

Textual Affect Sensing and Affective Communication

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Textual Sentiment Analysis and Affect Sensing

We define here:

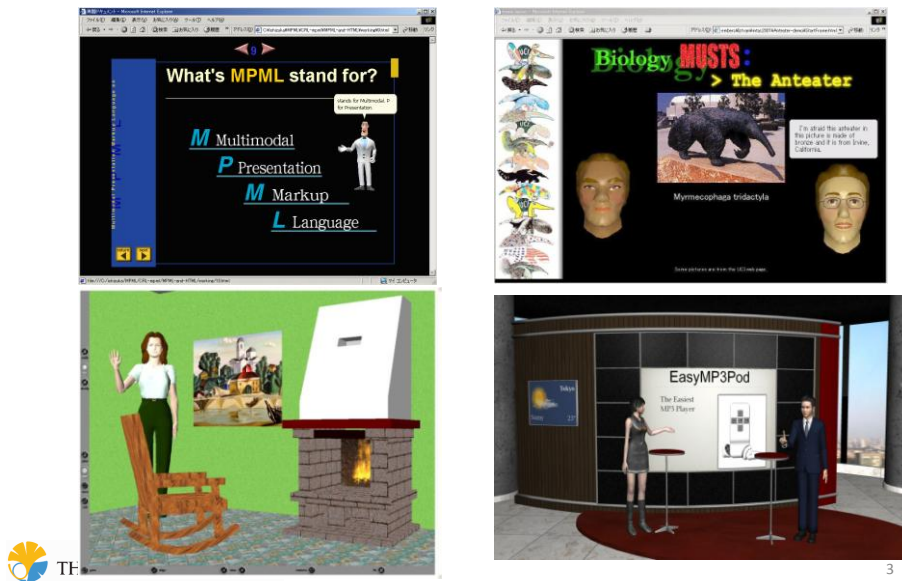
□ Textual Sentiment Analysis

- Positive / Negative (or Neutral)
- Popular in opinion mining

□ Textual Affect Sensing

- more detailed affective or emotional states appearing in text, such as happy, sad, anger, fear, disgust, surprise and much more.

Why we got interested in Textual Affect Sensing: Some of *MPML* Presentations (1)



Some of *MPML* Presentations (2)



MPML (Multimodal Presentation Markup Language) with Emotion Functions

(from 1998)

```
<mpml>
<head>
  <spot id="spot1" location="200,260" />
  <agent id="simasan" system="MSAgent" character="simasan"
    voice="LH" agreeableness="50" activity="50" spot="spot1" />
</head>
<body>
  <seq>
    <scene agents="simasan">
      <page ref="page0.html">
        <play agent="simasan" act="greet" />
        <speak agent="simasan">
          <emotion assign="simasan.happy+" />
          Hello! My name is Sima. Welcome to our Web.
        </speak>
      </page> </scene> </seq>
    </body>
  </mpml>
```

Emotion
Assignment

Several Emotion (or Affect) Models

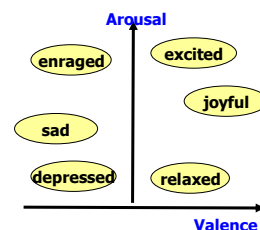
□ Six Basic Emotions (by Ekman)

- happy, sad, surprise, anger, fear, disgust

□ Two-dimensional Emotion Model

(Lang's model or Russell's model)

- **Valence** (positive or negative dimension of feeling)
- **Arousal** (intensity of emotional response)



□ OCC (Ortony, Clore & Collins) Emotion Model

(Cognitive Appraisal Structure Model)

- 22 emotions : most comprehensive

Our Two Approaches

1. A Textual Affect Analysis Model based on Linguistic Compositionality Principle

– An Extended Affective Lexicon: SentiFul

2. Textual OCC Emotion Analysis through Cognitive Variables



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Methods of Textual Affect Sensing and our contribution

Method	Strengths	Weaknesses
Keyword spotting technique	Simple and fast	Restricted to lexicon of sentiment-bearing words Disregards syntactic and semantic information Inaccurate
Commonsense approach	Considers contextual information Relies on real-world knowledge	Relies on manually created network of concepts Strong dependency on well grammatically structured sentences
Machine learning method	(Efficient to classify Neg/Pos, Subjective/Objective opinion) Fast and suitable for large scale data Better for domain specific classification	Requires large annotated corpora Difficult to formulate the diverse set of features Mostly disregards modifiers, negation and condition constructions, syntactic relations and semantic dependencies in sentences Semantically weak Less accurate for sentence-level analysis
Rule-based approach	Works well on sentence and document levels Considers contextual information Easy to improve the rules and extend the lexicon	Relies on manually annotated lexicon Always rules have exceptions Slow performance with large documents Strong dependency on well grammatically structured sentences
plus compositionality principle and the semantics of terms	plus Fine-grained classification of attitude Determines strength of attitude Relies on the extensive set of modifiers, valence shifters, and rules elaborated for semantically distinct verb classes Robust in handling complex cases	← Main contributions

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Rule-based Textual Affect Sensing

- [Boucouvalas(2003)] extracted six basic emotions from chat texts, only if an emotional word referred to the person himself/herself, and the sentence was in present continuous or present perfect continuous tense.

NG “*Onion pie is disgusting.*” “*It was the most joyous feeling!*”

- [Chaumartin(2007)] analyzed news headlines relying on lexicon from WordNet-Affect and SentiWordNet.

- **Linguistic analysis has been weak so far in these researches.**



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Other methods most probably misclassify...

I spent the whole day eating junk food without feeling **guilty**.
[negative => neutral]

**Polarity
Shift**

My whole **enthusiasm** and **excitement** disappear like a bubble touching a hot needle. [positive => negative]

She **never** lost her **animosity** for my brother. [positive => negative]

They discontinued **helping** children. [positive => negative]

It should have been the **greatest** trip of my entire life, but it was a total **nightmare**. [positive/negative? => negative]

Audible chewing is rather **disgusting**, especially if you are also trying to **enjoy** food. . [negative/positive? => negative]

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Affect, Judgement, and Appreciation

‘Attitudinal meanings tend to spread out and colour a phase of discourse as speakers and writers take up a stance oriented to affect, judgment or appreciation.’ by Martin and White (2005)

Attitude types define the specifics of appraisal being expressed .

Affect –

personal emotional state



Judgement –

social or ethical appraisal of other’s behaviour



Appreciation –

evaluation of phenomena, events, objects



Objective: fine-grained sensing of attitude in text



□ **Judgment:** appraisal of person’s character, behaviour, skills

- ‘My Mum is brilliant when she comes to making cakes!!’ (**‘POS jud’**)
- ‘How can people be so mean to hurt an innocent little animal.’ (**‘NEG jud’**)

□ **Appreciation:** evaluation of phenomena, events, objects

- ‘I’ve always thought of life as a precious gift.’ (**‘POS app’**)
- ‘I think those objects are unfriendly for the environment’ (**‘NEG app’**)



WordNet-Affect: our Base Affective Lexicon Database

WordNet-Affect (Strapparava and Valitutti 2004) contains in total

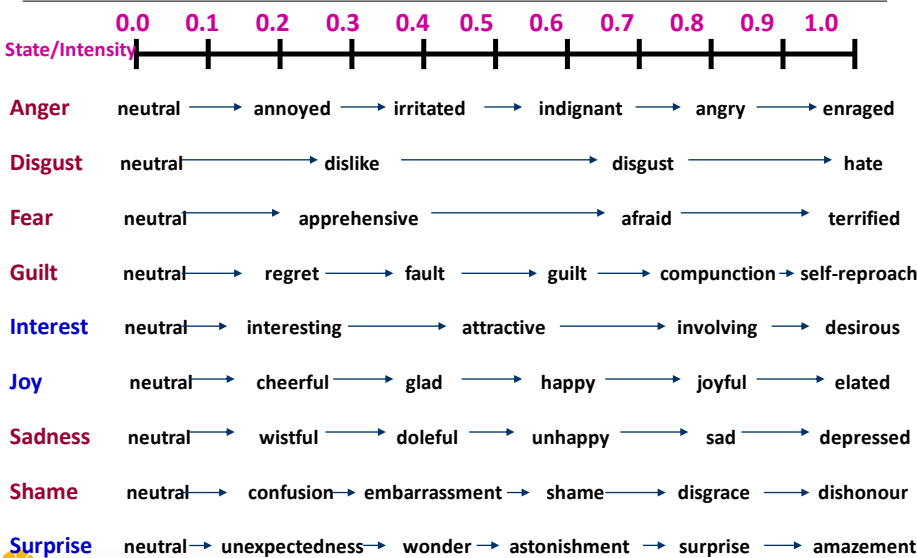
2438 direct and indirect emotion-related entries:

- 918 adjectives (e.g., 'euphoric', 'hostile')
- 243 adverbs (e.g., 'luckily', 'miserably')
- 900 nouns (e.g., 'fright', 'mercy')
- 377 verbs (e.g., 'reward', 'blame')

The affective features are encoded using **nine emotions** and are represented as a **vector of emotional state intensities [0.0-1.0]**

e(word) = (Anger, Disgust, Fear, Guilt, Interest, Joy, Sadness, Shame, Surprise)

Examples of Intensity Levels



Extending Affective Lexicon

- The performance largely depends on the coverage of affective lexicon database.
- Many researchers have attempted so far to extend new words through synonymy/antonymy relations and/or co-location statistics with known words.
 - Relying on direct synonymy relations, we automatically extracted **4190 new words** from WordNet: **1122 adjectives**, **107 adverbs**, **1731 nouns**, and **1230 verbs**.
 - From antonymy relations, we extracted **288 new words** from WordNet: **123 adjectives**, **13 adverbs**, **73 nouns**, and **79 verbs**.
 - In addition, we examined hyponym relation --> next page.
- The derivation of new affective lexicon by manipulating morphological structure and compounding has not been well explored.

Examining Hyponymy Relation

When the features characterizing synset {A} are all included among the features characterizing synset {B}, but not vice versa, then {B} is a hyponym of {A}.
(Miller 1999)

We assume that affect features of a term, along with other features, are to some extent inherited by its hyponym.

'success' (hypernym) => **'winning'** (hyponym)

The algorithm takes into account only one level of specialization.

In total, **1085 new nouns** were added.

Four Types of Affixes (Prefixes and Suffixes)

Propagating affixes preserve sentiment features of the original lexeme and propagate them to newly derived lexical unit

'en-' + 'rich' => 'enrich', 'harmony' + '-ous' => 'harmonious', 'scary' + '-fy' => 'scarify'

Reversing affixes change the orientation of sentiment features of the original lexeme

'dis-' + 'honest' => 'dishonest', 'harm' + '-less' => 'harmless'

Intensifying affixes increase the strength of sentiment features of the original lexeme (coefficient = 2.0)

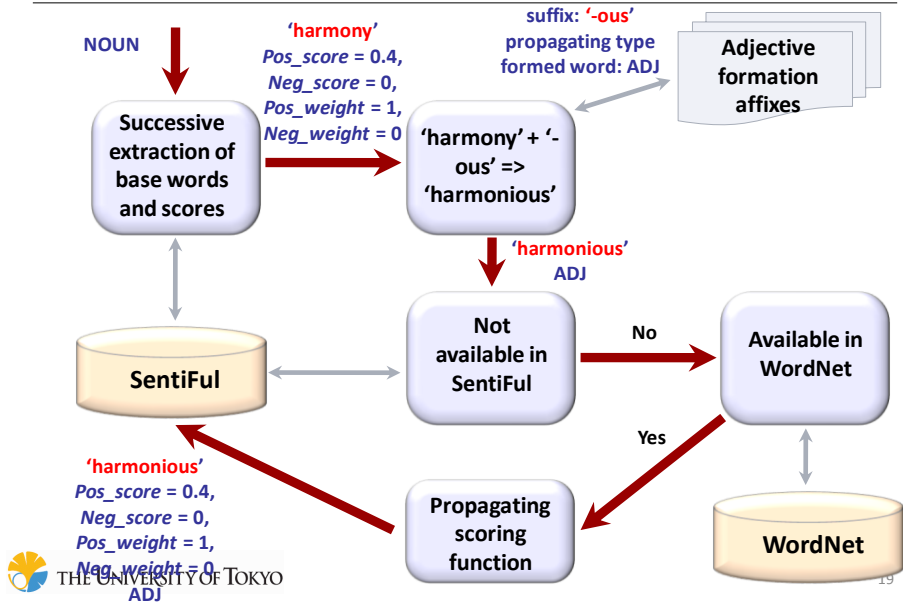
'super-' + 'hero' => 'superhero', 'over-' + 'awe' => 'overawe'

Weakening affixes decrease the strength of sentiment features of the original lexeme (coefficient = 0.5)

'semi-' + 'sweet' => 'semisweet'

Affix type	Prefix (+class of base lexeme); (class of base lexeme+) suffix
Adjective formation	
Propagating	pro- (+a); (a+) -ish; (v+) {-able, -ant, -ent, -ible, -ing}; (n+) {-al, -en, -ful, -ic, -like, -type, -y}; (v/n+) {-ate, -ed, -ive, -ous}
Reversing	{a-, ab-, an-, anti-, contra-, counter-, de-, dis-, dys-, il-, im-, in-, ir-, mal-, mis-, non-, pseudo-, un-, under-} (+a); (n+) -less
Intensifying	{extra-, hyper-, mega-, super-, ultra-} (+a)
Weakening	semi- (+a)
Adverb formation	
Propagating	pro- (+adv); (a+) -ly; (n+) {-wise, -wards}
Reversing	{a-, ab-, an-, anti-, contra-, counter-, de-, dis-, dys-, il-, im-, in-, ir-, mal-, mis-, non-, pseudo-, un-, under-} (+adv)
Intensifying	{extra-, hyper-, mega-, super-, ultra-} (+adv)
Weakening	semi- (+adv)
Noun formation	
Propagating	{neo-, re-} (+n); (v+) {-age, -al, -ant, -ation, -ent, -ication, -ification, -ion, -ment, -sion, -tion, -ure}; (a+) {-ity, -ness}; (n+) {-ful, -ist, -ship}; (v/a+) {-ance, -ence, -ee}; (v/n+) {-er, -ing, -or}; (a/n+) {-cy, -dom, -hood}; (v/n/a) {-ery, -ry}
Reversing	{anti-, counter-, dis-, dys-, in-, mal-, mis-, non-, pseudo-, under-} (+n)
Intensifying	{arch-, hyper-, mega-, super-, ultra-} (+n)
Weakening	{mini-, semi-} (+n); (n+) {-ette, -let}
Verb formation	
Propagating	{be-, co-, fore-, inter-, pre-, pro-, re-, trans-} (+v); {em-, en-} (+n/a); (n/a+) {-ate, -en, -fy, -ify, -ise, -ize}
Reversing	{de-, dis-, dys-, mis-, un-, under-} (+v)
Intensifying	{out-, over-} (+v)

Extension through manipulating Prefixes and Suffixes



Extension through morphological modifications

- Using this morphologically inspired method, we automatically derived and scored **4029 new words**:
1405 adjectives, 484 adverbs, 1800 nouns, and 340 verbs.

POS	Top 10 most productive affixes									
adjective	-ed	-ing	un-	-able	-less	-ive	-y	-ful	-al	in-
adverb	-ly	un-	a-	in-	im-	dis-	-wise	-wards	-	-
noun	-er	-ing	-ness	-or	-ion	-ation	-ment	-ist	-ery	-ity
verb	re-	over-	-en	dis-	un-	de-	out-	mis-	-ize	-ise

Compounding using known affect-carrying base components

Compounding functions as a linguistic economy-mechanism that allows expressing in a concise way something which would otherwise have to be rendered by means of a phrase. (Meys 1975)

Patterns	Structure in terms of paraphrasing	Examples of compound words	Valence-based interpretation	Rule
Formation of noun compounds				
noun + noun	'modifier-head'	<i>love-affair</i> <i>death-feud</i>	pos-neutral => pos neg-neg => neg	Rule 1 Rule 2a
noun + noun/verb-er	'verb-object'	<i>peace-lover</i> <i>pain-killer</i>	pos-pos => pos neg-neg => pos	Rule 3a Rule 3b
noun + verb-ing	'verb-object'	<i>law-breaking</i>	neutral-neg => neg	Rule 1
adjective + noun	'modifier-head'	<i>good-neighborliness</i> <i>no-nonsense</i>	pos-neutral => pos 'negation'-neg=> pos	Rule 1 Rule 5
verb + noun	'modifier-head'	<i>cry-baby</i>	neg-neutral => neg	Rule 1
verb-ing + noun	'modifier-head'	<i>loving-kindness</i>	pos-pos => pos	Rule 2a
pronoun + noun	'modifier-head'	<i>self-pity</i>	neutral-neg => neg	Rule 1
noun + preposition + noun	'modifier-head'	<i>wall-of-death</i>	neutral-neg => neg	Rule 1
Formation of adjectival compounds				
noun + verb-ing	'verb-object'	<i>award-winning</i> <i>health-destroying</i> <i>quarrel-loving</i>	pos-pos => pos pos-neg => neg neg-pos => neg	Rule 3a Rule 3c Rule 3d
pronoun + verb-ing	'verb-object'	<i>self-destructing</i>	neutral-neg => neg	Rule 1
adjective + verb-ing	'modifier-head'	<i>pleasant-testing</i>	pos-neutral => pos	Rule 1
adverb + verb-ing	'modifier-head'	<i>equally-damaging</i>	neutral-neg => neg	Rule 1
noun + verb-en	'verb-PP'	<i>fortune-favored</i> <i>war-torn</i> <i>love-agonized</i>	pos-pos => pos neg-neg => neg pos-neg => neg	Rule 4a Rule 4a Rule 4b
pronoun + verb-en	'verb-PP'	<i>self-convicted</i>	neutral-neg => neg	Rule 1
adjective + verb-en	'modifier-head'	<i>kind-hearted</i>	pos-neutral => pos	Rule 1
adverb + verb-en	'modifier-head'	<i>poorly-adapted</i> <i>well-merited</i> <i>ill-famed</i>	neg-neutral => neg pos-pos => pos neg-pos => neg	Rule 1 Rule 2a Rule 2b
verb-en + preposition	'verb-preposition'	<i>broken-down</i>	neg-neutral => neg	Rule 1
adjective + verb	'modifier-head'	<i>easy-follow</i> <i>difficult-to-master</i>	pos-neutral => pos neg-pos => neg	Rule 1 Rule 2b
noun + adjective	'modifier-head'	<i>crash-proof</i> <i>error-free</i>	neg-'valence shifter' => pos neg-'valence shifter' => pos	Rule 6 Rule 6
pronoun + adjective	'modifier-head'	<i>self-conscious</i>	neutral-pos => pos	Rule 1
adjective + preposition + pronoun	'adjective-PP'	<i>spurious-to-me</i> <i>good-for-nothing</i>	neg-neutral => neg pos-'negation' => neg	Rule 1 Rule 5
adjective + noun	'modifier-head'	<i>no-win</i>	'negation'-pos=> neg	Rule 5
adjective + adjective	'modifier-head'	<i>manic-depressive</i>	neg-neg => neg	Rule 2a
adverb + adjective	'modifier-head'	<i>critically-ill</i> <i>not-too-pleasant</i>	neg-neg => neg 'negation'-pos => neg	Rule 2a Rule 5
verb + noun	'verb-object'	<i>ban-the-bomb</i>	neg-neg => pos	Rule 3b
verb + adjective	'verb-adjective'	<i>get-rich-quick</i>	neutral-pos => pos	Rule 1 [±]
verb + adverb	'modifier-head'	<i>die-hard</i>	neg-(indirect)pos => pos	Rule 2b

Compounding Rules (1)

Rule 1: If one of the constituent elements of a compound conveys sentiment features, and another element, which is not 'negation' or 'valence shifter' word, is neutral, then sentiment-features are propagated to the whole compound:

'good' (0.3 / 0.0) + *'neighborliness'* => *'good-neighborliness'* (0.3 / 0.0)

Rule 2: If a compound is interpreted in such a way that one member modifies another member (so called '**modifier-head**' structure), and both the 'modifier' and the 'head' are sentiment-conveying terms, then:

Rule 2a: if both components are predominantly positive (or negative), then their sentiment features (scores and weights) are averaged, and the result is assigned to the whole word:

'loving' (0.9 / 0.0) + *'kindness'* (0.6 / 0.0) => *'loving-kindness'* (0.75 / 0.0)

Rule 2b: if both components have contrasting sentiment features, then sentiment features of the 'modifying' member are considered as dominant and are propagated to the whole word:

'ill' (0.0 / 0.467) + *'famed'* (0.475 / 0.0) => *'ill-famed'* (0.0 / 0.467)



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Compounding Rules (2)

Rule 3: If a compound corresponds to one of the patterns, which can be paraphrased as 'verb + direct object' (so called '**verb-object**' structure), and both components are sentiment-conveying terms, then:

Rule 3a: if both 'noun' and 'verb/verbal' members are predominantly positive, then their sentiment features (scores and weights) are averaged:

'award' (0.55 / 0.0) + *'winning'* (0.8 / 0.0) => *'award-winning'* (0.675 / 0.0)

Rule 3b: if both 'noun' and 'verb/verbal' members are predominantly negative, then their sentiment features are averaged, and the inverted result is assigned to the word:

'pain' (0.0 / 0.8) + *'killer'* (0.0 / 0.35) => *'pain-killer'* (0.575 / 0.0)

Rule 3c: if 'noun' member is positive and 'verb/verbal' member is negative, then sentiment features of the 'verb/verbal' member are considered as dominant:

'health' (0.25 / 0.0) + *'destroying'* (0.0 / 0.65) => *'health-destroying'* (0.0 / 0.65)

Rule 3d: if 'noun' member is negative and 'verb/verbal' member is positive, then sentiment features of the 'noun' member are considered as dominant:

'quarrel' (0.0 / 0.35) + *'loving'* (0.9 / 0.0) => *'quarrel-loving'* (0.0 / 0.35)



Compounding Rules (3)

Rule 4: If a compound corresponds to the pattern, which can be paraphrased as 'verb-en by/with/in/from noun' (so called '**verb-PP structure**'), where 'noun' member represents agent, instrument, location etc., and both components are sentiment-conveying terms.

Rule 4a: if both components are predominantly positive (or negative), then their sentiment features (scores and weights) are averaged:

'fortune' (0.7 / 0.0) + *'favored'* (0.6 / 0.0) => *'fortune-favored'* (0.65 / 0.0)

Rule 4b: if both components have contrasting sentiment features, then sentiment features of the 'verbal' member (verb-en) are considered as dominant:

'love' (0.9 / 0.0) + *'agonized'* (0.0 / 0.85) => *'love-agonized'* (0.0 / 0.85)

Rule 5: If one of the elements of a compound conveys sentiment features, and another element is '**negation word**', then sentiment features are reversed:

'good' (0.3 / 0.0) + *'for'* + *'nothing'* (negation) => *'good-for-nothing'* (0.0 / 0.3)

Rule 6: If left-hand member conveys sentiment features, and right-hand member is '**valence shifter**' (e.g., '*safe*', '*free*', '*proof*', etc.), then sentiment features are reversed:

'risk' (0.0 / 0.567) + *'free'* (valence shifter) => *'risk-free'* (0.567 / 0.0)

Neoclassical Compounds

□ Compounds with key ending elements of **Latin or Greek origins**, that have strongly affective content, were automatically extracted:

- **'-cide'** (meaning: '*murder*' (0.0 / 0.8)): '*genocide*', '*suicide*' etc.
- **'-itis'** (meaning: '*disease*' (0.0 / 0.3)): '*appendicitis*', '*radiculitis*' etc.
- **'-phobe'** (meaning: '*fear*' (0.0 / 0.9)): '*claustrophobe*', '*technophobe*' etc.

SentiFul: An Extended Rich Affect Lexicon thus constructed

SentiFul		Available affective lexicons	
Core of SentiFul (WordNet-Affect)	2438	HM lexicon (<i>Hatzivassiloglou and McKeown 1997</i>)	1336
Synonymy	4190	SentiGI (<i>Esuli and Sebastiani 2006</i>)	3596
Antonymy	288	General Inquirer polarity lexicon (http://www.wjh.harvard.edu/~inquirer/)	4002
Hyponymy	1085	Subjectivity lexicon (<i>Wilson, Wiebe, and Hoffmann 2005</i>)	~8000
Derivation (Affixes)	4029		
Compounding	853		
SentiFul TOTAL	12883		

Evaluation based on manual annotations

- 1000 terms were randomly extracted from SentiFul and manually annotated with dominant polarity label (positive, negative, or neutral) and polarity score by two humans. **“Gold standard”**: words with complete agreement on the polarity label, excluding words with neutral label.

Results of evaluation of polarity assignments

Method	Kappa	Words with complete agreement	Percentage distribution of labels, %			Words in the “gold standard”	Accuracy, %	Precision, %		Recall, %		F-score, %	
			pos	neg	neutral			pos	neg	pos	neg	pos	neg
Synonymy	0.78	179	27.9	69.8	2.2	175	95.4	86.2	100	100	93.6	92.6	96.7
Antonymy	0.66	156	44.2	26.3	29.5	110	94.5	97.0	90.7	94.2	95.1	95.6	92.9
Hyponymy	0.87	187	31.6	67.4	1.1	185	98.9	96.7	100	100	98.4	98.3	99.2
Derivation	0.91	191	35.6	60.7	3.7	184	97.8	95.7	99.1	98.5	97.4	97.1	98.3
Compounding	0.93	193	45.6	53.9	0.5	192	99.5	98.9	100	100	99.0	99.4	99.5

Accuracy with regard to different parts-of-speech

Method	Accuracy, %			
	adjectives	adverbs	nouns	verbs
Synonymy	95.7	90.5	97.8	97.6
Antonymy	91.7	75.0	100	96.2
Hyponymy	-	-	98.9	-
Derivation	93.8	97.9	100	100
Compounding	100	100	98.8	100

Examples of erroneous outcomes

based on derivation:

'reprise', 'lovage', 'truster' => positive in SentiFul
'chanceful', 'fanciful', 'oddish' => positive in SentiFul
'modestly' => negative in SentiFul

based on compounding:

'half-truth' => positive in SentiFul
'trouble-shoot' => negative in SentiFul

Emoticons and Abbreviations (especially for IM)

Symbolic representation	Meaning	Category	Intensity
AMERICAN EMOTICONS (164)			
:~)	happy	Joy	0.6
:~o	surprise	Surprise	0.8
:~S	worried	Fear	0.4
:~h	bye-bye	Farewell	-
JAPANESE EMOTICONS (200)			
/(^O^)/	very excited	Joy	1.0
(>_<)	pain	Sadness	0.8
(~_~)	grumpy	Anger	0.3
m(_._)m	bowing, thanks	Thanks	-
ABBREVIATIONS (337 with 168 plain entries)			
JK	just kidding	Joy	0.3
IHA	I hate acronyms	Disgust	0.9
4U	for you	-	-
PLZ	please	-	-

Lexicon for Attitude (Affect) Analysis -- Related Functional Words

□ 'Reversing'/'Neutralizing' type of

- ✓ **adjectives** ('*reduced*')
 - ✓ **nouns** ('*reduction*', '*termination*')
 - ✓ **verbs** ('*to reduce*', '*to limit*')
 - reverse/neutralize the prior polarity of a related word

□ 'Intensifying' type of

- ✓ **adjectives** ('*rapidly-growing*')
 - ✓ **nouns** ('*upsurge*')
 - ✓ **verbs** ('*to increase*')
 - increase the strength of attitude of related words

240 functional words in total

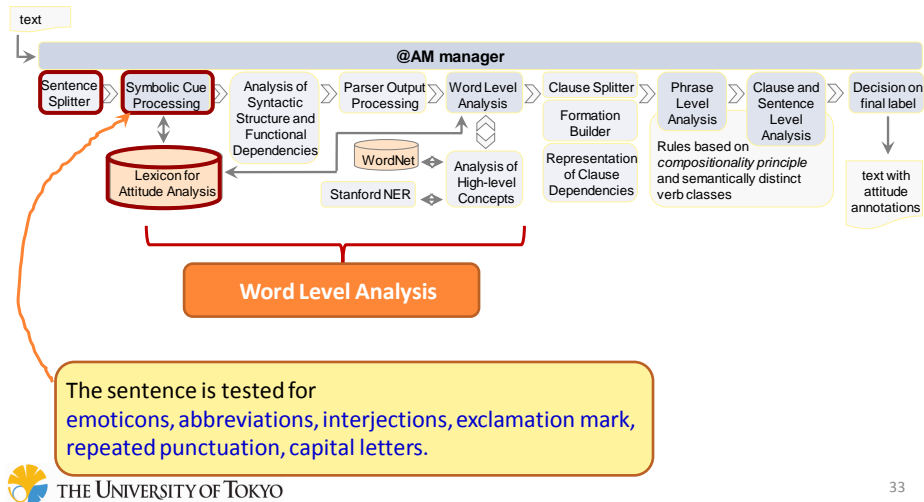
Lexicon for Attitude (Affect) Analysis -- Related Modifiers

- **Adverbs of degree** ('*significantly*', '*slightly*') and **adverbs of affirmation** ('*absolutely*', '*seemingly*') influence **the strength** of attitude of the related words through coefficients for intensity degree strengthening or weakening (from 0.0 to 2.0)
- **Prepositions** such as '*without*', '*despite*' etc., **neutralize** the attitude of related words
- **Negation words** ('*never*', '*nothing*', '*no*'), **adverbs of doubt** ('*scarcely*', '*hardly*') and **adverbs of falseness** ('*incorrectly*', '*wrongly*') **reverse/neutralize the polarity** of related statement
- **Condition operators** ('*although*', '*as if*', '*even though*') **neutralize** the attitude of related words

138 related modifiers in total

Affect Analysis – Word Level

Word Level → Phrase Level → Clause and Sentence Level Analyses



Emoticons and Abbreviations that relate to emotional states

- If they exist, they dominate the affect of the entire sentence.

Thank you so much for your kind encouragement Sad: 0.8 :-([sad].

Joy: 0.6 G [grin], nice song too, or was Joy: 0.3 ;-) [winking].

I did not save that song Fear: 0.4 :S [worry] , please send it once more Shame: 0.5 :"> [blushing].

I'll take that as a compliment Joy: 0.3 ;) thnx Thanks

am because
 I m stressed bc i have frequent headaches

Word-level Analysis -- comparative and superlative forms, and modifier coefficients

Affective word is represented as a **vector** of emotional state intensities:

$e = [\text{Anger}, \text{Disgust}, \text{Fear}, \text{Guilt}, \text{Interest}, \text{Joy}, \text{Sadness}, \text{Shame}, \text{Surprise}]$

EXAMPLE: $e(\text{"frustrated"}) = [0.2, 0, 0, 0, 0, 0, 0, 0.7, 0, 0]$

Emotional vectors of **adjectives and adverbs in comparative and superlative forms** are multiplied by the values 1.2 and 1.4, respectively:

$e(\text{"glad"}) = [0, 0, 0, 0, 0, 0.4, 0, 0, 0];$

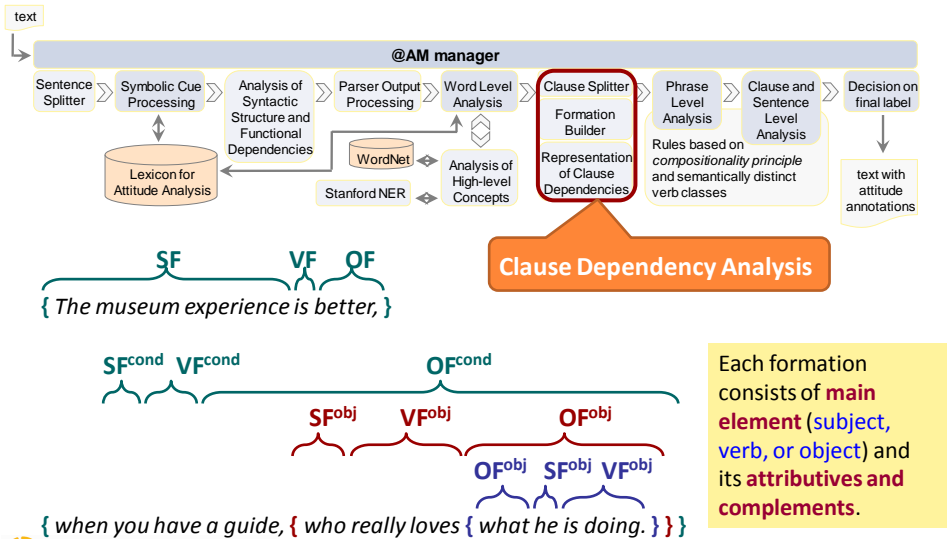
$e(\text{"gladder"}) = [0, 0, 0, 0, 0, 0.48, 0, 0, 0];$

$e(\text{"gladdest"}) = [0, 0, 0, 0, 0, 0.56, 0, 0, 0].$

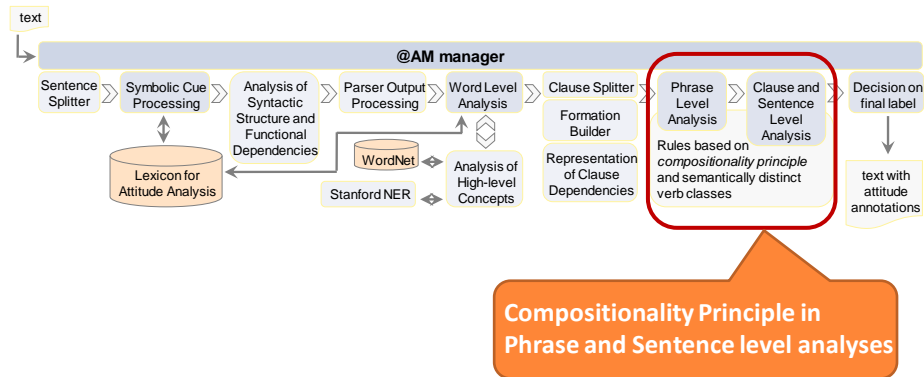
Modifier (112) coefficients are identified (to strengthen or weaken the intensity):

Ex) $\text{coeff}(\text{"very"}) = 1.4$, $\text{coeff}(\text{"certainly"}) = 1.2$,
 $\text{coeff}(\text{"slightly"}) = 0.2$, $\text{coeff}(\text{"hardly"}) = 0$,

Clause Dependency Analysis into the formations of subject (SF), verb(VF) and object(OF)



Affect Analysis in Phrase, Clause and Sentence Levels



Compositionality Principle

‘The full story of how lexical items reflect attitudes is more complex than simply counting the valences of terms’ (Polanyi and Zaenen 2004)

Compositionality principle: the attitudinal meaning of a sentence is determined by composing a pieces that correspond to lexical units or other linguistic constituent types governed by the rules of

- ✓ *polarity reversal*
- ✓ *aggregation (fusion)*
- ✓ *propagation*
- ✓ *domination*
- ✓ *neutralization* , and
- ✓ *intensification* at various grammatical levels.

Phrase-level Analysis (1)

Types of phrases to analyze and rules for processing

- Adjective phrase:** “*extremely sad*” → modify the vector of adjective
- Noun phrase:** “*brotherly love*” } → output vector with the maximum intensity within each corresponding emotional state
- Verb plus adverbial phrase:** “*shamefully deceive*” }
- Verb plus noun phrase:** } opposite polarity in verb-object formation
- “*(break)⁻ (favourite vase)⁺*” } → consider vector of verb as dominant
- “*(enjoy)⁺ (bad weather)⁻*” } → output vector with the *maximum intensity* within each corresponding emotional state
- “*(like)⁺ (honey)⁺*” } →
- “*(hate)⁻ (crying)⁻*” } →
- Verb plus adjective phrase:** } → output vector of adjective phrase
- “*is very kind*” }
- “*feel bad*” }

Phrase-level Analysis (2)

Rules for modifiers

Intensifiers (“*very*”, “*extremely*”, “*slightly*”, “*hardly*”, “*less*” etc.) **multiply or decrease** emotional intensity values.

Negation modifiers such as “*no*”, “*not*”, “*never*”, “*any*”, “*nothing*”, and connector “*neither...nor*” **cancel** (set to zero) vectors of related words.

Yesterday I went to a party, but *nothing exciting* happened there.

Prepositions such as “*without*”, “*except*”, “*against*”, “*despite*” **cancel** vectors of related words.

I climbed the mountain *without fear*.

Phrase-level Analysis (3)

Conditional clause phrases beginning with
“if”, “when”, “whenever”, “after”, “before” etc.

Statements with

- words like *“think”, “believe”, “sure”, “know”*
- modal operators like *“can”, “may”, “would”* etc.

ARE DISREGARDED

I eat **when** I'm angry, sad, bored...

If only my brain was like a thumb drive, how splendid it **would** be.

Sentence-level Analysis (1)

Emotional vector of a simple sentence (or of a clause)

1. First, we derive emotion vector of **Verb-Object formation** relation.
2. The estimation of the emotion vector of a clause (**Subject plus Verb-Object formations**) is then performed in the following manner:

- ✓ if valences of Subject formation and Verb formation are **opposite**, we consider the vector of the **Verb-Object formation as dominant**

SF(+): My darling VF(-): smashed OF: his guitar

SF(-): Troubled period VF(+): luckily comes to an end

- ✓ **otherwise**, we output the vector with **maximum intensities** in corresponding emotional states of vectors of Subject and Verb-Object formations

Sentence-level Analysis (2): modification according to tense and first person pronouns

Overall affect of simple sentence (or each clause) is modified by coefficient of intensity correction.

Tense	First person pronouns	
	yes	no
present	1 <i>My vase is broken</i>	0.8 <i>She is annoying</i>
past	0.8 <i>He made me angry</i>	0.4 <i>It was the most joyous feeling</i>
future	0.4 <i>I will enjoy the trip to Egypt</i>	0 <i>The game will definitely bring them triumph</i>

Paul Ekman: “Emotions typically occur in response to an event, usually a social event, **REAL**, **REMEMBERED**, **ANTICIPATED**, or **IMAGINED**.” [Ekman P., 1993]

Sentence-level Analysis (3) an example of affect sensing in a simple sentence

“My darling smashed his most favorite guitar without regret ”

	word:	word-level:	phrase-level:
SF:	my darling	$e^0 = [0,0,0,0,0,0,0,0,0]$ $e^+ = [0,0,0,0,0,0.7,0,0,0]$	$e^+ = [0,0,0,0,0,0.7,0,0,0]$
VF:	smashed without regret	$e^- = [0,0,0.6,0,0,0,0.8,0,0]$ modif. coeff=0.0 $e^- = [0,0,0,0.2,0,0,0.1,0,0]$	$e^- = [0,0,0.6,0,0,0,0.8,0,0]$ $e^0 = [0,0,0,0,0,0,0,0,0]$ $e^- = [0,0,0.6,0,0,0,0.8,0,0]$
OF:	his most favourite guitar	$e^0 = [0,0,0,0,0,0,0,0,0]$ modif. coeff = 1.4 $e^+ = [0,0,0,0,0,0.6,0,0,0]$ $e^0 = [0,0,0,0,0,0,0,0,0]$	$e^0 = [0,0,0,0,0,0,0,0,0]$ $e^+ = [0,0,0,0,0,0.84,0,0,0]$ $e^0 = [0,0,0,0,0,0,0,0,0]$ $e^+ = [0,0,0,0,0,0.84,0,0,0]$

sentence-level:

1. (SF⁺ and VF⁻) yields domination of (VF and OF);
2. (VF⁻ and OF⁺) yields domination of VF;
3. e (sentence) = e (VF⁻) = $[0,0,0.6,0,0,0,0.8,0,0]$;
4. e (sentence) * coeff (tense: ‘past’; FPP: ‘yes’) = $[0,0,0.6,0,0,0,0.8,0,0] * 0.8 = [0,0,0.48,0,0,0,0.64,0,0]$
5. **result (“My darling smashed his favourite guitar without regret”): ‘sadness:0.64’**

$e = [\text{anger, disgust, fear, guilt, interest, joy, sadness, shame, surprise}]$

Sentence-level Analysis (4) in case of compound sentence

1. With coordinate conjunctions “**and**” and “**so**”:
output vector with the **maximum intensity** within each
corresponding emotional state in the resulting vectors of both
clauses.

*It is my fault, **and** I am worrying about consequences.*
*Exotic flowers in the park were amazing, **so** we took nice pictures.*

2. With coordinate conjunction “**but**”: the resulting vector
of a clause following after the conjunction is dominant.

*They attacked, **but** we luckily got away!*

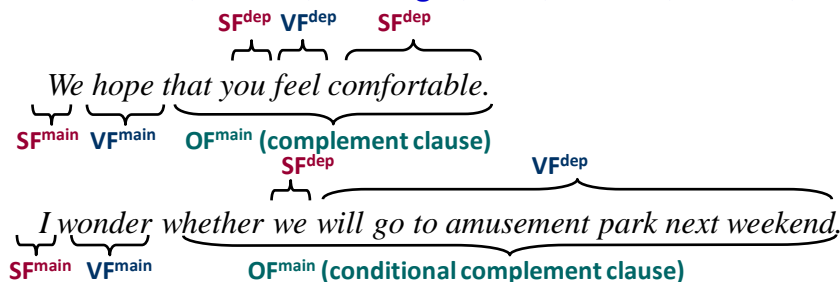
[7 coordinate conjunctions: and, but, or, nor, for, yet, so]



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Sentence-level Analysis (5): Complex Sentence -1

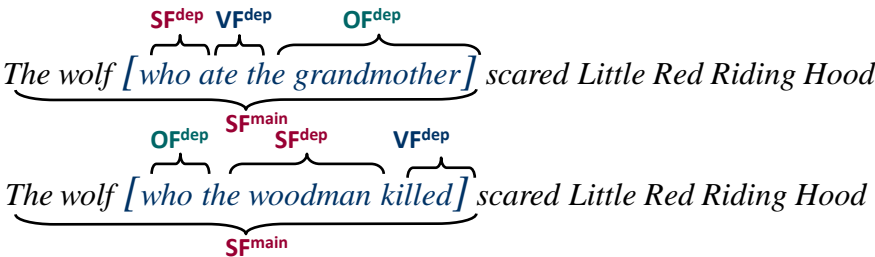
Complement clauses are introduced by special subordinating conjunctions, so called complementizers (“**that**”, “**as**”, “**because**”, “**since**”, “**though**”, “**till**”, “**when**”, “**while**”, etc.):



1. First derive **the emotional vector of a complement clause**,
2. then **create Object formation for the main clause** using this vector, and
3. finally estimate resulting **emotional vector of main clause** with added Object formation.

Sentence-level Analysis (6): Complex Sentence-2

Relative (adjective) clauses modify a noun, and are introduced by “**who**” , “**whom**” , “**whose**” , “**that**” , “**which**” , and “**where**” :



1. Estimate **the emotional vector of adjective clause**;

2. then, this emotional vector **is added to the Subject or Object formation of the main clause** depending on the role of word, which the adjective clause relates to, and

3. estimate **the emotional vector of whole sentence**.

Dataset for Evaluation

Dataset 1: 1000 sentences from Experience Project (www.experienceproject.com)

Annotations by 3 humans: one of 14 attitude labels and the strength of attitude

TOP	POS					NEG							neutral	
MID	POS aff			POS jud	POS app	NEG aff						NEG jud	NEG app	neutral
ALL	interest	joy	surprise	POS jud	POS app	anger	disgust	fear	guilt	sadness	shame	NEG jud	NEG app	neutral

Distribution of sentences in three “gold standards”, where at least two annotators completely agreed
($k_{ALL}=0.62$; $k_{MID}=0.63$; $k_{TOP}=0.74$)



Baseline: a simple method selecting the attitude label with maximum intensity from the annotations of sentence tokens found in the database.

ALL level		MID level	
Label	Number	Label	Number
anger	45	POS aff	233
disgust	21	NEG aff	332
fear	54	POS jud	66
guilt	22	NEG jud	78
interest	84	POS app	100
joy	95	NEG app	29
sadness	133	neutral	87
shame	18	total	565 (925)
surprise	36	TOP level	
POS jud	66	Label	Number
NEG jud	78	POS	437
POS app	100	NEG	473
NEG app	29	neutral	87
neutral	87	total	997
total	508 (868)		

Level	Label	Baseline method				@AM			
		Accuracy	Precision	Recall	F-score	Accuracy	Precision	Recall	F-score
ALL	anger	0.437	0.742	0.511	0.605	0.621	0.818	0.600	0.692
	disgust		0.600	0.857	0.706		0.818	0.857	0.837
	fear		0.727	0.741	0.734		0.768	0.796	0.782
	guilt		0.667	0.364	0.471		0.833	0.455	0.588
	interest		0.380	0.357	0.368		0.772	0.524	0.624
	joy		0.266	0.579	0.364		0.439	0.905	0.591
	sadness		0.454	0.632	0.528		0.528	0.917	0.670
	shame		0.818	0.500	0.621		0.923	0.667	0.774
	surprise		0.625	0.694	0.658		0.750	0.833	0.789
	POS jud		0.429	0.227	0.297		0.824	0.424	0.560
	NEG jud		0.524	0.141	0.222		0.889	0.410	0.561
	POS app		0.349	0.150	0.210		0.755	0.400	0.523
	NEG app		0.250	0.138	0.178		0.529	0.310	0.391
	neutral		0.408	0.483	0.442		0.559	0.437	0.490
MID	POS aff	0.524	0.464	0.695	0.557	0.709	0.668	0.888	0.762
	NEG aff		0.692	0.711	0.701		0.765	0.910	0.831
	POS jud		0.405	0.227	0.291		0.800	0.424	0.554
	NEG jud		0.458	0.141	0.216		0.842	0.410	0.552
	POS app		0.333	0.150	0.207		0.741	0.400	0.519
	NEG app		0.222	0.138	0.170		0.474	0.310	0.375
	neutral		0.378	0.483	0.424		0.514	0.437	0.472
TOP	POS	0.732	0.745	0.796	0.770	0.879	0.918	0.920	0.919
	NEG		0.831	0.719	0.771		0.912	0.922	0.917
	neutral		0.347	0.483	0.404		0.469	0.437	0.452

Evaluation

Experiment with different part-of-speech words

Method	Accuracy		
	ALL	MID	TOP
@AM (adj)	0.325	0.357	0.491
@AM (adj & adv)	0.347	0.376	0.516
@AM (adj & adv & n)	0.397*	0.452**	0.626**
@AM (adj & adv & n & v)	0.621**	0.709**	0.879**

*significant difference comparing with preceding method, $p < 0.05$
 ** significant difference comparing with preceding method, $p < 0.001$

Functional ablation experiment

Method	Accuracy		
	ALL	MID	TOP
@AM with all functionalities	0.621	0.709	0.879
@AM w/o all additional functionalities	0.581	0.665*	0.830**
@AM w/o polarity reversal by negations, modifiers, and functional words	0.609	0.692	0.843*
@AM w/o neutralization due to condition, preposition, and connector but	0.614	0.708	0.875
@AM w/o adjustment of labels based on analysis of pronouns, WordNet high-level concepts, and Stanford NER labels	0.588	0.685	0.878



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* significant difference comparing with @AM with all functionalities, $p < 0.05$
 ** significant difference comparing with @AM with all functionalities, $p < 0.0150$

Some Examples of Miss Classification

Error type (ALL level)	#	Sample sentence (gold standard — @AM label)
confused similar states	106	<i>When I first saw that you could have a chance to swim with dolphins I was very excited.</i> (joy — interest)
common sense	63	<i>For me every minute on my horse is alike an hour in heaven!</i> (joy — neutral)
correct label in the final vector, but not dominant	15	<i>My former boss was not good at communication and used manipulation and fear to motivate.</i> (NEG jud — fear)
sense ambiguity	12	<i>The planet has so many incredible things to offer.</i> (POS app — surprise)
negation	6	<i>I couldn't let myself reach the depression level that I had reached five weeks ago.</i> (sadness — joy)
connector “but”	5	<i>Sometimes I still struggle with depression but I've learned how to be successful.</i> (sadness — joy)
condition	3	<i>I know that even though I panic at the thought of going to school, once I'm there it's not so bad.</i> (fear — POS app)
incorrect opposite emotion due to reversal	3	<i>And now, although I don't do bodily harm, I'm definitely not fun to be around if I'm woken up!</i> (anger — sadness)
verb rule	2	<i>Zebra, Oreo, halfbreed, these names and more seemed to be my first name instead of my given — Mike — and over time, they ceased to bother me.</i> (anger — joy)
no neutralization of “instead of”	1	<i>Instead of doing a few things spectacular, I am doing many things mediocre.</i> (guilt — interest)

Interface

Input Texts

Results of Analysis

@AM - Attitude Analysis Model

@AM parameters

Intensifying coefficients
bold size: 12.0

coeff for all-capital words 1.2

coeff for comparative degree 1.2

coeff for superlative degree 1.4

coeff for intensifying adjectives and nouns 1.5

reinforcement coefficient for clause-level analysis 1.2

@AM functionality

Word level

Intensification ☒

Parser ☒ Connector Machine Syntax ☒

Phrase level

Intensification by modifiers (adverbs of degree or affirmation) ☒

Reversal by modifiers (adverbs of doubt or falseness) ☒

Reversal by intensifying adjectives and nouns ☒

Reversal by reversing adjectives and nouns ☒

Reversal by negative determiner ☒

Neutralization by prepositions ☒

Clause/sentence level

Reversal by negations ☒

Reversal by modifiers (adverbs of doubt or falseness) ☒

Neutralization due to condition ☒

Text for attitude analysis:

I like food that's made without nasty things like MSG. That incident was certainly scary, when she knocked into the big ocean-going ship. The wounds were horrible, but they eventually healed. It's no wonder kids have no respect for anyone, when they aren't even taught to respect themselves. My diet isn't particularly bad. She never lost her animosity for my brother. Audible chewing can be rather disgusting, especially if you're also trying to enjoy food.

[Selected example] Load

@AM result

I like food that's made without nasty things like MSG. => [INTEREST:0.5]

That incident was certainly scary, when she knocked into the big ocean-going ship. => [FEAR:0.9][emphasis: 1.2][modal confidence: 1.0]

The wounds were horrible, but they eventually healed. => [JOY:0.4][emphasis: 0.8]

It's no wonder kids have no respect for anyone, when they aren't even taught to respect themselves. => [DUDneg:0.1][emphasis: 1.05][verb confidence: 0.9]

My diet isn't particularly bad. => [APPpos:0.28][emphasis: 0.9]

Clear

☒ Sentence level ☐ Clause level ☐ Word level

Sentence level, Clause level, Word level

Attitude Distribution

Anger

Disgust

Fear

Guilt

Interest

Joy

Sadness

Shame

Surprise

Jud Pos

Jud Neg

App Pos

App Neg

neutral

Attitude Dynamics

Intensity [0 to 1]

Anger Disgust Fear Guilt Interest Joy Sadness Shame Surprise Jud Pos Jud Neg App Pos App Neg neutral

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AffectIM: Affect-sensitive Instant Messaging



Neutral Joy Sadness

Avatar displays:

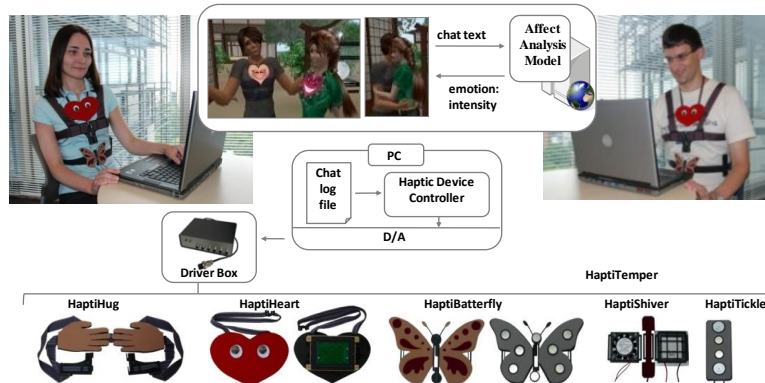
- emotions
- communicative behaviour
- idle states

EmoHeart: application in Second Life



- ✓ about 180 users in SL (July 2010)
- ✓ 4 research projects (University of Sydney, Loyola Marymount University, NII, University of Tokyo)

iFeel_IM!: communication system with rich emotional and haptic channels



- ✓ demo at 4 Int. Conferences (about 500 participants experienced iFeel_IM!)
- ✓ featured at Daily Planet Show on Discovery Channel (April 07, 2010)

Our Two Approaches

1. A Textual Affect Analysis Model based on Linguistic Compositionality Principle

— An Extended Affective Lexicon: SentiFul

2. Textual OCC Emotion Analysis through Cognitive Variables

Features of the 2nd Method

- Challenge to classify **22 types of OCC emotions**.
 - “First to implement the OCC model in NLP domain”-
by **Andrew Ortony** [one of the authors of the OCC model]
- Text understanding for **Cognitive Appraisal**
Structure of emotions through the use of
Cognitive Variables.
- **Valence-based** Interpretation
- The use of **Commonsense (Real-world) Knowledge**
in addition to linguistic knowledge
- First approach to textual sensing of OCC emotions;
yet, there are **certain rough approximations** and
rooms for refinement.



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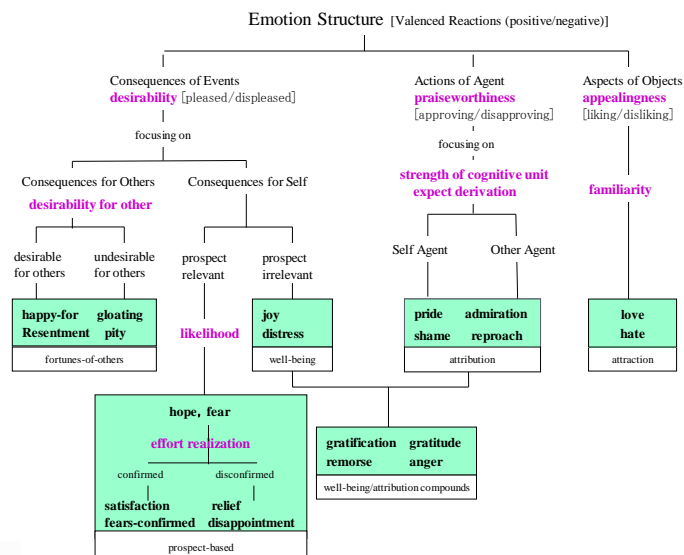
Cognitive Structure of the OCC Emotions

- **Six groups** and
22 emotion
categories based
on **valenced**
reactions to
situations

- **Purple texts**
indicate **cognitive**
variables

- Challenges are:

- ✓ **How to use this**
model in NLP
- ✓ **How to compute**
the variables



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OCC Emotions (日本語)

嬉しい (happy-for)	他者の望ましい結果を喜ぶ	Compound Emotions
同情 (pity)	他者の望ましくない結果に同情	
嫉妬 (resentment)	他者の望ましい結果に不機嫌	
嘲笑 (gloating)	他者の望ましくない結果を喜ぶ	
喜び (joy)	自分の望ましい結果に満足	
苦痛 (distress)	自分の望ましくない結果を悲しむ	
期待 (hope)	望ましい結果を予測し喜ぶ	
心配 (fear)	望ましくない結果を予測し心配する	
達成感 (satisfaction)	予測した望ましい結果が実現し喜ぶ	
不安の中 (fears-confirmed)	予測した望ましくない結果が実現し不機嫌	
安堵 (relief)	予測した望ましくない結果が実現せず喜ぶ	
落胆 (disappointed)	予測した望ましい結果が実現せず不機嫌	
誇り (pride)	自分の褒めるべき行動を認める	
恥 (self-reproach)	自分の非難されるべき行動に不満	
賞賛 (appreciation)	他者の褒めるべき行動を認める	
非難 (reproach)	他者の非難すべき行動に不満	
感謝 (gratitude)	他者の褒めるべき行動を認め、それから導かれた望ましい結果に喜ぶ	
怒り (anger)	他者の非難すべき行動を不満に思い、それから導かれた望ましくない結果に不機嫌	
自己満足 (gratification)	自分の褒めるべき行動を認め、それから導かれた望ましい結果を喜ぶ	
後悔 (remorse)	自分の非難すべき行動を不満に思い、それから導かれた望ましくない結果に不機嫌	
好む (liking)	魅力的な対象を好む	
嫌悪 (disliking)	魅力ない対象を嫌う	

emotion-inducing variables

16 Cognitive Variables		
Type	Variable Name	Possible Enumerated Values
agent based	agent_fondness (<i>af</i>)	liked, unliked
	direction_of_emotion (<i>de</i>)	self, other
object based	object_fondness (<i>of</i>)	liked, unliked
	object_appealing (<i>oa</i>)	attractive, unattractive
event based (typically from a verb-object structure)	self_reaction (<i>sr</i>)	pleased, displeased
	self_presumption (<i>sp</i>)	desirable, undesirable
	other_presumption (<i>op</i>)	desirable, undesirable
	prospect (<i>pros</i>)	positive, negative
	status (<i>stat</i>)	unconfirmed, confirmed, disconfirmed
	unexpectedness (<i>unexp</i>)	true, false
	self appraisal (<i>sa</i>)	praiseworthy, blameworthy
	valenced_reaction (<i>vr</i>)	true, false
intensity	event_deservingness (<i>ed</i>)	high, low
	effort_of_action (<i>eo</i> <i>a</i>)	obvious, not obvious
	expected_deviation (<i>edev</i>)	high, low
	event_familiarity (<i>ef</i>)	common, uncommon

18 Emotions +3	Definition
Joy	Pleased about a Desirable event
Distress	Displeased about an Undesirable event
Happy-for	Pleased about an event Desirable for a Liked agent
Sorry-for	Displeased about an event Undesirable for a Liked agent
Resentment	Displeased about an event Desirable for another Disliking agent
Gloating	Pleased about an event Undesirable for another Disliking agent
Pity	Displeased about an event Undesirable for a Liked agent
Hope	Pleased about Positive Prospect of a Desirable Unconfirmed event
Fear	Displeased about Negative Prospect of an Undesirable Unconfirmed event
Satisfaction	Pleased about Confirmation of Positive Prospect of a Desirable event
Fears-Confirmed	Displeased about Confirmation of Negative Prospect of a Undesirable event
Relief	Pleased about Disconfirmation of Negative Prospect of an Undesirable event
Disappointment	Displeased about Disconfirmation of Positive Prospect of a Desirable event

Joy: Pleased about a Desirable event, Consequence for Self

Happy-for: Pleased about an event Desirable for a Liked agent,
(Consequence for Others)

Fear: Displeased about Negative Prospect of an Undesirable Unconfirmed event

Relief: Pleased about Disconfirmation of Negative Prospect of an Undesirable event

Rules for Emotions (in a simple sentence) [1/3]

- if ($vr=true$ & $sr="pleased"$ & $sp="desirable"$ & $de="self"$), "**joy**" is true.
- if ($vr=true$ & $sr="displeased"$ & $sp="undesirable"$ & $de="self"$), "**distress**" is true.
- if ($vr=true$ & $sr="pleased"$ & $sp="desirable"$ & $de="other"$), "**happy-for**" is true.
- if ($vr=true$ & $sr="displeased"$ & $op="undesirable"$ & $af="liked"$ & $de="other"$), "**sorry-for**" is true.
- if ($vr=true$ & $sr="displeased"$ & $op="desirable"$ & $af="unliked"$ & $de="other"$), "**resentment**" is true.
- if ($vr=true$ & $sr="pleased"$ & $op="undesirable"$ & $af="unliked"$ & $de="other"$), "**gloating**" is true.
- if ($vr=true$ & $sr="pleased"$ & $pros="positive"$ & $sp="desirable"$ & $status="unconfirmed"$ & $de="self"$), "**hope**".
- if ($vr=true$ & $sr="displeased"$ & $pros="negative"$ & $sp="undesirable"$ & $status="unconfirmed"$ & $de="self"$), "**fear**" is true.
- if ($vr=true$ & $sr="pleased"$ & $pros="positive"$ & $sp="desirable"$ & $status="confirmed"$ & $de="self"$), "**satisfaction**" is true.
- if ($vr=true$ & $sr="displeased"$ & $pros="negative"$ & $sp="undesirable"$ & $status="confirmed"$ & $de="self"$), "**fears-confirmed**" is true.
- if ($vr=true$ & $sr="pleased"$ & $pros="negative"$ & $sp="undesirable"$ & $status="disconfirmed"$ & $de="self"$), "**relief**".
- if ($vr=true$ & $sr="displeased"$ & $pros="positive"$ & $sp="desirable"$ & $status="disconfirmed"$ & $de="self"$), "**disappointment**" is true.
- if ($vr=true$ & $sr="pleased"$ & $sa="praiseworthy"$ & $sp="desirable"$ & $de="self"$), "**pride**" is true.
- if ($vr=true$ & $sr="displeased"$ & $sa="blameworthy"$ & $sp="undesirable"$ & $de="self"$), "**shame**" is true.
- if ($vr=true$ & $sr="pleased"$ & $sa="praiseworthy"$ & $op="desirable"$ & $de="other"$), "**admiration**" is true.
- if ($vr=true$ & $sr="displeased"$ & $sa="blameworthy"$ & $op="undesirable"$ & $de="other"$), "**reproach**" is true.
- if ($vr=true$ & $sp="desirable"$ & $sr="pleased"$ & $of="liked"$ & $oa="attractive"$ & event valence="positive" & $de="other"$), "**love**" is true.
- if ($vr=true$ & $sp="undesirable"$ & $sr="displeased"$ & $of="not liked"$ & $oa="unattractive"$ & event valence="negative" & $de="other"$), "**hate**" is true.

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2nd Phase Rules for Emotions [2/3]

The OCC model has **four compound emotions**.

The rules for these emotions are:

- If both “joy” and “pride” are true, “**gratification**” is true.
- If both “distress” and “shame” are true, “**remorse**” is true.
- If both “joy” and “admiration” are true, “**gratitude**” is true.
- If both “distress” and “reproach” are true, “**anger**” is true.

Additional cognitive (emotional) states ‘**shock**’ and ‘**surprise**’ are ruled as;

- If both “distress” and **unexp** are true, “**shock**” is true.
(e.g., *the bad news came unexpectedly.*)
- If both “joy” and **unexp** are true, “**surprise**” is true.
(e.g., *I suddenly met my school friend in Tokyo University.*)

Rules for Emotions [3/3] in compound sentences, etc.

In case of compound sentence with the **coordinating conjunction “and”**,
apply the rule of ‘**and**’-logic’ to collapse two emotions.

- ‘hope’ and ‘satisfaction’ are collapsed to ‘satisfaction’
- ‘fear’ and ‘fear-confirmed’ are collapsed to ‘fear-confirmed’
- ‘pride’ and ‘gratification’ are collapsed to ‘gratification’
- ‘shame’ and ‘remorse’ are collapsed to ‘remorse’
- ‘admiration’ and ‘gratitude’ are collapsed to ‘gratitude’

In case of compound sentence with the **coordinating conjunction “but”**,
apply ‘**but**’-logic’ for the emotions.

- ‘negative emotion’ but ‘positive emotion’, accept ‘positive emotion’
- ‘positive emotion’ but ‘negative emotion’, accept ‘negative emotion’

The same as
the first method

Some extra rules in ‘**but**’-logic’ ,

- if ‘fears-confirmed’ or ‘fear’ but ‘satisfaction’ is found, then output ‘relief’
- if ‘hope’ but ‘fears-confirmed’ or ‘fear’ is found, then output ‘disappointment’
- if ‘anger’ but ‘gratification’ or ‘gratitude’ is found, then output ‘gratitude’
- if ‘remorse’ but ‘gratification’ or ‘gratitude’ is found, then output ‘gratitude’

How to compute the Cognitive Variables

Sub-variables (continuous values)

- **Polarity-Valence** of a word, an event, and a sentence
- **Prospective value of** a verb and an event
- **Praiseworthiness** of a verb and to an event
- **Familiarity** of a noun and to an event
- **Self/Others**

- Word-level computation
- Phrase-level computation
- Clause and Sentence-level computation



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From WordNet

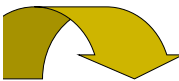
- Contains 207,016 word-senses (78,695 polysemous senses).
- Employing WordNet 2.1 for two purposes.
 - **Assign a numerical value** (either positive or negative) to each of our enlisted words based on manual investigation of senses of each word
 - **Obtain the synonyms** for a word that is not found in the SenseNet list and to examine this list with respect to pre-assessed list for which numerical values are assigned.

Polarity Value = $\text{Average}(((\text{Positive-Sense Count} - \text{Negative-Sense Count}) / \text{Total Sense Count}) * 5.0)$

Prospective Value = $\text{Average}((\text{Positive-Sense Count} / \text{Total Sense Count}) * 5.0)$

Praiseworthy Value = $\text{Average}(\text{Polarity Value} + \text{Prospective Value})$

We scored **723 verbs**, **205 phrasal verbs**, **948 adjectives** and **144 adverbs**.



Scored Verbs

Verb Word	Polarity Val	Pros. Val.	Praise. Val
amuse	3.750	4.375	4.063
attack	-3.333	0.833	-1.250
battle	-5.000	0.000	-2.500
kill	-3.167	-0.333	-1.750
thank	5.000	5.000	5.000
wish	4.643	4.643	4.643
yell	-1.250	0.625	-0.313

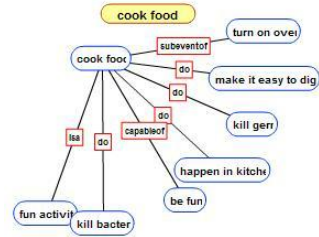
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From ConceptNet (a Commonsense Knowledge-base)

- ConceptNet (MIT) is a semantic network of common-sense knowledge; 1.6 million edges connecting more than 300,000 nodes.
- Nodes are interrelated by ontology of twenty semantic relations extracted from 700,000 sentences contributed by 14,000 authors.



- We calculated prior valence and familiarity for each noun.



```
conceptnet 2.0.0rc1 & browser
friend
SHOWS CONTEXT PROJECTION ANALOGY GUESSES CONCEPT GUESSES TOPIC
(friend)
**OUT:**
==ConceptuallyRelatedTo==> person (766, 13)
==ConceptuallyRelatedTo==> person *a friend (33, 4)
==CapableOfReceivingAction==> camerast (0, 32)
==ConceptuallyRelatedTo==> that change be frank (24, 0)
==ConceptuallyRelatedTo==> dinner (10, 1)
==ConceptuallyRelatedTo==> fun (10, 1)
==ConceptuallyRelatedTo==> friend (12, 5)
==ConceptuallyRelatedTo==> dog (11, 1)
==ConceptuallyRelatedTo==> company (12, 0)
==ConceptuallyRelatedTo==> book (12, 0)
==ConceptuallyRelatedTo==> party (11, 0)
==ConceptuallyRelatedTo==> love (10, 0)
==CapableOfReceivingAction==> call (0, 5)
==ConceptuallyRelatedTo==> game (9, 0)
==ConceptuallyRelatedTo==> movie (9, 0)
==CapableOfReceivingAction==> invite (0, 0)
==ConceptuallyRelatedTo==> mine (8, 0)
==ConceptuallyRelatedTo==> enemy (8, 0)
==CapableOfReceivingAction==> close (0, 7)
```

Lexical Words and their prior valence values (semantic orientation)

Adjectives	Adverbs	Concepts (Nouns)
infatuation 3.333333333	angrily -5	pane train 0
cooperative 5	pessimistically -5	magic news donovan 0
dainty 5	inquisitively 5	pride 3.62029999975
galvanized 5	fearfully -5	hormone 2.63960452366
abundant 5	doubtfully -5	risk 3.749241148
hate -5	rarely -5 <except>	rise 3.85775
mellow 4.5	praiseworthy 5	jack 3.65974796037
devoted 5	tightly 5	politician -3.487
dreadful -5	next 3.33333333333	school 4.3356
unfeeling -2.5	wonderfully 5	investigator 5.0
uneven -0.8333333333	disgustingly -5	wednesday 3.51183333322
appreciative 5	more 5	pincu 0
misty 0	malevolently -5	bernanke 0
concerned 3.75	exuberantly 5	force 0.66859977226
cushy 5	expansively 5	mcclaren 0
young 2	sharply 5	gator 0
sparkling 2.5	gladly 5	human experience 1.335
humored 5		panda 3.13690476205
unruffled 5		asia 4.4213458334
fervor 3.75		spokesman 2.95512628056
dirty -5		surprise there 0
sorry -4.0833333333		
pleasing 5		

The Word List includes 1600+ verbs, 3000+ adjectives, 400+ adverbs, 1700+ nouns, and 700+ named-entities.

From Opinion Web (Opinionmind)



- We calculate prior valence for each **Named-Entity**.
- Starting from initial 2300 entries, the list can grow automatically whenever the system detects a new named entity.

Named Entity	(Concept)	Prior Valence
Bin Laden	terrorist	-4.80
Discovery	space shuttle	+4.10
George W. Bush	president	-3.15
Katrina	cyclone	-4.50
Microsoft	company	-2.30
NASA	agency	+3.80

(in 2008)

Phrase-level Composition -- Adjective

- $ADJ_{pos+} (CON_{neg} \text{ or } NE_{neg}) \rightarrow \text{neg. Valence}$ (e.g., **strong cyclone**)
- $ADJ_{pos+} (CON_{pos} \text{ or } NE_{pos}) \rightarrow \text{pos. Valence}$ (e.g., **brand new car**; **final exam**)
- $ADJ_{neg+} (CON_{pos} \text{ or } NE_{pos}) \rightarrow \text{neg. Valence}$ (e.g., **broken computer**; **terrorist group**)

The sign of the resultant valence is toggled by the adjectives when there is a **negative scored adjective** qualifying a CON_{pos} or NE_{pos} .

- $ADJ_{neg+} (CON_{neg} \text{ or } NE_{neg}) \rightarrow \text{neg. Valence}$ (e.g., **ugly witch**; **scary night**)

Phrase-level Composition -- Adverb

AV: affective verb; V: non-affective verb

- $ADV_{pos} + (AV_{pos} \text{ or } V_{pos}) \rightarrow \text{pos. Valence}$ (e.g., *write nicely*; *sleep well*)
- $ADV_{pos} + (AV_{neg} \text{ or } V_{neg}) \rightarrow \text{neg. Valence}$ (e.g., *often miss*; *always fail*)
- $ADV_{neg}(\text{except}) + (AV_{pos} \text{ or } V_{pos}) \rightarrow \text{neg. Valence}$ (e.g., *rarely complete*; *hardly make*)
- $ADV_{neg} + AV_{pos} \rightarrow \text{pos. Valence}$ (e.g., *badly like*; *love blindly*)
- $ADV_{neg} + (AV_{neg} \text{ or } V_{neg}) \rightarrow \text{ambiguous}$ (e.g., *hardly miss*)

Rules to resolve the ambiguity

- $ADV_{neg}(\text{except}) + (AV_{neg} \text{ or } V_{neg}) \rightarrow \text{pos. Valence}$ (e.g., *rarely forget*; *hardly hate*)
- $ADV_{neg}(\text{not except}) + (AV_{neg} \text{ or } V_{neg}) \rightarrow \text{neg. Valence}$ (e.g., *suffer badly*; *be painful*)

Computing Rules for Action-Object Pairs

- Neg. Action Valence + Pos. Object Valence \rightarrow Neg. Action-Object Pair Valence (e.g., *kill innocent people*, *miss morning lecture*, *fail the final examination*)
- Neg. Action Valence + Neg. Object Valence \rightarrow Pos. Action-Object Pair Valence (e.g., *quit smoking*, *hate the corruption*)
- Pos. Action Valence + Pos. Object Valence \rightarrow Pos. Action-Object Pair Valence (e.g., *buy a brand new car*, *listen to the teacher*, *look after you family*)
- Pos. Action Valence + Neg. Object Valence \rightarrow Neg. Action-Object Pair Valence (e.g., *buy a gun*, *patronize a famous terrorist gang*, *make nuclear weapons*)

In the sentence "*She likes horror movies*", this rule fails to detect as conveying positive sentiment.

- $AV_{pos} + (\text{pos. or neg. Object Valence}) = \text{pos. Action-Object Pair Valence}$ (e.g., *I like romantic movies*, *She likes horror movies*.)
- $AV_{neg} + (\text{neg. or pos. Object Valence}) = \text{neg. Action-Object Pair Valence}$ (e.g., *I dislike digital camera*, *I dislike this broken camera*.)

Computing Rules for a Triplet

- (CON_{pos} or NE_{pos}) + Pos. Action-Object Pair Valence → Pos. Triplet Valence
(e.g., **the professor explained the idea to his students.**)
- (CON_{pos} or NE_{pos}) + Neg. Action-Object Pair Valence → Neg. Triplet Valence
(e.g., **John rarely attends the morning lectures.**) The same as the first approach
- (CON_{neg} or NE_{neg}) + Pos. Action-Object Pair Valence → Tagged Neg. Triplet Valence (e.g., **the robber appeared in the broad day light.**) **to process further.**
- (CON_{neg} or NE_{neg}) + Neg. Action-Object Pair Valence → Neg. Triplet Valence
(e.g., **the strong cyclone toppled the whole city.**)

But the input sentence “**The kidnapper freed the hostages and retuned the money.**”

- If a **negative valenced actor** is associated with **all positively scored** ‘action-object pair valence’, the ‘tagged negative triplet valence’ is **considered as positive**.

A negative-role actor is not necessarily always do negative actions.



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In the case of “to_dependency”

If there are two triplets, having a “to_dependency” relationship,

$$|\text{contextualValence}| = (|\text{valence of T1}| + |\text{valence of T2}|) / 2$$

- Pos. valence of T1 + Pos. valence of T2 → Pos. contextualValence
(e.g., **I am interested to go for a movie.**)
- Neg. valence of T1 + Pos. valence of T2 → Neg. contextualValence
(e.g., **It was really hard to swim across this lake.**)
- Pos. valence of T1 + Neg. valence of T2 → Neg. contextualValence
(e.g., **It is easy to catch a cold at this weather.**)
- Neg. valence of T1 + Neg. valence of T2 → Pos. contextualValence
(e.g., **It is difficult to take bad photo with this camera.**)

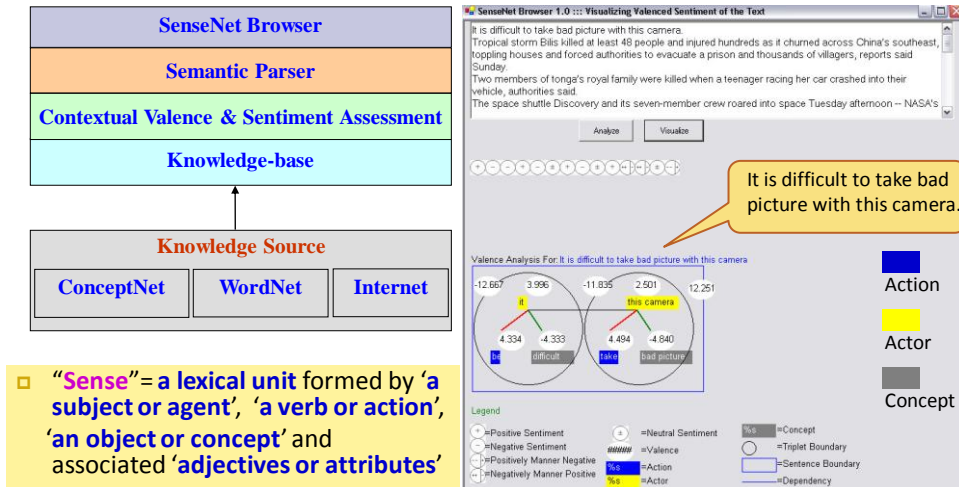
difficult sentence in other methods



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SenseNet: A Contextual Valence Calculator



How to Assign Cognitive Values (1)

Self_Presumption (sp) towards Event [desirable, undesirable]

An Event with Positive Valence is set as **"desirable"**.

An Event with Negative Valence is set as **"undesirable"**.

Example Sentences:

- John **bought** Mary an **ice-cream**. ["buy ice-cream": +7.83 → **sp=desirable**]
- My mother **presented** me a **nice wrist watch** on my birthday and **made** delicious **pancakes**. ["present a nice wrist watch": +8.82 → **sp=desirable**]
- The attack **killed** three **innocent** civilians.
["kill innocent civilians": -8.46 → **sp=undesirable**]

How to Assign Cognitive Values (2)

Self_Appraisal (sa) [praiseworthy, blameworthy]

- Considered as the semantic orientation score of a **verb** with respect to "praise" and "blame".
- Empirically, if event's valence $\geq +4.5$, event is set "praiseworthy" and ≤ -4.5 , event is "blameworthy"; otherwise "neutral".
- For events,
 - "pass final exam" (+7.95, sa= praiseworthy) ,
 - "forget friend's birthday" (-9.31, sa= blameworthy), and
 - "kick ball" (-3.87, sa=neutral)

How to Assign Cognitive Values (3)

Object_Appealing (oa) [attractive, unattractive]

Need two values: Object-valence and Familiarity.

- If the object has a positive valence with a familiarity value less than a certain threshold, then "attractive".
- If the object has a negative valence with a familiarity value higher than a certain threshold, then "unattractive".
- If the threshold is 0.10%, then, for example,
 - "diamond ring" familiarity=0.013% oa="attractive",
 - "thief" familiarity=0.120% oa="unattractive", and
 - "restaurant" familiarity=0.242% oa=null .

How to Assign Cognitive Values (4)

Status (stat) [unconfirmed, confirmed, disconfirmed]

- If the tense of the verb associated with the event is **present**, **future** or **modal**, then **"unconfirmed"**.
- If the verb has **positive valence** and the tense is **past**, then **"confirmed"**.
- If the verb has **negative valence** and the tense is **past without a negation**, then **"confirmed"**.
- If the verb has **negative valence** and the tense is **past with a negation**, then **"disconfirmed"**.

How to Assign Cognitive Values (5)

Direction_of_Emotion (de) [self, other]

whether the consequence of event is for itself or for others.

- **"other"** is set, if the **object** of an emotion-inducing event is a **person** (e.g., John) or a **personal pronoun** (e.g., he, they).
The recognized emotion is **anchored to the author or the subject of the event**.

Examples: "Mary congratulates John for having won a prize.", and

"I heard Jim having a tough time in his new job."

emotion-inducing event

- **"self"** is set, if the **author/agent** of the event is recognized as **self**. The sensed emotion is **anchored to the author himself**.

Examples: "It is a very interesting idea." and

"I won a lottery last week."

Not always clear

An Example of Analysis (1)

An example sentence: “I didn’t see John for the last few hours; I thought he might miss the flight but I suddenly found him on the plane.”

Output of a dependency parser

Triplet 1: [['Subject Name:', 'I', 'Subject Type:', 'Person', 'Subject Attrib:', []], ['Action Name:', 'see', 'Action Status:', 'Past', 'Action Attrib:', ['negation', 'duration: the last few hours ', 'dependency: and']], ['Object Name:', 'john', 'Object Type:', 'Person', 'Object Attrib:', []]]

Triplet 2: [['Subject Name:', 'I', 'Subject Type:', 'Self', 'Subject Attrib:', []], ['Action Name:', 'think', 'Action Status:', 'Past', 'Action Attrib:', ['dependency: to']], ['Object Name:', '', 'Object Type:', '', 'Object Attrib:', []]]

Triplet 3: [['Subject Name:', 'john', 'Subject Type:', 'Person', 'Subject Attrib:', []], ['Action Name:', 'miss', 'Action Status:', 'Modal Infinitive ', 'Action Attrib:', ['dependency: but']], ['Object Name:', 'flight', 'Object Type:', 'Entity', 'Object Attrib:', ['Determiner: the']]]

Triplet 4: [['Subject Name:', 'I', 'Subject Type:', 'Person', 'Subject Attrib:', []], ['Action Name:', 'find', 'Action Status:', 'Past ', 'Action Attrib:', ['ADV: suddenly', 'place: on the plane']], ['Object Name:', 'john', 'Object Type:', 'Person', 'Object Attrib:', []]]

An Example of Analysis (2)

There are **three events** as indicated below:

e1: “not see john the last few hours”, [agent: I, tense: ‘Past’, ‘dependency: and’]

e2: “think <no obj>, might miss flight” [agent: John, object: flight, tense: ‘Modal’, dependency: but]

e3: “find john on the plane” [agent: I, tense: ‘Past’]

Analysis of the recognition of OCC emotions for the given example sentence			
Events	e1	e2	e3
Event Dependency	dependency: and	dependency: but	
SenseNet Value (returned for each event)	event valence:-9.33 prospect value:-9.11 praiseworthy val:-9.22 agent valence:+5.0 object valence:+4.2	event valence:-8.69 prospect value:-7.48 praiseworthy val:-8.09 agent valence:+4.2 object valence:+2.72	event valence:+9.63 prospect value:+8.95 praiseworthy val:+9.29 agent valence:+5.0 object valence:+4.2
ConceptNet Value	familiarity valence: ‘john’ 0.059% ‘see’ 0.335% action-actor deviation: “I-see”: null	familiarity valence: ‘flight’ 0.113% ‘miss’ 0.14% action-actor deviation: “John-miss”: null	familiarity valence: ‘john’ 0.059% ‘find’ 0.419% action-actor deviation: “I-find”: null

“I didn’t see John for the last few hours; I thought he might miss the flight but I suddenly found him on the plane.”

Events	<i>e1</i>	<i>e2</i>	<i>e3</i>
Values of Cognitive Variables	<i>of</i> : liked <i>de</i> : other <i>oa</i> : attractive <i>sr</i> : displeased <i>sp</i> : undesirable <i>pros</i> : negative <i>stat</i> : confirmed <i>unexp</i> : false <i>sa</i> : blameworthy <i>vr</i> : true <i>ed</i> : low <i>eo</i> : not obvious <i>edev</i> : low <i>ef</i> : common	<i>of</i> : liked <i>af</i> : liked <i>de</i> : self <i>oa</i> : neutral <i>sr</i> : displeased <i>sp</i> : undesirable <i>op</i> : undesirable <i>pros</i> : negative <i>stat</i> : unconfirmed <i>unexp</i> : false <i>sa</i> : blameworthy <i>vr</i> : true <i>ed</i> : low <i>eo</i> : not obvious <i>edev</i> : low <i>ef</i> : uncommon	<i>of</i> : liked <i>de</i> : other <i>oa</i> : attractive <i>sr</i> : pleased <i>sp</i> : desirable <i>pros</i> : positive <i>stat</i> : confirmed <i>unexp</i> : true <i>sa</i> : praiseworthy <i>vr</i> : true <i>ed</i> : high <i>eo</i> : obvious <i>edev</i> : low <i>ef</i> : common
Apply Rules Phase 1	distress, sorry-for, fears-confirmed, reproach	distress, fear, shame	joy, happy-for, satisfaction, admiration
Apply Rules Phase 2	sorry-for, fears-confirmed, anger	fear, remorse	happy-for, satisfaction, gratitude
Apply ‘and’-logic	sorry-for, fears-confirmed , anger		happy-for, satisfaction, gratitude
Apply ‘but’-logic	happy-for, relief , gratitude		

Rules for Emotions [3/3] in compound sentences, etc.

In case of compound sentence with the **coordinating conjunction “and”**,
apply the rule of **‘and’-logic** to collapse two emotions.

- ‘hope’ and ‘satisfaction’ are collapsed to ‘satisfaction’
- ‘fear’ and ‘fear-confirmed’ are collapsed to ‘fear-confirmed’
- ‘pride’ and ‘gratification’ are collapsed to ‘gratification’
- ‘shame’ and ‘remorse’ are collapsed to ‘remorse’
- ‘admiration’ and ‘gratitude’ are collapsed to ‘gratitude’

applied

applied

In case of compound sentence with the **coordinating conjunction “but”**,
apply **‘but’-logic** for the emotions.

- ‘negative emotion’ but ‘positive emotion’, accept ‘positive emotion’
- ‘positive emotion’ but ‘negative emotion’, accept ‘negative emotion’

applied

Some extra rules proposed,

- if ‘fears-confirmed’ or ‘fear’ but ‘satisfaction’ is found, then output ‘relief’
- if ‘hope’ but ‘fears-confirmed’ or ‘fear’ is found, then output ‘disappointment’
- if ‘anger’ but ‘gratification’ or ‘gratitude’ is found, then output ‘gratitude’
- if ‘remorse’ but ‘gratification’ or ‘gratitude’ is found, then output ‘gratitude’

applied

Outputs of EmpathyBuddy and Ours

- Input: I avoided the accident luckily.
- Liu's EmpathyDuddy: fearful(26%), happy (18%), angry(12%), sad(8%) , surprised (7%)
- Ours: valence: +11.453; [gratification, relief, surprise]
- Input: Susan bought a lottery ticket and she was lucky to win the million dollar lottery.
- Liu's EmpathyDuddy: sad (21%), happy (18%), fearful (13%),angry(11%)
- Ours: valence: +12.533; [joy, love, hope, happy-for, surprise]
- Input: I missed the train to home yesterday.
- Liu's EmpathyBuddy: happy (23%), fearful (23%),sad (20%), angry (5%)
- Ours: valence: -10.866; [distress, sorry-for, hate]



EmpathyBuddy-- Hugo Liu, Henry Lieberman, and Ted Selker. 2003. "A Model of Textual Affect Sensing using Real-World Knowledge", In Proc. IUI 03, pp. 125-132, Miami, USA.

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Comparison to EmpathyBuddy

- Sensing when compared to human-ranked scores (as "gold standard") for 200 sentences, which were collected from reviews of products and movies, news, and emails.
- Upon receiving the outputs, 5 judges could accept either both outputs or anyone of the two or rejected both.

Data-Set of 200 Sentences				
	Our System	EmpathyBuddy	Both	Failed to Sense
Number of Sentences accepted to be correct	41	26	120	13
Total number of Sentences correctly sensed	161	146		
Accuracy	80.5%	73%		



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There are still rooms for refinement.


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Comparison of Two Approaches

	1. @AM	2. OCC Emotion Sensing
Sensing Target	9 emotions with each intensity	22 emotions (first challenge)
Main Methodology	Linguistic Compositionality Principle	Cognitive Appraisal Structure of Emotions using Cognitive Variables
	Certain parts of linguistic composition rules are common	
Prior Information of Elementary Lexicon	9-dimentional vector with intensities	Valence and some other sub-variable values
Accuracy (in different conditions)	62%	80.5%

Both systems have achieved deep linguistic analyses toward affect sensing more than ever.

Web Online System



please input sentence(s). [e.g., Computer can sense emotion.]

Output

Input Sentence:An earthquake measuring 6.0 on the Richter scale shook the northern part of Indonesia's Sulawesi island on Tuesday, but there were no immediate reports of damage or casualties, the meteorology agency said.	
Output of System 1	Output of System 2
angry:36.39 fearful:28.42 surprised:18.17 sad:11.28 happy:0.00 disgusted:0.00	distress:(60.04%) disappointment:(30.02%)
The Sentence Primarily Expresses angry Emotion.	

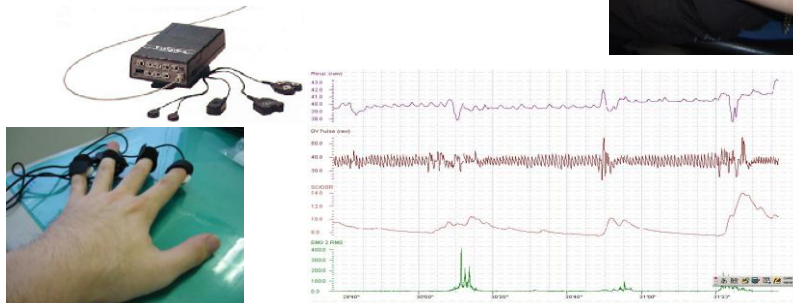
ASNA: An Agent for Retrieving and Classifying News on the basis of Emotion-Affinity



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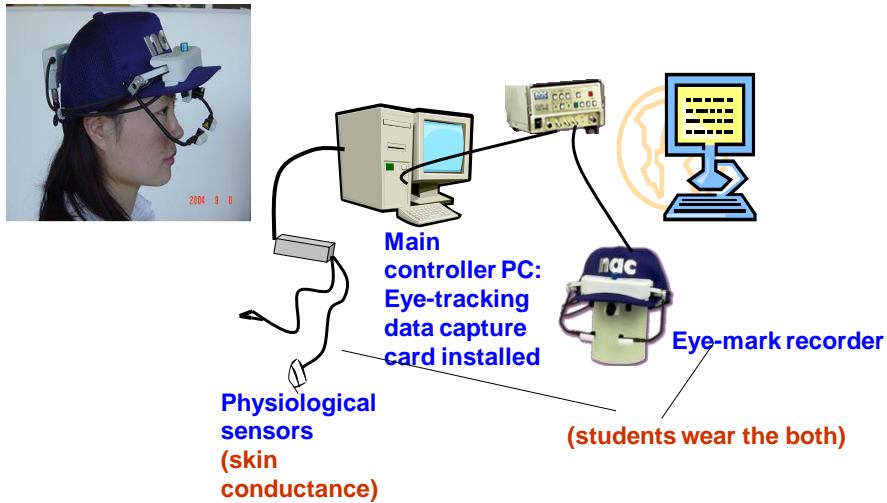
Physiological Emotion Sensors

- **Skin-conductivity** (associated with **Arousal**)
- **Heart-pulse rate** (associated with **Valence**)
- **Others**
 - **Blood pressure, Temperature, Breath rate,**
 - **Electrocardiogram (ECG), Brain waves (EEG), Electromyography (EMG)**

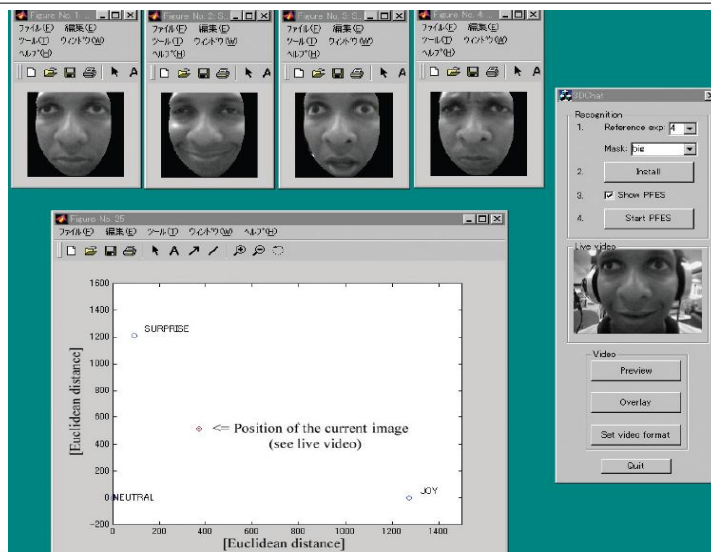


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Eye-tracker in addition to physiological sensors for affective interactions



Facial Emotion Sensing



Emotions and Voice Parameters



Emotion	<i>Fear</i>	<i>Anger</i>	<i>Sadness</i>	<i>Happiness</i>	<i>Disgust</i>
Speech rate	much faster	slightly faster	slightly slower	faster or slower	very much slower
Pitch average	very much higher	very much higher	slightly lower	much higher	very much lower
Pitch range	much wider	much wider	slightly narrower	much wider	slightly wider
Intensity	normal	higher	lower	higher	lower
Pitch changes	normal	abrupt on stressed syllables	downward inflections	smooth upward inflections	wide downward terminal inflections

(The emotion of “grief” is omitted.)

Emotion	<i>Fear</i>	<i>Anger</i>	<i>Sadness</i>	<i>Happiness</i>	<i>Disgust</i>
Speech rate	+30	+10	-10	+20/-20	-40
Average pitch	+40	+40	-10	+30	-40
Loudness	—	+6	-2	+3	—

Voice parameter changes for five emotions available for the Eloquent TTS system.
Speech rate is words per minute (WPM). Average pitch (AP) in Hz. Loudness (G5) in dB.

Thank You

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