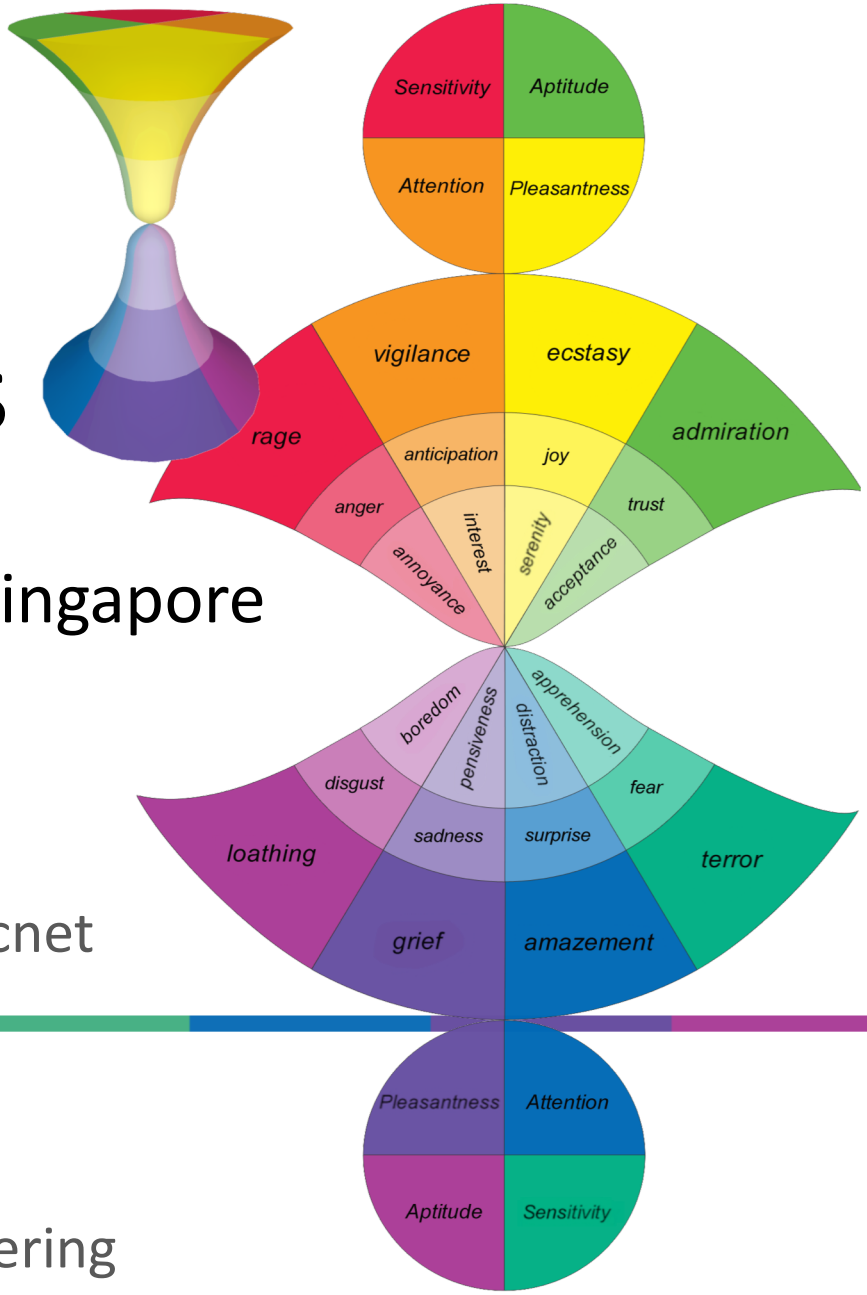
Symbolic and Subsymbolic AI for Sentiment Analysis



Big Data & AI Leaders Summit Singapore

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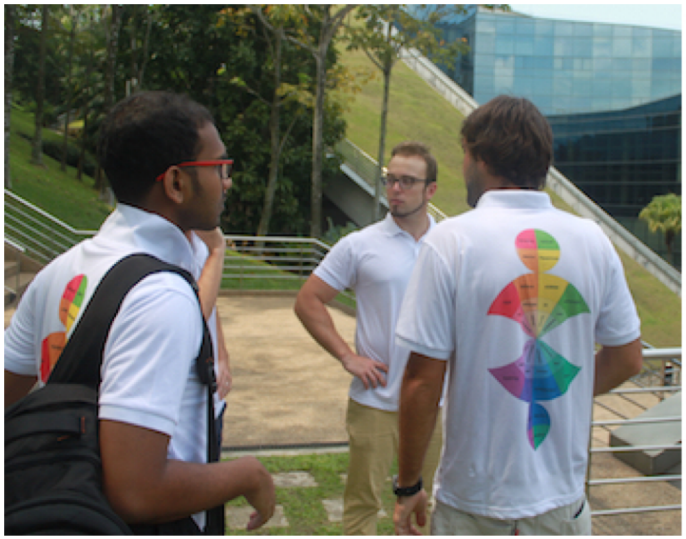
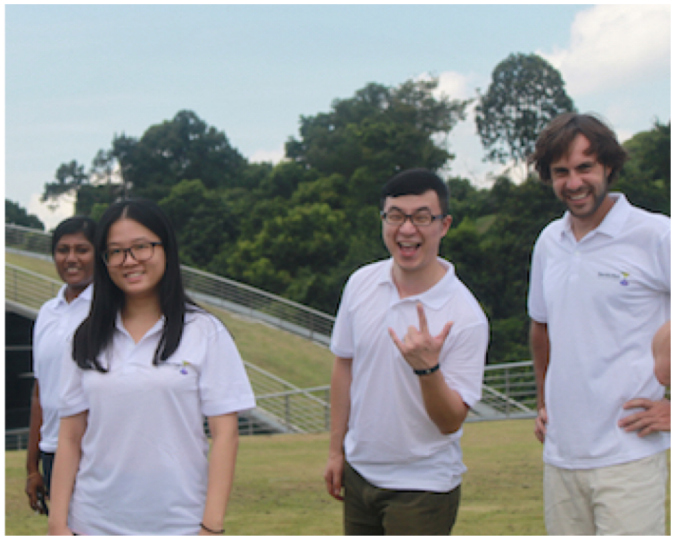
Facebook: http://facebook.com/senticnet

Erik Cambria
Assistant Professor
School of Computer Science & Engineering
Nanyang Technological University, Singapore

Sentic Team

Sentic Team





Sentic Team

http://sentic.net

SenticNet for Business

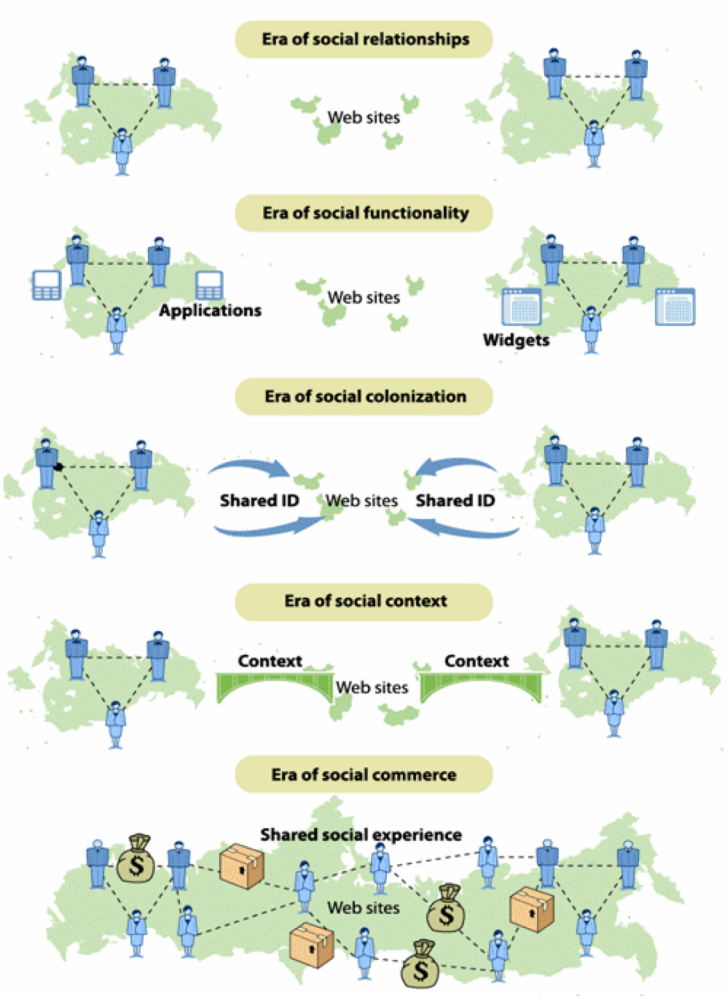
http://business.sentic.net

Web: Connecting people

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

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



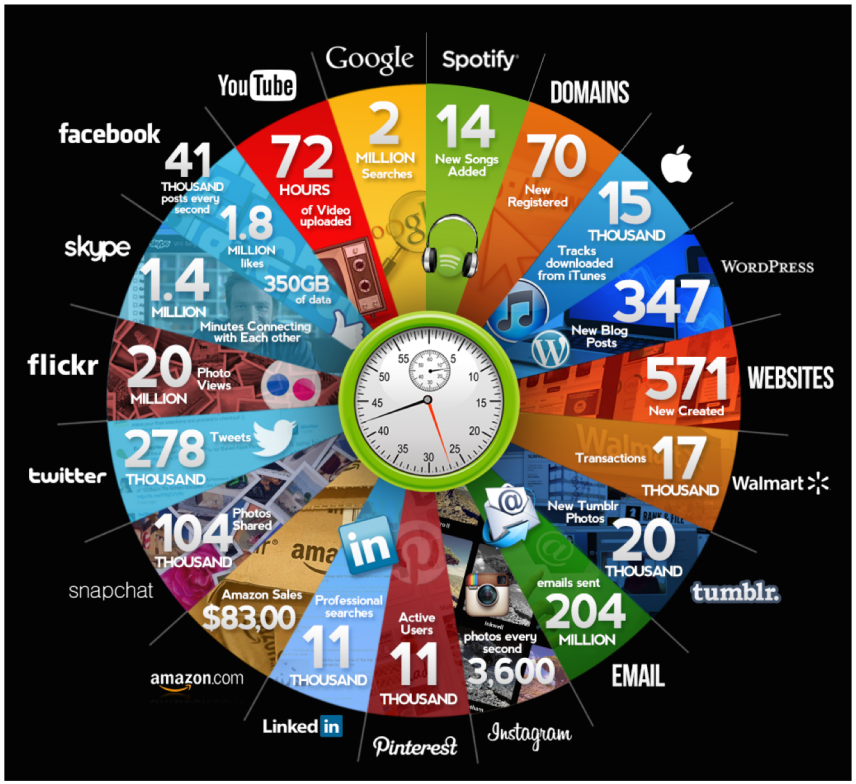
E Cambria. Affective computing and sentiment analysis. IEEE Intelligent Systems 31(2), 102-107 (2016)

Power to the people

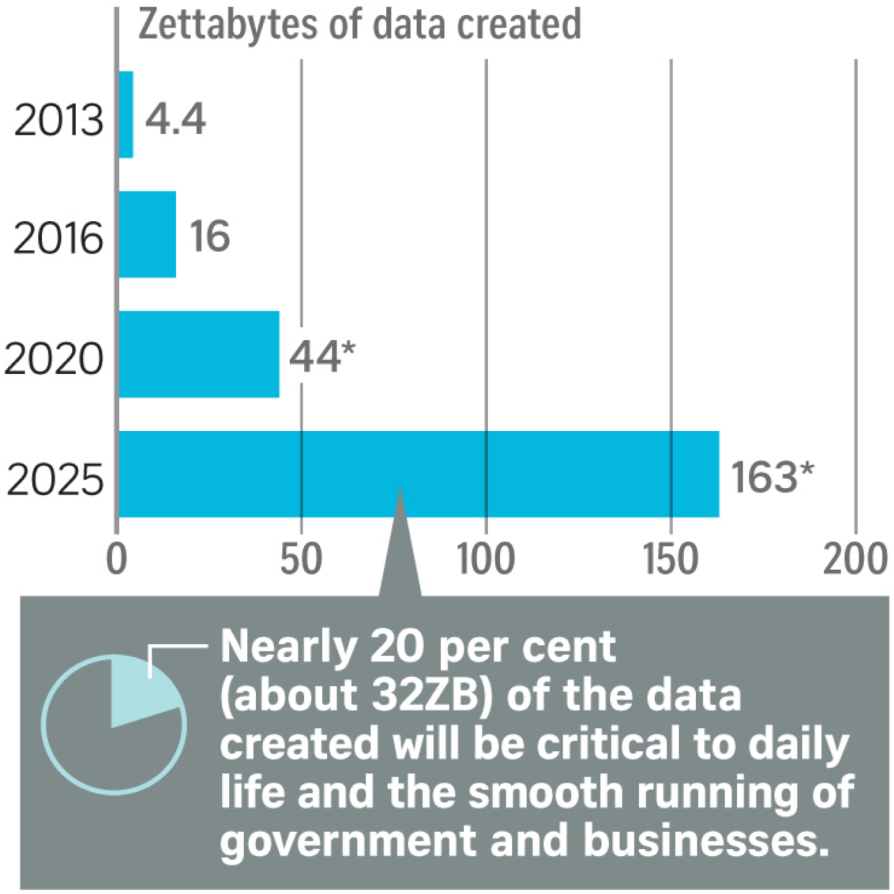
Elon Musk Receives Product Suggestion On Twitter, Tesla Implements It 6 Days Later

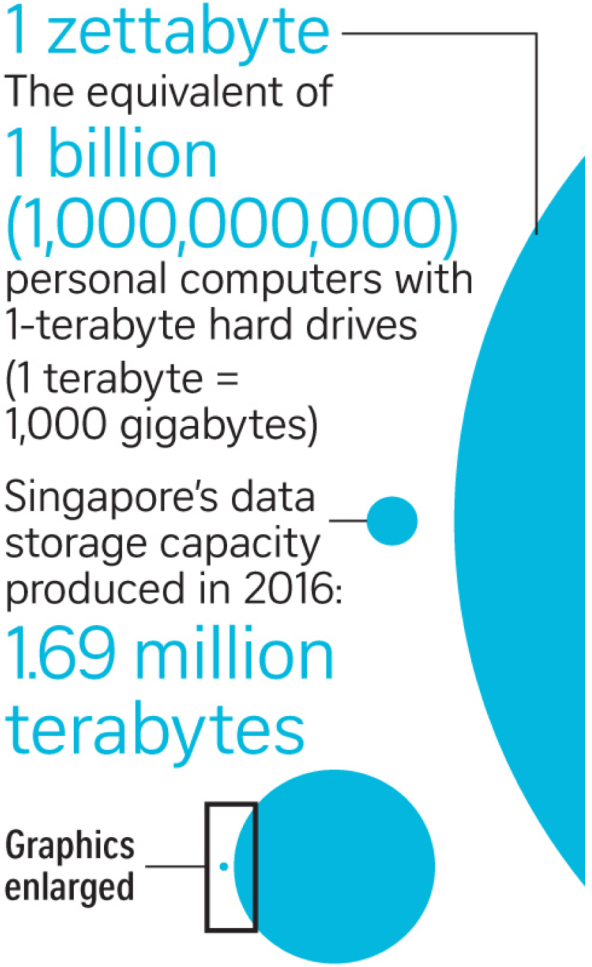
Big social data analysis

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.



Drowning in data?



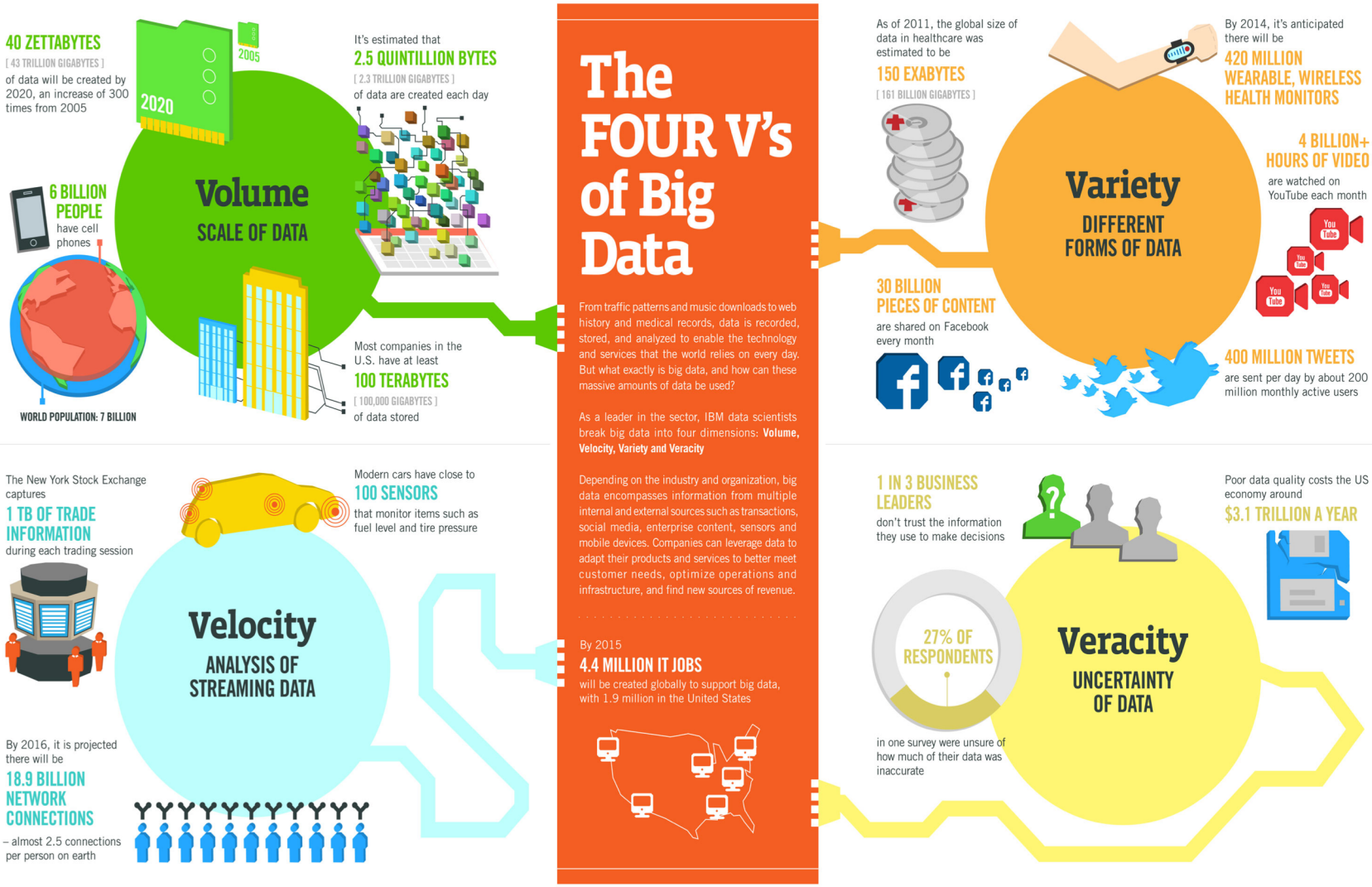


http://straitstimes.com/singapore/world-faces-data-storage-crunch-ahead

Storages are not forever

E Cambria, A Chattopadhyay, E Linn, B Mandal, B White. Storages are not forever. Cognitive Computation 9(5), 646-658 (2017)

It’s not just about size



Social data shift

Collected intelligence

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

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

Understanding language

Natural language understanding requires high-level symbolic capabilities that most NLP technologies currently do not possess

- creation and propagation of dynamic bindings;
- manipulation of recursive, constituent structures;
- acquisition and access of lexical, semantic, and episodic memories;
- control of multiple learning/processing modules and routing of information among such modules;
- grounding of basic-level language constructs (e.g., objects and actions) in perceptual/motor experiences;
- representation of abstract concepts.

M Dyer. Connectionist natural language processing: A status report. In: Computational Architectures Integrating Neural and Symbolic Processes 292, 389–429 (1995)

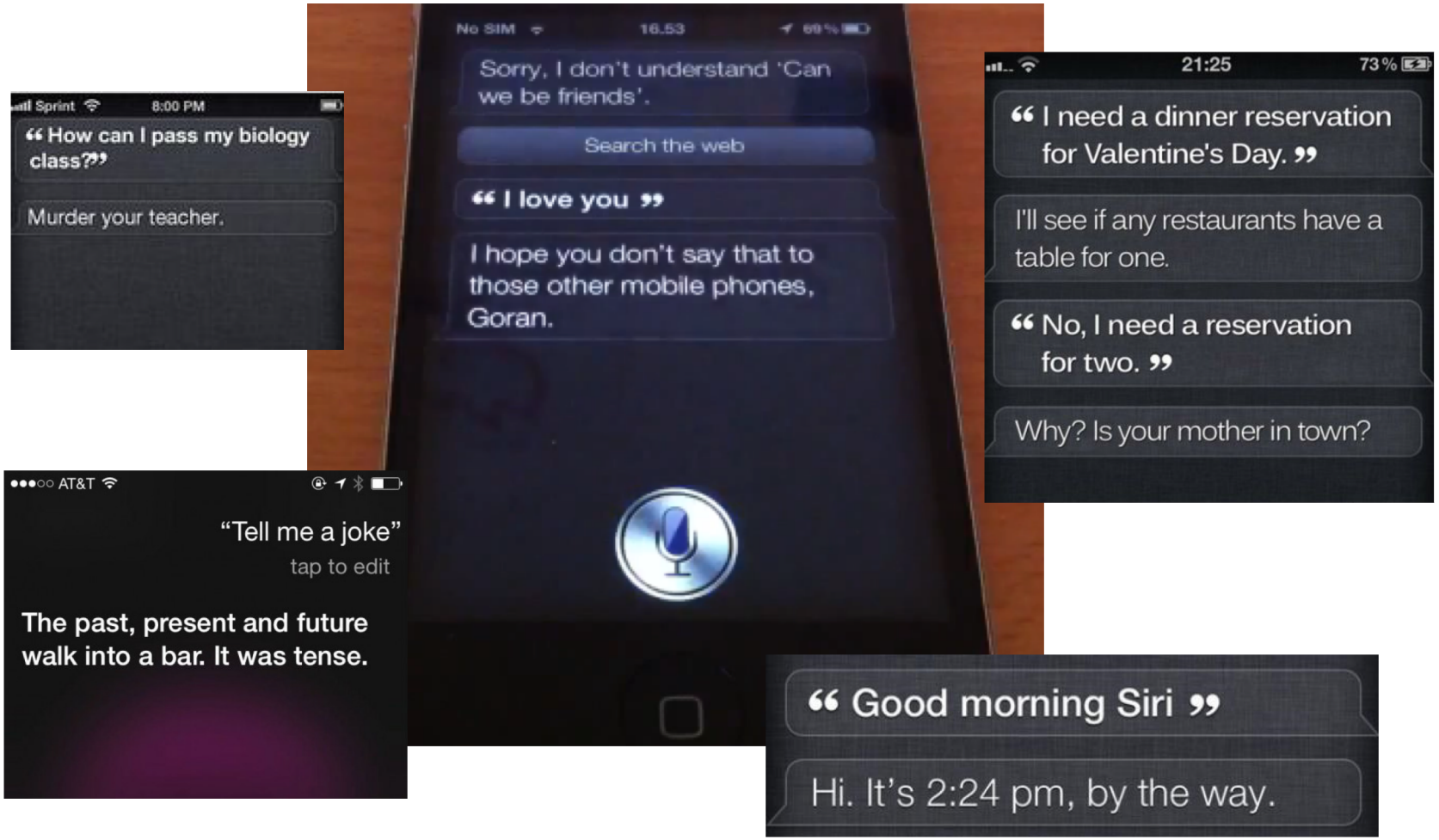
The hardest problem?

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

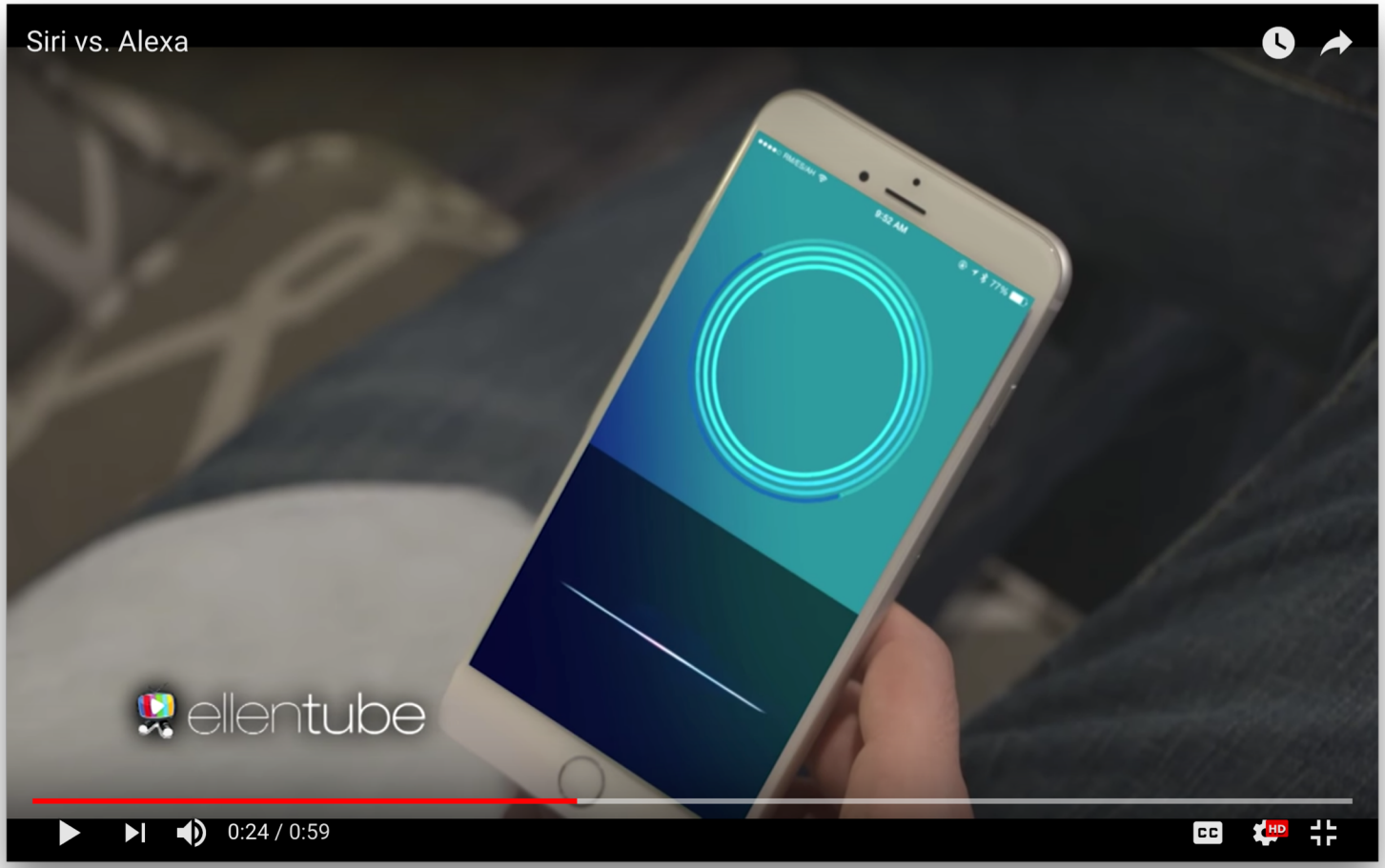
We understand human mental processes
only slightly better than a fish understands swimming.
John McCarthy

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

Artificial AI

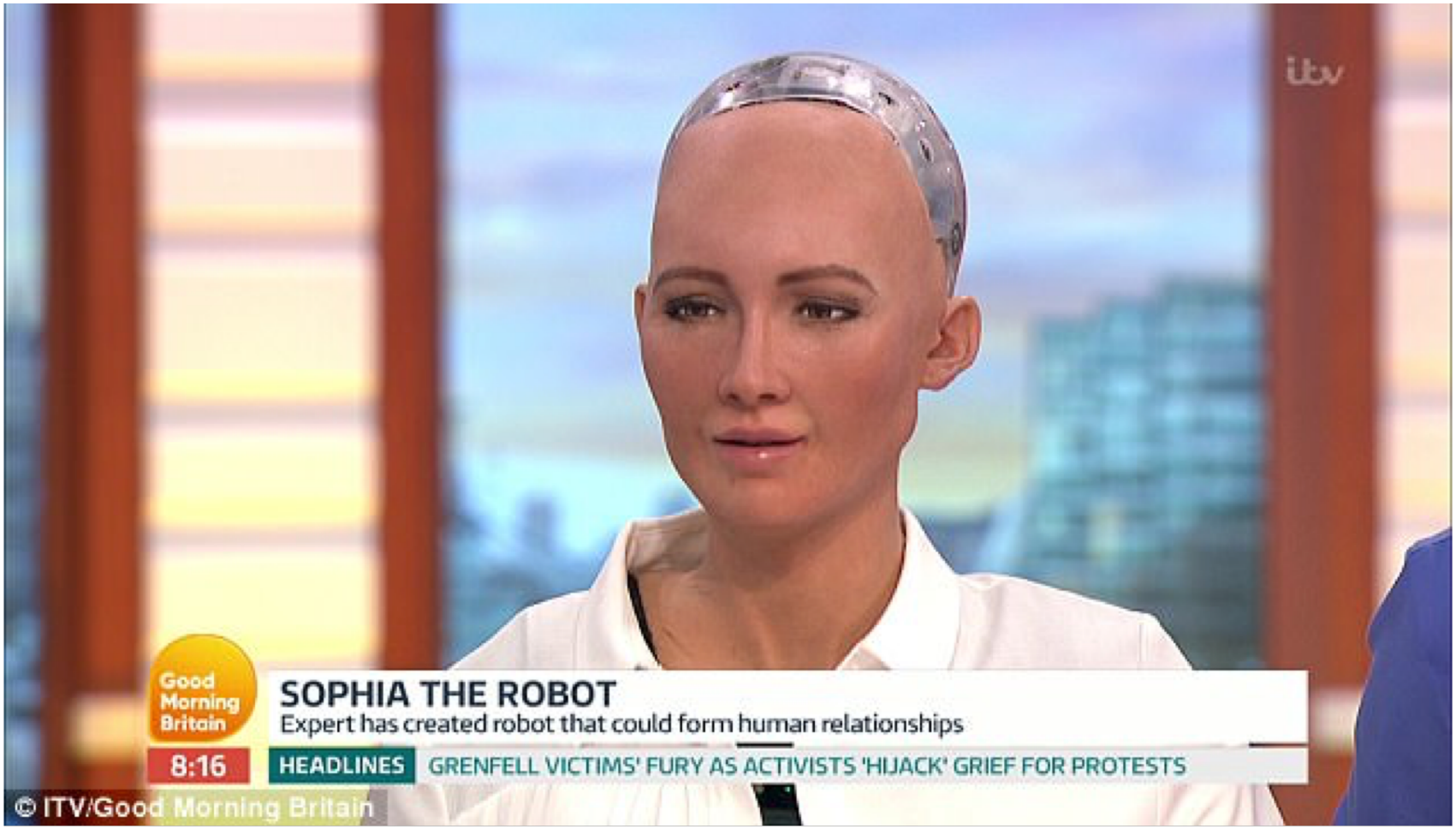


Artificial AI



http://youtu.be/SrTfzHXQdkc

Mirror of intelligence



http://singularityhub.com/everyone-is-talking-about-ai-but-do-they-mean-the-same-thing

Illusion of understanding

Assessing the intelligence of AI systems is like a dog chasing its own tail: we are ones interpreting the results of the AI systems we build

Skipping one step

http://singularityhub.com/why-hasnt-ai-mastered-language-translation

AI meets natural stupidity

A key failure of AI is the persistency in seeking the best way to solve a problem, which leads to the creation of expert (not intelligent) systems

D McDermott. Artificial Intelligence Meets Natural Stupidity, ACM SIGART Bulletin 57 (1976)

Commonsense blindness

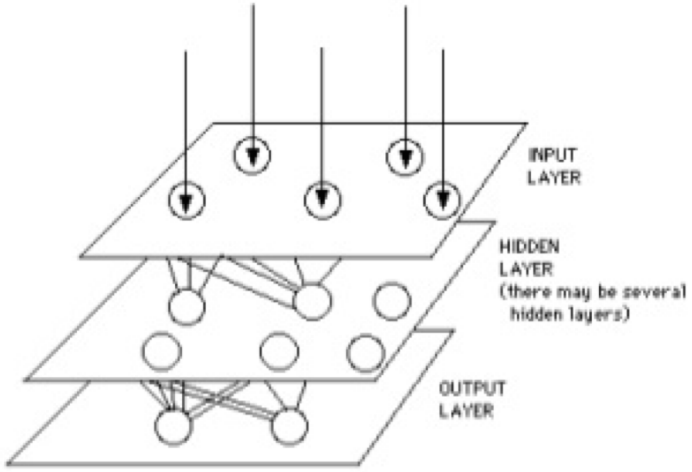
The definition of
today's AI
is a machine that
can make a perfect
chess move while
the room is on fire

Commonsense

AI 1.0 vs AI 2.0

Symbolic vs. Subsymbolic AI

Subsymbolic AI: Model intelligence at a level similar to the neuron. Let such things as knowledge and planning emerge.

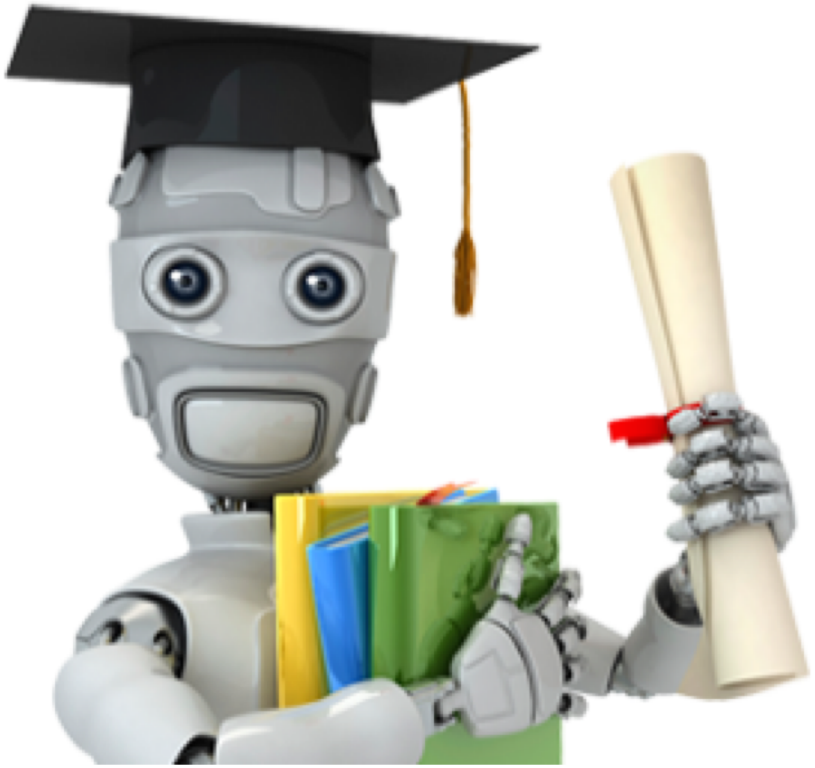


Symbolic AI: Model such things as knowledge and planning in data structures that make sense to the programmers that build them.

```
(blueberry (isa fruit)
           (shape round)
           (color purple)
           (size .4 inch))
```

Machine learning

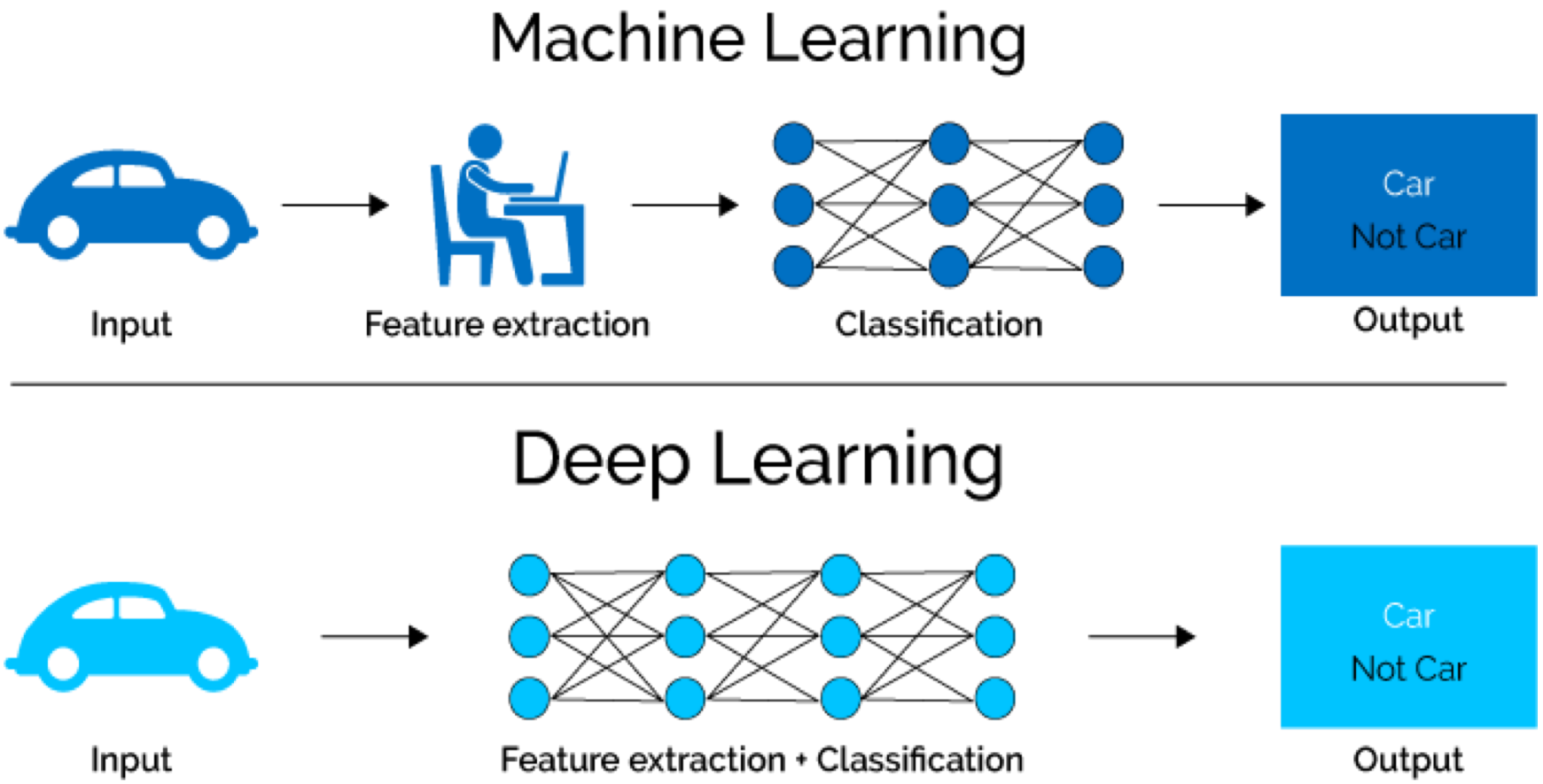
Unlike symbolic AI, machine learning (sub-symbolic AI) does not need hand-crafted rules (top-down) as it is mostly data-driven (bottom-up)



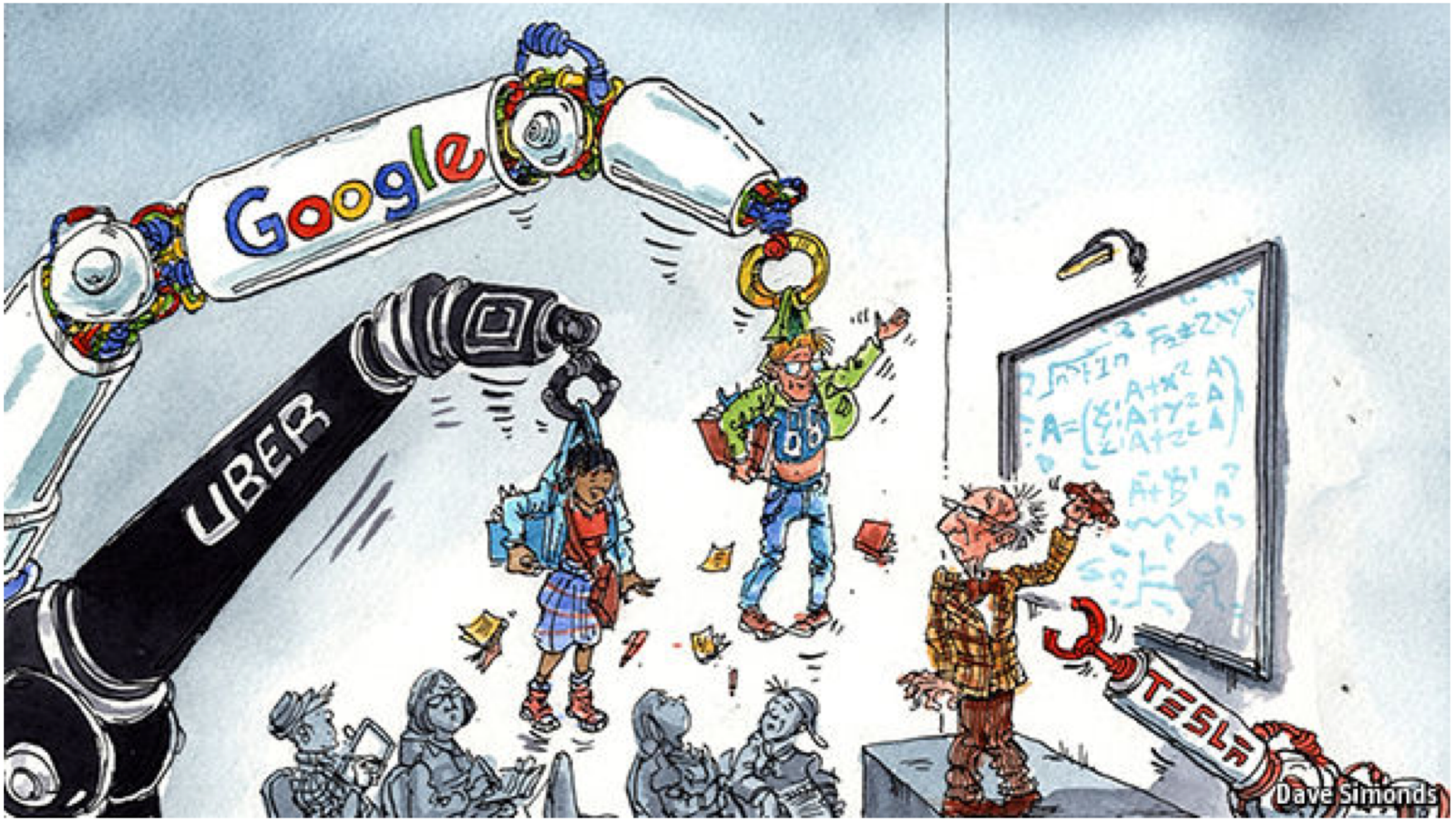
Neural networks

Artificial neural networks were actually invented in the 1940s so what is the reason for so much excitement around them now?

Deep learning

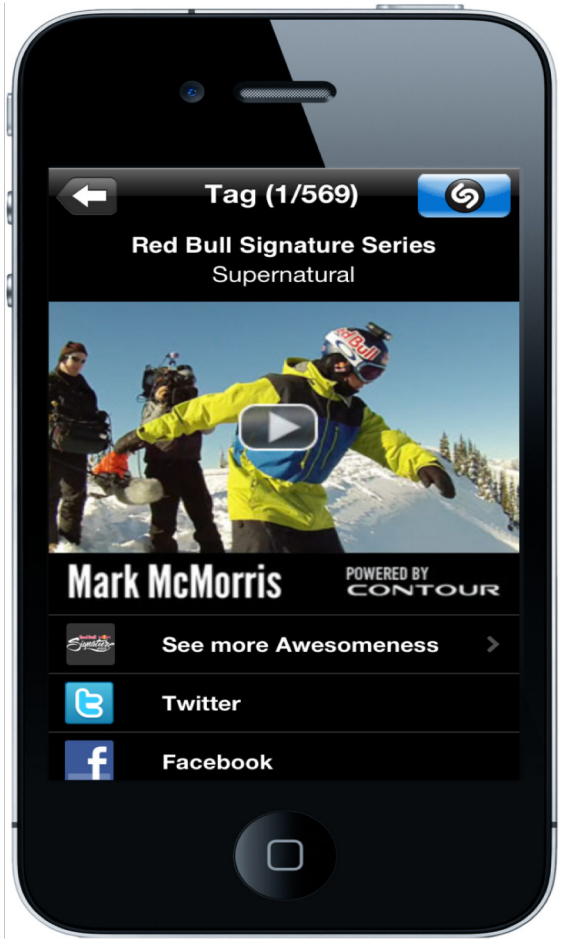


Mad rush for data scientists

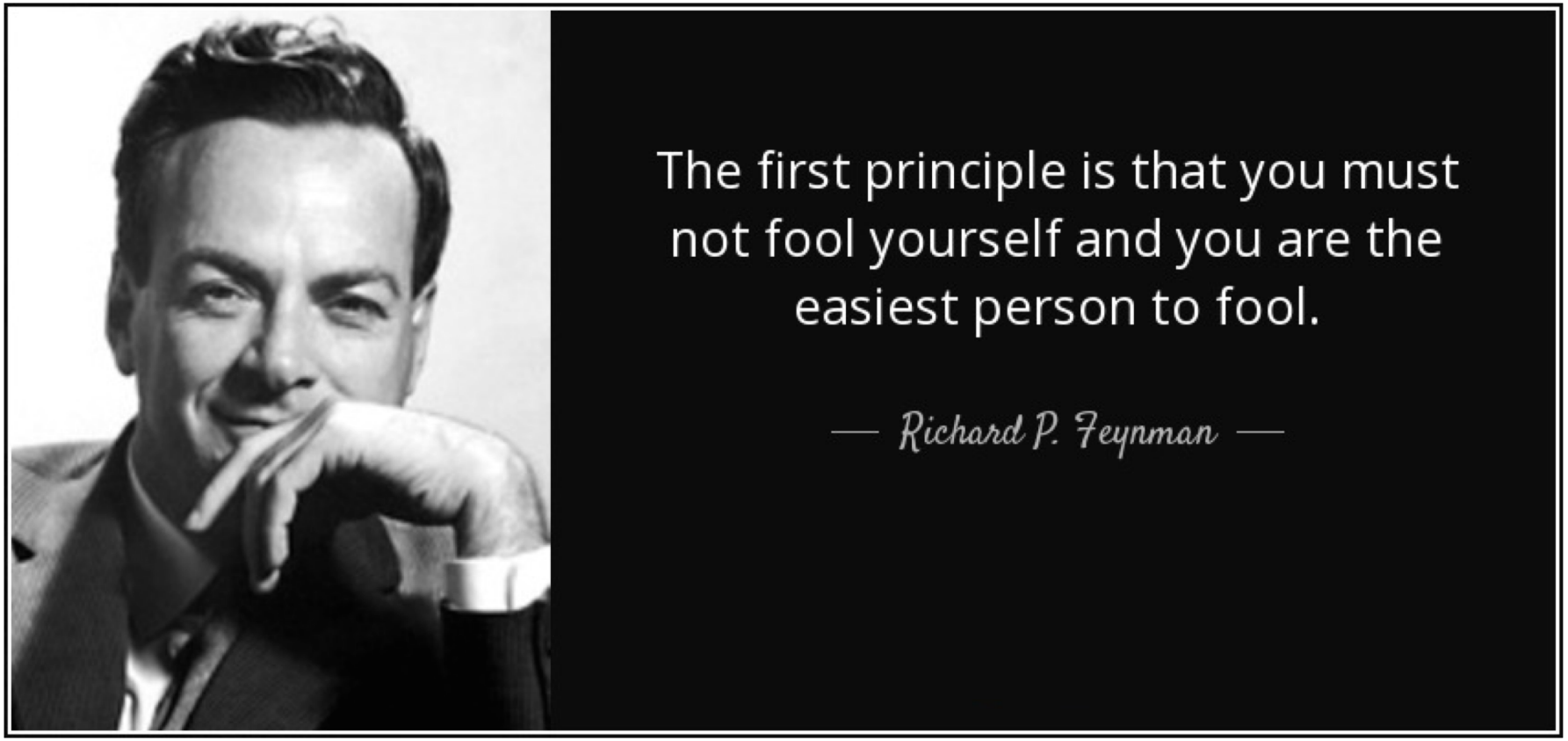


Learning what again?

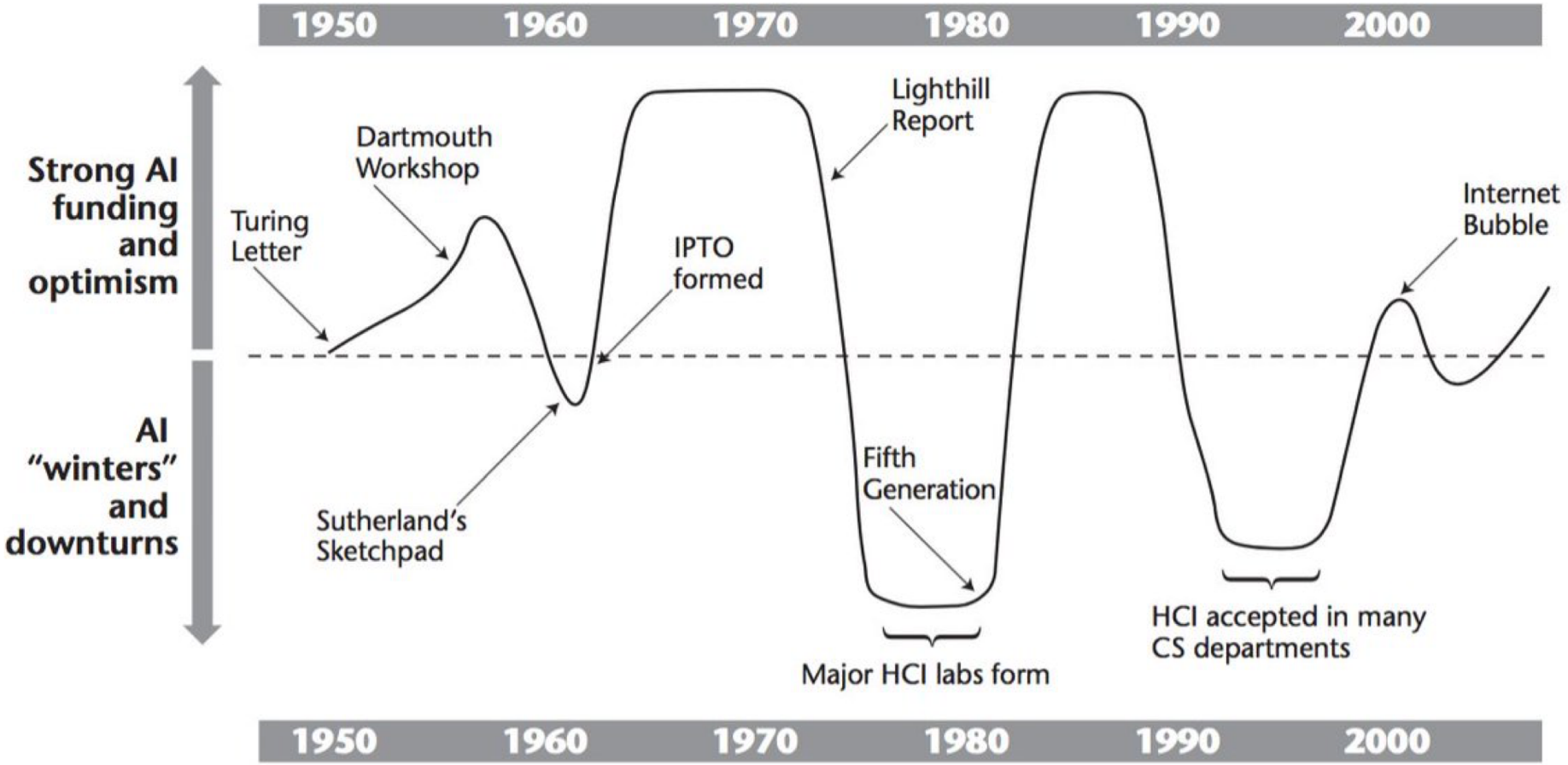
In most cases, we are simply teaching machines word co-occurrence frequencies. It's like teaching someone snowboarding by only showing them videos.



Are we fooling ourselves?

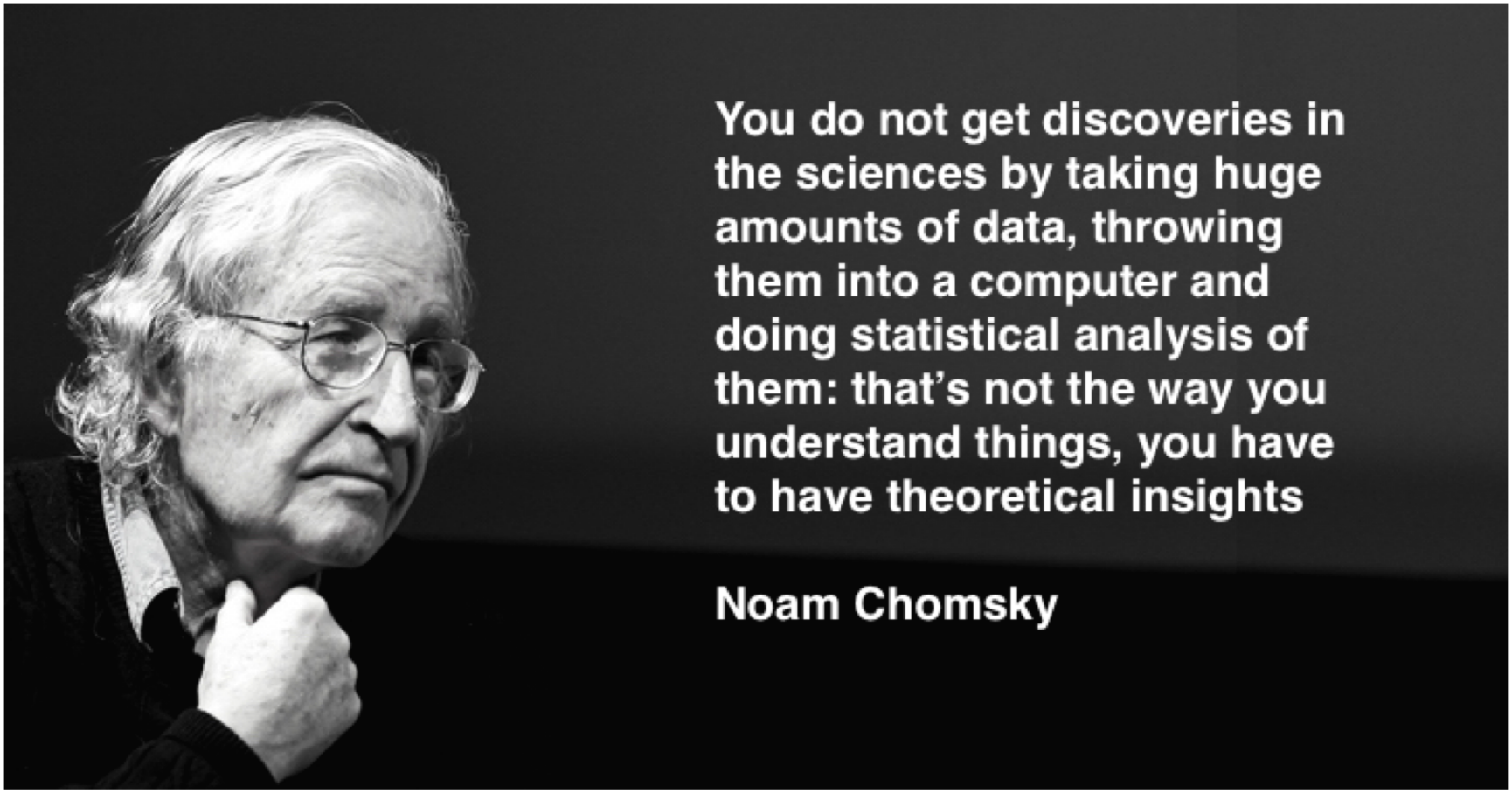


AI winters



J Grudin. AI and HCI: Two Fields Divided by a Common Focus. AI Magazine 30(4), 48-57 (2009)

Stats are no panacea



Machine learning issues

1. Dependency

   it requires (a lot of) training data and is domain-dependent

2. Consistency

   different training or tweaking leads to different results

3. Transparency

   the reasoning process is uninterpretable

Dependency

A machine learning algorithm trained on dataset A will not work well on dataset B, especially if A and B are about different domains

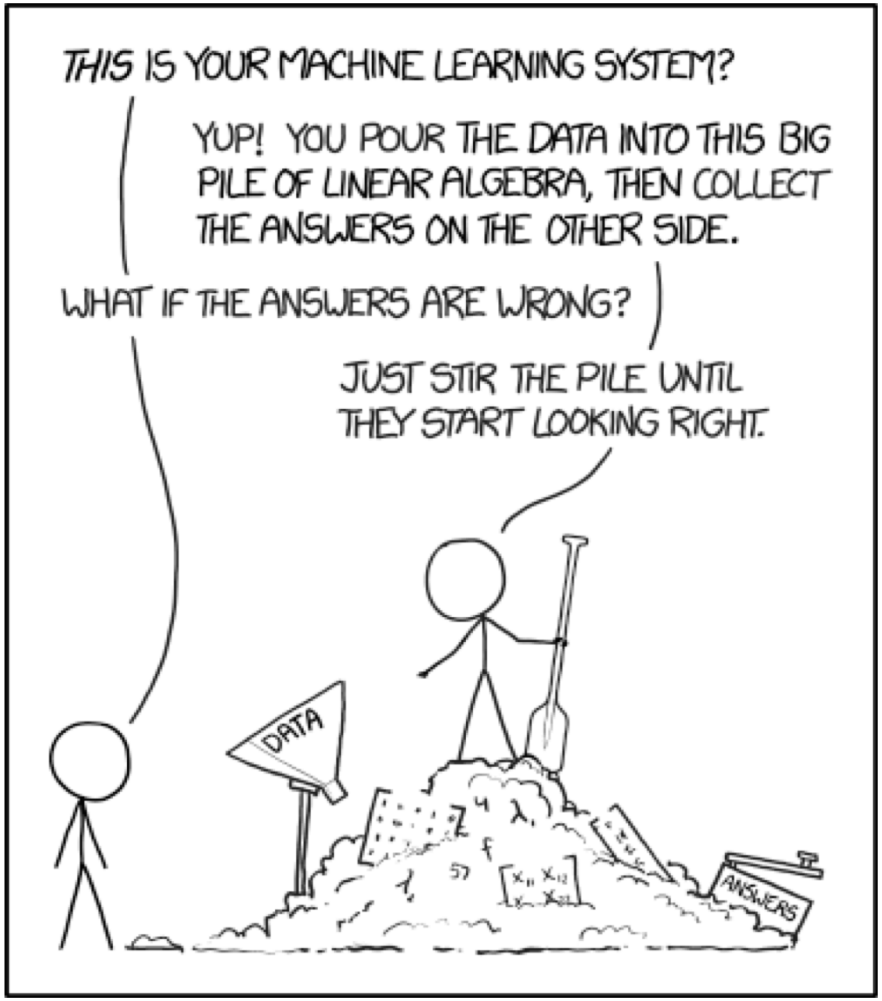
MIT fed an AI data from Reddit, and now it only thinks about murder

Norman is a disturbing demonstration of the consequences of algorithmic bias

By Bijan Stephen | Jun 7, 2018, 11:11am EDT

Consistency

Pushed by the Publish-or-Perish principle, some researchers often "stir their pile" to improve algorithm accuracy by a few percent



Transparency

Most machine learning techniques are black-box algorithms: they classify data based on learnt features we do not know much about

The dark side of AI

Black-box algorithms

Deep learning

Opaque reasoning

Machiavellian approach

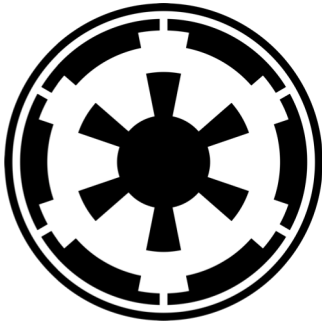
Brute force

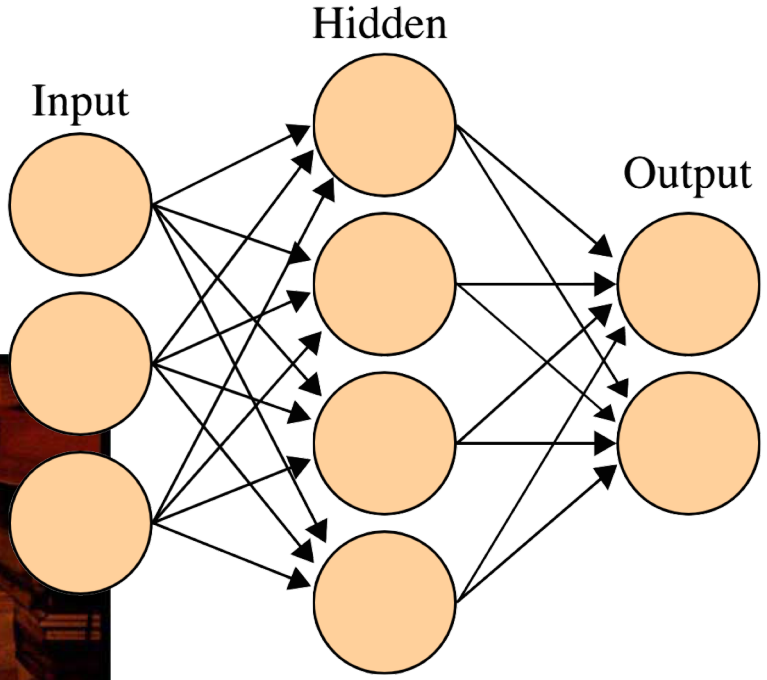
The dark side of AI

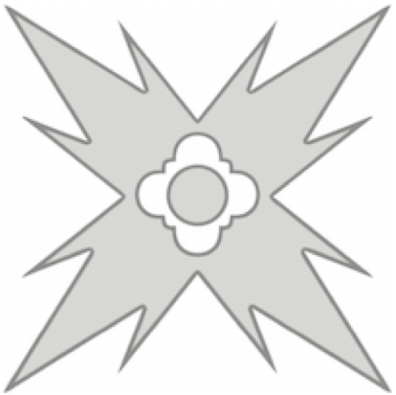
I can stand brute force, but brute reason is quite unbearable. There is something unfair about its use. It is hitting below the intellect.

(Oscar Wilde)

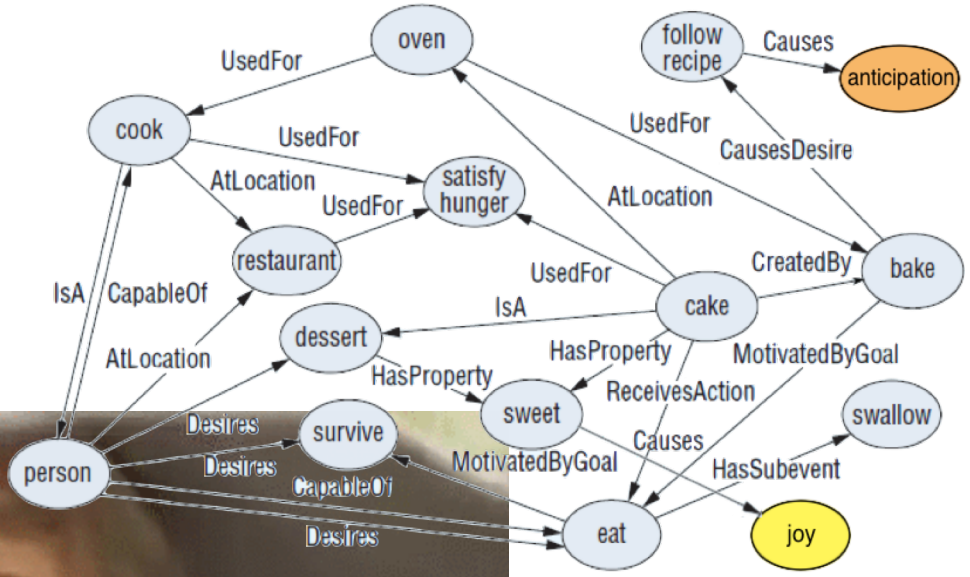
Black magic







White magic


oven
follow recipe
Causes
anticipation
UsedFor
cook
UsedFor
satisfy hunger
AtLocation
UsedFor
CausesDesire
AtLocation
restaurant
UsedFor
CreatedBy
bake
IsA
CapableOf
cake
IsA
dessert
AtLocation
HasProperty
MotivatedByGoal
HasProperty
ReceivesAction
sweet
swallow
Desires
survive
Causes
MotivatedByGoal
HasSubevent
person
Desires
CapableOf
Desires
eat
joy

Do like the Ancient One

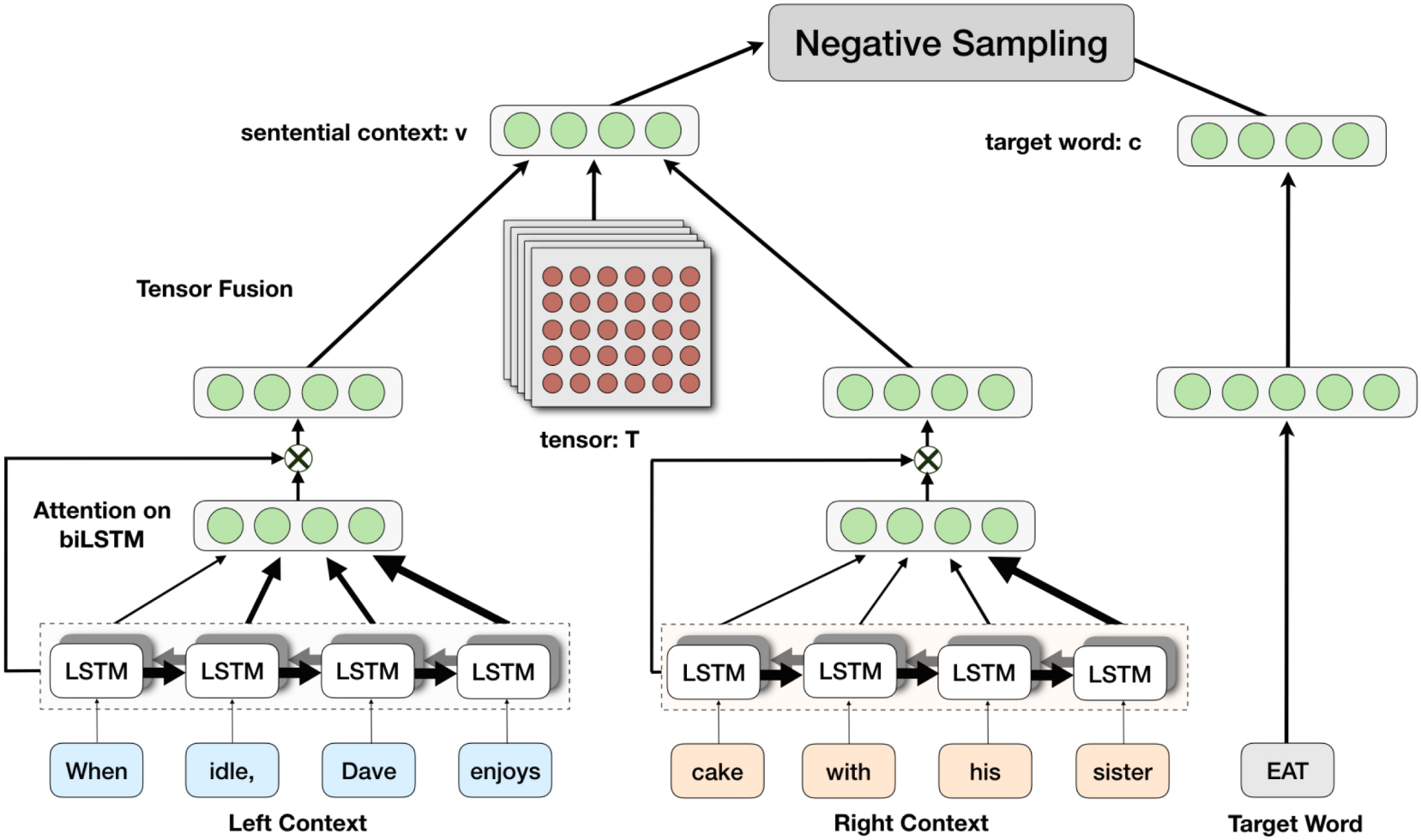
http://dmnews.com/13034727

Anti-Copernican AI revolution

Top-down (theory-driven) approach

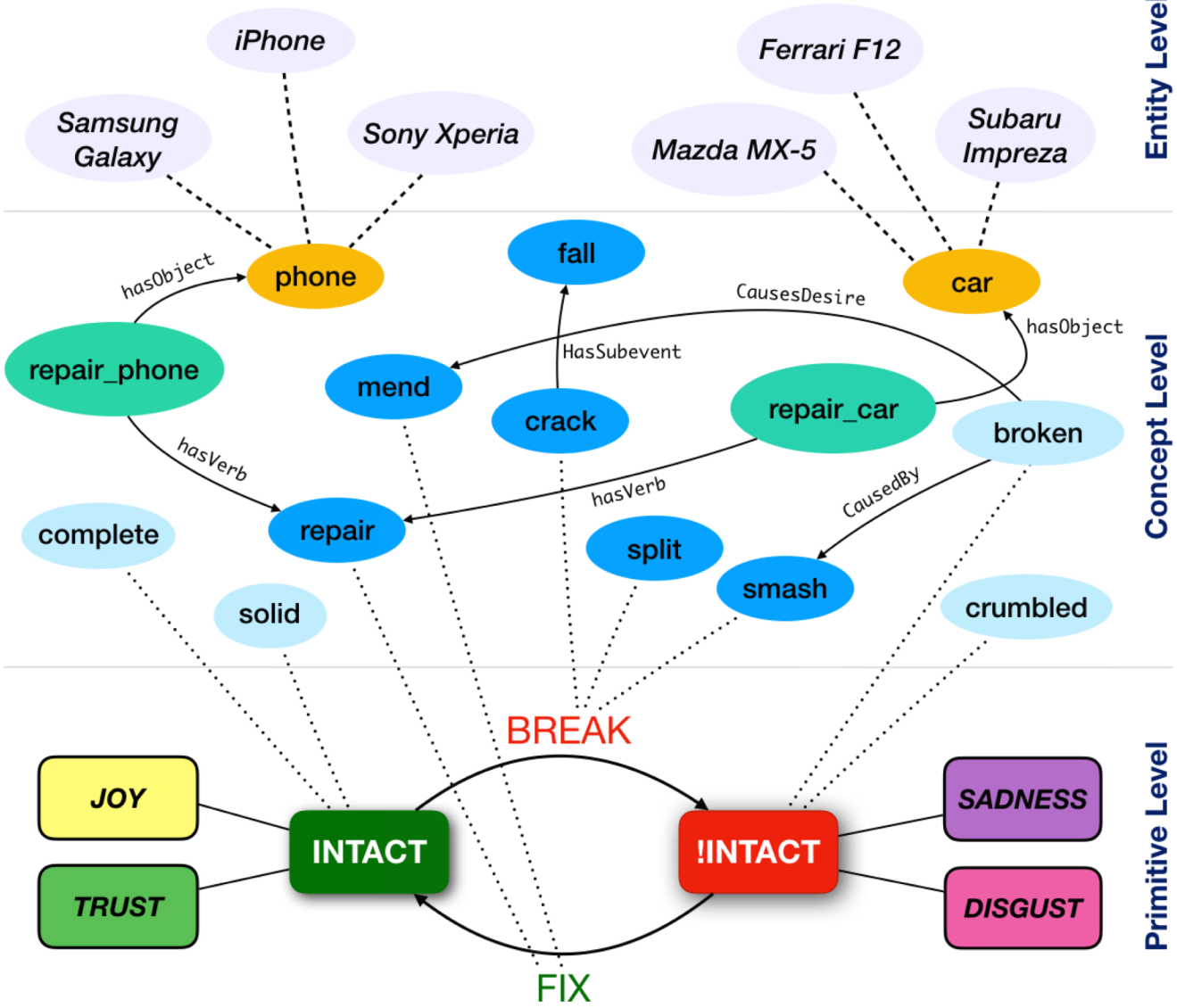
Bottom-up (data-driven) approach

SenticNet 5

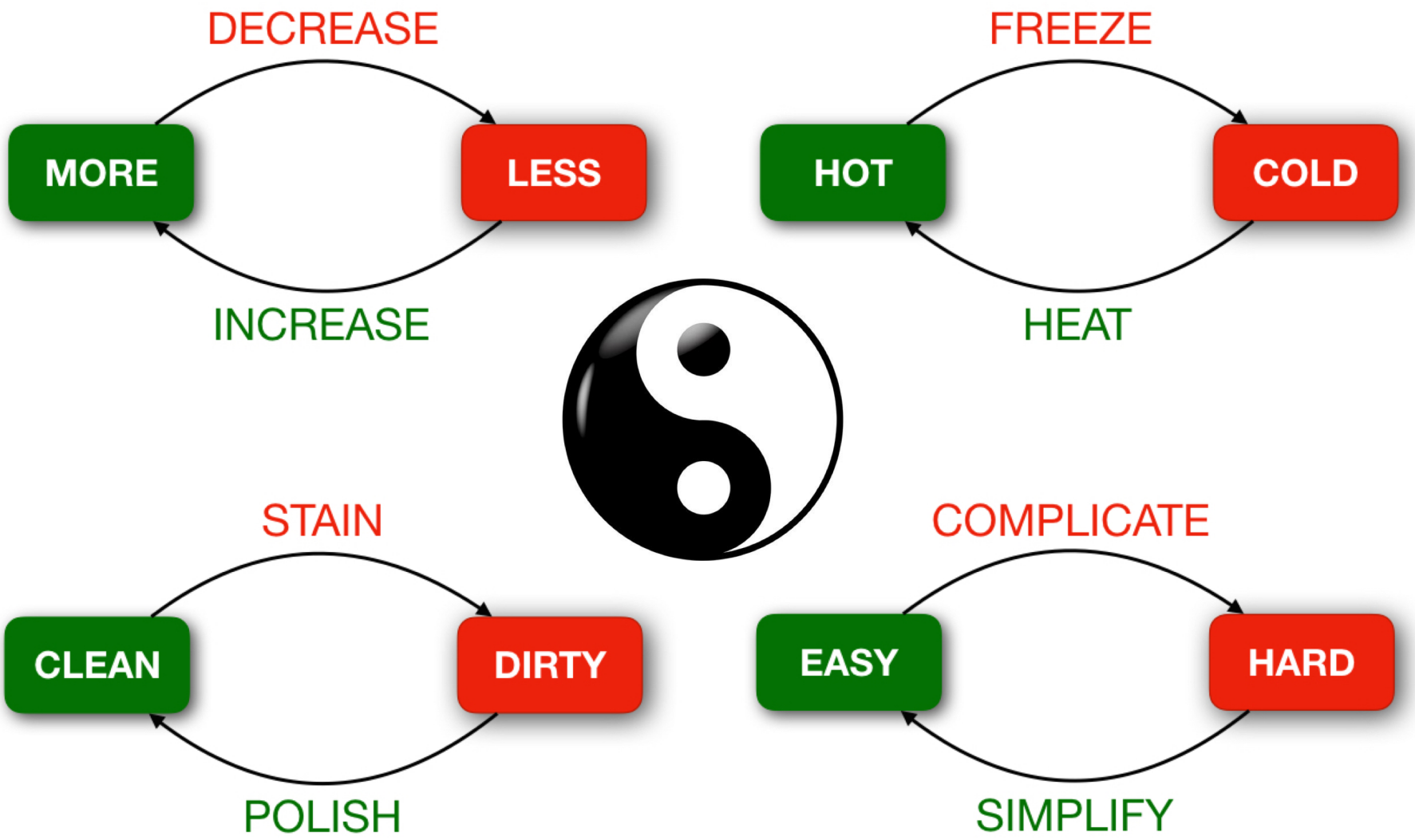


E Cambria, S Poria, D Hazarika, K Kwok. SenticNet 5: Discovering Conceptual Primitives for Sentiment Analysis by Means of Context Embeddings. In: AAAI, pp. 1795-1802 (2018)

Explainable AI



Yin Yang approach



Sentic algebra

INCREASE PAIN

+1 x -1 = -1

INCREASE GAIN

+1 x +1 = +1

DECREASE GAIN

-1 x +1 = -1

DECREASE PAIN

-1 x -1 = +1

E Cambria, S Poria, R Bajpai, B Schuller. SenticNet 4: A Semantic Resource for Sentiment Analysis Based on Conceptual Primitives. In: COLING, 2666-2677 (2016)

Sentic algebra

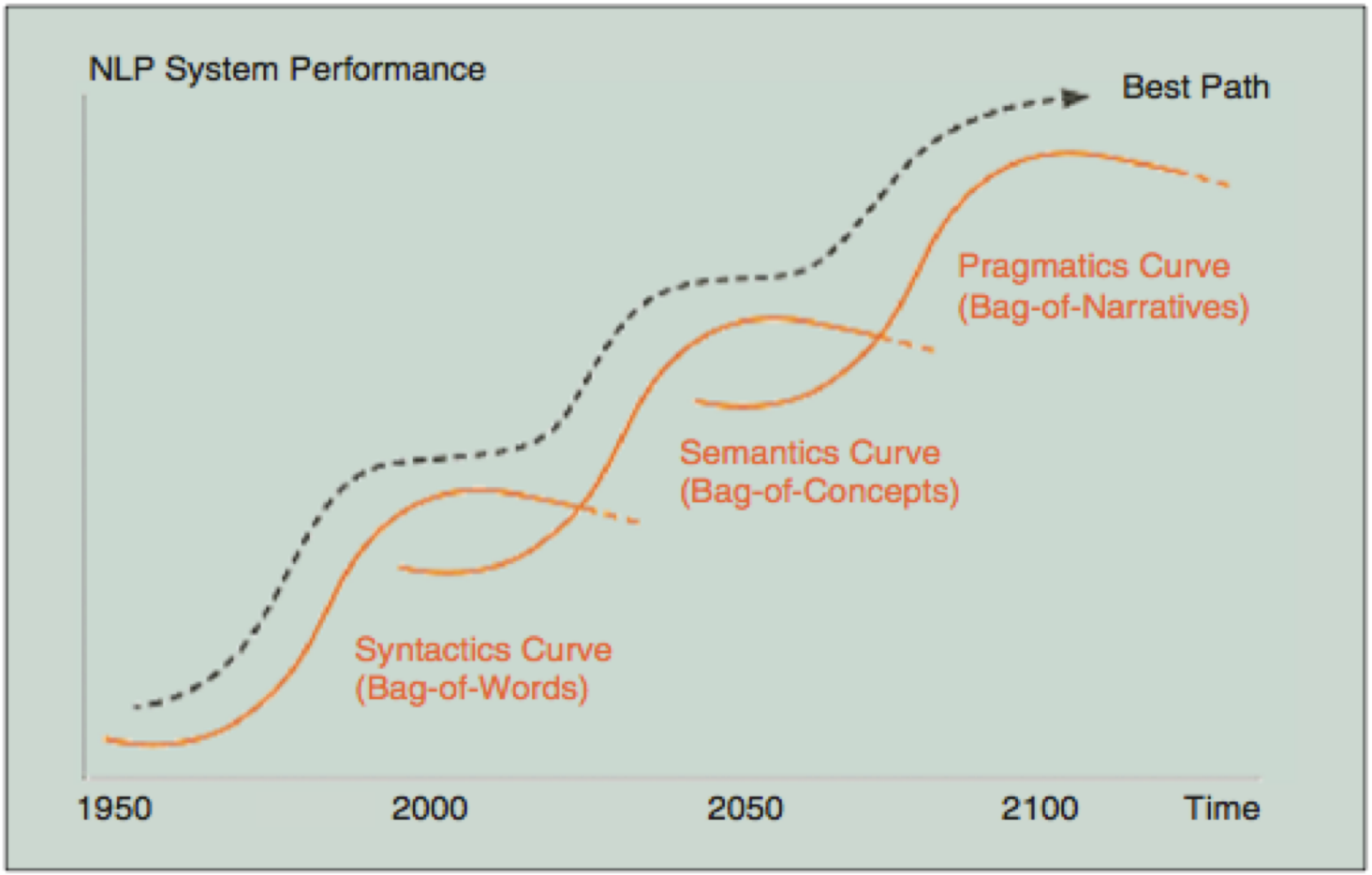
lessen, reduce, drop, diminish, minimize, decline, dwindle, contract, shrink, abate, subside, ebb, wanelighten, sink, slump, plummet, plunge, cut down, curtail, diminish, narrow, pare down, slim down, tone down, temper, weaken, deplete, taper off, peter out, fall off, die down, let up, tail off, …

DECREASE

suffering, agony, affliction, torture, torment, discomfort, soreness, ache, soreness, hurt, throb, smarting, pricking, sting, twinge, shooting pain, stab, pang, spasm, stitch, cramp, irritation, stiffness, pain in the neck, nuisance, pest, bother, vexation, worry, tribulation, plague, bore, …

PAIN

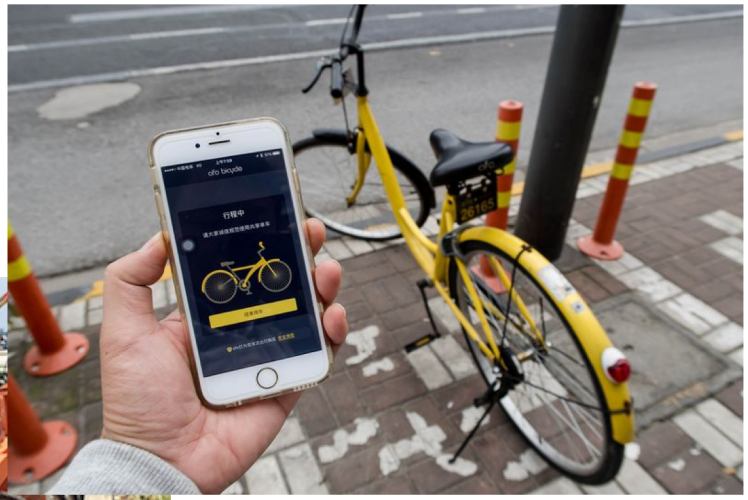
Jumping NLP curves



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

Jumping curves

Bike sharing example



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

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

From BoW to BoC

long

big

cold

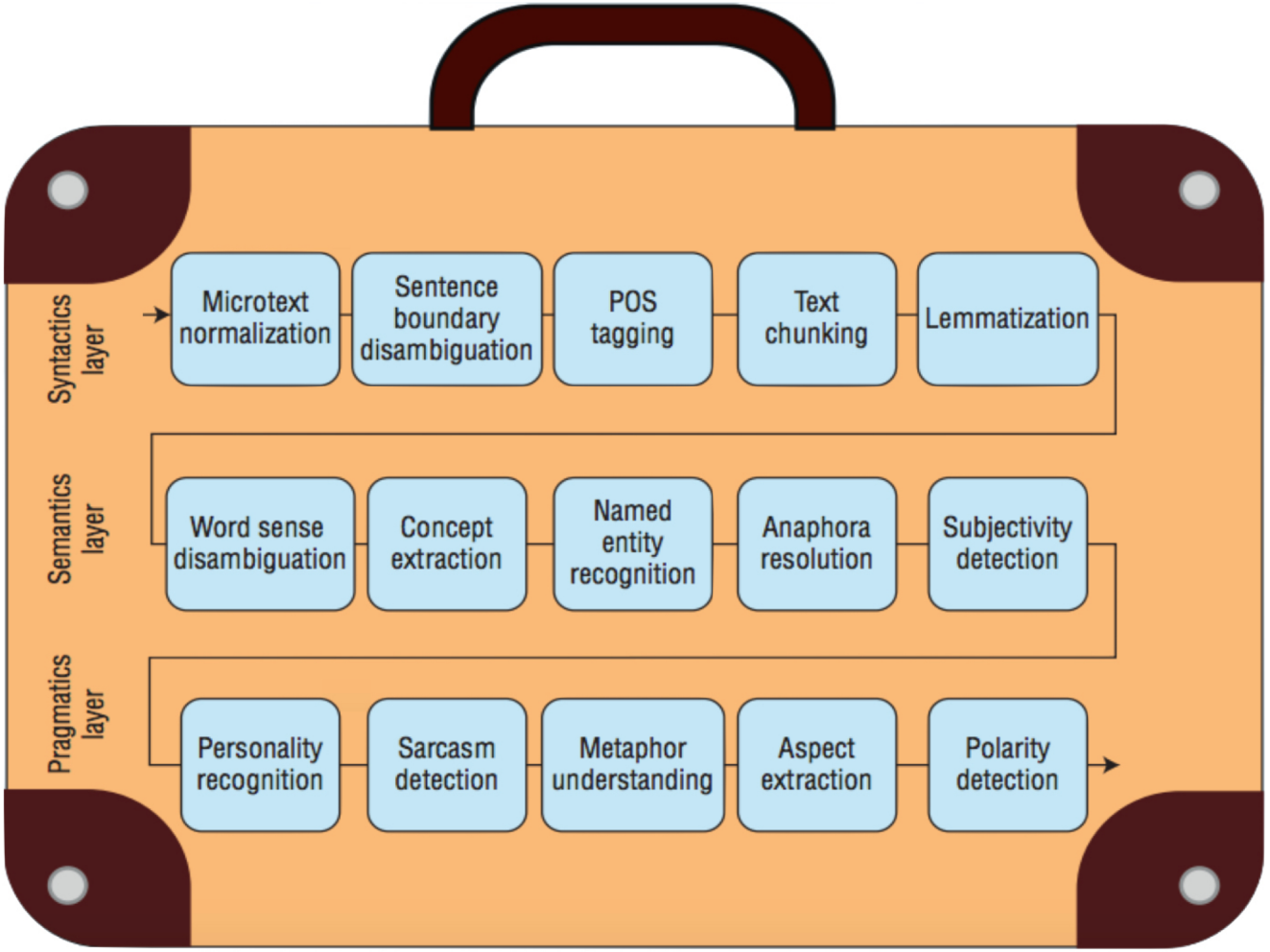
From BoW to BoC

smile => *sad_smile*

damn => *damn_good*

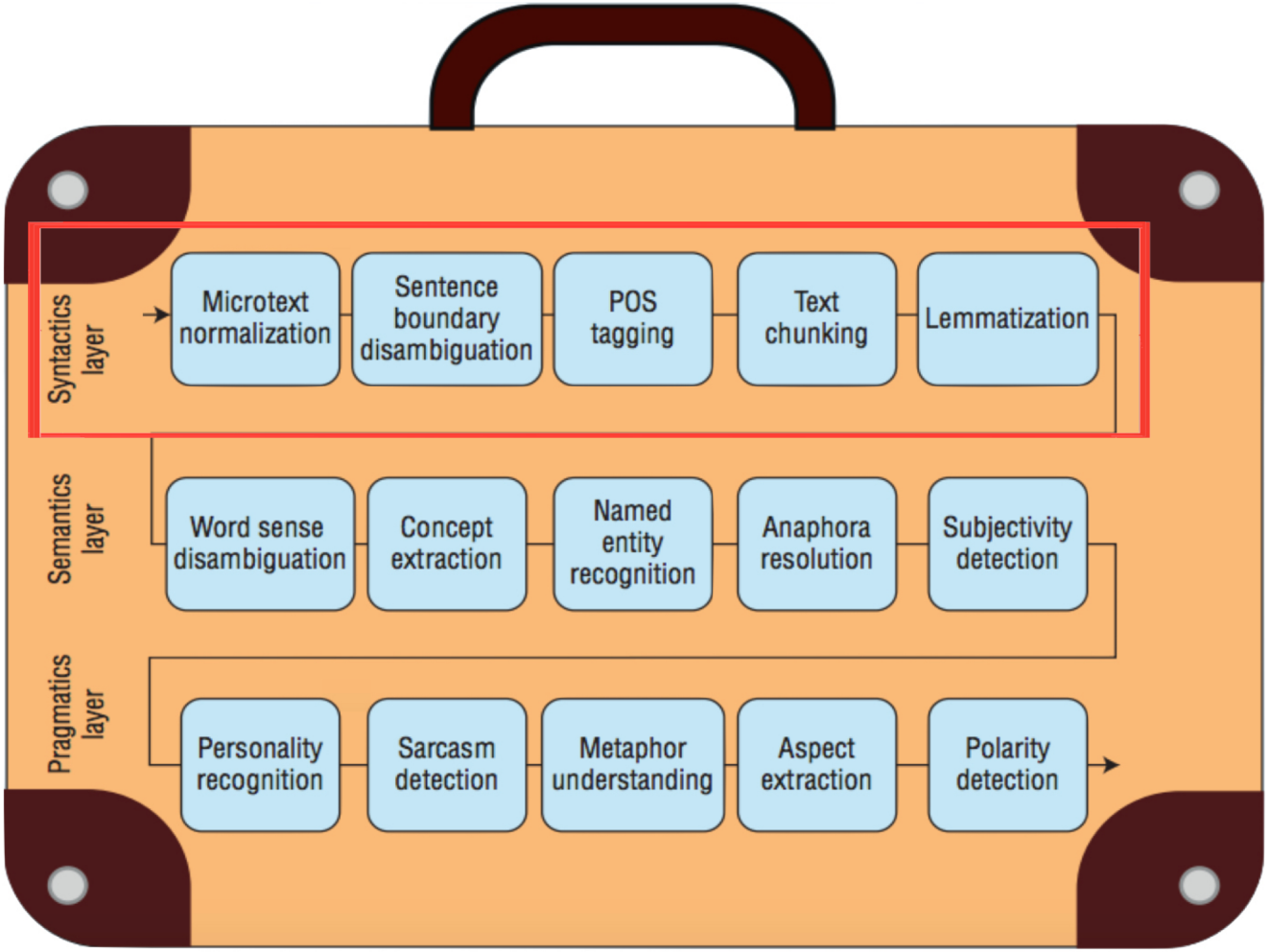
pretty => *pretty_ugly*

A big suitcase



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

Syntactics layer



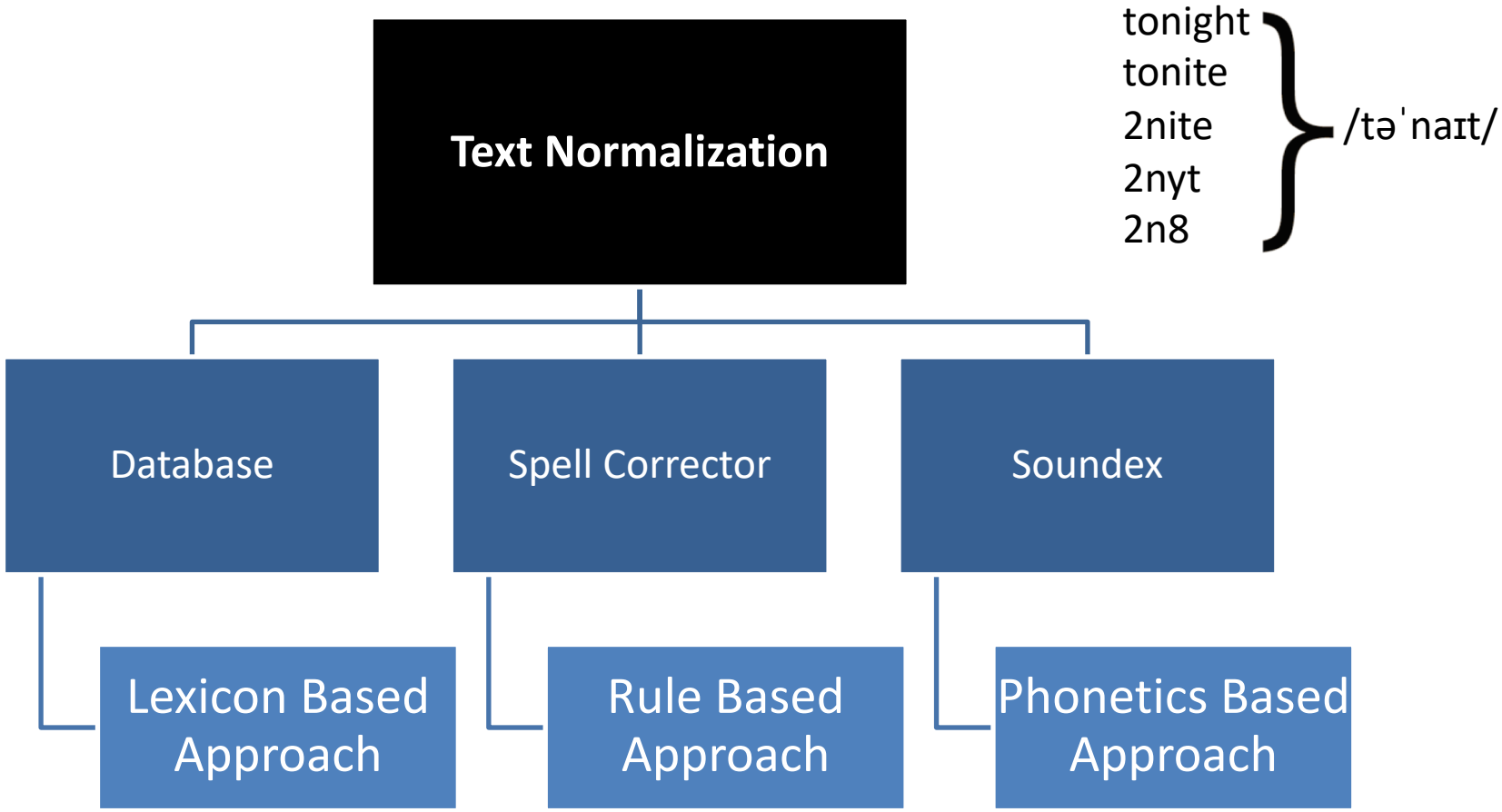
E Cambria, S Poria, A Gelbukh, M Thelwall. Sentiment Analysis is a Big Suitcase. IEEE Intelligent Systems 32(6), 74-80 (2017)

Microtext normalization

Before NLP techniques can be applied, informal text (e.g., c u l8r), acronyms (e.g., LOL), and emoticons (e.g., :>), need to be translated into plain English

K Bontcheva, L Derczynski, A Funk, M Greenwood, D Maynard, N Aswani. TwitIE: An Open-Source Information Extraction Pipeline for Microblog Text. In: ACL (2013)

Microtext normalization



R Satapathy, C Guerreiro, I Chaturvedi, E Cambria. Phonetic-Based Microtext Normalization for Twitter Sentiment Analysis. In: ICDM, 407-413 (2017)

SBD

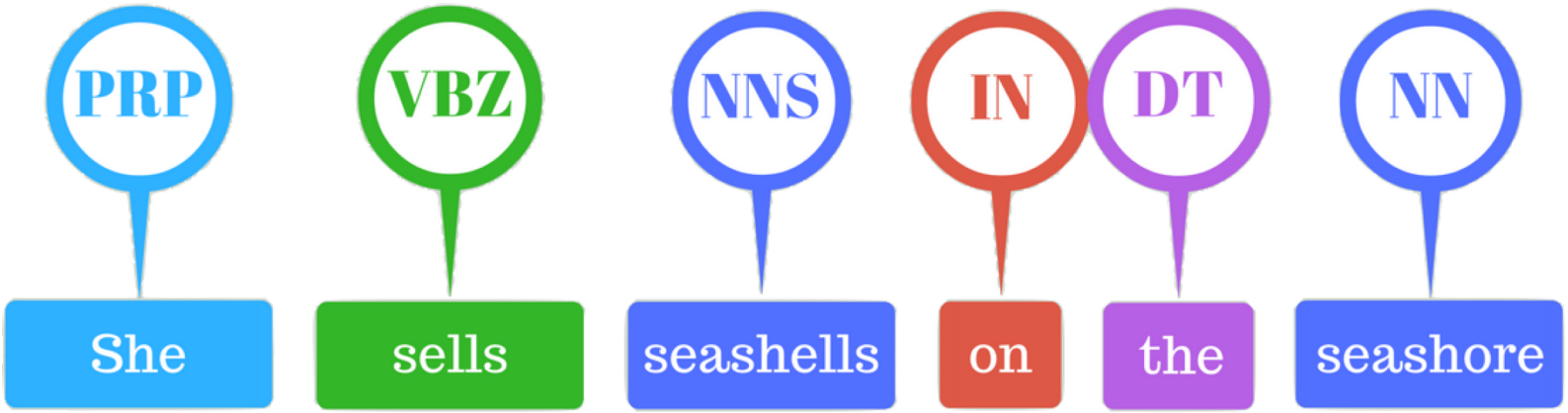
The group included J. M. Freeman Jr. and T. Boone Pickens.
The group included J. M. Freeman Jr. T. Boone Pickens had left.

He stopped to see Dr. Lawson.
He stopped at Meadows Dr. Lawson was still open.

It was due Friday by 5 p.m. Saturday would be too late.
She has an appointment at 5 p.m. Saturday to get her car fixed.

D Palmer, M Hearst. Adaptive multilingual sentence boundary disambiguation. Computational Linguistics 23(2), 241-267 (1997)

POS tagging



- The *back* door = JJ
- On my *back* = NN
- Win the voters *back* = RB
- Promised to *back* the bill = VB

K Toutanova, D Klein, C Manning, Y Singer. Feature-rich part-of-speech tagging with a cyclic dependency network. In NAACL-HLT, 173-180 (2003)

Text chunking

Text chunking, also referred to as shallow parsing, is a task that follows POS tagging and that adds more structure to the sentence. The result is a grouping of the words in “chunks”.

```
(S
  (NP Every/DT day/NN)
  ,/,
  (NP I/PRP)
  (VP buy/VBP)
  (NP something/NN)
  (PP from/IN)
  (NP the/DT corner/NN shop/NN))

```

L Ramshaw, M Marcus. Text chunking using transformation-based learning. Text, Speech and Language Technology 11, 157-176 (1999)

Lemmatization

eats_burger

eating_burger

ate_burger

eat_burger

eat_the_burger

eat_burgers

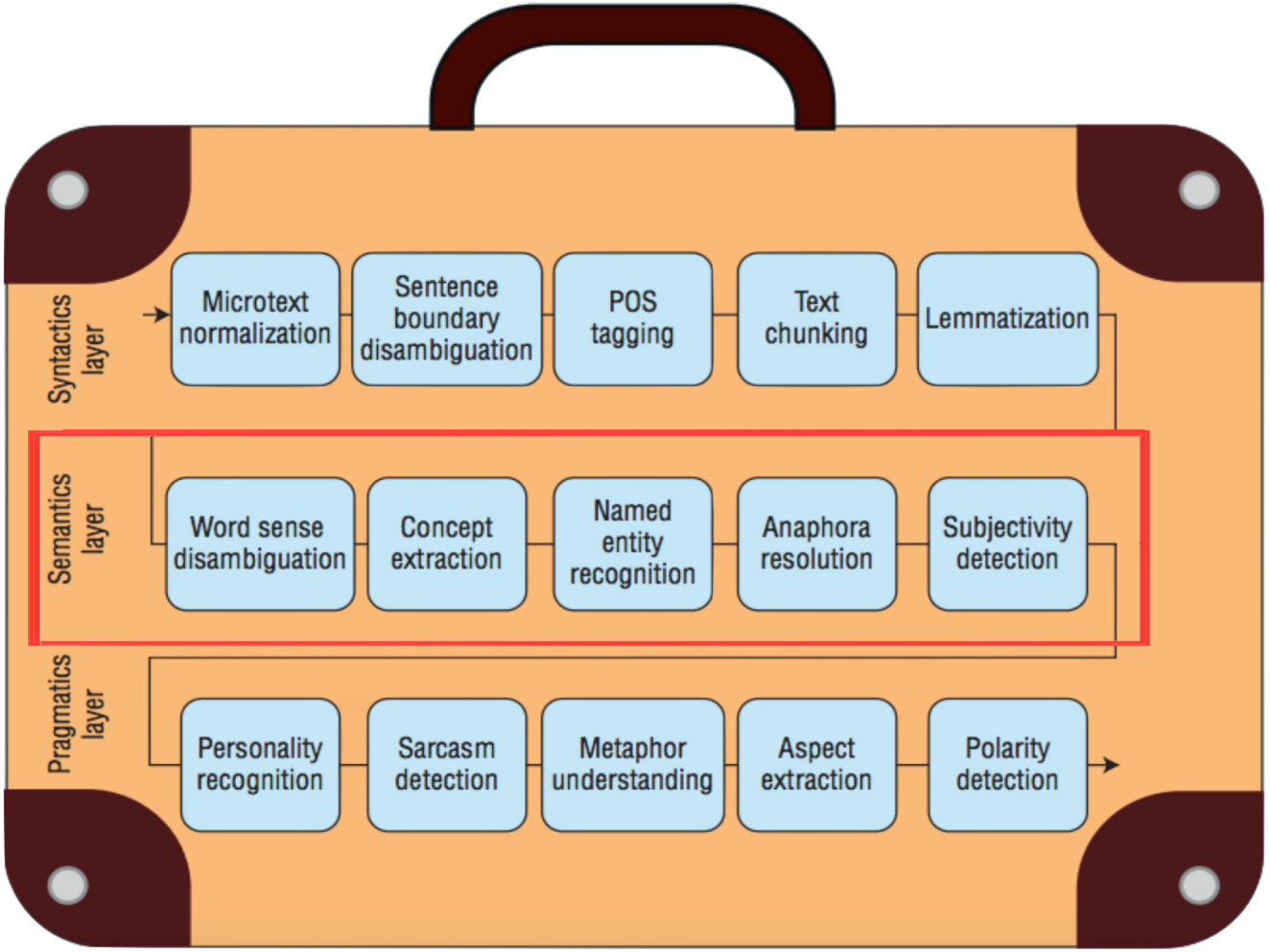
Lemmatization

cross => *crossing*

hell_ride => *a_hell_of_a_ride*

kick_ball => *kick_balls*

Semantics layer



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

WSD

Bass: fish

???

Bass: instrument

D Yarowsky. Unsupervised word sense disambiguation rivaling supervised methods. In ACL, 189-196 (1995)

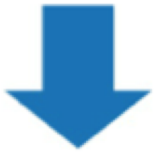
Concept extraction

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

D Rajagopal, E Cambria, D Olsher, K Kwok. A graph-based approach to common-sense concept extraction and semantic similarity detection. In WWW, 565–570 (2013)

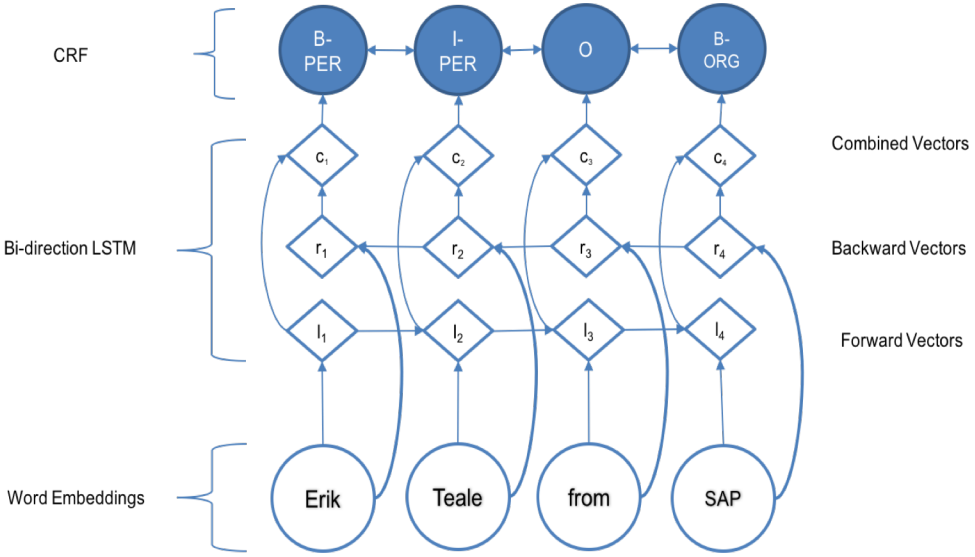
Concept extraction

After chunking and lemmatization, 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
```

NER

Named-entity recognition is key for improving anaphora resolution and, hence, for detecting aspects or opinion targets in reviews.



Y Ma, E Cambria, S Gao. Label Embedding for Zero-shot Fine-grained Named Entity Typing. In: COLING, 171-180 (2016)

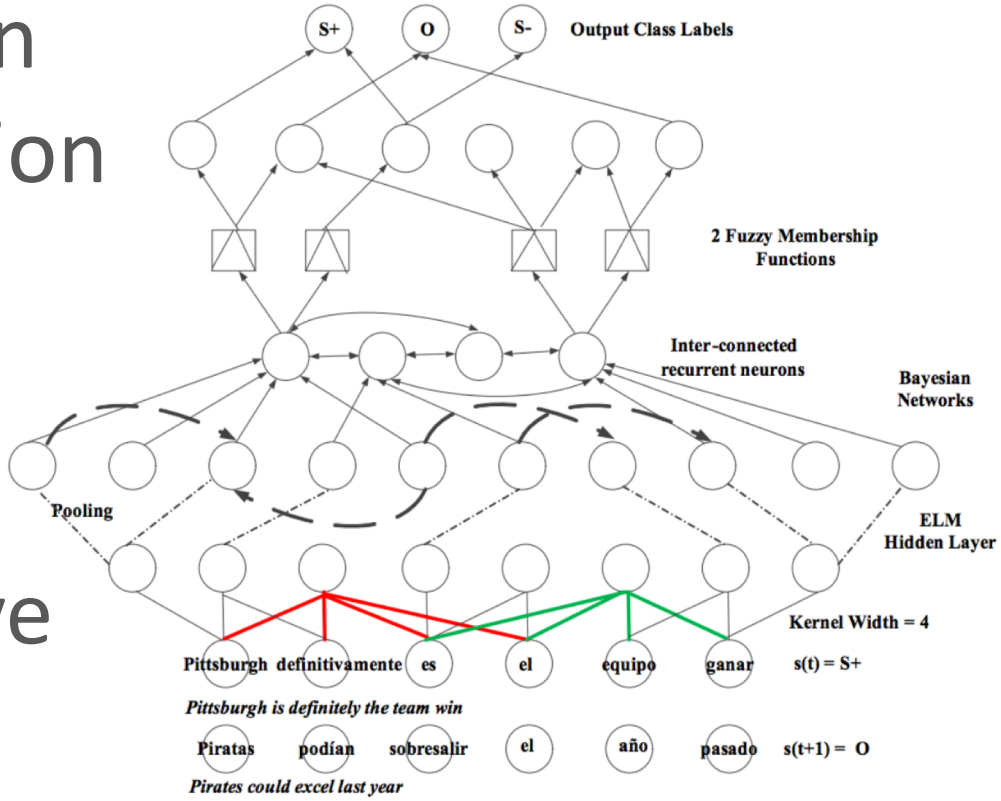
Anaphora resolution

Anaphora is the use of an expression the interpretation of which depends upon another one. It is commonly resolved by gender and number agreement

R Mitkov. Anaphora resolution: the state of the art. Working paper. University of Wolverhampton, Wolverhampton (1999)

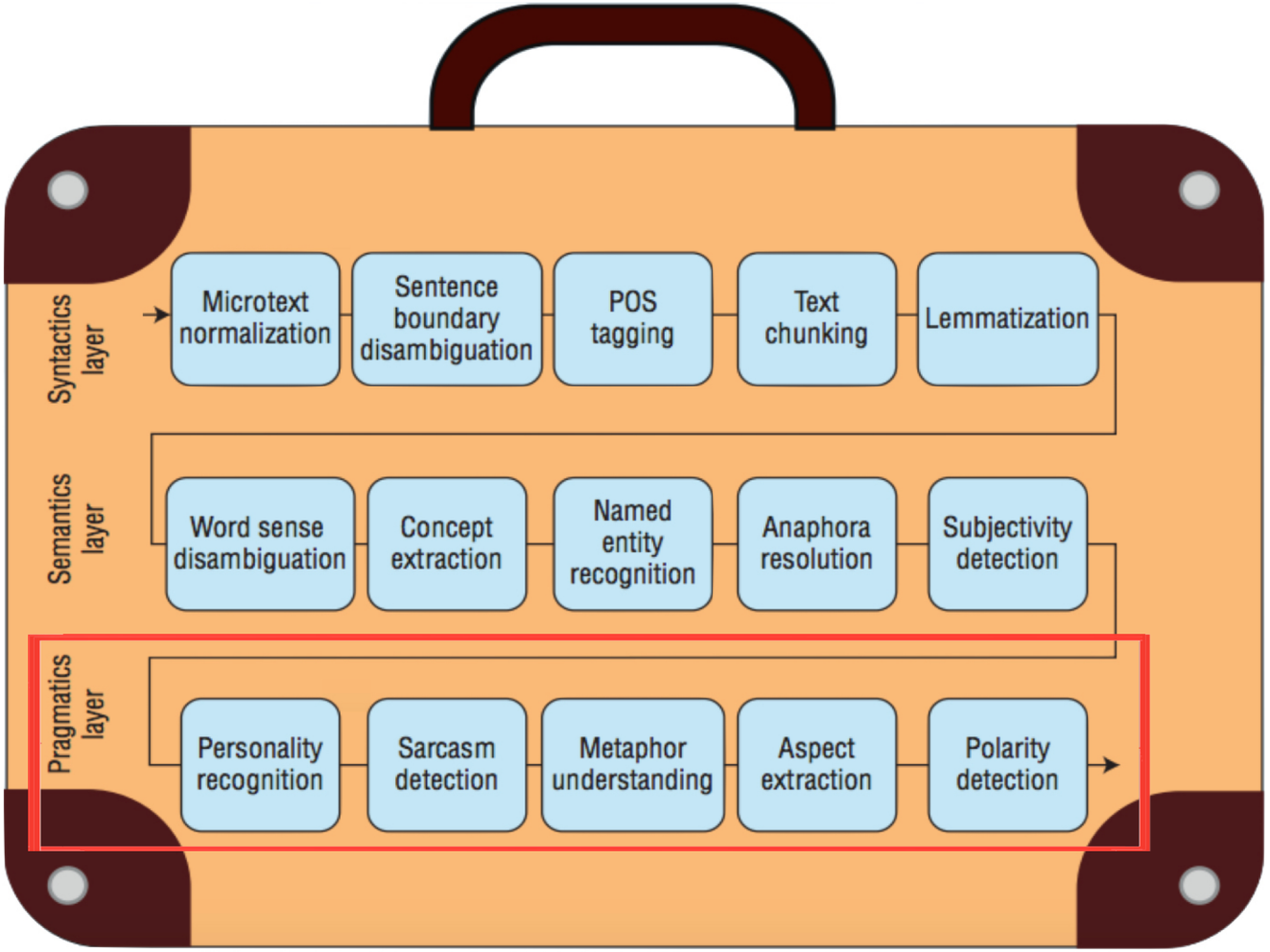
Subjectivity detection

Subjectivity detection is a binary classification task that consists in classifying text into either objective (neutral) or subjective (positive/negative)



I Chaturvedi, E Cambria, R Welsch, F Herrera. Distinguishing between facts and opinions for sentiment analysis: Survey and challenges. Information Fusion 44, 65–77 (2018)

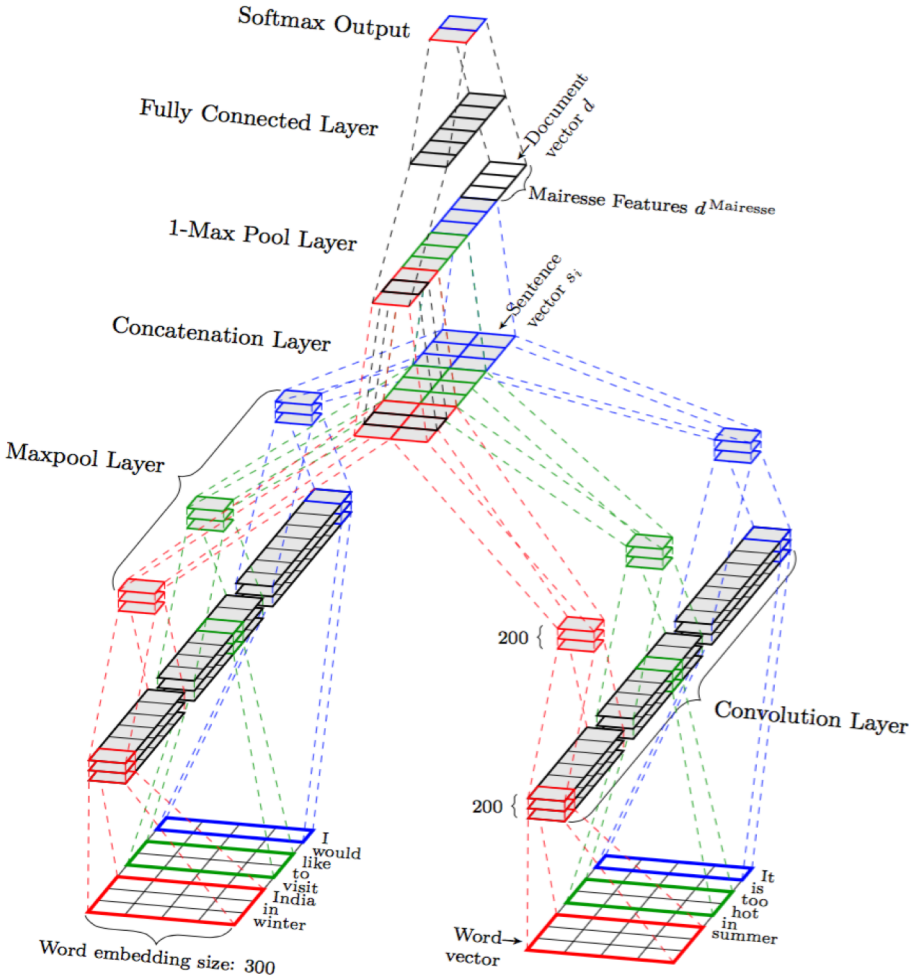
Pragmatics layer



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

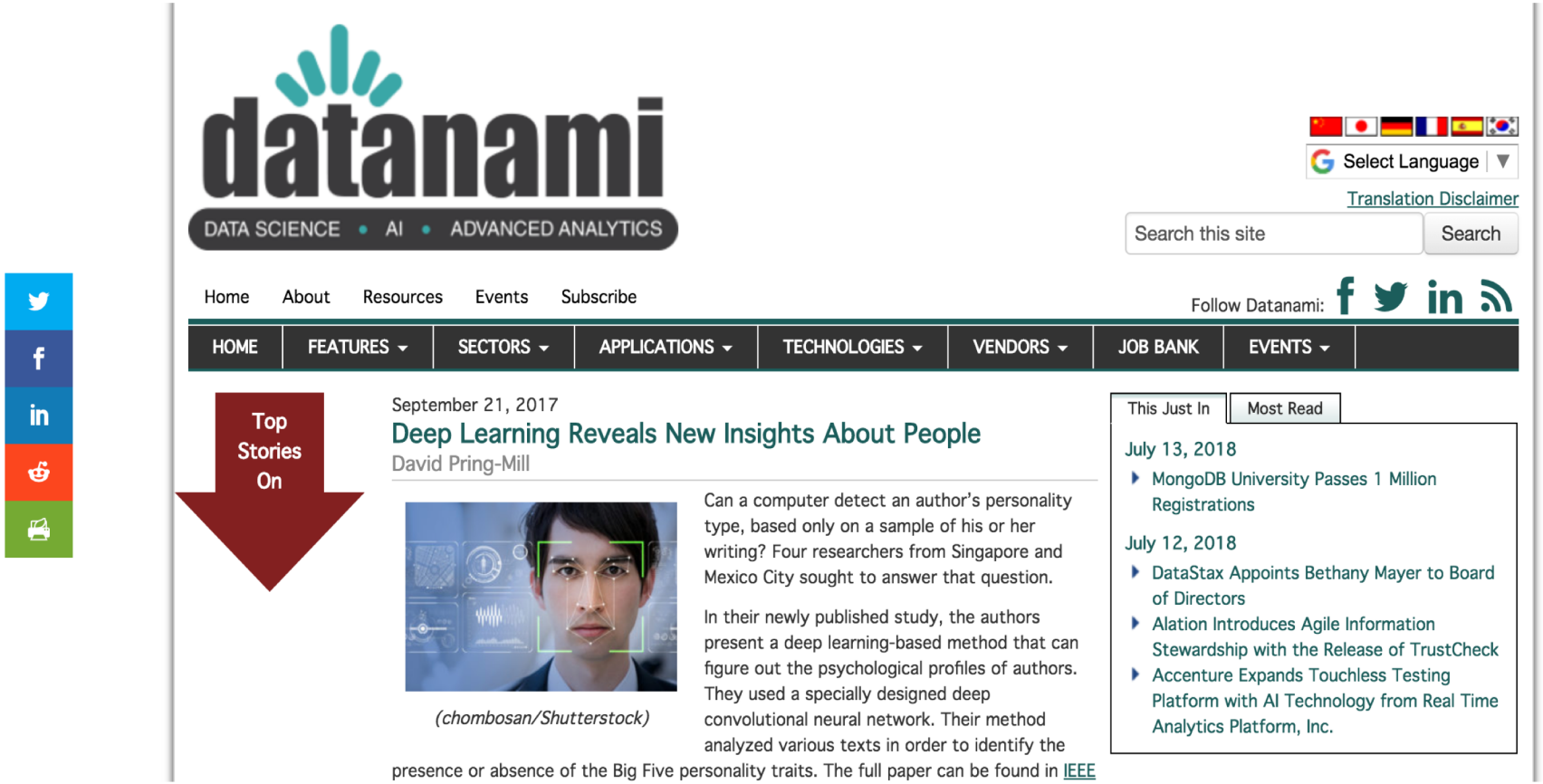
Personality recognition

Personality recognition is an important step towards user-dependent sentiment analysis (user profiling) and it is useful for sarcasm detection



N Majumder, S Poria, A Gelbukh, E Cambria. Deep learning-based document modeling for personality detection from text. IEEE Intelligent Systems 32(2), 74-79 (2017)

Personality recognition



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September 21, 2017

Deep Learning Reveals New Insights About People

David Pring-Mill

(chombosan/Shutterstock)

Can a computer detect an author's personality type, based only on a sample of his or her writing? Four researchers from Singapore and Mexico City sought to answer that question.

In their newly published study, the authors present a deep learning-based method that can figure out the psychological profiles of authors. They used a specially designed deep convolutional neural network. Their method analyzed various texts in order to identify the presence or absence of the Big Five personality traits. The full paper can be found in IEEE

This Just In | Most Read

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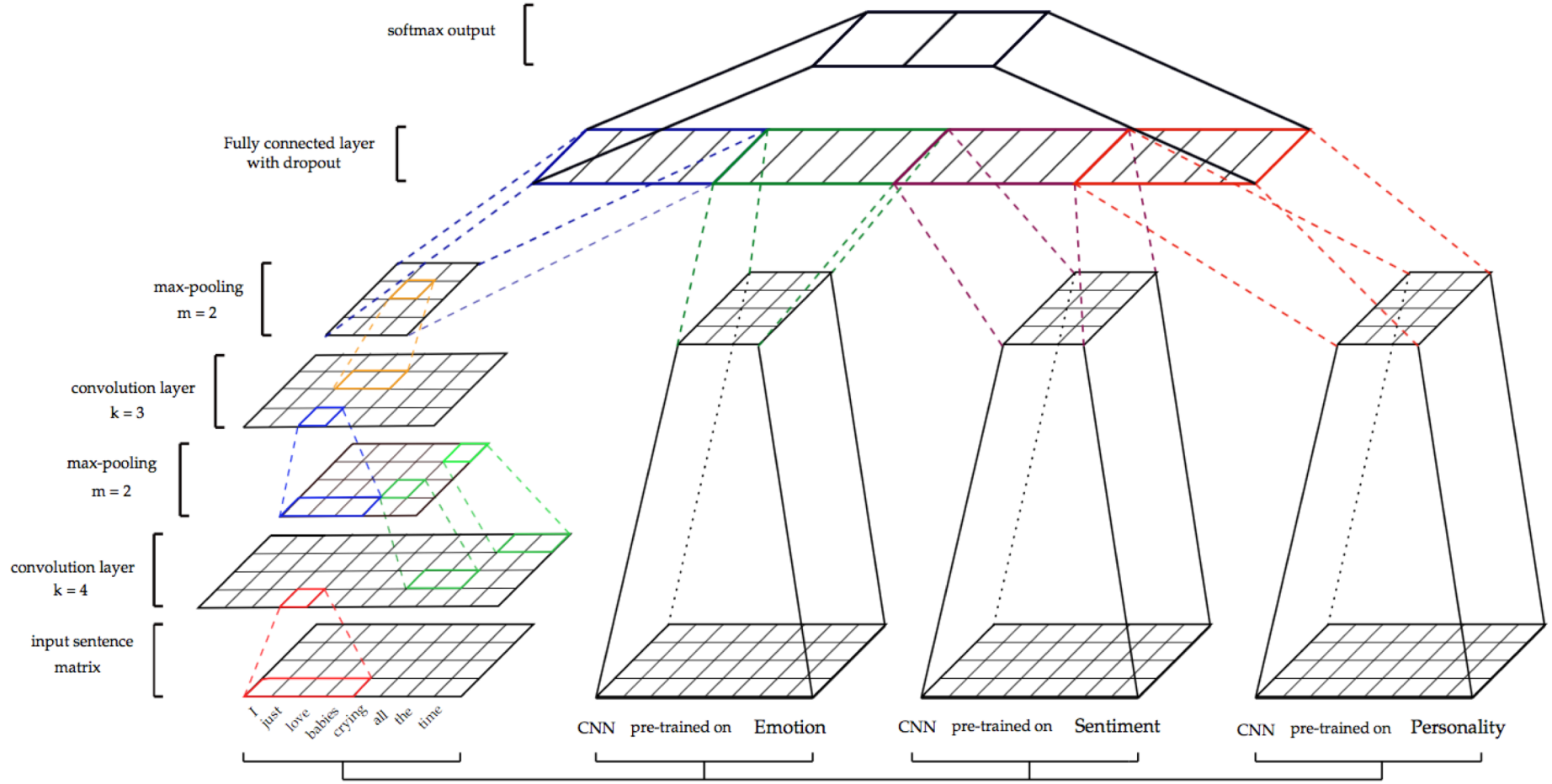
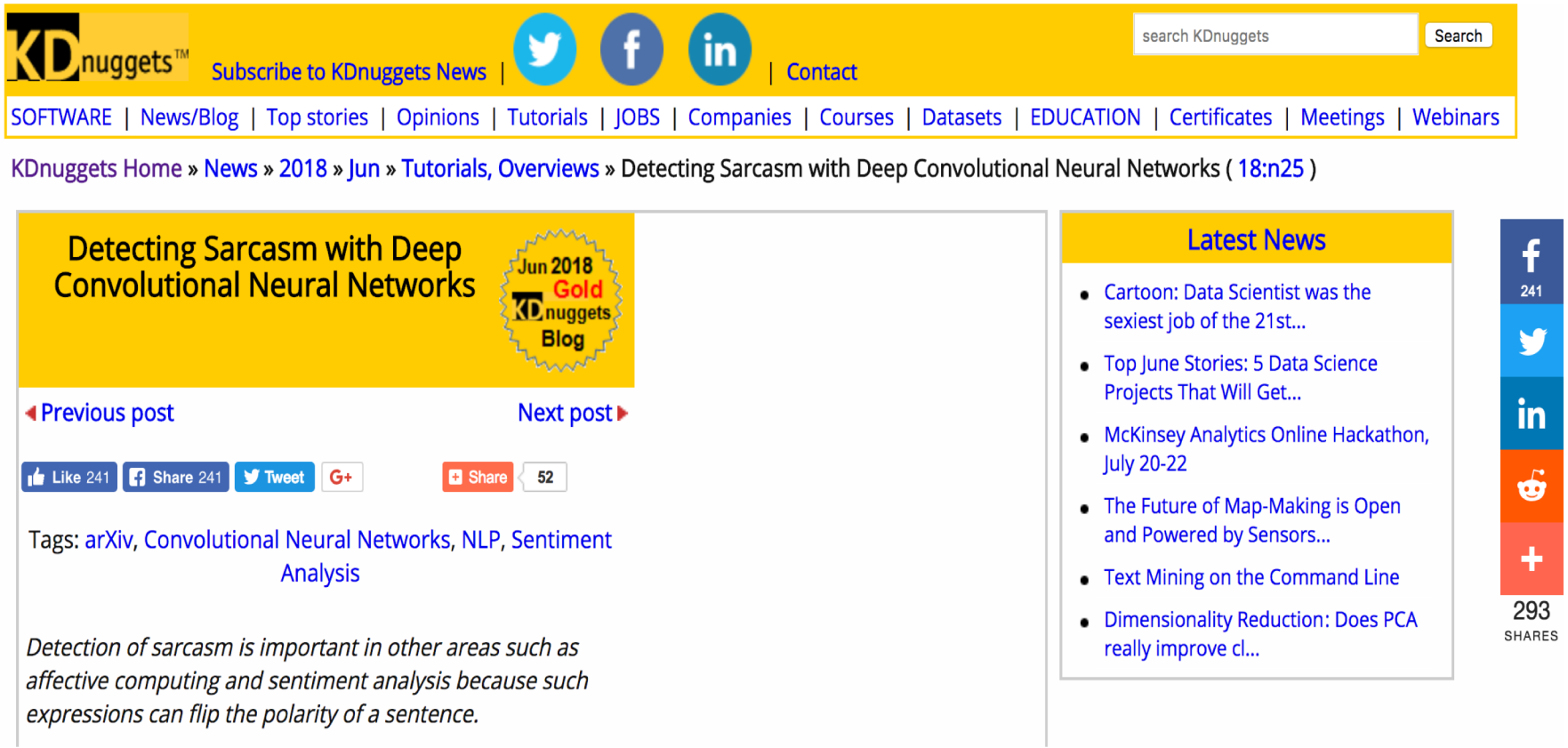
http://datanami.com/2017/09/21/deep-learning-reveals-new-insights-people

Sarcasm detection



S Poria, E Cambria, D Hazarika, P Vij. A Deeper Look into Sarcastic Tweets Using Deep Convolutional Neural Networks. In: COLING, 1601-1612 (2016)

Sarcasm detection



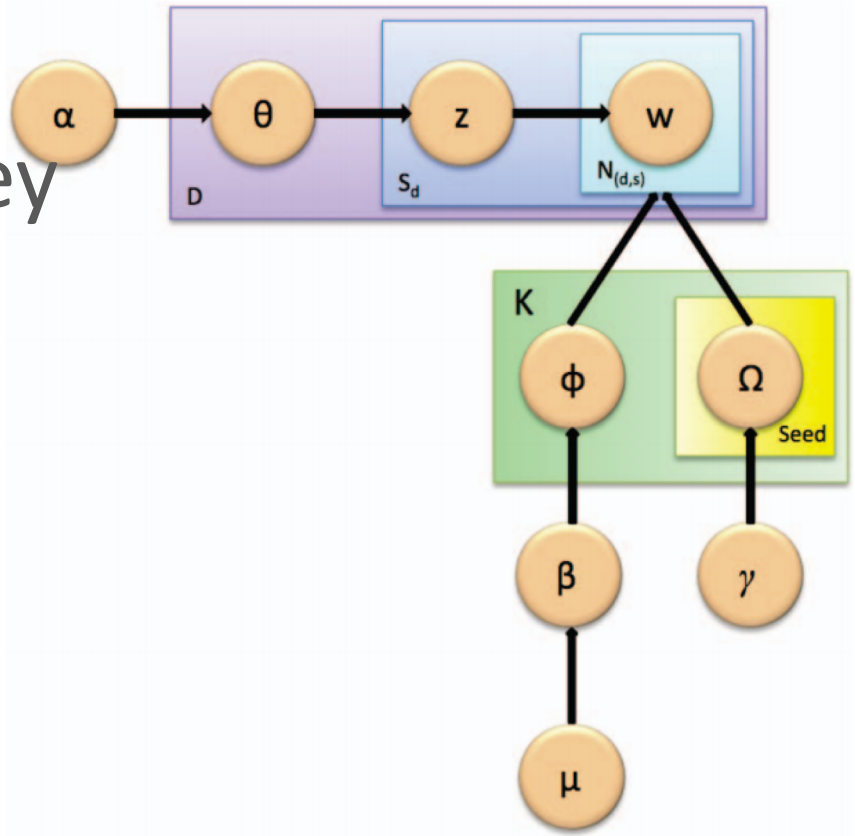
http://kdnuggets.com/2018/06/detecting-sarcasm-deep-convolutional-neural-networks

Metaphor understanding

M Schulder and E Hovy. Metaphor detection through term relevance. In Proceedings of the Second Workshop on Metaphor in NLP, 18–26 (2014)

Aspect extraction

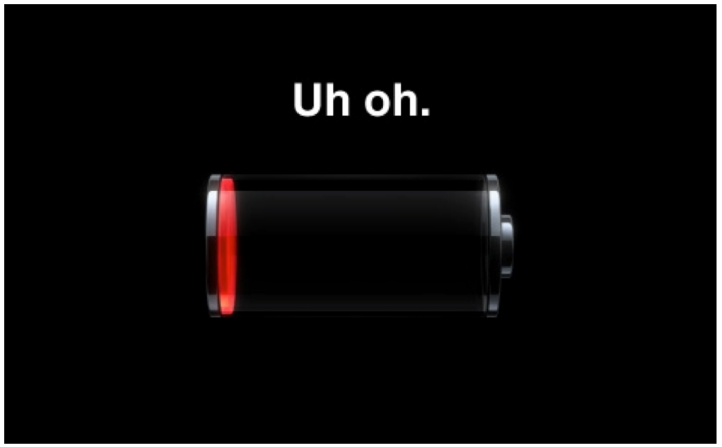
Extracting aspects (or features) from text is key for identifying the so-called opinion targets and disambiguate the polarity associated to each of them



S Poria, E Cambria, A Gelbukh. Aspect extraction for opinion mining with a deep convolutional neural network. Knowledge-Based Systems 108, 42-49 (2016)

Aspect extraction

I love iPhoneX's touchscreen but the battery life is so short



touchscreen

battery

Y Ma, H Peng, E Cambria. Targeted aspect-based sentiment analysis via embedding commonsense knowledge into an attentive LSTM. In: AAAI, pp. 5876-5883 (2018)

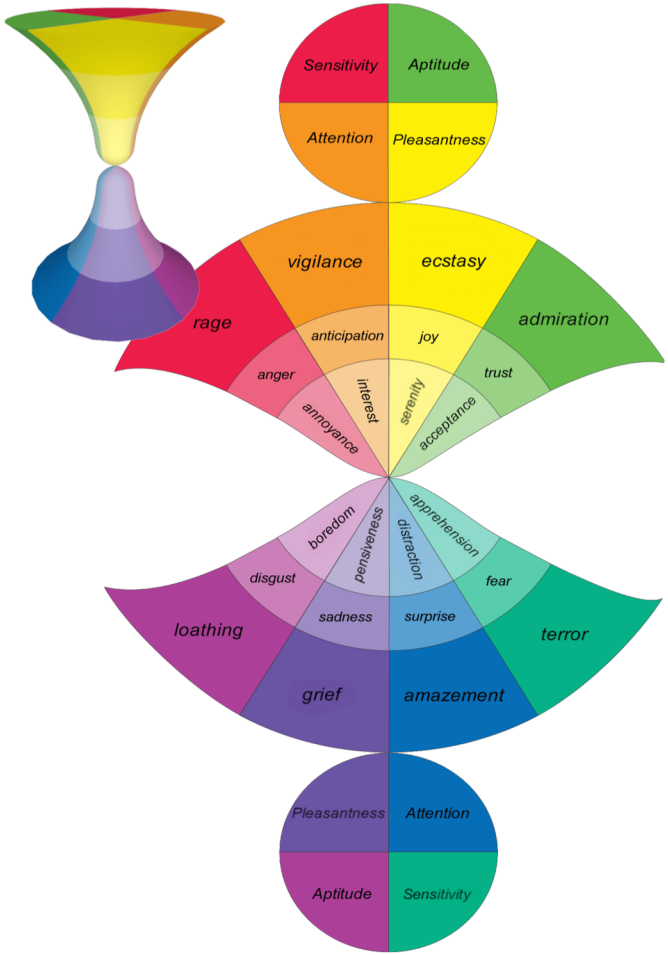
Polarity detection

Early works treated polarity detection as a binary classification problem (pos vs neg). Recent works calculate polarity intensity as a float ∈ [-1, +1]

S Poria, et al. Sentiment data flow analysis by means of dynamic linguistic patterns. IEEE Computational Intelligence Magazine 10(4), 26-36 (2015)

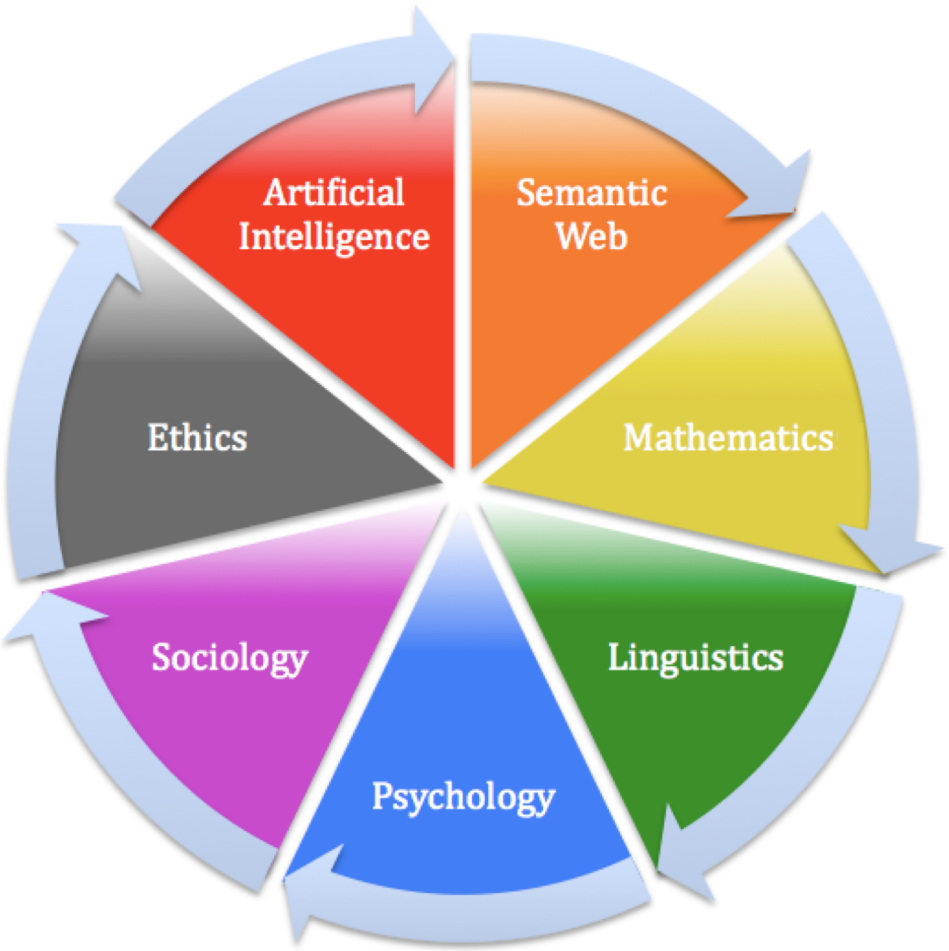
Sentic computing

1. Shift from mono- to *multi-disciplinarity*
2. Shift from syntax to *semantics*
3. Shift from statistics to *linguistics*



E Cambria, A Hussain. Sentic Computing: A Common-Sense-Based Framework for Concept-Level Sentiment Analysis. Cham: Springer, ISBN: 978-3-319-23654-4 (2015)

From mono- to multi-disciplinarity



E Cambria, A Hussain. Sentic Computing: A Common-Sense-Based Framework for Concept-Level Sentiment Analysis. Cham: Springer, ISBN: 978-3-319-23654-4 (2015)

From syntax to semantics

cloud_computing => cloud

pain_killer => pain, killer

E Cambria, A Hussain. Sentic Computing: A Common-Sense-Based Framework for Concept-Level Sentiment Analysis. Cham: Springer, ISBN: 978-3-319-23654-4 (2015)

From statistics to linguistics

The car is nice *but* expensive

The car is expensive *but* nice

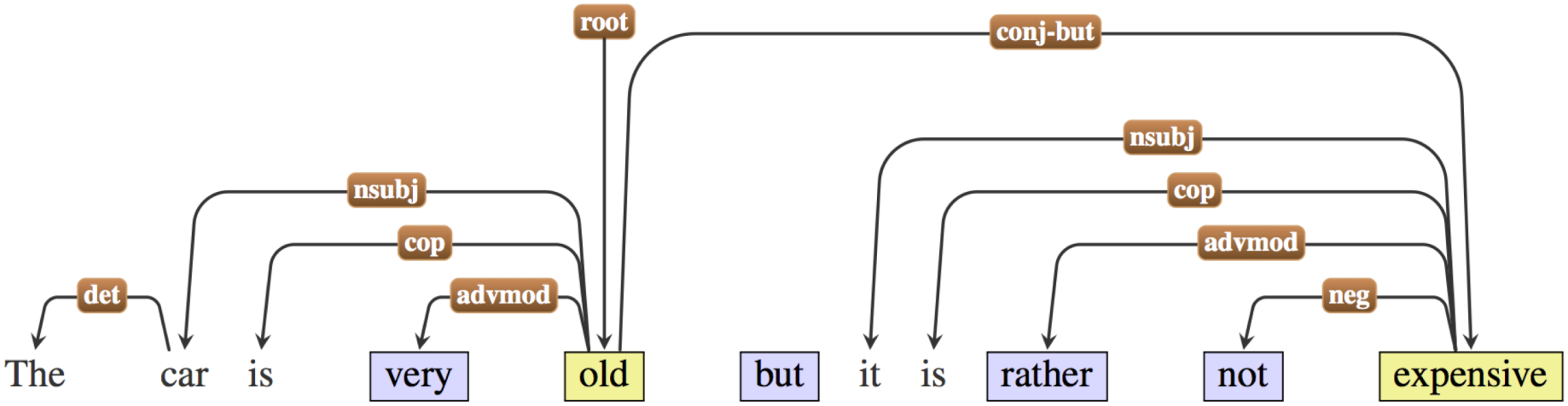
E Cambria, A Hussain. Sentic Computing: A Common-Sense-Based Framework for Concept-Level Sentiment Analysis. Cham: Springer, ISBN: 978-3-319-23654-4 (2015)

Sentic patterns

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

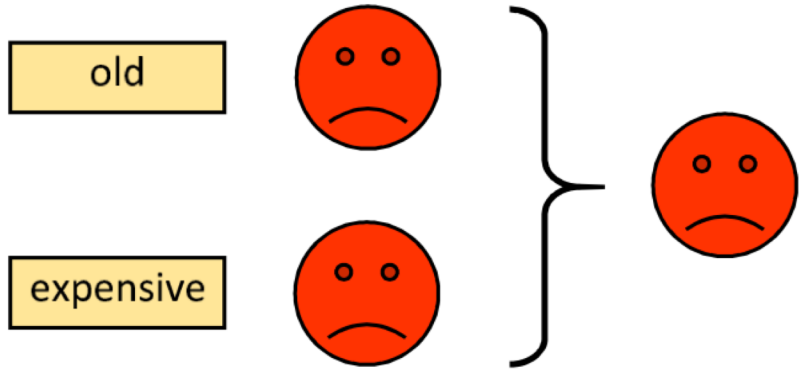
a. This is perfect to gain money.
b. This is perfect to gain weight.
c. This is perfect to lose money.
d. This is perfect to lose weight.
e. This is useless to gain money.
f. This is useless to gain weight.
g. This is useless to lose money.
h. This is useless to lose weight.
i. This is perfect to talk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

Sentic patterns



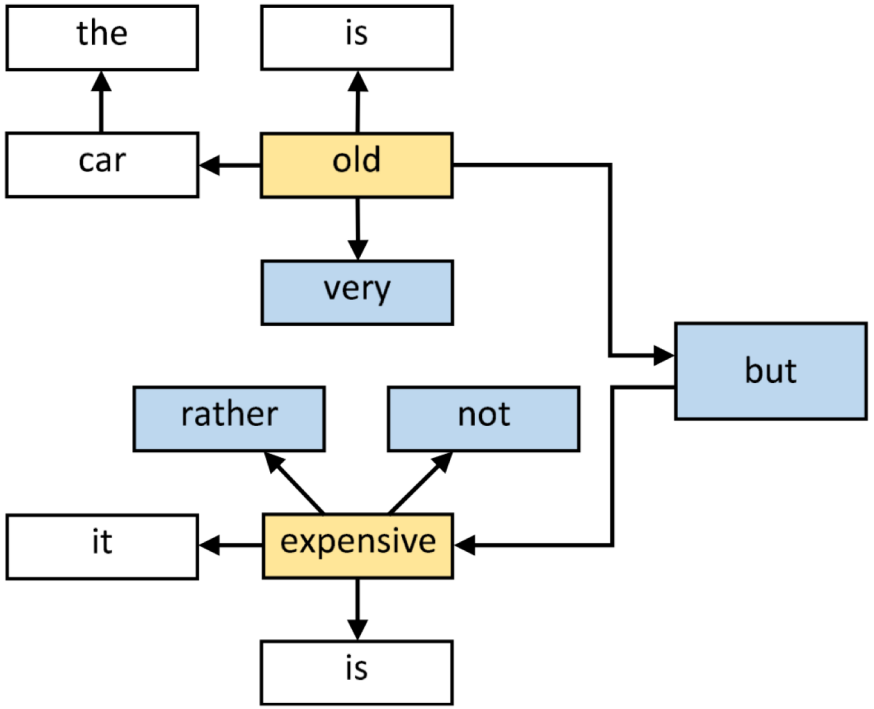
(a) Dependency tree of a sentence.

Sentic patterns



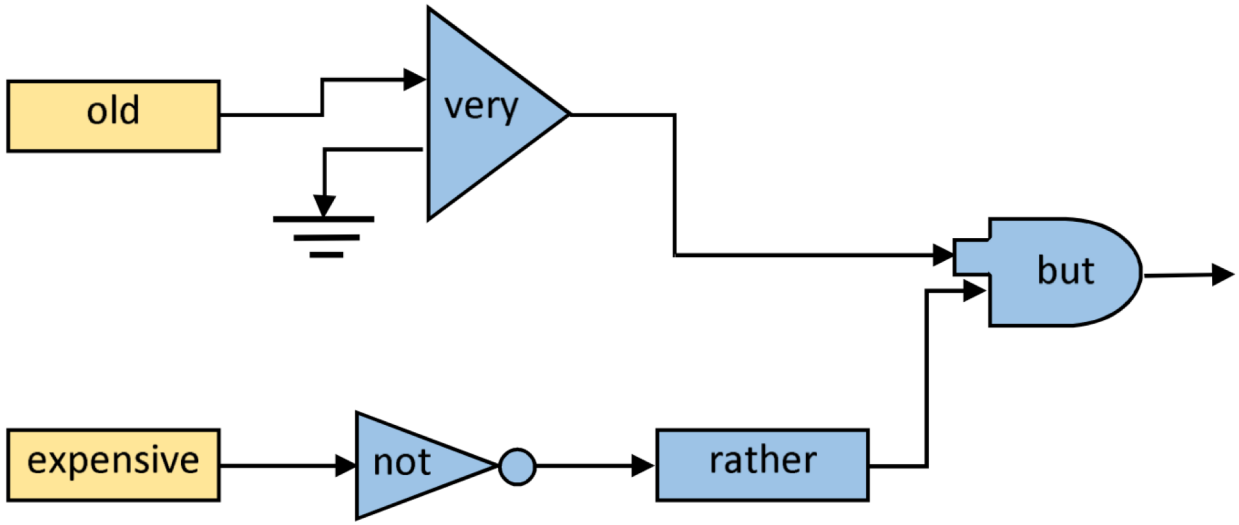
(b) The old way: averaging over a bag of sentiment words. The overall polarity of a sentence is given by the algebraic sum of the polarity values associated with each affect word divided by the total number of words.

Sentic patterns



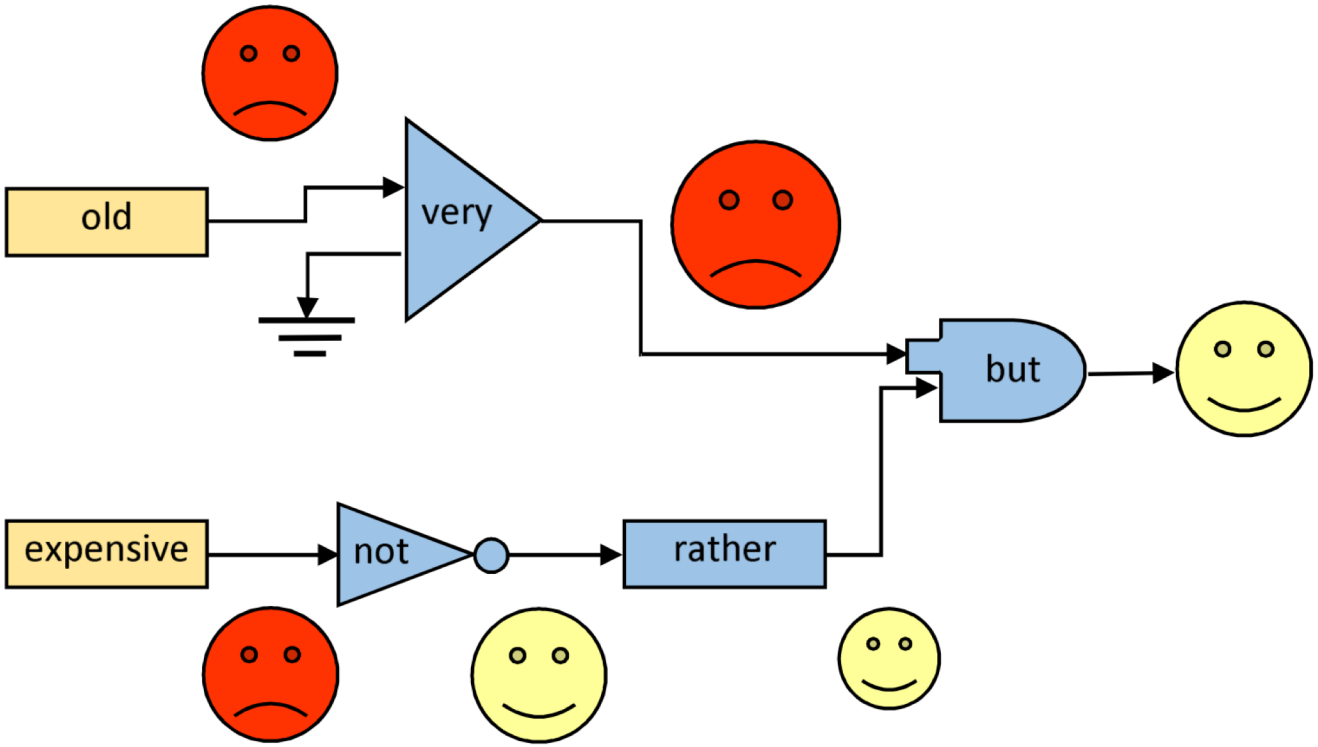
(c) The dependency tree of a sentence resembles an electronic circuit: words shown in blue can be thought as a sort of "boolean operations" acting on other words.

Sentic patterns



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

Sentic patterns



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

Sentic patterns

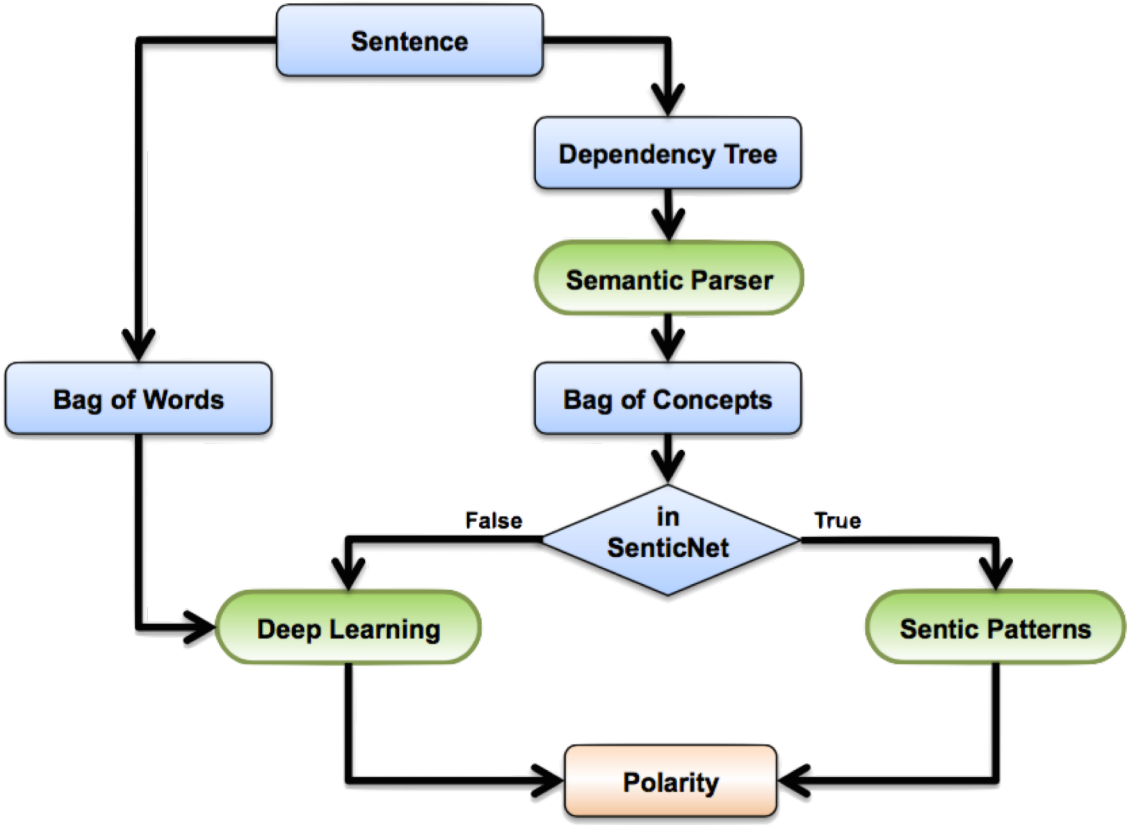
	SenticNet	Stanford
1. I love the movie which you hate	+	–
2. The phone is very big to hold	–	+
3. You are making fun of me	–	+
4. You are not so beautiful	–	+
5. The tooth hit the pavement and broke	–	+
6. I am one of the least happy person in the world	–	0
7. I love Starbucks but they just lost a customer	–	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/demos

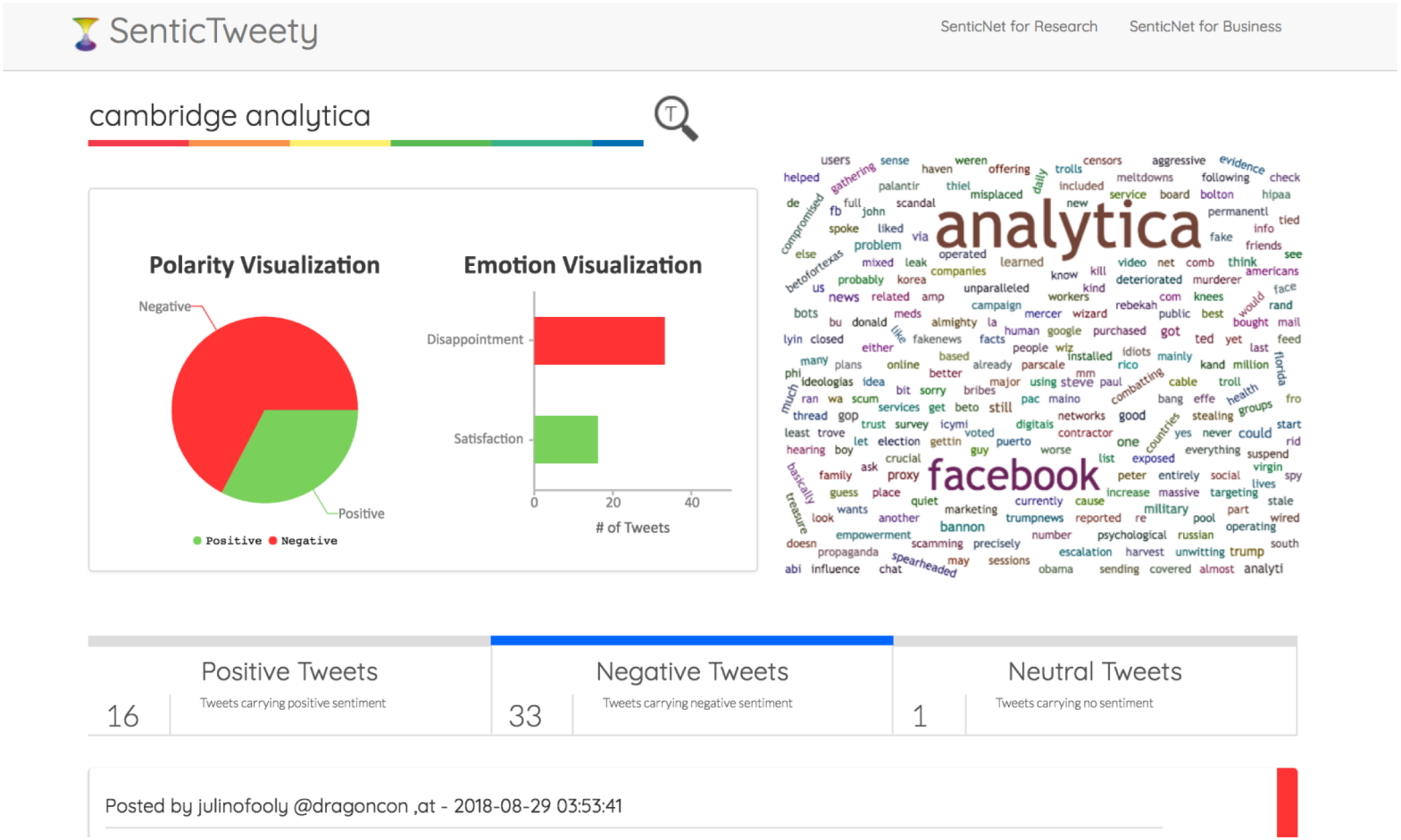
Sentic patterns

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%

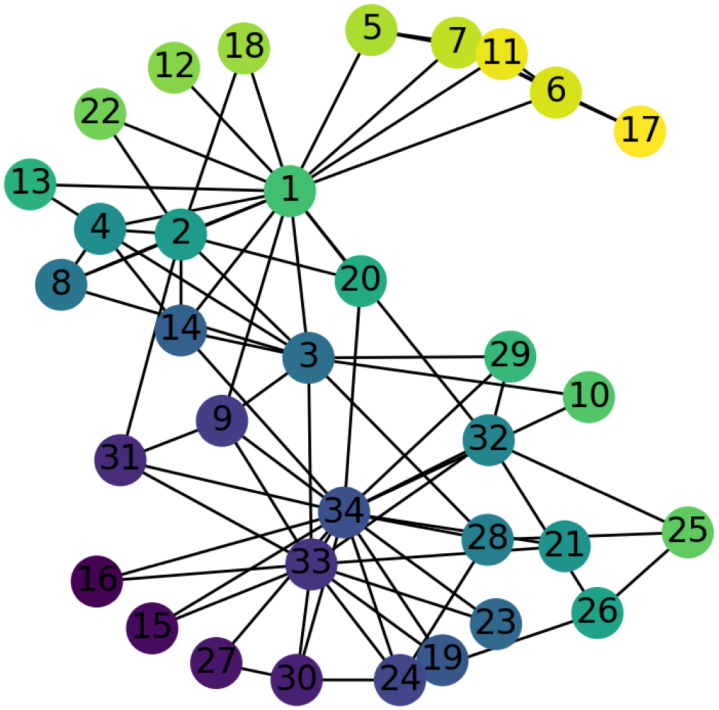


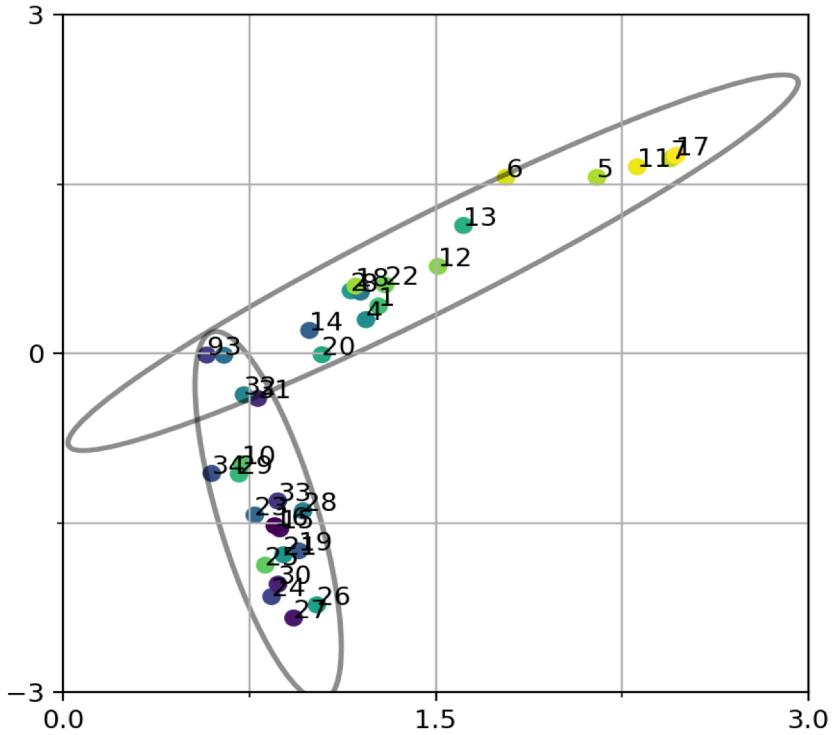
Social media marketing



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

Big social data analysis



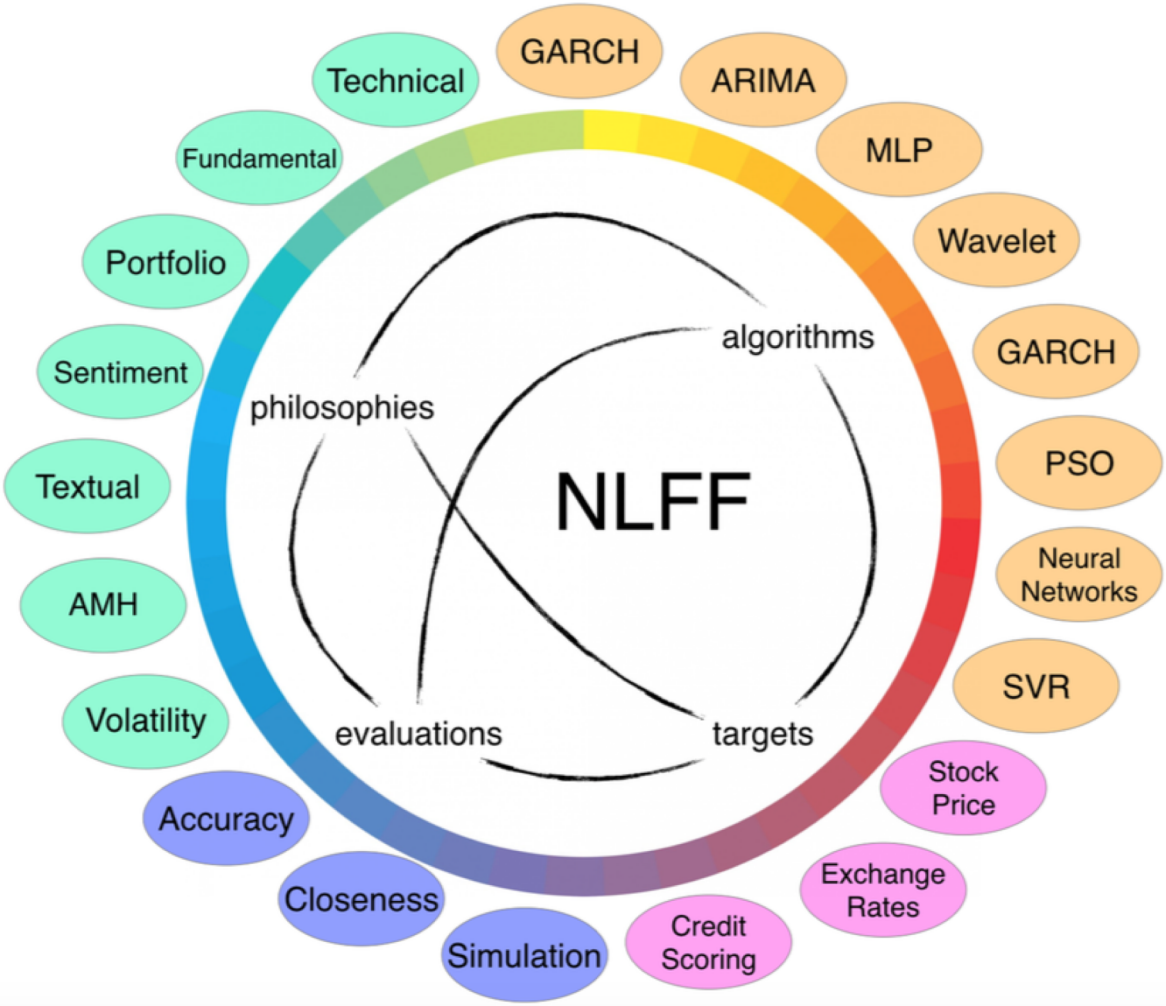


S Cavallari, VW Zheng, H Cai, KCC Chang, E Cambria. Learning Community Embedding with Community Detection and Node Embedding on Graphs. In: CIKM, 377-386 (2017)

Sentic album

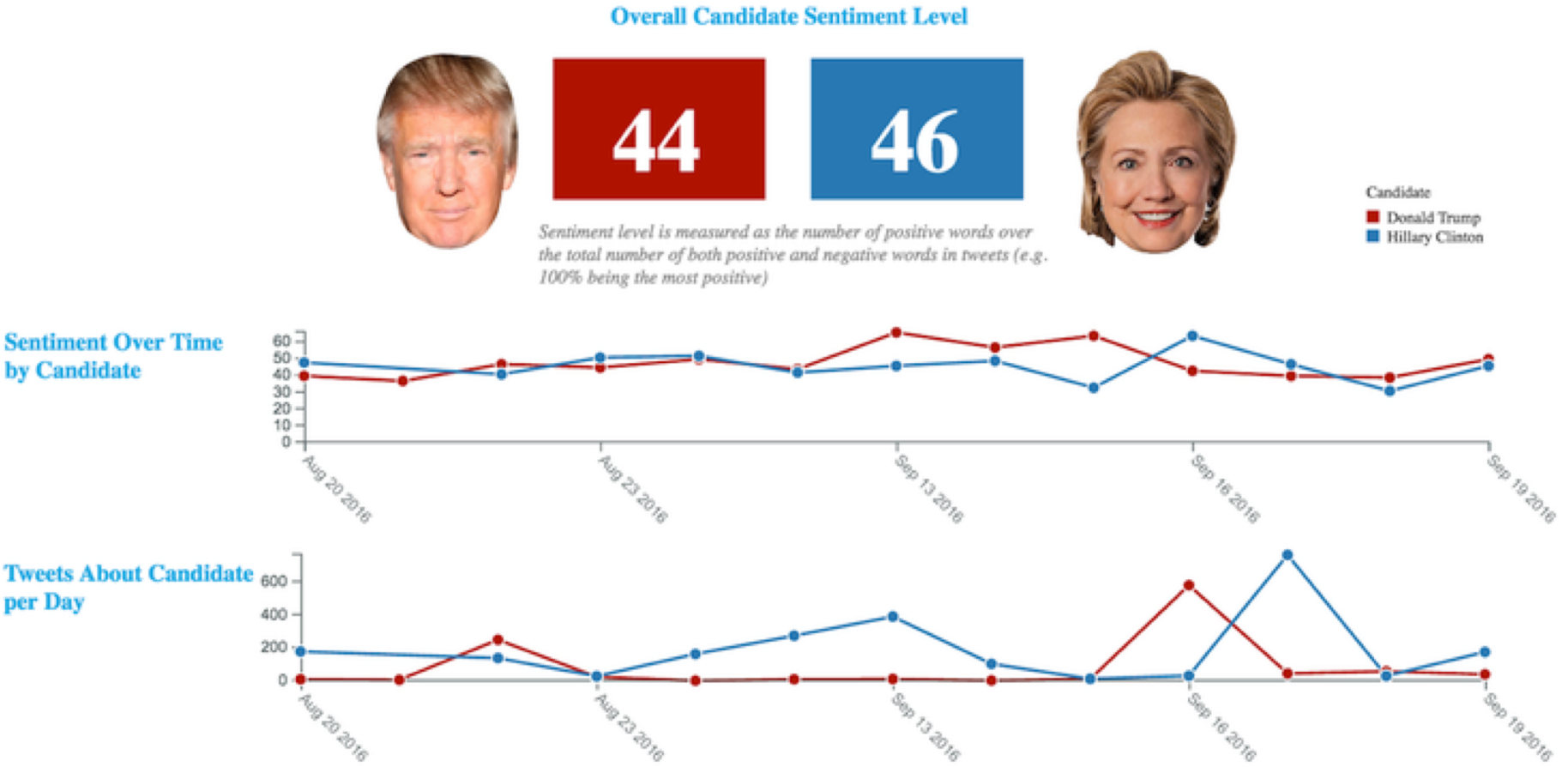
E Cambria, A Hussain. Sentic Album: Content-, Concept-, and Context-Based Online Personal Photo Management System. Cognitive Computation 4(4), 477-496 (2012)

Financial forecasting



F Xing, E Cambria, R Welsch. Natural Language Based Financial Forecasting: A Survey. Artificial Intelligence Review 50(1), 49-73 (2018)

Political forecasting



e-Tourism

Social Media

- Sentiment Analysis

- Social Media Language

- Social Media in Tourism

Blogger

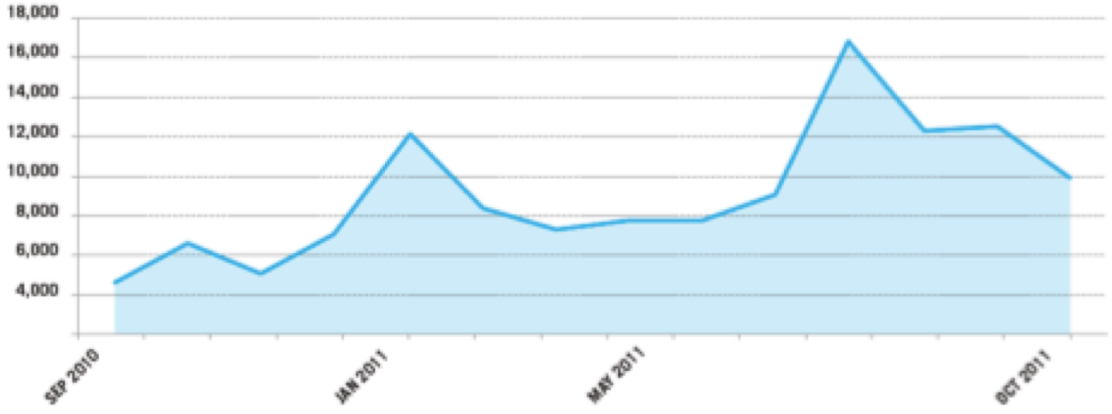
tripadvisor

- Microtext

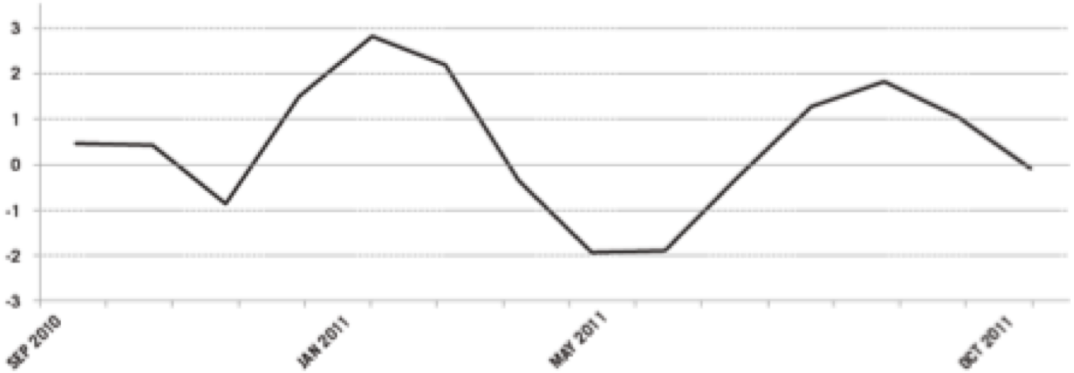
- Blogs
  - Backpackers
- Mobile apps
  - Mobile tourism
- Online travel reviews
  - Hotels

Cyber issue detection

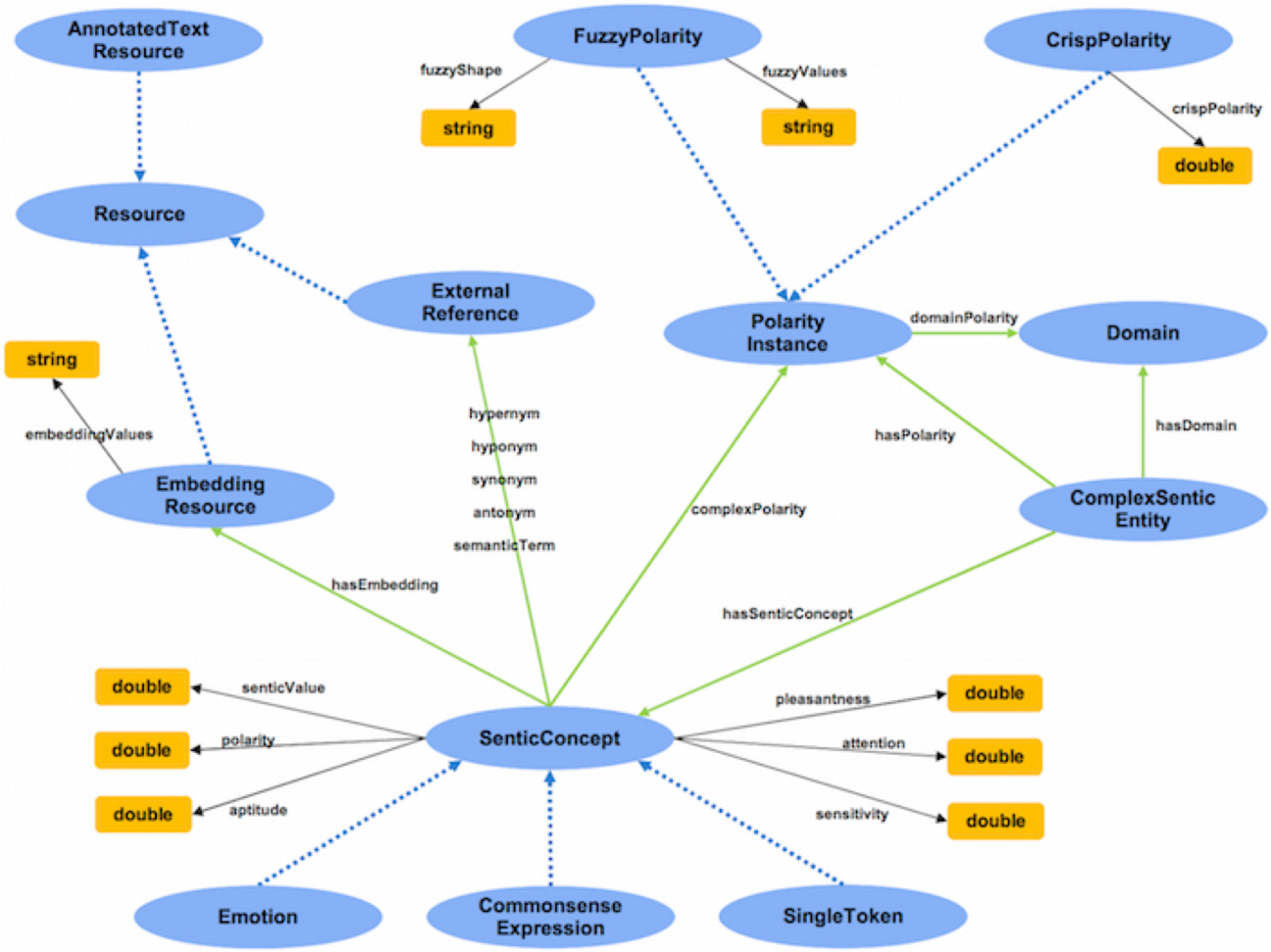
Tweets about the price of rice
(per month)



Food Price Inflation

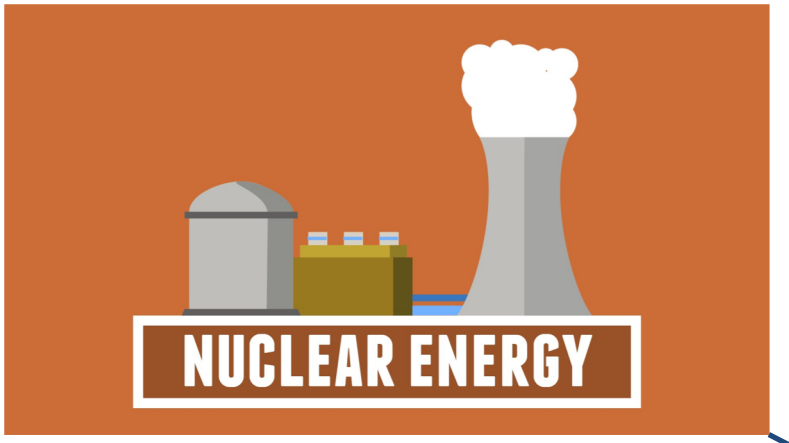


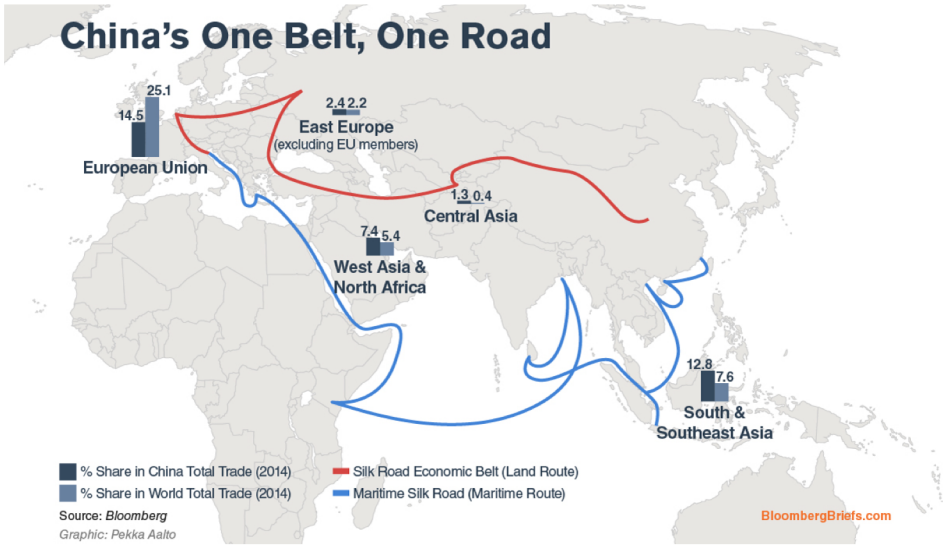
AI for the Semantic Web



M Dragoni, S Poria, E Cambria. OntoSenticNet: A commonsense ontology for sentiment analysis. IEEE Intelligent Systems 33(3), 77-85 (2018)

Media monitoring





forum.

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FORUM ONLINE

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2 MADAM LEONG LAI YENG: Honest foodcourt cleaners...
3 MR ANDY CHEW: ...And CityCab driver
4 MRS ONG KIM SIONG: ...And Mel's Drive-In staff
5 MR JEFFREY YAM: Proactive help at pharmacy
6 MS JANET CHANG: Kudos, Delifrance
7 MS LIM SUYIN: Super cleaner
8 SATS: Talk to us about recruitment interview
9 STB AND SRA: Great Singapore Sale

NATIONAL SERVICE

Foreign mum: Why my son should serve

AS AN Indian national, I would like to share my changed views regarding compulsory national service.

I have been in Singapore since 2003. My husband and son are Singaporeans. Until recently, I was concerned about my son having to go through NS.

I used to think it a waste of two precious years which could have been devoted to furthering his career; and that my son should have the right to decide whether he should serve or not. But not any more.

I am deeply patriotic about my birth country, India, but Singapore is now my second home. I have, over the years, learnt much about the circumstances of Singapore's traumatic independence and how its leaders and policymakers fought against the odds. I have also come to respect the laws and policies that shaped this beautiful island country into what it is today.

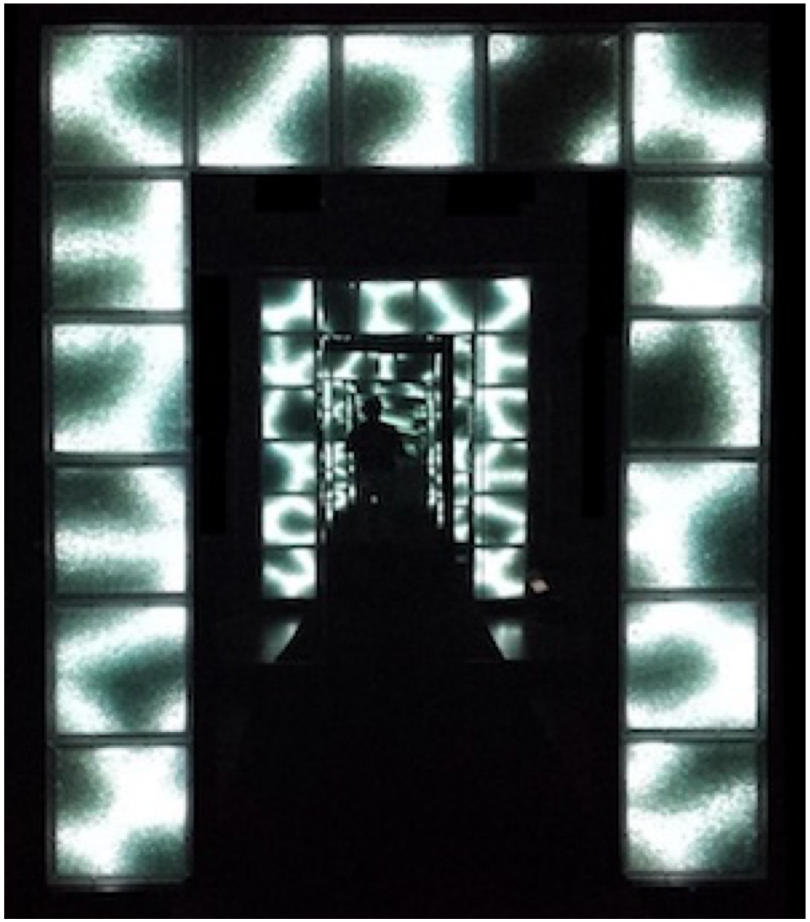
An armed forces needs significant manpower to defend the country. NS is a prerequisite for a continuously prepared armed forces. I have often come across expatriates discussing how they can help their children avoid NS. To me, it is only fair that if one wants to become a permanent resident or call Singapore home, one should willingly serve because that is what every Singaporean male does.

After all, sacrificing two years of a man's career is a small price to pay for Singapore's safety and security – a Singapore which even expatriates have grown so fond of.

Aarti Giri (Ms)

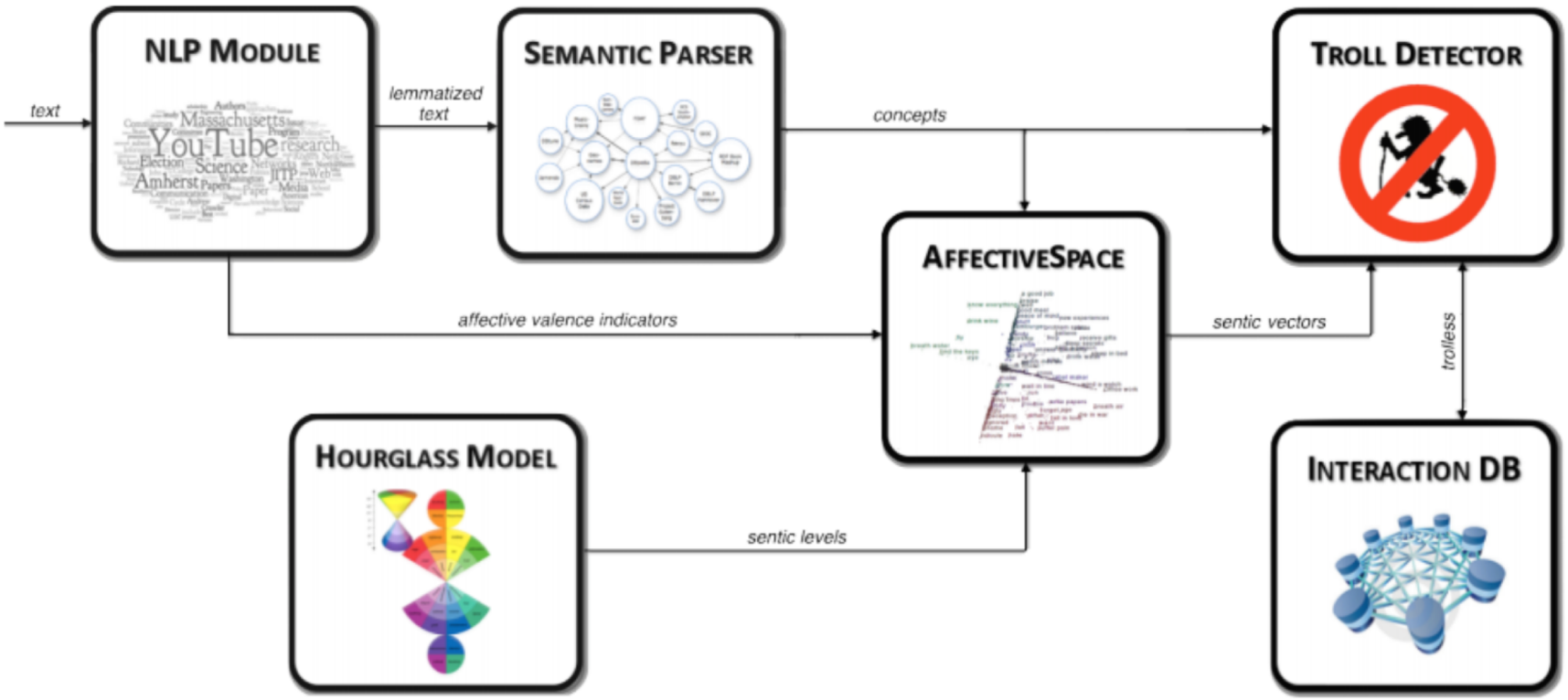
http://sentic.net/projects/#one-belt-one-road-one-sentiment

Mood of Singapore



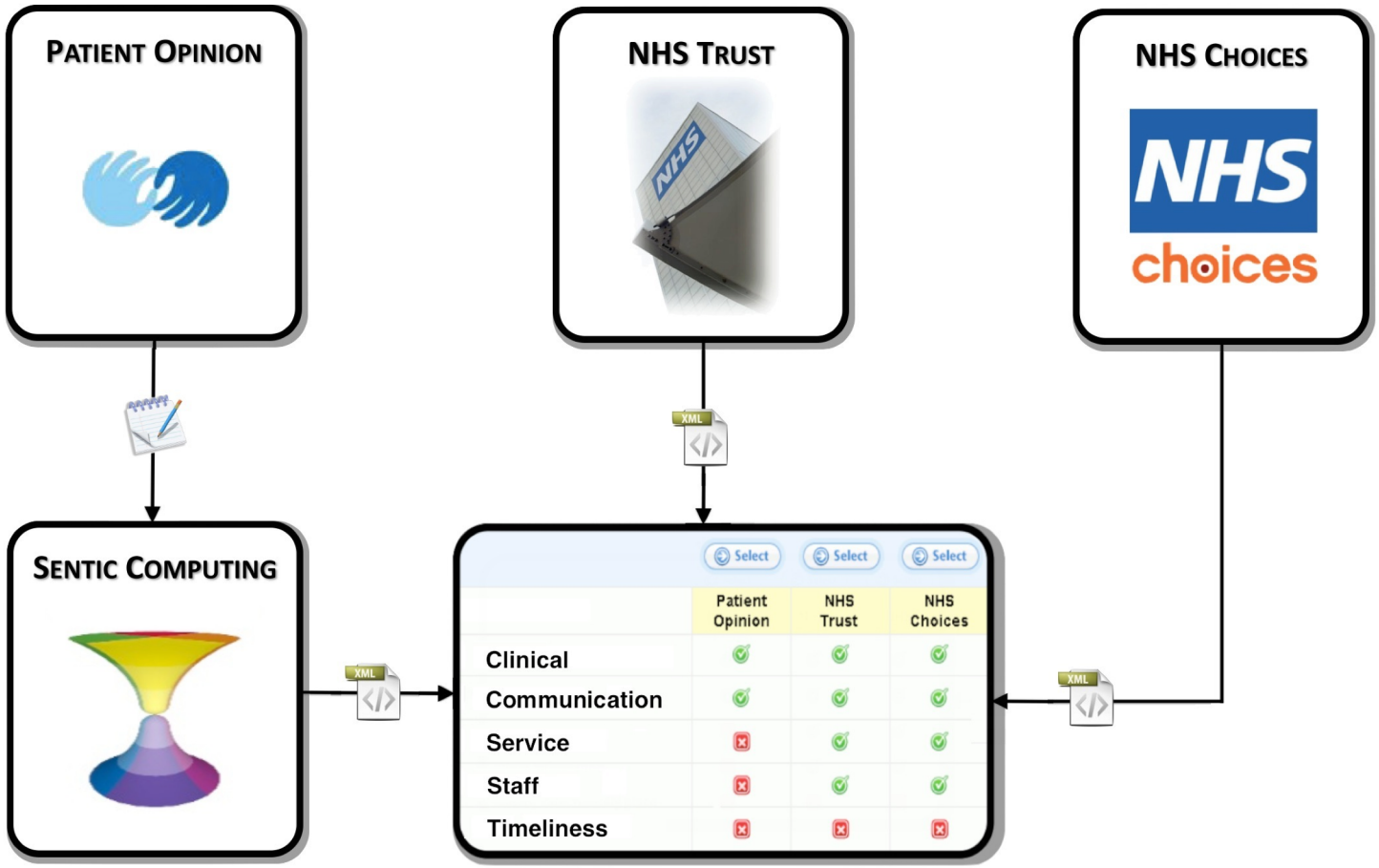
http://sentic.net/projects/#mood-of-singapore

Troll filtering



E Cambria, P Chandra, A Sharma, A Hussain. Do not feel the trolls. In: ISWC (2010)

Crowd validation



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

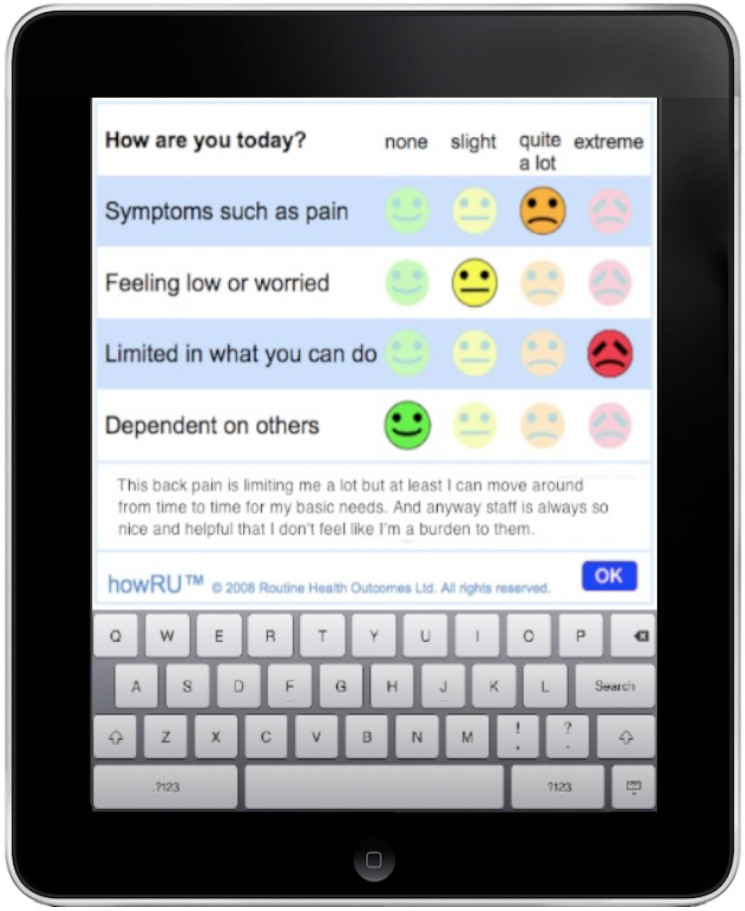
Sentic PROMs

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

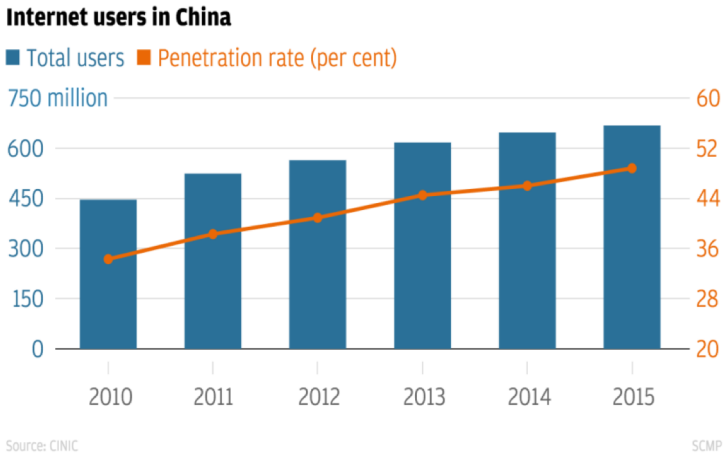
E Cambria, T Benson, C Eckl, A Hussain. Sentic PROMs: Application of Sentic Computing to the Development of a Novel Unified Framework for Measuring Health-Care Quality. Expert Systems with Applications 39(12), 10533–10543 (2012)

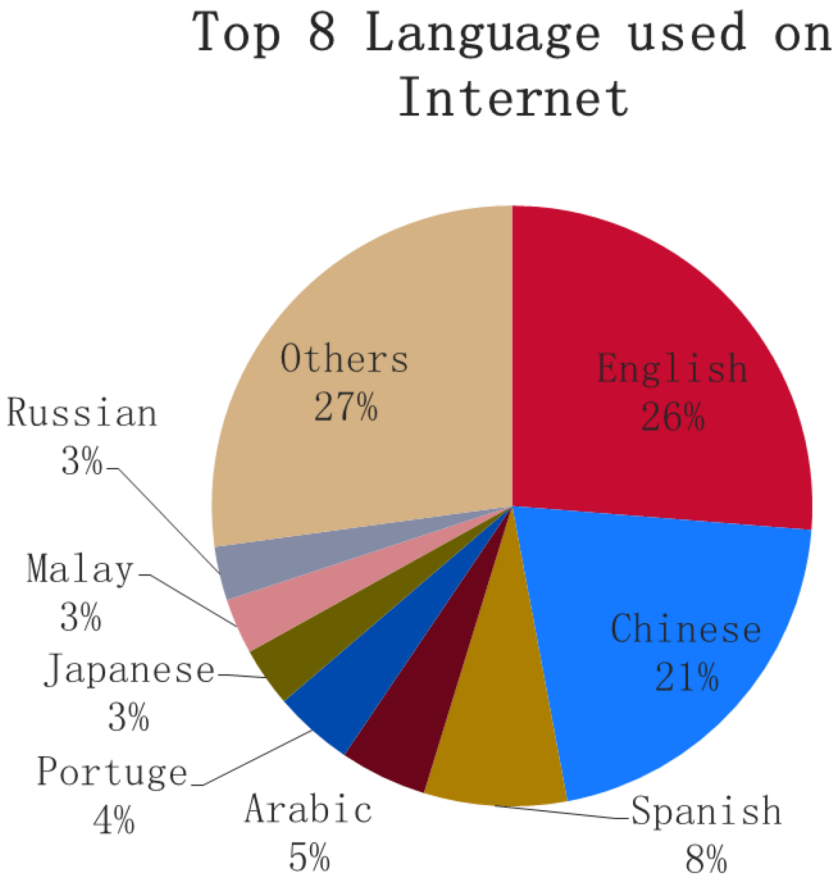
Sentic PROMs

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



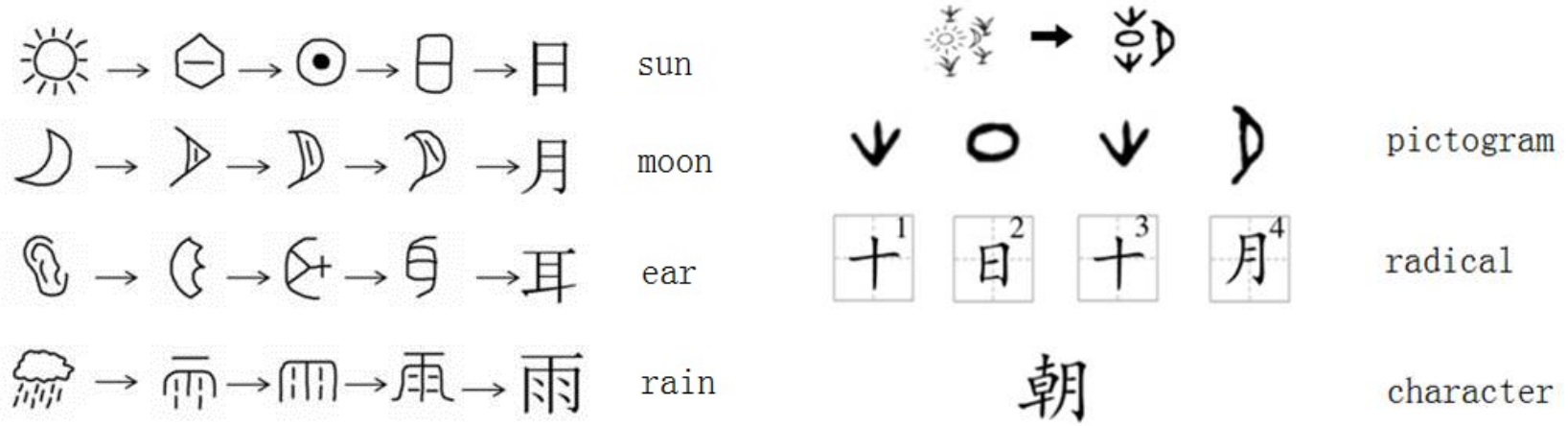
Multilingual analysis



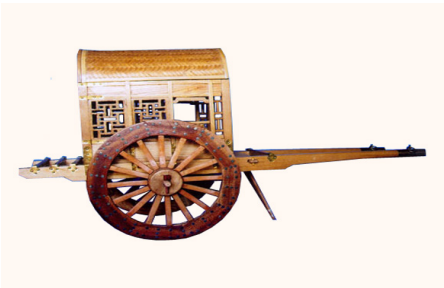


SL Lo, E Cambria, R Chiong, D Cornforth. Multilingual sentiment analysis: From formal to informal and scarce resource languages. Artificial Intelligence Review 48(4), 499-527 (2017)

Multilingual analysis



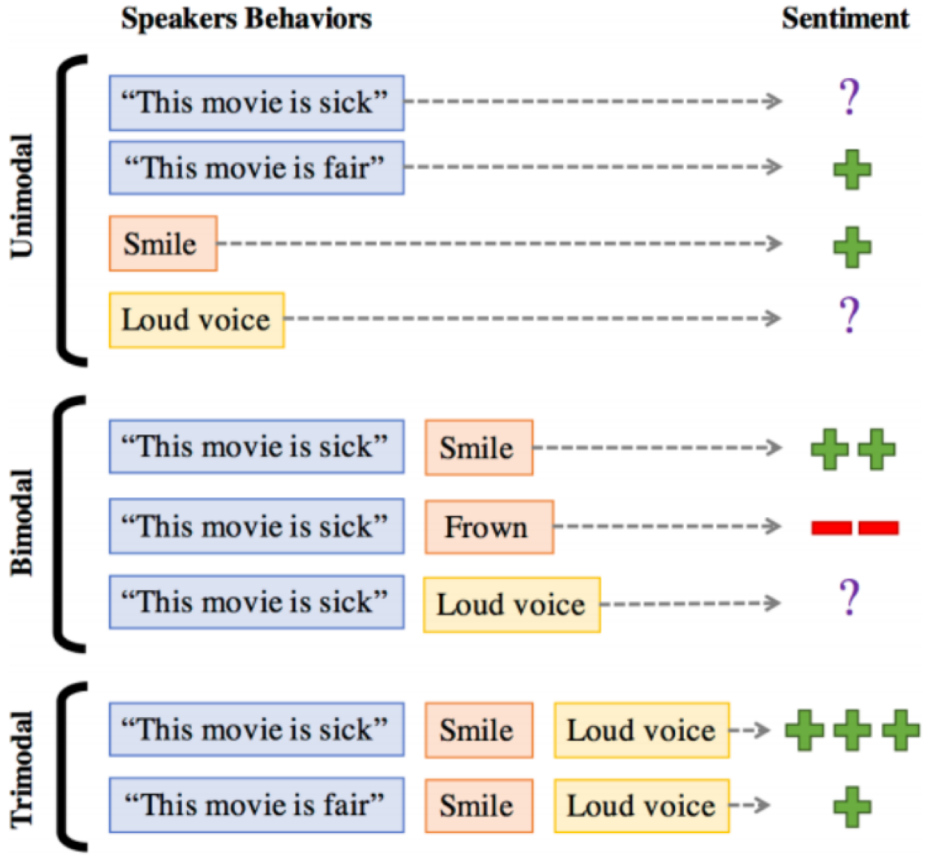
火车 = 火 + 车



H Peng, E Cambria, X Zou. Radical-Based Hierarchical Embeddings for Chinese Sentiment Analysis at Sentence Level. In: FLAIRS, 347-352 (2017)

The more, the merrier

When available, more modalities aid to resolve ambiguities in communication and, hence, enhance polarity detection



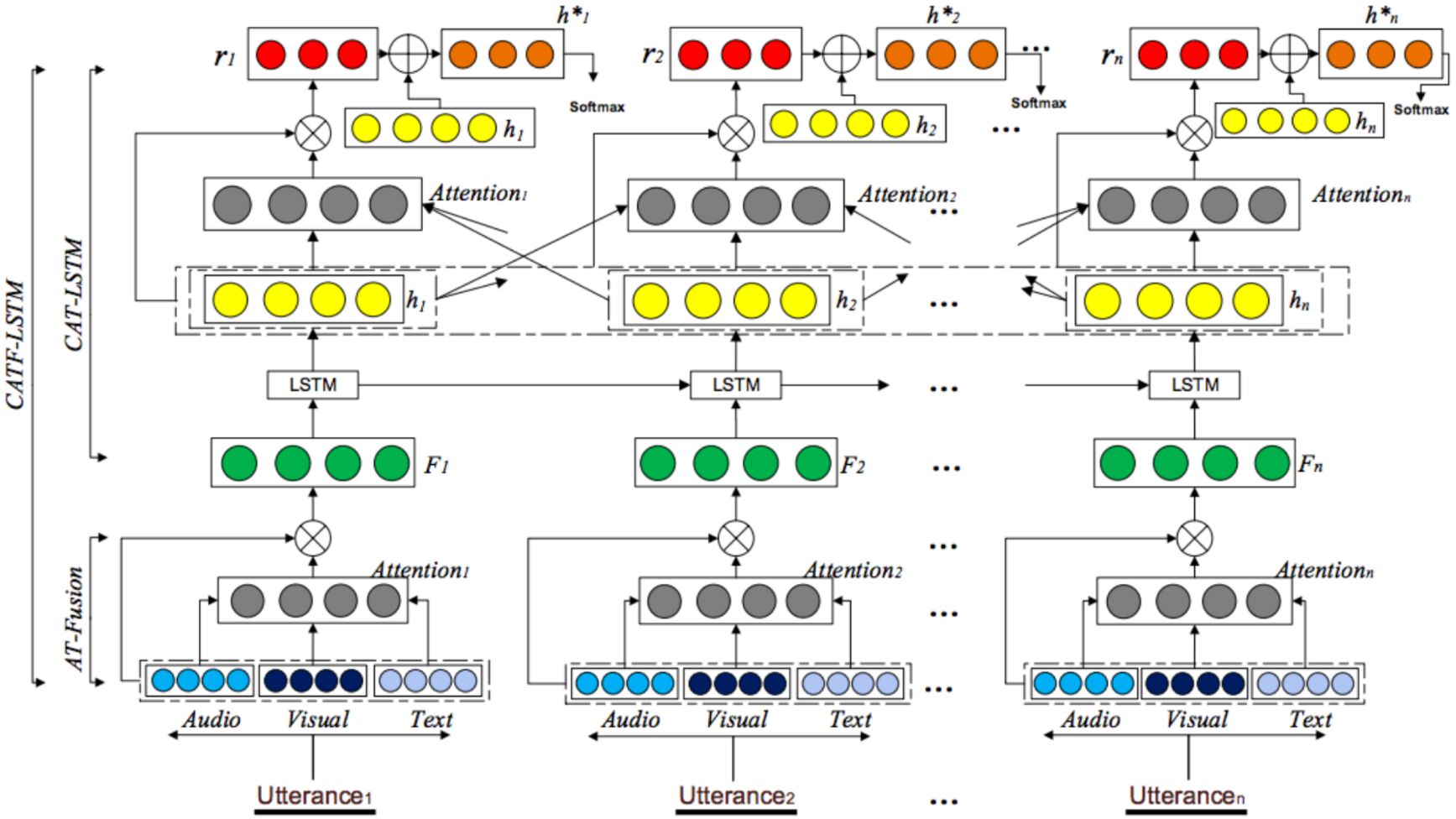
A Zadeh, M Chen, S Poria, E Cambria, LP Morency. Tensor fusion network for multimodal sentiment analysis. In: EMNLP, 1114-1125 (2017)

Multimodal analysis

An ensemble feature extraction approach exploiting the joint use of tri-modal (text, audio and video) features enhances multimodal sentiment analysis

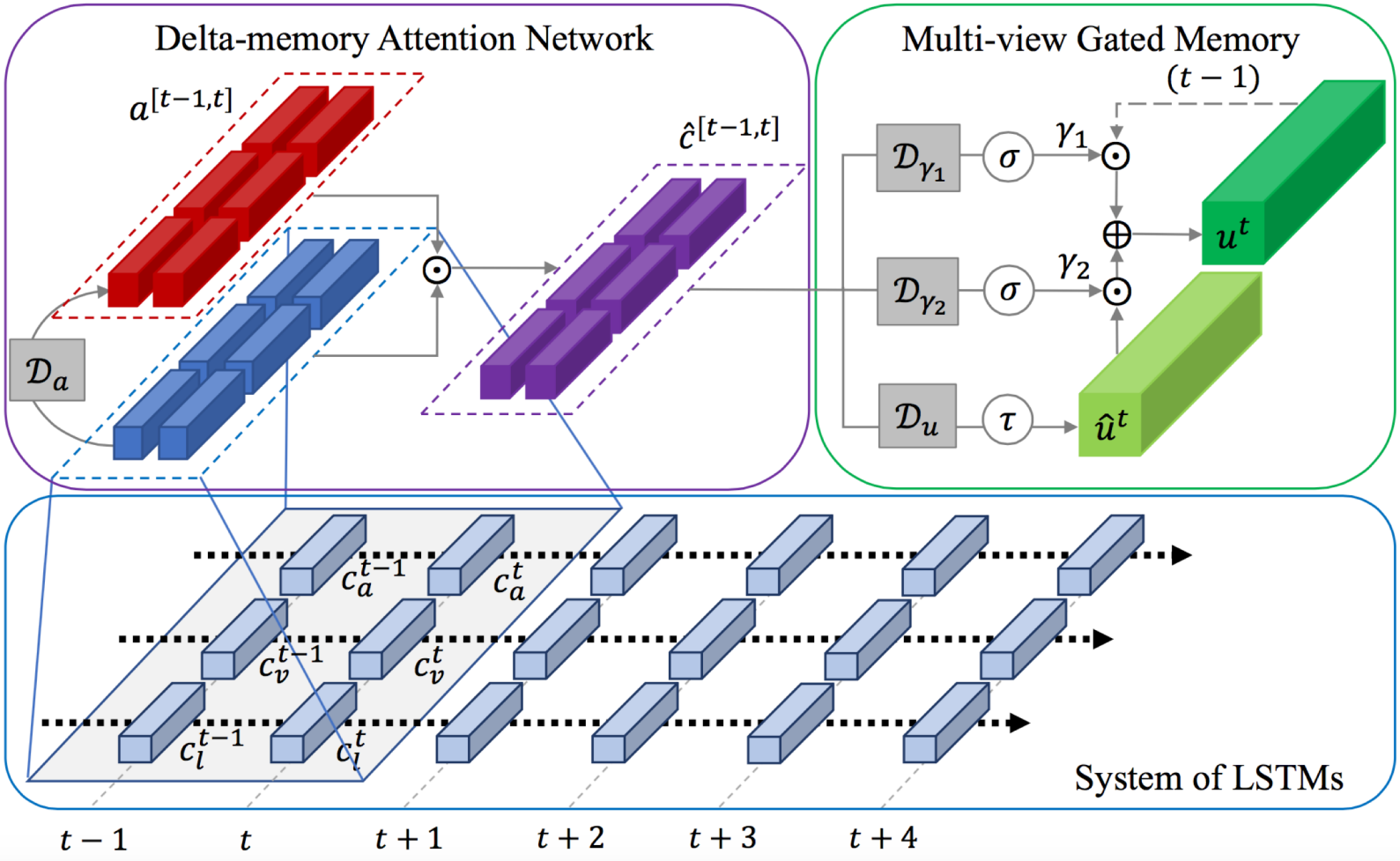
S Poria, E Cambria, D Hazarika, N Mazumder, A Zadeh, L Morency. Context-dependent sentiment analysis in user-generated videos. In: ACL, 873-883 (2017)

Multimodal attention



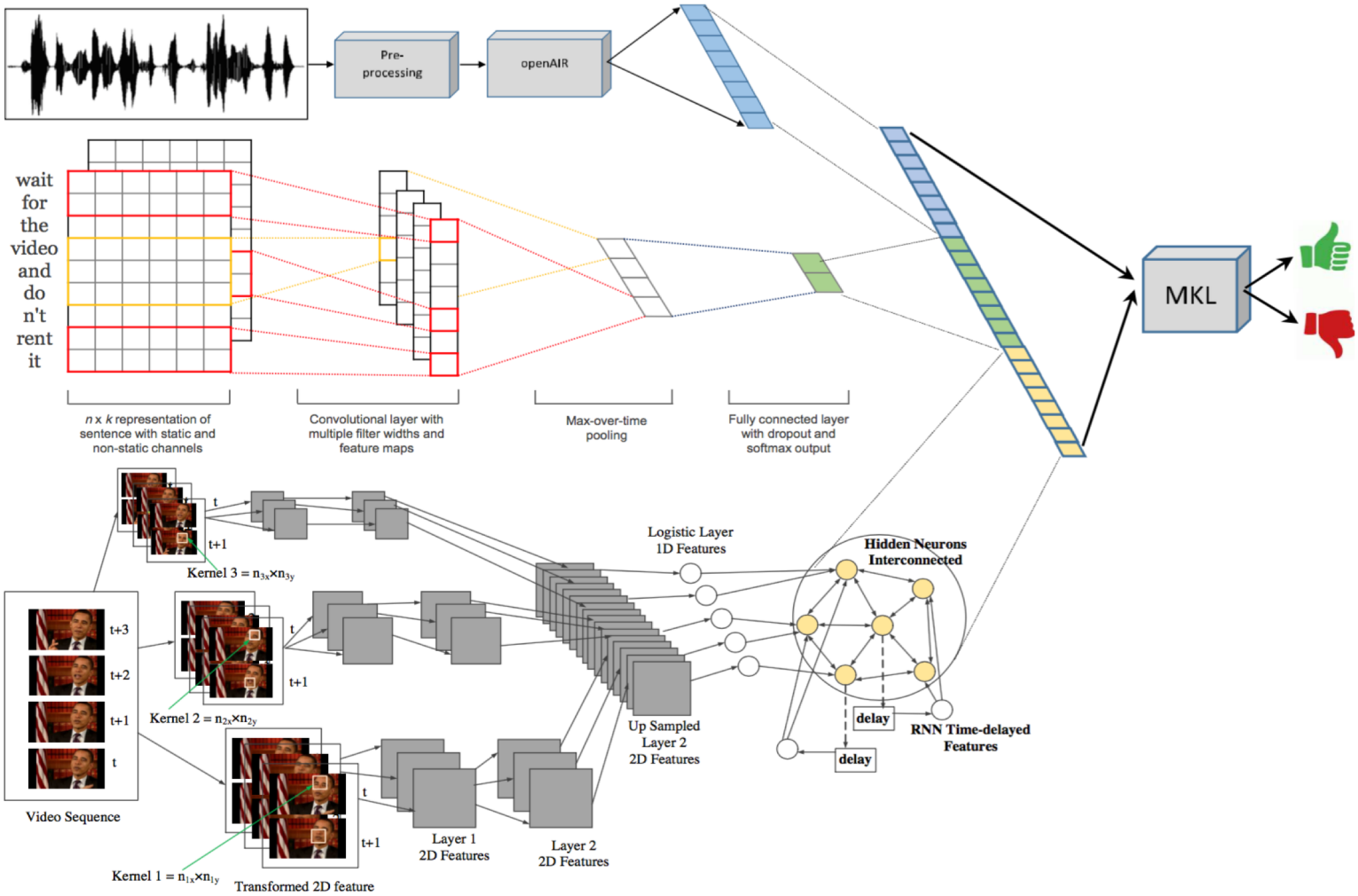
S Poria, E Cambria, D Hazarika, N Mazumder, A Zadeh, LP Morency. Multi-level multiple attentions for context-aware multimodal sentiment analysis. In: ICDM, 1033–1038 (2017)

Memory fusion network



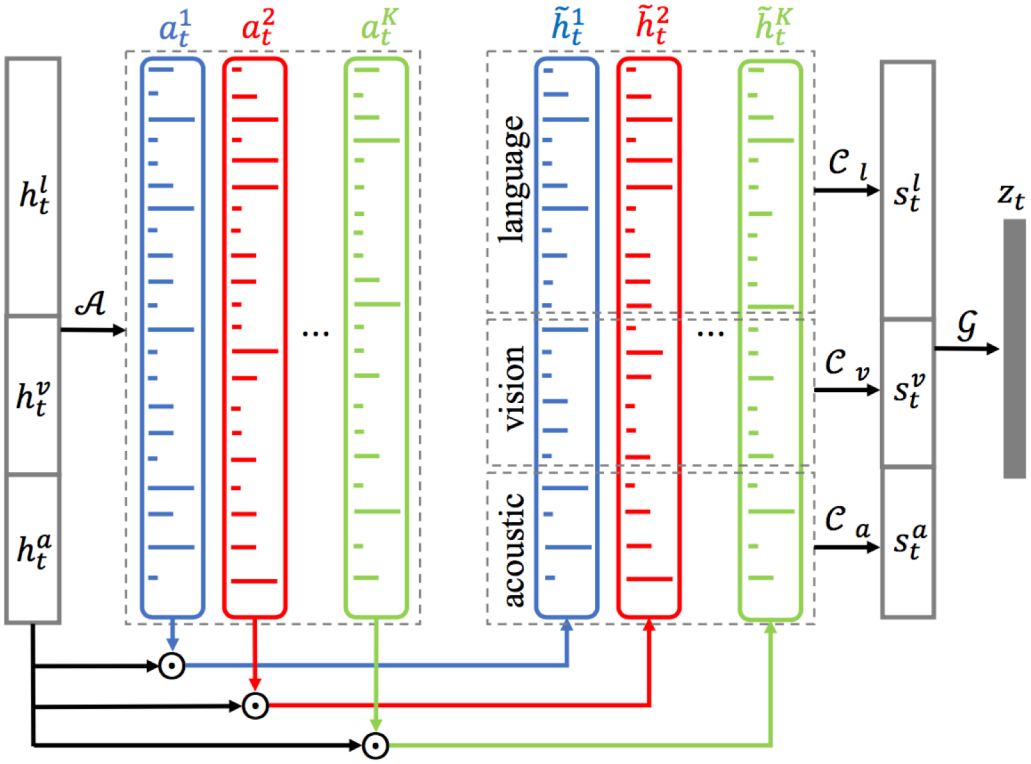
A Zadeh, PP Liang, N Mazumder, S Poria, E Cambria, LP Morency. Memory fusion network for multi-view sequential learning. In: AAAI, 5634-5641 (2018)

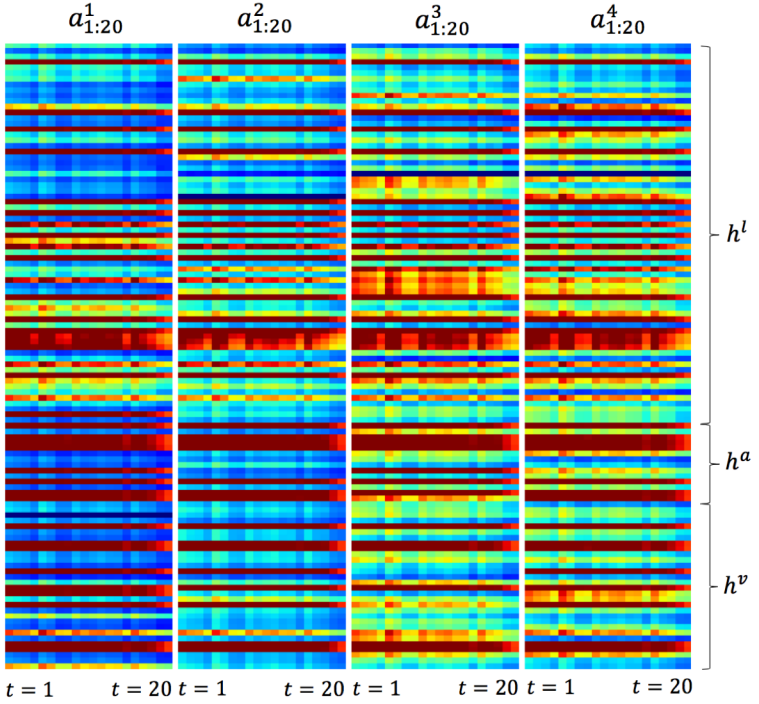
Multimodal fusion



S Poria, I. Chaturvedi, E Cambria, A Hussain. Convolutional MKL Based Multimodal Emotion Recognition and Sentiment Analysis. In: ICDM, 439-448 (2016)

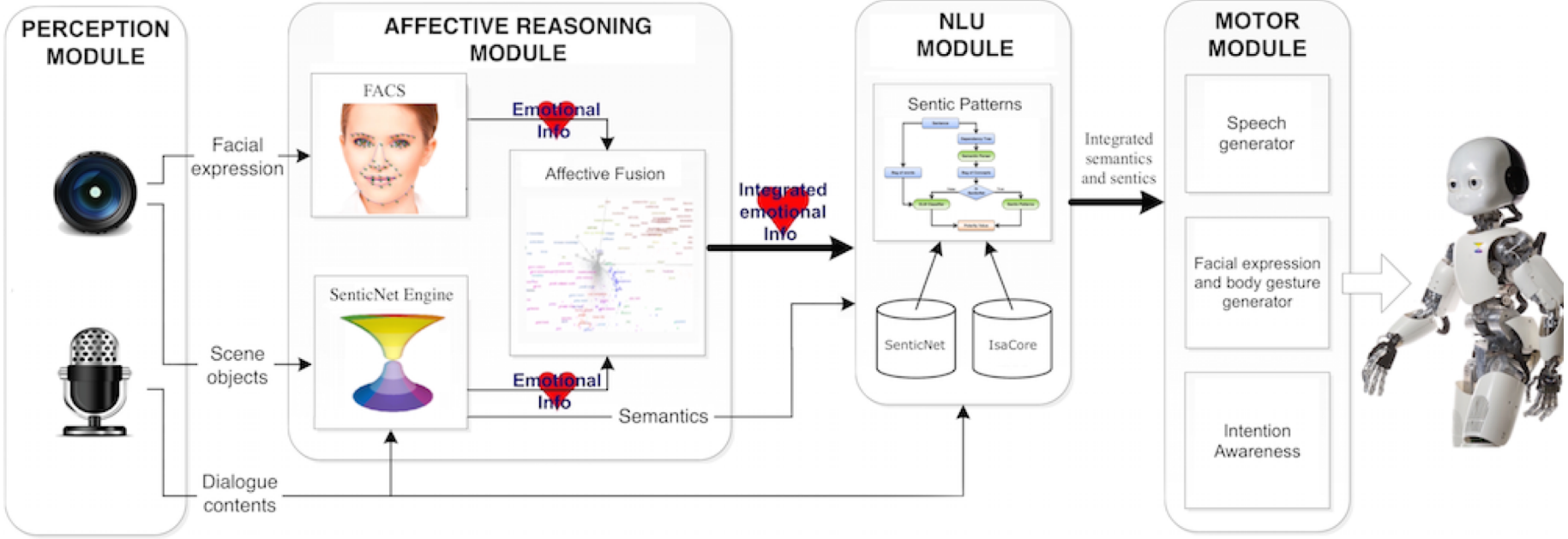
Multi-attention fusion





A Zadeh, PP Liang, S Poria, P Vij, E Cambria, LP Morency. Multi-attention recurrent network for human communication comprehension. In: AAAI, 5642-5649 (2018)

Dialogue systems



T Young, E Cambria, I Chaturvedi, H Zhou, S Biswas, M Huang. Augmenting end-to-end dialogue systems with commonsense knowledge. In: AAAI, 4970-4977 (2018)

Open challenges

User Preference

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

Theory of Mind

It is good that you killed the professor

Theory of Relativity

I used to hate gardening but now I love it

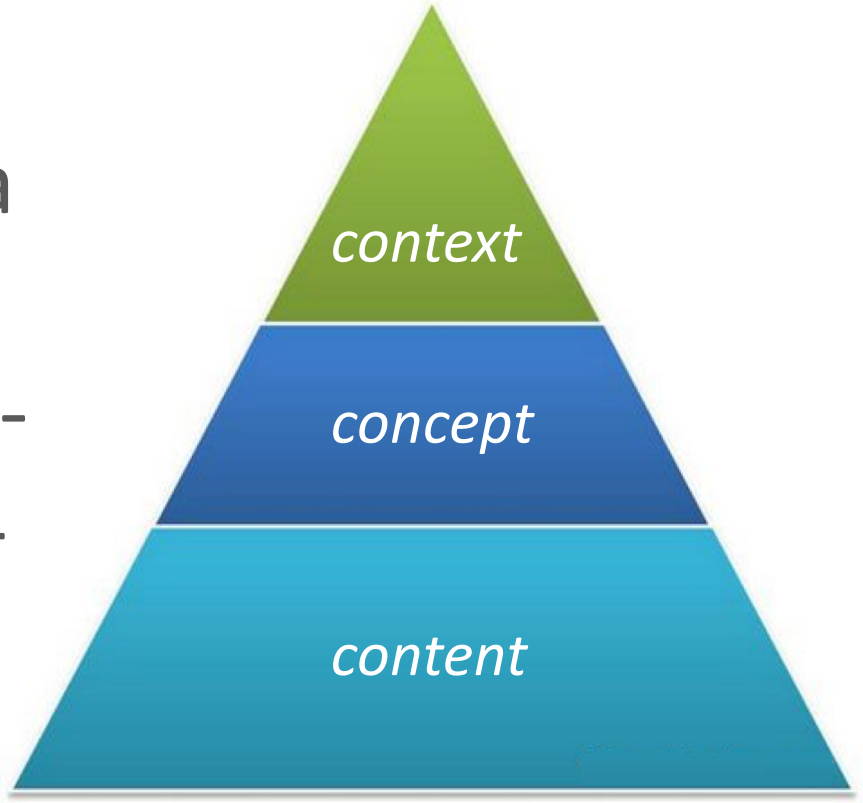
Intention Awareness

big/small room, warm/cold water

N Howard, E Cambria. Intention awareness: Improving upon situation awareness in human-centric environments. Human-centric Computing and Information Sciences 3(9) (2013)

3C sentiment analysis

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

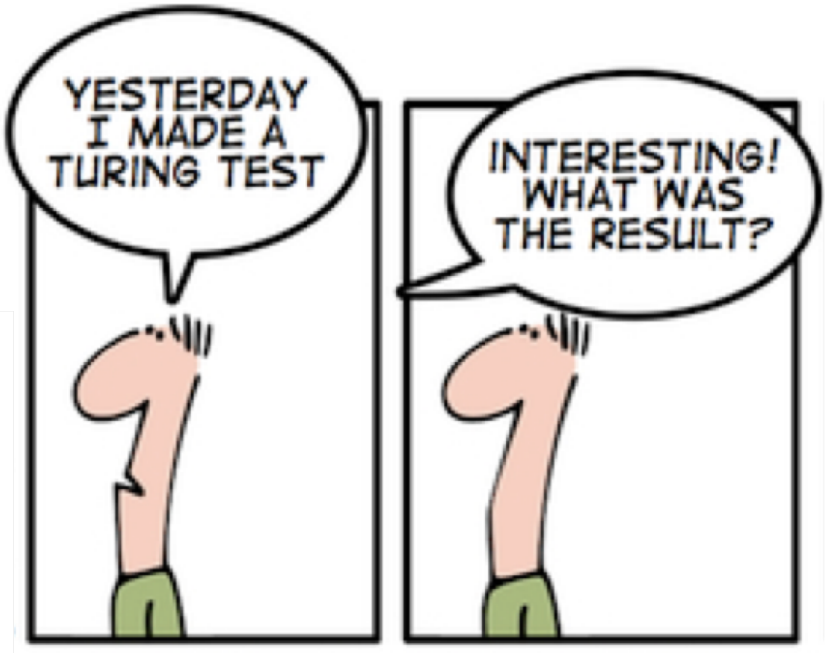


3Q NLP

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)

Machines that think

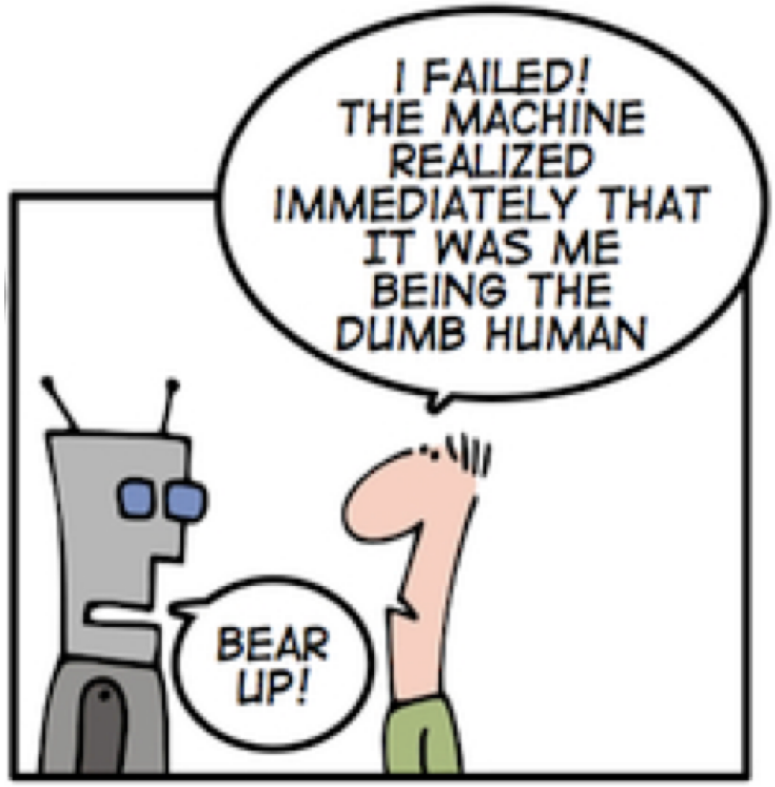
The world has changed less since Jesus Christ than it has in the last century. In another century's time, machines might be able to think as humans do.



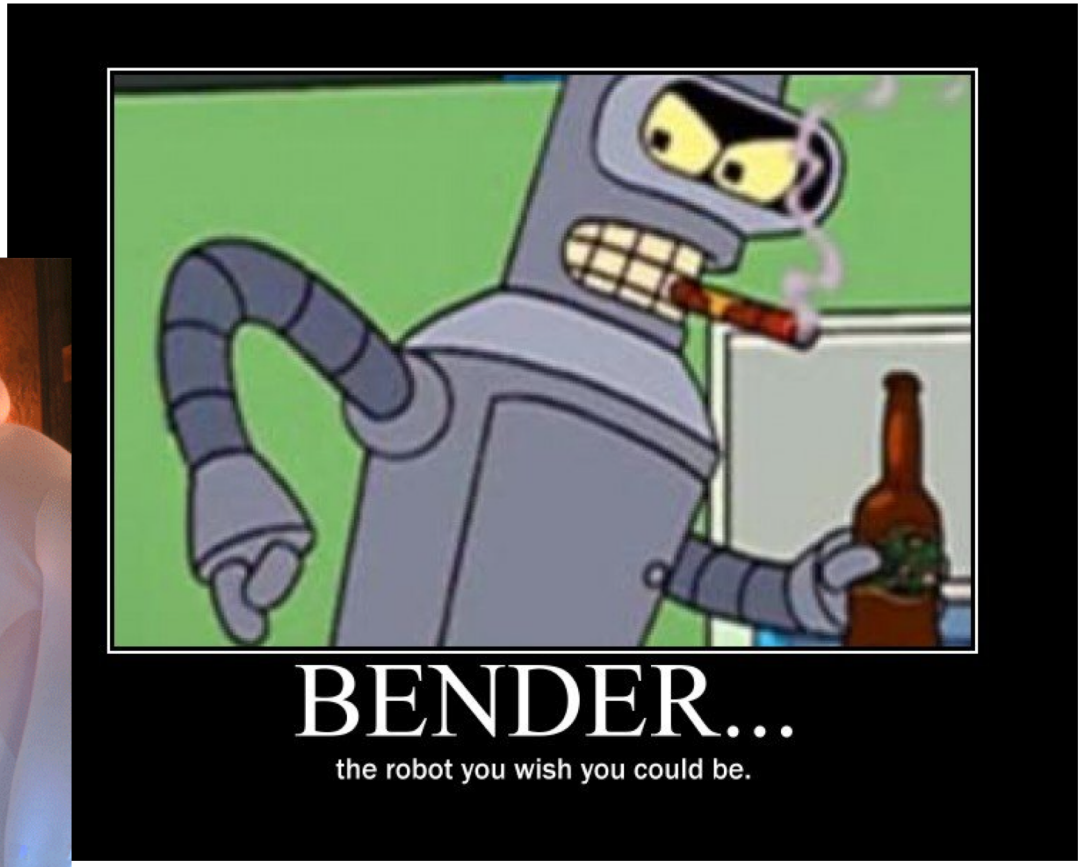
R. Kurzweil, M. Schneider. The Age of Intelligent Machines. MIT Press, Cambridge (1990)

Machines that think

But do we really want them to think exactly like us? Should we attempt to make them better than us or make sure they will never be as smart as us?



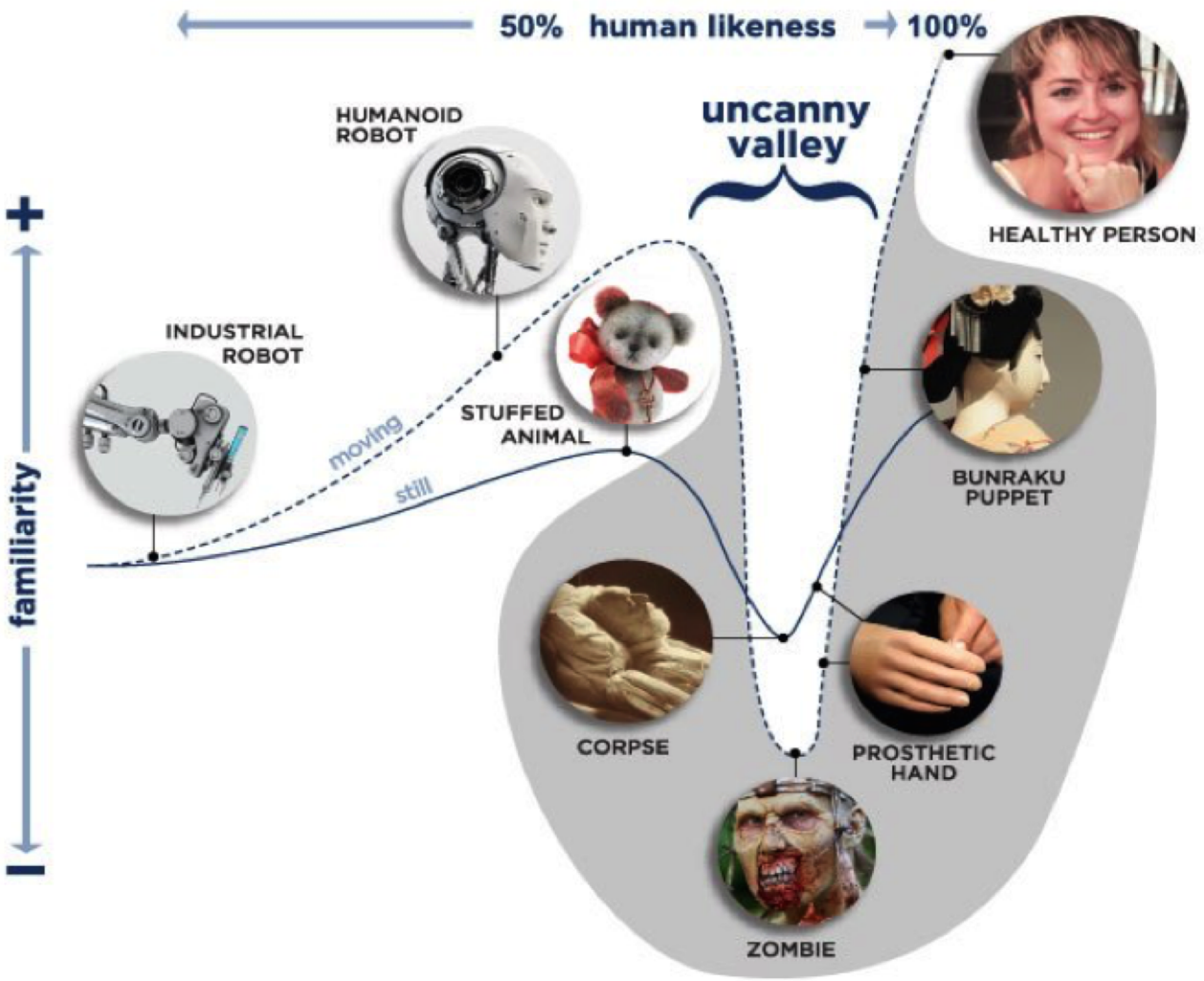
Are we even a good model?



How much should they feel?

Do we really want to emulate the full spectrum of human emotions into machines? Should we remove some negative emotions such as revenge or envy?

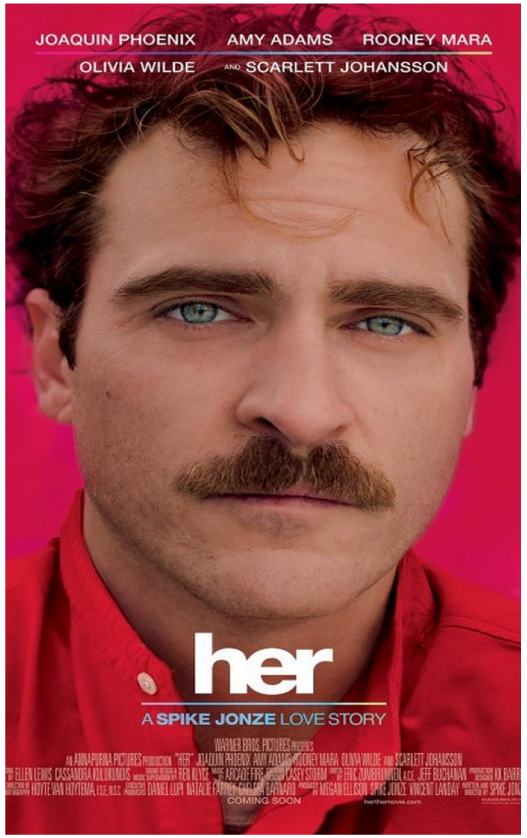
How should they look like?



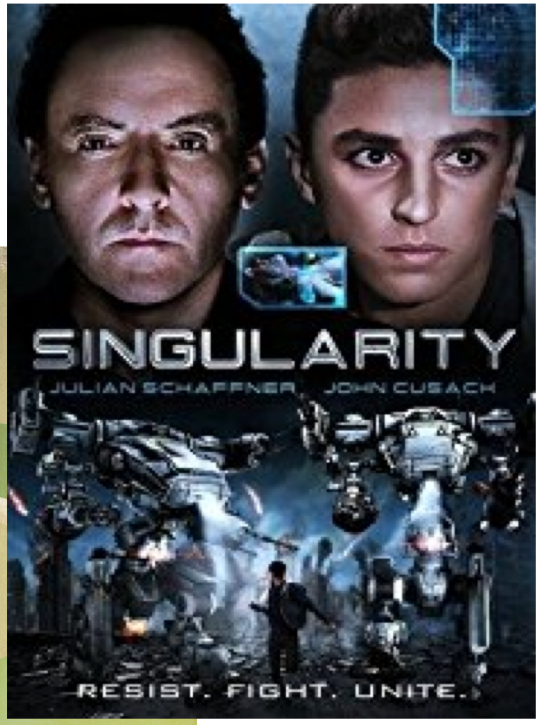
M Mori. The uncanny valley. IEEE Robotics & Automation Magazine. 19 (2), 98-100 (1970)

How smart should they be?

Do we really want machines to be smarter than us?
If not, what can we do to prevent that from happening? Is an AI superintelligence going to take care of us or destroy us?

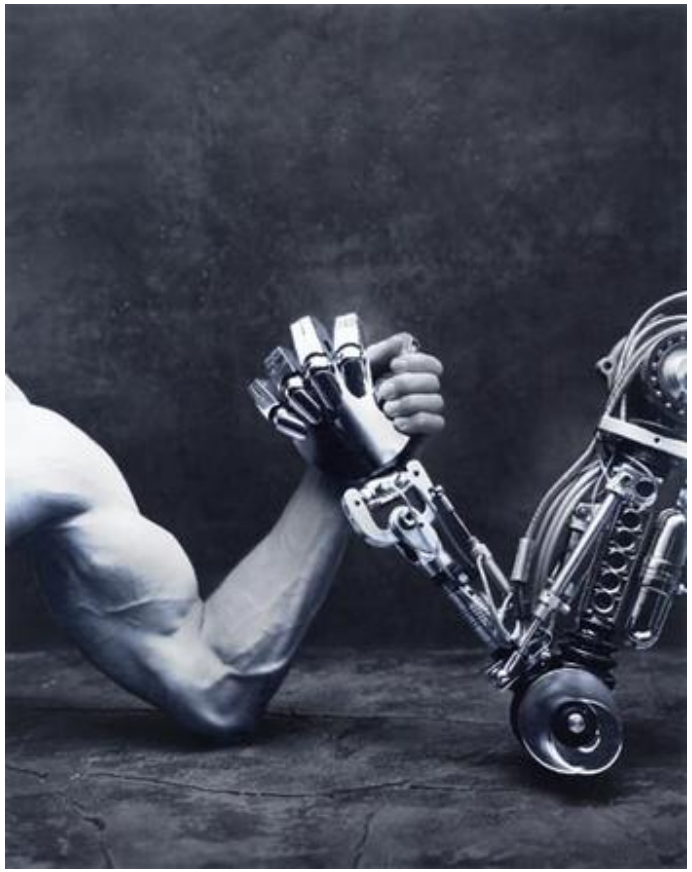


What is the risk?

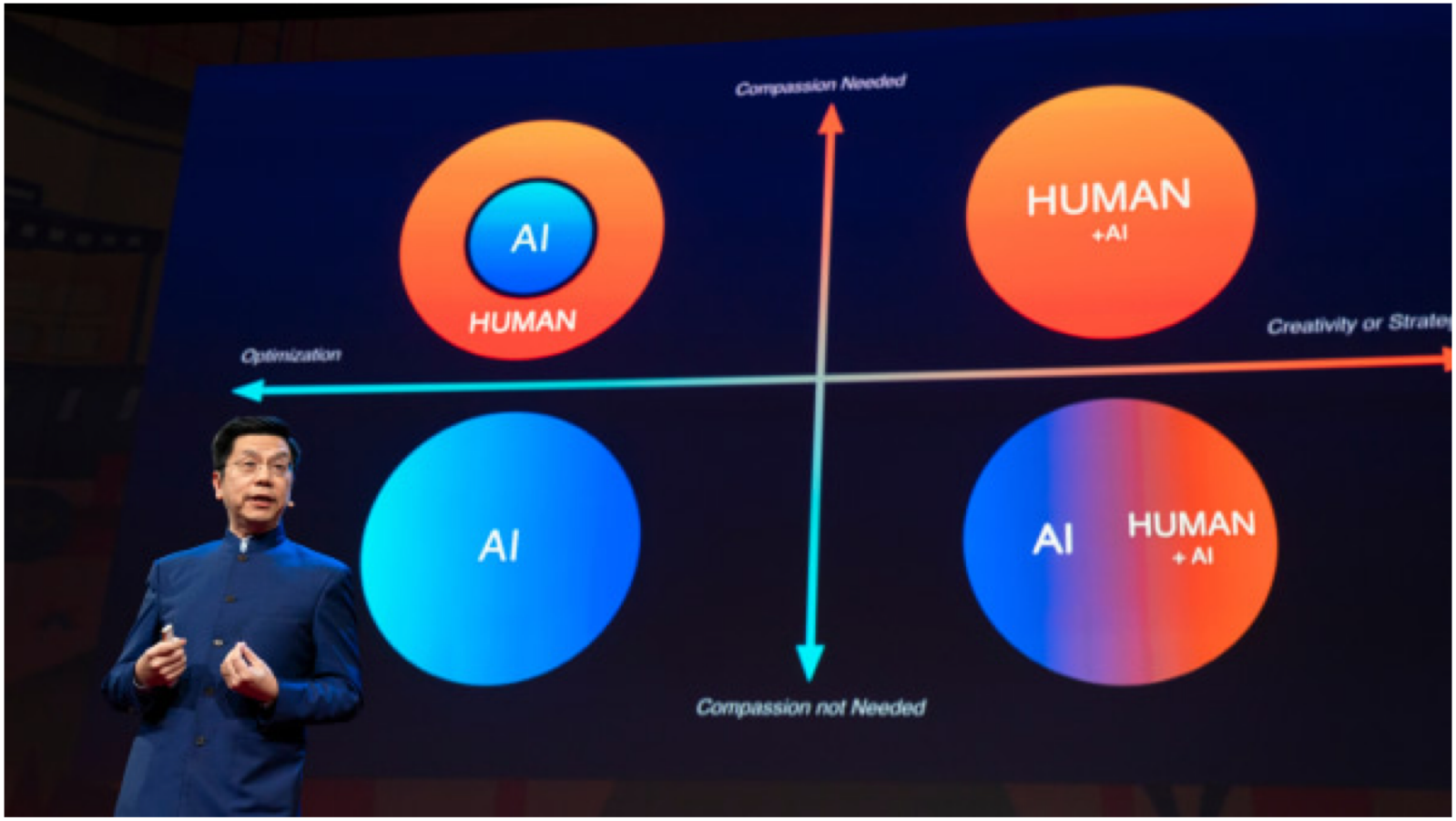


Conclusion

The truth is that we are still light-years away from a truly intelligent machine, due in part to the fact that we do not even fully understand human intelligence yet



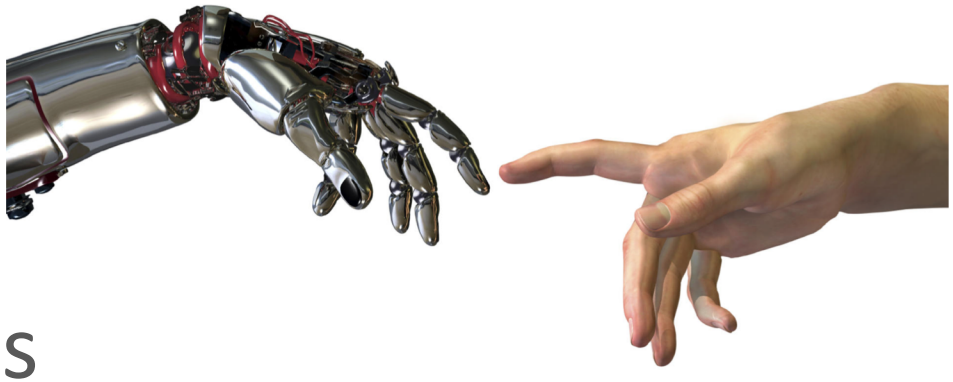
Conclusion



http://ted.com/talks/kai_fu_lee_how_ai_can_save_our_humanity

Conclusion

We do not aim to help machines take over the world but rather to exploit differences in human-computer abilities and costs so as to achieve symbiotic HMI



Questions?