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Ten Years of Sentic Computing

Yosephine Susanto[1] · Erik Cambria[1] · Bee Chin Ng[1] · Amir Hussain[2]

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Abstract

Sentic computing is a multi-disciplinary approach to sentiment analysis at the crossroads between affective computing and commonsense computing, which exploits both computer and social sciences to better recognize, interpret, and process opinions and sentiments over the Web. In the last ten years, many different models (such as the Hourglass of Emotions and Sentic Patterns), resources (such as AffectiveSpace and SenticNet), algorithms (such as Sentic LDA and Sentic LSTM), and applications (such as Sentic PROMs and Sentic Album) have been developed under the umbrella of sentic computing. In this paper, we review all such models, resources, algorithms, and applications together with the key shifts and tasks introduced by sentic computing in the context of affective computing and sentiment analysis. We also discuss future directions in these fields.

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 multidisciplinary 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.

In this paper, we review key sentic computing models, resources, algorithms, and applications together with the works that have been using them in the context of affective computing and sentiment analysis during the last decade. The remainder of this paper is organized as follows: Sentic Computing's Key Shifts describes the three key shifts introduced by sentic computing; Sentic Computing's Key Tasks lists the fifteen key tasks of sentic computing; Sentic Computing's Key Models illustrates the two key models on which sentic computing is based; Sentic Computing's Key Resources introduces two key sentic resources; Sentic Computing's Key Algorithms explains two key sentic algorithms; Sentic Computing's Key Applications showcases two key sentic applications; Future Directions discusses future directions; finally, Conclusion provides concluding remarks.

Sentic Computing's Key Shifts

Sentic computing's new approach to NLP gravitates around three key shifts:

1. Shift from mono- to multi-disciplinarity—evidenced by the concomitant use of symbolic and subsymbolic AI, for knowledge representation and reasoning; semiotics, for meaning encoding and decoding; mathematics, for carrying out tasks such as graph mining and multidimensionality reduction; linguistics, for discourse analysis and pragmatics;

✉ Erik Cambria
cambria@ntu.edu.sg

[1] School of Computer Science and Engineering, Nanyang Technological University, Nanyang, Singapore

[2] School of Computing, Edinburgh Napier University, Edinburgh, United Kingdom

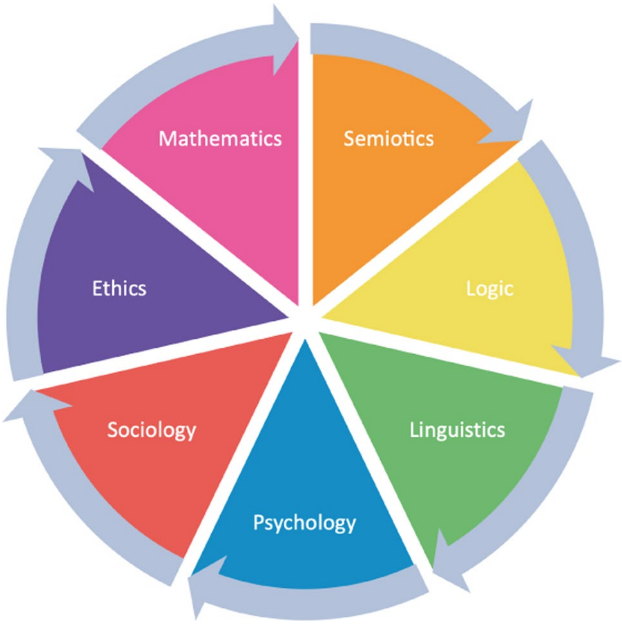


Fig. 1 Sentic computing disciplines

psychology, for cognitive and affective modeling; sociology, for understanding social network dynamics and social influence; finally ethics, for understanding-related issues about the nature of mind and the creation of emotional machines (Fig. 1).

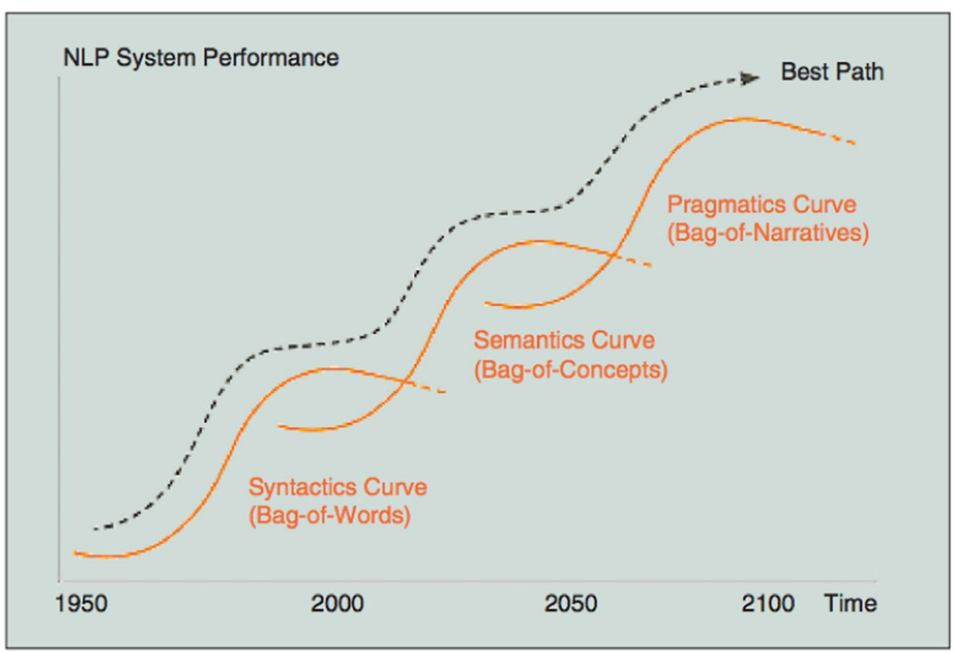
2. Shift from syntax to semantics—enabled by the adoption of the bag-of-concepts model instead of simply counting word co-occurrence frequencies in text (Fig. 2). Working at concept level entails preserving the meaning carried by multiword expressions such as cloud_computing, which represent 'semantic atoms' that should never be broken down into single words. In the bag-of-words model, for example, the concept cloud_computing would be split into computing and cloud, which may wrongly activate concepts related to the weather and, hence, compromise categorization accuracy.

3. Shift from statistics to linguistics—implemented by allowing sentiments to flow from concept to concept based on the dependency relation between clauses (Fig. 3). The sentence "iPhone12 is expensive but nice", for example, is equal to "iPhone12 is nice but expensive" from a bag-of-words perspective. However, the two sentences bear opposite polarity: the former is positive as the user seems to be willing to make the effort to buy the product despite its high price, and the latter is negative as the user complains about the price of iPhone12 although he/she likes it.

Sentic Computing's Key Tasks

Sentic computing takes a holistic approach to natural language understanding by handling the many sub-problems involved in extracting meaning and polarity from text. While most works approach it as a simple categorization problem, in fact, sentiment analysis is actually a suitcase research problem that requires tackling many NLP tasks (Fig. 4). As Marvin Minsky would say, the expression 'sentiment analysis' itself is a big suitcase (like many others related to affective computing, e.g., emotion recognition or opinion mining) that all of us use

Fig. 2 Jumping NLP curves [2]



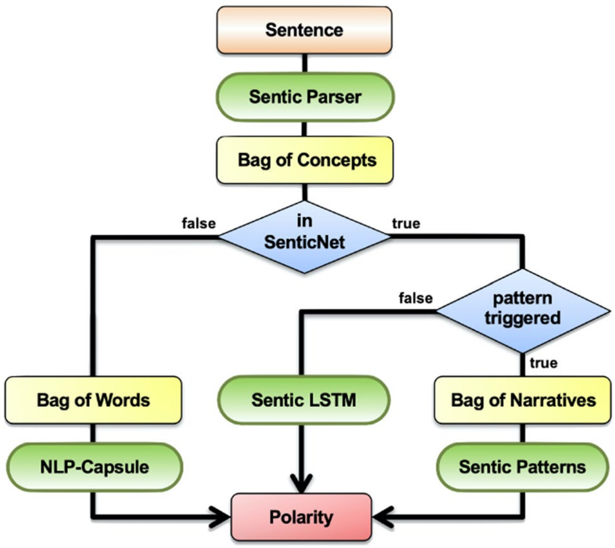


Fig. 3 Sentic computing framework [1]

to encapsulate our jumbled idea about how our minds convey emotions and opinions through natural language.

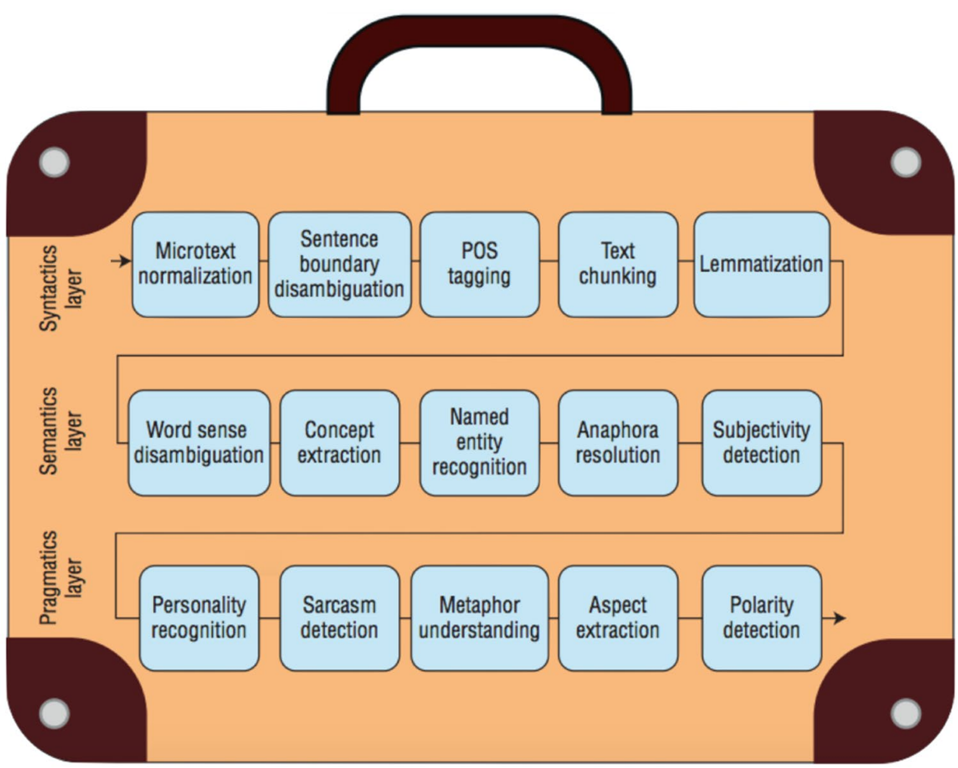
Sentic computing addresses the composite nature of the problem via a three-layer structure that concomitantly handles tasks such as microtext normalization [4], to decode informal text, subjectivity detection [5], to filter out neutral content, anaphora resolution [6], to link pronouns with the entities of a sentence, personality recognition [7], for distinguishing between different personality types of the users, and more. Such structure is inspired by the jumping NLP curves paradigm (Fig. 2) and consists of 15 NLP tasks organized into three layers:

1 Syntactics layer—which aims to preprocess text so that informal text is reduced to plain English, inflected forms of verbs and nouns are normalized, and basic sentence structure is made explicit.
2 Semantics layer—which aims to deconstruct the normalized text obtained from the syntactics layer into concepts, resolve references (that is, named entities and anaphora), and filter out neutral content from the input to improve sentiment classification accuracy.
3 Pragmatics layer—which aims to extract meaning from both sentence structure and semantics obtained from syntactics and semantics layers, respectively. After performing some kind of user profiling (personality and sarcasm detection), the pragmatics layer interprets metaphors (if any) and extracts opinion targets and the polarity associated with each of them.

Sentic Computing's Key Models

The symbolic part of the sentic computing engine leverages two key models, which regulate how emotions are assigned to specific words and multiword expressions in a sentence and

Fig. 4 Sentiment analysis is a suitcase problem [3]



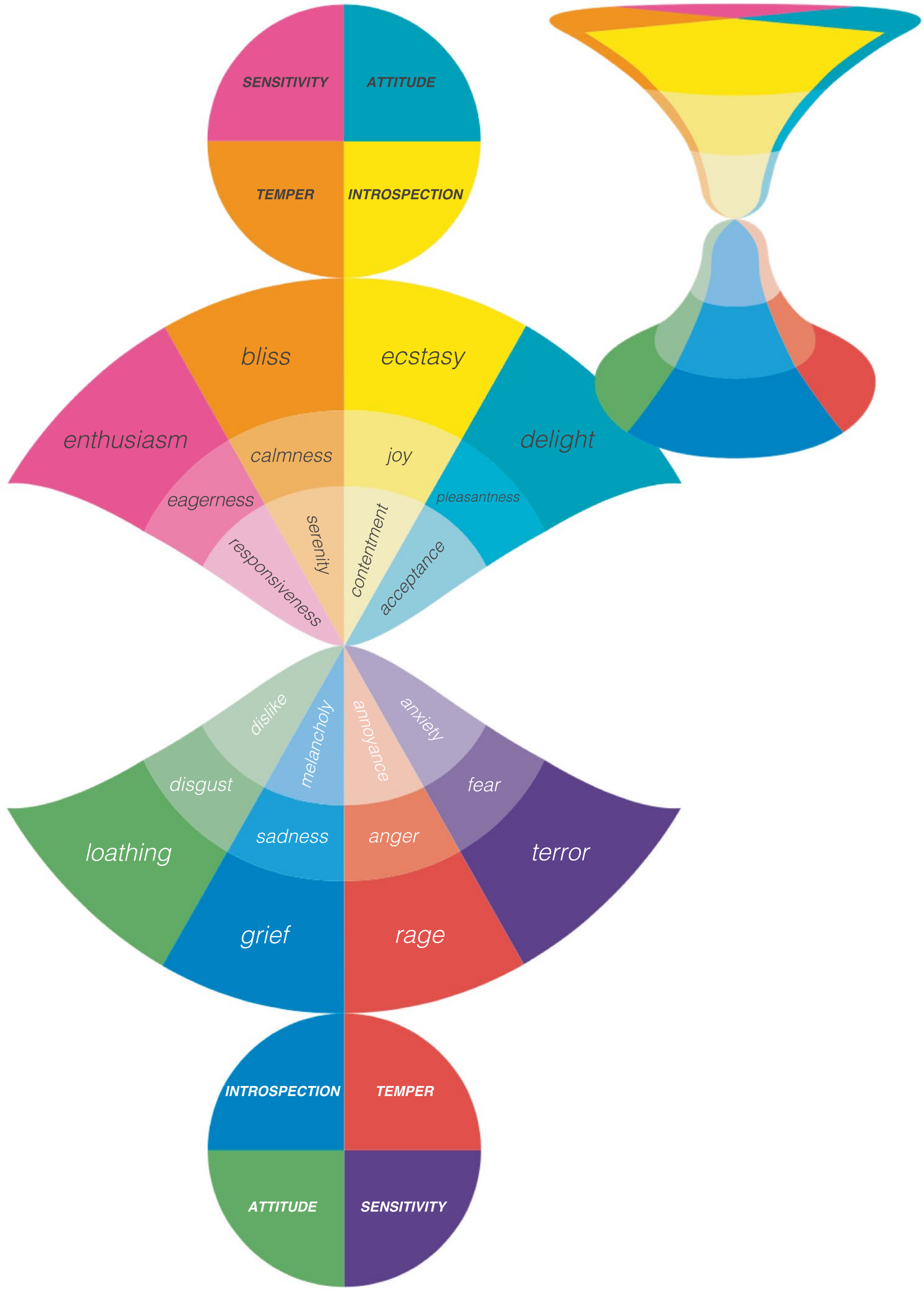


Fig. 5 The Hourglass of Emotions [22]

how such emotions flow throughout the sentence to determine its polarity, respectively. This section describes these two models, namely the Hourglass of Emotions, a brain-inspired and psychologically motivated emotion categorization model (Hourglass Model), and Sentic Patterns, sentiment-specific linguistic patterns that model how polarity flows from concept to concept based on the dependency tree of sentences (Sentic Patterns).

Hourglass Model

The Hourglass of Emotions is a new emotion model that goes beyond mere categorical and dimensional approaches (Fig. 5). Beside emotion classification, the model has been used for tasks like polarity detection from text [8, 9], audio and video [10, 11], and multiple languages [12], but also knowledge representation [13], psycholinguistics [14],

INTROSPECTION					
ECSTASY	JOY	CONTENTMENT	MELANCHOLY	SADNESS	GRIEF
elation	happiness	satisfaction	pensiveness	unhappiness	desperation
jubilation	cheerfulness	gratification	abandonment	sorrow	gloom
exultation	joviality	fulfilment	emptiness	dejection	depression
glee	gaiety	light-heartedness	down-heartedness	heavy-heartedness	broken-heartedness
felicity	high-spiritedness	frivolity	nostalgia	low-spiritedness	woe
TEMPER					
BLISS	CALMNESS	SERENITY	ANNOYANCE	ANGER	RAGE
placidity	tranquillity	quietude	disquietude	vexation	fury
peacefulness	equanimity	comfort	discomfort	exasperation	wrath
beatitude	composure	ease	unease	aggressiveness	ferocity
gladness	restfulness	imperturbability	perturbability	madness	enragement
relief	soothingness	carefreeness	frustration	acrimoniousness	vengeance
ATTITUDE					
DELIGHT	PLEASANTNESS	ACCEPTANCE	DISLIKE	DISGUST	LOATHING
admiration	appreciation	approval	disapproval	disappointment	contempt
adoration	fondness	favorability	distaste	detestation	revulsion
glorification	predilection	propensity	rejection	disdain	scorn
devotion	respect	belief	disbelief	disrespect	repugnance
enthrallment	trust	worthiness	worthlessness	distrust	abhorrence
SENSITIVITY					
ENTHUSIASM	EAGERNESS	RESPONSIVENESS	ANXIETY	FEAR	TERROR
zeal	keenness	decisiveness	indecisiveness	fright	horror
zest	willingness	receptiveness	apprehension	dread	panic
passion	motivation	agreeableness	helplessness	trepidation	appalment
avidity	inspiration	approachableness	agitation	angst	petrification
fervor	dedication	amenability	discouragement	scare	aghastness

Fig. 6 Emotion classification with five sample emotion words for each category

cognitive and cultural modeling [15, 16], social network analysis [17], and the arts [18–21]. The Hourglass model represents affective states both through labels and through four independent but concomitant affective dimensions, namely Introspection (the *joy*-versus-*sadness* dimension), Temper (the *calmness*-versus-*anger* dimension), Attitude (the *pleasantness*-versus-*disgust* dimension), and Sensitivity (the *eagerness*-versus-*fear* dimension).

Each affective dimension is characterized by six levels of activation measuring the strength of an emotion. Such levels are also labeled as a set of 24 primary emotions (Fig. 6) in a way that allows the model to specify the affective information associated with text both in a dimensional and in a discrete form. For each dimension, thus, each level of activation represents the intensity thresholds of the perceived emotion both in positive terms (e.g., *ecstasy* > *joy* > *contentment*) and negative ones (*melancholy* < *sadness* < *grief*). The dimensional form, instead, is a four-dimensional *float* vector, which can potentially describe the full range of emotional experiences that are rooted in any of us. In the model, the vertical dimension represents the intensity of the different affective dimensions, while the radial dimension models the activation of different emotional configurations, resembling Minsky's *k*-lines [23].

The model, in fact, is based on the idea that the mind is made of different independent resources and that emotional states result from turning some set of these resources on and turning another set of them off [24]. Each such selection changes how we think by changing our brain's activities: the state of anger, for example, appears to select a set of resources that help us react with more speed and strength while also suppressing some other resources that usually make us act prudently. Evidence of this theory is also given by several fMRI experiments, showing that there is a distinct pattern of brain activity that occurs when people are experiencing different emotions.

The model follows the pattern used in color theory and research [25] in order to obtain judgments about combinations, i.e., the emotions that result when two or more fundamental emotions are combined, in the same way as primary colors can be combined to form new ones (Fig. 7). Such combinations can be bidimensional, e.g., *love* (*joy*+*pleasantness*), tridimensional, e.g., *bittersweetness* (*sadness*+*anger*+*pleasantness*), and even four-dimensional, e.g., *jealousy* (*anger*+*fear*+*sadness*+*disgust*).

Fig. 7 Examples of compound emotions

JOY	PLEASANTNESS	love	enjoyment	amusement
	EAGERNESS	euphoria	excitement	thrill
	CALMNESS	enlightenment	relaxation	sweet idleness
SADNESS	DISGUST	hate	guilt	remorse
	FEAR	distress	troubledness	misery
	ANGER	envy	bitterness	resentment
CALMNESS	PLEASANTNESS	assertiveness	compassion	empathy
	EAGERNESS	focus	determination	perseverance
	FEAR	carelessness	laxity	looseness
ANGER	DISGUST	hatred	ruthlessness	viciousness
	FEAR	nastiness	coercion	possessiveness
	EAGERNESS	stubborness	obstinacy	mulishness
PLEASANTNESS	DISGUST	shamelessness	cheekiness	brazenness
	EAGERNESS	kindness	audacity	hospitality
	FEAR	awe	submission	reverence
DISGUST	JOY	morbidness	schadenfreude	gloat
	FEAR	impiety	cowardness	inhospitality
	EAGERNESS	recklessness	temerity	rashness
EXPECTATION	JOY	hope	anticipation	optimism
	SADNESS	hopelessness	despair	pessimism
	EAGERNESS	vigilance	alertness	caution
SURPRISE	ANGER	shock	outrage	thunderstruckness
	FEAR	alarm	dismay	dumbstruckness
	PLEASANTNESS	amazement	astonishment	wonderstruckness

Sentic Patterns

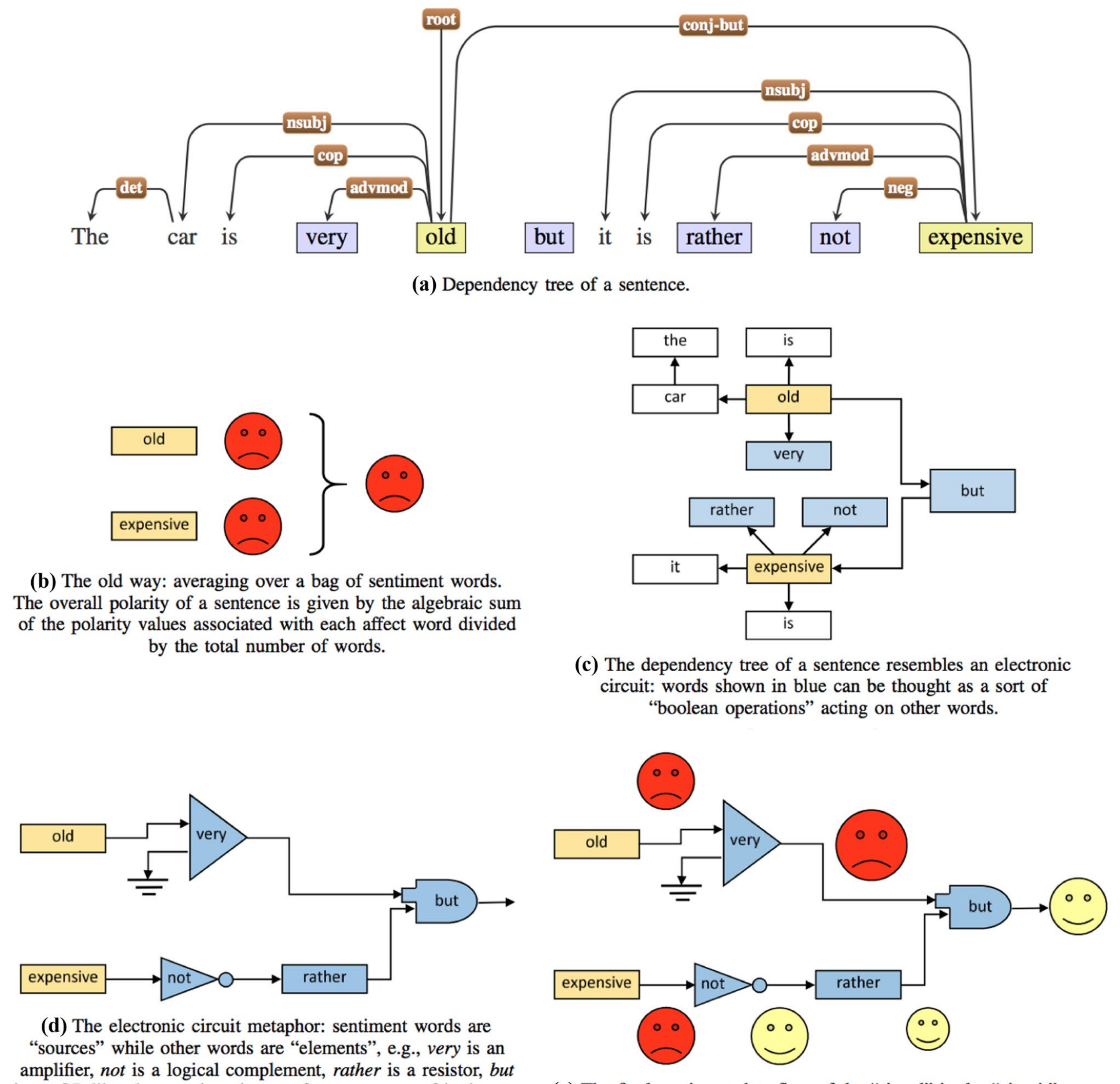
Sentic patterns [26] are sentiment-specific linguistic patterns that model how polarity flows from concept to concept based on the dependency relation of the input sentence and, hence, to generate a binary (positive or negative) value reflecting the feeling of the speaker. Several studies have documented the performance increase sentic patterns enable on different sentiment analysis datasets [27, 28]. Sentic patterns are applied to the dependency syntactic tree of a sentence, as shown in Fig. 8a. The only two words that have intrinsic polarity are shown in yellow color; the words that modify the meaning of other words in the manner similar to contextual valence shifters are shown in blue. A baseline that completely ignores sentence structure, as well as words that have no intrinsic polarity, is shown in Fig. 8b: the only two words left are negative and, hence, the total polarity is negative. However, the syntactic tree can be re-interpreted in the form of a 'circuit' where the 'signal' flows from one element (or subtree) to another, as shown in Fig. 8c. After removing the words not used for polarity calculation (in white), a circuit with elements resembling electronic amplifiers, logical complements, and resistors is obtained, as shown in Fig. 8d.

Sentic Computing's Key Resources

Sentic computing leverages both subsymbolic and symbolic AI to extract emotion and polarity from sentences. A good example of this approach is provided by two key resources, which represent affective commonsense knowledge as a vector space model and a semantic network, respectively. This section describes these two resources, namely AffectiveSpace, the subsymbolic representation of 200,000 affective commonsense concepts in the form of embeddings (AffectiveSpace), and SenticNet, the symbolic representation of the same 200,000 commonsense concepts and their interconnections in the form of nodes and edges (SenticNet).

AffectiveSpace

AffectiveSpace [30] is a 100-dimensional vector space model representing affective commonsense concepts in the form of embeddings. The model is based on the principle that the human mind constructs intelligible meanings by continuously compressing over vital relations [31]. This compression principle aims to transform diffuse and distended conceptual structures to more focused versions so as to become more congenial for human understanding. In order to emulate such a process, the first version of AffectiveSpace applied principal component analysis on the matrix representation of AffectNet [32], a semantic network in which commonsense concepts are linked to semantic and affective features (Table 1). In order to cope with the ever-growing number of concepts and semantic features, the second version of AffectiveSpace applied random projections, a data-oblivious method that mapped the original high-dimensional matrix into a much lower-dimensional subspace, while preserving pair-wise distances with high probability.



(a) Dependency tree of a sentence.

(b) The old way: averaging over a bag of sentiment words. The overall polarity of a sentence is given by the algebraic sum of the polarity values associated with each affect word divided by the total number of words.

(c) The dependency tree of a sentence resembles an electronic circuit: words shown in blue can be thought as a sort of "boolean operations" acting on other words.

(d) The electronic circuit metaphor: sentiment words are "sources" while other words are "elements", e.g., *very* is an amplifier, *not* is a logical complement, *rather* is a resistor, *but* is an OR-like element that gives preference to one of its inputs.

(e) The final sentiment data flow of the "signal" in the "circuit".

Fig. 8 An example of how sentic patterns model sentiment data flows in the sentence "The car is very old but rather not expensive" [29]

In AffectiveSpace, commonsense concepts and emotions are represented by vectors of k coordinates. These coordinates can be seen as describing concepts in terms of 'eigenmoods' that form the axes of AffectiveSpace, i.e., the basis $e_0,...,e_{k-1}$ of the vector space. For example, the most significant eigenmood, e_0, represents concepts with positive affective valence. That is, the larger a concept's component in the e_0 direction is, the more affectively positive it is likely to be. Concepts with negative e_0 components, then, are likely to have negative affective valence.

Thus, by exploiting the information sharing property of dimensionality reduction, concepts with the same affective valence are likely to have similar features—that is, concepts conveying the same emotion tend to fall near each other in AffectiveSpace (Fig. 9). Concept similarity does not depend on their absolute positions in the vector space, but rather on the angle they make with the origin. For example, concepts such as `learn_subject`, `receive_degree`, and `read_book` are found very close in direction in the vector space, while concepts like `depression`, `deject`, and `wretched` are found in a completely different direction (nearly opposite with respect to the center of the space).

Table 1 A snippet of the AffectNet matrix

AffectNet	IsA-pet	KindOf-food	Causes-joy	...
dog	0.981	0	0.789	...
cupcake	0	0.922	0.910	...
songbird	0.672	0	0.862	...
gift	0	0	0.899	...
sandwich	0	0.853	0.768	...
rotten_fish	0	0.459	0	...
win_lottery	0	0	0.991	...
bunny	0.611	0.192	0.594	...
police_man	0	0	0	...
cat	0.913	0	0.699	...
rattlesnake	0.432	0.235	0	...
...	...	...	...	...

SenticNet

The core element of sentic computing is SenticNet, a semantic network that models how words and multiword expressions are interconnected to each other and to the emotion labels of the Hourglass model. Unlike many other sentiment analysis resources, SenticNet is not built by manually labeling pieces of knowledge coming from general NLP resources such as WordNet or DBPedia. Instead, it is automatically constructed by applying graph-mining and multi-dimensional scaling techniques on the affective commonsense knowledge collected from three different sources, namely WordNet-Affect [33], Open Mind Common Sense [34], and GECKA [35]. This knowledge is represented redundantly at three levels (semantic network, matrix, and vector space) following Minsky's panalogy principle [24]. Subsequently, semantics and sentics are calculated through the ensemble application of spreading activation [36], sentic neurons [37] and the Hourglass model (Fig. 10).

The different versions of SenticNet are accessible in RDF/XML format: SenticNet 1 [38] simply associated polarity scores with almost 6,000 ConceptNet concepts; in addition to polarity, SenticNet 2 [39] also assigned semantics and sentics to commonsense concepts and extended the breadth of the knowledge base to about 13,000 entries; SenticNet 3 [40] broadened the spectrum of the semantic network to 30,000 concepts; SenticNet 4 [41] introduced the concept of semantic primitives to further extend the knowledge base to 50,000 entries; SenticNet 5 [42] reached 100,000 commonsense concepts by employing recurrent neural networks to infer primitives by lexical substitution; finally, SenticNet 6 [28] contains 200,000 commonsense concepts and it is built by leveraging both symbolic models (i.e., logic and semantic networks) to encode meaning and subsymbolic methods (i.e., biLSTM and BERT) to implicitly learn syntactic patterns from data (Fig. 11). SenticNet is also available in 40 different languages under the name of BabelSenticNet [43], and it can also be downloaded in OWL format as an ontology under the name of OntoSenticNet [44].

Sentic Computing's Key Algorithms

Since 2010, many algorithms have been developed on top of sentic models and resources for tasks such as emotion inference and polarity detection from text, audio, and video. This section describes two of such algorithms, namely Sentic

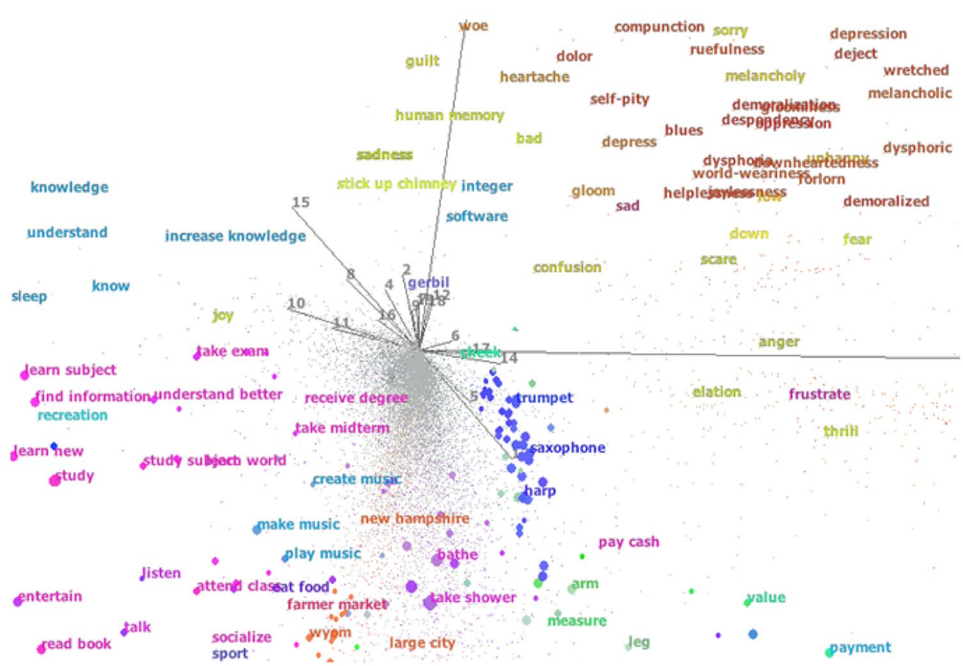


Fig. 9 AffectiveSpace [30]

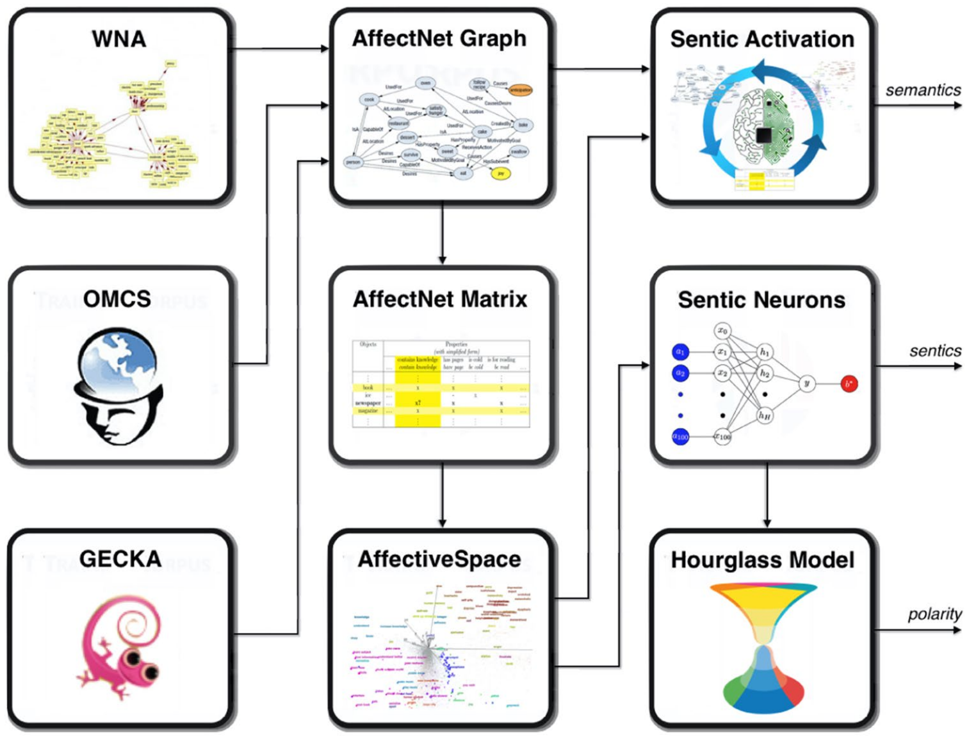


Fig. 10 SenticNet framework [1]

LDA, a knowledge-enriched version of latent Dirichlet allocation that exploits SenticNet to shift LDA clustering from a syntactic to a semantic level (Sentic LDA), and Sentic LSTM, an extension of long short-term memory network that leverages AffectiveSpace to enhance aspect-based sentiment analysis (Sentic LSTM).

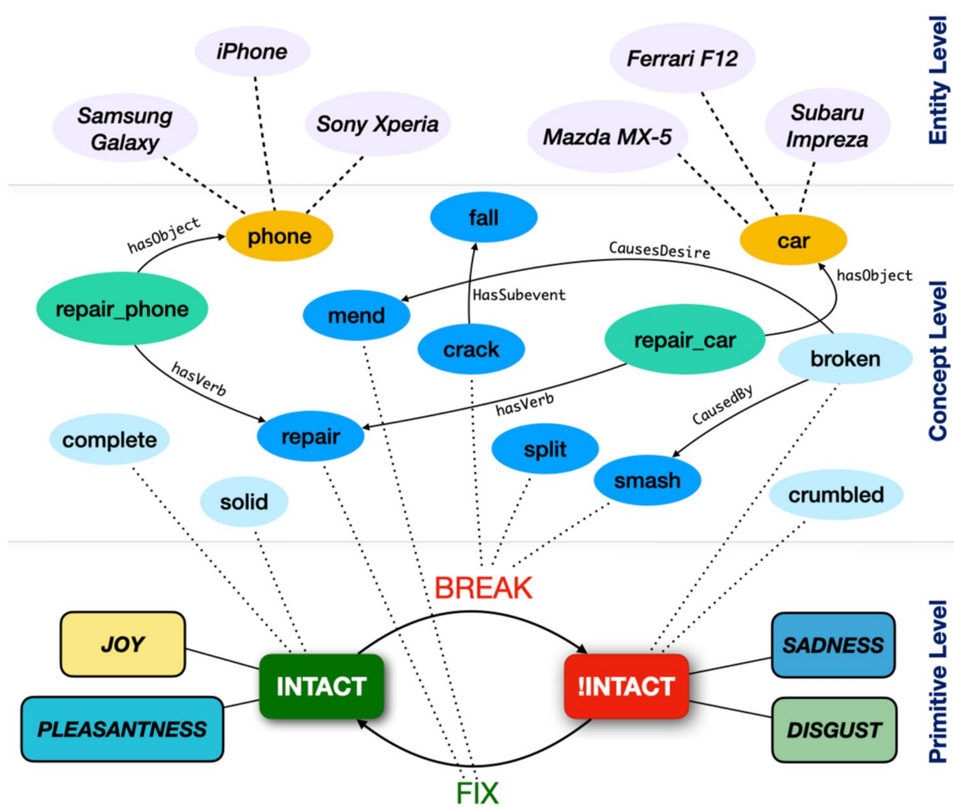


Fig. 11 A sketch of SenticNet 6's semantic network [28]

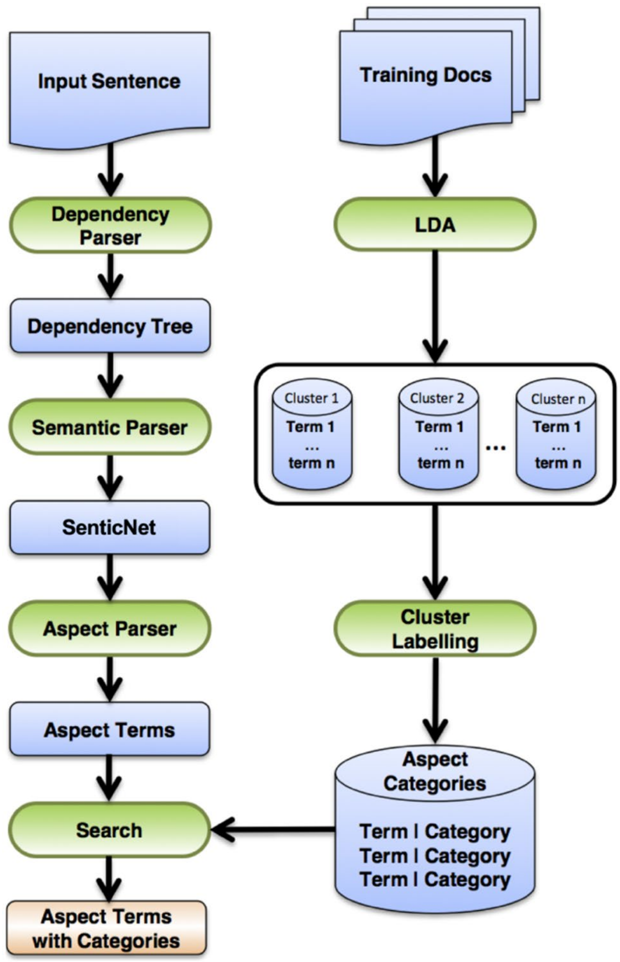


Fig. 12 Sentic LDA [45]

Sentic LDA

Sentic LDA integrates SenticNet in the calculation of word distributions within the standard LDA algorithm, thus enabling the shift from syntax to semantics in aspect-based sentiment analysis (Fig. 12). In particular, Sentic LDA leverages the semantic similarity between two words for supervising the clustering process. As a consequence, words are not only clustered depending on word frequency measure, but also considering the semantic similarity between each pair of words.

The basic steps of the proposed framework can be summarized as follows:

1 LDA produces a set of clusters where each cluster represents an aspect category.
2 After clustering, each cluster is labeled based on its constitutive elements. The metric for labeling a cluster with a specific aspect category is a majority-based criterion, counting the aspect terms belonging to a certain aspect category. The number of clusters is fixed a priori based on the training corpus.
3 An unsupervised aspect term extraction process is employed to detect meaningful aspect terms in the input sentence. In particular, this process leverages a semantic parser to deconstruct the input sentence into words and multiword expressions and later categorize these as either polarity concepts (from SenticNet) or opinion targets (aspects).
4 Each aspect term is searched among the clusters produced by LDA in Step 1. If the term is found in more than one cluster, then the cluster for which the aspect term has the highest probability to belong to is chosen and the corresponding aspect category is assigned.

Sentic LDA is highly scalable as it enables unsupervised aspect extraction. The ensemble application of the LDA algorithm and an unsupervised aspect term extraction algorithm allows Sentic LDA to automatically find the categories of aspect terms and, hence, improve aspect-based sentiment analysis.

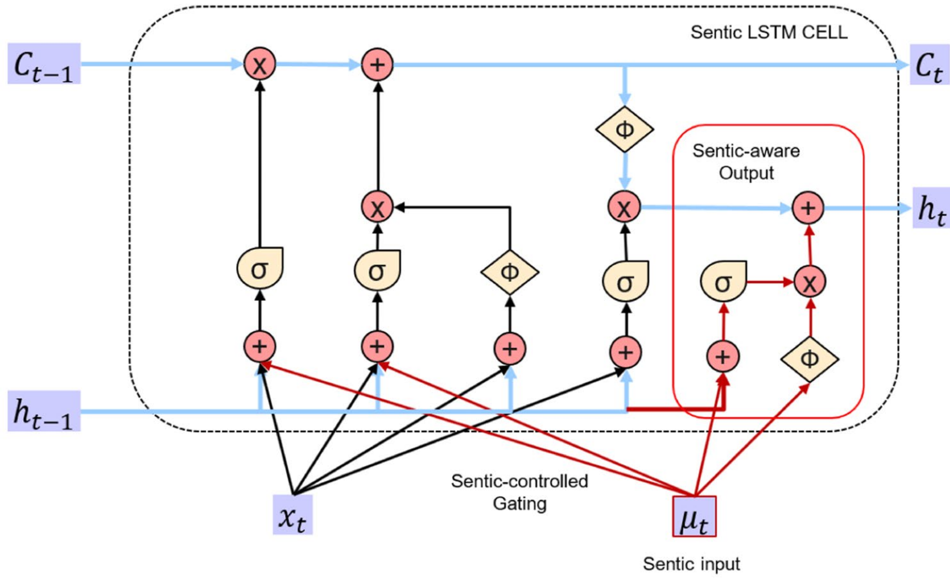
Sentic LSTM

Sentic LSTM [46] incorporates commonsense knowledge of sentiment-related concepts into the end-to-end training of an LSTM model to increase the accuracy of aspect-based sentiment analysis. In particular, the LSTM model is extended by integrating AffectiveSpace embeddings into gate mechanisms under the assumption that sentiment concepts are key in controlling the flow of word-level information through the LSTM cell (Fig. 13). Sentic LSTM consists of two main components: a sequence encoder and a hierarchical attention component. The sequence encoder, which is based on a bidirectional LSTM, transforms the word embeddings into a sequence of hidden outputs. The attention component is built on top of the hidden outputs. The target-level attention takes as input the hidden outputs at the positions of target expression and computes a self-attention vector over these words.

For instance, a multiword aspect rotten_fish might suggest that the word 'rotten' was a sentiment-related qualifier of the word 'fish' so that less information need to be filtered out at the next time step. Thus, to filter the information, knowledge concepts are incorporated into the forget, input, and output gate of standard LSTM. The input gate uses sentiment concepts to prevent the memory cell from being affected by input tokens conflicting with knowledge. Similarly, such knowledge is utilized by the output gate to filter out the irrelevant information stored in the memory.

Sentic LSTM is a good example of how sentic computing aims to apply an ensemble of symbolic and subsymbolic AI for natural language understanding. Sentic LSTM, in fact, is one of the first examples of knowledge-enriched deep

Fig. 13 Sentic LSTM [46]



learning algorithms and hopefully can pave the way for the development of more explainable AI systems.

Sentic Computing's Key Applications

Over the last decade, sentic computing has positioned itself as a horizontal technology that serves as a back-end to many different applications in the areas of e-commerce, e-health, e-learning, e-tourism, e-mobility, e-entertainment, e-governance, e-security, e-business, and more (Fig. 14). Several sentic computing models, resources, and algorithms that were made freely available in various forms (e.g., APIs[1], knowledge bases[2], code[3]) have been employed for the development of sentiment-aware applications in fields such as financial forecasting [47–55], business intelligence [56–65], recommendation systems [66–76], aspect-based sentiment analysis [77–88], multilingual sentiment analysis [89–100], multimodal sentiment analysis [101–104], irony and sarcasm detection [105–110], cyber-harassment prevention [111–118], e-health [119–131], e-learning [132–134], psycholinguistics [135–137], social media monitoring [138–140], social network analysis [141–143], political forecasting [144, 145], opinion summarization [146, 147], crisis management [148, 149], personalized sentiment analysis [150, 151], dialogue systems [152], Semantic Web applications [153–156], and many other prediction and detection tasks [157–161].

1 http://sentic.net/api
2 http://sentic.net/downloads
3 http://github.com/senticnet

The remainder of this section describes two of such applications, namely Sentic PROMs, an extension of patient reported outcome measures (PROMs) that allow patients to evaluate their health status and experience in a semi-structured way (Sentic PROMs), and Sentic Album, a personal photo management system that exploits both data and metadata of online personal pictures to intelligently annotate, organize, and retrieve them (Sentic Album).

Sentic PROMs

Sentic PROMs [162] are a new generation of short and easy-to-use tools to monitor patient outcomes on a regular basis. Barriers to use health related quality of life measuring systems include the time needed to complete forms and the need for staff to be trained to understand results. To this end, Sentic PROMs combine sentic computing with standard PROMs to create an ideal system of health assessment that is clinically useful, timely, sensitive to change, culturally sensitive, low burden, low cost, involving for the patient and built into standard procedures. This way, Sentic PROMs allow patients to evaluate their health status and experience in a semi-structured way and accordingly aggregate input data by means of sentic computing, while tracking patients' physio-emotional sensitivity (Fig. 15).

The importance of physio-emotional sensitivity in humans has been proven by health sciences, which have shown that individuals who feel loved and supported by friends and family, or even by a loving pet, tend to have higher survival rates following heart attacks than other cardiac patients who experience a sense of social isolation. Such concept is also reflected in natural language as we use terms such as 'heartsick', 'broken-hearted' and

Fig. 14 Application areas of sentic computing

'heartache' to describe extreme sadness and grief, idioms like 'full of gall' and 'venting your spleen' to describe anger, and expressions such as 'gutless', 'yellow belly' and 'feeling kicked in the gut' to describe shame.

Sentic PROMs leverages sentic computing to interpret such expressions and, hence, monitor both users' health and physio-emotional sensitivity on a regular basis, as a means of patient affective modeling. In particular, the dimensional affective information coming from both questionnaire data (PROMs aggregated score) and natural language data (sentic vectors) is stored separately by the system every time patients conclude a Sentic PROMs session and plotted on four different bi-dimensional diagrams. Such diagrams represent the pairwise fusion of the four dimensions of the Hourglass model and allow to detect more complex (compound) emotions that can be particularly relevant for monitoring patients' health, e.g., frustration, anxiety, optimism, disapproval, and rejection.

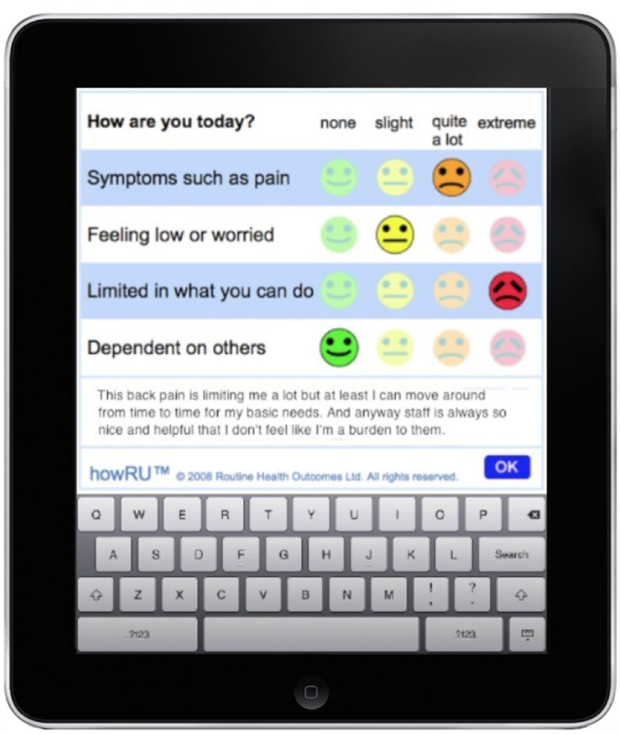


Fig. 15 Sentic PROMs [162]

Sentic Album

Sentic Album [163] is a content, concept, and context-based online personal photo management system that exploits both data and metadata of online personal pictures to intelligently annotate, organize, and retrieve them (Fig. 16). Many salient features of pictures, in fact, are only noticeable in the viewer's mind, and the cognitive ability to grasp such features is a key aspect for accordingly analyzing and classifying personal photos. To this end, Sentic Album exploits not just colors and texture of online images (content), but also the cognitive and affective information associated with their metadata (concept), and their relative timestamp, geolocation, and user interaction metadata (context).

Sentic Album is based on the assumption that, rather than assigning particular cognitive and affective valence to a specific visual stimulus, we more often balance the importance of personal pictures according to how much information contained in them is pertinent to our lives, goals, and values (or perhaps, the lives and values of people we care about). For this reason, a bad-quality picture can be ranked high in the mind of a particular user, if it reminds him/her of a notably important moment or person of his/her life. Events and situations, in fact, are likely to be organized in the human mind as interconnected concepts and most of the links relating such concepts are probably weighted by affect, as we tend to better recall memories associated with either very positive or very negative emotions, just as we usually tend to more easily forget about concepts associated with very little or null affective valence.

Future Directions

The AI gold rush has become increasingly intense for the huge potential AI offers for human development and growth. Most of what is considered AI today is actually subsymbolic AI, i.e., machine learning: an extremely powerful tool for exploring large amounts of data and, for instance, making predictions, suggestions, and categorizations based on them. All such classifications are made by transforming real items that need to be classified into numbers or features in order to later calculate distances between them.

While this is good for making comparison between such items and cluster them accordingly, it does not tell us much

Fig. 16 Sentic Album [163]

about the items themselves. Thanks to machine learning, we may find out that apples are similar to oranges but this information is only useful to cluster oranges and apples together: it does not actually tell us what an apple is, what it is usually used for, where it is usually found, how does it taste, etc. Throughout the span of our lives, we learn a lot of things by example but many others are learnt via our own personal (kinaesthetic) experience of the world and taught to us by our parents, mentors, and friends. If we want to replicate human intelligence into a machine, we cannot avoid implementing this kind of top-down learning.

Integrating logical reasoning within deep learning architectures has been a major goal of modern AI systems. Most of such systems, however, merely transform symbolic logic into a high-dimensional vector space using neural networks. Sentic computing, instead, attempts to do the opposite: it employs subsymbolic AI for recognizing meaningful patterns in natural language text and, hence, represents these in SenticNet using symbolic logic. In particular, sentic computing uses deep learning to generalize words and multiword expressions into primitives, which are later defined in terms of superprimitives (Fig. 17).

For example, expressions like shop_for_iphone12, purchase_samsung_galaxy_S20, or buy_huawei_mate are all generalized as BUY(PHONE) and later reduced to smaller units thanks to definitions such as BUY(x) = GET(x) ∧ GIVE($), where GET(x) for example is defined in terms of the superprimitive HAVE as !HAVE(x) → HAVE(x). While this does not solve the symbol grounding problem, it helps reducing it to a great degree and, hence, improves the accuracy of NLP tasks for which statistical analysis alone is usually not enough, e.g., narrative understanding, dialogue systems and sentiment analysis.

By deconstructing multiword expressions into primitives and superprimitives, in fact, there is no need to build a lexicon that assigns polarity to thousands of words and multiword expressions: all we need is the polarity of superprimitives. For example, expressions like grow_profit, enhance_reward, or intensify_benefit are all generalized as INCREASE(GAIN) and, hence, classified as positive. Likewise, this approach is also superior to most subsymbolic approaches that simply classify text based on word occurrence frequencies. For example, a purely statistical approach would classify expressions like lessen_agony, reduce_affliction, or diminish_suffering as negative because of the statistically negative words that compose them. In SenticNet, however, such expressions are all generalized as DECREASE(PAIN) and thus correctly classified (Fig. 18).

In future years, sentic computing will follow this line of thought in order to slowly shift from mere language processing to true language understanding. New sentic computing models,

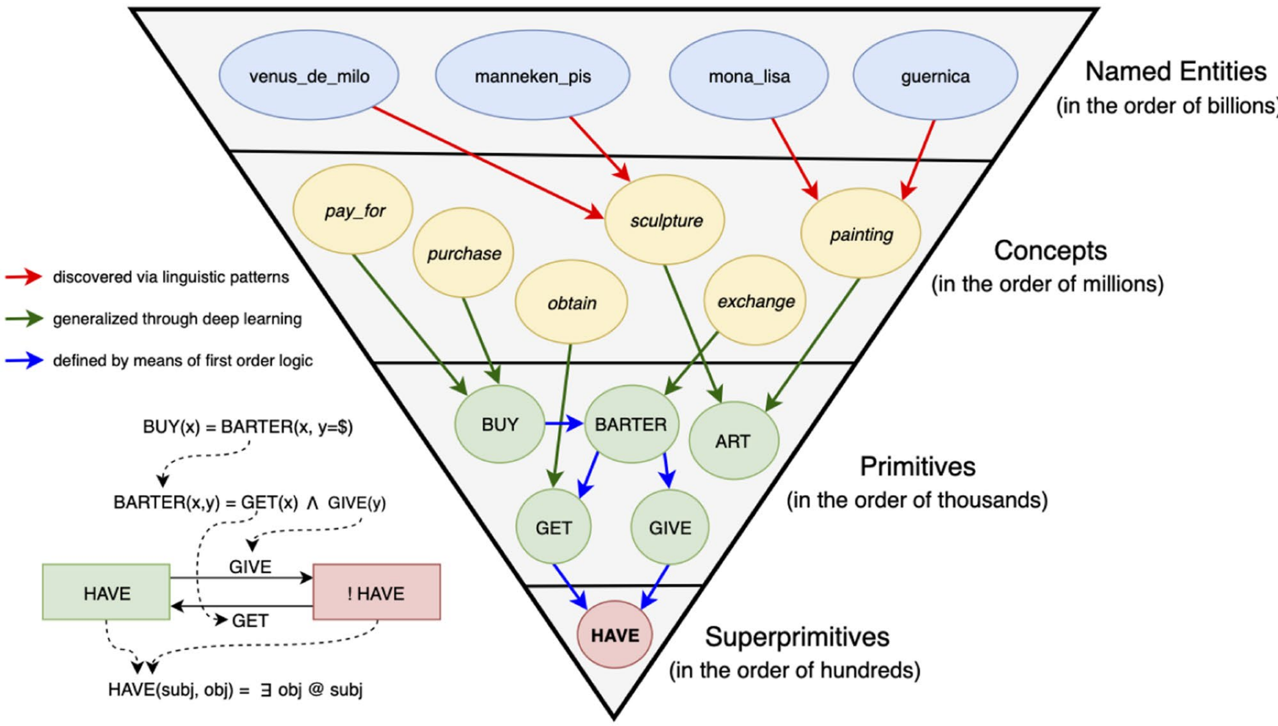
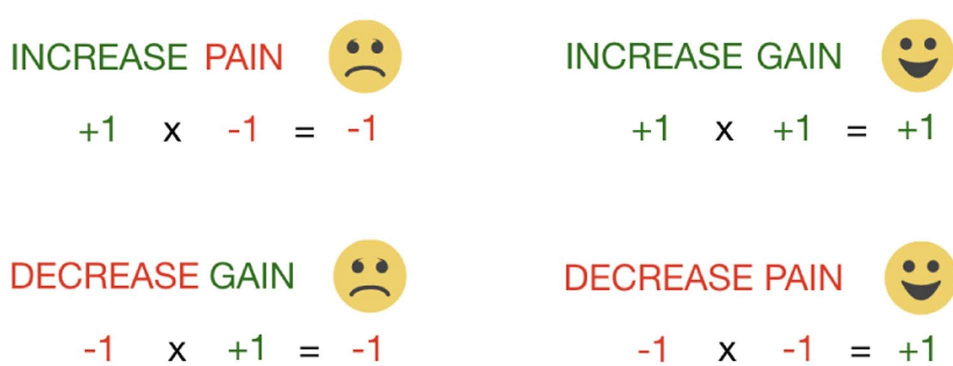


Fig. 17 SenticNet's dependency graph structure [28]

resources, algorithms, and applications will take an approach to NLP that is both top-down and bottom-up: top-down for the fact that sentic computing leverages symbolic models such as semantic networks and conceptual dependency representations to encode meaning; bottom-up because it uses subsymbolic methods such as deep neural networks and multiple kernel learning to infer syntactic patterns from data.

We believe that coupling symbolic and subsymbolic AI are key for stepping forward in the path from NLP to natural language understanding. Machine learning is only useful to make a 'good guess' based on past experience because it simply encodes correlation and its decision-making process is merely probabilistic. As professed by Noam Chomsky, natural language understanding requires much more than that: "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".

Fig. 18 Sentic algebra [28]



Conclusion

This survey investigated the literature of sentic computing, a multi-disciplinary approach to sentiment analysis, over the past ten years. In particular, the survey reviewed different models (such as the Hourglass of Emotions and Sentic Patterns), resources (such as AffectiveSpace and SenticNet), algorithms (such as Sentic LDA and Sentic LSTM), and applications (such as Sentic PROMs and Sentic Album) that have been developed since 2010 under the umbrella of sentic computing. The survey also explained the key shifts and tasks introduced by sentic computing in the context of affective computing and sentiment analysis and discussed future directions in these fields.

Compliance with Ethical Standards

Conflicts of Interest The authors declare that they have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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