



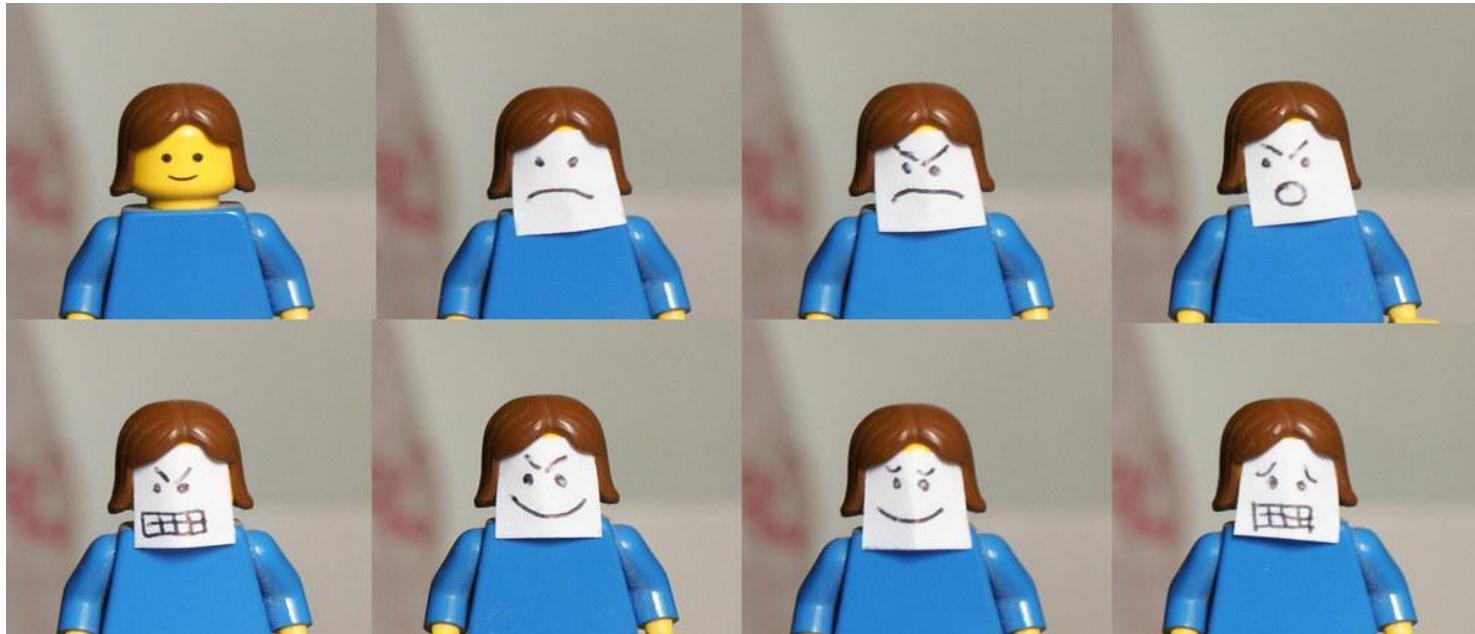
# Natural Language Processing

## 08: Sentiment Analysis

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Version: 2022-06-06

# What and How People Think or Feel: Sentiment Analysis



# The “Sentiment“ in Sentiment Analysis

- Affective dimension of text
- Text contains sentiment as **affective connotation**
- Model the lexical semantics to determine and/or quantify:
  - 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”, hate speech detection, business decisions
  - **Replicating:** Chatbots, AI

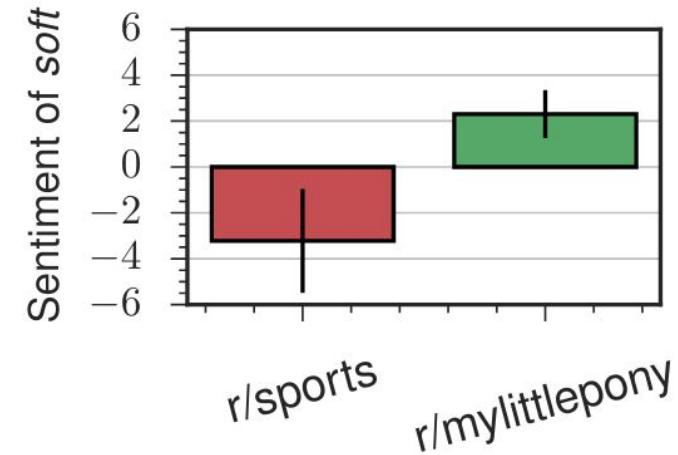
# How is Affective Connotation Expressed (in Text)?

Choice of words:

- “What a disappointment.”

Other tokens:

- “Why did you do that?!?!?!?!”
- “That was nice of you! :-)”
- “I finally passed the exam 🎉”
- → tokens and sequences that carry sentiment in text
- Context dependency (figure on the right)



# A Definition of Emotion

Emotion (Scherer 2000):

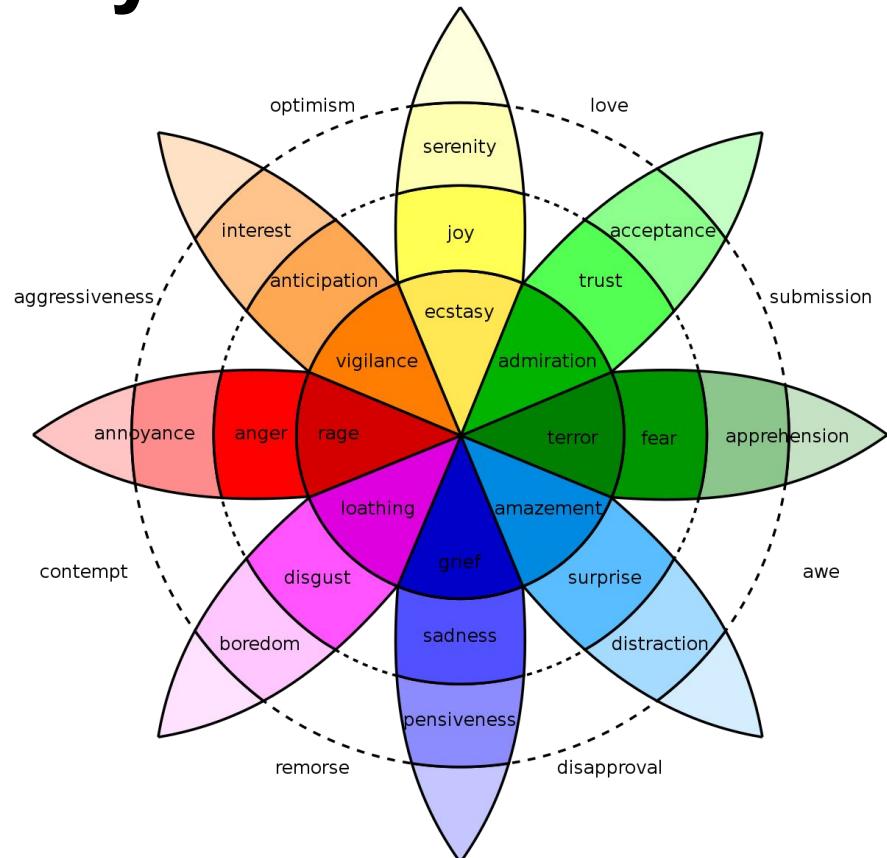
- “relatively brief episode of response to the evaluation of an external or internal event as being of major significance”

Two main concepts of emotion:

- 1) **Basic Emotions Theory** (Tomkins '62, Plutchik '64)
- 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



# Spatial Models of Emotion

## 1-dimensional models

- **Polarity**
  - Discrete levels: Positive, Neutral, Negative
    - . however: good → positive, superb → positive (!)

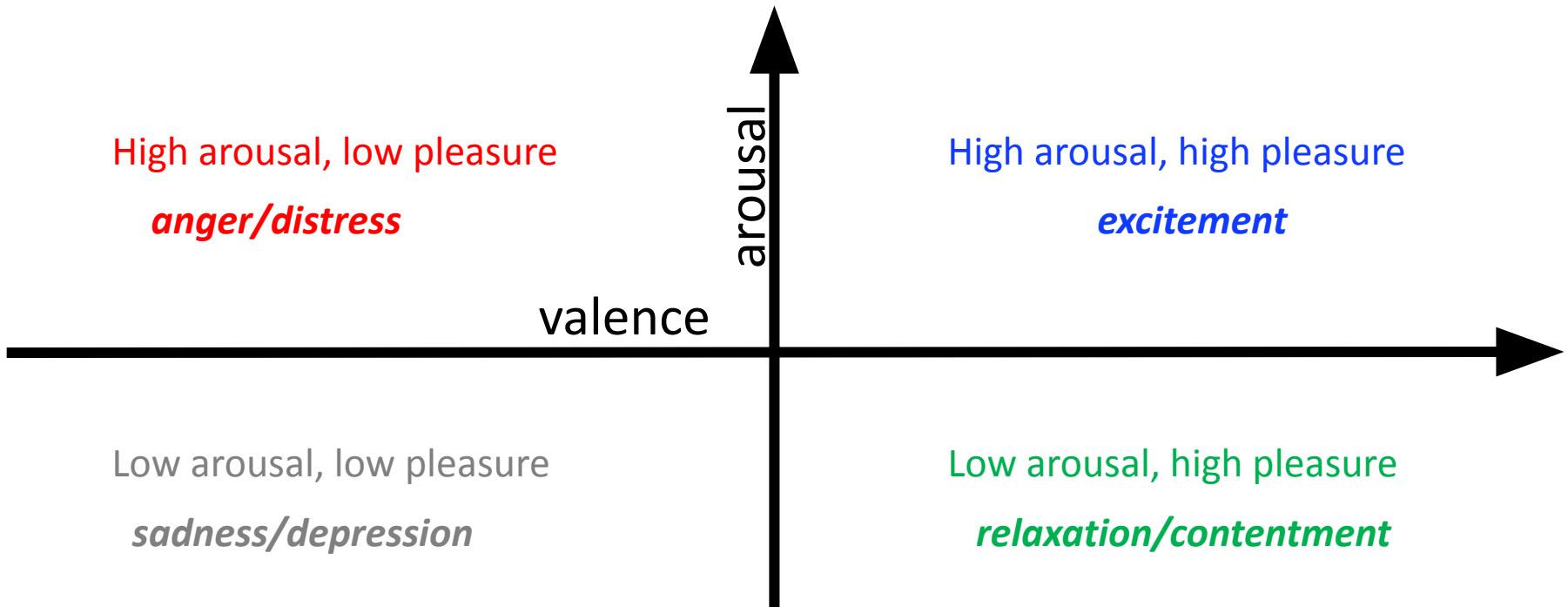
## 2-dimensional models

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

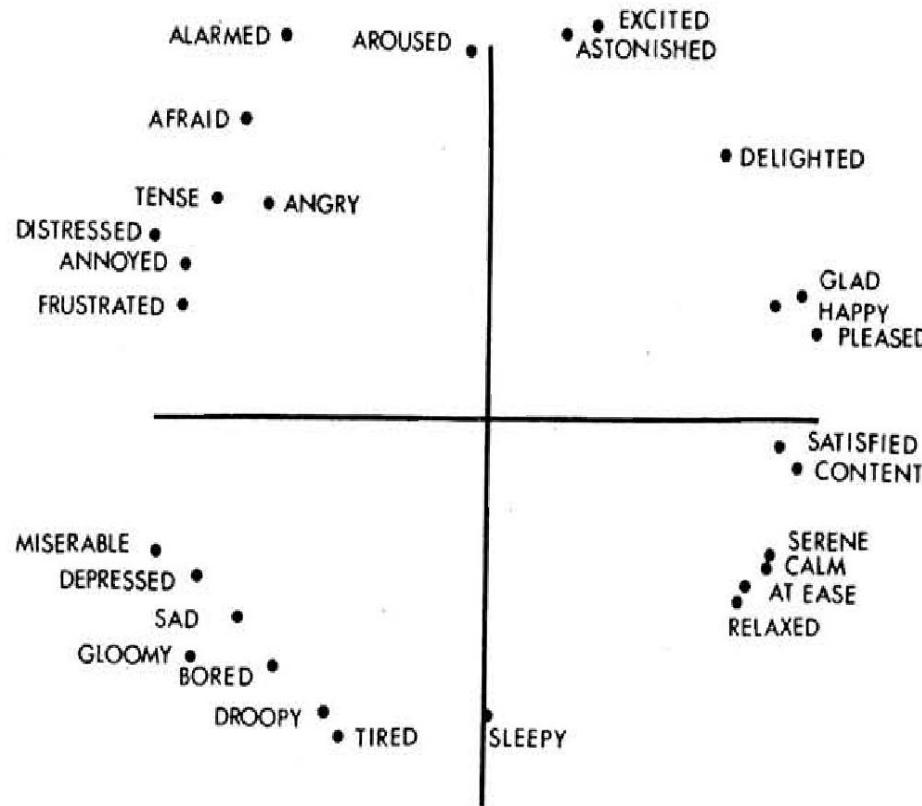
## Other 2- or 3-dimensional models (Russel '80)

- **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



# Example: Multidimensional scaling solution



# 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



A face expressing hatred and jealousy (left) and a face expressing despair (right). Engravings after C. Le Brun. Wellcome Collection. Public Domain Mark

# 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/affective connotation**
- Different **forms of sentiment lexicons**:
  - positive/negative words
  - words with polarity and intensity (valence)
  - positive/negative n-grams
  - Plutchik's emotions
  - ...

# 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.

**NOT AVAILABLE (AT THE MOMENT)!**

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

# Multi Perspective Question Answering Subjectivity Cues Lexicon (MPQA)

- a) Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity in Phrase-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=sorenness 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>

<https://saifmohammad.com/WebPages/nrc-vad.html>

- 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)

[GERMAN VERSION OF THE LEXICON]

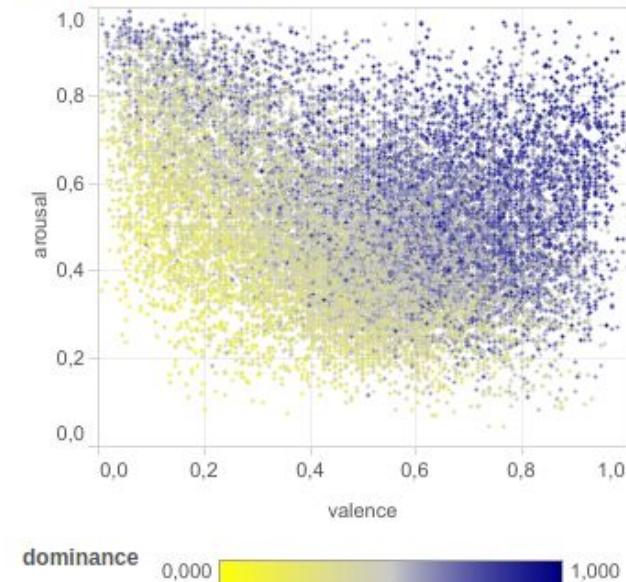
hatred	Hass	anger	0.953
hateful	hasserfüllt	anger	0.940
terrorize	terrorisieren	anger	0.939
Violently	heftig	anger	0.938
infuriated	wütend	anger	0.938
furious	wütend	anger	0.929
enraged	wütend	anger	0.927
furiously	wütend	anger	0.927
screwy you	NO TRANSLATION	anger	0.924
murderer	Mörder	anger	0.922
fury	Wut	anger	0.922
execution	Ausführung	anger	0.917
angered	verärgert	anger	0.916
savagery	Wildheit	anger	0.915
slaughter	Schlachtung	anger	0.914
Very angry	NO TRANSLATION	anger	0.913
fuck off	Verpisss dich	anger	0.912
annihilation	Vernichtung	anger	0.912
assassinate	ermorden	anger	0.912

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

The NRC VAD Lexicon

term	A z	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
abomination		0,521	0,275	0,220

valence vs. arousal



# Valence, Arousal, and Dominance: Bonus

<https://emosaic.de/>

- Emosaic - Visualizing Affective Content of Text at Varying Granularity.
  - based on Warriner, A.B., Kuperman, V., & Brysbaert, M. (2013). Norms of valence, arousal, and dominance for 13,915 English lemmas. Behavior Research Methods, 45, 1191-1207. (similar to NRC-VAD)
- Example for how to use lexicons methodically

**Discuss: What could you use this kind of sentiment Data for?**

# Domain Specific Language

- Domains:
  - Sports, Politics, Arts, ...
  - Social Media, Newspaper, TV, ...
  - Subreddit of people who are born with 12 toes, ...
  - ...
- Different domains have different languages
  - Use of emojis, technical terms, slang, punctuation, memes
  - Domain specific connotations: f.e. “to kill” in video games

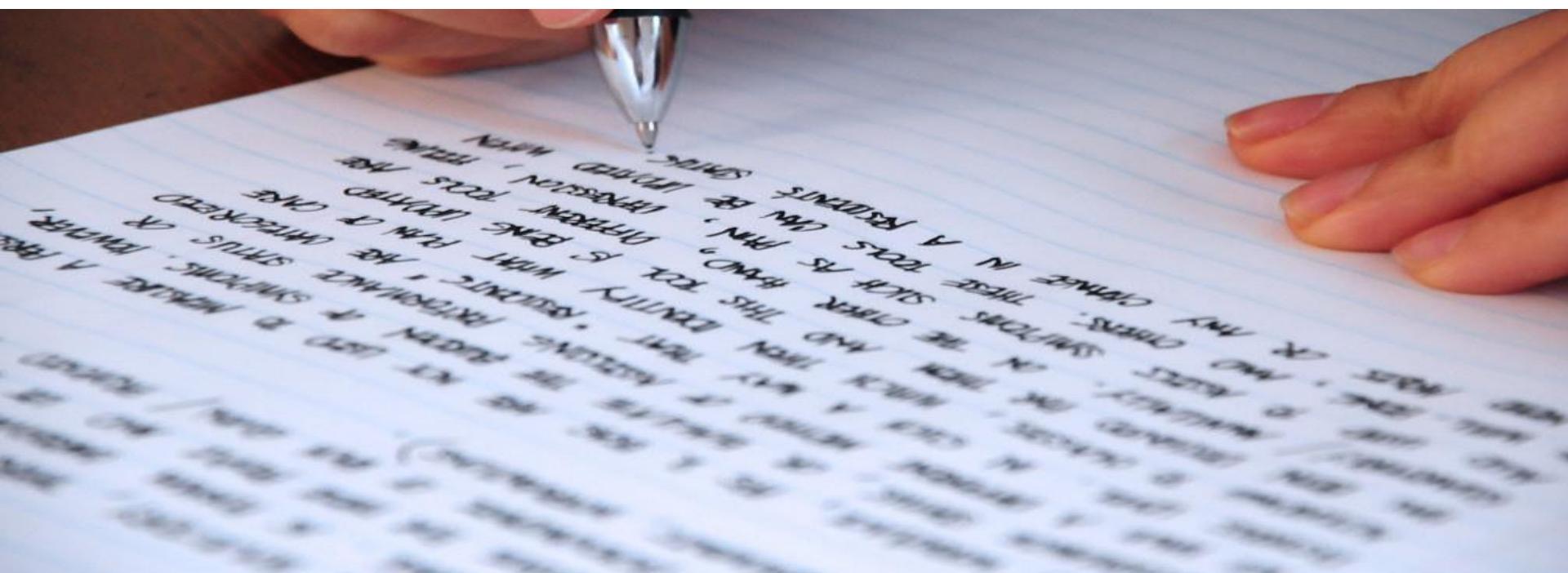
# VADER Sentiment Lexicon

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>

- (Valence Aware Dictionary and sEntiment Reasoner)
  - normalized valence score (compound), and percentages of pos, neg, neu
- „specifically attuned to **sentiments expressed in social media**“
- Negations, contractions, punctuation, 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

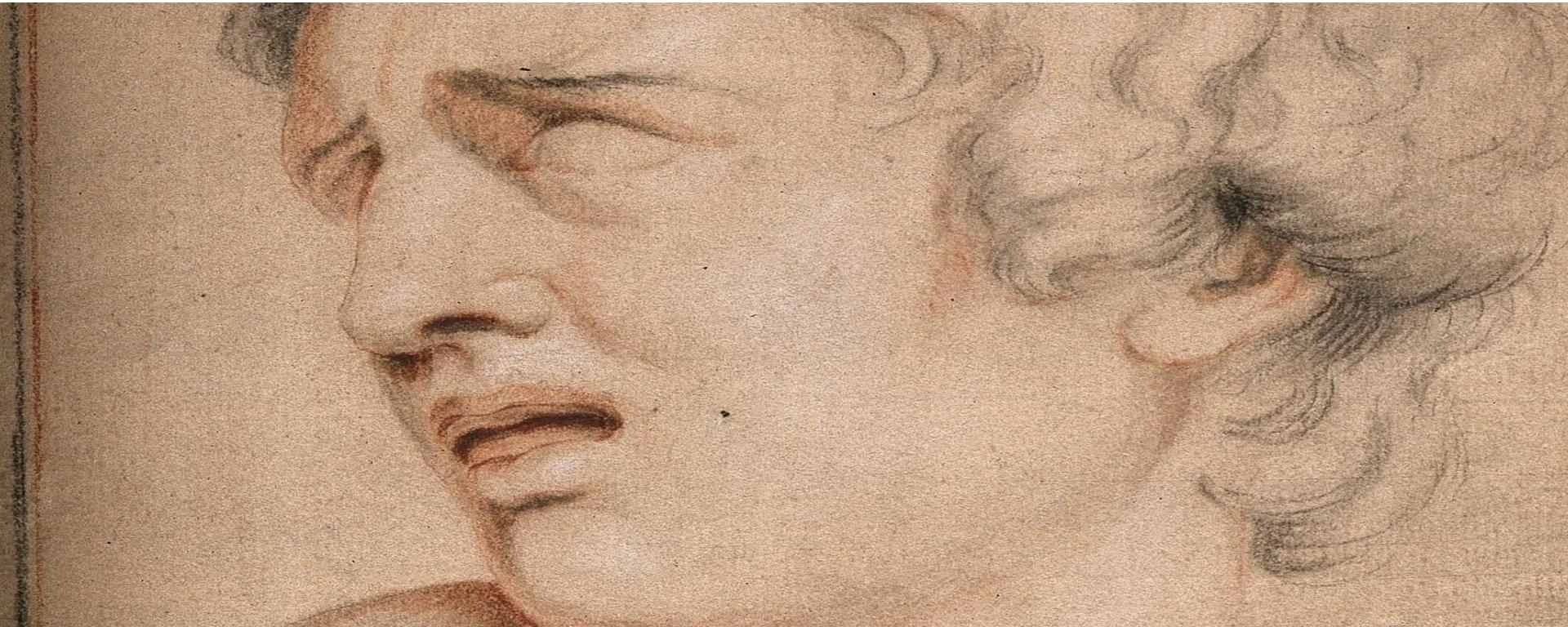
# Issues with Human Labeled Lexicons

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



Manual annotation is complicated and expensive!

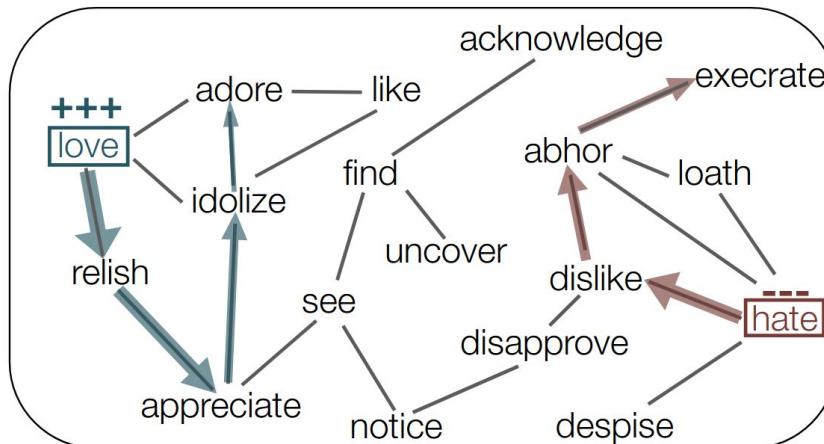
# Building Lexicons: Automated Induction of Affect Lexicons



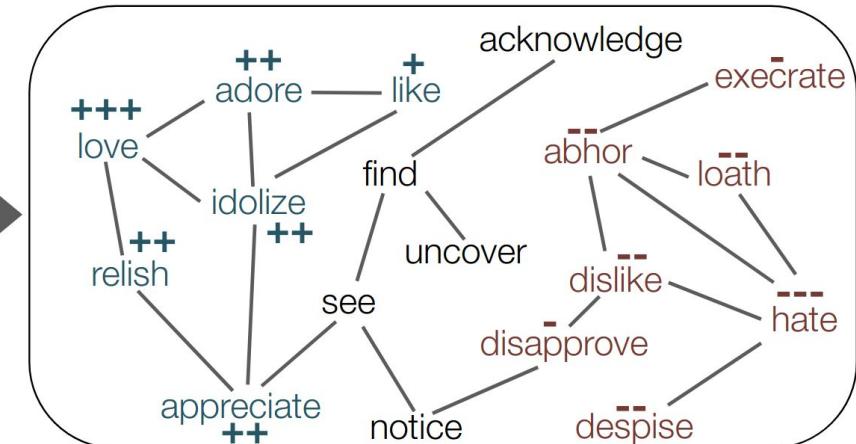
Head of a man expressing acute pain. Pencil drawing after Charles Le Brun. Wellcome Collection. Public Domain Mark

# Semi-supervised Approaches

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



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: Semantic Axis

- Main concept: Generate lexicons based on (vector-based) 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:

$$\mathbf{v}^+ = \frac{1}{n} \sum_1^n E(w_i^+) \quad \mathbf{v}^- = \frac{1}{m} \sum_1^m E(w_i^-) \quad \mathbf{V}_{axis} = \mathbf{V}^+ - \mathbf{V}^-$$

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

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

# Semi-supervised: Label Propagation

- Main concept: Generate 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”

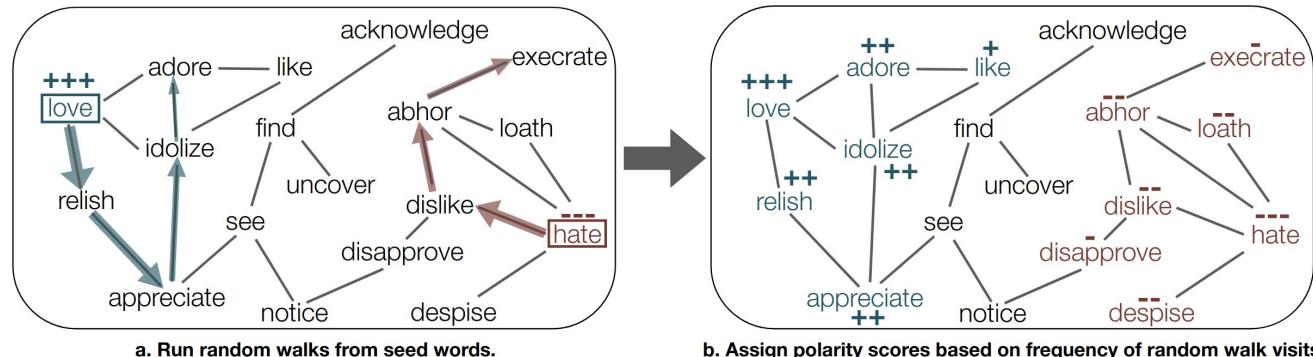


Image: Hamilton, W.L., Clark, K., Leskovec, J., & Jurafsky, D. (2016). Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora. Proceedings of the Conference on Empirical Methods in Natural Language Processing. Conference on Empirical Methods in Natural Language Processing, 2016, 595-605 .

# Semi-supervised Approaches: Domains

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

# Other Semi-supervised Approaches

- Based on other similarity measures:
  - Morphological similarity (f.e. common stems)
  - Synonyms, hypernyms 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

# Supervised Learning of Word Sentiment

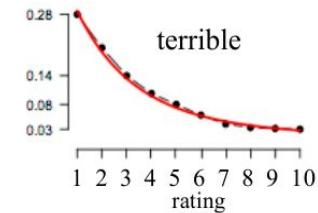
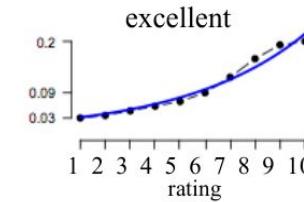
- Approach: Derive positive and negative words from corpus of labelled texts
- Corpora: Reviews of movies (IMDb), products (Amazon), places (Yelp, Google), ...
- Derive rating (Potts Score):

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

→likelihood instead of counts

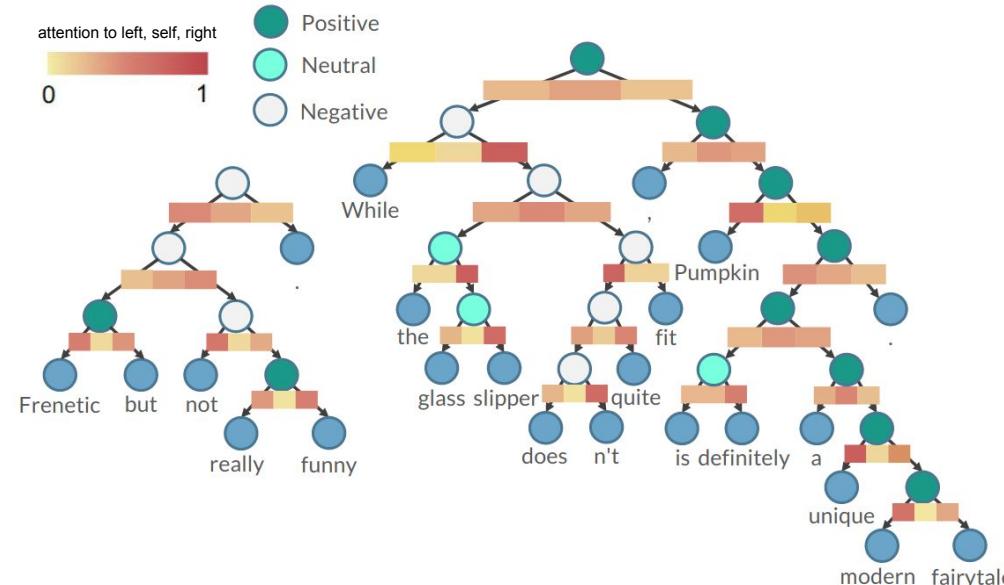
$$\text{PottsScore}(w) = \frac{P(w|c)}{\sum_c P(w|c)}$$

→divide  $P(w|c)$  values by the sum of all the  $P(w|c)$  values

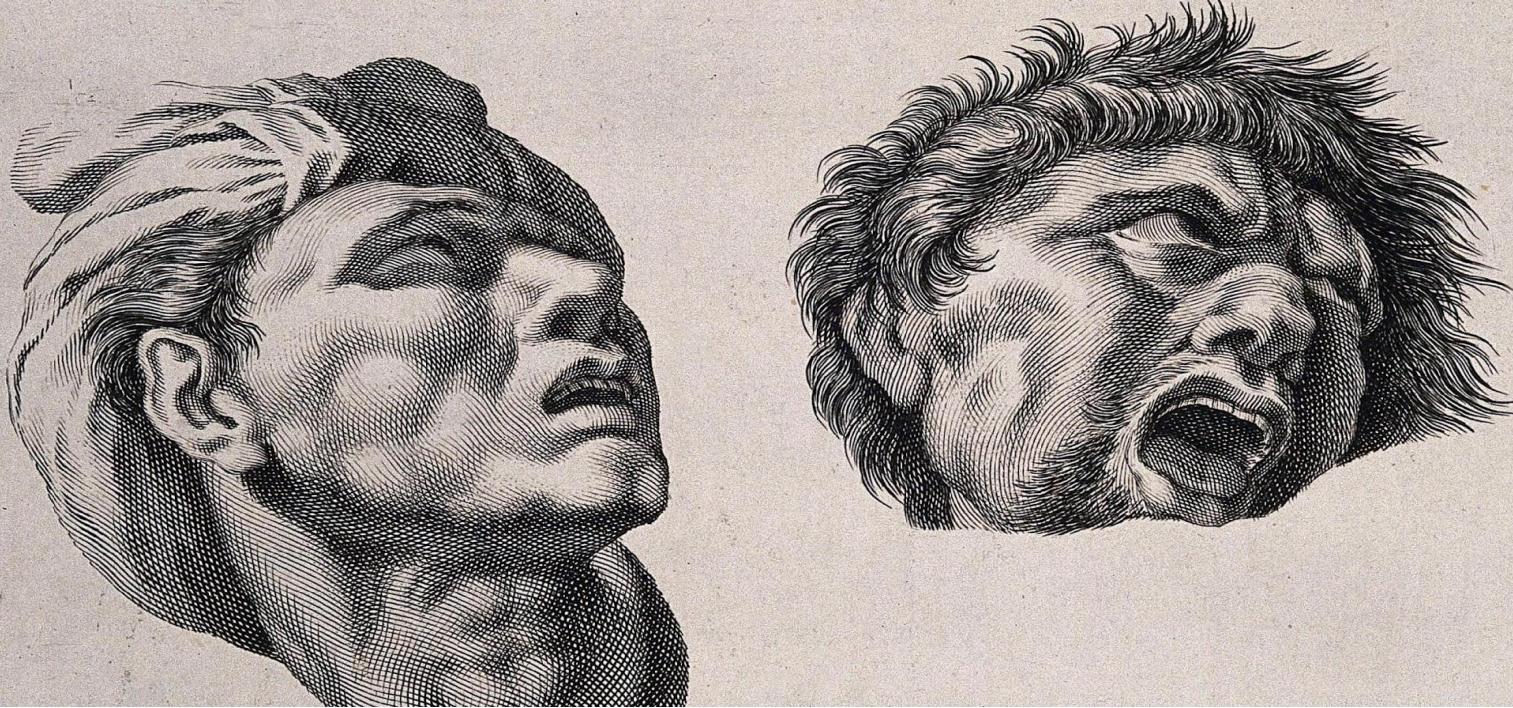


# Other Supervised Machine Learning Approaches

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



# Using Lexicons for Sentiment Recognition



Two heads, both in states of fear. Engraving after C. Le Brun. Wellcome Collection. Public Domain Mark

# Using Sentiment Analysis: Sentences and Texts

- Sentiment on different levels: Word, sentence, paragraph, text, ...
- Different Approaches:
  - 1) Ratio of positive to negative words
  - 2) Sum of sentiment scores of all words
  - 3) Machine Learning binary classification
  - 4) 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](http://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

Goal: Semi-supervised creation of domain specific emoji lexicons

# Solution: Co-Occurrence 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**

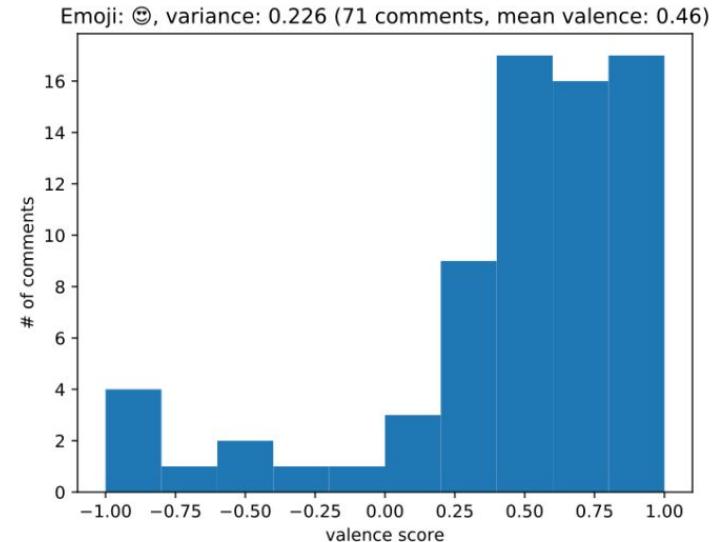
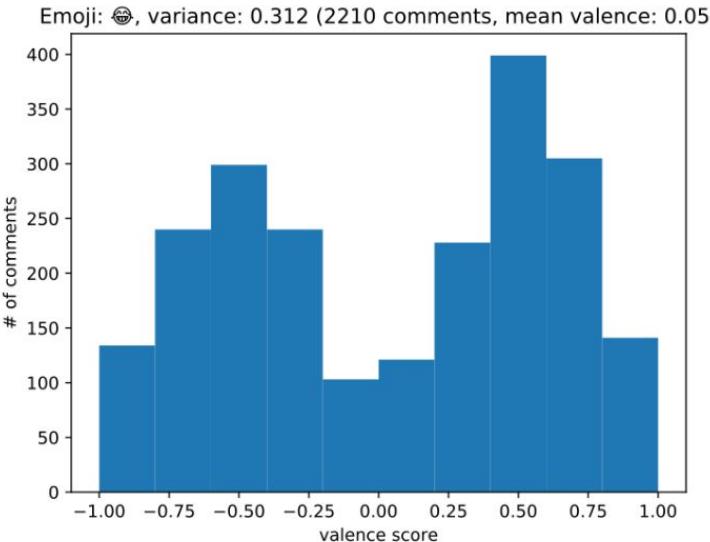
Der schöne, sonnige Tag war super toll!!! 😊

Ein Erfolg auf ganzer Linie 😊

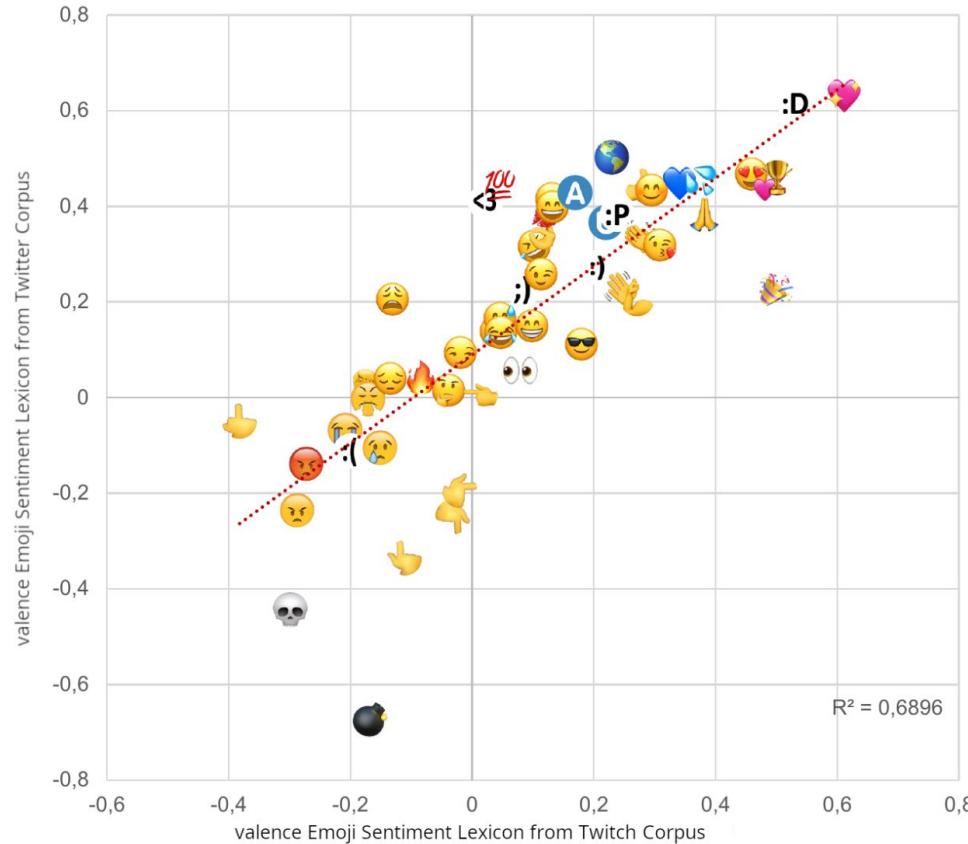
# Development of an Emoji Sentiment Lexicon

- 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

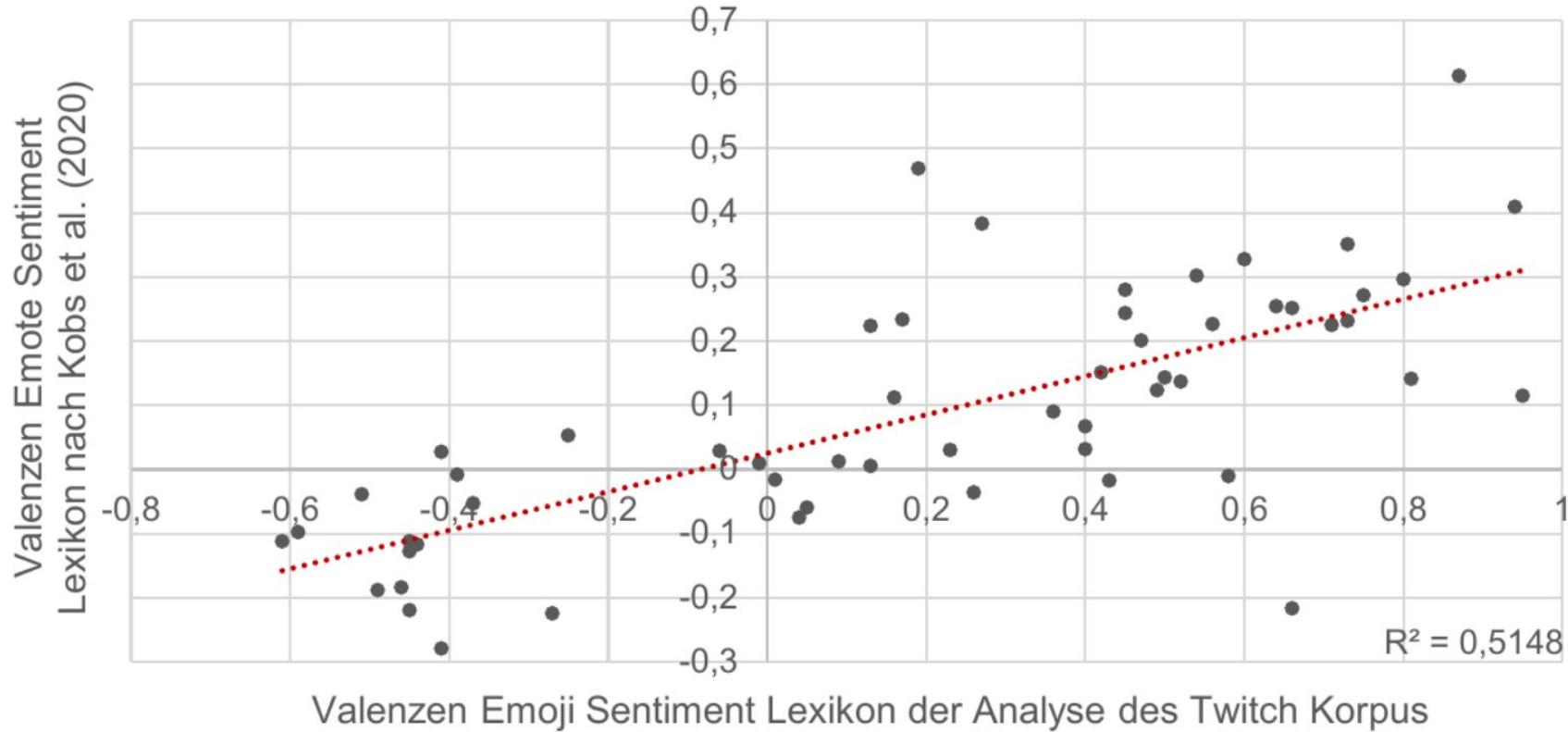
# Distribution of Valence Scores



# 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 (your Bachelor Thesis?):
  - 1) Bigger corpus, bigger lexicon: “ESR 2.0”
  - 2) Study on effects in sentiment analysis
  - 3) Domain specific lexica with domain specific corpora

# References

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