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SPICE

Social cohesion, Participation, and Inclusion through Cultural Engagement

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Project Contacts

Project Coordinator

Silvio Peroni

ALMA MATER STUDIORUM - UNIVERSITÀ DI BOLOGNA
Department of Classical Philology and Italian Studies – FICLIT

E-mail: silvio.peroni@unibo.it

Project Scientific Coordinator

Aldo Gangemi

Institute for Cognitive Sciences and Technologies of the Italian National Research Council

E-mail: aldo.gangemi@cnr.it

Project Manager

Adriana Dascultu

ALMA MATER STUDIORUM - UNIVERSITÀ DI BOLOGNA
Executive Support Services

E-mail: adriana.dascultu@unibo.it

SPICE Consortium

No.	Short name	Institution name	Country
1	UNIBO	ALMA MATER STUDIORUM - UNIVERSITÀ DI BOLOGNA	Italy
2	AALTO	AALTO KORKEAKOULUSAATIO SR	Finland
3	DMH	DESIGNMUSEON SAATIO - STIFTELSEN FOR DESIGN-MUSEET SR	Finland
4	AAU	AALBORG UNIVERSITET	Denmark
5	OU	THE OPEN UNIVERSITY	United Kingdom
6	IMMA	IRISH MUSEUM OF MODERN ART COMPANY	Ireland
7	GVAM	GVAM GUIAS INTERACTIVAS SL	Spain
8	PG	PADAONE GAMES SL	Spain
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11	FTM	FONDAZIONE TORINO MUSEI	Italy
12	H-FARM	H-FARM SRL	Italy
13	UH	UNIVERSITY OF HAIFA	Israel
14	CNR	CONSIGLIO NAZIONALE DELLE RICERCHE	Italy

Executive Summary

SPICE is an EU H-2020 project dedicated to research on novel methods for citizen curation of cultural heritage through an ecosystem of tools co-designed by an interdisciplinary team of researchers, technologists, and museum curators and engagement experts, and user communities.

This technical report D6.6 presents the results of Task 4 of Work Package 6: " Knowledge based exploration support". This task provides novel sensemaking systems supporting the grouping and linking of digital items via knowledge-enabled reasoning technologies. Specifically, this Deliverable finalizes the system prototypes presented in the Deliverable 6.3 and presents novel results obtained by exploiting such tools on the collected data coming from the Museums.

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Table of contents

1.Introduction

This technical report D6.6 presents the final realization and results of the sensemaking tools leveraging the knowledge graphs and ontologies developed in the Work Package 6 and leveraging on affective, thematic and value-based knowledge. Specifically, this deliverable reports the main advancements and results obtained by the DEGARI affective system ((1),(2)), and by the Thematic and Value Reasoners, whose prototypes were already presented in Deliverable 6.3.

The rest of the deliverable is structured as follows. Chapter 2 is dedicated to the main novelties of the DEGARI system used for the automatic generation of affective-based labelling, grouping and suggestion of cultural items. Next, Chapter 3 reports on the updates and results of the Thematic Reasoner, while Chapter 4 reports on the main updates and results of the Value Reasoner. Chapter 5, presents a novel approach trying to combine emotion and value based extraction. Finally, Chapter 6 concludes the report.

2.DEGARI

2.1. Introduction

The core component of DEGARI relies on a probabilistic extension of a typicality-based Description Logic called $\mathbf{T}^{\text{CL}}$, (Typicality-based Compositional Logic, introduced in (3)). This framework allows one to describe and reason upon an ontology with commonsense (i.e. *prototypical*) descriptions of emotional concepts, as well as to dynamically generate novel prototypical concepts in a knowledge base as the result of a human-like recombination of the existing ones (4). The first version of the system and the first obtained results are described in Deliverable 6.3. The novel experiments that we report below have been done at the GAM Torino (with the help of Istituto dei Sordi di Torino) and have additionally involved also the stories created by the users of Design Museum, Helsinki (DMH).

2.2. System Updates and Usage

The novel version of the system, called DEGARI 2.0 (2) exploits the affective classification of museum items to make different types of recommendations aiming at improving the experience of emotional inclusion and critical reflection in museum fruition. The main idea is that, in order to open the users' view towards more inclusive and empathy-based interpretations of cultural content, the system suggests also items sharing different emotional stances compared to those elicited by the users during a museum visit.

2.3. Experiments

In the last year, we have tested DEGARI 2.0 for a number of tasks in the context of 1) affective classification coverage, 2) perceived level of explainability for the provided emotional labels and 3) story-based affective linking.

2.3.1. Affective classification: comparison with SenticNet 7 and SOPHIA

In order to assess the feasibility of the affective classifications provided by our system we compared the results of DEGARI 2.0 with SenticNet 7 (5), (6): a state of the art emotion extraction system that employs a plethora of neural language models and that is able to classify both basic and complex emotions since it relies on an extension of Plutchik's model called the Hourglass model (7). The ability of classifying both basic and complex emotions represents one of the major differences with respect to DEGARI 2.0 that, on the other hand, is targeted explicitly on generating and classifying only complex emotions.

As shown in Table 2.1, for the GAM dataset selected by the museum curators for the SPICE project (a total of 56 items displayed in the museum), SenticNet 7 was able to extract, in total, 13 different types of emotions, of which 2 are complex ones (namely *enthusiasm* and *delight*, colored in green in Table 2.3). DEGARI 2.0, on the other hand, was able to extract a total of 28 different types of complex emotions. Their coverage (i.e. how many museum items the two systems were able to classify) is almost similar (i.e. 100% vs 97,7% in favor of SenticNet 7). These two data, consider together show, how DEGARI 2.0-despite focusing only on the subset of complex emotions in the Plutchik's model-is able to capture more nuanced, richer, and fine-grained emotional classifications. Surprisingly, DEGARI 2.0 was also able to provide - on average - more emotional labels for each item. Table 2.3 shows an excerpt from the GAM dataset outlining the differences in the affective classifications executed by both systems.

Total DEGARI 2.0 extracted emotions	108
Total SenticNet 7.0 extracted emotions	88
Total DEGARI 2.0 artworks classification	97,7%
Total SenticNet artworks classification	100%
Type of extracted emotions by DEGARI 2.0	28
Type of extracted emotions by SenticNET	13
Total compound emotion extracted by SenticNET	2

Table 2.1: The Table shows the aggregate statistics on the GAM dataset artworks. SenticNet 7 classifies all GAM artworks (100%) while DEGARI 97.7% of the total. The complex emotions extracted by DEGARI extending the overall emotions (basic + complex) extracted by SenticNet 7. Finally, SenticNet 7 is able to extract only 2 compound emotions according to the Plutchik's ontology while DEGARI 2.0 extracts only complex emotions (28)

GAM Artefact	SenticNet7 emotions	DEGARI 2.0 emotions
 Ritorno alla stalla - Back to the barn	joy; calmness	Aggressiveness Contempt Dominance Envy Outrage Pride
 Contadini al sole - Farmers in the sun	joy; eagerness	Despair Disapproval Envy Pessimism Remorse Sentimentality
 Miracolo Olocausto - Miracle (Holocaust)	rage; loathing	Despair

Table 2.2: An excerpt comparing the SenticNet 7 extracted emotions with DEGARI 2.0 classification

Extracted emotion with SenticNet7	**13**	
enthusiasm	delight	
joy	eagerness	calmness
grief	rage	pleasentness
bliss	contentment	enthusiam
terror	ecstasy	
Extracted combined emotions with DEGARI 2.0:	**28**	
hope	despair	guilt
disapproval	envy	pessimism
remorse	sentimentality	aggressiveness
contempt	dominance	outrage
pride	awe	pessimism
unbelief	curiosity	disgust
fear	anxiety	morbidness
love	curiosity	optimism
sentimentality	joy	cynism
guilt		

Table 2.3: Simple and combined emotions extracted by SenticNet 7 compared with the complex emotions extracted by DEGARI 2.0. In green are highlighted the compound emotions extracted by SenticNet 7 while DEGARI 2.0 is more nuanced in assigning the combined emotions of the Plutchik's wheel.

By following the same rationale, we also compared the affective classifications of DEGARI 2.0 with the ones obtained by the the SOPHIA Engine developed by CELI/H-FARM and used in Work Package 3 (see (8)) since both such systems also rely on the very same Plutchik's model.

We have compared the results of the two systems on a subset of selected items provided by the GAM museum curators. In this case, we collected answers, comments and tags from users in English and Italian in order to trigger the affective classification using the two systems. Thus, here the focus was to compare the results of the two systems on the user-generated content associated to each museum item. An example of the questions are the following: How many different emotions can visual art evoke in viewers? How are these emotions verbalized? The question we asked ("How does this artwork make you feel? Write your feelings, emotions, thoughts") was answered in different ways, even in front of the same work of art. For example, looking at The Siren by G. A. Sartorio one answer was "Love, romantic, calm, a bit sensual. Does it suppose to be a sad ending?", the second one was "Serene, curious, happy", the third one was "I feel anxiety", etc.

Total GAM artworks	24	
Total DEGARI 2.0 artworks classification	12	(50%)
Total SOPHIA artworks classification	24	(100%)
% of items where DEGARI 2.0 classification extended SOPHIA classification	29%	

Table 2.4: The Table shows the aggregate statistics on the 24 selected GAM artworks. SOPHIA classifies all 24 GAM artworks (100%) while DEGARI 12 (50% of the total), extending SOPHIA's coverage with compound emotions. As mentioned, it is worth-remembering that DEGARI 2.0 is only able to classify complex emotions, while SOPHIA classifies both basic and (a subset of) complex emotions.

The overall results are reported in Table 2.4, where we have grouped the emotions extracted from all the answers relating to each picture. Importantly, SOPHIA shows a better coverage of the itemset while DEGARI 2.0 (which, as mentioned, focus exclusively on complex emotions) is able to perform a fine-grained emotional classification. To this end, Tables A.1 and A.2 (in the Appendix) provide both a detailed and synthetic description of the way in which the emotional nuances detected by DEGARI 2.0 extend the basic ones detected by SOPHIA. In particular Table A.1 shows, for the subset of artworks where DEGARI 2.0 is able to label the user comments with complex emotions, the difference with the affective classification reported by SOPHIA. In the column reporting the SOPHIA results, in bold, are highlighted the complex emotions (DYADS) extracted by SOPHIA. Table A.2, finally, reports the overlap of the two affective systems for the subset of artworks considered in Table A.1

Looking at Table A.1, we see that 12 emotion categories have been included for “Aracne”, 11 for Asphissia, 10 for The Siren (from Anger to Trust). This result does not mean that the automatic system faces overcategorization issues: the manual annotation confirmed that users expressed different emotions in front of the same work.

Interestingly, and similarly to what also showed for SenticNet 7, the results provided by the two systems (SOPHIA and DEGARI) are complementary and cumulative in nature. They, in fact, contribute to enrich the same knowledge graph that is queried to retrieve emotional concepts associated, by means of users answers, comments and tags, to the set of cultural items.

Overall, the results of these experiments suggested a combined use of different emotion extraction systems to enrich the affective knowledge. This combination is technically obtained by automatically updating knowledge graphs of cultural items available in a Linked Data Format (9) More importantly, such enriched knowledge can be used to feed personalized recommendations to citizens engaging with cultural items in museum.

2.3.2. Evaluating the Perceived Explainability: Results and Discussion

Another major evaluation carried out concerned the analysis of the explanatory capabilities of the system according to the target group of the DEAF community in the GAM case study. In this experiment, 11 items from the GAM collection were selected by Museum curators with the aim of having a balanced collection of types of items (e.g paintings, sculptures, etc.) and of represented subjects (e.g. containing both abstract and physical entities).

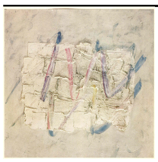
Table 2.5 reports the scores assigned to each explanation by the deaf users. The overall average rating assigned by the users to the feature-based explanation of the emotional classification provided by the system was is 5.81 out of 10, with a median value of 6/10. The column “keyword trigger" indicates the keyword found in the description of the items (on in the content generated by the user in the GAMGame[1] the application used by DEGARI 2.0, including both comments or emojis) that has been used by the system to trigger the emotional classification and is also the element used in the explanation part. Therefore, the association *item-keyword-emotion* represents the triple evaluated by the users to assess and rate how much, in their view, the system explains and make transparent the emotional association triggering the entire recommendation process.

A second part of this evaluation focused on the perceived level of explainability, consisted in a focus group (here it was involved the Istituto dei Sordi di Torino, the Institute for the Deaf of Turin, that provided a professional translator from Italian to Italian Sign Language and viceversa). The thematic line of the focus group revolved around the use of language-based explanations (like the ones presented by our system) as a tool for the deaf participants to gain insight about the process of emotion attribution done by the system. Different suggestions emerged, some which may have a general valence for explainable systems, while others are more relevant for the specificity of the deaf community.

In particular, the deaf participants generally expressed that the possibility of knowing the triggers of the emotional classifications (which is the basis of the overall emotion-based recommendation mechanism provided by the system) improved their trust in the system, but also suggested that **explanations are a space for reflection**, since they stimulate a deeper reflection on the emotions conveyed by the artwork.

In this line, they suggested a set of improvements, some of which are specifically tailored on the needs of the deaf. In particular, the participants suggested that, whenever possible, **more than one word** should be provided **as**

[1] http://spice.padaonegames.com/gam-game/consumer/visit/62cc4f819f7c9c7e6739a46b/home

GAM Artefact	Median	Dev.Standard	Mean	Keyword trigger	Generated emotion
 Miracolo (Olocausto)	9,0	2,35	8,00	Tragedy	Despair
 I Santi Anargiri	6,0	2,59	6,20	Anticipation	Hope
 Il torrente d'inverno	5,0	2,07	5,17	Truth	Hope
 Angles	2,0	2,87	4,25	Torture	Awe
 Maternità	7, 5	3,16	7,00	Tragedy	Despair
 Ritorno alla stalla	3,5	2,83	5,00	Brutality	Aggressivness

explanation. This would reduce the ambiguity intrinsic to the single word, helping the user to built a network-like representation of the words employed by the systems to classify the artwork emotionally. Following the same line of though, participants suggested to include in the explanation also the **words in context** (i.e. providing the snippet where the word triggering the emotional classification of the artwork was included).

A third suggestion specifically addressed the needs of deaf, and of speakers of sign languages in particular. In practice, some participants suggested to **accompany the words with some type of visual representation**. Interestingly, however, this suggestion was challenged by other participants in the focus group because of the arbitrariness of symbolic representations (e.g. truth), which may be affected by culture, age, education, etc. As an alternative, some participants suggested to use, instead of images, **short clips with the signed version of the word**, performed with the due expressiveness by a human signer, in order to convey also the emotional connotation of the words. Although this last suggestion is specifically tailored to deaf users, it finds some correspondence in previous

GAM Artefact	Median	Dev.Standard	Mean	Keyword trigger	Generated emotion
 Contadini al sole	7,0	1,52	6,00	Tragic	Pessimism
 I funerali di Tiziano	8,0	1,30	7,50	Horror	Hope
 La femme de Claude	5,5	3,19	5,25	Honor	Hope
 La ragazza rossa	4,0	2,24	4,00	Truth	Hope
 Pugilatore	6,0	0,55	5,50	Truth	Hope
Total answers:	54				
Median:	6				
Dev.Standard:	2,24				
Mean:	5,81				

Table 2.5: Details of all average ratings assigned, for each item, to provided explanations generated by DEGARI 2.0

work on the relevance of non-verbal communicative modalities in the expression of emotions (10).

Finally, the presentation of items associated with negative emotions was also discussed in the focus group, with the intent to clarify the field of the hypothesis that the exposition of participants to negative emotions as part of the recommendation process may have affected their opinion concerning the explanations. Here, the participants agreed that this type of recommendation, although in principle more prone to rejection, was particularly useful to broaden the user experience of the collection, and to prompt the reflection on the emotional meaning of artworks. Notice that this is in line with the investigations in negative feelings made by (11), according to which negative feelings constitute an intrinsic component of audience experience in entertainment and art, especially in participatory contexts.

2.3.3. Affective based story linking

We finally tested the capability of DEGARI 2.0 to provide emotional labels (and suggest alterative, diversity-seeking, emotion-based suggestions) to aggregates of items (that we call stories) selected by the users. During the researchers' night event (promoted by University of Torino), we collected data for a total of 55 users. They registered via google-form with the generation of an anonymous id and session. For each (anonymous) user, in the registration phase, we asked to provide the following information: Gender, age, relationship with art, with museum, and if he is interested in LIS (sign language) content or not.

Once the registration phase is completed (Figure 2.1), the user will be redirected to the dashboard of the GAMGame app where it is possible to start the creation of his story.

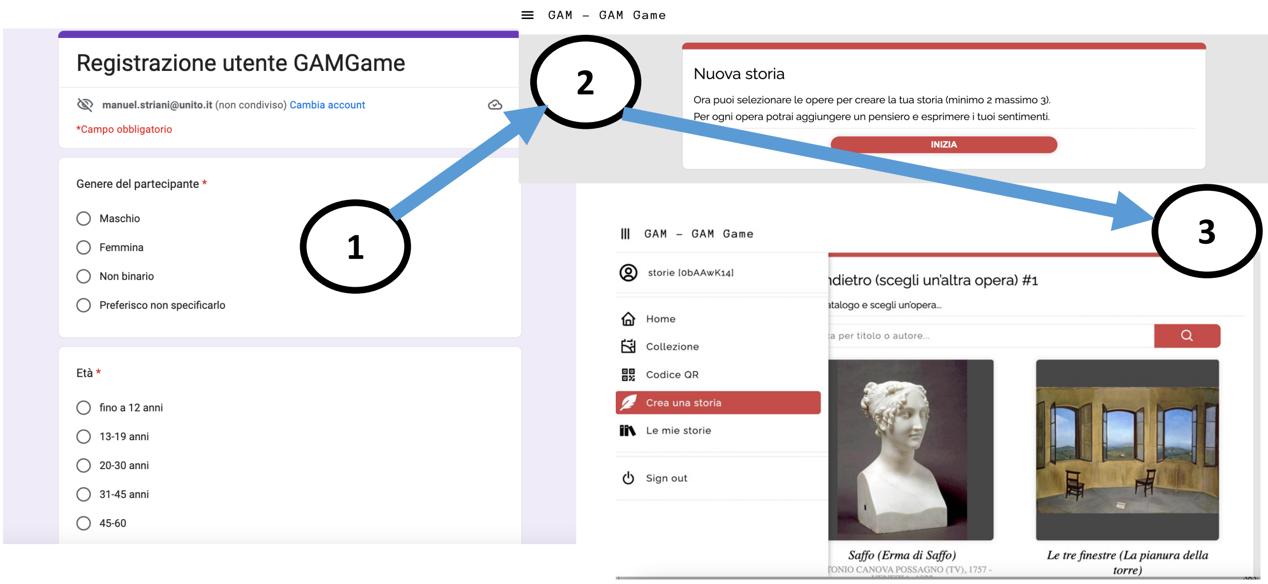


Figure 2.1: Google-form for user registration at GAMGame during the UNITO researchers' night

The whole architecture pipeline of the DEGARI 2.0 service is sketched in Figure 2.2 and relies on the following workflow, working without any manual intervention:

1. Users (via a client call initiated by a web app) can create a story and send a JSON file by using POST method. This JSON file contains the description of a particular story (i.e., "The course of nature") and annotations collected by the users over the artifact (e.g. tags about the emotions generated, emojies etc.).
2. the JSON file with the ID of the story and its description/items and comments is stored into the Linked data Hub (LDH)
3. The algorithms running on the HPC4AI server (server located in the Department of Computer Science at University of Torino) periodically download the data from the LDH. They execute the annotations process both with DEGARI 2.0 and with SOPHIA, the semantic annotator (by CELI/H-FARM), finally, they execute the RDF-SPARQL queries for update stories and artefacts into the Fuseki knowledge graph
4. DEGARI 2.0 algorithms downloads the new update (Knowledge Graph) KG and start reasoning in local by using Hermit reasoning algorithm in order to get the inferences on KG

5. DEGARI 2.0 algorithms update LDH with the new enriched stories (stories + DEGARI 2.0 emotions + Semantic Annotator)
6. In the last step, the enriched data are sent back to the LDH and and
7. By using the GAMGame, it is possible to perform the task of story recommendation, executing RDF-SPARQL queries directly on the Fuseki server

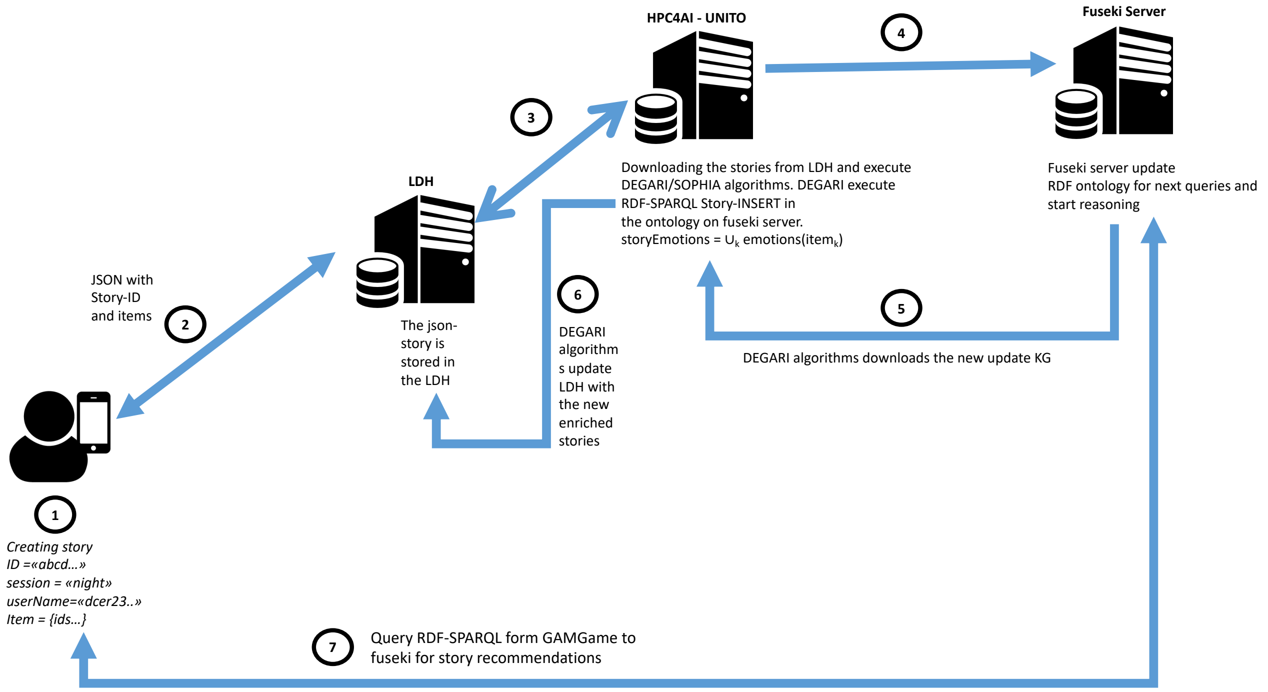


Figure 2.2: Architecture and Workflow for DEGARI 2.0 Story

In the Figure 2.3 is shown an example of a story entitled "The course of nature" created by the GAMGame user and the associated Plutchik's wheel for the extracted emotions.

The Figure 2.4 shows an example of RDF-SPARQL query on Fuseki server. Given a story-ID, this query select the sets of the stories which have the opposite emotions with the current story. In particular, in this example, it is possible to see that,

Figure 2.5 shows an example of RDF-SPARQL query for retrieving stories which have same emotions with the current one.

In the Table 2.6 is reported an example of a story. In particular, user with id="6rK3p7za" creates a story entitled "Sad sea", selecting three different artworks 39138,35362, 35249. Figure 2.6 shows the Plutchik's wheel extracted from the story "Sad sea". The emotional wheel was calculated by averaging the $i-$emotions extracted from the union of each artworks that characterise the whole story $Plutchik_{wheel} = \cup_{i=0}^{|artworks|} em_i$.

StoryID	UserID	StoryTitle	ArtefactID	Artefact name
6333f37613a6b278b06dc2e7	6rK3p7za	Sad sea	39138 35362 35249	(Der) Matrose Fritz Múller aus Pieschen Sheds by the sea (Capanni sul mare) Composition T. 50 - 5

Table 2.6: Story example

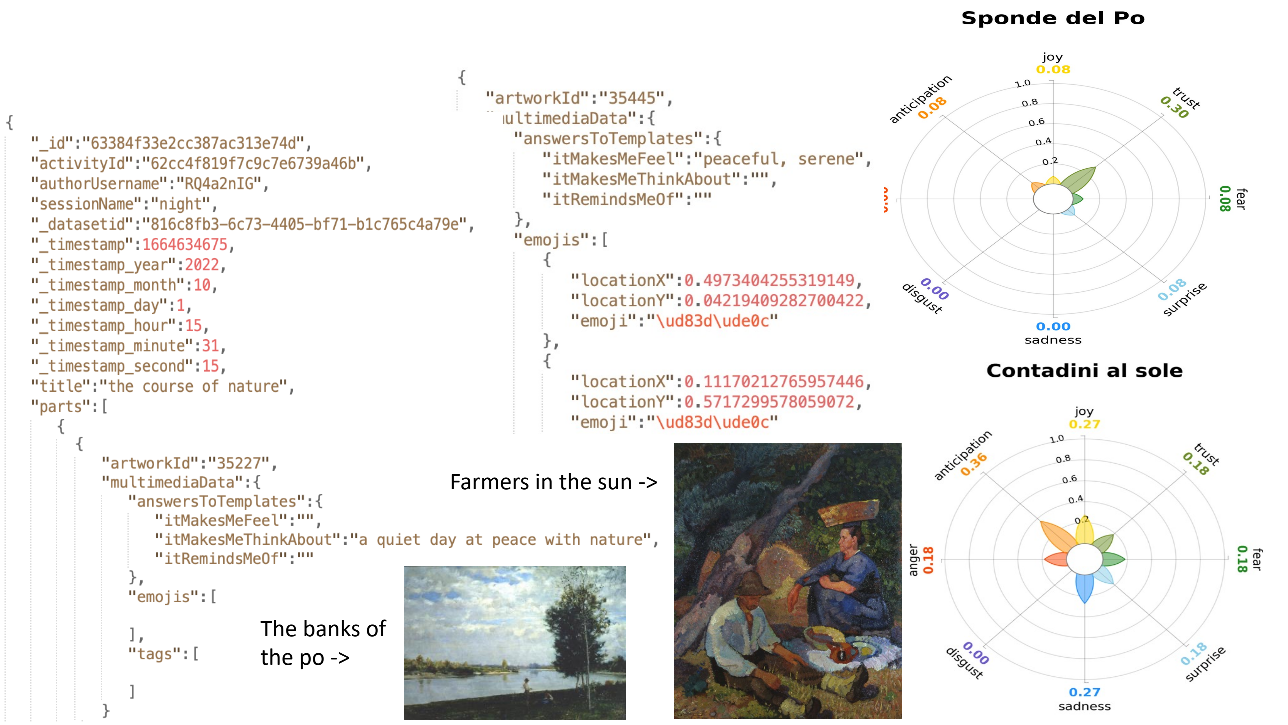


Figure 2.3: Example of user story with Plutchik's wheel

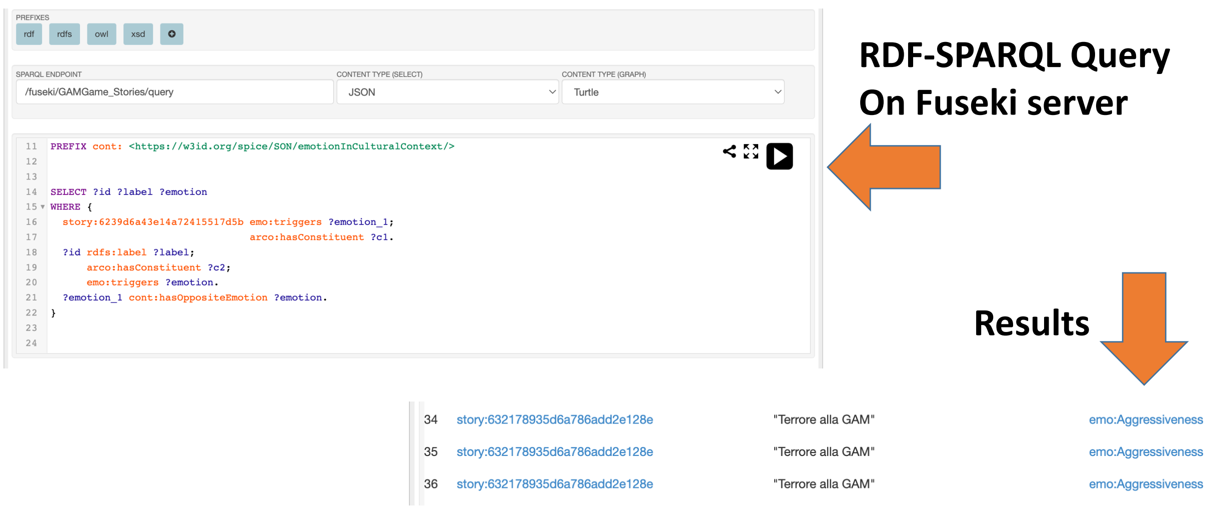


Figure 2.4: Example of RDF-SPARQL query on Fuseki server for retrieving stories with opposite emotions

2.4. DMH Stories from VR-Museum of Helsinki

A second experiment conducted with DEGARI 2.0 was on the stories of the virtual museum (Pop-up VR Museum) in Helsinki (the used dataset is on the Linked Data Hub (LDH) [2] and has been used also for further analysis by the Thematic and Value Reasoners). In this case the term *story* refers to the users generated contents on specific

[2]https://spice.kmi.open.ac.uk/dataset/details/104

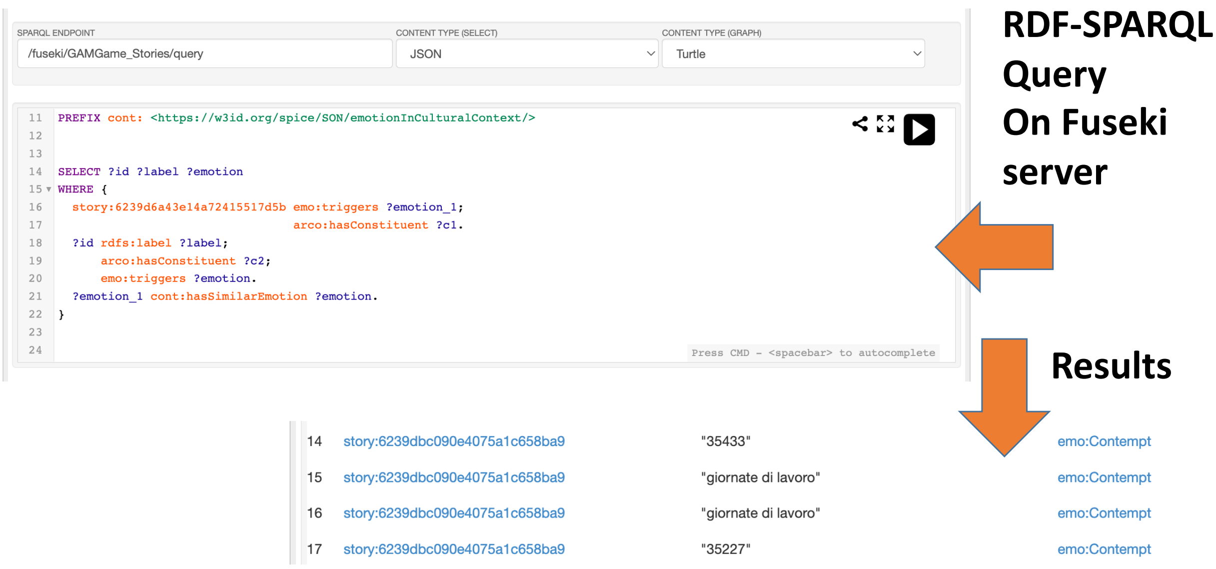


Figure 2.5: Example of RDF-SPARQL query on Fuseki server for retrieving stories with same emotions

artifacts. In particular, the first part of Table 2.7 (a), shows some statistics calculated from the use of our DEGARI 2.0 system for the extraction of emotions on user-generated comments. The set of tuple of emotions that have been extracted by DEGARI 2.0 most frequently are {Delight, Joy},{Love, Optimism} and {Love, Joy}.

Table 2.7(b) shows for each extracted emotion from user-generated comments on stories, the relative frequency. The emotion that DEGARI 2.0 extracted most frequently, was *Joy* with 36 followed by *Delight* with 25.

2.5. Discussion and Concluding Remarks

Summing up, the key outcomes of our experiments show that our system, when compared with a state of the art emotion extraction system like SenticNet 7, for the task of emotional labelling (i.e. the precursor for both the tasks of affective-driven inclusive recommendations and the provided explanations) achieve better performances. On the other hand, when compared with SOPHIA, the system shows a wider capability of providing affective nuances but less coverage. As a consequence, a suitable strategy that has been put in place in SPICE has been to use both SOPHIA and DEGARI 2.0 in a complementary way.

In addition, from the experiment concerning the perceived explainability of the provided categorization, some key elements emerged as guidelines to design and improve the next generation of inclusive and transparent AI systems, potentially going beyond the specific needs of the deaf community. In this regard, it is important to point out how state of the art neural systems and language models, like SenticNet 7, do not have, as a built-in, this feature. It represents, however, one of the major requirements for modern AI systems interacting with the humans (see, for example, the recent General Data Protection Regulation (GDPR) that emphasized the users' right to explanation (12).

In future research we aim at extending our approach in different directions. First, for what directly concerns the development of the system, we are studying the application of the optimization techniques proposed in (13; 14) in order to improve its efficiency and, a consequence, the usability and scalability of the overall pipeline. In addition, we aim at extending the evaluation in two directions: the first one concerns the extension of the current evaluation to a larger number of users of the deaf community. The second one plan to extend the evaluation to the collections of the other museum partners of the SPICE project (i.e., the Hecht Museum in Haifa, the IMMA Museum in Dublin, and the Museum of Natural Science in Madrid).

```
emotions =
    {
        'joy':      [0.27027027027027O3,0.0980392156862745, 0.19736842105263157 ],
        'trust':    [0.2702702702702703,0.0980392156862745,0.19736842105263157],
        'fear':     [0.06756756756756757, 0.0, 0.19736842105263157],
        'surprise':[0.13513513513513514, 0.0, 0.19736842105263157 ],
        'sadness':[0.06756756756756757, 0.196078431372549,0.0 ],
        'disgust':  [0.0, 0.0, 0.0],
        'anger':    [0.06756756756756757, 0.0, 0.06578947368421052],
        'anticipation': [0.13513513513513514,0.196078431372549, 0.2631578947368421]
    }
```

Matrose Fritz Müller aus Pieschen - 39138

Sheds by the sea (Capanni sul mare) - 35362

Composition T. 50 – 5 - 35249

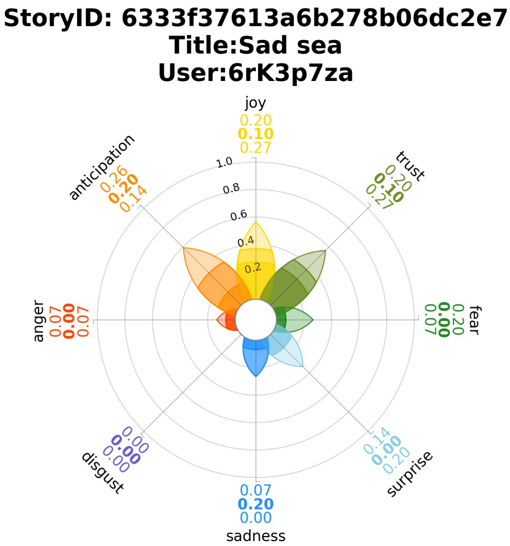


Figure 2.6: Example of "Sad sea" story created by user with ID: 6rK3p7za

Finally, we have also shown how our system is able to provide affective classifications and suggestions based on aggregates of items (stories) in the GAM Game. We are currently in the process of organizing experiments (in the GAM museum) to check the acceptability of diversity-seeking stories based on different emotional nuances. The approach of story-centered emotions recommendations will be extended also the Helsinki Design Museum and the Museum data.

Total stories	213
Total stories with extracted emotions	78
Total extracted emotions by DEGARI 2.0	86
Mean extracted emotions foreach story	1
MIN extracted emotions for each item	0
MAX extracted emotions for each item	2

(a)

Emotion	**Frequency**
Joy	36
Delight	25
Love	8
Optimism	5
Curiosity	1
Pessimism	3
Disapproval	3
Hope	2
Anxiety	1
Shame	1
Outrage	1

(b)

Table 2.7: Statistics for DEGARI 2.0 extracted emotions from DHM-Stories (a) and Frequency for DEGARI 2.0 extracted emotions (b)

3.Thematic Reasoner

The Thematic Reasoner (TR) is a tool able to deduce the thematic subject of a collection of entities (e.g. the artworks located in a room of a museum). This tool enables to carry out non-trivial analysis of the interests of a user or of a community which, in turn, supports tasks such as classifying a user (or a community) according to the artworks s/he interacts with. Such reasoning capabilities are offered as a software service that integrated with the other tools supporting the IRL processes (cf. D2.1 and D2.2).

The Deliverable D6.3 presented the first release of the tool whose reasoning capabilities were limited to the ability of associating the artworks with themes. The second release of the TR (presented in this document) extends the capabilities of the TR so as to support the reasoning over the semantically annotated text as produced by the Semantic Annotator (cf. D3.4).

Section 3.1 describes how the TR evolved so as to reason over the semantically annotated text and how to use the system. Section 3.2 reports on the results of the experiments with the TR over the data collected by a case study of the project.

3.1. System Updates and Usage

As an application scenario of the D6.3 we considered the case study involving the Hecht Museum, and, specifically, an artificially constructed exhibition about the Jewish and non-Jewish settlement in the 1st century CE and the events of the rebellions in the Galilee and Judea. Therefore, the object of the analysis of the TR was the collection of artifacts of the exhibition.

In this deliverable, we focus on a different kind of objects, that is, the natural language generated by the users during the activities of the case studies. The analysis performed by the TR allows us to connect pairs of topically-associated textual content. As a running example we consider the collection of stories collected by the Design Museum Helsinki (DMH) during the workshop. The collection of stories has been annotated by the Semantic Annotator (cf. D3.4) and uploaded to the Linked Data Hub (cf. D4.2)[1]. Each story is available in JSON-LD format shaped according to the SPICE Ontology Network (cf. D6.5). An example of such a semantically-annotated story is shown in the Listings A.1. A collection of such files is passed as input to the TR. Once received the collection, the TR proceeds as follows. The TR passes through each file, and, it performs the following activities:

1. Retrieving the story from each file. This can be done via the following SPARQL query.

```
PREFIX earmark: <http://www.essepuntato.it/2008/12/earmark#>
SELECT ?t ?d {
    ?d a earmark:StringDocuverse ;
        earmark:hasContent ?t
}
```

2. Retrieving the semantic annotations of each story via the following query:

```
prefix semiotics: <http://ontologydesignpatterns.org/cp/owl/semiotics.owl#>
prefix earmark: <http://www.essepuntato.it/2008/12/earmark#>
SELECT ?entity ?associatedEntity {
    ?pr semiotics:denotes ?associatedEntity .
    FILTER (STRSTARTS(STR(?associatedEntity), "http://dbpedia.org/"))
    ?pr earmark:refersTo ?entity .
}
```

[1] https://spice.kmi.open.ac.uk/dataset/details/91

Once the story and its semantic annotations are retrieved the TR can proceed as showed in the D6.3. Specifically, the TR retrieves the themes (i.e. the Wikipedia Categories) directly associated with each DBPedia entity and their ancestor themes (i.e. the set of DBPedia categories that are broader than the direct ones). Finally, the TR computes the weighted list of themes associated with each story.

The result of the analysis of the Thematic Reasoner are available in RDF format (complying with the SON's Theme Ontology - cf. D6.3) and can be queried via the SPARQL endpoint at the following link[2]. Moreover, the results can be explored via the Stories Explorer Web Application available at the following link[3].

3.1.1. Exploring stories via SPARQL Endpoint

The dataset generated by the Thematic Reasoner can be queried via SPARQL[4]. This interface allows users to explore and query data to accommodate any information need. In the following, we go through a series of SPARQL queries that allows the user to interact with the dataset and compute statistics.

Listing 3.1: Compute the number of stories

```
PREFIX earmark: <http://www.essepuntato.it/2008/12/earmark#>
SELECT (COUNT (DISTINCT ?d) AS ?nOfStories) {
    ?d a earmark:StringDocuverse .
}
```

Listing 3.2: Count the number of topics associated with the stories of the dataset

```
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX theme: <https://w3id.org/spice/SON/theme/>
prefix earmark: <http://www.essepuntato.it/2008/12/earmark#>

select distinct (COUNT(DISTINCT ?t) AS ?nOfThemes) where {
  ?s a earmark:StringDocuverse .
  ?s theme:hasTheme ?t .
}
```

Listing 3.3: Retrieve all the pairs of topically-associated stories with the themes they have in common.

```
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX theme: <https://w3id.org/spice/SON/theme/>
prefix earmark: <http://www.essepuntato.it/2008/12/earmark#>

select  ?story1 ?story2  (GROUP_CONCAT(?themeLabel; separator=", ") AS ?sharedThemes
    ) (COUNT(?t) AS ?nOfsharedThemes) WHERE {
  ?s earmark:hasContent ?story1 .
  ?o earmark:hasContent ?story2 .
  ?o theme:hasTheme ?t .
  ?s theme:hasTheme ?t .
  ?t rdfs:label ?themeLabel.
  FILTER(STR(?s) < STR(?o))
}
GROUP BY ?story1 ?story2
ORDER BY DESC(?nOfsharedThemes)
```

[2] https://w3id.org/spice/tr_explorer/yasgui
[3] https://w3id.org/spice/tr_explorer/
[4] https://w3id.org/spice/tr_explorer/yasgui

Listing 3.4: Retrieve all the stories associated with the theme "Sexuality".

```
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX theme: <https://w3id.org/spice/SON/theme/>
prefix earmark: <http://www.essepuntato.it/2008/12/earmark#>

select ?story WHERE {
  ?s earmark:hasContent ?story ;
   theme:hasTheme ?t .
  ?t rdfs:label ?themeLabel.
  FILTER(REGEX(?themeLabel, "Sexuality"))
}
```

3.1.2. Exploring stories with the Story Explorer

The Story Explorer is a simple web application that provides a user interface for exploring the stories analysed by the Thematic Reasoner. Specifically, it allows users to select a theme and retrieve all the stories associated with it. A running instance of the application is available at the following link[5].

Figure 3.1 shows a screenshot of the Story Explorer, and ,in particular, shows the two stories related to the topic “Human Sexuality”. Moreover, as showed in the Figure, themes can be filtered by typing a query string in the text field on the left-top of the page. Finally, the web application enables the users to access to the user interface of the SPARQL endpoint (cf. Figure 3.2).

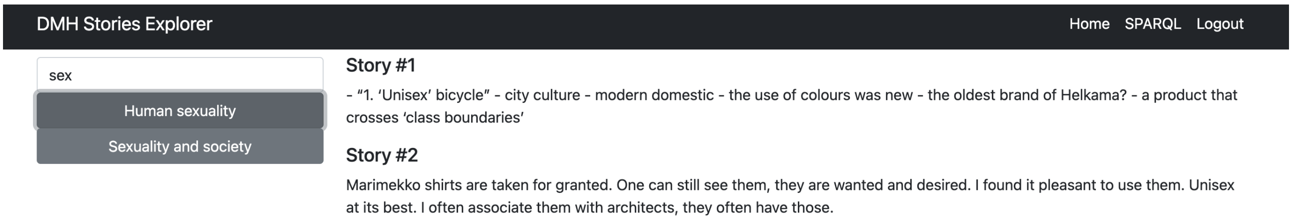


Figure 3.1: An example of theme filtering

[5] https://w3id.org/spice/tr_explorer/. To get the credentials for accessing the application please send an email to luigi.asprino@unibo.it

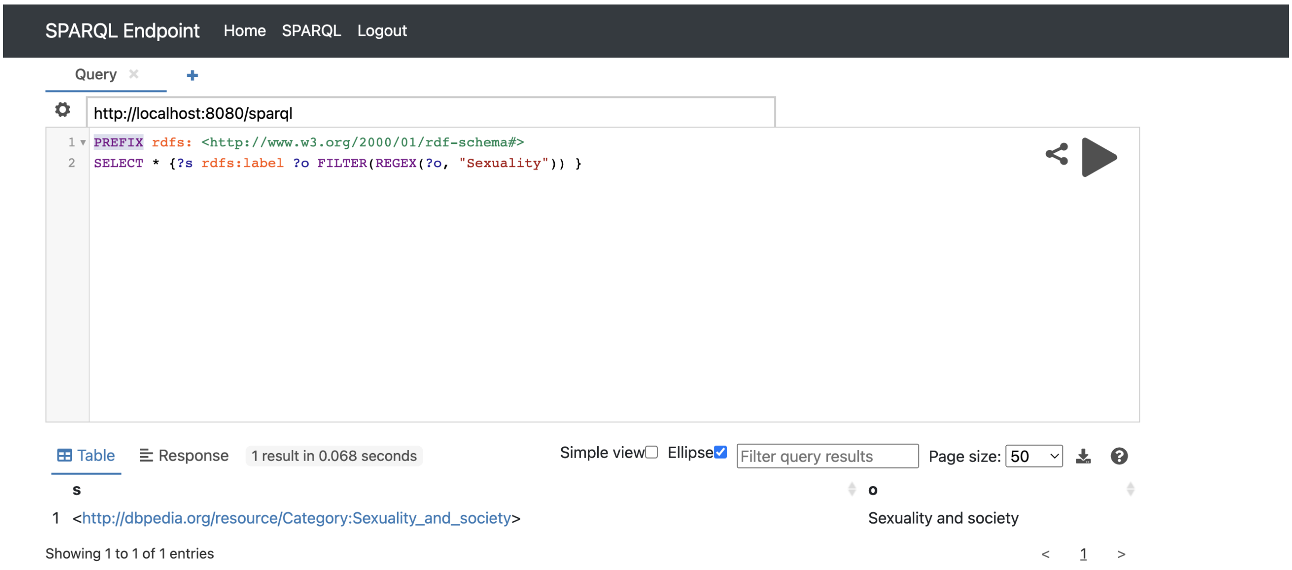


Figure 3.2: The graphical user interface of the SPARQL endpoint

3.2. Experiments

We experimented the Thematic Reasoner with data collected in the case study of Design Museum Helsinki (DMH). The Design Museum Helsinki (DMH) made available through the Linked Data Hub 213 stories collected during the workshop. This collection has been annotated by the Semantic Annotator and is available at the following link[6] as a collection of JSON-LD objects complying with SPICE Ontology Network (SON). The Thematic Reasoner detected 1564 different themes which allowed to topically associate 79 stories with at least another story of the dataset. As a result, the dataset contains 892 topically associated pairs of stories.

3.3. Concluding remarks

This section reported on the latest developments of the Thematic Reasoner, whose prototypical implementation has already been presented in the Deliverable D6.3, and the experiments with the case studies. It is noteworthy that the Thematic Reasoner relies on a series of components of the SPICE's socio-technological framework:

- The data spawning the reasoning process comes from the Linked Data Hub (cf. D4.1 and D4.2) which enables the different applications to interact in a common data space.
- The data used in the experiments comes from the stories collected in the DMH case study (cf. D7.3).
- The stories collected at the DMH have been enriched by the Semantic Annotator (cf. D3.2 and D3.4).
- The annotated stories are specified in RDF according to the SPICE Ontology Network (cf. D6.2 and D6.5) which creates an interoperable space, where applications can interact with a shared semantics.

[6] https://spice.kmi.open.ac.uk/dataset/details/91

4.Value Reasoner

4.1. Introduction

The Value Reasoner is a tool that aims at representing and extracting from natural language different moral, cultural and personal values of a User in relation to some Item from a Collection. The Value Reasoner can be used to detect the "Value profile" (namely the set of values evoked by a single artifact or collection) of some item and it allows Cultural Heritage Institutions and Curators to cluster them and organize them in a meaningful way according to their design intentions.

It is theoretically based on the Basic Human Values (BHV) (15), by Shalom Schwartz (in its most recent version (16)), and the Moral Foundations Theory (MFT) (17), by Graham and Haidt, as formalised in (18), shown in Figure 4.1. We present here values as defined in MFT, namely as six innate moral foundations across cultures and societies:

- Care vs Harm is grounded in the attachment systems and some form of empathy, intended as the ability to not only understand, but also feel, the same feelings as others, thus being able to imagine hypothetical scenarios, in which we are living some positive or negative mental or physical state, which we actually don't live.
- Fairness vs Cheating is grounded in the evolutionary process of reciprocal altruism.
- Loyalty vs Betrayal is grounded in the clans and family-based dimension that for a long time characterized most of our tribal societies. The ability to create links and alliances was a way to increase the surviving percentage possibilities for oneself and his/her close group.
- Authority vs Subversion is grounded in the hierarchical social interactions directly inherited by primates' societies.
- Sanctity vs Degradation is grounded in the CAD triad emotions (Contempt, Anger, Disgust) and the psychology of disgust, it is one of the most spread dyadic oppositions, underlying religious (and not only) notions of living in an elevated, less carnal, more ascetic way. It underlies the idea of "the body as a temple" which can be contaminated by immoral activities and it is foundational for the opposition between soul and flesh.
- Liberty vs Oppression is grounded in feelings and experiences like solidarity, vs. episodes of unjustified violence or liberty restrictions.

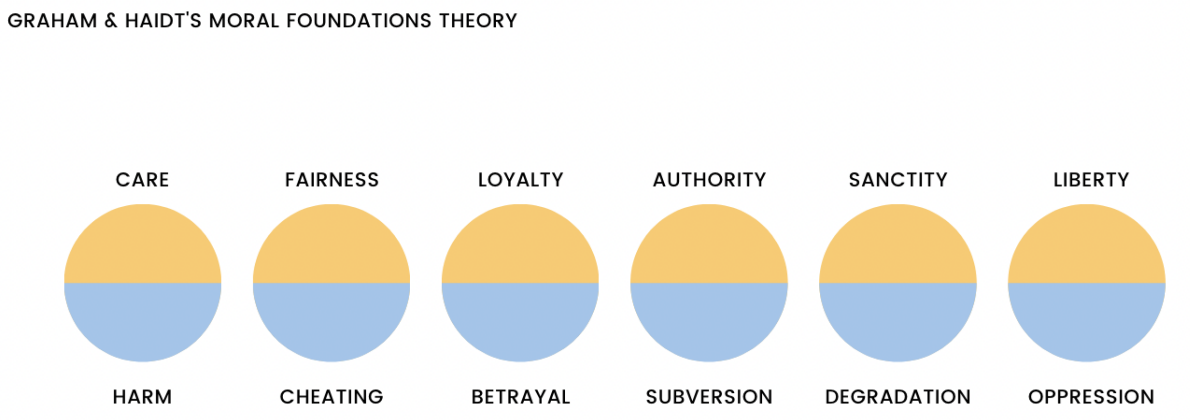


Figure 4.1: The Moral Foundations Theory dyadic structure.

4.2. System Updates and Usage

The main improvements regarding the value detection are: (i) MFTriggers: the full finalised lexical and factual grounding for MFT, described in Sec. 4.2.1; (ii) the development of a frame-based Value Detector as online open service, described in Sec. 4.2.2; (iii) experiments performed on the DMH stories dataset from the SPICE LDH, described in Sec. 4.3.

4.2.1. MFTriggers

It consist in a knowledge graph including more than 10k triples declaring the activation of some value-violation from MFT, considering entities from pre-existing semantic web resources like WordNet, VerbNet, FrameNet, Propbank, DBpedia, BabelNet etc. already aligned together in the Framester ontological hub. The development workflow is as follows:

- Considering all MFT definitions of each Value-Violation, it was manually scraped the state of the art literature to collect all the lexical units used to describe the value-violation opposition, and to provide examples. The heuristic applied in fact is: if a certain term, locution or definition is given as explanation for e.g. the notion of "Harm" in MFT, it means that that the extensional semantics of the `mft:Harm` value should cover the portion of the world that is segmented by that specific sense of the used lexical unit;
- Using this non-disambiguated lexical units to extract and manually select WordNet synsets (sets of contextual synonyms) and FrameNet frames
- Perform a query expansion as in Figure 4.2 to gather triggering entities from other resources. Entities activating values or violations, represented as rectangular boxes, are retrieved via SPARQL queries, represented as oval shapes and described in the next sections. Figure 4.2 furthermore shows how some entities, being retrieved by some query, are used as input for other queries. Rectangular boxes with no incoming output and only `varFor` arrow represent those steps that need a human in the loop (e.g. the semantic type query, to produce meaningful results, requires some domain expert which analyzes all results and filters them manually). Ovals with no `varFor` incoming arrow represent those queries that need a human in the loop providing some input variable. All other steps can be automatized, although, due to the great amount of knowledge in Framester resource, a manual check could result in higher quality data.

4.2.2. Frame-based Value Detector

A beta version of the frame-based value detector, extracting values from natural language according to Moral Foundations Theory, is now available online[1]. To perform automatic latent moral content extraction from natural language the Value Detector is articulated in 3 steps: (i) it takes as input some text string e.g. the transcription of some user's sentence in relation to some cultural artifact; (ii) thanks to the FRED tool[2] (a tool to automatically generate knowledge graph from strings of natural language, able to perform semantic frame detection, lexical units disambiguation and factual entity recognition aligning entities to the Framester resource) the Value Detector generates from the input sentence a knowledge graph of semantic dependencies in the sentence; (iii) navigating the graph, the Value Detector selects a subset of meaningful nodes (namely those entities retrieved from WordNet, VerbNet, FrameNet, DBpedia etc. resources, aligned in Framester) and for each of them performs a SPARQL query checking if the entity is a trigger of some value, as shown in Fig 4.3 (in particular the each entity of the meaningful subset is substituted to the `?s` in the example query. Once it finds a correspondence it attaches the triple declaring the triggering of some value to the original graph, adding a value layer to the knowledge extracted from text. The frame-based value detector was tested on Moral Foundations Twitter Corpus (19) in (20), showing upsides of having an explainable methodology for value detection from natural language, not needing training and based on knowledge graph automatically generated from text.

[1] The beta version of the Value Detector is available here: http://framester.istc.cnr.it/semanticdetection/values
[2] The FRED tool is available online here: http://wit.istc.cnr.it/stlab-tools/fred/demo/

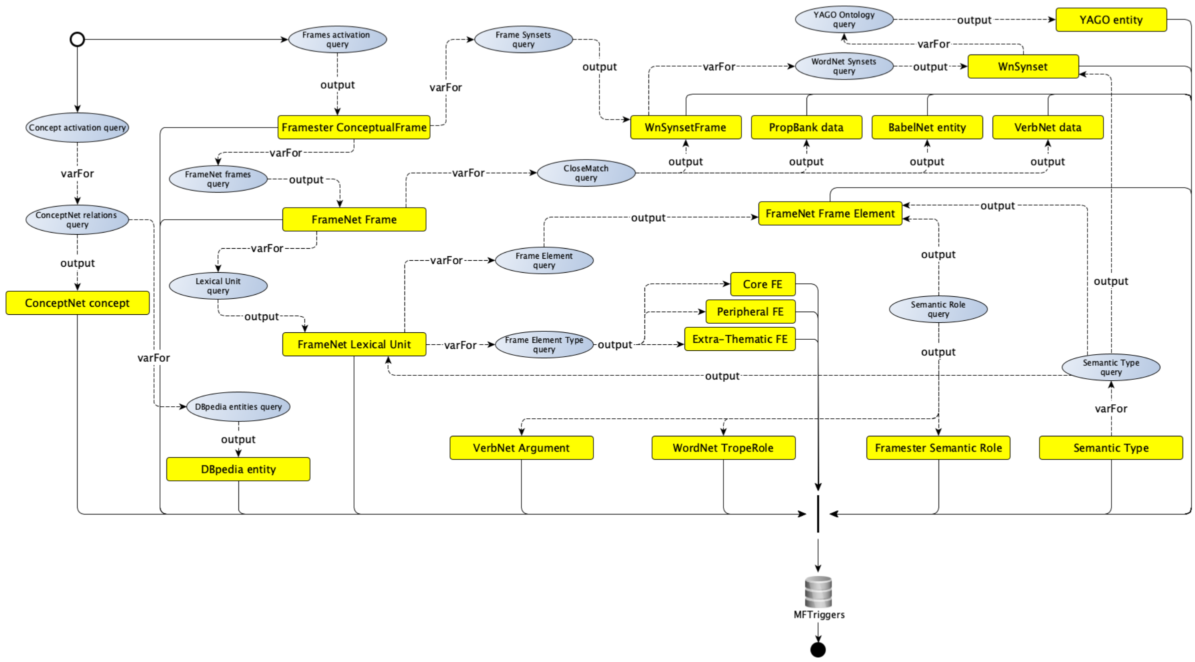


Figure 4.2: The Value-Violations triggers knowledge graph population workflow from pre-existing semantic web resources.

4.3. Experiments and Discussion

To test the Value Reasoner in the SPICE context some initial experiments of value extraction have been performed on Cultural Heritage data, in particular using the Design Museum of Helsinki Stories dataset from the SPICE LDH.

4.3.1. DMH Value Extraction Experiment

For the experiment were used “user stories” in the form of textual data generated as described in in D7.4. The user stories are about 11 items, resulting, after some semi-automatic data pre-processing (mainly splitting strings too long to be processed as single sentences), in 187 chunks of text to be passed through the pipeline described in Sec. 4.2.2. The final value extraction resulted in the detection of the following MFT values and violations: `mft:Care`, `mft:Harm`, `mft:Loyalty`, `mft:Fairness`, `mft:Subversion` and `mft:Liberty`.

To provide some examples: Figure 4.4 shows the graph produced for the string: “I received this pot as a present from my mother-in-law. My son dropped it from the balcony. The only time enamel has broken.” about the item “Cast Iron Pot”. As shown in Figure 4.4, the VerbNet entry `vn:Break_45010000` triggers `mft:Harm`.

Longer and more complex sentences produce possibly more triggering occurrences, albeit the DMH stories – due to their shape, and the rationale with which they were collected – offer the possibility for a more profound reflection. Being user stories the transcription of personal experiences *in some way* related to the cultural artifact, it has to be considered that there is the possibility that values (as well as themes and emotions), extracted via any mean, do not stem directly from cultural artifacts in the collection, they are, in fact, the result of a semantics analysis on anecdotal knowledge produced by the user. Consider a sentence like the one as follows, expressed about the cultural item "Stool 60", shown in Figure 4.5 :

> *And this kind of, by Alvar Aalto, this three-legged chair. Yeah, this one is really handy, as one can stack them up. And the height is nice. And sturdy to sit on. What I have. . . It comes to mind how I was helping an old couple to move, and there were quite a few Alvar Aalto objects there. And then they were going to*

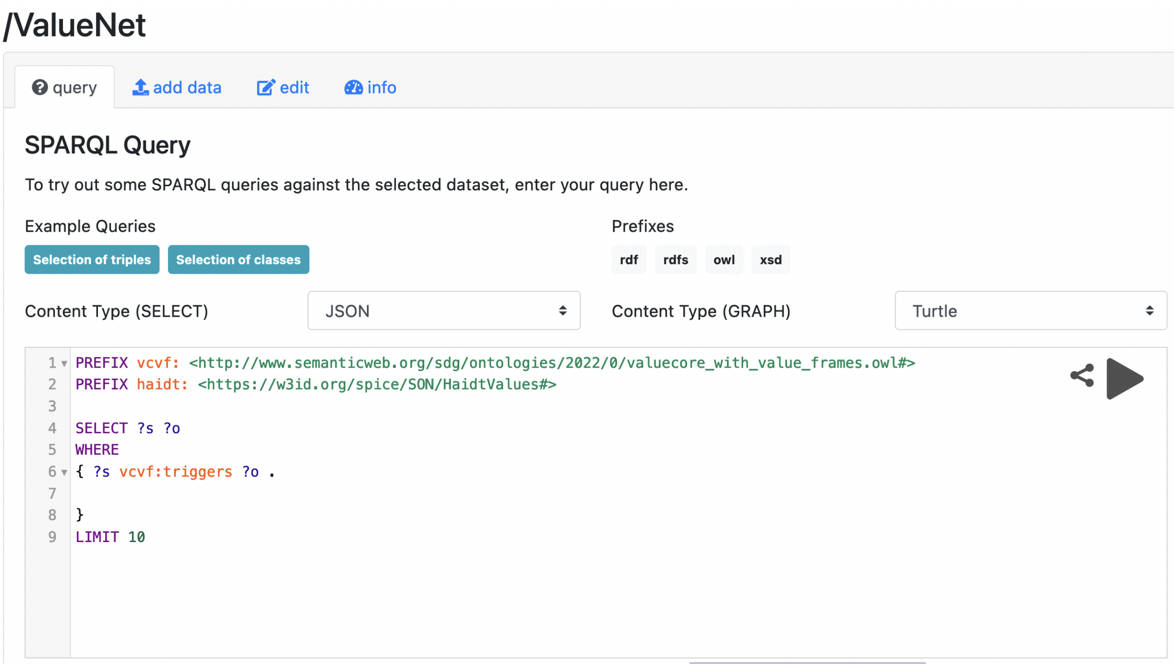


Figure 4.3: Example query to retrieve entities triggering some value via SPARQL query performed to the ValueNet endpoint.

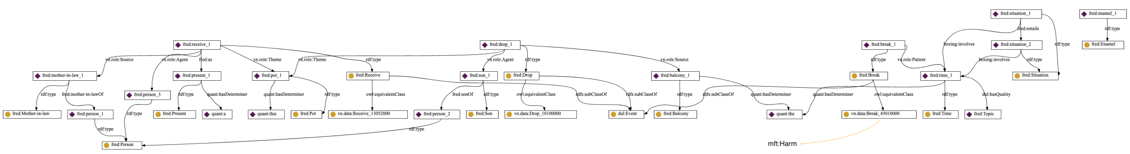


Figure 4.4: Knowledge Graph with value triggers for the sentence: “I received this pot as a present from my mother-in-law. My son dropped it from the balcony. The only time enamel has broken.”

Figure 4.5: "Stool 60" from Alvar Aalto Foundation.

throw these in the trash. Now, they were a bit, they did not have that cover, so they were a little worn out. So I asked, if they would atleast let me take a few of them. They let me, and then I refurbished them. And they are in use, and one can stack them.

The long text chunk is passed to the FRED tool and a huge knowledge graph is generated (not shown here for reason of space, but it can be reproduced via providing as input the sentence to the online version of the Value

Detector), out of which the following entities are retrieved as triggers of some value from MFT: the VerbNet entity `vn:Help_72000100`, and the `fs:Assistance` frame.

Both these entities are triggers of the `mft:Care` value. Note that this does not mean that the "Stool 60" artifact *per se* triggers the `mft:Care` value, but in the context of DMH user stories the cultural artifact is the material expedient to produce a narrative content that triggers the Moral Foundations Theory `mft:Care` value.

As future works, on the technical side, a parallel module to MFTriggers, declaring lexical and factual triggers for the Basic Human Values theory, is being developed; on the experimental side, different kind of data in the LDH are going to be used to test the tool. The expectations, considering different kinds of data in the LDH as described in D7.4 are: (i) data from the GAM game could result in values more directly related to the content of the cultural artifact, and are expected to provide knowledge to be reused by curators to e.g. organise artifacts in a meaningful way according to a "value path" or "value clusters"; (ii) data from the Hecht museum, offering a political reflection, could provide values about users' epistemic stance towards matter represented by the cultural artifact, to be reused in the user community design, allowing to cluster users sharing similar values and offer them the viewpoint of similar or dissimilar users.

5.Hybridizing Values and Emotional categories

As an alternative approach to Value Reasoner, we have also tested the system DEGARI for value attribution by relying on the composite model of Values devised by Haidt.

Here, in order for the TCL engine to work, we characterized the typical features of the constituting the basic Value categories by using the eMFD (21), extended Moral Foundation Dictionary, assigning probability to each value concept. Here, the idea was to create hybrid typical value/emotion concepts combining eMFD vocabulary and the emotional prototypes already used in (1). Table 5.1 shows the manual mapping provided between Haidt model and Plutchik: moral emotions (from Haidt's model) are mapped onto the corresponding values (MFT), then onto Plutchik's emotions.

Emotion	**Value**	**Mapped emotion**
Admiration	Authority	Awe
Anger	Cheating (Fairness -)	Anger
Compassion	Harm (Care -)	Grief, Sadness, Pensiveness
Contempt	Betrayal (Loyalty -), Cheating (Fairness -)	Disapproval
Disgust	Degradation (Sanctity -)	Disgust, Loathing
Embarrassment	Cheating (Fairness -)	Annoyance
Evaluation	Sanctity	Awe
Fear	Subversion (Authority -)	Terror
Gratitude	Fairness	Vigilance, Anticipation, Interest
Guilt	Cheating (Fairness -)	Remorse
Pity	Harm (Care -)	Grief, Sadness, Pensiveness
Pride	Loyalty	Admiration, Trust, Acceptance
Rage	Betrayal (Loyalty -)	Rage
Remorse	Harm (Care -)	Grief, Sadness
Reproach	Betrayal (Loyalty -)	Aggressiveness
Respect	Authority	Submission, Fear
Shame	Loyalty -	Remorse

Table 5.1: Manual mapping between Haidt's model of moral values theory and Plutchik's theory

The obtained synthetic "symbolic hybrids" (they only contain up to 7 features for each generated concepts) are prototypes of value concepts able to capture in a better way the strong connection between emotions and values. Overall, once the association of lexical features to the emotional and value concepts in the is obtained and the hybrid emotion-values concepts are generated via the logic $\mathbf{T}^{\text{CL}}$, the system is able to reclassify cultural items (described in some catalogue), or textual descriptions associated to that cultural items.

The current version of the system, available as a web service, accepts JSON files containing a textual description of the cultural items and performs an automatic information extraction step generating a lemmatized version of the JSON descriptions of the cultural item and a frequentist-based extraction of the typical terms associated to each cultural item in its textual description (the assumption is that the most frequently used terms to describe an item are also the ones that are more typically associated to it). The frequencies are computed as the proportion of each term with respect to the set of all terms characterizing the item, in order to compare. These two tasks are performed by using standard libraries like Natural Language Toolkit [1] and TreeTagger [2]. Once this pre-processing step is automatically done, the final representation of the cultural items is compared with the representations of the typical compound values obtained with $\mathbf{T}^{\text{CL}}$: if a cultural item contains all the rigid properties and at least the 30% of the typical properties of the compound emotion under consideration, then the item is classified as belonging to it.

[1] https://www.nltk.org/

[2] https://www.cis.uni-muenchen.de/ schmid/tools/TreeTagger/

As anticipated before, the value model relies on the moral foundations theory.

5.1. DEGARI 4 Values Experiments

In order to test the application of value detection and value reasoning in relation with museum exhibits, we have preliminarily evaluated our system on data coming from Hecht Museum at the University of Haifa (22). The system has been launched on an experimental subset of 12 items, selected by the museum curators to stimulate diverse perspectives. For the description of the items, the relevant pages of the English edition of Wikipedia were considered.

Figure 5.1 shows the classification process for the item "Catapult" (on the left of the figure). It is possible to see that DEGARI 2.0 takes into account the prototypes (synthetic "symbolic hybrids") **{degradation}** and **{disgust}** (middle column in the figure) and recombines them into another concept called **{degradation-disgust}** for classifying the item (left column). Notice that the relevant keywords for the association with the prototypes are reported in bold.

Table 5.2 shows the results for DEGARI 2.0 values classification on three Hecht Museum's items, based on the corresponding Wikipedia pages. In particular, the item "Catapult" is classified by DEGARI with the {**degradation-disgust**} combined concept (column *DEGARI 2.0 with values*) because the description contains the keywords "molestation" and "weapons" (column *words matches*) that trigger the classification. The moral value 'degradation" (mapped as "$Sanctity^{-}$" in MFT) is triggered by the keyword "weapon". In addition to generating the association with values through the mapping shown in Table 5.1 (which shows the manual mapping provided between values and emotions), the system also generates the association with the emotions; for "Catapult", (Table 5.2), the keyword "molestation" acts as a trigger for the emotion "disgust" (column *emotions*), associated with that particular item. The item "Roman war gear", has been classified as {**betrayal-aggressiveness**} because the keywords "brutality" and "violently", contained in its description, trigger the emotion "aggressiveness", which is mapped onto "betrayal" ("$Loyalty^{-}$" in MFT, as illustrated in Table 5.1). The item "Bar Kochva Rebellion" (last row), has been classified as {**sanctity-awe**}, because the keywords "surprise", "torture" and "kill" trigger the emotion "awe", which is mapped onto "$Sanctity$.

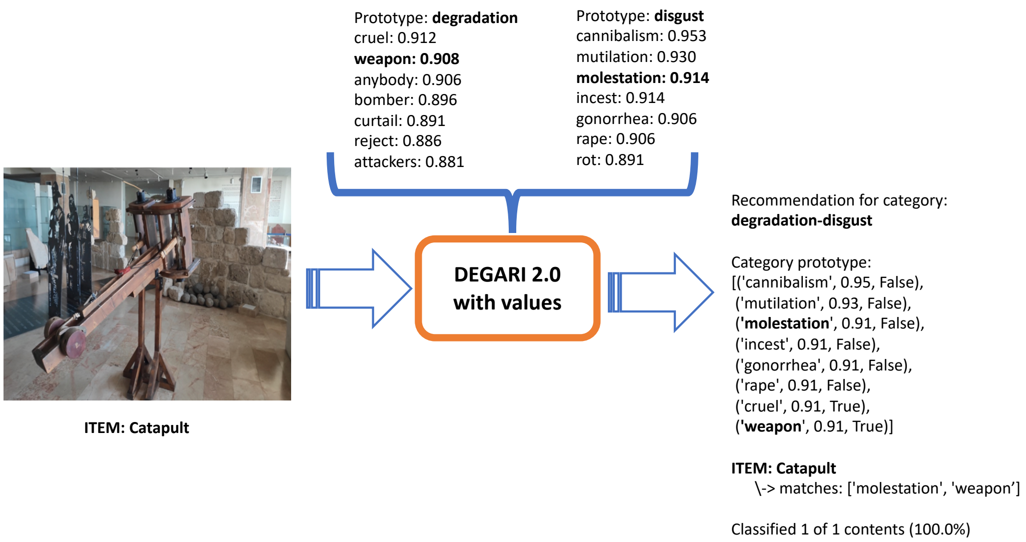


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Figure 5.1: Example of DEGARI 2.0 moral value classification for item "Catapult". The item has an associated textual description retrieved from Wikipedia.

Item	DEGARI 2.0 with values	words matches	emotions			moral values		
			disgust	aggressiveness	awe	degradation (Sanctity -)	betrayal (Loyalty -)	sanctity
Catapult	degradation-disgust	['molestation', 'weapon']	molestation			weapon		
Roman war gear	betrayal-aggressiveness	['brutality', 'violently']		brutality, violently				
Bar Kochva Rebellion	sanctity-awe	['surprise', 'torture', 'kill']			surprise, torture, kill			

Table 5.2: DEGARI 2.0 moral values classification with Hecht dataset

5.2. Discussion and Concluding Remarks

One of the goal of the Value Reasoner and of DEGARI 4 Values was to find innovative ways to engage museum audiences by leveraging on aspect that can leverage the notion cultural identity. In the context of SPICE we presented an adaptation of the DEGARI system to the creation of hybrid "Values/EMotion" classes which classifies museum items with value-emotion associations. For this experiment, only the relevant Wikipedia pages were considered, resulting in a limited number of classifications. In the future, however, the texts attached to the items are expected to include the comments and annotations provided by curators and citizens, thus opening the way to more classifications. The mapping of the items in the museum collection onto the combined values and emotions opens novel perspectives for the visitors interacting with the items. On the one side, it allows them to locate themselves in the value-emotion system, raising their awareness on multiple points of views. On the other side, it enables the recommendation of similar and opposite items based on values and emotions, which in turn enable forms of critical exploration of cultural items and (self)reflection on identity, bringing visitors out of the so-called echo chambers.

6.Conclusions

In this deliverable, we presented the novel developments of the reasoning tools developed in WP6 and leveraging the ontological models developed described in Deliverable 6.3. We have shown how currently the tools are available and have been applied to the available data on the Linked Daa Hub for different museums. The output of such systems will represent an important source of enriched knowledge for both the final recommender system and for the community modelling.

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A.Appendix

Listing A.1: JSON object


```
{
    "@context": {
        "spice": "https://w3id.org/spice/resource/",
        "owl": "http://www.w3.org/2002/07/owl#",
        "dbr": "http://dbpedia.org/resource/",
        "earmark": "http://www.essepuntato.it/2008/12/earmark#",
        "xsd": "http://www.w3.org/2001/XMLSchema#",
        "rdfs": "http://www.w3.org/2000/01/rdf-schema#",
        "dcterms": "http://purl.org/dc/terms/",
        "semiotics": "http://ontologydesignpatterns.org/cp/owl/semiotics.owl#",
        "emotion": "https://w3id.org/spice/SON/PlutchikEmotion/",
        "marl": "http://www.gsi.upm.es/ontologies/marl/ns#",
        "toxicity": "https://github.com/unitaryai/detoxify/labels#",
        "orca": "http://vocab.deri.ie/orca#"
    },
    "@graph": [
        {
            "@id": "spice:sa_1664873331873",
            "@type": "earmark:StringDocuverse",
            "@language": "en",
            "dcterms:source": "spice:test",
            "earmark:hasContent": "We had it as a water jug in the boat. We cruised on
                a hot summer day in Vesijarvi. The canister was a bit in the shade. ",
            "semiotics:denotes": []
        },
        {
            "@id": "ex:anno_528_entity_72-81",
            "@type": "earmark:PointerRange",
            "rdfs:label": "Vesijarvi",
            "semiotics:denotes": {
                "@id": "dbr:Vesijarvi",
                "@types": [
                    "http://dbpedia.org/ontology/BodyOfWater",
                    "http://dbpedia.org/ontology/NaturalPlace",
                    "http://dbpedia.org/ontology/Lake",
                    "http://dbpedia.org/ontology/Location",
                    "http://dbpedia.org/ontology/Place"
                ],
                "orca:hasSource": {
                    "@type": "xsd:string",
                    "@value": "ML"
                },
                "orca:hasConfidenceLevel": {
                    "@type": "xsd:double",
                    "@value": 0.87173456
                }
            },
```

```
            "earmark:refersTo": {
                "@id": "spice:sa_1664873331873"
            },
            "earmark:begins": {
                "@type": "xsd:nonNegativeInteger",
                "@value": 72
            },
            "earmark:ends": {
                "@type": "xsd:nonNegativeInteger",
                "@value": 81
            }
        },
        {
            "@id": "ex:anno_529_entity_21-24",
            "@type": "earmark:PointerRange",
            "rdfs:label": "jug",
            "semiotics:denotes": {
                "@id": "dbr:Jug",
                "@types": [
                    "http://dbpedia.org/ontology/Company"
                ],
                "orca:hasSource": {
                    "@type": "xsd:string",
                    "@value": "ML"
                },
                "orca:hasConfidenceLevel": {
                    "@type": "xsd:double",
                    "@value": 0.99471796
                }
            },
            "earmark:refersTo": {
                "@id": "spice:sa_1664873331873"
            },
            "earmark:begins": {
                "@type": "xsd:nonNegativeInteger",
                "@value": 21
            },
            "earmark:ends": {
                "@type": "xsd:nonNegativeInteger",
                "@value": 24
            }
        }
    ]
}
```

GAM Artefact	SOPHIA emotions	DEGARI emotions
 Asphissia	Anger Anticipation **Disapproval** Disgust Fear Interest Joy **Love** Sadness Surprise Trust	Aggressiveness Anxiety Cynism Delight Disapproval Guilt Hope Love Morbidness Optimism Pride
 Self-portrait of Owl	Anticipation **Disapproval** Disgust Fear Interest Sadness Surprise	Awe Curiosity Delight Disapproval Outrage Unbelief
 Daphne	Anger Anticipation Interest Joy **Love** Sadness Serenity Surprise	Delight Guilt Love Morbidness Optimism Pride Disapproval
 The Siren	Anger Anticipation Fear Interest Joy **Love** Sadness Serenity Surprise Trust	Anxiety Awe Shame Submission
 Aracne	Anger Anticipation **Disapproval** Disgust Fear Interest Joy **Love** Sadness Serenity Surprise Trust	Awe Curiosity Delight Disapproval Outrage Unbelief
 The mirror of life	Anger Anticipation Disgust Interest Joy Serenity Trust	Delight Guilt Love Morbidness Optimism Pride

Table A.1: Simple and complex emotions extracted by SOPHIA compared with the complex emotions extracted by

GAM item	DEGARI emotion classification	SOPHIA emotion classification	DEGARI ∩ SOPHIA
Asphissia, Angelo Morbelli	11	11	14%
Self-portrait of Owl by Alberto Savino	6	7	16%
Daphne by Felice Casorati	7	8	14%
The Siren by Giulio Aristide Sartorio	4	10	0%
Aracne by Carlo Stratta	6	12	16%
The mirror of life by Giuseppe Pellizza da Volpedo	6	7	0%

Table A.2: The Figure shows, for the 6 selected GAM artworks (the operas are listed in Table A.1), the complex emotions extracted by DEGARI extending the overall emotions (basic + complex) extracted by SOPHIA. The last column shows the overlap percentage between the emotions extracted for both emotional classification systems.