

Classify Visitor Behaviours in a Cultural Heritage Exhibition

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Abstract. Classify the dynamic of users in a cultural heritage exhibition in order to infer information about the event fruition is a very interesting research field. In this paper, starting from real data, we investigate the user dynamics related to the interaction with artworks and how a spectator interacts with available technologies. Accordingly with the fact that the technology plays a crucial role in supporting spectators and enhancing their experiences, the starting point of this research has been the art exhibition named *The Beauty or the Truth* that was located in Naples (Italy), where event was equipped with several technological tools. Here, the collected log files, stored in a suitable expert software system, are used in a flexible framework in order to analyse how the supporting pervasive technology influence and modify behaviours and visiting styles. Finally, we carried out some experiments to exploit the clustering facilities for finding groups that reflect visiting styles. The obtained results have revealed interesting issues also to understand hidden aspects in the data and unattended in the analysis.

Keywords: User profiling · Clustering · Data mining

1 Introduction

In the cultural heritage area, the requirements of innovative tools and methodologies to enhance the quality of services and to develop smart applications is an increasing requirement. Cultural heritage systems contain a huge amount of interrelated data that are more complex to classify and analyse. For example, considering an art exhibition, characterizing, studying, and measuring the level of knowledge of a visitor with respect to an artwork, and also the dynamics

of social interaction on a relationship network is an interesting research scenario. To understand and analyse how artworks observation can influence the social behaviours is a very hard challenges. Indeed, semantic web approaches have been increasingly used to organize different art collections not only to infer information about a cultural item, but also to browse, visualize, and recommend objects across heterogeneous collections [8]. Other methods are based on statistical analysis of user datasets in order to identify common paths (i.e., *patterns*) in the available information. Here, the main difficulty is the management and retrieval of large databases as well as issues of privacy and professional ethics [7]. Finally, models of artificial neural networks, typical of Artificial Intelligence field are also adopted. Unfortunately, these approaches seems to be, in general, too restrictive in describing complex dynamics of social behaviours and interactions in the Cultural Heritage framework [6].

In our previous works, we referred to a computational neuroscience terminology for which a cultural asset visitor is a *neuron* and its interest is *the electrical activity* which has been stimulated by appropriate currents. In detail, we adopted two different strategies to perform data classification: a Bayesian classifier [3], and an approach that finds data groupings in an unsupervised way [2]. Such a strategy resorts to a *clustering* task employing the well-known *K*-means algorithm [5]. The dynamics of the information flows, which are the social knowledge, are characterized by neural interactions in biological inspired neural networks. Reasoning by similarity, the users can be considered as neurons in a network and their interests the morphology; the common topics among users are the neuronal synapses; the social knowledge is the electrical activity in terms of quantitative and qualitative neuronal responses (spikes).

In [1] we dealt with the characterization of visitor behaviours starting from real datasets. As a real scenario, we have considered the art exhibition named *the Beauty or the Truth* located in Naples, Italy, where new ICT tools and methodologies, producing several users behavioural data, have been deployed and currently are still active. Our aim was also be to classify visiting styles of the spectators in the exhibit exploiting their user experience of the adopted technology, which allows to collect the data to analyse. Here, deeply investigating these aspects, we focus on tuning of the parameters influencing the classification results.

The paper is organized as follows. In Sect. 1 we introduce this research; in Sect. 2 we describe the fruition system framework of the proposed event. In Sect. 3 we deal with the visiting styles by resorting some basics definitions; in Sect. 4 we describe experiments on real data classification and finally in Sect. 5 we draw the conclusions.

2 The Digital Fruition System

The starting point of our research is an interesting and wide case study; it consists of a real art exhibition of 271 sculptures, divided into 7 thematic sections and named “*The Beauty or the Truth*”¹. This exhibition shows, for the first time

¹ <http://www.ilbellooilvero.it>.

in Italy, the Neapolitan sculpture of the late nineteenth century and early twentieth century, through the major sculptors of the time. The sculptures are exhibited in the beautiful monumental complex of *San Domenico Maggiore*, in the historical centre of Naples. In order to better understand motivations behind this work, it is important to deeply analyse the kind of relations that exist among cultural spaces, people and technological tools that nowadays are pervasive in such environments. Accordingly, the behaviour of a person/visitor, when it is immersed inside a space and consequently among several objects, has to be analysed in order to design the most appropriate ICT architecture and to establish the relationship between people and technological tools that have to be non-invasive. For this reason, it should be preferable to provide cultural objects with the capability to interact with people, environments and other objects, and to transmit the related knowledge to users through multimedia facilities. In an intelligent cultural space, technologies must be able to connect the physical world with the world of information, in order to amplify the knowledge, but also and especially the fruition, involving the visitors as active players to which is offered the pleasure of the perception and the charm of the discovery of a new knowledge.

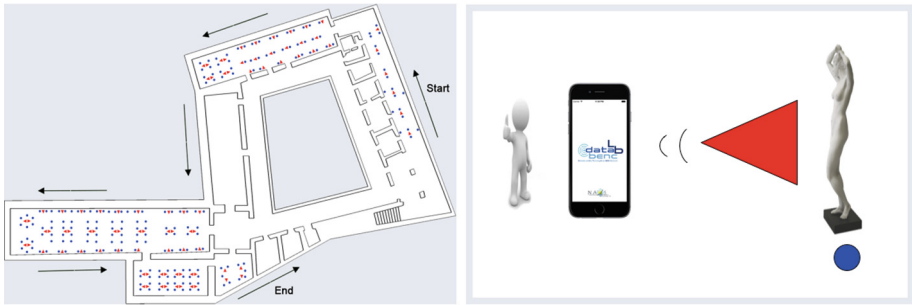


Fig. 1. Digital fruition system.

In the follow, the architecture of an Internet of Things (IoT) system, the technological sensors immersed in the cultural environment and the communication framework are presented. The sensors aimed to transform cultural items in *smart objects*, that now are able to communicate with each other, the visitors and the network; this acquired identity plays a crucial role for the smartness of a cultural space. Accordingly, in order that this system can perform its role and improve end-users cultural experience transferring knowledge and supporting them, a mobile application has been designed; in this way people have the opportunity to enjoy the cultural visit and be more at ease simply using their own mobile device. The proposed IoT system was entirely deployed inside the exhibition, as illustrated in Fig. 1. In the proposed system we have, on the left of Fig. 1 a physical space where the exhibition was located. It is important to observe that the combination of the technologies, artworks and path inside the event influences the visiting style of a spectator. On the right of Fig. 1 we have a

detailed description of the interaction of the user with the artwork. The artworks start to talk and interact with the spectator through an “ad hoc” technology named smart cricket.

The overall technology in the proposed fruition system is used in order to collect the data that are necessary to characterize the visiting styles discussed in the following sections.

3 Visiting Styles Definition

In order to classify visiting styles in art exhibition, we start from work shown in [9], where personalized information presentation in the context of mobile museum guides are reported and visitor movements are classified comparing these to the behaviours of four typical animals. In our work, we adapt this classification to find how visitors interact with the ICT technology. Accordingly, the visitor’s behaviour can be compared to that of:

- an ANT (**A**), if this tends to follow a specific path in the exhibit and intensively enjoys the furnished technology;
- a FISH (**F**), if this moves around in the centre of the room and usually avoids looking at media content details;
- a BUTTERFLY (**B**), if this does not follow a specific path but rather is guided by the physical orientation of the exhibits and stops frequently to look for more media contents;
- a GRASSHOPPER (**G**), if this seems to have a specific preference for some preselected artworks and spends a lot of time observing the related media contents.

The classification of the visiting styles is characterized by three different parameters related to the visitor: (a) the number of artworks viewed, (b) the average time spent by interacting with the viewed artworks, and (c) the path determining the order of visit of the exhibit sections.

Table 1. Characterization of the visiting styles’ classification.

Animal	(a) Viewed artworks	(b) Average time	(c) Path
A	high	-	high
B	high	-	low
F	low	low	-
G	low	high	-

As we can observe in Table 1, high values for the parameter (a) characterize both **As** and **Bs**, while low values are related to **Fs** and **Gs**. Moreover, the parameter (b) does not influence the classification of **As** and **Bs**, while high

values are typical for **F**s and low values are inherent in **G**s. Finally, the parameter (c) does not influence the classification of **F**s and **G**s, whereas high values are related to **A**s and low values characterize **B**s.

Each parameter is associated with a numerical value normalized between 0 and 1. For the parameters (a) and (b), its values respectively correspond to percentages of viewed artworks and average time spent for these. In the following we show how to assign a value to the parameter (c).

Assume that the N sections (rooms) of a museum are organized in increasing order as follows:

$$\text{entrance } \boxed{1} \rightarrow \boxed{2} \rightarrow \dots \rightarrow \boxed{N-1} \rightarrow \boxed{N} \text{ exit,}$$

Let us denote by

$$S_1 \rightarrow S_2 \rightarrow \dots \rightarrow S_{M-1} \rightarrow S_M$$

the path of a visitor. Assuming the entrance in 1 and the exit in N , it results $S_1 = 1$ and $S_M = N$. Moreover, because a visitor could visit each room more than once or never, the length M of the path is independent on the number N of rooms. To assign a value to the quality of a path, we consider the $M - 1$ movements $S_{j-1} \rightarrow S_j$, for $j = 2, \dots, M$, and we assign at each of them the value m_j in the following way

$$m_j = \begin{cases} 1, & \text{if } S_j = S_{j-1} + 1 \\ 0.5, & \text{if } S_j > S_{j-1} + 1 \\ S_j - S_{j-1}, & \text{if } S_j < S_{j-1} \end{cases}$$

Finally, the value of the path will be

$$p = \max \left\{ 0, \frac{1}{N-1} \sum_{j=2}^M m_j \right\}.$$

The ratio by $N - 1$ ensures that $p \leq 1$, while the max operation avoids negative values, so that the property $0 \leq p \leq 1$ is achieved. For example, with $N = 7$ rooms, the *chaotic* path

$$\begin{array}{ccccccc} \text{entrance} & \boxed{1} & \xrightarrow{m_2=0.5} & \boxed{3} & \xrightarrow{m_3=1} & \boxed{4} & \xrightarrow{m_4=0.5} \\ & & & & & & \\ \boxed{6} & \xrightarrow{m_5=-4} & \boxed{2} & \xrightarrow{m_6=0.5} & \boxed{6} & \xrightarrow{m_7=1} & \boxed{7} \text{ exit,} \end{array}$$

will be evaluated

$$\begin{aligned} p &= \max \left\{ 0, \frac{1}{6} (0.5 + 1 + 0.5 - 4 + 0.5 + 1) \right\} \\ &= \max \left\{ 0, \frac{-0.5}{6} \right\} = 0. \end{aligned}$$

While the more ordered path

$$\begin{array}{ccccccc} \text{entrance} & \boxed{1} & \xrightarrow{m_2=1} & \boxed{2} & \xrightarrow{m_3=1} & \boxed{3} & \xrightarrow{m_4=1} & \boxed{4} & \xrightarrow{m_5=0.5} \\ & & & \boxed{6} & \xrightarrow{m_6=1} & \boxed{7} & \text{exit}, \end{array}$$

will be evaluated

$$\begin{aligned} p &= \max \left\{ 0, \frac{1}{6}(1 + 1 + 1 + 0.5 + 1) \right\} \\ &= \max \left\{ 0, \frac{4.5}{6} \right\} = 0.75 \end{aligned}$$

Observe that, in general, the perfect path

$$\text{entrance} \boxed{1} \rightarrow \boxed{2} \rightarrow \dots \rightarrow \boxed{N-1} \rightarrow \boxed{N} \text{ exit},$$

will always receive the evaluation $p = 1$.

Observe that our model infers information from data stored in the structured JSON file. The overall data collected by the described ICT framework will be used as the input of the proposed classification approach. More in details, *LOG* files are structured in order to store main informations about the visitor behaviour in the exhibit. A listing that shows the JSON schema diagram of a log file, characterized by the fruition information w.r.t. the artworks is discussed in [1].

4 Experiments on Data Classification

The experiments described in this Section were carried out from a dataset of 253 log files, one for each visitor of the exhibition. Experiments have been executed exploiting the computing resources provided by CRESCO/ENEAGRID High Performance Computing infrastructure [4]. We have tracked the visitor behaviour by using a suitable Extrapolation Algorithm (EA), which has a JSON file as input data. A typical EA output is shown in the following:

```
IDUser : e7a5774700c1e88e1417618582735
# of artworks: 271
# of viewed artworks: 44
% of viewed artworks : 17.5%

...
-----
i-th viewed artwork : 2
ID artwork : 128
Available audio (sec.) : 32.922
Listen audio (sec.) : 32.922
Available images : 3
Viewed images : 0
```

```

Available text : True
Viewed text : False
Interaction time (sec.) : 58.259
Path is followed : True
-----
...
-----
i-th viewed artwork : 6
ID artwork : 17
Available audio (sec.) : 85.141
Listen audio (sec.) : 85.141
Available images : 4
Viewed images : 2
Available text : True
Viewed text : True
Interaction time (sec.) : 103.141
Path is followed : False
-----

```

Such files are particularly suitable to identify user behaviour not only regarding their interactions with artworks, but also w.r.t. the whole artwork exhibition. In fact, properly looking at the JSON files, for each user it is possible to determine if the exhibition path is followed, the sequence of visited sections, the time spent to enjoy audio and image contents, and if text information about a specific artwork are visualized or not.

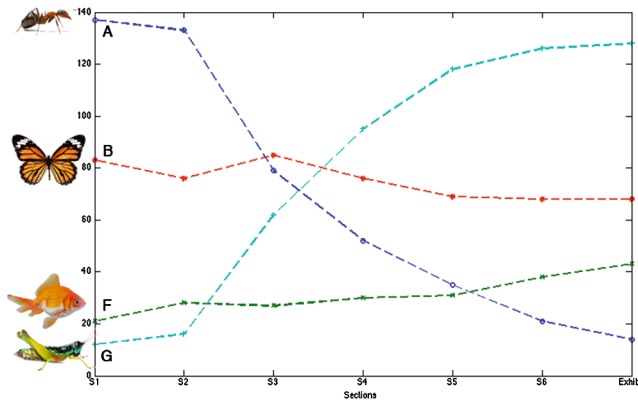


Fig. 2. Visitor classification starting from the section S_1 to all other sections (number of visitors).

Starting from the data collected in the exhibit, we deployed a classifier in order to characterize the visiting behaviours by means of some heuristics and to investigate how visitors interact with the supporting technology. According with

Table 2. Visitor classification starting from the section S_1 to all other sections (in %).

Animal	$S_1 \rightarrow S_1$	$S_1 \rightarrow S_2$	$S_1 \rightarrow S_3$	$S_1 \rightarrow S_4$	$S_1 \rightarrow S_5$	$S_1 \rightarrow S_6$	$S_1 \rightarrow S_7$
A	137	133	79	52	35	21	14
B	21	28	27	30	31	38	43
F	83	76	85	76	69	68	68
G	12	16	62	95	118	126	128

this and with the characterization of the classification illustrated in Table 1, we defined thresholds to better identify the three parameters of our dataset. In a preliminary phase, we set 10 % for viewed artwork, 60 % for average time, and 70 % for path.

Based on these thresholds, Fig. 2 and Table 2 show, respectively, the distribution number and percentage of the visitor style in all the exhibit sections calculated by our classifier. It is easy to note that **As** and **Gs** have specular trends among the sections, since **As** start with a high population in the first two sections (i.e., 53 % moving from S_1 to S_2) but drastically decrease up to the 6 % at the end of the exhibit, whereas **Gs** are thinly populated at the beginning of the exhibit but there is a strong increment starting from section S_3 (i.e., 25 %) that culminates at the end of the exhibit (i.e., 51 %).

On the other hand, we observe that **Bs** and **Fs** population trends are quite similar since tend to remain stable for the entire duration of the exhibition. In fact, **Bs** have a max increment equal to 8 % from beginning (i.e., 8 %) to end (i.e., 16 %) of the exhibition, while **Fs** have a 6 % of decrement starting from section S_1 (i.e., 33 %) and moving to the last section S_7 (i.e., 27 %).

We characterize the variations in the population distribution as metamorphosis. In Fig. 3 we summarize these distributions (number of visitors) for the sections $S_1 \rightarrow S_2$ (red columns), the sections $S_1 \rightarrow S_4$ (green columns) and the sections $S_1 \rightarrow S_7$ (blue columns) of the cultural heritage event.

From these experiments we deduce that at the beginning of the exhibit, visitors are motivated to enjoy the furnished technology. In fact, 64 % of these (i.e., **As** and **Bs**) intensively interacted with the artworks at the end of section S_2 . Afterwards, as the time spent in the exhibit grows (i.e., starting from section S_3), the interaction with the artworks strongly decreases. At the end of the exhibit, we can observe that the 78 % of the visitors are distributed in two different groups: visitors that definitively abandon the technology (i.e., 27 % of **Fs**) and visitors that choose to use the furnished technology only with a small number of specific artworks (i.e., 51 % of **Gs**).

We performed a further experimental phase based on clustering algorithm. The aim of this step consists in executing an unsupervised data mining algorithm in order to achieve data groups that can reflect the user classification obtained with our classifier. In this direction, we propose a data structure that reflects the above mentioned observations about path and media content fruition. The dataset is built from the log files and is structured in ARFF Weka format, as shown in the following.

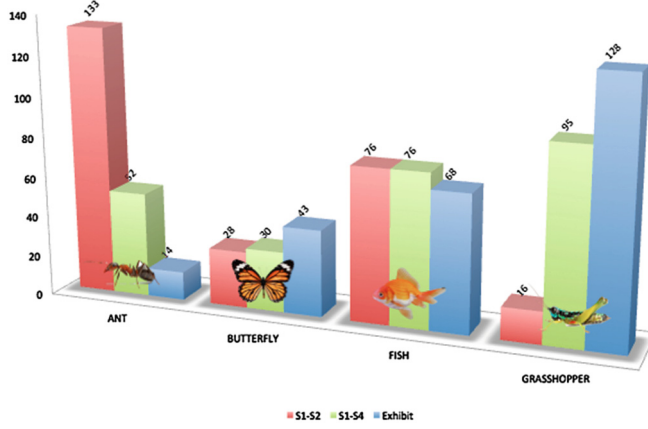


Fig. 3. Visitor metamorphosis for exhibit sections $S_1 \rightarrow S_2$, $S_1 \rightarrow S_4$ and the entire exhibit ($S_1 \rightarrow S_7$) (Color figure online).

```

@RELATION ARTWORKS
@ATTRIBUTE viewed NUMERIC [0..1]
@ATTRIBUTE avg_time NUMERIC [0..1]
@ATTRIBUTE path NUMERIC [0..1]
@ATTRIBUTE class {A,B,F,G}
@DATA
...
0.14741,1,1,A
0.0517928,0.94078,1,G
0.0119522,0.1273,1,F
0.135458,1,0.166667,B
...

```

In particular, the dataset contains fields regarding the percentage of viewed artworks (i.e., **viewed**), the average time spent in artwork interaction (i.e., **avg_time**), and the percentage of followed path during the visit (i.e., **path**). Note that these three attributes reflect the parameters introduced in Sect. 3, used to characterize the animal behaviours.

We have resorted to the well-known K -means partitional clustering algorithm [5] and set the number of classes to $K = 4$.

In Table 3 we report the results of the clustering (with $K = 4$) for the entire exhibit. Note that **Cluster0** corresponds to **G**, **Cluster1** is **F**, **Cluster2** represents **B** and **Cluster3** is **A**, as this is a typical majority voting based cluster assignment. This clustering session provides very interesting results that can be seen in the Table. In fact, the four categories in our data have been correctly identified by our classifier with an accuracy very close to the K -means results, with a number of incorrectly clustered instances equal to about 5%.

Table 3. Results of the clustering for $K = 4$ for the entire exhibit ($S_1 \rightarrow S_7$). In brackets the result of our classification.

Animals	Cluster0	Cluster1	Cluster2	Cluster3
A	0	0	0	14 [14]
B	0	0	38 [43]	5
F	8	60 [68]	0	0
G	127 [128]	0	0	1

Figure 4 shows the cluster assignments for tuples in the dataset. These are coloured by following the class attribute, whereas on the axes there are class-ID and cluster-ID.

**Fig. 4.** K means cluster assignment ($K = 4$).

Clustering results confirmed what we addressed in the classification task, as the algorithm correctly identify classes **A** and **G**, achieving a very high accuracy results. Note that only one instance has a bad clustering assignment for **G**, whereas all the instances correctly clustered for **G**. The poor clustering error is due to the classes **B** and **F**, with the error of 5 tuples for **B** and 8 tuples for **F**. This is not a surprising result, since we yet noticed in the previous classification task that **B** and **F** are have very similar trends.

4.1 Tuning of the Parameters

In the previous experimental phase, we obtained very interesting results in terms of accuracy, with a very low clustering error (i.e., 5%). However, such results came from an our intuition in setting proper thresholds in classifying visitor behaviours. In this section, we focus on the tuning of the classification parameters, in order to show how they bias the cluster accuracy.

We described in Sect. 3 how setting thresholds in order to classify visiting styles reflecting the ethnographic behaviour. Based on a possible range of values for each parameter, we defined a set of experiments in which the classification changes and the clustering strategy/setting remains the same. The goal here is to discover the best setting for the classification that produces the highest accuracy result in clustering phase for the entire exhibit ($S_1 \rightarrow S_7$).

We found several clustering accuracy results. In Table 4 we show only three most relevant setting, which produce the best, the medium and the worst quality results.

Table 4. Tuning of the classification parameters.

Quality	Parameters (%)			Accuracy error (%)	# Misclassified
	(a)	(b)	(c)		
Best	10 %	50 %	60 %	1.19	3
Medium	10 %	65 %	75 %	10.67	27
Worst	20 %	60 %	70 %	35.57	90

In Table 4, the first column expresses the quality evaluation of the tuning and the following three columns represent the settings for the three classification parameters, that are “viewed” artworks (a), “average time” (b), and “path” (c). We can notice that the first setting produces the best accuracy in clustering (1.19% error). However, this result is very close to the one we obtained without the tuning (5 % error), and this confirms that our preliminary intuitions were right. In average, we had several parameter configurations which produce an error of about 10 %, which corresponds to a very good error rate in clustering. The worst setting produces an error of about 35 %, which is acceptable in clustering especially if we consider that our dataset is not so big (i.e., 253 tuples).

5 Conclusions

In this paper we have dealt with the user dynamics and behaviours starting from real datasets. Our aim has been to classify visitor visiting styles starting from data collected by the available technology. In order to validate the classification results, we resorted to the well-known K-means clustering algorithm to discover data groups reflecting visitor behaviours in all the sections of the exhibit. Experimental results have shown that clustering approach correctly identify visitor behaviours, providing high accuracy clusters that reflect the classification results. We have observed visitor behaviour modifications at the different exhibition sections, and this introduces the concept of metamorphosis in the visiting styles. An interesting observation and challenge for future works is to adapt, in a smart way, this computational framework to many different application topics, such as the context-aware profiling, feedback based and/or recommendation systems.

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