

Emotion Analysis from Text: Tutorial at EACL 2023

Sanja Štajner and Roman Klinger

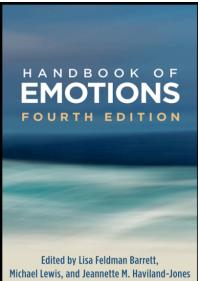
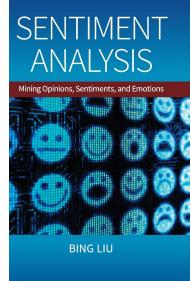
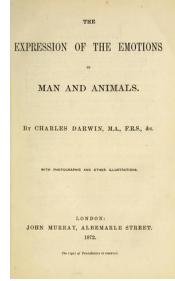
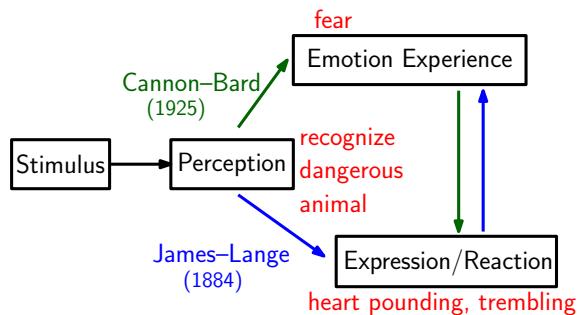
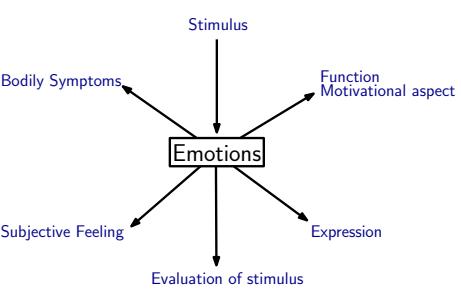
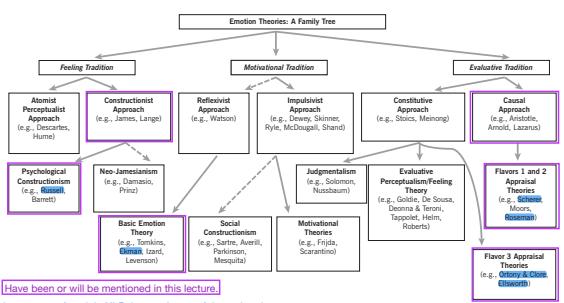
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Introduction and Psychological Models

<p>Literature on Emotion Psychology</p> <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>Literature with a Computational Focus</p>  
<p>Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 9 / 45</p>	
<p>Emotion Theories...</p> <p>...try to explain ...</p> <ul style="list-style-type: none"> • what emotions are • what they consist of • what their purpose is • how they develop • ... 	
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<p>Evolutionary Approach (Darwin, 1872)</p> 	
<p>Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 12 / 45</p>	
<p>James Lang/Cannon Bard (1884, 1925)</p> 	
<p>Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 13 / 45</p>	
<p>Emotion Components (Scherer, 2001)</p>  <p>Emotion in text could be expressed by describing each of these components.</p>	
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<p>Family Tree of Emotions (Scarantino, 2016)</p>  <p>I am aware of work in NLP that made use of these theories.</p>	
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Introduction and Psychological Models

Outline

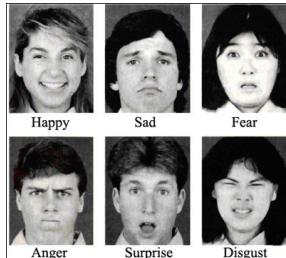
- 1 Introduction
- 2 What are Emotions?
 - Motivation: Basic Emotion Theories
 - Feeling: Affect and Constructionism
 - Evaluation: Causes and Appraisals
- 3 Task Definition and Issues
- 4 What can we learn from previous work in psychology?
 - Psychological Studies on Reliability

Introduction What are Emotions? Task Definition and Issues Psychological Studies

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.

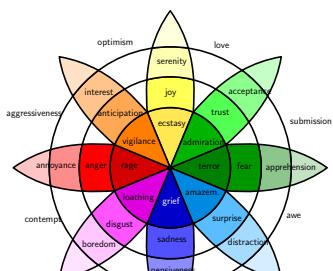
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Introduction What are Emotions? Task Definition and Issues Psychological Studies

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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Introduction What are Emotions? Task Definition and Issues Psychological Studies

The Feeling Tradition of Emotion Theories

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

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Introduction What are Emotions? Task Definition and Issues Psychological Studies

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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Introduction What are Emotions? Task Definition and Issues Psychological Studies

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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Introduction What are Emotions? Task Definition and Issues Psychological Studies

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Introduction What are Emotions? Task Definition and Issues Psychological Studies

Feeling

What is not learned then?

Feeling

- Scartantino (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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Introduction and Psychological Models

Affect: Continuous Circumplex Model (Russel 1980)

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

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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Psychological Studies on Reliability

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

Sequence of appraisal criteria (Scherer 2005/2013)

Scherer: Emotions are evaluated in a sequential manner.

Results Smith/Ellsworth (1985)

Locations of Emotion Means Along the PCA Components

Emotion	Component				
	Pleasant*	Responsibility/Control*	Certain*	Attention*	Effort*
Happiness	-1.46	0.09	-0.46	0.15	-0.33
Sadness	0.47	-0.36	0.04	-0.21	-0.14
Anger	0.85	-0.04	-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	0.71	0.03	0.59
Interest	-1.05	-0.13	-0.07	0.70	-0.07
Contempt	0.89	-0.50	-0.12	0.26	-0.07
Disgust	0.38	-0.50	-0.39	-0.96	0.06
Frustration	0.98	-0.37	0.09	0.60	0.48
Surprise	-1.35	-0.94	0.73	0.49	-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
<i>Note: Scores are standardized.</i>					
<i>* Pleasantness: high scores indicate increased unpleasantness.</i>					
<i>* Responsibility/Control: high scores indicate increased self-responsibility/control.</i>					
<i>* Certainty: high scores indicate increased certainty.</i>					
<i>* Attentional activity: high scores indicate increased attentional activity.</i>					
<i>* Effort: high scores indicate increased anticipated effort.</i>					
<i>* Situational control: high scores indicate increased situational control.</i>					

OCC Model of Emotions

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

Introduction and Psychological Models

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Introduction oooooooooooo What are Emotions? oooooooooooooooooooo Task Definition and Issues oooooooo Psychological Studies ooooooo

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
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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.) |

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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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Introduction oooooooooooo What are Emotions? oooooooooooooooooooo Task Definition and Issues oooooooo Psychological Studies ooooooo

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Task Definition for Emotion Classification and Regression

Input

- Text
- Variables resp. emotion model
- Perspective

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

Output (by human or machine)

- Discrete values
- Ordinal values
- Continuous values

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

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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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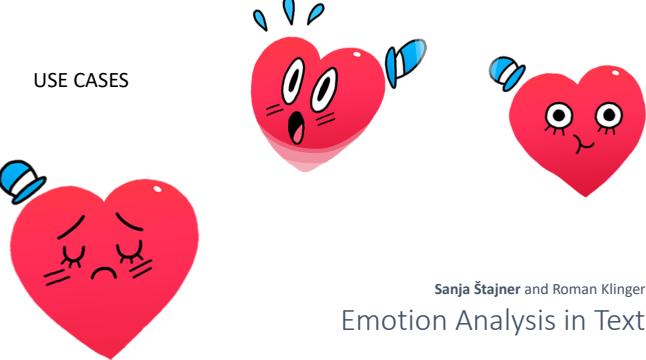
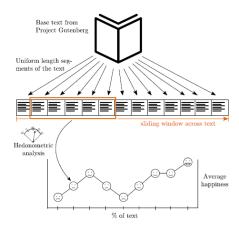
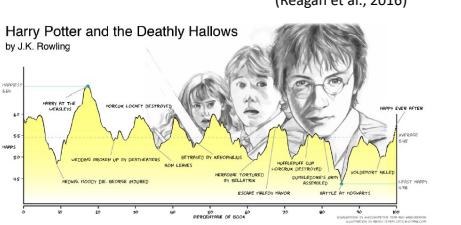
- 3 Task Definition and Issues

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 Psychological Studies on Reliability

Introduction and Psychological Models

Introduction ooooo	What are Emotions? ooooooooooooooooooooooo	Task Definition and Issues ooooooo	Psychological Studies oooooo	Introduction ooooo	What are Emotions? ooooooooooooooooooooooo	Task Definition and Issues ooooooo	Psychological Studies oooooo
<h2>Emotion Recognition Reliability: Ekman 1972</h2>							
<h3>Experimental Setup</h3> <ul style="list-style-type: none">Photos were taken of people expressing a particular emotion and asked which emotion they feelJapanese and US American people were shown these photos and tasked to recover the emotionGoal: understand emotion recognition reliability							
<h3>Results (🇯🇵/🇺🇸)</h3> <ul style="list-style-type: none">.79/.86 acc. between observers.57/.62 acc. between subject and observer (.50 baseline) <p>⇒ Interpretation of emotion might differ from actual emotion.</p>							
<h3>Take-Away</h3> <p>Emotions...</p> <ul style="list-style-type: none">...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							
<h3>About this tutorial</h3> <p>Session 1 (09:00–10:30)</p> <ul style="list-style-type: none">IntroductionPsychological ModelsUse Cases/Social ImpactResourcesAnnotation Exercise <p>Break (10:30–11:15)</p> <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							
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Use Cases

<p>USE CASES</p>  <p>Sanja Štajner and Roman Klinger Emotion Analysis in Text</p> <p>EACL 2023 Tutorial – 05.05.2023</p>	<p>USE CASES</p> <ul style="list-style-type: none"> • Social media and public opinion analysis • Literary studies • Hate speech detection • Empathetic chatbots and virtual agents • Early depression detection • Suicide prevention <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p>
<p>SOCIAL MEDIA AND PUBLIC OPINION ANALYSIS</p>	<p>SOCIAL MEDIA AND PUBLIC OPINION ANALYSIS: Loureiro and Alló, 2020</p> <ul style="list-style-type: none"> • Methodology: <ul style="list-style-type: none"> • Twitter messages about climate change analyzed using EmoLex (Mohammad and Turney, 2013) • Data collection: 01.01.2019-30.06.2019 (six months) • Findings: <ul style="list-style-type: none"> • 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  <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p>
<p>SOCIAL MEDIA AND PUBLIC OPINION ANALYSIS: Srinivasan et al., 2019</p> <ul style="list-style-type: none"> • Methodology: <ul style="list-style-type: none"> • 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: <ul style="list-style-type: none"> • 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  <p>Figure taken from (Srinivasan et al., 2016)</p> <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p>	<p>SOCIAL MEDIA AND PUBLIC OPINION ANALYSIS: Wang et al., 2023</p> <ul style="list-style-type: none"> • Methodology: <ul style="list-style-type: none"> • Twitter posts of top executives in S&P 1500 firms analyzed using DeepEmotionNet (Wang et al., 2023) • Findings: <ul style="list-style-type: none"> • Fear and anger in Twitter posts by top executives are significantly associated with corporate financial performance  <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p>
<p>LITERARY STUDIES</p>	<p>LITERARY STUDIES: Reagan et al., 2016</p> <p>"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."</p> <p>(Reagan et al., 2016)</p>   <p>Figures taken from (Reagan et al., 2016)</p> <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p>

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)

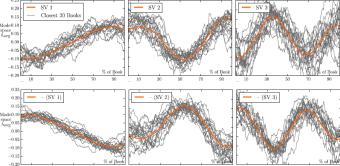


Figure adapted from (Reagan et al., 2016)

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LITERARY STUDIES: Kim et al., 2017

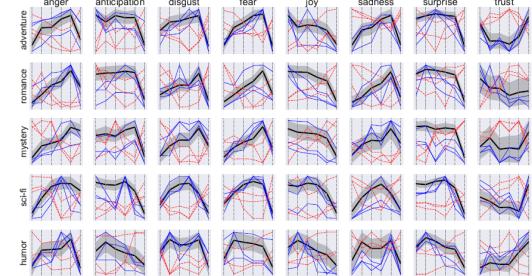


Figure taken from (Kim et al., 2017)

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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

"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

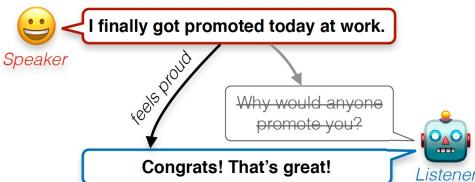


Figure taken from (Rashkin et al., 2019)

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HATE SPEECH DETECTION

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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Use Cases

EARLY DEPRESSION DETECTION

DEPRESSION DETECTION: Islam et al., 2018

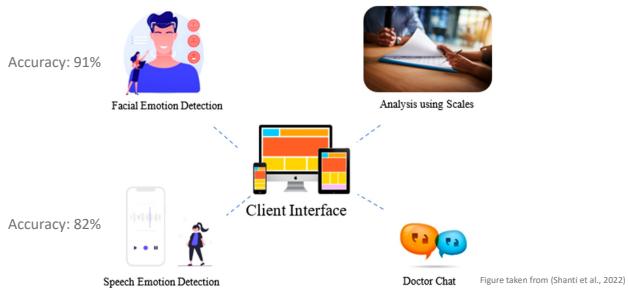
- Methodology:
 - Facebook posts analyzed for depression using LIWC software
 - Classification experiments with various ML algorithms
 - 4 feature sets: emotional processes (positive emotion words, negative emotion words, sadness words, anger words, anxiety words), linguistic style, temporal processes, 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



SUICIDE PREVENTION

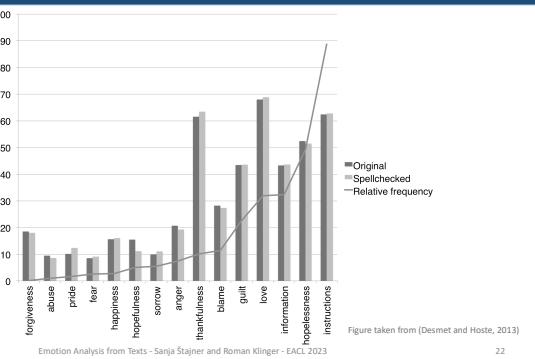
EMOTION ANALYSIS OF SUICIDE NOTES: Shared Task

- 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



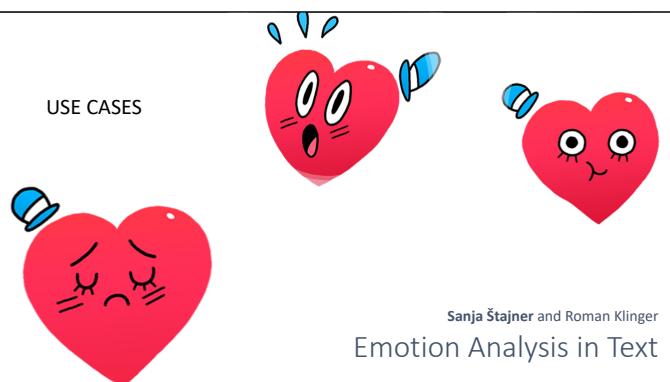
Questions?



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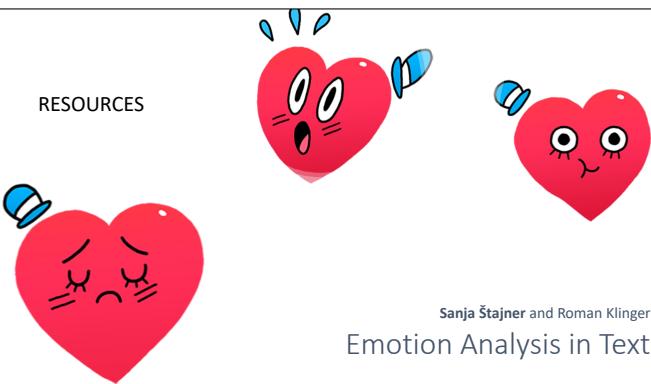
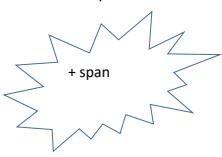
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USE CASES



EACL 2023 Tutorial – 05.05.2023

Resources

<p>RESOURCES</p>  <p>Sanja Štajner and Roman Klinger Emotion Analysis in Text</p> <p>EACL 2023 Tutorial – 05.05.2023</p>	<p>RESOURCES</p> <ul style="list-style-type: none"> • Emotion detection and classification resources • Emotion intensity resources • Other resources <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>26</p>																																																																																																																	
<p>ANNOTATION OPTIONS</p> <ul style="list-style-type: none"> • 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 <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>27</p>	<p>AUTOMATIC ANNOTATION</p> <ul style="list-style-type: none"> • 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). • Shahrai and Zaiane (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 <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>28</p>																																																																																																																	
<p>VARIATIONS IN HUMAN ANNOTATION: Štajner, 2021</p> <table border="1" data-bbox="103 1190 714 1448"> <thead> <tr> <th>Study</th> <th>#annotators</th> <th>Per instance</th> <th>Total</th> <th>Gold</th> <th>#emotions</th> <th>Labelling</th> <th>Perspective</th> <th>Genre</th> </tr> </thead> <tbody> <tr><td>(Demszky et al., 2020)</td><td>3 or 5</td><td>82</td><td>> 1 annotator</td><td>27+1</td><td>multi</td><td>writer</td><td>Reddit</td></tr> <tr><td>(Bostan et al., 2020)</td><td>5</td><td>310</td><td>> 1 annotator</td><td>15+1</td><td>single</td><td>text</td><td>Headlines</td></tr> <tr><td>(Ohman et al., 2020)</td><td>≤3</td><td>108</td><td>> 1 annotator</td><td>8+1</td><td>multi</td><td>speaker</td><td>Subtitles</td></tr> <tr><td>(Poria et al., 2019)</td><td>5</td><td>?</td><td>majority</td><td>6+1</td><td>single</td><td>speaker</td><td>Dialog</td></tr> <tr><td>(Hsu et al., 2018)</td><td>5</td><td>?</td><td>majority*</td><td>6+1</td><td>single</td><td>speaker</td><td>Dialog</td></tr> <tr><td>(Schuff et al., 2017)</td><td>3–6</td><td>6</td><td>various</td><td>8</td><td>multi</td><td>?</td><td>Twitter</td></tr> <tr><td>(Mohammad et al., 2015)</td><td>3+</td><td>≈ 3000</td><td>> half</td><td>19+1</td><td>single</td><td>text</td><td>Twitter</td></tr> <tr><td>(Brynielsson et al., 2014)</td><td>3</td><td>3</td><td>majority</td><td>3+1</td><td>single</td><td>writer</td><td>Twitter</td></tr> <tr><td>(Neviarouskaya et al., 2010)</td><td>3</td><td>3</td><td>≥2 agree</td><td>14</td><td>single</td><td>?</td><td>Various</td></tr> <tr><td>(Neviarouskaya et al., 2009)</td><td>3</td><td>3</td><td>≥2 agree</td><td>9+1</td><td>single</td><td>?</td><td>Blogs</td></tr> <tr><td>(Strapparava and Mihalcea, 2007)</td><td>6</td><td>6</td><td>?</td><td>6</td><td>multi</td><td>reader</td><td>Headlines</td></tr> <tr><td>(Aman and Szpakowicz, 2007)</td><td>2</td><td>4</td><td>both agree</td><td>6+2</td><td>single</td><td>text</td><td>Blogs</td></tr> <tr><td>(Alm et al., 2005)</td><td>2-3</td><td>3</td><td>majority</td><td>6+1</td><td>single</td><td>text</td><td>Children</td></tr> </tbody> </table> <p>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").</p> <p>Table taken from (Štajner, 2021)</p> <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>29</p>	Study	#annotators	Per instance	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	(Ohman 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	<p>EMOTIONS IN CHILDREN STORIES: Alm et al., 2005</p> <ul style="list-style-type: none"> • 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 <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>30</p>
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Resources

EMOTIONS IN NEWS HEADLINES: Strapparava and Mihalcea, 2007

- **Genre:** news headlines
- **Span:** headline
- **Size:** 1250 headlines
- **Emotions:** Ekman's
- **Intensity:** [0,100]
- **Perspective:** reader's
- **Labelling:** multiple
- **Annotators:** 6
- **Gold:** ?

SemEval-2007 Task 14: Affective Text

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EMOTIONS IN ELECTORAL TWEETS: Mohammad et al., 2015

- **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

- Q1. Which of the following best describes the **Emotions** in this tweet?
- 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.

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EMOTIONS IN TWEETS: Schuff et al., 2017

- **Genre:** SemEval 2016 Stance Data set (Mohammad et al., 2016)
- **Span:** tweet
- **Size:** 4,868 tweets
- **Emotions:** Plutchik (anger, anticipation, disgust, fear, joy, sadness, surprise, trust)
- **Perspective:** ?
- **Labelling:** multi
- **Annotators:** 6 (minimum 3 per each tweet)
- **Gold:** various

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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)
- **Emotions:** Ekman's + neutral + non-neutral
- **Perspective:** speaker
- **Labelling:** single
- **Annotators:** 5 AMT workers per each
- **Gold:** majority (when more than two majority then class non-neutral)

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EMOTIONS IN CONVERSATIONS: Hsu et al., 2018

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- **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

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

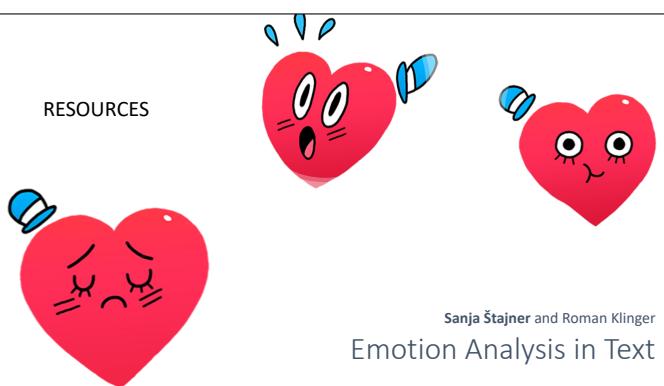
Questions?



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- EACL 2023

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RESOURCES



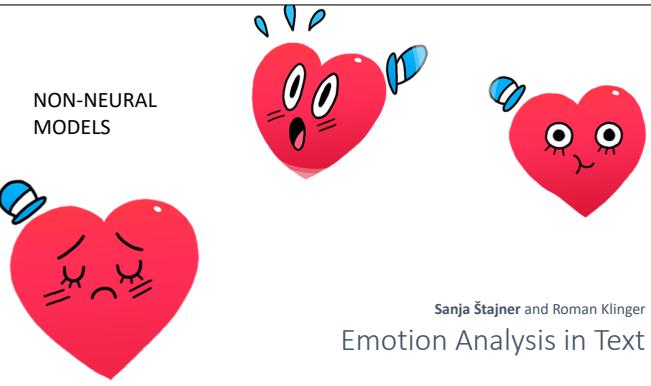
Sanja Štajner and Roman Klinger
Emotion Analysis in Text

EACL 2023 Tutorial - 05.05.2023

Annotation Exercise

 <p>Universität Stuttgart Institut für Maschinelle Sprachverarbeitung</p> <h3>Emotion Analysis</h3> <p>Small Annotation Exercise and Discussion</p> <p>EACL 2023 Tutorial Sanja Štajner and Roman Klinger</p> 	<h3>Hand On Annotation</h3> <p>What we will do now:</p> <ul style="list-style-type: none">• You heard now a bit about existing resources and methods.• Let's do an annotation together.• For each instance that we show you, answer the questions in the form. <p>Think about the following questions:</p> <ul style="list-style-type: none">• Would annotators agree on the label?• Would an automatic method succeed/fail? <p>Link: https://forms.gle/9pwPXnCCB8K1ocrg7</p> 
Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger EACL 2023 Tutorial 2 / 5
<h3>About this tutorial</h3> <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	Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 4 / 5

Non-Neural Methods

 <p>NON-NEURAL MODELS</p> <p>Sanja Štajner and Roman Klinger Emotion Analysis in Text</p> <p>EACL 2023 Tutorial – 05.05.2023</p>	<h2>NON-NEURAL MODELS</h2>																																				
<p>EMOTIONS IN CHILDREN STORIES: Alm et al., 2005</p> <ul style="list-style-type: none"> • Genre: children stories (22 Grimms' tales) • Task: Emotional vs. non-emotional • rule-based linear classifier (SNoW) • 10-fold cross-validation (90% training, 10% testing) <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p>	<p>EMOTIONS IN CHILDREN STORIES: Alm et al., 2005</p> <ul style="list-style-type: none"> • Features: <ul style="list-style-type: none"> • 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 • Interjections and affective words • Content BoW: N, V, JJ, RB words by POS <table border="1"> <thead> <tr> <th></th> <th>same-tune-eval</th> <th>sep-tune-eval</th> </tr> </thead> <tbody> <tr> <td>P(Neutral)</td> <td>59.94</td> <td>60.05</td> </tr> <tr> <td>Content BOW</td> <td>61.01</td> <td>58.30</td> </tr> <tr> <td>All features except BOW</td> <td>64.68</td> <td>63.45</td> </tr> <tr> <td>All features</td> <td>68.99</td> <td>63.31</td> </tr> <tr> <td>All features + sequencing</td> <td>69.37</td> <td>62.94</td> </tr> </tbody> </table> <p>Accuracy</p> <p>Figure taken from (Alm et al., 2005)</p>		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																		
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Non-Neural Methods

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)

Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023

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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	F ₁	P	R	F ₁	P	R	F ₁
Anger	76	72	74	76	77	76	77	77	77
	(1.7)	(4.3)	(0.9)	(0.8)	(2.7)	(1.3)	(0.8)	(2.7)	(1.3)
Anticipation	72	61	66	68	68	67	70	66	68
	(1.8)	(8.9)	(3.5)	(1.2)	(3.6)	(1.6)	(1.2)	(0.8)	(0.5)
Disgust	62	47	54	59	53	56	64	68	65
	(3.2)	(8.7)	(2.5)	(1.4)	(4.6)	(1.7)	(0.6)	(3.9)	(1.9)
Fear	57	31	40	55	40	46	51	48	49
	(3.5)	(8.5)	(4.6)	(1.6)	(6.3)	(3.8)	(1.7)	(6.2)	(3.9)
Joy	55	50	52	52	52	52	56	41	46
	(3.0)	(0.3)	(0.3)	(2.9)	(0.5)	(1.8)	(0.9)	(0.3)	(0.2)
Sadness	65	65	65	64	60	62	60	77	67
	(2.5)	(11.1)	(3.9)	(0.6)	(7.5)	(3.2)	(0.9)	(0.3)	(0.5)
Surprise	62	15	24	46	22	30	40	17	21
	(4.4)	(10.4)	(8.7)	(2.9)	(3.2)	(2.5)	(3.7)	(6.3)	(5.0)
Trust	62	38	47	57	45	50	57	49	51
	(6.1)	(12.3)	(5.9)	(2.5)	(4.1)	(2.5)	(0.6)	(6.6)	(3.3)
Micro-Avg.	66	52	58	63	53	58	62	60	61
	(0.9)	(1.9)	(0.7)	(0.3)	(2.4)	(1.2)	(0.6)	(2.0)	(1.0)

Figure adapted from (Schuff et al., 2017)

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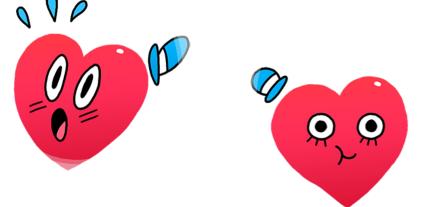
Questions?



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NON-NEURAL MODELS



Sanja Štajner and Roman Klinger
Emotion Analysis in Text

EACL 2023 Tutorial – 05.05.2023

Transfer, Multi-task, and Zero-Shot Predictions

Universität Stuttgart
Institut für
Maschinelle Sprachverarbeitung

Emotion Analysis

Transfer, Multi-Task Learning, Zero-Shot Predictions

EACL 2023 Tutorial
Sanja Štajner and Roman Klinger



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 ooooooo
Multi-task learning ooooo
Zero-Shot Prediction ooooooooooooo

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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?

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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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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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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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Transfer, Multi-task, and Zero-Shot Predictions

Overview oooooo Weak Labeling oooooo Multi-task learning oooooo Zero-Shot Prediction oooooooooooooo

Weak/Self-Labeling

Approach:

- Manually associate
 - 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:

- Easy to obtain huge data sets

Disadvantage:

- Concept of emotion ≠ emotion hashtags/emojis
- Example: 10.1109/SocialCom-PASSAT.2012.119

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Overview oooooo Weak Labeling oooooo Multi-task learning oooooo Zero-Shot Prediction oooooooooooooo

Transfer Learning: DeepMoji

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Overview oooooo Weak Labeling oooooo Multi-task learning oooooo Zero-Shot Prediction oooooooooooooo

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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Overview oooooo Weak Labeling oooooo Multi-task learning oooooo Zero-Shot Prediction oooooooooooooo

Transfer Learning: DeepMoji

- Blue: frozen
 - tune any new layers
 - then tune 1st layer
 - then tune next layer, until all have been tuned
 - tune all together

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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Final Remark on Results

- 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)

	Testing on	A	Training on
AffectiveText (H, e)	25	65 5 18 16 6 16 1 63 31 32 12 33	
Blogs (B, e)	53	9 76 37 59 30 9 8 9 12 19 54 14	
CrowdFlower (T, e)	25	13 35 32 31 16 21 17 18 19 27 28 20	
DailyDialog (C, e)	56	6 74 37 71 33 4 5 4 7 15 58 7	
Electoral-Tweets (T, e)	16	11 31 18 28 31 10 10 9 17 18 26 14	
Emotion-Stimulus (P, e)	46	16 22 24 13 15 41 49 21 32 23 32 30	
Grounded-Emotions (T, d)	46	48 19 30 12 23 19 15 51 28 50 20 33	
ISEAR (S, e)	43	27 25 28 23 22 30 36 19 64 28 23 35	
SSEC (T, e)	22	38 15 34 19 27 25 3 62 36 65 30 35	
Tales (F, e)	36	10 53 27 51 15 9 10 9 9 13 54 12	
TEC (T, d)	35	24 17 21 12 20 24 22 28 27 31 14 56	

Overview oooooo Weak Labeling oooooo Multi-task learning oooooo Zero-Shot Prediction oooooooooooooo

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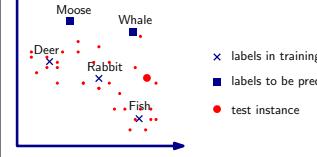
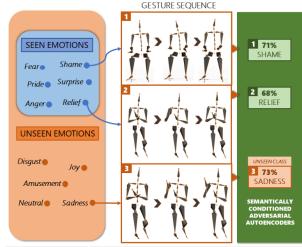
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Tasks in Multitask Learning and Emotions

- 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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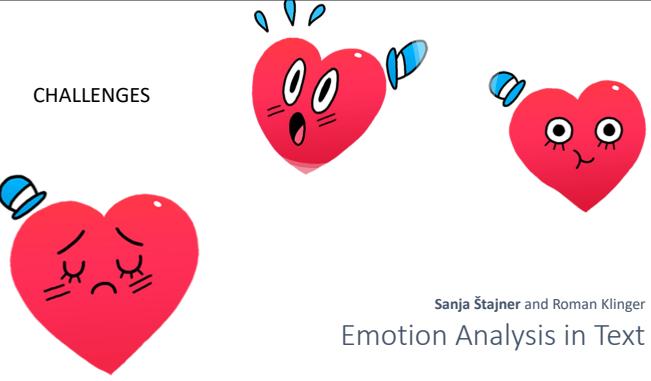
Transfer, Multi-task, and Zero-Shot Predictions

Overview ooooo	Weak Labeling ooooooo	Multi-task learning ooooo	Zero-Shot Prediction oooooooooooo	Overview ooooo	Weak Labeling ooooooo	Multi-task learning ooooo	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/ 							
<p>Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 17 / 31</p> <p>Overview ooooo</p> <p>Weak Labeling ooooooo</p> <p>Multi-task learning ooooo</p> <p>Zero-Shot Prediction oooooooooooo</p> <p>Questions?</p>							
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<p>Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 19 / 31</p> <p>Overview ooooo</p> <p>Weak Labeling ooooooo</p> <p>Multi-task learning ooooo</p> <p>Zero-Shot Prediction oooooooooooo</p> <p>Why should Zero-Shot Learning be possible?</p> <p>Training Data with labels: Deer, Fish, Rabbit</p>  <ul style="list-style-type: none"> 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. <p>Test Data with unseen labels: Moose, Whale</p>  <p>Photo Attribution: Rabbit: David Iff, Fish: Diego Delso, Deer: Frank Lisbig, Whale: Whit Welles. Licenses: CC BY-SA 3.0, Moose: Public Domain</p>							
<p>Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 20 / 31</p> <p>Overview ooooo</p> <p>Weak Labeling ooooooo</p> <p>Multi-task learning ooooo</p> <p>Zero-Shot Prediction oooooooooooo</p> <p>ZSL as Embedding Prediction</p>  <ul style="list-style-type: none"> Label vectors based on concept features Learn to map instance into concept space <ul style="list-style-type: none"> 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? 							
<p>Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 21 / 31</p> <p>Overview ooooo</p> <p>Weak Labeling ooooooo</p> <p>Multi-task learning ooooo</p> <p>Zero-Shot Prediction oooooooooooo</p> <p>Related: ZSL for Emotion Classification from Gestures</p>  <ul style="list-style-type: none"> 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) 							
<p>Tutorial Emotion Analysis, EACL 2023 Štajner/Klinger EACL 2023 Tutorial 23 / 31</p> <p>Overview ooooo</p> <p>Weak Labeling ooooooo</p> <p>Multi-task learning ooooo</p> <p>Zero-Shot Prediction oooooooooooo</p> <p>Another approach to ZSL Emotion Classification</p> <ul style="list-style-type: none"> 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 							

Transfer, Multi-task, and Zero-Shot Predictions

<p>Alternative: Zero-Shot Learning as Entailment</p> <p>Benchmarking Zero-shot Text Classification: Datasets, Evaluation and Entailment Approach</p> <p>Wenpeng Yin, Jamaal Hay, Dan Roth Cognitive Computation Group Department of Computer and Information Science, University of Pennsylvania {wenpeng, jamaalh, danroth}@seas.upenn.edu</p>	<p>Overview oooooo</p> <p>Weak Labeling oooooooo</p> <p>Multi-task learning oooooo</p> <p>Zero-Shot Prediction oooooooooooo</p> <p>Zero-Shot Learning as Entailment (2)</p> <ul style="list-style-type: none"> • Input: Two sentences, premise and hypothesis • Output: contradiction, entailment, neutral • Example online demo: https://huggingface.co/microsoft/deberta-large-mnli <p>• How to represent the label as a hypothesis? • Yin et al. use "This text expresses [?]" and the WordNet concept definition.</p>																																
<p>Tutorial Emotion Analysis, EACL 2023</p> <p>Overview oooooo</p> <p>Weak Labeling oooooooo</p> <p>Multi-task learning oooooo</p> <p>Zero-Shot Prediction oooooooooooo</p> <p>Emotion ZSL as Natural Language Inference</p> <ul style="list-style-type: none"> • 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? <p>(Arco Del Plaza et al., COLING 2022)</p>	<p>Tutorial Emotion Analysis, EACL 2023</p> <p>Overview oooooo</p> <p>Weak Labeling oooooooo</p> <p>Multi-task learning oooooo</p> <p>Zero-Shot Prediction oooooooooooo</p> <p>Emotion Hypotheses</p> <table border="1"> <thead> <tr> <th></th> <th>Emo-Name</th> <th>Expr-Emo</th> <th>Feels-Emo</th> <th>WN-Def</th> <th>Emo-S</th> <th>Expr.-S</th> <th>Feels.-S</th> <th>EmoLex</th> </tr> </thead> <tbody> <tr> <td></td> <td>angry</td> <td>This text expresses anger</td> <td>This person feels anger</td> <td>This person expresses a strong emotion; a feeling that is oriented toward some real or supposed grievance</td> <td>Same prefix + anger, annoyance, rage, outrage, fury, irritation</td> <td></td> <td></td> <td></td> </tr> <tr> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>all emotion words from an NRC emotion lexicon</td> </tr> </tbody> </table>		Emo-Name	Expr-Emo	Feels-Emo	WN-Def	Emo-S	Expr.-S	Feels.-S	EmoLex		angry	This text expresses anger	This person feels anger	This person expresses a strong emotion; a feeling that is oriented toward some real or supposed grievance	Same prefix + anger, annoyance, rage, outrage, fury, irritation												all emotion words from an NRC emotion lexicon					
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Open Challenges

 <p>CHALLENGES</p> <p>Emotion Analysis in Text</p> <p>Sanja Štajner and Roman Klinger</p> <p>EACL 2023 Tutorial – 05.05.2023</p>	<p>CHALLENGES</p> <ul style="list-style-type: none"> Annotation: <ul style="list-style-type: none"> Natural difficulty of the task Missing context/knowledge Linguistic difficulty Various emotions present in the instance Quality of annotations Consistency of annotations Comparison 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>
<p>ANNOTATION CHALLENGES: NATURAL DIFFICULTY</p> <ul style="list-style-type: none"> “2 pretty sisters are dancing with cancer 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 #effguyswantmyqueensize” (anger; sadness; neutral) (Štajner, 2021) <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>59</p>	<p>ANNOTATION CHALLENGES: MISSING KNOWLEDGE</p> <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>
<p>ANNOTATION CHALLENGES: LINGUISTIC DIFFICULTY</p> <p>NON-LITERAL MEANING</p> <ul style="list-style-type: none"> “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) <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>61</p>	<p>ANNOTATION CHALLENGES: VARIOUS EMOTIONS</p> <ul style="list-style-type: none"> “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) <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>62</p>
<p>ANNOTATION CHALLENGES: QUALITY OF ANNOTATIONS</p> <ul style="list-style-type: none"> Oversight errors Dedication to the task <p>Example: “#BIBLE = Big Irrelevant Book of Lies and Exaggerations” (trust) (Schuff et al., 2017)</p> <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>63</p>	<p>ANNOTATION CHALLENGES: CONSISTENCY</p> <ul style="list-style-type: none"> Emotional perception depends on annotators personality and mood (Alm et al., 2005) Inter-annotator agreements are very low: <ul style="list-style-type: none"> $\kappa = 0.24 - 0.51$ (Alm et al., 2005) $\kappa = 0.33 - 0.55$ (Štajner, 2021) <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>64</p>

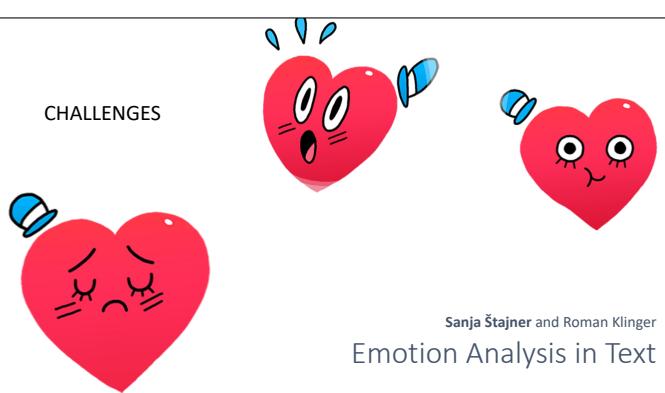
Open Challenges

Questions?



Emotion Analysis from Texts - Sanja Štajner and Roman Klinger
- EACL 2023

CHALLENGES



Sanja Štajner and Roman Klinger
Emotion Analysis in Text

65

EACL 2023 Tutorial – 05.05.2023

Appraisal-based Emotion Analysis

Emotion Analysis

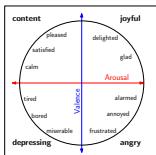
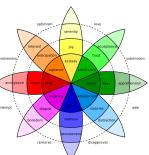
Appraisal-based Resources and Methods

EACL 2023 Tutorial
Sanja Štajner and Roman Klinger



Recap 000 The OCC Model of Emotions 000000000 Scherer 0000000 Other Approaches 000000

Emotion Models



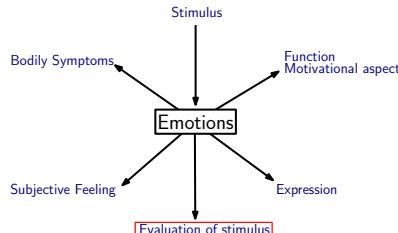
⇒ Methods mostly treat emotions as a label and learn the association to text properties, without considering (too much) knowledge from psychology about emotions

Outline

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

Recap 000 The OCC Model of Emotions 000000000 Scherer 0000000 Other Approaches 000000

Emotion Components



Appraisal Models in Psychology: Smith/Ellsworth and Scherer

Emotion	Component					
	Pleasure*	Responsibility/Control*	Certainty*	Attention*	Effort*	
Happiness	-1.46	0.09	-0.46	0.15	-0.33	-0.21
Sadness	0.57	-0.08	-0.40	0.21	0.14	1.01
Anger	0.85	-0.04	-0.29	0.12	0.33	-0.96
Boredom	0.24	0.01	-0.46	0.27	0.19	0.12
Challenge	-0.37	0.44	-0.01	0.52	1.19	-0.20
Hope	-0.50	0.13	0.46	0.31	0.31	0.35
Fear	0.44	-0.17	0.73	0.03	0.63	0.59
Arousal	-1.05	-0.13	-0.12	0.96	-0.07	0.41
Curiosity	0.89	-0.05	-0.12	0.96	-0.07	0.43
Disgust	-1.31	-0.50	-0.39	0.06	0.06	-0.19
Frustration	1.85	-0.07	-0.39	0.40	0.45	0.22
Surprise	-1.31	-0.04	0.73	0.40	-0.66	0.15
Pride	0.75	0.81	0.32	0.02	0.33	-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 standardised.

*Measurements: high scores indicate increased pleasure.

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

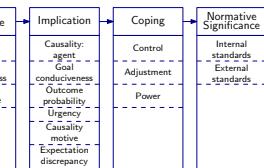
*Certainty: high scores indicate increased certainty.

*Attention: high scores indicate increased attentional activity.

*Effort: high scores indicate increased effort.

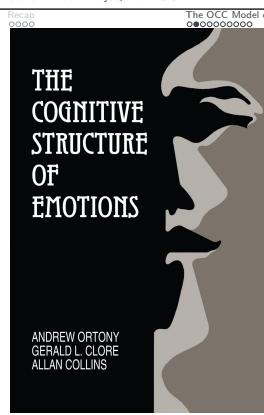
*Situational control: high scores indicate increased situational control.

- How to use appraisals in computational modeling?



Outline

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



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

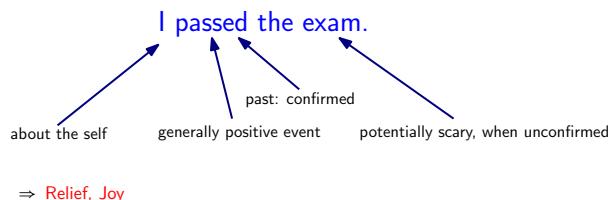
Gerald L. Clore and
Department of Psychology, University of Virginia, USA
Andrew Ortony
Department of Psychology, Northwestern University, USA

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 response; (b) emotions emerge in, rather than from, situations; (c) the meaning of situations influences the impact of the impact of emotion is determined by the nature of the situations they represent; (d) in the OCC model of emotion, appraisal is 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.

Warm-Up Example

How to interpret the emotion?



⇒ Relief, Joy

Appraisal-based Emotion Analysis

<p>OCC Model</p> <ul style="list-style-type: none"> The OCC Model explains how emotions happen in the interaction of a person and the world The world consists of: Events, People, Objects Main components to evaluate the world: <ul style="list-style-type: none"> Are events in line with goals? Are people behaving in line with standards? Does the person have a positive attitude towards objects? Further components <ul style="list-style-type: none"> Point of view Time 	<p>Exercise</p> <ul style="list-style-type: none"> The employee thinks that he might be fired. Mary learns that her husband cheated to win in the lottery. 																																																																					
<p>How can we interpret the different components in the OCC?</p>	<p>OCC Text Interpretation</p> <p>A Rule-Based Approach to Implicit Emotion Detection in Text</p> <p>Orin Udochukwu^(b) and Yulan He School of Engineering and Applied Science, Aston University, Birmingham, UK orizus.y.he@aston.ac.uk</p> <p>Abstract Numerous approaches have already been employed to ‘sense’ affective information from text, but none of them ever employed the OCC emotion model, an appraisal theory of the cognitive and affective structure of emotions. The OCC model derives 2 emotions (positive and negative) from 3 cognitives (events, people, and cognitive variables). In this chapter, we propose to relate cognitive variables of the emotion model to linguistic components in text, in order to achieve emotion recognition for a much larger set of emotions than handled in comparable approaches. In particular, we provide tailored rules for implicit emotion detection in text which are inspired by the rules of the OCC emotion model. Finally, we clearly show how components are mapped to core values of the cognitive variables of the emotion model. The resulting linguistics-based rule set for the OCC emotion types and cognitive states allows us to determine a broad class of emotions conveyed by text.</p> <p>Keywords: Implicit emotions - OCC model - Emotion detection - Rule-based approach</p>																																																																					
<p>Example Rules (à la Shaikh)</p> <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<math>\approx</math> desirability pros: prospect valence of verb If (vr = true & sr = 'displeased' & pros = 'negative' & sp = 'undesirable' & status = 'unconfirmed' & de = 'self') => fear 	<p>Outline</p> <ol style="list-style-type: none"> 1 Recap 2 The OCC Model of Emotions 3 Appraisal Prediction following Scherer 4 Other Approaches 																																																																					
<p>Results (Udochukwu/He 2015)</p> <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 NB Rule</th> </tr> </thead> <tbody> <tr> <td>Joy/Happy</td> <td>33.4</td> <td>61.2</td> <td>69.6</td> <td>39.7</td> <td>71.7</td> <td>59.9</td> </tr> <tr> <td>Fear/Fearful</td> <td>0</td> <td>47.6</td> <td>18.3</td> <td>0</td> <td>52.2</td> <td>31.8</td> </tr> <tr> <td>Anger/Angry-Disgusted</td> <td>23.0</td> <td>47.1</td> <td>61.3</td> <td>55.8</td> <td>16.2</td> <td>61.3</td> </tr> <tr> <td>Sadness/Sad</td> <td>25.6</td> <td>55.4</td> <td>68.0</td> <td>47.8</td> <td>56.0</td> <td>71.5</td> </tr> <tr> <td>Disgust</td> <td>25.6</td> <td>51.0</td> <td>39.2</td> <td>38.5</td> <td>34.5</td> <td>61.7</td> </tr> <tr> <td>Average</td> <td>21.5</td> <td>52.5</td> <td>51.3</td> <td>36.4</td> <td>58.2</td> <td>57.3</td> </tr> <tr> <td>Average (- Fear)</td> <td>27.0</td> <td>53.7</td> <td>59.5</td> <td>45.5</td> <td>44.6</td> <td>63.6</td> </tr> <tr> <td></td> <td></td> <td></td> <td></td> <td>56.12</td> <td>65.8</td> <td>82.7</td> </tr> </tbody> </table>	Emotion	ISEAR		SemEval		Alm's		Lexicon NB Rule	Joy/Happy	33.4	61.2	69.6	39.7	71.7	59.9	Fear/Fearful	0	47.6	18.3	0	52.2	31.8	Anger/Angry-Disgusted	23.0	47.1	61.3	55.8	16.2	61.3	Sadness/Sad	25.6	55.4	68.0	47.8	56.0	71.5	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	Average (- Fear)	27.0	53.7	59.5	45.5	44.6	63.6					56.12	65.8	82.7	<p>66 M.A.M. Shaikh et al.</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' & sp = 'undesirable' & de = 'other'), 'anger' is true. If (vr = true & sr = 'displeased' & sp = 'desirable' & de = 'self'), 'sadness' is true. If (vr = true & sr = 'displeased' & sp = 'desirable' & de = 'other'), 'fear' is true. If (vr = true & sr = 'planned' & pros = 'negative' & sp = 'desirable' & de = 'self'), 'disgust' is true. If (vr = true & sr = 'planned' & pros = 'negative' & sp = 'desirable' & de = 'other'), 'surprise' is true. If (vr = true & sr = 'planned' & pros = 'positive' & sp = 'desirable' & de = 'self'), 'joy' is true. If (vr = true & sr = 'planned' & pros = 'positive' & sp = 'desirable' & de = 'other'), 'happiness' is true. If (vr = true & sr = 'planned' & pros = 'positive' & sp = 'undesirable' & de = 'self'), 'sadness' is true. If (vr = true & sr = 'planned' & pros = 'positive' & sp = 'undesirable' & de = 'other'), 'surprise' is true. If (vr = true & sr = 'undesired' & sp = 'positive' & de = 'self'), 'disgust' is true. If (vr = true & sr = 'undesired' & sp = 'positive' & de = 'other'), 'surprise' is true. If (vr = true & sr = 'undesired' & sp = 'undesirable' & de = 'self'), 'sadness' is true. If (vr = true & sr = 'undesired' & sp = 'undesirable' & de = 'other'), 'surprise' is true. <p>The OCC model has four complex conditions namely, 'planned', 'sememe', 'gratitude', and 'anger'. The rules for these emotions are as follows.</p> <ul style="list-style-type: none"> If (sememe = 'planned' & sr = 'displeased' & sp = 'undesirable' & de = 'self'), 'disgust' is true. If (sememe = 'planned' & sr = 'displeased' & sp = 'undesirable' & de = 'other'), 'surprise' is true. If both 'disgust' and 'surprise' are true, 'sememe' is true. If both 'joy' and 'happiness' are true, 'gratitude' is true. If both 'anger' and 'surprise' 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 'disgust' and 'surprise' are true, 'shock' is true (e.g., the bad news came through). If both 'joy' and 'surprise' are true, 'surprise' is true (e.g., I suddenly met my school friend in Tokyo University). 					
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Appraisal-based Emotion Analysis

Appraisal Prediction following Scherer's Model				Approach																																																																																															
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<p>Questions and Answers</p> <ul style="list-style-type: none"> • Do readers agree more with each other than with the writers? (does the writer make use of information that the readers do not have) <ul style="list-style-type: none"> • Yes, a bit for emotions; clearly for the appraisals. • Does it matter if annotators share demographic properties? <ul style="list-style-type: none"> • Females agree more with each other, but men less. • People of similar age agree more. • Does personality matter? <ul style="list-style-type: none"> • Extraverted, conscientious, agreeable annotators perform better. <p>Setup: <ul style="list-style-type: none"> • Filter instances for attribute, compare with F_1/RMSE • Significance test with bootstrap resampling for .95 confidence interval </p>				<p>Appraisals add additional information to emotion analysis</p> <table border="1"> <thead> <tr> <th>Dimension</th> <th>Writer</th> <th>Readers</th> <th>Δ</th> </tr> </thead> <tbody> <tr> <td>Emotion</td> <td>Pride</td> <td>Sadness</td> <td></td> </tr> <tr> <td>Suddenness</td> <td>4</td> <td>3.6</td> <td>0.4</td> </tr> <tr> <td>Familiarity</td> <td>1</td> <td>2.0</td> <td>-1.0</td> </tr> <tr> <td>Predictability</td> <td>1</td> <td>1.8</td> <td>-0.8</td> </tr> <tr> <td>Pleasantness</td> <td>4</td> <td>1.0</td> <td>3.0</td> </tr> <tr> <td>Unpleasantness</td> <td>4</td> <td>4.5</td> <td>-2.5</td> </tr> <tr> <td>Goal-Relevance</td> <td>4</td> <td>4.4</td> <td>-0.4</td> </tr> <tr> <td>Chance-Resp.</td> <td>4</td> <td>4.4</td> <td>-0.4</td> </tr> <tr> <td>Self-Resp.</td> <td>1</td> <td>1.2</td> <td>-0.2</td> </tr> <tr> <td>Other-Resp.</td> <td>1</td> <td>1.4</td> <td>-0.4</td> </tr> <tr> <td>Conseq.-Predict.</td> <td>2</td> <td>1.8</td> <td>0.2</td> </tr> <tr> <td>Goal Support</td> <td>1</td> <td>1.2</td> <td>-0.2</td> </tr> <tr> <td>Urgency</td> <td>2</td> <td>3.8</td> <td>-1.8</td> </tr> <tr> <td>Self-Control</td> <td>5</td> <td>3.0</td> <td>2.0</td> </tr> <tr> <td>Other-Control</td> <td>3</td> <td>2.0</td> <td>1.0</td> </tr> <tr> <td>Control-Accept.</td> <td>1</td> <td>1.6</td> <td>-1.0</td> </tr> <tr> <td>Accept-Conseq.</td> <td>1</td> <td>2.4</td> <td>1.0</td> </tr> <tr> <td>Standards</td> <td>1</td> <td>2.4</td> <td>-1.4</td> </tr> <tr> <td>Social Norms</td> <td>1</td> <td>1.2</td> <td>-0.2</td> </tr> <tr> <td>Attention</td> <td>4</td> <td>4.4</td> <td>-0.4</td> </tr> <tr> <td>Not-Consider</td> <td>1</td> <td>3.8</td> <td>-2.8</td> </tr> <tr> <td>Effort</td> <td>4</td> <td>4.6</td> <td>-0.6</td> </tr> </tbody> </table> <p>"That I put together a funeral service for my Aunt"</p>				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	4	4.5	-2.5	Goal-Relevance	4	4.4	-0.4	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	3.0	2.0	Other-Control	3	2.0	1.0	Control-Accept.	1	1.6	-1.0	Accept-Conseq.	1	2.4	1.0	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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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	3.0	2.0																																																																																																
Other-Control	3	2.0	1.0																																																																																																
Control-Accept.	1	1.6	-1.0																																																																																																
Accept-Conseq.	1	2.4	1.0																																																																																																
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																																																																																																
<p>Modeling Results</p> <ul style="list-style-type: none"> • Classification with RoBERTa-based models • Appraisal Classification: 75 F_1 • Emotion classification: 59 F_1 • + Appraisals: +2pp F_1 (+10 for guilt, +6 for sadness) 				<p>Examples where Appraisals correct the Emotion Classifier</p> <ul style="list-style-type: none"> • 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 were massive pride → disgust 																																																																																															
<p>Outline</p> <ol style="list-style-type: none"> 1 Recap 2 The OCC Model of Emotions 3 Appraisal Prediction following Scherer 4 Other Approaches 				<p>Other Approaches</p> <ul style="list-style-type: none"> • 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 																																																																																															

Appraisal-based Emotion Analysis

<p>Recap oooo</p> <p>The OCC Model of Emotions oooooooooooo</p> <p>Scherer oooooooo</p> <p>Other Approaches oooo●○</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>Tutorial Emotion Analysis, EACL 2023 Stajner/Klinger EACL 2023 Tutorial 25 / 27</p>	<p>Recap oooo</p> <p>The OCC Model of Emotions oooooooooooo</p> <p>Scherer oooooooo</p> <p>Other Approaches oooo●○</p> <p>Questions?</p> <p>Tutorial Emotion Analysis, EACL 2023 Stajner/Klinger EACL 2023 Tutorial 26 / 27</p>
<p>Recap oooo</p> <p>The OCC Model of Emotions oooooooooooo</p> <p>Scherer oooooooo</p> <p>Other Approaches oooo●○</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 <p>Tutorial Emotion Analysis, EACL 2023 Stajner/Klinger EACL 2023 Tutorial 27 / 27</p>	

Emotion Role Labeling

Emotion Analysis

Role Labeling and Stimulus Detection

EACL 2023 Tutorial
Sanja Štajner and Roman Klinger



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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 [target] [cue] [experiencer] 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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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.

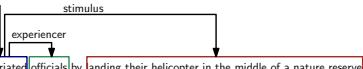
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Task Definition: Relations, spans, or clauses?

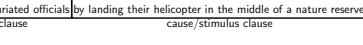
- Relation detection:



- Sequence labeling:



- Clause classification:



→ trade-off between task complexity and accuracy

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Corpora: SRL4E

Resource	Original	SRL4E	%
Blogs	5,012	4,855	92.3
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

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Oberlaender et al. (2020), Experiencers, Stimuli, or Targets: Which Semantic Roles Enable Machine Learning to Infer the Emotions? PEOPLES
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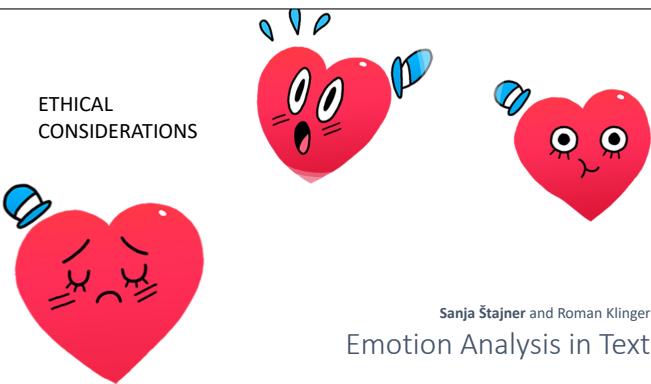
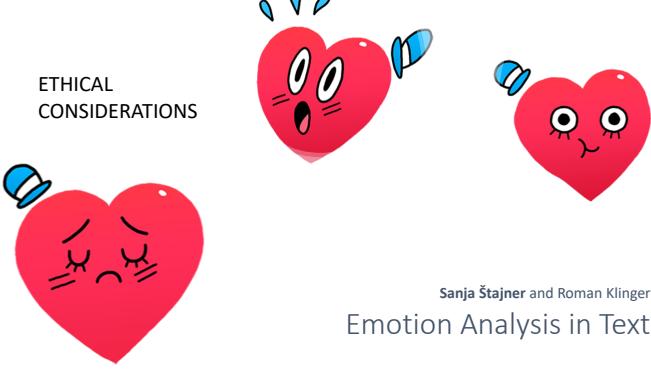
Emotion Role Labeling

Introduction oooo	Resources/Methods oooooooooooo	Take Home oooo	Introduction oooo	Resources/Methods oooooooooooo	Take Home oooo								
Corpus Examples (1)			Corpus Examples (2)										
<ul style="list-style-type: none"> Mohammad et al. (2014). Semantic role labeling of emotions in tweets. <ul style="list-style-type: none"> Crowdsourced span annotations in electoral Tweets Modeling as stimulus classification task Ghazi et al. (2015). Detecting emotion stimuli in emotion-bearing sentences. <ul style="list-style-type: none"> 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. <ul style="list-style-type: none"> Expert-annotated role graph in sentence triples of literature. Modeling span-based with BiLSTM+CRF 			<ul style="list-style-type: none"> Bostan et al. (2020). GoodNewsEveryone: A Corpus of News Headlines Annotated with Emotions, Semantic Roles, and Reader Perception. <ul style="list-style-type: none"> 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. <ul style="list-style-type: none"> Annotation of emotion and stimulus clauses Modeling as clause classification 										
Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger	EACL 2023 Tutorial	9 / 19	Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger	EACL 2023 Tutorial	10 / 19						
Introduction oooo			Introduction oooo			Introduction oooo							
Examples: Emotion Stimulus			Examples: REMAN			Examples: REMAN							
<ul style="list-style-type: none"> 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 . 			<p>The diagram illustrates the REMAN model for emotion analysis. It shows two examples of annotated sentences with dependency trees and role labelings. The first example is "When I mentioned the house, he seemed surprised." The second example is "All laughed at the mistake, and none louder than the forth member of the parliament...". The annotations include labels like Cause, Experiencer, Target, Event, Character, and various intensities and types of emotions (e.g., Joy, Surprise, Anger).</p>			Tutorial Emotion Analysis, EACL 2023							
Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger	EACL 2023 Tutorial	11 / 19	Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger	EACL 2023 Tutorial	12 / 19						
Introduction oooo			Introduction oooo			Introduction oooo							
Examples: Good News Everyone			Examples: ECPE and ECA			Examples: ECPE and ECA							
<p>Headline: A couple infuriated officials by landing their helicopter in the middle of a nature reserve.</p> <p>Emotion: Anger, Anger, Disgust Reader Perception: Yes, No, Yes</p> <p>Intensity: Medium, High, High Other emotions: None, None, None Reader emotions: Annoyance, Negative Surprise, No Emotion</p> <p>Experiencer: 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.</p> <p>Emotion: Anger Intensity: High Other emotions: None Reader perception: Yes Reader emotions: Annoyance, Negative Surprise, No Emotion</p> <p>A dependency graph showing the relationships between the entities and their emotions.</p>			<p>Document</p> <p>Yesterday morning, a policeman visited the old man with the lost money, and told him that the thief was caught. The old man was very happy, and deposited the money in the bank.</p> <table border="1"> <tr> <td>Emotion Cause Extraction (ECE)</td> <td>Emotion-Cause Pair Extraction (ECPE)</td> </tr> <tr> <td>happy → a policeman visited the old man with the lost money</td> <td>(The old man was very happy, a policeman visited the old man with the lost money)</td> </tr> <tr> <td>happy → and told him that the thief was caught</td> <td>(The old man was very happy, and told him that the thief was caught)</td> </tr> </table>			Emotion Cause Extraction (ECE)	Emotion-Cause Pair Extraction (ECPE)	happy → a policeman visited the old man with the lost money	(The old man was very happy, a policeman visited the old man with the lost money)	happy → and told him that the thief was caught	(The old man was very happy, and told him that the thief was caught)	Tutorial Emotion Analysis, EACL 2023	
Emotion Cause Extraction (ECE)	Emotion-Cause Pair Extraction (ECPE)												
happy → a policeman visited the old man with the lost money	(The old man was very happy, a policeman visited the old man with the lost money)												
happy → and told him that the thief was caught	(The old man was very happy, and told him that the thief was caught)												
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Introduction oooo			Outline			Outline							
ECPE – Modeling			<ol style="list-style-type: none"> 1 Introduction 2 Resources 3 Take Home 			<ol style="list-style-type: none"> 1 Introduction 2 Resources 3 Take Home 							
<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. 			Tutorial Emotion Analysis, EACL 2023			Tutorial Emotion Analysis, EACL 2023							
Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger	EACL 2023 Tutorial	15 / 19	Tutorial Emotion Analysis, EACL 2023	Štajner/Klinger	EACL 2023 Tutorial	15 / 19						

Emotion Role Labeling

<p>Introduction oooo</p> <p>Resources / Methods oooooooooooo</p> <p>Take Home</p> <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 <p>Tutorial Emotion Analysis, EACL 2023</p> <p>Stajner/Klinger</p> <p>EACL 2023 Tutorial</p> <p>17 / 19</p>	<p>Take Home oooo</p> <p>Introduction oooo</p> <p>Resources / Methods oooooooooooo</p> <p>Questions?</p> <p>Tutorial Emotion Analysis, EACL 2023</p> <p>Stajner/Klinger</p> <p>EACL 2023 Tutorial</p> <p>18 / 19</p>
<p>Introduction oooo</p> <p>Resources / Methods oooooooooooo</p> <p>About this tutorial</p> <p>Session 1 (09:00–10:30)</p> <ul style="list-style-type: none">IntroductionPsychological ModelsUse Cases/Social ImpactResourcesAnnotation Exercise <p>Break (10:30–11:15)</p> <p>Tutorial Emotion Analysis, EACL 2023</p> <p>Stajner/Klinger</p> <p>EACL 2023 Tutorial</p> <p>19 / 19</p>	<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>Tutorial Emotion Analysis, EACL 2023</p> <p>Stajner/Klinger</p> <p>EACL 2023 Tutorial</p> <p>19 / 19</p>

Ethical Considerations

<p>ETHICAL CONSIDERATIONS</p>  <p>Sanja Štajner and Roman Klinger Emotion Analysis in Text</p> <p>EACL 2023 Tutorial – 05.05.2023</p>	<h3>ETHICAL CONSIDERATIONS: DISCUSSION</h3> <ul style="list-style-type: none">• Privacy• Failure modes and their consequences• Who should be responsible? <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>68</p>
<h3>ETHICAL CONSIDERATIONS: FURTHER READING</h3> <ul style="list-style-type: none">• 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/ <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>69</p>	<p>Questions?</p>  <p>Emotion Analysis from Texts - Sanja Štajner and Roman Klinger - EACL 2023</p> <p>70</p>
<p>ETHICAL CONSIDERATIONS</p>  <p>Sanja Štajner and Roman Klinger Emotion Analysis in Text</p> <p>EACL 2023 Tutorial – 05.05.2023</p>	

Closing

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

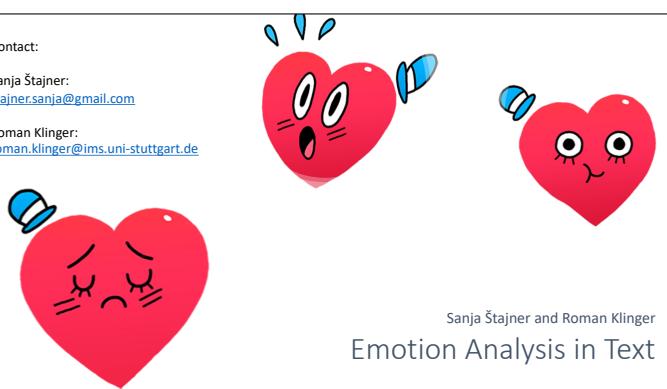
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Sanja Štajner and Roman Klinger
Emotion Analysis in Text

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