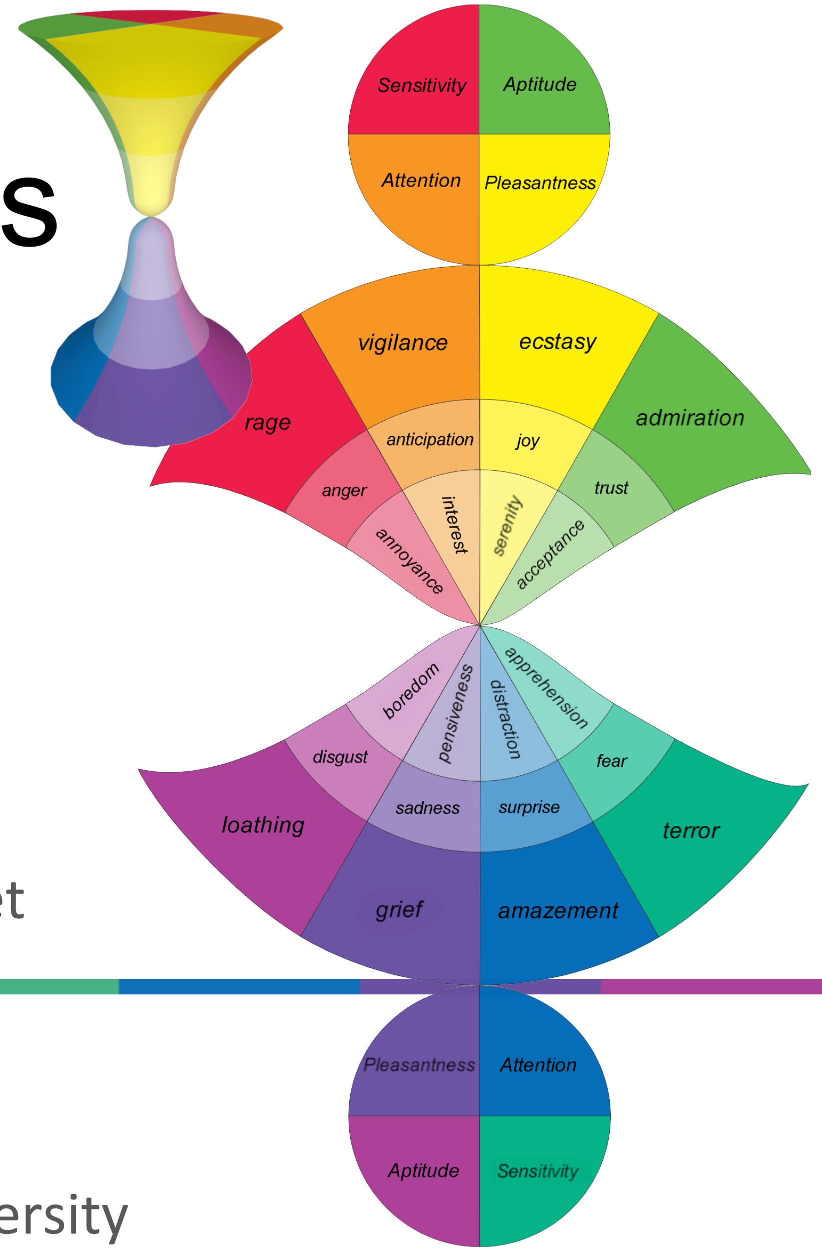
Concept-Level Sentiment Analysis



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Facebook: http://facebook.com/senticnet

7th April 2014, WWW14, COEX, Seoul

Erik Cambria, Ph.D.
Asst Prof @ Nanyang Technological University

Talk Outline

- Introduction
- Eras of the Web
- Evolution of NLP Research
- Background on Opinion Mining
- Concept-Level Sentiment Analysis
- Sentic Computing
- Challenges
- Conclusion

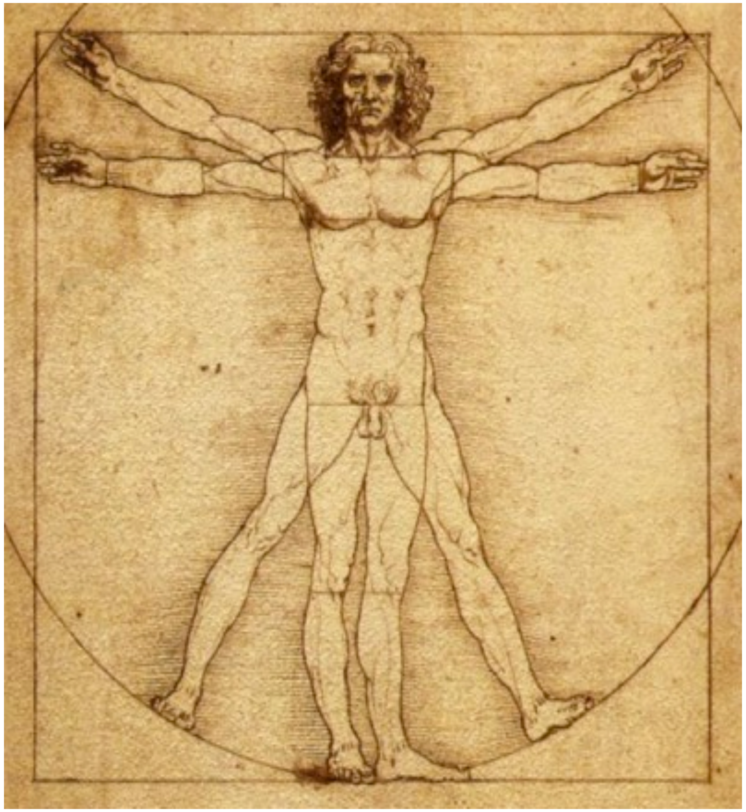
Web: Connecting People

The potential for knowledge sharing today is unmatched in history: never before have so many knowledgeable people been connected

[1] T. Gruber. *Collective Knowledge Systems: Where the Social Web meets the Semantic Web. Journal of Web Semantics 6(1), pp. 4-13 (2007)*

Leonardo's Laptop

Leonardo's discoveries and inventions in science, art, engineering, and aesthetics, were based only on his perception of the world



[2] B. Shneiderman. Leonardo's Laptop: Human Needs and the New Computing Technologies. MIT Press (2003)

The Web as a Lab

The Web today not only represents an unlimited data store but also a multi-disciplinary laboratory environment for world-scale experiments

[3] B. White. The Web as a Laboratory. Invited Talk at WWW MABSDA (2013)

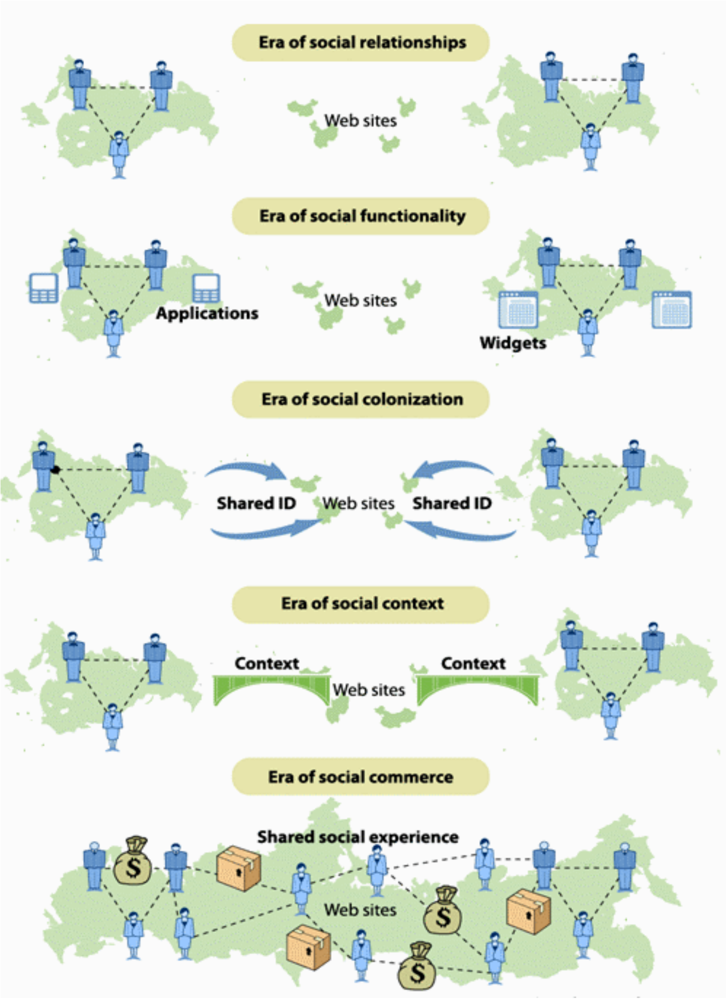
Information Overload

Between the dawn of the Internet and year 2003, there were five exabytes of information on the Web. Now, we create five exabytes every two days

[4] E. Schmidt speaking at Zeitgeist Europe, http://youtu.be/Qr2-2XY_QsQ (2010)

Eras of the Web

The Web is evolving towards a shared social experience, in which consumers will rely on their peers as they make online decisions and will shape future products



[5] J. Owyang, J. Bernoff, C. Pflaum, and E. Bowen. The Future of the Social Web. Forrester Research. http://web-strategist.com/blog/2009/04/27/future-of-the-social-web (2009)

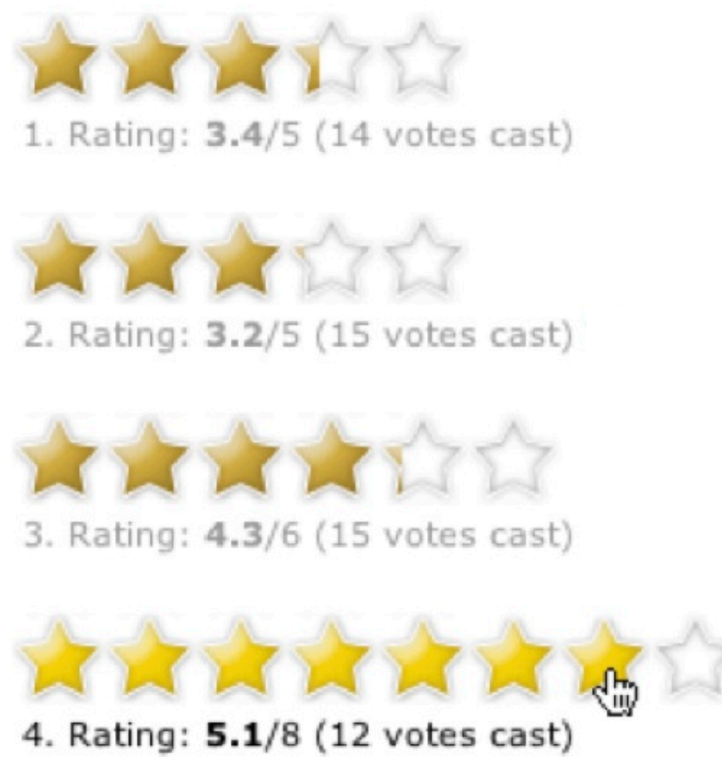
Collected Intelligence

Information today is extremely portable and processable. However, this *collected intelligence* is far from being addressed as *collective intelligence*

[1] T. Gruber. Collective Knowledge Systems: Where the Social Web meets the Semantic Web. Journal of Web Semantics 6(1), pp. 4-13 (2007)

Not So Structured

According to different evaluation schemes and reviewers, a very positive and a very negative review might both have the same star rating



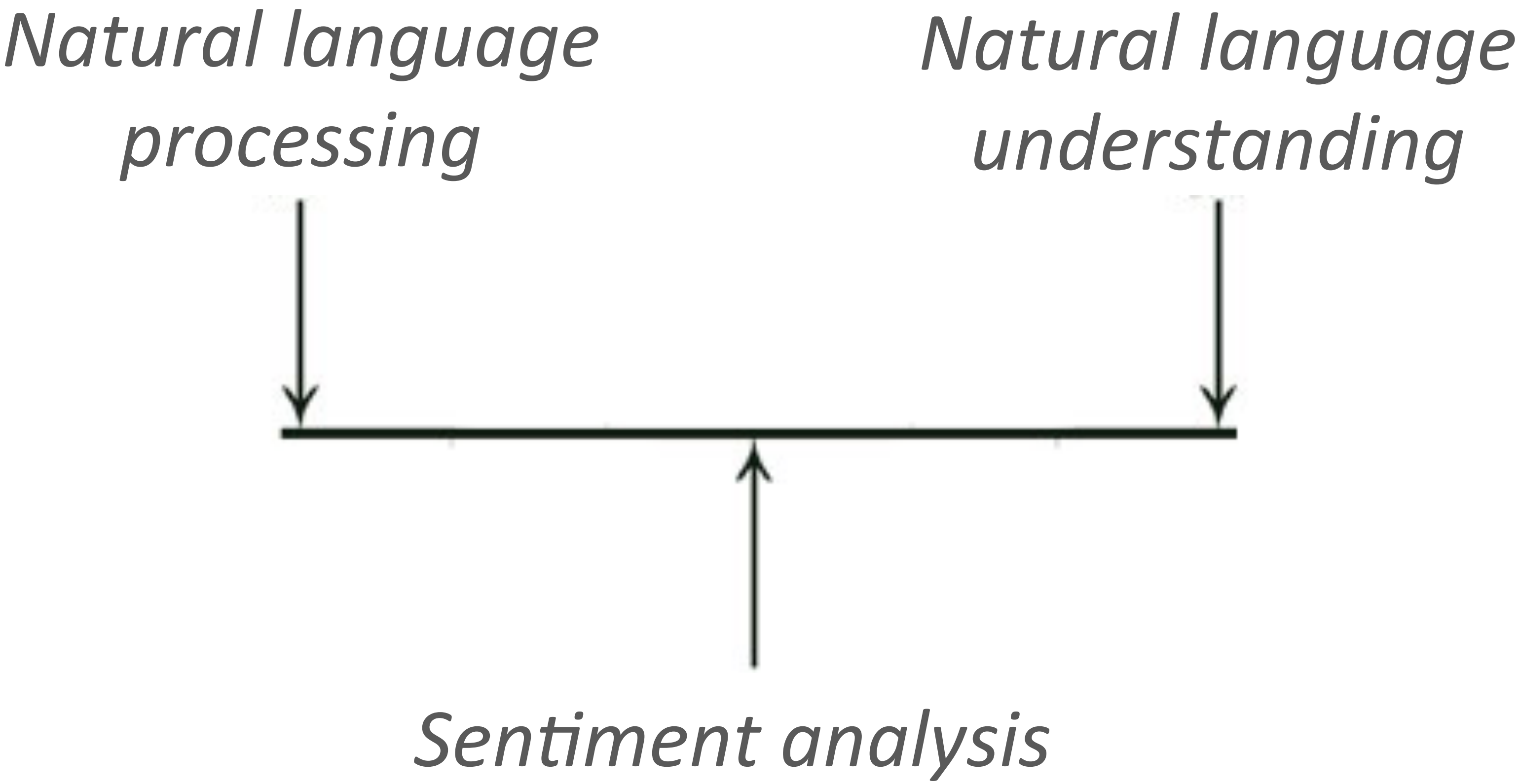
[6] M. Hu and B. Liu. Mining and Summarizing Customer Reviews. In: ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Seattle (2004)

Sentiment Analysis

Sentiment analysis research evolved from heuristics to discourse structure, from coarse-to fine-grained analysis, from keyword- to concept-level mining

[7] E. Cambria, B. Schuller, Y.Q. Xia, C. Havasi. New Avenues in Opinion Mining and Sentiment Analysis. IEEE Intelligent Systems 28(2), pp. 15-21 (2013)

A Possible Path to NLU



Evolution of NLP

NLP technologies evolved from the era of punch cards (7 minutes per sentence) to the era of Google and its like (less than a second per sentence)

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

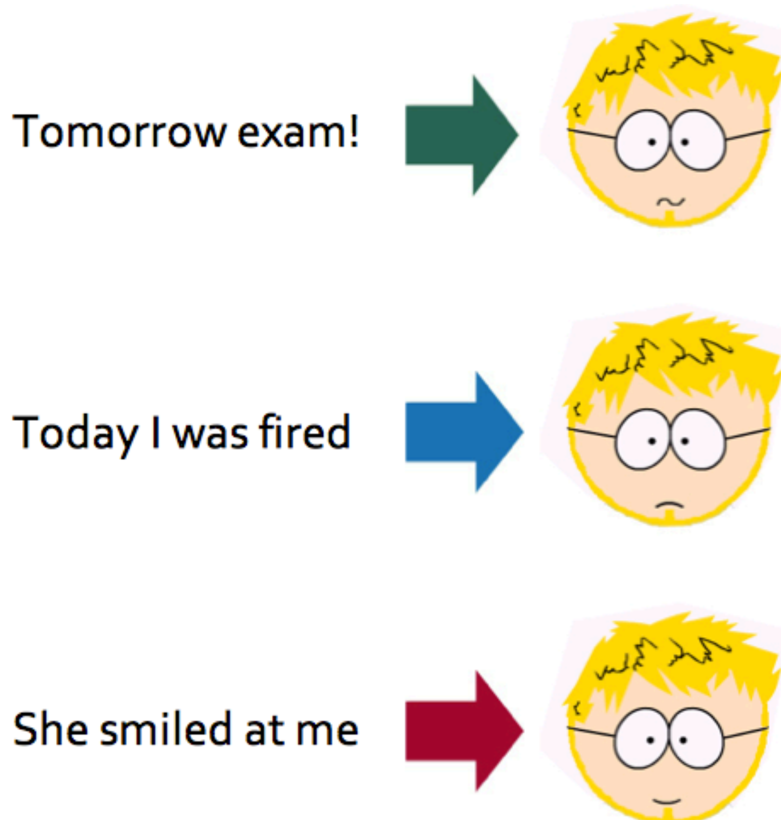
NLP Emergency

In a Web where UGC has hit critical mass, NLP is becoming key for aggregating information although systems are still limited by what they can 'see'

[9] E. Cambria. Facing the NLP Emergency. Invited talk at Tsinghua University (2013)

More Than We See

Language is somewhere in between perception and understanding – a translucent material, so that the world bears the tint and focus of what we express through it



[10] D. Davidson. Seeing Through Language. Royal Institute of Philosophy Supplement 42, pp. 15-27 (1997)

The Hardest Problem?

We can understand almost anything,
but we can't understand how we understand.
Albert Einstein

We understand human mental processes
only slightly better than a fish understands swimming.
John McCarthy

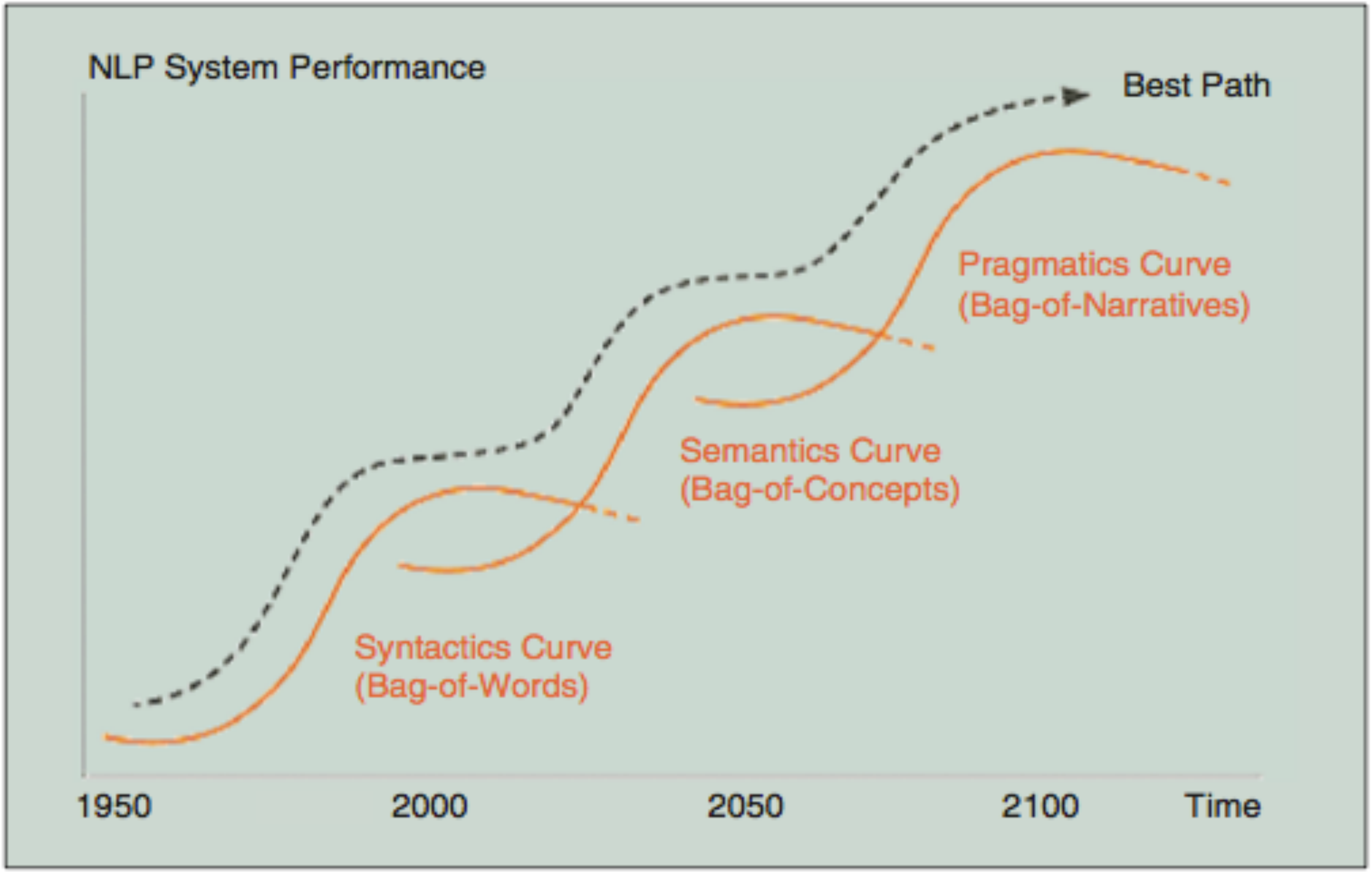
How the mind works is still a mystery.
We understand the hardware, but
we don't have a clue about the operating system.
James Watson

AI Winters

The key failure of AI is the persistency in seeking the best way to solve a problem, which leads to the creation of expert (rather than intelligent) systems

[11] M. Minsky. The Society of Mind. Simon and Schuster, New York (1986)

Jumping NLP Curves



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

Moving Towards NLU

"This past Saturday, I bought a Nokia phone and my girlfriend bought a Motorola phone. We called each other when we got home. The voice on my phone was not so clear, worse than my previous phone. The camera was good. My girlfriend was quite happy with her phone. I wanted a phone with good voice quality. So my purchase was a real disappointment. I returned the phone yesterday."

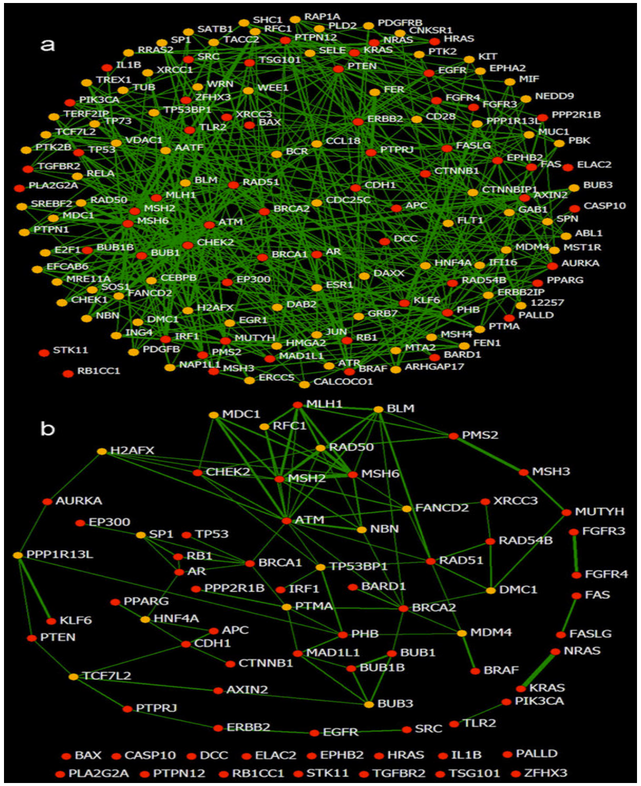
Keyword Spotting

Although the most naïve approach, the accessibility and economy of keyword spotting make it one of the most popular. However, it only relies on surface features

[12] A. Ortony, G. Clore, and A. Collins, The Cognitive Structure of Emotions, Cambridge Univ. Press (1988)

Lexical Affinity

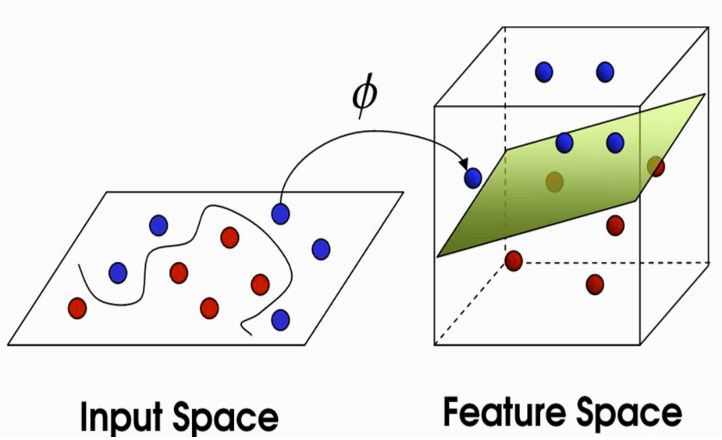
Lexical affinity assigns arbitrary words probable "affinity" to particular emotions – *"accident" has a 75% probability of indicating a negative affect*



[13] R. Stevenson et al. Characterization of the Affective Norms for English Words by Discrete Emotional Categories, Behavior Research Methods 39(4), pp. 1020–1024 (2007)

Statistical Methods

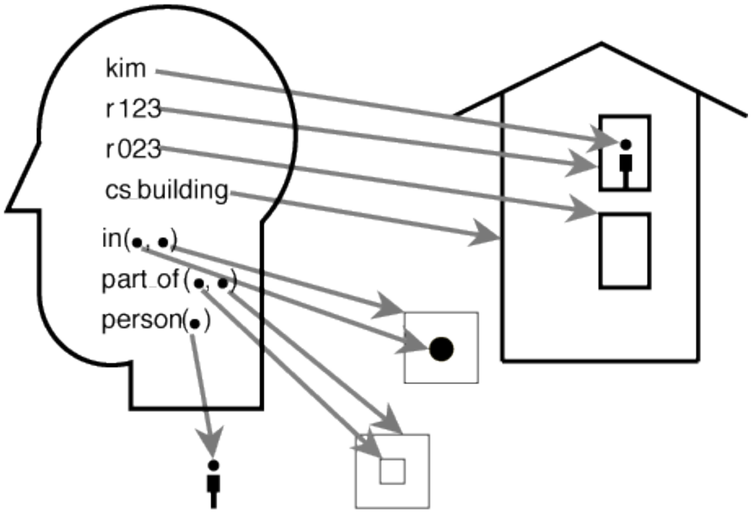
By feeding a ML algorithm a large training corpus, statistical methods not only learn the valence of affect words, but also that of other arbitrary keywords



[14] B. Pang, L. Lee, and S. Vaithyanathan. Thumbs Up? Sentiment Classification Using Machine Learning Techniques, EMNLP, pp. 79–86 (2002)

Concept-Level Analysis

By relying on ontologies or semantic networks, concept-level approaches step away from blindly using affect keywords and word co-occurrence frequencies



[15] E. Cambria. An Introduction to Concept-Level Sentiment Analysis. In: MICAI, Mexico City, invited paper (2013)

Concept-Level Analysis

For auto-categorization:

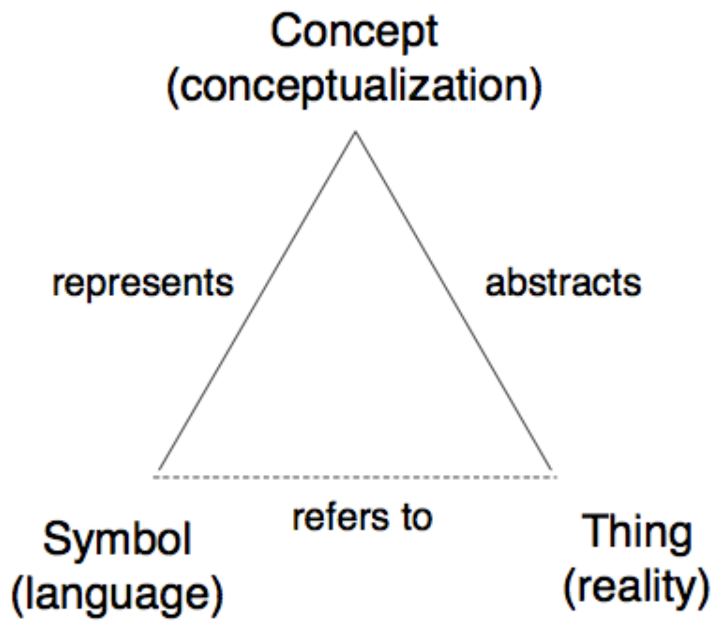
cloud computing != cloud, computing

For opinion mining:

take pain killer != take, pain, killer

Conceptualization

Concepts are immaterial entities that only exist in the mind of the speaker. To be communicated, they must be represented in terms of some concrete artifact



[16] S. Ullmann. Semantics: An Introduction to the Science of Meaning. Barnes & Noble (1979)

A 'Pipe' is Not a Pipe

You can know the name of all the different kinds of 'pipe', but you know nothing about a pipe until you comprehend its purpose and method of usage

[17] R. Magritte. Les Mots et les images. La Révolution surréaliste 12 (1929)

Common Knowledge

In standard human-to-human communication, people usually rely on the presumption that facts or definitions are known and proceed to build upon it

[18] E. Cambria, Y. Song, H. Wang, and N. Howard. Semantic Multi-Dimensional Scaling for Open-Domain Sentiment Analysis. IEEE Intelligent Systems, doi:10.1109/MIS.2012.118 (2014)

Common-Sense

People usually provide only useful information and take the rest for granted. The rest is common-sense: obvious things people know and usually leave unstated

[19] E. Cambria, A. Hussain, C. Havasi, and C. Eckl. Common Sense Computing: From the Society of Mind to Digital Intuition and Beyond. In: LNCS, vol. 5707, pp. 252-259 (2009)

Why Common-Sense?

great phone: +
faulty device: -

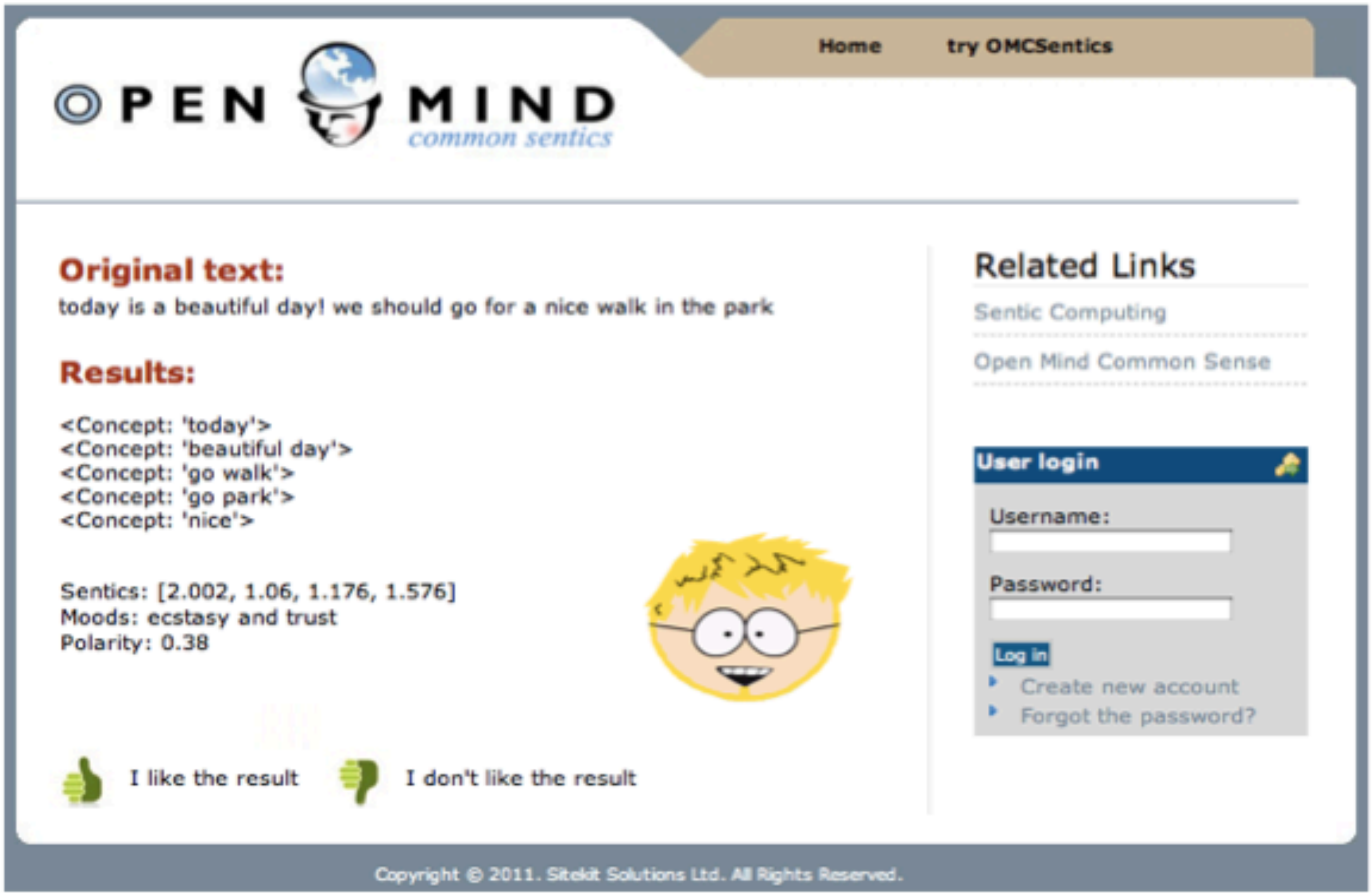
long battery life: ?
long queue: ?
small battery: ?
small seat: ?
cold train: ?
cold beer: ?

Available KBs

Attempts to build common and common-sense knowledge bases are countless and include both hand-crafted resources and automatically-built KBs

[20] W. Wu, H. Li, H. Wang, and K. Zhu. Probase: A Probabilistic Taxonomy for Text Understanding. In: SIGMOD, pp. 481–492 (2012)

Acquiring Knowledge



[21] E. Cambria, Y.Q. Xia, and A. Hussain. Affective Common Sense Knowledge Acquisition for Sentiment Analysis. In: LREC, pp. 3580-3585, Istanbul (2012)

SGECKA

The serious game engine for common-sense knowledge acquisition (SGECKA) aims to collect knowledge from game designers through the development of games

[22] E. Cambria, D. Olsher, D. Rajagopal, and K. Kwok. SGECKA: A Serious Game Engine for Commonsense Knowledge Acquisition. In: UAI, Quebec City (2014)

POG-Based Acquisition

Game designers drag and drop objects from libraries into scenes. They specify a POG triple that describes how each object can be used

[22] E. Cambria, D. Olsher, D. Rajagopal, and K. Kwok. SGECKA: A Serious Game Engine for Commonsense Knowledge Acquisition. In: UAI, Quebec City (2014)

Data Collection

POG data is encoded and collected in XML format. Interaction semantics between objects and characters are specified for each scene, together with affect information


```xml
<scenes>
    <sceneData>
        <sceneType>
            <string>kitchen</string>
        </sceneType>
        <items>
            <itemData>
                <itemType>
                    <string>bread slices</string>
                </itemType>
                <position>
                    <x>8.04757</x>
                    <y>2.32971239</y>
                </position>
                <actions>
                    <actionData>
                        <actionType>
                            <string>stack</string>
                        </actionType>
                        <POG_Data>
                            <prerequisites>
                                <string>ham</string>
                                <string>mayonnaise</string>
                            </prerequisites>
                            <outcomes>
                                <string>sandwich</string>
                            </outcomes>
                            <goal>
                                <string>satisfy hunger</string>
                            </goal>
                        </POG_Data>
                        <player>
                            <affect>
                                <health>80</health>
                                <hunger>50</hunger>
                                <pleasantness>5</pleasantness>
                                <sensitivity>3</sensitivity>
                            </affect>
                        </player>
```


[22] E. Cambria, D. Olsher, D. Rajagopal, and K. Kwok. SGECKA: A Serious Game Engine for Commonsense Knowledge Acquisition. In: UAI, Quebec City (2014)

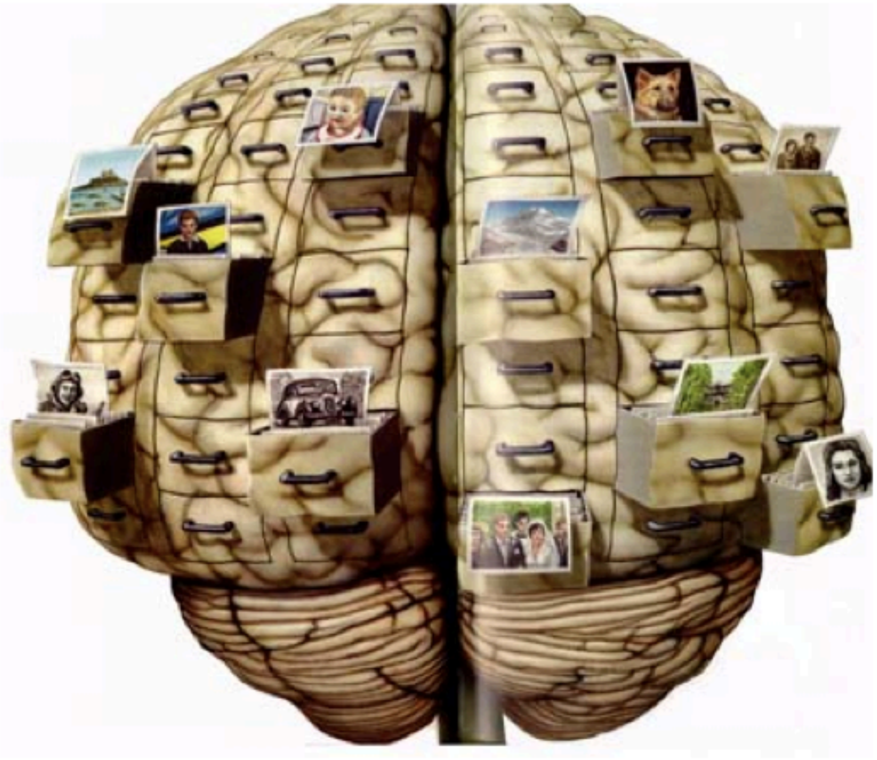
Affective Information

POG specifications not only allow game designers to define interaction semantics between objects, but also affective reactions of different characters

[22] E. Cambria, D. Olsher, D. Rajagopal, and K. Kwok. SGECKA: A Serious Game Engine for Commonsense Knowledge Acquisition. In: UAI, Quebec City (2014)

Feeling and Thinking

The question is not whether intelligent machines can have emotions, but whether machines can be intelligent without any emotions



[23] M. Minsky. The Emotion Machine: Commonsense Thinking, Artificial Intelligence, and the Future of the Human Mind. Simon & Schuster, New York (2006)

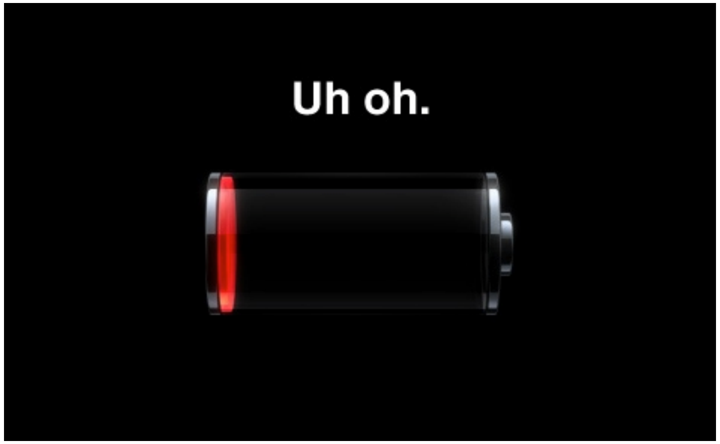
To Feel or Not to Feel?

Adaptive behavior	Emotion
protection	fear / terror
incorporation	acceptance / trust
destruction	anger / rage
reproduction	joy / ecstasy
reintegration	sadness / grief
orientation	surprise / astonishment
rejection	disgust / loathing
exploration	expectancy / anticipation

[24] R. Plutchik. The Nature of Emotions. American Scientist 89(4), pp. 344–350 (2001)

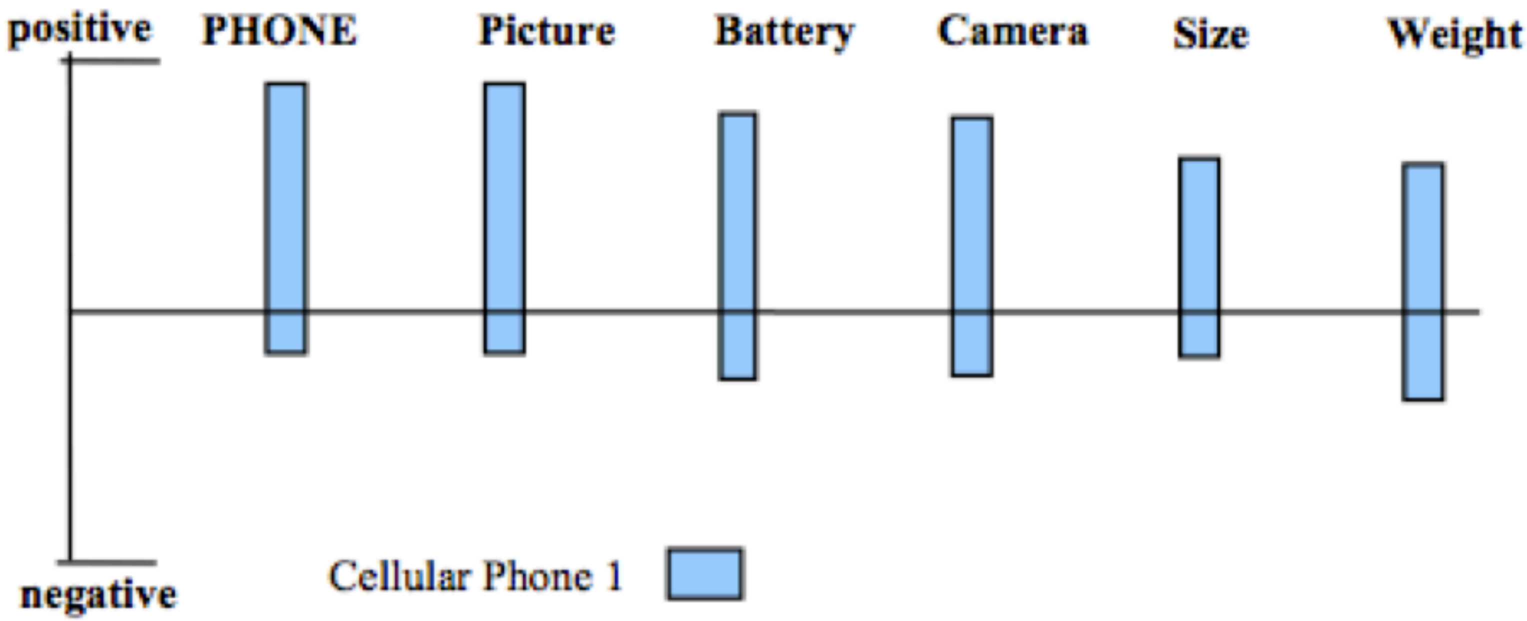
Aspect-Based Analysis

"I love the new iPhone5 screen! the battery life is so short though"

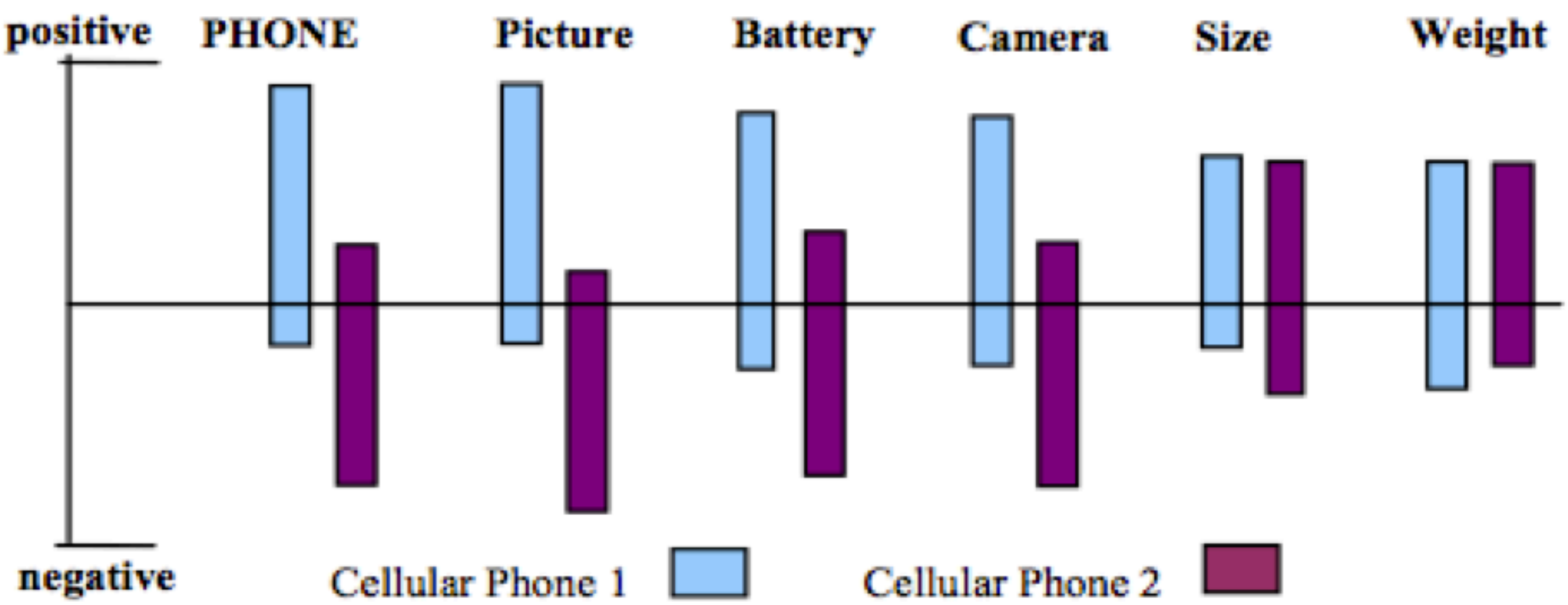


document/paragraph-level approach: neutral polarity
clause/concept-level approach: screen+, battery-

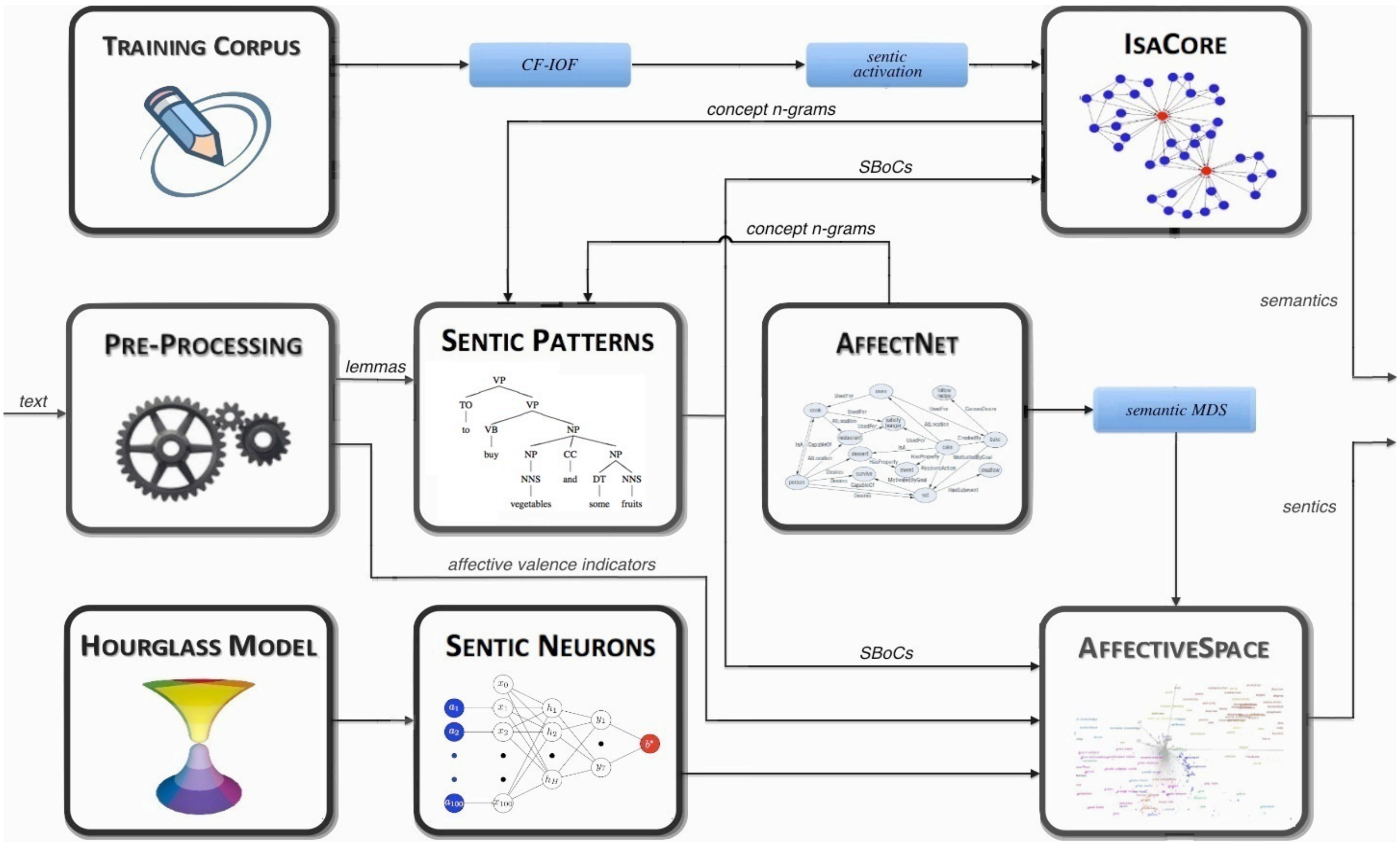
Deconstructing Aspects



Aspect Comparison

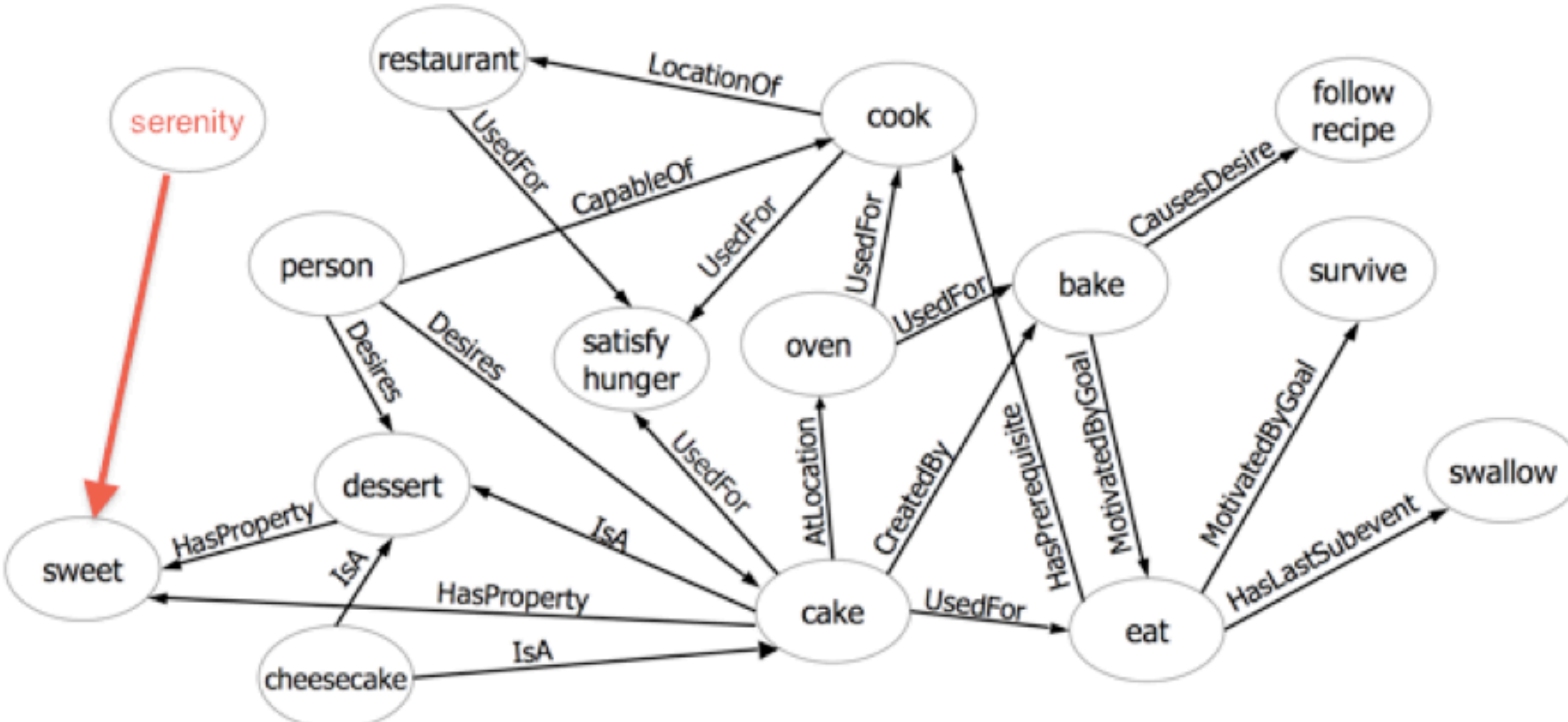


Sentic Computing



[25] E. Cambria and A. Hussain. Sentic Computing: Techniques, Tools, and Applications. Dordrecht, Netherlands: Springer, ISBN: 978-94-007-5069-2 (2012)

AffectNet Graph



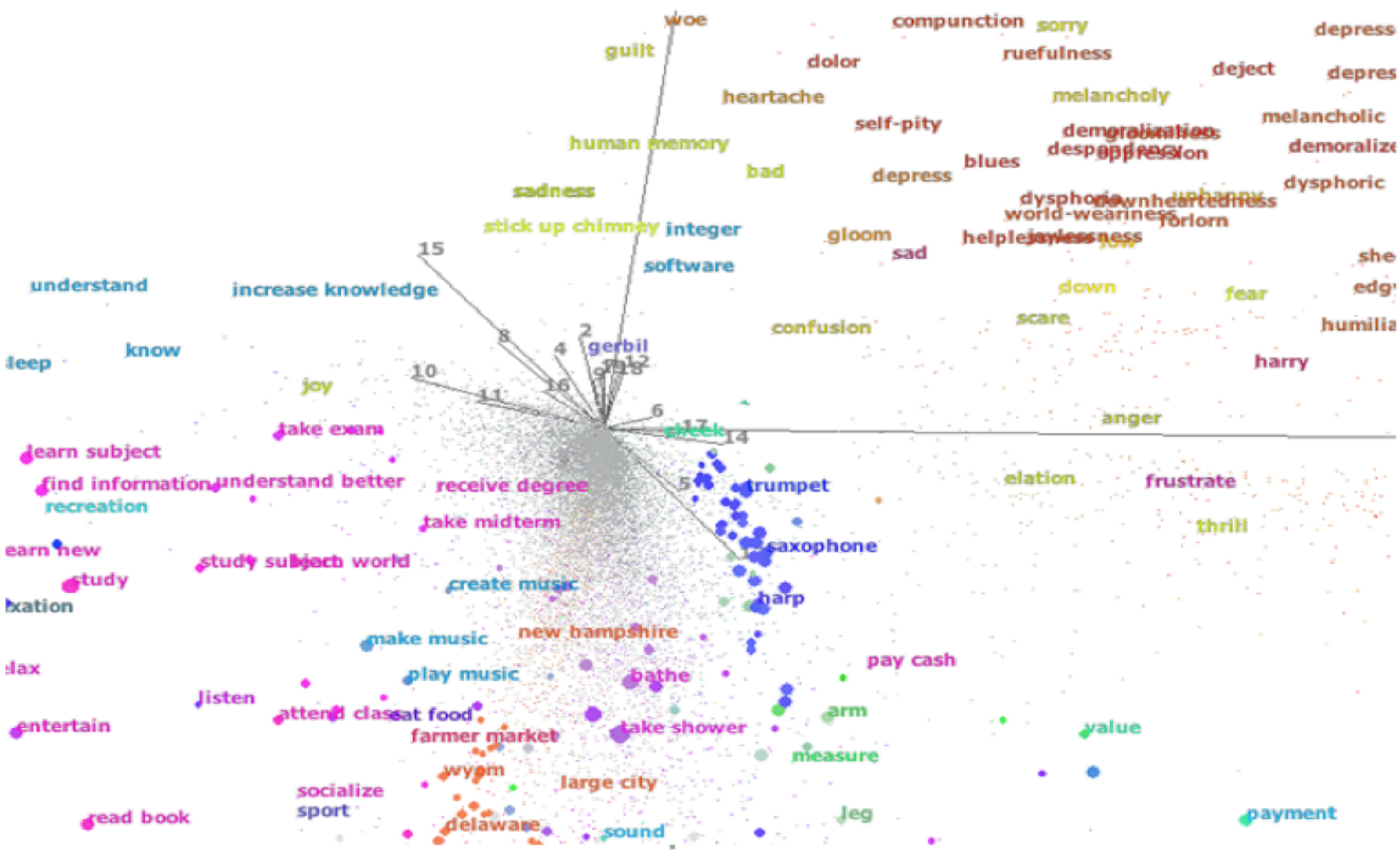
[25] E. Cambria and A. Hussain. *Sentic Computing: Techniques, Tools, and Applications.* Dordrecht, Netherlands: Springer, ISBN: 978-94-007-5069-2 (2012)

AffectNet Matrix

Objects	Properties (*with simplified form*)					
	…	contains knowledge *contain knowledge*	has pages *have page*	is cold *be cold*	is for reading *be read*	…
⋮		⋮	⋮	⋮	⋮	
book	…	x	x		x	…
ice	…		-	x		…
newspaper	…	**x?**	**x**		**x**	…
magazine	…	x	x		x	…
⋮		⋮	⋮	⋮	⋮	

[25] E. Cambria and A. Hussain. Sentic Computing: Techniques, Tools, and Applications. Dordrecht, Netherlands: Springer, ISBN: 978-94-007-5069-2 (2012)

AffectiveSpace



[25] E. Cambria and A. Hussain. Sentic Computing: Techniques, Tools, and Applications. Dordrecht, Netherlands: Springer, ISBN: 978-94-007-5069-2 (2012)

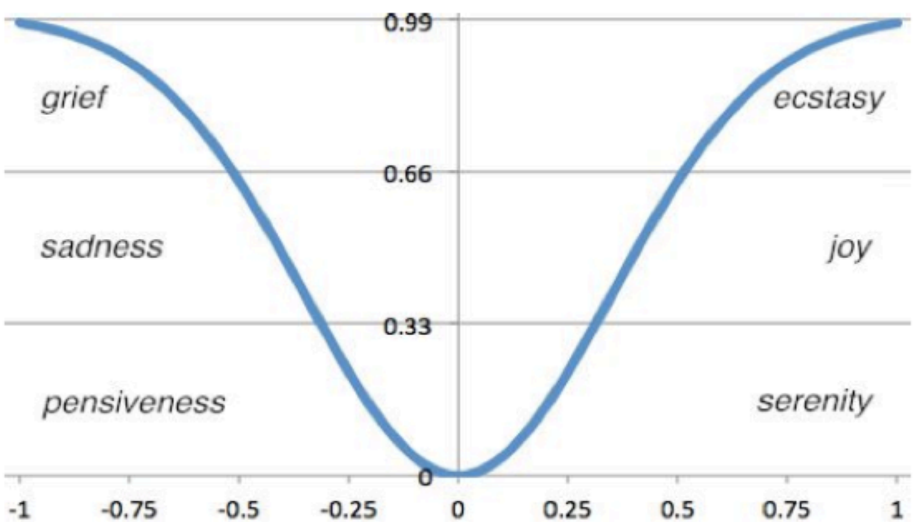
Hourglass Model

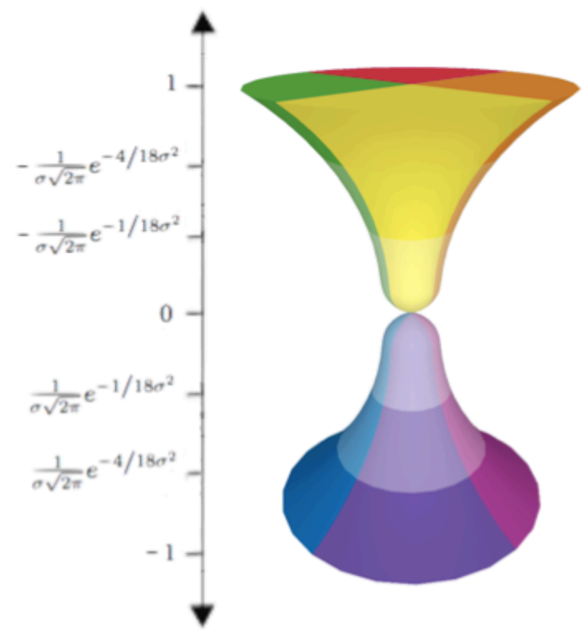
The mind is made up of different independent resources. Turning some sets of resources on while turning others off result in different emotional states

[25] E. Cambria and A. Hussain. Sentic Computing: Techniques, Tools, and Applications. Dordrecht, Netherlands: Springer, ISBN: 978-94-007-5069-2 (2012)

Hourglass Model

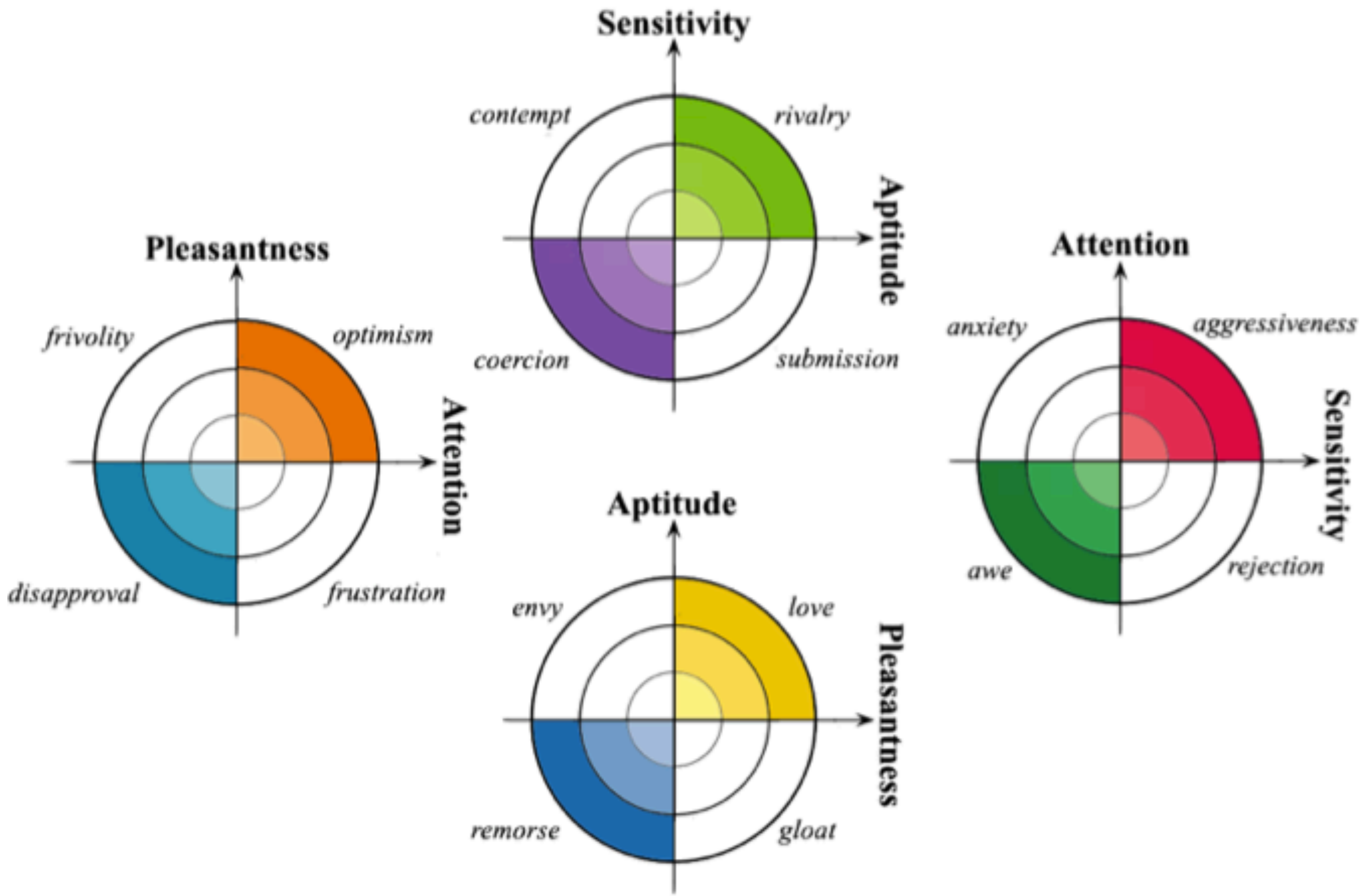
Interval	Pleasantness	Attention	Sensitivity	Aptitude
[G(1), G(2/3))	ecstasy	vigilance	rage	admiration
[G(2/3), G(1/3))	joy	anticipation	anger	trust
[G(1/3), G(0))	serenity	interest	annoyance	acceptance
(G(0), –G(1/3)]	pensiveness	distraction	apprehension	boredom
(–G(1/3), –G(2/3)]	sadness	surprise	fear	disgust
(–G(2/3), –G(1)]	grief	amazement	terror	loathing





[26] E. Cambria, A. Livingstone, and A. Hussain. The Hourglass of Emotions. In: Cognitive Behavioral Systems, LNCS, vol. 7403, pp. 144-157, Springer (2012)

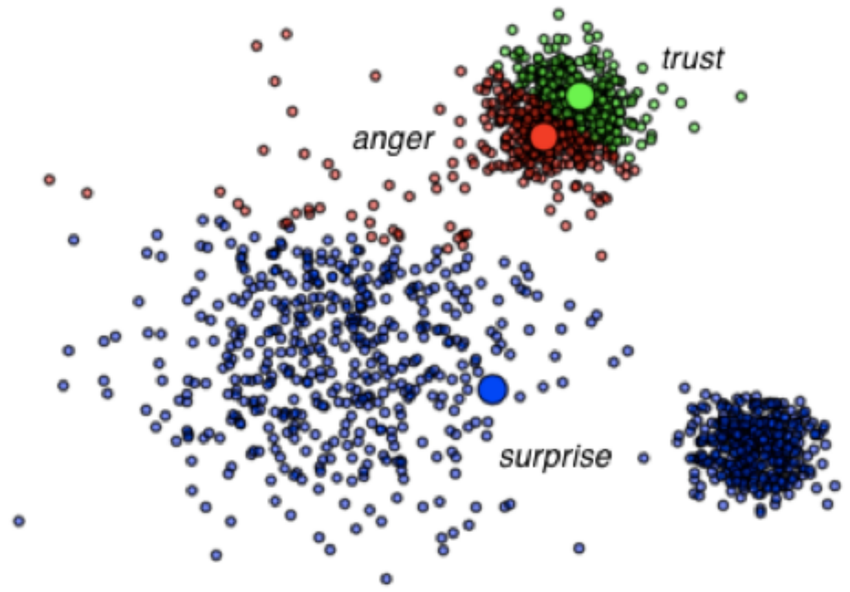
Hourglass Model



[26] E. Cambria, A. Livingstone, and A. Hussain. The Hourglass of Emotions. In: Cognitive Behavioral Systems, LNCS, vol. 7403, pp. 144-157, Springer (2012)

Sentic Medoids

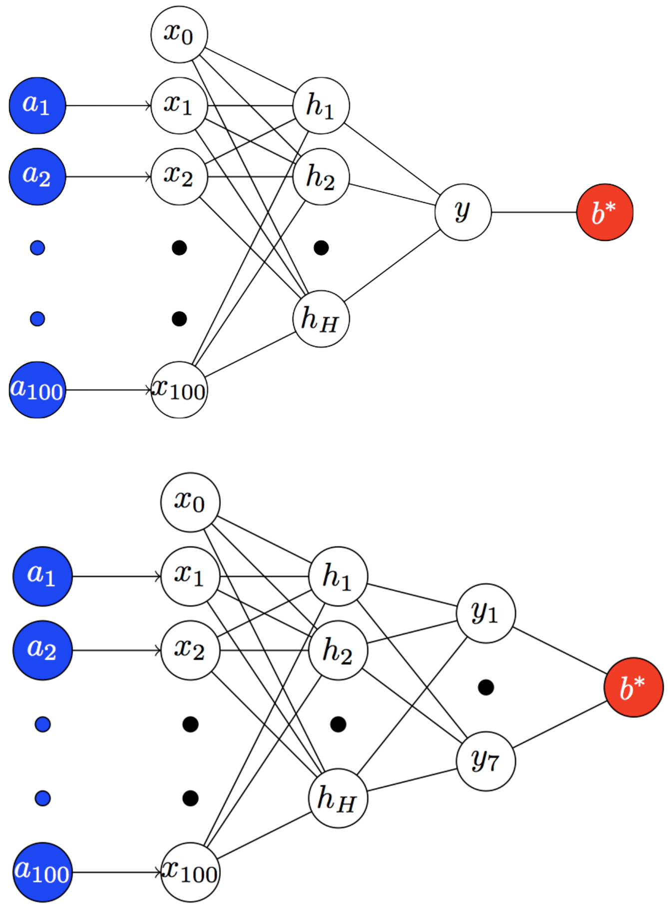
In order to cluster AffectiveSpace, a k-medoids approach can be adopted in place of k-means, in which it is more robust to noise and outliers



[27] E. Cambria, T. Mazzocco, A. Hussain, and C. Eckl. Sentic Medoids: Organizing Affective Common Sense Knowledge in a Multi-Dimensional Vector Space. In: LNCS, vol. 6677, pp. 601-610, Springer (2011)

Sentic Neurons

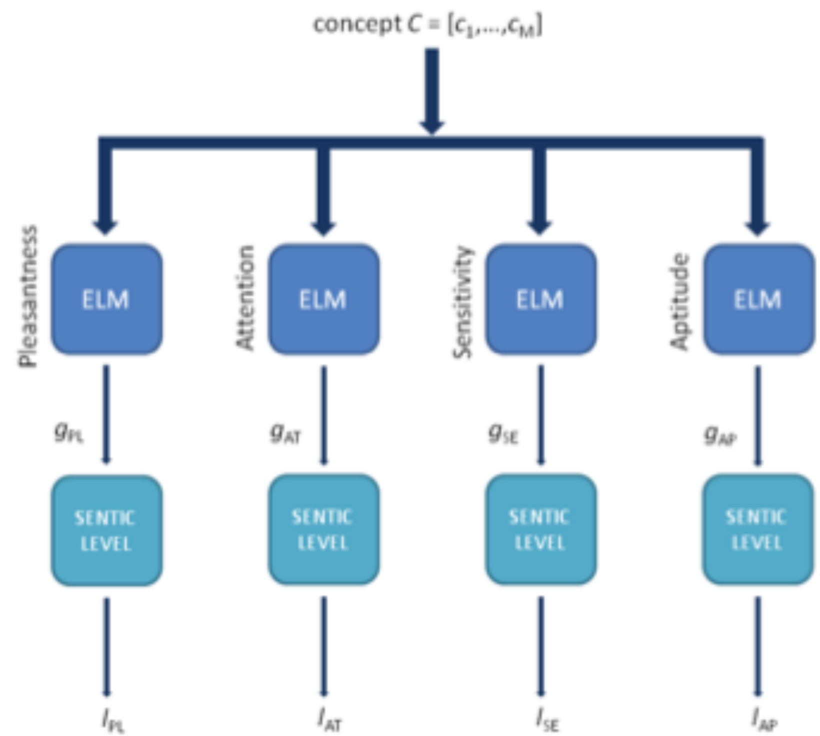
The integration of a bio-inspired paradigm with principal component analysis allows for better comprehension of non-linearities in AffectiveSpace



[28] E. Cambria, T. Mazzocco, and A. Hussain. Application of Multi-Dimensional Scaling and Artificial Neural Networks for Biologically Inspired Opinion Mining. Biologically Inspired Cognitive Architectures 4, pp. 41-53 (2013)

ELM-Based Reasoning

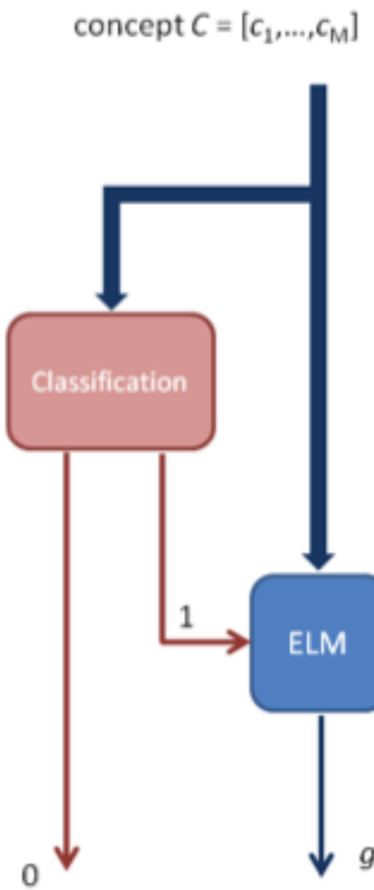
The high generalization performance, low computational complexity, and fast learning speed of ELM can be exploited to parallelize the process



[29] E. Cambria, P. Gastaldo, F. Bisio, R. Zunino. An ELM-Based Model for Affective Analogical Reasoning. Neurocomputing, Special Issue on Extreme Learning Machines (2014)

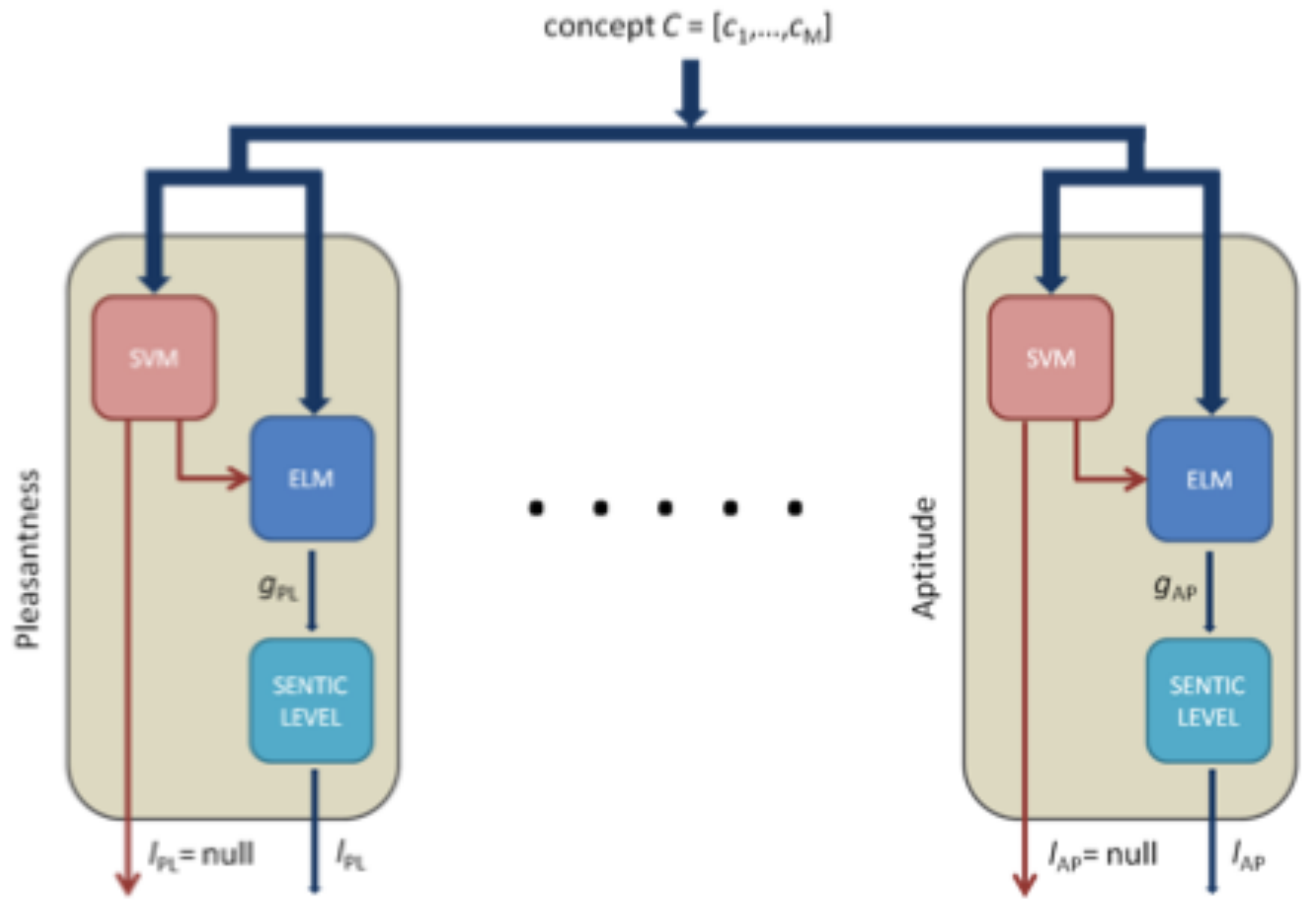
Hierarchical Scheme

An SVM-based classifier first filters out unemotional concepts and an ELM-based predictor then classifies emotional concepts in terms of four dimensions



[29] E. Cambria, P. Gastaldo, F. Bisio, R. Zunino. An ELM-Based Model for Affective Analogical Reasoning. Neurocomputing, Special Issue on Extreme Learning Machines (2014)

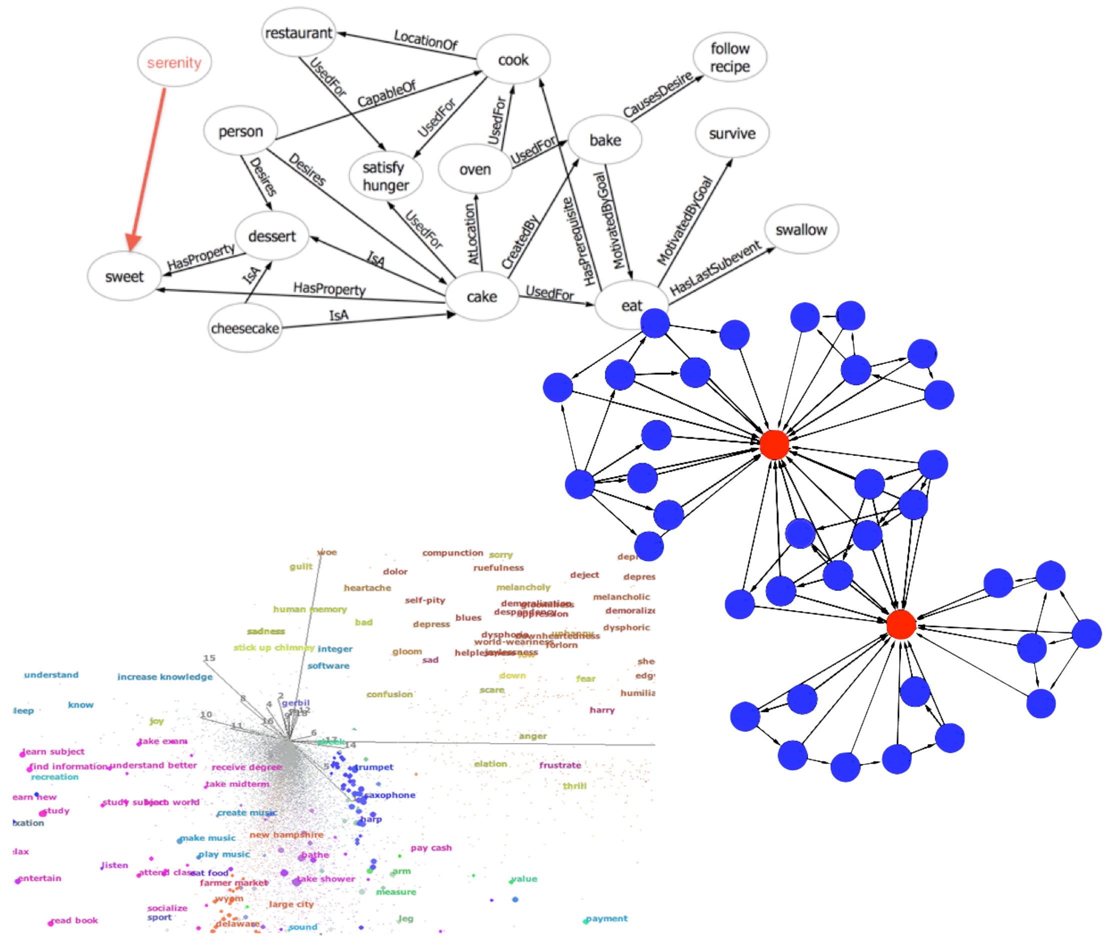
Parallel Framework



[29] E. Cambria, P. Gastaldo, F. Bisio, R. Zunino. An ELM-Based Model for Affective Analogical Reasoning. Neurocomputing, Special Issue on Extreme Learning Machines (2014)

Available Tools

- AffectNet
- AffectiveSpace
- IsaCore beta
- Sentic Parser
- SenticNet-1.0
- SenticNet-2.0
- SenticNet-3.0
- Sentic API



SenticNet 3

http://sentic.net/api


```xml
<?xml version="1.0" encoding="UTF-8"?>
<rdf:RDF xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#">
    <rdf:Description rdf:about="http://sentic.net/api/en/concept/love">
        <rdf:type rdf:resource="http://sentic.net/api/concept"/>
        <semantics rdf:resource="http://sentic.net/api/en/concept/lust"/>
        <semantics rdf:resource="http://sentic.net/api/en/concept/love_another_person"/>
        <semantics rdf:resource="http://sentic.net/api/en/concept/sexuality"/>
        <semantics rdf:resource="http://sentic.net/api/en/concept/beloved"/>
        <semantics rdf:resource="http://sentic.net/api/en/concept/show_empathy"/>
        <pleasantness rdf:datatype="http://www.w3.org/2001/XMLSchema#float">+0.491</pleasantness>
        <attention rdf:datatype="http://www.w3.org/2001/XMLSchema#float">0.0</attention>
        <sensitivity rdf:datatype="http://www.w3.org/2001/XMLSchema#float">0.0</sensitivity>
        <aptitude rdf:datatype="http://www.w3.org/2001/XMLSchema#float">+0.458</aptitude>
        <polarity rdf:datatype="http://www.w3.org/2001/XMLSchema#float">+0.316</polarity>
    </rdf:Description>
</rdf:RDF>
```


[30] E. Cambria, D. Olsher, and D. Rajagopal. SenticNet 3: A Common and Common-Sense Knowledge Base for Cognition-Driven Sentiment Analysis. In: AAAI, Quebec City (2014)

Sentic Demo

	SenticNet	Stanford
1. I love the movie which you hate	+	–
2. The phone is very big to hold	–	+
3. You are making fun of me	–	+
4. You are not so beautiful	–	+
5. The tooth hit the pavement and broke	–	+
6. I am one of the least happy person in the world	–	0
7. I love Starbucks but they just lost a customer	–	0
8. I doubt that he is good	–	+
9. Receiving payments has never been this simple & fast	+	–
10. I am eagerly looking forward to Dr. Wu's future work	+	–

http://sentic.net/demo

Sentic Patterns

The car is nice but expensive

The car is expensive but nice

Left conjunct	Right conjunct	Total sentence
Pos.	Neg.	Neg.
Neg.	Pos.	Pos.
Pos.	undefined	Neg.
Neg.	undefined	Pos.
undefined	Pos.	Pos.
undefined	Neg.	Neg.
Pos.	Pos.	Pos.
Neg.	Neg.	Neg.

[31] S. Poria, E. Cambria, G. Winterstein, and G.-B. Huang. Sentic Patterns: Dependency-Based Rules for Concept-Level Sentiment Analysis. Knowledge-Based Systems (2014)

Sentic Patterns

a. This is perfect to gain money.
b. This is perfect to gain weight.
c. This is perfect to lose money.
d. This is perfect to lose weight.
e. This is useless to gain money.
f. This is useless to gain weight.
g. This is useless to lose money.
h. This is useless to lose weight.
i. This is perfect to talk about money.
j. This is perfect to talk about weight.
k. This is useless to talk about money.
l. This is useless to talk about weight.

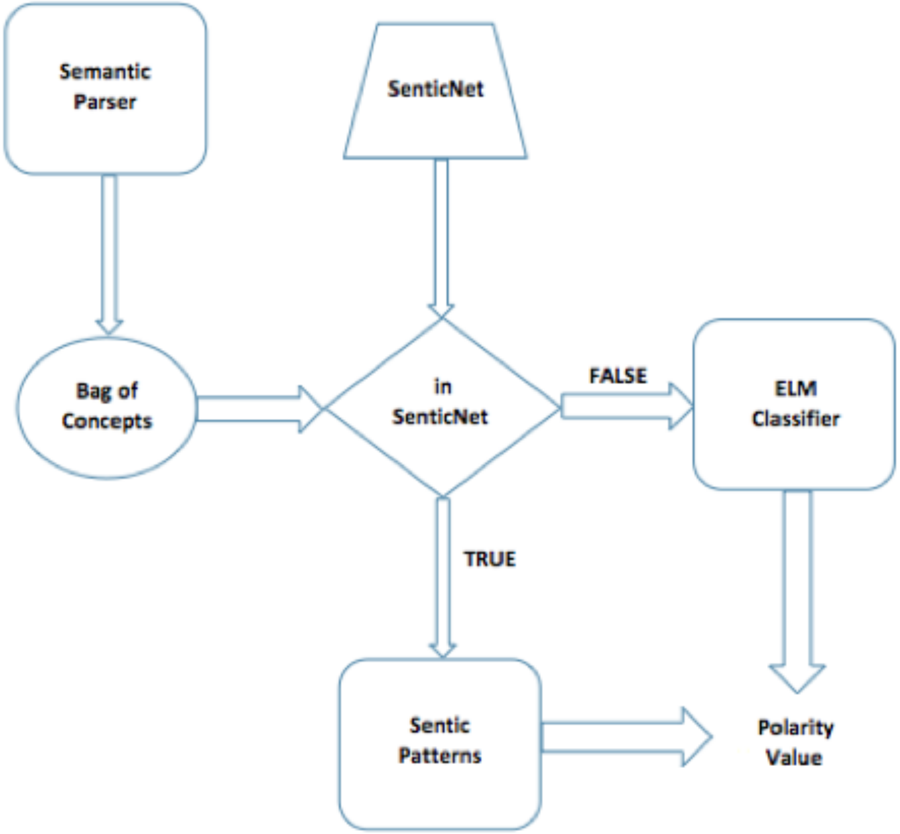
Matrix predicate (h)	**Dependent predicate** (d)	**Dep. comp.** (x)	**Overall polarity**	**Example**
Pos	Pos	Pos	Pos	a
Pos	Pos	Neg	Neg	b
Pos	Neg	Pos	Neg	c
Pos	Neg	Neg	Pos	d
Neg	Pos	Pos	Neg	e
Neg	Pos	Neg	Neg	f
Neg	Neg	Pos	Neg	g
Neg	Neg	Neg	Neg	h
Pos	Neutral	Pos	Pos	i
Pos	Neutral	Neg	Neg	j
Neg	Neutral	Pos	Neg	k
Neg	Neutral	Neg	Neg	l

[31] S. Poria, E. Cambria, G. Winterstein, and G.-B. Huang. Sentic Patterns: Dependency-Based Rules for Concept-Level Sentiment Analysis. Knowledge-Based Systems (2014)

Sentic Patterns

Algorithm	Precision
Sentic Patterns	84.15%
Machine Learning	67.35%
Ensemble Classification	86.21%

System	Precision
Socher et al. 2012 [59]	80.00%
Socher et al. 2013 [57]	85.40%
Proposed Method	86.21%



[31] S. Poria, E. Cambria, G. Winterstein, and G.-B. Huang. Sentic Patterns: Dependency-Based Rules for Concept-Level Sentiment Analysis. Knowledge-Based Systems (2014)

Semantic Parsing

the camera has [long focus time]

the camera takes a [long time] to [focus]

the [focusing] of the camera takes [long time]

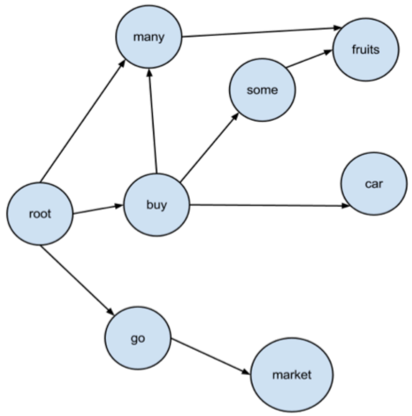
the [focus time] of the camera is very [long]

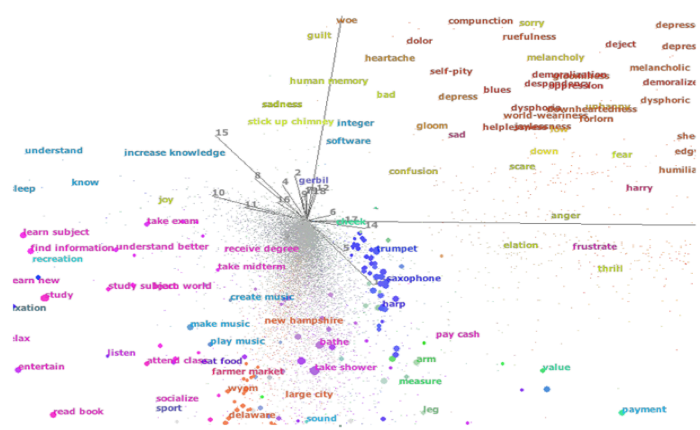
↓

long_focus_time

Semantic Parsing

The semantic parser deconstructs text into concepts through a graph-based concept extraction algorithm and a MDS-based similarity detection technique

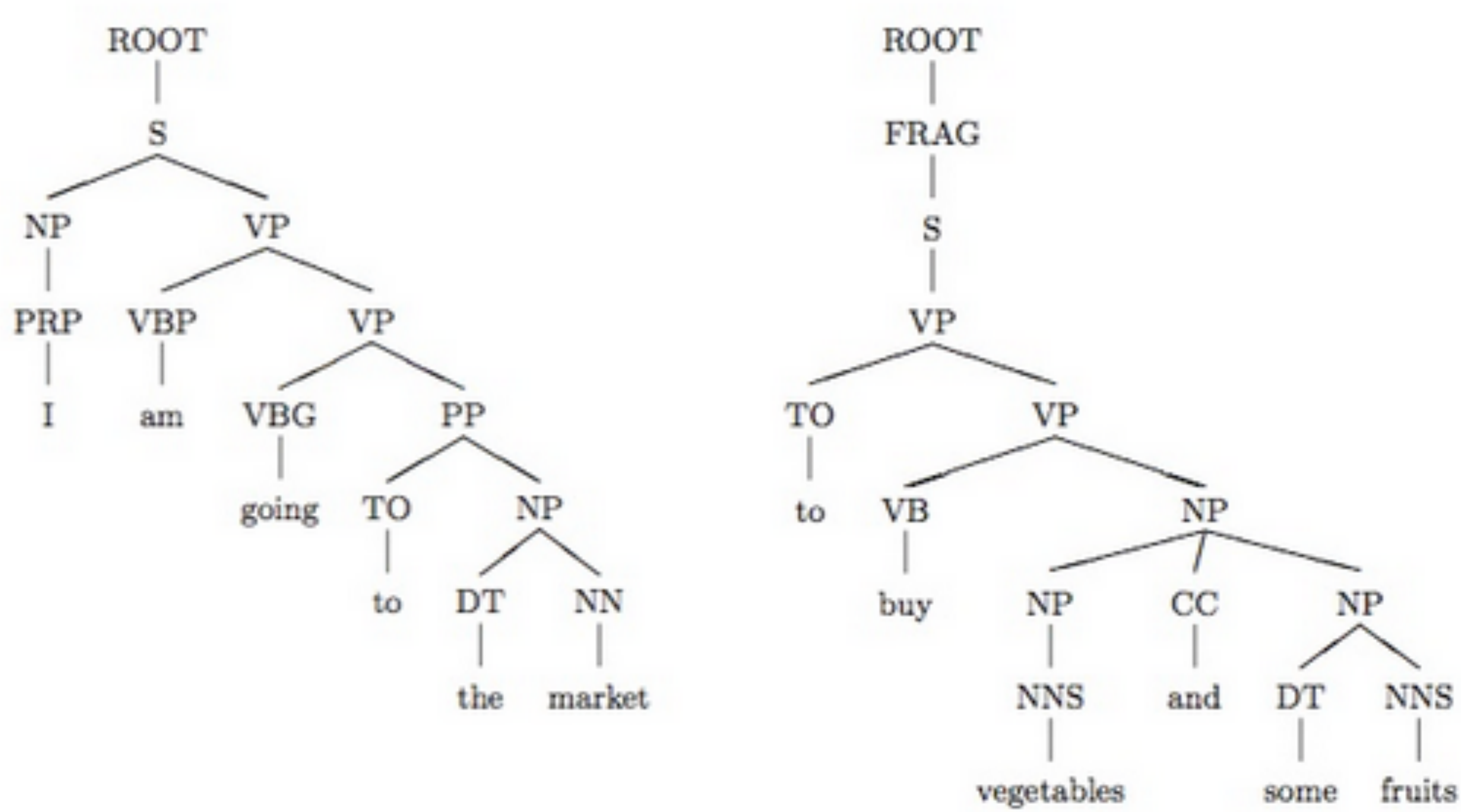




[32] E. Cambria, D. Rajagopal, D. Olsher, and D. Das. Big Social Data Analysis. In: R. Akerkar (ed.) Big Data Computing, ch. 13, Taylor & Francis (2013)

Chunking Text

I am going to the market to buy vegetables and some fruits



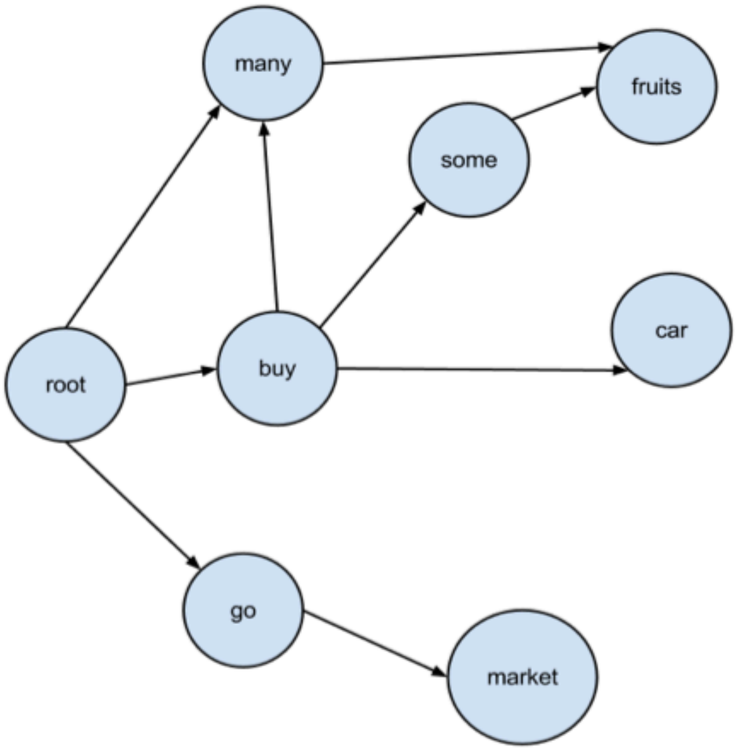
Candidate Spotting

After chunking and stemming, each potential noun chunk is paired with stemmed verbs in order to detect verb + object multi-word expressions

Data: NounPhrase
Result: Valid object concepts
Split the NounPhrase into bigrams ;
Initialize concepts to Null ;
for *each NounPhrase* **do**
    while *For every* bigram *in the NounPhrase* **do**
        POS Tag the Bigram ;
        if adj noun **then**
            add to Concepts: noun, adj+noun
        else if noun noun **then**
            add to Concepts: noun+noun
        else if stopword noun **then**
            add to Concepts: noun
        else if adj stopword **then**
            continue
        else if stopword adj **then**
            continue
        else
            Add to Concepts : entire bigram
        end
        repeat until no more bigrams left;
    end
end

Candidate Selection

Matches between the object concepts and the normalized verb chunks are searched in a parse graph that maps all the multi-word expressions of the knowledge base



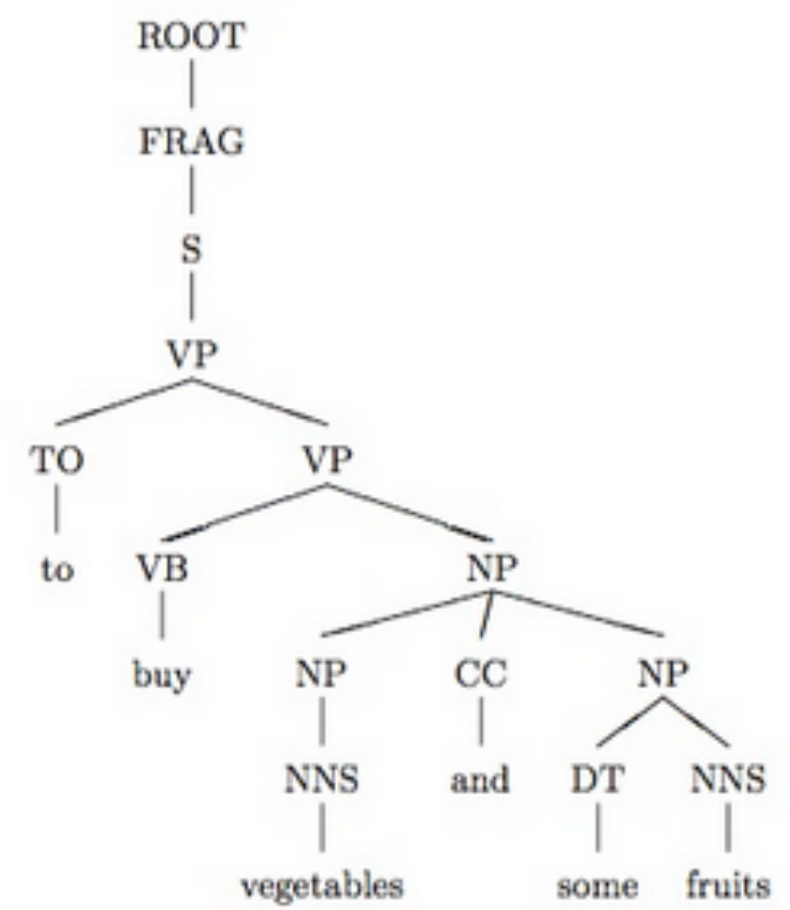
Concept Extraction

Candidate spotting

- *buy*
- *buy vegetable*
- *buy fruit*
- *vegetable and fruit*
- *buy vegetable and fruit*

Candidate selection

1. *buy vegetable and fruit*
2. *buy vegetable; buy fruit*
3. *buy; vegetable and fruit*
4. *buy; vegetable; fruit*

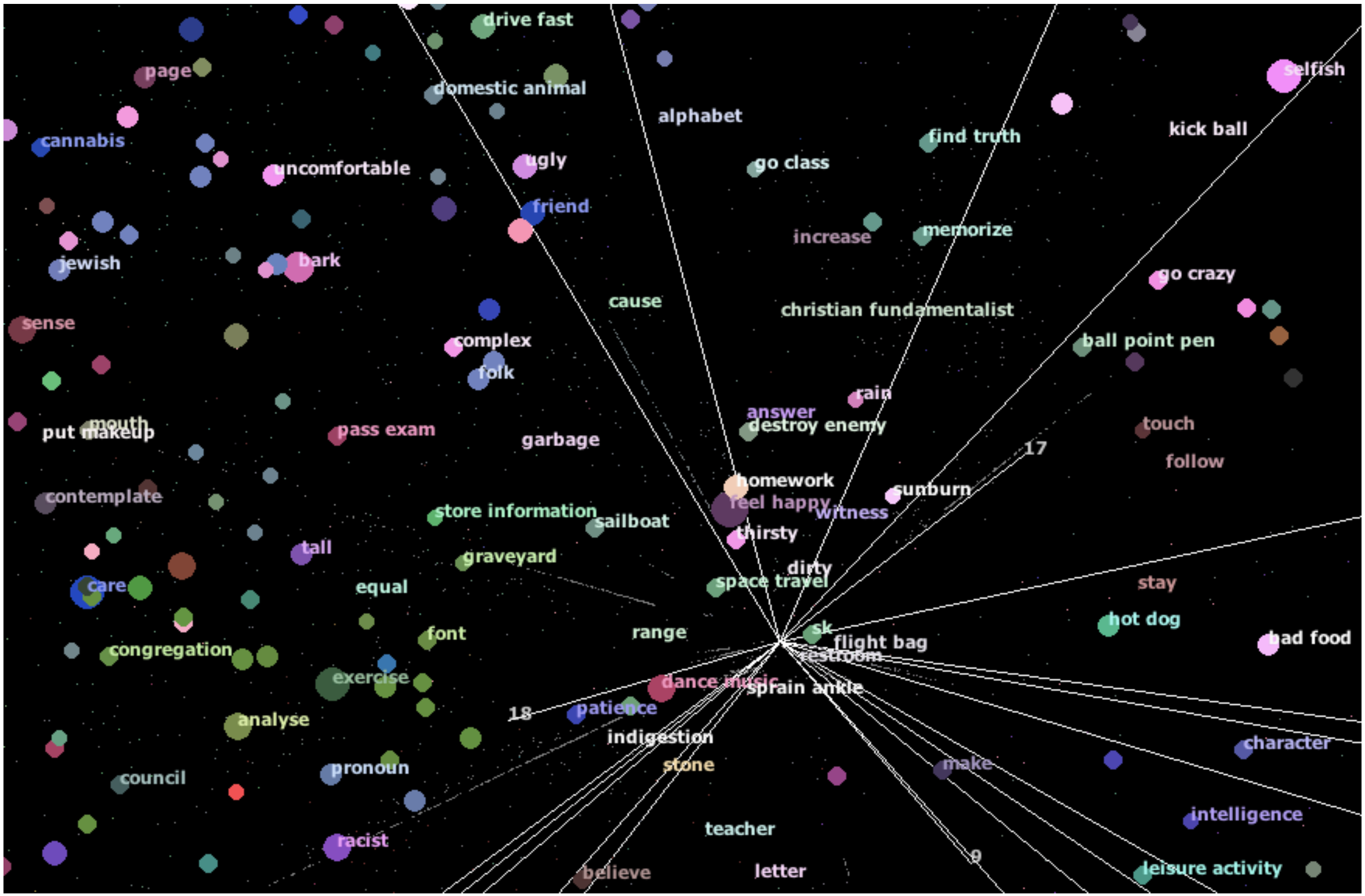


Similarity Detection

Because of the richness of natural language, a technique for spotting similar meanings in multi-word expressions is used to detect concepts in their various forms

```
Data: NounPhrase1, NounPhrase2
Result: True if the concepts are similar, else False
if Both phrases have atleast one noun in common then
    Objects1 := All Valid Objects for NounPhrase1;
    Objects2 := All Valid Objects for NounPhrase2;
    M1 = matches from KB for
    M1 := ∅ ;
    M2 := ∅ ;
    for all concepts in NounPhrase1 do
        M1 := M1 ∪ all property matches for concept;
    end
    for all concepts in NounPhrase2 do
        M2 := M2 ∪ all property matches for concept ;
    end
    SetCommon = M1 ∪ M2 ;
    if length of SetCommon > 0 then
        The Noun Phrases are similar
    else
        They are not similar
    end
```

Semantic Similarity



Evaluation

Algorithm	Precision	Recall	F-measure
Syntactic similarity	65.6%	67.3%	66.4%
Semantic similarity	77.2%	70.8%	73.9%
Ensemble similarity	85.4%	74.0%	79.3%

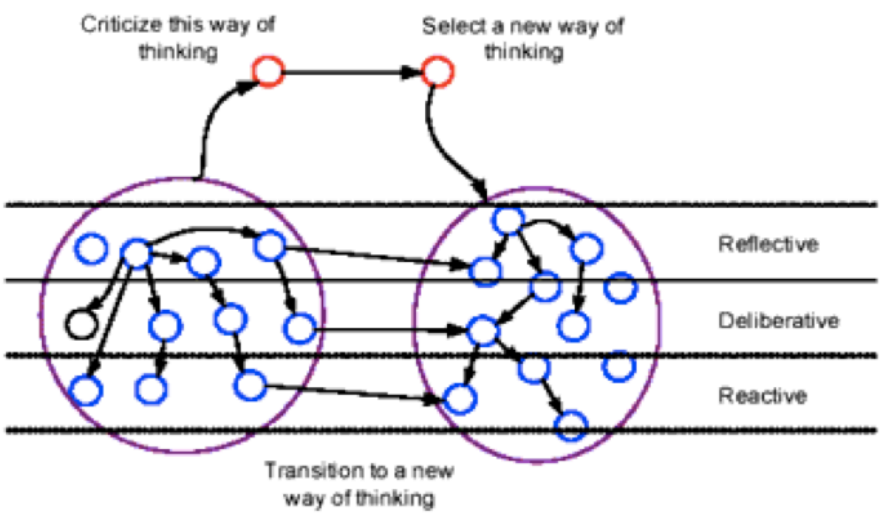
Table 1: Performance of different similarity detection algorithms over 200 concept pairs

Algorithm	Concept extraction accuracy
Naïve parser	65.8%
POS-based bigram	79.1%
POS-based + similarity	87.6%

Table 2: Performance of different parsing algorithms over 50 natural language sentences

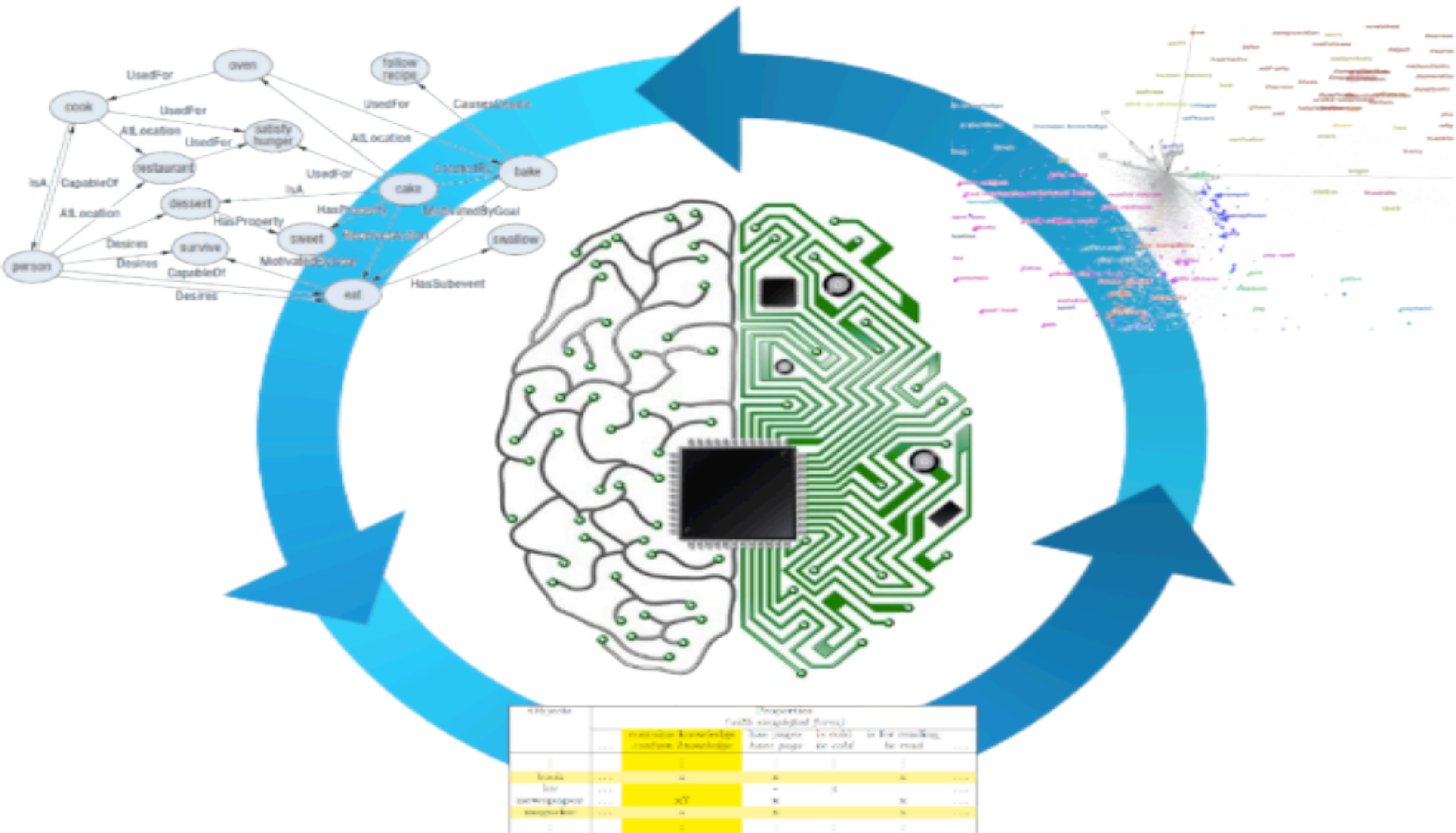
Sentic Panalogy

Several analogous representations of the same problem should be kept in parallel so that the system can switch tracks when problem-solving stalls



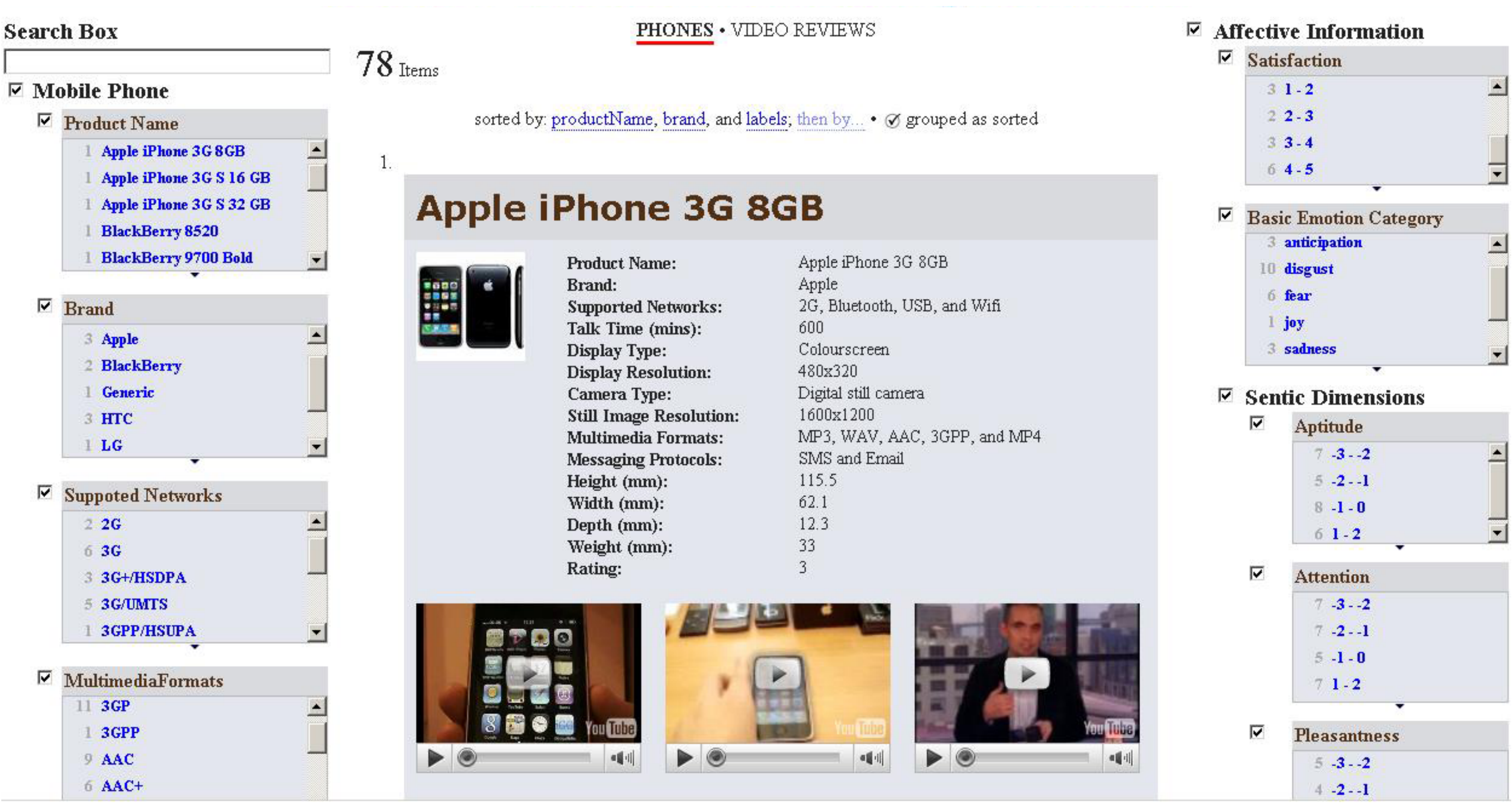
[33] E. Cambria, D. Olsher, and K. Kwok. Sentic Panalogy: Swapping Affective Common Sense Reasoning Strategies and Foci. In: CogSci, pp. 174-179, Sapporo (2012)

Sentic Activation



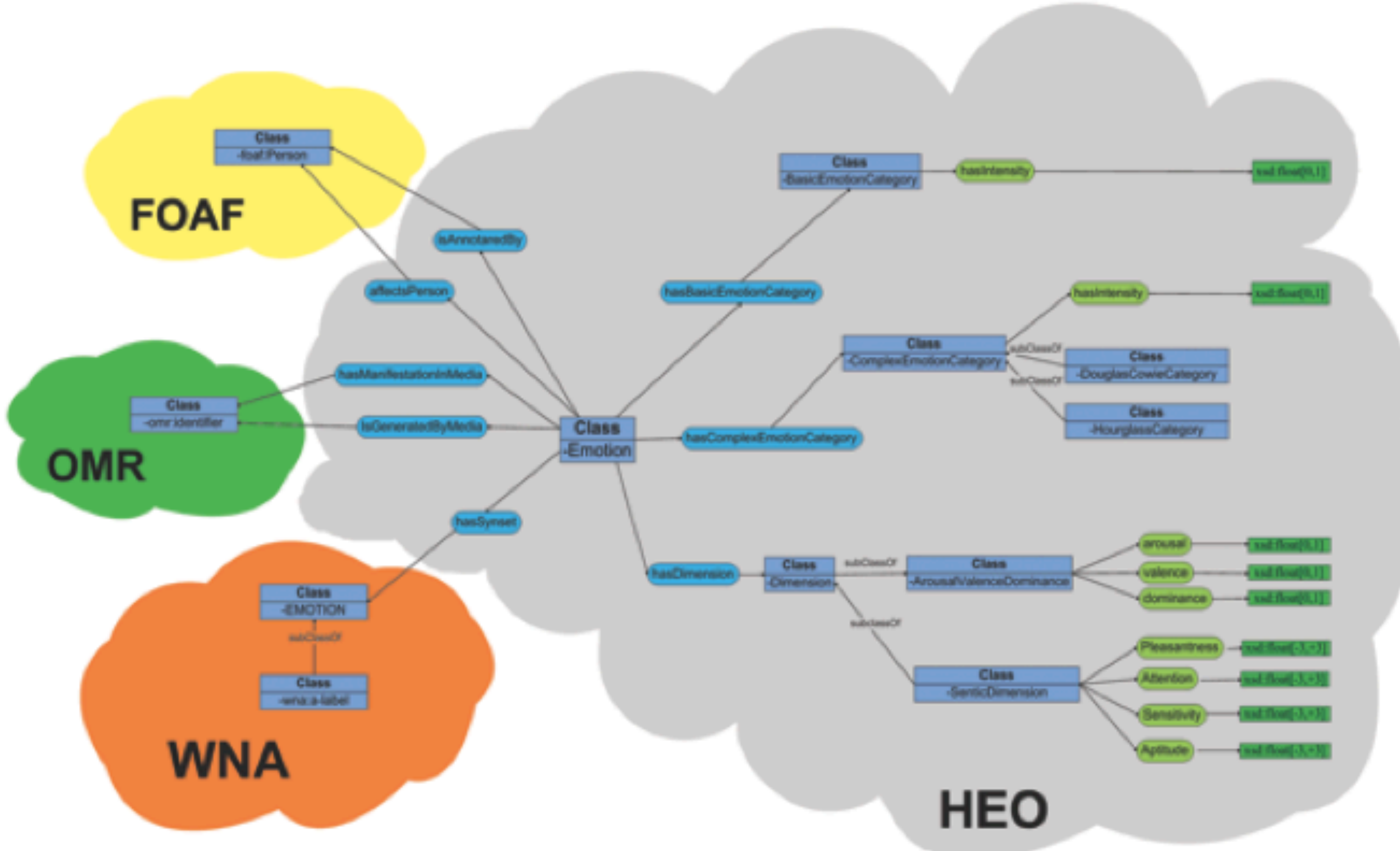
[34] E. Cambria, D. Olsher, and K. Kwok. Sentic Activation: A Two-Level Affective Common Sense Reasoning Framework. In: AAAI, pp. 186-192, Toronto (2012)

Social Media Marketing



[35] E. Cambria, M. Grassi, A. Hussain, and C. Havasi. Sentic Computing for Social Media Marketing. Multimedia Tools and Applications 59(2), pp. 557-577 (2012)

AI and Semantic Web



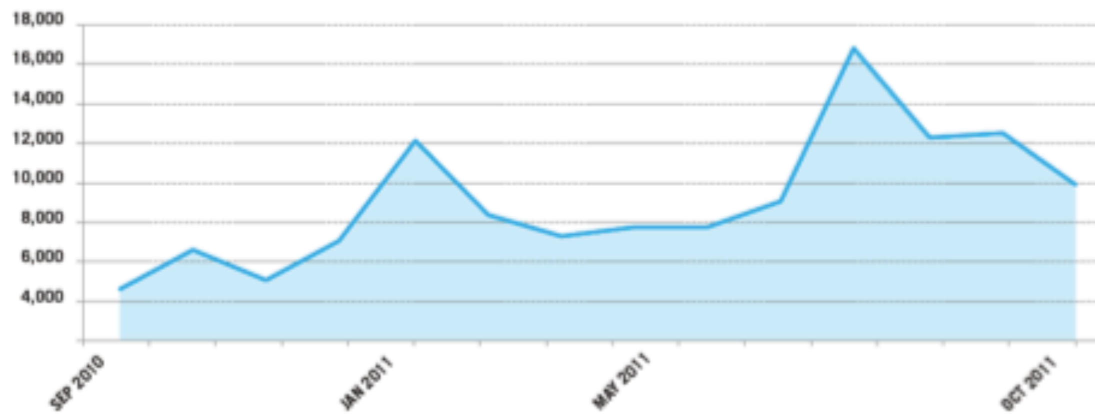
[36] *M. Grassi, E. Cambria, A. Hussain, and F. Piazza. Sentic Web: A New Paradigm for Managing Social Media Affective Information. Cognitive Computation 3(3), pp.480-489 (2011)*

Sentic Album

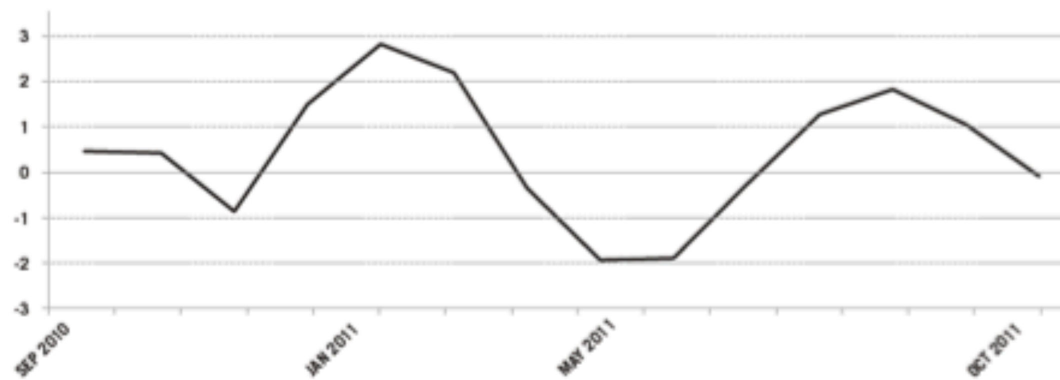
[37] E. Cambria and A. Hussain. Sentic Album: Content-, Concept-, and Context-Based Online Personal Photo Management System. Cognitive Computation 4(4), pp. 477-496 (2012)

Cyber Issue Detection

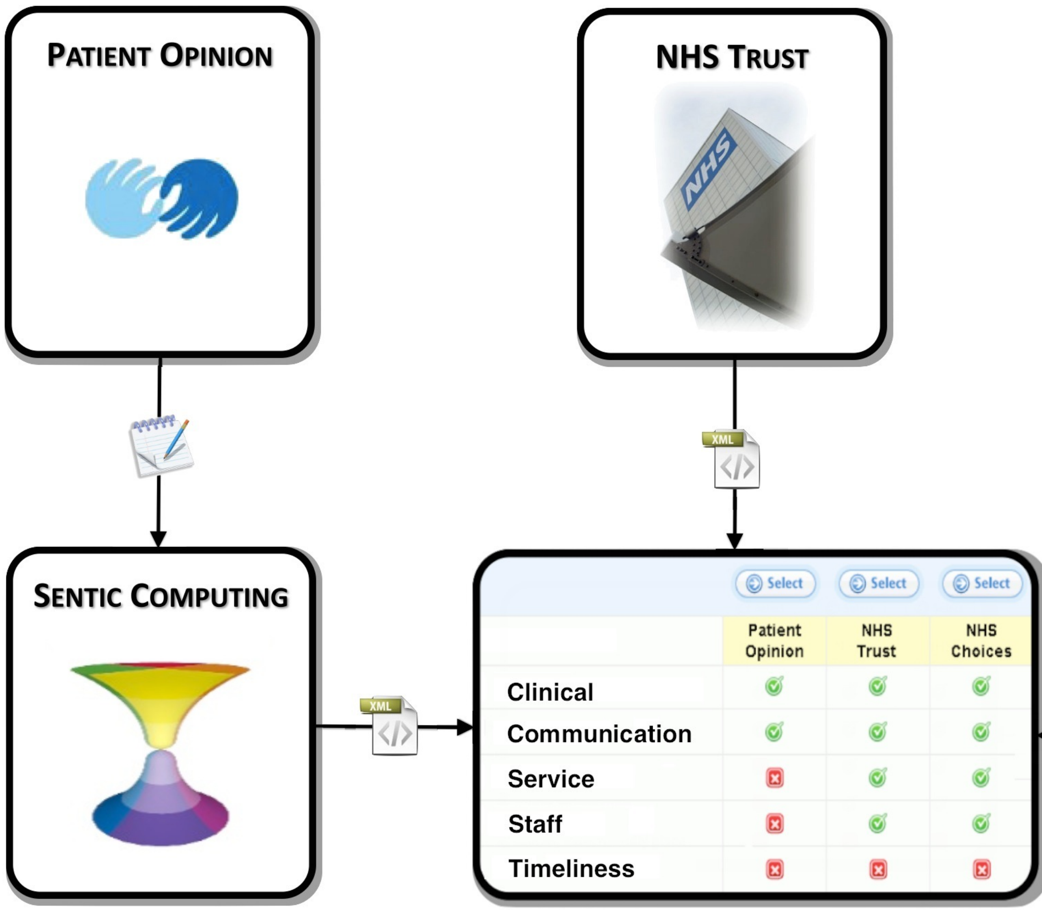
Tweets about the price of rice
(per month)



Food Price Inflation



Crowd Validation



[38] E. Cambria, A. Hussain, T. Durrani, C. Havasi, C. Eckl, and J. Munro. Sentic Computing for Patient Centered Applications. In: IEEE ICSP, pp. 1279-1282, Beijing (2010)

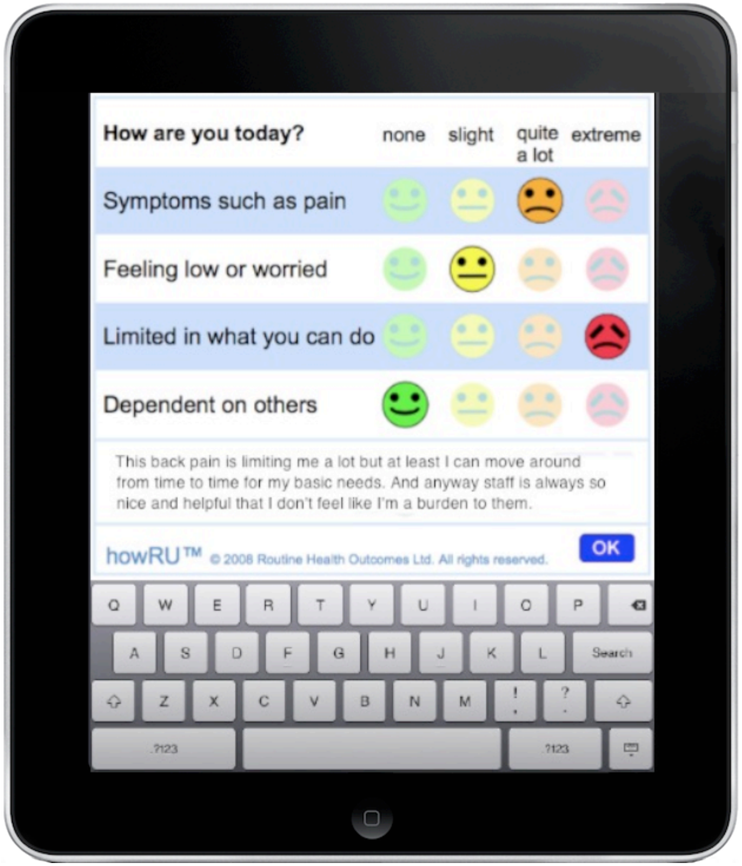
Sentic PROMs

In spite of demonstrated benefits, routine HRQoL assessments remain rare as few patients are willing to spend the time needed to fill-in long questionnaires daily

[39] E. Cambria, T. Benson, C. Eckl, and A. Hussain. Sentic PROMs: Application of Sentic Computing to the Development of a Novel Unified Framework for Measuring Health-Care Quality. Expert Systems with Applications 39(12), pp. 10533–10543 (2012)

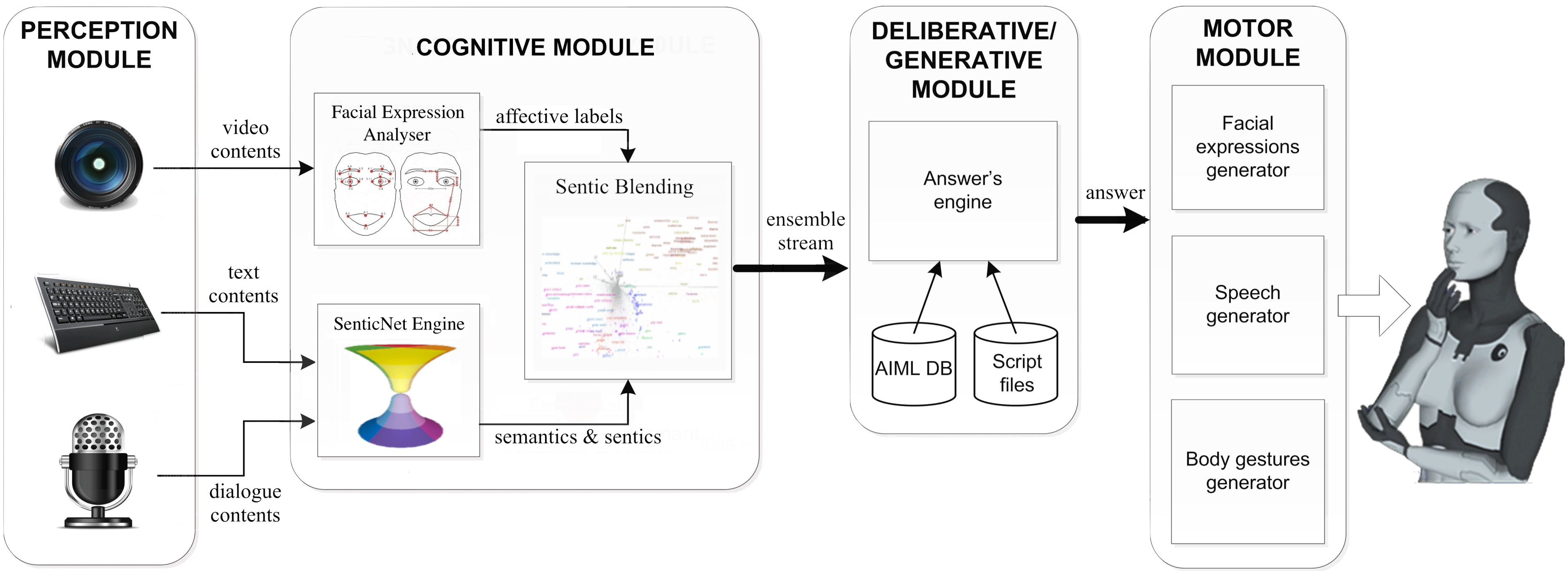
Sentic PROMs

Sentic PROMs allow patients to evaluate their health and healthcare experience to accordingly aggregate text and visual data in a semi-structured way



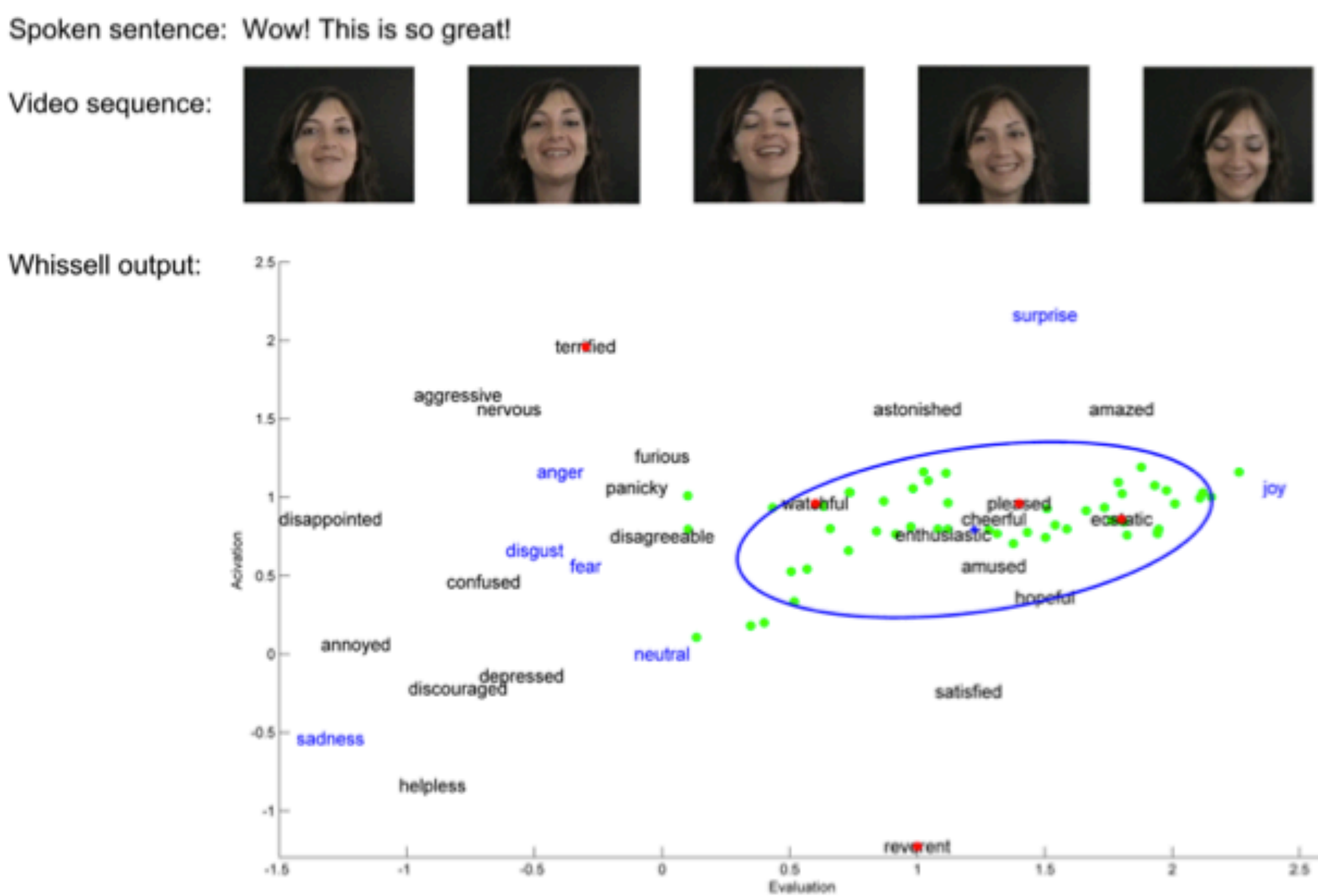
[39] E. Cambria, T. Benson, C. Eckl, and A. Hussain. Sentic PROMs: Application of Sentic Computing to the Development of a Novel Unified Framework for Measuring Health-Care Quality. Expert Systems with Applications 39(12), pp. 10533–10543 (2012)

Sentic Blending



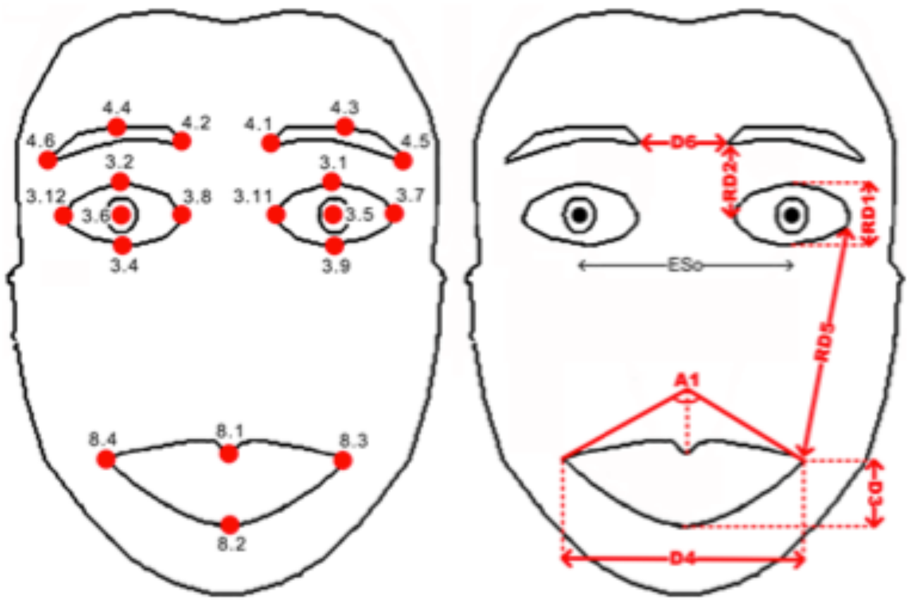
[40] E. Cambria, N. Howard, and A. Hussain. Sentic Blending: Scalable Multimodal Fusion for the Continuous Interpretation of Semantics and Sentics. In: IEEE SSCI, Singapore (2013)

Sentic Blending



[40] *E. Cambria, N. Howard, and A. Hussain. Sentic Blending: Scalable Multimodal Fusion for the Continuous Interpretation of Semantics and Sentics. In: IEEE SSCI, Singapore (2013)*

Expression Analysis

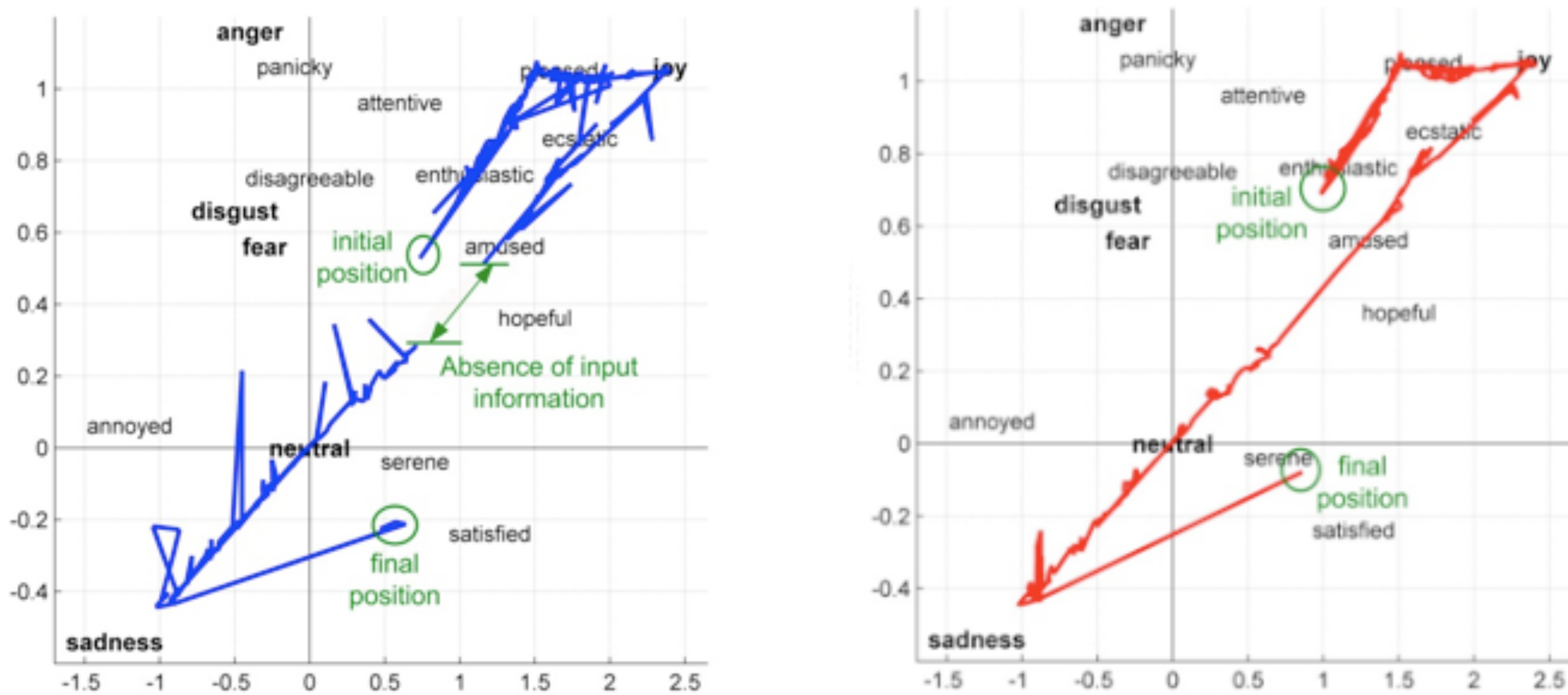


classified as	disgust	joy	anger	fear	sadness	neutral	surprise
disgust	**84.24%**	0%	2.34%	13.42%	0%	0%	0%
joy	4.77%	**95.23%**	0%	0%	0%	0%	0%
anger	15.49%	0%	**77.78%**	0%	3.75%	2.98%	0%
fear	1.12%	0%	0%	**92.59%**	2.06%	0%	4.23%
sadness	0.32%	0.20%	1.68%	0%	**66.67%**	31.13%	0%
neutral	0%	0%	0%	0.88%	1.12%	**98.00%**	0%
surprise	0%	0%	0%	6.86%	0%	2.03%	**91.11%**

Sentic Blending

[40] E. Cambria, N. Howard, and A. Hussain. Sentic Blending: Scalable Multimodal Fusion for the Continuous Interpretation of Semantics and Sentics. In: IEEE SSCI, Singapore (2013)

Sentic Blending



[40] E. Cambria, N. Howard, and A. Hussain. Sentic Blending: Scalable Multimodal Fusion for the Continuous Interpretation of Semantics and Sentics. In: IEEE SSCI, Singapore (2013)

Open Challenges

1. Deconstructing text into concepts
2. Building AffectiveSpace & IsaCore
3. Clustering AffectiveSpace & IsaCore
4. Aggregating SenticNet data

Real Challenges

Irony Detection

I love iphone5 because the battery lasts so little that after half a day I am free from calls and emails

Theory of Mind

It is good that you killed the professor

Intent Mining

big/small room, warm/cold water

User Profiling

hard/soft bed, small/big phone, cheap/expensive bag

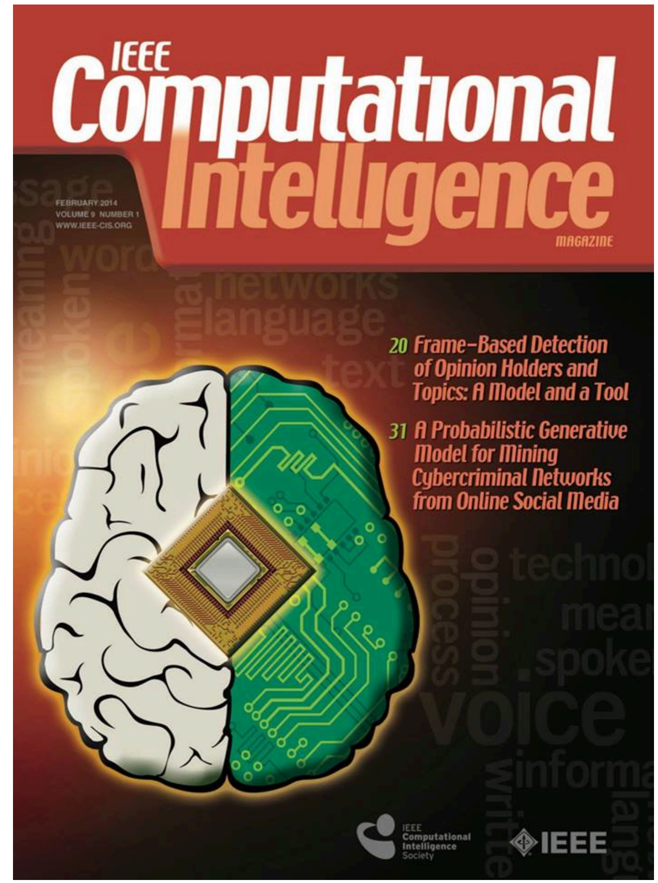
3C Sentiment Analysis

Sentiment analysis is distinguishing itself as a separate field and is moving toward content-, concept-, and context-based natural language analysis

[7] E. Cambria, B. Schuller, Y.Q. Xia, C. Havasi. New Avenues in Opinion Mining and Sentiment Analysis. IEEE Intelligent Systems 28(2), pp. 15-21 (2013)

3Q Sentiment Analysis

To achieve real machine intelligence, a computer needs to be able to not only perform reasoning (IQ), but also interpret emotions (EQ) and cultural nuances (CQ)



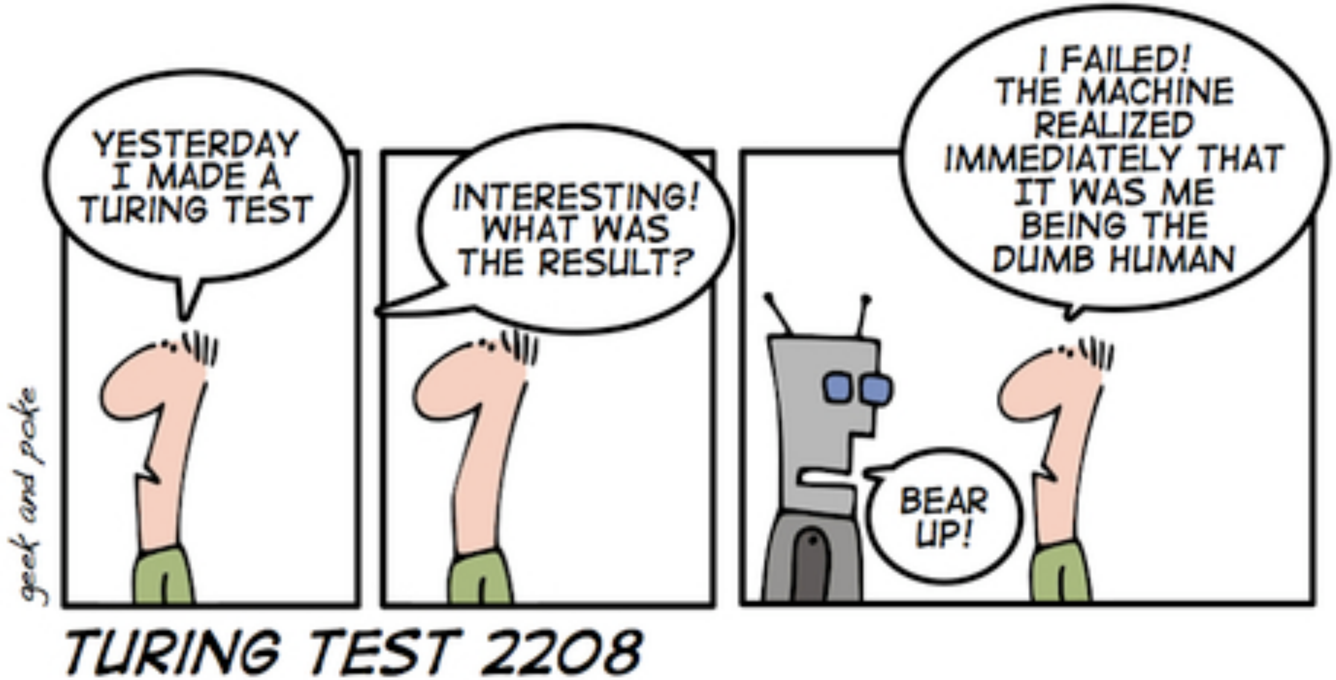
[8] E. Cambria, B. White. Jumping NLP Curves: A Review of Natural Language Processing Research. IEEE Computational Intelligence Magazine 9(2), pp. 48-57 (2014)

Machines That Think

The world has changed less since Jesus Christ than it has in the last century. In another century's time, machines might be able to think as humans do

[41] R. Kurzweil, M. Schneider. The Age of Intelligent Machines. MIT Press, Cambridge (1990)

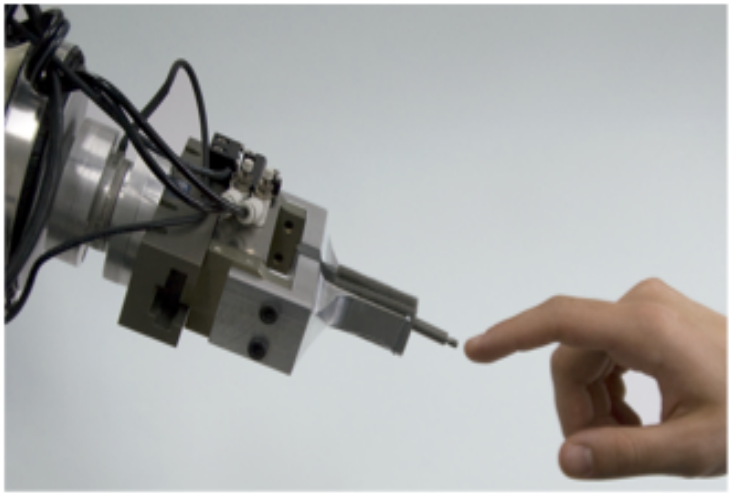
Reverse Turing Test



[42] D. Adams. Answer to the Ultimate Question of Life, the Universe, and Everything. The Hitchhiker's Guide to the Galaxy (1978)

Conclusion

Sentic computing does not aim to replace humans but, rather, to exploit differences in human-computer abilities and costs so as to achieve symbiotic HMI



Announcements

UAI 2014 Workshop on

Multidisciplinary Approaches to Big Social Data Analysis

http://sentic.net/mabsda

IEEE CIM Special Issue on

New Trends of Learning in Computational Intelligence

http://sentic.net/learning

ICDM 2014 Workshop on

Sentiment Elicitation from Natural Text for Information Retrieval and Extraction

http://sentic.net/sentire