

Emotion Analysis from Text: Tutorial at EACL 2023

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Emotion Analysis

Introduction and Psychology

EACL 2023 Tutorial

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Outline

1 Introduction

2 What are Emotions?

- Motivation: Basic Emotion Theories
- Feeling: Affect and Constructionism
- Evaluation: Causes and Appraisals

3 Task Definition and Issues

4 What can we learn from previous work in psychology? Psychological Studies on Reliability

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3 Task Definition and Issues

4 What can we learn from previous work in psychology? Psychological Studies on Reliability

Introduction
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What are Emotions?
ooooooooooooooooooooooo

Task Definition and Issues
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Psychological Studies
oooooooo

Which emotion does the person who says this experience?

"I am happy to be here!"

"Tears ran down my face."

"I heard a loud sound when I was alone in the forest."

Introduction and Psychological Models

Introduction
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What are Emotions?
○oooooooooooooooooooo

Task Definition and Issues
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Psychological Studies
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About Us



- **Sanja Stajner**
- Independent Researcher based in Karlsruhe, Germany
- Research on emotion analysis, personality modeling, text simplification, accessibility, readability



- **Roman Klinger**
- Professor at the Institute for Natural Language Processing University of Stuttgart, Germany
- Research on sentiment analysis, emotion analysis, social media mining, biomedical NLP, fact-checking

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Introduction
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What are Emotions?
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Task Definition and Issues
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Psychological Studies
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About this tutorial

Session 1 (09:00–10:30)

- Introduction
- Psychological Models
- Use Cases/Social Impact
- Resources
- Annotation Exercise

Break (10:30–11:15)

Session 2 (11:15–12:45)

- Non-Neural Methods
- Multi-task, transfer, zero-shot methods
- Open Challenges
- Appraisal Theories
- Role Labeling
- Ethical Considerations
- Closing

Purpose of this Tutorial

Target Audience

- Computationally oriented researchers
- Scholars interested in digital humanities, computational social sciences

Goal

- Provide psychological background knowledge
- Provide overview of existing resources, tasks, challenges, models
- Draft potential future research directions

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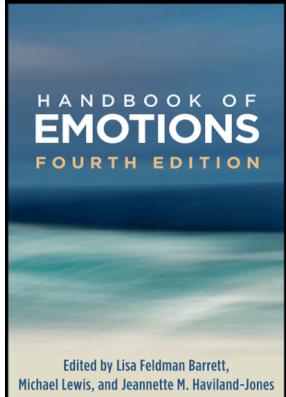
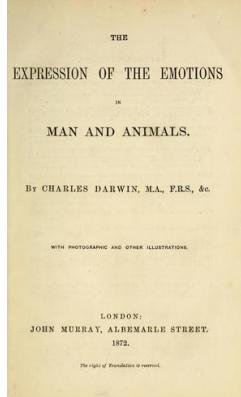
2 What are Emotions?

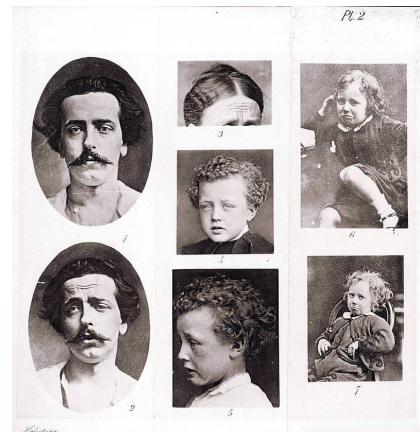
- Motivation: Basic Emotion Theories
- Feeling: Affect and Constructionism
- Evaluation: Causes and Appraisals

3 Task Definition and Issues

4 What can we learn from previous work in psychology?

Psychological Studies on Reliability

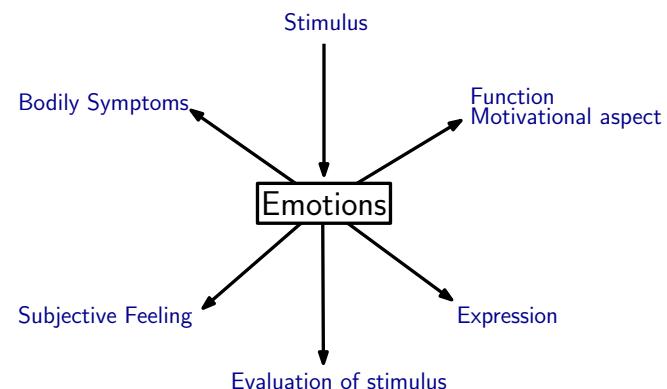
Introduction ooooo	What are Emotions? oooooooooooooooooooooo	Task Definition and Issues oooooooo	Psychological Studies oooooo	Introduction ooooo	What are Emotions? oooo●oooooooooooooooooooo	Task Definition and Issues oooooooo	Psychological Studies oooooo
Literature on Emotion Psychology				Literature with a Computational Focus			
<ul style="list-style-type: none"> • Philosophy, history and sociology • Literature and art • Decision making, Computational models • Biological perspectives • Social and personality perspectives • Cognitive Perspectives • Health • Specific Emotions 				 <p>HANDBOOK OF EMOTIONS FOURTH EDITION</p> <p>Edited by Lisa Feldman Barrett, Michael Lewis, and Jeannette M. Haviland-Jones</p>			
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Introduction ooooo	What are Emotions? oooooooooooooooooooooo	Task Definition and Issues oooooooo	Psychological Studies oooooo	Introduction ooooo	What are Emotions? oooo●oooooooooooooooooooo	Task Definition and Issues oooooooo	Psychological Studies oooooo
Emotion Theories...				Evolutionary Approach (Darwin, 1872)			
...try to explain ...				 <p>THE EXPRESSION OF THE EMOTIONS IN MAN AND ANIMALS. By CHARLES DARWIN, M.A., F.R.S., &c. WITH PHOTOGRAPHIC AND OTHER ILLUSTRATIONS. LONDON: JOHN MURRAY, ALDEMARLE STREET. 1872.</p>	<ul style="list-style-type: none"> • Focuses on expressions, as they can be observed. • Emotion expressions support communication • Emotions and their expressions have a function: <ul style="list-style-type: none"> • Surprise: Eyes wide open to support perception • Fear: Activation (fight, freeze, flight) • Disgust: Increase distance to stimulus • ... • Emotions are not learned 		
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https://en.wikipedia.org/wiki/The_Expression_of_the_Emotions_in_Man_and_Animal

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Emotion Components (Scherer, 2001)



Emotion in text could be expressed by describing each of these components.

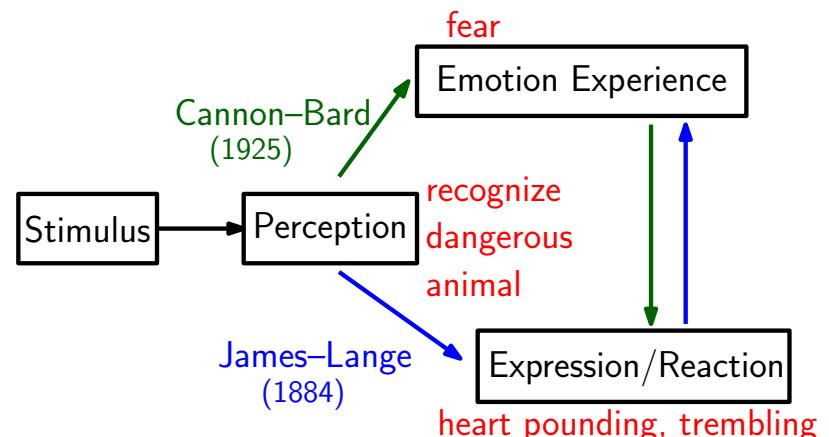
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James Lange/Cannon Bard (1884, 1925)



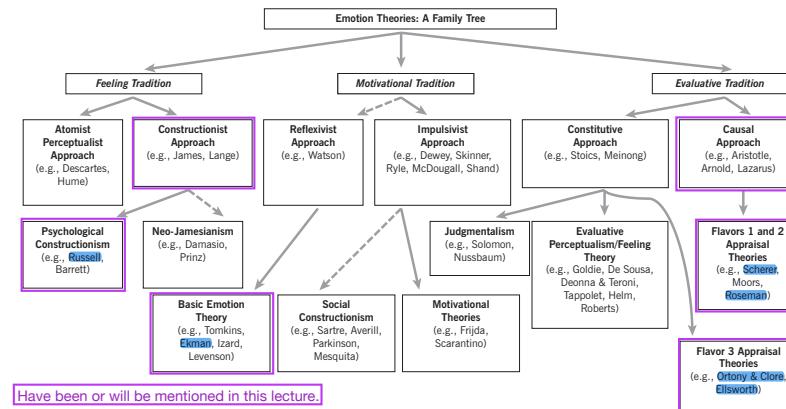
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Family Tree of Emotions (Scarantino, 2016)



I am aware of work in NLP that made use of these theories

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What are Emotions?
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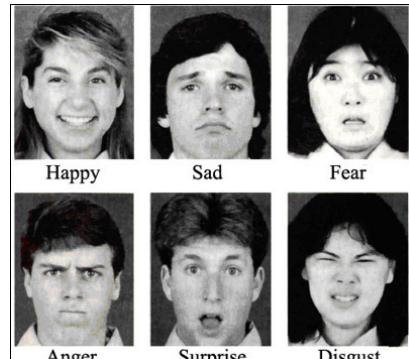
Task Definition and Issues
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Ekman's model of basic emotions

How to define a categorical system of emotions?

- Distinctive universal signals
- Presence in other primates
- Distinctive physiology
- Distinctive universals in antecedent events
- Coherence among emotional response
- Quick onset
- Brief duration
- Automatic appraisal
- Unbidden occurrence



Ekman (1992): An argument for basic emotions.

Introduction
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What are Emotions?
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Basic Emotion Theories

Basic emotion theories state that:

- There is a distinction between basic and non-basic emotions
- There are criteria that decide if an emotion is basic.

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Ekman: What are non-basic emotions?

- "I do not allow for non-basic emotions" (Ekman, 1999)
 - ⇒ They do not exist.
- What is love, depression, or hostility?
 - Personality traits (hostility, openness)
 - Moods (depression, anxiety, long-term disturbances are clinically relevant)
 - Emotional plots (love, grief, jealousy)

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Models of Basic Emotions: Plutchik's Wheel (Plutchik, 1970)

An emotion is a patterned bodily reaction that follows a function

- protection – **fear**
- destruction – **anger**
- reproduction – **joy**
- deprivation – **sadness**
- incorporation – **acceptance**
- rejection – **disgust**
- exploration – **anticipation**
- orientation – **surprise**

⇒ Basic emotions according to Plutchik

- Non-basic: Gradations and mixtures

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The diagram illustrates Plutchik's Wheel of Emotions, a model of human emotion. It features a central circle with twelve primary emotions arranged around it: love, acceptance, submission, awe, surprise, distraction, disapproval, pensiveness, sadness, loathing, contempt, and rage. Each primary emotion is associated with a specific color and has a corresponding gradation or mixture. The gradations are represented by the petals of the wheel, which are colored in shades of the primary emotion's color. For example, the petal between 'love' and 'acceptance' is labeled 'serenity', while the petal between 'submission' and 'awe' is labeled 'apprehension'. The mixtures are represented by the petals between the primary emotions, such as 'interest' (between love and acceptance), 'anticipation' (between acceptance and submission), 'vigilance' (between submission and awe), 'amazement' (between awe and surprise), 'disgust' (between surprise and contempt), 'boredom' (between contempt and rage), 'remorse' (between rage and loathing), and 'contempt' (between loathing and contempt).

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 - Psychological Studies on Reliability

Introduction ooooo What are Emotions? ooooooooooooo●oooooooooooo Task Definition and Issues ooooooo Psychological Studies oooooo

The Feeling Tradition of Emotion Theories

- Emotions are not innate
- They are learned constructs
- Depend on culture and contingent situations

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Feeling

What is not learned then?

Feeling

- Scarantino (2016): "Feeling is a conscious experience or a sensation or a subjective quality or a quale or a what-it-is-likeness."
- Feldman-Barrett (2018): Affect is "the general sense of feeling that you experience throughout each day [...] with two features. The first is how pleasant or unpleasant you feel, which scientists call valence. [...] The second feature of affect is how calm or agitated you feel, which is called arousal."

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Affect: Continuous Circumplex Model (Russel 1980)

The diagram illustrates the Affect: Continuous Circumplex Model (Russell 1980). It features a circle divided into four quadrants by a horizontal red arrow labeled "Arousal" and a vertical blue arrow labeled "Valence". The top-right quadrant is labeled "joyful", the top-left "satisfied", the bottom-left "depressing", and the bottom-right "angry". The left side of the circle contains words like "pleased", "delighted", "glad", "calm", "tired", "alarmed", "annoyed", "frustrated", "bored", and "miserable".

- So-called dimensional model
- Discrete emotion names are placed in a coordinate system
- Other dimensional models:
 - Valence–Arousal–Dominance (not discussed here)
 - Appraisals (later)

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Feldman-Barrett (2017): Theory of Constructed Emotion

How to link affect and emotion names? Lisa Feldman-Barrett attempts to explain this link.

- **Paradoxon:** We experience discrete emotion categories, but there is nearly no evidence from neuroscience for those.
- **Affect (valence and arousal)** is what we experience directly, not the emotion.
- Based on context, **the brain predicts** which emotion makes sense.
- **Prediction is important**, to motivate or warn us.
- This **learned construction** of emotions bridges the paradoxon.
- Very nice overview video:
https://www.youtube.com/watch?v=M10dhdI_3eI

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Appraisal Theories (according to Scherer)

Scherer, 2005

Emotions are “an episode of interrelated, synchronized changes ... in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism”

Appraisal Theories (according to Scherer)

Emotions have different components...

- Cognitive appraisal:**
an evaluation of events and objects
- Bodily symptoms:**
physiological component of emotional experience
- Action tendencies:**
a motivational component for the preparation and direction of motor responses
- Expression:** facial and vocal expression, body language, gestures, almost always accompanies an emotional state
- Subjective perceptions/Feeling:**
subjective experience of emotional state once it has occurred

Results Smith/Ellsworth (1985)

Locations of Emotion Means Along the PCA Components

Emotion	Component				
	Pleasant ^a	Responsibility/ Control ^b	Certain ^c	Attention ^d	Effort ^e
Happiness	-1.46	0.09	-0.46	0.15	-0.33
Sadness	0.87	-0.36	0.00	-0.21	-0.14
Anger	0.85	-0.94	-0.29	0.12	0.53
Boredom	0.34	-0.19	-0.35	-1.27	-1.19
Challenge	-0.37	0.44	-0.01	0.52	1.19
Hope	-0.50	0.15	0.46	0.31	-0.18
Fear	0.44	-0.17	0.73	0.03	0.63
Interest	-1.05	-0.13	-0.07	0.70	-0.07
Contempt	0.89	-0.50	-0.12	-0.36	-0.07
Disgust	0.38	-0.50	-0.39	-0.96	0.06
Frustration	0.88	-0.37	-0.08	0.60	0.48
Surprise	-1.35	-0.94	0.73	0.40	-0.66
Pride	-1.25	0.81	-0.32	0.02	-0.31
Shame	0.73	1.31	0.21	-0.11	0.07
Guilt	0.60	1.31	-0.15	-0.36	0.00
					-0.29

Note. Scores are standardized.

^a Pleasantness: high scores indicate increased unpleasantness.

^b Responsibility/Control: high scores indicate increased self-responsibility/control.

^c Certainty: high scores indicate increased uncertainty.

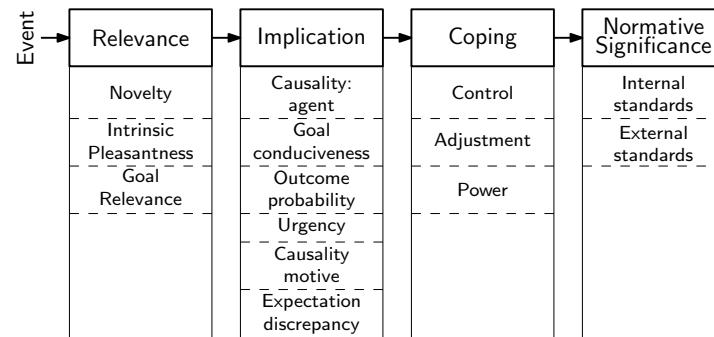
^d Attentional activity: high scores indicate increased attentional activity.

^e Effort: high scores indicate increased anticipated effort.

^f Situational control: high scores indicate increased situational control.

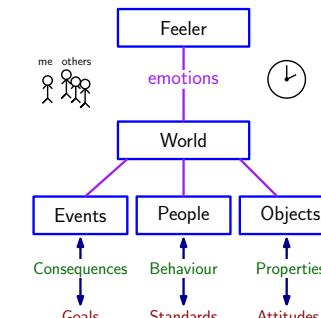
Sequence of appraisal criteria (Scherer 2005/2013)

Scherer: Emotions are evaluated in a sequential manner.



OCC Model of Emotions

Ortony, Clore, Collings (1988):
The Cognitive Structure of Emotions.



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Example 1

I am happy to be here!

Circumplex model (Russell):

Valence? high low

Arousal? high low

Appraisals (Smith/Ellsworth):

Pleasantness? high low

Responsible? high low

Certain? high low

Attention? high low

Effort? high low

Control? high low

Emotion Wheel (Plutchik):

- Protection/Fear
- Destruction/Anger
- Reproduction/Joy
- Deprivation/Sadness
- Incorporation/Acceptance
- Rejection/Disgust
- Exploration/Anticipation
- Orientation/Surprise

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Example 2

I needed to walk alone through the dark forest and heard a loud noise behind me.

Circumplex model (Russell):

Valence? high low

Arousal? high low

Appraisals (Smith/Ellsworth):

Pleasantness? high low

Responsible? high low

Certain? high low

Attention? high low

Effort? high low

Control? high low

Emotion Wheel (Plutchik):

- Protection/Fear
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- Exploration/Anticipation
- Orientation/Surprise

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Task Definition for Emotion Classification and Regression

Input

- Text
- Variables respres. emotion model
- Perspective

Arousal, Valence, Emotion Category, Intensity
Reader, Writer, Text, mentioned entity

Output (by human or machine)

- Discrete values
- Ordinal values
- Continous values

emotion categories
intensities or appraisals
intensities, valence/arousal/dominance

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Annotation Perspective and Reliability

Example: “I thought that Wayan might beat Putu.”

- Writer: **fear** (pretty obvious case, but still, we don't know what the person really felt)
- Reader: **fear?** (depends on context)

Factors that influence decision

- | | |
|-------------------|---------------------------------------------|
| • World knowledge | (to be beaten is something to be afraid of) |
| • Context | (Speaker is friend of Putu.) |
| • Personality | (Speaker might be neurotic.) |
| • Demographics | (Might influence world knowledge.) |

Annotation Setup: Trained Experts or Crowdsourcing?

Trained Experts:

- Might be preferable if variables follow challenging concepts

Crowdsourcing:

- If the study is more of an experiment to study subjective perceptions
- “What emotion do you feel when reading the text?”
- “What would an average reader feel”? (Buechel, 2017)

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It really depends on the task and domain.

Hypothetical setting:

Given news articles, what is the emotional impact on the reader?

“If we continue to fly to conferences around the globe our children will not have anything to eat anymore because of global warming.”

- Person who does believe global warming is not caused by humans: **anger**
- Average member of the society: **fear**
- Some NLP researcher: **sadness**

⇒ We can probably never access all relevant information.

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Emotion Recognition Reliability: Ekman 1972

Experimental Setup

- Photos were taken of people expressing a particular emotion and asked which emotion they feel
- Japanese and US American people were shown these photos and tasked to recover the emotion
- Goal: understand emotion recognition reliability

Results (🇯🇵/🇺🇸)

- .79/.86 acc. between observers
- .57/.62 acc. between subject and observer (.50 baseline)

⇒ Interpretation of emotion might differ from actual emotion.

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Take-Away

Emotions...

- ...are quite well understood in psychology
- ...can be represented via affect, appraisal, or categorical names
- ...cannot be reliably annotated, because of potentially missing relevant information
- ...are just hard to recognize

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Factors for emotion recognition reliability (Döllinger, 2021)

Follow-up studies investigated factors for recognition reliability:

- Emotion category**
 - Some emotions are easier to recognize than others (joy vs. fear: Mancini 2018)
- Peer status**
 - Friends are better in recognizing their emotions (Wang 2019)
- Status of observer**
 - People with depression are more challenged in recognizing emotions (Dalili 2015)
 - Personality traits: conscientious and open people are better to recognize emotions, shy and neurotic people are worse (Hall 2016)
- Does that affect our annotation study design?**
⇒ We might be able to prescreen annotators (though I have never seen any study doing that in NLP)

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Questions?

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About this tutorial

Session 1 (09:00–10:30)

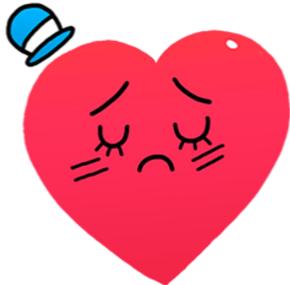
- Introduction
- Psychological Models
- Use Cases/Social Impact
- Resources
- Annotation Exercise

Break (10:30–11:15)

Session 2 (11:15–12:45)

- Non-Neural Methods
- Multi-task, transfer, zero-shot methods
- Open Challenges
- Appraisal Theories
- Role Labeling
- Ethical Considerations
- Closing

USE CASES



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Emotion Analysis in Text

EACL 2023 Tutorial – 05.05.2023

USE CASES

- Social media and public opinion analysis
- Literary studies
- Hate speech detection
- Empathetic chatbots and virtual agents
- Early depression detection
- Suicide prevention

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2

SOCIAL MEDIA AND PUBLIC OPINION ANALYSIS

SOCIAL MEDIA AND PUBLIC OPINION ANALYSIS: Loureiro and Alló, 2020

- Methodology:
 - Twitter messages about climate change analyzed using EmoLex (Mohammad and Turney, 2013)
 - Data collection: 01.01.2019-30.06.2019 (six months)
- Findings:
 - Messages in the UK less negative than in Spain
 - The most evoked feeling is **anticipation** in the UK and **fear** in Spain
 - Similar views about preferences for energy policies: renewable sources are perceived positively, coal negatively, and nuclear energy is associated with heterogeneous perceptions



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Use Cases

SOCIAL MEDIA AND PUBLIC OPINION ANALYSIS: Srinivasan et al., 2019

- Methodology:**
 - Twitter messages mentioning Hillary Clinton or Donald Trump analyzed using EmoLex (Mohammad and Turney, 2013)
 - Data collection: 26.09.2016 – 6.11.2016 (six weeks)
- Findings:**
 - 90% accuracy for swing directions for 17 out of 19 states
 - Better accuracy than from 9 different pollsters (79% accuracy; correctly predicted swing directions for 15 out of 19 states)
 - Swing in the emotions aligned with various political events

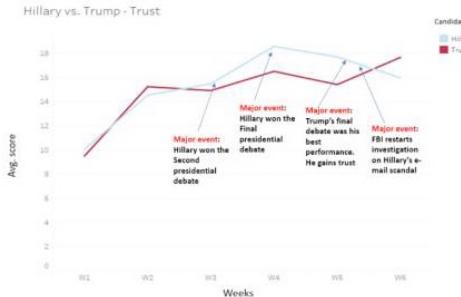


Figure taken from (Srinivasan et al., 2019)

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LITERARY STUDIES

SOCIAL MEDIA AND PUBLIC OPINION ANALYSIS: Wang et al., 2023

- Methodology:**
 - Twitter posts of top executives in S&P 1500 firms analyzed using DeepEmotionNet (Wang et al., 2023)
- Findings:**
 - Fear and anger in Twitter posts by top executives are significantly associated with corporate financial performance



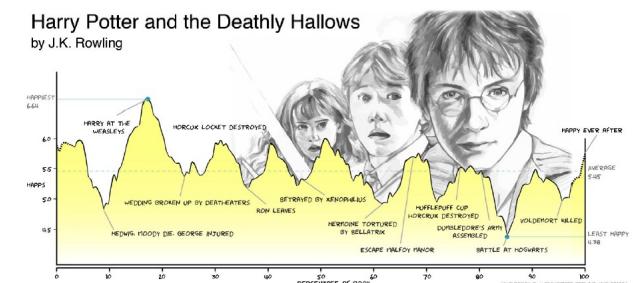
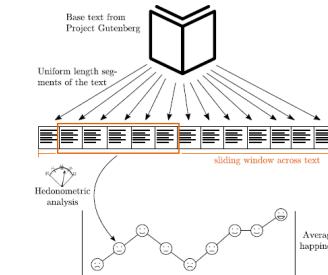
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LITERARY STUDIES: Reagan et al., 2016

"Our ability to communicate relies in part upon a shared emotional experience, with stories often following distinct emotional trajectories and forming patterns that are meaningful to us."

(Reagan et al., 2016)



Figures taken from (Reagan et al., 2016)

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Use Cases

LITERARY STUDIES: Reagan et al., 2016

- Data and emotion detection:
 - 1327 books from Project Gutenberg (mostly fictional)
 - Happiness using [Hedonometer](#) (Dodds et al., 2011)

- 6 most common emotional arcs:
 - 'Rags to riches' (rise)
 - 'Tragedy', or 'Riches to rags' (fall)
 - 'Man in a hole' (fall-rise)
 - 'Icarus' (rise-fall)
 - 'Cinderella' (rise-fall-rise)
 - 'Oedipus' (fall-rise-fall)

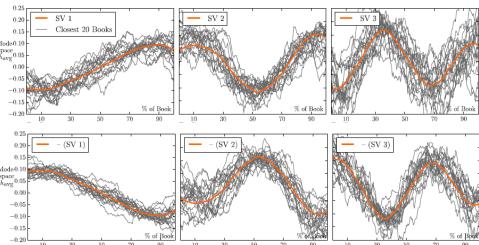


Figure adapted from (Reagan et al., 2016)

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LITERARY STUDIES: Kim et al., 2017

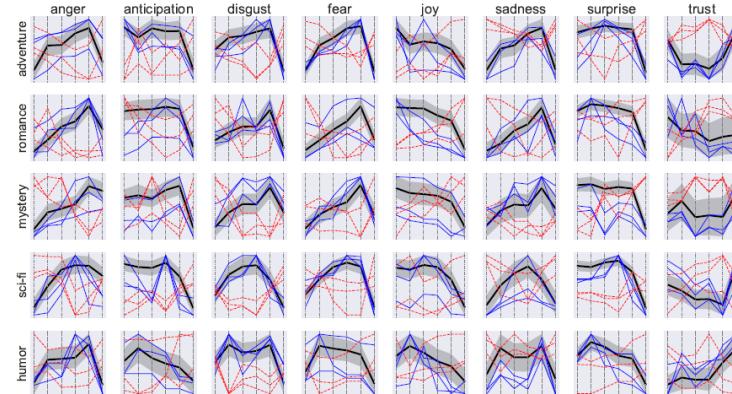


Figure taken from (Kim et al., 2017)

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LITERARY STUDIES: Kim et al., 2017

- Genre classification feature sets
 - EmoLex ([Mohammad and Turney, 2013](#))
 - Bag of Words (BoW)
 - Emotion arcs
 - Ensemble

Genre	Count
adventure	569
humor	202
mystery	379
romance	327
science fiction	542
Σ	2019

Table taken from (Kim et al., 2017)

- Results:
 - Use of EmoLex outperforms the use of BoW (81% vs. 80% for micro average F1-score)
 - Use of emotion arcs instead of lexical features leads to worse classification results
 - Ensemble model performs significantly better than the best single model (84% vs. 81% for micro average F1-score)

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HATE SPEECH DETECTION

HATE SPEECH DETECTION

“Any strongly impolite, rude or hurtful language using profanity, that can show a debasement of someone or something, or show intense emotion”

Fortuna and Nunes (2018)

Some of the studies that use emotion analysis in hate speech detection:

- “Hate speech classification in social media using emotional analysis” (Martins et al., 2018)
- “Automatic Detection of Hate Speech on Facebook Using Sentiment and Emotion Analysis” (Rodriguez & Argueta, 2019)



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EMPATHETIC DIALOGUES

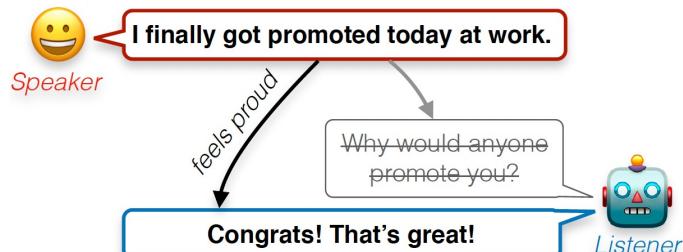


Figure taken from (Rashkin et al., 2019)

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EMPATHETIC CHATBOTS AND VIRTUAL AGENTS

EMPATHETIC DIALOGUES DATASET: Rashkin et al., 2019

Label: Afraid

Situation: Speaker felt this when...

“I've been hearing noises around the house at night”

Conversation:

Speaker: I've been hearing some strange noises around the house at night.

Listener: oh no! That's scary! What do you think it is?

Speaker: I don't know, that's what's making me anxious.

Listener: I'm sorry to hear that. I wish I could help you figure it out

Label: Proud

Situation: Speaker felt this when...

“I finally got that promotion at work! I have tried so hard for so long to get it!”

Conversation:

Speaker: I finally got promoted today at work!

Listener: Congrats! That's great!

Speaker: Thank you! I've been trying to get it for a while now!

Listener: That is quite an accomplishment and you should be proud!

Figure taken from (Rashkin et al., 2019)

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EARLY DEPRESSION DETECTION

DEPRESSION DETECTION: Islam et al., 2018

- Methodology:
 - Facebook posts analyzed for depression using LIWC software
 - Classification experiments with various ML algorithms
 - 4 feature sets: [emotional processes \(positive emotion words, negative emotion words, sadness words, anger words, anxiety words\)](#), linguistic style, temporal processes, and the combination of all
- Findings:
 - Up to 73% F-measure for binary classification (depression yes or no)
- Drawbacks:
 - Ground truth?
 - Who is depressed?



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DEPRESSION DETECTION: Shanti et al., 2022

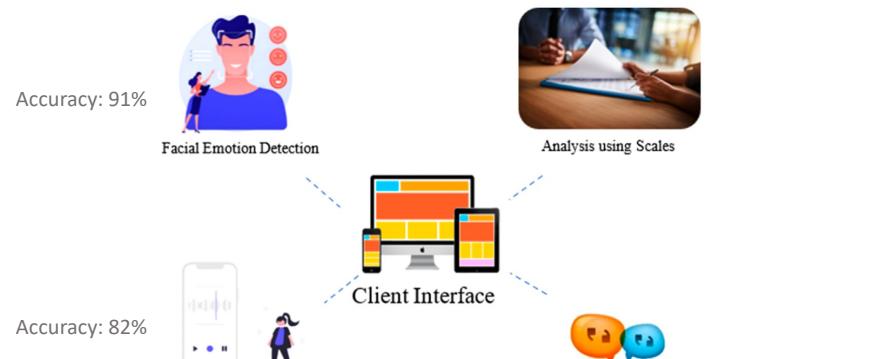


Figure taken from (Shanti et al., 2022)

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SUICIDE PREVENTION

Use Cases

EMOTION ANALYSIS OF SUICIDE NOTES: Shared Task

- Shared task in 2011 (Pestian et al., 2012)
- Ground truth (annotation):
 - Annotators were asked to identify abuse, anger, blame, fear, guilt, hopelessness, sorrow, forgiveness, happiness, peacefulness, hopefulness, love, pride, thankfulness, instructions, and information
 - Annotators were survivors of suicide loss, active in suicide communities

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EMOTION ANALYSIS OF SUICIDE NOTES: Desmet and Hoste, 2013

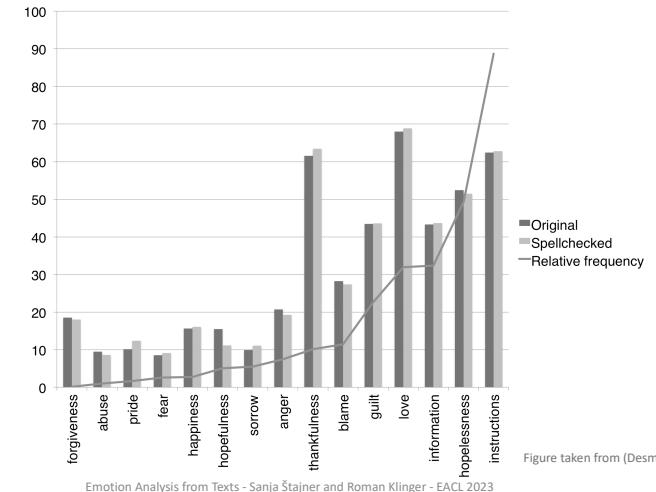


Figure taken from (Desmet and Hoste, 2013)

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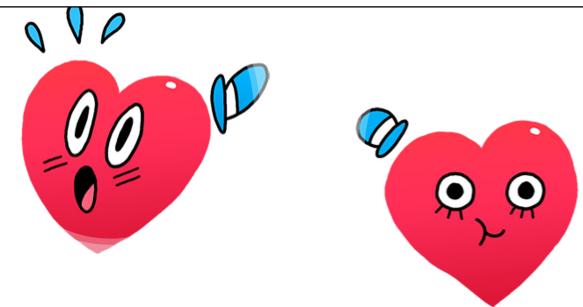
Questions?



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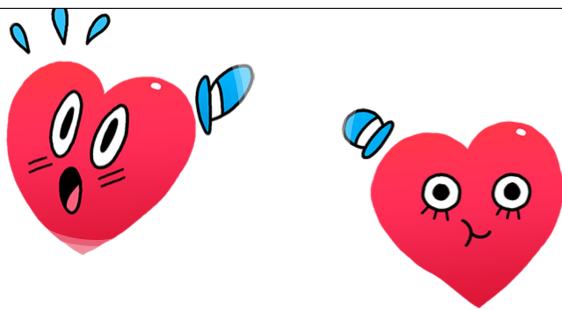
USE CASES



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RESOURCES



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ANNOTATION OPTIONS

- Automatic or human
- Number of annotators per instance
- Total number of annotators
- Expertise of the annotators
- Ground truth assignment
- Set of emotions
- Labelling type (single or multi)
- Perspective (reader, writer, text)
- Genre and context length

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RESOURCES

- Emotion detection and classification resources
- Emotion intensity resources
- Other resources

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AUTOMATIC ANNOTATION

- Wang et al. (2012): 131 emotion hashtags as keywords (hashtag at the end of tweet) for collecting **5 million tweets** in seven emotion categories (**joy, sadness, anger, love, thankfulness, surprise**).
- Shahraki and Zaïane (2017): based on 15 explicit hashtags appearing in them compiled **Clean Balanced Emotional Dataset (CBET)** with **27,000 annotated tweets** (3,000 per each emotion: **anger, fear, joy, love, sadness, surprise, thankfulness, disgust, and guilt**)
- Mohammad (2012): **21,051 tweets** which contained one of the six **Ekman's emotions** (**anger, disgust, fear, joy, sadness, surprise**) as the last hashtag

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Resources

VARIATIONS IN HUMAN ANNOTATION: Štajner, 2021

Study	#annotators Per instance	#annotators Total	Gold	#emotions	Labelling	Perspective	Genre
(Demszky et al., 2020)	3 or 5	82	> 1 annotator	27+1	multi	writer	Reddit
(Bostan et al., 2020)	5	310	> 1 annotator	15+1	single	text	Headlines
(Öhman et al., 2020)	≤3	108	> 1 annotator	8+1	multi	speaker	Subtitles
(Poria et al., 2019)	5	?	majority	6+1	single	speaker	Dialog
(Hsu et al., 2018)	5	?	majority*	6+1	single	speaker	Dialog
(Schuff et al., 2017)	3–6	6	various	8	multi	?	Twitter
(Mohammad et al., 2015)	3+	≈ 3000	> half	19+1	single	text	Twitter
(Brynielsson et al., 2014)	3	3	majority	3+1	single	writer	Twitter
(Neviarouskaya et al., 2010)	3	3	≥2 agree	14	single	?	Various
(Neviarouskaya et al., 2009)	3	3	≥2 agree	9+1	single	?	Blogs
(Strapparava and Mihalcea, 2007)	6	6	?	6	multi	reader	Headlines
(Aman and Szpakowicz, 2007)	2	4	both agree	6+2	single	text	Blogs
(Alm et al., 2005)	2-3	3	majority	6+1	single	text	Children

Table 1: Annotation procedures used in previous studies (“?” signifies that the particular aspect was not specified in the paper. “+1” in the #emotions column signifies the additional class for “other” or “no emotion”).

Table taken from (Štajner, 2021)

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EMOTIONS IN BLOGS: Aman and Szpakowicz, 2007

- **Genre:** blogs (selected by using seeds!)
- **Span:** sentence
- **Size:** 1466 emotional + 2800 no emotion
- **Emotions:** extended Ekman’s (added mixed emotion and no emotion)
- **Intensity:** low, medium, and high
- **Perspective:** writer’s
- **Labelling:** single
- **Annotators:** 2 per sentence (4 in total)
- **Gold:** both agree

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EMOTIONS IN CHILDREN STORIES: Alm et al., 2005

- **Genre:** children stories (22 Grimms’ tales)
- **Span:** sentence
- **Size:** 1580 sentences
- **Emotions:** extended Ekman’s (added neutral and split surprise into positive and negative)
- **Perspective:** text’s (the feeler in the sentence)
- **Labelling:** single
- **Annotators:** 2
- **Gold:** both agree

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EMOTIONS IN BLOGS: Neviarouskaya et al., 2009

- **Genre:** diary-like blog posts (BuzzMetrics)
- **Span:** sentence
- **Size:** 700 sentences
- **Emotions:** subset of emotional states defined by Izard (interest, joy, surprise, anger, disgust, fear, guilt, sadness, shame)
- **Intensity:** [0.0, 1.0]
- **Perspective:** ?
- **Labelling:** single
- **Annotators:** 3
- **Gold:** at least 2 agree (656 sentences)

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Resources

<h3>EMOTIONS IN NEWS HEADLINES: Strapparava and Mihalcea, 2007</h3>	<h3>EMOTIONS IN ELECTORAL TWEETS: Mohammad et al., 2015</h3>
<ul style="list-style-type: none">• Genre: news headlines• Span: headline• Size: 1250 headlines• Emotions: Ekman's (anger, disgust, fear, joy, sadness, surprise)• Intensity: [0,100]• Perspective: reader's• Labelling: multiple• Annotators: 6• Gold: ? <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p>	<p>SemEval-2007 Task 14: Affective Text</p> <ul style="list-style-type: none">• Genre: electoral tweets• Span: tweet• Size: 2,000 tweets• Emotions: Plutchik (19->8)• Intensity: low, medium, high• Perspective: various• Labelling: single• Annotators: ~ 30,000 crowdsourced (AMT and CrowdFlower), at least 5 per each• Gold: belongs to category X if it was annotated with X more times than with all others combined <p>Q1. Which of the following best describes the Emotions in this tweet?</p> <ul style="list-style-type: none">• This tweet expresses or suggests an emotional attitude or response to something.• This tweet expresses or suggests two or more contrasting emotional attitudes or responses.• This tweet has no emotional content.• There is some emotion here, but the tweet does not give enough context to determine which emotion it is.• It is not possible to decide which of the above options is appropriate. <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p>
<h3>EMOTIONS IN TWEETS: Schuff et al., 2017</h3>	<h3>EMOTIONS IN CONVERSATIONS: Hsu et al., 2018</h3>
<p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p>	<p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p>

EMOTIONS IN CONVERSATIONS: Hsu et al., 2018

- **Genre:** multi-party conversations (Friends TV scripts and FB personal dialogues)
- **Span:** utterance
- **Size:** 29,245 utterances (2,000 dialogues)

	# of Utterances	Utterance Length	Emotion Label Distribution (%)									kappa (%)
			Neu	Joy	Sad	Fea	Ang	Sur	Dis	Non		
Friends	14,503	10.67	45.03	11.79	3.43	1.70	5.23	11.43	2.28	19.11	33.83	
EmotionPush	14,742	6.84	66.85	14.25	3.49	0.28	0.95	3.85	0.72	9.62	33.64	

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EMOTIONS IN SUBTITLES: Öhman et al., 2020

- **Genre:** movie subtitles from OPUS (Lison and Tiedemann, 2016)
- **Languages:** Finnish and English (human annotation) + 30 others (projections)
- **Span:** subtitle (roughly 1 sentence)
- **Size:** 25,000 sentences (Finnish) + 30,000 sentences (English)
- **Emotions:** Plutchik (8) + neutral
- **Perspective:** speaker
- **Labelling:** single
- **Annotators:** 60-100 students (2-3 per instance)
- **Gold:** at least 2 agreed

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EMPATHETIC DIALOGUES DATASET: Rashkin et al., 2019

- Approximately 25000 dialogues grounded in situations prompted by specific emotion labels (32 different emotion labels)

Label: Afraid
Situation: Speaker felt this when...
 "I've been hearing noises around the house at night"
Conversation:
Speaker: I've been hearing some strange noises around the house at night.
Listener: oh no! That's scary! What do you think it is?
Speaker: I don't know, that's what's making me anxious.
Listener: I'm sorry to hear that. I wish I could help you figure it out

Label: Proud
Situation: Speaker felt this when...
 "I finally got that promotion at work! I have tried so hard for so long to get it!"
Conversation:
Speaker: I finally got promoted today at work!
Listener: Congrats! That's great!
Speaker: Thank you! I've been trying to get it for a while now!
Listener: That is quite an accomplishment and you should be proud!

Figure taken from (Rashkin et al., 2019)

OTHER RESOURCES

Resources

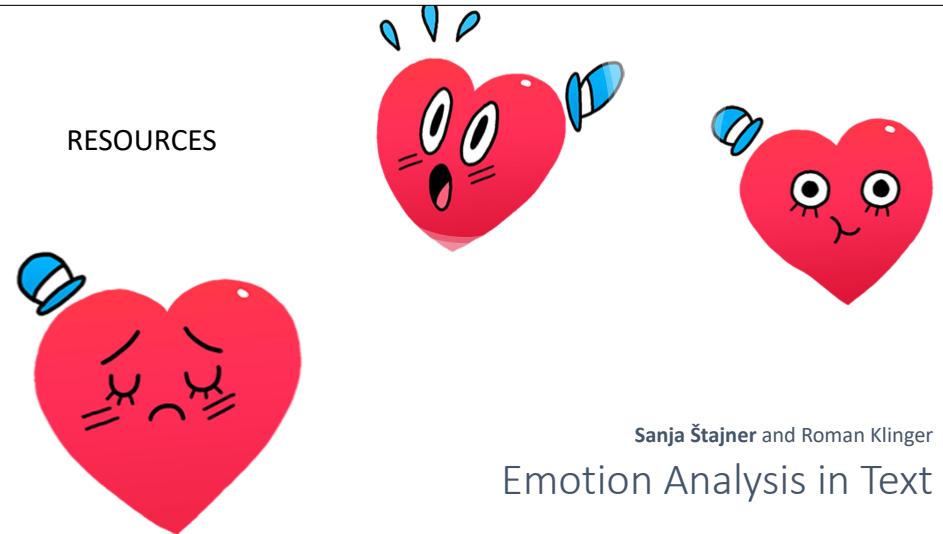
Questions?



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RESOURCES



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Emotion Analysis

Small Annotation Exercise and Discussion

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Hand On Annotation

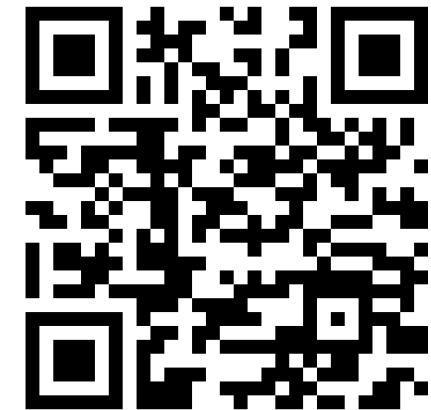
What we will do now:

- You heard now a bit about existing resources.
- Let's do an annotation together.
- For each instance that we show you, answer the questions in the form.

Think about the following questions:

- Would annotators agree on the label?
- Would an automatic method succeed/fail?

Link: <https://forms.gle/9pwPXnCCB8K1ocrg7>



Questions

- Did you miss annotation labels?
- Would you have preferred to annotate multiple emotions?
- Would you prefer a neutral label?
- What are properties of instances that you assume would never be correctly predicted by machines?

About this tutorial

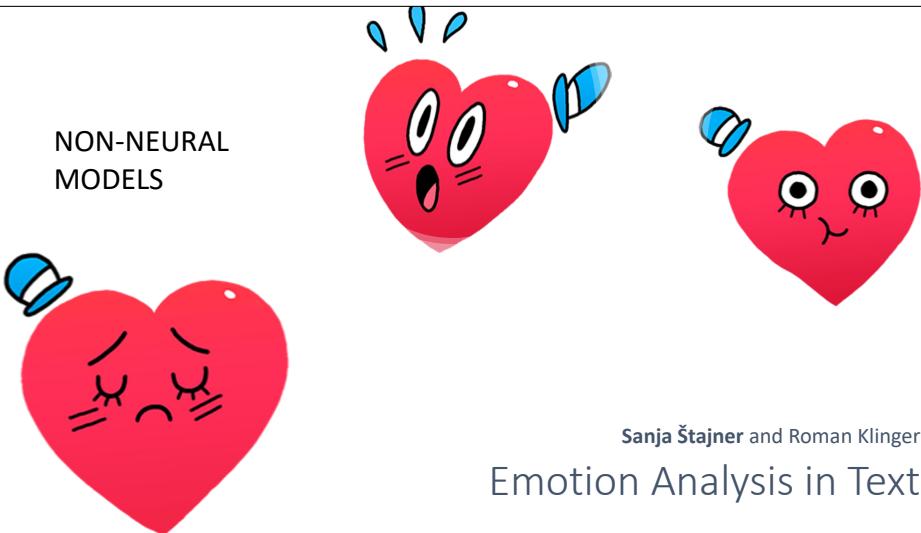
Session 1 (09:00–10:30)

- Introduction
- Psychological Models
- Use Cases/Social Impact
- Resources
- Annotation Exercise

Break (10:30–11:15)

Session 2 (11:15–12:45)

- Non-Neural Methods
- Multi-task, transfer, zero-shot methods
- Open Challenges
- Appraisal Theories
- Role Labeling
- Ethical Considerations
- Closing



NON-NEURAL MODELS

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EMOTIONS IN CHILDREN STORIES: Alm et al., 2005

- **Genre:** children stories (22 Grimms' tales)
- **Task:** Emotional vs. non-emotional
- rule-based linear classifier (SNoW)
- 10-fold cross-validation (90% training, 10% testing)

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NON-NEURAL MODELS

EMOTIONS IN CHILDREN STORIES: Alm et al., 2005

- **Features:**
 - First sentence in the story
 - Conjunctions of selected features
 - Direct speech
 - Thematic story type
 - Special punctuation
 - Complete upper-case word
 - Sentence length in words
 - Ranges of story progress
 - Percent of JJ, N, V, RB
 - V counts in sentence, excluding participles
 - Positive and negative word count
 - WordNet emotion Words

	same-tune-eval	sep-tune-eval
P(Neutral)	59.94	60.05
Content BOW	61.01	58.30
All features except BOW	64.68	63.45
All features	68.99	63.31
All features + sequencing	69.37	62.94

Accuracy

Figure taken from (Alm et al., 2005)

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EMOTIONS IN BLOGS: Aman and Szpakowicz, 2007

- **Genre:** blogs (selected by using seeds!)
- **Span:** sentence
- **Size:** 1466 emotional + 2800 no emotion
- **Task:** Emotional vs. non-emotional
- For feature extraction used emotional dictionaries:
 - General Inquirer (Stone et al., 1966)
 - WordNet-Affect (Strapparava and Valitutti, 2004)

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EMOTIONS IN BLOGS: Aman and Szpakowicz, 2007

GI Features	WN-Affect Features	Other Features
Emotion words	Happiness words	Emoticons
Positive words	Sadness words	Exclamation ("!") and question ("?") marks
Negative words	Anger words	
Interjection words	Disgust words	
Pleasure words	Surprise words	
Pain words	Fear words	

Features	Naïve Bayes	SVM
GI	71.45%	71.33%
WN-Affect	70.16%	70.58%
GI+WN-Affect	71.7%	73.89%
ALL	72.08%	73.89%

Accuracy

Figures taken from (Aman and Szpakowicz, 2007)

EMOTIONS IN ELECTORAL TWEETS: Mohammad et al., 2015

- **Genre:** electoral tweets
- **Emotions:** Plutchik (8)
- 10-fold stratified cross-validation
- SVM with linear kernel (also tried logistic regression and different SVM kernels)

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EMOTIONS IN ELECTORAL TWEETS: Mohammad et al., 2015

- **Features:**
 - word unigrams and bigrams
 - Punctuations
 - Elongated words
 - Emotions
 - Emotion lexicons
 - Negations
 - Position features
 - Combined features

	Accuracy
random baseline	30.26
majority baseline	47.75
automatic SVM system	56.84
human performance	69.80

Figure taken from (Mohammad et al., 2015)

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EMOTIONS IN SUBTITLES: Öhman et al., 2020

- Features:

- Word unigrams, bigrams, trigram

SVM per class f1	emotion
0.8073	anger
0.8296	anticipation
0.8832	disgust
0.8763	fear
0.8819	joy
0.8762	sadness
0.8430	surprise
0.8832	trust

Figure taken from (Öhman et al., 2020)

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NON-NEURAL VS. NEURAL: Öhman et al., 2020

data	f1	accuracy
English without NER, BERT	0.530	0.538
English with NER, BERT	0.536	0.544
English NER with neutral, BERT	0.467	0.529
English NER binary with surprise, BERT	0.679	0.765
English NER true binary, BERT	0.838	0.840
Finnish anno., FinBERT	0.507	0.513
English NER, one-vs-rest SVM (LinearSVC) ⁷	0.746	

Figure taken from (Öhman et al., 2020)

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NON-NEURAL VS. NEURAL: Öhman et al., 2020

Dataset	Language-specific BERT	SVM
Finnish projected	0.4461	0.5859
Turkish projected	0.4685	0.6080
Arabic projected	0.4627	0.5729
German projected	0.5084	0.6059
Dutch projected	0.5155	0.6140
Chinese projected	0.4729	0.5044

Data taken from (Öhman et al., 2020)

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NON-NEURAL VS. NEURAL: Schuff et al., 2017

Bag-of-words	Linear			Neural											
	MAXENT			SVM			LSTM			Bi-LSTM			CNN		
Emotion	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Anger	76	72	74	76	69	72	76	77	76	77	77	77	77	77	77
Anticipation	72	61	66	70	60	64	68	68	67	70	66	68	68	60	64
Disgust	62	47	54	59	53	56	64	68	65	61	64	63	62	61	62
Fear	57	31	40	55	40	46	51	48	49	58	43	49	53	46	49
Joy	55	50	52	52	52	52	56	41	46	54	59	56	54	56	55
Sadness	65	65	65	64	60	62	60	77	67	62	72	67	63	72	67
Surprise	62	15	24	46	22	30	40	17	21	42	20	27	36	24	28
Trust	62	38	47	57	45	50	57	49	51	59	44	50	53	49	50
Micro-Avg.	66	52	58	63	53	58	62	60	61	64	60	62	62	59	60

Figure adapted from (Schuff et al., 2017)

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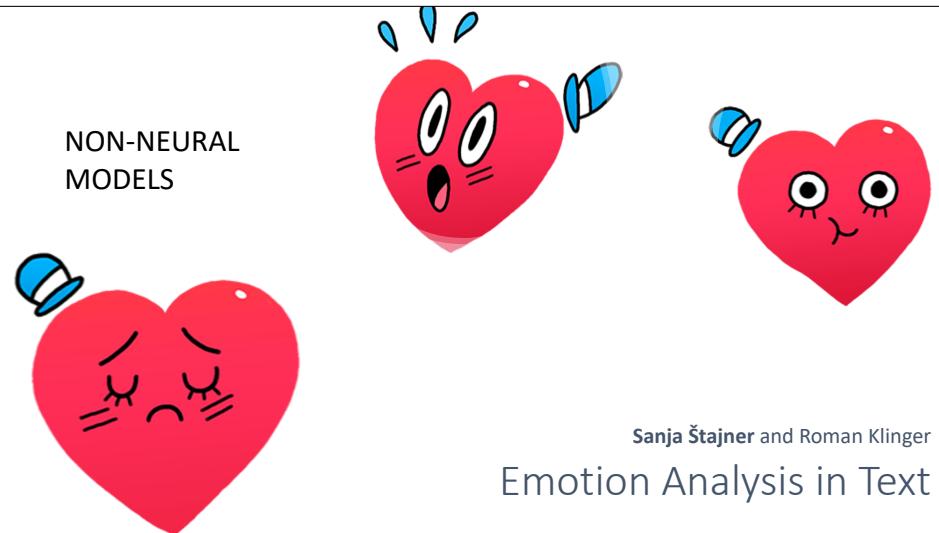
Questions?



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NON-NEURAL
MODELS



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Emotion Analysis

Transfer, Multi-Task Learning, Zero-Shot Predictions

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Outline

① Overview

② Weak and Distant Labeling

 • Obtaining Automatically Annotated Corpora
 • Transfer Learning

③ Multi-task learning

④ Zero-Shot Prediction

Outline

① Overview

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④ Zero-Shot Prediction

Overview
ooooo

Weak Labeling
ooooooo

Multi-task learning
ooooo

Zero-Shot Prediction
oooooooooooo

Emotion Analysis as Text Classification

Where are we?

- Emotion classification as text classification
- Meaningful features can be extracted for the task
- [What's happening in the deep learning world?](#)

Overview oo•oo	Weak Labeling oooooo	Multi-task learning oooo	Zero-Shot Prediction oooooooooooo
-------------------	-------------------------	-----------------------------	--------------------------------------

Shared Tasks on the Topic

- Affective Text (Headlines), 2007 (SemEval)
- Emotion Intensity, 2017 (WASSA), 2018 (SemEval)
- Emotion Classification (E-c) 2018 (SemEval)
- Implicit Emotions, 2018 (WASSA)
- More shared tasks at SemEval and WASSA

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Overview
oooo•

Weak Labeling
oooooo

Multi-task learning
oooo

Zero-Shot Prediction
oooooooooooo

Implicit Emotions Shared Task: Data and Task



- Input:
Tweet with emotion synonym replaced by unique string
- Output:
Emotion for which the removed word is a synonym

Example

sadness [USERNAME] can you send me a tweet? I'm [#TRIGGERWORD#] because I'm feeling invisible to you

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Overview oo•oo	Weak Labeling oooooo	Multi-task learning oooo	Zero-Shot Prediction oooooooooooo
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Emotion Classification E-c SemEval, Setting

Task Definition

Emotion Classification (E-c): Given a tweet, classify it as 'neutral or no emotion' or as one, or more, of eleven given emotions that best represent the mental state of the tweeter

- Annotation via crowdsourcing
- Aggregation:
Accept emotion label with at least 2/7 annotations

(Mohammad et al., SemEval 2018)

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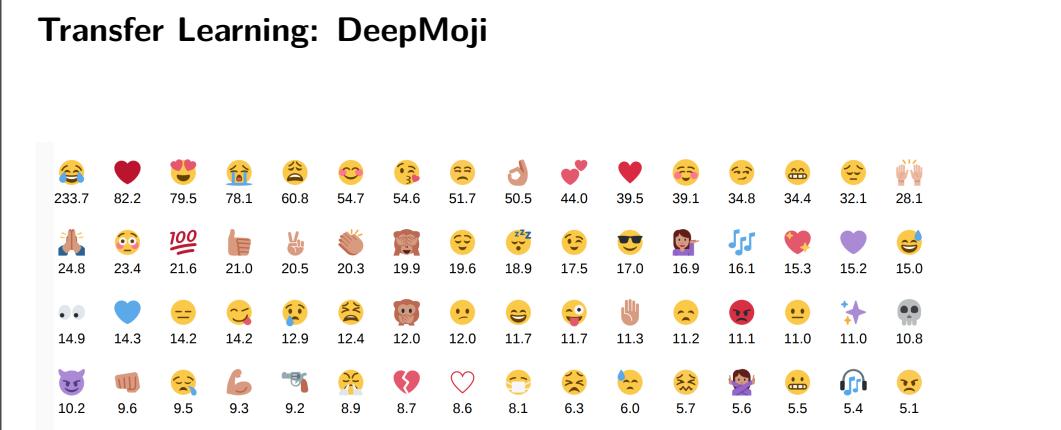
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Outline

- 1 Overview
- 2 Weak and Distant Labeling
 - Obtaining Automatically Annotated Corpora
 - Transfer Learning
- 3 Multi-task learning
- 4 Zero-Shot Prediction

Overview ooooo	Weak Labeling ○●○○○	Multi-task learning ooooo	Zero-Shot Prediction oooooooooooo
Weak/Self-Labeling			
Approach:			
<ul style="list-style-type: none"> Manually associate <ul style="list-style-type: none"> hashtags with emotions emojis with emotions Assume that occurrence of hashtag/emoji marks emotion Predict "self-labeled emotion" from text after removing hashtag/emoji Apply to other texts 			
Advantage:			
<ul style="list-style-type: none"> Easy to obtain huge data sets 			
Disadvantage:			
<ul style="list-style-type: none"> Concept of emotion ≠ emotion hashtags/emojis Example: 10.1109/SocialCom-PASSAT.2012.119 			

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Overview ooooo	Weak Labeling ○○○●○	Multi-task learning ooooo	Zero-Shot Prediction oooooooooooo



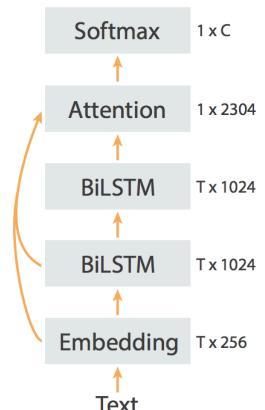
Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger	EACL 2023 Tutorial	11 / 31
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Outline

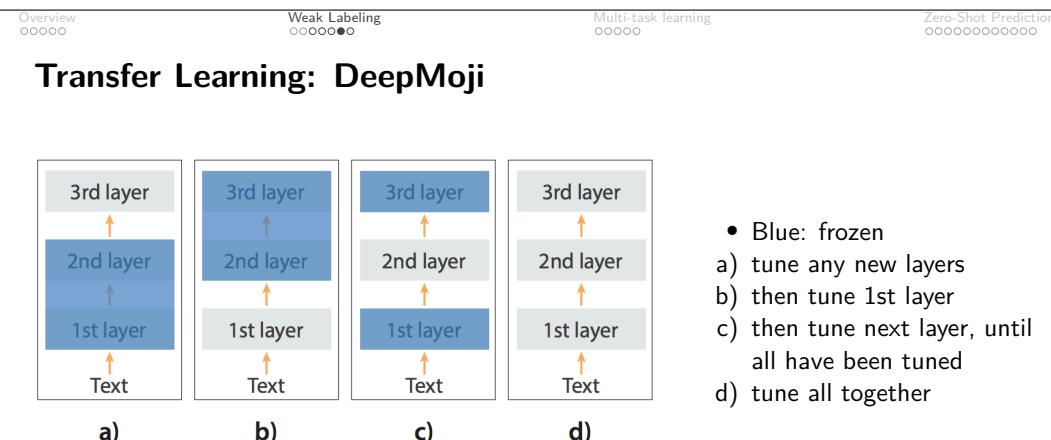
- 1 Overview
- 2 Weak and Distant Labeling
 - Obtaining Automatically Annotated Corpora
 - Transfer Learning
- 3 Multi-task learning
- 4 Zero-Shot Prediction

Transfer Learning: DeepMoji

- Develops a deep learning method for emotion classification (amongst other tasks)
- Pretrain model on huge data set to predict the occurrence of an emoji
- Fine-tune: Keep subset of parameters fixed while learning on actual data set.



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Bjarke Felbo, Alan Mislove, Anders Søgaard, Iyad Rahwan, Sune Lehmann: Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion and sarcasm. EMNLP 2017.

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Outline

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- 3 Multi-task learning
- 4 Zero-Shot Prediction



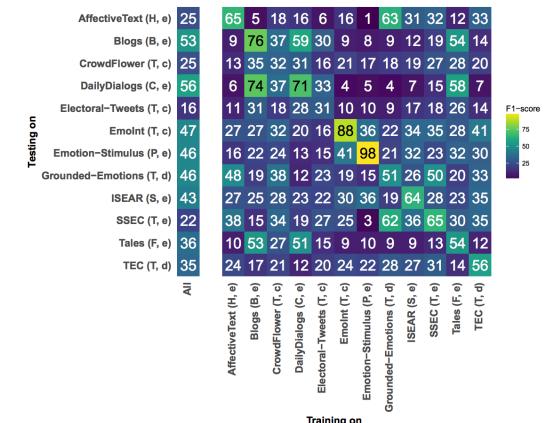
- Results differ a lot between data sets

- Data sets are pretty incomparable

Cross-corpus experiment

- Split corpora in train/val
- Train BOW-MaxEnt-L2 on all train parts, apply on all val parts
- Join all train parts, apply on each val part

(Bostan/Klinger, COLING 2018)



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Tasks in Multitask Learning and Emotions

- Akhtar et al, NAACL 2019: Multi-task Learning for Multi-modal Emotion Recognition and Sentiment Analysis
<https://www.aclweb.org/anthology/N19-1034.pdf>
- Chauhan et al, ACL 2020: Sentiment and Emotion help Sarcasm? A Multi-task Learning Framework for Multi-Modal Sarcasm, Sentiment and Emotion Analysis
<https://www.aclweb.org/anthology/2020.acl-main.401.pdf>
- Dankers et al, EMNLP 2019: Modelling the interplay of metaphor and emotion through multitask learning
<https://www.aclweb.org/anthology/D19-1227.pdf>

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Overview ooooo	Weak Labeling oooooooo	Multi-task learning oo●oo	Zero-Shot Prediction oooooooooooo
Tasks in Multitask Learning and Emotions			
<ul style="list-style-type: none"> Tafreshi et al, CoNLL 2018: Emotion Detection and Classification in a Multigenre Corpus with Joint Multi-Task Deep Learning https://www.aclweb.org/anthology/C18-1246.pdf Rajamanickam et al, ACL 2020: Joint Modelling of Emotion and Abusive Language Detection https://www.aclweb.org/anthology/2020.acl-main.394.pdf Saha et al, ACL 2020: Towards Emotion-aided Multi-modal Dialogue Act Classification https://www.aclweb.org/anthology/2020.acl-main.402.pdf Casel et al, KONVENS 2021: Emotion Recognition under Consideration of the Emotion Component Process Model. https://aclanthology.org/2021.konvens-1.5/ 			

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Overview ooooo	Weak Labeling oooooooo	Multi-task learning oooo●	Zero-Shot Prediction oooooooooooo

Questions?

Overview ooooo	Weak Labeling oooooooo	Multi-task learning oo●oo	Zero-Shot Prediction oooooooooooo
Summary			
<ul style="list-style-type: none"> Feature-based emotion analysis research came up with rich feature sets Deep learning, transfer learning commonly outperforms such approaches Current research is a lot about finding beneficial proxy tasks and to adapt input representations 			

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Overview ooooo	Weak Labeling oooooooo	Multi-task learning oooo●	Zero-Shot Prediction ●oooooooooooo

Zero-Shot Predictions

- “Zero-Shot” means: predict labels for instances that have some property that has not been seen during training.
- Most popular cases:
 - Cross-lingual Zero-Shot Transfer:** Learn on language A and apply model to language B. (example: use multi-lingual pretrained language models)
 - Zero-Shot Labeling:** Predict labels from a set that have not been seen during training
- Motivation:** No need to know the exact required emotion concepts at model development time.
- That is a realistic requirement. Deciding on the emotion set is hard.

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Overview ooooo	Weak Labeling oooooooo	Multi-task learning oooo●	Zero-Shot Prediction ●oooooooooooo

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Overview ooooo	Weak Labeling oooooooo	Multi-task learning oo●oo	Zero-Shot Prediction oooooooooooo

Overview ooooo Weak Labeling oooooo Multi-task learning ooooo Zero-Shot Prediction ooooooooooooooo

Why should Zero-Shot Learning be possible?

Training Data with labels: Deer, Fish, Rabbit



Test Data with unseen labels: Moose, Whale



Photos Attribution: Rabbit: David Iliff, Fish: Diego Delso, Deer: Frank Liebig, Whale: Whit Welles. Licenses: CC BY-SA 3.0. Moose: Public Domain

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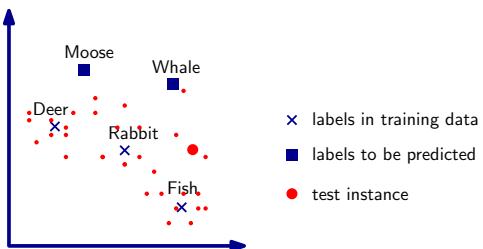
- How do we make these assignments?
- We decide on properties of the instances to classify.
- We compare the extracted properties to those of the classes.
- We need some **meaningful representation of each label**.
- We need some **meaningful representation of each instance**.

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Overview ooooo Weak Labeling oooooo Multi-task learning ooooo Zero-Shot Prediction ooooooooooooooo

ZSL as Embedding Prediction



- Label vectors based on concept features
- Learn to map instance into concept space

- In ZSL, we would assign "whale".
- In Generalized ZSL, we assign "fish".
- **Hubness problem:** It's more likely to predict vectors that have been seen at model development time.
- **Emotion analysis:** Where do we get the concept embeddings from?

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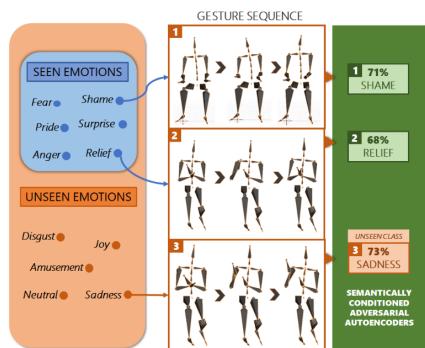
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Overview ooooo Weak Labeling oooooo Multi-task learning ooooo Zero-Shot Prediction ooooooooooooooo

Related: ZSL for Emotion Classification from Gestures



- Banerjee et al., AAAI 2022: "Learning Unseen Emotions from Gestures [...]"
 - Concept vectors: Word2Vec embeddings for emotion names
- Other ideas: Appraisal vectors, vectors learned end-to-end, ... (we experimented with that, but did not get any positive results in the generalized ZSL setting)

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Overview ooooo Weak Labeling oooooo Multi-task learning ooooo Zero-Shot Prediction ooooooooooooooo

Another approach to ZSL Emotion Classification

- Recent unpublished work: Chochlakis et al (Oct 2022): Using Emotion Embeddings to Transfer Knowledge between Emotions, Languages, and Annotation Formats. <https://arxiv.org/pdf/2211.00171.pdf>
- Idea: Provide set of emotions at inference time that are to be predicted
- Predefine emotions clusters, neural network predicts cluster embeddings
- Regularize such that similar emotions (according to prior knowledge) are close in parameter space

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Alternative: Zero-Shot Learning as Entailment

Benchmarking Zero-shot Text Classification: Datasets, Evaluation and Entailment Approach

Wenpeng Yin, Jamaal Hay, Dan Roth

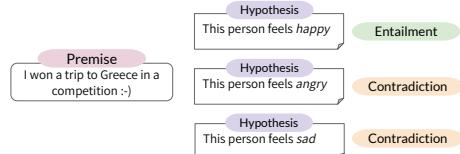
Cognitive Computation Group

Department of Computer and Information Science, University of Pennsylvania

{wenpeng, jamaalh, danroth}@seas.upenn.edu

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Emotion ZSL as Natural Language Inference



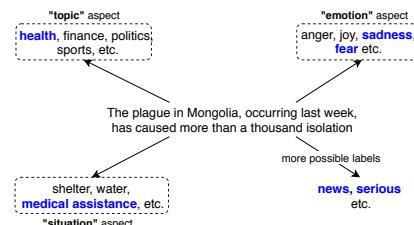
- Does it matter which NLI model we use as a backbone?
- How to represent the emotion?
- Should we use multiple emotion representations to increase coverage?

(Arco Del Plaza et al, COLING 2022)

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Overview ooooo	Weak Labeling ooooooo	Multi-task learning ooooo	Zero-Shot Prediction oooooooo•oooooo
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Zero-Shot Learning as Entailment (2)



- How to represent the label as a hypothesis?
- Yin et al. use "This text expresses [?]" and the WordNet concept definition.

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Overview ooooo	Weak Labeling ooooooo	Multi-task learning ooooo	Zero-Shot Prediction oooooooo•ooooo

Emotion Hypotheses

Emo-Name	angry	Emo-S	Same prefix + anger, annoyance, rage, outrage, fury, irritation
Expr-Emo	This text expresses anger	Expr.-S	
Feels-Emo	This person feels anger	Feels.-S	
WN-Def	This person expresses a strong emotion; a feeling that is oriented toward some real or supposed grievance	EmoLex	all emotion words from an NRC emotion lexicon

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Overview ooooo

Weak Labeling ooooooo

Multi-task learning ooooo

Zero-Shot Prediction ooooooooo●oo

The role of the prompt design

Dataset	Emo-Name	Emo-S	Expr-Emo	Expr-S	Feels-Emo	Feels-S	WN-Def
TEC	~0.42	~0.45	~0.40	~0.40	~0.38	~0.38	~0.30
Blogs	~0.32	~0.38	~0.40	~0.40	~0.38	~0.32	~0.28
ISEAR	~0.55	~0.58	~0.60	~0.60	~0.55	~0.55	~0.48

(Supervised RoBERTa model:
TEC/Blogs: ≈.69, ISEAR: ≈.73)

Overview ooooo

Weak Labeling ooooooo

Multi-task learning ooooo

Zero-Shot Prediction ooooooooo●oo

Questions?

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Overview ooooo

Weak Labeling ooooooo

Multi-task learning ooooo

Zero-Shot Prediction ooooooooo●

About this tutorial

Session 1 (09:00–10:30)

- Introduction
- Psychological Models
- Use Cases/Social Impact
- Resources
- Annotation Exercise

Break (10:30–11:15)

Session 2 (11:15–12:45)

- Non-Neural Methods
- Multi-task, transfer, zero-shot methods
- Open Challenges
- Appraisal Theories
- Role Labeling
- Ethical Considerations
- Closing

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Overview ooooo

Weak Labeling ooooooo

Multi-task learning ooooo

Zero-Shot Prediction ooooooooo●



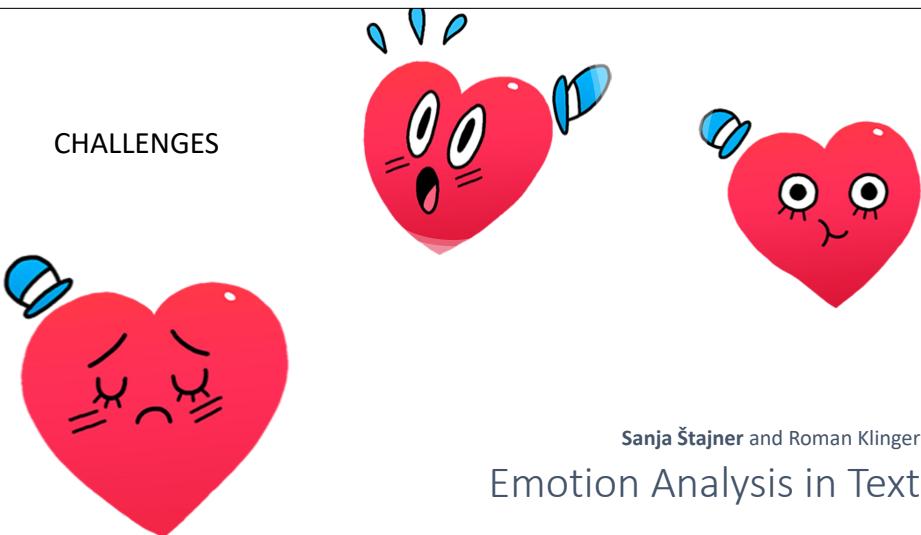
Emotion Analysis

Transfer, Multi-Task Learning, Zero-Shot Predictions

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Sanja Štajner and Roman Klinger



<p>CHALLENGES</p>  <p>Sanja Štajner and Roman Klinger Emotion Analysis in Text</p> <p>EACL 2023 Tutorial – 05.05.2023</p>	<h2>CHALLENGES</h2> <ul style="list-style-type: none">Annotation:<ul style="list-style-type: none">Natural difficulty of the taskMissing context/knowledgeLinguistic difficultyVarious emotions present in the instanceQuality of annotationsConsistency of annotationsComparison of different approaches (What is s.o.t.a. in emotion analysis?) <p>Emotion Analysis from Texts – Sanja Štajner and Roman Klinger – EACL 2023</p> <p>58</p>
<h2>ANNOTATION CHALLENGES: NATURAL DIFFICULTY</h2> <ul style="list-style-type: none">“2 pretty sisters are dancing with cancered kid” (fear+sadness, joy+sadness) (Schuff et al., 2017)“That moment when Canadians realised global warming doesn’t equal a tropical vacation” (anger+sadness; surprise) (Schuff et al., 2017)“Relatives here. Hafta sleep on a couch in the basement. #cantsleep #effuguiswantmyqueensize” (anger; sadness; neutral) (Štajner, 2021) <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>59</p>	<h2>ANNOTATION CHALLENGES: MISSING KNOWLEDGE</h2> <p>“At the dentist bright and early ” (joy; sadness; neutral) (Štajner, 2021)</p> <p>“Another evening, another cup of coffee” (joy; sadness; neutral) (Štajner, 2021)</p> <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>60</p>

ANNOTATION CHALLENGES: LINGUISTIC DIFFICULTY

NON-LITERAL MEANING

- “Global Warming! Global Warming! Global Warming! Oh wait, it’s summer.” ([joy](#)) (Schuff et al., 2017)
- “I love the smell of Hillary in the morning. It smells like Republican Victory” ([joy](#)) (Schuff et al., 2017)

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ANNOTATION CHALLENGES: VARIOUS EMOTIONS

- “No school, getting up at 8 for a seven hour car ride at least i have #noschool” ([joy; sadness](#)) (Štajner, 2021)
- “Finally done with work and have to be back in less than 12 hours” ([joy; sadness](#)) (Štajner, 2021)
- “ The movie click is old but one of my favs the ending when he dies makes me tear up” ([joy; sadness](#)) (Štajner, 2021)
- “ My team is starting to heat up you can’t contain us too long let the blowout begin ducks attack the duck” ([joy; anger; neutral](#)) (Štajner, 2021)

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ANNOTATION CHALLENGES: QUALITY OF ANNOTATIONS

- Oversight errors
- Dedication to the task

Example: “#BIBLE = Big Irrelevant Book of Lies and Exaggerations” ([trust](#)) (Schuff et al., 2017)

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ANNOTATION CHALLENGES: CONSISTENCY

- Emotional perception depends on annotators personality and mood (Alm et al., 2005)
- Inter-annotator agreements are very low:
 - $\kappa = 0.24 - 0.51$ (Alm et al., 2005)
 - $\kappa = 0.33 - 0.55$ (Štajner, 2021)

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Open Challenges

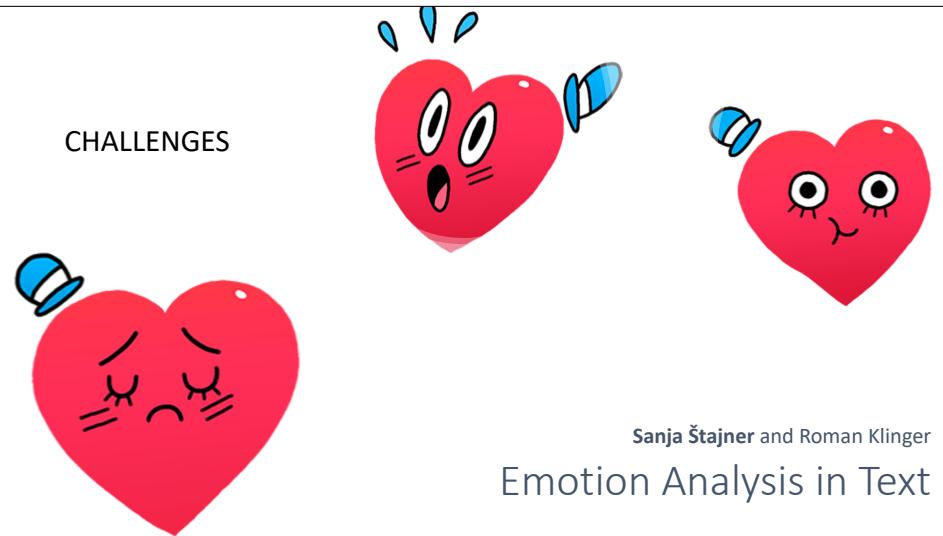
Questions?



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CHALLENGES



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Emotion Analysis in Text

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Emotion Analysis

Appraisal-based Resources and Methods

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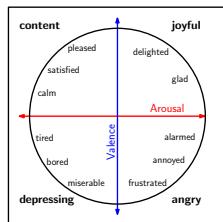
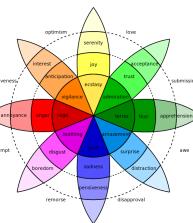
Recap
○○○

The OCC Model of Emotions
oooooooooooo

Scherer
ooooooo

Other Approaches
oooooo

Emotion Models



⇒ Methods mostly treat emotions as a label and learn the association to text properties, without considering (too much) knowledge from psychology about emotions

Outline

1 Recap

2 The OCC Model of Emotions

3 Appraisal Prediction following Scherer

4 Other Approaches

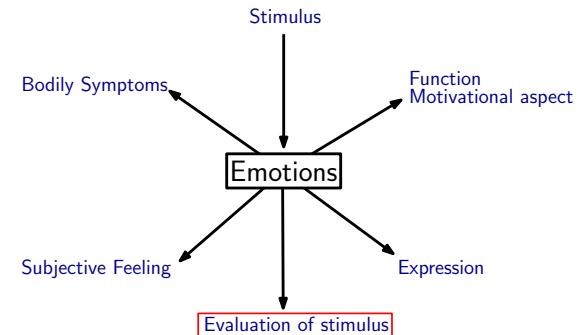
Recap
○○○

The OCC Model of Emotions
oooooooooooo

Scherer
ooooooo

Other Approaches
oooooo

Emotion Components



Appraisal-based Emotion Analysis

Recap ooo● The OCC Model of Emotions oooooooooo Scherer oooooo Other Approaches ooooo

Appraisal Models in Psychology: Smith/Ellsworth and Scherer

Locations of Emotion Means Along the PCA Components

Emotion	Component					
	Pleasant ^a	Responsibility/ Control ^b	Certain ^c	Attention ^d	Effort ^e	
Happiness	-1.46	0.09	-0.46	0.15	-0.33	-0.21
Sadness	0.87	-0.36	0.00	-0.21	-0.14	1.15
Anger	0.85	-0.94	-0.29	0.12	0.53	-0.06
Boredom	0.24	-0.19	-0.35	0.27	-1.19	0.12
Challenge	-0.37	0.44	-0.01	0.52	1.19	-0.20
Hope	-0.50	0.15	0.46	0.31	-0.18	0.35
Fear	0.44	-0.17	0.73	0.03	0.63	0.56
Interest	-1.05	-0.13	0.77	0.10	-0.07	0.41
Contempt	0.89	-0.50	-0.12	0.26	-0.07	-0.63
Disgust	0.38	-0.50	-0.39	-0.96	0.06	-0.19
Frustration	0.88	-0.37	-0.08	0.60	0.48	0.22
Surprise	-1.35	-0.94	0.73	0.40	-0.06	0.14
Pride	-1.25	0.81	0.23	0.02	-0.31	-0.46
Shame	0.73	1.31	0.21	-0.11	0.07	-0.07
Guilt	0.60	1.31	-0.15	-0.36	0.00	-0.29

Note. Scores are standardized.
^a Pleasantness: high scores indicate increased pleasantness.
^b Responsibility/Control: high scores indicate increased self-responsibility/control.
^c Certainty: high scores indicate increased certainty.
^d Attentional activity: high scores indicate increased attentional activity.
^e Effort: high scores indicate increased anticipated effort.
^f Situational control: high scores indicate increased situational control.

- How to use appraisals in computational modeling?

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Recap oooo The OCC Model of Emotions oooooooooo Scherer oooooo Other Approaches ooooo

THE COGNITIVE STRUCTURE OF EMOTIONS
ANDREW ORTONY
GERALD L. CLORE
ALLAN COLLINS

Published in final edited form as:
Emot Rev. 2013 October ; 5(4): 335–343. doi:10.1177/1754073913489751.

Psychological Construction in the OCC Model of Emotion

Gerald L. Clore and
Department of Psychology, University of Virginia, USA
Andrew Ortony
Department of Psychology, Northwestern University, USA

Abstract
This article presents six ideas about the construction of emotion: (a) Emotions are more readily distinguished by the situations they signify than by patterns of bodily responses; (b) emotions emerge from, rather than cause, emotional thoughts, feelings, and expressions; (c) the impact of emotions is constrained by the nature of the situations they represent; (d) in the OCC account (the model proposed by Ortony, Clore, and Collins in 1988), appraisals are psychological aspects of situations that distinguish one emotion from another, rather than triggers that elicit emotions; (e) analyses of the affective lexicon indicate that emotion words refer to *internal mental states focused on affect*; (f) the modularity of emotion, long sought in biology and behavior, exists as mental schemas for interpreting human experience in story, song, drama, and conversation.

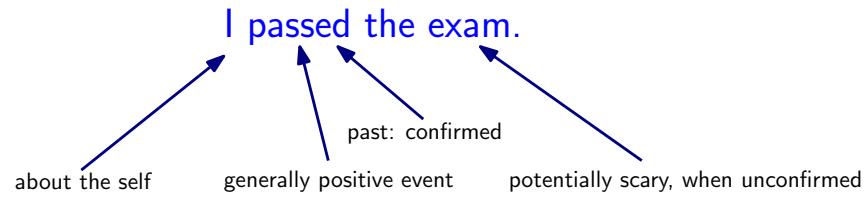
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- 2 The OCC Model of Emotions
- 3 Appraisal Prediction following Scherer
- 4 Other Approaches

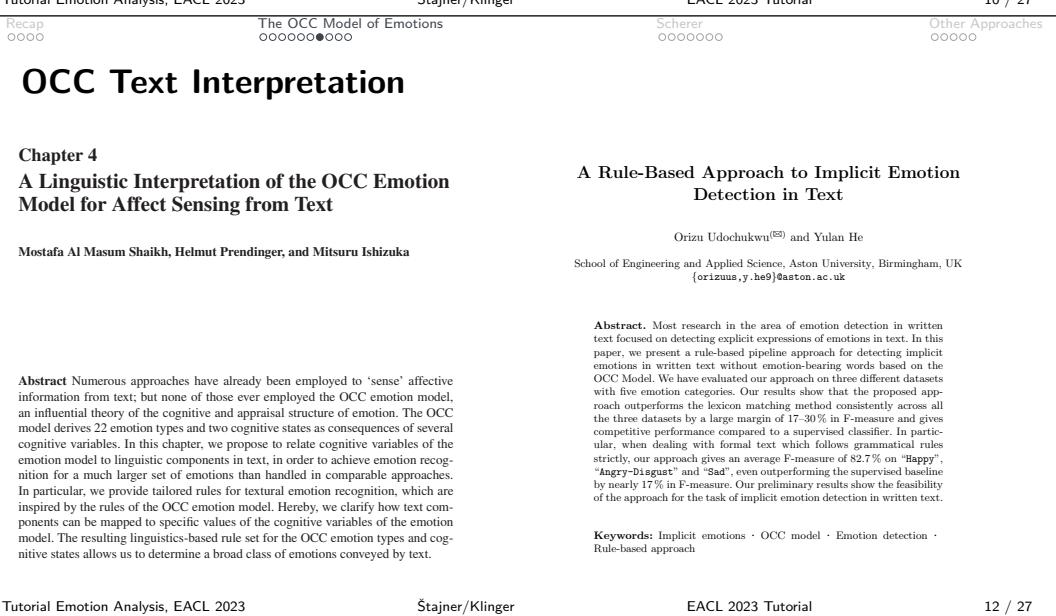
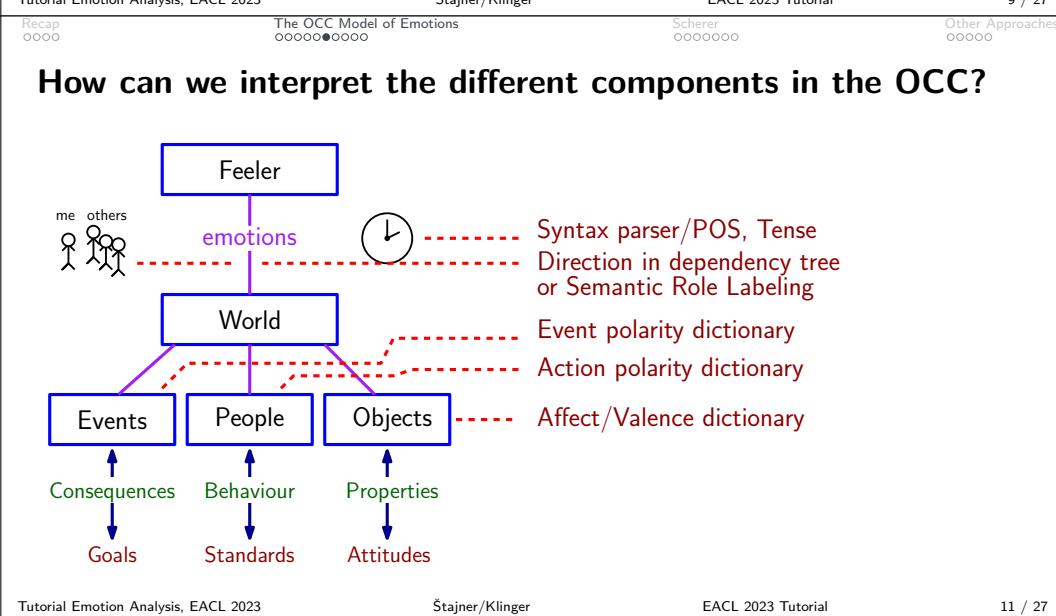
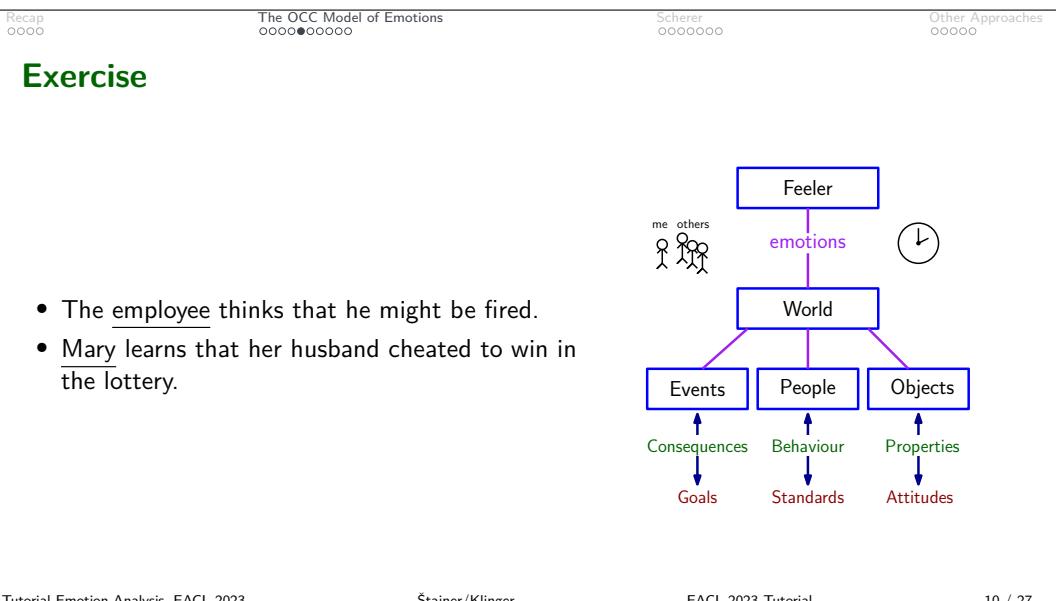
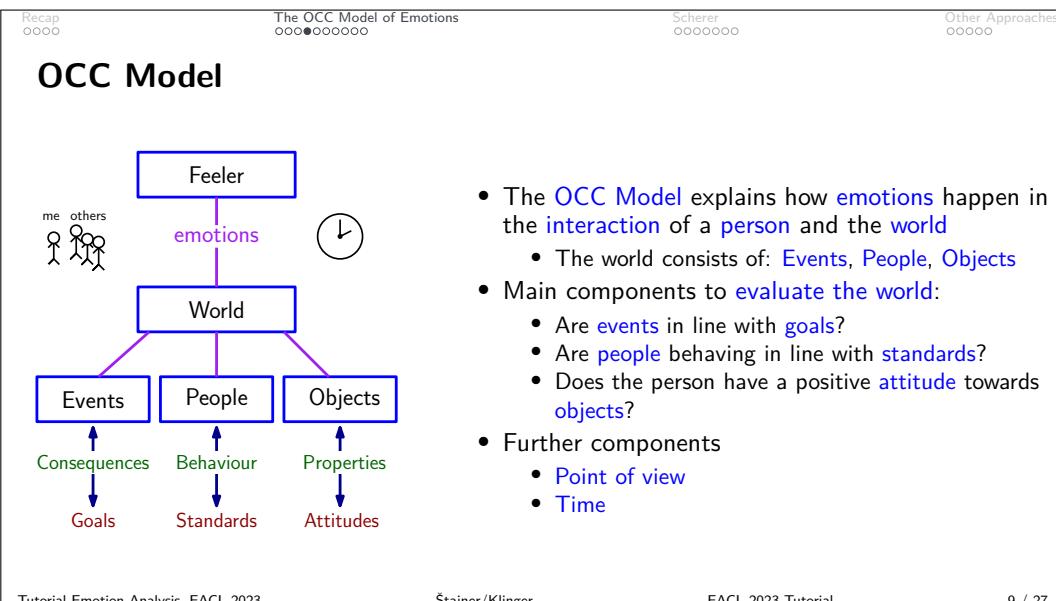
Warm-Up Example

How to interpret the emotion?



⇒ Relief, Joy

Appraisal-based Emotion Analysis



Recap oooo	The OCC Model of Emotions oooooooo●○○	Scherer ooooooo	Other Approaches ooooo		
<h2>Example Rules (à la Shaikh)</h2> <p>"The employee thinks that he might be fired."</p> <p>Variables:</p> <ul style="list-style-type: none"> • vr: valenced reaction as sentence valence • sr: self reaction valence of event≈ desirability • pros: prospect valence of verb • If (vr = true & sr = 'displeased' & pros = 'negative' & sp = 'undesirable' & status = 'unconfirmed' & de = 'self') ⇒ fear • sp: self presumption valence of event≈ desirability • status tense of verb • de: direction of emotion other if object is person/pronoun 					
<p>66</p> <p>The rules for the emotion are listed as follows.</p> <ul style="list-style-type: none"> • If vr = true & sr = 'displeased' & sp = 'undesirable' & de = 'self', 'distress' is true. • If vr = true & sr = 'displeased' & op = 'undesirable' & af = 'liked' & de = 'other', 'sorry-for' is true. • If vr = true & sr = 'displeased' & op = 'desirable' & af = 'not liked' & de = 'other', 'resentment' is true. • If vr = true & sr = 'pleased' & op = 'undesirable' & af = 'not liked' & de = 'other', 'shame' is true. • If vr = true & sr = 'pleased' & pros = 'positive' & sp = 'desirable' & status = 'unconfirmed' & de = 'self', 'hope' is true. • If vr = true & sr = 'displeased' & pros = 'negative' & sr = 'undesirable' & status = 'unconfirmed' & de = 'self', 'fear' is true. • If vr = true & sr = 'positive' & pros = 'positive' & sp = 'desirable' & status = 'confirmed' & de = 'self', 'satisfaction' is true. • If vr = true & sr = 'displeased' & pros = 'negative' & sr = 'undesirable' & status = 'confirmed' & de = 'self', 'fear-confirmed' is true. • If vr = true & sr = 'pleased' & pros = 'negative' & sr = 'undesirable' & status = 'confirmed' & de = 'other', 'relief' is true. • If vr = true & sr = 'displeased' & sr = 'positive' & sp = 'desirable' & status = 'disconfirmed' & de = 'self', 'disappointment' is true. • If vr = true & sr = 'pleased' & sr = 'praiseworthy' & sp = 'desirable' & de = 'self', 'pride' is true. • If vr = true & sr = 'displeased' & sr = 'blameworthy' & sp = 'undesirable' & de = 'self', 'guilt' is true. • If vr = true & sr = 'pleased' & sr = 'praiseworthy' & op = 'desirable' & de = 'other', 'admiration' is true. • If vr = true & sr = 'displeased' & sr = 'blameworthy' & op = 'undesirable' & de = 'other', 'shame' is true. • If both 'joy' and 'pride' are true, 'gratification' is true. • If both 'distress' and 'shame' are true, 'remorse' is true. • If both 'joy' and 'admiration' are true, 'gratitude' is true. • If both 'distress' and 'reproach' are true, 'anger' is true. <p>The OCC model has four complex emotions, namely, 'gratification,' 'remorse,' 'gratitude,' and 'anger.' The rules for these emotions are as follows.</p> <ul style="list-style-type: none"> • If both 'joy' and 'pride' are true, 'gratification' is true. • If both 'distress' and 'shame' are true, 'remorse' is true. • If both 'joy' and 'admiration' are true, 'gratitude' is true. • If both 'distress' and 'reproach' are true, 'anger' is true. <p>The cognitive states 'shock' and 'surprise' are ruled as follows.</p> <ul style="list-style-type: none"> • If both 'joy' and 'pride' are true, 'shock' is true (e.g., the bad news came unexpectedly). • If both 'joy' and 'shame' are true, 'surprise' is true (e.g., I suddenly met my school friend in Tokyo University). 					
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Recap oooo	The OCC Model of Emotions oooooooo●○○	Scherer ooooooo	Other Approaches ooooo																																																																
<h2>Results (Udochukwu/He 2015)</h2> <table border="1"> <thead> <tr> <th rowspan="2">Emotion</th> <th colspan="2">ISEAR</th> <th colspan="2">SemEval</th> <th colspan="2">Alm's</th> </tr> <tr> <th>Lexicon</th> <th>NB Rule</th> <th>Lexicon</th> <th>NB Rule</th> <th>Lexicon</th> <th>NB Rule</th> </tr> </thead> <tbody> <tr> <td>Joy/Happy</td> <td>33.4</td> <td>61.2 69.6</td> <td>39.7</td> <td>71.7 59.9</td> <td>58.8</td> <td>63.5 81.8</td> </tr> <tr> <td>Fear/Fearful</td> <td>0</td> <td>47.6 18.3</td> <td>0</td> <td>52.2 31.8</td> <td>0</td> <td>26.7 14.0</td> </tr> <tr> <td>Anger/Angry-Disgusted</td> <td>23.0</td> <td>47.1 61.3</td> <td>55.8</td> <td>16.2 61.3</td> <td>48.9</td> <td>58.6 86.6</td> </tr> <tr> <td>Sadness/Sad</td> <td>25.6</td> <td>55.4 68.0</td> <td>47.8</td> <td>56.0 71.5</td> <td>61.0</td> <td>56.0 79.6</td> </tr> <tr> <td>Disgust</td> <td>25.6</td> <td>51.0 39.2</td> <td>38.5</td> <td>34.5 61.7</td> <td>-</td> <td>-</td> </tr> <tr> <td>Average</td> <td>21.5</td> <td>52.5 51.3</td> <td>36.4</td> <td>58.2 57.3</td> <td>42.2</td> <td>56.0 65.5</td> </tr> <tr> <td>Average (- Fear)</td> <td>27.0</td> <td>53.7 59.5</td> <td>45.5</td> <td>44.6 63.6</td> <td>56.12</td> <td>65.8 82.7</td> </tr> </tbody> </table>						Emotion	ISEAR		SemEval		Alm's		Lexicon	NB Rule	Lexicon	NB Rule	Lexicon	NB Rule	Joy/Happy	33.4	61.2 69.6	39.7	71.7 59.9	58.8	63.5 81.8	Fear/Fearful	0	47.6 18.3	0	52.2 31.8	0	26.7 14.0	Anger/Angry-Disgusted	23.0	47.1 61.3	55.8	16.2 61.3	48.9	58.6 86.6	Sadness/Sad	25.6	55.4 68.0	47.8	56.0 71.5	61.0	56.0 79.6	Disgust	25.6	51.0 39.2	38.5	34.5 61.7	-	-	Average	21.5	52.5 51.3	36.4	58.2 57.3	42.2	56.0 65.5	Average (- Fear)	27.0	53.7 59.5	45.5	44.6 63.6	56.12	65.8 82.7
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Recap oooo	The OCC Model of Emotions oooooooo●○○	Scherer ooooooo	Other Approaches ooooo	
Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger	EACL 2023 Tutorial	15 / 27	<h2>Outline</h2> <ol style="list-style-type: none"> 1 Recap 2 The OCC Model of Emotions 3 Appraisal Prediction following Scherer 4 Other Approaches

Appraisal-based Emotion Analysis

Recap oooo	The OCC Model of Emotions oooooooooo	Scherer ○●○○○○○	Other Approaches ooooo
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Appraisal Prediction following Scherer's Model

Relevance	Implication	Coping	Normative Significance
Novelty (1) suddenness (2) familiarity (3) predictability (16) attention* (17) att. removal*	Causality: agent (7) own responsibility (8) other's respons. (9) situational respons.	Control (19) own control* (20) others' control* (21) chance control*	Internal standards compatibility (14) clash with own standards/ideals
Intrinsic Pleasantness (4) pleasant (5) unpleasant	Goal conduciveness (10) goal support	Adjustment (13) anticipated acceptance (18) effort*	External standards compatibility (15) clash with laws/norms
Goal Relevance (6) goal-related	Outcome probability (11) consequence anticipation		
	Urgency (12) response urgency		

Troiano, Oberlaender, Klinger, MIT CL 2023:
Dimensional Modeling of Emotions in Text with Appraisal Theories: Corpus Creation, Annotation Reliability, and Prediction.

- Can appraisals be annotated reliably?
- Do appraisals help emotion categorization?

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Questions and Answers

- Do readers agree more with each other than with the writers?
 (does the writer make use of information that the readers do not have)
 - Yes, a bit for emotions; clearly for the appraisals.
- Does it matter if annotators share demographic properties?
 - Females agree more with each other, but men less.
 - People of similar age agree more.
- Does personality matter?
 - Extraverted, conscientious, agreeable annotators perform better.

Setup:

- Filter instances for attribute, compare with F_1 /RMSE
- Significance test with bootstrap resampling for .95 confidence interval

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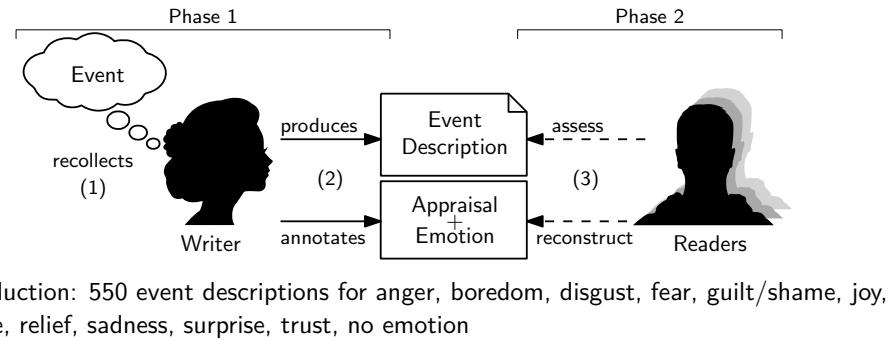
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Approach



- Production: 550 event descriptions for anger, boredom, disgust, fear, guilt/shame, joy, pride, relief, sadness, surprise, trust, no emotion

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Appraisals add additional information to emotion analysis

Dimension	Writer	Readers	Δ
Emotion	Pride	Sadness	
Suddenness	4	3.6	0.4
Familiarity	1	2.0	-1.0
Predictability	1	1.8	-0.8
Pleasantness	4	1.0	3.0
Unpleasantness	2	4.8	-2.8
Goal-Relevance	4	2.6	1.4
Chance-Resp.	4	4.4	-0.4
Self-Resp.	1	1.2	-0.2
Other-Resp.	1	1.4	-0.4
Conseq.-Predict.	2	1.8	0.2
Goal Support	1	1.2	-0.2
Urgency	2	3.8	-1.8
Self-Control	5	3.2	1.8
Other-Control	3	2.0	1.0
Chance-Control	1	4.6	-3.6
Accept-Conseq.	4	2.4	1.6
Standards	1	2.4	-1.4
Social Norms	1	1.2	-0.2
Attention	4	4.4	-0.4
Not-Consider	1	3.8	-2.8
Effort	4	4.6	-0.6

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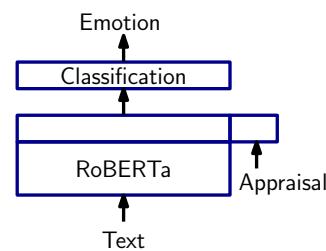
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Modeling Results

- Classification with RoBERTa-based models
- Appraisal Classification: 75 F₁
- Emotion classification: 59 F₁
- + Appraisals: +2pp F₁
(+10 for guilt, +6 for sadness)



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- 2 The OCC Model of Emotions
- 3 Appraisal Prediction following Scherer
- 4 Other Approaches

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Examples where Appraisals correct the Emotion Classifier

- When my child settled well into school trust→relief
- broke an expensive item in a shop accidentally guilt→shame
- my mother made me feel like a child shame→anger
- I passed my Irish language test pride→relief
- His toenails where massive pride→disgust

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Other Approaches

- Balahur et al., 2011, EmotiNet:
Knowledge base of events motivated by appraisal theories
- Stranisci et al., 2022, APPReddit:
Reddit post corpus, focus on coping strategies
- Hofmann et al., 2020:
Appraisal-based Emotion Analysis, annotated corpus for Smith/Ellsworth concepts

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Appraisal-based Emotion Analysis

<p>Recap oooo</p> <p>The OCC Model of Emotions oooooooooooo</p> <p>Scherer oooooooo</p> <p>Other Approaches oooo●oo</p> <p>Take-Away</p> <ul style="list-style-type: none">• Appraisal dimensions are an additional emotion model that serves as a fundamental for analysis in text• It provides additional knowledge and supports the categorization into emotion concepts• Could it support affect (valence/arousal) prediction? Not yet known.	<p>Recap oooo</p> <p>The OCC Model of Emotions oooooooooooo</p> <p>Scherer oooooooo</p> <p>Other Approaches oooo●oo</p> <p>Questions?</p>
<p>Tutorial Emotion Analysis, EACL 2023</p> <p>Štajner/Klinger</p> <p>EACL 2023 Tutorial</p> <p>25 / 27</p>	<p>Tutorial Emotion Analysis, EACL 2023</p> <p>Štajner/Klinger</p> <p>EACL 2023 Tutorial</p> <p>26 / 27</p>
<p>Recap oooo</p> <p>The OCC Model of Emotions oooooooooooo</p> <p>Scherer oooooooo</p> <p>Other Approaches oooo●oo</p> <p>About this tutorial</p> <p>Session 1 (09:00–10:30)</p> <ul style="list-style-type: none">• Introduction• Psychological Models• Use Cases/Social Impact• Resources• Annotation Exercise <p>Break (10:30–11:15)</p> <p>Session 2 (11:15–12:45)</p> <ul style="list-style-type: none">• Non-Neural Methods• Multi-task, transfer, zero-shot methods• Open Challenges• Appraisal Theories• Role Labeling• Ethical Considerations• Closing	



Emotion Analysis

Role Labeling and Stimulus Detection

EACL 2023 Tutorial

Sanja Štajner and Roman Klinger



Introduction
ooo

Motivation (1)

What cannot be done with document/sentence-level emotion analysis?

Given a corpus, extract the information:

who is the target? who experiences the emotion?

Couple **infuriated** **officials** by **landing helicopter in nature reserve**

which words describe the emotion?

what caused the emotion?

- **Relevancy:** Social media mining, literature analysis, network analysis, ...

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Take Home
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Relation to Aspect-based sentiment analysis

Formulation 1:

- Closed set of aspects, classify polarity for each aspect.
- “The food was good, but the waiter was unfriendly.
food → positive; staff → negative.
- e.g., Ganu et al. (2009). “Beyond the Stars: Improving Rating Predictions using Review Text Content.”

Formulation 2:

- Given text, detect phrases that describe an aspect.
- Classify these aspects into sentiment polarities.
- “The food⁺ was good, but the waiter⁻ was unfriendly.
- e.g., Kessler et al. 2010. The 2010 ICWSM JDPA Sentiment Corpus for the Automotive Domain.

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Task Definition: Relations, spans, or clauses?

- Relation detection:**

- Sequence labeling:**

A couple **infuriated** **officials** by **landing their helicopter in the middle of a nature reserve.**

target cue experiencer stimulus
- Clause classification:**

A couple	infuriated	officials	by landing their helicopter in the middle of a nature reserve.
emotion clause			cause/stimulus clause

→ trade-off between task complexity and accurateness

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Corpora: SRL4E

Resource	Original	SRL4E	%
Blogs	5,202	4,855	93.3
Elections	1,385	1,024	73.9
EmoTweet	15,553	15,553	100.0
GNE	5,000	5,000	100.0
NTCIR (ZH)	2,022	1,956	96.7
NTCIR (EN)	1,826	1,796	98.4
REMAN	1,720	1,705	99.1
All	32,708	31,889	97.5

Resource	cue	stim.	exp.	targ.
Blogs	✓	—	—	—
Elections	✓	✓	✓	✓
EmoTweet	✓	—	—	—
GNE	✓	✓	✓	✓
NTCIR	✓	✓	—	—
REMAN	✓	✓	✓	✓

- Campagnano et al., ACL 2022** aggregate a set of corpora into common format and conduct prediction experiments for the identification of all roles
- <https://github.com/sapienzanlp/srl4e>

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Corpora

Dataset	Whole Instance		Stimulus	
	#	avg. len	#	avg. len
ES, Ghazi2015	2414	20.60	820	7.29
ET, Mohammad2014	4056	19.14	2427	6.25
GNE, Bostan2020	5000	13.00	4798	7.29
REMAN, Kim2018	1720	72.03	609	9.33
ECA, Gao2017	2558	62.24	2485	9.52

Dataset	Cue		Target		Exp.	
	#	avg. len	#	avg. len	#	avg. len
ET	2930	5.08	2824	1.71	29	1.76
GNE	4736	1.60	4474	4.86	3458	2.03
REMAN	1720	3.82	706	5.35	1050	2.04

Oberländer et al. (2020), Experiencers, Stimuli, or Targets: Which Semantic Roles Enable Machine Learning to Infer the Emotions? PEOPLES Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 8 / 19

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Corpus Examples (1)

- Mohammad et al. (2014). Semantic role labeling of emotions in tweets.
 - Crowdsourced span annotations in electoral Tweets
 - Modeling as stimulus classification task
- Ghazi et al. (2015). Detecting emotion stimuli in emotion-bearing sentences.
 - Expert-based span annotations in FrameNet sentences
 - Modeling span-based with feature-based CRF
- Kim/Klinger (2018). Who feels what and why? Annotation of a literature corpus with semantic roles of emotions.
 - Expert-annotated role graph in sentence triples of literature.
 - Modeling span-based with BiLSTM+CRF

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Corpus Examples (2)

- Bostan et al. (2020). GoodNewsEveryone: A Corpus of News Headlines Annotated with Emotions, Semantic Roles, and Reader Perception.
 - Crowdsourced annotation of full graph.
 - Modeling span-based with ELMo+BiLSTM+CRF
- Gao et al. (2017). Overview of NTCIR-13 ECA task; Xia (2019). Emotion-Cause Pair Extraction: A New Task to Emotion Analysis in Texts.
 - Annotation of emotion and stimulus clauses
 - Modeling as clause classification

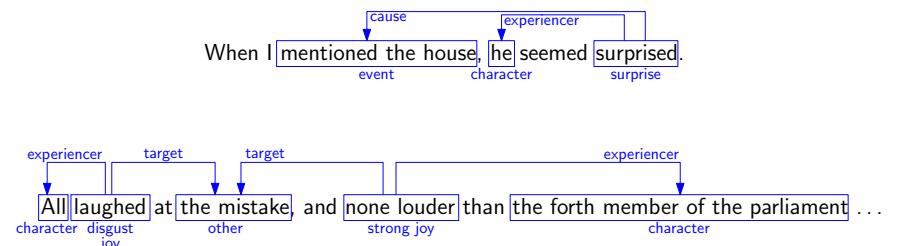
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Examples: Emotion Stimulus

- happy: I suppose I am happy being so ' tiny' ; it means I am able to surprise people with what is generally seen as my confident and outgoing personality .
- sad: Anne was sad at the death of the Misses Dolan but too much was happening for her to dwell on it .
- anger: I was very very angry to read Batty 's comments about Leeds .

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Examples: REMAN



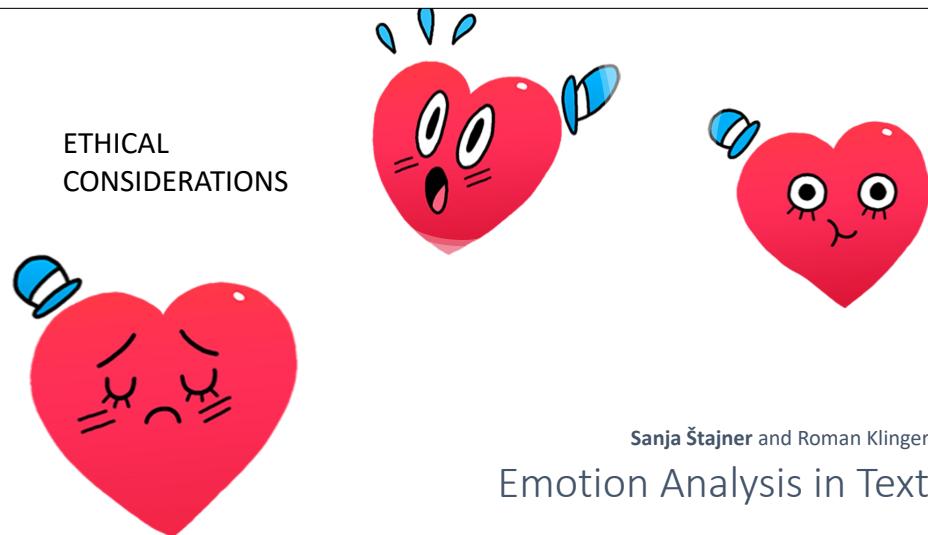
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Emotion Role Labeling

<p>Introduction oooo</p> <p>Resources/Methods oooooooo●○○</p> <p>Examples: Good News Everyone</p> <p>phase 1</p> <table border="1"> <tr> <td>Headline: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.</td> </tr> <tr> <td>Emotion: Anger, Anger, Disgust Reader Perception: Yes, No, Yes</td> </tr> </table> <p>phase 2</p> <table border="1"> <tr> <td>Experiencer: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.</td> </tr> <tr> <td>Cue: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.</td> </tr> <tr> <td>Cause: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.</td> </tr> <tr> <td>Target: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.</td> </tr> </table> <p>aggregated</p> <table border="1"> <tr> <td>Emotion: Anger Intensity: High Other emotions: None Reader perception: Yes Reader emotions: Annoyance, Negative Surprise, No Emotion</td> </tr> <tr> <td></td> </tr> </table> <p>Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 13 / 19</p>	Headline: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.	Emotion: Anger, Anger, Disgust Reader Perception: Yes, No, Yes	Experiencer: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.	Cue: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.	Cause: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.	Target: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.	Emotion: Anger Intensity: High Other emotions: None Reader perception: Yes Reader emotions: Annoyance, Negative Surprise, No Emotion		<p>Take Home oooo</p> <p>Introduction oooo</p> <p>Resources/Methods oooooooo●○○</p> <p>Take Home oooo</p> <p>Examples: ECPE – Modeling</p> <p>Outline</p> <ul style="list-style-type: none"> • Attracted a lot of attention • Often two steps: <ul style="list-style-type: none"> • (1) detect emotion (clauses) and cause clauses separately • (2) pair emotion and cause • Example for one approach which does end-to-end modeling: Wei, Zhao, Mao. ACL 2020. • Oberländer/Klinger *SEM 2020 compared clause classification and sequence labeling settings for English corpora: task formulation seems to be appropriate for Mandarin, but not for English. <p>Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 15 / 19</p>
Headline: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.									
Emotion: Anger, Anger, Disgust Reader Perception: Yes, No, Yes									
Experiencer: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.									
Cue: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.									
Cause: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.									
Target: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.									
Emotion: Anger Intensity: High Other emotions: None Reader perception: Yes Reader emotions: Annoyance, Negative Surprise, No Emotion									

Introduction oooo	Resources/Methods oooooooooo	Take Home ooo	Introduction oooo	Resources/Methods oooooooooo	Take Home ooo○		
<h3>Take Home</h3>			<h3>Questions?</h3>				
<ul style="list-style-type: none">Quite some work on clause classification and sequence labelingNearly (?) no work on full graph reconstructionNo work on linking stimulus detection with appraisal analysis							
Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger	EACL 2023 Tutorial	17 / 19	Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger	EACL 2023 Tutorial	18 / 19
Introduction oooo	Resources/Methods oooooooooo	Take Home ooo●					
<h2>About this tutorial</h2>							
<p>Session 1 (09:00–10:30)</p> <ul style="list-style-type: none">IntroductionPsychological ModelsUse Cases/Social ImpactResourcesAnnotation Exercise		<p>Session 2 (11:15–12:45)</p> <ul style="list-style-type: none">Non-Neural MethodsMulti-task, transfer, zero-shot methodsOpen ChallengesAppraisal TheoriesRole LabelingEthical ConsiderationsClosing					
<p>Break (10:30–11:15)</p>							
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ETHICAL CONSIDERATIONS

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Emotion Analysis in Text

EACL 2023 Tutorial – 05.05.2023

ETHICAL CONSIDERATIONS: FURTHER READING

- Gremsl and Hödl. 2022. "Emotional AI: Legal and ethical challenges":
https://www.researchgate.net/publication/360210704_Emotional_AI_Legal_and_ethical_challenges
- Stark and Hoey. 2021. "The Ethics of Emotion in Artificial Intelligence Systems":
<https://dl.acm.org/doi/10.1145/3442188.3445939>
- Brian Green. 2016. "Social Robots, AI, and Ethics":
<https://www.scu.edu/ethics/focus-areas/technology-ethics/resources/social-robots-ai-and-ethics/>

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ETHICAL CONSIDERATIONS: DISCUSSION

- Privacy
- Failure modes and their consequences
- Who should be responsible?

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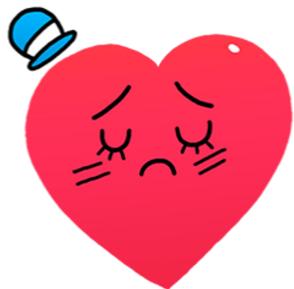
Questions?



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ETHICAL
CONSIDERATIONS



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CLOSING

- TOPICS COVERED:
 - Emotions in psychology
 - Use cases
 - Resources for emotion analysis in texts
 - Computational approaches to emotion analysis in texts
 - Challenges
 - Ethical considerations

- TOPICS NOT COVERED (only mentioned):
 - Emotion analysis from audio or video sequences
 - Multimodal emotion analysis
 - Resources for languages other than English
 - Universality of emotions

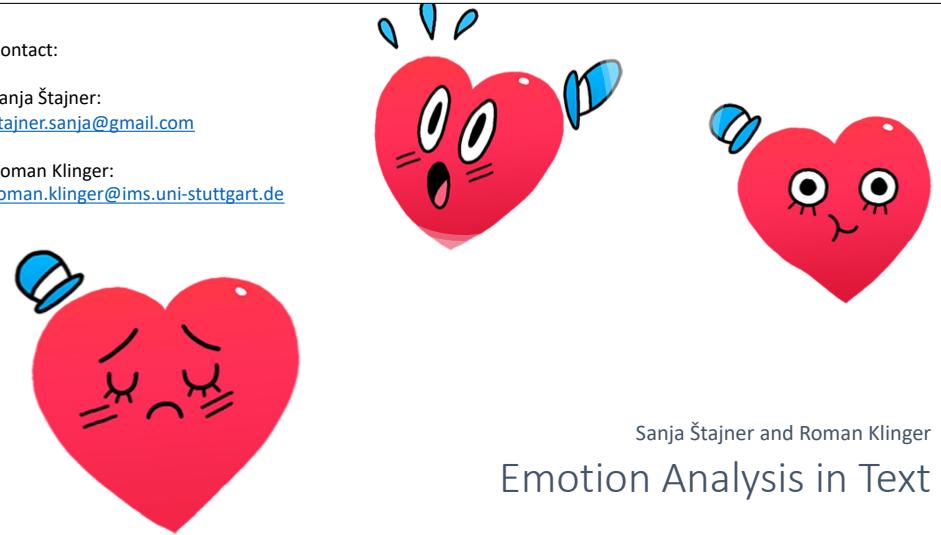
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