Natural Language Processing

08: Sentiment Analysis

Fabian Haak, Technische Hochschule Köln, Cologne, Germany

Technology
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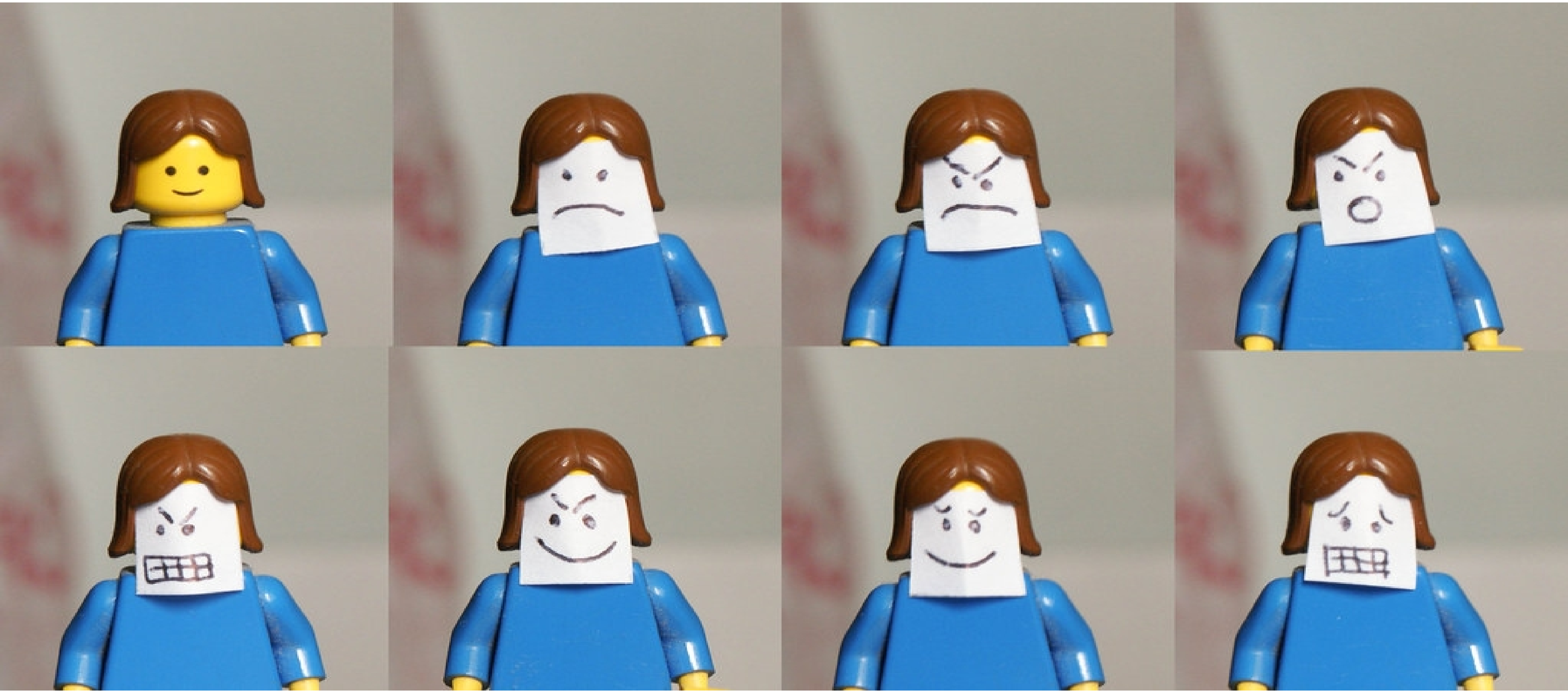
What People Think about Things: Sentiment Analysis



The „Sentiment“ in Sentiment Analysis

- **affective dimension** of text
- Text contains sentiment as **affective connotation**

- model the lexical semantics relevant to:
  - Sentiment
  - Emotion
  - Personality
  - Mood
  - Attitudes

Why do We Care about Affective Meaning?

- Sentiments are expression of **opinions** and **stances**
- Many relevant scenarios:
  - Sentiment towards politicians, products, countries, ideas, etc.
    - Detecting hate and biased language
    - Understanding product performance
    - …
- Where could we use this?
  - **Understanding**: Virtual assistants, recommendation systems, „shitstorm“ and hate detection, business decisions
  - **Replicating**: Chatbots, AI

How is Affective Connotation Expressed?

Choice of words:

- „Das ist ja gestern nicht so gut gelaufen.“

Other tokens:

- „Was hast du dir dabei gedacht?!?!?!?!!??“
- „Das war echt nett! :-)“
- „Ich habe die Klausur grade so bestanden ___“

- → patterns and structures that carry sentiment in text

A Definition of Emotion

Emotion (Scherer 2000):

- „relatively brief episode of response to the evaluation of an external or internal event as being of major significance“

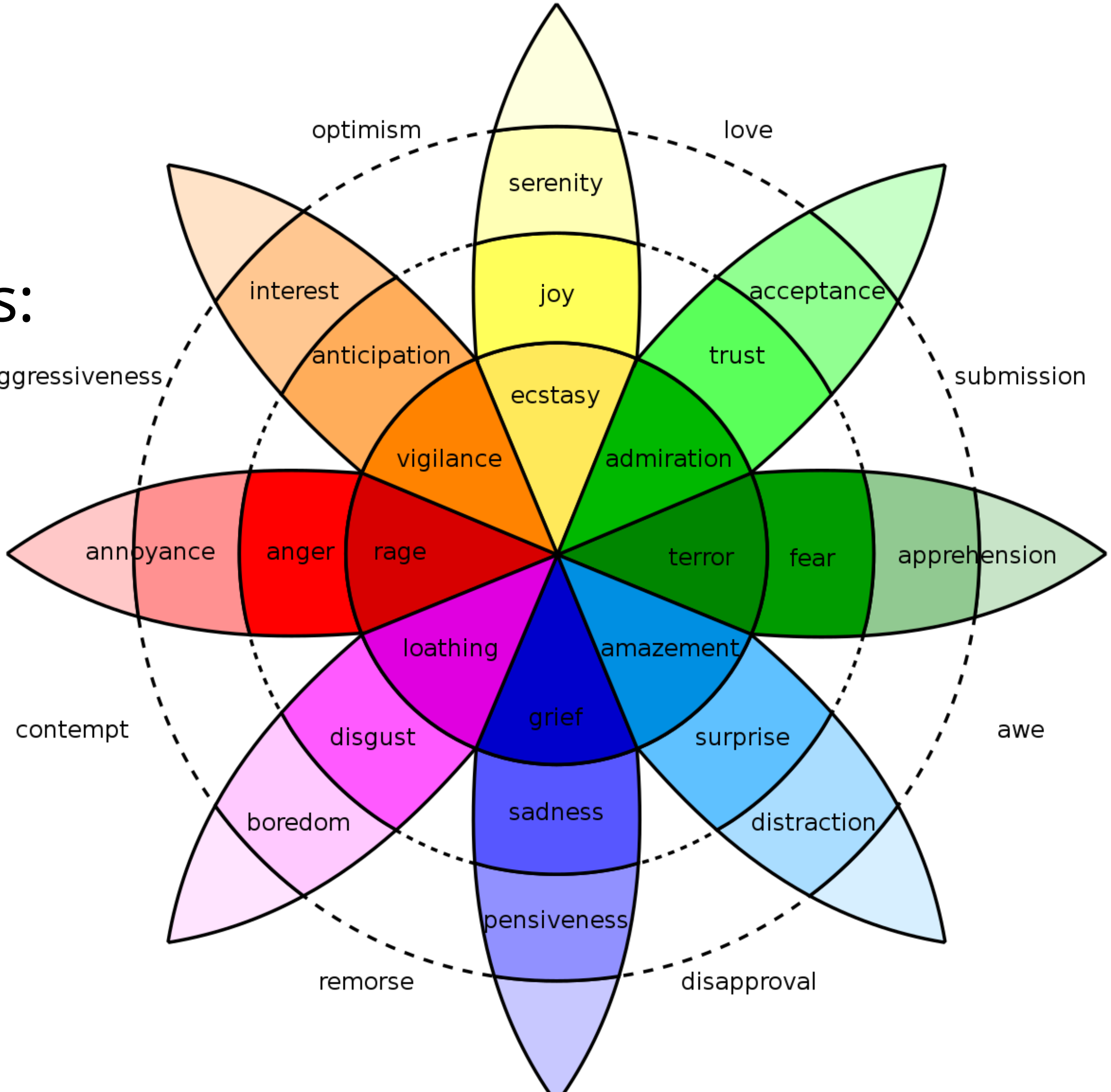
Two main concepts of emotion:

1) **Basic Emotions Theory** (Tomkins ’62, Plutchik ’62)

2) **Spatial models** with 2-3 dimensions (f.e. Russel ’80)

Basic Emotions Theory: Plutchik‘s Wheel of Emotions

8 basic emotions
in four opposing pairs:
joy–sadness
anger–fear
trust–disgust
anticipation–surprise



Robert Plutchik's Wheel of Emotions. By: Machine Elf 1735 – Creative Commons Lizenz.

Spatial Models of Emotion

1-dimensional models

- **Polarity**
  - Discrete levels: Positive, Neutral, Negative
    - Good → positive, superb → positive

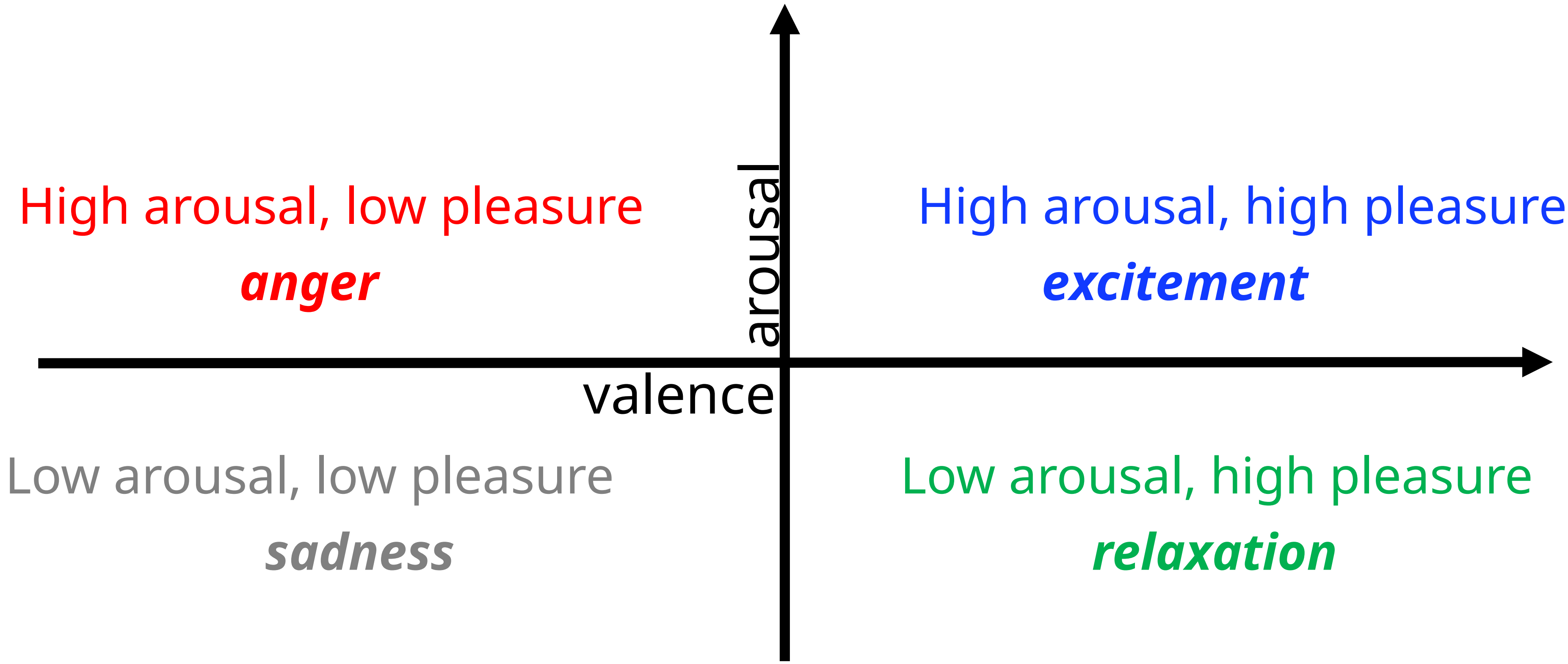
2-dimensinal models

- **Polarity** + **Intensity** (=**Valence**)
    - Good → moderately positive, superb → highly positive

Other 2- or 3-dimensional models (Russel ’80)

- **Valence** → the pleasantness of the stimulus
- **Arousal** → the intensity of emotion provoked by the stimulus
- [**Dominance** → the degree of control exerted by the stimulus]

Example: Valence/Arousal Dimensions



c.f. Russell, J. A. (1980). A circumplex model of affect. Journal of Personality and Social Psychology, 39(6)

Different Models for Different Tasks

- Basic Emotions are complex
- Most common sentiment analysis task: **Opinion mining**
  - Does not require complexity of basic emotions models
- Most sentiment analysis approaches utilize spatial models

Granularity Levels of Sentiment Analysis

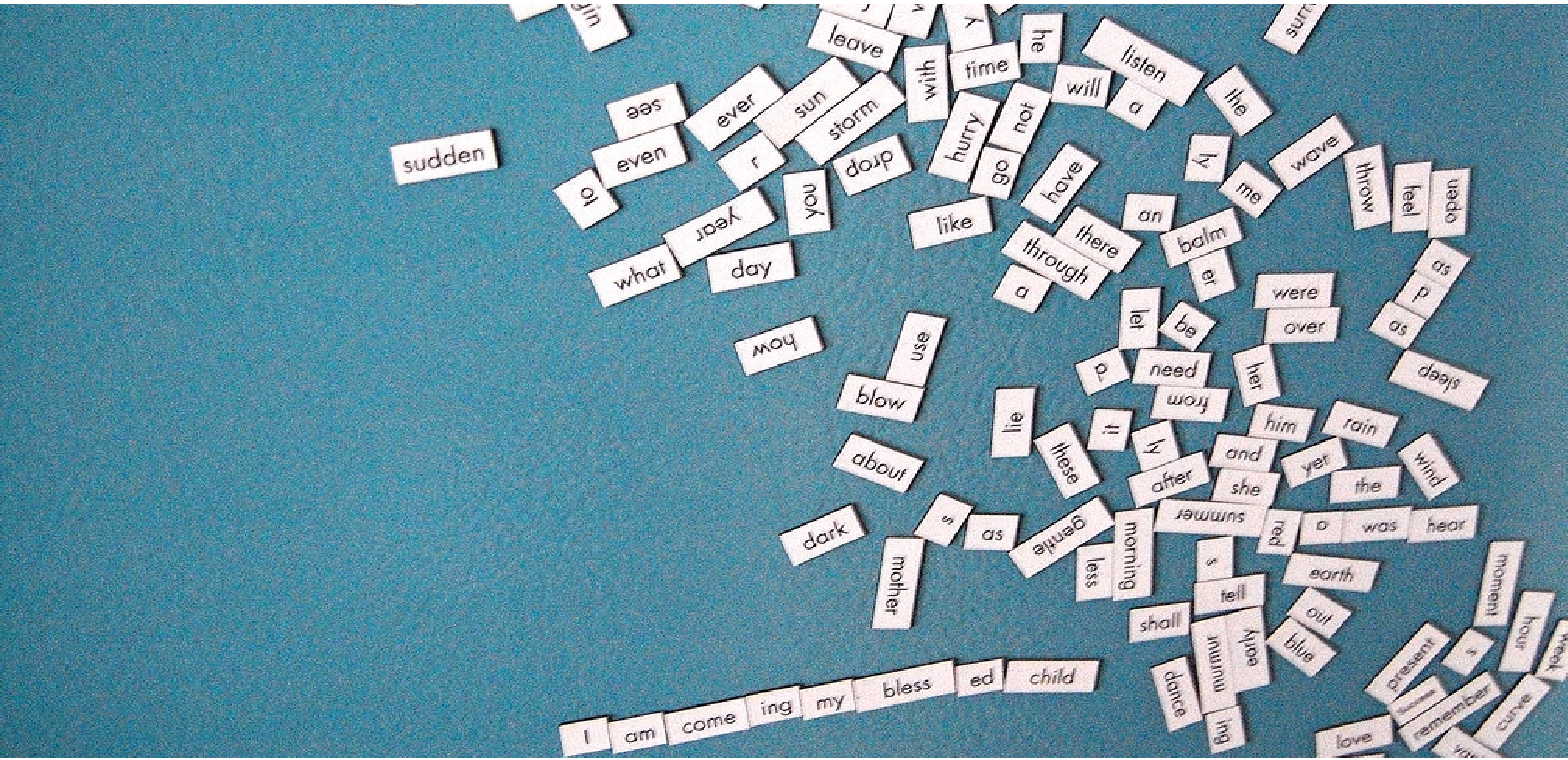
- **Text-/document-level**

What is the general tone/ stance expressed by the author of a text?

- **Entity-level**
    - What attitude/stance/opinion towards an entity is expressed in the document?
    - Example: Opinions on different bikes in a review of bikes.
- **Aspect-level**
    - What attitude/stance/opinion towards aspect(s) of an entity is expressed?
    - Example: Opinions on different components of a bike.
- **Sentence-level**
- **Word-/Token-level**

Different granularity levels for different tasks

Analysing Expressed Sentiments: Sentiment Lexicons



Sentiment Lexicons as Tools

- Sentiment lexicons (sometimes: dictionaries) contain, for a number of words/tokens (keys), information on emotional dimensions (values)
- Can be used to determine **sentimental connotation**
- Different **forms of sentiment lexicons**:
  - Lists of positive/negative words
  - List of words with polarity and intensity
  - List of positive negative n-grams
  - …

General Inquirer Lexicons

Philip J. Stone, Dexter C Dunphy, Marshall S. Smith, Daniel M. Ogilvie. 1966. The General Inquirer: A Computer Approach to Content Analysis. MIT Press.

http://www.wjh.harvard.edu/~inquirer/homecat.htm

General Inquirer (GI) contains different lists of words of sentimental/qualitative dimensions:

- Positive/negative
- Cognitive orientation
- Words for yes/no
- Negations
- Various other category tags

General Inquirer Lexicons

Other categories

1	Entry	Source	Positiv	Negativ	Pstv	Affil	Ngtv	Hostile	Strong	Power	Weak	Submit	Active	Passive
2			1915	2291	1045	557	1160	833	1902	689	755	284	2045	911
3	A	H4Lvd												
4	ABANDON	H4Lvd		Negativ			Ngtv				Weak			
5	ABANDONMENT	H4		Negativ							Weak			
6	ABATE	H4Lvd		Negativ										Passive
7	ABATEMENT	Lvd												
8	ABDICATE	H4		Negativ							Weak	Submit		Passive
9	ABHOR	H4		Negativ				Hostile						Passive
10	ABIDE	H4	Positiv			Affil							Active	
11	ABILITY	H4Lvd	Positiv						Strong					
12	ABJECT	H4		Negativ							Weak	Submit		Passive
13	ABLE	H4Lvd	Positiv		Pstv				Strong					
14	ABNORMAL	H4Lvd		Negativ			Ngtv							
15	ABOARD	H4Lvd												
16	ABOLISH	H4Lvd		Negativ			Ngtv	Hostile	Strong	Power			Active	
17	ABOLITION	Lvd												
18	ABOMINABLE	H4		Negativ					Strong					
19	ABORTIVE	Lvd												
20	ABOUND	H4	Positiv											Passive
21	ABOUT#1	H4Lvd												
22	ABOUT#2	H4Lvd												
23	ABOUT#3	H4Lvd												

MPQA Subjectivity Cues Lexicon

a) Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity inPhrase-Level Sentiment Analysis. Proc. of HLT-EMNLP-2005.

b) Riloff and Wiebe (2003). Learning extraction patterns for subjective expressions. EMNLP-2003.

http://mpqa.cs.pitt.edu/lexicons/

- List of subjective words with 2 dichotomous dimensions:
  - Positive/negative
  - Strong subjectivity/weak subjectivity
- Word form
- Stemmed verbs
- 6885 words in total

MPQA Subjectivity Cues Lexicon

```
type=weaksubj   len=1 word1=solemn pos1=noun stemmed1=n priorpolarity=negative
type=strongsubj len=1 word1=solicitous pos1=anypos stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=solicitously pos1=anypos stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=solicitude pos1=noun stemmed1=n priorpolarity=positive
type=weaksubj   len=1 word1=solid pos1=adj stemmed1=n priorpolarity=positive
type=weaksubj   len=1 word1=solid pos1=noun stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=solidarity pos1=adj stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=solidarity pos1=noun stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=soliloquize pos1=verb stemmed1=y priorpolarity=neutral
type=strongsubj len=1 word1=somber pos1=adj stemmed1=n priorpolarity=negative
type=strongsubj len=1 word1=soothe pos1=verb stemmed1=y priorpolarity=positive
type=strongsubj len=1 word1=soothingly pos1=anypos stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=sophisticated pos1=adj stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=sore pos1=adj stemmed1=n priorpolarity=negative
type=strongsubj len=1 word1=sore pos1=noun stemmed1=n priorpolarity=negative
type=strongsubj len=1 word1=sorely pos1=anypos stemmed1=n priorpolarity=negative
type=weaksubj   len=1 word1=soreness pos1=noun stemmed1=n priorpolarity=negative
type=strongsubj len=1 word1=sorrow pos1=noun stemmed1=n priorpolarity=negative
```

NRC Emotion Intensity Lexicon (NRC-EIL) and NRC Valence, Arousal, and Dominance (NRC-VAD) Lexicon

Saif M. Mohammad. In Proceedings of the 11th Edition of the Language Resources and Evaluation Conference (LREC-2018), May 2018, Miyazaki, Japan.

https://saifmohammad.com/WebPages/AffectIntensity.htm

- Both available in 100 languages (Google translated!)
- NRC-EIL:
  - 8 Basic emotions (Tomkins)
  - 1 to 8 emotion scores per word
- NRC-VAD:
- Valence, Arousal, and Dominance scores for words

The NRC Emotion Intensity Lexicon (NRC-EIL)

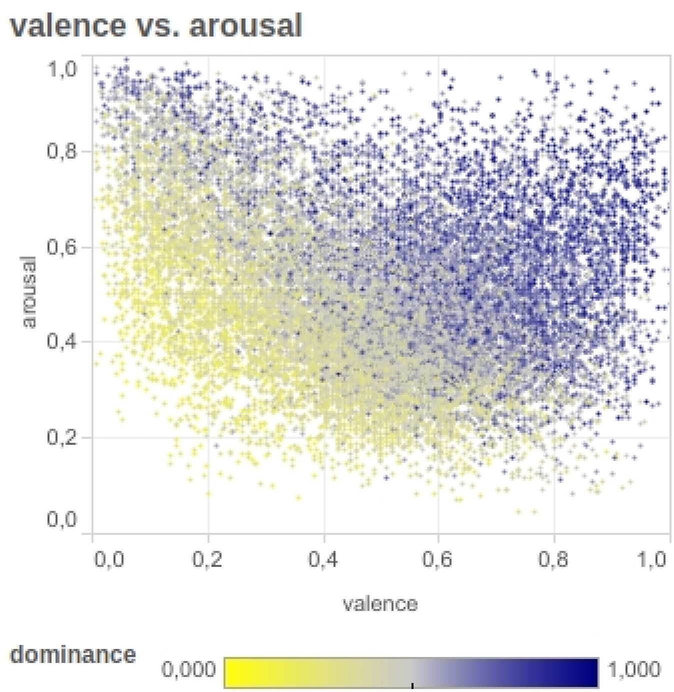
hatred	Hass	anger	0.953
hateful	hasserfüllt	anger	0.940
terrorize	terrorisieren	anger	0.939
Violently	heftig	anger	0.938
infuriated	wütend	anger	0.938
furious	wütend	anger	0.929
enraged	wütend	anger	0.927
furiously	wütend	anger	0.927
screwyou	NO TRANSLATION	anger	0.924
murderer	Mörder	anger	0.922
fury	Wut	anger	0.922
execution	Ausführung	anger	0.917
angered	verärgert	anger	0.916
savagery	Wildheit	anger	0.915
slaughtering	Schlachtung	anger	0.914
Veryangry	NO TRANSLATION	anger	0.913
fuckoff	Verpiss dich	anger	0.912
annihilation	Vernichtung	anger	0.912
assassinate	ermorden	anger	0.912

NRC Valence, Arousal, and Dominance (NRC-VAD) Lexicon

https://public.tableau.com/views/TheNRCValenceArousalandDominanceLexiconViz/Dashboard1?:embed=y&:embed_code_version=3&:loadOrderID=0&:display_count=y&publish=yes&:origin=viz_share_link

The NRC VAD Lexicon

term	valence	arousal	dominance
aaaaaaah	0,479	0,606	0,291
aaaah	0,520	0,636	0,282
aardvark	0,427	0,490	0,437
aback	0,385	0,407	0,288
abacus	0,510	0,276	0,485
abalone	0,500	0,480	0,412
abandon	0,052	0,519	0,245
abandoned	0,046	0,481	0,130
abandonment	0,128	0,430	0,202
abashed	0,177	0,644	0,307
abate	0,255	0,696	0,604
abatement	0,388	0,338	0,336
abba	0,562	0,500	0,480
abbey	0,580	0,367	0,444
abbot	0,427	0,321	0,483



Domain Specific Language

- Different domains have different languages
  - Use of emojis, technical terms, slang,
- Can be used to determine sentimental connotation on a granularity level of choice
- Different forms of sentiment lexicons:
  - Lists of positive/negative words
  - List of words with polarity and intensity
  - List of positive negative n-grams
  - …

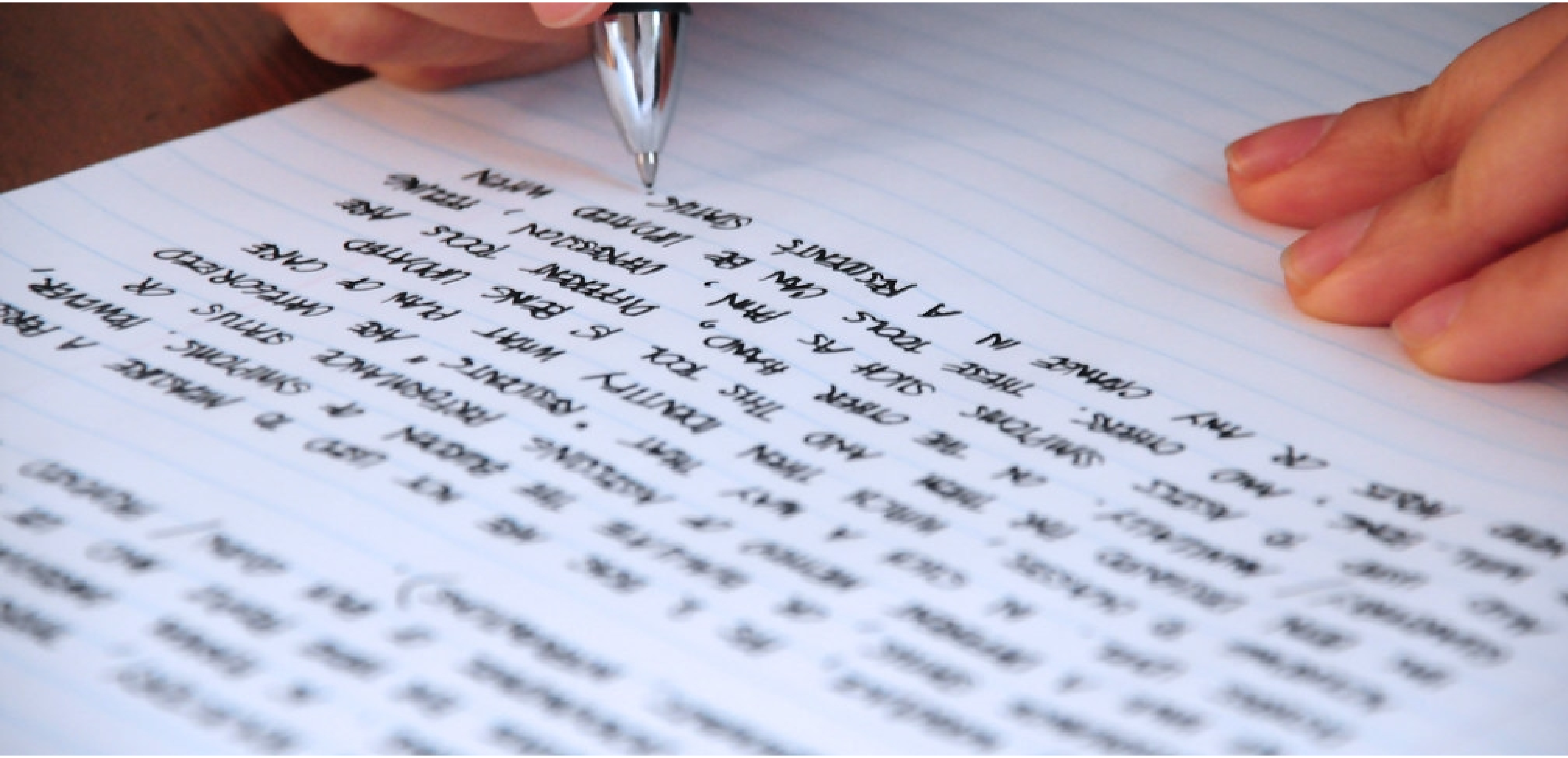
VADER Sentiment Lexicon

Hutto, C.J. & Gilbert, E.E. (2014). VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text. Eighth International Conference on Weblogs and Social Media (ICWSM-14). Ann Arbor, MI, June 2014.

https://github.com/cjhutto/vaderSentiment

- „specifically attuned to **sentiments expressed in social media**“
- Negations, contractions, puntuation, word-shape (insane vs INSANE), and modifier aware
- Emoticons and utf-8 encoded emojis
- sentiment-laden slang words as words (e.g., 'sux') or as modifiers such as 'uber' or 'friggin' or 'kinda'
- sentiment-laden initialisms and acronyms (for example: 'lol')
- **Included in NLTK**

Building Lexicons: Human Labels



Method: Human Annotation

- Recruit „novice“ crowdworkers or experts for annotation
- Annotators label candidate words or random words
- Example: NRC Valence, Arousal, Dominance (VAD) lexicon, dimension valence:
  - Q1. Which of the four words below is associated with the MOST happiness / pleasure / positiveness / satisfaction / contentedness / hopefulness OR LEAST unhappiness / annoyance / negativeness / dissatisfaction / melancholy / despair?
  - vacation, consolation, whistle, torture
- → different heuristics to derive lists

Issues with Human Labeled Lexicons

- Native speakers
- Clear task description
- Susceptible for bias
  - Cultural bias
  - Personal bias
  - Questionnaire bias
  - Response bias
- Different levels of measurement
  - Dichotomous
  - Ordinal (Likert)

Manual annotation is complicated and expensive!

Building Lexicons: Automated Induction of Affect Lexicons

Semi-supervised Approaches

- Main concept: Generate lexicons based on similarity to positive and negative seedwords

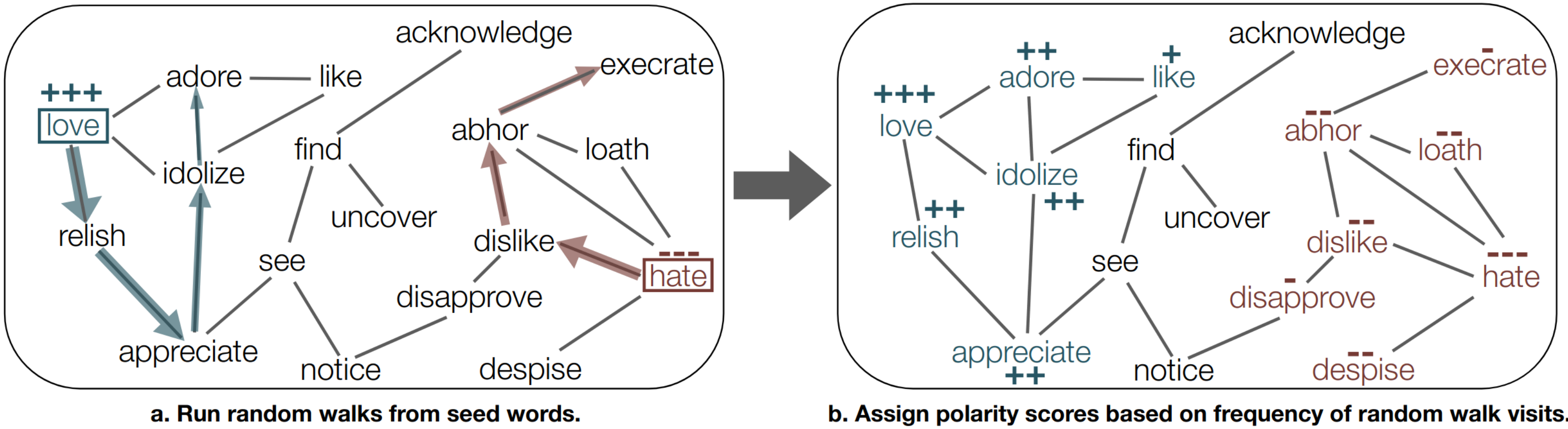


Image: Hamilton, W.L., Clark, K., Leskovec, J., & Jurafsky, D. (2016). Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora. Proceedings of the Conference on Empirical Methods in Natural Language Processing. Conference on Empirical Methods in Natural Language Processing, 2016, 595-605 .

Semi-supervised: Semantic Axis

- Main concept: Generate lexicons based on similarity to positive and negative seedwords

1) Generate **list of seed words**
2) Generate **word embeddings** (f.e. Word2Vec)
3) Optional: fine tune embeddings with domain-specific corpus
4) Calculate pole centroids and semantic axis:

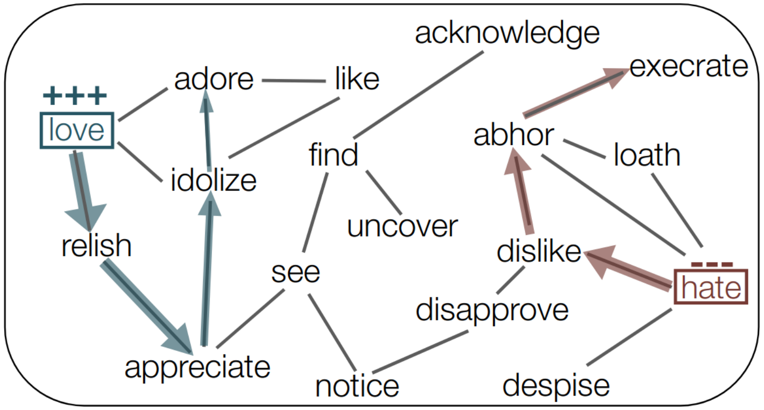
$$\mathbf{V}^{+} = \frac{1}{n}\sum_{1}^{n} E(w_i^{+}) \qquad \mathbf{V}^{-} = \frac{1}{m}\sum_{1}^{m} E(w_i^{-}) \qquad \mathbf{V}_{axis} = \mathbf{V}^{+} - \mathbf{V}^{-}$$

5) For each candidate word, calculate distance to poles:

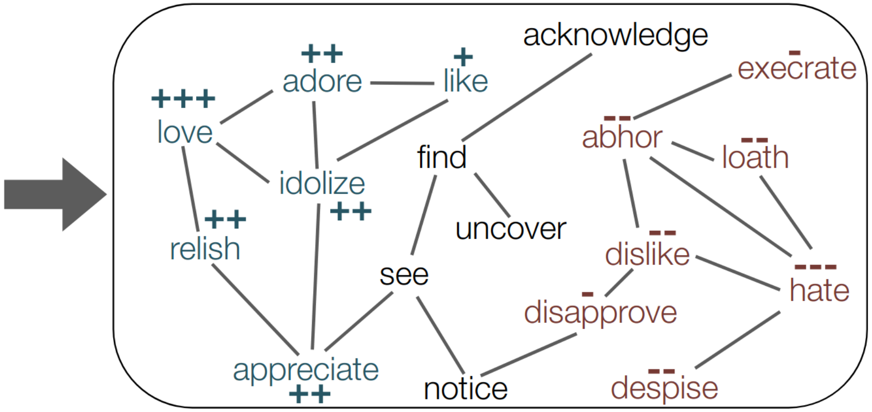
$$\begin{aligned} \text{score}(w) &= \left(\cos(E(w), \mathbf{V}_{\text{axis}}\right) \\ &= \frac{E(w) \cdot \mathbf{V}_{\text{axis}}}{\|E(w)\|\|\mathbf{V}_{\text{axis}}\|} \end{aligned}$$

Semi-supervised: Label Propagation

- Main concept: Generate **domain specific** lexicons based on **random walk** through **graph** of embeddings, starting from **seed words**
- Travel to probability derived from similarity
- Assign confidence based on “visits in N travels”



a. Run random walks from seed words.



b. Assign polarity scores based on frequency of random walk visits.

Image: Hamilton, W.L., Clark, K., Leskovec, J., & Jurafsky, D. (2016). Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora. Proceedings of the Conference on Empirical Methods in Natural Language Processing. Conference on Empirical Methods in Natural Language Processing, 2016, 595-605 .

Semi-supervised Approaches: Problems

- Different domains have different positive and negative words
- Approaches:
  - Full range of general seed words, trust system
  - Domain-specific embeddings
  - Domain-specific selection seed words:

Domain	Positive seeds	Negative seeds
General	good, lovely, excellent, fortunate, pleasant, delightful, perfect, loved, love, happy	bad, horrible, poor, unfortunate, unpleasant, disgusting, evil, hated, hate, unhappy
Twitter	love, loved, loves, awesome, nice, amazing, best, fantastic, correct, happy	hate, hated, hates, terrible, nasty, awful, worst, horrible, wrong, sad
Finance	successful, excellent, profit, beneficial, improving, improved, success, gains, positive	negligent, loss, volatile, wrong, losses, damages, bad, litigation, failure, down, negative

Table: Dan Jurafsky and James H. Martin (2021). Speech and Language Processing. P.399.

Other Semi-supervised Approaches

- Based on other similarity measures:
  - Morphological similarity (f.e. common stems)
  - Synonyms and antonyms (WordNet)

- → Sentiwordnet:

Synset	Pos	Neg	Obj
good#6 ‘agreeable or pleasing’	1	0	0
respectable#2 honorable#4 good#4 estimable#2 ‘deserving of esteem’	0.75	0	0.25
estimable#3 computable#1 ‘may be computed or estimated’	0	0	1
sting#1 burn#4 bite#2 ‘cause a sharp or stinging pain’	0	0.875	.125
acute#6 ‘of critical importance and consequence’	0.625	0.125	.250
acute#4 ‘of an angle; less than 90 degrees’	0	0	1
acute#1 ‘having or experiencing a rapid onset and short but severe course’	0	0.5	0.5

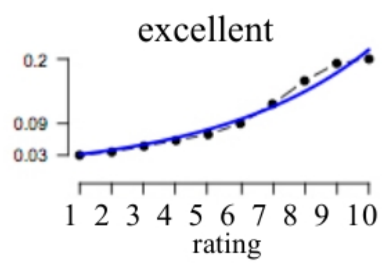
Dan Jurafsky and James H. Martin (2021). Speech and Language Processing. P.402., from: Baccianella, S., Esuli, A., and Sebas-tiani, F. (2010). Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining. LREC.

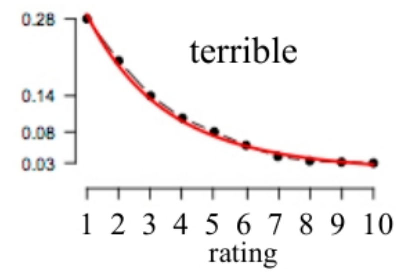
Supervised Learning of Word Sentiment

- Approach: Derive positive and negative words from corpus of labelled texts
- Corpora: Reviews of movies (IMDb), products (Amazon), places (Yelp, Google), …
- Derive rating (Potts Score):

$$P(w|c) = \frac{count(w,c)}{\sum_{w \in C} count(w,c)}$$

$$PottsScore(w) = \frac{P(w|c)}{\sum_c P(w|c)}$$

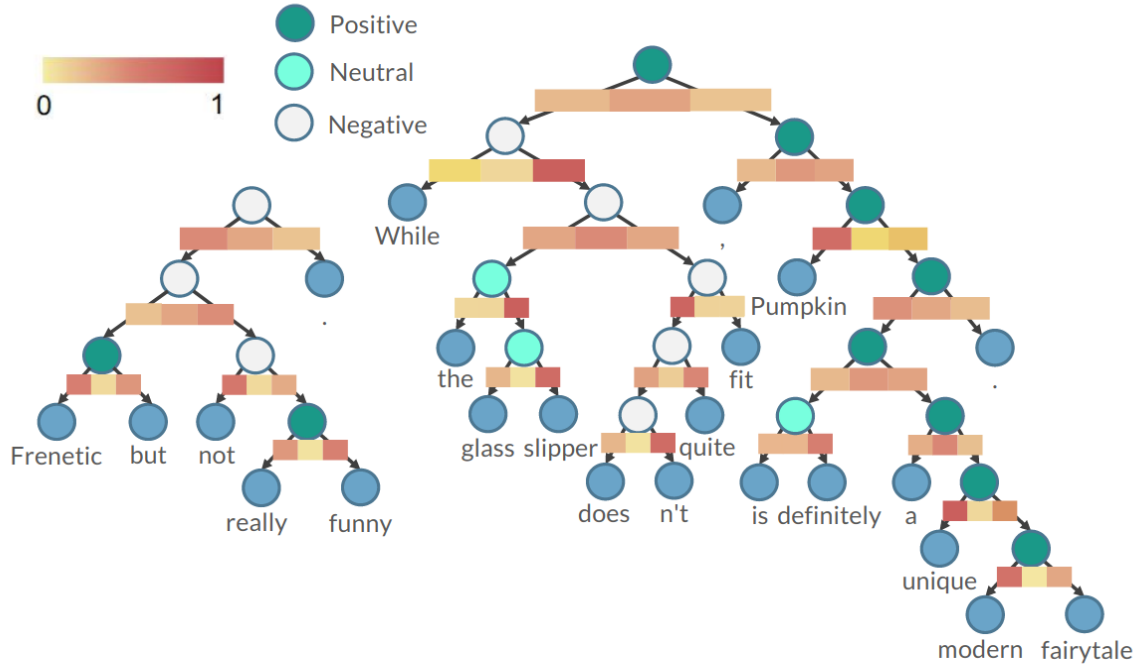




Potts, C. (2011). On the negativity of negation. Li, N. and Lutz, D. (Eds.), Proceedings of Semantics and Linguistic Theory 20, 636–659. CLC Publications, Ithaca, NY.

Other Supervised Machine Learning Approaches

- Recently very successful: **Language model** based sentiment classification
- Learn sentiment connotations from training data
- For example: Modified BERT: SentiBERT



Yin, D., Meng, T., & Chang, K. (2020). SentiBERT: A Transferable Transformer-Based Architecture for Compositional Sentiment Semantics. ACL.

Using Lexicons for Sentiment Recognition

Using Sentiment Analysis: Sentences and Texts

1) Ratio of positive to negative words
2) Sum of sentiment scores of all words
3) Rule-based approaches (e.g. VADER)
    - Includes negations, punctuation, emojis etc.

Extra: Building a Platform-specific Emoji Sentiment Lexicon

Plattform: Twitch.tv

www.twitch.tv

https://www.twitch.tv/creatorcamp/de-de/learn-the-basics/emotes/

- (Gaming) streaming platform
- Platform specific emojis: Twitch Emotes

:-)

Concept of the Approach

- Multimodal emojis carry **nonverbal functions** of non-formal chat communication (whatsapp, twitch, etc.)
  - Via iconographic properties
- Problem: Platforms with **high number of custom emojis** (> 300.000 twitch emotes)
- Utf-8 emojis:
  - Often not supported
  - Most sentiment scores older than 5 years
- Gold Standard: Emoji Sentiment Ranking ESR http://kt.ijs.si/data/Emoji_sentiment_ranking/

Goal: Semi-supervised creation of domain specific emoji lexicons

Solution: Cooccurence with Sentiment Words

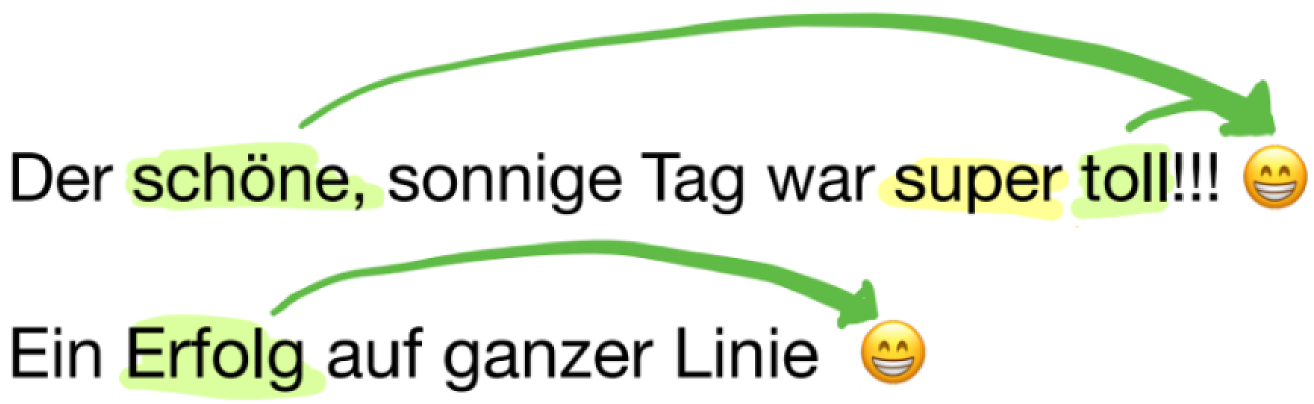
- Emojis have 3 main functions:

  1) Express sentiment

  2) Amplify sentiment

  3) Reverse sentiment

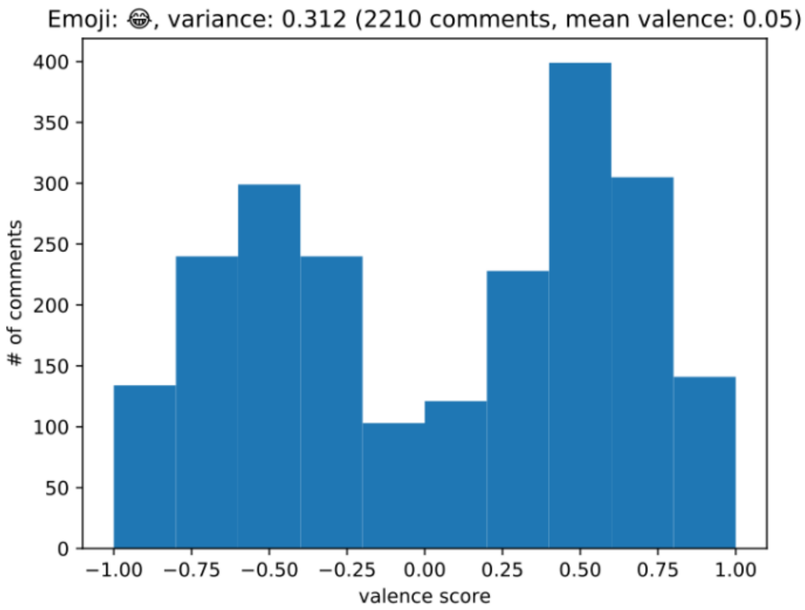
→ Derive emoji sentiment by assuming expression function: **Occurrence in chat messages with positive VADER score**

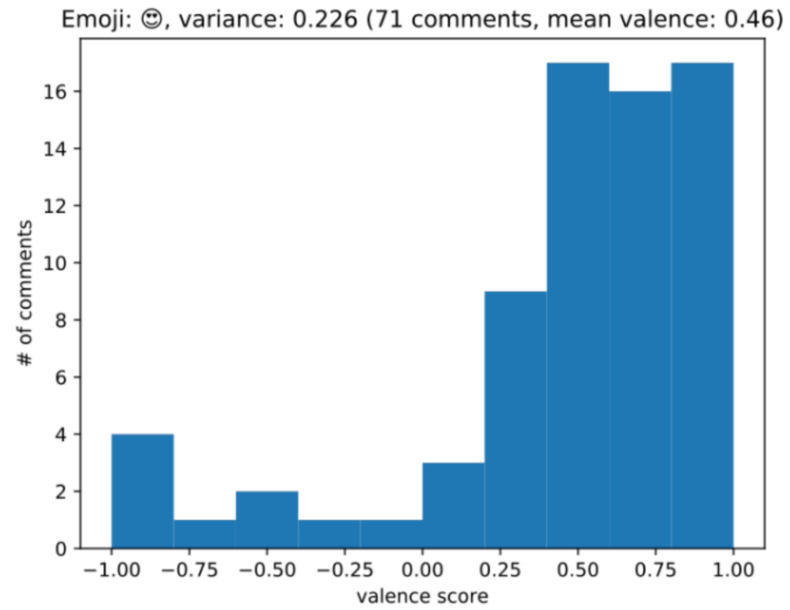


Developement of an Emoji Sentiment Lexicon

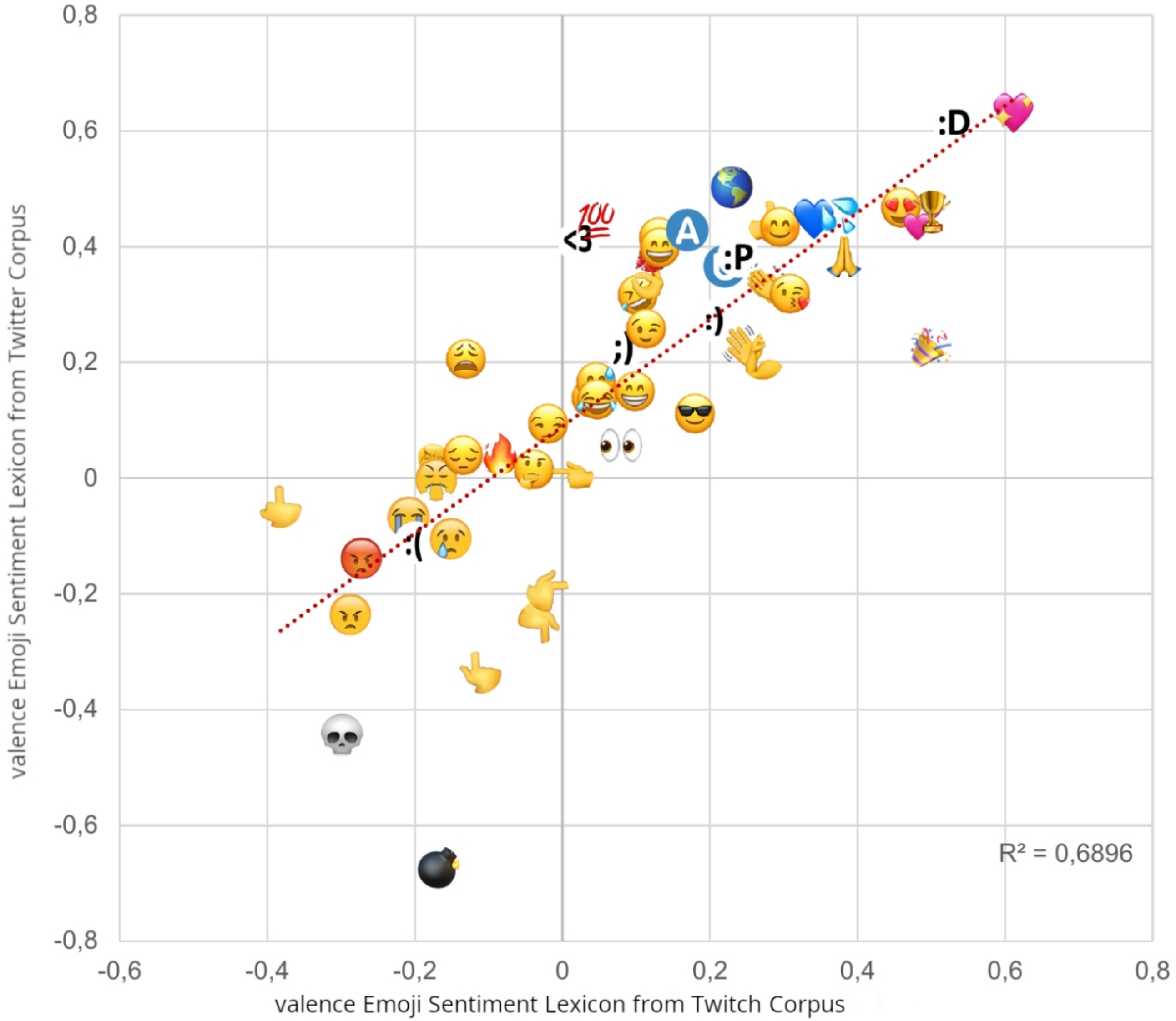
- Corpus 1 (utf-8 emojis): 1.5m tweets
- Corpus 2 (twitch emotes): 2.8m chat messages
-
- Edited VADER Lexicon: Emojis and emoticons removed
- Derive emoji sentiment scores by **mean sentiment value** of all texts containing the emoji
- Standard deviation and minimum cases for validity measure
- Two modes → expression of irony or sarcasm

Distribution of Valence Scores

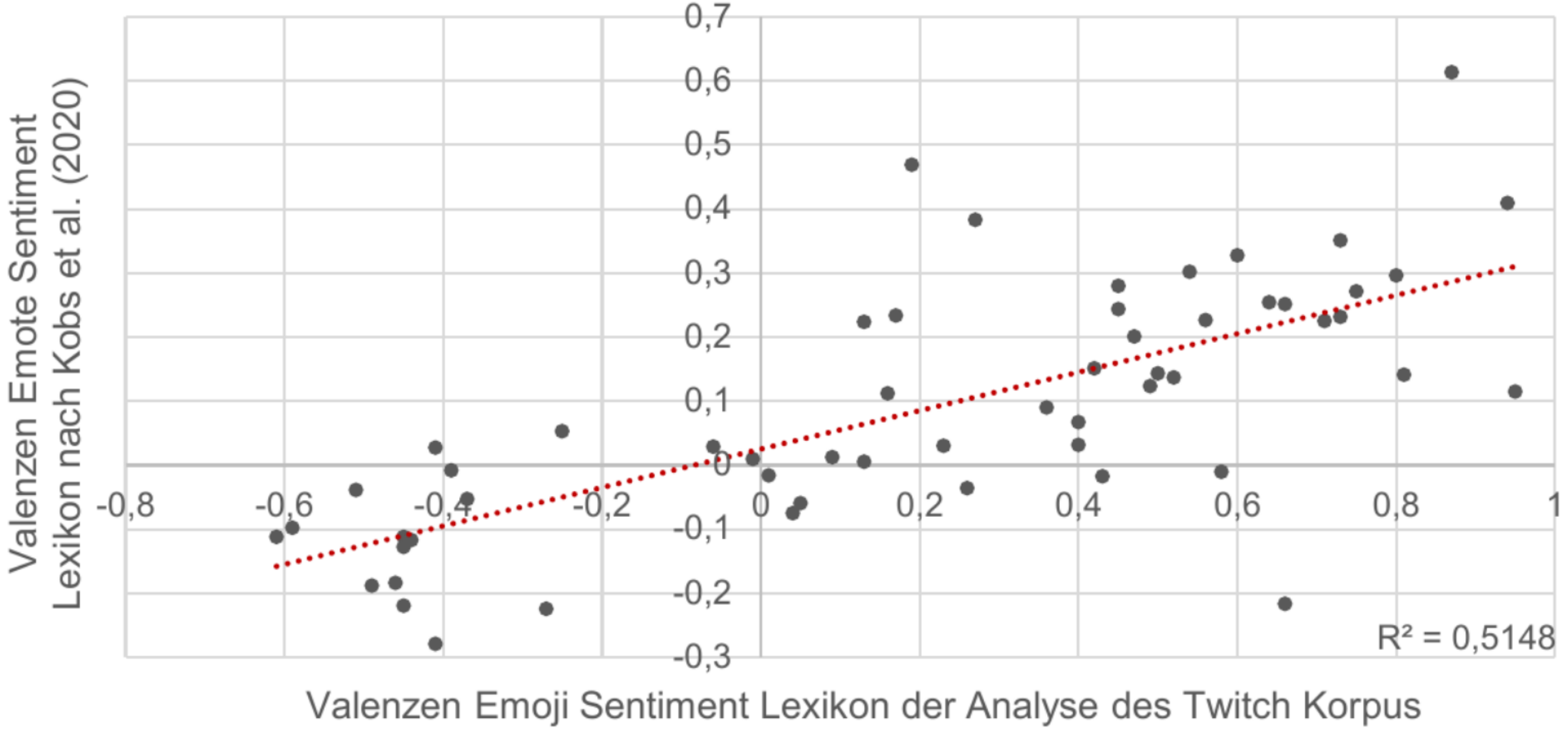




Results: UTF-8 Emojis



Results: Twitch Emotes



Conclusion

- Automatically derived sentiment scores for close to 200 twitch emotes and 200 utf-8 emojis
- The results have significantly (<0.01) high correlation with human labels
- Use with VADER: Doubles amount of text with sentiment in twitch corpus
- Possible follow-up studies:

1) Bigger corpus, bigger lexicon: “ESR 2.0”
2) Study on effects in sentiment analysis
3) Domain specific lexica with domain specific corpora