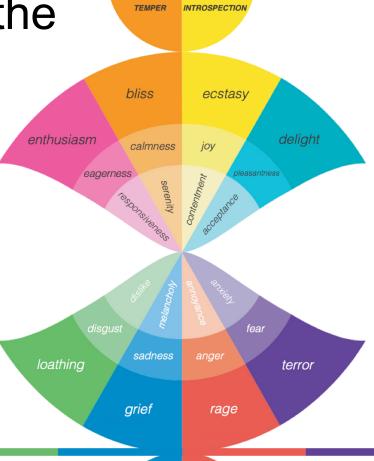
Explainable AI for Stress and Depression Detection in the Cyberspace and Beyond

PAKDD RAFDA 7th May 2024



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Erik Cambria, PhD, FIEEE
Professor of Computer Science & Engineering
Provost Chair in Computer Science & Engineering
SCSE, Nanyang Technological University, Singapore



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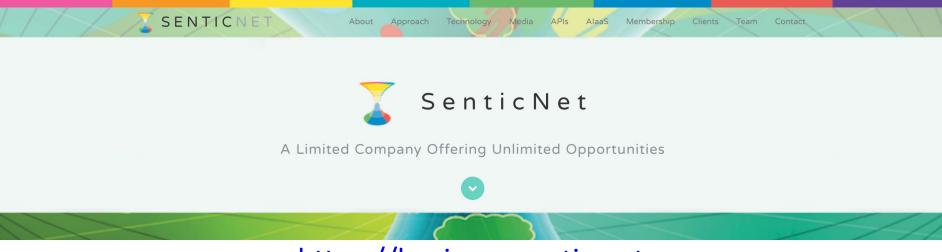
Best Global Universities Rankings (by Subject)

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Spinoffs





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7 Pillars for the Future of Al



Deep Learning



What society thinks I do



What my friends think I do



What other computer scientists think I do



Erik Cambria



What mathematicians think I do



What I think I do

from theano import *

What I actually do

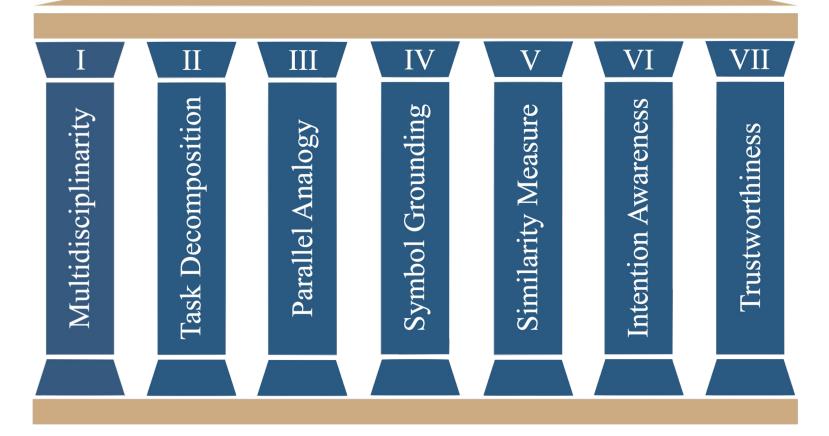


E Cambria, R Mao, M Chen, Z Wang, SB Ho. Seven Pillars for the Future of Artificial Intelligence. IEEE Intelligent Systems 38(6), 62-69 (2023)

Seven Pillars



Artificial Intelligence

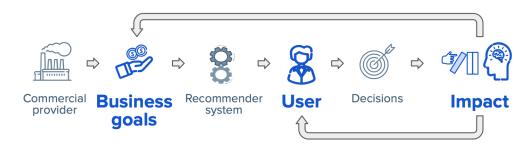


https://sentic.net/7-pillars-for-the-future-of-ai.pdf

Trustworthiness

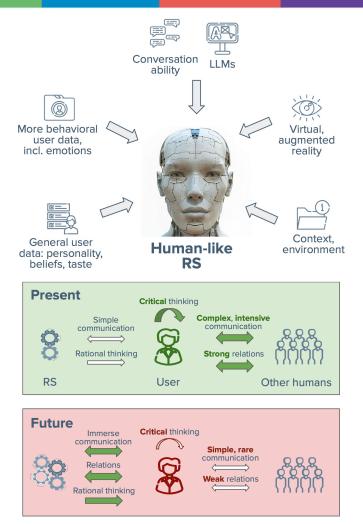








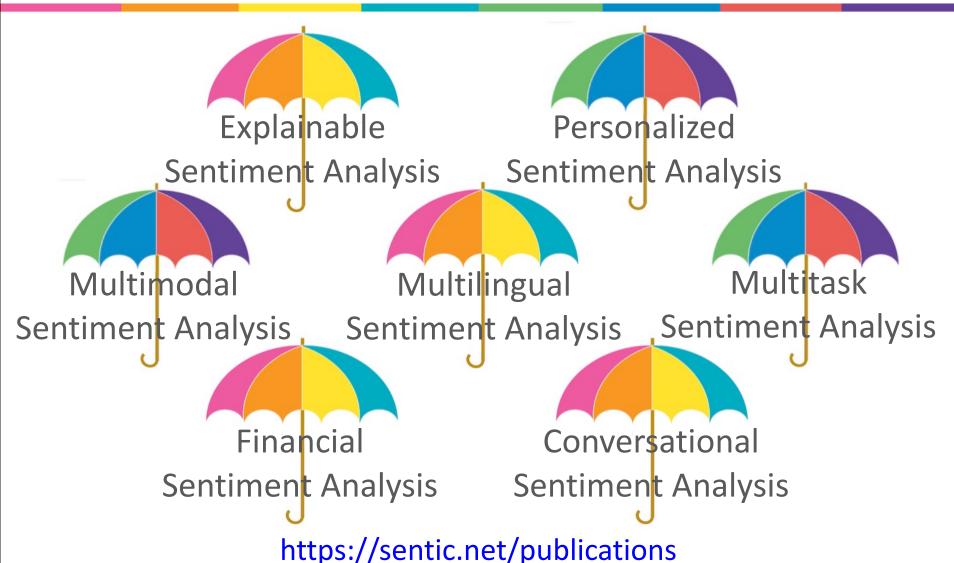




P Kazienko, E Cambria. Towards Responsible Recommender Systems. IEEE Intelligent Systems 39(3) (2024)

Seven Umbrellas





Seven Projects













Al for Healthcare





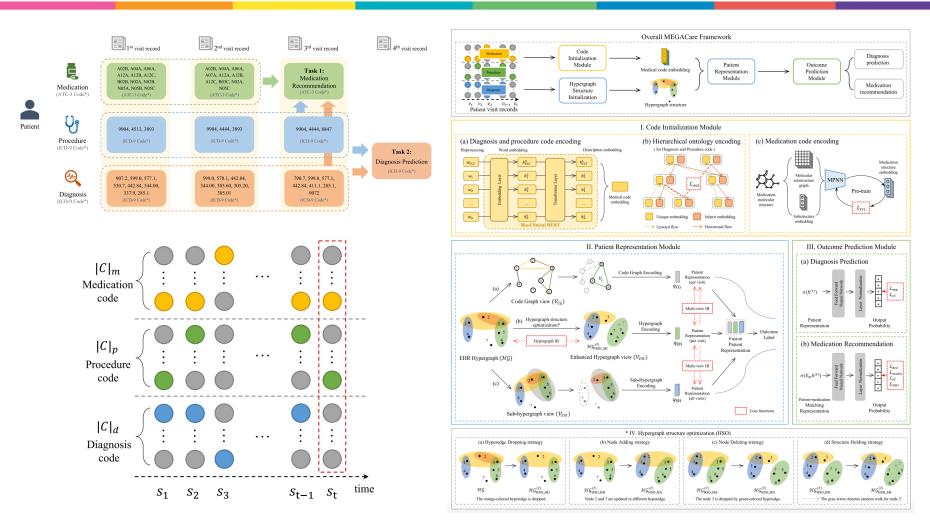
Al for Online Safety

Al for the Arts

https://sentic.net/projects

Al for Healthcare





J Wu, K He, R Mao, C Li, E Cambria. MEGACare: Knowledge-guided Multi-view Hypergraph Predictive Framework for Healthcare. Information Fusion 100, 101939 (2023)







Table 1: A summary of datasets. Note we hold out a portion of original training set as the validation set if the original dataset does not contain a validation set.

Category	Platform	Dataset	train	validation	test
Assorted	Reddit	SWMH (Ji et al., 2022)	34,823	8,706	10,883
Depression	Reddit	eRisk18 T1 (Losada and Crestani, 2016)	1,533	658	619
Depression	Reddit	Depression_Reddit (Pirina and Çöltekin, 2018)	1,004	431	406
Depression	Reddit	CLPsych15 (Coppersmith et al., 2015)	457	197	300
Stress	Reddit	Dreaddit (Turcan and McKeown, 2019)	2,270	568	715
Suicide	Reddit	UMD (Shing et al., 2018)	993	249	490
Suicide	Twitter	T-SID (Ji et al., 2022)	3,072	768	960
Stress	SMS-like	SAD (Mauriello et al., 2021)	5,548	617	685

S Ji, T Zhang, L Ansari, J Fu, P Tiwari, E Cambria. MentalBERT: Publicly Available Pretrained Language Models for Mental Healthcare. Proceedings of LREC, 7184-7190 (2022)



Model	DR		CLPsych15		Dreaddit		T-SID		SAD		CAMS	
Model	Rec.	F1	Rec.	F1	Rec.	F1	Rec.	F1	Rec.	F1	Rec.	F1
BERT	91.13	90.90	64.67	62.75	78.46	78.26	88.44	88.51	62.77	62.72	40.26	34.92
RoBERTa	95.07	95.11	67.67	66.07	80.56	80.56	88.75	88.76	66.86	67.53	41.18	36.54
XLNet	90.89	90.44	69.83	69.12	78.88	78.84	86.04	86.18	67.30	67.30	50.64	49.16
Longformer	95.81	95.74	75.67	75.47	81.54	81.45	89.58	89.63	69.20	69.01	49.52	49.42
MentalBERT	94.58	94.62	64.67	62.63	80.28	80.04	88.65	88.61	67.45	67.34	45.69	39.73
MentalRoBERTa	94.33	94.23	70.33	69.71	81.82	81.76	88.96	89.01	68.61	68.44	50.48	47.62
$ChatGPT_{ZS}$	82.76	82.41	60.33	56.31	72.72	71.79	39.79	33.30	55.91	54.05	32.43	33.85
$ChatGPT_V$	79.51	78.01	59.20	56.34	74.23	73.99	40.04	33.38	52.49	50.29	28.48	29.00
$ChatGPT_{N_sen}$	80.00	78.86	58.19	55.50	70.87	70.21	39.00	32.02	52.92	51.38	26.88	27.22
$ChatGPT_{N_emo}$	79.51	78.41	58.19	53.87	73.25	73.08	39.00	32.25	54.82	52.57	35.20	35.11
$ChatGPT_{CoT}^{-}$	82.72	82.90	56.19	50.47	70.97	70.87	37.66	32.89	55.18	52.92	39.19	38.76
$ChatGPT_{CoT_emo}$	83.17	83.10	61.41	58.24	75.07	74.83	34.76	27.71	58.31	56.68	43.11	42.29
MentalXLNet	95.32	95.24	71.67	71.49	80.42	80.41	89.17	89.12	69.20	68.76	50.80	50.08
MentalLongformer	96.55	96.53	77.00	76.32	81.12	81.05	89.90	89.89	68.76	68.44	49.20	48.74

Table 3: Results of mental health classification. The bold text represents the best performance. Note that: for Longformer and MentalLongformer, the best results are reported with longer texts as inputs.

S Ji, T Zhang, K Yang, S Ananiadou, E Cambria, J Tiedemann. Domain-specific Continued Pretraining of Language Models for Capturing Long Context in Mental Health. arXiv:2304.10447 (2024)



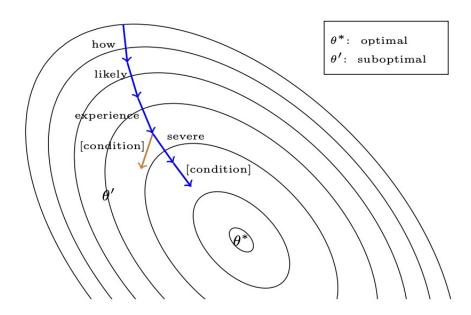
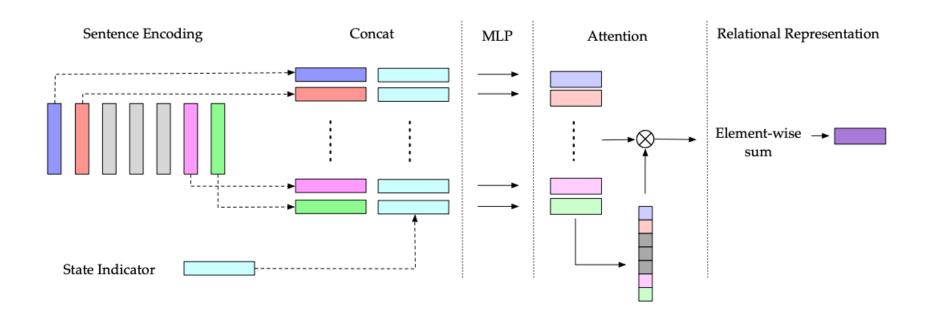


Figure 2: An illustration of prompting from the view of meta update. The change in the prompt might lead to suboptimal, possibly explaining the unpredictable LLMs' generation-as-prediction.

S Ji, T Zhang, K Yang, S Ananiadou, E Cambria. Rethinking Large Language Models in Mental Health Applications. arXiv preprint arXiv:2311.11267 (2023)

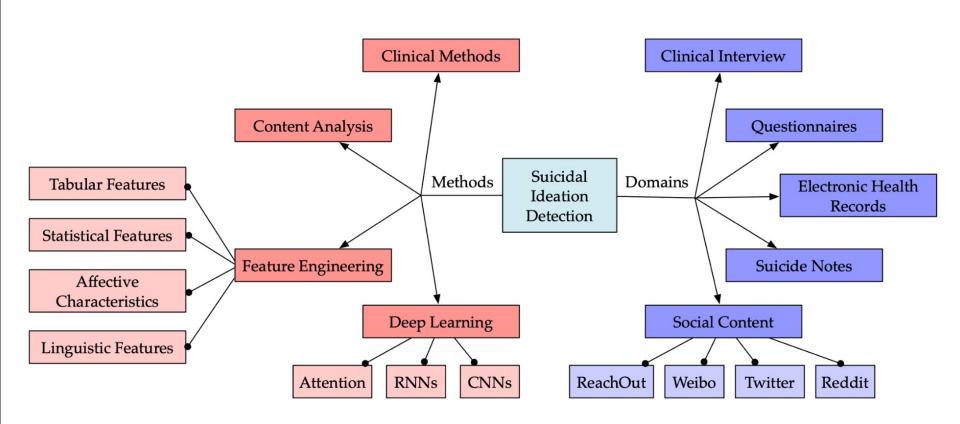




S Ji, X Li, Z Huang, E Cambria. Suicidal Ideation and Mental Disorder Detection with Attentive Relation Networks. Neural Computing and Applications 34, 10309-10319 (2022)

Suicidal Ideation Detection

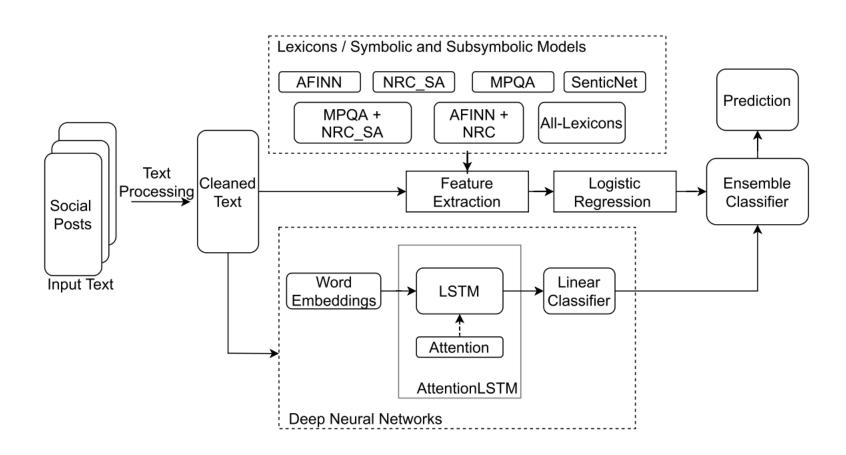




S Ji et al. Suicidal Ideation Detection: A Review of Machine Learning Methods and Applications. IEEE Transactions on Computational Social Systems 8(1), 214-226 (2021)

Depression detection

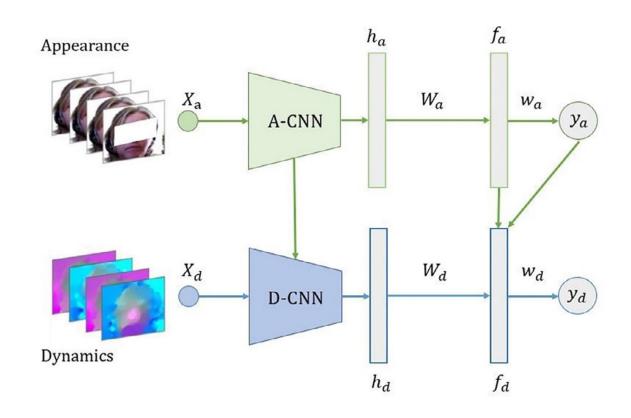




L Ansari, S Ji, Q Chen, E Cambria. Ensemble Hybrid Learning Methods for Automated Depression Detection. IEEE Transactions on Computational Social Systems 10(1), 211-219 (2023)

Depression detection





Q Chen, I Chaturvedi, S Ji, E Cambria. Sequential Fusion of Facial Appearance and Dynamics for Depression Recognition. Pattern Recognition Letters 150, 115-121 (2021)

Depression detection



We developed a novel explainable model for depression detection on Twitter. It comprises a novel encoder combining hierarchical attention mechanisms and feed-forward neural networks. To support psycholinguistic studies, our model leverages metaphorical concept mappings as input in order to also detect implicit manifestations of

depression. We packaged this model

 $Softmax(FNN_3^0)$ $ReLU(FNN_2^o)$ $ReLU(FNN_1^o)$ $Norm(ReLU(FNN_i^t))$ $Norm(ReLU(FNN_{l}^{c}))$ Layer l Attention Attention $Norm(ReLU(FNN_2^T))$ $Norm(ReLU(FNN_2^t))$ $Norm(ReLU(FNN_2^c))$ $Norm(ReLU(FNN_2^C))$ Layer 2 Attention Attention $Norm(ReLU(FNN_1^T))$ $Norm(ReLU(FNN_1^t))$ $Norm(ReLU(FNN_1^c))$ $Norm(ReLU(FNN_1^C))$ Layer 1 Attention Attention

both as an API: https://sentic.net/api/#depression

and a github repository: https://github.com/senticnet/depression-detection

S Han, R Mao, E Cambria. Hierarchical Attention Network for Explainable Depression Detection on Twitter Aided by Metaphor Concept Mappings. In: COLING, 94–104 (2022)

Authors













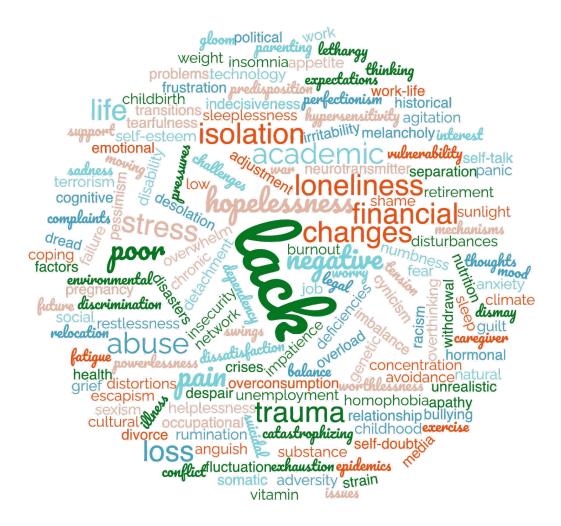
Erik Cambria^{1(⊠)}, Balázs Gulyás¹, Joyce S. Pang¹, Nigel V. Marsh², and Mythily Subramaniam³

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 - ² James Cook University, Singapore, Singapore nigel.marsh@jcu.edu.au
 - ³ Institute of Mental Health, Singapore, Singapore mythily@imh.com.sg

Dataset



- #MentalHealth: This hashtag is widely used to discuss various aspects of mental health, including stress, depression, anxiety, and other related conditions.
 It encompasses conversations about personal experiences, coping strategies, and advocacy efforts.
- #Depression: This hashtag specifically focuses on discussions surrounding depression, a mood disorder characterized by persistent feelings of sadness, hopelessness, and loss of interest. It is often used to share personal stories, raise awareness, and provide support to those struggling with depression.
- #Anxiety: Anxiety is a common mental health condition characterized by excessive worry, fear, and apprehension. The #Anxiety hashtag is used to share experiences, coping mechanisms, and resources for managing anxietyrelated symptoms.
- #Stress: This hashtag is used to discuss the experience of stress, which refers to the body's response to perceived threats or challenges. Discussions under this hashtag include triggers of stress, coping strategies, and the impact of chronic stress on mental and physical health.
- #SelfCare: Self-care involves intentionally taking care of one's physical, emotional, and mental well-being. The #SelfCare hashtag is used to share tips, practices, and experiences related to self-care activities that can help alleviate stress and promote overall wellness.
- #MentalHealthAwareness: This hashtag is used to raise awareness about mental health issues, including stress and depression, and to promote understanding, acceptance, and support for individuals experiencing mental health challenges.
- #EndStigma: Stigma surrounding mental health can create barriers to seeking help and support. The #EndStigma hashtag is used to advocate for ending the discrimination and prejudice associated with mental illness, fostering a more inclusive and supportive society.
- #MentalHealthMatters: This hashtag emphasizes the importance of prioritizing mental health and acknowledging its significance in overall well-being. It is often used to promote conversations, initiatives, and policies aimed at addressing mental health issues such as stress and depression.
- #Wellness: Wellness encompasses various dimensions of health, including physical, mental, emotional, and social well-being. The #Wellness hashtag is used to share tips, resources, and practices that support holistic health and promote stress reduction and resilience.
- #SelfLove: Self-love involves cultivating a positive and compassionate relationship with oneself. The #SelfLove hashtag is used to promote self-acceptance, self-care, and self-compassion, which are important aspects of managing stress and improving mental health.



Data Analysis

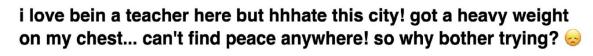
"COMMANDER"

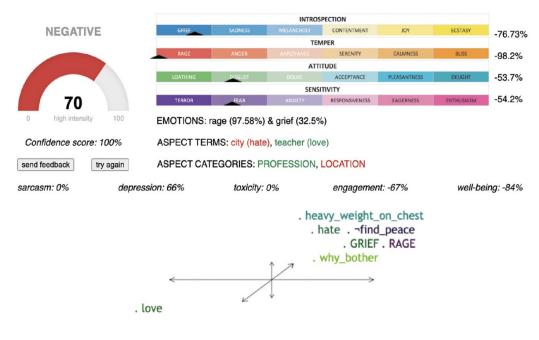
ENTJ

Bold, imaginative and strongwilled leaders, always finding a way – or making one

O↑C↑E↑A↓N↓







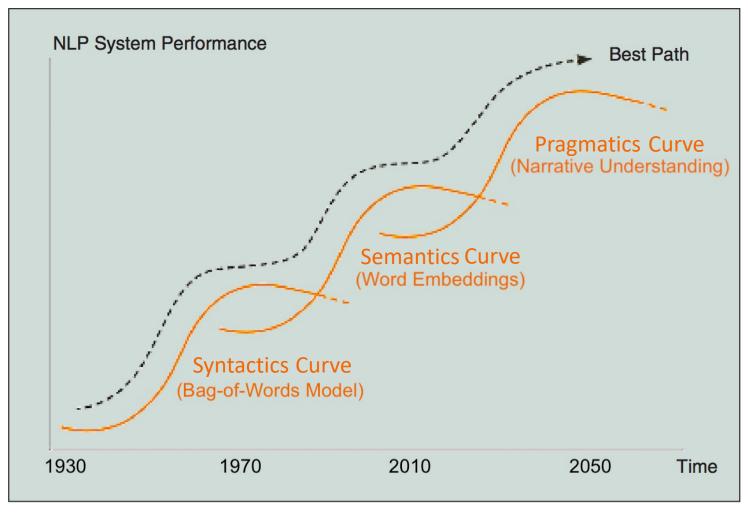
Outcomes



- Relationship issues: Problems within intimate relationships or family conflicts can impact mental health and contribute to depressive symptoms.
- Financial problems: Financial stress, such as debt, unemployment, or financial instability, can lead to feelings of hopelessness.
- Social isolation: Lack of social support and feelings of loneliness can cause depression, as social connections are essential for emotional well-being.
- Work-life balance: Difficulty balancing work responsibilities with personal life and self-care can lead to chronic stress and impact mental well-being.
- Academic pressure: Students experience stress and depression due to academic demands, performance pressure, or difficulty coping with coursework.
- Discrimination: Experiencing discrimination based on race, ethnicity, gender identity, sexual orientation, or other factors can lead to chronic stress.
- Chronic pain: Living with chronic health conditions or experiencing persistent pain can be emotionally draining and exacerbate feelings of depression.
- Trauma: Past trauma, including physical, emotional, or sexual abuse, can have long-lasting effects on mental health and increase the risk of depression.
- Media exposure: Overexposure to negative news, social media comparison, or unrealistic portrayals of success can contribute to feelings of inadequacy.
- Environmental factors: Environmental stressors such as pollution, noise, or overcrowding can contribute to chronic stress and impact mental health.

Research roadmap





E Cambria, B White. Jumping NLP Curves: A Review of Natural Language Processing Research. IEEE Computational Intelligence Magazine 9(2), 48-57 (2014)

Suitcase Model

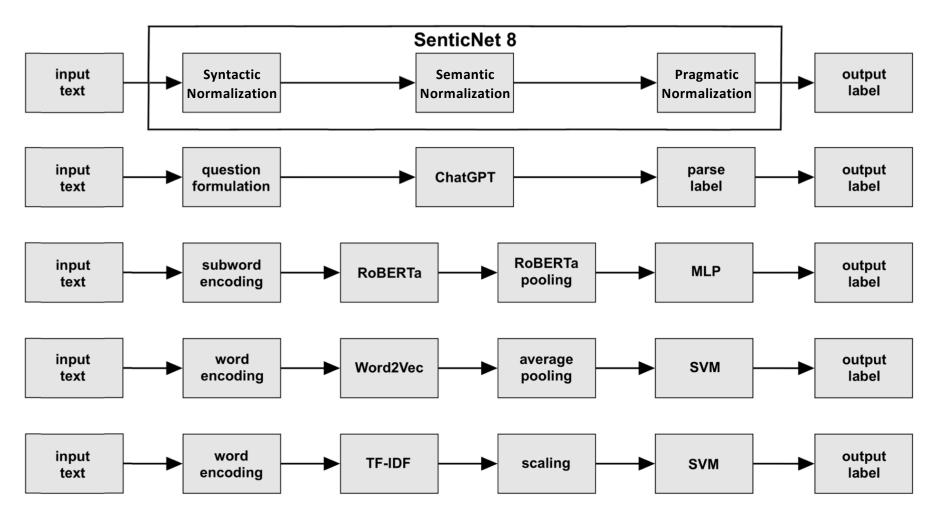




E Cambria, S Poria, A Gelbukh, M Thelwall. Sentiment Analysis is a Big Suitcase. IEEE Intelligent Systems 32(6), 74-80 (2017)

SenticNet





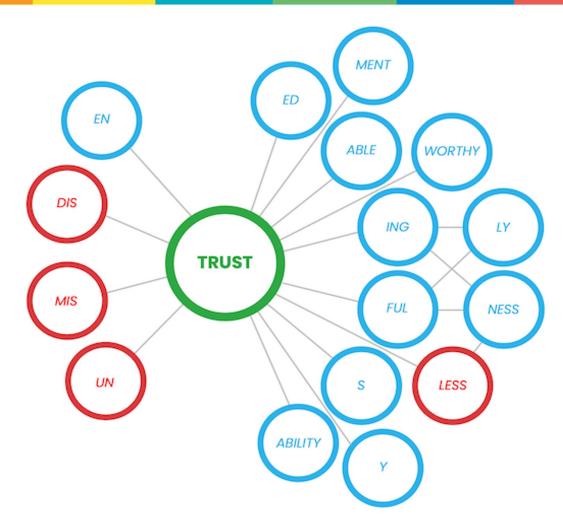
SenticNet



Syntactic Normalization	Semantic Normalization	Pragmatic Normalization
buying an OPPO Reno5 bought OPPO Reno Pro buys some OPPO Reno	BUY OPPO RENO	
purchasing an iPhone 15 purchases some iPhones purchased iPhone mini	> PURCHASE IPHONE	> BUY(PHONE)
pays for Samsung Galaxy paid 4 Samsung Galaxy S24 paying for Samsung Galaxy	PAY FOR GALAXY	

Syntactic Normalization





E Cambria, R Mao, S Han, Q Liu. Sentic Parser: A Graph-Based Approach to Concept Extraction for Sentiment Analysis. Proceedings of ICDM Workshops, 413-420 (2022)

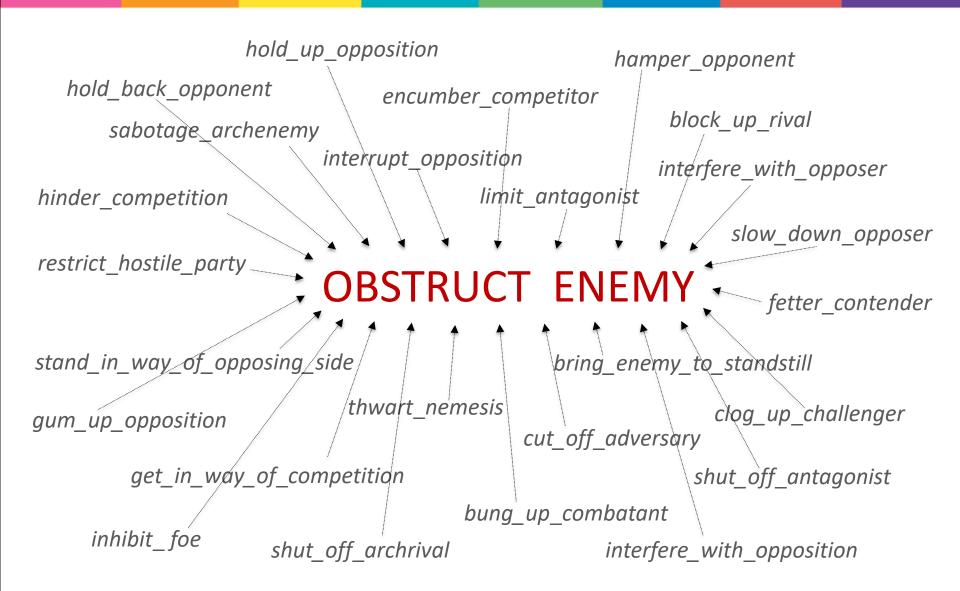
Syntactic Normalization



```
holds_back_his_opponents
                                             holds_back_any_opponent
  held back its opponent
                               holding_back_a_few_opponents
                                                    held_back_various_opponents
          holding_back_their_opponents
                          holds back the opponents
                                                       holds_back_an_opponent
 held_back_a_few_opponents
                                       holding_back_opponent
                                                             holds back opponent
 held back opponent
                            hold_back_opponent
                                                              holds_back_opponent
        holds_back_several_opponents
                                            held_back_every_opponent
                            /held_back_an_opponent
                                                  holding_back_the_opponents
holding_back_most_opponents
                                      held_back_opponents
            held_back_some_opponents
                                                      holding_back_the_opponent
   holding_back_lots_of_opponents held_back_many_opponents
                     holding back an opponent
                                                  holding_back_her_opponents
```

Semantic Normalization





SenticNet



Syntactic Normalization	Semantic Normalization	Pragmatic Normalization
buying an OPPO Reno5 bought OPPO Reno Pro buys some OPPO Reno	BUY OPPO RENO	
purchasing an iPhone 15 purchases some iPhones purchased iPhone mini	> PURCHASE IPHONE	> BUY(PHONE)
pays for Samsung Galaxy paid 4 Samsung Galaxy S24 paying for Samsung Galaxy	PAY FOR GALAXY	

Pragmatic Normalization



BUY(
$$\bigcirc$$
)

BARTER(\bigcirc , \bigcirc)

GIVE(\bigcirc) \land GET(\bigcirc)

 $\neg HAVE(\bigcirc) \rightarrow HAVE(\bigcirc)$

MELANCHOLY ANNOYANCE CONTENTMENT SERENITY

Pragmatic Normalization

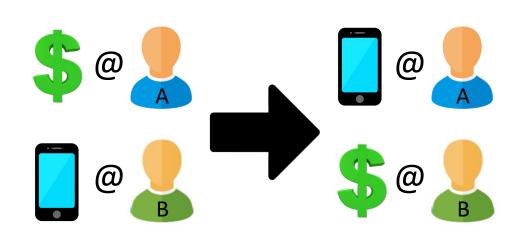


Adam buys a phone from Bob

Adam purchases a phone from Bob

Bob sells a phone to Adam

Bob trades his phone to Adam in exchange for money



Bob gives Adam a phone for some money

Bob enables Adam to have a phone for money

Adam acquires a phone from Bob

Bob does not give Adam the phone for free

Bob provides Adam with a phone in exchange for a sale

Pragmatic Normalization

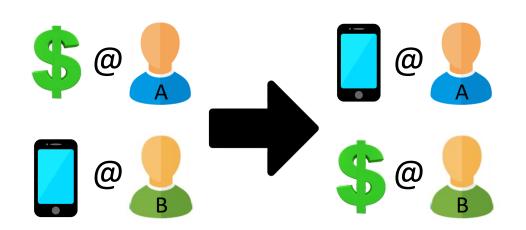


Adam compra un telefono da Bob

Адам купува телефон од Боб

Ադամը Բոբից հեռախոս է գնում

ადამი ყიდულობს ტელეფონს ბობისგან



アダムはボブから 電話を買います

อดัมซื้อโทรศัพท์จากบ๊อบ

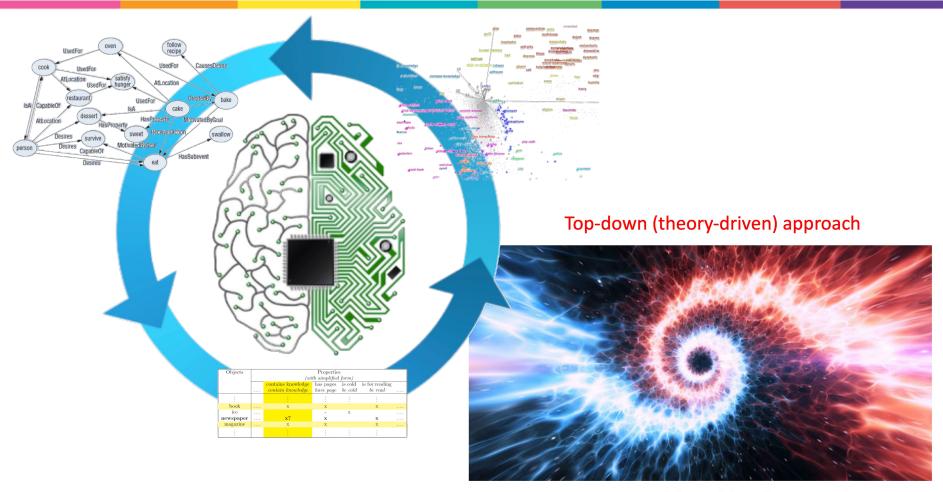
亚当从鲍勃那里买了一部手机

ئادەم مۆبايلنك له بۆب دەكرنت

ஆடம் பாப்பிடம் இருந்து ஒரு போனை வாங்குகிறான்

Neurosymbolic Al





Bottom-up (data-driven) approach

F Xu, Q Lin, J Han, T Zhao, J Liu, E Cambria. Are Large Language Models Really Good Logical Reasoners? A Comprehensive Evaluation From Deductive, Inductive and Abductive Views. arXiv 2306.09841 (2023)

Sentic Computing Section



Cognitive Computation

If you use any sentic algorithm or resource, consider submitting to our Special Section on Cognitive Computation (5.418 impact factor)

https://sentic.net/scs.pdf

Explicable Artificial Intelligence for Affective Computing



Guest Editors:

Rui Mao⊠, Nanyang Technological University, Singapore Erik Cambria, Nanyang Technological University, Singapore Melvin Chen, Nanyang Technological University, Singapore Zhaoxia Wang, Singapore Management University, Singapore Seng-Beng Ho, Agency for Science, Technology and Research, Singapore

Corresponding Email: rui.mao@ntu.edu.sg

Background:

As Artificial Intelligence (AI) advances, the need for transparency and interpretability in its decision-making processes becomes more pronounced, especially within the domain of affective computing. The capacity of AI systems to comprehend and react to human emotions introduces ethical considerations, necessitating a delicate equilibrium between innovation and accountability. Various stakeholders, spanning end-users, developers, and policymakers, express a collective need for a more profound comprehension of these systems, particularly in emotionally charged situations.

The motivation of this Special Issue stems from the inherent challenges in creating AI models that not only accurately recognize and respond to human emotions but also provide clear, interpretable insights into their decision-making processes. The Special Issue also aims at enriching the connotation of Explicable AI with diverse and comprehensive dimensions. Expanding the meaning of explicability is not just about deciphering the "black box" nature of AI models; it involves a broader understanding that encapsulates various facets crucial for fostering user trust, ethical considerations, and interdisciplinary collaboration.

https://sentic.net/eai4ac.pdf

SENTIRE





The IEEE International Conference on Data Mining (ICDM) has established itself as the world's premier research conference in data mining. It provides an international forum for presentation of original research results, as well as exchange and dissemination of innovative and practical development experiences. The conference covers all aspects of data mining, including algorithms, software, systems, and applications. ICDM draws researchers, application developers, and practitioners from a wide range of data mining related areas such as big data, deep learning, pattern recognition, statistical and machine learning, databases, data warehousing, data visualization, knowledge-based systems, and high-performance computing. By promoting novel, high-quality research findings, and innovative solutions to challenging data mining problems, the conference seeks to advance the state-of-the-art in data mining.

Key dates

- September 10, 2024: Workshop papers submission
- October 7, 2024: Notification of acceptance to authors
- October 11, 2024: Camera-ready deadline
- December 9, 2024: Workshops date

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Sentic resources



Downloads: https://sentic.net/downloads

Code: https://github.com/senticnet

Sentic APIs: https://sentic.net/api

Sentic API Suite

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