A Decade of Sentic Computing

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1 Introduction

With the recent development of deep learning, research in artificial intelligence (AI) has gained new vigor and prominence. Machine learning, however, suffers from three big issues, namely:

1. Dependency: it requires (a lot of) training data and is domain-dependent;
2. Consistency: different training or tweaking leads to different results;
3. Transparency: the reasoning process is uninterpretable (black-box algorithms).

Sentic computing [1] addresses such issues in the context of natural language processing (NLP) through a multi-disciplinary approach that aims to bridge the gap between statistical NLP and many other disciplines that are necessary for understanding human language, such as linguistics, commonsense reasoning, semiotics, and affective computing. Sentic computing, whose term derives from the Latin sensus (as in commonsense) and sentire (root of words such as sentiment and sentience), enables the analysis of text not only at document, page or paragraph level, but also at sentence, clause, and concept level.

This is possible thanks to the fact that sentic computing is both top-down and bottom-up: top-down for the fact that it leverages symbolic models such as semantic networks and conceptual dependency representations to encode meaning; bottom-up because it uses sub-symbolic methods such as deep neural networks and multiple kernel learning to infer syntactic patterns from data.

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Coupling symbolic and sub-symbolic AI is key for stepping forward in the path from NLP to natural language understanding. Relying solely on machine learning, in fact, is simply useful to make a ‘good guess’ based on past experience, because sub-symbolic methods only encode correlation and their decision-making process is merely probabilistic. Natural language understanding, however, requires much more than that. To use Noam Chomsky’s words, “you do not get discoveries in the sciences by taking huge amounts of data, throwing them into a computer and doing statistical analysis of them; that’s not the way you understand things, you have to have theoretical insights”.

In the past ten years, sentic computing positioned itself as a horizontal technology that served as a back-end to many different applications in the areas of e-business, e-commerce, e-health, e-governance, e-security, e-learning, e-tourism, e-mobility, e-entertainment, and more. Some examples of such applications include financial forecasting [2], social media monitoring [3], marketing [4], and multimodal sentiment analysis [5].

In this light, this Cognitive Computation Special Issue focused on the introduction, presentation, and discussion of novel approaches that further develop and apply sentic computing models (such as the Hourglass of Emotions [6] and Sentic Patterns [7]), resources (such as AffectiveSpace [8] and SenticNet [9]), algorithms (such as Sentic LDA [10] and Sentic LSTM [11]), and applications (such as Sentic PROMs [12] and Sentic Album [13]).

2 Contents of the special issue

This special issue represents the inaugural issue for the Special Section of Cognitive Computation on Sentic Computing. We received 41 valid paper submissions. After several rounds of rigorous reviews and revisions, we decided to publish 18 of them in this special issue.

The first article, which was independently reviewed, is entitled “Ten Years of Sentic Computing” [14] and opens the special issue with an overview of sentic computing models, resources, algorithms and applications developed between 2010 and 2020. Additionally, Susanto et al. explain sentic computing’s key shifts and key tasks. Finally, they provide insights on future directions of the research field.

The second article, entitled “A Decade of Sentic Computing: Topic Modeling and Bibliometric Analysis” [15], also provides an overview of the development of sentic computing in the last ten years by combining bibliometric analysis and structural topic modeling. In particular, the work examines various aspects of sentic computing literature, including tendency of annual article count, top journals, countries/regions, institutions, authors, scientific collaborations between major contributors, as well as the major topics and their tendencies.

1 http://sentic.net/scs.pdf
Next, “An Ensemble Method for Radicalization and Hate Speech Detection Online Empowered by Sentic Computing” [16] proposes two novel feature extraction methods that use AffectiveSpace and SenticNet. In addition, this paper presents a machine learning framework using an ensemble of different features to improve the overall classification performance. Authors perform a thorough evaluation of the proposed features across five different datasets that cover radicalization and hate speech detection tasks.

The article “DomainSenticNet: An Ontology and a Methodology Enabling Domain-Aware Sentic Computing” [17] proposes an extension of the OntoSenticNet ontology, named DomainSenticNet, and contributes an unsupervised methodology to support the development of domain-aware Sentic applications. Authors developed an unsupervised methodology that, for each concept in OntoSenticNet, mines semantically related concepts from WordNet and Probase knowledge bases and computes domain distributional information from the entire collection of Kickstarter domain-specific crowdfunding campaigns.

In “An Effective Sarcasm Detection Approach Based on Sentimental Context and Individual Expression Habits” [18], the authors focus on the problem of detecting sarcastic content in social media. A dual-channel convolutional neural network is proposed that analyzes not only the semantics of the target text, but also its sentimental context. In addition, SenticNet is used to add commonsense to the LSTM model. The attention mechanism is then applied to take the user’s expression habits into account. A series of experiments were carried out on several public datasets, the results of which show that the proposed approach can significantly improve the performance of sarcasm detection tasks.

The paper “CAT-BiGRU: Convolution and Attention with Bi-Directional Gated Recurrent Unit for Self-Deprecating Sarcasm Detection” [19] also focuses on the problem of detecting sarcastic content. Authors propose a novel Convolution and Attention with Bi-directional Gated Recurrent Unit (CAT-BiGRU) model, which consists of an input, embedding, convolutional, BiGRU, and two attention layers. The efficacy of the proposed model is evaluated on two SenticNet-based sentic computing resources: Amazon word embedding and AffectiveSpace. The experimental results are significantly better than many neural network-based baselines and state-of-the-art methods.

“A Multitask Framework to Detect Depression, Sentiment and Multi-label Emotion from Suicide Notes” [20] proposes a deep multitask framework that features a knowledge module that uses SenticNet’s IsaCore and AffectiveSpace vector-spaces to infuse external knowledge specific features into the learning process. The system models emotion recognition (the primary task), depression detection and sentiment classification (the secondary tasks) simultaneously. Evaluation results show that all proposed multitask models perform better than their single-task variants.

The work “Sentic Computing for Aspect-Based Opinion Summarization Using Multi-Head Attention with Feature Pooled Pointer Generator Network” [21] proposes a cognitive aspect-based opinion summarizer, Feature Pooled Pointer Generator Network (FP2GN), which selectively attends to thematic and con-
textual cues to generate sentiment-aware review summaries. In particular, FP2GN identifies aspect terms in review text using sentic computing (SenticNet 5 and concept frequency-inverse opinion frequency) and statistical feature engineering.

In “Stock Price Prediction Incorporating Market Style Clustering” [22], the authors investigate how to characterize market styles to improve stock prediction performance under varying market styles. Experiments are conducted with five years of real Hong Kong Stock Exchange data that includes both stock prices and corresponding news. Two famous sentiment dictionaries (i.e., SenticNet 5 and the Loughran-McDonald financial sentiment dictionary 2018) are employed to analyze the news sentiments.

The article “Hybrid Deep Learning Models for Thai Sentiment Analysis” [23] proposes a framework for sentiment analysis in Thai along with the Thai-SenticNet5 corpus. The framework employs different types of features, namely, word embedding, part-of-speech, sentic features, and all combinations of these features. Three datasets in Thai were used in this work: ThaiTales, ThaiEconTwitter, and Wisesight datasets. The experimental results show that combining all three features and fusing deep learning algorithms were able to improve overall performance.

Next, “Ordered Weighted Averaging for Emotion-Driven Polarity Detection” [24] introduces a fuzzy framework for computing user mood based on SenticNet and sentic patterns, which are used to guide an ordered weighted averaging operator. This operator allows the aggregation to be computed in such a way as to provide an understanding of why some positive or negative aspects are considered to a greater or lesser extent. The performance and advantages of this proposal are illustrated in depth via a variety of scenarios applied to real data.

In “Multitask Learning for Complaint Identification and Sentiment Analysis” [25], the authors propose a deep multitask framework that features a knowledge element that uses AffectiveSpace to infuse commonsense knowledge specific features into the learning process. The framework models complaint identification (the primary task) and sentiment classification (supplementary task) simultaneously. The proposed multitask system outperforms the single-task systems indicating a strong correlation between sentiment analysis and complaint classification tasks, thus benefiting from each other when learned concurrently.

The work by Weichselbraun et al. [26] entitled “Automatic Expansion of Domain-Specific Affective Models for Web Intelligence Applications” introduces expansion techniques for affective models, combining common and commonsense knowledge available in knowledge graphs with language models and affective reasoning, improving coverage and consistency as well as supporting domain-specific interpretations of emotions. An extensive evaluation compares the performance of different expansion techniques: (i) a quantitative evaluation based on the revisited Hourglass of Emotions model to assess performance on complex models that cover multiple affective categories, using manually com-
piled gold standard data, and (ii) a qualitative evaluation of a domain-specific affective model for television programme brands.

Next, “Towards Sentiment-Aware Multi-Modal Dialogue Policy Learning” [27] presents a multi-intent-based dialogue policy by utilizing a unified hierarchical deep reinforcement learning framework. The system is trained to serve multiple intents of the user for a particular domain by leveraging from abstractions exhibited at different hierarchical levels developed to execute diverse tasks at different time-steps. Multi-modal information elicitation strategy is employed to identify user’s preference for different entities in the dialogue system.

“Design and Deployment of an Image Polarity Detector with Visual Attention” [28] presents a novel hardware-friendly detector of image polarity, enhanced with the ability of saliency detection. The approach stems from a hardware-oriented design process, which trades off prediction accuracy and computational resources. The final solution combines lightweight deep-learning architectures and post-training quantization. Experimental results on standard benchmarks confirmed that the design strategy can infer automatically the salient parts and the polarity of an image with high accuracy.

“Incremental Word Vectors for Time-Evolving Sentiment Lexicon Induction” [29] is about automatically inducing continuously updated sentiment lexicons from Twitter streams by training incremental word sentiment classifiers from time-evolving distributional word vectors. Authors experiment with various sketching techniques for efficiently building incremental word context matrices and study how the lexicon adapts to drastic changes in the sentiment pattern.

In “Automatically Building Financial Sentiment Lexicons While Accounting for Negation” [30], the authors construct new lexicons by leveraging 200,000 messages from StockTwits. They evaluate the constructed financial sentiment lexicons in two different sentiment classification tasks (unsupervised and supervised). In addition, the created financial sentiment lexicons are compared with each other and with other existing sentiment lexicons.

Finally, the work by Wawer et al. [31] entitled “Single and Cross-Disorder Detection for Autism and Schizophrenia” explores the limits of automated detection of autism spectrum disorder and schizophrenia. The article tests the effectiveness of several baseline approaches, such as bag of words and dictionary-based vectors, followed by a machine learning model. Authors employed two more refined Sentic text representations using affective features and concept-level analysis on texts. The best breed of automated methods outperformed human raters (psychiatrists).

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References


