NUI Galway
OÉ Gaillimh

Introduction to NLP

Opinion Mining, Ethics & Data Privacy

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Learning Outcomes of This Lecture

Understand different applications of opinion mining

Understand standard approaches in sentiment analysis

Gain some insight into emotion analysis and suggestion mining

Insight into ethics & data privacy considerations in opinion mining and NLP in general

Overview

Opinion mining

Sentiment analysis

Ethics and data privacy

Overview

Opinion mining

Sentiment analysis

Ethics and data privacy

Opinion Mining

- Text analytics is now a requirement for large companies
- Multiple sources of unstructured data
- "Voice of the Customer" on steroids
- Ability to understand why NPS metrics are going up or down
- Ability to respond quickly to service issues
- Compelling ROI for recent deployments

Opinion Mining - Some Definitions

Opinion mining is concerned with **analyzing opinionated text** in terms of sentiment, subjectivity, emotions, suggestions, arguments etc.

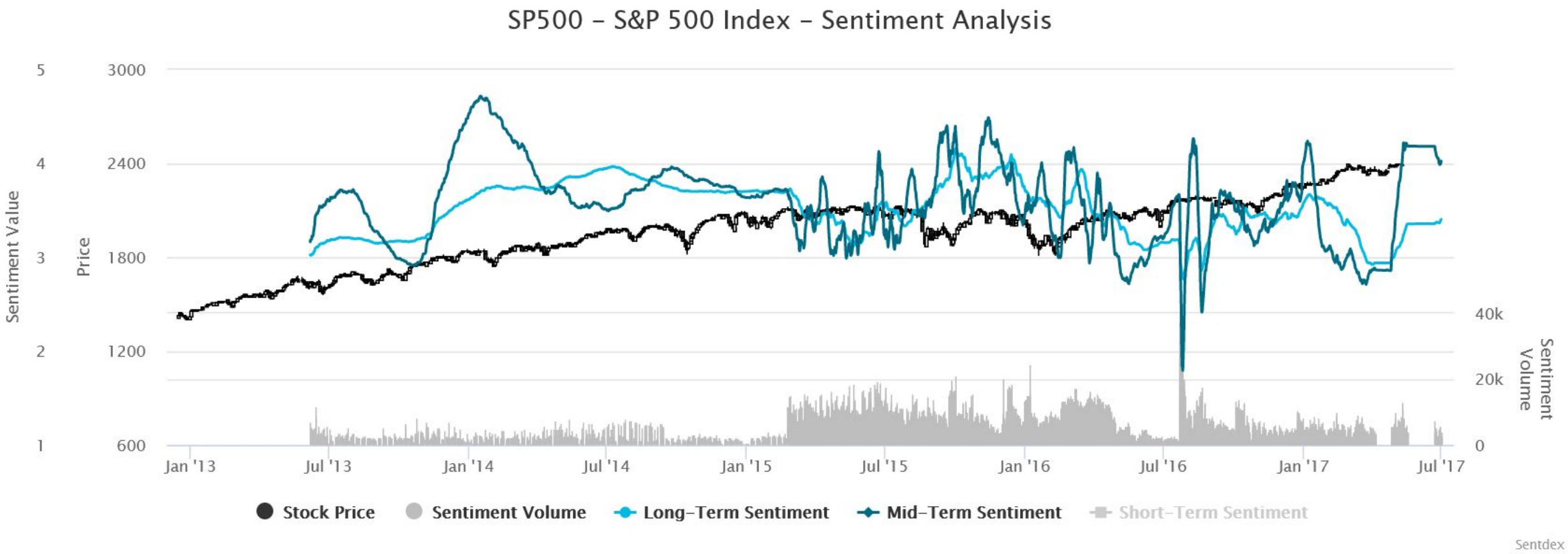
Opinionated text: hotel, movie or other reviews (product ratings), political discourse and commenting (election polls), business and financial analysis (stock value prediction), ...

Please note that 'opinion mining', 'sentiment analysis', 'subjectivity classification', 'emotion analysis' are often used interchangeably

Image from https://reputize.com/review-analytics

https://www.forbes.com/sites/waynerash/2020/09/29/new-big-data-sentiment-analysis-show-potential-biden-election-landslide/?sh=41200bb7f0b6

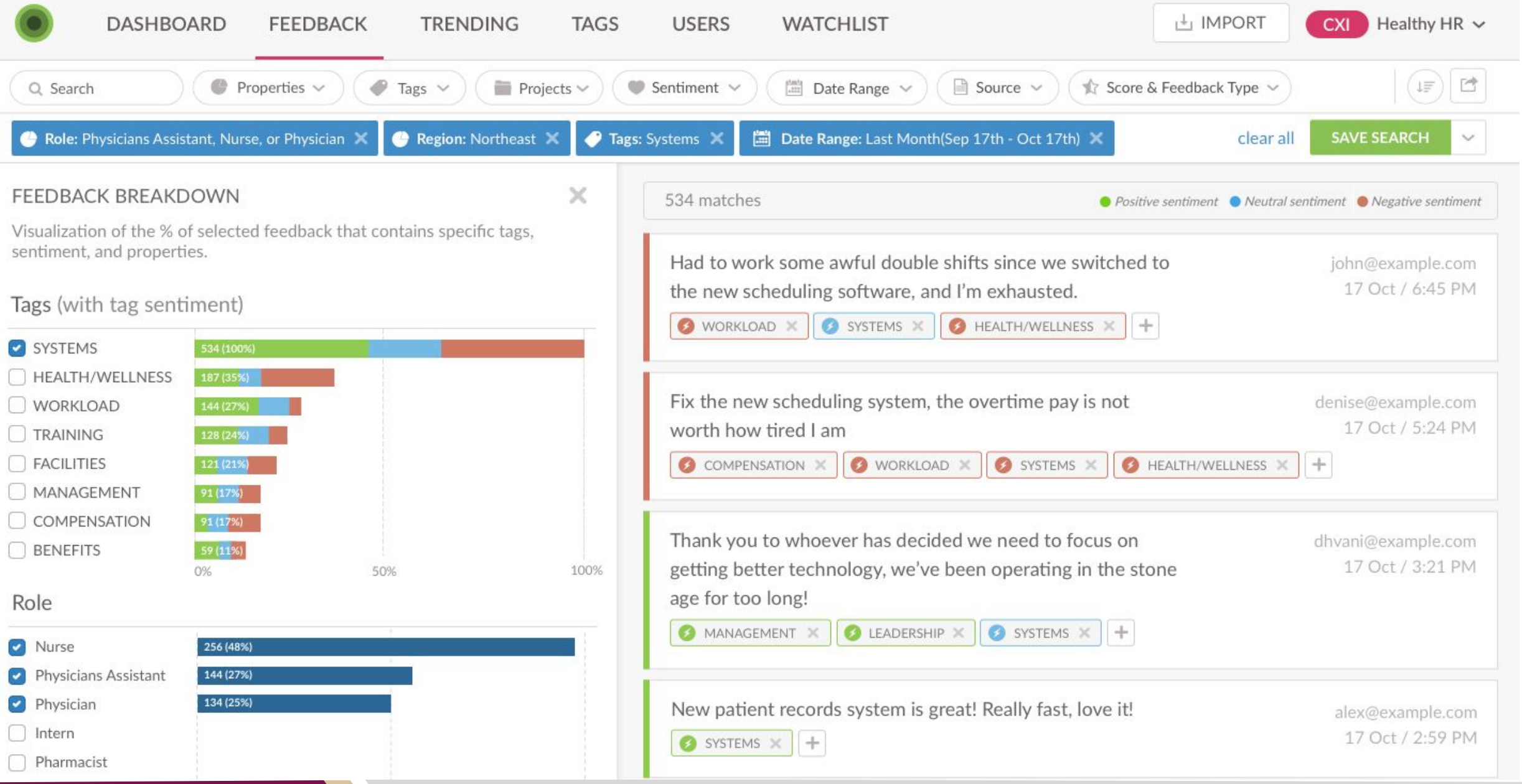
7 Days | 30 Days | 6 months | 1 Year | All-Time | Search for More Companies | Regular Version



S&P 500 Index Description:

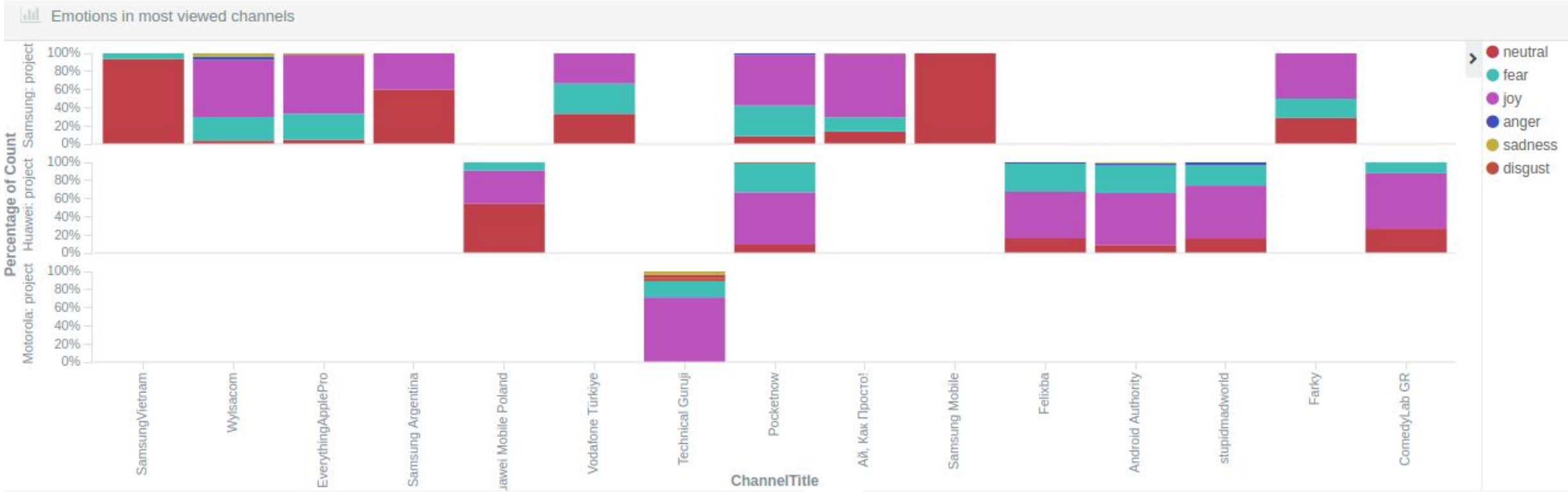
Index of the largest 500 US companies.

Image generated with http://sentdex.com



https://www.wootric.com/blog/how-sentiment-analysis-improves-employee-engagement-in-healthcare/

Emotions


Emotions in most viewed channels
Percentage of Count
Samsung: project
Huawei: project
Motorola: project
100%
80%
60%
40%
20%
0%
neutral
fear
joy
anger
sadness
disgust
SamsungVietnam
Wyłsacom
EverythingApplePro
Samsung Argentina
Vodafone Türkiye
Technical Guruji
Pocketnow
Samsung Mobile
Felixba
Android Authority
stupidmadworld
Farky
ComedyLab GR
ChannelTitle

Suggestions

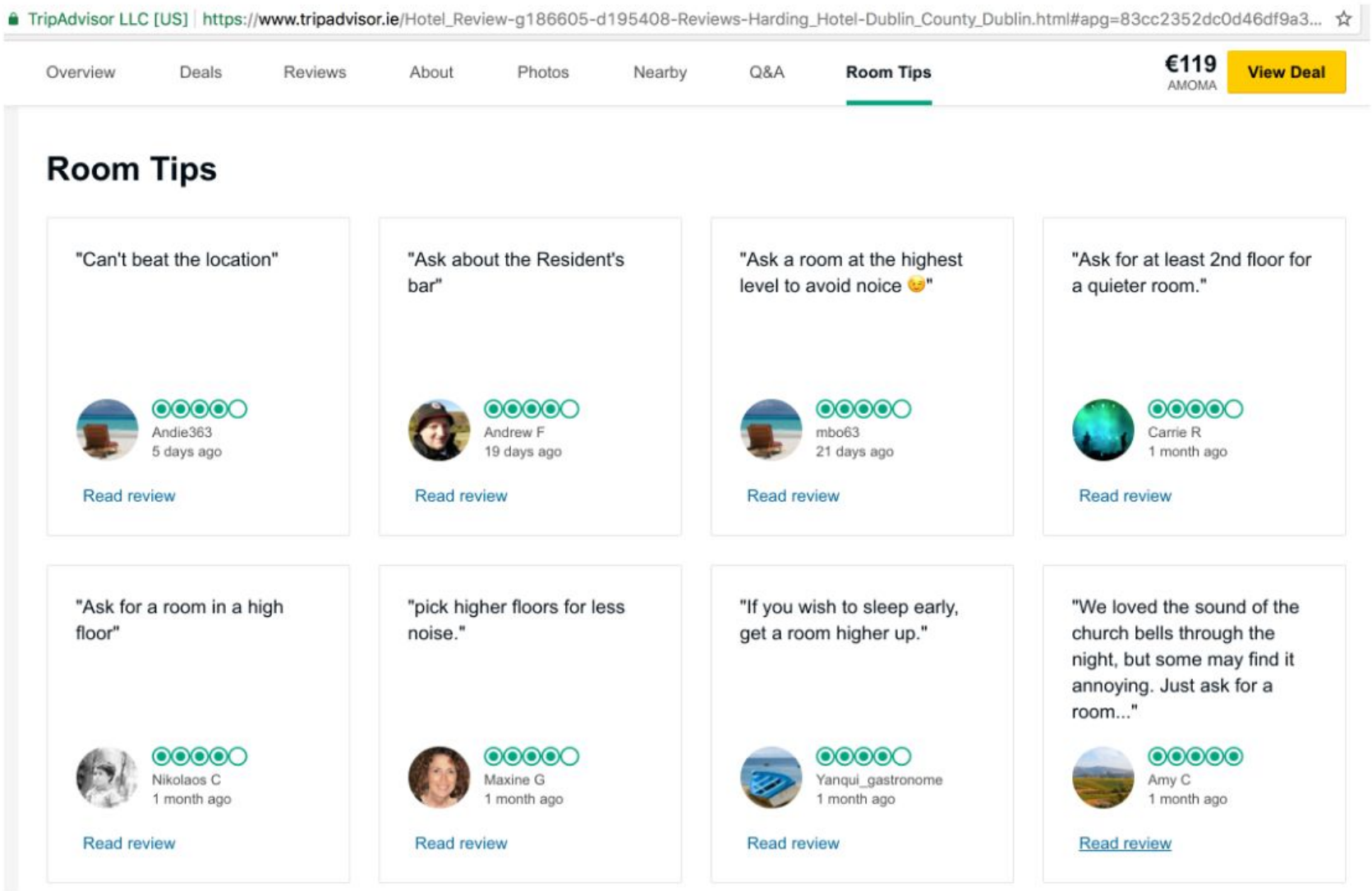


Image from: Sapna Negi. *Suggestion mining from text*. 2019. PhD Thesis. NUI Galway.

Overview

Opinion mining

Sentiment analysis

Ethics and data privacy

Sentiment Analysis

Classification task to identify if a given text has positive or negative sentiment

Challenges are in implicit, ambiguous and informal language

Classifier can be developed on the basis of a **sentiment lexicon** (unsupervised) or **sentiment labeled data** (supervised)

Challenges - Implicit Sentiment

Neutral words used but POS sentiment implied

“Go read the book!”

Neutral words used but NEG sentiment implied

“If you are reading this because it is your darling fragrance, please wear it at home exclusively and tape the windows shut.”

Challenges - Ambiguity

Same words used in different contexts express NEG vs. POS sentiment

*“This car's steering is **unpredictable**!”* NEG

*“This film is **unpredictable**!“* POS

Challenges - Irony & Sarcasm

Positive words used but NEG sentiment implied

*"**Great job** Rogers! Raise rates but not service."*

*"**Yeah, sure**!"*

Challenges - Negation

Positive words used but NEG sentiment implied

> *"I **don't like** this new Nokia model"*

Negation has diverse forms, so can be hard to detect:

> *I **didn't** enjoy it.*
>
> *I **never** enjoy it.*
>
> ***No one** enjoys it.*
>
> *I **have yet to** enjoy it.*

Challenges - Informal Language

Social media content uses non-standard, informal language such as hashtags

Sentiment	Tweet mention
Positive	Maybe I'm mad but I'm now the proud owner of a potentially #bendy #iPhone6, it's so much bigger than the #4s
	Finally got to see an iPhone 6 today. Not revolutionary at all but it's absolutely gorgeous. (And I want one). #iPhone6
Negative	I'm not sure I want it. It's too big to fit in my back pocket! lol #iphone6
	I'm really disappointed with the #iPhone6. It took them 2 years to change the screen & size. Let down.

Example from: He, W., Xu, G., Kim, Y., Dwivedi, R., Zhang, J., & Jeong, S. R. (2016). Competitive intelligence in social media Twitter: iPhone 6 vs. Galaxy S5. *Online Information Review*.

Challenges - Indirect Sentiment

Sentiment expressed may not be that of the author

*“Although this product is **disliked by many**, …”*

Classification with a Sentiment Lexicon

Sentiment lexicon provides a **list of positive and negative words**

Calculate percentage of positive/negative words in text to be classified

Highest percentage determines sentiment, for example:

Sentiment Lexicon: *POS [great, easy-to-use, ...] NEG [bad, ...]*

*"The camera's focus was **bad**, but has a **great** size and is **easy-to-use**."*

POS: 2/13 = 0.153 ; NEG: 1/13 = 0.077

f (0.153, 0.077) = POS

Sentiment Lexicon - SentiWordNet

SentiWordNet adds **sentiment polarity on words in WordNet synsets**

Apply **Word Sense Disambiguation** to identify correct sense (synset)

Rank	Positive	Negative
1	good#n#2 goodness#n#2	abject#a#2
2	better_off#a#1	deplorable#a#1 distressing#a#2 lamentable#a#1 pitiful#a#2 sad#a#3 sorry#a#2
3	divine#a#6 elysian#a#2 inspired#a#1	bad#a#10 unfit#a#3 unsound#a#5
4	good_enough#a#1	scrimy#a#1
5	solid#a#1	cheapjack#a#1 shoddy#a#1 tawdry#a#2
6	superb#a#2	unfortunate#a#3
7	good#a#3	inauspicious#a#1 unfortunate#a#2
8	goody-goody#a#1	unfortunate#a#1
9	amiable#a#1 good-humored#a#1 good-humoured#a#1	dispossessed#a#1 homeless#a#2 roofless#a#2
10	gainly#a#1	hapless#a#1 miserable#a#2 misfortunate#a#1 pathetic#a#1 piteous#a#1 pitiable#a#2 pitiful#a#3 poor#a#1 wretched#a#5

Table from: Baccianella, S., Esuli, A., & Sebastiani, F. (2010). Sentiwordnet 3.0: an enhanced lexical resource for sentiment analysis and opinion mining. In *LREC* (Vol. 10, pp. 2200-2204).

Sentiment Lexicon - SentiWordNet

Synsets can be positive as well as negative (or neutral)

Synset_ID	Pos(s)	Neg(s)	SynsetTerms
1207406	0.0	0.75	cold#a#1
1212558	0.0	0.75	cold#a#2
1024433	0.0	0.0	cold#a#3
2443231	0.125	0.375	cold#a#4
1695706	0.625	0.0	cold#a#5

Table from: Gatti, L., Guerini, M., & Turchi, M. (2015). SentiWords: Deriving a high precision and high coverage lexicon for sentiment analysis. *IEEE Transactions on Affective Computing*, *7*(4), 409-421.

Sentiment Lexicon - LIWC

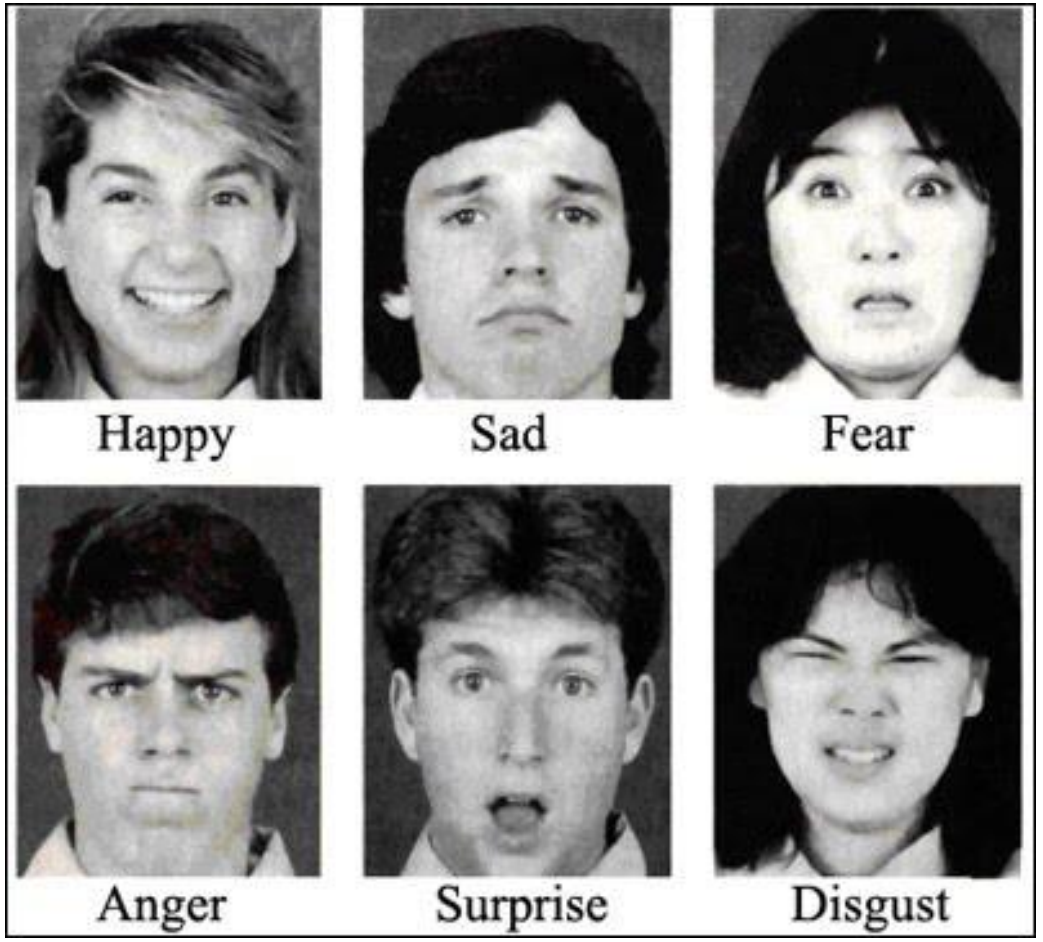
LIWC (Linguistic Inquiry and Word Count) lexicon of **emotion words**

LIWC category	Example words
Positive emotions	Happy, pretty, good
Optimism	Ease, trust, hope
Negative emotions	Hate, worthless, enemy
Anxiety	Nervous, afraid, tense
Anger	Hate, kill, pissed
Sadness	Grief, cry, sad

Table from: Settanni, M., & Marengo, D. (2015). Sharing feelings online: studying emotional well-being via automated text analysis of Facebook posts. *Frontiers in psychology*, *6*, 1045.

Emotion Models - Ekman

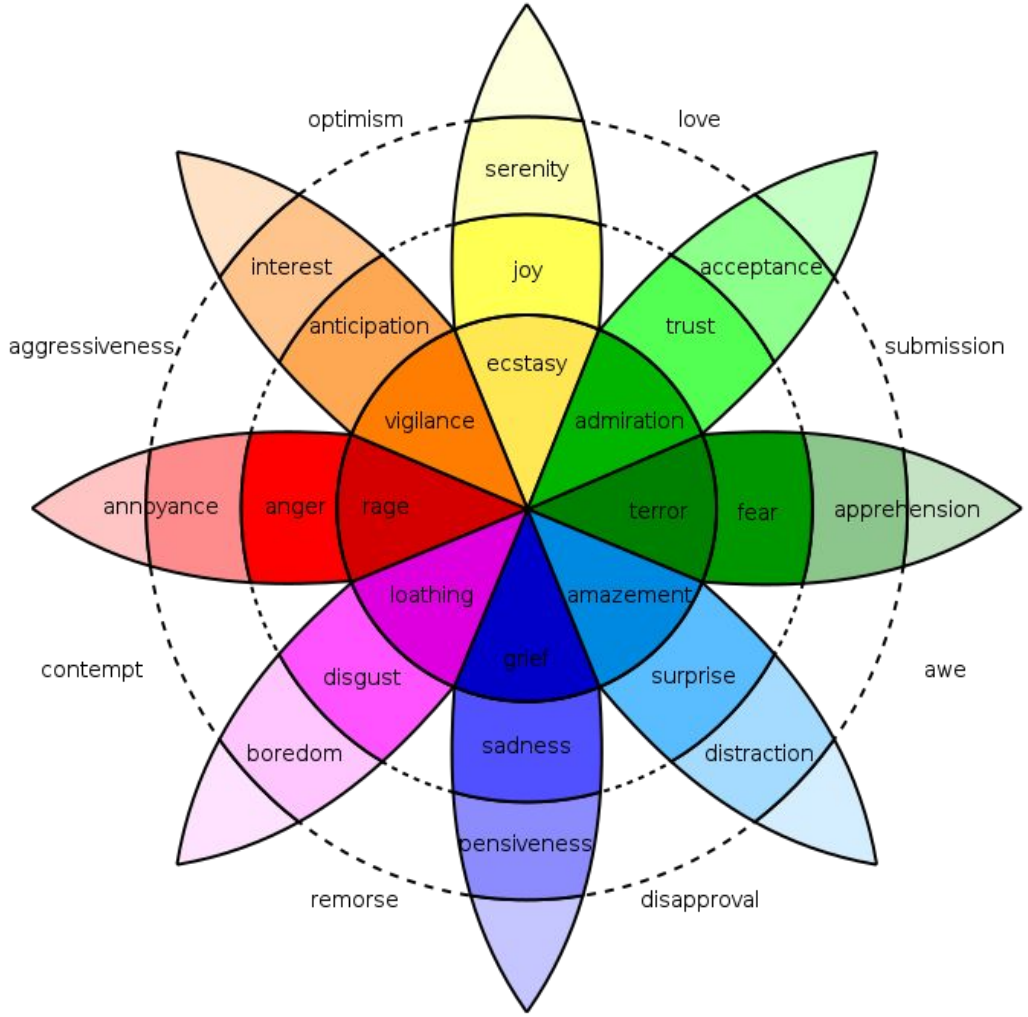
Most widely used model is **Ekman's** with **6 basic facial emotions**



Ekman, P. (1993). Facial expression and emotion. *American Psychologist, 48*(4), 384–392.

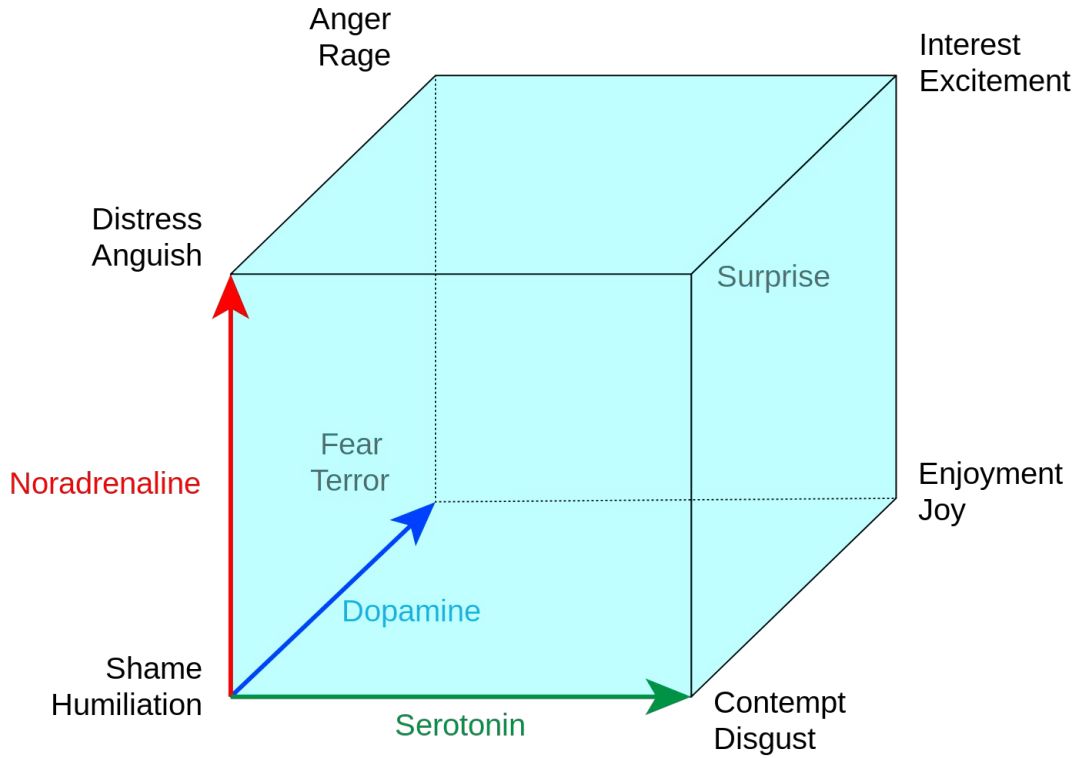
Emotion Models - Plutchik

‘Plutchik’s wheel’ has 2 more categories (Trust, Anticipation) and 4 levels of intensity to give **32 emotions**



Plutchik, R. (1980). A general psychoevolutionary theory of emotion. In *Theories of emotion* (pp. 3-33). Academic press.

Continuous Models



Lövheim's model uses 3 continuous values related to neurotransmitters that have been interpreted as:

- **Valence** - from sad to happy
- **Arousal** - from calm to excited
- **Dominance** - from submissive to agency

Positive and negative sentiment can be expressed by these models as a combination of continuous values for V/A/D

Lövheim, H. (2012). A new three-dimensional model for emotions and monoamine neurotransmitters. *Medical hypotheses*, *78*(2), 341-348.

Classification with Sentiment Labeled Data

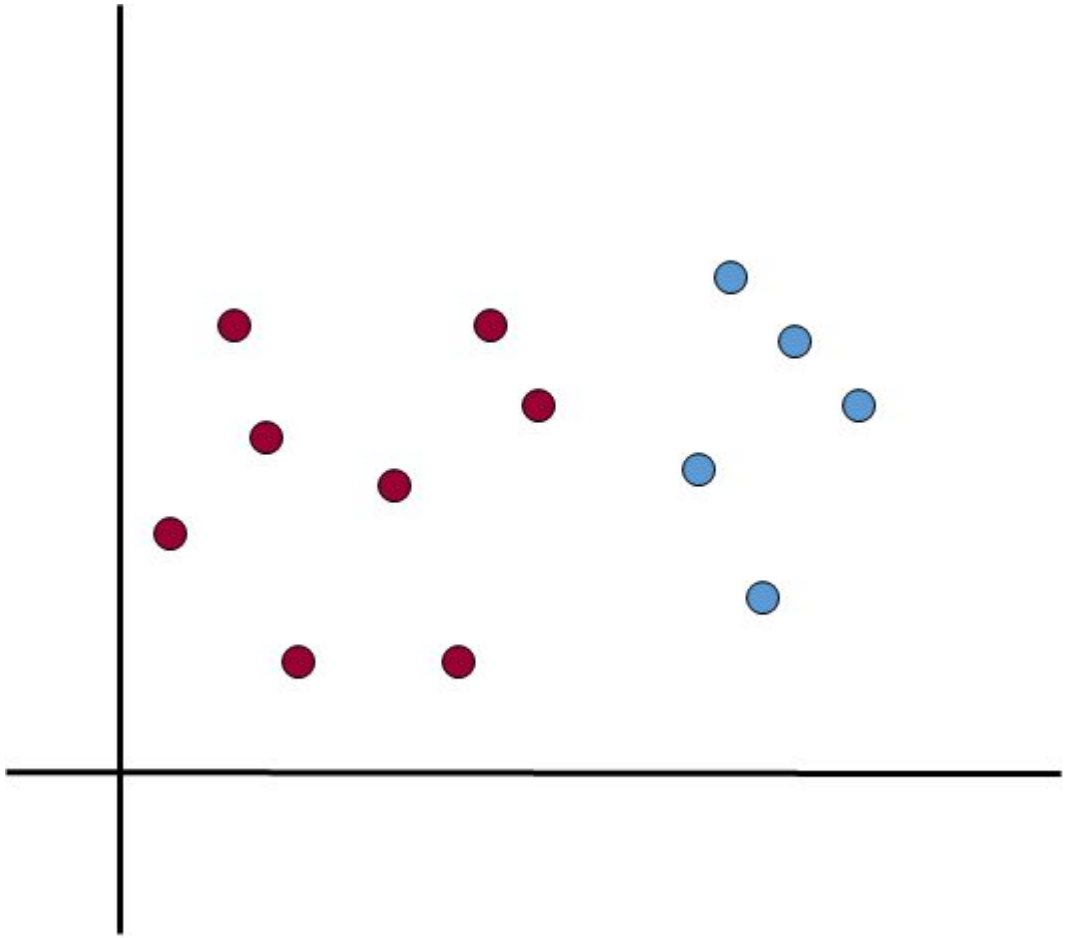


Image from slides by Georgios Paltoglou

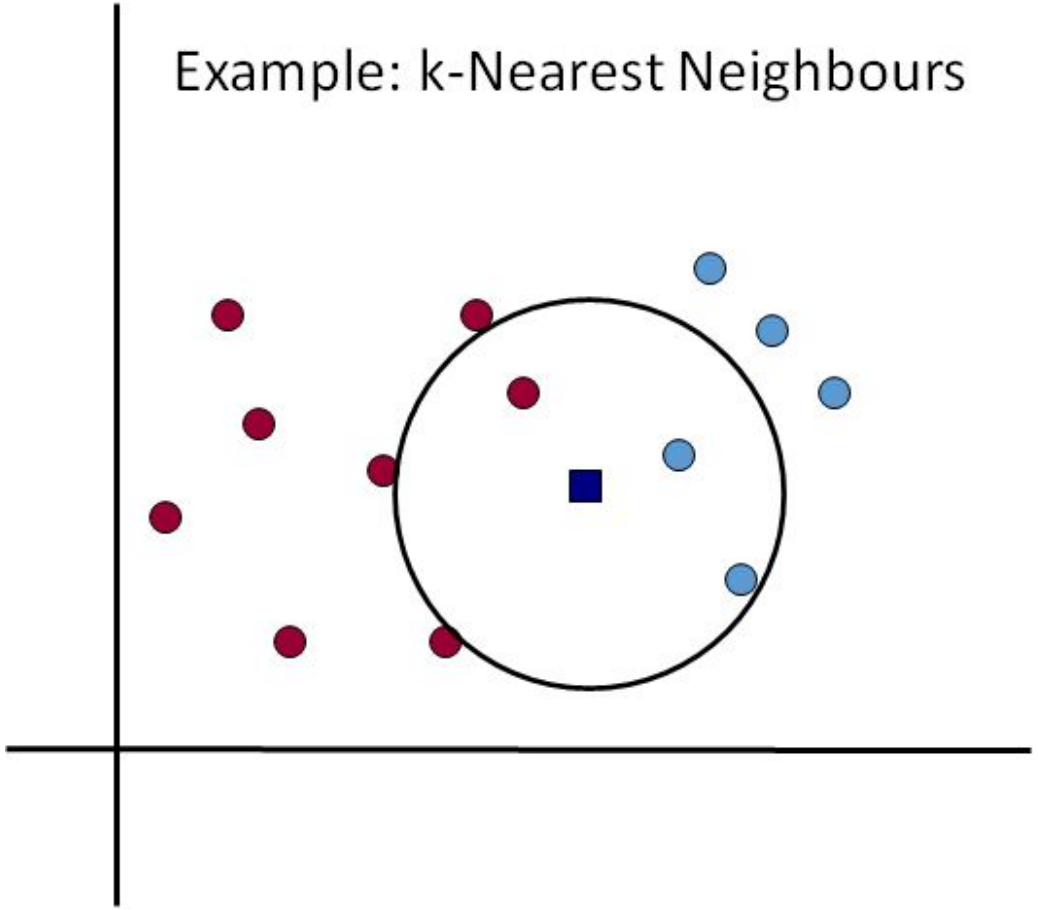
Classification - Supervised Methods

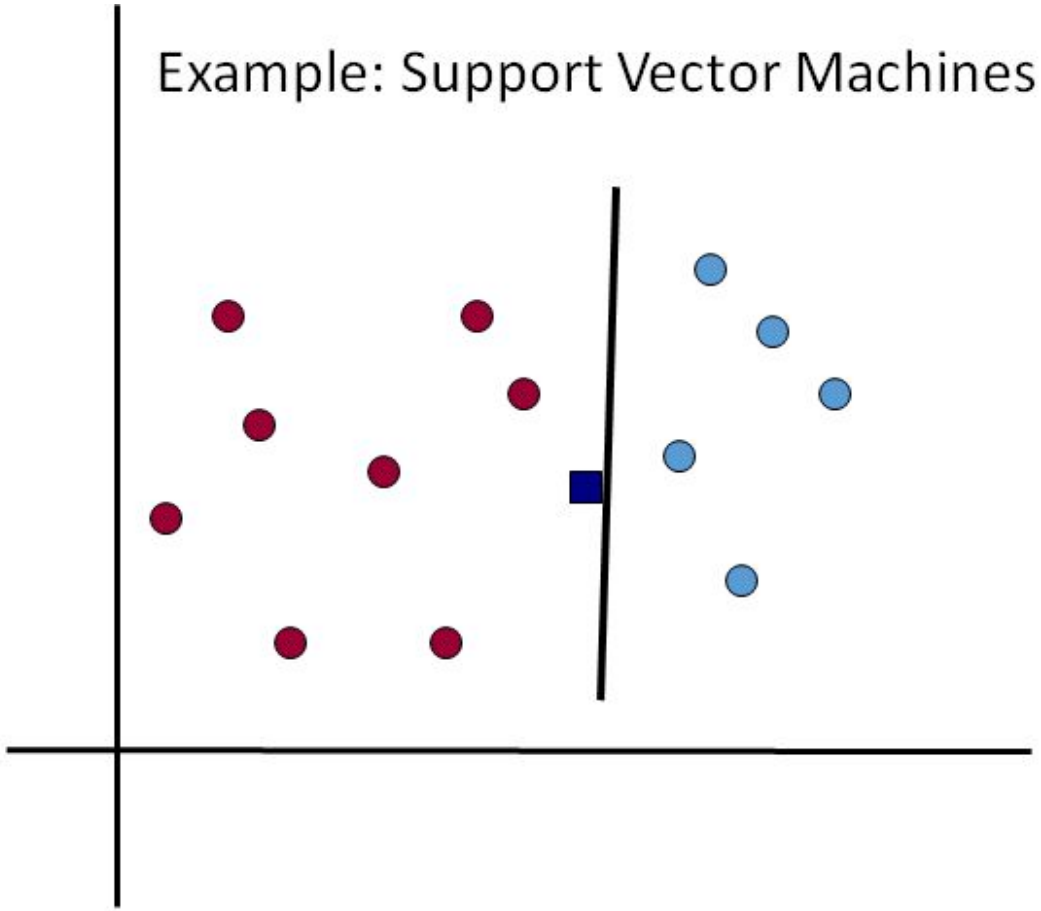
Traditional ML: Support Vector Machines (**SVM**)

Deep Learning (neural networks)

In general, set up a vector space for your data set

Classification with SVMs





Examples from slides by Georgios Paltoglou

Features for Sentiment Analysis

Feature selection and engineering is key to good performance!

Features: words vs. n-grams, part-of-speech, opinion words (sentiment lexicon), negation, modal verbs (could be, should be, …), syntactic dependency

Feature selection and weighting: occurrence (binary) vs. frequency, PMI, TF-IDF

Part of Speech

A word can express different sentiments according to PoS

“fine” NEG as a verb, POS as an adjective

Word+POS as combined feature can improve sentiment analysis

“It is fine if you fine me, but don't rub it in!”

“It/PRP is/VBZ fine/JJ if/IN you/PRP fine/VBP me/PRP ,/, but/CC don't/NN rub/VBP it/PRP in/IN !/.”

Negation

Positive words used but NEG sentiment implied

*"I **don't like** this new Nokia model."*

Simplest approach is to append 'NOT' to all words after the occurrence of a ‘negation word’ until next punctuation:

*I do not **NOT_like NOT_this NOT_new NOT_Nokia NOT_model .***

Aspect-based Sentiment Analysis

Sofar we considered sentiment on the whole input string, e.g.

"The staff was very friendly, the room was comfortable and breakfast was tasty, but the bathroom was very small." POS (?)

More fine-grained sentiment analysis identifies the 'aspect' of the sentiment, i.e. 'what does the sentiment refer to'?

Aspect-based Sentiment Analysis

"The staff was very friendly, the room was comfortable and breakfast was tasty, but the bathroom was very small."

Aspect	Sentiment
Staff	POS
Breakfast	POS
Room	POS
Bathroom	NEG

Aspect-based SA - Unsupervised

Define aspect categories, e.g. ‘Staff, Breakfast, Room, …’

Check for aspect categories in a window around sentiment words from a sentiment lexicon

Compute sentiment for aspect categories in window

Aspect-based SA - Supervised

Construct a labeled dataset with aspects and corresponding sentiments

> *“The [Staff:POS staff was very friendly] and I really enjoyed my stay, but the [Bathroom:NEG bathroom was very small].”*

Build a multi-label classifier which labels the aspect and sentiment

Suggestions

Opinionated texts may express **suggestions for others or for improvement**

Often in text segments with **neutral sentiment**

Dear Microsoft, release a new zune with your wp7 launch on the 11th.

Be sure to specify a room at the back of the hotel.

I suggest to keep a set of normal, macro and telephoto lens

Sapna Negi, 2019. *Suggestion mining from text* (Doctoral dissertation, NUI Galway)

Suggestion Mining

Suggestion Mining comprises two tasks:

- **suggestion classification** - binary (y/n) classification of input string
- **suggestion extraction** - span identification of the suggestion

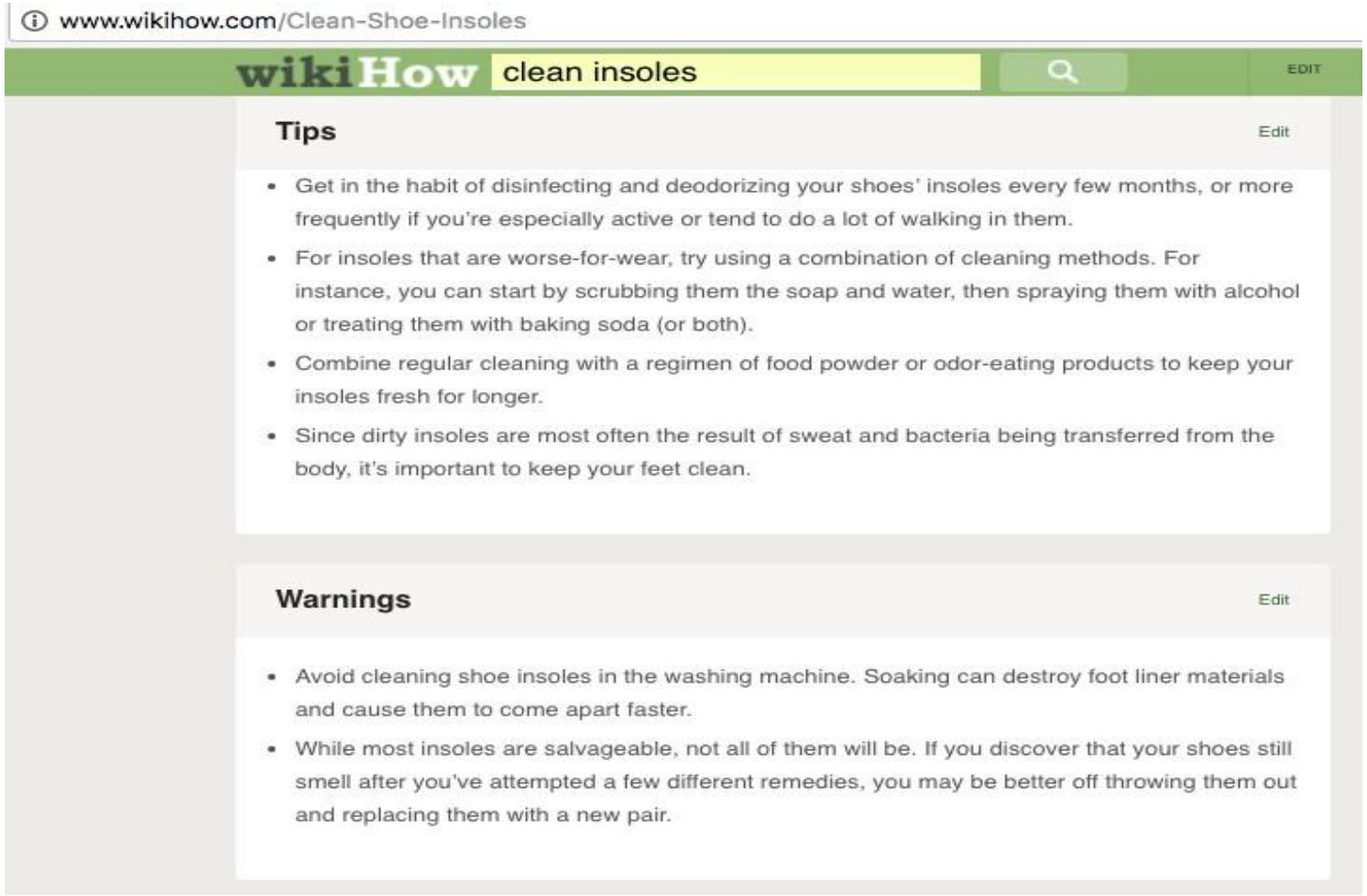
Sapna Negi, 2019. *Suggestion mining from text* (Doctoral dissertation, NUI Galway)

Suggestion Mining - Features

Keywords and Phrases
needs to, need to, suggest, recommend, if, I wish, go for, should have, would, could have been, I would like, I'd like, I would love, I'd love, love to see, there should be, I wish, allow us to
Syntactic Patterns
there should be (DT), I cannot (VB), MD be () (ADV) ADJ, MD (like/prefer/love) to, stop VBG, ability (to/of)

Sapna Negi, 2019. *Suggestion mining from text* (Doctoral dissertation, NUI Galway)

Suggestion Mining - Distant Supervision



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Overview

Opinion mining

Sentiment analysis

Ethics and data privacy

Ethics - Chatbots

Ethics - Natural Language Generation

BBC | Sign in | Home | News | Sport | Reel | Worklife | Travel

NEWS

Home | US Election | Coronavirus | Video | World | UK | Business | Tech | Science | Stories | Entertainment & Arts

Tech

'Dangerous' AI offers to write fake news

By Jane Wakefield
Technology reporter

27 August 2019

Ethics - Text Classification

World Business Markets Breakingviews Video More

RETAIL OCTOBER 11, 2018 / 12:04 AM / UPDATED 2 YEARS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

By Jeffrey Dastin

8 MIN READ

Ethics - Gender Bias

he (109)

she (91)

Try this out for yourself at http://wordbias.umiacs.umd.edu/

Ethics - Addressing Bias in NLP

Data Statements for Natural Language Processing:
Toward Mitigating System Bias and Enabling Better Science

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Batya Friedman
The Information School
University of Washington
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Bias can be on **gender, ethnic identity, social demography, geographical location, …**

"A **data statement** is a characterization of a dataset that provides context to allow developers and users to better understand … **what biases might be reflected in systems built on the software**."

Emily M. Bender and Batya Friedman. 2018. Data statements for NLP: Toward mitigating system bias and enabling better science. TACL 6, 587–604.

Ethics - Use of Personal & Social Media Data

Obvious **ethical considerations in use of personal data** such as patient health records -- *more on personal data later on in the lecture*

Ethical considerations also in **use of social media data** (e.g. text mining)

- *Who owns social media data? Is compensation required?*
- *Should users or platforms control use of social media data?*
- *Who owns knowledge obtained from processing social media data?*

Data Privacy

General Data Protection Regulation (GDPR)

"Regulation … 2016/679 of the European Parliament and of the Council ... regulates the processing by an **individual, a company or an organisation** of **personal data** relating to **individuals** in the EU."

https://ec.europa.eu/info/law/law-topic/data-protection/reform/what-does-general-data-protection-regulation-gdpr-govern_en

Personal Data

"Personal data is **any information that relates to an identified or identifiable living individual**. Different pieces of **information, which collected together can lead to the identification of a particular person, also constitute personal data**.

Personal data that has been **de-identified, encrypted or pseudonymised but can be used to re-identify a person remains personal data** and falls within the scope of the GDPR.

Personal data that has been rendered anonymous in such a way that the individual is not or no longer identifiable **is no longer considered personal data**. For data to be truly anonymised, the **anonymisation must be irreversible**."

https://ec.europa.eu/info/law/law-topic/data-protection/reform/what-personal-data_en

Personal Data in NLP

Language data is also personal data as individuals can be identified by their language data use (i.e. how they write or speak)

Natural language processing can lead to ‘fingerprinting’ of individuals

Data Protection Impact Assessment

Identify **potential data privacy and data protection issues associated with the data collection for a specific (NLP) task** by answering questions such as:

- *Have you identified the minimally sufficient amount of data for your purpose?*
- *Have you informed affected individuals what you are doing with their data?*
- *Have you identified a secondary use for personal data you collected?*
- *Have you established the maximum time period required for keeping the data?*
- *Have you developed appropriate data anonymization strategies?*

Data Protection Impact Assessment to be discussed with and approved by the **Data Protection Officer** at the **Data Controller** (the organisation where the task is done)

Lab of this Week

Exercises in sentiment analysis

QA