DEGARI 2.0: A Diversity-Seeking, Explainable, and Affective Art Recommender for Social Inclusion

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Abstract

We present DEGARI 2.0 (Dynamic Emotion Generator And ReclassIfier): an explainable, affective-based, art recommender relying on the commonsense reasoning framework $\mathbf{T}^{\text{CL}}$ and exploiting an ontological model formalizing the Plutchik's theory of emotions. The main novelty of this system relies on the development of diversity-seeking affective recommendations obtained by exploiting the spatial structure of the Plutchik's 'wheel of emotion'. In particular, such development allows to classify and to suggest, to museum users, cultural items able to evoke not only the very same emotions of already experienced or preferred objects (e.g. within a museum exhibition), but also novel items sharing different emotional stances. The system's goal, therefore, is to break the filter bubble effect and open the users' view towards more inclusive and empathy-based interpretations of cultural content. The system has been tested, in the context of the EU H2020 SPICE project, on the community of deaf people and on the collection of the GAM Museum of Turin. We report the results and the lessons learnt concerning both the acceptability and the perceived explainability of the received diversity-seeking recommendations.

Keywords: Explainable AI, diversity-seeking emotional recommendations, Description Logics, Commonsense Reasoning

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1. Introduction and Background

According to the data of the World Health Organization (WHO)[1], the number of people who live with some form of disability currently exceeds 1 billion worldwide and are dramatically increasing (Guidelines Review Committee (2011)). A major emergency concerns deafness: the WHO report points out that 432 million adults currently experience a form of disabling hearing loss, and these impairments are expected to involve nearly 2.5 billion by 2050.

Given this background, the role of cultural heritage is two-fold: on the one side, it is necessary to ensure the access to cultural entities to all, resorting to technologies to bridge all forms of disabilities; on the other side, cultural heritage itself represents a powerful tool for inclusion, as clearly stated by the FARO Convention (Council of Europe (2005)[2]. Signed in 2005, the FARO convention assigns to cultural heritage institutions the role of drivers of reflection and inclusion in society. According to Fairclough et al., indeed, FARO Convention "puts people's values, aspirations and needs first, and celebrates the diversity and plurality of their views and values" (Fairclough et al. (2014). As a consequence, the development of AI systems working for social good, as part of the framework of the United Nations' Sustainable Development Goals (SDGs)[3], cannot be separated by the goal of supporting and promoting cultural engagement in a universal perspective.

The work presented in this paper is framed within this global challenge and, in particular, within the context of the H2020 SPICE project[4]. SPICE (Social cohesion, Participation, and Inclusion through Cultural Engagement) aims at putting cultural heritage, and museums in particular, at the center of social inclusion processes, with the goal of creating bonds between individual and groups through art. In order to do so,

[1] https://www.who.int/news-room/fact-sheets/detail/disability-and-health

[2] http://conventions.coe.int/Treaty/EN/Treaties/Html/199.htm

[3] In particular, for the achievement of the goal number 10: Reducing Inequality, see https://sdgs.un.org/goals.

[4] G.A. 870811 https://spice-h2020.eu/

SPICE relies on the paradigm of *citizen curation* for engaging museum visitors, onsite and online. Citizen curation reverses the traditional paradigm of curation, where art interpretation is exclusively entrusted to curators and art historians and critics: citizens are put at the center of the interpretation process, thanks to curation methods which prompt personal responses to art, and promote their sharing across people and communities (Bruni et al. (2020); Daga et al. (2022).

In SPICE, citizen curation methods – such as creating personal collections of artworks, attaching personal responses and affective annotations to them – are supported by a socio-technical infrastructure which allows museum visitors to create and share their own interpretation of artworks, and to react to other people's interpretations.

In this context, our work has been focused on developing knowledge-based and reasoning technologies which leverage the role of emotions in the tasks of interpretation, fruition and reflection on the cultural heritage items displayed in museums. Emotions, indeed, have been acknowledged as a primary component of the artistic experience for centuries; recently, their role in art has been demonstrated through physiological experiments showing how correlates of emotions, such as brain response and face expressions, are affected by the experience of art (Van Dongen et al. (2016); Leder et al. (2014). In addition to their role in defining the way people experience artistic expression (Schindler et al. (2017), from paintings and musical works to movies and novels, emotions also provide an universal language through which people convey their experience of art, well beyond words. Despite the differences in the expression of emotions across languages, and the influence of cultural factors, in fact, emotions own an universal origin (Ekman & Friesen (1971): rooted in evolution, they provide the basis for intercultural communication, as effectively demonstrated by the advancements in face expression recognition (Cordaro et al. (2018); Revina & Emmanuel (2021). In this sense, emotions can provide a suitable means for connecting people belonging to different groups, intended as culture, age, education, and different sensory characteristics. Pervasive in human communication, emotions are expressed through multiple channels, ranging from face expression and body posture to spoken and written language. The expression of emotions through language, in particular, lies at the basis of several models of emotions, including Shaver's (Shaver et al. (1987) and Plutchik's

(Plutchik (2001), and has prompted the creation of a number of resources for sentiment analysis in language (Mohammad (2018); Cambria et al. (2020); Susanto et al. (2020). The application of these resources to art is straightforward: for example, the WikiArt Emotions project (Mohammad & Kiritchenko (2018) has collected the emotional response to the WikiArt online art collection, yielding a dataset of 4,105 artworks with annotations for the emotions evoked in the observer. Experiments such as WikiArt Emotions have paved the way to the extraction of emotions from text and tags to create affective art recommenders, like ArsEmotica (Patti et al. (2015); Bertola & Patti (2016) or the first version of DEGARI (Lieto et al. (2021), able to classify and group artistic items well beyond the standard 6 basic emotions of Ekman's theory (Ekman & Friesen (1971) and embracing richer, finer-grained models.

Despite such richer emotion models, however, state of the art affective recommenders for the artistic domain are not yet able to deal with the 'echo chamber' problem (i.e. they are only able to suggest and aggregate items evoking the same emotion) and, in addition, they have never been tested on the ground of diversity and inclusions. In this paper, we show how DEGARI 2.0 can be used as an inclusive, explainable and diversity-seeking affective art recommender, aimed at bridging the differences in the experience of art between different communities, including people with sensory impairments like the Deaf; the latter, indeed, represent the target group of our system and of its evaluation. In particular, our system aims at overcoming the limitations of traditional recommendation approaches by exploiting a novel, publicly available, ontological version of Plutchik's model of emotions Plutchik (2001), equipped with opposition and similarity relations between (basic and complex) emotions, as established in the Plutchik's theory. In practice, DEGARI 2.0 employs such ontological structure to suggest museum items not only labeled with the same emotions, but - as mentioned - also to group and recommend artworks evoking *similar* (but not exactly the same) emotions or *opposite* emotions. This kind of alternation in the content suggestion mechanism aims at leading to more comprehensive exploration and fruition of museum collections. Indeed, suggesting museum items evoking different emotions from the ones already experienced via the fruition of other artworks, is based on the notion of perspective taking (Pedersen et al. (2021), i.e. seeing the world (e.g. an exhibition in this case) from other perspectives. Since this approach is used to promote empathy, cohesion and inclusion across social groups, reaching this goal would represent a huge advancement with respect to the current technologies (e.g. like social media or standard recommender systems) that often lead people toward content that fits their own viewpoint, promoting fragmentation and fostering confirmation biases, instead of cohesion, inclusive reflection, and critical thinking.

Overall, the key contributions provided in this work are the following:

- an entirely explainable AI system for automatic emotion re-classification and recommendation based on a well founded emotion theory (Plutchik model) and on a cognitively-inspired probabilistic logic framework modelling human-like for concept combination (i.e. the $\mathbf{T}^{\text{CL}}$ logic); In particular, the main novelty of the DEGARI 2.0 system relies on the development and testing of diversity-seeking affective recommendations obtained by exploiting the spatial structure of the Plutchik's 'wheel of emotion' (a feature not available in the first version of DEGARI (Lieto et al. (2021).
- the availability of the system as a web service whose reasoning results are accessible via a SPARQL endpoint at `http://di.unito.it/degarireasoner`;

The paper is organized as follows: in Section 2.1, we recall the $\mathbf{T}^{\text{CL}}$ logic while describing its application in the context of our system in Section 2.2. The modular architecture of the system is described in 2.3. In Section 3, we present the GAMGame, i.e. the museum web app we developed by using the DEGARI 2.0 system and its underlying $\mathbf{T}^{\text{CL}}$ formalism to recommend novel, emotionally diverse museum items, other than the ones merely based on their previously expressed affective preferences. Section 4, and its subsections, details the experiments and discusses: i) the results of the diversity-seeking affective recommendations obtained by DEGARI 2.0 and evaluated with the deaf community, ii) the results of the emotional classifications provided by our systems with human annotators and with the affective system SenticNet 7 (Cambria et al. (2022), iii) the results coming from a small scale evaluation on the perceived explainability of the system. Section 5 discusses the main findings of the work and conclude the paper.

2. DEGARI 2.0: Reasoning Framework and System Overview

2.1. The $\mathbf{T}^{\textsf{CL}}$ *logic*

The core component of DEGARI 2.0 relies on a probabilistic extension of a typicality-based Description Logic called $\mathbf{T}^{\textsf{CL}}$ (Typicality-based Compositional Logic), introduced in (Lieto & Pozzato (2020)). This framework allows one to describe and reason upon an ontology with commonsense (i.e. *prototypical*) descriptions of 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. Overall, this specific combinatorial and generative capability represents a crucial aspect of knowledge processing in human cognition and concerns high-level capacities associated to creative thinking and problem solving. (Boden (2009). Dealing with this problem, however, requires, from an AI and cognitive modelling perspective, the harmonization of two conflicting requirements that are hardly accommodated in symbolic systems (Frixione & Lieto (2011): the need of a syntactic and semantic compositionality (typical of logical systems) and that one concerning the exhibition of typicality effects. According to a well-known argument (Osherson & Smith (1981), in fact, prototypes (i.e. commonsense conceptual representations based on typical properties) are not compositional. The argument runs as follows: consider a concept like *pet fish*. It results from the composition of the concept *pet* and of the concept *fish*. However, the prototype of *pet fish* cannot result from the composition of the prototypes of a pet and a fish: e.g. a typical pet is furry and warm, a typical fish is grayish, but a typical pet fish is neither furry and warm nor grayish (typically, it is red). The main cognitive grounding of $\mathbf{T}^{\textsf{CL}}$ is based both on its ability to account for this type of human-like concept combination, as shown in (Lieto et al. (2019), (Chiodino et al. (2020b), and - as we show below - on the explicit adoption of heuristics strategies coming from the field of cognitive semantics for dealing with the problem in hand[5] .

More in detail, the logic $\mathbf{T}^{\textsf{CL}}$ (Lieto & Pozzato (2020)) is the result of the integration of two main features: (i) the extension of a nonmonotonic Description Logic of

[5]See Lieto (2021) for a more general account on cognitively inspired heuristics in AI systems.

typicality $\mathcal{ALC} + \mathbf{T_R}$, introduced in Giordano et al. (2015, 2014), with a distributed semantics based on the DISPONTE semantics of Riguzzi et al. (2015) and restricted to typicality inclusions; (ii) the adoption of the HEAD/MODIFIER heuristics (a well established heuristics inspired by cognitive semantics for concept combination and generation (Hampton (1987) where, in order to formalize a dominance effect between the concepts to be combined, for every combination we distinguish: a HEAD, representing the stronger element of the combination (i.e. the one from which we want to inherit more properties in the final output of the combination), and one or more MODIFIERS. The basic idea is to extend an initial knowledge base (ontology) with a prototypical description of a novel concept, obtained by the combination of two existing ones, namely a HEAD concept and a MODIFIER concept.

In the logic $\mathbf{T}^{\textsf{CL}}$, typical properties can be directly specified by means of a *typicality operator* $\mathbf{T}$ enriching the underlying Description Logic, and a knowledge base can contain inclusions of the form $p \ :: \ \mathbf{T}(C) \sqsubseteq D$ to represent that "typical Cs are also Ds", where p is a real number between 0.5 and 1, representing the probability of finding elements of C being also D. Formally, we consider a language built upon an alphabet $\mathtt{C}$ of concept names, $\mathtt{R}$ of role names, and $\mathtt{O}$ of individual constants, from which we define *concepts* by means of the following grammar:

$$C, D := A \mid \top \mid \bot \mid \neg C \mid C \sqcap C \mid C \sqcup C \mid \forall R.C \mid \exists R.C$$

where $A \in \mathtt{C}$ and $R \in \mathtt{R}$. Concepts are used to build an ontology/knowledge base $\mathcal{K}$, a structured description formalized by a tuple $\mathcal{K} = \langle \mathcal{R}, \mathcal{T}, \mathcal{A} \rangle$ where:

- $\mathcal{R}$ is a finite set of rigid properties of the form $C \sqsubseteq D$;
- $\mathcal{T}$ is a finite set of typicality properties of the form $p \ :: \ \mathbf{T}(C) \sqsubseteq D$, where $p \in (0.5, 1) \subseteq \mathbb{R}$ is the probability of the inclusion;
- $\mathcal{A}$ is the ABox, i.e. a finite set of formulas of the form either $C(a)$ or $R(a, b)$, where $a, b \in \mathtt{O}$.

From a semantic point of view, we consider models equipped by a preference relation among domain elements as in Giordano et al. (2015), where $x < y$ means that x is "more normal" than y, and that the typical members of a concept C are the minimal elements of C with respect to this relation. An element x is a *typical instance* of a given concept C if x belongs to the extension of the concept C, written $x \in C^{\mathcal{I}}$, and there is no element in $C^{\mathcal{I}}$ "more normal" than x. In order to perform useful nonmonotonic inferences, we consider the stronger semantics introduced in Giordano et al. (2015), where entailment is restricted to a class of *minimal canonical* models, intuitively those minimizing the atypical instances of concepts. The resulting logic corresponds to a notion of *rational closure* built on the top of $\mathcal{ALC} + \mathbf{T_R}$. A query F is minimally entailed from a knowledge base/ontology if it holds in all its minimal canonical models. In Giordano et al. (2015) it is shown that query entailment in the nonmonotonic $\mathcal{ALC} + \mathbf{T_R}$ is in EXPTIME.

As anticipated, $\mathbf{T}^{\mathsf{CL}}$ extends the Description Logic $\mathcal{ALC} + \mathbf{T_R}$ with the distribution semantics known as DISPONTE (Riguzzi et al. (2015), which is able to deal with probabilities equipping inclusions and allowing us to describe the notion of *scenario* (Lieto & Pozzato (2020): intuitively, a scenario is a knowledge base obtained by considering all rigid properties in $\mathcal{R}$ as well as all ABox facts in $\mathcal{A}$, but only a subset of typicality properties in $\mathcal{T}$. The idea is to assume that each typicality inclusion is independent from each other in order to define a probability distribution over *scenarios*: roughly speaking, a scenario is obtained by choosing, for each typicality inclusion of $\mathcal{T}$, whether it is considered as true of false.

As an example, consider the following knowledge base:

$$\mathit{TrapSinger} \sqsubseteq \mathit{Singer} \tag{1}$$

$$0.9 \ :: \ \mathbf{T}(\mathit{TrapSinger}) \sqsubseteq \mathit{AutoTuneUser} \tag{2}$$

$$0.7 \ :: \ \mathbf{T}(\mathit{Singer}) \sqsubseteq \mathit{Famous} \tag{3}$$

$$\mathit{TrapSinger}(\mathit{blanco}) \tag{4}$$

$$\mathit{Singer}(\mathit{gianni}) \tag{5}$$

The inclusion (1) expresses that *all* Trap singers are singers, whereas the typicality inclusions (2) and (3) represent that, normally, Trap singers make use of the auto-tune with probability 90%, and that, typically, singers are famous persons with probability 70%, respectively. We can then consider the following four possible different scenarios:

$$\{((2),0),((3),0)\},\ \{((2),0),((3),1)\}$$
$$\{((2),1),((3),0)\},\ \{((2),1),((3),1)\}$$

representing all possible combinations of considering/not considering each typicality inclusion. For instance, the world $\{((2),1),((3),0))\}$ represents the situation in which we have that (2) holds whereas (3) does not. In this case, we can infer that $blanco$ is a typical Trap singer, then that he makes use of the auto-tune, whereas we do not conclude anything about $gianni$.

Reasoning can then be restricted to either all or some scenarios. We also equip each scenario with a probability, easily obtained as the product, for each typicality inclusion, of the probability p in case the inclusion is involved, $(1-p)$ otherwise. It immediately follows that the probability of a scenario introduces a probability distribution over scenarios, that is to say the sum of the probabilities of all scenarios is 1.

In the logic $\mathbf{T}^{\textsf{CL}}$, in order to deal with the problem of combining prototypical descriptions of concepts as in (Lieto & Pozzato (2020), we adopt typicality inclusions in order to formalize typical properties for both the HEAD and the MODIFIERS concepts, and then to exploit the DISPONTE semantics in order to select *only* some typical properties belonging to them characterizing the combined concept. The preferential semantics underlying the logic $\mathbf{T}^{\textsf{CL}}$, together with the HEAD-MODIFIER heuristics, are able to tackle the problem of conflicting properties.

Formally, given a knowledge base $\mathcal{K} = \langle \mathcal{R}, \mathcal{T}, \mathcal{A} \rangle$ and given two concepts C_H and C_M occurring in $\mathcal{K}$, our logic allows one to define the compound concept C as the combination of the HEAD C_H and the MODIFIER C_M, where $C \sqsubseteq C_H \sqcap C_M$ and the typical properties of the form $\mathbf{T}(C) \sqsubseteq D$ to ascribe to the concept C are obtained in the set of scenarios that:

1. are consistent;
2. are not *trivial*, in the sense that the scenarios considering *all* typical properties of the HEAD that can be consistently ascribed to C are discarded;
3. are those giving preference to the typical properties of the HEAD C_H (with respect to those of the MODIFIER C_M) with the highest probability.

In order to select the desired scenarios, points 1, 2, and 3 above are applied to blocks of scenarios with the same probability, in decreasing order, starting from the highest one. First, all inconsistent scenarios are discarded, then the remaining – consistent – scenarios are taken into account in decreasing order by their probabilities. Blocks of scenarios with the same probability are considered and processed as follows:

- *trivial* scenarios, that is to say those consistently inheriting all the typical properties from the HEAD concept, are discarded;
- among the remaining ones, scenarios inheriting typical properties from the MODIFIER in conflict with typical properties inherited from the HEAD in another scenario of the same block (i.e., with the same probability) are discarded;
- if the set of scenarios of the current block is empty, i.e. all the scenarios have been discarded,the procedure is repeated by considering another block of scenarios, the one whose scenarios all have the immediately lower probability.

The set of scenarios not discarded in the current block are those selected by the logic $\mathbf{T}^{\textsf{CL}}$ as the result of the procedure.

The knowledge base obtained as the result of combining concepts C_H and C_M into the compound concept C is called C-*revised* knowledge base:

$$\mathcal{K}_C = \langle \mathcal{R}, \mathcal{T} \cup \{p \, : \, \mathbf{T}(C) \sqsubseteq D\}, \mathcal{A} \rangle,$$

for all D such that $\mathbf{T}(C) \sqsubseteq D$ belongs to the selected scenario(s). The probability p is defined as follows: if D is a typical property inherited either from the HEAD (or from both the HEAD and the MODIFIER), then p corresponds to the probability of such inclusion of the HEAD in the initial knowledge base, i.e. $p \, : \, \mathbf{T}(C_H) \sqsubseteq D \in \mathcal{T}$; otherwise, p corresponds to the probability of such inclusion of a MODIFIER in the initial knowledge base, i.e. $p \, : \, \mathbf{T}(C_M) \sqsubseteq D \in \mathcal{T}$.

2.2. DEGARI 2.0: Overall rationale and application of $\mathbf{T}^{\textsf{CL}}$

DEGARI 2.0 exploits the logic $\mathbf{T}^{\textsf{CL}}$ in order to provide an ontological formalization of the circumplex theory of emotions devised by the cognitive psychologist Robert

Plutchik (Plutchik (1980), Plutchik (2001))[6]. According to this theory, emotions, and their interconnections, can be represented on a spatial structure, a wheel (as reported in the left of the Figure 1), in which the affective distance between different emotional states is a function of their radial distance. The Plutchik's ontology, formalizing such a theory, encodes emotional categories in a taxonomy, representing: basic or primary emotions; complex (or compound) emotions; opposition between emotions; similarity between emotions. In particular, by following Plutchik's account, complex emotion are considered as resulting from the composition of two basic emotions (where the pair of basic emotions involved in the composition is called a dyad). The compositions occurring between similar emotions (adjacent on the wheel) are called primary dyads. Pairs of less similar emotions are called secondary dyads (if the radial distance between them is 2) or tertiary dyads (if the distance is 3), while opposites cannot be combined[7]. An illustrative example showing the rationale used by DEGARI 2.0 to generate the compound emotions (in this case, the emotion Love as composed by the basic emotions Joy and Trust, according to Plutchik's theory) is reported in Figure 1.

The lexical features associated to each basic emotion (and the corresponding probabilities) comes from the NRC lexicon Mohammad (2018) and, in the context of DEGARI 2.0, represent the prototypical (i.e. commonsense) features characterizing emotional concepts and taken by the system to leverage the $\mathbf{T}^{\text{CL}}$ reasoning framework and to generate the prototypical representations of the compound emotions. Once the pro-

[6]The reasons leading to the choice of this model as grounding element of the DEGARI 2.0 system is twofold: on the one hand, this it is well-grounded in psychology and general enough to guarantee a wide coverage of emotions, thus giving the possibility of going beyond the emotional classification and recommendations in terms of the standard basic emotions suggested by models like the Ekman's one (widely used in computer vision and sentiment analysis tasks). This affective extension is aligned with the literature on the psychology of art suggesting that the encoding of complex emotions, such as *Pride* and *Shame*, could give further interesting results in AI emotion-based classification and recommendation systems (Silvia (2009). Second, as anticipated above, the Plutchik wheel of emotions is perfectly compliant with the generative model underlying the $\mathbf{T}^{\text{CL}}$ logic.

[7]The ontology is available here: `https://raw.githubusercontent.com/spice-h2020/SON/main/PlutchikEmotion/ontology.owl` and queryable via SPARQL endpoint at: `http://130.192.212.225/fuseki/dataset.html?tab=query&ds=/ArsEmotica-core`

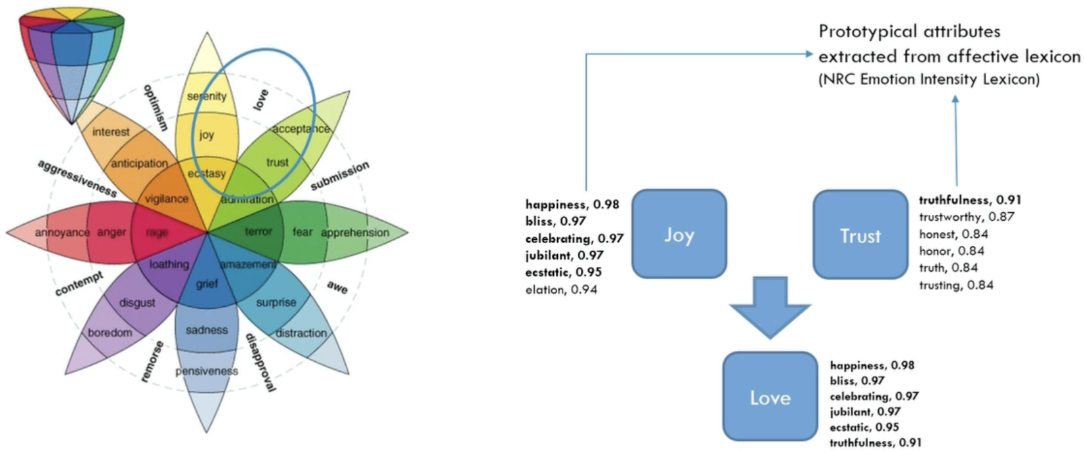


Figure 1: Generation of novel Compound Emotions with DEGARI 2.0 by exploiting the Plutchik's ontology (e.g. Love as composed by Joy and Trust in the picture). The features and the probabilities characterizing each basic emotion are obtained from the NRC lexicon. The Plutchik's wheel of emotion in this figure reports only the compound emotions representing the primary dyads, but our system works on the entire spectrum of dyads.

totypes of the compound emotions are generated, DEGARI 2.0 is able to reclassify museum items taking the new, derived emotions into account. As a consequence, such a reclassification allows the system to group and recommend museum items based on the novel assigned labels and, as mentioned, a novel prerogative of DEGARI 2.0 consists in the possibility of delivering also diversity-seeking recommendations.

The Figure 2 reports an example of these different kinds of suggestions for the artefact entitled "Ritorno alla stalla" ("Back to the barn") of the GAM museum (Galleria Arte Moderna, in Turin). Based on the system's output, this item is emotionally linked to "Maternità" ('Maternity": a statue of the GAM collection classified as evoking the same emotional content of the original painting: "Pride"), to "Contadini al sole" ("Farmers in the sun", a painting labelled with the similar emotion "Disapproval"; note that this emotion is considered "similar" according to the Plutchik's model since it is the one spatially adjacent to the category "Outrage" that is one of the categories, a "tertiary dyad" in the Plutchik's theory, to which the system has assigned the original

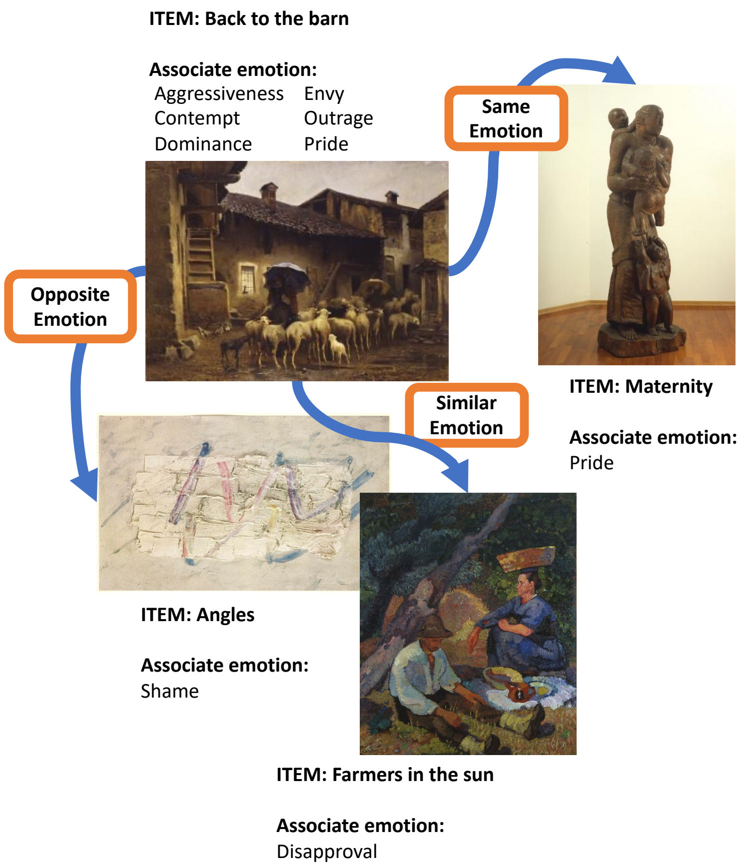


Figure 2: Example of Same, Similar and Opposite emotion recommendations of DEGARI 2.0 from the GAM dataset. This figure shows how the system is able not only to generate new compound emotions (see e.g. Figure 1) but also to group and suggest cultural items according to their obtained Plutchik's-based affective classification. The entire dyadic structure of the Plutchik's model is exploited to recommend items evoking different emotional stances with the aim of providing a more inclusive and affective-based interpretations of cultural content.

item) and, finally, to the abstract painting "Angles", labelled with the opposite emotion "Shame" (in this case the opposition concerns the label "Pride"). Overall, the system tries to categorize and link the items with respect to any of the original emotional categories found.

As anticipated, a final crucial feature of the DEGARI 2.0 classification system is represented by the fact that the rationales of its classifications are entirely transparent and explainable. In the Figure 3 below, an example of explanation provided by the system showing why this collection of artifacts from GAM Museum about the "Miracolo (Olocausto)" (Miracle (Holocaust) is classified with the label "remorse" (generated by combining the basic emotions of "disgust" and "sadness"). In particular, the system shows how the lexical triggers of this classification have been the words "tragic", that is also included in the prototypical description of the generated compound emotion "remorse".

As anticipated, $\mathbf{T}^{\textsf{CL}}$ is adopted in DEGARI 2.0 to automatically build the prototypical representations of the compound emotions according to the Plutchik's theory and the information about the emotional concepts and their corresponding features to combine via $\mathbf{T}^{\textsf{CL}}$ are extracted from the NRC Emotion Intensity Lexicon (Mohammad (2018)[8]. This lexicon associates words to emotional concepts in descending order of emotional intensity and, for our purposes, we considered the most intensively associated terms for each basic emotion as typical features of such emotion. In this way, the prototypes of the basic emotions were formed, and the $\mathbf{T}^{\textsf{CL}}$ reasoning framework is used to generate the compound emotions. Such prototypes of basic emotions are formalized by means of a $\mathbf{T}^{\textsf{CL}}$ knowledge base, whose TBox contains both *rigid* inclusions of the form

$$BasicEmotion \sqsubseteq Concept,$$

in order to express essential desiderata but also constraints, as an example $Joy \sqsubseteq PositiveEmotion$ as well as *prototypical* properties of the form

$$p \ :: \ \mathbf{T}(BasicEmotion) \sqsubseteq TypicalConcept,$$

representing typical concepts of a given emotion, where p is a real number in the range $(0.5, 1]$, expressing the frequency of such a concept in items belonging to that emotion: for instance, $0.72 \ :: \ \mathbf{T}(Surprise) \sqsubseteq Delight$ is used to express that the typical

[8]Such lexicon provides a list of English words, each with real-values representing intensity scores for the eight basic emotions of Plutchik's theory. The intensity scores were obtained via crowd-sourcing, using best-worst scaling annotation scheme.

```
Recommendation for category: remorse-disgust_sadness

Category prototype:

[('straziante', 0.97, False),
      ('lutto', 0.97, False),
      ('tragico', 0.96, False),
      ('olocausto', 0.95, False),
      ('miseria', 0.94, False),
      ('cannibalismo', 0.95, True)]
['onore', 'felicità', 'giubilante']

Recommended artworks:

       -> GAM Museum - Miracolo (Olocausto)
       \-> matches: ['tragico’]
Classified 1 of 1 contents (100.0%)
```

Figure 3: An example of the DEGARI 2.0 explanations provided for each emotional classification for the GAM Museum artefact called “Miracle (Holocaust)”. The attributes describing the prototype of the complex category “Remorse” (obtained by combining “Disgust” and “Sadness”) are defined by the keywords “heartbreaking” (straziante), “mournful” (lutto), “tragic” (tragico) etc., Each of these keywords has a likelihood that characterises the artefact. In particular, the keyword “tragic” is found within the textual snippet of the artefact description (shown in Figure 5), provided by the museum curators and stored in the digital catalogue, and acts as a trigger for the complex emotion “Remorse”, used as emotional label in the classification task.

feature of being surprised contains/refers to the emotional concept *Delight* with a frequency/probability/degree of belief of the 72%.

Once the association of lexical features to the emotional concepts in the Plutchik's ontology is obtained and the compound emotions are generated via the logic $\mathbf{T}^{\text{CL}}$, the system is able to reclassify the cultural items in the novel formed emotional categories. Intuitively, an item belongs to the new generated emotion if its metadata (name, description, title) contain all the rigid properties as well as at least the 30% of the typical properties of such a derived emotion. The 30% threshold was empirically determined: i.e., it is the percentage that provides the better trade-off between over-categorization and missed categorizations (Chiodino et al. (2020a).

2.3. DEGARI 2.0 Software Modules and Architecture

Overall, the system is composed by four software modules, as depicted in Figure 4. The modules adopting $\mathbf{T}^{\text{CL}}$ and involved in the processes of (basic) emotion formation and (compound) emotion generation correspond to the Modules 2 (Emotion combination) and 3 (Generation of combined emotion prototypes) of the architecture in the Figure. Module 1 (Generation of prototypes), on the other hand, represents the entry point of the system and manages the metadata associated to each museum item. Finally, Module 4 (Recommender system), is the one devoted to group, reclassify and recommend the cultural items according to the novel emotional labels created by DEGARI 2.0. In particular, the reclassification step requires matching the output of Module 1. Namely: matching the extracted metadata of each museum item (or the user-generated texts associated with it), with the ones characterizing the compound emotions generated in Modules 2 and 3.

In the current version of the system, Module 1 accepts JSON files containing a textual description of the cultural items (e.g. coming from user comments or from the museum catalogues) and performs an 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 pro-

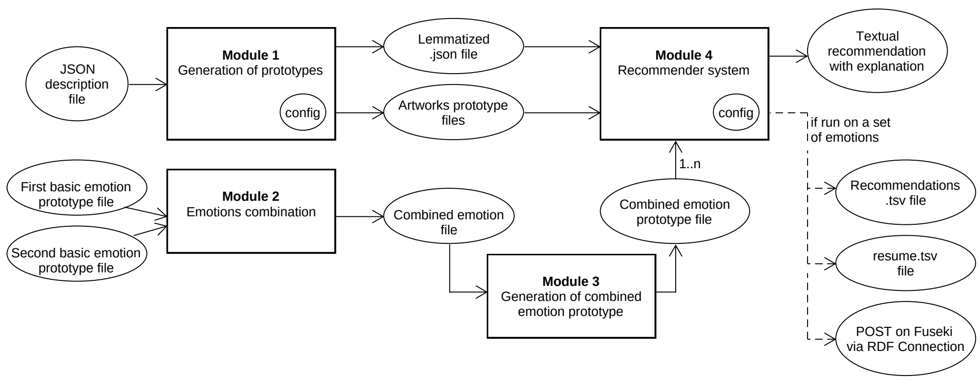


Figure 4: The overall software architecture of DEGARI. Module 1 represents the entry point of the system. It accepts JSON files containing a textual description of the cultural items (coming from user comments or from the museum catalogues) and performs an automatic information extraction step generating a lemmatized version of the JSON descriptions and a frequentist-based extraction of the typical terms associated to the cultural item. Modules 2 and 3 are devoted respectively i) to the acquisition of the basic Emotions to combine (Module 2) and ii) to the generation of the compound Emotions (Module 3). Module 4 is the one classifying, grouping and recommending the cultural item according to the novel generated emotions.

portion of each term with respect to the set of all terms characterizing the item. These two tasks (lemmatization and frequency attribution) are performed by using standard libraries like Natural Language Toolkit [9] and TreeTagger [10]. Once this pre-processing step is done, the final representation of the cultural items is compared with the representations of the typical compound emotions obtained in Module 3. This comparison, and the corresponding classification, is done in Module 4 that implements, we recall, the following categorization heuristics: 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. After the categorization has taken place, DEGARI is eventually able to classify and group together the items evoking the same emotions (e.g., Despair in the Figure 5) or, as shown in the examples from the Figure 2, items having opposite or similar emotions.

The current version of the system is available as a web service that that can be invoked via standard HTTP requests and whose reasoning output is made automatically available to a queryable SPARQL [11] endpoint. As we will show in the next section, this advancement allowed us to call the DEGARI 2.0 reasoning services and to integrate its output within a web app (called GAMGame) built to collect user data on cultural items, during a museum visit.

The whole architecture pipeline of the DEGARI 2.0 service is sketched in Figure 6 and relies on the following workflow, working without any manual intervention:

1. Users (via a client call initiated by a web app) can send a JSON file artefact by using POST method. This JSON file contains the description of a particular artefact (i.e., "The Scream of Munch") and annotations collected by the users over the artifact (e.g. tags about the emotions generated, emojies etc.). All these annotations will be used as a description of the cultural item under consideration.
2. the JSON file with the ID of the item and its description is stored into the file system of DEGARI-REST server (phase 2 in the Figure 6).

[9] https://www.nltk.org/
[10] https://www.cis.uni-muenchen.de/ schmid/tools/TreeTagger/
[11] https://www.w3.org/TR/rdf-sparql-query/

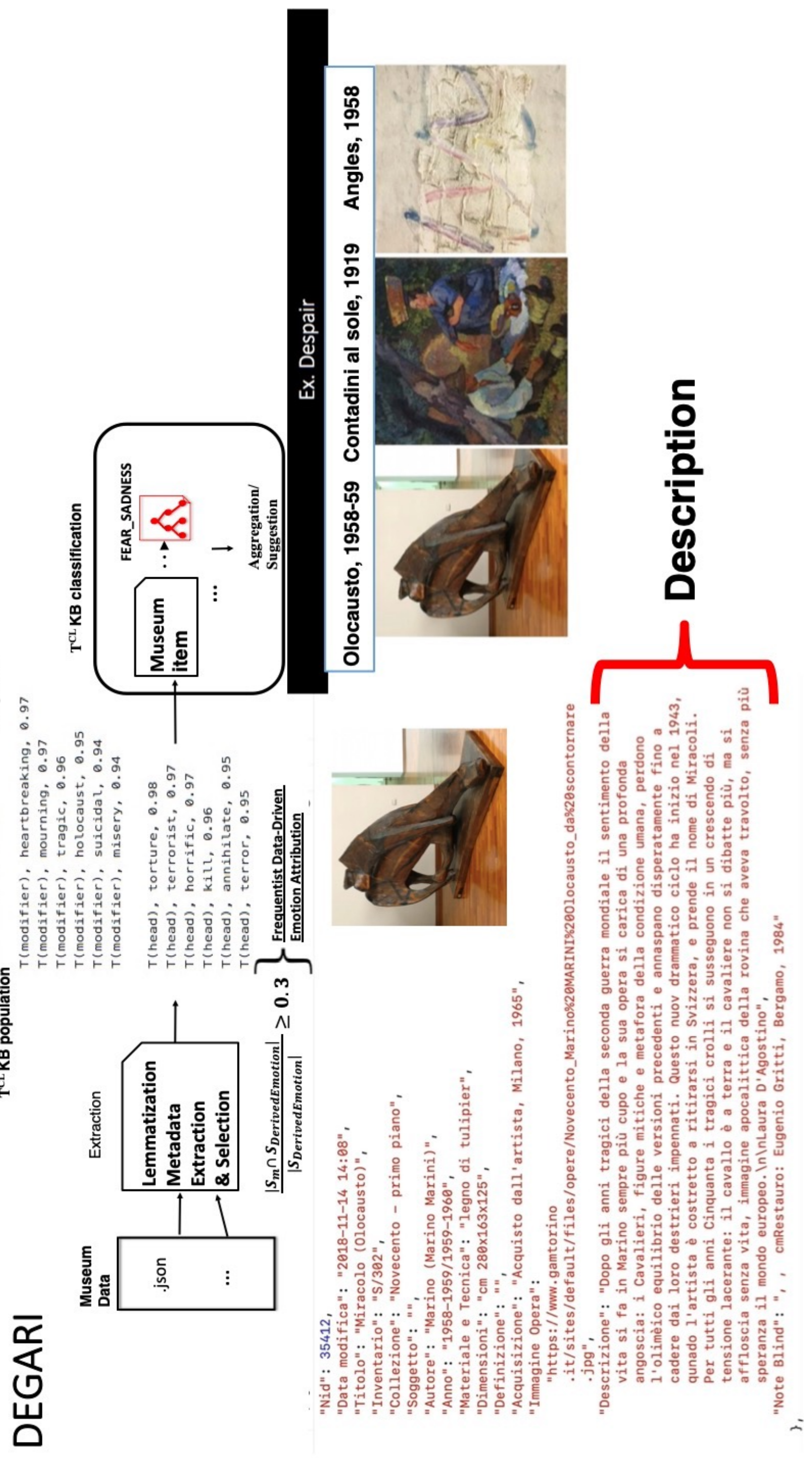


Figure 5: A pictorial example of the categorization pipeline used by DEGARI 2.0 for emotion attribution and content aggregation/suggestion based on the artwork "Miracolo Olocausto" from the GAM. The item is associated with a textual description coming, in this case, from the museum collection (user-generated contents are also handled via the same format). This JSON snippet is the element entering the Module 1 of the system and triggering its entire processing until the recommendation step (in this case based on the classical "same-emotion" suggestion).

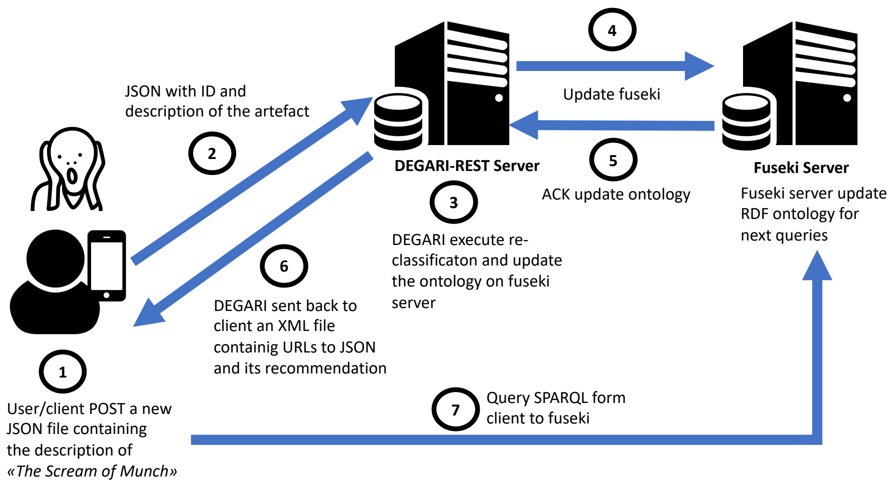


Figure 6: DEGARI-POST - pipeline architecture

3. DEGARI-REST server executes the emotional reclassification of the JSON artefact and communicates with a Fuseki server hosting the Plutchik's ontology by automatically updating the knowledge base with the RDF triples associating to each item a specific emotion. The update is done by using the RDF connection SPARQL Update method provided by the SPARQL APIs (phases 3 and 4 in the Figure 6).
4. After the SPARQL update query, Fuseki server sends to DEGARI-REST server an ACK response (phase 5 in the Figure 6).
5. DEGARI 2.0 sends to the client/application an XML file containing URLs to JSON and its recommendation (phase 6 in the Figure 6).
6. The last step (phase 7 in the Figure 6) shows how the client application used by the user can also execute a SPARQL query to Fuseki in order to get the classification results for the artefact sent at step 1.

3. The GAMGame App

The reasoning engine and the recommendation services provided by DEGARI 2.0 have been used to feed the GAMGame. GAMGame is a web application, inspired by mobile apps, designed by the University of Turin in collaboration with the GAM museum that allows users to create personal narratives from artworks in a simple and intuitive fashion. For example, by selecting pictures of cultural items that are of interest for the user and sharing stories about those (including memories, opinions, emoji, hashtags).

Within the app, the use of the DEGARI 2.0 emotional recommendations is aimed not only at supporting the users in the selection of the artworks as part of the creation of their stories, but also at inspiring them with novel suggestions, with goal of enhancing the diversity of the interpretations created through the app.

As mentioned earlier, within the SPICE project, the community of interest for testing our system is represented by the one of deaf people (in particular deaf teenagers).

In order to comply with the characteristics of the Deaf (using Sign Language), the design of the interface has been inspired to a set of guidelines, issued from the cooperation of the Turin Institute for the Deaf who advises the University of Turin[12] on the usability of the tools implemented within the SPICE project: since, for most deaf users, written language is a second language with respect to the corresponding Sign Language, and its use can be a hindrance for this category of users, the use of text is limited to the minimum in app. Textual instructions have been kept as short and simple as possible, and they has been accompanied and, where possible, replaced by icons. In accordance with Web Content Accessibility Guidelines (WCAG 2.0[13]), contrast, font type and size has been selected in order to improve readability. Finally, the complexity of the interaction has been kept to the bare minimum: the creation of stories and personal responses to the artworks in the stories rely on the paradigm of direct manipulation of the objects in the interface; story creation steps (selection, ordering and annotation of artworks) are pipelined, and backtracking is disabled; interaction conventions (e.g. dragging and dropping for selection) are re-used throughout the steps to alleviate the task of learning new commands. Finally, in order to alleviate the task of expressing one's emotional response to the artworks in the story, textual labels can be used jointly

[12] `https://istitutosorditorino.org/index.php/en`
[13] https://www.w3.org/TR/WCAG20/

with emojis, which can selected by dragging them onto the artwork. The usefulness of emojis lies in the fact that they allow the user to express emotions in a more immediate and, visual way. There is also increasing evidence (Wolny (2016), Barbieri et al. (2018), Ronzano et al. (2018), Shoeb et al. (2019)) that in social media they are similar to a widely used jargon, especially for new generations, and that it is necessary to support them for a better understanding of affect in today's communication. It is a type of user-friendly communication that can be used to express impressions in a very intuitive and simple way, also by categories of users who may have difficulties in producing written text on technological devices (such as older people, people with disabilities or children, who generally do not produce long and content-rich texts). As reported in Mack et al. (2020), recent surveys highlight the inclination of Deaf and Hard of Hearing towards visual communication forms in social media, including emojis. The latter in particular, have been described as closer to the type of facial expressiveness which characterizes Sign Languages. For these reasons, emojis can be functional to making the fruition process easier and, consequently, increase the engagement of citizens and the incisiveness of the project. Concerning the emojis included in the artwork annotation panel (love, curiosity, delight, joy, fear, sadness and disgust), the selection was driven by the museum curators based on their experience with the social media of the institution, and with the preferences of the audience of teenagers. On the other hand, following the considerations put forth in (Bolioli et al. (2022) for emotion extraction in artwork annotation, the association between emojis and emotions was established based on Emojipedia (`https://emojipedia.org/`), which, in the last decade, has become an authoritative source for interpreting emojis' meaning (Rodrigues et al. (2018).

The Museum curators of Galleria d'Arte Moderna (GAM)[14] of Turin provided the catalogue metadata of their collection of artifacts containing descriptions of the narrative aspects depicted in the visual artworks (e.g., title, author, date, characters, actions, objects) for 586 items. The descriptions of these items were encoded as JSON-LD files, so that the resulting description of each item was compliant with the input of DEGARI

[14] `https://www.gamtorino.it/en`

2.0 system. In particular, they selected 43 artworks for the inclusion in the app, with the goal of presenting the audience with a variety of subjects, styles, techniques and historical periods. In the following, we describe the three main activities that can be carried out with the GAMGame app:

Figure 7: GAMGame's first page. The yellow title on the top of the page (in italian, meaning "Select three artworks to create your story") invites the user to select some items, by dragging them from the grid on the left and dropping them into the yellow box on the right. In this example we selected two artworks.After any artworks are selected, the blue button *Avanti* (meaning "Continue") under the yellow box becomes available. The button allows proceeding to the next page.

Selection and ordering. In this first activity, users can choose 1 to 3 artworks to create their own story, by dragging artworks from the "catalogue" on the left to the selection area (yellow) on the right. The catalogue can be browsed (items are randomly ordered each time the page is loaded so as to avoid a preference for the first items). Selected artworks can be dragged back to the catalogue to cancel the selection. The "Continue" button (*Avanti*, in Figure 7), becomes active when at least one artwork is selected.

Figure 8: GAMGame's annotation page. In the second page of GAMGame, the user is invited to express their personal view of the selected items (the title of the page *Mettici qualcosa di personale* literally meaning "Put something personal on it"). The three buttons top right provide the three possible annotation templates: Text, Hashtags and Emojis. In this example we annotated "Beethoven giovinetto" by Giuseppe Grandi, adding an Emoji and an Hashtag. The top left Button *Non so cosa dire* ("Nothing to say") allows skipping the annotation of an artwork.

Artwork annotation. In this step, users can add something personal to each selected artwork, one by one, by using the annotation panel (top, right) with functions Text (T), Hashtags (#) and Emoji. The Text function provides 3 templates: "It reminds me of ..." , "It makes me think of ... " or "I like it because ...". The annotation elements can be added by dragging them onto the artwork, and multiple elements of each type can be added. Finally, any added element can be removed: when the user clicks on an element, a dustbin appears at center of the image for discarding it. The user can go to the following artwork only when at least one element has been added or the link

“Nothing to say” (*Non ho nulla da dire*) has been clicked. (Figure 8).

Figure 9: GAMGame’s recommendation page. In this page the system provides two recommendations based on the selected artworks. The user is invited to indicate if they want to include any suggestion to their story (the top left title *Quali opere aggiungeresti alla tua storia?* means “Which artworks would you add to your story?”). The drag and drop selection recalls the first page, while the bottom left button *Nessuna opera* (“No artworks”) allows refusing both the recommendations. In this example, one of the two recommended artworks has been accepted by selecting it. After the selection, the bottom right blue button *Crea la storia* (“Create the story”) can be pressed to end GAMGame. Then, on a final page, the selected artworks are shown together with the annotations and the accepted recommendations, thus visualising the created user’s personal story.

Recommendation and story creation. After annotating the selected artworks, the user receives a recommendation based on the emotional features associated by DEGARI 2.0 to the selected artworks. Recommended artworks (top left) can be accepted by dragging them onto the yellow selection area (Figure 9). Alternatively, the user can click the link “No artwork” (*Nessuna opera*). After accepting/rejecting the recommendations, the button “Create your story” (*Crea la tua storia*) appears, with a text field to add a title (optional). Finally, users can visualize their story.

4. Evaluation

To the best of our knowledge, there is no available evaluation standard to test a system about its diversity-seeking affective recommendation (not only referred to the deaf community). As a matter of fact, indeed, standard recommendation systems are evaluated on their ability to confirm one own's points of view. On the other hand, the purpose of a system like DEGARI 2.0 is exactly the opposite: i.e. to break the filter bubble effect by adopting an inclusive approach aiming at extending (not confirming) the typology of experienced cultural items through the exploitation of an affective lens trying to include, in the user's perspectives and potential experience, also cultural items that do not directly fit their usual, expressed, preferences.

As a consequence, the system has been evaluated in a threefold way, all involving the community of deaf people engaged via the Istituto dei Sordi di Torino (the Turin Institute for the Deaf) via an availability sampling strategy [15]. The first reported evaluation focuses on the acceptability of the received inclusive-based affective recommendations. In particular, it aimed at measuring the satisfaction of the potential users of the GAMGame when exposed to the suggestions of the novel categories suggested by DEGARI 2.0. It consisted in a user study[16] where 74 deaf participants, after having been exposed to a number of affective-based recommendations based on their original selection, were asked to compile an online questionnaire about the received suggestions. Here they had to rate, on a 10-point scale (from 1 to 10), the received recommendations based on the 'same-emotion' 'similar-emotions' and 'opposite emotions' categories . Overall they rated 91 recommendations. The second evaluation directly compares the results of the affective labeling provided by our system with both human annotations (coming from the 74 deaf participants above) and with the state of the art emotion

[15]The availability sampling is a sampling of convenience, based on subjects available to the Institute. Even though random sampling is the best way of having a representative sample, these strategies require a great deal of time and money. Therefore, much research in human-computer interaction, in particular for for groups of minority, is based on samples obtained through non-random selection (Straits (2005); Young & Temple (2014)

[16]This is one of the most commonly used methodology for the evaluation of recommender systems based on controlled small groups analysis, see Shani & Gunawardana (2011).

extraction system SenticNet 7.

A final evaluation campaign, aiming at exploring the level of explainability of our system, was conducted as a two-step experiment carried out (on a different date and with a different participants) on a smaller group (10 people: 4 females, 6 males) of the deaf community.

In this case the goal of the evaluation was to assess the effectiveness of the explanatory capability of our system. Such an assessment was made with respect to the original emotional classification of the museum items made by the system. In other words: the participants had to assess, again on a 10-point scale, how much it was clear the reason why the system had originally classified the selected item(s) as belonging to a given emotional category. Note note that such initial classification, as mentioned, works as a pivot for the entire recommendation strategies, since the associations and suggestions of same-similar-opposite emotional items relies on it. In total, 54 explanations were rated by this group of participants. This rating-based experiment concerning the explanations was followed by a focus group where the participants were asked to discuss the problematic issues raised by the explanations provided by the system. The whole discussion with the community of deaf people was done and supervised by a professional translator of the Institute (the Figure 10 shows a frame of this experiment) who translated questions, feedback, and comments from Italian to LIS (Lingua Italiana dei Segni, Italian Sign Language) and vice versa.

4.1. Results and Discussion for the Inclusive Recommendations

Below, we report the results of the prototype applications of DEGARI 2.0 to the datasets provided by Gallery of Modern Art (GAM).

The overall obtained results about the ratings are shown in Table 1. The users showed a moderate acceptance of the received content suggestions. The average rating assigned to the total set of emotion category proposed by DEGARI was 5.79 with a median value of 6/10. Table 1 shows the mean, median and standard deviation values for each emotion recommendation group (same, similar and opposite emotions). The recommendations that received a better rating were the ones suggesting items linked to the original one through the property “similar emotion”. The recommendations of

Figure 10: A professional translator from Istituto dei Sordi explains to the participants, during the second experiment, how the focus group will be conducted by translating from LIS (Lingua Italiana dei Segni, Italian Sign Language) to Italian.

Mean score:	5,79		
Median total score:	6		
	Same Emotion	**Similar Emot.**	**Opposite Em.**
mean	5,78	6,23	5,25
median	6	6	5
standard deviation	0,61	0,71	1,06

Table 1: Results of the ratings of the deaf group in GAM on the DEGARI recommendations

items evoking opposite emotions (with respect to the original item selected in the game) were the ones that received the worst rating.

In particular, this latter datum suggests that there are mechanisms of cognitive resistance that prevent a full acceptance of suggestions going in a different direction from one's own preferences. This datum, even if tested on deaf people, can arguably be extended also to the general audience. In particular, a first guideline that can be extracted for the improvement of diversity-seeking affective recommenders concerns the opportunity to adopt presentation devices for the **mitigation of cognitive resistance effects**. Although the search for mitigation measures that wrap diversity into some meaning frame is an open research area, the effectiveness of narrative formats (Wolff et al. (2012); Damiano et al. (2016)) and of ethically-driven digital nudging techniques (Augello et al. (2021); Gena et al. (2019) is worth exploring. A more immediate strategy that could be adopted in our system is also represented by the progressive recommendation of items evoking emotions that are gradually more distant from the starting one (where the distance can still rely on the radial structure of the Plutchik's wheel encoded in the ontology).

4.2. Degari 2.0 vs Human Annotations and SenticNet 7: Results and Discussion

In order to investigate the overlapping between the set of emotion categories proposed by system and the ones assigned by deaf users (e.g. via emoji or text) for each of the items of the GAMGame, we conducted a second analysis, whose overall results are shown in Table 3. Overall, deaf users were able to associate to cultural items much more emotions with respect to the ones extracted by DEGARI (74 vs 34). This ratio is indicated in the measure "Total Overlapping" (45,94%). In addition, however, we also measured how many times the emotional labels provided by the system matched the ones available in the list provided the users. In this case, for the 58,33% of the cases, at least one of the emotions by DEGARI 2.0 was also in the list provided by the users. Finally, in the last measure we considered the extended vocabulary of the emotional labels provided by the users. In particular, we extended their categorization by considering the "similar emotions" obtained by exploiting the different combination of dyads provided by the Plutchik's theory. This datum was considered to assess a more

user emotions	DEGARI 2.0 emotions	DYADS
pessimism sadness	pessimism	Pessimism (sadness , anticipation)

Table 2: Comparison between generated user emotions, DEGARI 2.0 emotions and the extended DYADS

relaxed version of the “perfect match” between human and system labels considered in both the “Total Overlapping” and the “DEGARI Emotion containment”. The reason why we recorded these metrics relies on the fact that in many cases the “perfect match” hypothesis left out - in a Boolean way - many interesting labels attributed by the system (and semantically related to the ones also selected by human users) that were not exactly the ones attributed by the users.

Table 2 shows an example of the overlapping between the generated user emotions {pessimism, sadness}, DEGARI 2.0 emotions, and its extensions by exloiting the emotional DYADS (Kołakowska et al. (2015)). In particular, the perfect match between user generated emotions and DEGARI 2.0 classification is given only by the emotion ({*pessimism*}) (detected by the system). However, by using the extended DYAD related to emotion {*pessimism*}, it is possible to include also the emotion {*sadness*} (originally not detected by the system but present in the user annotation). In this way, we were able to record a greater coverage.

In particular, with this measure, we obtained (see 3) that the largest part (83,33%) of the emotions attributed by DEGARI 2.0 is contained in the extended list of emotions considering both user labels and the list of “similar emotions”. This datum is compliant with the findings shown in Table 1, where the recommendations of items sharing “similar emotions” where the ones that obtained the highest ratings.

In order to assess the feasibility of the affective classifications provided by our system, and crucial for the above presented recommendation part, we also compared the results

	GAMGame
Total user generated emotions	74
Proposed emotion	34
Total Overlapping (% of overlapping of the total emotions provided by DEGARI and the total emotions labelled by users)	45,94%
DEGARI Emotion Containment (how often the emotional labels provided by DEGARI coincide with those provided by the users)	58,33%
Extended DEGARI Emotion Containment (how often the emotional labels provided by DEGARI coincide with the ones provided by the users by considering also extended DYADS)	83,33%

Table 3: Overlapping of the tags provided by deaf users with the ones by DEGARI

of DEGARI 2.0 with SenticNet7 (Cambria et al. (2022), (Susanto et al. (2022): 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 (Susanto et al. (2020). 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 4, for the Gam dataset 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 6). 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.

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

Table 4: The Figure 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 extracts only complex emotions (28)

Surprisingly, DEGARI 2.0 was also able to provide - on average - more emotional labels for each item. Table 5 shows an excerpt from the GAM dataset outlining the differences in the affective classifications executed by the two systems.

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 5: An excerpt comparing the SenticNet 7 extracted emotions with DEGARI 2.0 classification. Both classification systems use, as underlying reference affective model, the Plutchik's one.

4.3. Evaluating the Perceived Explainability: Results and Discussion

The third major evaluation carried out concerned the analysis of the explanatory capabilities of the system according to the target group of the DEAF community. The participants in this experiment were different from the previous one. In this analysis, 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).

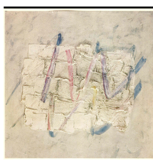
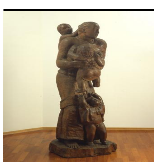
Table 7 reports the scores assigned to each explanation by the users. The overall average rating assigned by the users to the feature-based explanation of the emotional classification provided by the system was is 5.81 out of 10, with a median value of $6/10$. The column "keyword trigger" indicates the keyword found in the description of the items (on in the content generated by the user in the GAMGame inclusing 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.

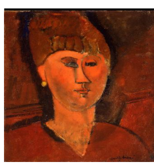
Finally, the Effect-size Eff (1994) correlation index between the two groups of experiments (item emotion attribution rating and explanation rating) was calculated on a total sample of $|n| = 11$ artefacts, obtaining for experiment 1, an average value of $\mu_1 = 5.84$, and a standard deviation $\sigma_1 = 2,41$. For the experiment 2, an average value of $\mu_2 = 5.81$, and a standard deviation $\sigma_2 = 2,24$. The Cohen's d calculated index was $cohen_d = 0,0164$. This value means that there is no effect-size between item emotion-based recommendations ratings and explanations ratings.

As mentioned, the second part of this evaluation focused on the perceived level of explainability consisted in a focus group. Here, the thematic line 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.

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 6: 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.

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

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

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 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 work on the relevance of non-verbal communicative modalities in the expression of emotions (Bänziger et al. (2012)).

Interestingly enough, what emerges from the effect-size is that the ratings concerning the appreciation of the diversity-seeking emotional recommendations does not affect the ones concerning the clarity of the explanations proposed by our system. This implies that the guidelines drawn for the explanation part can be generalized independently of the type of acceptance of the received recommendations.

Finally, the presentation of items associated with negative emotions was also discussed in the focus group, with the intent to clear 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 Benford et al. (2012), according to which negative feelings constitute an intrinsic component of audience experience in entertainment and art, especially in participatory contexts.

5. Summing up and Looking ahead

Summing up, the key outcomes of our experiments show that the effort of tackling diversity-seeking, affective-based and explainable museum recommendations received a moderate, improvable, acceptance from the deaf community. This is an encouraging result considering the challenge of the cognitive barriers involved in the process of the accepting suggestions that do not fit one's own preferences and viewpoints. In the section 4.1 we also pointed out a possible way-out to this problem based on the adoption of persuasive technologies leveraging narrative and storytelling techniques aiming at overcoming these barriers. In addition, we have shown how our system when compared with human annotators and 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 with respect to the compared system, but only a partial overlap with human annotations. In this latter case, in particular, the affective vocabulary used by humans results greatly larger than the one extracted by our system (a problem that can be partly ascribed to the spectrum of emotions assumed in the Plutchik's model in itself). However, a more detailed analysis has shown how this gap is reduced by taking into account a more relaxed and extend notion "emotional matching' between the system classification and the human annotations.

Finally, 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 (Goodman & Flaxman (2017).

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 (Alberti et al. (2017); Bellodi et al. (2017) 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 provided in this paper 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, the Design Museum in Helsinki and the Museum of National Science in Madrid) in order to assess to what extent the different typologies of items contained in these diverse range of museums (consider that the GAM is a modern art museum and, as a consequence, for many items about abstract art it may be more difficult to extract a shared emotional interpretation between humans and system) affect the overall assessment of the inclusive based-recommendations and of the explainability feature of our system.

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