Sentiment Analysis of Primary Historical Sources

Andrea Nanetti
School of Arts, Design, and Media
Nanyang Technological University
Singapore
andrea.nanetti@ntu.edu.sg

John Pavlopoulos
Department of Informatics
Athens University of Economics and Business, Greece
ioannis@dsv.su.se

Erik Cambria
School of Computer Science and Engineering
Nanyang Technological University
Singapore
cambria@ntu.edu.sg

***Abstract*—Sentiment analysis is a research area that has experienced considerable growth over the last decade. The scope of sentiment analysis is to extract feelings, opinions, and emotions from text. This paper employs state-of-the-art multilingual sentiment analysis algorithms in the field of primary historical sources to assist historians in discovering new insights. In particular, we use Sentic APIs, a neurosymbolic AI toolkit, to process the travel accounts of Ibn Battuta (in Arabic), Marco Polo (in Italian), and Ma Huan (in Chinese), available in the Engineering Historical Memory web application. Results show that sentiment analysis can be a powerful tool for historians and researchers to extract valuable insights from historical resources, shedding light on the emotions, opinions, and societal changes that shaped the past.**

***Index Terms*—Primary Historical Sources, Digital History, Sentiment Analysis, Ibn Battuta, Ma Huan, Marco Polo**

I. Introduction

One of the central challenges of natural language processing (NLP) systems is to derive essential insights from a wide variety of written materials. Contributing sources for a training dataset for a new NLP algorithm could be as linguistically diverse as Twitter, broadsheet newspapers, and scientific journals, with all the appellant eccentricities unique to each of just those three sources. When an NLP algorithm has to consider material that comes from multiple eras, it typically struggles to reconcile the very different ways that people speak or write across national and sub-national communities, and especially across different periods in history[1]. Yet, using primary historical sources (PHSs) that straddles epochs is a potentially useful method of generating a historical oversight of a topic. This paper presents a preliminary exploration about applying sentiment analysis to historical texts, using PHSs published by the international initiative Engineering Historical Memory [1] (EHM)[2].

Sentiment analysis concerns the development and application of algorithms and tools for the extraction and analysis of subjective information [2], including not only opinions and attitudes [3], but also emotions [4] and other affective states of the creator [5] or the receivers [6] of a text or other modalities [7]. As mentioned above, the already challenging task of automatically extracting such subjective information becomes even more demanding when the sources of the material under investigation are historical or ancient.

[1]https://tinyurl.com/historical-language-and-ai
[2]https://engineeringhistoricalmemory.com

Linguistic expressions may diverge significantly compared to modern forms, which makes the translated versions of the original material noisy. In the absence of sentiment annotations on the original material, however, this becomes necessary. For example, ancient Chinese literature went through its translation to modern Chinese, in order to classify sentiment [8]. Similarly, a Modern Greek translation of the ancient Homeric text was used for the annotation of sentiment polarity and emotions [6]. Although a modern language is expected to be close to its ancient variant, which motivates the methodology in the previous two examples, researchers have also opted for paths that disregard this assumption, as for example the classification of sentiment in Aeschylus's ancient Greek tragedies by using English translations [9].

The significance of sentiment analysis for PHSs lies in its ability to provide valuable insights into the emotions, attitudes, and opinions of people during a specific time period. This can help historians and researchers better understand the social and cultural context of a given time period and how it may have influenced events and outcomes.

In this work, we leverage SenticNet [10], a commonsense knowledge base for multilingual sentiment analysis, to analyze PHSs written in different languages or from different cultural contexts. There are several limitations of past sentiment analysis work that SenticNet is designed to address, including detecting the subjectivity of text, which can make it difficult to identify sentiment accurately and consistently in text. SenticNet addresses this limitation by providing a structured representation of commonsense concepts and their affective meanings, which can help algorithms better understand and interpret the context and meaning of words and expressions in text.

Finally, cultural, and linguistic differences can be a challenge for sentiment analysis algorithms [11], [12]. SenticNet is designed to be cross-lingual and culturally sensitive, with affective meanings for a large number of concepts in multiple languages. This can help algorithms better understand and interpret sentiment in text written in different languages and cultural contexts. Overall, SenticNet is designed to address several limitations of past sentiment analysis work, including the subjectivity of sentiment analysis, the complexity of language, the limited availability and quality of annotated datasets, cultural and linguistic differences, explainability and interpretability [13].

2375-9259/23/$31.00 ©2023 IEEE
DOI 10.1109/ICDMW60847.2023.00104

The key motivation for researching sentiment analysis on PHSs is to use computers to analyze large amounts of text and extract insights for historians. Sentiment analysis algorithms can quickly and accurately process large amounts of text, identifying patterns and trends in sentiment and providing valuable insights without the need for manual analysis. By using sentiment analysis, researchers can save time and effort, and focus on interpreting and contextualizing the insights identified by the algorithms to gain a more comprehensive understanding of the attitudes and emotions of people during a specific time period.

The remainder of this paper is organized as follows: Section II introduces related works; Section III describes our methodology; Section IV discusses results; finally, Section V offers concluding remarks.

II. Related Works

Sentiment analysis is an NLP field in which computational methods are leveraged to determine the polarity or emotional tone expressed in a piece of text [14]. Different AI techniques have been leveraged to improve both accuracy and interpretability of sentiment analysis algorithms, including symbolic AI [15], [16], subsymbolic AI [17], [18], and neurosymbolic AI [19], [20]. Besides traditional algorithms focusing on English text, multilingual [21], [22] and multimodal [23], [24] sentiment analysis have also attracted increasing attention recently. Typical applications of sentiment analysis include social network analysis [25], finance [26], and healthcare [27]. However, the field of historical sources has been largely left unexplored.

Sprugnoli et al. [28] integrated sentiment analysis into ALCIDE, an online platform for historical context analysis using a prior polarity lexicon-based approach to discover the opinion about a topic and how it changes over time. The authors found that sentiment analysis presents a valuable utility within the domain of historical text information retrieval, offering scholars the means to quantitatively assess the prevailing emotional tone within individual historical documents. This analytical technique also facilitates the examination of evolving attitudes towards particular subjects or entities across an extensive corpus of texts over time, enabling precise sentiment-based searches within the historical record.

Koncar et al. [29] analyzed sentiment analysis on 18th century texts. This study reveals notable distinctions in the average sentiment expressed within spectator periodicals across five languages: Spanish consistently exhibits a more negative sentiment, while Italian and French periodicals tend to convey a more positive sentiment. The authors also conducted an analysis of the top 50 most central words based on degree, betweenness, and closeness centrality in each language. Interestingly, in Italian and Spanish, the majority of these central words convey a positive sentiment, whereas in French, German, and Portuguese, they tend to convey a negative sentiment across all centrality metrics.

Furthermore, the research delves into biases in semantic relationships among words with similar sentiments, highlighting the influence of cultural factors on the treatment of significant issues. It is important to note that the scope of sentiment analysis is vast, and previous efforts in historical text analysis have primarily focused on a limited range of sentiment dimensions. While these studies have provided valuable insights, there remains significant untapped potential in expanding the dimensions of sentiment analysis within historical texts.

III. Methodology

We chose three PHSs from the EHM database, namely: Ibn Battuta (Arabic), Marco Polo (Italian), and Ma Huan (Chinese). Ma Huan is a historical account written in an objective format, whereas Marco Polo is a historical account written with some level of subjectivity. Ibn Battuta's text is somewhere in the middle, leaning more towards objectivity.

In this work, we use Sentic APIs[3], a suite of application programming interfaces, which employ neurosymbolic AI to perform various sentiment analysis tasks in a fully interpretable manner (Fig. 1). A short description of each API and its usage within this work is provided in the next 8 subsections.

A. Concept Parsing

This API provides access to Sentic Parser [30], a knowledge-specific concept parser based on SenticNet [10], which leverages both inflectional and derivational morphology for the efficient extraction and generalization of affective multiword expressions from English text. In particular, Sentic Parser is a hybrid semantic parser that uses an ensemble of constituency and dependency parsing and a mix of stemming and lemmatization to extract 'semantic atoms' like pain_killer, go_bananas, or get_along_with, which would carry different meaning and polarity if broken down into single words. We use the API for extracting words and multiword expressions from text in order to better understand what are the key concepts related to each of the three PHSs. As shown in Fig. 1, for example, concepts extracted are king, galley, fit_out, brother, legate, and honor.

B. Subjectivity Detection

Subjectivity detection is an important NLP task that aims to filter out 'factual' content from data, i.e., objective text that does not contain any opinion. This API leverages a knowledge-sharing-based multitask learning framework powered by a neural tensor network, which consists of a bilinear tensor layer that links different entity vectors [31]. We used the API to classify a PHS text as either objective (unopinionated) or subjective (opinionated) but also to handle neutrality, that is, a text that is opinionated but neither positive nor negative (ambivalent stance towards the opinion target).

[3]https://sentic.net/api

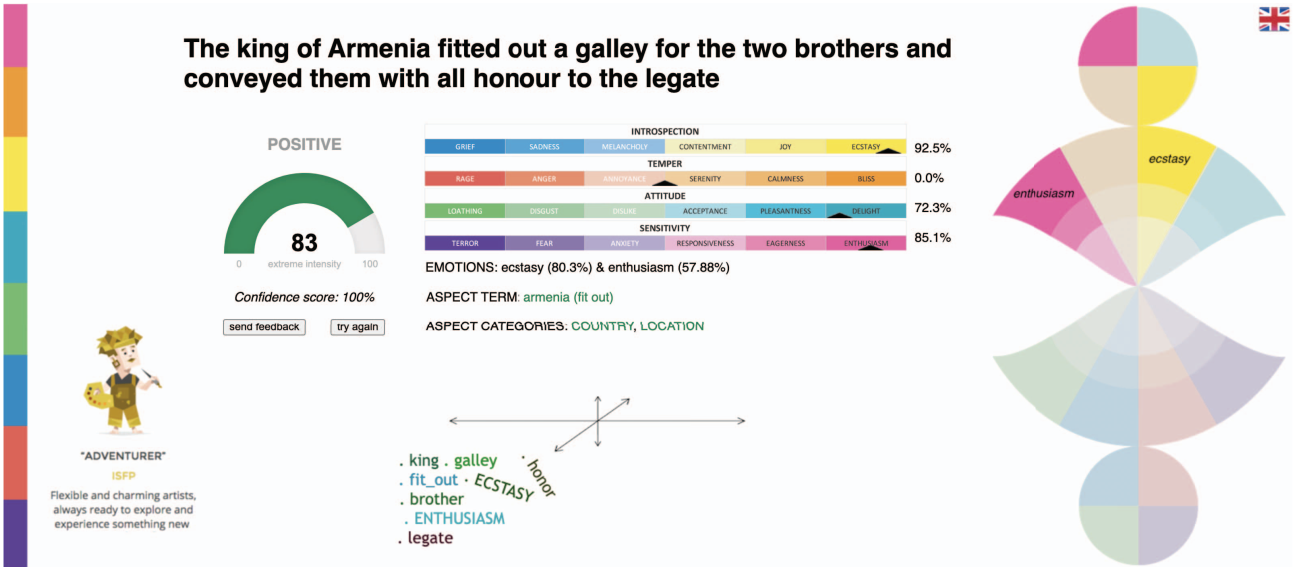

Fig. 1. A sample Sentic API output visualization in English.

C. Polarity Classification

Once an opinionated text is detected using the *Subjectivity Detection API*, the *Polarity Classification API* further categorizes this text as either positive or negative. This is one of the most important APIs we use to understand the stance of each of the three PHS authors towards different topics. It leverages an explainable fine-grained multiclass sentiment analysis method [32], which involves a multi-level modular structure designed to mimic natural language understanding processes, e.g., ambivalence handling process, sentiment strength handling process, etc. As shown in Fig. 1, for example, the extracted polarity is POSITIVE.

D. Intensity Ranking

For a finer-grained analysis, we further process PHSs classified by the *Polarity Classification API* using the *Intensity Ranking API* to infer their degree of negativity (floating-point number between -100 and 0) or positivity (floating-point number between 0 and 100). In particular, the API leverages a stacked ensemble method for predicting sentiment intensity by combining the outputs obtained from several deep learning and classical feature-based models using a multi-layer perceptron network [33]. As shown in Fig. 1, for example, the extracted polarity is 83 (extreme intensity).

E. Emotion Recognition

This API employs the Hourglass of Emotions [34], a biologically-inspired and psychologically-motivated emotion categorization model, that represents affective states both through labels and through four independent but concomitant affective dimensions, which can potentially describe the full range of emotional experiences that are rooted in any of us (Fig. 2). We use the API to go beyond polarity and intensity by examining what are the specific emotions conveyed through each PHS. As shown in Fig. 1, for example, the emotion spectrum of the input is visualized in terms of the Hourglass Model's affective dimensions, namely: +92.5% Introspection, +85.1% Attitude, and +72.3% Sensitivity. From these, the API also extracts the two top resulting emotion labels, ecstasy and enthusiasm, with an intensity of 80.3% and 57.88%, respectively.

F. Aspect Extraction

This API uses a meta-based self-training method that leverages both symbolic representations and subsymbolic learning for extracting aspects from text [35]. We use the API to better understand each PHS in terms of subtopics or opinion targets. Instead of simply identifying a polarity associated with the whole text, the *Aspect Extraction API* deconstructs input text into a series of specific aspects or features to then associate a polarity to each of them. This is particularly useful to process antithetic PHS texts, e.g., sentences in which the author lists pros and cons about a specific topic. As shown in Fig. 1, for example, the aspect term extracted is armenia, which belongs to the aspect categories COUNTRY and LOCATION.

G. Personality Prediction

This API uses a novel hard negative sampling strategy for zero-shot personality trait prediction from text using both OCEAN and MBTI models. In particular, the API leverages an interpretable variational autoencoder sampler, to pair clauses under different relations as positive and hard negative samples, and a contrastive structured constraint, to disperse the paired samples in a semantic vector space [36]. We use the API to study the different personalities and personas involved in each PHS narrative. As shown in Fig. 1, for example, the MBTI personality extracted is ISFP (Introversion, Sensing, Feeling, and Perceiving).

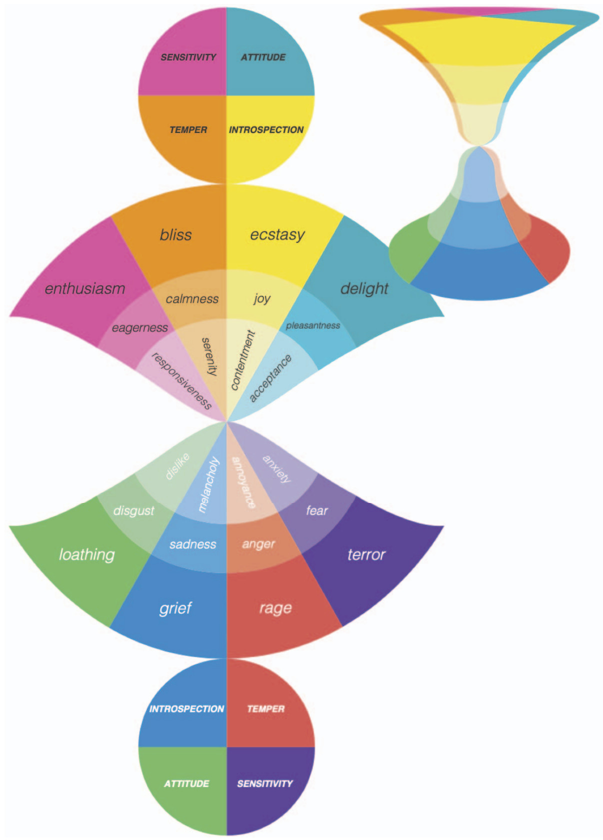

Fig. 2. The Hourglass of Emotions.

H. Sarcasm Identification

This API combines commonsense knowledge and semantic similarity detection methods to better detect and process sarcasm in text. It also employs a contrastive learning approach with triplet loss to optimize the spatial distribution of sarcastic and non-sarcastic sample features [7]. We use the API to understand how much each PHS narrative is subject to satire and critique but also to increase the accuracy and reliability of the *Polarity Classification API*. As sarcasm often involves expressing a sentiment that is opposite to the intended emotion, in fact, it may lead to polarity misclassification and, hence, generate wrong insights and conclusions.

IV. Results

Data cleaning had to be performed on texts with special characters. The digital texts were stored in an Excel file and data cleaning was performed with Python using different libraries. For example, the *HTMLParser* library was employed to strip the html tags associated with some of the data in the PHS text, particularly Ma Huan's, as well as the API output.

The *Concept Parsing API* enabled us to discover what are the key topics related to each PHS. Below are some of the most frequent concepts (words and multiword expressions) parsed from Ibn Battuta (translated from Arabic to English).

- geography
- islamic_culture
- governance
- politics
- trade
- commerce
- cultural_diversity
- religion
- travel_experiences
- customs_and_traditions
- language
- mode_of_transportation
- accommodations
- challenges_of_travel
- economic_conditions
- natural_world
- architecture
- monuments
- islamic_scholarship
- social_life

These, instead, are the most frequent concepts extracted from Marco Polo (translated from Italian to English).

- silk_road
- trade
- chinese_culture
- geography
- religion
- kublai_khan
- mongol_empire
- yuan_dynasty
- travel_experiences
- adventures
- court_life
- exploration
- economic_activities
- commodities
- routes_and_navigation
- different_cultures
- customs_and_traditions
- language
- historical_events
- natural_world

Finally, below are the most frequent concepts parsed from Ma Huan (translated from Chinese to English).

- maritime_expeditions
- indian_ocean_trade
- southeast_asia
- different_cultures
- ming_dynasty
- spread_of_islam
- muslim_communities
- geography
- maritime_technology
- shipbuilding
- ports
- language
- political_systems
- diplomatic_relations
- commodities_traded
- treasure_fleet
- voyages
- societal_observations
- religious_practices
- exploration

Through the use of the other APIs, we realized that the two predominant emotions among all PHSs were 'enthusiasm' and 'ecstasy', while the most common MBTI personality type associated to most of the writings was ISFP. Moreover, the *Subjectivity Detection API*, showed that Ma Huan and Ibn Battuta's PHSs are written in a historical narrative format (mostly objective statements) while Marco Polo's writing are more prone to personal opinion (mostly subjective statements). Finally, the *Aspect Extraction API* helped us individuate the key aspects shared by the PHSs of Ibn Battuta, Marco Polo, and Ma Huan. We list the 10 most frequent ones below along with a short elucubration on why such aspects emerged from PHS texts as the most prominent.

- `Travel`: All three travelers embarked on extensive journeys that took them to various parts of the known world. They covered vast distances and explored regions far from their places of origin.
- `Culture`: They offered detailed descriptions of the cultures, customs, traditions, and ways of life of the people they encountered.

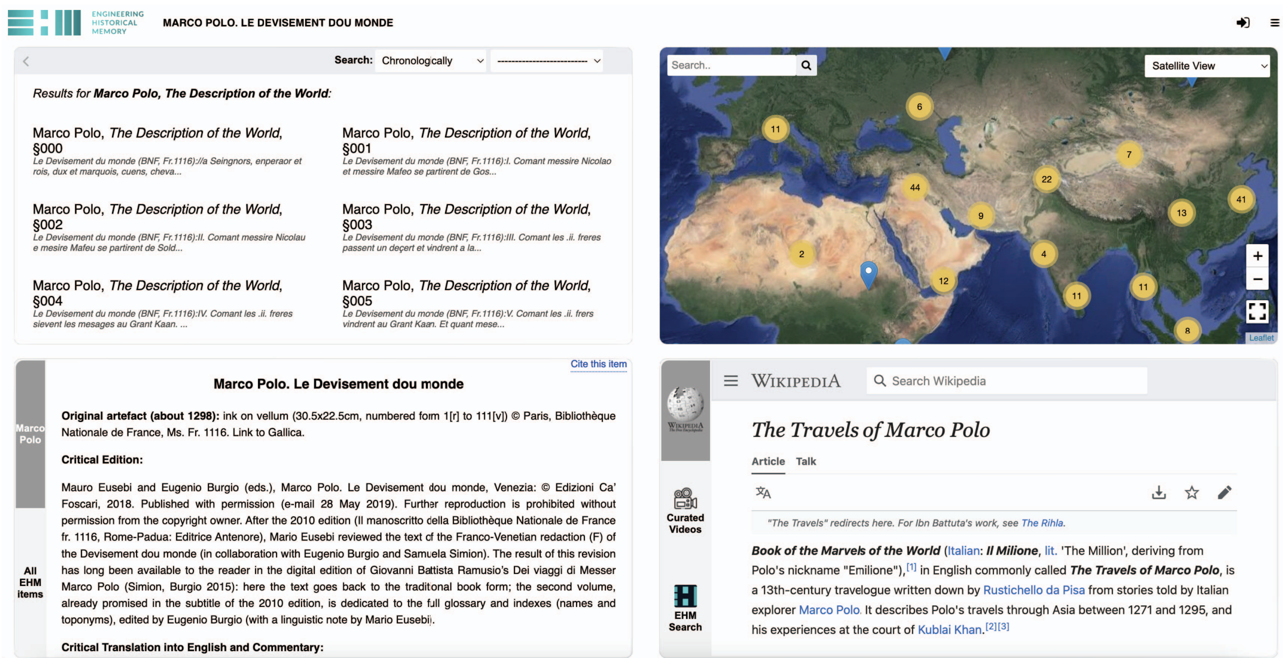

Fig. 3. A sample EHM output visualization.

- `Trade`: Their travels frequently intersected with major trade routes and commercial centers, and they wrote about the economic activities, commodities, and trade networks they encountered.
- `Governance`: Ibn Battuta, Marco Polo, and Ma Huan had interactions with rulers and members of royal courts during their journeys. They provided insights into the political systems, governance, and diplomacy of the regions they visited.
- `Religion`: Religion played a significant role in their travels. They commented on religious practices, the spread of Islam (in the case of Ibn Battuta and Ma Huan), and the religious diversity they encountered.
- `Geography`: All three travelers provided geographical descriptions of the places they visited, including landmarks, landscapes, and geographical features.
- `Food`: They often described local cuisines and food customs in the places they visited, providing insights into the culinary diversity of the regions they explored.
- `Architecture`: All travelers had an interest in architecture and frequently described mosques, palaces, and other significant buildings and monuments they encountered.
- `Society`: They documented the social structures, class systems, and economic conditions in the places they visited, shedding light on the daily lives of the people they encountered.
- `Nature`: All three travelers also mentioned the flora and fauna they encountered during their travels, offering observations on the natural world.

V. Conclusion

In this work, we employed multilingual sentiment analysis in the field of primary historical sources to assist historians in discovering new insights. In particular, we used Sentic APIs, a neurosymbolic AI toolkit, to process the travel accounts of Ibn Battuta (in Arabic), Marco Polo (in Italian), and Ma Huan (in Chinese) and integrated results into the Engineering Historical Memory web-based application (Fig. 3). Results show that sentiment analysis can be a powerful tool for historians and researchers to extract valuable insights from historical resources, shedding light on the emotions, opinions, and societal changes that shaped the past. It complements traditional historical research methods by providing a quantitative and data-driven perspective on history.

Acknowledgments

This research project is supported by the Ministry of Education, Singapore, under its Academic Research Fund Tier 1 (2023-2026, RT20/22, Technical challenges, linguistic obstacles, and cultural barriers in bringing knowledge societies into the metaverse. With a metaverse showcase of how the peoples of Afro-Eurasia saw each other transitioning into modernity; PI, Andrea Nanetti). The authors would like to thank Yue Jie Alphaeus Ng (student at NTU School of Computer Science and Engineering at the time of this investigation) for collecting, cleaning and processing some of the data related to this work and for the development of the EHM web application.

References

[1] A. Nanetti, *Computational Engineering of Historical Memories. With a Showcase on Afro-Eurasia (ca 1100-1500 CE).* Routledge, 2023.

[2] D. Rajagopal, E. Cambria, D. Olsher, and K. Kwok, "A graph-based approach to commonsense concept extraction and semantic similarity detection," in *WWW*, 2013, pp. 565–570.

[3] C. Duong, Q. Liu, R. Mao, and E. Cambria, "Saving earth one tweet at a time through the lens of artificial intelligence," in *2022 International Joint Conference on Neural Networks (IJCNN)*, Padua, Italy, 2022, pp. 1–9.

[4] W. Li, L. Zhu, R. Mao, and E. Cambria, "SKIER: A symbolic knowledge integrated model for conversational emotion recognition," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 37, no. 11, pp. 13 121–13 129, 2023.

[5] S. Han, R. Mao, and E. Cambria, "Hierarchical attention network for explainable depression detection on Twitter aided by metaphor concept mappings," in *Proceedings of the 29th International Conference on Computational Linguistics (COLING)*, 2022, pp. 94–104.

[6] J. Pavlopoulos, A. Xenos, and D. Picca, "Sentiment analysis of Homeric text: The 1st book of iliad," in *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, 2022, pp. 7071–7077.

[7] T. Yue, R. Mao, H. Wang, Z. Hu, and E. Cambria, "KnowleNet: Knowledge fusion network for multimodal sarcasm detection," *Information Fusion*, vol. 100, p. 101921, 2023.

[8] H. Zhao, B. Wu, H. Wang, and C. Shi, "Sentiment analysis based on transfer learning for Chinese ancient literature," in *2014 International Conference on Behavioral, Economic, and Socio-Cultural Computing (BESC2014).* IEEE, 2014, pp. 1–7.

[9] V. K. Yeruva, M. Chandrashekar, Y. Lee, J. Rydberg-Cox, V. Blanton, and N. A. Oyler, "Interpretation of sentiment analysis in aeschylus's Greek tragedy," in *Proceedings of the 4th Joint SIGHUM Workshop on Computational Linguistics for Cultural Heritage, Social Sciences, Humanities and Literature*, 2020, pp. 138–146.

[10] E. Cambria, Q. Liu, S. Decherchi, F. Xing, and K. Kwok, "SenticNet 7: A commonsense-based neurosymbolic AI framework for explainable sentiment analysis," in *LREC*, 2022, pp. 3829–3839.

[11] R. Mao, C. Lin, and F. Guerin, "Word embedding and WordNet based metaphor identification and interpretation," in *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (ACL)*, vol. 1, 2018, pp. 1222–1231.

[12] R. Mao, X. Li, M. Ge, and E. Cambria, "MetaPro: A computational metaphor processing model for text pre-processing," *Information Fusion*, vol. 86-87, pp. 30–43, 2022.

[13] E. Cambria, R. Mao, M. Chen, Z. Wang, and S.-B. Ho, "Seven pillars for the future of AI," *IEEE Intelligent Systems*, vol. 38, no. 6, 2023.

[14] L. Oneto, F. Bisio, E. Cambria, and D. Anguita, "Statistical learning theory and ELM for big social data analysis," *IEEE Computational Intelligence Magazine*, vol. 11, no. 3, pp. 45–55, 2016.

[15] E. Cambria, A. Hussain, C. Havasi, and C. Eckl, "Common sense computing: From the society of mind to digital intuition and beyond," in *Biometric ID Management and Multimodal Communication*, ser. Lecture Notes in Computer Science. Berlin Heidelberg: Springer, 2009, vol. 5707, pp. 252–259.

[16] F. Xing, F. Pallucchini, and E. Cambria, "Cognitive-inspired domain adaptation of sentiment lexicons," *Information Processing and Management*, vol. 56, no. 3, pp. 554–564, 2019.

[17] E. Cambria, T. Mazzocco, A. Hussain, and C. Eckl, "Sentic medoids: Organizing affective common sense knowledge in a multi-dimensional vector space," ser. Lecture Notes in Computer Science. Berlin Heidelberg: Springer-Verlag, 2011, vol. 6677, pp. 601–610.

[18] E. Cambria, B. Schuller, B. Liu, H. Wang, and C. Havasi, "Statistical approaches to concept-level sentiment analysis," *IEEE Intelligent Systems*, vol. 28, no. 3, pp. 6–9, 2013.

[19] A. Valdivia, V. Luzón, E. Cambria, and F. Herrera, "Consensus vote models for detecting and filtering neutrality in sentiment analysis," *Information Fusion*, vol. 44, pp. 126–135, 2018.

[20] H. T. Nguyen, P. H. Duong, and E. Cambria, "Learning short-text semantic similarity with word embeddings and external knowledge sources," *Knowledge-Based Systems*, vol. 182, no. 104842, 2019.

[21] D. Vilares, H. Peng, R. Satapathy, and E. Cambria, "BabelSenticNet: A commonsense reasoning framework for multilingual sentiment analysis," in *IEEE SSCI*, 2018, pp. 1292–1298.

[22] H. Peng, Y. Ma, S. Poria, Y. Li, and E. Cambria, "Phonetic-enriched text representation for chinese sentiment analysis with reinforcement learning," *Information Fusion*, vol. 70, pp. 88–99, 2021.

[23] E. Cambria, N. Howard, J. Hsu, and A. Hussain, "Sentic blending: Scalable multimodal fusion for continuous interpretation of semantics and sentics," in *IEEE SSCI*, Singapore, 2013, pp. 108–117.

[24] L. Stappen, A. Baird, E. Cambria, and B. Schuller, "Sentiment analysis and topic recognition in video transcriptions," *IEEE Intelligent Systems*, vol. 36, no. 2, pp. 88–95, 2021.

[25] S. Cavallari, E. Cambria, H. Cai, K. Chang, and V. Zheng, "Embedding both finite and infinite communities on graph," *IEEE Computational Intelligence Magazine*, vol. 14, no. 3, pp. 39–50, 2019.

[26] F. Xing, E. Cambria, and R. Welsch, "Intelligent asset allocation via market sentiment views," *IEEE Computational Intelligence Magazine*, vol. 13, no. 4, pp. 25–34, 2018.

[27] E. Cambria, T. Benson, C. Eckl, and A. Hussain, "Sentic PROMs: Application of sentic computing to the development of a novel unified framework for measuring health-care quality," *Expert Systems with Applications*, vol. 39, no. 12, pp. 10 533–10 543, 2012.

[28] R. Sprugnoli, S. Tonelli, A. Marchetti, and G. Moretti, "Towards sentiment analysis for historical texts," *Digital Scholarship in the Humanities*, vol. 31, no. 4, pp. 762–772, 2016.

[29] P. Koncar, A. Fuchs, E. Hobisch, B. C. Geiger, M. Scholger, and D. Helic, "Text sentiment in the age of enlightenment: an analysis of spectator periodicals," *Applied Network Science*, vol. 5, pp. 1–32, 2020.

[30] E. Cambria, R. Mao, S. Han, and Q. Liu, "Sentic parser: A graph-based approach to concept extraction for sentiment analysis," in *Proceedings of ICDM Workshops*, 2022, pp. 413–420.

[31] R. Satapathy, S. Rajesh Pardeshi, and E. Cambria, "Polarity and subjectivity detection with multitask learning and bert embedding," *Future Internet*, vol. 14, no. 7, p. 191, 2022.

[32] Z. Wang, Z. Hu, S.-B. Ho, E. Cambria, and A.-H. Tan, "MiMuSA—Mimicking human language understanding for fine-grained multi-class sentiment analysis," *Neural Computing and Applications*, vol. 35, no. 21, pp. 15 907–15 921, 2023.

[33] M. S. Akhtar, A. Ekbal, and E. Cambria, "How intense are you? predicting intensities of emotions and sentiments using stacked ensemble," *IEEE Computational Intelligence Magazine*, vol. 15, no. 1, pp. 64–75, 2020.

[34] Y. Susanto, A. Livingstone, B. C. Ng, and E. Cambria, "The Hourglass Model revisited," *IEEE Intelligent Systems*, vol. 35, no. 5, pp. 96–102, 2020.

[35] K. He, R. Mao, T. Gong, C. Li, and E. Cambria, "Meta-based self-training and re-weighting for aspect-based sentiment analysis," *IEEE Transactions on Affective Computing*, vol. 15, 2024.

[36] L. Zhu, W. Li, R. Mao, V. Pandelea, and E. Cambria, "PAED: Zero-shot persona attribute extraction in dialogues," in *ACL*, 2023, pp. 9771–9787.