalze,…	Hashtag website	1,0 (yes/no)

Clustering of Item Descriptions: Results

Method: **K-medoids**
Calculate optimal number of clusters: **Silhouette analysis** (The location of the maximum is considered as the appropriate number of clusters)





Cluster	*Derived descriptions of the item clusters*	*# items sales*
1	BAG	969
2	DRESS	1171
3	TROUSERS	794
4	KNIT	678
5	T-SHIRT	674
6	ACCESSORIES (HAT - FOULARD - SCARF - NECKLACE)	596
7	SHIRT	838
8	COAT	388
9	SHOES	341
10	SKIRT	530
11	JACKET	292
12	BELT	237
13	CHILDREN'S CLOTHING	126

Features engineering for customers

Interest Cluster1	Interest Cluster2	………… …	Interest Cluster1 3	# buyed cluster1	# buyed cluster2	………….	# buyed cluster1 3

$\underbrace{\text{Interest Cluster1} \ldots \text{Interest Cluster13}}_{\text{Max interest for item in the cluster}}$ $\underbrace{\text{\# buyed cluster1} \ldots \text{\# buyed cluster13}}_{\text{Number purchased item in the cluster}}$

Max interest for item in the cluster

Number purchased item in the cluster

0: No interest

1: Observed (Totem, Online, etc.)

2: Tried

3: Purchased item

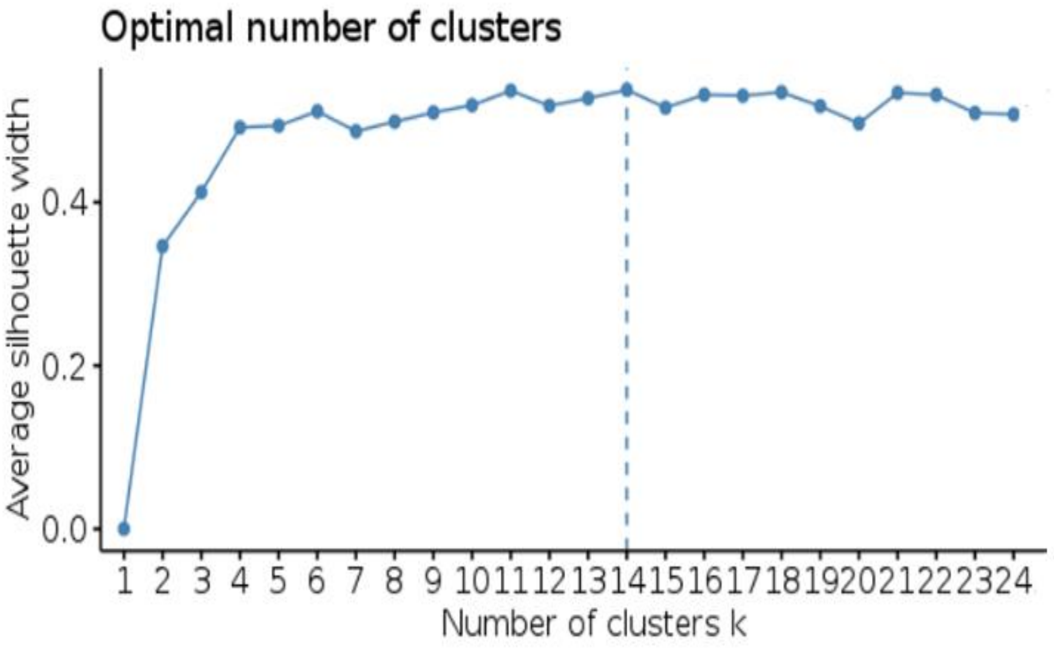
- ***Recency*** *is defined as the number of days passed since the last visit or access in a store or online;*
- ***Frequency*** *represents the frequency of purchase in number of days;*
- ***Average spending*** *is the average value of single ticket for the customer (estimated on the basis of the admin track record)*

Clustering on user profiling

Name profile feature	Description
RFM_TRN_DaysFrequency	Frequency transaction
RFM_TRN_DaysRecency	Recency transaction
RFM_TRN_AvgAmount	Average spending transaction
RFM_PRS_ONLINE_DaysFrequency	Frequency presence online
RFM_PRS_ONLINE_DaysRecency	Recency presence online
RFM_PRS_ONPREM_DaysFrequency	Frequency presence store
RFM_PRS_ONPREM_DaysRecency	Recency presence store
FidelityUsageRange	Fidelity card use
CUS_FIDELITY_CARD_LEVEL_CD	Fidelity card level
Cluster_k_Interest size[13]	Max interest for each cluster
Cluster_k_Purchased size[13]	Number of items purchased

Method: **K-means**

Calculate optimal number of clusters: **Silhouette analysis** (The location of the maximum is considered as the appropriate number of clusters)



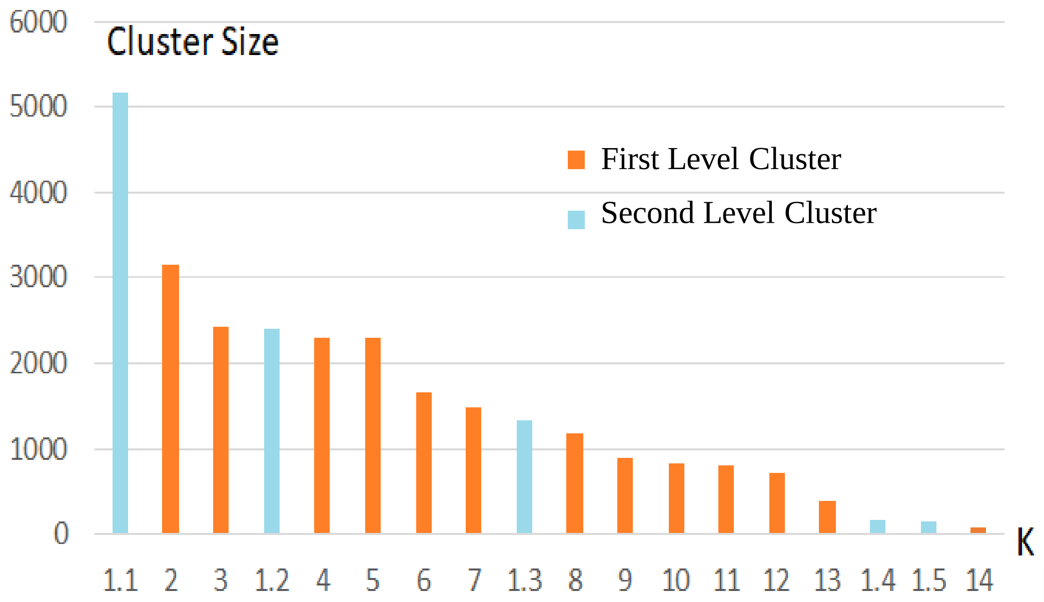
Clustering on user profiling

Cluster	*Derived Description from Customer cluster analysis*	*# total customer*
1	Customers with average spending amount not defined; the frequency is not defined neither in store neither online; day of the last purchase not defined	9195
2	Customers with low average spending amount, mainly online with undefined frequency and last purchase older than two years	3158
3	Customers with undefined average spending amount, mainly in store, with undefined frequency and last purchase older than two years mainly online	2433
4	Customers with low average spending amount, last purchase older than one year.	2302
5	Customers with low average spending amount in store, with frequency of about 4 months in store; last purchase has been made within one year. often using the fidelity card	2302
6	Customers with low average spending amount, more frequent in store with annual frequency; last purchase older than one year.	1657
7	Customer with low average spending amount, more frequent online, but also buying in store with frequency of about 2 months online and about 6 months in store; last purchase older than one year, use fidelity card	1493
8	Customer with average spending amount not defined, mainly online; last purchase mid term days	1186
9	Customer with very high average spending amount in store	887
10	Customer with medium average spending amount more frequent in store but also buys in store with frequency about 230 days; last purchase about 262 days, use fidelity card	819
11	Customer with average spending medium amount in store; last purchase one year ago; frequency is not defined	797
12	Customer with average spending amount not defined, mainly online, with frequency of about 270 days; last purchase one year	717
13	Customer with medium average spending amount, mainly in store, with not defined frequency and last purchase older than one year	391
14	Online customers with annual frequency	9

Clustering on user profiling

Cluster	*Derived Description from Customer cluster analysis*	*# total customer*
1	Customers with average spending amount not defined; the frequency is not defined neither in store neither online; day of the last purchase not defined	9195

Cluster	*Derived Description from Customer cluster analysis*	*# total customer*
1.1	Customers with average spending amount undefined; the frequency is undefined neither in store nor online; day of the last purchase undefined	5167
1.2	Customers with low average spending amount. They mainly buy in the product cluster #12	2411
1.3	Customers with very low average spending amount, mainly in the product clusters: #2, #10 and #12	1330
1.4	Customers with: recency of about 23 days, frequency of about 18 days	173
1.5	Customers with average spending amount of about 150 Euro; mainly buying in the product cluster #1	148



Suggestions

customer similarity for each customer cluster the most representative items are suggested;
item similarity: considering the last items purchased by the customer according to the information contained into its profile, and randomly selecting items in the same item clusters;
item complementary: considering items that may complement the last items that have been bought by the customer according to a table of complementary items;
item associated: in order to improve a customer's purchase frequency, we generated suggestions for customers who purchased an item in the last three months;
suggestions for serendipity: randomly selecting items to be suggested from the whole present collection, taking also into account what is available in the physical shop;

Item Cluster	Complementary Item Clusters				
	cluster	support	confidence	lift	count
1	2	0.26486066	0.6069351	1.106003	12935
	7	0.24864345	0.5697729	1.253423	12143
	3	0.24465057	0.5606231	1.213722	11948
	8	0.24336057	0.5576670	1.277549	11885
	4	0.22298667	0.5109797	1.282096	10890
2	3	0.34351004	0.6259701	1.355196	16776
	7	0.32391425	0.5902612	1.298495	15819
	8	0.31392182	0.5720522	1.310504	15331
	4	0.29840080	0.5437687	1.364367	214573
3	2	0.34351004	0.7436830	1.355196	16776
	7	0.30397035	0.6580814	1.447690	14845
	8	0.29868747	0.6466442	1.481385	14587
	4	0.27753548	0.6008511	1.507592	13554
	1	0.24465057	0.5296569	1.213722	11948
4	2	0.29840080	0.7487156	1.364367	214573
	3	0.27753548	0.6963625	1.507592	13554
	7	0.26578209	0.6668722	1.467029	12980
	8	0.27260069	0.6839807	1.566918	13313
	1	0.22298667	0.5594945	1.282096	10890

Item selection
1. Item previously not purchased
2. Confidence recommended item. Confidence established with Market Basket Analysis

Validation

- Where: store located in Florence

How

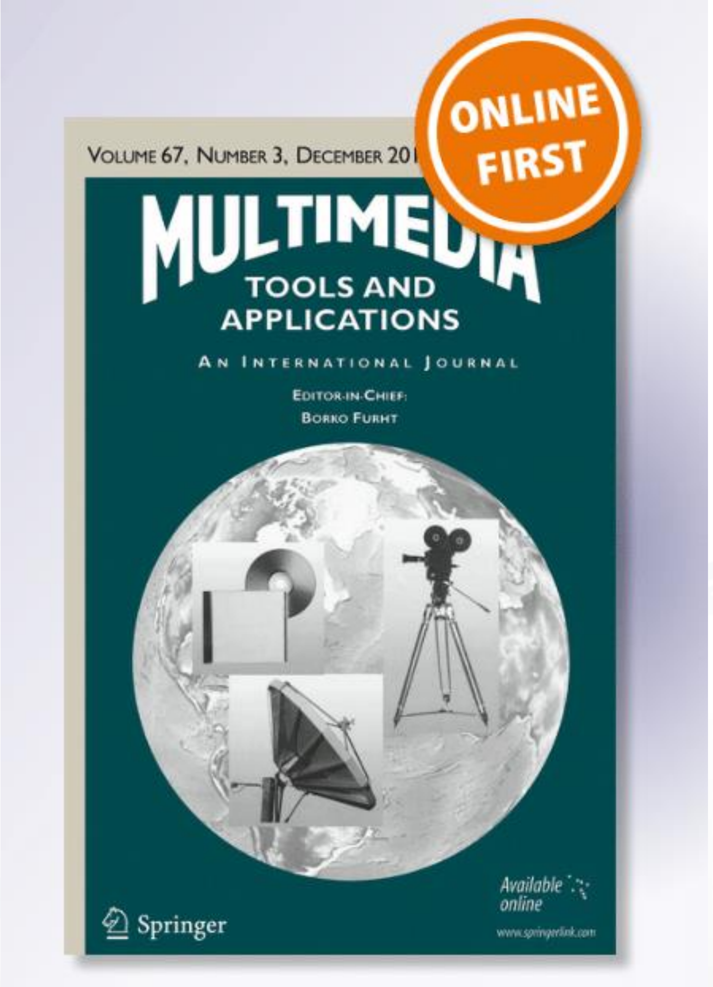
- **data collected until December 2019** to test and tune the solution, verifying if the suggestions produced were also provided by the Assistant in shops and finally acquired by the customers.
- **January - June 2020**, through transactions and verifying the shop assistants (which are the reference experts), if there was a match between suggestions and items purchased by customers. This analysis showed that on about 400 customers who bought, about 10000 suggestions were generated. On suggestions generated, the 6.36% items were purchased or tested.
- **July 2020 until December 2020**, the recommendation system was tuned on operative to stimulate a certain class of users, entering in the store, using the totem in the store and by mail for ecommerce. This analysis with the stimulated customers showed that from 67 selected customers in the trial, 3050 suggestions have been generated, while only about the 20% has been actually sent to the customers (on shops and/or email). On the items suggested, the 9.84% of them were actually acquired or tested.

Discussion

- Using the stimulus of the recommendation system, we have increased the customers' attention of the 3.48%
- The solution is also functional in presence of a low number of customers and items
- The solution solved the cold start problems
- GDPR compliant

- P. Bellini, L. A. Ipsaro Palesi, P. Nesi, G. Pantaleo, "Multi Clustering Recommendation System for Fashion Retail", Multimedia Tools and Applications, Springer, 2022.

- https://link.springer.com/article/10.1007/s11042-021-11837-5



Springer

Multimedia Tools and Applications
https://doi.org/10.1007/s11042-021-11837-5

1225: SENTIENT MULTIMEDIA SYSTEMS AND UNIVERSAL VISUAL LANGUAGES

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Multi Clustering Recommendation System for Fashion Retail

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Abstract
Fashion retail has a large and ever-increasing popularity and relevance, allowing customers to buy anytime finding the best offers and providing satisfactory experiences in the shops. Consequently, Customer Relationship Management solutions have been enhanced by means of several technologies to better understand the behaviour and requirements of customers, engaging and influencing them to improve their shopping experience, as well as increasing the retailers' profitability. Current solutions on marketing provide a too general approach, pushing and suggesting on most cases, the popular or most purchased items, losing the focus on the customer centricity and personality. In this paper, a recommendation system for fashion retail shops is proposed, based on a multi clustering approach of items and users' profiles in online and on physical stores. The proposed solution relies on mining techniques, allowing to predict the purchase behaviour of newly acquired customers, thus solving the cold start problems which is typical of the systems at the state of the art. The presented work has been developed in the context of Feedback project partially founded by Regione Toscana, and it has been conducted on real retail company Tessilform, Patrizia Pepe mark. The recommendation system has been validated in store, as well as online.

Keywords Recommendation systems · Clustering · Customer and items clustering composed

1 Introduction

The competitiveness of retailers strongly depends on the conquered reputation, brand relevance and on the marketing activities they carry out. The latter aspect is exploited to increase the sales and thus a retailer, through marketing, should be capable to stimulate customers to buy more items or more valuable items. Today, consumers tend to buy more on ecommerce and the COVID-19 situation also stressed this condition. Online shopping

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