Applied Soft Computing 118 (2022) 108246

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Editorial

Soft computing for recommender systems and sentiment analysis

1. Introduction

The World Wide Web is becoming a bottomless source of unstructured data, with quintillions of bytes of data generated daily and publicly accessible [1]. Social media, customer reviews, and online news articles, as well as the comments associated with them, are just some examples of what the Internet is producing in terms of text data. Text data is usually not standalone like digitalized books, but associated with a lot of information about user behaviors and preferences. This has led to a growing interest in the research of social media analysis and many applications, including sentiment analysis and recommender systems. Closely related to the two mentioned are other tasks, such as opinion retrieval, opinion summarization, subjectivity classification, sarcasm/irony detection and more.

We only see a strengthening trend of the online presence of text data bounded with our daily activities as we migrate to the metaverse. In such a world, sentiment analysis and recommender systems are really two sides of the same coin [2]: one about passively knowing about the users, the other about actively reaching to the users. The main of sentiment analysis is to understand the correct information from versatile expressions. The main challenge of recommender systems is to filter and transform busy online information streams into structured data that can be used for content push decisions.

These challenges are partially due to the huge volume of text data and its interaction with other dimensions [3]. For example, social media text data often represent implicit or explicit user feedback, expressed in different formats, such as star ratings and Facebook likes, and are collected from multiple sources. The multifaceted information allows for the development of new tools for recommending items according to aspects such as reputation, trustworthiness, credibility, fame, etc. Sentiment analysis itself involves many soft computing techniques, such as neural networks and fuzzy sentiment dimension. These computing methods have provided powerful tools for decision-making in different fields, including politics, marketing, and healthcare. Some sectors also provide ad-hoc functionalities like in the case of Stocktwits, in the context of financial markets, and LinkedIn, in the context of human resources.

In spite of the fact that the volume of text data is huge and complex, another important observation is that our language carries ambiguity, partial truth, and imprecision. Text data bears the same nature, which makes it difficult to be processed with hard computing. For this reason, different soft computing techniques, such as deep neural networks and (neuro-) fuzzy logic, have been increasingly adopted for natural language processing and understanding. Such techniques have gained increasing momentum in the past years, with a remarkable enhancement of their accuracy, and they have been sided by a boost in application-specific methodologies able to emulate the cognitive processes behind decision-making.

This Special Issue focuses on covering three scopes: (1) the combination of soft computing and natural language processing techniques, that is soft computing on text data, for the development of sentiment analysis and recommender systems; (2) the application of such sentiment analysis methods and recommender systems to social media mining and knowledge representation; and (3) reviews and surveys that summarize or compare soft computing methods used for sentiment analysis and recommender systems.

2. Contents of the special issue

We received 66 valid submissions in total for this special issue. After several rounds of rigorous reviews and revisions, we decided to publish 22 out of them, resulting in an acceptance rate of circa 32%.

The collection of 22 articles has a balanced weight with 12 of them focus on the application of recommender systems [4–14], and 9 of them focus on the application of sentiment analysis [15–23]. One paper "An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews" [24] is really a hybrid of both applications, which uses the result of sentiment analysis for hotel recommendation. Most of the articles feature research contibutions, except for 2 review papers [19,21]. Neural network models dominate the collection, but we are glad to see a good portion of other soft computing techniques studied, i.e., fuzzy logic [4,8,9,16,22] and heuristic algorithms [5,7,14].

The first article, "A linguistic multi-criteria decision making methodology for the evaluation of tourist services considering customer opinion value", by bueno et al. [25], presents employ different decision-making techniques for ranking hotels based on customer's reviews. The relevance of each user's comments are evaluated using three criteria: recency, frequency and helpfulness. The information about the user is collected on social networks and aggregated by means of a novel 2-tuple, multi granular, fuzzy linguistic approach. Finally, the method is evaluated through a case study, using reviews and metadata from Tripadvisor.

In the article "Predicting political sentiments of voters from Twitter in multi-party contexts", by Khatua et al. [15] employ

https://doi.org/10.1016/j.asoc.2021.108246

"mix-tweeting" patterns to learn voters' political leaning in a context where more than one party are mentioned. From a methodological standpoint, authors employ multi-nomial logit regression to test the hypothesized causal relation between "mix-tweeting" patterns and the political leaning of users, and neural network-based algorithms to predict political leaning.

In "A T1OWA and aspect-based model for customizing recommendations on eCommerce", Serrano-Guerrero et al. [4] propose a novel fuzzy aspect-based sentiment analysis approach to rank products based on the perspective of both the user who wrote the review and the recommendations' recipient. To this aim, authors employ a T1OWA-based mechanism to characterize the user profile, capturing the influence of positive and negative opinions on the user, a mechanism for determining their preferences, and a variation coefficient method for weighting the importance of the aspects of the product reviews.

"A metric for Filter Bubble measurement in recommender algorithms considering the news domain", by Lunardi et al. [5], proposed a KNN item-based recommendation with diversification approach for mitigating the filter bubble effect in recommendation systems. The effects of such an environment are tested in the users' exposition to fake news in the Brazilian presidential election of 2018.

Gang Sun et al. [6], in "Attention distribution guided information transfer networks for recommendation in practice", study the problem of User to Item (U2I) reviews in real-world settings, i.e., to extract user preferences together with their related item attributes from review texts. To do this, they propose a novel method, called ADGITIN, that learns two attention distributions, one over user reviews and one over item reviews, by auxiliary tasks. These two distributions are used to guide the learning of attention distributions between user reviews and item reviews of the main model.

The work by Bansal and Baliyan [7], "Bi-MARS: A Bi-clustering based Memetic Algorithm for Recommender Systems", discusses a novel Bi-clustering based Memetic Algorithm for Recommender Systems (Bi-MARS) based on the collaborative behavior of memes to discover the precise and localized neighborhood of the target user. Finally, the authors improve the similarity results among neighbors proposing a novel method for local search.

In the article "A product ranking method combining the features–opinion pairs mining and interval-valued Pythagorean fuzzy sets" Fu et al. [8] develop a ranking method that blends features opinion pairs mining and interval-valued pythagoric fuzzy (IVPF) sets to mine opinions from online reviews that are relevant for both consumers and producers. First, the authors extract the feature–opinion terms using two deep learning models. Second, they employ sentiment analysis to get the consumers' opinions. Finally, they use operators and operations derived from IVPF information to rank the products.

Camada et al. [16], in "Computational model for identifying stereotyped behaviors and determining the activation level of pseudo-autistic" proposed a method for autism diagnosis through the presence of stereotyped behaviors (SBs). The method is not limited to SBs detection but also intends to infer its activation level, to better suggest some therapeutic approaches. The authors employ classical machine learning approaches to recognize SBs, and propose a low intrusiveness model to infer activation levels from recognized SBs. Finally, the authors propose a metric to evaluate the performance of machine learning models based on the time needed to classify the SBs.

In "A fuzzy matrix factor recommendation method with forgetting function and user features", Chen et al. [9] develop a new recommendation model based on fuzzy matrix decomposition and trace norm minimization. The authors add a forget function to historical scores to make the algorithm more efficient; then, a user score is used to extract valuable suggestions. The convergence of the proposed algorithm is demonstrated theoretically and an extensive set of experiments is performed on synthetic and real-world datasets.

In "An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews", by Ray et al. [24], aspect-based based categorization of customer reviews and sentiment analysis are used to provide hotel recommendations with a high degree of personalization by users. To this aim, the authors employ a mixture of two models: a random forest with word embeddings as input features and an ensemble of BERT models. Then, reviews are categorized through fuzzy logic by several aspects. Eventually, an appropriate hotel, along with their reviews, is provided to the user based on his query.

Dezfouli et al. [10], in "Deep neural review text interaction for recommendation systems", present a novel recommender system, named MatchPyramid Recommender System (MPRSU), which computes a matching score for each user-item pair based on the text of the user's reviews and item description, respectively. The matching score is computed by feeding a Convolutional Neural Network (CNN) with a matching matrix composed of the cosine similarity of the vector representation of all the words in the two texts.

In "Analyzing the effectiveness of semi-supervised learning approaches for opinion spam classification", Ligthart et al. [17] studied the detection of opinion spam when labeled data is limited. The proposed self-training algorithm with Naive Bayes as the base classifier is less costly but yields a quite high accuracy of 93%.

In "Syntax-type-aware graph convolutional networks for natural language understanding", Du et al. [18] explored a new way of using syntactic information for Aspect-Based Sentiment Analysis (ABSA). The model encodes word dependency with gated Graph Convolutional Network (GCN) and can well incorporate BERT representations.

"User trustworthiness in online social networks: A systematic review" [19] is a survey article that focuses on the emerging challenges of anonymous attackers and malicious users on social media. The review analyzes eight years of research on solutions such as anti-spam protection, fake news detection, and rating the truthfulness of user-generated content.

"Stock trading rule discovery with double deep Q-network" [11] presents an end-to-end Double DQN model for financial time series analysis and the stock recommendation problem. The reinforcement learning-based model also takes into account the transaction cost in both training and testing phases.

In "Hybrid attention-based Long Short-Term Memory network for sarcasm identification", Pandey et al. [20] extend the attention mechanism for LSTM from a single type to a blend of many, handling different linguistic features. This new model improves the state-of-the-art models for sarcasm identification, which is an important component of the sentiment analysis suitcase [26].

Next, "Deep learning and multilingual sentiment analysis on social media data: An overview" by [21] surveys twenty-four research papers on multilingual sentiment analysis in the recent three years. The main observation is that the backbone model — comprising word embeddings, a feature extractor, and a classifier — is unable to maintain state-of-the-art results for more complex scenarios.

In "Building a fuzzy sentiment dimension for multidimensional analysis in social networks", Guti at al. [22] propose fuzzy logic-based sentiment analysis as a dimension of social network representation. As such, sentiment can be analyzed together with other dimensions, i.e., date and context, to provide good flexibility and supervision-free results.

In "Topic-level sentiment analysis of social media data using deep learning", Pathak et al. [23] described a method that can perform sentiment analysis at topic-level on streaming data. The method uses online latent semantic indexing to dynamically extract topics from the streaming data. Meanwhile, LSTM is used with a topic-level attention mechanism to classify the final sentiment result. The model is easy to scale up and does not need re-training when the topic distribution changes.

Collaborative filtering is probably the most widely-used framework for recommender systems. Neural networks can be used to model the features of users and items, as well as the user-item interaction information. We have two papers aiming at improving the network designs, i.e., "Collaborative filtering via factorized neural networks" and "Collaborative filtering via heterogeneous neural networks". The first paper proposes factorized neural network model (FNN) to significantly reduce the parameters required for deep learning-based collaborative filtering [12]; the second paper designs a network-in-network architecture with global layers and local neural blocks [13].

Finally, "Group article recommendation based on ER rule in Scientific Social Networks" [14] developed a model for research article recommendation for scientific communities. After individual recommendations are made, a graph is built based on the evidential reasoning (ER) rule to assist group aggregation. This method would lead to better communication and information dissemination on social platforms.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The guest editors are grateful to the support of Editor-in-Chief, Mario Köppen, as well as the help from many colleagues of the Elsevier production team. We would like to also take this opportunity to thank the many reviewers for their timely and insightful feedback on the submissions, which is indispensable for the review on some very popular research topics.

References

[1] M. Grassi, E. Cambria, A. Hussain, F. Piazza, Sentic web: A new paradigm for managing social media affective information, Cogn. Comput. 3 (3) (2011) 480–489.
[2] C. Angulo, Z. Falomir, D. Anguita, N. Agell, E. Cambria, Bridging cognitive models and recommender systems, Cogn. Comput. 12 (2) (2020) 426–427.
[3] E. Cambria, H. Wang, B. White, Guest editorial: Big social data analysis, Knowl.-Based Syst. 69 (2014) 1–2.
[4] J. Serrano-Guerrero, J.A. Olivas, F.P. Romero, A T1OWA and aspect-based model for customizing recommendations on eCommerce, Appl. Soft Comput. 97 (2020) 106768.
[5] G.M. Lunardi, G.M. Machado, V. Maran, J.P.M. de Oliveira, A metric for filter bubble measurement in recommender algorithms considering the news domain, Appl. Soft Comput. 97 (2020) 106771.
[6] G. Sun, Y. Li, H. Yu, V. Chang, Attention distribution guided information transfer networks for recommendation in practice, Appl. Soft Comput. 97 (2020) 106772.
[7] S. Bansal, N. Baliyan, Bi-MARS: a bi-clustering based memetic algorithm for recommender systems, Appl. Soft Comput. 97 (2020) 106785.
[8] X. Fu, T. Ouyang, Z. Yang, S. Liu, A product ranking method combining the features–opinion pairs mining and interval-valued Pythagorean fuzzy sets, Appl. Soft Comput. 97 (2020) 106803.
[9] J. Chen, Y. Lu, F. Shang, Y. Wang, A fuzzy matrix factor recommendation method with forgetting function and user features, Appl. Soft Comput. 100 (2021) 106910.
[10] P.A.B. Dezfouli, S. Momtazi, M. Dehghan, Deep neural review text interaction for recommendation systems, Appl. Soft Comput. 100 (2021) 106985.
[11] Y. Shi, W. Li, L. Zhu, K. Guo, E. Cambria, Stock trading rule discovery with double deep Q-network, Appl. Soft Comput. 107 (2021) 107320.
[12] X. Zhao, W. Zeng, Y. He, Collaborative filtering via factorized neural networks, Appl. Soft Comput. 109 (2021) 107484.
[13] W. Zeng, G. Fan, S. Sun, B. Geng, W. Wang, J. Li, W. Liu, Collaborative filtering via heterogeneous neural networks, Appl. Soft Comput. 109 (2021) 107516.
[14] G. Wang, H.-R. Wang, Y. Yang, D.-L. Xu, J.-B. Yang, F. Yue, Group article recommendation based on ER rule in Scientific Social Networks, Appl. Soft Comput. 110 (2021) 107631.
[15] A. Khatua, A. Khatua, E. Cambria, Predicting political sentiments of voters from Twitter in multi-party contexts, Appl. Soft Comput. 97 (2020) 106743.
[16] M.Y. Camada, J.J. Cerqueira, A.M. Lima, Computational model for identifying stereotyped behaviors and determining the activation level of pseudo-autistic, Appl. Soft Comput. 99 (2021) 106877.
[17] A. Ligthart, C. Catal, B. Tekinerdogan, Analyzing the effectiveness of semi-supervised learning approaches for opinion spam classification, Appl. Soft Comput. 101 (2021) 107023.
[18] C. Du, J. Wang, H. Sun, Q. Qi, J. Liao, Syntax-type-aware graph convolutional networks for natural language understanding, Appl. Soft Comput. 102 (2021) 107080.
[19] M. Alkhamees, S. Alsaleem, M. Al-Qurishi, M. Al-Rubaian, A. Hussain, User trustworthiness in online social networks: A systematic review, Appl. Soft Comput. 103 (2021) 107159.
[20] R. Pandey, A. Kumar, J.P. Singh, S. Tripathi, Hybrid attention-based long short-term memory network for sarcasm identification, Appl. Soft Comput. 106 (2021) 107348.
[21] M.M. Agüero-Torales, J.I. Abreu Salas, A.G. López-Herrera, Deep learning and multilingual sentiment analysis on social media data: An overview, Appl. Soft Comput. 107 (2021) 107373.
[22] K. Gutiérrez-Batista, M.-A. Vila, M.J. Martin-Bautista, Building a fuzzy sentiment dimension for multidimensional analysis in social networks, Appl. Soft Comput. 108 (2021) 107390.
[23] A.R. Pathak, M. Pandey, S. Rautaray, Topic-level sentiment analysis of social media data using deep learning, Appl. Soft Comput. 108 (2021) 107440.
[24] B. Ray, A. Garain, R. Sarkar, An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews, Appl. Soft Comput. 98 (2021) 106935.
[25] I. Bueno, R.A. Carrasco, C. Porcel, G. Kou, E. Herrera-Viedma, A linguistic multi-criteria decision making methodology for the evaluation of tourist services considering customer opinion value, Appl. Soft Comput. 101 (2021) 107045.
[26] E. Cambria, S. Poria, A. Gelbukh, M. Thelwall, Sentiment analysis is a big suitcase, IEEE Intell. Syst. 32 (6) (2017) 74–80.

Lorenzo Malandri
University of Milano Bicocca, Italy
CRISP Research Centre, University of Milano Bicocca, Italy

Carlos Porcel
University of Jaen, Spain

Frank Xing
National University of Singapore, Singapore

Jesus Serrano-Guerrero
University of Castilla-La Mancha, Spain

Erik Cambria
Nanyang Technological University, Singapore