Wherever there are sensations, ideas, emotions, there must be words.

Swami Vivekananda

This is a talk on **'Sentiment Analysis'** by **Aditya Joshi**

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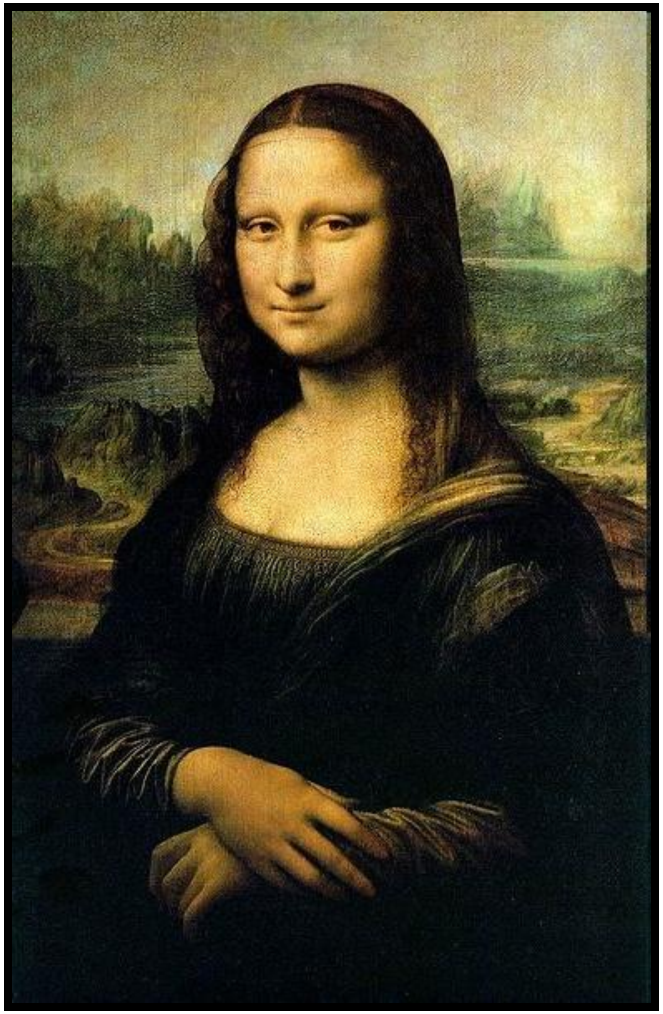
Please ask questions.

I'll try and answer! ☺

Aditya

Image from wikimedia commons
Source: Wikipedia



Mona Lisa
16th century
Artist: Leonardo da Vinci

Smile of Mona Lisa

Is she smiling at all?

Is she happy?

What is she smiling about?

What is she happy about?

Sentiment analysis (SA)

Task of tagging text with orientation of opinion

This is a good movie. 

This is a bad movie. 

Subjective

The movie is set in Australia. 

Objective

Sentiment Analysis

The world within

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Outline

- Introduction to SA
  - Definition & Jargon
  - Challenges & Flavours
  - Opinion on the web
- Lexicons
  - SentiWordnet
  - LIWC
  - Trends
- SA Systems
  - Rule-based SA
  - ML-based SA
  - Subjectivity detection
  - Trends
- Branches of SA
- Applications of SA&EA
  - Mental health monitoring
  - Web applications
- **The World Within**

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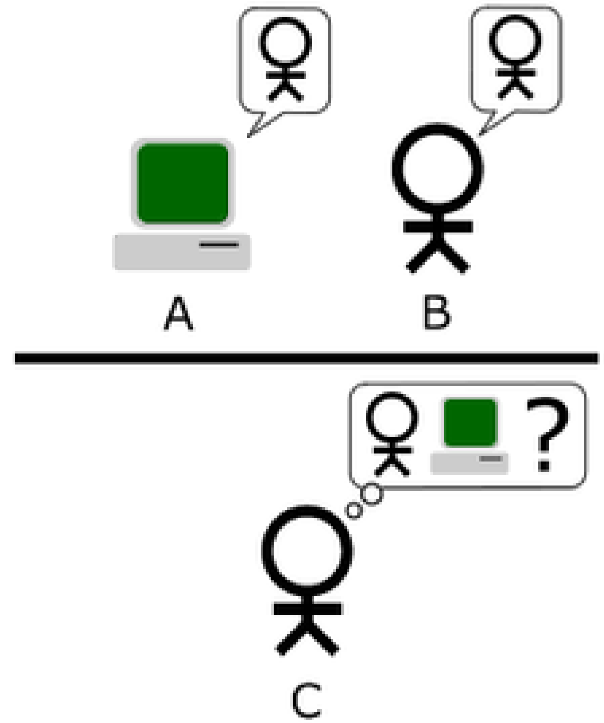
Turing Test & Sentiment-aware computers

Goal: The human must not be able to identify if (s)he is talking to a human or a computer



Sentiment-aware computers are a step towards a successful Turing test.

Piccard (2000)

Human: “My pet died last night.”

Agent:

“Okay. Thank you for your information.”

“Oh, that’s sad to know.”

Terminology/Jargon

- Sentiment Analysis
- Opinion Mining
- Sentiment detection

Positive / negative

- Emotion Analysis
- Affective computing
- Affect analysis

Happy/Sad/Angry/Surprised/Afraid...

Challenges of SA

- Domain dependent
- Sarcasm
- Thwarted expressions
- Negation
- Implicit polarity
- Time-bounded

"This phone allows me to send SMS."

"This phone has a touch-screen."

Flavours of SA

- Subjective/Objective
- Emotion analysis
- SA with magnitude
- Entity-specific SA
- Aspect-specific SA
- Perspectivization

“The Leftists were arrested yesterday by the police.”

Opinion on the Web

- Does web really contain sentiment-related information?
- Where?
- How much?
- What?

User-generated content

- Web 2.0 empowers the user of the internet
- They are most likely to express their opinion there
- Temporal nature of UGC: ‘Live Web’
- **Can SA tap it?**

Where?

- Blogs
- Review websites
- Social networks
- User conversations

Conversations between users on one of the above

Reference : www.technorati.com/state-of-the-blogosphere/

How much?

- Size of blogosphere
  - Through the ‘eyes’ of the blog trackers

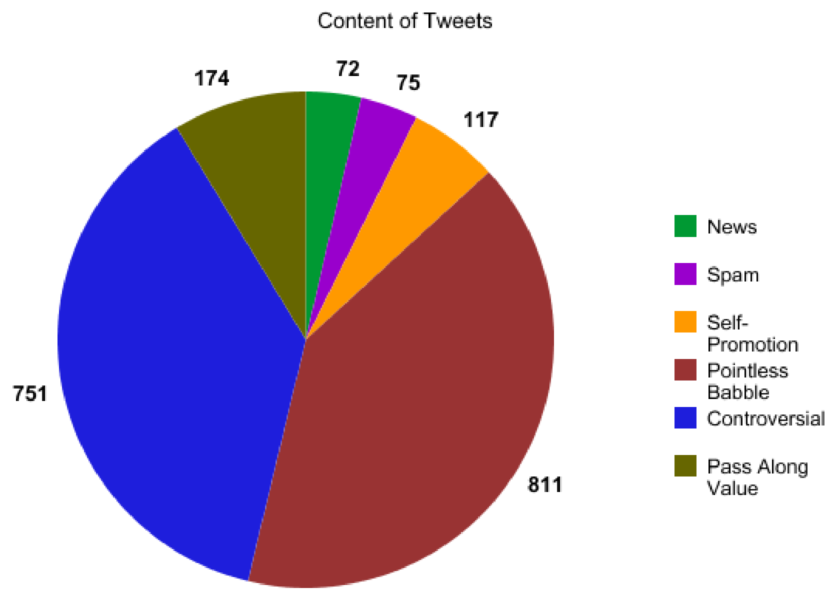
- Technorati : 112.8 million blogs (excluding 72.82 million blogs in Chinese as counted by a corresponding Chinese Center)
- A blog crawler could extract 88 million blog URLs from blogger.com alone
- 12,000 new weblogs daily

Reference : http://www.ebizmba.com/articles/social-networking-websites

How much?

- 12,22,20,617 unique visitors to facebook in December 2009
- Twitter:

2,35,79,044



Kelly, Ryan, ed. (2009-08-12), "Twitter Study - August 2009" (PDF), Twitter Study Reveals Interesting ResultsAbout Usage, San Antonio, Texas: Pear Analytics. http://www.pearanalytics.com/wp-content/uploads/2009/08/Twitter-Study-August-2009.pdf

What? Reviews

- www.burrrp.com
- www.mouthshut.com
- www.justdial.com
- www.yelp.com
- www.zagat.com
- www.bollywoodhungama.com
- www.indya.com

Restaurant reviews (now, for a variety of 'lifestyle' products/services)

A wide variety of reviews

Professionals: Well-formed

User: More mistakes

Movie reviews by professional critics, users. Links to external reviews also present

A typical Review website

Snapshot: www.mouthshut.com

Sample Review 1

(This, that and this)

FLY E300 is a good mobile which i purc
is not familiar in Market as well known
with almost all the features for a good
would come around 19k Indian Ruppees.. But this one i

Touch Screen, good resolution, good talk time, 3.2Mega

BUT BEWARE THAT THE CAMERA IS NOT THAT GOOD, T
ITS NOT AS GOOD AS MY PREVIOUS MOBILE SONY ERIC
Pixel.

Sony ericsson was excellent with the feature of came
please excuse. This model of FLY is not apt for you.. A

Audio is not bad, infact better than Sony Ericsson K7

FLY is not user friendly probably since we have just started to use this Brand.

this Brand
cheap
of features

‘Touch screen’ today signifies a positive feature.
Will it be the same in the future?

Comparing old products

The confused conclusion

From: www.mouthshut.com

Sample Review 2

Hi,

I have Haier phone.. It was good when i was buing this
phone.. But I invented A lot of bad features by this phone
those are It's cost is low but Software is not good and Battery
is very bad..,,Ther are no signals at out side of the city..,,
People can't understand this … en't
features in this phone, Desig … also
bad..So I'm not intrest this si … nes
it is good. They are giving mo … e
are also good.They are giving colour screen at display time it
is also good because other phones aren't this type of
feature.It is also low wait.

Lack of punctuation marks, Grammatical errors

Wait.. err.. Come again

From: www.mouthshut.com

Sample Review 3

(Subject-centric or not?)

I have this personal experience of using this cell phone. I bought it one and half years back. It had modern features that a normal cell phone has, and the look is excellent. I was very impressed by the design. I bought it for Rs. 8000. It was a gift for someone. It worked fine for first one month, and then started the series of multiple faults it has. First the speaker didnt work, I took it to the service centre (which is like a govt. office with no work). It took 15 days to repair the handset, moreover they charged me Rs. 500. Then after 15 days again the mike didnt work, then again same set of time was consumed for the repairs and it continued. Later the camera didnt work, the speakes were rubbish, it used to hang. It started restarting automatically. And the govt. office had staff which I doubt have any knoledge of cell phones??

These multiple faults continued for as long as one year, when the warranty period ended. In this period of time I spent a considerable amount on the petrol, a lot of time (as the service centre is a govt. office). And at last the phone is still working, but now it works as a paper weight. The company who produces such items must be sacked. I understand that it might be fault with one prticular handset, but the company itself never bothered for replacement and I have never seen such miserable cust service. For a comman man like me, Rs. 8000 is a big amount. And I spent almost the same amount to get it work, if any has a good suggestion and can gude me how to sue such companies, please guide.

For this the quality team is faulty, the cust service is really miserable and the worst condition of any organisation I have ever seen is with the service centre for Fly and Sony Erricson, (it's near Sancheti hospital, Pune). I dont have any thing else to say.

From: www.mouthshut.com

Sample Review 4

(Good old sarcasm)

"I've seen movies where there was practically no plot besides explosion, explosion, catchphrase, explosion. I've even seen a movie where nothing happens. But *White on Rice* was new on me: a collection of really wonderful and appealing characters doing completely baffling and uncharacteristic things."

Review from: www.pajiba.com

What? Comments

- Two types of comments:
  - Comments about the article/ blogpost:
    - *Very well-written indeed…*
  - Comments about the topic of the article:
    - *I agree with you.. I used to love **’s movies at a point of time but these days all he comes out with is trash. <Often leads to a conversation>*

(- Comments about the blogger:

- *If you think Shahid Kapoor is ugly, go buy glasses. While you are at it, buy yourself a brain too*

)

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Lexicons

- SentiWordnet (SWN)
- Linguistic Inquiry and Word Count (LIWC)

excellent

extravagance

Over-the-top

pathetic

poor

blunder

fabulous

worthwhile

functional

illegal

disaster

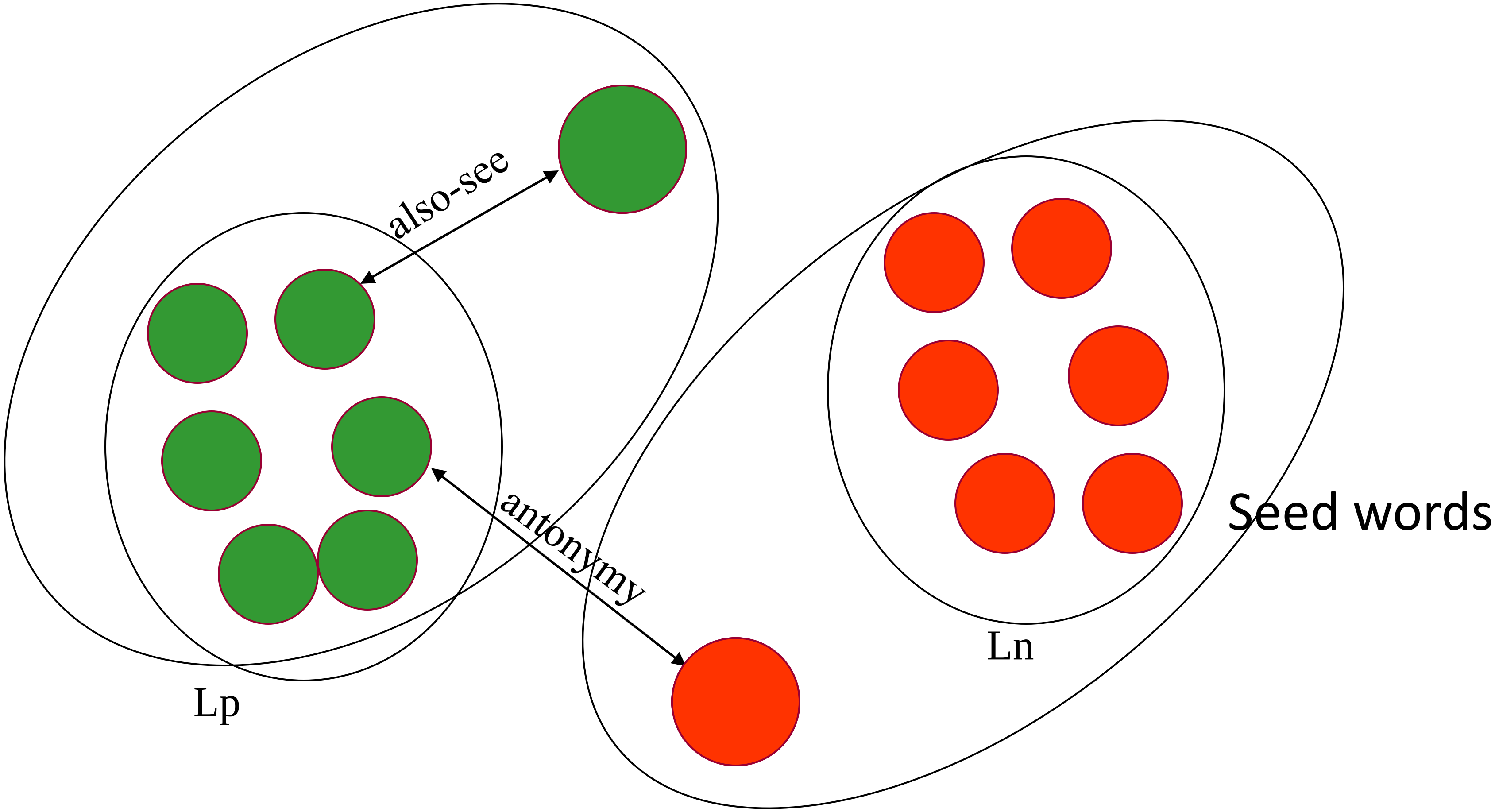
SentiWordnet (SWN)

- Maximum of triple score (for labeling)
- Difference of polarity score (for semantic orientation)

pestering
P = 0,
N = 0.625,
O = 0.375

Diff(P,N) = - 0.625
Negative

Construction of SWN



The sets at the end of kth step are called Tr(k,p) and Tr(k,n)

Tr(k,o) is the set that is not present in Tr(k,p) and Tr(k,n)

Building SentiWordnet

- Classifier combination used: **Rocchio (BowPackage) & SVM(LibSVM)**
    - Different training data based on expansion
    - POS –NOPOS and NEG-NONEG classification
- Total eight classifiers
- Score Normalization

Linguistic Inquiry &Word Count (LIWC)

Core dictionary of 4500 words and word stems (e.g. happ*) organized in 4 categories

Linguistic processes

Pronouns
Prepositions
Conjunctions

Speaking processes

Interjections
Fillers (“hmm”, “oh”)

Personal concerns

Words related to work, home, etc.

Psychological processes

Words dealing with affect and opinion

713 words

Cognitive processes

Tentative *(possible)*
Certainty *(definitely)*
Inhibition *(prevented)*
....

915 words

Affective processes

Positive emotion
Negative emotion
Anxiety
Anger
Sadness

Creation of LIWC

Define Category Scales

- Determine categories
- Determine how they can be grouped into a hierarchy

Populate Manually

- Manual evaluation by three judges
- For each word, decide whether or not a word should be placed in this category or moved higher up in the hierarchy

Trends of Lexicons

	Approach	Labels	Key takeaway
LIWC	Manual	Hierarchy of categories	Decide hierarchy of categories; have judges interacting with each other
ANEW & ANEW for Spanish	Manual	Valence, Arousal, Dominance	ScanSAM lists; have a set of annotators annotating in parallel
EmoLexi	Manual	Five emotions	Use crowd-sourcing. Attention to quality control.
WordnetAffect	Semi-supervised	Affective labels	Annotate a seed set. Expand using Wordnet relations.
Chinese emotion lexicon	Semi-supervised	Five emotions	Annotate a seed set. Expand using similarity matrices

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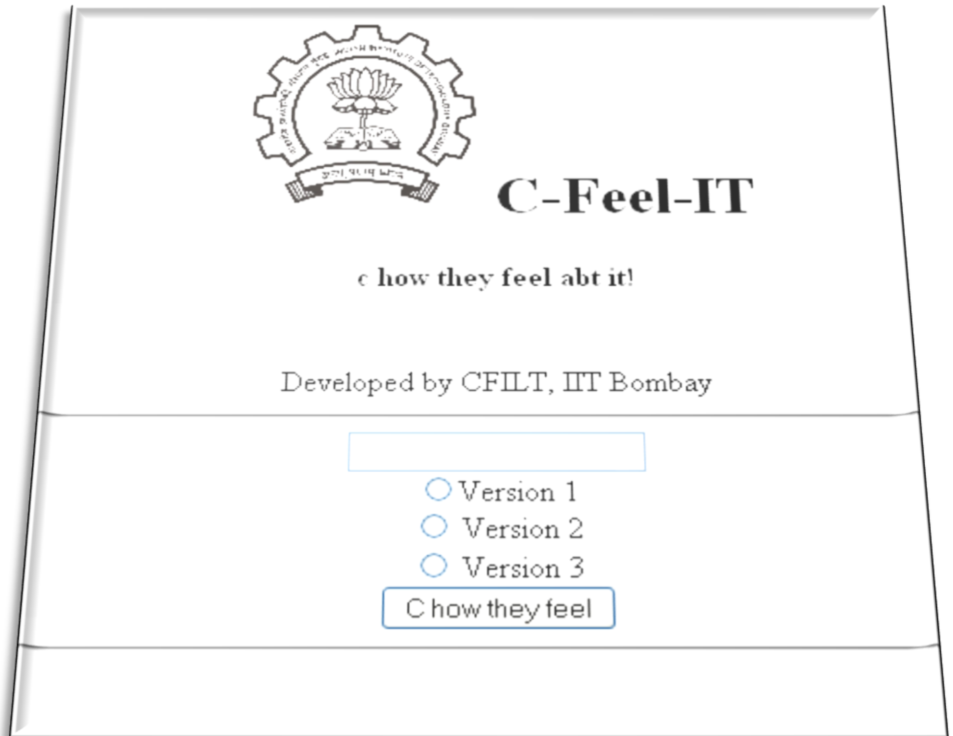
A rule-based SA engine



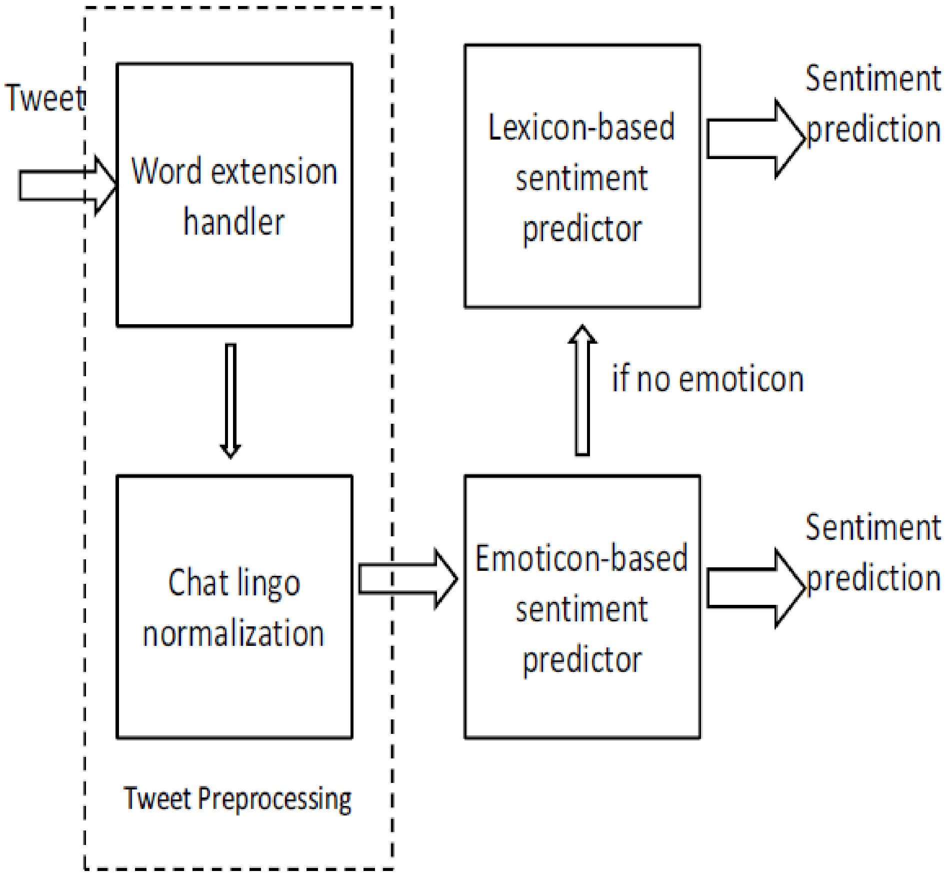
Aditya Joshi, Balamurali A.R>, Pushpak Bhattacharyya and Rajat Mohanty, *C-Feel-It: A Sentiment Analyzer for Micro-blogs* (demo paper), Annual Meeting of the Association of Computational Linguistics (**ACL 2011**), Oregon, USA, June 2011.

Challenges with tweets

Tweets as opposed to **blog posts/reviews**:

- Short: Unstructured/grammatically incorrect
- Links, smileys
- Extensions of words (‘haapppyy’ for ‘happy’)
- Contractions of words (‘abt’ for ‘about’)

Architecture



Resources used

- SentiWordNet (Andrea & Sebastani,2006)
- Subjectivity clues (Weibi et al, 2004)
- Taboada (Taboada & Grieve, 2004)
- Inquirer (Stone et al, 1966)

A ML-based SA engine

Pang, Bo, Lillian Lee, and Shivakumar Vaithyanathan. "Thumbs up?: sentiment classification using machine learning techniques." *Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10*. Association for Computational Linguistics, 2002.

Goal

- Predicting reviews as positive or negative on the document level
- Simple ML-based classifiers
  - Term presence/Term frequency
  - Unigram/bigram
  - Adjectives

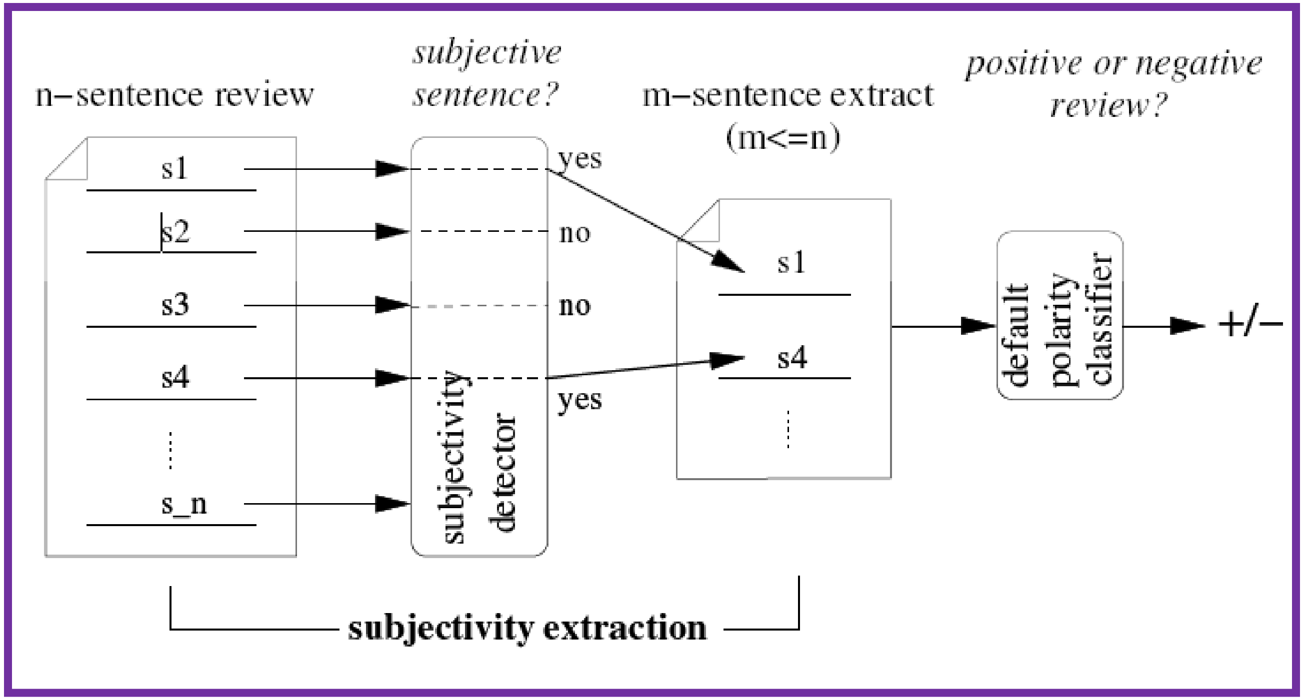
Results

	Features	# of features	frequency or presence?	NB	ME	SVM
(1)	unigrams	16165	freq.	**78.7**	N/A	72.8
(2)	unigrams	”	pres.	81.0	80.4	**82.9**
(3)	unigrams+bigrams	32330	pres.	80.6	80.8	**82.7**
(4)	bigrams	16165	pres.	77.3	**77.4**	77.1
(5)	unigrams+POS	16695	pres.	81.5	80.4	**81.9**
(6)	adjectives	2633	pres.	77.0	**77.7**	75.1
(7)	top 2633 unigrams	2633	pres.	80.3	81.0	**81.4**
(8)	unigrams+position	22430	pres.	81.0	80.1	**81.6**

Reference : [Pang-Lee,2004]

Subjectivity detection

- **Aim**: To extract subjective portions of text
- **Algorithm used**: Minimum cut algorithm



Reference : [Pang-Lee,2004]

Constructing the graph

- Why graphs?
- Nodes and edges?
- Individual Scores
- Association scores

Prediction whether two sentences should have the same subjec $Pr_{sub}^{NB}(s_i)$ l

$$assoc(s_i, s_j) \stackrel{def}{=} \begin{cases} f(j-i)\cdot c & \text{if } (j-i) \leq T; \\ 0 & \text{otherwise.} \end{cases}$$

T : **Threshold** – maximum distance upto which sentences may be considered proximal
f: The **decaying** function
i, *j* : **Position** numbers

Reference : [Pang-Lee,2004]

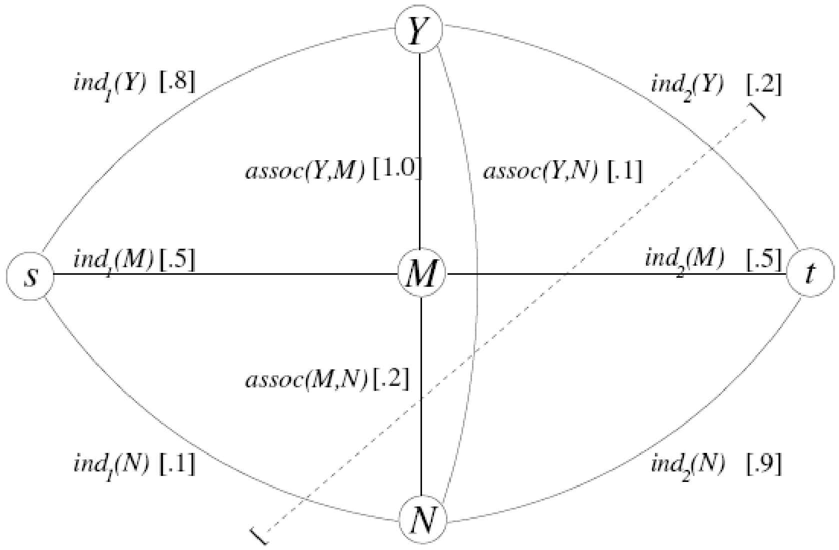
Constructing the graph

- Build an undirected graph G with vertices $\{v1, v2\ldots, s, t\}$ (sentences and s, t)
- Add edges (s, v_i) each with weight $ind_1(x_i)$
- Add edges (t, v_i) each with weight $ind_2(x_i)$
- Add edges (v_i, v_k) with weight $assoc\,(v_i, v_k)$

- Partition cost:

$$\boxed{\sum_{x \in C_1} ind_2(x) + \sum_{x \in C_2} ind_1(x) + \sum_{\substack{x_i \in C_1, \\ x_k \in C_2}} assoc(x_i, x_k).}$$

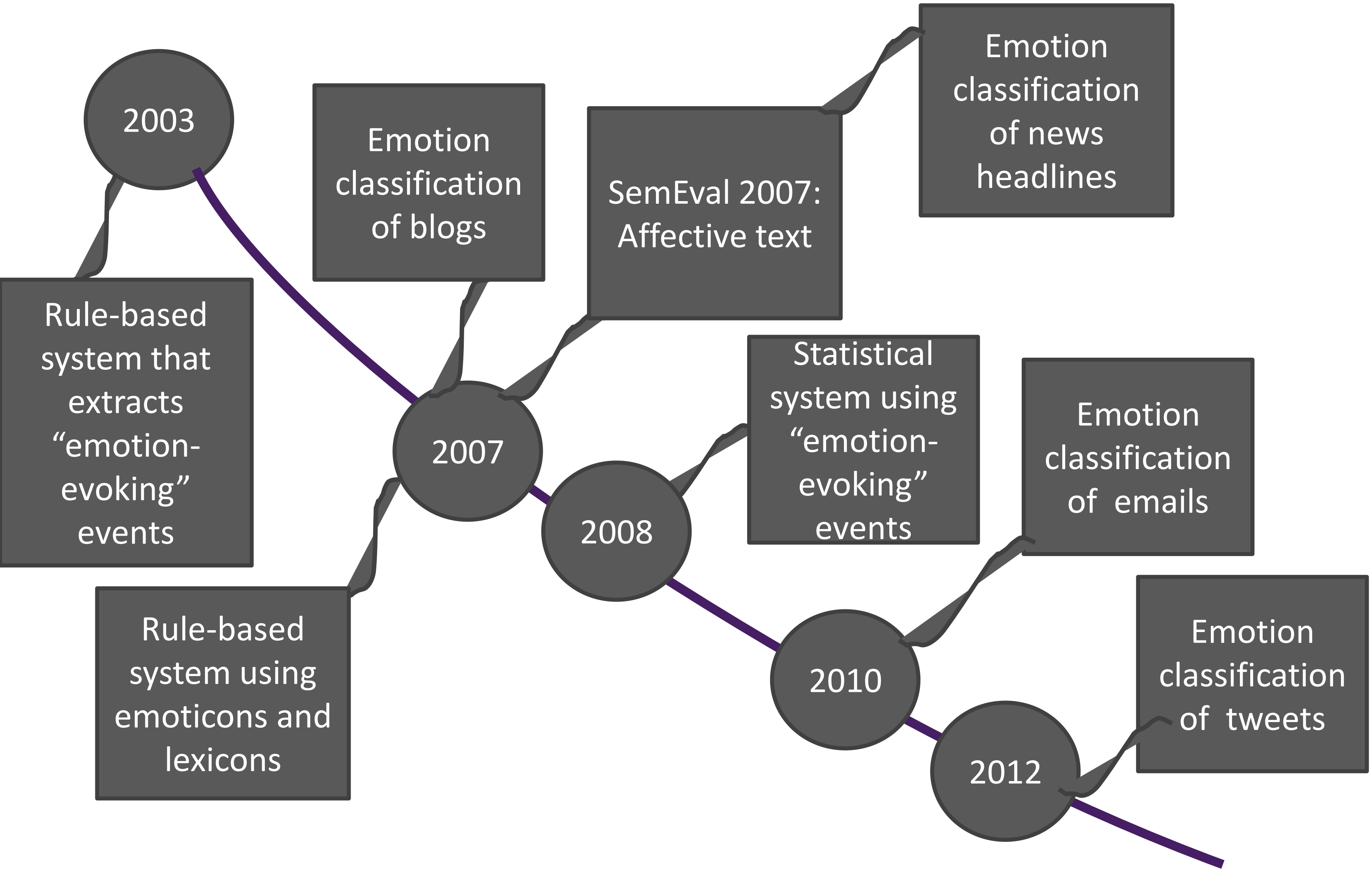
Example



Sample cuts:

C_1	Individual penalties	Association penalties	Cost
{Y,M}	.2 + .5 + .1	.1 + .2	1.1
(none)	.8 + .5 + .1	0	1.4
{Y,M,N}	.2 + .5 + .9	0	1.6
{Y}	.2 + .5 + .1	1.0 + .1	1.9
{N}	.8 + .5 + .9	.1 + .2	2.5
{M}	.8 + .5 + .1	1.0 + .2	2.6
{Y,N}	.2 + .5 + .9	1.0 + .2	2.8
{M,N}	.8 + .5 + .9	1.0 + .1	3.3

Trends


2003
Rule-based system that extracts "emotion-evoking" events
2007
Emotion classification of blogs
Rule-based system using emoticons and lexicons
SemEval 2007: Affective text
Emotion classification of news headlines
2008
Statistical system using "emotion-evoking" events
2010
Emotion classification of emails
2012
Emotion classification of tweets

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Branches of SA

- Cross-domain SA
- Cross-lingual SA
- Aspect-specific SA
- Opinion Summarization
- Sentiment-aware MT

Can SA help MT?

Translate this word:

‘

Applications of EA

Email clients that tell you who the angry customer is

An AI teacher who understands mood of her students

Dialogue systems that are more "human" because they understand emotion

Chat clients that tell you how your friend is feeling

Monitoring emotions for mental heath signals

Why mental health?

- Mental health issues pose risk to lives and wellness of millions of people

- “Everyone is susceptible”. Thompson et al (2014) talks about suicide risks in military officials.

Mental health and Emotion Analysis

- Can emotion analysis be used to predict or assess mental health risks?

- The first confluence of mental health practitioners and NLP researchers was held in ACL 2014: *1st Workshop on "Computational Linguistics and Clinical Psychology – From Linguistic Signals to Clinical Reality" collocated with ACL 2014*

Goal

How do I implement a mental health monitoring system for some illness X?

Train: A labelled dataset

Test: Predict health risk of illness X for a set of unlabeled textual units

A Recipe for Implementing Mental Health Monitors

Step 1: Get data

Step 2: Decide your goal

Step 3: Obtain inputs from clinical psychology

Step 4: Implement the desired classifier/topic model

Step 1: Get data

- As NLP researchers, we look at forms of written text that can be used for health risk signals

Datasets (1/2)

Medical Transcripts

("Doctor, I had a severe pain in my head when I woke up this morning....")

Audio transcripts

Thompson et al (2014) use medical transcripts of military officers talking to therapists as a part of Durkheim Project. Output labels are: contemplating suicide, attempted suicide and not contemplating suicide.

Chat transcripts as in Howes et al (2014)

Experience Descriptions

("I used to be low on Friday evenings. That was strange!..")

Discussion Forums

Ji et al (2014) use data from Aspies, a discussion forum which is used by autism patients and their family members and caretakers.

Datasets (2/2)

Written communications

("Don't you dare to...")

Threat notes

Glasgow et al (2014) use datasets containing threat notes sent to judges.

Social media!

("can't sleep.. Feeling so low tonight.")

Tweets

Coppersmith et al (2014) use tweets of people who have "mentioned" their psychological illness in their tweets.

Step 2: Decide your goal

Do you wish to...

- Predict the risk of an individual to a given mental illness? **Classifier**

- Analyze aspects of a given illness? **Topic Model**

Step 3: Obtain inputs from clinical psychology

- Parameter: What are the typical traits of the mental health issue being considered?

- **How it helps**: Engineering features on the basis of these traits

Orimeye et al (2014) predict Alzheimer’s disease using medical transcript data. Morphemes are used as features. Why?

Caines et al (2014) aim to identify linguistic impairments using disfluency features.

Step 4: Implement the desired system

We discuss in detail two works:

1) A classifier that predicts linguistic impairments due to progressive aphasia

2) Assessment of discussion forums about autism using an author-topic model

Step 4: Implement the desired system

We discuss in detail two works:

1) **A classifier that predicts linguistic impairments due to progressive aphasia**

2) Assessment of discussion forums about autism using an author-topic model

Classifier that predicts progressive aphasia Fraser et al (2014)

- Primary progressive aphasia (PPA) is characterized by linguistic impairment without other notable impairments.

- Two subtypes of PPA:
  - Semantic dementia: Fluent but spared grammar and syntax, etc.
  - Progressive non-fluent aphasia: Reduced syntactic complexity, word-finding difficulties, etc.
- Output labels: SD, PNFA, Typical

Dataset

- 24 patients with PPA and 16 typical individuals were selected.

- Given a topic, say, describe the story of Cinderella, and their speech was recorded and later transcripted

Features in the classifier

- **POS features:** # adjectives, nouns, etc.
- **Complexity features:** Depth of parse tree, etc.
- **CFG Features:** Average phrase length, etc.
- **Fluency features:** Indicators for “umm”s, etc.
- **Psycholinguistic features:** Age of language acquisition, etc.
- **Acoustic features:** Jitters, pause, etc.
- **Vocabulary richness features**

Results

Feature set	SD vs. controls	PNFA vs. controls	SD vs. PNFA
All	**.963**	**.931**	.708
Acoustic	.778	.862	.167
Psycholinguistic	**.963**	.724	.708
POS	**.963**	.690	.375
Complexity	.852	.621	.667
Fluency	.667	.828	.500
Vocab. richness	.481	.586	.583
CFG	.630	.690	**.792**

Step 4: Implement the desired system

We discuss in detail two works:

1) A classifier that predicts linguistic impairments due to progressive aphasia

2) **Assessment of discussion forums about autism using a author-topic model**

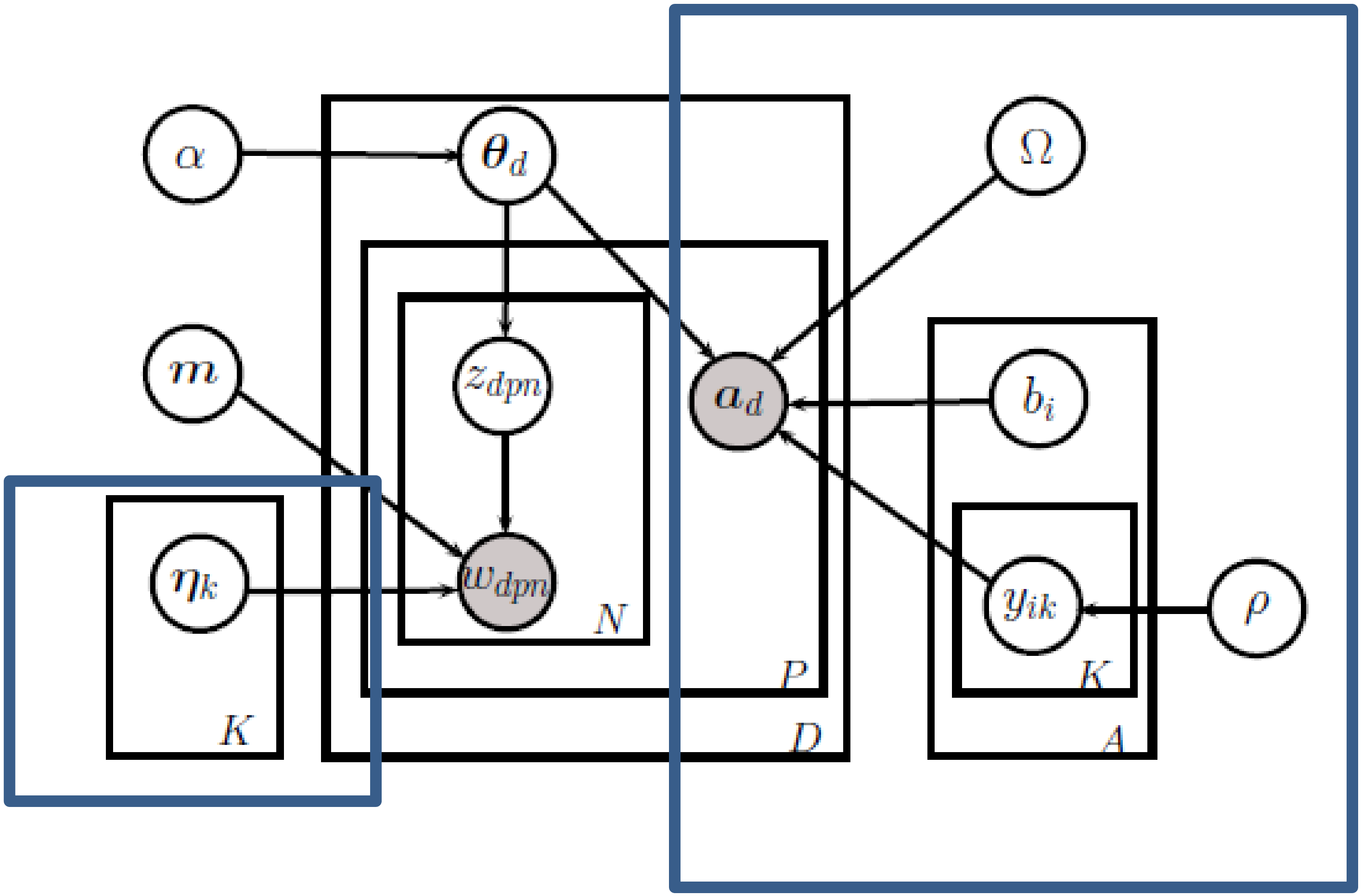
Assessment of topics in Autism communities Ji et al (2014)

- Aspies Central Forum is a discussion forum where individuals with autism and their family, practitioners write on these forums.

- **Goal:** Discover topics that these users talk about on the forum

- A topic model based on LDA was proposed

Proposed topic model



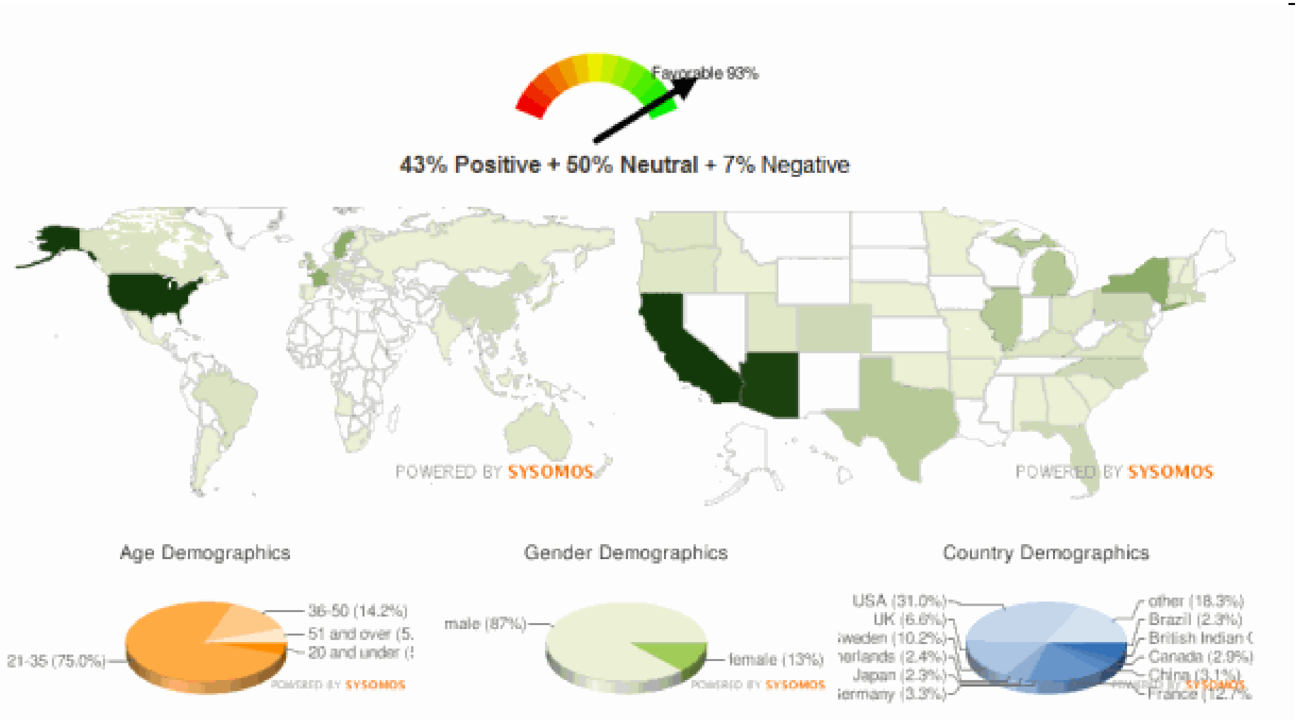
Qualitative Evaluation

Following topics were discovered:

- *weed marijuana pot smoking fishing*
- *empathy smells compassion emotions emotional*
- *relationship women relationships sexual sexually*
- *classroom campus tag numbers exams*
- *yah supervisor behavior taboo phone*
- *depression beleive christianity buddhism becouse*

Some web applications

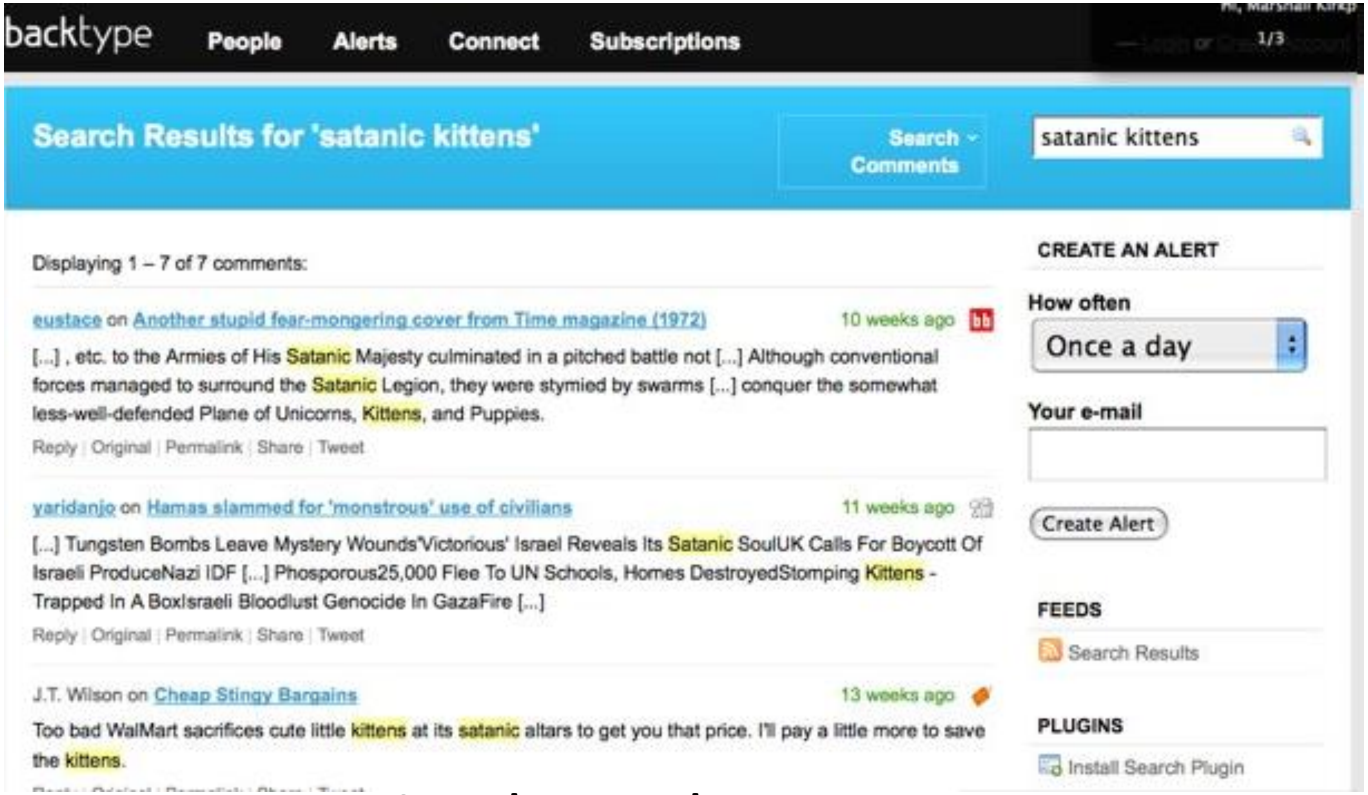
- Spans blogs, social media, news media reports



Snapshot: Sysomos

Conversation analysis

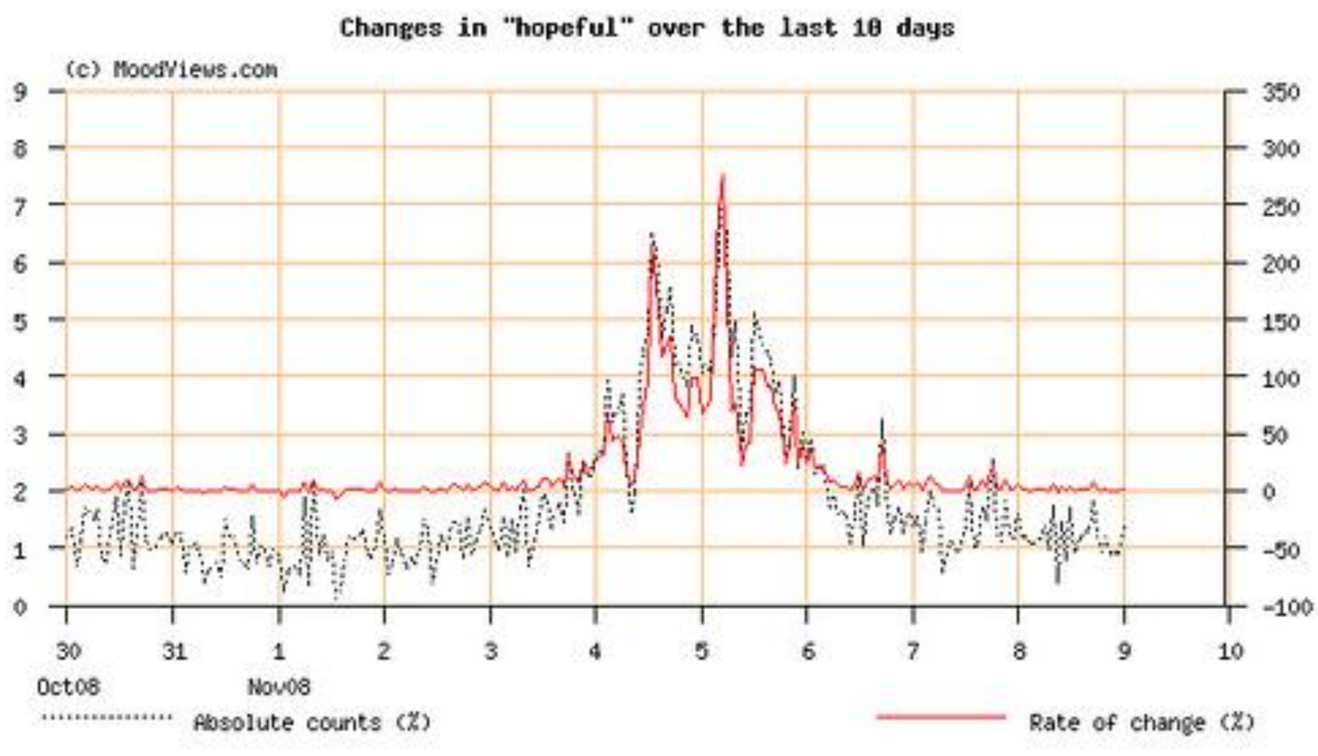
- Tracking conversation on social networking sites



Snapshots: Backtype

Mood analysis

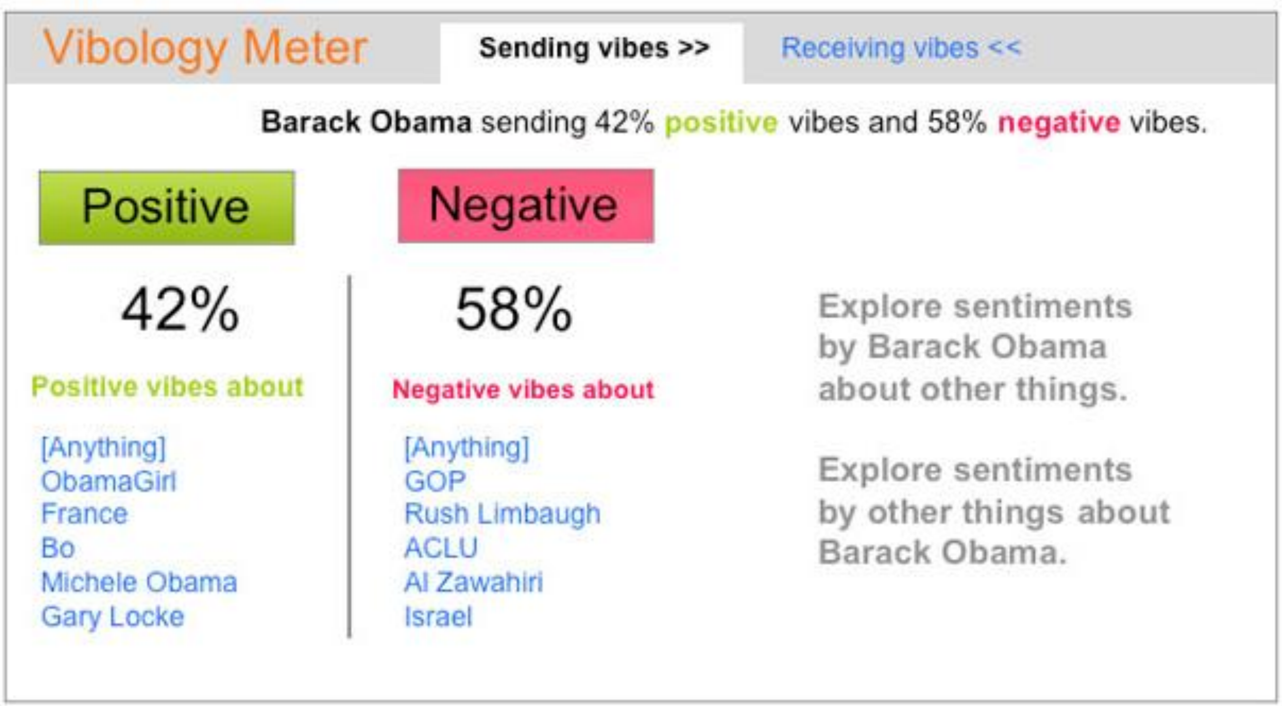
- Real-time updation of moods w. r. t. a topic



Snapshot: MoodViews

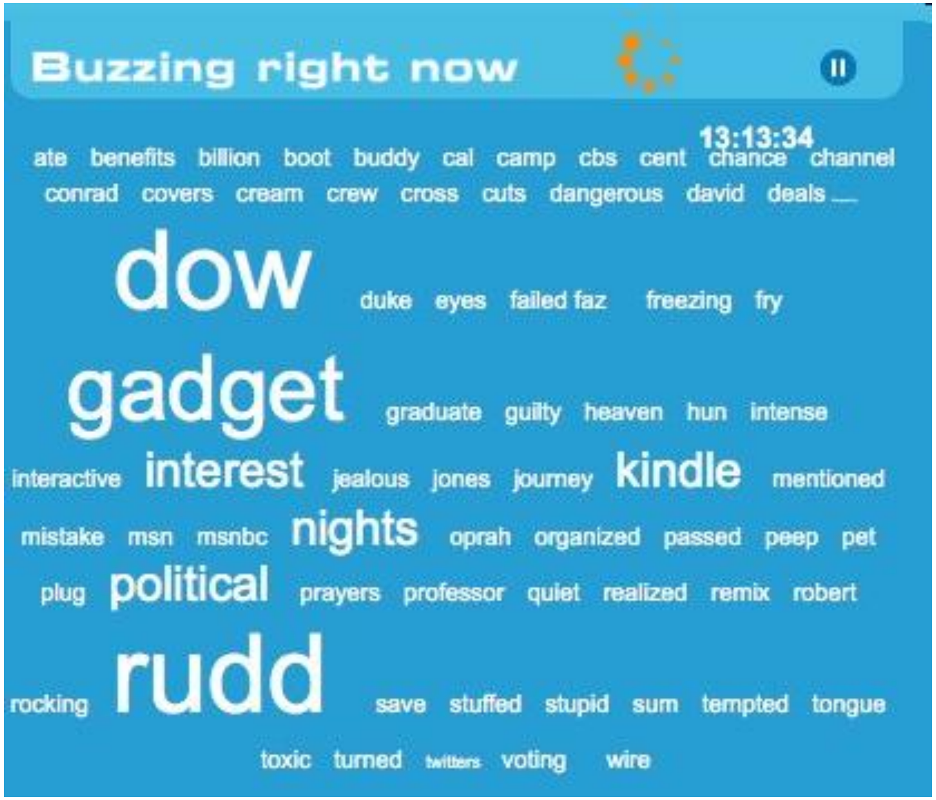
Semantic search

- Sentiment search API by Evri
- Claims to allow deeper answers like “who”, “why”



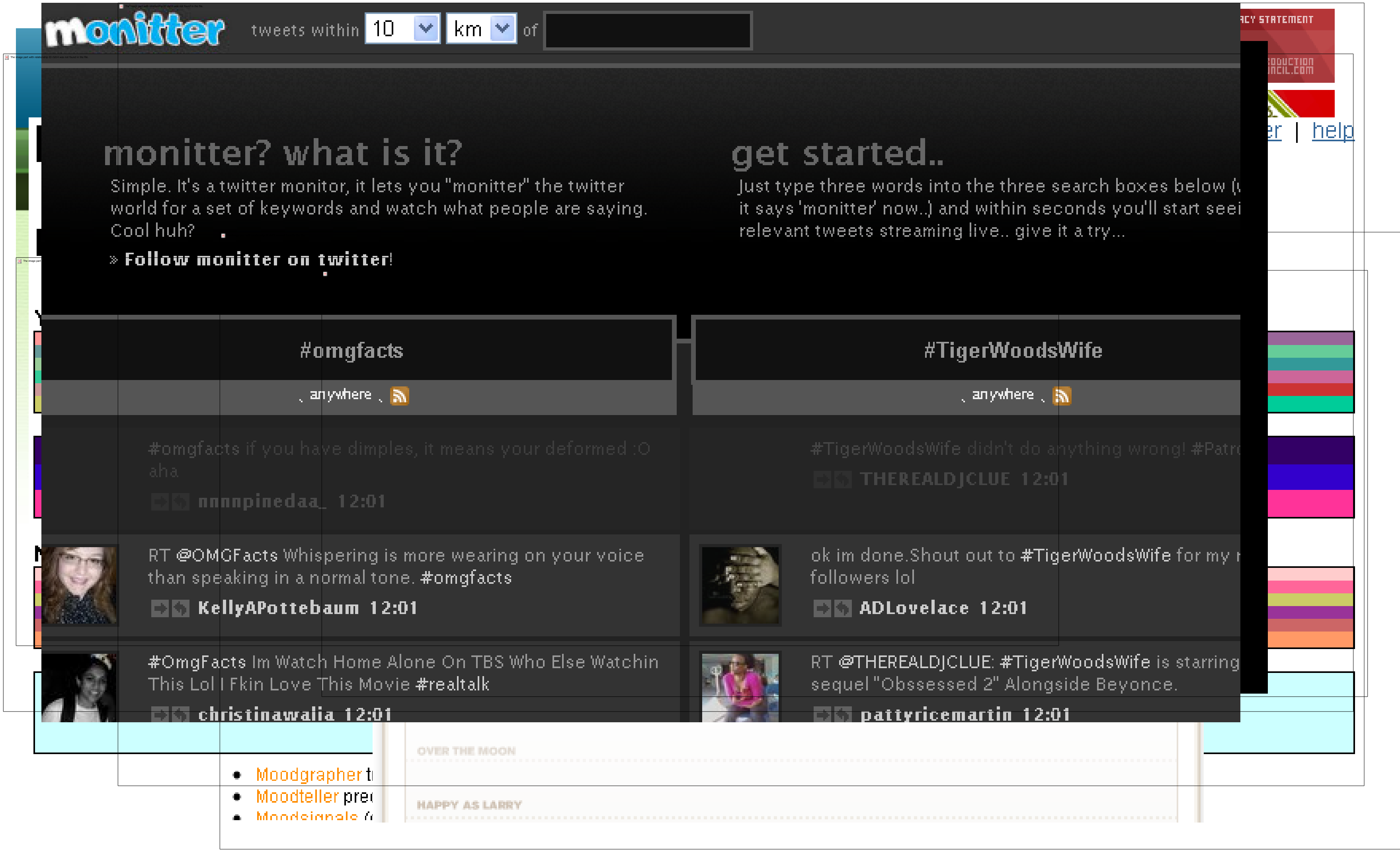
A zeitgeist

- Understanding the 'climate'



Snapshot: Twitscoop

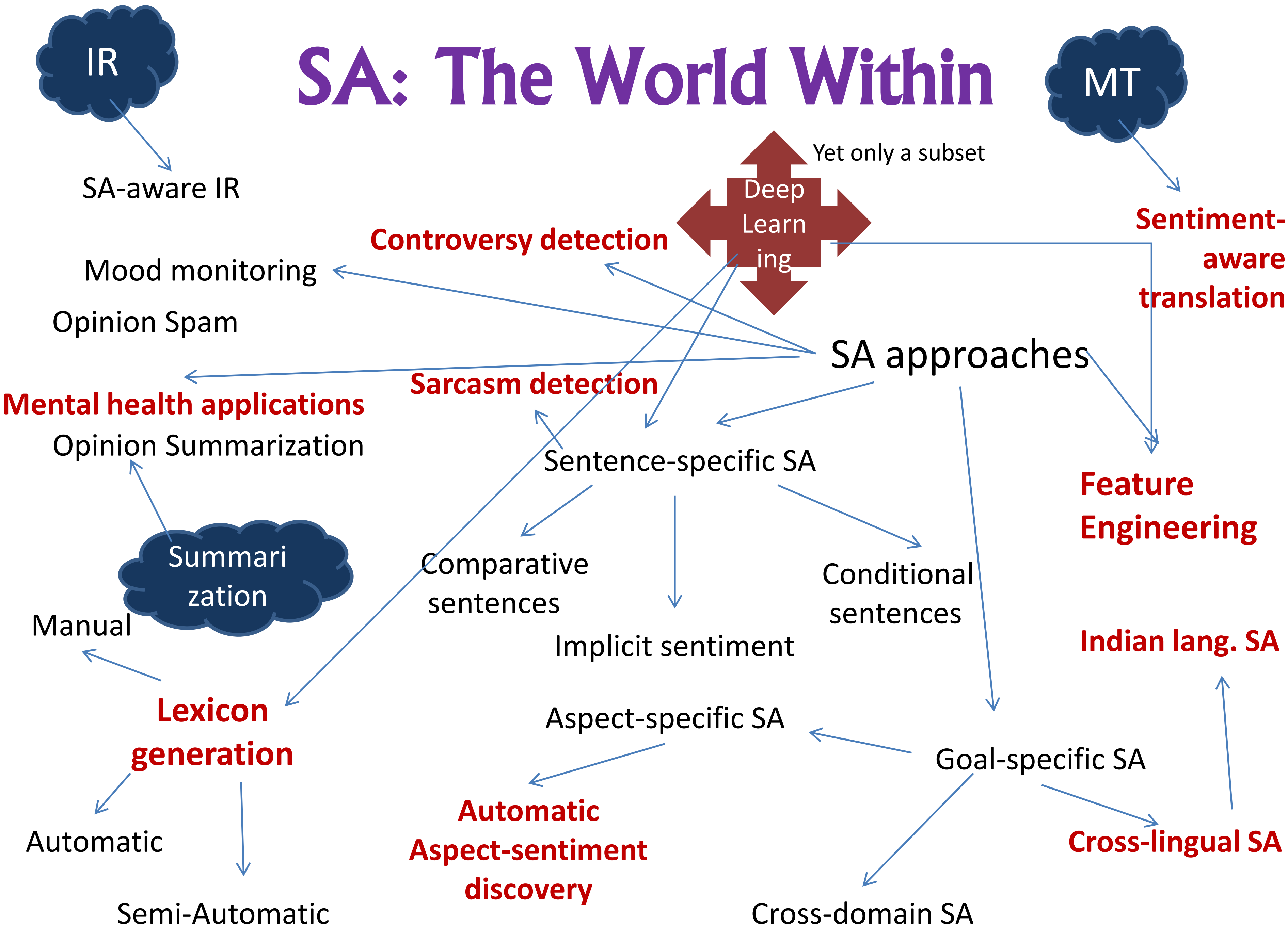
… and many more

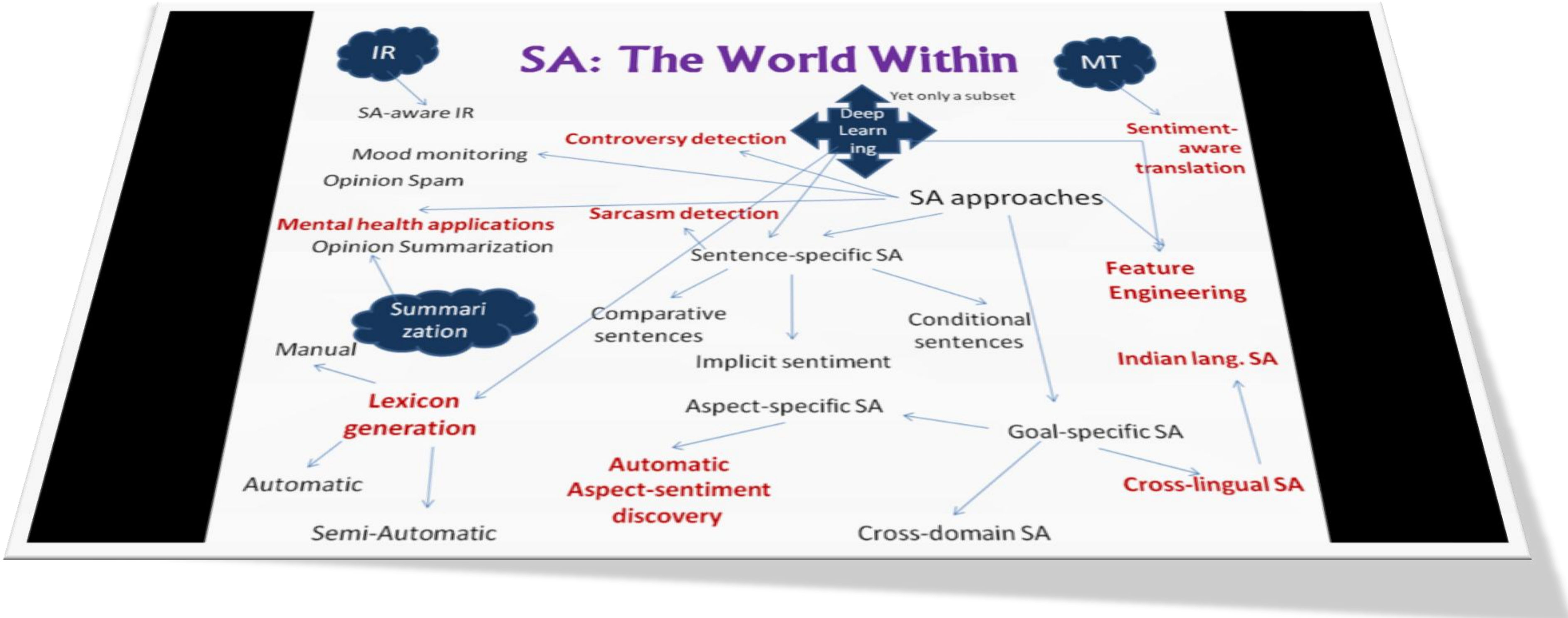


Standard datasets for SA

– Congressional floor-debate transcripts
http://www.cs.cornell.edu/home/llee/data/convote.html
– Cornell movie-review datasets
http://www.cs.cornell.edu/people/pabo/movie-review-data/
– Customer review datasets
http://www.cs.uic.edu/~liub/FBS/CustomerReviewData.zip
– Economining
http://economining.stern.nyu.edu/datasets.html
– MPQA Corpus
http://www.cs.pitt.edu/mpqa/databaserelease
– Multiple-aspect restaurant reviews
http://people.csail.mit.edu/bsnyder/naacl07
– Review-search results sets
http://www.cs.cornell.edu/home/llee/data/search-subj.html
– Saif Mohammed's lexicons
http//www.saifmohammed.com

SA: The World Within





thank you.

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