A short Introduction to Sentiment Analysis

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main contribution from "Opinion Mining" by Bing Liu (Chpt. 11)
and "Opinion Mining and Sentiment Analysis" by B. Pang & L. Lee

Overview

Introduction to the overall notion of Sentiment Analysis
- The defintion of sentiment and subjectvity
- The model fo the tasks
- Types of Opinion Mining tasks

Major Approaches to the different tasks

Knowledge and Lexical Resources for OM

Architectural and Technological Issues

Evaluation and Benchmarking Champaign

Neural Approaches to SA
- SA in Twitter

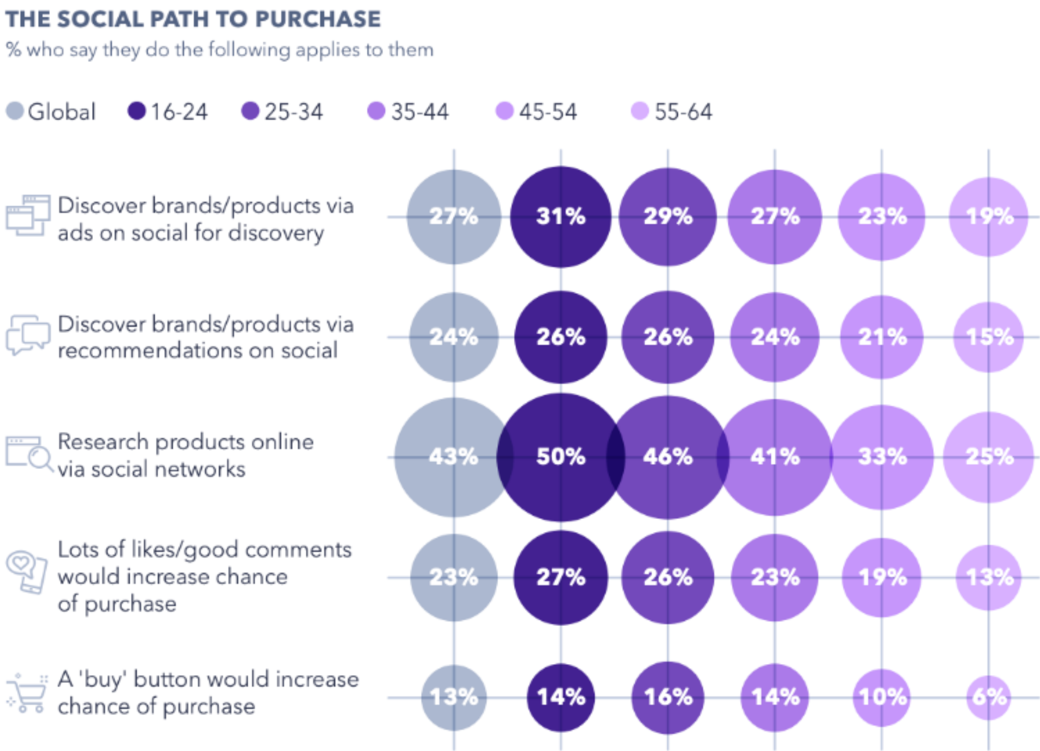
A Web of people and opinions

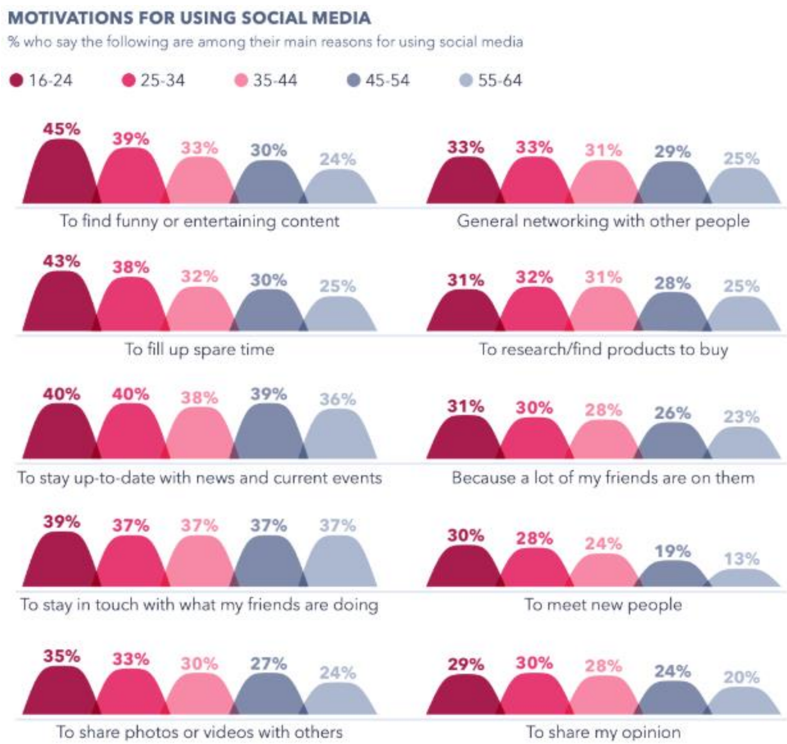
31.7% of the more than 200 million bloggers worldwide blog about opinions on products and brands (Universal McCann, July 2009)

71% of all active Internet users read blogs.

2009 Survey of **25,000** Internet users in **50** countries: **70%** of consumers trust opinions posted online by other consumers (Nielsen Global Online Consumer, 2010).

Social Media & Digital culture





Source: https://blog.hootsuite.com/twitter-demographics/

"First, they do an on-line search."

Authority

Does the opinion of one user (e.g. a blogger) actually matter?

"*If a tree falls in a forest and no one is around to hear it, does it make a sound?*"

Authority and reputation of users are key factors to understand and account for their opinions

What is OM?

Opinion Mining or also *sentiment analysis* is **the computational study of opinions, sentiments and emotions expressed in text**

How to model, code and compute the irrational aspects of our affects in an analytical way …

It deals with rational models of emotions, rumors and trends within user communities

… and with the word-of-mouth inside specific domains

It has to integrate objective models of subjective behaviors

What is OM? (2)

Opinion Mining or Sentiment Analysis involve more than one linguistic task

What is the *opinion* of a text

- Who is author (or *opinion holder*, OH)
- What is the *opinion target* (Object)
- What are the *features* of the Object
- What is the *subjective position* of the user wrt to the Object or the individual features

What about the (dynamics of) opinions of large OH communities

Introduction – facts and opinions

Two main types of information on the Web.

- Facts and Opinions

Current search engines search for facts (assume they are true)

- Facts can be expressed with topic keywords.

Search engines should also be able to search for opinions

- Opinions are hard to express with a few keywords
  - How do people think of Motorola Cell phones?
- Current search ranking strategy is not appropriate for opinion retrieval/search.

Introduction – user generated content

Word-of-mouth on the Web

- One can express personal experiences and opinions on almost anything, at review sites, forums, discussion groups, blogs ..., (called the user generated content.)
- They contain valuable information
- Web/global scale
  - No longer limited to your circle of friends
- Graph-based models

Focus of this lesson: to mine opinions expressed in the user-generated content

- An intellectually very challenging problem.
- Practically very useful.

Opinion search (Liu, Web Data Mining book, 2007)

Can you search for opinions as conveniently as general Web search?

Whenever you need to make a decision, you may want some opinions from others,

- Wouldn't it be nice? you can find them on a search system instantly, by issuing queries such as
  - Opinions: "Samsung cell phones"
  - Comparisons: "Samsung vs. Motorola"

Cannot be done yet!

Two types of evaluation

Direct Opinions: sentiment expressions on some objects, e.g., products, events, topics, persons

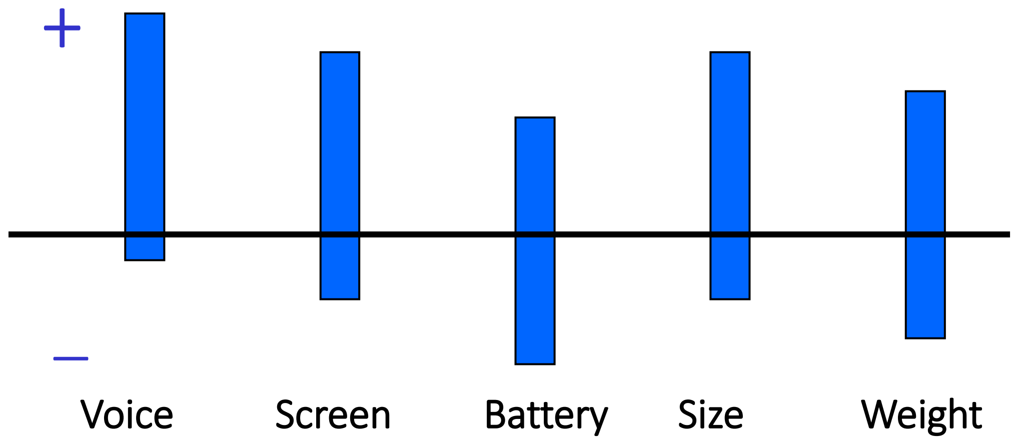
- E.g., "the picture quality of this camera is great"
- Subjective

Comparisons: relations expressing similarities or differences of more than one object. Usually expressing an ordering.

- E.g., "car x is cheaper than car y."
- Objective or subjective.

Opinion Summarization through Visual Comparison (Liu et al. WWW-2005)

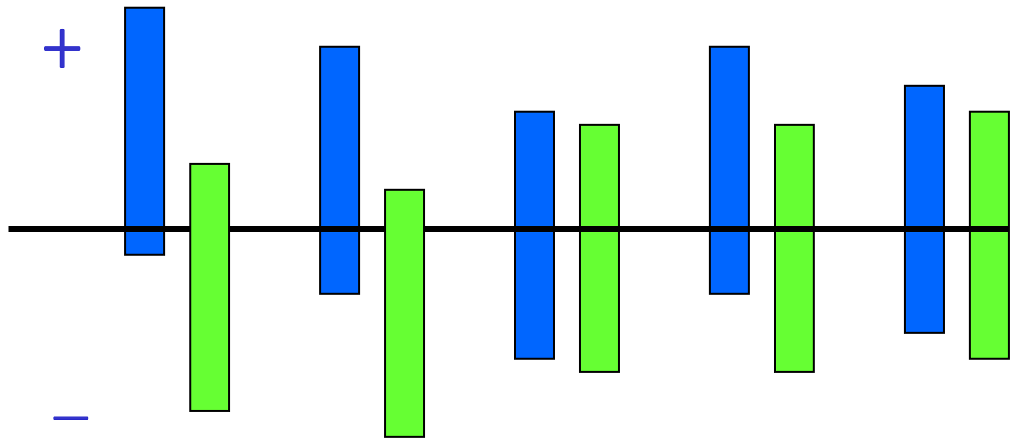
- Summary of reviews of Cell Phone 1



- Comparison of reviews of

Cell Phone 1

Cell Phone 2



Find the opinion of a person on X

In some cases, the general search engine can handle it, i.e., using suitable keywords.

- Bill Clinton's opinion on abortion

Reason:

- One person or organization usually has only one opinion on a particular topic.
- The opinion is likely contained in a single document.
- Thus, a good keyword query may be sufficient.

Find opinions on an object X

We use product reviews as an example:

Searching for opinions in product reviews is different from general Web search.

- E.g., search for opinions on "HUAWEI Nova 9"

General Web search for a fact: rank pages according to some authority and relevance scores.

- The user views the first page (if the search is perfect).
- **One fact = Multiple facts**

Opinion search: rank is desirable, however

- reading only the review ranked at the top is dangerous because it is only the opinion of one person.
- **One opinion ≠ Multiple opinions**

Search opinions (contd)

Ranking:

- produce two rankings
  - Positive opinions and negative opinions
  - Some kind of summary of both, e.g., # of each
- Or, one ranking but
  - The top (say 30) reviews should reflect the natural distribution of all reviews (assume that there is no spam), i.e., with the right balance of positive and negative reviews.

Questions:

- Should the user reads all the top reviews? OR
- Should the system prepare a summary of the reviews?

Reviews are similar to surveys

Reviews can be regarded as traditional surveys.

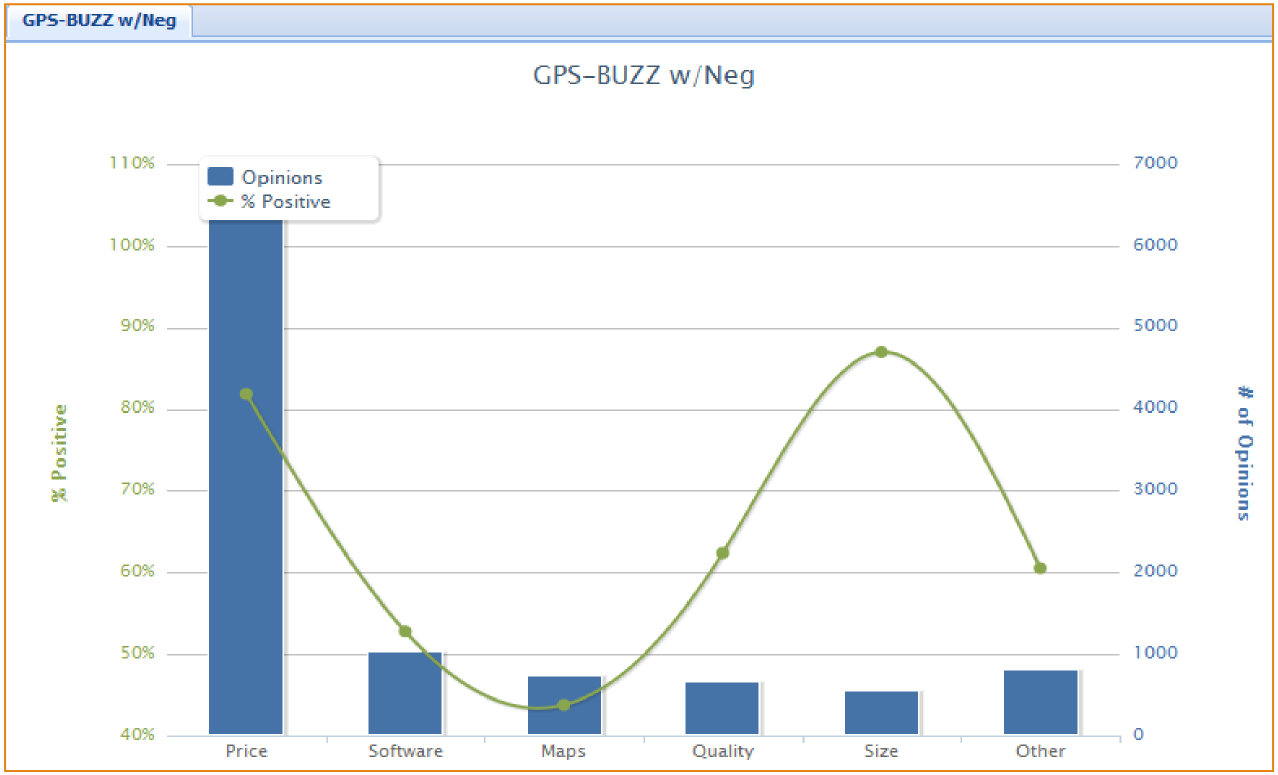
- In traditional survey, returned survey forms are treated as raw data.
- Analysis is performed to summarize the survey results.
  - E.g., % against or for a particular issue, etc.

In opinion search,

- Can a summary be produced?
- What should the summary be?

Features: opinions vs. mentions

People talked a lot about prices than other features. They are quite positive about price, but not bout maps and software.



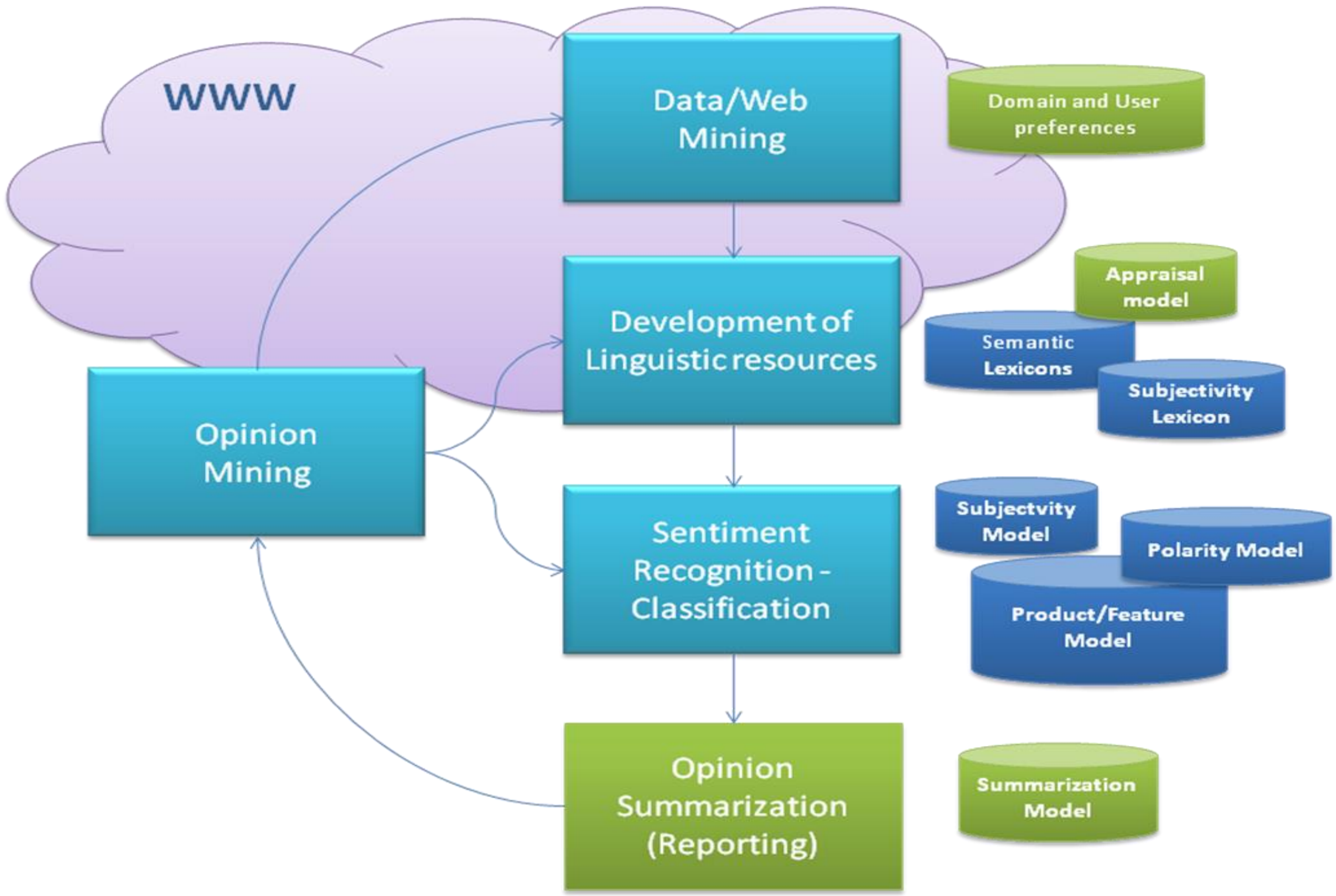
It seems very appealing

but…

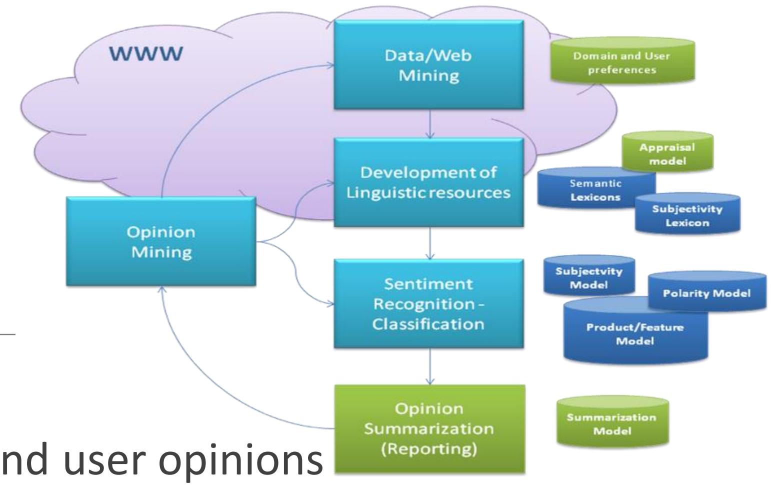
Sentiment Analysis is Challenging!

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

… and corresponds to a very complex process!!



Tasks



Data Gathering

- Objective: to access information relevant to understand user opinions
- Resources: Individual Profiles, Community sites, blogs

Linguistic Resources Development:

- Objective: to develop linguistic models (as ontologies, dictionaries, embeddings, …)
- Resources: general-purpose corpora, domain corpora, opinion datasets
- Outcome: Semantic Lexicons, Subjectivity Lexicons

Sentiment Recognition:

- SubTasks: Subjectivity, Aspect and Polarity Recognition, Opinion Summarization
- Resources: Subjectivity models, Appraisal models, Polarity Models

Opinion Summarization:

- Objective: Summarize opinions across large user communities

"I'd like your honest, unbiased and possibly career-ending opinion on something."

NL vs. Opinions

Although subjectivity seems to preserve across domains and sublanguages, knowledge about *subjectivity (e.g. affective lexicons) is not fully portable*

- For example, the polarity of some terms change across domains (e.g. *small* about laptops vs. TV screen)

These issues trigger a number of inductive tasks

- How to *model the uncertainty* of lexical information with respect to subjectivity
- How to *validate (or adapt) existing lexicons* to newer domains
- How to *acquire novel lexical information*
- How to *support inference* according to the above lexical information

Two (closely related) notions

- Subjectivity and emotion.
- **Sentence subjectivity**: An *objective sentence* presents some factual information, while a *subjective sentence* expresses some personal feelings, views, emotions, or beliefs.
- **Emotion**: Emotions are people's subjective

Tasks: definitions and models

Opinion mining – the abstraction

Domain level sentiment classification

Sentence level sentiment analysis

Feature-based sentiment analysis and summarization

Summary

Opinion mining – the abstraction
(Hu and Liu, KDD-04)

Basic components of an opinion

- Opinion holder: A person or an organization that holds an specific opinion on a particular object.
- Object: on which an opinion is expressed
- Opinion: a view, attitude, or appraisal on an object from an opinion holder.

Objectives of opinion mining: many ...

We use consumer reviews of products to develop the ideas. Other opinionated contexts are similar.

Object/entity

Definition (**object**): An object *O* is an entity which can be a product, person, event, organization, or topic. *O* is represented as a tree or taxonomy of components (or parts), sub-components, and so on.

- Each node represents a component and is associated with a set of **attributes**.
- *O* is the root node (which also has a set of attributes)

An opinion can be expressed on any node or attribute of the node.

To simplify our discussion, we use "**features**" to represent both components and attributes.

- The term "feature" should be understood in a ***broad sense***,
  - Product feature, topic or sub-topic, event or sub-event, etc

Note: the object *O* itself is also a feature.

A model of a review

An object is represented with a finite set of features,

$$F = \{f_1, f_2, \ldots, f_n\}.$$

- Each feature f_i in F can be expressed with a finite set of words or phrases W_i, which are **synonyms**.

That is to say: we have a set of corresponding synonym sets $W = \{W_1, W_2, \ldots, W_n\}$ for the features.

Model of a review: An opinion holder j comments on a subset of the features $S_j \subseteq F$ of an object O.

- For each feature $f_k \in S_j$ that j comments on, he/she
  - chooses a word or phrase from W_k to describe the feature, and
  - expresses a positive, negative or neutral opinion on f_k.

Opinion mining tasks

At the document (or review) level:

Task: sentiment classification of reviews

- Classes: positive, negative, and neutral
- Assumption: each document (or review) focuses on a single object *O* (not true in many discussion posts) and contains opinion from a single opinion holder.

At the sentence level:

Task 1: identifying subjective/opinionated sentences

- Classes: objective and subjective (opinionated)

Task 2: sentiment classification of sentences

- Classes: positive, negative and neutral.
- Assumption: a sentence contains only one opinion
  - not true in many cases.
- Then we can also consider clauses.

Opinion mining tasks (contd)

At the feature level:

Task 1: Identifying and extracting object features that have been commented on in each review.

Task 2: Determining whether the opinions on the features are positive, negative or neutral in the review.

Task 3: Grouping feature synonyms.

- Produce a feature-based opinion summary of multiple reviews (more on this later).

Opinion holders: identify holders is also useful, e.g., in news articles, etc, but they are usually known in user generated content, i.e., the authors of the posts.

More at the feature level

F: the set of features

W: synonyms of each feature

Problem 1: Both *F* and *W* are unknown.

- We need to perform all three tasks:

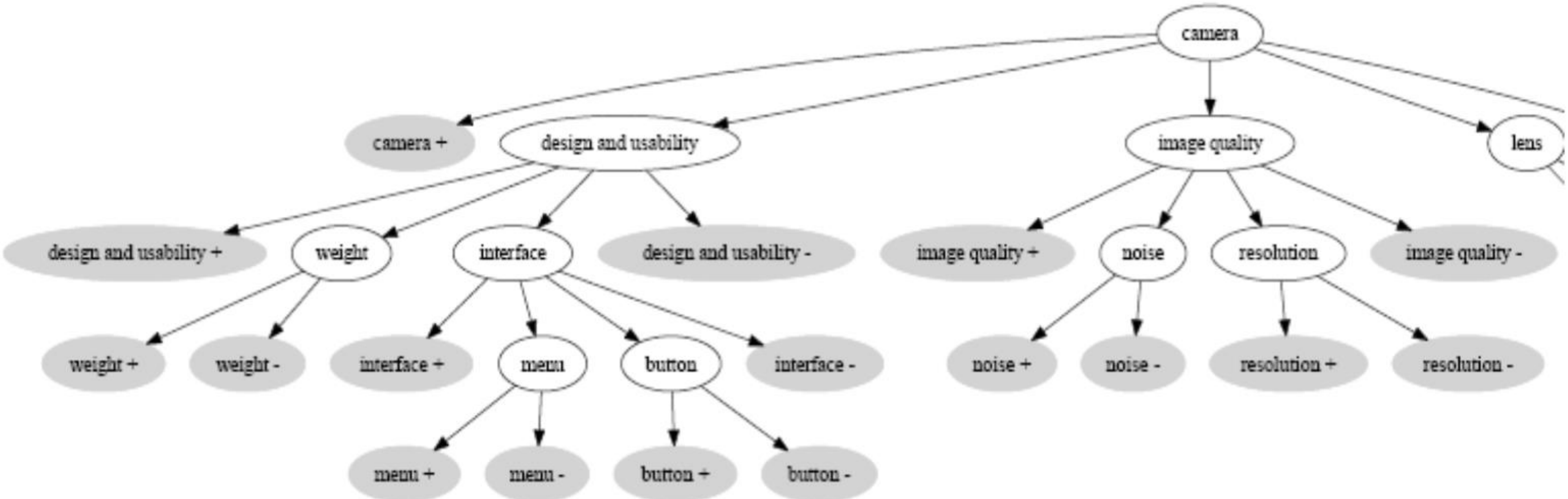
Problem 2: *F* is known but *W* is unknown.

- All three tasks are needed. Task 3 is easier. It becomes the problem of matching discovered features with the set of given features *F*.

Problem 3: *W* is known (*F* is known too).

- Only task 2 is needed.

Opinion Ontologies



Tasks: definitions and models

Opinion mining – the abstraction

Document level sentiment classification

Sentence level sentiment analysis

Feature-based sentiment analysis and summarization

Summary

Sentiment classification

Classify documents (e.g., reviews) based on the overall sentiments expressed by authors,

- Positive, negative, and (possibly) neutral
- Since in our model an object *O* itself is also a feature, then sentiment classification essentially determines the opinion expressed on *O* in each document (e.g., review).

Similar but not identical to *topic-based text classification*.

- In topic-based text classification, topic words are important.
- In sentiment classification, sentiment words are more important, e.g., great, excellent, horrible, bad, worst, etc.

Unsupervised review classification (Turney, ACL-02)

Data: **reviews** from epinions.com on

- automobiles,
- banks,
- movies,
- travel destinations.

The approach: Three steps

Step 1: Feature Extaction

- Part-of-speech tagging
- Extracting two consecutive words (two-word phrases) from reviews if their tags conform to some given patterns, e.g., (1) JJ, (2) NN.

Step 2: Estimate the semantic orientation of the extracted phrases

Step 2: Estimate the semantic orientation of the extracted phrases

- Use **Pointwise mutual information**

$$PMI(word_1, word_2) = \log_2\left(\frac{P(word_1 \wedge word_2)}{P(word_1)P(word_2)}\right)$$

- **Semantic orientation** (SO):

*SO(*phrase*) = PMI(*phrase*, "excellent") - PMI(*phrase*, "poor")*

- Using AltaVista for **estimation**
  - Search to find the **number of hits** in the indexed Web pages to compute PMI and SO
  - The "near" operator is applied to constraint the search

Step 2: Estimate the semantic orientation of the extracted phrases

Estimate the Pointwise Mutual Information for Semantic orientation (SO):

$$SO(phrase) = PMI(phrase, \text{“excellent”}) - PMI(phrase, \text{“poor”})$$

$$SO(phrase) = \log_2 \frac{hits(phrase\ \text{NEAR “excellent”})\ hits(\text{“poor”})}{hits(phrase\ \text{NEAR “poor”})\ hits(\text{“excellent”})}$$

Step 3: Estimate the SO of the entire text by averaging

Step 3: **Compute the average SO of all phrases**

Classify the review as

- recommended if average SO is positive,
- not recommended otherwise.

Final classification accuracy:

- automobiles - 84%
- banks - 80%
- movies - 65.83
- travel destinations - 70.53%

Sentiment classification using supervised machine learning methods (Pang et al, EMNLP-02)

The paper applied several machine learning techniques to classify movie reviews into positive and negative.

Three classification techniques were tried:

- Naïve Bayes
- *Maximum entropy (mixture model + Par Est)*
- Support vector machine

Pre-processing settings: negation tag, unigram (single words), bigram, POS tag, position.

SVM: the best accuracy 83% (unigram)

More recent approaches apply Convolutional Neural networks and LSTMs, improvement is significant (+5-10%)

Tasks: definitions and models

Opinion mining – the abstraction

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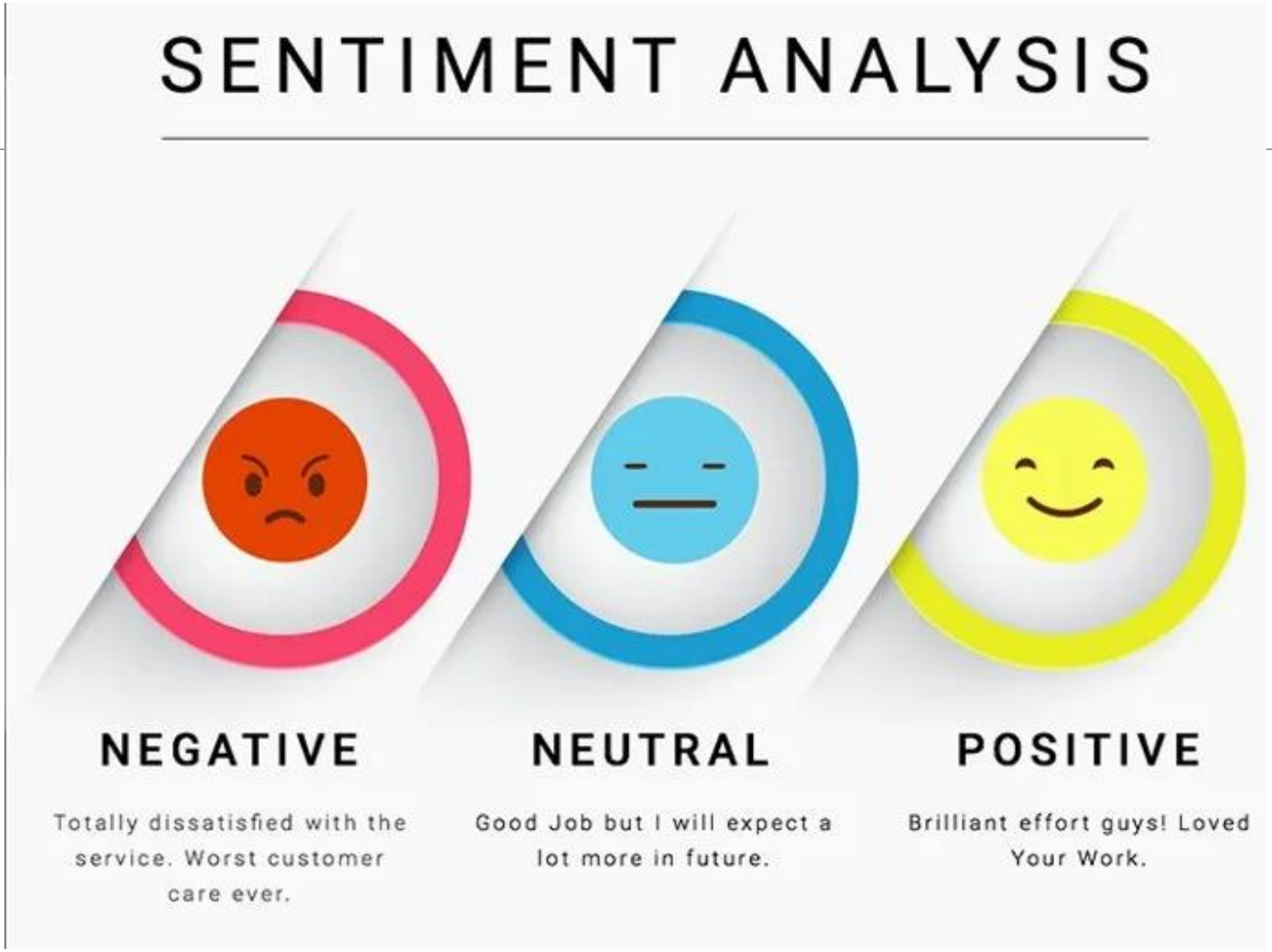
Sentence-level sentiment analysis

Document-level sentiment classification is too coarse for most applications.

Let us move to the sentence level.

Much of the work on sentence level sentiment analysis focus on identifying subjective sentences in news articles.

- Classification: objective and subjective.
- All techniques use some forms of machine learning.
- E.g., using a naïve Bayesian classifier with a set of data features/attributes extracted from training sentences (Wiebe et al. ACL-99).


SENTIMENT ANALYSIS
NEGATIVE
Totally dissatisfied with the service. Worst customer care ever.
NEUTRAL
Good Job but I will expect a lot more in future.
POSITIVE
Brilliant effort guys! Loved Your Work.

Let us go further?

Sentiment classifications at both document and sentence (or clause) level are useful, but

- They do not find what the opinion holder liked and disliked.

A negative sentiment on an object

- does not mean that the opinion holder dislikes everything about the object.

A positive sentiment on an object

- does not mean that the opinion holder likes everything about the object.

We need to go to the feature level.

But before we go further

Many approaches to opinion, sentiment, and subjectivity analysis rely on **lexicons** of words that may be used to express subjectivity.

(1) He is a **disease** to every team he has gone to.
Converting to SMF is a **headache**.
The concert left me **cold**.
That guy is such a **pain**.

(2) Early symptoms of the **disease** include severe **headaches**, red eyes, fevers and **cold** chills, body **pain**, and vomiting.

But before we go further

Let us discuss **Opinion Words or Phrases** (also called polar words, opinion bearing words, etc). E.g.,

- **Positive**: *beautiful, wonderful, good, amazing*,
- **Negative**: *bad, poor, terrible*, *cost someone an arm and a leg* (idiom).

They are instrumental for opinion mining (obviously)

Three main ways to compile such a list:

- Manual approach: not a bad idea, only an one-time effort
- Corpus-based approaches
- Dictionary-based approaches

Important to note:

- **Some opinion words are context independent.**
- **Some are context dependent**.

Sentiment (or opinion) lexicons

- Sentiment lexicon: lists of words and expressions used to express people's subjective feelings and sentiments/opinions.
  - Not just individual words, but also phrases and idioms, e.g., "cost an arm and a leg"
- There seems to be endless variety of sentiment bearing expressions.
  - We have compiled more than 6,700 individual words.
  - There are also a large number of phrases.

Affective Lexicons

They have been extensively used in the field either for lexicon-based approaches or in machine-learning solutions

- Additional features
- Bootstrapping: unsupervised solutions (see previous)

Can be created manually, automatically or semi-automatically

Can be domain-dependent or independent

A lot of them are already available:

- Manual
  - LIWC: Linguistic Inquiry and Word Count [10]
  - ANEW: Affective norms for English words [11]
- Automatic:
  - WordNet-Affect [9]
  - SentiWordNet [31] …

LIWC: Linguistic Inquiry and Word Count (https://liwc.wpengine.com/)

II. PSYCHOLOGICAL PROCESSES

Social Processes	talk, us, friend	455
Friends		
Family		
Humans		
Affective Processes		
Positive Emotions		
Negative Emotions		
Anxiety		
Anger		
Sadness		
Cognitive Processes		
Insight		
Causation		
Discrepancy		
Tentative		
Certainty		
Inhibition		
Inclusive		
Exclusive		
Perceptual Processes		
Seeing		
Hearing		
Feeling	touch, hold, felt	75
Biological Processes	eat, blood, pain	567
Body	ache, heart, cough	180

125 Affect						126 Posemo			127 Negemo			
abandon*	damn*	fume*	kindn*	privileg*	supporting	accept	freed*	partie*	abandon*	enrag*	maddening	snob*
abuse*	danger*	fuming	kiss*	prize*	supportive*	accepta*	freeing	party*	abuse*	envie*	madder	sob
abusi*	daring	fun	laidback	problem*	supports	accepted	freely	passion*	abusi*	envious	maddest	sobbed
accept	darlin*	funn*	lame*	profit*	suprem*	accepting	freeness	peace*	ache*	envy*	maniac*	sobbing
accepta*	daze*	furious*	laugh*	promis*	sure*	accepts	freer	perfect*	aching	evil*	masochis*	sobs
accepted	dear*	fury	lazie*	protest	surpris*	active*	frees*	play	advers*	excruciat*	melanchol*	solemn*
accepting	decay*	geek*	lazy	protested	suspicio*	admir*	friend*	played	afraid	exhaust*	mess	sorrow*
accepts	defeat*	genero*	liabilit*	protesting	sweet	ador*	fun	playful*	aggravat*	fail*	messy	sorry
ache*	defect*	gentle	liar*	proud*	sweetheart*	advantag*	funn*	playing	aggress*	fake	miser*	spite*
aching	defenc*	gentler	libert*	puk*	sweetie*	adventur*	genero*	plays	agitat*	fatal*	miss	stammer*
active*	defens*	gentlest	lied	punish*	sweetly	affection*	gentle	pleasant*	agoniz*	fatigu*	missed	stank
admir*	definite	gently	lies	radian*	sweetness*	agree	gentler	please*	agony	fault*	misses	startl*
ador*	definitely	giggl*	like	rage*	sweets	agreeab*	gentlest	pleasing	alarm*	fear	missing	steal*
advantag*	degrad*	giver*	likeab*	raging	talent*	agreed	gently	pleasur*	alone	feared	mistak*	stench*
adventur*	delectabl*	giving	liked	rancid*	tantrum*	agreeing	giggl*	popular*	anger*	fearful*	mock	stink*
advers*	delicate*	glad	likes	rape*	tears	agreement*	giver*	positiv*	angr*	fearing	mocked	strain*
affection*	delicious*	gladly	liking	raping	teas*	agrees	giving	prais*	anguish*	fears	mocker*	strange
afraid	deligh*	glamor*	livel*	rapist*	tehe	alright*	glad	precious*	annoy*	feroc*	mocking	stress*
aggravat*	depress*	glamour*	LMAO	readiness	temper	amaz*	gladly	prettie*	antagoni*	feud*	mocks	struggl*
aggress*	depriv*	gloom*	LOL	ready	tempers	amor*	glamor*	pretty	anxi*	fiery	molest*	stubborn*
agitat*	despair*	glori*	lone*	reassur*	tender*	amus*	glamour*	pride	apath*	fight*	mooch*	stunk
agoniz*	desperat*	glory	longing*	rebel*	tense*	aok	glori*	privileg*	appall*	fired	moodi*	stunned
agony	despis*	goddam*	lose	reek*	tensing	appreciat*	glory	prize*	apprehens*	flunk*	moody	stuns
agree	destroy*	good	loser*	regret*	tension*	assur*	good	profit*	argh*	foe*	moron*	stupid*
agreeab*	destruct*	goodness	loses	reject*	terribl*	attachment*	goodness	promis*	argu*	fool*	mourn*	stutter*
agreed	determina*	gorgeous*	losing	relax*	terrific*	attract*	gorgeous*	proud*	arrogan*	forbid*	murder*	submissive*
agreeing	determined	gossip*	loss*	relief	terrified	award*	grace	radian*	asham*	fought	nag*	suck
agreement*	devastat*	grace	lost	reliev*	terrifies	awesome	graced	readiness	assault*	frantic*	nast*	sucked
agrees	devil*	graced	lous*	reluctan*	terrify	beaut*	graceful*	ready	asshole*	freak*	needy	sucker*
alarm*	devot*	graceful*	love	remorse*	terrifying	beloved	graces	reassur*	attack*	fright*	neglect*	sucks
alone	difficult*	graces	loved	repress*	terror*	benefic*	graci*	relax*	aversi*	frustrat*	nerd*	sucky
alright*	digni*	graci*	lovely	resent*	thank	benefit	grand	relief	avoid*	fuck	nervous*	suffer

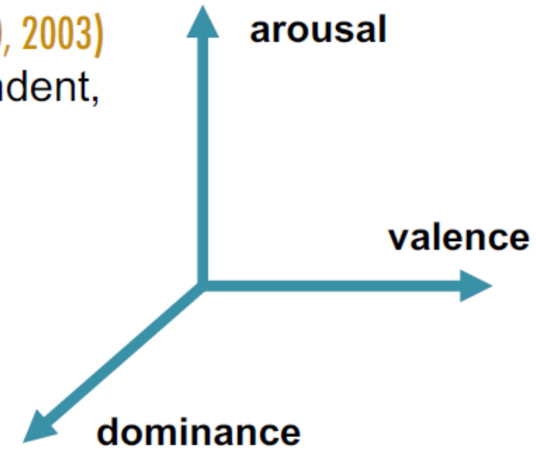
The VAD model

V: Pleasantry
A: Intensity
D: Control

Core Dimensions of Connotative Meaning

Influential factor analysis studies (Osgood et al., 1957; Russell, 1980, 2003) have shown that the three most important, largely independent, dimensions of word meaning:

- valence (V): positive/pleasure – negative/displeasure
- arousal (A): active/stimulated – sluggish/bored
- dominance (D): powerful/strong – powerless/weak



Thus, when comparing the meanings of two words, we can compare their V, A, D scores. For example:

- *banquet* indicates more positiveness than *funeral*
- *nervous* indicates more arousal than *lazy*
- *queen* indicates more dominance than *delicate*

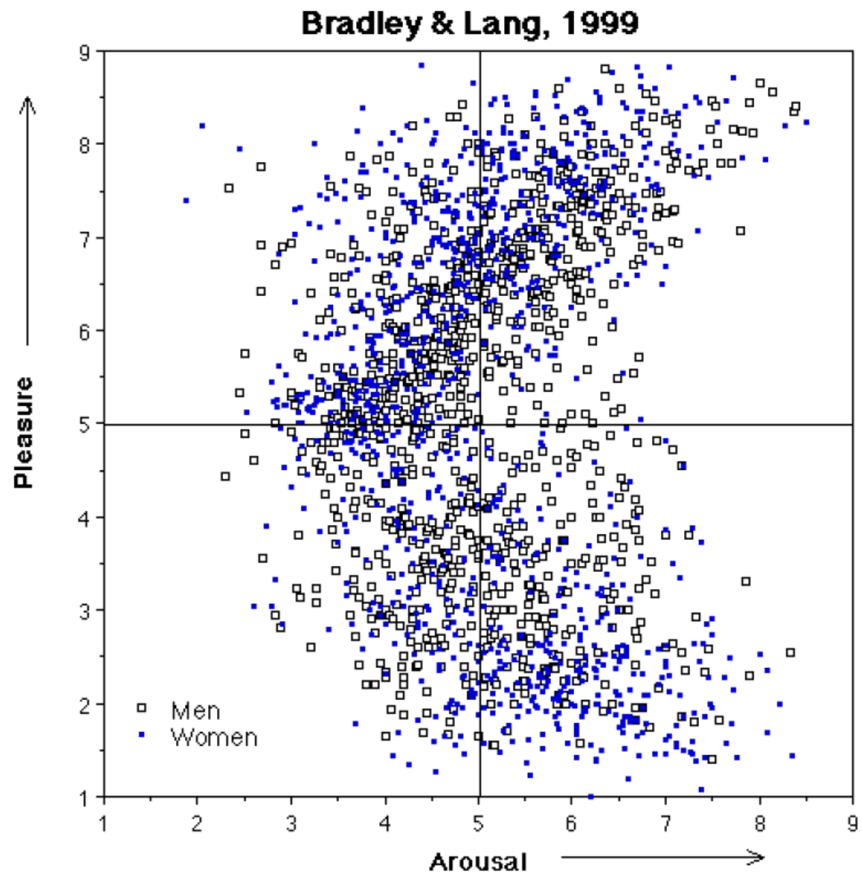
VAD lexicons: examples of entries

Dimension	Word	Score↑	Word	Score↓
valence	*love*	1.000	*toxic*	0.008
	happy	1.000	*nightmare*	0.005
	happily	1.000	*shit*	0.000
arousal	*abduction*	0.990	*mellow*	0.069
	exorcism	0.980	*siesta*	0.046
	homicide	0.973	*napping*	0.046
dominance	*powerful*	0.991	*empty*	0.081
	leadership	0.983	*frail*	0.069
	success	0.981	*weak*	0.045

ANEW: Affective norms for English words

Description	Word No.	Valence Mean(SD)	Arousal Mean(SD)	Dominance Mean (SD)	Word Frequency
abduction	621	2.76 (2.06)	5.53 (2.43)	3.49 (2.38)	1
abortion	622	3.50 (2.30)	5.39 (2.80)	4.59 (2.54)	6
absurd	623	4.26 (1.82)	4.36 (2.20)	4.73 (1.72)	17
abundance	624	6.59 (2.01)	5.51 (2.63)	5.80 (2.16)	13
abuse	1	1.80 (1.23)	6.83 (2.70)	3.69 (2.94)	18
acceptance	625	7.98 (1.42)	5.40 (2.70)	6.64 (1.91)	49
accident	2	2.05 (1.19)	6.26 (2.87)	3.76 (2.22)	33
ace	626	6.88 (1.93)	5.50 (2.66)	6.39 (2.31)	15
ache	627	2.46 (1.52)	5.00 (2.45)	3.54 (1.73)	4
achievement	3	7.89 (1.38)	5.53 (2.81)	6.56 (2.35)	65
activate	4	5.46 (0.98)	4.86 (2.56)	5.43 (1.84)	2
addict	581	2.48 (2.08)	5.66 (2.26)	3.72 (2.54)	1
addicted	628	2.51 (1.42)	4.81 (2.46)	3.46 (2.23)	3
admired	5	7.74 (1.84)	6.11 (2.36)	7.53 (1.94)	17
adorable	6	7.81 (1.24)	5.12 (2.71)	5.74 (2.48)	3
adult	546	6.49 (1.50)	4.76 (1.95)	5.75 (2.21)	25
advantage	629	6.95 (1.85)	4.76 (2.18)	6.36 (2.23)	73
adventure	630	7.60 (1.50)	6.98 (2.15)	6.46 (1.67)	14
affection	7	8.39 (0.86)	6.21 (2.75)	6.08 (2.22)	18
afraid	8	2.00 (1.28)	6.67 (2.54)	3.98 (2.63)	57

The multidimensional view on emotions



Corpus-based approaches

Rely on syntactic or co-occurrence patterns in large corpuses. (Hazivassiloglou and McKeown, ACL-97; Turney, ACL-02; Yu and Hazivassiloglou, EMNLP-03; Kanayama and Nasukawa, EMNLP-06; Ding and Liu, 2007)

- Can find domain (not context) dependent orientations (positive, negative, or neutral).

(Turney, ACL-02) and (Yu and Hazivassiloglou, EMNLP-03) are similar.

- Assign opinion orientations (polarities) to words/phrases.
- (Yu and Hazivassiloglou, EMNLP-03) is different from (Turney, ACL-02) in that
  - using more seed words (rather than two) and using log-likelihood ratio (rather than PMI).

Corpus-based approaches (contd)

Use constraints (or conventions) on connectives to identify opinion words (Hazivassiloglou and McKeown, ACL-97; Kanayama and Nasukawa, EMNLP-06; Ding and Liu, SIGIR-07). E.g.,

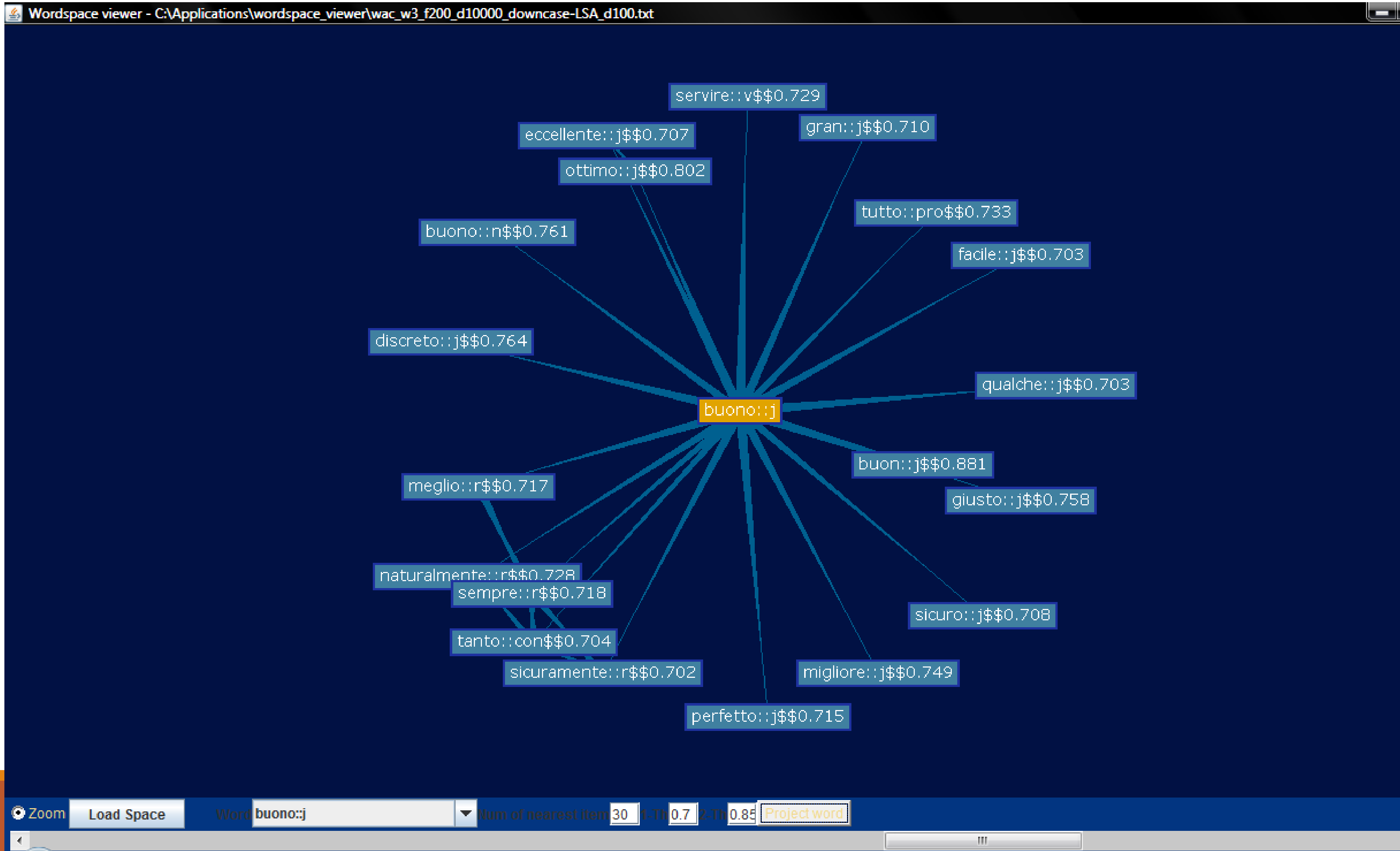
- Conjunction: conjoined adjectives usually have the same orientation (Hazivassiloglou and McKeown, ACL-97).
  - E.g., "This car is *beautiful* **and** *spacious*." (conjunction)
- AND, OR, BUT, EITHER-OR, and NEITHER-NOR have similar constraints

Learning using

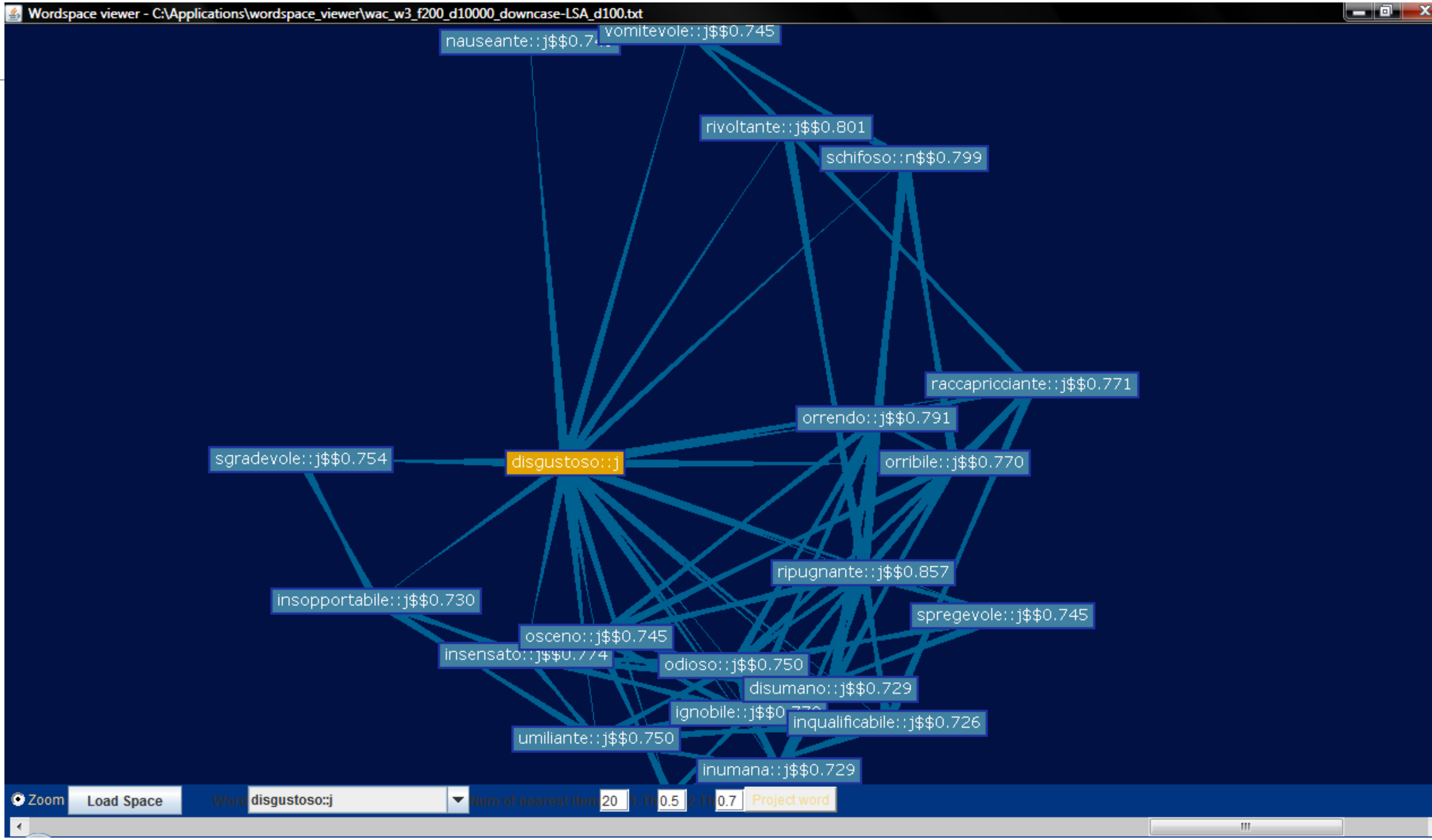
- log-linear model: determine if two conjoined adjectives are of the same or different orientations.
- Clustering: produce two sets of words: positive and negative

Corpus: 21 million word 1987 Wall Street Journal corpus.

Corpus-based approaches – A LSA Example



Corpus-based approaches – A LSA Example



Dictionary-based approaches

Typically use WordNet's synsets and hierarchies to acquire opinion words

- Start with a small seed set of opinion words
- Use the set to search for synonyms and antonyms in WordNet (Hu and Liu, KDD-04; Kim and Hovy, COLING-04).
- Manual inspection may be used afterward.

Use additional information (e.g., glosses) from WordNet (Andreevskaia and Bergler, EACL-06) and learning (Esuli and Sebastiani, CIKM-05).

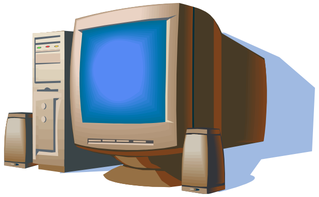
Weakness of the approach: Do not find domain and/or context dependent opinion words, e.g., small, long, fast.

Who does lexicon development ?

Humans

Semi-automatic

Fully automatic



What?

Find relevant words, phrases, patterns that can be used to express subjectivity

Determine the polarity of subjective expressions

Words

Adjectives (e.g. Hatzivassiloglou & McKeown 1997, Wiebe 2000, Kamps & Marx 2002, Andreevskaia & Bergler 2006)

- positive
- negative: harmful hypocritical inefficient insecure
  - It was a macabre and hypocritical circus.
  - Why are they being so inefficient ?
-

Words

Adjectives (e.g. Hatzivassiloglou & McKeown 1997, Wiebe 2000, Kamps & Marx 2002, Andreevskaia & Bergler 2006)

- positive
- negative
- Subjective (but not positive or negative sentiment): curious, peculiar, odd, likely, probable
  - He spoke of Sue as his probable successor.
  - The two species are likely to flower at different times.

Words

Other parts of speech (e.g. Turney & Littman 2003, Riloff, Wiebe & Wilson 2003, Esuli & Sebastiani 2006)

- Verbs
  - positive: **praise, love**
  - negative: **blame, criticize**
  - subjective**: predict**

- Nouns
  - positive: **pleasure, enjoyment**
  - negative: **pain, criticism**
  - subjective: **prediction, feeling**

Attitude Intensity

Table 6.2: Measures of intensity for different attitude types.

Attitude Type	Measure of Intensity	Example
Positive Sentiment	degree of positiveness	*like* < *love*
Negative Sentiment	degree of negativeness	*criticize* < *excoriate*
Positive Agreement	degree of agreement	*mostly agree* < *agree*
Negative Agreement	degree of disagreement	*mostly disagree* < *completely disagree*
Positive Arguing	degree of certainty/strength of belief	*critical* < *absolutely critical*
Negative Arguing	degree of certainty/strength of belief	*should not* < *really should not*
Positive Intention	degree of determination	*promise* < *promise with all my heart*
Negative intention	degree of determination	*no intention* < *absolutely no intention*
Speculation	degree of likelihood	*might win* < *really might win*

Bootstrapping by pattern acquisition
[Riloff & Wiebe 2003]

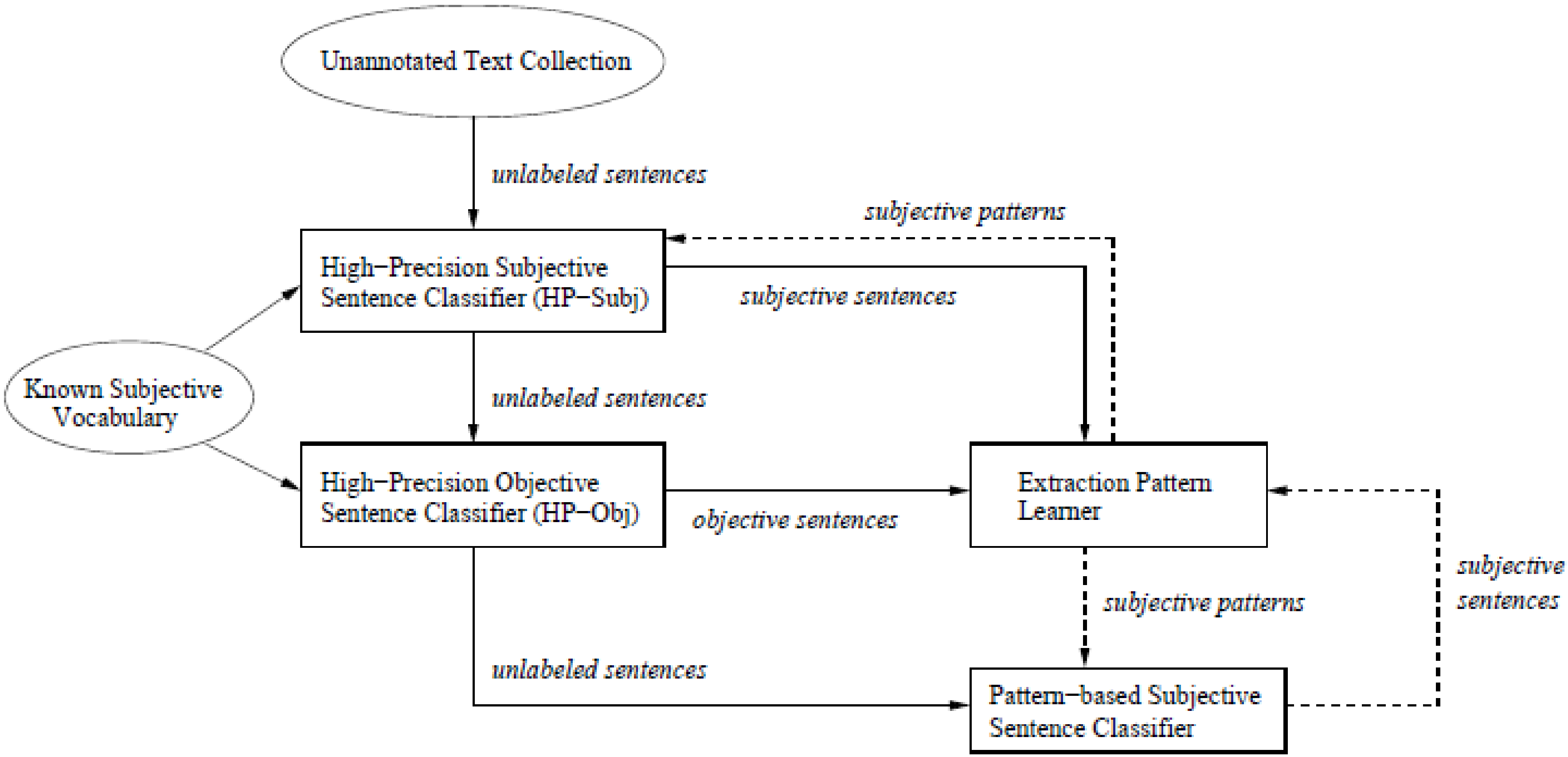


Figure 1: Bootstrapping Process

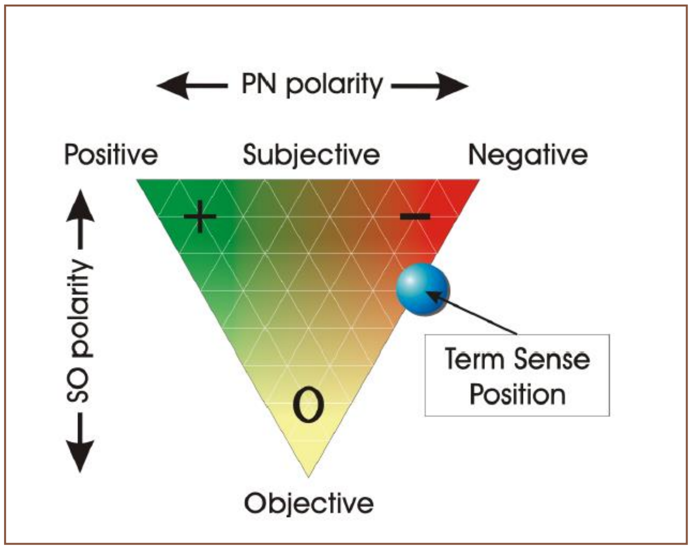
Bing Liu's Opinion Lexicon

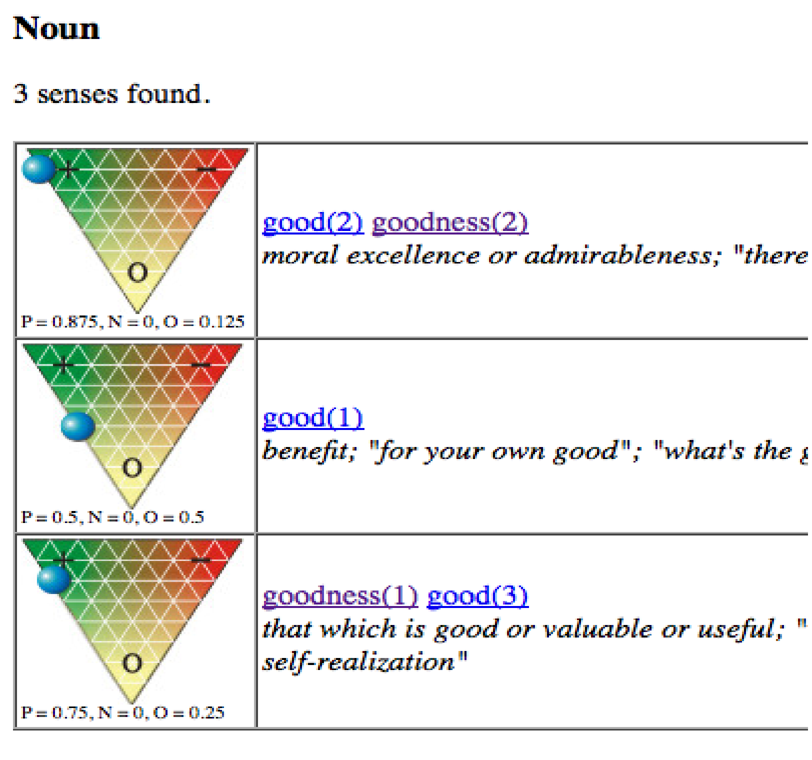
Minqing Hu and Bing Liu. Mining and Summarizing Customer Reviews. ACM SIGKDD-2004.

- http://www.cs.uic.edu/~liub/FBS/opinion-lexicon-English.rar
- 6786 words
  - 2006 positive
    - … abound, abounds, abundance, abundant, accessable, accessible, acclaim, acclaimed, acclamation, accolade, accolades, accommodative, accomodative, accomplish, accomplished, accomplishment, accomplishments, accurate, ...
  - 4783 negative
    - …., abnormal, abolish, abominable, abominably, abominate, abomination, abort, aborted, aborts, abrade, abrasive, …

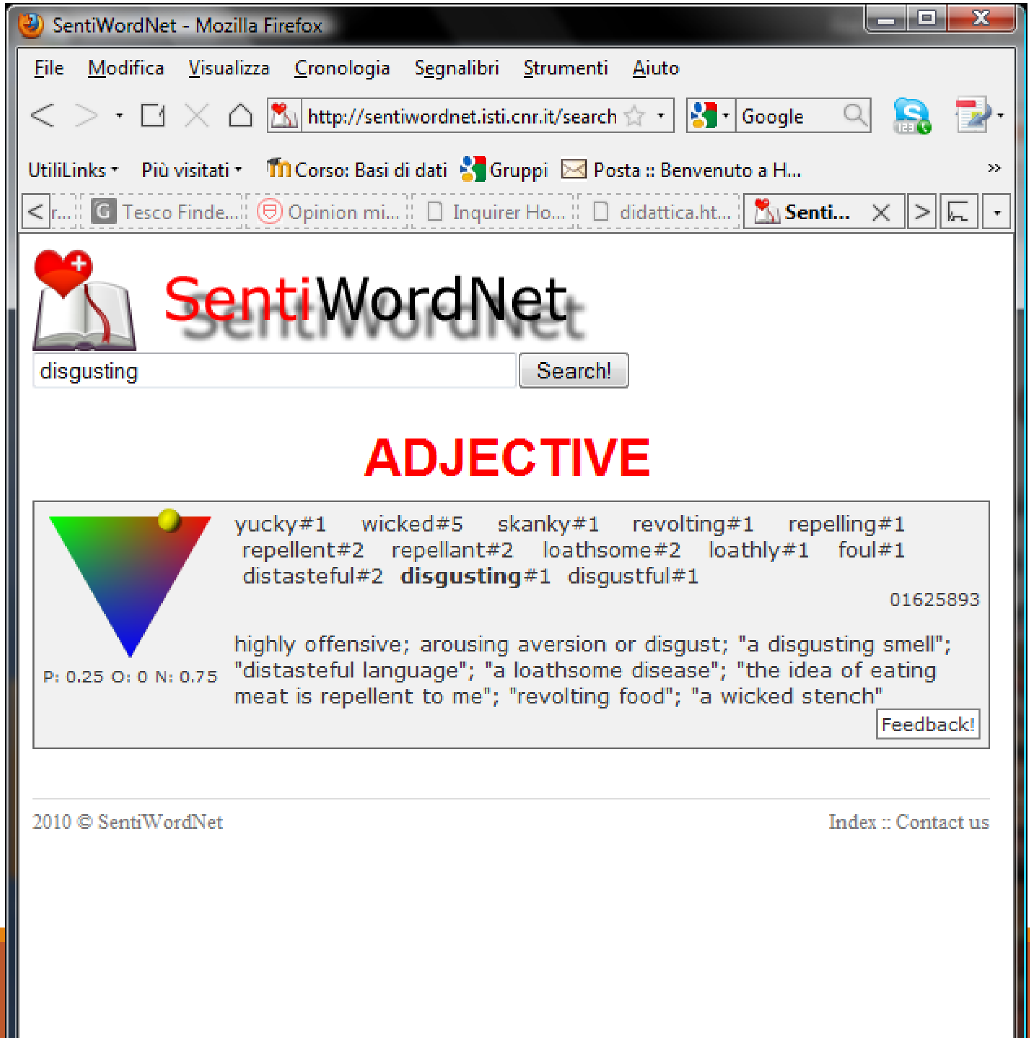
OM resources: SentiWordnet

SentiWN (Sebastiani & Esuli, 2008)





Sentiwordnet



Semi-automatic approach to the design

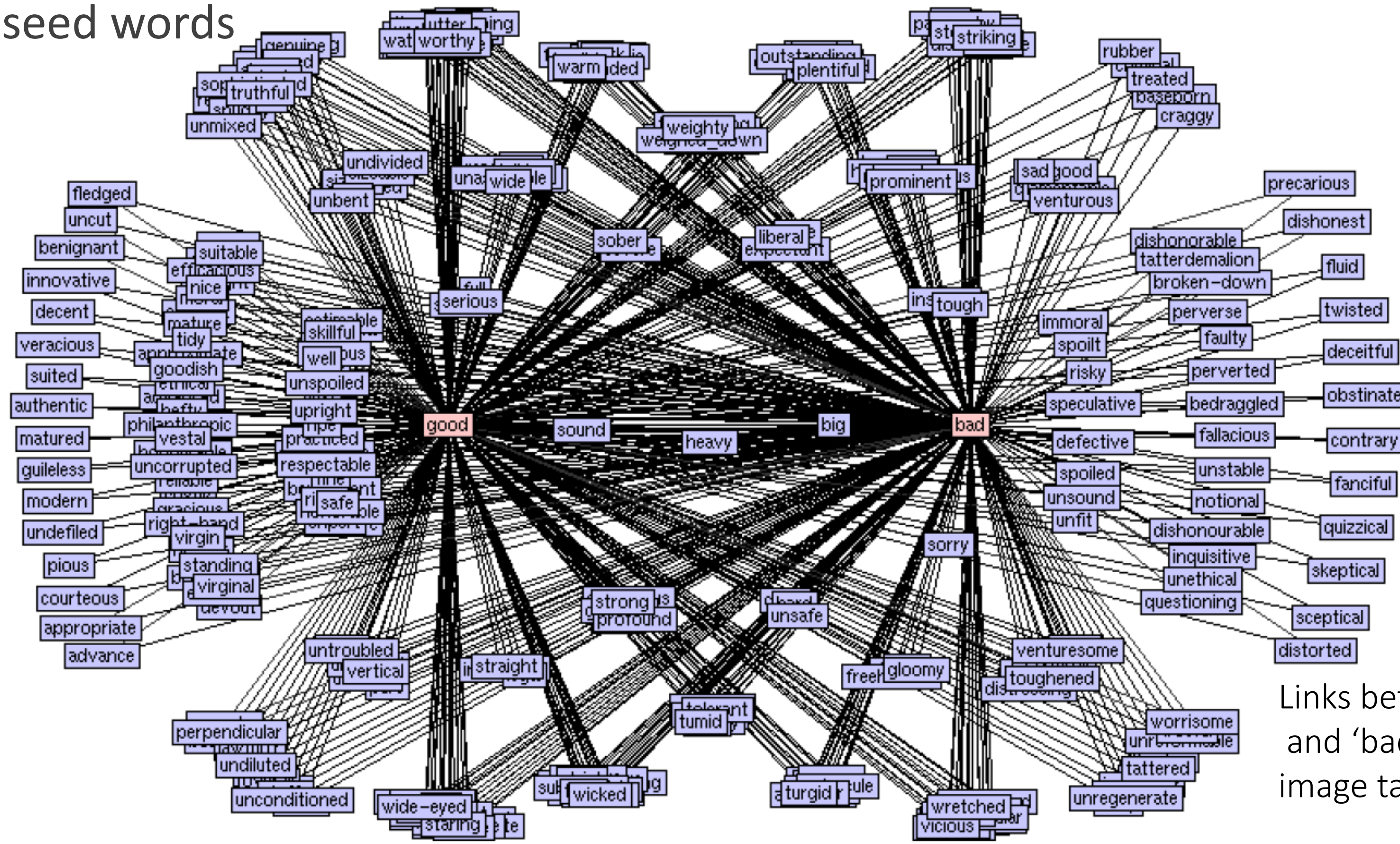
A SNA methods applied to lexical semantics (Sebastani & Esuli, 2008)

- PageRank over word senses

Creating affective lexicons: using WordNet

WordNet: A lexical database for the English language, that provides various semantic relations between tokens (e.g., synonyms, antonyms)

Can be used to classify positive/negative tokens, based on distance from seed words



Links between 'good' and 'bad' in WordNet image taken from [5]

NCSR Lexicon (Mohammad & Turney, 2013)

Saif Mohammad and Peter D. Turney. 2013. *Crowd- sourcing a word-emotion association lexicon*. Computational Intelligence, 29(3):436–465.

Term	positive	negative	anger	anticipation	disgust	fear	joy	sadness	surprise	trust
agitated	0	1	1	0	0	0	0	0	0	0
agitation	0	1	1	0	0	0	0	0	0	0
agnostic	0	0	0	0	0	0	0	0	0	0
ago	0	0	0	0	0	0	0	0	0	0
agonizing	0	1	0	0	0	1	0	0	0	0
agony	0	1	1	0	0	1	0	1	0	0
agree	1	0	0	0	0	0	0	0	0	0
agreeable	1	0	0	0	0	0	0	0	0	1
agreed	1	0	0	0	0	0	0	0	0	1
agreeing	1	0	0	0	0	0	0	0	0	1
agreement	1	0	0	0	0	0	0	0	0	1
agricultural	0	0	0	0	0	0	0	0	0	0
agriculture	1	0	0	0	0	0	0	0	0	0
aground	0	1	0	0	0	0	0	0	0	0
agua	0	0	0	0	0	0	0	0	0	0
ahead	1	0	0	0	0	0	0	0	0	0
aid	1	0	0	0	0	0	0	0	0	0
aiding	1	0	0	0	0	0	0	0	0	0

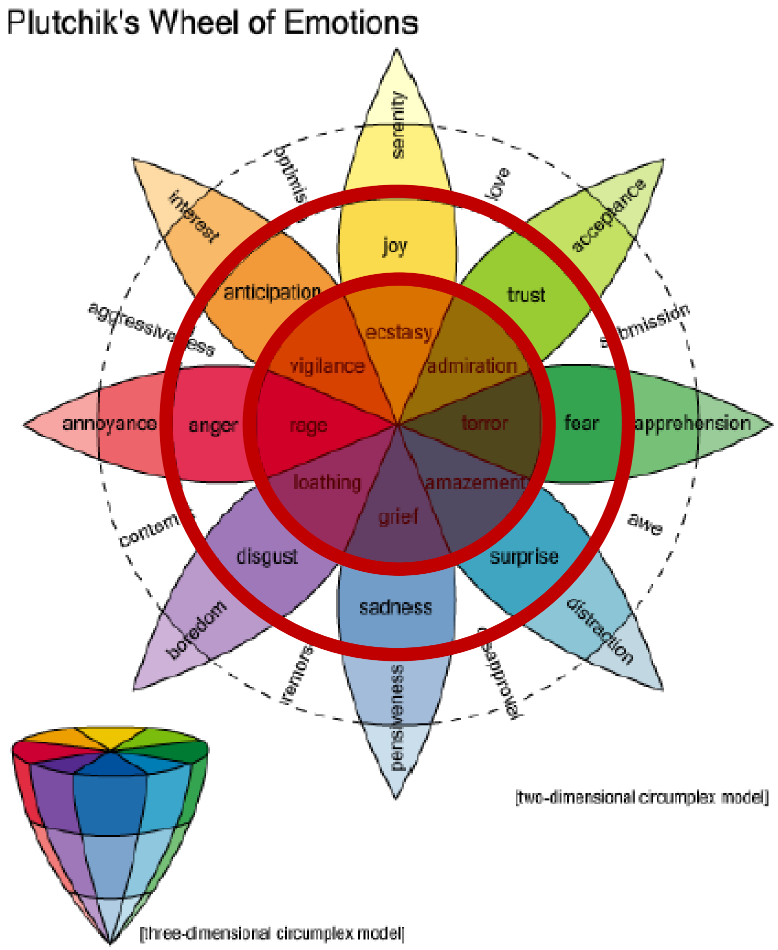


FIGURE 1. Plutchik's wheel of emotions. Similar emotions are placed next to each other. Contrasting emotions are placed diametrically opposite to each other. Radius indicates intensity. White spaces in between the basic emotions represent primary dyads—complex emotions that are combinations of adjacent basic emotions. (The image file is taken from Wikimedia Commons.)

Tasks: definitions and models

Opinion mining – the abstraction

Document level sentiment classification

Sentence level sentiment analysis

Feature-based sentiment analysis and summarization

Summary

The tasks

Recall the three tasks in our model.

- *Task* 1: Extracting *object features (aspects)* that have been commented on in each review.
- *Task* 2: Determining whether the opinions on the features are positive, negative or neutral.
- *Task* 3: Grouping feature synonyms.
  - Summary

Task 2 may not be needed depending on the format of reviews.

Different review format

Format 1 - Pros, Cons and detailed review: The reviewer is asked to describe Pros and Cons separately and also write a detailed review. Epinions.com uses this format.

Format 2 - Pros and Cons: The reviewer is asked to describe Pros and Cons separately. C|net.com used to use this format.

Format 3 - free format: The reviewer can write freely, i.e., no separation of Pros and Cons. Amazon.com uses this format.

Format 1

My SLR is on the shelf

by camerafun4. Aug 09 '04

Pros: Great photos, easy to use, very small
Cons: Battery usage; included memory is stingy.

I had never used a digital camera prior to purchasing th have always used a SLR … **Read the full review**

Format 2

User rating Perfect **10** out of 10

"It is a great digitbal still camera for this century"

September 1, 2004

Pros:
It's small in size, and the rotatable lens is great. It's very easy to use, and has fast response from the shutter. The LCD has increased from 1.5 in to 1.8, which gives bigger view. It has lots of modes to choose from in order to take better pictures.

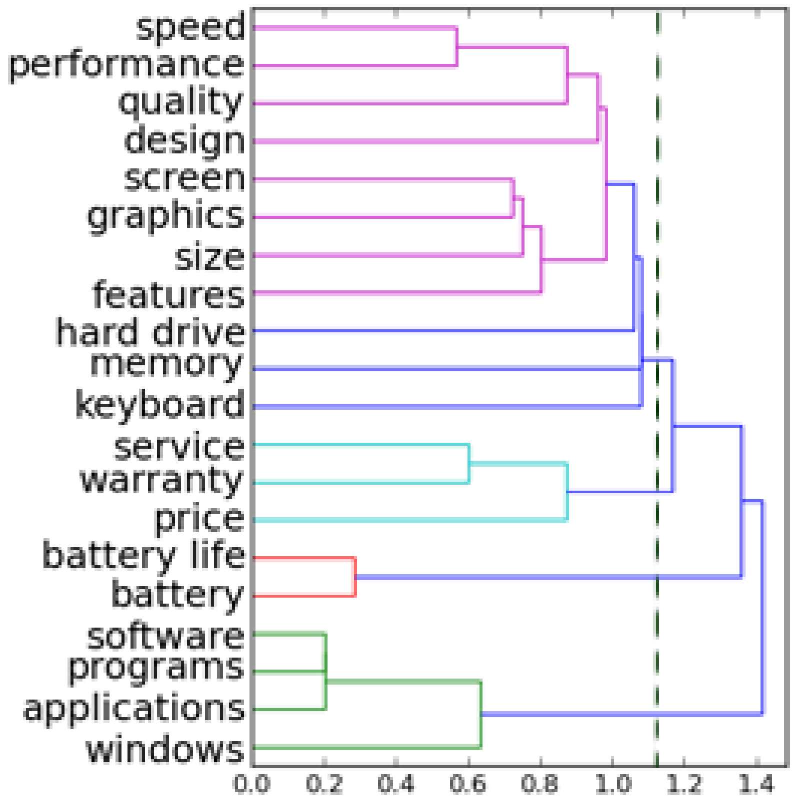
Cons:
It almost has no cons, it would be better if the LCD is bigger and it's going to be best if the model is designed to a smaller size.

Format 3

GREAT Camera., Jun 3, 2004
Reviewer: jprice174 from Atlanta, Ga.

I did a lot of research last year before I bought this camera... It kinda hurt to leave behind my beloved nikon 35mm SLR, but I was going to Italy, and I needed something smaller, and digital. The pictures coming out of this camera are amazing. The 'auto' feature takes great pictures most of the time. And with digital, you're not wasting film if the picture doesn't come out.

Laptop aspects hierarchy



Restaurant aspects hierarchy

Architectural and Technological Issues

SA as Text Classification: Supervised/unsupervised

- **Supervised learning** methods are the most commonly used one, yet also some **unsupervised** methods have been successfully.
- Unsupervised methods rely on the shared and recurrent characteristics of the sentiment dimension across topics to perform classification by means of hand-made heuristics and simple language models.
- Supervised methods rely on a **training set** of labeled examples that describe the correct classification label to be assigned to a number of documents.
- A learning algorithm then exploits the examples to model a general classification function.

VADER

VADER (Valence Aware Dictionary for sEntiment Reasoning)uses a curated lexicon derived from well known sentiment lexicons that assigns a positivity/negativity score to 7k+ words/emoticons.

It also uses a number of hand-written pattern matching rules (e.g., negation, intensifiers) to modify the contribution of the original word scores to the overall sentiment of text.

Reference paper: Hutto and Gilbert. VADER: A *Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text*. ICWSM 2014.

VADER is integrated into NLTK

```
NEGATE - {"aint", "arent", "cannot", "cant", "couldn
 "ain't", "aren't", "can't", "couldn't", "daren't",
 "dont", "hadnt", "hasnt", "havent", "isnt", "mightn
 "don't", "hadn't", "hasn't", "haven't", "isn't", "m
 "neednt", "needn't", "never", "none", "nope", "nor"
 "oughtnt", "shant", "shouldnt", "uhuh", "wasnt", "w
 "oughtn't", "shan't", "shouldn't", "uh-uh", "wasn't
 "without", "wont", "wouldnt", "won't", "wouldn't",

# booster/dampener 'intensifiers' or 'degree adverbs
# http://en.wiktionary.org/wiki/Category:English_deg

BOOSTER_DICT = \
{"absolutely": B_INCR, "amazingly": B_INCR, "awfully
 "decidedly": B_INCR, "deeply": B_INCR, "effing": B_
 "entirely": B_INCR, "especially": B_INCR, "exceptio
 "fabulously": B_INCR, "flipping": B_INCR, "flippin"
 "fricking": B_INCR, "frickin": B_INCR, "frigging":
 "greatly": B_INCR, "hella": B_INCR, "highly": B_INC
 "intensely": B_INCR, "majorly": B_INCR, "more": B_I
 "purely": B_INCR, "quite": B_INCR, "really": B_INCR
 "so": B_INCR, "substantially": B_INCR,
 "thoroughly": B_INCR, "totally": B_INCR, "tremendou
 "uber": B_INCR, "unbelievably": B_INCR, "unusually"
 "very": B_INCR,
 "almost": B_DECR, "barely": B_DECR, "hardly": B_DEC
 "kind of": B_DECR, "kinda": B_DECR, "kindof": B_DEC
 "less": B_DECR, "little": B_DECR, "marginally": B_D
 "scarcely": B_DECR, "slightly": B_DECR, "somewhat":
 "sort of": B_DECR, "sorta": B_DECR, "sortof": B_DEC

# check for special case idioms using a sentiment-la
SPECIAL_CASE_IDIOMS = {"the shit": 3, "the bomb": 3,
                       "cut the mustard": 2, "kiss o
```

The supervised classification pipeline

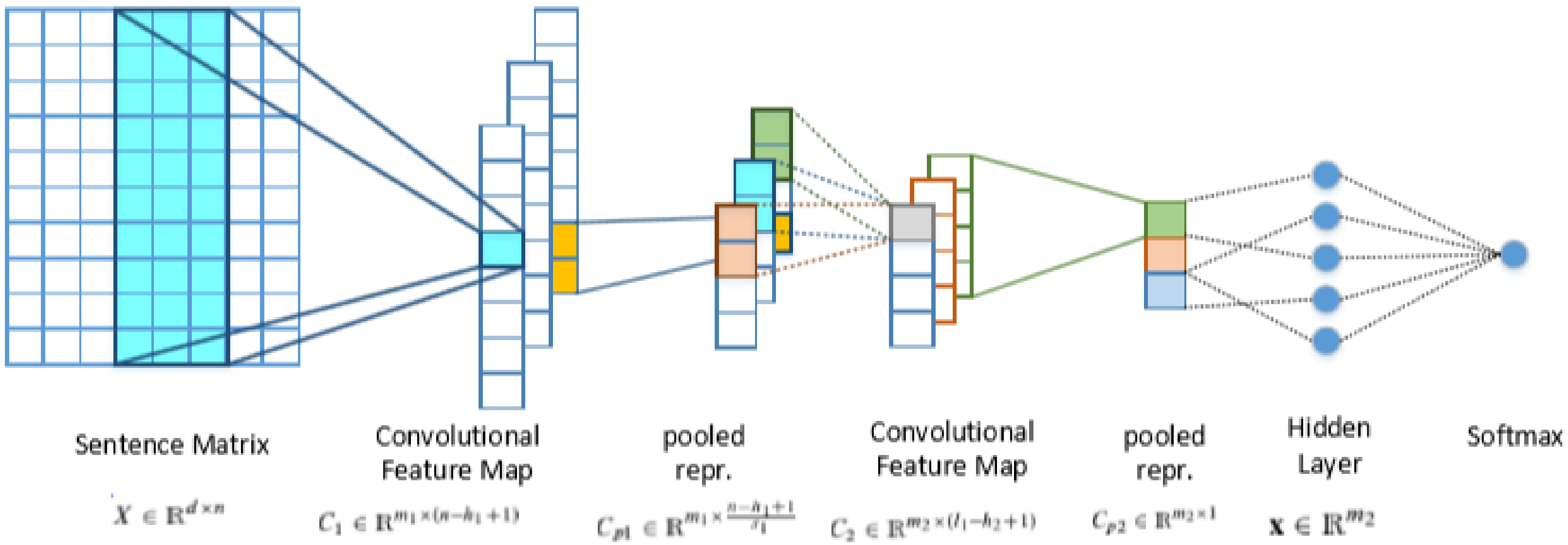
The elements of a classification pipeline are:

1. Tokenization
2. Feature extraction
3. Feature selection
4. Weighting
5. Learning

Steps from 1 to 4 define the feature space and how text is converted into vectors.

Step 5 creates the classification model.

SwissCheese at SemEval 2016



Three-stage procedure:

1. Creation of word embeddings for initialization of the first layer. Word2vec on an unlabelled corpus of 200M tweets.
2. Distant supervised phase, where the network weights and word embeddings are trained to capture aspects related to sentiment. Emoticons used to infer the polarity of a balanced set of 90M tweets.
3. Supervised phase, where the network is trained on the provided supervised training data.

USE CASES

COVID study (2020): https://mdpi-res.com/d_attachment/applsci/applsci-12-03709/article_deploy/applsci-12-03709.pdf?version=1649318517

SURVEY on DNNs for SA (2020): https://arxiv.org/ftp/arxiv/papers/2006/2006.03541.pdf

Brand Reputation: Opinion_Mining for Brand Reputation: a use case_v1.1.pptx

OM: Technological directions

Open Issues:

- **Adaptivity**: semi-supervised models, aka Few Shot Learning
  - For the affective lexicon acquisition (e.g. Li et al., ACL 2009)
  - For the representation (encoding) of target texts
  - For generalizing resource across languages and domains (MultiTask learning)
- **Fine-grained OM** through
  - Neural nets (e.g. (Kim, 2014)
- Social Dynamics through
  - Complex architectures
  - Models of Social profiles and comunications

Benchmarking SA

Recent Benchamrks on Twitter Sentiment Analysis

ACL SemEval champaigns:

- Example 2014, Task 4: https://alt.qcri.org/semeval2014/task4/

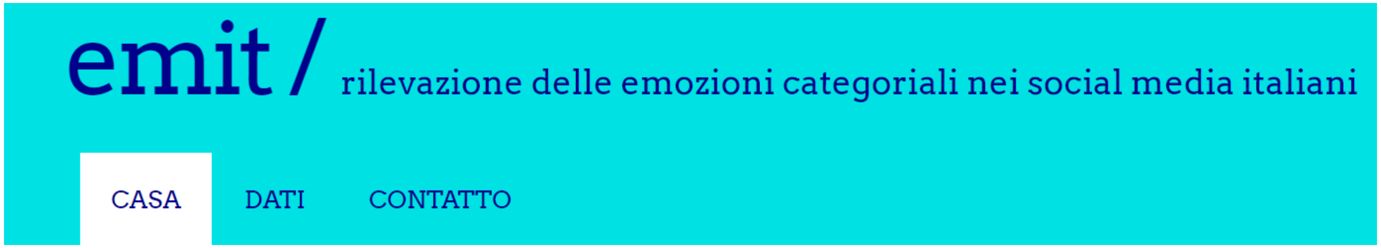
EvalIta champaigns:

- Example, 2016, ABSITA: http://sag.art.uniroma2.it/absita/

EvalIta 2023
(https://www.evalita.it/campaigns/evalita-2023/tasks/)

- EMit – Categorical Emotion Detection in Italian Social Media (O. Araque, S. Frenda, D. Nozza, V. Patti, R. Sprugnoli)

- EmotivITA – Dimensional and Multi-dimensional emotion analysis (G. Gafà, F. Cutugno, M. Venuti)



EmotivIta (2023)

What, why and how

EmotivITA includes two tasks, both constraint and unconstraint. In proposing these tasks, we aim to promote dimensional emotion analysis, a problem who has received increasing attention within the field of sentiment analysis in the English-speaking community, but not yet so among the Italian speakers.

- **Task A: Dimensional emotion regression**

  Prediction of Valence, Arousal and Dominance values based on a set of Italian sentences and annotations, using only the target annotated dimension for training.

- **Task B. Multi-dimensional emotion regression**

  Prediction of Valence, Arousal and Dominance values based on a set of Italian sentences and annotations, using all mentioned dimensions for training (so to exploit possible correlations within them, see below).

EmIt (2023)

task description

EMit is organized according to two subtasks, both designed as multilabel classification problems:

- **Task A**: Categorial Emotion Detection (required): given a text, the system decides the emotions expressed in it or the absence of emotions. In other words, the text could be classified as neutral, or expressing one or more of the 8 basic emotions defined by Plutchik [8] (anger, anticipation, disgust, fear, joy, sadness, surprise, trust) plus the additional emotion "love" that is one of the primary dyads in the Plutchik's wheel of emotions.
- **Task B**: Target Detection (optional): given a text, the system decides what is the target addressed by the author of the text. The text could be classified as addressing the topic, or the direction, or both or neither.

Further References

Bo Pang and Lillian Lee. 2008. Opinion Mining and Sentiment Analysis. *Found. Trends Inf. Retr.* 2, 1-2 (January 2008), 1-135. DOI=http://dx.doi.org/10.1561/1500000011

Social Media Analytics R. Lawrence, P. Melville, C. Perlich, V.Sindhwani, E.Meliksetian, P.Hsueh, Y. Liu Operations Research/Management Science Today, Feburary 2010

Bing Liu, Sentiment Analysis and Subjectivity, Handbook of Natural Language Processing, Second Edition, (editors: N. Indurkhya and F. J. Damerau), 2011

An Example Use case

See slides on «SA on Twitter at Semeval 2013»

More information in:

"***Injecting sentiment information in context-aware convolutional neural networks***" (Croce et Al, 2016), SocialNLP 2016 Proceedings, IJCAI 2016, New York. URL: https://sites.google.com/site/socialnlp2016/ .

References

NLP, IR & ML:

- «*Speech and Language Processing*”, D. Jurafsky and J. H .Martin, Prentice-Hall, 2009.
- “*Introduction to Information Retrieval*”, Manning, Raghavan & Schutze, Cambridge University Press 2008.

Opinion Mining

- [*Opinion Mining and Sentiment Analysis* (by Bo Pang and Lillian Lee)]
- [*Sentiment Analysis and Opinion Mining, by Bing Liu, 20*]

Sitografia:

- SAG, Univ. Roma Tor Vergata: http://sag.art.uniroma2.i