

# Sentiment analysis

by Miroslav Mirchev

Guest lecture at TU Graz

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# Personal background

- Education

- BSc in Informatics and Computer Engineering at Ss. Cyril and Methodius University in Skopje, Macedonia (2004 - 2008)
- MSc in Computer Networks and E-technologies (focused on Complex networks) at Ss. Cyril and Methodius University in Skopje, Macedonia (2008 - 2009)
- PhD in Electronics and Communications (focused on Complex networks) at Polytechnic University of Turin, Italy (2011 - 2014)

- Work

- Teaching and research assistant at Ss. Cyril and Methodius University in Skopje (2009 - 2010)
- Professor in Computer science and engineering at Ss. Cyril and Methodius University in Skopje, N. Macedonia (2014 - today)
- Postdoctoral researcher at Complexity Science Hub in Vienna (2023 - today)

# Research interests

- Complex systems and complex networks
  - Dynamical processes in complex systems and networks
  - Synchronization, consensus, epidemic spreading
  - Inference in complex systems
- Network science and machine learning on graphs
  - Analysis and inference in online social networks
  - Enhancing portfolio management with NS and ML methods
  - Disinformation spreading in social networks

# Outline

- Background on emotions and sentiment analysis
- Dictionary and rule-based methods for sentiment analysis
- Machine learning methods for sentiment analysis
- Sentiment analysis with LLMs
- Applications of sentiment analysis

# What is emotion?

“*Emotions* are a process, a particular kind of automatic appraisal influenced by our evolutionary and personal past, in which we sense that something important to our welfare is occurring, and a set of psychological changes and emotional behaviors begins to deal with the situation.” – Paul Ekman

There is no generally accepted definition of *emotion*.

# Measuring, studying and recognizing emotions

- **Measuring emotions** – Emotions can be measured by observing various signals like facial expressions, voice, various physiological signals, text, etc.
- **Affective science** – an interdisciplinary field for study of emotions or affects, and their elicitation, experience and recognition
- **Affective computing** – interdisciplinary field for the study of emotions using computational methods and creation of systems for their processing, interpretation, recognition, modelling and simulation
- **Emotion recognition** – Identification of human emotions based on the measured signals
- **Sentiment analysis** – Identification of subjective state from text

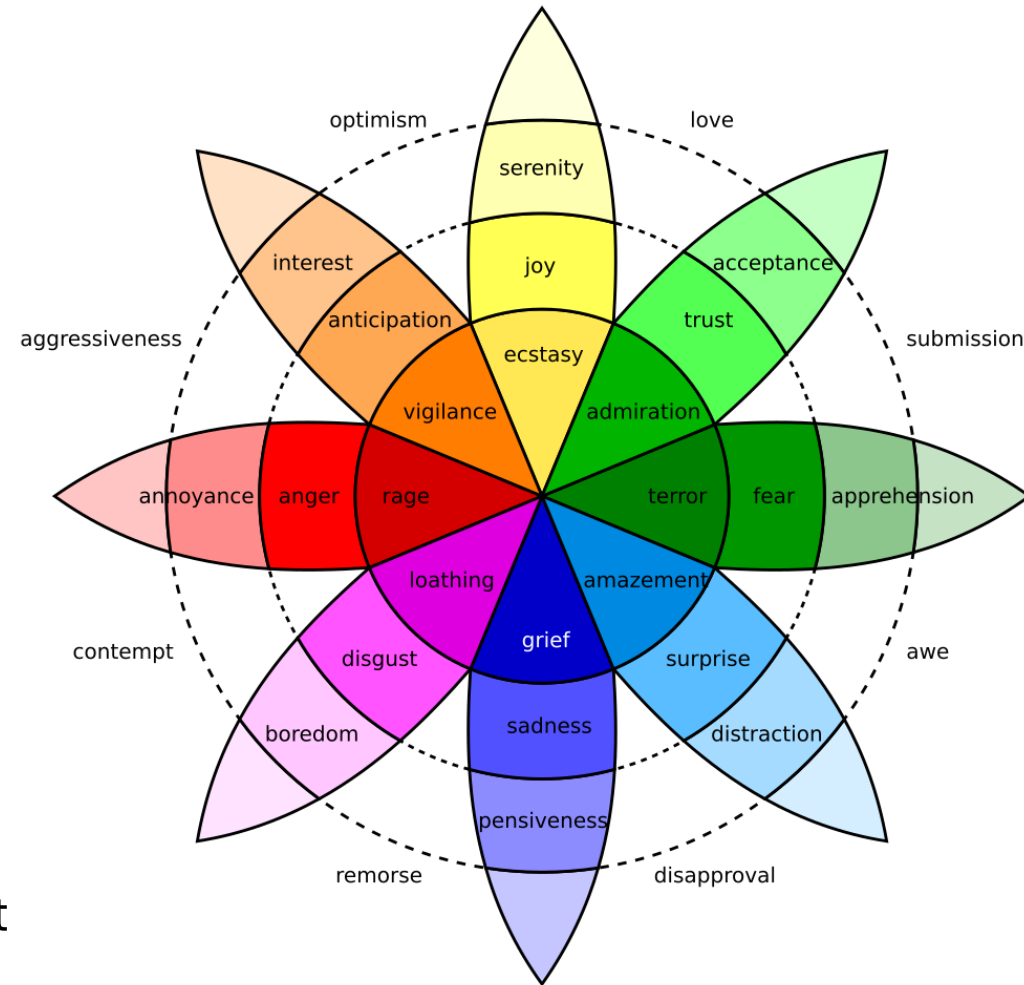
# Ekman's basic emotions

- Ekman's Emotion Theory
  - Emotions are distinct, measurable, and recognized across all cultures, even without media influence.
- Core Emotions Identified
  - Six universal emotions: anger, disgust, fear, happiness, sadness, and surprise.
  - Matching physical expressions trigger related physiological and emotional responses.
- Expanded Universal Emotions
  - Ekman's students later added amusement, awe, contentment, desire, embarrassment, pain, relief, and sympathy.
  - They also found facial expressions for boredom, confusion, interest, pride, and shame, and vocal ones for contempt, relief, and triumph.



# Plutchik's wheel of emotions

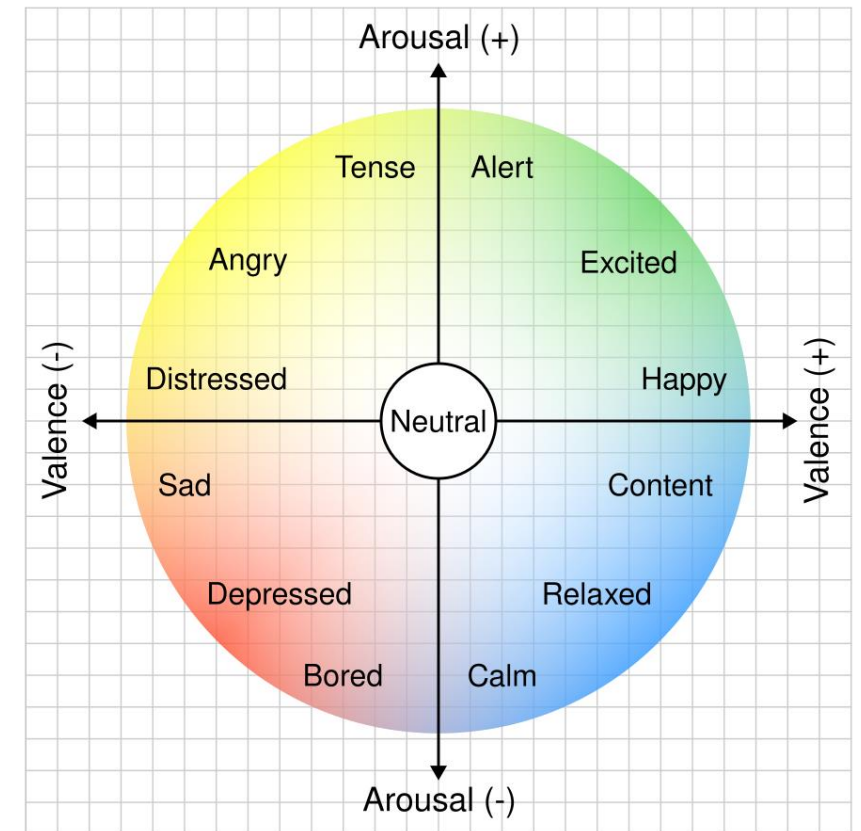
- Eight Primary Emotions
  - anger, fear, sadness, disgust, surprise, joy, *anticipation*, and *trust*
- Ten Key Postulates of Plutchik's Theory
  - Emotions are universal across species, evolving over time.
  - Serve adaptive functions in survival and environmental interaction.
  - Despite varied expressions, emotions share common patterns across species.
  - Few primary emotions exist; other emotions are blends or derivatives.
  - Primary emotions are hypothetical constructs with identifiable properties.
  - Emotions exist in polar pairs (e.g., joy vs. sadness).
  - Emotions vary in similarity and can exist at different intensity levels.
- Plutchik's Wheel of Emotions





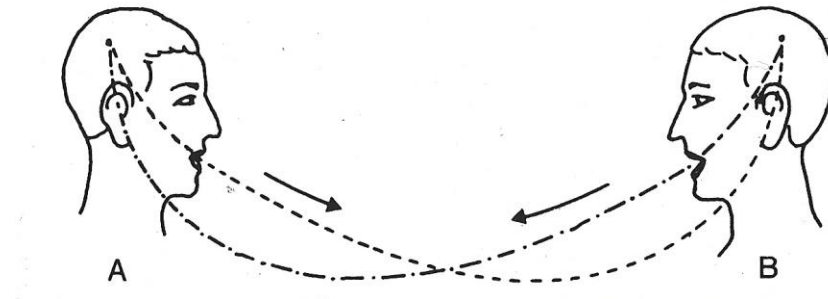
# Circumplex model

- Circumplex Model of Emotion
  - Developed by James Russell to map emotions in a circular space.
- Two Dimensions
  - Arousal (intensity) on the vertical axis.
  - Valence (positive/negative) on the horizontal axis.
- Flexible Representation
  - Emotions vary across both dimensions.
- Applications
  - Used for testing emotion words, facial expressions, and affective states.
- Core Affect
  - Basic feelings (not object-focused); distinct emotions mapped by arousal and pleasure.



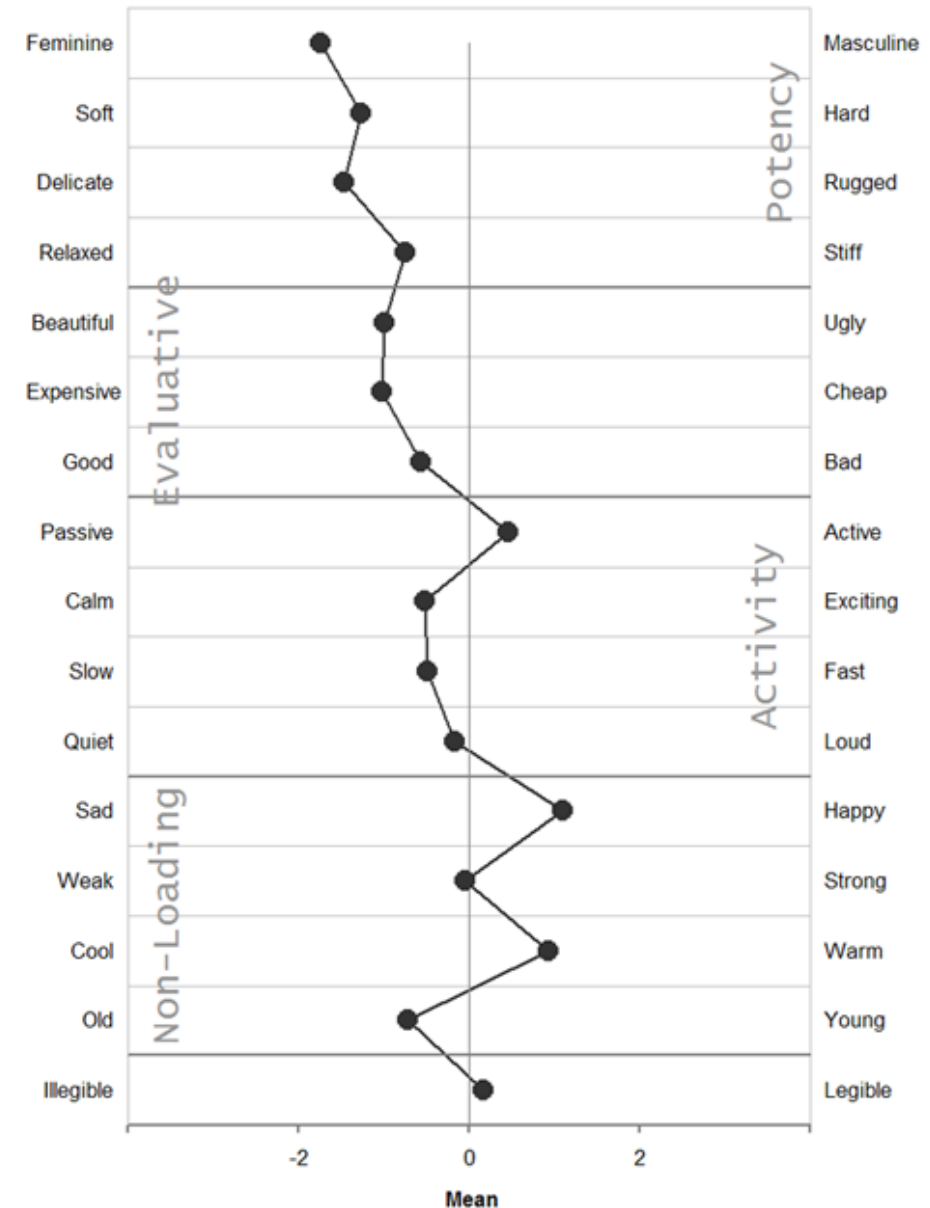
# De Saussure's model of language

- Language serves as a link between the meanings (signified) and the words (signifier), which are learned through experience
  - **Denotative meaning:** Definition of a word in reference to other meanings
  - **Connotative meaning:** Emotional association of the use of a word
- Human communication involves two main processes
  - **Encoding** – Converting thoughts into language
  - **Decoding** – Interpreting language back into thoughts
  - **Noise** – factors that cause interference in the communication



# The semantic differential

- Originally crafted by Charles E. Osgood to explore the deeper meaning behind words and concepts.
- Captures how people feel about concepts, objects, or events through their subjective perceptions and emotions.
- Uses pairs of opposite adjectives (“happy-sad,” “safe-dangerous”) to rate their feelings on a scale.
- Provides reliable and nuanced insights into people’s attitudes, capturing complex opinions in a structured way.
- Essential in areas like marketing, psychology, and sociology to assess public perception of products and experiences.
- Three principal dimensions of meaning:
  - **Evaluation:** good, desirable -- bad, undesirable
  - **Potency:** strong, powerful -- weak, powerless
  - **Activation:** active, fast -- passive, slow



# Sentiment analysis

- **Sentiment analysis** (SA) is a process for determining the emotional tone or opinion expressed in a piece of text, or other data
- It is a subfield of NLP that deals with the **classification of sentiment** behind words, phrases, or texts, often as *positive*, *negative*, or *neutral*, according to the valence/ evaluation dimension
- It **leverages** machine learning, lexicons, and computational linguistics to evaluate subjective information and understand customer opinions, feedback, or social media posts.
- It is **widely applied** in fields like marketing, customer service, finance, and politics, where insights into public opinion or customer satisfaction are valuable for decision-making.

# Sentiment analysis methods

- Methods based on lexicons and rules
  - Use expert knowledge, like psychologists, to create dictionaries or rules, which can be later applied for evaluation
  - Simple for implementation, but lack context and have noise
- Supervised learning
  - Uses machine learning methods trained on annotated data, which can come from the content creators or subsequent evaluators
  - It can employ various machine learning methods, such as random forest, support vector machines, or deep learning
- Language models
  - They are trained using self-supervised learning and can be either used with fine-tuning on annotated data or even directly (LLMs)

# The General Inquirer

- Developed by Philip Stone in the 1960s: One of the earliest tools for computer-aided text analysis.
- **Lexicon-Based Approach:** Uses a pre-defined dictionary with words categorized by sentiment and other dimensions.
- **Categorical Analysis:** Classifies words into various semantic categories (e.g., positive, negative, strong, weak).
- **Application in Sentiment Analysis:** Identifies the emotional tone, orientation, and other psycholinguistic attributes in text.
- **Psychosocial Insight:** Helps understand social, political, and psychological implications within textual data.
- **Used in Multiple Fields:** Widely applied in social science research, psychology, and linguistics.
- **Extended version:** Released in 1990s, has >10.000 words, and is publicly available

# Linguistic Inquiry and Word Count



- “Luke” is a popular tool developed in 2001 by James Pennebaker
- Inspired by the General Inquirer, it counts word frequencies matched with a dictionary of pre-defined categories including psychological, linguistic, and social content.
- The dictionaries are assembled by experts and there have been several versions for English (2001, 2007 and 2015),
  - There are translated dictionaries in several languages such as Brazilian Portuguese, Chinese, Dutch, French, German, Italian, Japanese, Marathi, Norwegian, Romanian, Russian, Serbian, Spanish, Turkish, and Ukrainian.
- It works by tokenization of the words in the text and matching them with the words in the dictionary, either as soft (prefixes) or hard matches
- Newest version supports emoticons and internet slang

# LIWC for excerpt from the poem “The Raven”

Traditional LIWC Dimension	Your Text	Average for Story Language
I-words (I, me, my)	6.16	3.22
Positive Tone	2.01	2.18
Negative Tone	2.84	1.75
Social Words	4.86	10.50
Cognitive Processes	6.99	8.70
Allure	3.55	5.48
Moralization	0.36	0.21
<b>Summary Variables</b>		
Analytic	51.71	60.28
Authentic	89.80	39.78

<https://www.liwc.app/demo>



# SentiStrength



- **Sentiment Analysis tool:** Developed by Mike Thelwall in 2010. Free for academic use for analyzing texts with near-human accuracy for English
- **Dual Sentiment Scoring:** Provides separate scores for positive (1 to 5) and negative (-1 to -5) sentiment strengths, reflecting the psychological basis of parallel processing of emotions.
- **Versatile Output Formats:** Supports binary (positive/negative), trinary (positive/negative/neutral), and single-scale (-4 to +4) outputs.
- **Optimized for Informal Text:** Designed specifically for short, informal web texts; adaptable to specific contexts by modifying configuration.
- **Language Support:** Primarily for English but easily configurable for other languages.

# VADER

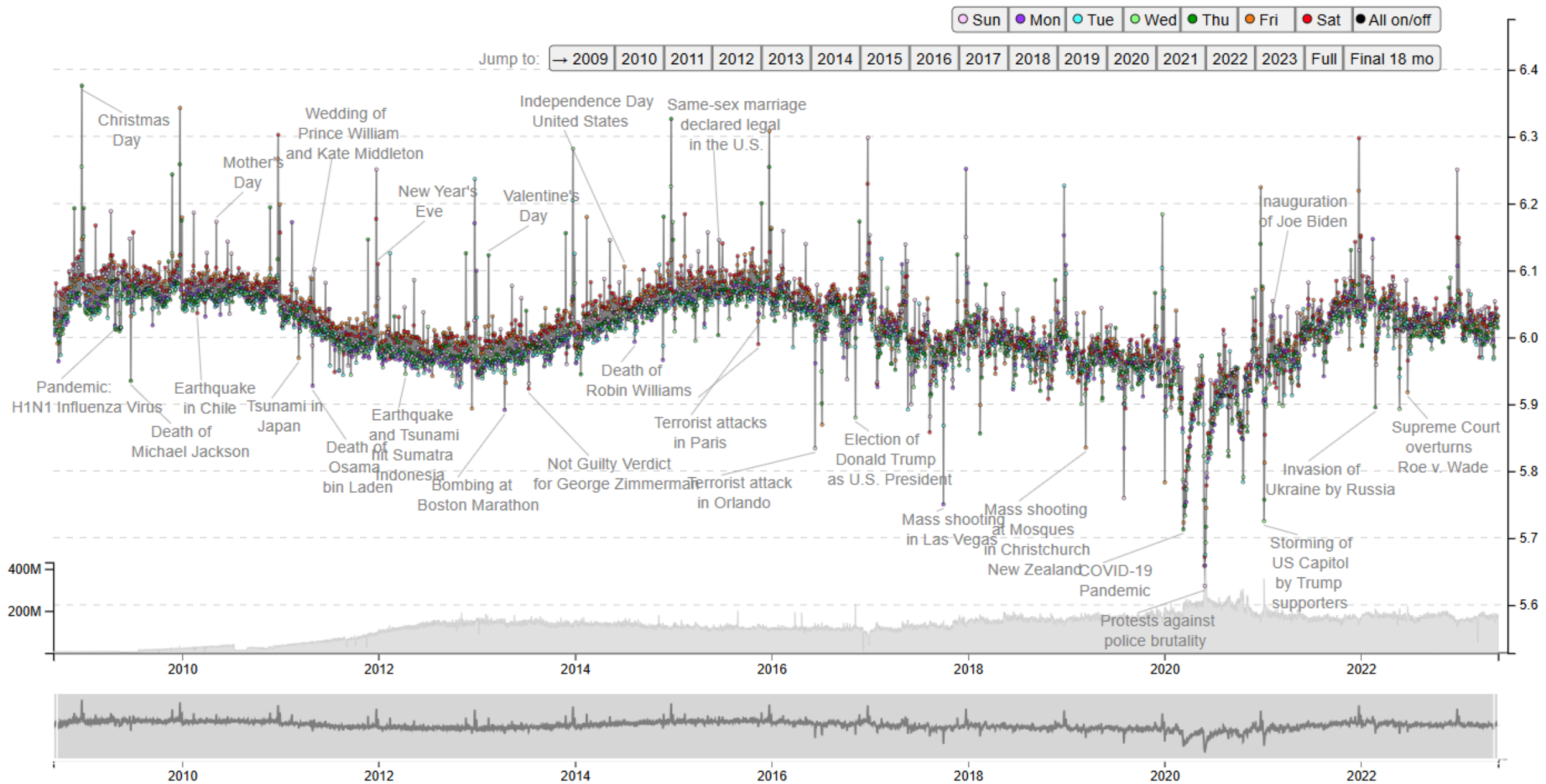
- VADER (Valence Aware Dictionary and sEntiment Reasoner) is a sentiment analysis tool developed by Hutto and Gilbert in 2014
- It is an open-source software available as a Python package and within the NLTK library, but there is an R package as well
- It is a lexicon and rule-based tool for sentiment analysis, designed with a focus on capturing sentiments commonly found in social media content
  - Text preprocessing
  - Word matching between text and dictionary
  - Application of modifiers based on language rules

# Hedonometer

- Language Assessment by Mechanical Turk (**labMT**) dataset
- Contains scores for happiness for more than 10,000 words
- The list was compiled from the most frequently appearing words in more contemporary sources such as Twitter, Google Books, the New York Times, and music lyrics.
- Human annotators were asked to score a word using a scale of 1–9, with 1 being the least happy, 9 being the happiest, and 5 being neutral.
- It is available in several languages with several versions from 2011, 2014, and 2022 (labMT-v2), in German, Korean, Spanish, Russian, English, Indonesian, Portuguese, Arabic, Chinese, French, and Ukrainian

# Average Happiness for Twitter

All Tweets in English.



# Supervised learning

- Supervised learning models for sentiment analysis rely on previously annotated sentiment labels/scores to a given dataset from which they can learn to generalize on other data
- Various labels/scores can be assigned:
  - Negative, neutral, positive
  - Very negative, moderately negative, slightly negative, neutral, ...
  - Real valued score in a certain range, like  $[-1, 1]$  or  $[-3, 3]$
- Different machine learning can be applied
  - Classical models such as decision trees and support vector machines
  - Language models like BERT
  - Large language models like GPT

# Annotated data

- The data can be annotated in two ways:
  - Ideally by the content creator, for example during a review of a product
  - Assessed by an annotator or a group of annotators
- Some texts can contain a mixture of sentiments

Text Sample	Annotated Sentiment	Sentiment Score
Impressed with the fast service!	Positive	0.9
Waited too long for a simple order. Not happy.	Negative	0.6
Decent food but the ambiance lacks warmth.	Neutral	0.1

POSITIVE

NEUTRAL

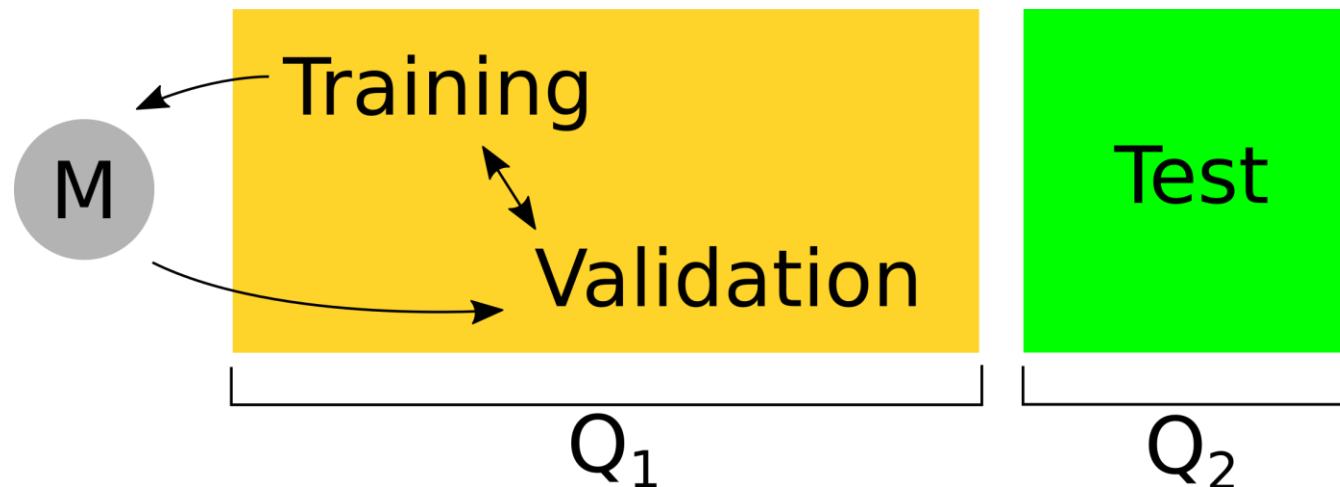
NEGATIVE

My Experience with the service has been **fantastic**, but the product was **ok**. The support was useless since the team did not had the basic product knowledge, which was **frustrating**.

★ ★ ★ ★ ★

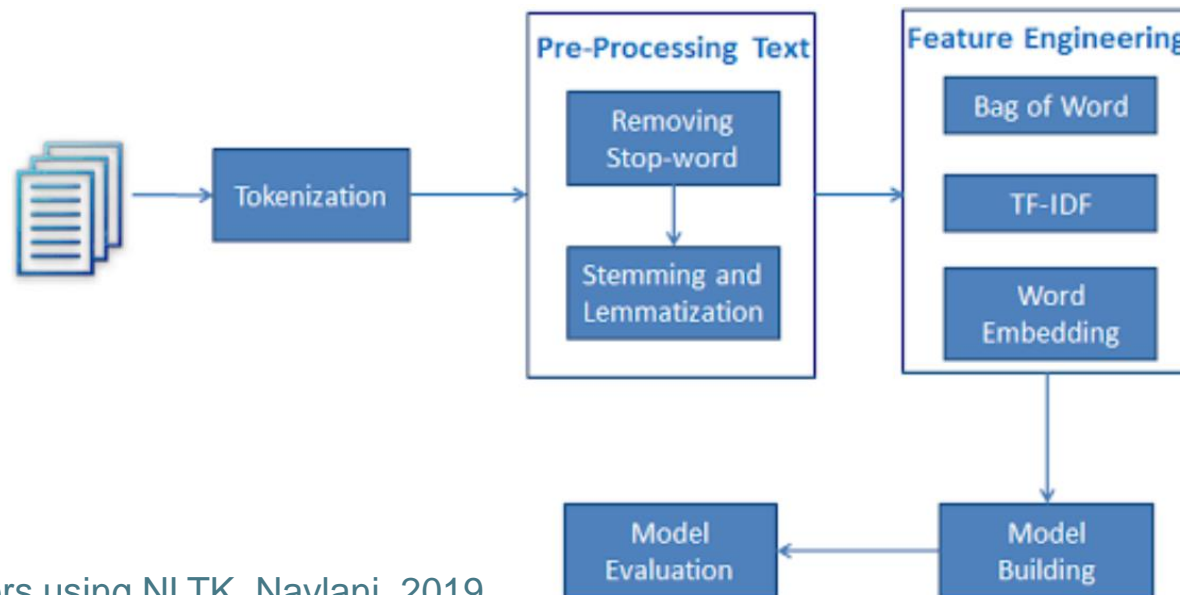
# Supervised learning

- The annotated data is divided into three parts:
  - **Training data** – used for fitting the model parameters
  - **Validation data** – used for evaluating the trained model performance and fitting the model's hyper-parameters
  - **Test data** – used at the end to evaluate the final trained model



# Data cleaning and pre-processing

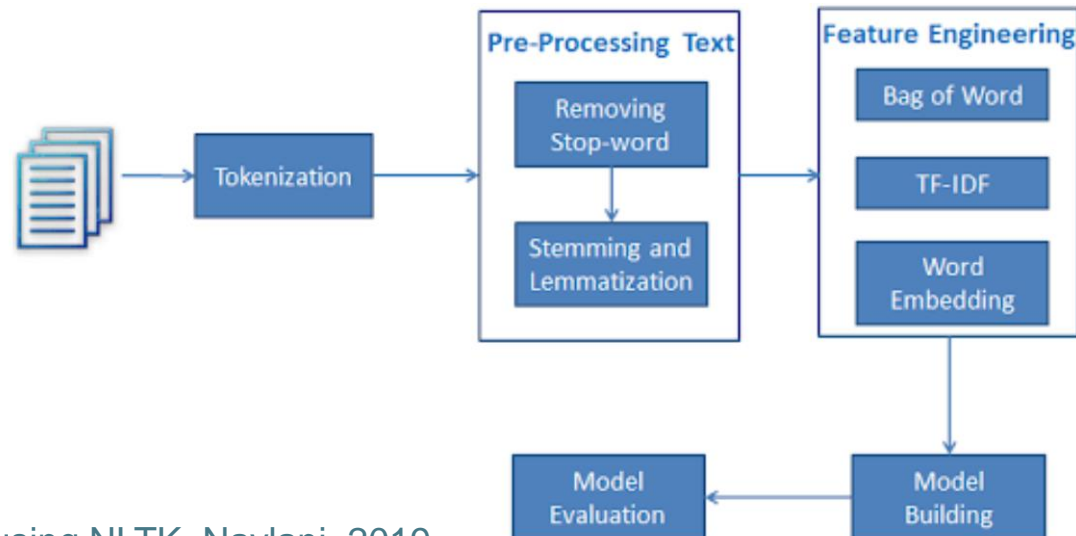
- **Data cleaning** – removal of non relevant data such as URLs, dates and special characters, that can act as a noise in the process
- **Data preprocessing** – removal off stop-words, stemming and lemmatization





# Feature engineering

- **Bag of words** – simple count of word occurrences in a text
- **TF-IDF** – weight frequency that normalizes the term frequency by the overall term frequency across all the documents
- **Word embedding** – representation of text in an embedded space



# Machine learning for sentiment analysis

- Classic machine learning models
  - **Support Vector Machine:** Implicitly maps the data into a higher dimensional space where it can easily separate the classes
  - **Random Forest:** Independently builds multiple decision trees to split the data based on the target label and outputs an average
  - **XGBoost:** Builds decision trees sequentially and provides superior performance
- Deep learning models
  - **Convolutional and recurrent neural networks:** Have been used for sentiment classification but lag behind transformer models
  - **BERT (Bidirectional Encoder Representations from Transformers):** Pre-trained on a large text corpus and fine-tuned for sentiment classification
  - **GPT (Generative Pre-trained Transformer):** While primarily generative, can be fine-tuned for classification tasks, including sentiment analysis

# Evaluating classifiers

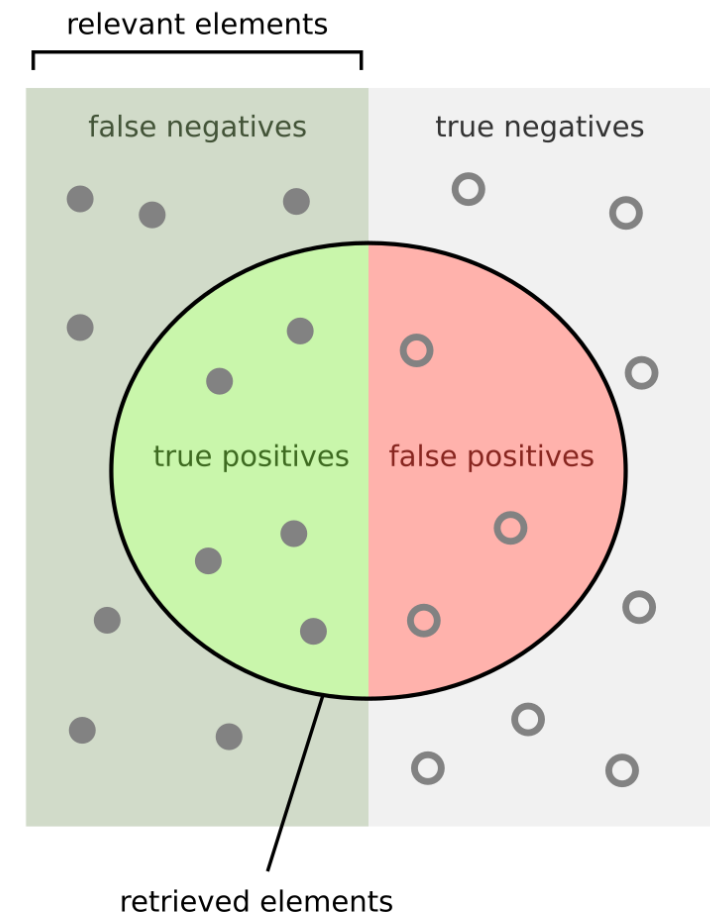
- There are different evaluation measures

$$Precision = \frac{TP}{TP + FP} \quad Recall = \frac{TP}{TP + FN}$$

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

- We should be careful what measures we use, especially if the classes are imbalanced



How many retrieved items are relevant?

$$Precision = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are retrieved?

$$Recall = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

# Using proprietary black-box models

- Easy to use, but we do not have insight into how they work, and often we can not fine-tune them to annotated data

**Watson™** Natural Language Understanding


Sentiment Emotion Keywords Entities Categories Concept

Semantic Roles

Review the overall sentiment and targeted sentiment of the content. [JSON ^](#)

```
{
  "sentiment": {
    "document": {
      "score": -0.74758,
      "label": "negative"
    }
  }
}
```

Overall Sentiment

Negative  -0.75



A sample `analyzeSentiment` response to the [Gettysburg Address](#) is shown below:

```
{
  "documentSentiment": {
    "score": 0.2,
    "magnitude": 3.6
  },
  "language": "en",
  "sentences": [
    {
      "text": {
        "content": "Four score and seven years ago our fathers brought forth on this continent a new nation, conceived in liberty and dedicated to the proposition that all men are created equal.",
        "beginOffset": 0
      },
      "sentiment": {
        "magnitude": 0.8,
        "score": 0.8
      }
    }
  ],
}
```

# Using LLMs – OpenAI's GPT

- It can be used directly for classification, but it could be also fine-tuned or prompt-tuned

```
with open('TheRaven.txt', 'r', encoding='utf-8') as file:
    text = file.read()

response = client.chat.completions.create(
    model="gpt-4o-mini",
    messages=[
        {
            "role": "system",
            "content": "You will be provided with an text, and your task is to classify its sentiment with one of the labels  
'Very positive', 'Positive', 'Somewhat positive', 'Neutral', 'Somewhat negative', 'Negative', 'Very negative', or 'Mixed'."
        },
        {
            "role": "user",
            "content": text
        }
    ],
    temperature=0,
    max_tokens=32,
    top_p=0
)

response.choices[0].message.content
```

# Using LLMs – OpenAI's GPT

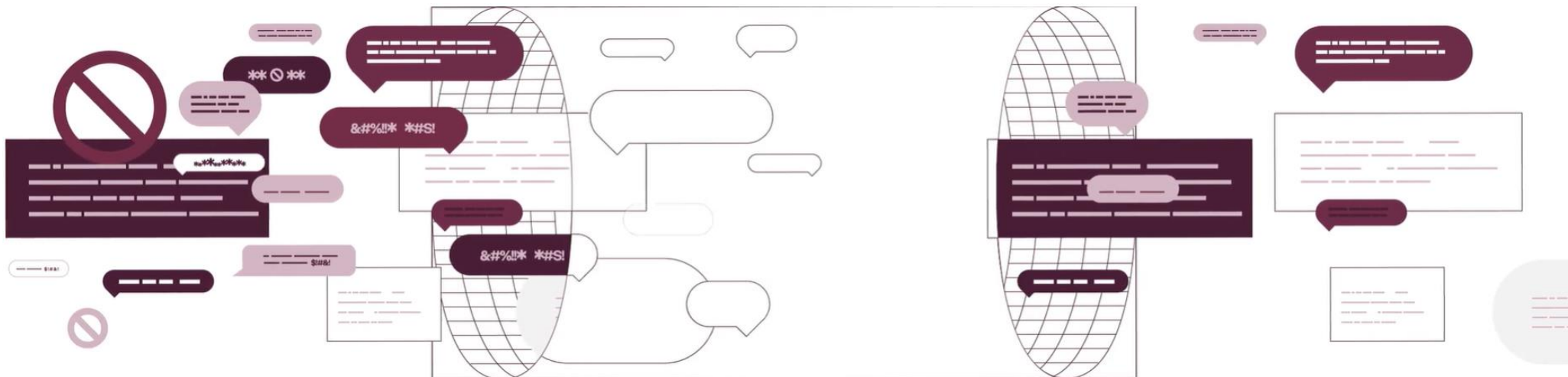
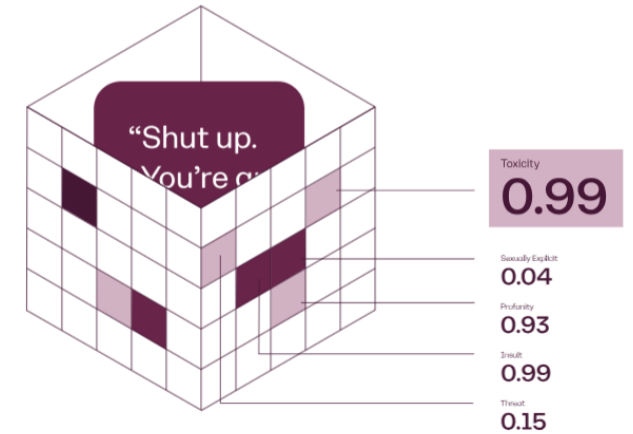
- GPT can be also used to easily annotate the sentiment, but also the corresponding word or entity that it is associated with:
  - My general experience with the service has been **fantastic** (Positive), but the actual product was **just ok** (Neutral). The support was **useless** (Negative) since the team **did not have the basic product knowledge** (Negative), which was **frustrating** (Negative).
- This type of annotation was very challenging previously

# Hate Speech & Toxicity

- **Hate speech** refers to language that targets individuals or groups based on attributes like race, gender, religion, sexual orientation, etc.
  - Hate speech detection is the identification of expressions that can incite violence or discrimination, with the goal of preventing the spread of divisive or harmful rhetoric and fostering inclusivity in online communities.
- **Toxicity** involves language that is generally offensive, rude, or aggressive but not necessarily targeted at a specific group
  - Toxic comments can disrupt conversations, create hostile environments, and deter engagement.
  - Toxicity analysis uses algorithms to detect high levels of negativity in language, helping to flag content that may degrade the quality of discourse and impact user experience so that appropriate measures can be taken

# Perspective API

- A tool by Google that provides analysis of the texts: toxicity, severe toxicity, profanity, insult, threat and identity attack
- Used for content moderation on social media platforms





# Toxicity analysis of The Raven

```
client = discovery.build(
    "commentanalyzer",
    "v1alpha1",
    developerKey=API_KEY,
    discoveryServiceUrl="https://commentanalyzer.googleapis.com/$discovery/rest?version=v1alpha1",
    static_discovery=False,
)
#text=df.loc[0]["Tělo"]
text='i hate him'
analyze_request = {
    'comment': { 'text': text },
    'requestedAttributes': { 'TOXICITY': {}, "SEVERE_TOXICITY": {}, "IDENTITY_ATTACK": {}, 'INSULT': {}, 'PROFANITY': {}, 'THREAT': {} },
    'languages': ['cs']
}

response = client.comments().analyze(body=analyze_request).execute()
print(json.dumps(response, indent=2))
toxicity_score = response['attributeScores']['TOXICITY']['summaryScore']['value']
severe_toxicity_score = response['attributeScores']['SEVERE_TOXICITY']['summaryScore']['value']
identity_attack_score = response['attributeScores']['IDENTITY_ATTACK']['summaryScore']['value']
insult_score = response['attributeScores']['INSULT']['summaryScore']['value']
profanity_score = response['attributeScores']['PROFANITY']['summaryScore']['value']
threat_score = response['attributeScores']['THREAT']['summaryScore']['value']
```

# Sentiment and toxicity of The Raven

- GPT evaluation of The Raven
  - The label for this poem is **moderately negative**.
  - Explanation: The tone is sorrowful and haunting, focusing on themes of loss, despair, and hopelessness, with phrases like "sorrow for the lost Lenore," "nevermore," and the pervasive presence of the Raven, symbolizing an unrelenting sense of doom and melancholy.
- The toxicity scores from Perspective API are relatively low, except for the basic toxicity score:
  - Toxicity = 0.10739898
  - Severe toxicity = 0.0045394897
  - Identity attack = 0.012943448
  - Insult score = 0.03158728
  - Profanity score = 0.050429728
  - Threat score = 0.015429466

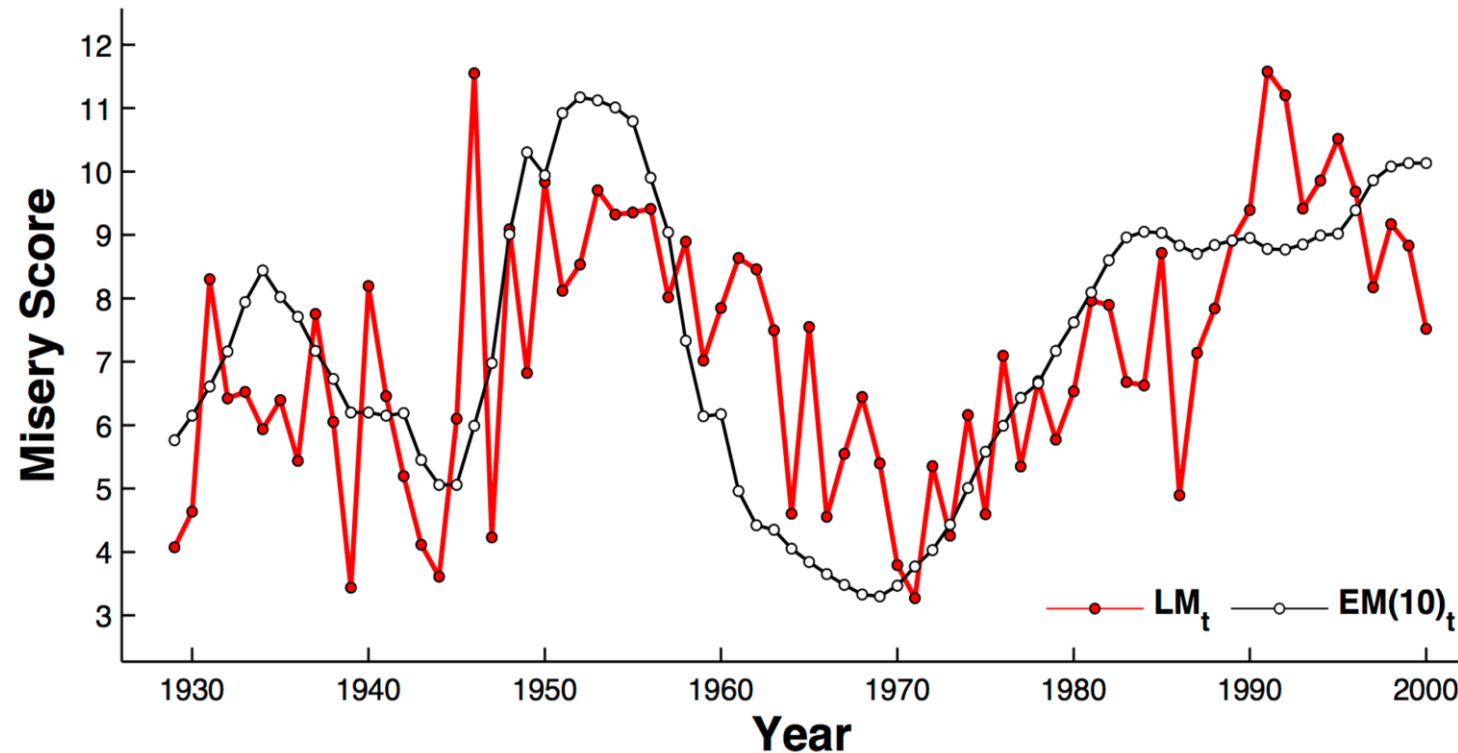
# Artificially generated content

- A large part of the online content is artificially generated
- A large cleanup was done on Twitter in 2018 when it was estimated that between 9% and 15% of the accounts were bots
  - This was again actualized during the takeover from Elon Musk, but the numbers today could be even higher
  - Botometer was a tool for assessing how likely Twitter users are bots developed by Observatory on Social Media Center at Indiana University
- With the advancement of LLMs this issue is becoming much more prevalent and challenging to detect and fight against it
- Ideally, studies should try to assess distinctively the sentiment of human and machine-generated content

# Applications of sentiment analysis

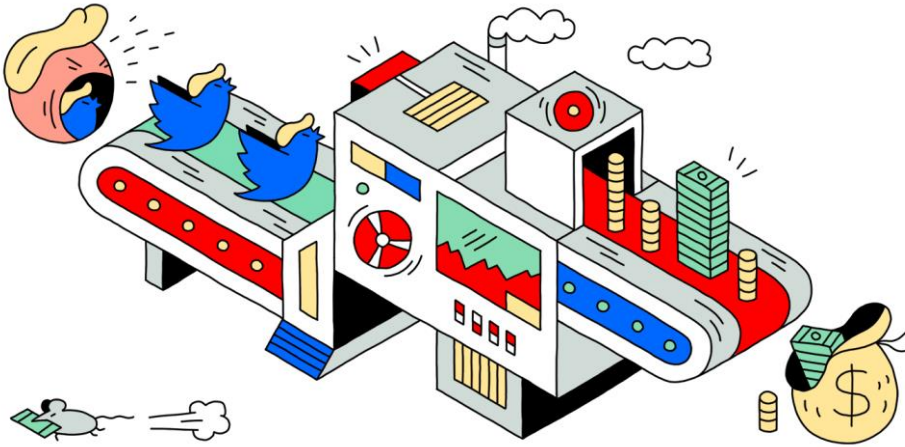
- Literary and economic misery
- Sentiment in song's lyrics
- Stock trading based on sentiment
- Sentiment analysis during political elections
- Sentiment analysis in chain emails

# Literary and economic miseries



- There is a cross-correlation between economic (lead) and literary (lag) misery
- Literary misery is calculated using LIWC for Germany.

# Trump2Cash

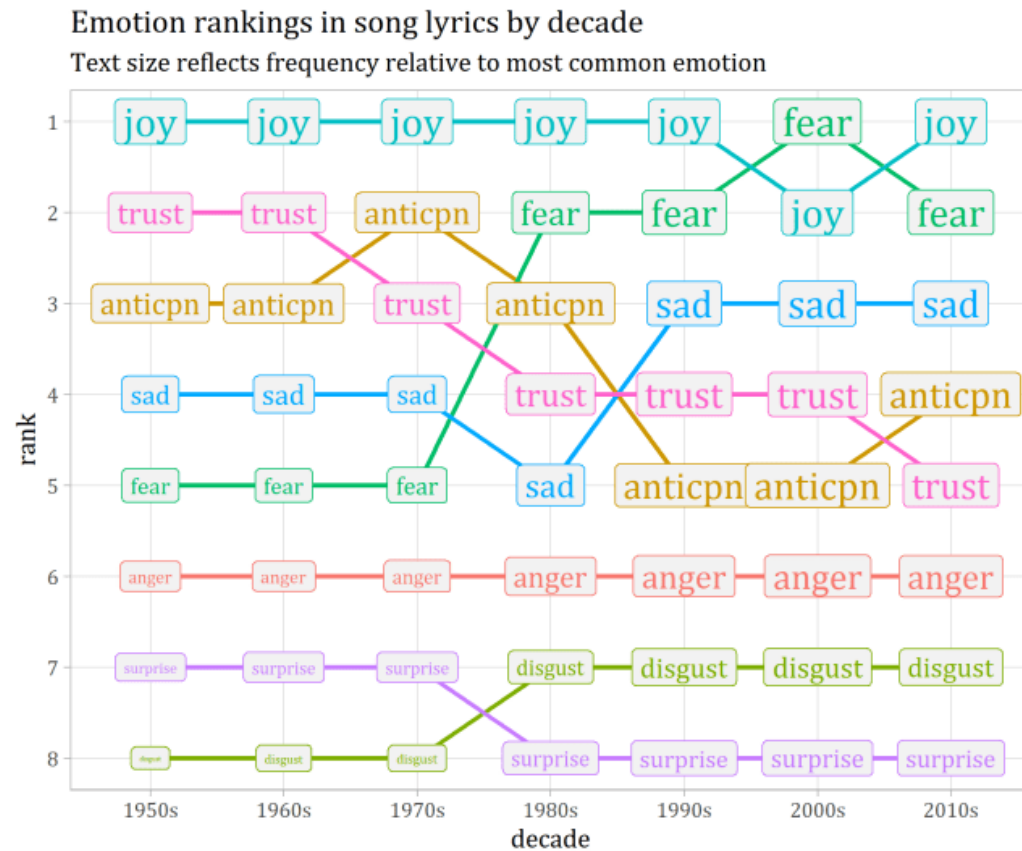


- Automatic stock trading tool by Max Braun
- **Twitter Streaming API:** To receive real-time notifications of Trump's tweets.
- **Google Cloud Natural Language API:** For entity detection and sentiment analysis.
- **Wikidata Query Service:** To retrieve company data.
- **TradeKing API:** To execute stock trades.



# Emotion scores of song lyrics in time

- Based on the NRC emotions lexicon

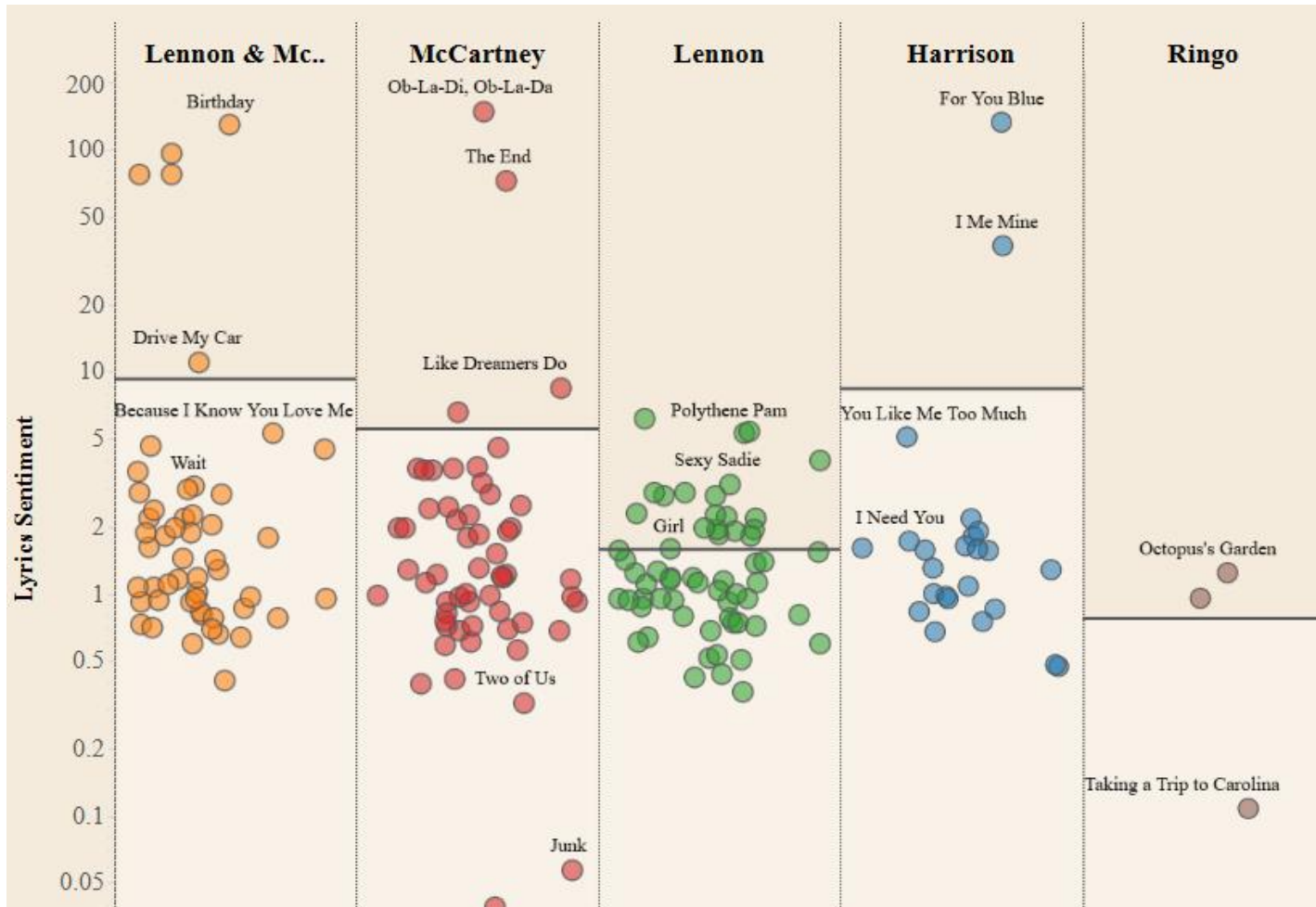


<https://musichistorystats.com/>

NRC Emotion Scores of Song Lyrics by Year

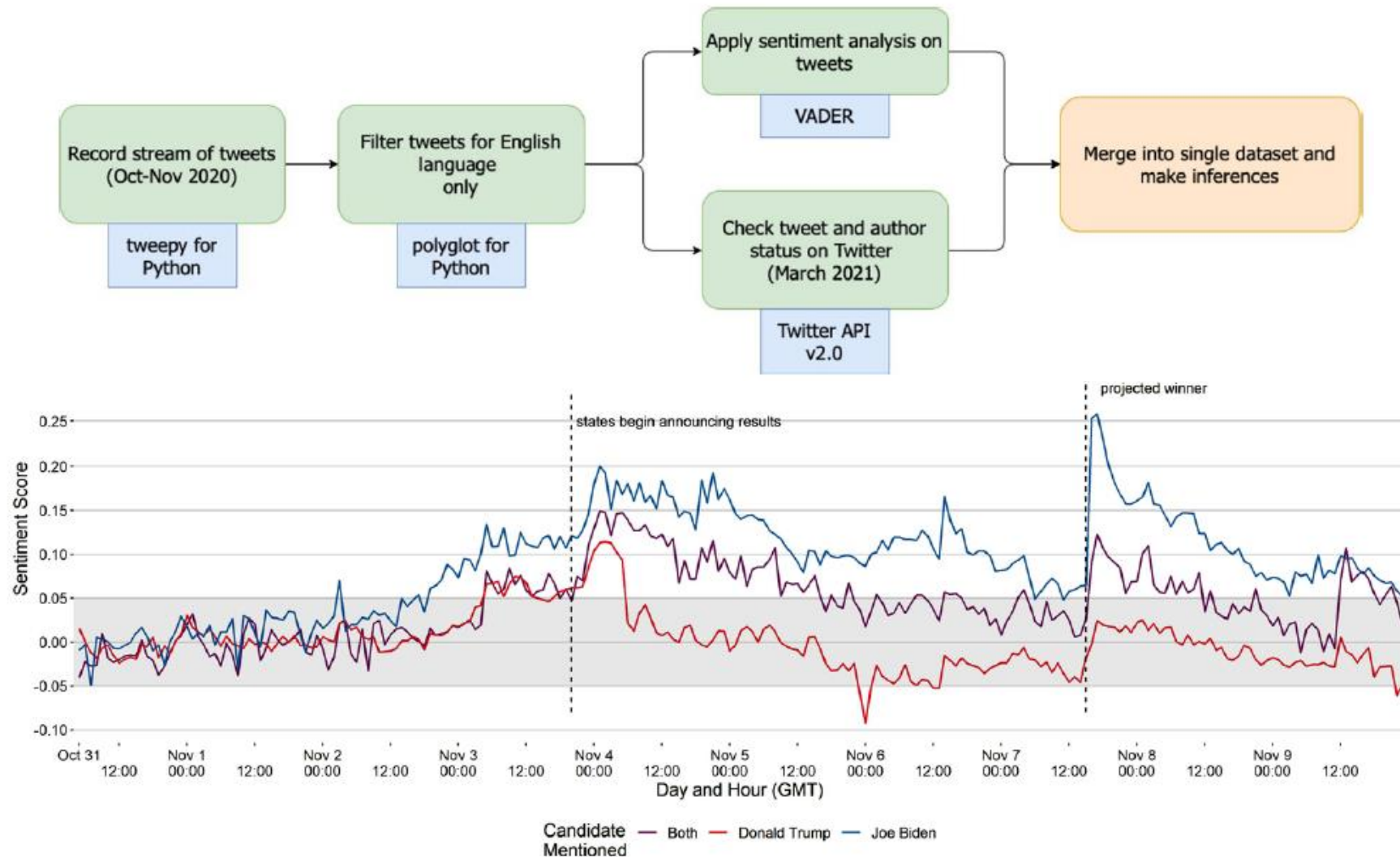


# Beatles Songs by Sentiment

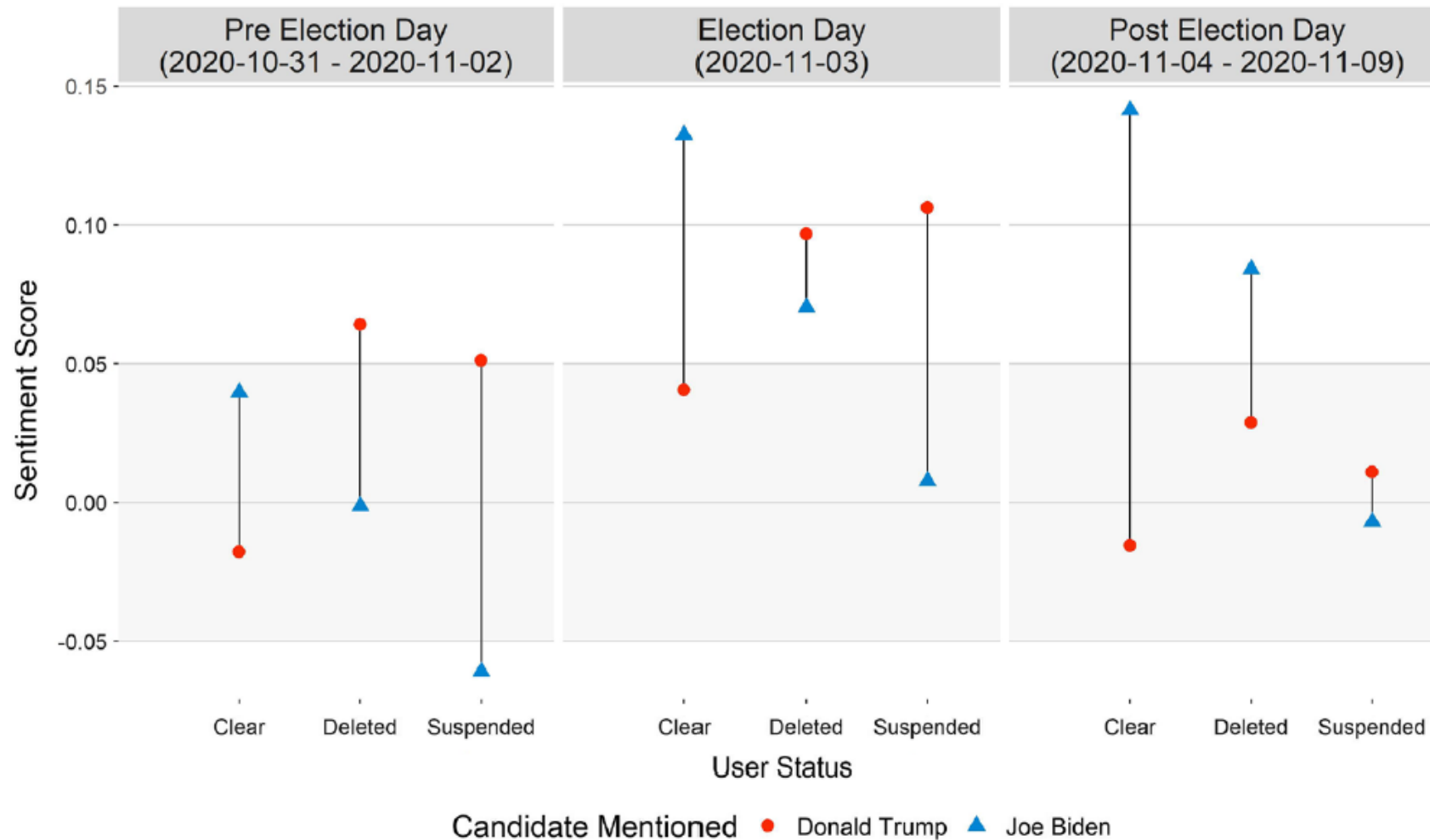




# Sentiment analysis during US Elections 2020



# Sentiment analysis during US Elections 2020



# Summary

- Background on emotions and sentiment analysis
  - Ekman's theory
  - Plutchik's wheel diagram
  - Semantic differential
- Dictionary and rule based sentiment analysis
  - LIWC, SentiStrength, Vader, Hedonometer,
- Supervised learning for sentiment analysis
  - Traditional machine learning methods
  - Language models
- Applications of sentiment analysis
  - Analysis of literary and economic misery
  - Sentiment analysis in song lyrics
  - Stock trading based on sentiment
  - Sentiment analysis during political elections
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