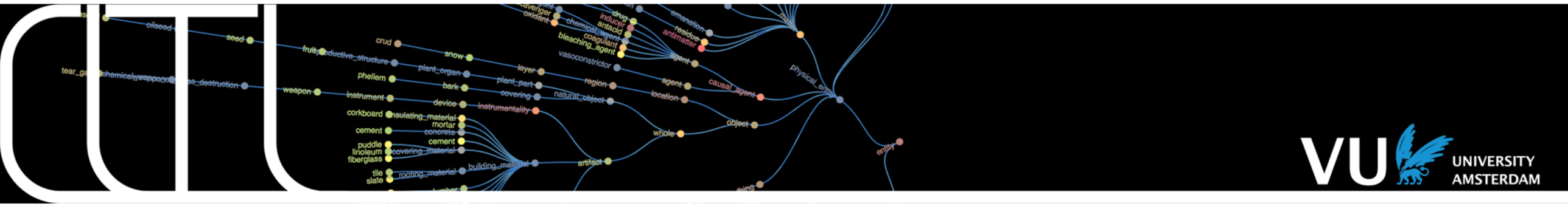
Text Mining CBS

Lecture 3: Subjectivity mining

Piek Vossen



Overview

- Part I: What is subjectivity? Many different things….
- Part II: Subjectivity mining
- Part III: Tools and resources

Part I
What is subjectivity in language?

- bella is the picture of health with boundless energy until a few days before she dies . this is absolutely and completely ridiculous and an insult to every family whose mother has suffered through the horrible pains of a death by cancer .

nltk_data/corpora/sentence_polarity/rt-polarity.neg

Part I
What is subjectivity in language?

- bella is the picture of health with **boundless energy** until a few days before **she dies** . this is absolutely and **completely ridiculous** and an **insult** to every **family** whose **mother** has **suffered** through the **horrible pains** of a **death** by **cancer** .

nltk_data/corpora/sentence_polarity/rt-polarity.neg

- **Explicit sentiment**: boundless energy, completely ridiculous, insult, horrible
- **Implicit sentiment**: dies, suffer, pains, death, cancer
- **Holders**:
  - ***Author***
  - **Participants** of the text: she, family, mother about the cancer, the pain and the death
- But also what is and is not mentioned in the text is subjective (agenda setting)

Part I
What is subjectivity in language?

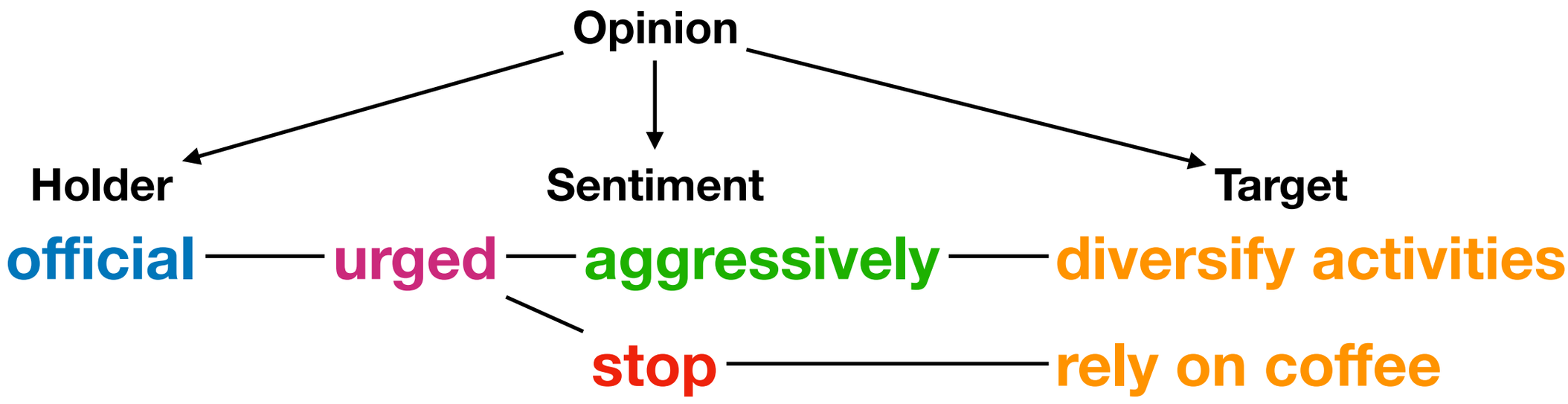
- A Colombia government trade official has urged the business community to aggressively diversify its activities and stop relying so heavily on coffee. Samuel Alberto Yohai, director of the Foreign Trade Institute, INCOMEX, said private businessmen should not become what he called "mental hostages" to coffee, traditionally Colombia's major export.

nltk_data/corpora/reuters/test/15198

Part I
What is subjectivity in language?

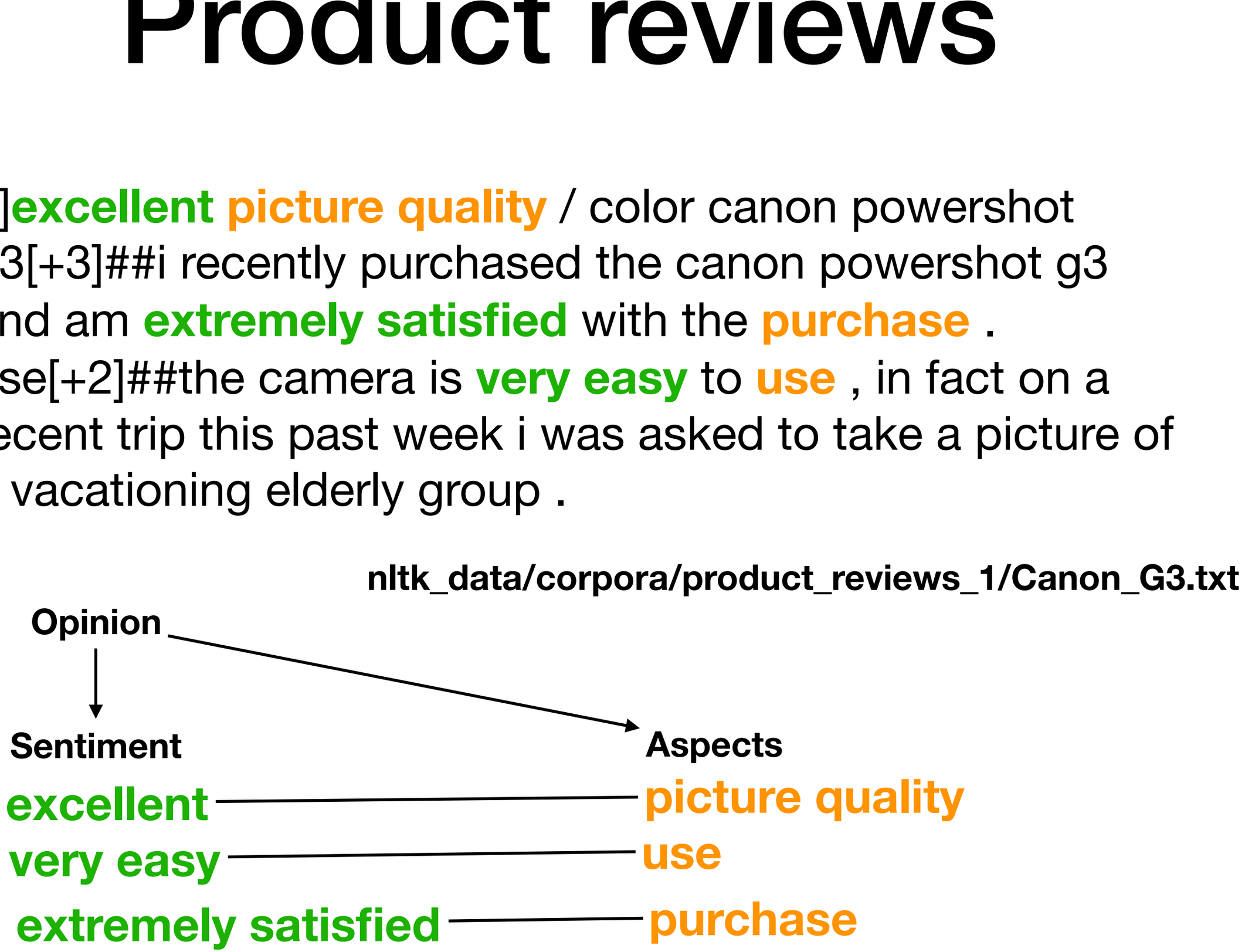
- A Colombia government trade **official** has **urged** the business community to **aggressively** **diversify** its **activities** and **stop** **relying** so heavily on **coffee**. **Samuel Alberto Yohai**, director of the Foreign Trade Institute, INCOMEX, said private businessmen should not become what he called "mental **hostages**" to coffee, traditionally Colombia's **major** export.

nltk_data/corpora/reuters/test/15198



Product reviews

- [t]**excellent picture quality** / color canon powershot g3[+3]##i recently purchased the canon powershot g3 and am **extremely satisfied** with the **purchase** . use[+2]##the camera is **very easy** to **use** , in fact on a recent trip this past week i was asked to take a picture of a vacationing elderly group .



Tweets & Irony?

- {"contributors": null, "coordinates": null, "text": "Everything in the **kids section** of IKEA is **so cute**. **Shame** I'm nearly 19 in 2 months :(“,.....}

nltk_data/corpora/twitter_samples/negative_tweets.json

Ekman (1972, ..)

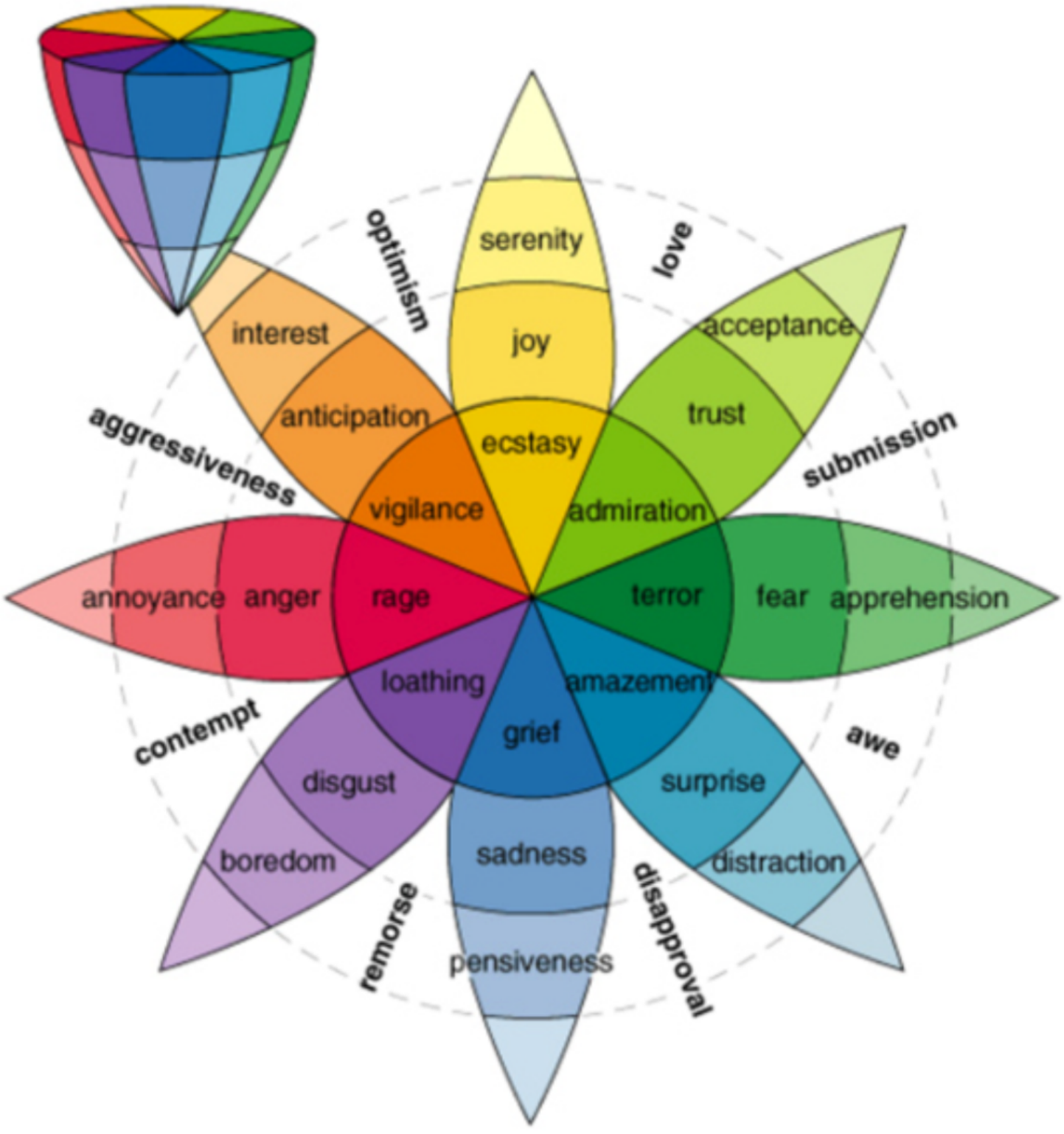
- 6 Basic emotions in many different cultures from facial expressions related to described situations

- Anger
- Disgust
- Fear
- Happiness
- Sadness
- (Surprise)

- Extension but not all facially expressed:

- Amusement
- Contempt
- Contentment
- Embarrassment
- ExcitementGuilt
- Pride in achievement
- Relief
- Satisfaction
- Sensory pleasure
- Shame

Plutchik's Wheel of Emotions (1980)



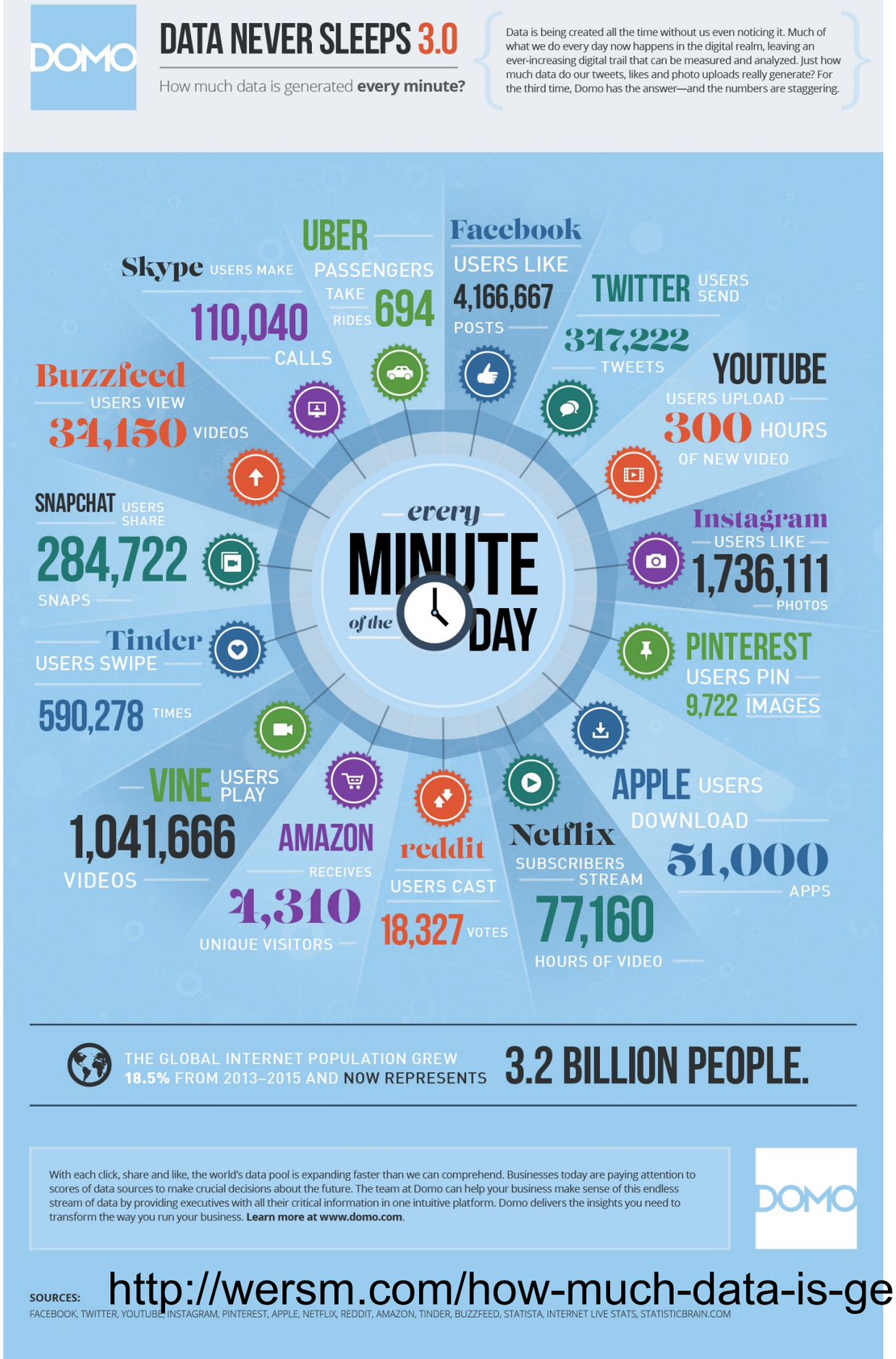
http://wndomains.fbk.eu/wnaffect.html

A-Labels and corresponding example synsets

A-Labels	Examples
EMOTION	*noun anger#1, verb fear#1*
MOOD	*noun animosisy#1, adjective amiable#1*
TRAIT	*noun aggressiveness#1, adjective competitive#1*
COGNITIVE STATE	*noun confusion#2, adjective dazed#2*
PHYSICAL STATE	*noun illness#1, adjective all in#1*
HEDONIC SIGNAL	*noun hurt#3, noun suffering#4*
EMOTION-ELICITING SITUATION	*noun awkwardness#3, adjective out of danger#1*
EMOTIONAL RESPONSE	*noun cold sweat#1, verb tremble#2*
BEHAVIOUR	*noun offense#1, adjective inhibited#1*
ATTITUDE	*noun intolerance#1, noun defensive#1*
SENSATION	*noun coldness#1, verb feel#3*

Relevance

http://www.internetlivestats.com/one-second



Social media 2015

- **Facebook**: 1.4 billion active monthly users, 4 million likes/minute
- **Instagram**: 300 million monthly users, 1.7 million likes/minute
- **Vine**: 1 million video's played/ minute
- **Tinder**: 290K matches/minute
- **Twitter**: 347K tweets/minute
- **Youtube**: 300 hours upload/minute
- **Buzzfeed**: 34K video watches/ minute

http://wersm.com/how-much-data-is-generated-every-minute-on-social-media/

We do not live in an information society

…

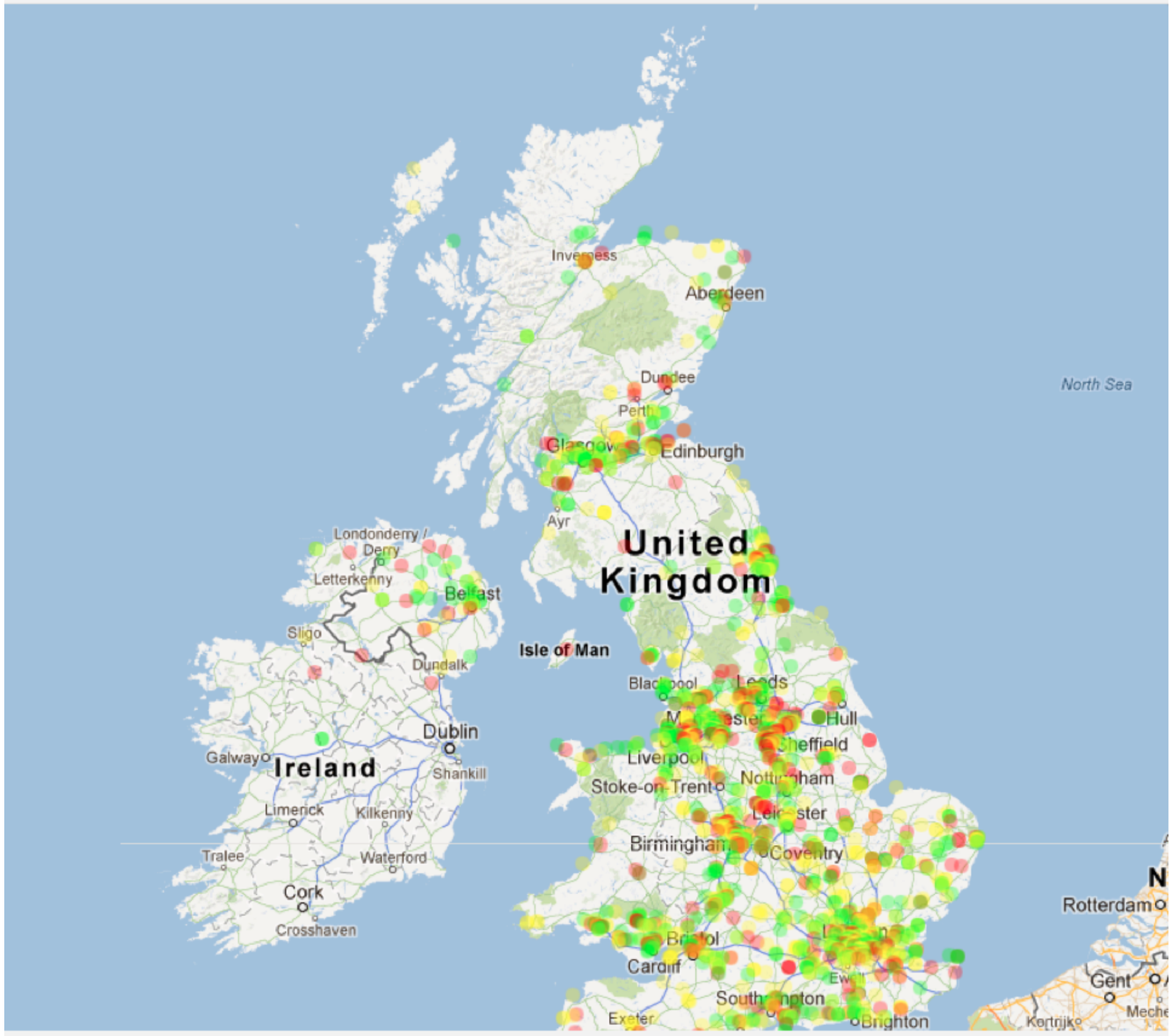
We live in a **communication** society

Sentiment & Stock market

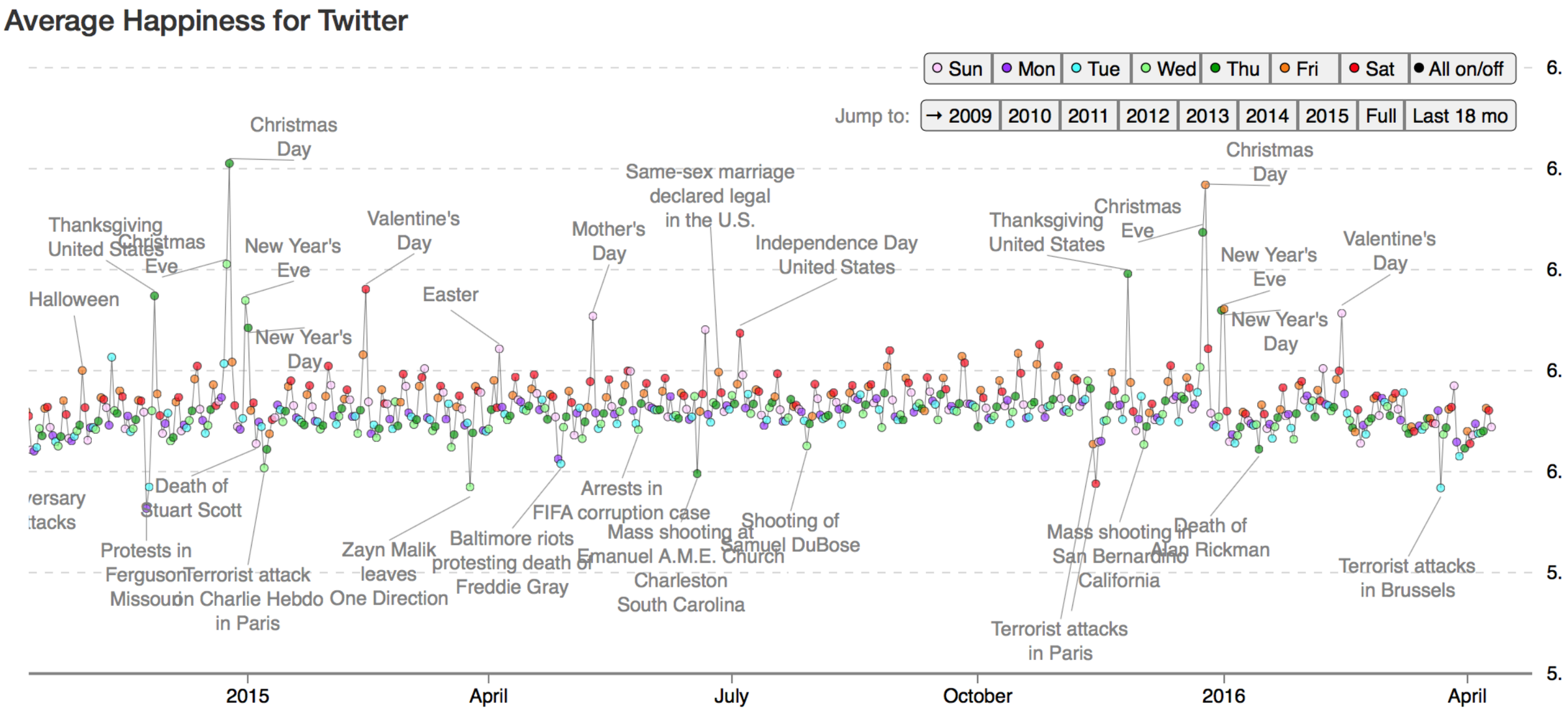
J. Sharma, 7/29 http://www.csee.umbc.edu/2013/07/ms-defense-sentiment-analysis-on-tweets-and-their-relationship-with-stock-market-trends-j-sharma-729/

moodmap

Created for Young Rewired State



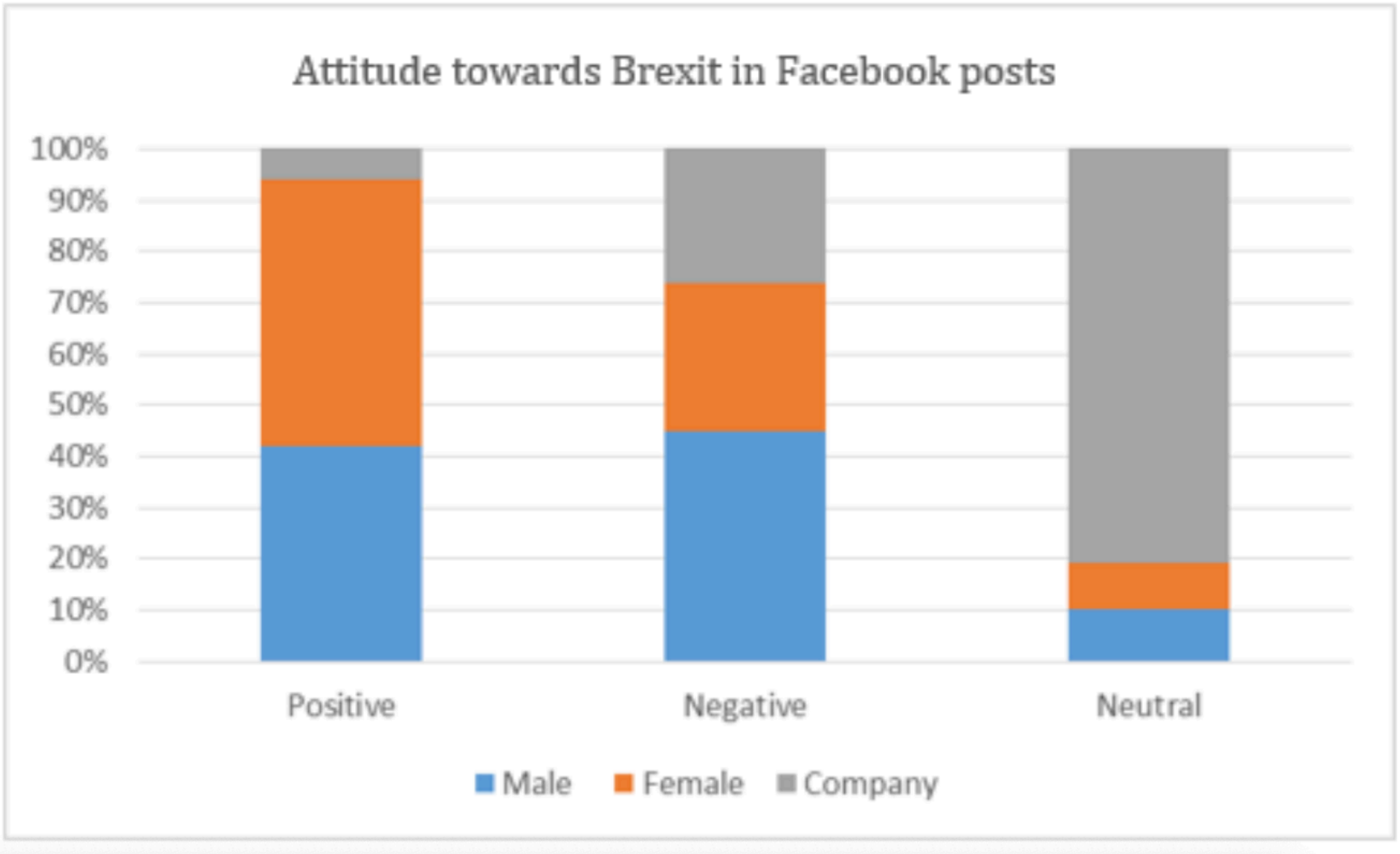
hedonometer.org



https://www.venndigital.co.uk/blog/the-eu-referendum-brexit-or-bremain-78807/

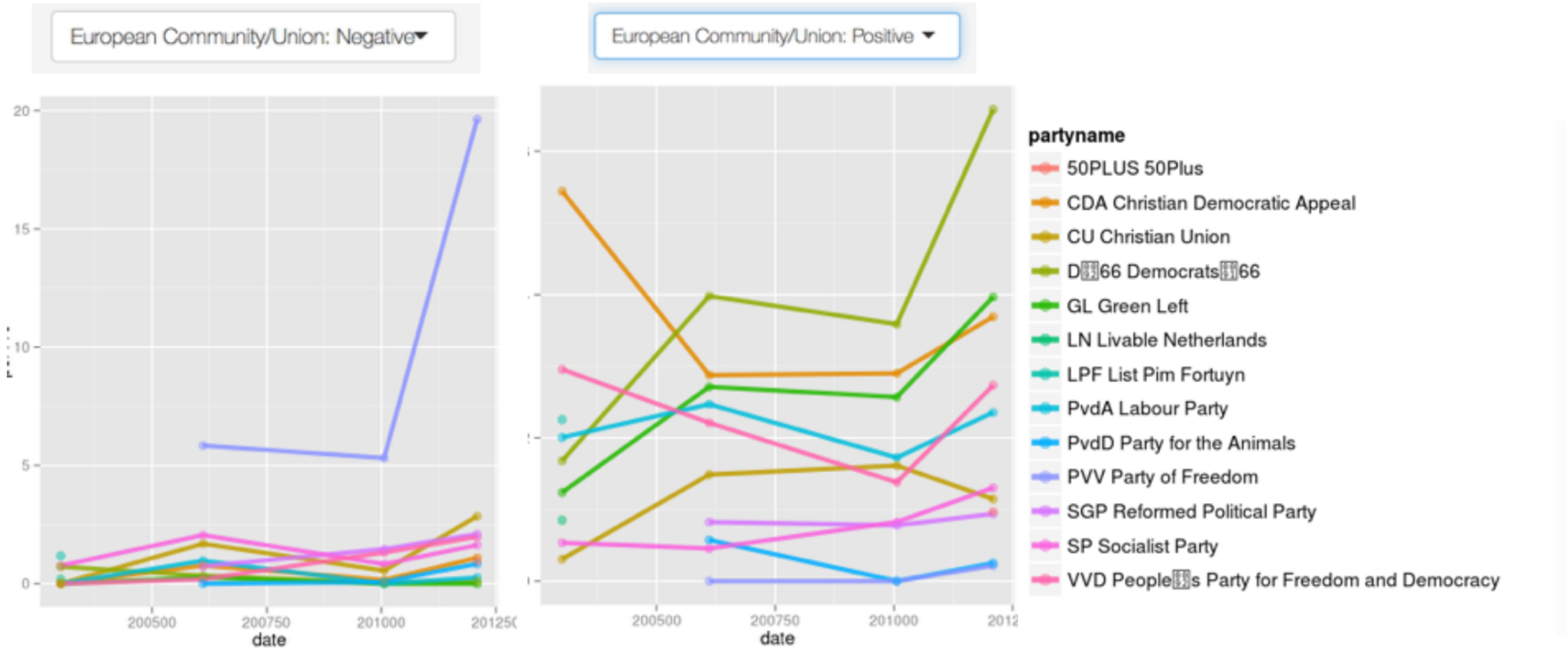
pro/against Brexit (2016)

Interestingly, females were most likely to post **for** Brexit (68%) followed by men (55%), while companies posted mainly neutral content (71%). 36% of the posts made by men were actually **against** Brexit while only 23% of women voiced a negative opinion.



The manifesto project:

The Manifesto Project provides the scientific community with parties' policy positions derived from a content analysis of parties' electoral manifestos. It covers over 1000 parties from **1945 until today** in over **50 countries** on five continents



Netherlands 2000-2015

https://manifesto-project.wzb.eu

Love & Hate Letters

348 posts from: lovingyou.com

279 fragments from the millennium project: https://ratbags.com/rsoles/categories.htm

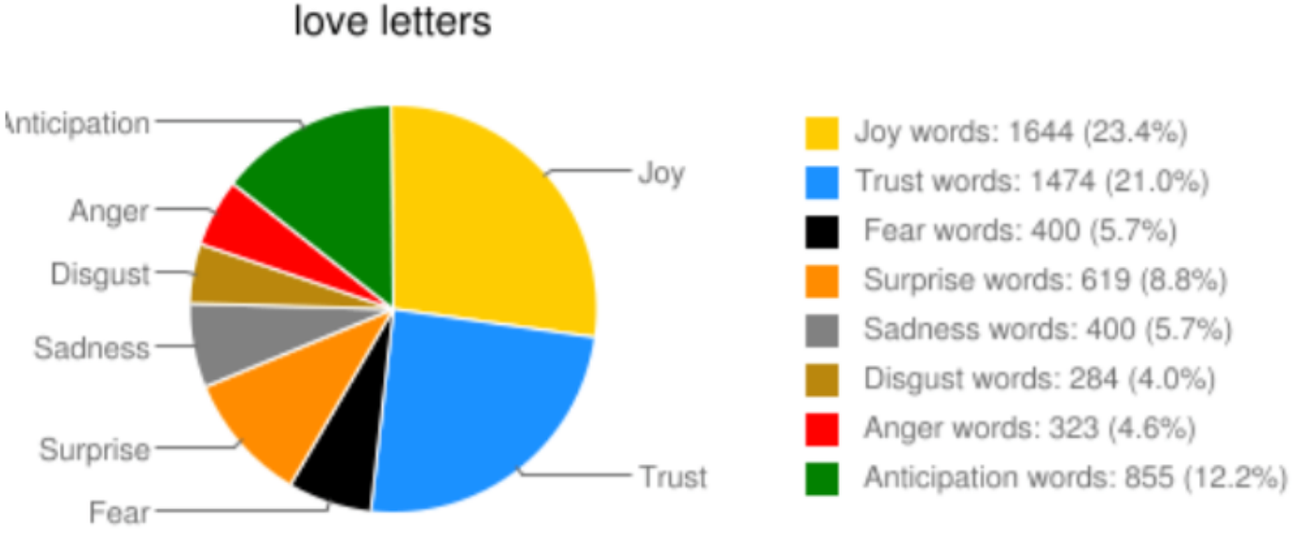
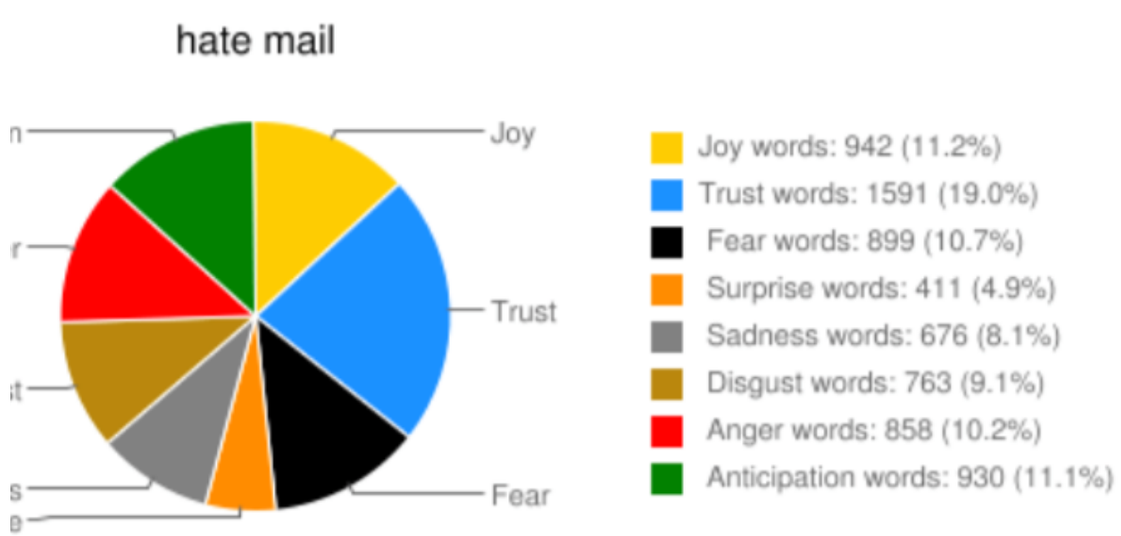


Figure 5: Percentage of emotion words in the love letters corpus.



e 6: Percentage of emotion words in the hate mail s.

Saif M. Mohammad, 2012

Terminology

- **Subjectivity** or A**ttitude**: broad term that covers all forms of opinion mining, sentiment analysis, stance but leaves open the lexical or structural realisation

- **Sentiment or Polarity**: explicit expression of being positive, negative or neutral about something/someone (**good**, **bad**)

- **Opinion**: a lexically or syntactically realised sentiment relation of a holder to a target (I **like** him, my **hero** failed)

- **Stance**: opinion in a debate, I **support** the anti-vaccination movement

- **Aspects-facets-features-properties**: opinion on an aspect of something such as products, (this iPhone has an **incredible good** battery)

- **Argumentation**: I like this iPhone **because** it has a very powerful battery

- **Emotion**: response to a situation that is deemed important: **anger, joy, sadness**

- **Attribution**: relation between a source, a cue (not differentiated) and some content, e.g. quotes

- **Perspective**: umbrella term for all the above as the values for the epistemic, emotional, deontic properties of a **source** with respect to an explicit or implicit **propositional content**

- **Other terms**: inner state, mental state, etc..

What is Subjectivity Mining?

- Software for automatically extracting **opinions, emotions and sentiment** in text.

- It allows us to track attitudes and feelings on the web. People write **blogs, comments, reviews and tweets** about all sorts of different topics

- We can track products, brands and people for example and determine whether they are **positively or negatively** on the web

- It allows individuals to get **an opinion an a global scale**

Sentiment analysis (2015)

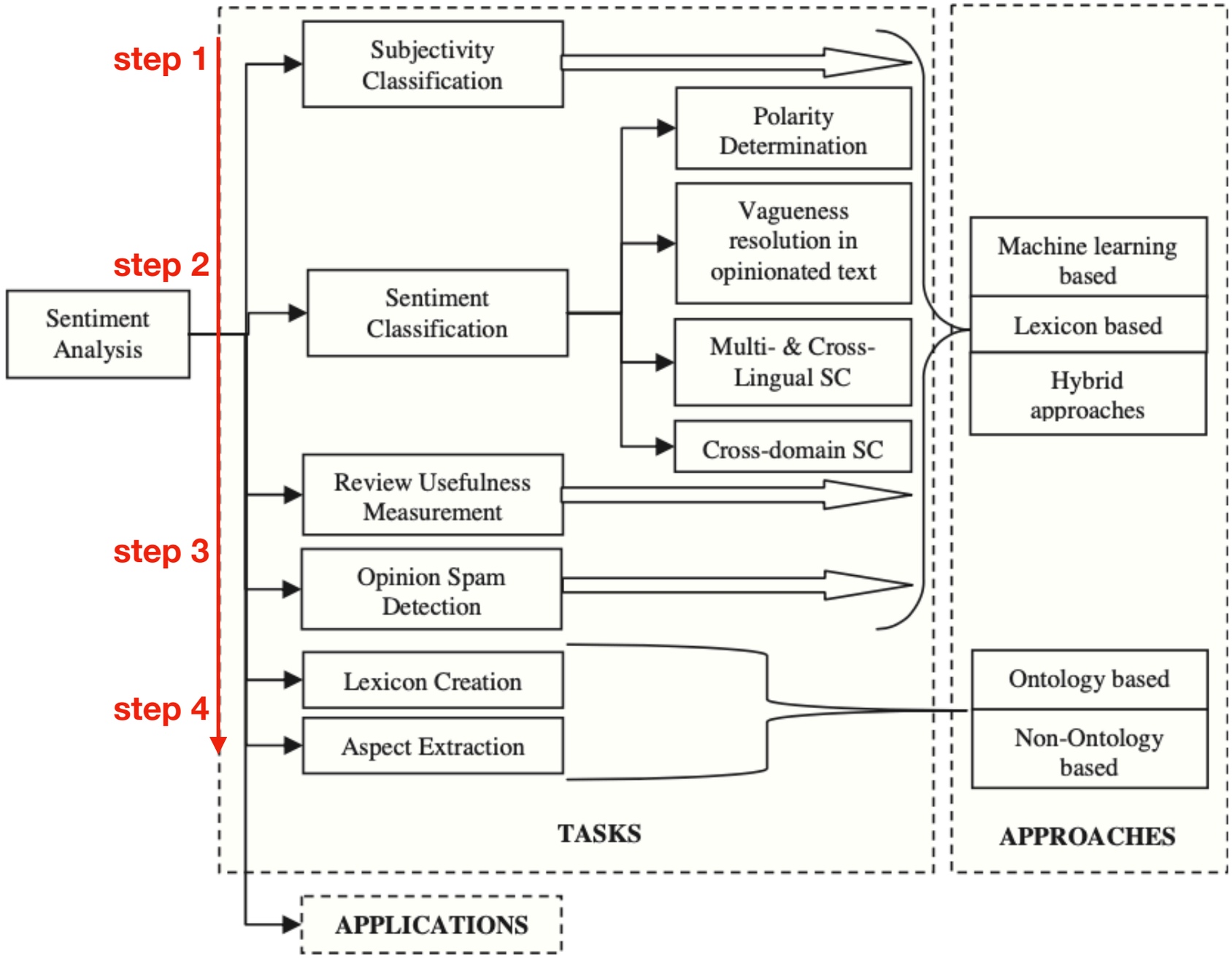


Fig. 1. Organization of the review.

Levels of Analysis

- Corpus or set of documents
- Document: one sentiment per document
- Sentence/ statement
    - Several opinions, on several topics by several opinion holders per document
- Opinions on entities, topics or aspects

subjective vs. non-subjective

- He was born in 1930 in Pennsylvania. He was an American actor best known for his portrayal in the HBO series the Sopranos. He died in New Jersey and was survived by his two sons.

- @USAirways please give Tara G a pat on the back and praise. She was very very helpful.

Sentiment tagger with interpretation rules

Coen was a person, **very modest** in life style, of **good** character, **not** a **drunkard**, **not haughty**, a **very proficient** council and **educated** in bookkeeping and business.

Intensification

- @USAirways please give Tara G a pat on the back and praise. She was very very helpful.
- Please go away!!!!!!!
- He was really very helpful

Stance detection

pro or against or neutral

ideological discussions about:
legalisation of abortus
gay rights
brexit
vaccinations
black pete

PRO_VACCINATION: I hate anti-vaxxers (negative)
ANTI_VACCINATION: Children die from vaccinations!!! (negative)

Aspect based sentiment analysis

	Sentence3	Sentence4
Entity (= opinion target)	Canon G12	Canon G12
Aspects (= related to opinion target)	Picture quality	Weight
Sentiment (=opinion expression)	Positive	Negative
Opinion holder	John Smith	Wife of John Smith
Time	September 2010	September 2010

- (1) I bought a Canon G12 camera six months ago. (2) I simply love it. (3) The picture quality is amazing. (4)However, my wife thinks it is too heavy for her. (John Smith, september 2010)

Do we agree on opinions?

- **Hotel reviews**
  - Document level - 3 classes (positive, negative, neutral) - 0.87 Kappa
- **Black Pete debate**
  - Tweet level - 4 classes / 3 annotators : 0.65 (a1-a2); 0.57 (a1-a3); 0.55 (a2-a3) Kappa
- **News annotations**
  - 0.70 Kappa on opinion expressions

Review text	User rating	Ann1	Ann2
The hotel is **fantastic**, but the area around the hotel is very very noisy.	4	-2	3
Good Hotel, in Down Town. Really for business. For holidays I had choose something else.	4	-2	-2

Nr. students

Opinion Annotation

Washington (AFP) - Obama said Thursday that he had included openly gay athletes in the US Olympic delegation to show the

32

United States would not abide discrimination in sport or anywhere else.

His comments, in an interview with NBC on the eve of the Sochi Winter Olympics, came after a senior Russian official activists

20

should not promote gay rights during the Olympics following the passage of controversial anti-gay legislation in Russia.

Obama picked several openly gay former athletes in the US

4

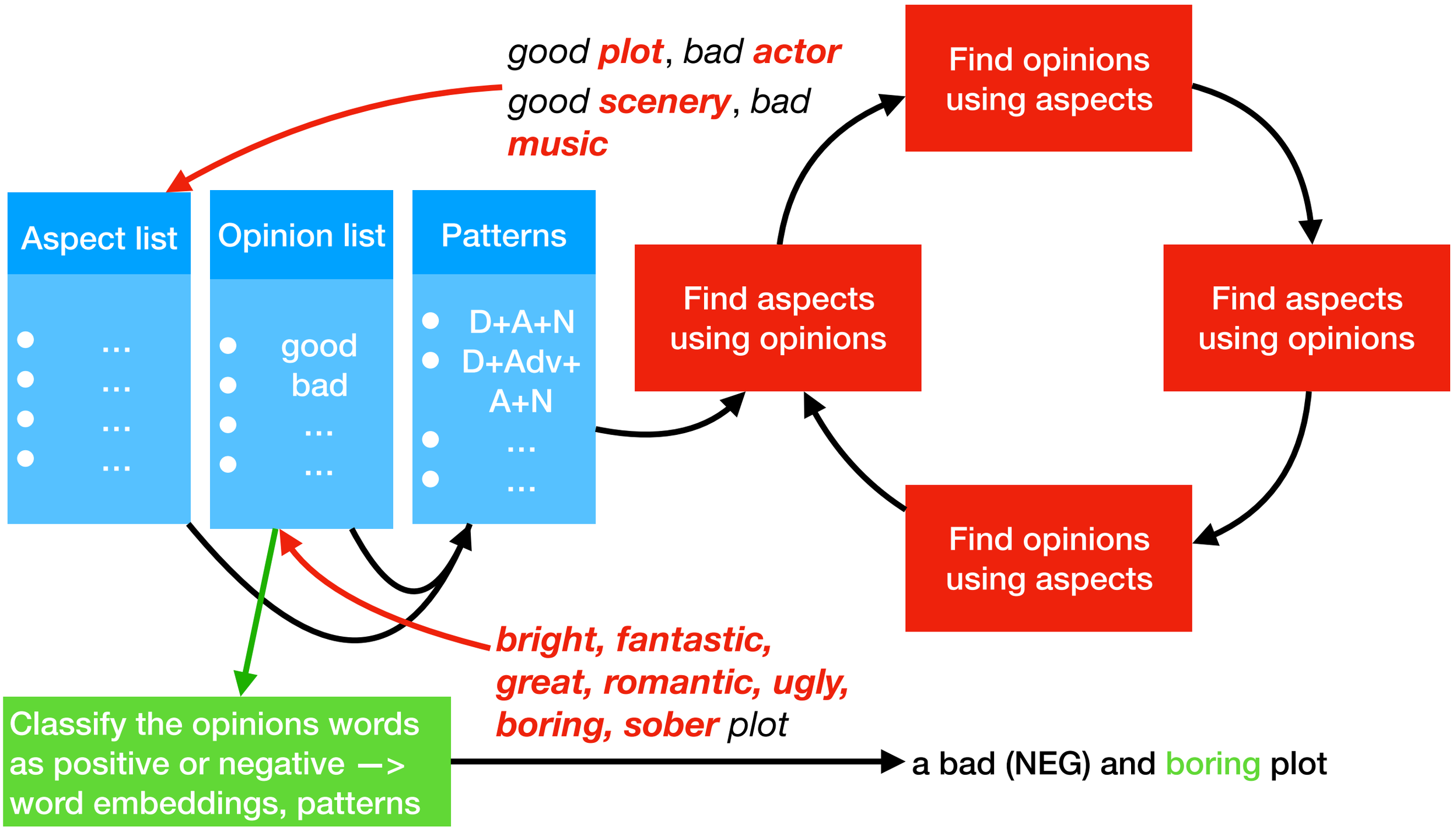
delegation to the opening of the games and pointedly did not dispatch a cabinet-level official or a member of his family to Sochi

Context dependence

- A **cold** person
- A **cold** soda
- A **cold** shower
  - to cool off
  - because the boiler broke (again!)
- Low prices, low ceilings, cheap fast food, cheap fast car

Learning sentiments & aspects from targeted data sets

"Double Propagation"



Top 15 ranked aspect terms for restaurants	Top 15 ranked aspect terms for laptops	Top 15 ranked aspect terms for hotels
1- food	1- battery life	1- hotel
2- service	2- keyboard	2- room
3- staff	3- screen	3- staff
4- bar	4- feature	4- service
5- drink	5- price	5- food
6- table	6- machine	6- view
7- menu	7- toshiba laptop	7- stay
8- dish	8- windows	8- breakfast
9- atmosphere	9- performance	9- pool
10- pizza	10- use	10- floor
11- meal	11- battery	11- area
12- bartender	12- program	12- location
13- price	13- speaker	13- bed
14- server	14- key	14- beach
15- dinner	15- hard drive	15- bar

Methods

- Rule-based approach, knowledge/lexicon based
  - Identify subjective sentences, exclude objective sentences
  - Count all positive and negative words (from a lexicon) per unit
  - Process negations
  - Process intensifiers: very, extremely, terribly
  - Aggregate sentiment at document level, corpus level, etc. (in order to generate opinions on a generic scale)
- Machine learning
  - need a lot of training data
  - classification problem
  - Decide on the features to use (feature engineering)

Document level sentiment classification with and without preprocessing

- Ex. (2) De kamers zijn niet schoon en hebben geen eigen badkamer. (*The rooms are not clean and do not have an own bathroom*)

- Rule and lexicon-based: negation flips vote

78.3

- Machine Learning Naive Bayes, 1171 hotel reviews
  - Bag-of-WORDS

82.3

  - Bag-of-words + LEMMA

83.6

- Bag-of-Words + sentiment lexicon and rules:

84.7

  - de kamer zijn niet schoon **neg_tag** en hebben geen eigen badkamer **negator_tag**

Machine Learning methods

Table 6
Distribution of articles based on intelligent techniques applied.

Applied techniques	#Articles	Articles' references
SVM	55	[21,26,29,33,44–46,50,51,53,54,57,58,66,67,73,76,77,86,88,90,91,94,95,97,101,108,109,111,114,116,118,125,131,148,157,160,163,165,167,169,172,176,177,183,195,197,200,209,210,212,214,225,228,240]
Dictionary based approaches (DBA)	41	[13,18,23–25,35,36,47,55,64,67–69,85,96,110,112,117,126,127,158,170,171,175,183,193–196,202,203,206,207,209,210,213,216,218,220,229,241]
NB	28	[33,46,50,54,56,73,80,86,90,94,98,101,111,114,116,118,121,124,125,131,148,156,163,167,197,209,217,228]
NN	11	[48,50–53,57,76,101,116,213,226]
DT	9	[53,66,73,76,86,94,116,118,209]
Maximum entropy	8	[33,46,54,60,63,66,148,156,174]
Logistic regression	9	[53,77,88,99,116,118,163,197,220]
Linear regression	8	[8,18,70,75,222–224,231]
Ontology	8	[30,41,62,98,182,194–196]
LDA	8	[61,92,107,185,189,191,182,240]
Random forest	4	[77,81,228,210,228]
SVR	5	[118,123,130,155,227]
CRF and rCRP	5	[37,88,93,186,190]
Boosting	4	[12,118,179,197]
SVM-SMO	4	[76,97,118,169]
Fuzzy logic	3	[23,41,62,213]
Rule miner	4	[37,100,112,217]
EM	3	[56,59,155]
K-medoids	1	[52]
RBF NN	1	[130]

Table 5
Sentiment classification accuracy reported on common datasets.

S#	Dataset	Articles	Obtained result
1	Pang and Lee [167]	[156]	92.70% accuracy
2		[112]	90.45% F_1
3		[169]	90.2% accuracy
4		[35]	89.6% accuracy
5		[54]	87.70% accuracy
6		[46]	87.4% accuracy
7		[50]	86.5% accuracy
8		[26]	85.35% accuracy
9		[162]	81% F_1
10		[124]	79% accuracy & 86% F_1
11		[61]	76.6% accuracy
12		[69]	76.37% accuracy
13		[48]	75% precision
14		[98]	79% precision
15	Pang et al. [33]	[109]	Approx. 90% accuracy
16		[165]	88.5% accuracy
17		[172]	87% accuracy
18		[33]	82.9% accuracy
19		[156]	78.08% accuracy
20		[180]	75% accuracy
21		[48]	60% precision
22		[195]	86.04%
23	Blitzer et al. [149]	[45]	84.15% accuracy
24		[99]	80.9% (Avg.) accuracy
25		[54]	85.15% (Avg.) Max. 88.65% accuracy on Kitchen reviews
28		[165]	88.7% accuracy
29		[61]	71.92% accuracy

Ravi & Ravi 2015

Features for sentiment mining

- **Features**:
  - Words (bag-of-words)
  - N-grams
  - Parts-of-speech (e.g. Adjectives and adjective-adverb combinations)
  - Opinion words (lexicon-based: dictionary or corpus)
  - Valence intensifiers and shifters (for negation); modal verbs; ...
  - Syntactic dependency
- **Feature selection based on**
  - frequency
  - information gain
  - Odds ratio (for binary-class models)
  - mutual information
- **Feature weighting**
  - Term presence or term frequency
  - Inverse document frequency (TF.IDF)
  - Term position : e.g. title, first and last sentence(s)

(Some) Tools

- OpinionFinder: subjective sentences , source (holder) of the subjectivity and words that are included in phrases expressing positive or negative sentiments: http://mpqa.cs.pitt.edu

- Basic sentiment tokenizer plus some tools, by Christopher Potts: http://sentiment.christopherpotts.net

- Sentiment for Tweets: VADER (for tweets); https://github.com/cjhutto/vaderSentiment

- Linguistic Inquiry and Word Count, Psychological features: http://liwc.wpengine.com

(Some) Tools

- SentiStrength (sentistrength.wlv.ac.uk)
- TheySay (apidemo.theysay.io)
- Sentic (sentic.net/demo)
- Sentdex (sentdex.com)
- Lexalytics (lexalytics.com)
- Sentilo (wit.istc.cnr.it/stlab-tools/sentilo)
- nlp.stanford.edu/sentiment

Lexicons

- Bing Liu‘s opinion lexicon: http://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html
- MPQA subjectivity lexicon: http://www.cs.pitt.edu/mpqa/
- SentiWordNet
  - Project homepage: http://sentiwordnet.isti.cnr.it
  - Python/NLTK interface: http://compprag.christopherpotts.net/wordnet.html
- WordNet Affect: http://wndomains.fbk.eu/wnaffect.html
- Harvard General Inquirer: http://www.wjh.harvard.edu/~inquirer/
- SenticNet: http://sentic.net
- NRC (emotions expressed by words): https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

Overview sentiment datasets (2015)

Table 9
List of publicly available datasets.

S#	Data set	Type	Lang.	Web resource	Details
1	Stanford large movie data set	Movie Reviews	English	http://ai.stanford.edu/~amaas/data/sentiment/	Movie Reviews
2	COAE2008	Product Reviews	Chinese	http://ir-china.org.cn/coae2008.html	2739 documents for movie, education, finance, economics, house, computer, mobile phones, etc. 1525 +ve, 1214 −ve
3	Boacar	Car Reviews	Chinese	http://www.riche.com.cn/boacar/	11 type of car TradeMarks and total review 1000 words, having 578 POS, 428 −ve reviews
4	[187]	Reviews, forums	English	http://sifaka.cs.uiuc.edu/~wang296/Data/	Accessed: 27 August, 2014
5	[188]	Reviews	English	http://uilab.kaist.ac.kr/research/WSDM11	Aspect oriented dataset. Accessed: 18 December, 2014
6	Movie-v2.0	Movie Reviews	English	http://www.cs.cornell.edu/people/pabo/movie-review-data/	Data size: 2000 Positive: 1000 Negative: 1000
7	Multi-domain	Multi-domain	English	http://www.cs.jhu.edu/~mdreze/datasets/sentiment	
8	SkyDrive de Hermit Dave	Spanish Word Lists	Spanish	https://skydrive.live.com/?cid=3732e80b128d016f&id=3732E80B128D016F%213584	
9	TripAdvisor	Reviews	Spanish	http://clic.ub.edu/corpus/es/node/106	18,000 customer reviews on hotels and restaurants from Hopinion
10	[38]	Multi-Domain	English	www2.cs.uic.edu/~liub/FBS/sentiment-analysis.html	6800 opinion words on 10 different products
11	TBOD [144]	Reviews	English		Product Review on Cars, Headphones, Hotels
12	[68]	Product Reviews	English	http://www.lsi.us.es/_fermin/index.php/Datasets	Product Reviews from Epinion.com on headphones 587 reviews, hotels 988 reviews and cars 972 reviews
13	[148]	Movie Reviews	Turkish	http://www.win.tue.nl/~mpechen/projects/smm/#Datasets	5331 positive and 5331 negative reviews on movie
14	[148]	Product Reviews	Turkish	http://www.win.tue.nl/~mpechen/projects/smm/#Datasets	700 +ve &700 −ve reviews on books, DVD, electronics, kitchen appliances
15	ISEAR	English sentences	English	www.affective-sciences.org/system/files/page/2636/ISEAR.zip	The dataset contains 7666 such statements, which include 18,146 sentences, 449,060 running words.
16	[149]	Product Reviews	English	http://www.cs.jhu.edu/~mdredze/datasets/sentiment/	Amazon reviews on 4 domain (books, DVDs, electronics, kitchen appliances)
17	DUC data, NIST	Texts	English	http://www-nlpir.nist.gov/projects/duc/data.html, http://www.nist.gov/tac/data/index.html	Text summarization data
18	[70]	Restaurant and Hotel Reviews	English	http://uilab.kaist.ac.kr/research/WSDM11	Restaurant and Hotel Reviews from Amazon and Yelp
19	[114]	Restaurant Reviews	Cantonese	http://www.openrice.com	Reviews on restaurant
20	[125]	Biographical Articles	Dutch	http://www.iisg.nl/bwsa	574 Biographical articles
21	Spinn3r dataset	Multi-Domain	English	http://www.icwsm.org/2011/data.php	
22	[86]	Ironic Dataset	English	http://users.dsic.upv.es/grupos/nle/	3163 ironic reviews on five products
23	HASH [179]	Tweets	English	http://demeter.inf.ed.ac.uk	31,861 Pos tweets, 64,850 Neg tweets, 125,859 Neu tweets
24	EMOT [179]	Tweets and Emoticons	English	http://twittersentiment.appspot.com	230,811 Pos & 150,570 Neg tweets
25	ISIEVE [179]	Tweets	English	www.i-sieve.com	1520 Pos tweets, 200 Neg tweets, 2295 Neu tweets
26	[177]	Tweets	English	e-mail: apoorv@cs.columbia.edu	11,875 tweets
27	[52]	Opinions	English	http://patientopinion.org.uk	2000 patient opinions
28	[96]	Tweets	English	http://goo.gl/UQvdx	667 tweets
29	[39]	Movie Reviews	English	http://ai.stanford.edu/~amaas/data/sentiment/	50,000 movie reviews
30	[164]	Tweets	English	http://cs.stanford.edu/people/alecmgo/trainingandtestdata.zip	
31	[210]	Spam Reviews	English	http://myleott.com/op_spam	400 deceptive and 400 truthful reviews in positive and negative category. Last Accessed by: 12 April, 2015
32	[230]	Sarcasm and nasty reviews	English	https://nlds.soe.ucsc.edu/iac	1000 discussions, ~390,000 posts, and some ~73,000,000 words

Ravi & Ravi 2015

(Some) datasets

- Data from Lillian Lee's group: http://www.cs.cornell.edu/home/llee/data/
- Data from Bing Liu: http://www.cs.uic.edu/~liub/
- Large movie review dataset: http://ai.stanford.edu/~amaas/data/sentiment/
- Pranav Anand & co. (http://people.ucsc.edu/~panand/data.php)
    - Internet Argument Corpus
    - Annotated political TV ads
    - Focus of negation corpus
    - Persuasion corpus (blogs)
- Data on AFS:
    - /afs/ir/data/linguistic-data/mnt/mnt4/PottsCorpora
      README.txt, Twitter.tgz, imdb-english-combined.tgz,
      opentable-english-processed.zip
    - /afs/ir/data/linguistic-data/mnt/mnt9/PottsCorpora
      opposingviews, product-reviews, weblogs
- Twitter data collected and organized by Moritz!
  /afs/ir.stanford.edu/data/linguistic-data/mnt/mnt3/TwitterTopics/

From Potts (2013), p.5

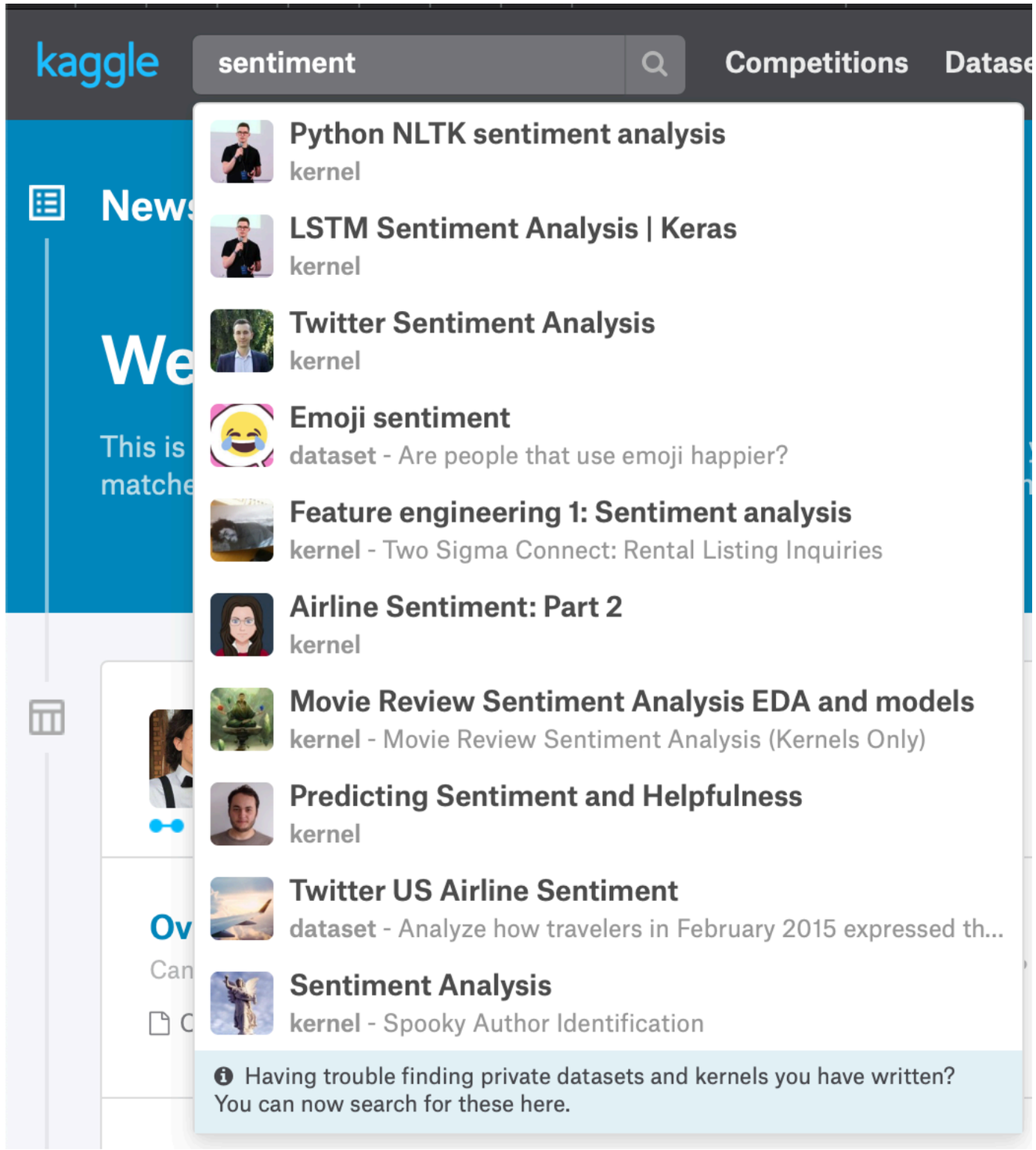
More datasets

- SNAP review datasets: http://snap.stanford.edu/data/

- Yelp dataset: http://www.yelp.com/dataset_challenge/

- More on Twitter datasets, including critical appraisal: Saif et al. (2013)

- Kaggle: https://www.kaggle.com/



https://www.kaggle.com/search?q=sentiment

sentiment

Searching for sentiment within

Comments 1,888 | Notebooks 1,420 | Topics 519 | Datasets 323 | Competitions 160 | Blogs 3

Filter by

4,313 Results Sort by: Relevancy

Date

- Last 90 days 451
- Last week 39
- Today 5

Dataset Size

- small 160
- medium 156
- large 7

Dataset File Types

- csv 225
- txt 55
- tsv 32

Notebook

Python NLTK sentiment analysis

by Peter Nagy

a year ago • 9m to run • Python • 159

Python NLTK **sentiment** analysis

Notebook

LSTM Sentiment Analysis | Keras

by Peter Nagy

a year ago • 2m to run • Python • 117

LSTM **Sentiment** Analysis | Keras

Notebook

Twitter Sentiment Analysis

by Paolo Pinamonti

https://www.kaggle.com/search?q=opinion

← opinion

Searching for opinion within

Comments 2,915 | Topics 480 | Notebooks 267 | Datasets 73 | Competitions 4

Filter by

3,739 Results Sort by: Relevancy

Date

- Last 90 days 454
- Last week 28
- Today 5

Dataset Size

- small 51
- medium 21
- large 1

Dataset File Types

- csv 49
- pdf 10
- json 9

Notebook

Political Opinion with Machine Learning

by Yunus Emre Gündoğmuş

2 years ago • 27s to run • Python • 49

Political **Opinion** with Machine Learning

Notebook

Comprehensive data exploration with Python

by Pedro Marcelino

3 months ago • 28s to run • Python • 5920

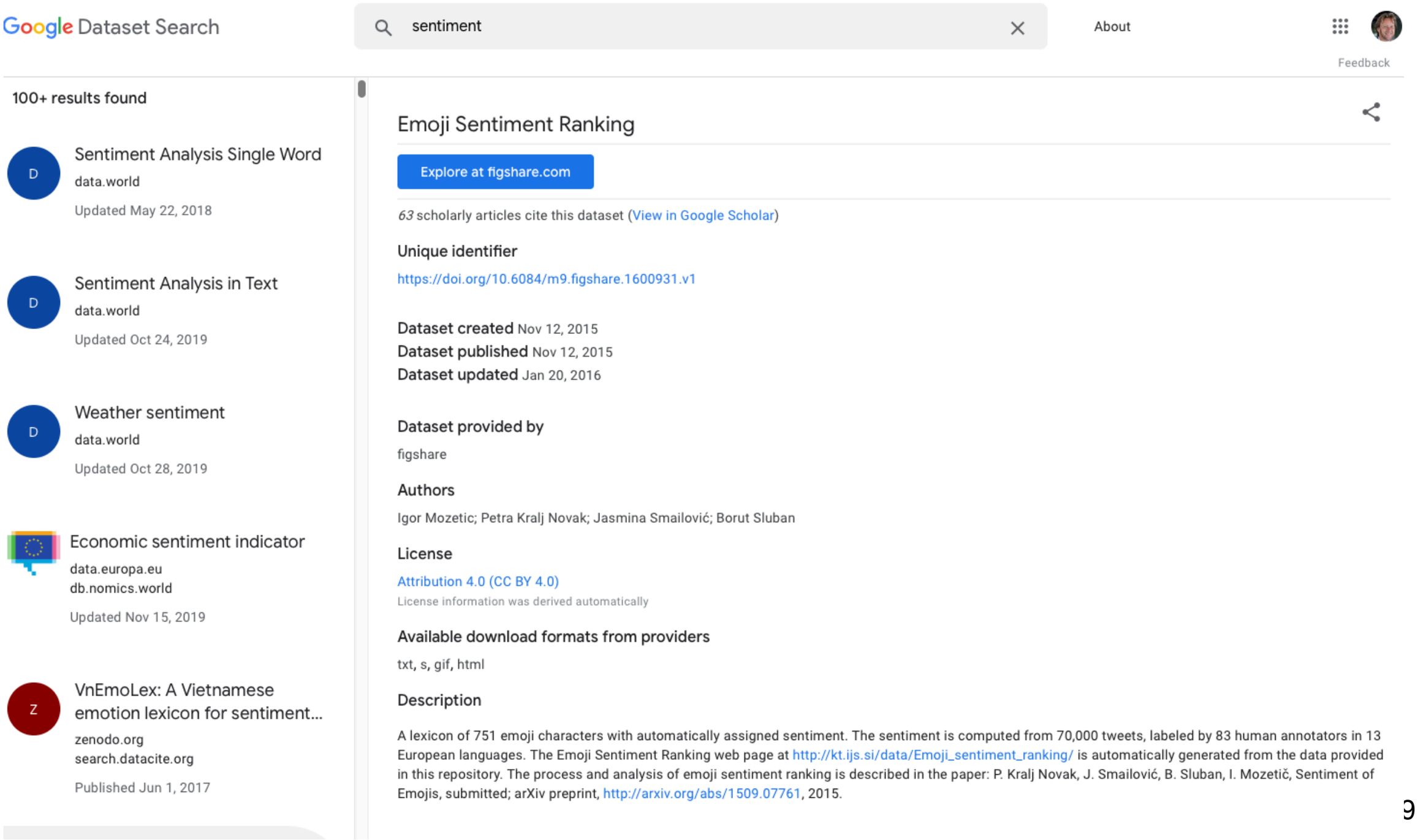
In my **opinion**, this heatmap is the best way to get a quick overview of our 'plasma soup' and its relationships

Dataset

Deceptive Opinion Spam Corpus

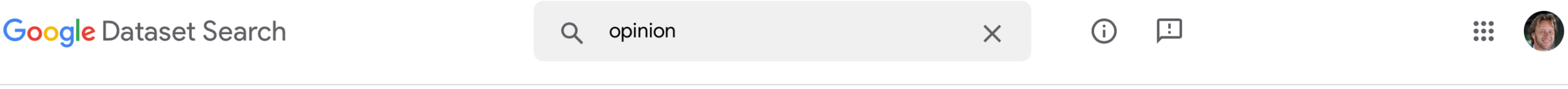
Google dataset search

https://toolbox.google.com/datasetsearch



Google dataset search

https://toolbox.google.com/datasetsearch



100+ results found

The Opinions of the Committee of the Regions
data.europa.eu
data.wu.ac.at
Updated Jul 25, 2019

statista
Opinion of the French on the relevance of their research onlin...
www.statista.com

European Data Protection Supervisor opinions
data.europa.eu
Updated Jan 25, 2018

GREATER LONDON AUTHORITY
London 2012 Opinion Research
data.gov.uk
find-data-beta-staging.cloudapps.digital

Consumer Opinion Surveys: Consumer Prices: Future Tendency of Inflation: European Commission and National Indicators for Spain
CSINFT02ESM460S

Explore at FRED

Dataset updated Nov 13, 2019

License

https://research.stlouisfed.org/fred_terms.html#copyright-citation-required

Description

Graph and download economic data for Consumer Opinion Surveys: Consumer Prices: Future Tendency of Inflation: European Commission and National Indicators for Spain (CSINFT02ESM460S) from Jun 1986 to Oct 2019 about consumer sentiment, consumer prices, Spain, consumer, and inflation.

Table 9
List of publicly available datasets.

S#	Data set	Type	Lang.	Web resource	Details
1	Stanford large movie data set	Movie Reviews	English	http://ai.stanford.edu/~amaas/data/sentiment/	Movie Reviews
2	COAE2008	Product Reviews	Chinese	http://ir-china.org.cn/coae2008.html	2739 documents for movie, education, finance, economics, house, computer, mobile phones, etc. 1525 +ve, 1214 −ve
3	Boacar	Car Reviews	Chinese	http://www.riche.com.cn/boacar/	11 type of car TradeMarks and total review 1000 words, having 578 POS, 428 reviews
4	[187]	Reviews, forums	English	http://sifaka.cs.uiuc.edu/~wang296/Data/	Accessed: 27 August, 2014
5	[188]	Reviews	English	http://uilab.kaist.ac.kr/research/WSDM11	Aspect oriented dataset. Accessed: 18 December, 2014
6	Movie-v2.0	Movie Reviews	English	http://www.cs.cornell.edu/people/pabo/movie-review-data/	Data size: 2000 Positive: 1000 Negative: 1000
7	Multi-domain	Multi-domain	English	http://www.cs.jhu.edu/~mdreze/datasets/sentiment	
8	SkyDrive de Hermit Dave	Spanish Word Lists	Spanish	https://skydrive.live.com/?cid=3732e80b128d016f&id=3732E80B128D016F%213584	
9	TripAdvisor	Reviews	Spanish	http://clic.ub.edu/corpus/es/node/106	18,000 customer reviews on hotels and restaurants from Hopinion
10	[38]	Multi-Domain	English	www2.cs.uic.edu/~liub/FBS/sentiment-analysis.html	6800 opinion words on 10 different products
11	TBOD [144]	Reviews	English		Product Review on Cars, Headphones, Hotels
12	[68]	Product Reviews	English	http://www.lsi.us.es/_fermin/index.php/Datasets	Product Reviews from Epinion.com on headphones 587 reviews, hotels 988 revi and cars 972 reviews
13	[148]	Movie Reviews	Turkish	http://www.win.tue.nl/~mpechen/projects/smm/#Datasets	5331 positive and 5331 negative reviews on movie
14	[148]	Product Reviews	Turkish	http://www.win.tue.nl/~mpechen/projects/smm/#Datasets	700 +ve &700 −ve reviews on books, DVD, electronics, kitchen appliances
15	ISEAR	English sentences	English	www.affective-sciences.org/system/files/page/2636/ISEAR.zip	The dataset contains 7666 such statements, which include 18,146 sentences, 449,060 running words.
16	[149]	Product Reviews	English	http://www.cs.jhu.edu/~mdredze/datasets/sentiment/	Amazon reviews on 4 domain (books, DVDs, electronics, kitchen appliances)
17	DUC data, NIST	Texts	English	http://www-nlpir.nist.gov/projects/duc/data.html, http://www.nist.gov/tac/data/index.html	Text summarization data
18	[70]	Restaurant and Hotel Reviews	English	http://uilab.kaist.ac.kr/research/WSDM11	Restaurant and Hotel Reviews from Amazon and Yelp
19	[114]	Restaurant Reviews	Cantonese	http://www.openrice.com	Reviews on restaurant
20	[125]	Biographical Articles	Dutch	http://www.iisg.nl/bwsa	574 Biographical articles
21	Spinn3r dataset	Multi-Domain	English	http://www.icwsm.org/2011/data.php	
22	[86]	Ironic Dataset	English	http://users.dsic.upv.es/grupos/nle/	3163 ironic reviews on five products
23	HASH [179]	Tweets	English	http://demeter.inf.ed.ac.uk	31,861 Pos tweets, 64,850 Neg tweets, 125,859 Neu tweets
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28	[96]	Tweets	English	http://goo.gl/UQvdx	667 tweets
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Ravi & Ravi 2015

Survey Literature

- Ronen Feldman: Techniques and applications for sentiment analysis. Commun. ACM 56(4): 82-89 (2013).

- Bing Liu, Lei Zhang: A Survey of Opinion Mining and Sentiment Analysis. Mining Text Data 2012: 415-463.

- Bo Pang, Lillian Lee: Opinion Mining and Sentiment Analysis. Foundations and Trends in Information Retrieval 2(1-2): 1-135 (2007).

- Potts (2013). Introduction to Sentiment Analysis. http://www.stanford.edu/class/cs224u/slides/2013/cs224u-slides-02-26.pdf

- Mikalai Tsytsarau, Themis Palpanas: Survey on mining subjective data on the web. Data Min. Knowl. Discov. 24(3): 478-514 (2012)

- Saif M. Mohammad, (2012) From once upon a time to happily ever after: Tracking emotions in mail and books, Decision Support Systems 53 (2012) 730–741

- Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: tasks, approaches and applications. Knowledge-Based Systems, 89, 14-46.

The OpeNER project

- https://www.opener-project.eu

- Opinion detection and Named Entity recognition for 6 European languages

- Sentiment lexicons for 6 European languages

- Demonstrator: http://tour-pedia.org/about/

A hotel review

Nothing special really. Comfortable and clean but very boring decor in comparison to other NH hotels. I stayed in NH in Brussels and Zurich and I really liked them because of their modern and stylish design and big rooms. This one was just like any other hotel. Basic rooms with basic and dull decor - bit disappointing. The customer service was average. The rate was very expensive and I still had to pay for Internet and 20 euros for breakfast!!! It was good but way overpriced! The best thing about the hotel was the location - city centre, 2min from a metro stop.

A hotel review

Nothing special really. Comfortable and clean but very boring decor in comparison to **other NH hotels**. I stayed in **NH** in **Brussels** and **Zurich** and I really liked **them** because of **their** modern and stylish design and big rooms. **This one** was just like any **other** hotel. Basic rooms with basic and dull decor - bit disappointing. The customer service was average. The rate was very expensive and I still had to pay for Internet and **20 euros** for breakfast!!! It was good but way overpriced! The best thing about **the hotel** was **the location** - city centre, 2min from a metro stop.

Named entities

- this NH hotel
- NH Brussels
- NH Zurich

http://en.wikipedia.org/wiki/NH_Hoteles
http://dbpedia.org/page/NH_Hoteles
http://en.wikipedia.org/wiki/Brussels
http://en.wikipedia.org/wiki/Zurich

A hotel review

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Named entities:
- this NH hotel
- NH Brussels
- NH Zurich

Co-references:
- other
- them
- this one

Properties:
- décor
- design
- room
- clean (hygiene)
- service
- rate
- Internet
- breakfast

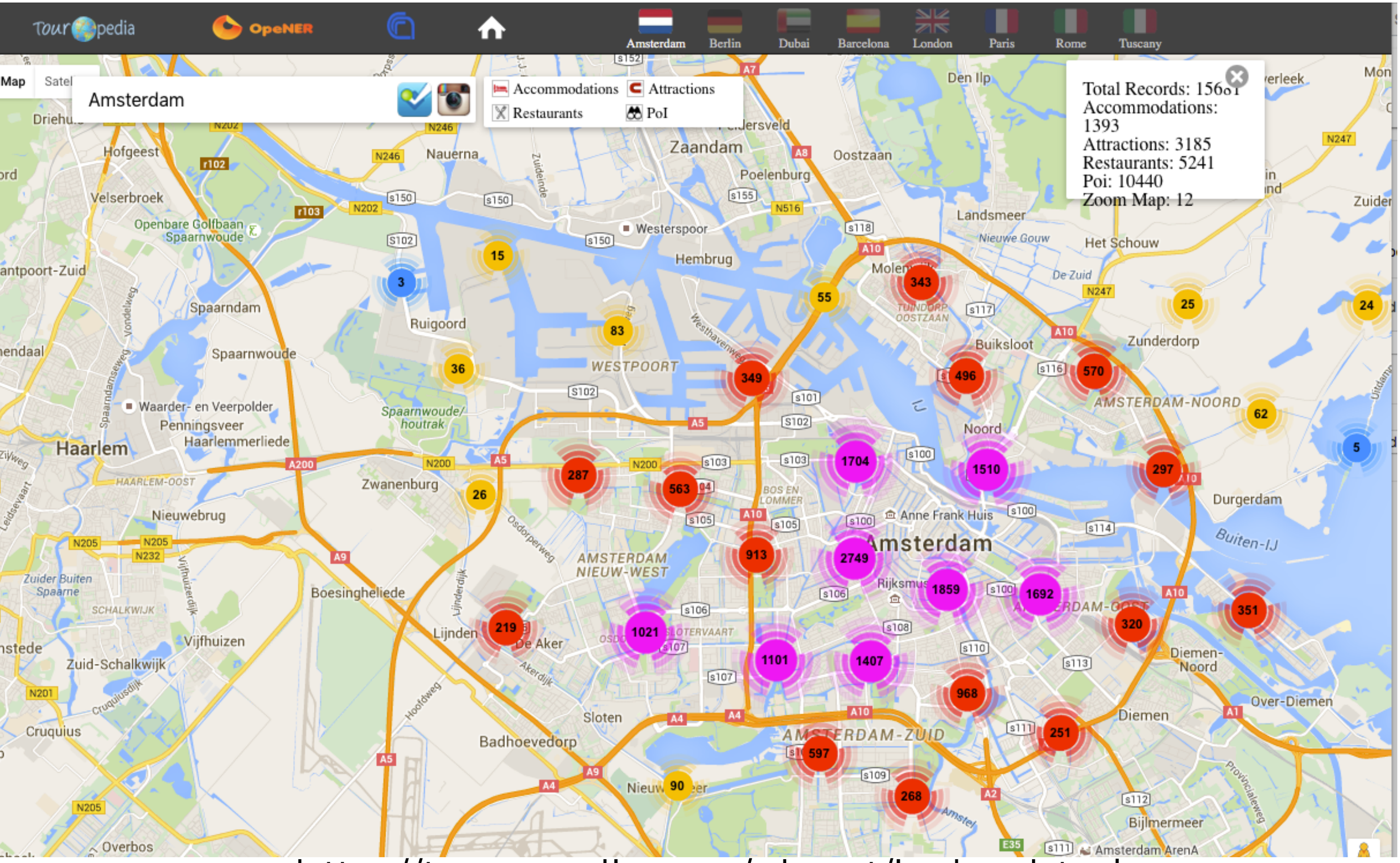
Sentiments:
- nothing special really
- comfortable and clean
- boring
- really liked
- modern and stylish
- big
- just
- basic and dull

A hotel review

- Nothing special really. Comfortable and clean but very boring decor in comparison to **other NH hotels**. I stayed in **NH** in **Brussels** and **Zurich** and I really liked **them** because of **their** modern and stylish design and big rooms. **This one** was just like any **other** hotel. Basic rooms with basic and dull decor - bit disappointing. The customer service was average. The rate was very expensive and I still had to pay for Internet and **20 euros** for breakfast!!! It was good but way overpriced! The best thing about **the hotel** was **the location** - city centre, 2min from a metro stop.

Scale 1 (negative) to 5 (positive)

	Overall	Design	Room	Service	Price	Location	Transport
This NH	2	1,5	2	3	1	4	4
NH Brussels	4	4	4				
NH Zurich	4	4	4				



http://tour-pedia.org/about/index.html

TourPedia OpeNER

Amsterdam Berlin Dubai Barcelona London Paris Rome Tuscany

Map Satel

Amsterdam

Accommodations Attractions
Restaurants PoI

Name:
Jamin

Address:
Damrak 25, Amsterdam, Netherlands

Official website:
http://www.jamin.nl/

Links:
Foursquare Page
GooglePlaces Page

Category: restaurant

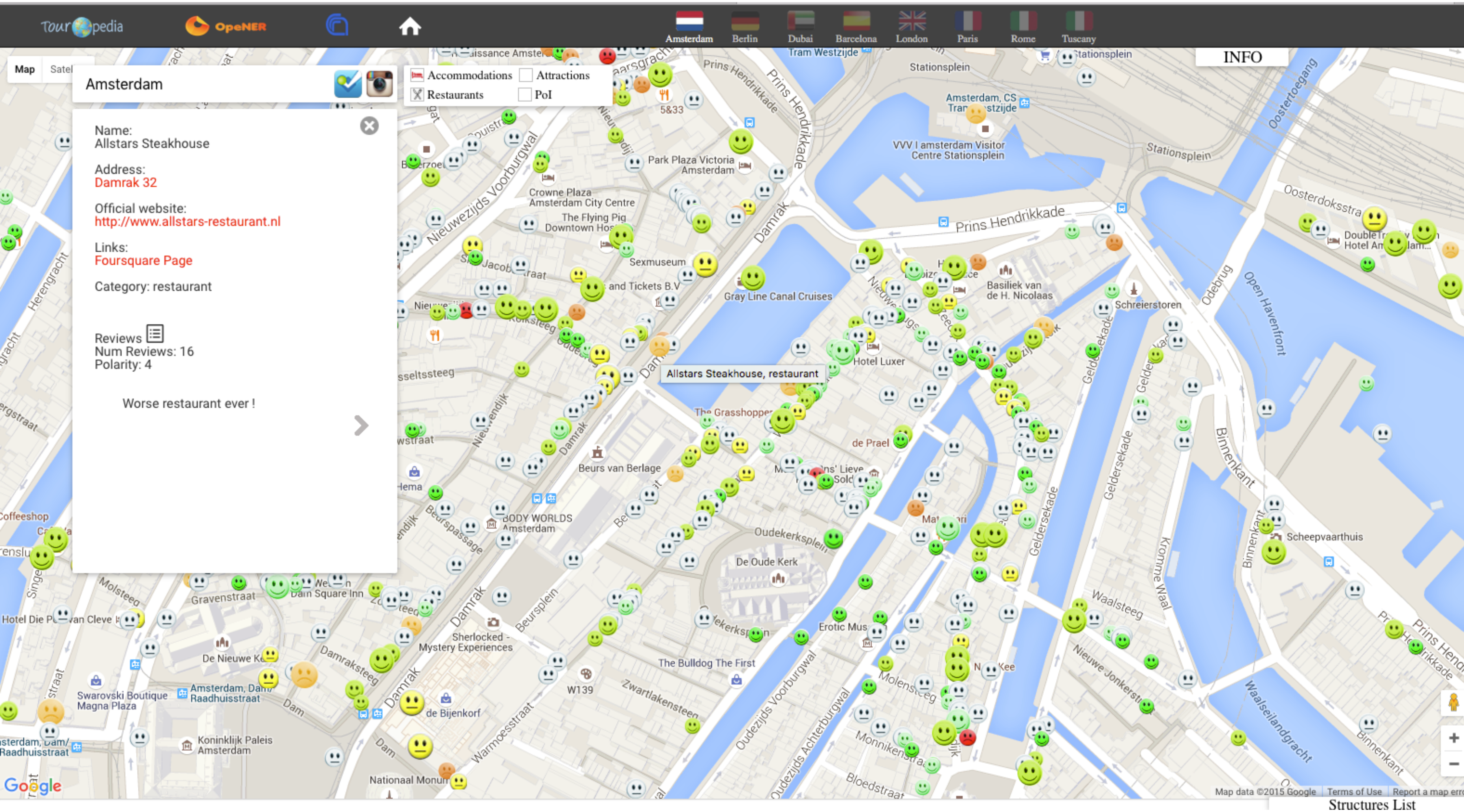
Reviews
Num Reviews: 30
Polarity: 7

Awesome food, low price, definitely recommend!

INFO

Jamin, restaurant

Structures List



Tour pedia
OpeNER
Amsterdam
Berlin
Dubai
Barcelona
London
Paris
Rome
Tuscany
Map
Amsterdam
Accommodations
Attractions
Restaurants
PoI
INFO
Name:
Allstars Steakhouse
Address:
Damrak 32
Official website:
http://www.allstars-restaurant.nl
Links:
Foursquare Page
Category: restaurant
Reviews
Num Reviews: 16
Polarity: 4
Worse restaurant ever !
Allstars Steakhouse, restaurant
Structures List

Cross-lingual/cultural sentiment

- 2,486 expressions in hotel reviews
- annotated in 6 languages
- 8 aspect groups (food, clean, price, behaviour, general evaluation, size, location, noise, size),

GENERAL-EVALUATION 669		
en	definitely recommend;	strong positive
es	recomendariamos sin duda alguna	positive
fr	recommander chaleureusement	strong positive
it	consiglio vivamente	positive

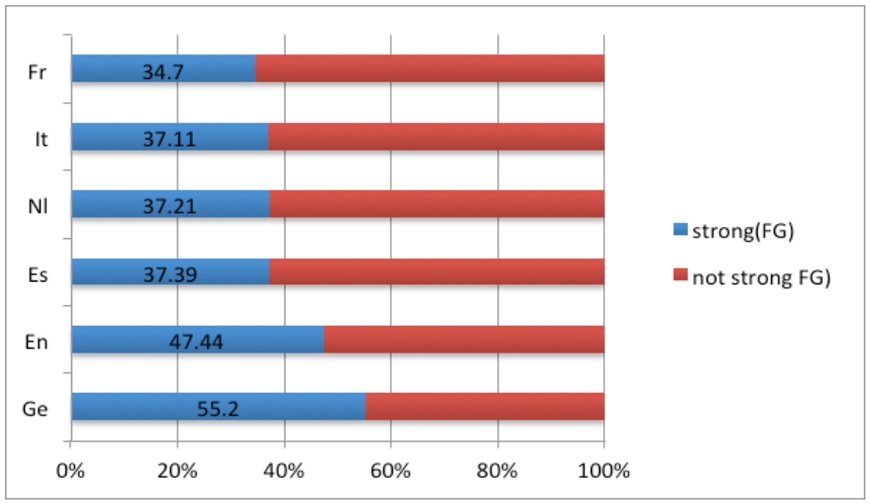
NOISE 1117		
en	a lot of noise	strong negative
fr	énormement de bruit	strong negative
it	molto rumore	negative
nl	veel lawaai	negative
nl	ontzettend veel lawaai	strong negative

http://opener-fp7project.rhcloud.com

Cultural Normalization

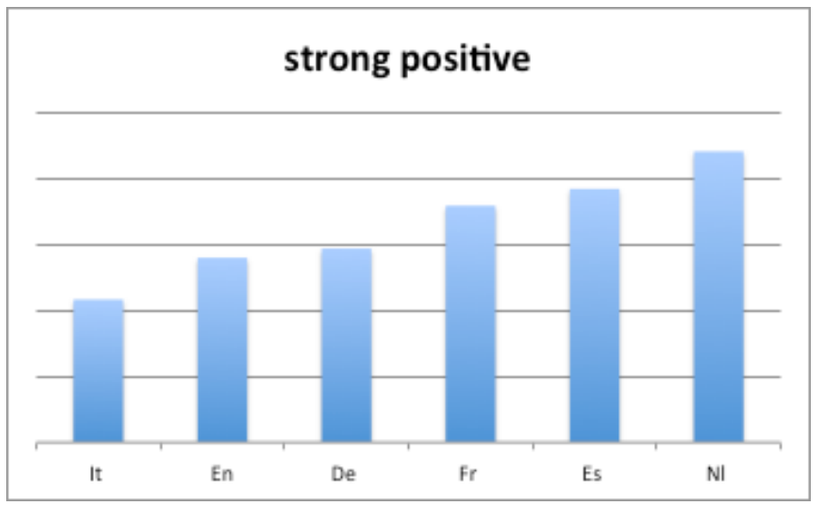
Differences in ratings in hotel reviews:

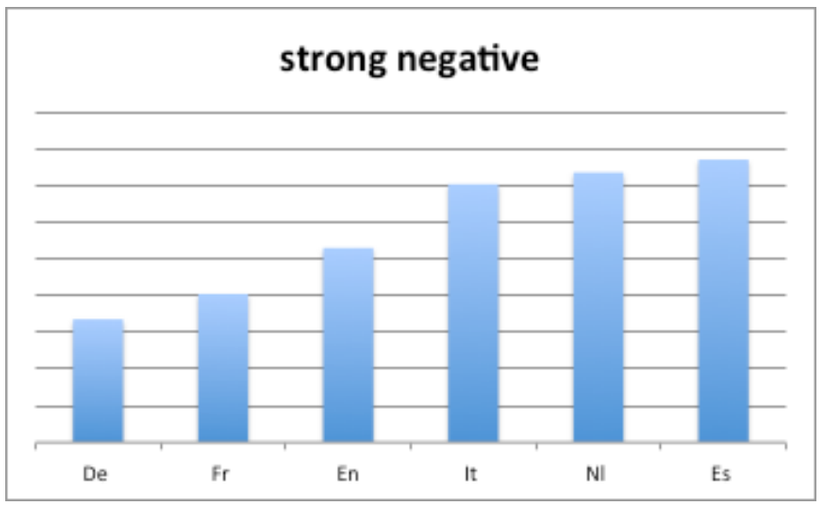
- English and Germans give more extreme (strong positive and strong negative) ratings than the other cultures



Differences in language use in hotel reviews:

- Dutch and Spanish are more expressive as they show a relative over-use of strong expressions
- German and English are less expressive as they show a relative under-use of strong expressions





=> People from German and English culture are quite strong when expressing their emotions in ratings, but they seem to downgrade their emotions when expressing them with language

Reviewer & reader ratings

- The hotel seems rather outdated. The breakfast room is just not big enough to cope with the Sunday-morning crowds.

Reviewer & reader ratings

- The hotel seems rather outdated. The breakfast room is just not big enough to cope with the Sunday-morning crowds.
- Maks and Vossen (RANLP-2013)

Review rating ***7***

Reader rating ***negative***

Target= hotel, holiday

Target= aspects in the text

9% - 37% sentiment mismatch at document level

Cross-lingual/cultural sentiment

- 2,486 expressions in hotel reviews
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- 8 aspect groups (food, clean, price, behaviour, general evaluation, size, location, noise, size),

GENERAL-EVALUATION 669		
en	definitely recommend;	strong positive
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NOISE 1117		
en	a lot of noise	strong negative
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nl	veel lawaai	negative
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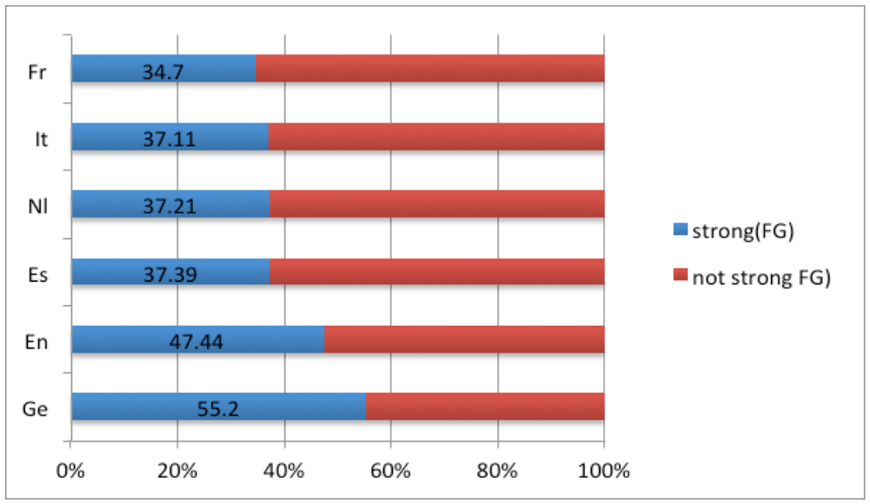

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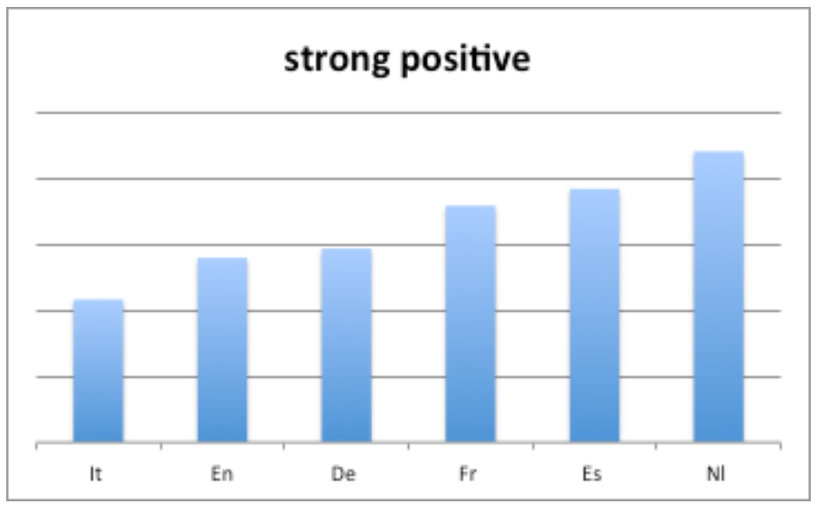

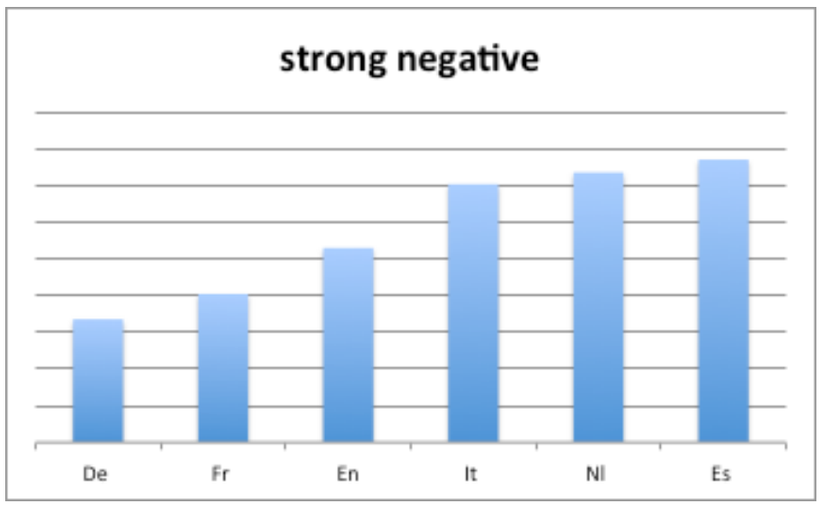

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