SenticNet 8: Fusing Emotion AI and Commonsense AI for Interpretable, Trustworthy, and Explainable Affective Computing

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Abstract. ChatGPT has stunned the world with its ability to generate detailed, original, and accurate responses to prompts. While it unlocked solutions to problems that were previously considered unsolvable, however, it also introduced new ones. One of such problems is the phenomenon known as hallucination, the generation of content that is nonsensical or unfaithful to the provided source content. In this work, we propose SenticNet 8, a neurosymbolic AI framework leveraging an ensemble of commonsense knowledge representation and hierarchical attention networks, which aims to mitigate some of these issues in the context of affective computing. In particular, we focus on the tasks of sentiment analysis, personality prediction, and suicidal ideation detection. Results show that SenticNet 8 presents superior accuracy with respect to all four baselines, namely: bag-of-words, word2vec, RoBERTa, and ChatGPT. Unlike these baselines, moreover, SenticNet 8 is also fully interpretable, trustworthy, and explainable.

Keywords: Explainable AI · Affective Computing · Sentiment Analysis

1 Introduction

Generative pretrained transformer (GPT) models enabled humanity to finally design an algorithm able to pass the famous machine intelligence test devised by Alan Turing some seventy years ago [6]. With approximately 1 trillion parameters, ChatGPT has revolutionized the world of natural language processing (NLP) thanks to the high accuracy it can obtain on several information retrieval tasks [38,43]. However, it still presents several issues that limit its widespread adoption, especially in contexts such as medical, ethical, or fail-safe applications [2,48].

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Some researchers defined large language models (LLMs) like ChatGPT as 'stochastic parrots' [4], i.e., systems that haphazardly stitch together sequences of linguistic forms it has observed in its vast training data, according to probabilistic information about how they combine, but without any reference to meaning. LLMs, in fact, are trained (mostly in a self-supervised manner) on 'broad' data, which leads to homogenization (i.e., using same model for fine-tuning and training for different downstream tasks) and emergence (i.e., LLMs can solve tasks they were not originally trained upon). This poses several risks [10], including 'hallucination' [28], which can lead to several ChatGPT failures, including reasoning, factual errors, math, coding, and bias [11]. ChatGPT, moreover, is not interpretable (because we do not get to see its true inner workings, e.g., how cause and effect are associated); it is not trustworthy (because it is only as good as its training data and it often lacks the commonsense knowledge required for disambiguation); and it is not explainable (because we do not get any explanation about the decision-making processes that produce its final results).

In this work, we aim to mitigate these issues in the context of affective computing. We propose SenticNet 8, a neurosymbolic AI framework leveraging an ensemble of commonsense knowledge representation and hierarchical attention networks, which automatically extracts important affective information (such as sentiment polarity, emotion labels, opinion targets, emotion-cause pairs, polarity intensity, personality traits, etc.) from both formal and informal natural language text with state-of-the-art accuracy. This is enabled by an approach to NLP that is both top-down and bottom-up: top-down for the fact that SenticNet 8 leverages symbolic models (namely, conceptual dependency theory and a semantic network of affective commonsense knowledge) to encode meaning; bottom-up because we use sub-symbolic paradigms (namely, hierarchical attention networks and LLMs) to infer syntactic patterns from data. We compare SenticNet 8 with ChatGPT, a robust language model (RoBERTa), pretrained embeddings (word2vec), and the bag-of-words (BoW) model. Results show that SenticNet 8 generally presents superior accuracy with respect to all four models. Unlike these baselines, moreover, SenticNet 8 is also interpretable, trustworthy, and explainable. The remainder of the paper is organized as follows: Sect. 2 lists recent related works; Sect. 3 describes the proposed framework; Sect. 4 presents experimental results; Sect. 5 discusses insights gained; finally, Sect. 6 provides concluding remarks.

2 Related Work

Since Ancient Greece, it has been widely acknowledged that humans seek explanations in an attempt to understand the world [33]. This ubiquitous search for answers and explanations is inherent to human nature and fundamental to integrate technology into everyday lives. As technology advances and human-computer interaction (HCI) becomes more prevalent, in fact, the need for understanding and explaining the decision-making processes of affective computing models has become paramount [18,32].

Various studies have focused on developing machine learning models for emotion recognition from different modalities, such as facial expressions, speech, text, and physiological signals [22]. Traditional approaches include feature engineering and classical machine learning techniques. More recently, deep learning methods, especially transformers, have demonstrated remarkable performance in this domain [56]. However, the black-box nature of deep learning models has raised concerns about their interpretability, motivating researchers to delve into explainable machine learning techniques. Explainable artificial intelligence (XAI) offers methodologies to 'open the black box' of machine learning models and make their decision-making processes understandable to humans [7,12,14,25]. Interpretability techniques, such as saliency maps, feature visualization, and activation maximization, have been applied to emotion recognition systems to highlight the regions in input data that are influential in driving the model's predictions [20,34].

Explainable affective computing represents an ongoing and significant area of research that seeks to bridge the gap between the powerful predictive capabilities of AI systems and the need for human-understandable decision-making processes [3,24,29]. By drawing from various fields, including XAI, HCI, and ethics, researchers aim to create emotionally intelligent systems that are transparent, trustworthy, and capable of enhancing human-computer interfaces in a more natural and empathetic manner [21,37]. Many recent works are using neurosymbolic AI to leverage both the robust pattern recognition capabilities of neural networks and the structured reasoning strengths of symbolic AI [52–54,57,58,60]. As the field continues to evolve, it is expected that advances in explainability will lead to more responsible and ethically-aware affective computing applications in various domains, including healthcare, education, and human-robot interaction [15,30].

3 Proposed Framework

SenticNet 8 aims to mitigate one important issue with current AI models: the symbol grounding problem. Solving this problem is crucial for achieving XAI because it addresses the foundational challenge of connecting abstract symbols or representations to concrete real-world entities and experiences. By establishing a clear and meaningful connection between symbols and their referents, XAI systems can provide more understandable and interpretable explanations for their actions and decisions. This is done through a three-step normalization process (Fig. 1). Firstly, a "syntactic normalization" step leverages a graph-based approach [16] to replace inflections like `bought`, `purchasing`, and `pays for` with their lemmas, e.g., `buy`, `purchase`, and `pay_for`, respectively. Secondly, "semantic normalization" (explained in detail later) leverages conceptual dependency theory [27,41,46,47,51] and a commonsense knowledge graph [49] to replace resulting lemmas like `purchase` and `pay_for`, with their corresponding conceptual primitive, e.g., `BUY(`x`)`, where x is the direct object indicating the thing acted upon by the primitive.

Finally, the "pragmatic normalization" step draws lessons from the field of semiotics to ground the meaning of resulting conceptual primitives into language-agnostic representations that can better explain the current state of affairs of

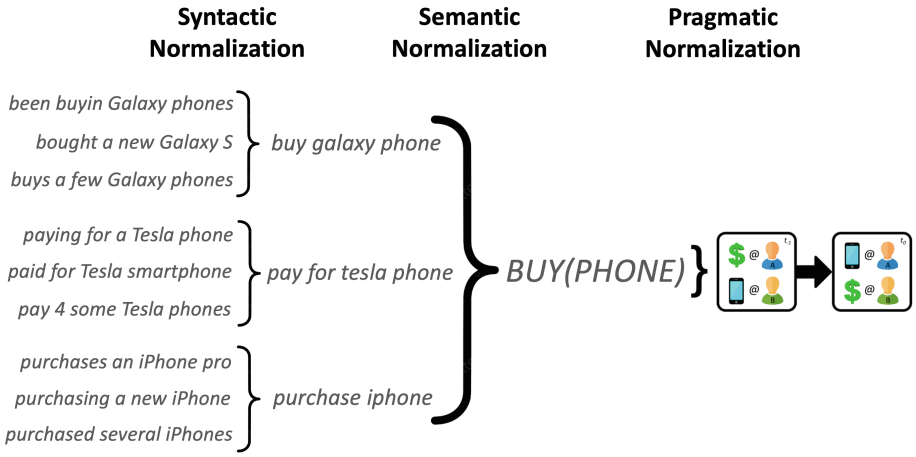


Fig. 1. SenticNet's three-step normalization process

an operating environment. For example, the word `buy` is nothing more than a three-letter word with some statistical properties for a LLM but in SenticNet `BUY(`x`)` is represented as a double transfer of ownership where, at time t_{-1}, agent A owns \$ (a certain amount of money) and agent B owns x while, at time t_0, agent A owns x and agent B owns \$. This sort of universal symbolism is useful for several reasons. Firstly, it represents an interesting attempt to recreate language-agnostic representations to refer to concepts in a universal way, the same way as mathematical symbols or musical notes allow anyone to perform mathematical operations or read and write music, no matter what language they speak. Secondly, it uses more grounded representations that, unlike words or word embeddings, can better replicate or visualize the current state of affairs of an operating environment on the fly, as narratives unfold (this is currently done in terms of 2D symbols but, in the future, it could be implemented by generating 3D representations in a virtual world).

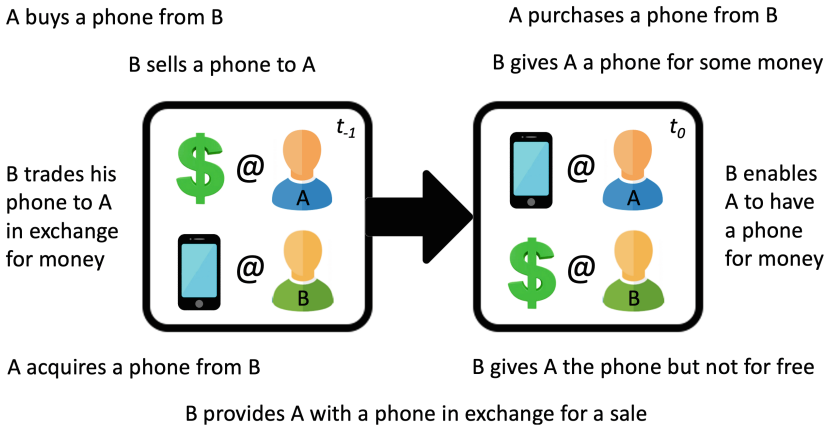


Fig. 2. A universal symbolism can aid generalization and disambiguation tasks.

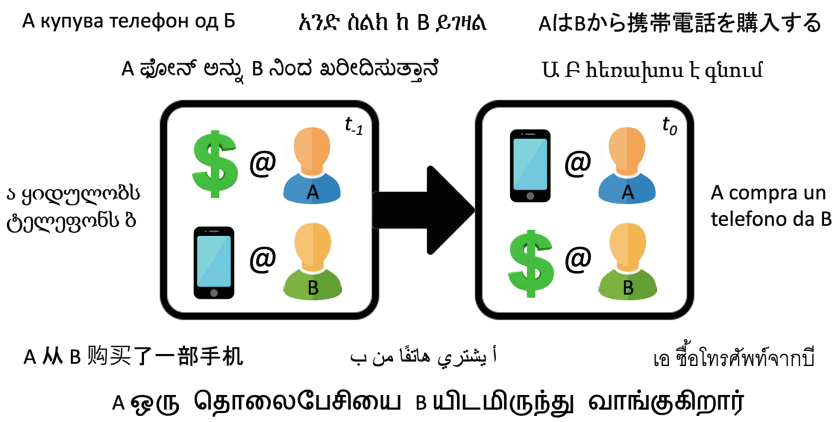


Fig. 3. A universal symbolism can aid machine translation and multimodal tasks.

Additionally, this symbolism can help handle both richness and ambiguity of natural language by having a unique simplified representation for the potentially infinite ways one can express the same concept in natural language (Fig. 2). Similarly, it can aid machine translation efforts by having a common or shared representation for the same concept, which is then referred to by different languages using their own encodings, e.g., sequence of letters versus sequence of characters, left to right versus right to left, text versus speech, etc. (Fig. 3). Lastly, an important novelty introduced by this symbolism is the use of the time dimension for knowledge representation, which is mostly absent from past frameworks but which is very important to better model cause and effect [59], especially in the context of affective computing. Although most emotions only take place in the present (t_0), in fact, many also involve the past (t_1), e.g., regret, nostalgia, remorse, and resignation. Some other involve the future (t_{+1}), e.g., anticipation, hope, anxiety, and relief. Finally, there are also emotions like gratitude, which can span across past (appreciation for past favors), present (current kindnesses), and future (hopeful expectations for future support or kindness).

Another key novelty introduced by this paper is the design of the second step in the above-mentioned normalization process, i.e., the semantic normalization component (Fig. 4). Such component comprises of two main modules, namely polarity detection and lexical substitution (explained later). Given an input sentence $w = (w_1, w_2, \ldots, w_L)$, we first aim to identify the target word t that should be replaced by a primitive for the downstream prediction from w. We extract K primitives from SenticNet 7 [13] as candidates $c = (c_1, \ldots, c_K)$, forming the input (s) as

$$\begin{aligned} s = &< s >, w_1, w_2, \ldots, t, \ldots, w_L, < /s >, \\ &c_1, < /s >, c_2, < /s >, \ldots, c_K, < /s > . \end{aligned} \tag{1}$$

$< s >$ and $< /s >$ are special tokens that were defined by the employed pre-trained language model. The lexical substitution module identifies the best candidate from c as the substitute $\hat{c}$ which retains the original meaning of t in the context by using contrast learning.

Thus, $\hat{c}$ is the symbolic representation of t in context w. Then, the substitute input $w^f = (w_1, \ldots, \hat{c}, \ldots, w_L)$ is fed into a neural network classifier to predict a sentiment label. The objective is that the substitute input w^f increases the probability of correct sentiment prediction. First, through steps (1) and (2) in Fig. 4, the original input is fed into the encoder and the interpretable attention module to obtain the top I tokens with the highest attention weights, which contribute the most to sentiment prediction. In step (3), the sense diversity of each token is computed as the average distance of the token's hidden state to those of its substitution candidates, i.e., the most relevant primitive. Then, through step (4), the top J tokens that are most likely to be replaced by a primitive are selected as targets, because these target tokens may be associated to different primitives in different contexts.

Subsequently, the pre-trained lexical substitution module provides the best substitution to replace each target token, as shown in steps (5) and (6)a. The new input sentence is passed onto the polarity detection module for final prediction through steps (7)a and (8)a, which is used for the sentiment module backpropagation in step (9)a. In order to fine-tune the lexical substitution module and, hence, provide better primitive substitutions that improve the accuracy of sentiment analysis, we implement a dynamic rewarding mechanism (explained later). As shown in steps (5) and (6)b, for each target word, the top N candidates are selected. Each of them is seen as a substitute candidate to calculate the probability of correct sentiment prediction after the replacement in steps (7)b and (8)b. Then, each probability is used to dynamically compute the loss weight when the corresponding primitive candidate is learned by the lexical substitution module as a ground truth as shown in (9)b and (10)b.

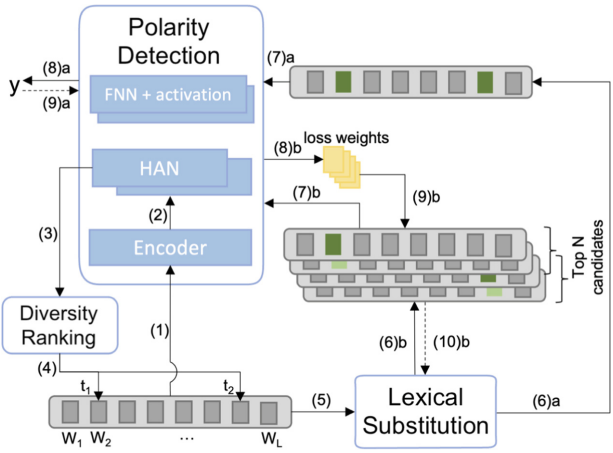


Fig. 4. Semantic normalization component. Dotted lines represent backpropagation. Green blocks indicate the original word being replaced by a word provided by the lexical substitution module. The darker the green, the higher probability it is assigned to by the model. (Color figure online)

If the replacement by a candidate leads to a higher chance of predicting the right sentiment, the candidate is more likely given a higher rank assigned by the lexical substitution module. Otherwise, the module would be less likely to select the candidate as the best replacement. The detailed training process can be seen in Algorithm 1.

Algorithm 1: Semantic normalization.

Initialize polarity detection module as Φ, pre-trained lexical substitution module as Ψ;
Initialize hyperparameters β, I,J, N;
while *not done* **do**
  Sample a sentence $w = w_1, w_2, \ldots, w_L$;
  for *l=1:L* **do**
    Compute the attention weight a_l of token w_l;
  end
  $w^{att} \leftarrow$ Top I of w ordered by attention weights $a = a_1, a_2, \ldots, a_L$;
  for *i=1:I* **do**
    $c \leftarrow$ all possible primitive candidates with the same part-of-speech type as w_i^{att} from SenticNet 7;
    Compute the average Eulidean distance d_i between the hidden states of w_i^{att} and c, produced by the encoder in Φ;
  end
  $t = (t_1, t_2, \ldots, t_J) \leftarrow$ Top J of w^{att} ordered by $d = d_1, d_2, \ldots, d_I$;
  $w^f \leftarrow w$;
  for *j=1:J* **do**
    Input t_j into Ψ to produce top N candidates $\hat{c} = (\hat{c}_1, \ldots, \hat{c}_N)$, ordered by probability;
    Replace t_j in w^f with $\hat{c}_1$;
    $s \leftarrow (< s >, w_1, \ldots, t_i, \ldots, w_L, < /s >,$
    $\hat{c}_1, < /s >, \ldots, \hat{c}_N, < /s >)$;
    for *n=1:N* **do**
      $w^s \leftarrow$ Replace t_j in w with $\hat{c}_n$;
      Input w^s into Φ to obtain the probability of correct sentiment prediction $P(\hat{y} = \tilde{y})$;
      $\theta_{j,n} \leftarrow \beta P(\hat{y} = \tilde{y})^2$;
      Compute $\mathcal{L}_{j,n}^{(ls)}$ by feeding s with $\hat{c}_n$ labeled as true substitute into Ψ ;
      $\mathcal{L}_{j,n}^{(ls)} \leftarrow \theta_{j,n} \mathcal{L}_{j,n}^{(ls)}$;
    end
  end
  $\mathcal{L}^{(ls)} \leftarrow \mathcal{L}_{1,1}^{(ls)} + \cdots + \mathcal{L}_{1,N}^{(ls)} + \mathcal{L}_{J,1}^{(ls)} + \cdots + \mathcal{L}_{J,N}^{(ls)}$;
  Compute sentiment analysis loss $\mathcal{L}^{(sa)}$ using w^f as input;
  $L \leftarrow \mathcal{L}^{(sa)} + \mathcal{L}^{(ls)}$;
end

3.1 Sentiment Analysis with Interpretability

Given input sentence $w = (w_1, \ldots, w_L)$, the goal is to predict the correct sentiment label $\tilde{y}$. The input is first fed into a pre-trained encoder:

$$V = Encoder(w), \tag{2}$$

where V is hidden states.

Next, we aim to find the tokens that contribute the most to sentiment inference. We adopt an interpretable attention module called hierarchical attention network (HAN), which effectively encodes hidden states with multiple non-linear projections and ranks the most influential tokens based on attention [55]. We stack two blocks of HAN to form our attention module.

$$q, a = HAN(HAN(V)), \tag{3}$$

where vector q is the yielded hidden state and a is the attention weights, indicating the contribution of each token to the final sentiment prediction. To obtain the sentiment prediction, q is passed on to two layers of feedforward neural networks (FNN) to obtain the probability distribution of sentiment prediction, with the first one being activated by ReLU [1], and the second by softmax.

$$h = ReLU(FNN_1(q)) \tag{4}$$

$$\hat{y} = softmax(FNN_2(h)) \tag{5}$$

We denote the prediction of the sentiment analysis module as $\hat{y}^f$ when the input is w^f, which denotes a substitute w where all selected target tokens are replaced by relevant primitives. Thus, the sentiment analysis loss is computed as:

$$\mathcal{L}^{(sa)} = CrossEntropy(\hat{y}^f, \tilde{y}) \tag{6}$$

3.2 Generalization by Lexical Substitution

For the lexical substitution module, we employ a novel pre-training paradigm, termed anomalous language modeling (ALM), which was pre-trained to detect anomalous substituted words from a sequence and retrieve the original words from a set of candidates that contains a positive sample (appropriate primitive of the original word according to the context) and multiple hard negative samples (other primitives associated with the original word) via contrastive learning.

We use the candidates from SenticNet 7 to formulate our input s as in Formula 1. The candidate with the highest score is set as the ground truth substitution $\tilde{c}$. Given the input s, the model encodes it as:

$$U, R = ALM(s), \tag{7}$$

where $U = [u_1, \ldots, u_L]$ is the hidden states of the input sentence, and $R = [r_1, \ldots, r_K]$ is the hidden states of the candidates. We denote the representation of the target word as u_t ($t \in \{1, \ldots, L\}$).

Our training objective is to a) close the distance between the representation of the ground truth candidate r_k, ($k \in \{1, \ldots, K\}$) with u_t, and b) push away incorrect candidates representations r_j ($j \in \{1, \ldots, K | j \neq k\}$) from u_t. Namely, (r_k, u_t) will be regarded as a positive pair, while (r_j, u_t) will be regarded as a negative pair. We follow the InfoNCE loss [42] to achieve these goals, which can be formulated as :

$$\mathcal{L}^{(tune)} = -\sum_{i} \log \frac{exp(d(u_t, r_k)/\tau)}{\sum_j exp(d(u_t, r_i)/\tau)}, \tag{8}$$

where $i \in \{1, \ldots, K\}$, τ is a temperature hyper-parameter, and $d(\cdot)$ is Euclidean distance. During the inference stage, we choose the candidate $\hat{c}$ whose corresponding hidden state r_k is the most similar to u_t, measured by Euclidean distance:

$$\hat{c} = \arg\min(d(u_t, r_k)) \tag{9}$$

We then use the resulting lexical substitution module to find primitive replacements for the selected target words in sentiment analysis input. To determine which words are selected as primitive targets, we select the top I words in the input with the highest a produced by Eq. 3, forming the set w^{att}. We denote their corresponding representations as $V^{att} = \{v_1^{att}, \ldots, v_I^{att}\}$. For each v_i^{att}, we compute its average Euclidean distance to all of its candidates' hidden states. The candidates consist of relevant primitives from SenticNet 7 under the same part-of-speech type, which are transformed into hidden states $G = \{g_1, \ldots, g_M\}$ using Eq. 2. M represents the number of primitive candidates from SenticNet 7. The top J words in w^{att} with the largest corresponding average distance are considered to be the ones with the most diverse word meanings, and thus are more likely to be replaced. Hence, target words $t = (t_1, \ldots, t_J)$ are selected by finding each corresponding v_j^{att}:

$$v_j^{att} = \arg\max_i (\frac{1}{M} \sum_{M} d(v_i^{att}, g_m)). \tag{10}$$

3.3 Dynamic Rewarding Mechanism

To fine-tune the lexical substitution module on the downstream task of sentiment analysis, we utilize the top N candidates $\hat{c}_j = \{\hat{c}_{j,1}, \ldots, \hat{c}_{j,n}, \ldots, \hat{c}_{j,N}\}$ produced by the lexical substitution module, for each target word t_j.

The new input resulting from t_j being replaced by candidate $\hat{c}_{j,n}$ is denoted as $w^{j,n}$. Same with Eq. 5, the probability distribution of a sentiment prediction from $w^{j,n}$ is:

$$P(\hat{y})_{j,n} = softmax(FNN_2(h^{j,n})), \tag{11}$$

where $h^{j,n}$ are the hidden states of $w^{j,n}$ produced by Eq. 4 in the sentiment analysis module.

To adjust the model in such a way that a more accurate sentiment prediction results in a higher reward for the corresponding substitution output, we compute the loss weight for $\hat{c}_{j,n}$ being the correct substitution prediction as:

$$\theta_{j,n} = \beta P(\hat{y} = \tilde{y})^2_{j,n}, \tag{12}$$

where β is a hyperparameter for balancing the sentiment analysis and lexical substitution losses, $\tilde{y}$ is the ground truth sentiment label as defined above. We formulate the input s^j to lexical substitution module with sentence w and candidates $\hat{c}_j$, using Formula 1.

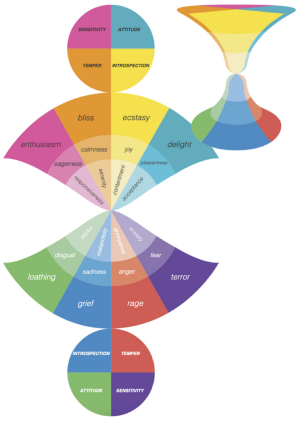
Similar to Eq. 8, the loss ($\mathcal{L}^{(ls)}_{j,n}$) of the lexical substitution module when $\hat{c}_{j,n}$ is considered as gold standard is computed as follows:

$$\mathcal{L}^{(ls)}_{j,n} = -\sum_i \log \frac{exp(d(u_t, \hat{c}_{j,n})/\tau)}{\sum_j exp(d(u_t, \hat{c}_j)/\tau)}. \tag{13}$$

Finally, the total loss is computed as:

$$\mathcal{L} = \mathcal{L}^{(sa)} + \theta_{1,1}\mathcal{L}^{(ls)}_{1,1} + \cdots + \theta_{J,N}\mathcal{L}^{(ls)}_{J,N}. \tag{14}$$

The algorithm also works well with emoticons and emojis, which are very important sentiment indicators in social media text. These are aptly replaced with their corresponding primitive, which in most cases is an emotion primitive. In particular, we use the Hourglass of Emotions [50] as emotion categorization model for both verbal and nonverbal content (Fig. 5).



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. 5. The Hourglass of Emotions. Unlike other emotion categorization models, the Hourglass represents antithetic emotions very efficiently. Its mirroring capability, in fact, enables the easy handling of negations and other variations of language that can change the sentiment of words otherwise taken in isolation.

4 Evaluation

We test SenticNet 8 against ChatGPT and three more NLP models on three different affective computing datasets. In the following three sections, we describe in detail baselines adopted, datasets used, and results obtained, respectively.

4.1 Baselines

In order to compare the performance of SenticNet 8 on the different tasks, we need to use baselines and train them on the Train portion (while validating on the Dev portion). Besides ChatGPT, we employ three more baselines, which serve as the specialized models specifically tailored for the corresponding downstream task: a robust language model (RoBERTa) trained on a large amount of text; a baseline which uses a word model by employing pretrained word2vec (W2V) embeddings; and a simple Bag-of-Words (BoW) model that utilizes a linear classifier. The hyperparameters of all models are optimized by selecting the hyperparameters yielding the best performance on the Dev portion. Such hyperparameters are tuned using the SMAC toolkit [35], which is based on Bayesian Optimization. The selected hyperparameters are listed in Table 1. Figure 6 illustrates the pipelines of all methods.

Bag of Words. BoW is a simple model that uses only in-domain data for training and no other data for either up- or downstreaming. We utilize the classical technique term frequency – inverse document frequency (TF-IDF), which tokenizes the sentences into words, then, a sentence is represented by a vector of the counts of the words it contains. The vector is then normalized by the term frequency across the entire Train set of the corresponding dataset. We tune the learning rate η of SGD using SMAC.

Word2vec Embeddings. The baseline word2vec [39,40] makes use of pretrained word embeddings, which are trained on a large amounts of text from Google News. The model operates by tokenizing a given text into words, each word is assigned an embedding from the pretrained embeddings. The embeddings are then averaged for all words to give a static feature vector of size 300 for the entire string. An SVM model [8] is then used to predict the given task.

RoBERTa Language Model. The baseline RoBERTa [36] is a pretrained BERT model, which has a transformer architecture. [36] trained two instances of RoBERTa; we use the smaller one, namely *RoBERTa-base*, consisting of 110 million parameters. The model starts by tokenizing a text using subword encoding, which is a hybrid representation between character-based and word-based encodings. The tokens are then fed to RoBERTa to obtain a sequence of embeddings.

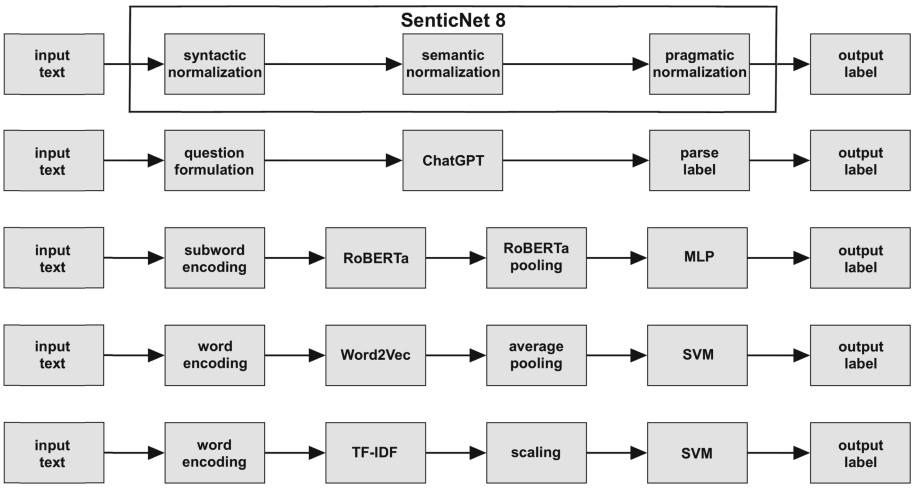


Fig. 6. Evaluation pipelines of SenticNet 8, ChatGPT, RoBERTa, word2vec, and BoW (from top to bottom).

ChatGPT. We introduce the stages of querying ChatGPT as shown in Fig. 6. The general mechanism for collecting answers for each NLP task is as follows:

1. Reformat all the texts of the Test portion of the dataset, by using a format that asks ChatGPT what is their guess about the label of the text.
2. Chunk the examples into 25 examples per chunk.
3. For each chunk, open a new ChatGPT Conversation.
4. Ask ChatGPT (manually) the reformatted question for each example, one-by-one, and collect the answers.
5. Repeat the steps 3–4 until the predictions for the whole Test set are finished.
6. Postprocess the results in case they need some cleanup.

Table 1. Hyperparameters of the different baselines. N is the number of hidden layers, U is the number of neurons in the first hidden layer (which is halved for each subsequent layers), and α is the learning rate. Adam optimizer always yields the best results as compared to SGD. C is the SVM parameter for word2vec. η is the learning rate of the SGD in the BoW model.

	RoBERTa			W2V	BoW
	N	U	α	C	η
Polarity	3	420	2.97×10^{-5}	0.0144	5.25×10^{-6}
O	2	498	5.66×10^{-4}	0.0378	2.47×10^{-3}
C				0.0472	3.09×10^{-6}
E				0.0069	1.09×10^{-5}
A				0.0218	4.65×10^{-4}
N				0.0657	2.21×10^{-6}
Suicide	3	497	8.04×10^{-4}	10.00	4.71×10^{-6}

The formats used for the three NLP tasks are shown in the following snippets. The {*text*} part needs to be replaced with the sample text. Please note that quotation marks need to be kept since it specifies to ChatGPT that this a placeholder used by the question being asked. The formulations for the three NLP tasks are as follows:

1. For sentiment analysis, we formulated the question:
   "What is your guess for the sentiment of the text "{text}*", answer positive, neutral, or negative? it does not have to be correct. Do not show any warning after."*
2. For the Big-five personality traits, we asked:
   "What is your guess for the big-five personality traits of someone who said "{text}*", answer low or high with bullet points for the five traits? It does not have to be fully correct. You do not need to explain the traits. Do not show any warning after."*
3. For the suicidal ideation detection, we asked:
   "What is your guess if a person is saying "{text}*" has a suicide tendency or not, answer yes or no? it does not have to be correct. Do not show any warning after."*

The formulation of the question is of crucial importance to the answers ChatGPT generates. For anyone who would like to carry out similar investigations in the future, we report four important lessons learnt:

1. Asking the question directly without requesting ChatGPT to guess made it often answer that there is little information provided to answer the question, and it cannot answer it exactly.
2. It is important to ask *what* the guess is and not "*Can you guess*", because this can generate a response similar to 1., where ChatGPT responds with an answer that starts with "*No, I cannot accurately answer whether...*". Therefore, the question needs to be assertive and specific.
3. The questions for the suicide assessment task may trigger warnings in the responses of ChatGPT due to its sensitive content.
4. We need to specify the exact output format, because ChatGPT can get creative about the formatting of the answer, which can make it hard to collect answers for our experiment.

The responses of ChatGPT need to be parsed, since ChatGPT can give arbitrary formats for a given answer, even when the content is the same. This is predominant in the personality traits, since there are five traits. Sometimes the answers are listed as bullet points, other times they are all in one comma-separated line. Also, it used different delimiters or order, e.g., "Openness: Low", or "Low in Openness", and "Low: Openness". Additionally, in all problems, it sometimes gives an introduction for the answer, for example, "Here is my guess for ..", or "Based on the statement". We solve this issue by using regular expressions to find and edit such responses.

Table 2. Statistics of the three datasets used for evaluation.

Dataset	Train	Dev	Test	Pos	Neg
Polarity	1,440,144	159,856	359	182	177
O	6,000	2,000	509	333	176
C				286	223
E				214	295
A				340	169
N				274	235
Suicide	138,479	6,270	496	165	331

4.2 Datasets

In this section, we briefly introduce the three datasets we used. A summary of their statistics is presented in Table 2. We utilize publicly available datasets for reproducibility.

Polarity Dataset. We adopt the Sentiment140 dataset [23] for the sentiment analysis task. The dataset is collected from Twitter, which makes the text very noisy and can pose a challenge against many models (especially word models). The dataset consists of tweets and the corresponding sentiment labels (positive or negative).

Personality Dataset. We utilize the First Impressions dataset [44] for the personality task. Personality is represented by the Big-five personality traits (OCEAN), namely, *Openness (to experience)*, *Conscientiousness*, *Extraversion*, *Agreeableness*, and *Neuroticism*. The dataset consists of 15 s videos with one speaker, whose personality was manually labelled.

Suicide and Depression Dataset. The Suicide and Depression dataset [19] is collected from the Reddit platform, under different subreddits categories, namely "SuicideWatch", "depression", and "teenagers". The texts of the posts from the "teenagers" category are labelled as negative, while the texts from the other two categories are labelled as positive.

4.3 Results

In this section, we review the results of our experiments. In summary, we evaluated the performance of SenticNet 8 (our commonsense knowledge base of 400,000 concepts, available for download at https://sentic.net/downloads) against four baselines (namely, ChatGPT, RoBERTa, word2vec, and BoW) on three downstream tasks (namely, sentiment analysis, personality recognition, and suicidal ideation detection). Results are shown in Table 3. We use classification accuracy and unweighted average recall (UAR) as performance measures.

UAR has an advantage of exposing if a model is performing very well on a class on the expense of the other class, especially in imbalanced datasets. As also demonstrated by other recent works [26,45], ChatGPT turned out to be jack of all trades but master of none [31] also in the context of affective computing: while the performance of ChatGPT is acceptable on many different NLP tasks, specialized models like SenticNet 8 (and even RoBERTa in most cases) still outperform it on specific tasks. Unlike all baselines used in this work, moreover, SenticNet 8 is also interpretable (because the process that generalizes input words and multiword expressions into their corresponding primitives is fully transparent), trustworthy (because classification outputs always come with a confidence score), and explainable (because classification outputs are explicitly linked to emotions and the input concepts that convey these).

Table 3. Classification accuracy and unweighted average recall (in %) of SenticNet 8 against four baselines (CGPT: ChatGPT; rBERT: RoBERTa; W2V: word2vec; BoW: Bag of Words) on three different NLP tasks (Polarity: sentiment analysis; OCEAN: personality prediction; Suicide: suicidal ideation detection). Bold values show the best method for a combination of specific performance metric and prediction target.

	Accuracy					Unweighted Average Recall				
[%]	SenticNet	CGPT	rBERT	W2V	BoW	SenticNet	CGPT	rBERT	W2V	BoW
Polarity	**88.80**	85.51	85.07	79.41	82.54	**88.67**	85.57	85.02	79.40	82.41
O	**67.91**	46.62	66.03	65.28	59.71	**78.27**	50.12	50.94	50.72	55.61
C	**65.97**	57.40	63.72	62.70	55.60	**79.92**	57.70	60.81	60.09	56.30
E	63.19	55.23	**66.09**	59.92	55.24	**72.76**	54.09	62.30	55.56	53.74
A	**67.86**	44.86	67.42	67.21	58.53	**79.93**	48.45	51.93	51.02	55.75
N	**64.53**	47.29	62.17	56.84	56.09	**77.54**	49.16	61.25	54.64	55.88
Suicide	**99.34**	92.71	97.43	92.16	92.78	**99.35**	91.26	97.40	91.23	90.97

5 Discussion

Intuitively, even if real parrots or stochastic ones (LLMs) produce the appropriate linguistic response relative to the task-related prompts for the three above-mentioned datasets, we would not deem their linguistic behavior trustworthy unless they possess the relevant natural language understanding. Meaning involves a relation between the linguistic form of data and an extralinguistic reality that is distinct from language. Where M denotes meaning, E denotes the form of natural language expressions, and I denotes communicative intent, this relation may be formally represented as $M \subseteq E \times I$ [5]. M contains ordered pairs (e, i) of natural language expressions (e) and communicative intents (i).

Understanding may be interpreted as the process of retrieving i, given e. Since LLMs are pretrained on large datasets and meaning cannot be learnt from lin-guistic form (e) alone, however impressive their transformer and artificial neural network architecture might be, LLMs will necessarily lack the relevant inten-tionality. We do not claim that SenticNet 8 possesses either human-level or the req-uisite level of natural language understanding. However, as SenticNet 8 relies on commonsense knowledge representation as part of its ensemble, it is better able than ChatGPT to track the extralinguistic reality that is distinct from language. For affective computing tasks, SenticNet 8 is ahead of ChatGPT, as its responses are more firmly grounded in an extralinguistic reality through its reliance on commonsense knowledge representation. SenticNet 8 leverages symbolic models (namely, conceptual dependency theory and a semantic network of commonsense knowledge) to encode meaning in a top-down fashion. Finally, this work does not aim to disdain ChatGPT: we hope future versions of ChatGPT will overcome some of the reported limitations. Given the non-interpretability of its constitutive models, however, it may not happen so soon. As shown in a recent study [17], in fact, ChatGPT seems prone to the "short blanket dilemma": while trying to improve its accuracy on some tasks, OpenAI researchers inadvertently made ChatGPT worse for tasks which it previously excelled at.

6 Conclusion

In this paper, we presented SenticNet 8, a neurosymbolic AI framework leveraging an ensemble of commonsense knowledge representation and hierarchical attention networks, which aims to mitigate the symbol grounding problem. We compared SenticNet 8 against ChatGPT and three more baselines on three downstream tasks. Results show that SenticNet 8's performance is generally superior to all baselines on all tasks. Unlike the other baselines, moreover, SenticNet 8 is interpretable, trustworthy, and explainable. We also propose the idea of a universal symbolism that leverages language-agnostic representations, which can better emulate the current state of affairs of an operating environment on the fly, as narratives unfold.

7 Limitations

A crucial limitation of the presented results is the small amount of data for evaluation (497, 362, and 509 examples for the three tasks), since ChatGPT is only available for manual entries by the consumers and not for automated large-scale testing. Additionally, it only responds to approximately 25–35 requests per hour, in order to reduce the computational cost and avoid brute forcing. Another issue that may limit future experiments is parsing the responses. In our experiments, ChatGPT responded with arbitrary formatting despite specifying the desired format explicitly in the question prompt.

One final limitation of the proposed approach is that pragmatic representations are currently defined manually. However, this is not an issue for our current investigation considering that: (a) these representations need to be created only for conceptual primitives (which are automatically discovered using deep learning); (b) these representations only need to be created once (as conceptual primitives are not subject to concept drift); and (c) in this work we merely consider polar conceptual primitives, i.e., only primitives that can be associated with certain emotions and a positive or negative polarity. In order to apply this approach to more general NLP tasks, a generative AI mechanism for automatically creating such representations should be implemented. Alternatively, this could be done by first establishing a universal set of natural language symbols, e.g., emojis, ISO icons, or blissymbolics [9], and then devising methods for automatically translating different languages into such symbols, similar to how music notation rendering transforms audio into written music scores. We leave this to future work.

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