Visitor Dynamics in a Cultural Heritage Scenario

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Abstract: We propose a biologically inspired mathematical model to simulate the personalized interactions of users with cultural heritage objects and spaces in the real case of an exhibition. The main idea is to measure the interests of a spectator with respect to an artwork by means of a model able to describe the users behavioural dynamics. In our approach, the user is assimilated to a computational neuron, and its interests are deduced by counting potential spike trains, generated by external currents. As an effort, we relies on an huge amount of log files that store visitors movements and interactions within a beautiful art exhibition named *The Beauty or the Truth* located in Naples, Italy. The technological tools deployed within the exhibition aim to create a novel metaphor stimulating user enjoyment and knowledge diffusion and the collected log files are useful data to analyse how such technology an influence and modify user behaviours. We also performed an experimental analysis exploiting clustering facilities to discover natural groups that reflect visiting styles. This is particularly suitable to provide the tuning of a heuristic classifier. The obtained results revealed to be particularly interesting also to understand other important aspects hidden in the data and unattended in our first analysis.

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 (Middleton et al., 2003). 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 (Kumar et al., 2010). 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 (Kleinberg, 2008). In this paper, we refer 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. More specifically, 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 this context, several works proposed a detailed comparative analysis in order to discover a reliable strategy to tune the model parameters. In general, two different strategies can be adopted to discover data groups: a Bayesian classifier (Cuomo

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et al., 2014a) and an approach that finds data groupings in an unsupervised way (Cuomo et al., 2014b). Such a strategy resorts to a *clustering* task employing the well-known *K*-means algorithm (Jain and Dubes, 1988). Here we deal with the characterization of user dynamics and 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 is also to classify visitors in the exhibit by using data collected by the available technology. These data are used as input current of the discussed model. The paper is organized as follows. In Section 2 we discuss the motivation example. In Section 3 we describe the cultural heritage information system. The Section 4 is devoted to the experiments. Finally, the conclusions are drawn in the Section 5.

2 MOTIVATION EXAMPLE

In order to better understand motivations behind this work, it is important to deeply analyse the kind of relations that exists between cultural spaces, people and technological tools that nowadays are pervasive in such environments. Accordingly, the behaviour of a person/visitor, when 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, other objects and transmitting 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 which offer the pleasure of perception and the charm of the discovery of a new knowledge. 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. Furthermore, we present 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 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. The proposed IoT system was entirely deployed inside the exhibition, as illustrated in Figure 1.

3 THE CULTURAL HERITAGE INFORMATION SYSTEM

The overall data collected by the described ICT framework will be used as the input of our computational model. In particular the LOG files are structured in order to store main informations about the visitor behaviour in the exhibit. The following listing shows the JSON schema diagram of a log file, characterized by the fruition information w.r.t. the artworks.

```
{
"USER":{
 "SESSION":[
  {
   "START_SESSION":"29/12/2014 16:15:10:540",
   "IDUSER":"fdb9eab819aa3f791419866070461",
   "PLATFORM":"Android",
   "START_LANG":"it",
   "IDEVENTO":10,
   "RANK_EVENTO":2.5,
   "NUMBER_OPERA":"271",
   "TRANSACTION":[
    {
     "REQUEST":{
      "REQUEST_PARAMETERS":{
       "CODECRICKET":"[1000&Cricket0019&]",
       "CODEOPERA":"128",
       "DATE":"29/12/2014 16:15:51:818",
       "LANGUAGE":"it"
      }
     },
     "PARAMETERS_LOG":{
      "RANK_TEXT":2.5,
      "RANK_AUDIO":2.5,
```

[1] http://www.ilbellooilvero.it

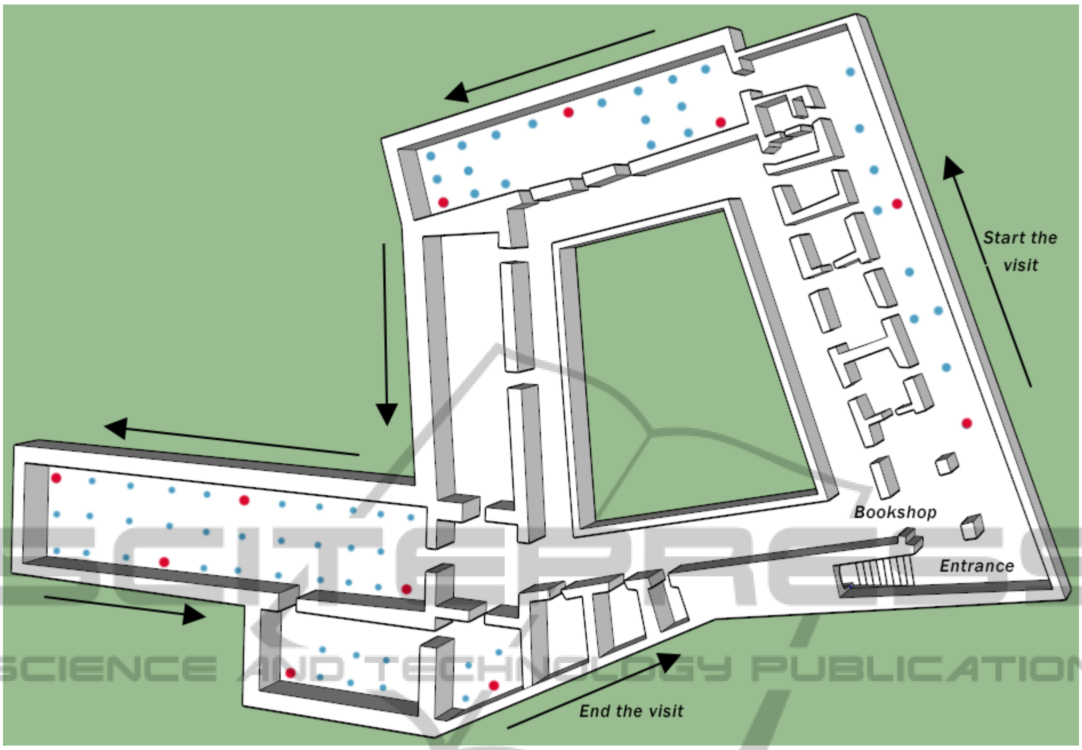

Figure 1: Exhibit map.


```
        "RANK_GALLERY":2.5,
        "ACTION":[
         {
          "TYPE":"AUDIO",
          "ID":"734",
          "HOUR_START":"29/12/2014 16:16:00:448",
          "HOUR_END":"29/12/2014 16:16:13:973",
          "TOT":"32.922"
         },
         {
          "TYPE":"IMAGE",
          "ID":"/Media/79/128/Image/2014-10-08_17-50-34.jpg"
         },
         ...
        ],
        "IMG_SIZE":3,
        "AUDIO_SIZE":2,
        "HOUR_OPERA_START":"29/12/2014 16:15:51:819",
        "HOUR_OPERA_STOP":"29/12/2014 16:16:14:15"
      }
    },
    ...
}
```


We can observe, from JSON example, that the visitor has viewed the image `2014-10-08_17-50-34.jpg` associated to an artwork. We notice that the exhibition *The Beauty or the Truth* is still open and in this paper we analyse over than 200 log files corresponding to the same number of users that enjoy the available technological instruments within such cultural space.
Respect to visitor classification, we start from (Zancanaro et al., 2007) where personalized information presentation in the context of mobile museum guides are reported. In (Zancanaro et al., 2007) is shown that visitor movements are compared to the behaviour of four typical animals. In our work, we adapt this classification to find how visitors interact with the ICT technology and how a lot they are interested in the exhibition. The visitor can be assimilated to:

- an ANT (**A**), if it tends to follow a specific path in the exhibit and spends a lot of time using the furnished technology;
- a FISH (**F**), if it moves around in the centre of the room and usually avoids looking at media content details;
- a BUTTERFLY (**B**), if it 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 content;
- a GRASSHOPPER (**G**), if it seems to have a specific preference for some preselected artworks and

spends a lot of time observing the related media contents.

In Section 4, we will define a model that, starting from data in the JSON file, is able to classify the user and to predict its interest on an artwork or on the overall exhibit.

4 USER BEHAVIOUR REPRODUCTION AND DATA MINING

The experiments described in this Section were carried out from a dataset of 253 regular visitors, and were performed on CRESCO HPC system (Bracco et al., 2009), integrated into the ENEA-GRID infrastructure, and located in the ENEA Portici Research Center.[2]. We have tracked the visitor behaviour by using a suitable Extrapolation Algorithm (EA) that has the 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 users' 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 followed, the sequence of visited sections, the time spent to enjoy audio and images contents, and if text information about a specific artwork are visualized or not. It is easy to note that such a set of information are useful to produce a detailed dataset, which is most enriched w.r.t. the one exploited in an our previous work.

This new dataset is suitable for the next step of our analysis, which consists in executing an unsupervised data mining algorithm in order to achieve data groups that can reflect the user classification described in the previous paragraph. In this direction, we propose a data structure containing not only user interaction with the artwork, but also the indication of how much he follows the path suggested by the exhibition. The dataset structure in ARFF Weka format is shown in the follow.

```
@RELATION ARTWORKS
@ATTRIBUTE audios NUMERIC [0..1]
@ATTRIBUTE images NUMERIC [0..1]
@ATTRIBUTE texts NUMERIC [0..1]
@ATTRIBUTE paths NUMERIC [0..1]
@ATTRIBUTE class {A,B,F,G}
@DATA
1,0.190476,0.190476,0.592593,G
0,0,0,0,F
...
0.84131,0.342857,0.114286,0.765432,?
...
0.573139,0.325581,0.697674,0.481481,G
```

The dataset contains, in its original version, boolean values for some fields, such as `paths` and `text`. However, it is well known in data mining literature that boolean fields are particularly critical for algorithms, that may produce inaccurate results in such cases. To avoid this problem, we propose a strategy to transform binary fields into continuous ones. For each binary field, we take into account the ratio between the number of benefited elements and the total number of elements, in order to have a percentage of benefit. A different consideration should be done for the `paths` field: to obtain a percentage of following path for a user, we counts the number of visited sections that are strictly consecutive, taking into account only close consecutive section in an increasing order, and perform the ratio of this count with the total number of sections.

Let we make an example. Assume that a user follows this path:

$$1 \rightarrow 4 \rightarrow 5 \rightarrow 2 \rightarrow 3 \rightarrow 6 \rightarrow 7$$

[2]http://www.cresco.enea.it

The count here is 4, as we have $1 \to 4$ and $3 \to 6$ are consecutive but not strictly consecutive (the contribute is 0.5 for each of these), while $4 \to 5$, $2 \to 3$ and $6 \to 7$ as strictly consecutive paths (the contribute is 1 for each of these). Moreover, $5 \to 2$ are not consecutive (the contribute is -1), as the user goes back to section 2 after visited the section 5). Note that the count starts from 1. Hence, the percentage of followed path is expressed as the ratio

$$\frac{count}{\#of sections} = \frac{4}{7} = 0.571428$$

Starting from the data collected in the exhibit, we classify the visiting behaviours by means of the mathematical model and some heuristics. More in detail, we assume that

- **F**s enjoy of almost the 7.5% of the overall media contents and has a “small” number of spikes;
- **B**s enjoy of at least the 50% of the overall media contents, does not follow a specific path and has a “medium” number of spikes uniformly distributed w.r.t. the artworks.
- **G**s enjoy of almost the 50% of the overall media contents, follows a specific path and has a “medium” number of spikes focused only on some artworks in the exhibit.
- **A**s enjoy of at least the 70% of the overall media contents, follows a specific path and has a “large” number of spikes.

We exploit such a modified dataset for our experiments. In a first phase, we execute the Expectation-Maximization (EM) algorithm to discover the best number of clusters for our dataset. The algorithm produces $K = 2$ as the number of classes, which indicates that only two of the four categories described before are present in our data. With this input, we resorted to the well-known K-means partitional clustering algorithm (Jain and Dubes, 1988) and set the number of classes to $K = 2$. Experiments underline that the two categories in our data have been correctly identified with an accuracy of almost 73%.

Investigating more deeply at the dataset, we have known that they are data from the overall exhibition, and the two behaviours present are **F** (i.e., fish), and **G** (i.e., grasshopper). This means that users are not typically interested in exploiting multimedia contents in all the sections. In fact, in order to have a proof for our intuition, we decided to take into account only data from the first two sections of the exhibition. We discovered here all the four classes, and this indicates that a user typically enjoys multimedia support only in the first phase of his visit.

In Table 1 we report the results of the clustering (with $K = 4$) for the first two sections of the exhibition. Note that **Cluster0** corresponds to **A**, **Cluster1** is **F**, **Cluster2** represents **G** and **Cluster3** is **B**, as this is a typical majority voting based cluster assignment. We achieved a slight improvement in terms of accuracy results (almost 81%). However, this clustering session provides very interesting intuitions which can be seen in the table. In fact, the behaviour labelled with **G** is the most ambiguous one, as the grasshopper is very difficult to characterize. Moreover, regarding **A**, these tuples are splitted mainly between two clusters, i.e., **Cluster0** and **Cluster3**, but the cluster labelling is negatively affected by **G** tuples. Finally, **F** and **B** are well grouped in their clusters, with $\sim 85\%$ and $\sim 84\%$ of accuracy, respectively.

Figure 2 shows the cluster assignments for the tuples in the dataset. Tuples are coloured by the class attribute, whereas on the axes there are class-ID and cluster-ID.

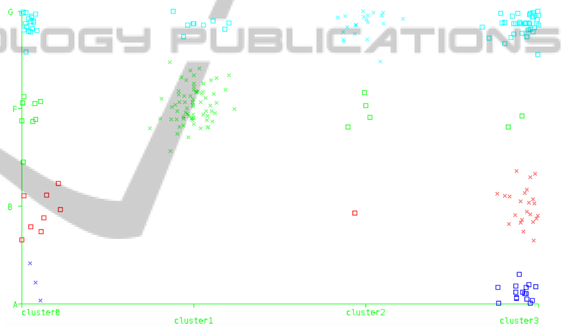

Figure 2: Kmeans cluster assignment ($K = 4$).

We can see in the figure what saw before regarding the difficulty of identifying with high accuracy the behaviour of some classes, i.e., **G** (in cyan) and **A** (in blue): they are mainly assigned to the right cluster, but lots of the remaining instances are also present in the other clusters.

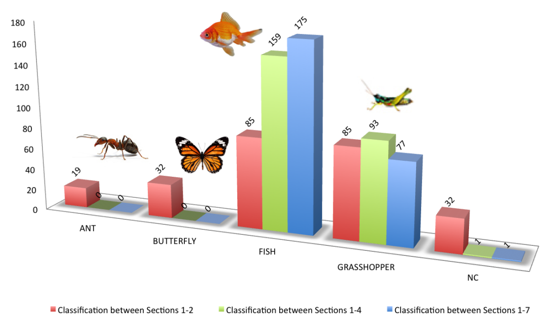

Figure 3: Visitor Metamorphosis.

In Figure 3 we report the visiting styles in the sections $1-2$ (red columns), the sections $1-4$ (green

Table 1: Results of the clustering for $K = 4$ for the first two sections of the exhibition.

Animals	Cluster0	Cluster1	Cluster2	Cluster3
A	14	11	4	22
B	4	0	1	27
F	7	72	4	2
G	16	9	30	30

columns) and sections $1-7$ (blue columns) of the cultural heritage event. For the first 2 sections, we observe that only the $\sim 7.5\%$ of the users are **A**s, while the $\sim 12.5\%$ are classified as **B**s. Moreover, the users classified as **F**s and **G**s are the same amount of the $\sim 33\%$. The remaining $\sim 12.5\%$ of users are not classified. Furthermore, from the section 1 to the section 4 we note that all the users become **F**s ($\sim 63\%$) or **G**s ($\sim 37\%$). Finally, by observing the blue columns of the histogram in Figure 3, from the section 1 to the section 7 (i.e., the entire exhibition) we note that there is an adjustment of these *metamorphosis* of the users in **F** ($\sim 69.5\%$) and **G** ($\sim 30.5\%$).

From these experiments we deduce that as the time spent in the exhibit grows, visitors choose to not use the available technology in an intensive way. We deduce that if the event had lasted only 2 sections, 54% of users would continue to use the supplied technology, instead of the 30.5% on the entire exhibition.

5 CONCLUSIONS

In this paper we have described a framework that reflects the computational methodology adopted to infer information about visitors in a cultural heritage context. Our challenge is to match, in a realistic way, the biological morphology of a neuron and its behaviour in this application scenario. In the model we propose, the (R, C) couple represents the sensitivity of an user respect to an artwork. Accordingly, we compared two different strategies for tuning model parameters in order to find an accurate approach that is able to provide the best setting for the neuronal model. In this respect, we shown experimental results for standard Bayesian classifier and a novel clustering methodology to obtain starting groups from which these electrical parameters can be tuned. From our experiments, it has been highlighted that clustering task is able to produce a more accurate setting.

Starting from the *state-of-art* about the Museum visitors' behaviour patterns, we have investigated how the use of technological tools within cultural spaces can affect visitors' behaviour, causing behavioural changes also during the same visit. In this particular case, we have analysed such behaviour modification, introducing the concept of metamorphosis and showing the analysis results in visitors' 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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