# A System for Automatic Emotion Attribution based on a Commonsense Reasoning Framework

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**Abstract**

This work describes an explainable system for emotion attribution and recommendation (called DEGARI (Dynamic Emotion Generator And ReclassIfier) relying on a recently introduced probabilistic commonsense reasoning framework (i.e. the TCL logic, see Lieto and Pozzato 2020 [5]) which is based on a human-like procedure for the automatic generation of novel concepts in a Description Logics knowledge base. In particular, in order to model human-like forms of concept combinations, the TCL logic combines a probabilistic description logics of typicality with the HEAD-MODIFIER heuristics coming from cognitive semantics (see [1] [4] for other applications of the logic).

In the context of our application of such framework (represented by the DEGARI system employing such a logic), starting from an ontological formalization of emotions based on the Plutchik's model (known as ArsEmotica and available at `http://130.192.212.225/fuseki/ArsEmotica-core`), our system exploits the logic TCL to automatically generate novel commonsense semantic representations of compound emotions (e.g. Love as derived from the combination of Joy and Trust according to Plutchik's model). The generated emotions corresponds to prototypes, i.e. commonsense representations of given concepts, and have been used to reclassify emotion-related contents in a variety of artistic domains, ranging from art datasets to the editorial content available in RaiPlay, the online multimedia platform of RAI Radiotelevisione Italiana (the Italian public broadcasting company). We have tested our system (i) by reclassifying the available contents in the tested datasets with respect to the new generated compound emotions ii) with an ablation experiment showing the im-

portance of the head-modifier heuristics adopted by TCL for obtaining useful emotion classifications (iii) by testing the DEGARI machinery on different emotional datasets (iv) with an evaluation, in the form of a controlled user study experiment, of the feasibility of using the obtained reclassifications as recommended emotional content.

Table 1 below reports the results of the obtained reclassifications for the 3 multimedia datasets of ArsMeteo, RaiPlay and WikiArt Emotions.

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| | **ArsMeteo (9171 artworks)** | | **RaiPlay (4612 media items)** | | **WikiArt Emotions (4105 artworks)** | |
|---|---|---|---|---|---|---|
| **Emotion** | **Reclassified Items** | **Percentage** | **Reclassified Items** | **Percentage** | **Reclassified Items** | **Percentage** |
| **aggressiveness (anger_anticipation)** | 12 | 0.13% | 7 | 0.15% | 0 | 0.00% |
| **aggressiveness (anticipation_anger)** | 11 | 0.12% | 2 | 0.04% | 0 | 0.00% |
| **anxiety (anticipation_fear)** | 33 | 0.36% | 88 | 1.91% | 0 | 0.00% |
| **awe (fear_surprise)** | 63 | 0.69% | 132 | 2.86% | 508 | 12.38% |
| **contempt (anger_disgust)** | 13 | 0.14% | 2 | 0.04% | 0 | 0.00% |
| **curiosity (surprise_trust)** | 47 | 0.51% | 49 | 1.06% | 508 | 12.38% |
| **cynicism (anticipation_disgust)** | 5 | 0.05% | 0 | 0.00% | 0 | 0.00% |
| **delight (joy_surprise)** | 52 | 0.57% | 117 | 2.54% | 1672 | 40.73% |
| **despair (fear_sadness)** | 19 | 0.21% | 20 | 0.43% | 0 | 0.00% |
| **disapproval (sadness_surprise)** | 58 | 0.63% | 64 | 1.39% | 404 | 9.84% |
| **dominance (anger_trust)** | 11 | 0.12% | 2 | 0.04% | 0 | 0.00% |
| **envy (anger_sadness)** | 25 | 0.27% | 21 | 0.46% | 0 | 0.00% |
| **envy (sadness_anger)** | 17 | 0.19% | 20 | 0.43% | 0 | 0.00% |
| **guilt (fear_joy)** | 22 | 0.24% | 73 | 1.58% | 1618 | 39.42% |
| **guilt (joy_fear)** | 24 | 0.26% | 73 | 1.58% | 1618 | 39.42% |
| **hope (anticipation_trust)** | 50 | 0.55% | 51 | 1.11% | 661 | 16.10% |

| | | | | | | |
|---|---|---|---|---|---|---|
| **hope (trust_anticipation)** | 44 | 0.48% | 52 | 1.13% | 661 | 16.10% |
| **love (joy_trust)** | 24 | 0.26% | 72 | 1.56% | 1618 | 39.42% |
| **morbidness (disgust_joy)** | 25 | 0.27% | 70 | 1.52% | 1618 | 39.42% |
| **optimism (anticipation_joy)** | 23 | 0.25% | 24 | 0.52% | 1413 | 34.42% |
| **outrage (anger_surprise)** | 41 | 0.45% | 46 | 1.00% | 508 | 12.38% |
| **pessimism (anticipation_sadness)** | 37 | 0.40% | 20 | 0.43% | 412 | 10.04% |
| **pessimism (sadness_anticipation)** | 29 | 0.32% | 20 | 0.43% | 0 | 0.00% |
| **pride (anger_joy)** | 20 | 0.22% | 72 | 1.56% | 1618 | 39.42% |
| **remorse (disgust_sadness)** | 31 | 0.34% | 20 | 0.43% | 0 | 0.00% |
| **sentimentality (sadness_trust)** | 18 | 0.20% | 20 | 0.43% | 0 | 0.00% |
| **sentimentality (trust_sadness)** | 28 | 0.31% | 20 | 0.43% | 0 | 0.00% |
| **shame (disgust_fear)** | 35 | 0.38% | 88 | 1.91% | 0 | 0.00% |
| **submission (fear_trust)** | 33 | 0.36% | 88 | 1.91% | 0 | 0.00% |
| **unbelief (disgust_surprise)** | 35 | 0.38% | 44 | 0.95% | 508 | 12.38% |
| **unbelief (surprise_disgust)** | 47 | 0.51% | 47 | 1.02% | 508 | 12.38% |
| **OVERALL**$^\star$ | 166 | 1.81% | 235 | 5.49% | 2434 | 59.29% |

Table 1: Automatic evaluation overall data. $^\star$ *This is NOT a sum: the overall count represents the total number of artworks classified for at least one emotion.*

The Table 2 reports the result of the ablation experiment showing the role of the HEAD-MODIFIER cognitive heuristics in the DEGARI classification of compound emotions.

Finally, the Tables 3-4 show how the emotional classifications reported by DEGARI have received on average good ratings when judged by human subjects. Overall, the obtained results are encouraging and pave the way to many possible further improvements and research directions.

To conclude, the collected data suggest that the emotion categories proposed by DEGARI as a result of the reclassification process are generally accepted by the users, with few exceptions that deserve further investigation. The acceptance is clear for the top ranked emotion, but a satisfactory degree of acceptance can be inferred also for the

Table 2: Ablation Experiment of DEGARI showing the difference of considering (or not) the Head/Modifier (H/M) Cognitive Heuristics and its crucial effect on emotion reclassifications

| | **ArsMeteo** | **WikiArt** | **RaiPlay** |
|---|---|---|---|
| **Total (with H/M)** | 607 | 1428 | 15853 |
| **Total (without H/M)** | 212 | 570 | 6531 |
| **Delta (n. of reclassifications)** | $-395$ | $-854$ | $-9322$ |
| **Delta (percentage of reclassifications)** | $-65.07\%$ | $-59.97\%$ | $-58.80\%$ |

Table 3: User ratings of the emotions proposed by DEGARI

| | **ArsMeteo** | **WikiArt** | **RaiPlay** | **All** |
|---|---|---|---|---|
| **Average rating** | 6.47 | 6.12 | 6.42 | 6.32 |
| **Standard deviation** | 2.48 | 2.47 | 2.1 | 2.41 |
| **Median** | 7 | 7 | 7 | 7 |

Table 4: Overlapping of user tags with DEGARI emotions

| | **ArsMeteo** | **WikiArt** | **RaiPlay** | **All** |
|---|---|---|---|---|
| **User tags** | 308 | 308 | 449 | 1065 |
| **Proposed emotions** | 36 | 50 | 41 | 127 |
| **Overlapping** | 27.28% | 20% | 19.50% | 22.05% |

remaining suggested categories, for which an overlapping of 20% and more with the user tags has been found in all datasets.

## 1. Discussion and Conclusion

In this paper [6], we presented DEGARI: an explainable AI system relying on the $\mathbf{T}^{\textsf{CL}}$ Description Logics and on the ArsEmotica knowledge base to generate, according to Plutchik's theory of emotion, compound emotional concepts starting from the basic ones. Such newly created categories, characterized by lexicon-based typical features, are then used in DEGARI to reclassify, in an emotional settings, the items of three different datasets. The novelty of this system relies on the fact that DEGARI is, to the best of our knowledge, the first emotion-oriented system employing a white box approach to emotion classification based on the human-like conceptual combination framework proposed in the $\mathbf{T}^{\textsf{CL}}$ logic. The explainability requirement comes for free as a consequence of this logic-based approach.

Overall, the white box approach proposed by DEGARI for emotionally-driven content reclassification could be useful for addressing the very well known filter bubble effect [7] in recommender systems, by introducing seeds of serendipity in content discovery by users. One fundamental discussion about the applicability of DEGARI in practice is whether or not it represents a truly innovative technical solution for an emotion-based recommender system. According to Sohail et al. [9], recommender systems "try to identify the need and preferences of users, filter the huge collection of data accordingly and present the best suited option before the users by using some well-defined mechanism". Despite the huge amount of proposals, the main families of recommender systems can be identified as based on: i) collaborative filtering; ii) content-based filtering; iii) hybrid filtering. At their core of functioning, collaborative filtering exploits similarities of usage patterns among mutually affine users, while content-based filtering exploits content similarity. DEGARI by definition falls into the latter category since in its current form it uses content description (obtained in different ways) as the input. From the technical point of view, however, it differs from the current mainstream approaches that are mostly based on the comparison and matching of visual and perceptual features of the content [10, 2]. In practice, our approach adds a logic layer capable of mapping and representing - in a commonsense and cognitively compliant fashion [3] - new emotional categories which can be used to affect user preferences and content consumption in a way that cannot be derived from the pure statistical analysis of content and/or the comparison of similar users. Moreover, the proposed approach has been applied to a well-known model, the Plutchik circumplex model of emotions [8] and to two different emotional lexica (NRC and Shaver's), but could in principle be applied to other models which organize emotions by similarity, opposition and composition, such as for example the extended version of the Hourglass model used in SenticNet [11]. Being independent from the specific application model and type of expression, this approach can work effectively in different domains, as shown by its use on the datasets of artworks and media illustrated in this paper. In this sense, it can promote the interoperability of affective annotations and the cross-domain reuse of techniques and methods.

In the future work, we plan to extend the evaluation currently conducted in the form of a user study to a large scale one to further validate the effectiveness of the proposed approach. We also plan to extend the applications of this system to different domains. A first extension will be in the field of the emotional-oriented recommendation of artworks within Museums and cultural heritage sites (this is a work currently under development within the H2020 European SPICE project[1]). In addition, also the field of music recommendation represents a current area of investigation.

Finally, as mentioned, we plan to improve the provided recommendations by justifying the content reclassification (and the derived recommendations) based on the probabilistic ranks assigned to the shared features between the generated emotion and the items being reclassified.

[1] https://spice-h2020.eu/

## References

[1] Chiodino, E., Luccio, D. D., Lieto, A., Messina, A., Pozzato, G. L., and Rubinetti, D. (2020). A knowledge-based system for the dynamic generation and classification of novel contents in multimedia broadcasting. In Giacomo, G. D., Catalá, A., Dilkina, B., Milano, M., Barro, S., Bugarín, A., and Lang, J., editors, *Proceedings of ECAI 2020 - 24th European Conference on Artificial Intelligence, 29 August-8 September 2020, Santiago de Compostela, Spain, 2020*, volume 325 of *Frontiers in Artificial Intelligence and Applications*, pages 680–687. IOS Press.

[2] Deldjoo, Y., Constantin, M. G., Eghbal-Zadeh, H., Ionescu, B., Schedl, M., and Cremonesi, P. (2018). Audio-visual encoding of multimedia content for enhancing movie recommendations. In Pera, S., Ekstrand, M. D., Amatriain, X., and O'Donovan, J., editors, *Proceedings of the 12th ACM Conference on Recommender Systems, RecSys 2018, Vancouver, BC, Canada, October 2-7, 2018*, pages 455–459. ACM.

[3] Lieto, A. (2021). *Cognitive Design for Artificial Minds*. Routledge.

[4] Lieto, A., Perrone, F., Pozzato, G. L., and Chiodino, E. (2019). Beyond subgoaling: A dynamic knowledge generation framework for creative problem solving in cognitive architectures. *Cognitive Systems Research*, 58:305–316.

[5] Lieto, A. and Pozzato, G. L. (2020). A description logic framework for commonsense conceptual combination integrating typicality, probabilities and cognitive heuristics. *Journal of Experimental & Theoretical Artificial Intelligence*, 32(5):769–804.

[6] Lieto, A., Pozzato, G. L., Zoia, S., Patti, V., and Damiano, R. (2021). A commonsense reasoning framework for explanatory emotion attribution, generation and re-classification. *Knowledge-Based Systems*, page 107166.

[7] Parisier, E. (2012). *The Filter Bubble: What the Internet Is Hiding from You*. Penguin Books Limited.

[8] Plutchik, R. (1980). A general psychoevolutionary theory of emotion. In *Theories of emotion*, pages 3–33. Elsevier.

[9] Sohail, S. S., Siddiqui, J., and Ali, R. (2017). Classifications of recommender systems: A review. *Engineering Science and Technology Review*, 10(4):132–153.

[10] Sun, M. S., Li, F., and Zhang, J. (2018). A multi-modality deep network for cold-start recommendation. *Big Data and Cognitive Computing*, 2(7).

[11] Susanto, Y., Livingstone, A. G., Ng, B. C., and Cambria, E. (2020). The hourglass model revisited. *IEEE Intelligent Systems*, 35(5):96–102.