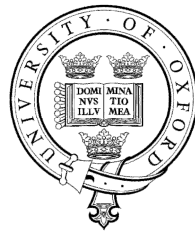


Sentiment Analysis

Advanced Topics in Language Processing



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Sentiment Analysis

- Detection and analysis of expressions of
 - opinions, emotions, evaluations, beliefs, and speculations
 - cognitive *private* states that are not open to objective outside observation or verification
 - author/speaker sentiment, not sentiment evoked in the reader/hearer
 - difficult (impossible?) to formalise
 - no right answer, just points of view
- This lecture focuses on text, not speech

Sentiment Analysis

- “Clear” cases

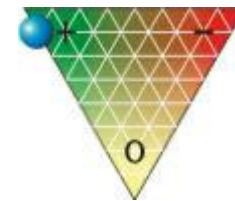
- *She is the **mother of all mothers**. She possessed character traits that other women **should strive to meet**. **Holiness, piety, and humbleness** are **valued very ...***
- ***HOT!haha**. Well a **nice Yamaha drum** but **not properly handled** wif **care,i had to ...** it sounds like.....**noise?really noisy** songs,vocals **totally crap.haha!**so i ...*

- Less clear cases

- *The patient scale consists of nine items: six subscales related to major **lung cancer symptoms** (**appetite, cough, dyspnea, fatigue, hemoptysis, and pain**), ...*
- *By midday, the FTSE Eurofirst 300 **rebounded** 1.9 per cent 1,354.11, while Germany’s Xetra Dax **rose** 2.1 per cent to 6,991.72 and in Paris the CAC 40 **added** 2.5 per cent to 4,988.80.*

Key Dimensions

- Subjectivity
 - subjective (*genius*), objective/factual (*hypertext markup language*)
- Polarity
 - positive (*love*), neutral (*fish*), mixed (*love-hate*), balanced
- Strength
 - weak (*nice*), strong (*extremely nice*)
- Affect
 - key universal categories (anger, disgust, fear, joy, sadness, surprise, ...)



Applications

- Classification
 - clustering, filtering
- Rating
 - ranking and labelling
- Summarisation
- Comparative analysis
 - pros vs. cons, support vs. opposition
- Role analysis
 - opinion holder, target
- Question Answering
- Lexicographic work

Applications

- Extraction
 - Information Extraction, Information Retrieval, Text Mining
- Affect analysis
 - Question/Answering and Dialogue
 - affective computing and HCI
- Tracking and visualisation
 - time series, regularities and irregularities, plotting, data summarisation, GUI design
- Financial analysis
- Media, marketing, financial, legal, and governmental organisations

Terminological Variance

- *Fully* standardised terminology still to emerge
 - subjectivity, sentiment, evaluation, private state, affect, emotion, opinion, attitude, appraisal, point of view, colouring, stance, perspective, tone, intent, modulation, ...
 - analysis, classification, mining, tagging, extraction, ...
 - positive, negative, thumbs up, thumbs down, good, bad, neutral, non-neutral, sentiment-bearing, recommended, not recommended, ...
 - polarity, valence, (semantic) orientation, direction, slant, ...
 - reversal, switcher, flipper, changing word, increase/decrease words...
 - strength, potency, force, ...
 - source, experiencer, holder, target, ...

Levels of Analysis

- **Document-level:** [*(movie review)*], [*(news article)*], ...
- **Paragraphs:** [*(conclusion)*], ...
- **Snippets:** [*(search engine results)*], [*(n chars/words)*], ...
- **Sentences:** [*The govt handled the crisis well*], ...
- **Clauses:** [*It's not perfect*] [*but it is still useful*], ...
- **Phrases:** *Life's nothing but* [*a bowl of rotten cherries*], ...
- **Words:** *The* [*govt*] [*handled*] *the* [*crisis*] [*well*], ...
- **Morphemes:** [*de-*][*conflict*], [*hope*][*-less*], ...
- **Senses:** [*depressed*] (*button*) vs. [*depressed*] (*person*), ...

Levels of Analysis

- **Entities/objects:** *[digital camera X], [person Y], [company W]...*
- **Features/subparts:** *[battery], [price], [keyboard layout], ...*
- **Roles:** *according to [person Z], [person Q] claimed that, ...*

Atomic Sentiment Carriers

- Single-word atomic carriers
 - *[victory]⁽⁺⁾, [wrath]⁽⁻⁾, [fondle]⁽⁺⁾, [mutilate]⁽⁻⁾, [brilliant]⁽⁺⁾, [corny]⁽⁻⁾, [admirably]⁽⁺⁾, [badly]⁽⁻⁾, ...*
 - adjectives, adverbs, nouns, and verbs
- Multi-word atomic carriers
 - *[do away with smth]⁽⁻⁾, [get it together]⁽⁺⁾, [friendly fire]⁽⁻⁾, [police state]⁽⁻⁾, [de rigueur]⁽⁺⁾, [head and shoulders above smth]⁽⁺⁾, [on cloud nine]⁽⁺⁾, [off the beaten track]⁽⁺⁾, [live in an ivory tower]⁽⁻⁾, [an old hand at smth]⁽⁺⁾, [step on smb's toes]⁽⁻⁾, ...*
- The expression inventory is vast
- Noticeably many infrequent instances

Case Study 1: Movie Reviews

- SA seen as an extension to standard text classification tasks
 - classify documents based on subject matter (SPORTS/ECONOMICS/...)
 - classify documents based on overall polarity
 - standard supervised text classification tools and techniques
- Learners
 - Naïve Bayes, MaxEnt, SVM
- Training
 - 700 (+) and 700 (-) movie reviews from the web
 - 3-fold cross validation

Case Study 1: Movie Reviews

- Features
 - unigrams, bigrams, adjectives, POS tags, position in document
 - no stemming or stoplists
 - rudimentary support for negation
 - append a NOT tag to each word between a negator (e.g. *not*, *isn't*) and the first punct token on the right
 - represented as binary (presence) or frequency values

Case Study 1: Movie Reviews

- Performance
 - random-choice baseline: 50
 - human-selected unigram baseline: 58 ~ 64
 - 82.9 accuracy (SVM, unigrams, binary)
- A further sentential subjectivity filter
 - classifier to filter out objective sentences
 - polarity classification proper done only subjective extracts
 - 86.4 accuracy
 - maintain the same level of performance with only 60% of the words in the text

Case Study 1: Movie Reviews

- Challenges
 - cf. accuracies of 90+ (with more classes) in standard text classification tasks
 - bag-of-features classifiers ignore discourse-temporal developments in text (e.g. the “*thwarted expectation*” rhetorical device in reviews)
 - reviews discuss multiple issues
 - events and actors in the movie
 - the style and art of the movie (the movie as a whole)
 - elaborative and contrasting devices
 - in web data, reviewers’ ratings and labels can be arbitrary
 - out-of-domain features perform poorly

Case Study 2: PMI-IR

- Assumption
 - the polarity (Semantic Orientation (SO)) of a word tends to correspond to the polarities of its neighbours
- The polarity of a term is calculated using
 - a Pointwise Mutual Information (PMI) score of the term against key paradigmatic polarity terms
 - Pos = {*good, nice, excellent, positive, fortunate, correct, superior*}
 - Neg = {*bad, nasty, poor, negative, unfortunate, wrong, inferior*}
 - a “live” search engine (or a static corpus)
 - phrasal templates
 - [JJ] [NN] “*romantic ambience*”, [RB] [JJ] “*very cool*”

Case Study 2: PMI-IR

- Context window
 - the original method used AltaVista's `NEAR` (± 10 words) search operator (now deprecated)
 - using the `AND` search operator yields inferior results

$$PMI(t, t_i) = \log \frac{\#("t \text{ NEAR } t_i'')}{\#("t'')\#("t_i'')}$$

$$SO(t) = \sum_{t_i \in Pos} PMI(t, t_i) - \sum_{t_i \in Neg} PMI(t, t_i)$$

- Also indicates strength of sentiment

Case Study 2: PMI-IR

- Accuracy of term polarities
 - 3596 unambiguous words (adjectives, adverbs, nouns, and verbs) labelled manually as *positive* (1614) and *negative* (1982) from General Inquirer
 - 82.8 accuracy
 - 95+ when “mild” words are excluded
 - 97.1 for top (=highest confidence) 25% of words (899 words)
 - corpus size is crucial (61.3-68.7 accuracy using a 10-million word corpus (cf. hundred billion words))

Case Study 2: PMI-IR

- Document-level sentiment
 - the average of the SO scores of all adjectives and adverbs
- Performance
 - 74 accuracy on 410 reviews
 - 66 (movie reviews)
 - 84 (car reviews)

| Extracted Phrase | Part-of-Speech Tags | Semantic Orientation |
|------------------------------|------------------------|-------------------------|
| online experience | JJ NN | 2.253 |
| low fees | JJ NNS | 0.333 |
| local branch | JJ NN | 0.421 |
| small part | JJ NN | 0.053 |
| online service | JJ NN | 2.780 |
| printable version | JJ NN | -0.705 |
| direct deposit | JJ NN | 1.288 |
| well other | RB JJ | 0.237 |
| inconveniently located | RB VBN | -1.541 |
| other bank | JJ NN | -0.850 |
| true service | JJ NN | -0.732 |
| Average Semantic Orientation | | 0.322 |

Case Study 3: Contextual Polarity

- Calculating the contextual polarities of sentiment expressions using
 - supervised machine learning (BoosTexter AdaBoost.HM, 5000 rounds boosting)
 - subjective expressions from the MPQA corpus annotated with contextual polarity tags (+, -, n, both) as training and test data
 - sentiment lexicon of 8000+ (manually and automatically derived) entries tagged with the above polarity tags and reliability indicators (strong, weak)
 - dependency parser
 - [neutral/polar classifier] → [polar classifier] architecture

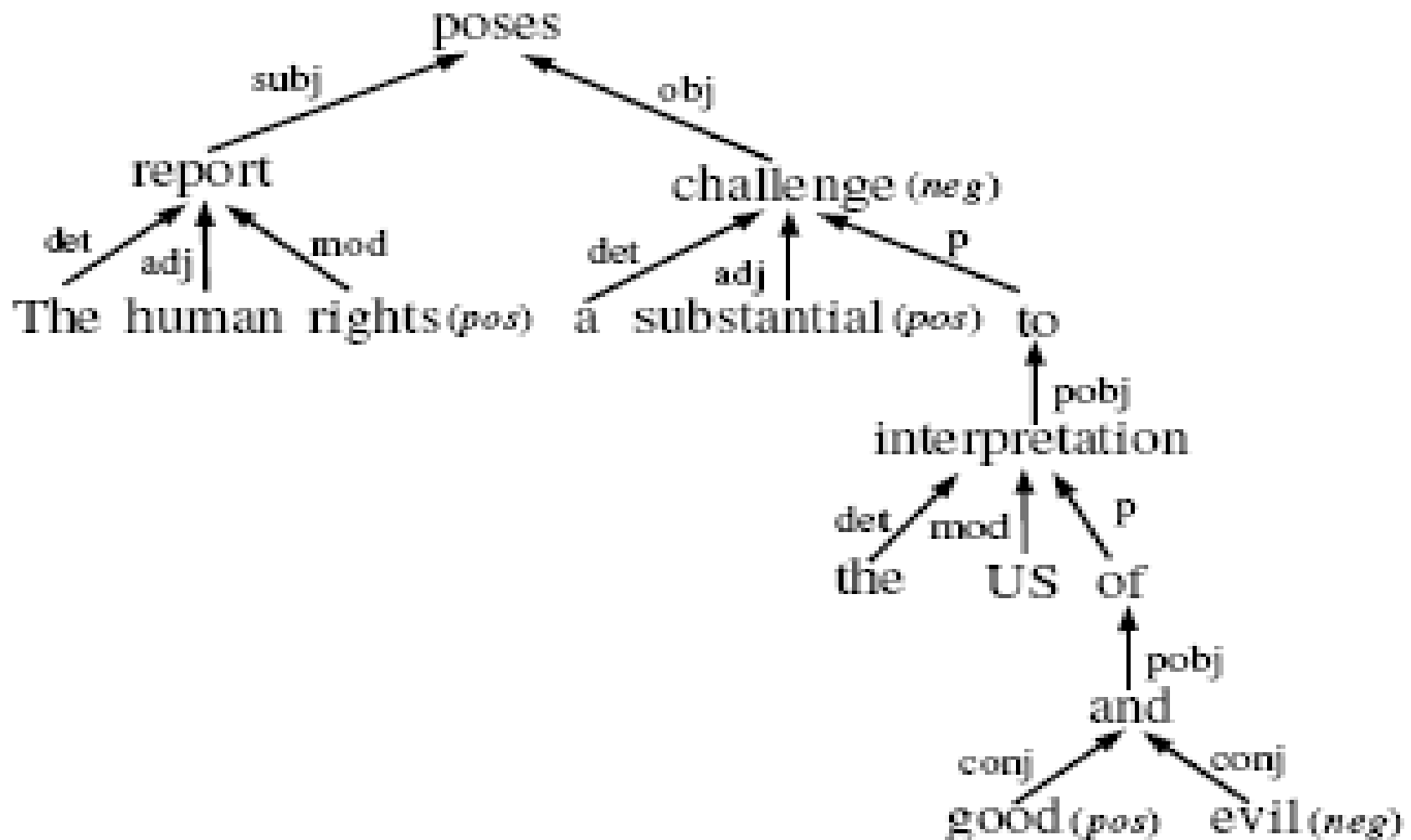
Case Study 3: Contextual Polarity

- Task
 - classify the contextual polarity of subjective expressions which contain subjectivity clues from the lexicon
 - give each clue instance its own label
 - NB. expression boundaries are not determined
- Baseline
 - accuracy of always using the prior polarity of a clue instance as its contextual polarity: only 48

Case Study 3: Contextual Polarity

- Neutral/polar classifier
 - word features
 - token (*loves*); POS (V); trigram context (*she loves me*); prior polarity (+); reliability (strong)
 - modification features
 - preceded by (ADJ/ADV/INTENSIFIER); is intensifier (*terribly*); modifies or is modified by a (strong/weak) clue
 - structural features
 - is in subject (*criminals exist*); is in copula (*is wonderful*); is passive (*were destroyed*)

Case Study 3: Contextual Polarity



[Wilson et al. (2005)]

Case Study 3: Contextual Polarity

- Neutral/polar classifier
 - sentence features
 - # of `strong` and `weak` clues in previous, current, next sentences; POS tags counts in current sentence
 - document features
 - one of 15 document topics (`ECONOMICS`, `KYOTO PROTOCOL`,...)

Case Study 3: Contextual Polarity

- Polar classifier
 - word features
 - token (*loves*); prior lexeme polarity (+)
 - negation features
 - is negated (*didn't love*); is negated subject (*not a single volunteer came forward*)
 - modification features
 - modifies (*substantial challenge*) or is modified (*substantial challenge*) by a (+, -, n, both) token, or (not mod)

Case Study 3: Contextual Polarity

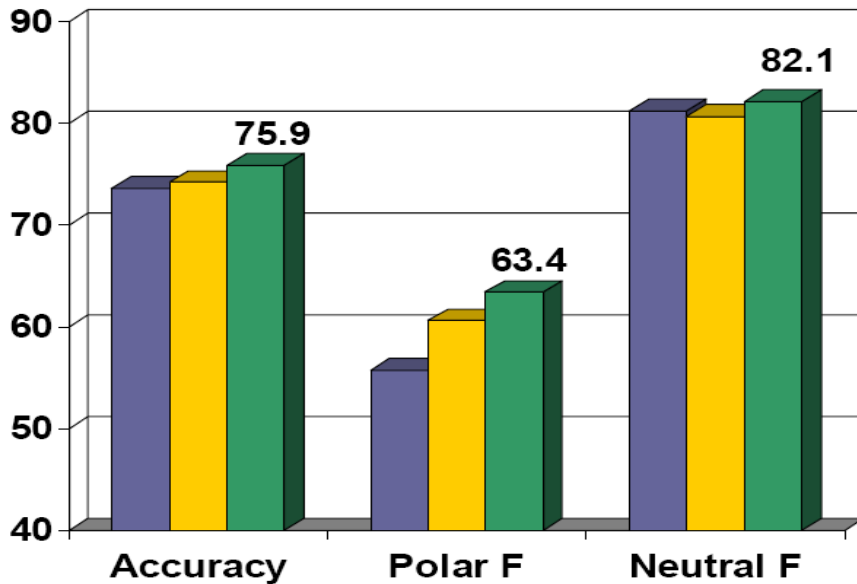
- Polar classifier
 - conjunction features
 - is in a conjunction (*sweet and sour*) (+, -, n, both, not mod)
 - polarity shifter features
 - is general polarity shifter (*hardly successful*); is positive polarity shifter (*alleviate smth*); is negative polarity shifter (*lack of smth*)

Case Study 3: Contextual Polarity

- Performance

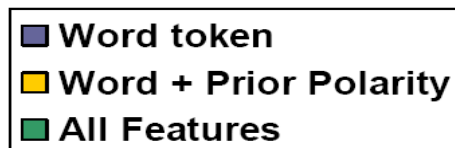
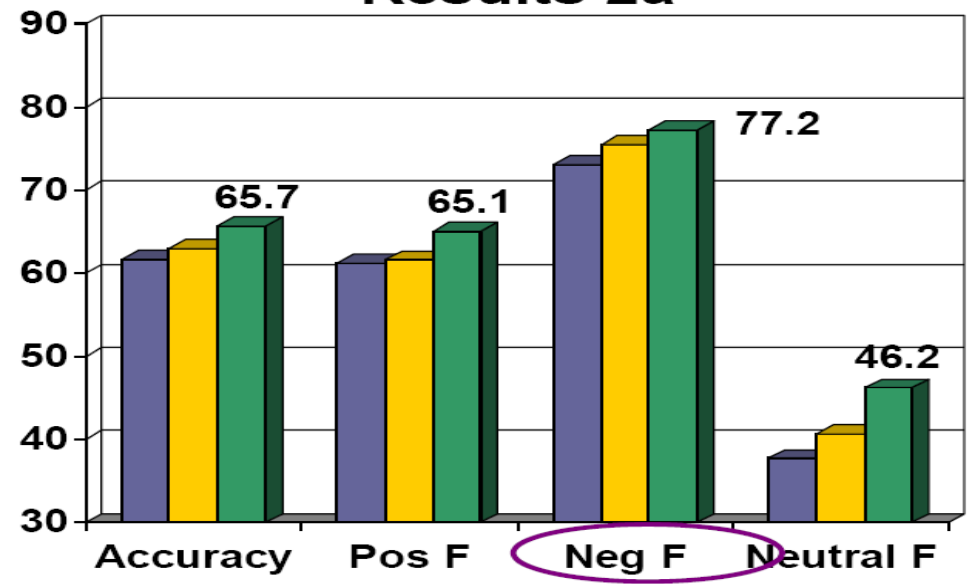
neutral/polar classifier

Results 1a



polar classifier

Results 2a



[Wilson et al. (2005)]

Case Study 4: Product Features

- Descend to (sub)-sentential levels
 - expressing individual parts, features, and components of X
 - laptop { *[+price]*, *[-keyboard]*, *[+sound card]*, ... }
- Tasks
 - #1: identify and extract relevant features
 - term extraction and co-reference resolution
 - #2: determine the sentiment of features
 - sentiment analysis proper
 - #3: generate feature summary
 - clustering and ranking

Case Study 4: Product Features

- Common review formats
 - pros, cons, and detailed review sections (Epinions.com)
 - pros and cons sections (C|net.com)
 - free format (Amazon.com)
- Challenges
 - potentially noisy domain (misspellings, fragmentary language)
 - product features described using many expression types, not just NPs
 - relevant vs. irrelevant sections
 - unmentioned (implied) features

Case Study 4: Product Features

- *Creative Soundblaster Live 5.1: This is a good all around {board} with good {software} but the lack of {support} and problems related with this board if something goes wrong is frustrating and to be avoided.*
- *Ok, I am on my computer and put a cd in turn the music on, But the {sound} is just not what I expect, I am very disappointed. ...*
- *The SoundBlaster Live 5.1 from Creative is a {well-priced} (oem version) sound card with excellent {features} and {sound}. Marred by {incompatibility} with many motherboards and needs to be {set up} by a real expert if you have a VIA chipset on your board.*
- *I have been using these {speakers} for some time and {they} rock ...*
- *Although some have said about random clicks, snaps and crackles which apparently is a common issue with some people, I have not come across such problems ...*

Case Study 4: Product Features

- Term extraction (Hu & Liu 2004)
 - find explicit frequent noun/NP features (≤ 3 words)
 - POS tagging, simple NP and VP chunking
 - association mining (CBA, Apriori) to find frequent itemsets with 1% minimum support
 - discard compact features
 - *I had searched for a digital camera for 3 months* [compact]
 - *The !camera does not have a !digital zoom* [not compact]
 - discard redundant single-word features
 - *!manual* is a subset of *manual mode* or *manual setting*
 - minimal p-support ≥ 3

Case Study 4: Product Features

- Term extraction (Yi & Niblack 2005)
 - pre-specified subject terms (*camera*) with *part-of* (*lens*) and *attribute-of* (*resolution*) terms
 - definite sentence-initial base NPs (the JJ* N+)
 - keep *bnps* with highest likelihood ratio (*lr*) scores ($-2\log\lambda$) across topical ($D+$) and non-topical ($D-$) documents

| | D_+ | D_- |
|-------------------------|----------|----------|
| <i>bnp</i> | C_{11} | C_{12} |
| $\overline{\text{bnp}}$ | C_{21} | C_{22} |

$$r_1 = \frac{C_{11}}{C_{11} + C_{12}}$$

$$r_2 = \frac{C_{21}}{C_{21} + C_{22}}$$

$$r = \frac{C_{11} + C_{21}}{C_{11} + C_{12} + C_{21} + C_{22}}$$

$$lr = (C_{11} + C_{21}) \cdot \log(r) + (C_{12} + C_{22}) \cdot \log(1 - r) - C_{11} \log(r_1) - C_{12} \log(1 - r_1) - C_{21} \log(r_2) - C_{22} \log(1 - r_2)$$

$$-2\log\lambda = \begin{cases} -2 * lr & \text{if } r_2 < r_1 \\ 0 & \text{if } r_2 \geq r_1 \end{cases}$$

Case Study 4: Product Features

- Sentiment analysis (Hu & Liu 2004)
 - list of opinion adjectives from the review corpus
 - the effective opinion of a frequent feature is the nearest adjective modifying the feature N/NP
 - *The [strap] is **horrible** and gets in the way of parts of the camera you need access to*
 - the noun/NP nearest to the opinion word invokes an infrequent feature
 - *Equally, the [bass]? can seem a little **lightweight** on thunderous [tracks]? but does retain focus.*

Case Study 4: Product Features

- Sentiment analysis (Yi & Niblack 2005)
 - sentiment lexicon (beautiful JJ +)
 - sentiment extraction database
 - <predicate><sent_category: +/-|[~] source><target>
 - the sentiment of the (SubjP/ObjP/CompP/PrepP) source phrase is transferred towards a (SubjP/ObjP/PrepP) target phrase
 - <impress><+><PrepP (by) >: *I was impressed by the build quality*
 - <offer><ObjP><SubjP>: *Dabs.com offers high quality products*
 - negation inside phrases and predicates

Case Study 4: Product Features

- Performance
 - Hu & Liu (2004)
 - tested on 500 manually-annotated product reviews of five products
 - 69.3 (r), 64.2 (p) on opinion sentence extraction
 - 84.2 on sentence polarity assignment
 - Yi et al. (2005)
 - tested on manually-annotated camera and music reviews
 - 56 (r), 87 (p)

Case Study 5: Compositionality

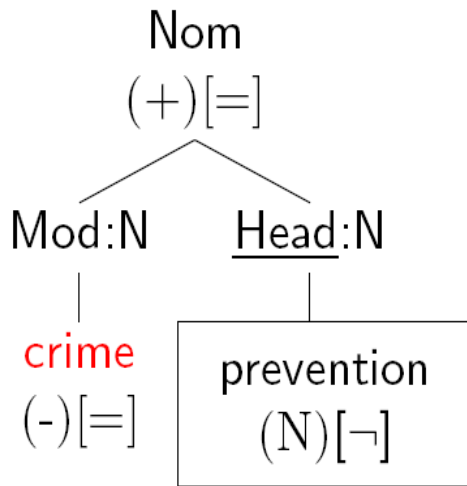
- **Goal**
 - to calculate in a systematic way the polarities of syntactic constituents as a function of the polarities of their subconstituents
- **Assumption**
 - if the meaning of a sentence is a function of the meanings of its parts...
 - then the global polarity of a sentence is a function of the polarities of its parts
- **Need**
 - POS tagging, chunking, and ‘deep’ parsing

Case Study 5: Compositionality

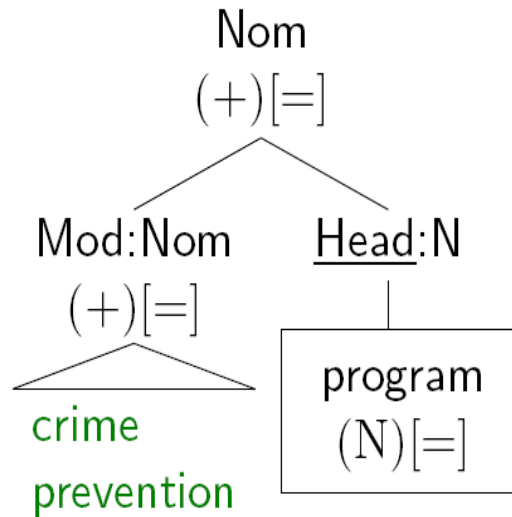
- Combine two elements
 - two morphemes, words, phrases, clauses, ...
- Element ranking
 - each syntactic situation (i.e. node in the parse tree) determines which one dominates
- Polarity ranking
 - $\{ (+), (-), (M) \} > (n)$
- Lexical tags
 - equal ($[=]$), reverse ($[\neg]$)

Case Study 5: Compositionality

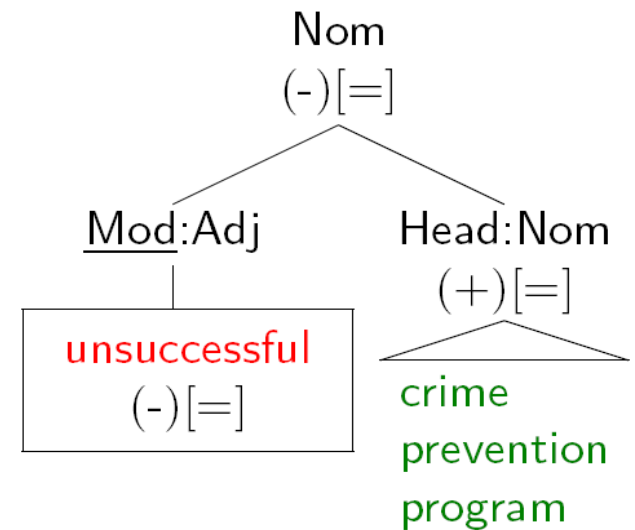
crime prevention



crime prevention program

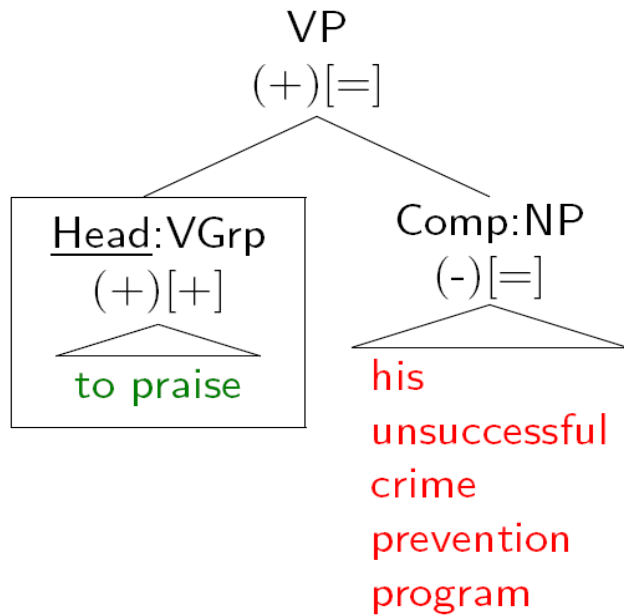


unsuccessful crime prevention program

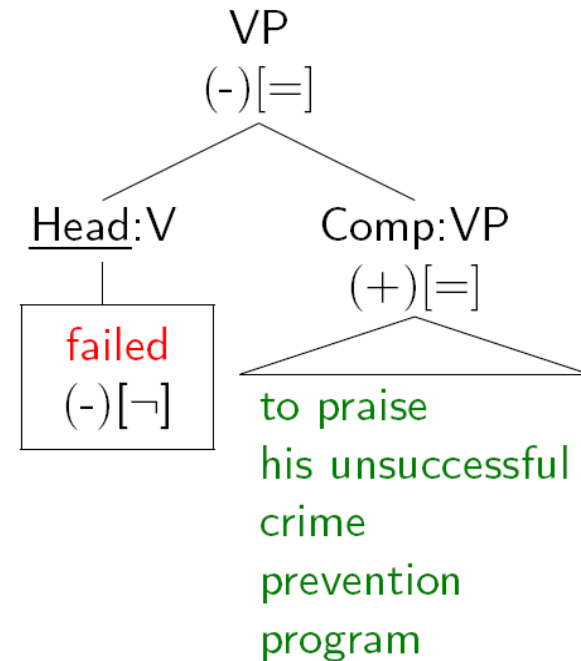


Case Study 5: Compositionality

to praise his unsuccessful
crime prevention program

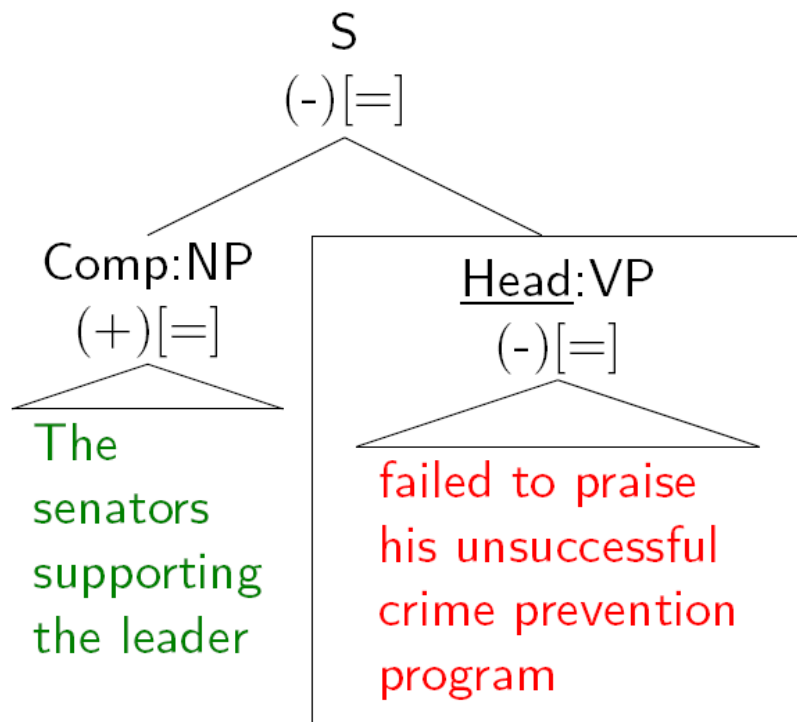


failed to praise his unsuccessful
crime prevention program



Case Study 5: Compositionality

The senators supporting the leader
failed to praise his unsuccessful
crime prevention program



- Performance
 - short headlines
 - 63 - 76.3
 - 81.7 - 90 (strong cases)
 - NPs
 - 72.5 - 85.5
 - 79.2 - 89.1 (strong cases)
- Challenges
 - tagging and parsing errors
 - lexicon coverage
 - paralogical devices

Evaluation Issues

- Sentiment is an inherently fuzzy phenomenon
- Typical gold standards
 - a very small number of annotators (2)
 - relatively small ad hoc hand-labelled datasets or large unverified hand-/automatically-labelled datasets
 - not all datasets are publicly available
- Common source of confusion in annotations
 - point of view, neutral polarity, category boundaries, category labels and scales, text region widths, ...

Evaluation Issues

- Reported inter-annotator agreement scores
 - vary depending on the task, genre, level of analysis, and labels used
- What constitutes an acceptable baseline/upper bound for the algorithm?
- Few attempts to measure human performance
- Do not treat gold standards as holy
- Extremely high results may indicate data overfitting

Corpora and Datasets

- Hand-labelled datasets
 - not many available
 - preferred option
 - limited size can be a problem
- Automatically-compiled datasets
 - abundant raw data available
 - noisy labels, rankings, and language
- Tag diversity
 - mapping between different annotation/analytical frameworks can introduce further complications

Corpora and Datasets

- MPQA:
 - phrases and sentences annotated with subjectivity, polarities, and roles
 - 535 documents, 11114 sentences
 - <http://www.cs.pitt.edu/wiebe/mpqa>
- SemEval-07 Task 14
 - -100 to +100 polarity scale, six affect categories
 - 1200 news headlines
 - <http://www.cse.unt.edu/~rada/affectivetext/>
- Movie Review Data:
 - 1000 (+) and 1000 (-) reviews
 - 5331 (+) and 5331 (-) sentences / snippets
 - 5000 subjective and 5000 objective sentences
 - documents with ratings
 - <http://www.cs.cornell.edu/people/pabo/movie-review-data/>
- FBS product features, 5 and 9 products
 - <http://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html>
- NPS: FBS product features with added base NP boundaries
 - (Contact me)
- The web...

Lexica

- General Inquirer
 - a manually-compiled word list, multi-dimensional affect tags
 - <http://www.wjh.harvard.edu/%7Einquirer/>
- SentiWordnet
 - WordNet 2.0 synsets annotated automatically with (+), (-), and (n) scores
 - <http://sentiwordnet.isti.cnr.it/>
- WordNetAffect
 - a subset of WordNet synsets labelled (semi-)automatically with multi-dimensional affect tags
 - <http://wndomains.itc.it/download.html>
- Sentiment and subjectivity clues by Wiebe et al.
 - <http://www.cs.pitt.edu/~wiebe/pubs/index.html>
- Affective Norms for English Words (ANEW)
 - a manually-compiled word list, multi-dimensional tags
 - <http://csea.phhp.ufl.edu/media/anewmessage.html>

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 - <http://www.cs.pitt.edu/~wiebe/pubs/papers/EUROLAN07/eurolan07bib.html>