

DEEPRETAIL2020

2nd WORKSHOP ON DEEP UNDERSTANDING SHOPPER BEHAVIOURS AND INTERACTIONS IN INTELLIGENT RETAIL ENVIRONMENTS Milan, Italy 11 January 2021



Data-Driven Knowledge Discovery in Retail: Evidences from the Vending Machine's Industry

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THE CONTEXT

- According to an Accenture study, 79% of enterprise executives agree that companies which do not embrace Big Data will lose their competitive position.
- One of the most relevant aspect deriving from these innovations is linked to the possibility of generating new forms of data-driven knowledge that can be adopted in several business practices as a fundamental element in decision making processes
- The adoption of technologies and tools based on big data analytics is able to generate an actionable knowledge
- According to the McKinsey Analytics report, the sales and marketing functions are those in which the Big Data is providing the largest contributions





While in many retail environments the adoption of big data analytics are consolidated practices, there is a lack of studies dealing with this topic in the vending machines (VM) industry.



AIM OF THE STUDY

In this study, we discuss the role of the new technologies that through Big Data Analytics are able to generate actionable knowledge for marketing purposes.

The aim of this study is to investigate new forms of marketing data-driven knowledge discovery in the (VM) industry.



LITERATURE REVIEW Big Data Analytics

- In 2011 the McKinsey Global Institute defined Big Data as "huge datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze."
- Cheng et al., (2012) defined Big Data Analytics as huge datasets requiring advanced and unique data storage, management, analysis and visualization technologies as well as statistical analysis.
- Several studies have confirmed the role of Big Data Analytics in supporting Organizations both in managing and solving problems, but also in making better decisions (Cheng et al., 2017) through the production of actionable informations (Rajpurohit, 2013).



THEORETICAL BACKGROUND

- Fayyad et al. (1996) defined the **Knowledge Discovery in Databases** as *"the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data".*
- One of the key component of data-driven knowledge discovery processes is **data mining** defined as *"the process of searching and analyzing data in order to find implicit, but potentially useful, information".*

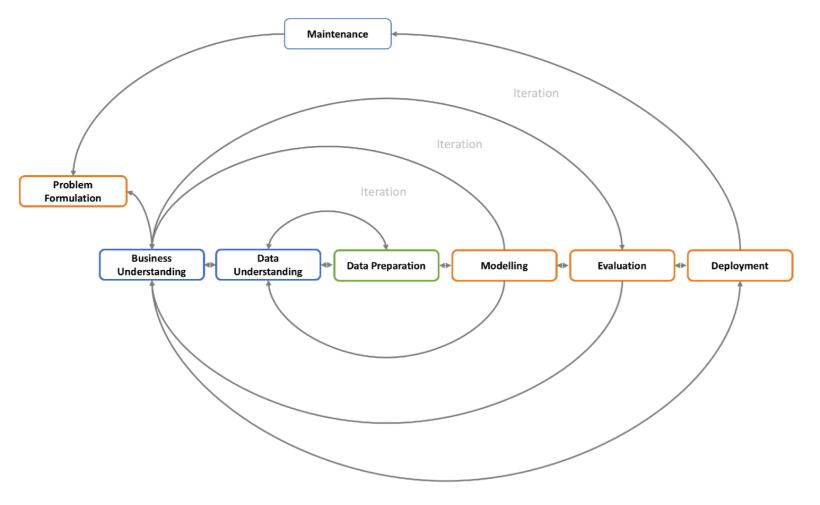


THEORETICAL BACKGROUND

- Due the progress of data collection and Big Data Analytics, traditional data-driven knowledge discovery models are not able to guarantee the success of data mining projects in the business
- In this scenario, Organizations are identifying new ways of the joint use of Information Technologies (IT) and advanced analytics techniques with the aim of improving the knowledge discovery process, making it faster, cheaper, more flexible and more reliable.



THEORETICAL BACKGROUND The KDDA "Snail shell" process model (Li et al., 2016)



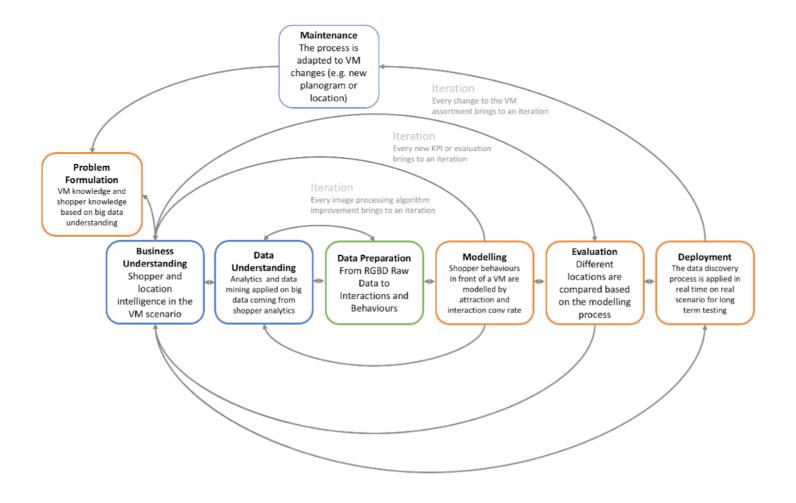


THE SYSTEM TECHNOLOGY

- The system technology is based on an RGBD camera installed in the topview configuration. The camera is positioned above the surface which is to be anal- ysed. These kind of cameras are chosen because of their availability, reliability and affordability
- The camera is able to detect the customer gestures when in front of a vending machine and a software is able to analyse the shoppers activities and report the results on a dashboard. The hearth of the technology is an innovative and cost-effective smart system able to understand the shoppers' behaviour and, in particular, their interactions with the VM.
- Data gathered from these sensors are used to evaluate the attraction (the level of attraction that the VM is creating on consumers), the attention (the time consumers spend in front of brand display) and the action (the number of consumers that stop in front of the VM and interact with merchandise).



EXPERIMENTAL RESULTS





EXPERIMENTAL RESULTS

- **PROBLEM FORMULATION**: shopper behavior understanding in front of a VM with a strong focus on attraction, interaction and location intelligence.
- BUSINESS UNDERSTANDING: we collected VM management and sales implicit knowledge by one-to-one interviews to understand the process of setting-up, evaluating and managing a VM in a specific location and location-related or target-related knowledge on specific needs.
- **DATA UNDERSTANDING**: data coming from vending interactions, sell out and behavior data coming from RGBD data are involved the in this phase. Different tests are performed in the DU process in a lab environment to prove mining and effectiveness of the collected data from cameras and VM interfaces
- **DATA PREPARATION**: different dataset collected from 4 different location and 8 different VMs were collected and analyzed.



EXPERIMENTAL RESULTS

- **MODELLING**: the technique selection in this phase was performed in the iterations described before and finally a multi-layer filter model with 3 filtering and modelling processes, going from the lower layer with raw data, to 2 different aggregation layers was performed.
- **EVALUATION**: the objective of this stage was to test and prove the effectiveness of the proposed analytics methodology and models to answer the main business questions derived from the BU phase. While analytics models are evaluated within the tool using objective KPIs measures such as accuracy, evaluation against business objectives is performed with focus groups with VM management teams.
- DEPLOYMENT: the deployment plan was the output of this phase and was confirmed as feasible with the following parameters: up to 50 different testing locations with more than 100 VMs monitored in real time; locations are statistical significant to test and prove performances.
- **MAINTENANCE**: a formal model process of maintenance was established with assigned roles for business users and for data quality manager. A weekly call between the 2 different users ensure data publication after a data quality assessment.



ACTIONABLE KNOWLEDGE

Table 2: VM attraction level and time spent by a standard consumer in front of a VM

			Model C Self- Service	
Visit the VM Area Stop at the VM (% stop vm/ visit area)	100% N=1,562	100%		
Interact with VM (% inter- act/visit)	· ·	N= 977 86%	N=1988 95%	n=381 69%
Buying (% buy- ing/ interact) Multi Buying (% multiple buying/ inter- act)	87% N=109	N=959 98% N=129 13%	N=1976 99% N=176 9%	100%

ACTIONABLE KNOWLEDGE

Table 3: Average time spent at VM by consumers is 14 sec University consumers investing more time for selection

	Model A Univer- sity	Model B Hospital		Model D Company	Total
Spend 5-15 Sec to chose what to buy	62%	58%	71%	68%	66%
Spend over 15 Sec to chose what to buy	36%	32%	29%	31%	34%
AVG. Time Spent in front of the VM by positive interactors	18 sec	12 sec	13 sec	13 sec	14 sec

CONCLUSIONS

- The results obtained from the tests show that the RGBD camera system can be adopted within a knowledge discovery process via data analytics (KDDA), through which it has been possible to obtain new forms of actionable knowledge.
- The adoption of big data analytics techniques, could allows VM companies – that represent a "traditional" industry – to perform more accurate decision-making processes through:
 - The location, category, brand and performance monitoring
 - The layout, location and planogram optimization
 - The marketing and promotional activities performance evaluation





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