University of Bamberg

Event-centered Emotion Classification from Text

Workshop Emotional Speech, Bochum/Germany, July 5, 2024

Roman Klinger
roman.klinger@uni-bamberg.de

@roman_klinger romanklinger
https://www.bamberg.de/nlproc/

About Myself

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- 1999–2006: Studies at University of Dortmund:
  Computer science with minor psychology

UNIVERSITÄT DORTMUND
FACHBEREICH INFORMATIK

Roman Klinger

Komposition von Musik mit Methoden der Computational Intelligence

– Diplomarbeit –

1. Juni 2006

Lehrstuhl 11
Computational Intelligence
Fachbereich Informatik
Universität Dortmund

Gutachter:
Prof. Dr. G. Rudolph
Dr. L. Hildebrand

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  Biomedical text mining, machine learning

Conditional Random Fields for
Named Entity Recognition

Feature Selection and Optimization in
Biology and Chemistry

Dissertation

zur Erlangung des Grades eines

Doktors der Naturwissenschaften

der Technischen Universität Dortmund
an der Fakultät für Informatik
von

Roman Klinger

Dortmund
2011

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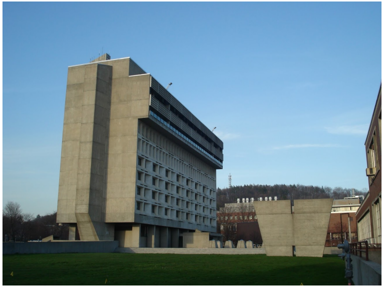
  Probabilistic machine learning, MCMC inference



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  Natural Language Understanding and Generation
- 03/2024: Full Professor for Fundamentals of NLP, Bamberg


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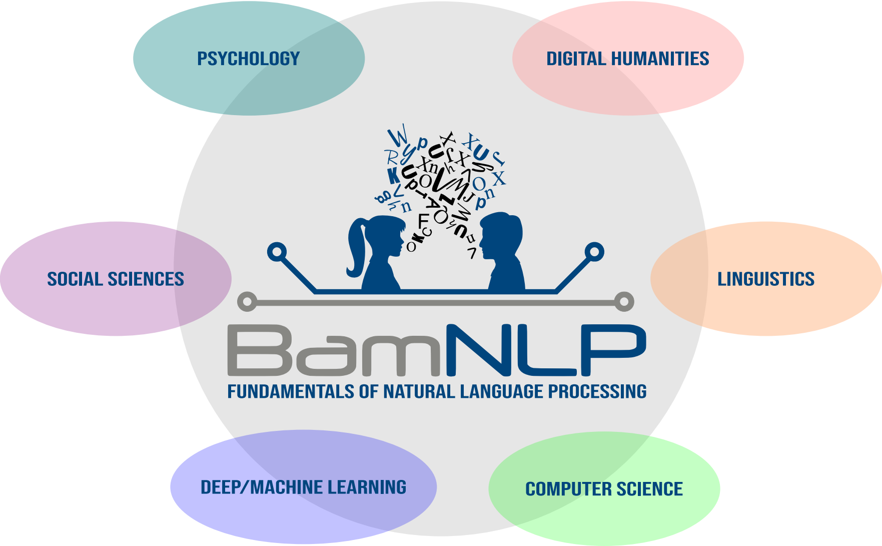
PSYCHOLOGY
DIGITAL HUMANITIES
SOCIAL SCIENCES
LINGUISTICS
BamNLP
FUNDAMENTALS OF NATURAL LANGUAGE PROCESSING
DEEP/MACHINE LEARNING
COMPUTER SCIENCE

Outline

1. Emotion Analysis
2. Emotions are Events
3. Appraisal-based Emotion Analysis
4. What's left to do?
5. Take Home

Outline

1 Emotion Analysis

2 Emotions are Events

3 Appraisal-based Emotion Analysis

4 What's left to do?

5 Take Home

Emotion Examples

Which emotion is associated with the examples?

How did you recognize that?

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- “She became angry.”

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How did you recognize that?

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- "We are going for a walk at the beach."
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With this exercise, we discussed:

- What is an appropriate set of emotions?
- How are they expressed/recognized?
- Emotions are subjective.

Emotion Analysis: What we want to do.

Emotion Analysis: What we want to do.

Roman Klinger
@roman_klinger

The @UniWiai organizes a "choose your chair" fair once every term to bring students and faculty together early, even before the next term starts. I've never seen such initiative anywhere before, and Lynn Greschner and I enjoyed our first participation a lot.

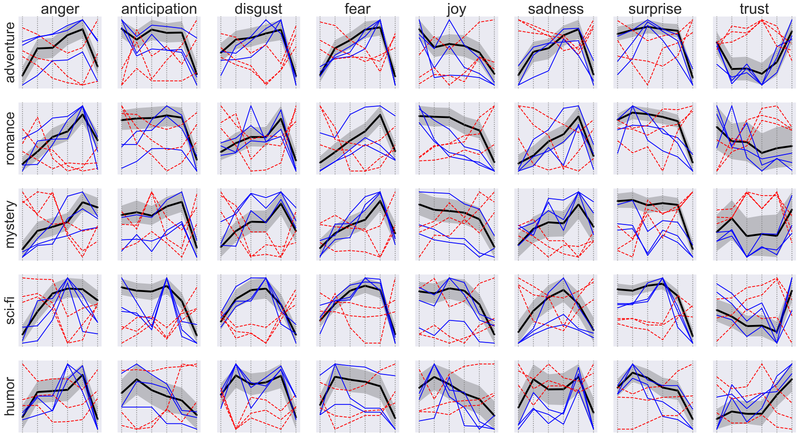
$\downarrow$

Emotion Analysis System

$\downarrow$

Emotion Representation
Joy

Literary Studies



Kim et al., 2017.
Investigating the Relationship between Literary Genres and Emotional Plot Development. LaTeCH@ACL

Dominant Emotions Expressed in News Articles

Emotion	Dominant Emotion
Anger	The Blaze, The Daily Wire, BuzzFeed
Annoyance	Vice, NewsBusters, AlterNet
Disgust	BuzzFeed, The Hill, NewsBusters
Fear	The Daily Mail, Los Angeles Times, BBC
Guilt	Fox News, The Daily Mail, Vice
Joy	Time, Positive.News, BBC
Love	Positive.News, The New Yorker, BBC
Pessimism	MotherJones, Intercept, Financial Times
Neg. Surprise	The Daily Mail, MarketWatch, Vice
Optimism	Bussines Insider, The Week, The Fiscal Times
Pos. Surprise	Positive.News, BBC, MarketWatch
Pride	Positive.News, The Guardian, The New Yorker
Sadness	The Daily Mail, CNN, Daily Caller
Shame	The Daily Mail, The Guardian, The Daily Wire
Trust	The Daily Signal, Fox News, Mother Jones

Bostan et al., 2020.
GoodNewsEveryone: A Corpus of News Headlines Annotated with Emotions, Semantic Roles, and Reader Perception. LREC

Emotion Models in Psychology – Basic Emotions

How to define a categorical system of emotions?

Ekman (1992): An argument for basic emotions.

Emotion Models in Psychology – 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

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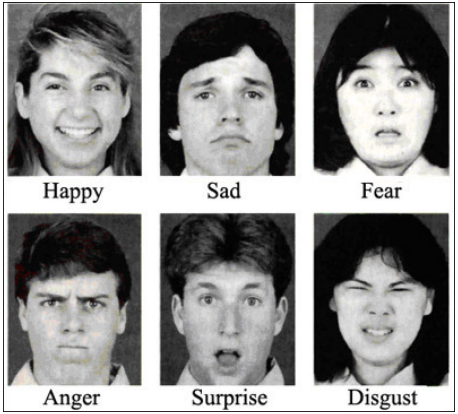

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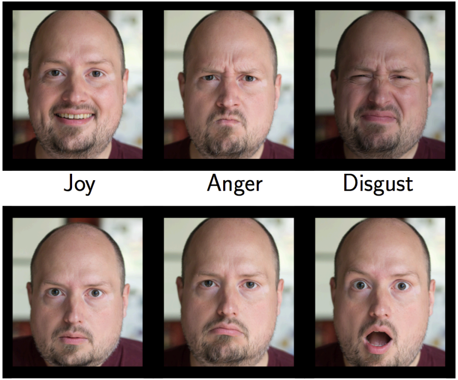

Joy Anger Disgust

Fear Sadness Surprise

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Joy | Anger | Disgust

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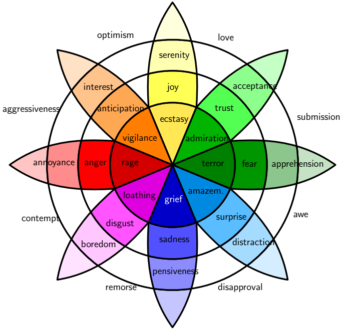

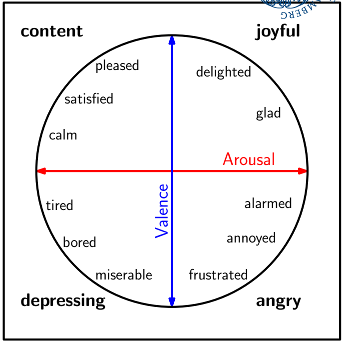

- Emotion models in psychology explain how emotions are developed.
- Text analysis models learn to associate textual realizations to emotion concepts. They do not (explicitly?) use knowledge from such theories.

Emotions and Events

Emotions and Events

Emotions and Events are linked in (at least) two ways:

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Emotions are events

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Events cause emotions

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  - Event: "happy"
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Events cause emotions

- "There is a car on fire."

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  - Relevant event for the speaker, might cause fear.

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  - Requires interpretation of events to infer possible emotions.

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⇒ Motivated the task of emotion semantic role labeling

Events cause emotions

- "There is a car on fire."
  - Relevant event for the speaker, might cause fear.
  - Requires interpretation of events to infer possible emotions.
  - Little previous work
    - Udochukwu/He (2015), Shaikh et al. (2009), Balahur et al. (2011)

Outline

Emotions are Events: Literature

Emotions are Events: Literature

cause experiencer

When I mentioned the house, he seemed surprised.

event character surprise

Emotions are Events: Literature

cause experiencer

When I mentioned the house, he seemed surprised.

event character surprise

experiencer target target experiencer

All laughed at the mistake, and none louder than the forth member of the parliament . . .

character disgust joy other strong joy character

Emotions are Events: Literature

cause experiencer

When I [mentioned the house], [he] seemed [surprised].

event character surprise

experiencer target target experiencer

[All] [laughed] at [the mistake], and [none louder] than [the forth member of the parliament] . . .

character disgust joy other strong joy character

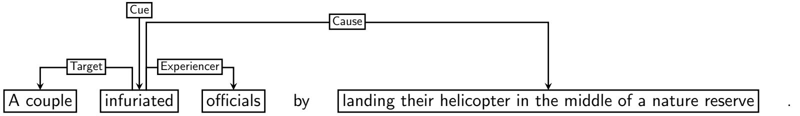
Who Feels What and Why?
Annotation of a Literature Corpus with Semantic Roles of Emotions

Evgeny Kim and **Roman Klinger**
Institut für Maschinelle Sprachverarbeitung
University of Stuttgart, Pfaffenwaldring 5b, 70569 Stuttgart, Germany
evgeny.kim@ims.uni-stuttgart.de
roman.klinger@ims.uni-stuttgart.de

Emotions are Events: News

Emotions are Events: News

Emotion: Anger
Intensity: High
Other emotions: None
Reader perception: Yes
Reader emotions: Annoyance, Negative Surprise, No Emotion



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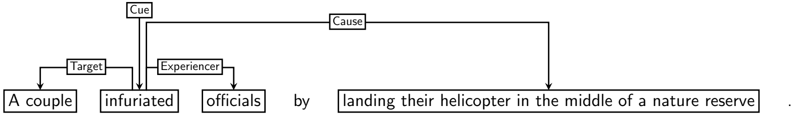

GoodNewsEveryone: A Corpus of News Headlines Annotated with Emotions, Semantic Roles, and Reader Perception

Laura Bostan, Evgeny Kim, Roman Klinger
Institut für Maschinelle Sprachverarbeitung, Universität Stuttgart
Pfaffenwaldring 5b, 70569 Stuttgart, Germany
{laura.bostan, evgeny.kim, roman.klinger}@ims.uni-stuttgart.de

Outline

Definition of Emotions: Components

Emotion (Scherer, 2005)

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Emotions are "an episode of interrelated, synchronized changes in the states of [...] five organismic subsystems in response to the evaluation of a [...] stimulus-event ..."

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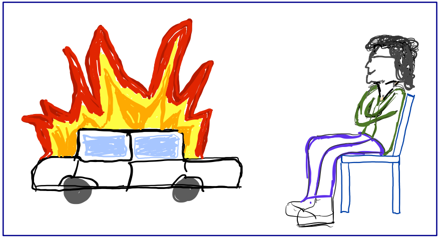

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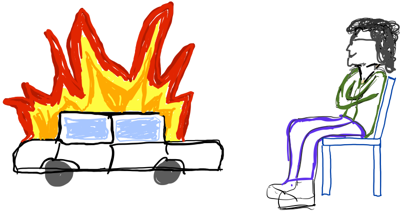

Event

Feeling Expression Bodily Symptom

Action Tendency Cognitive Appraisal

Components

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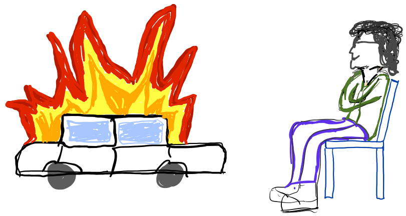


Event

Feeling | Expression | Bodily Symptom

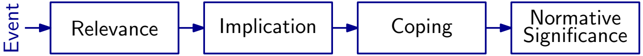
Action Tendency | Cognitive Appraisal

Components

Fear

Name

Cognitive Appraisal in Scherer's Component Process model



K.R. Scherer (2001). Appraisal Considered as a Process of Multilevel Sequential Checking.

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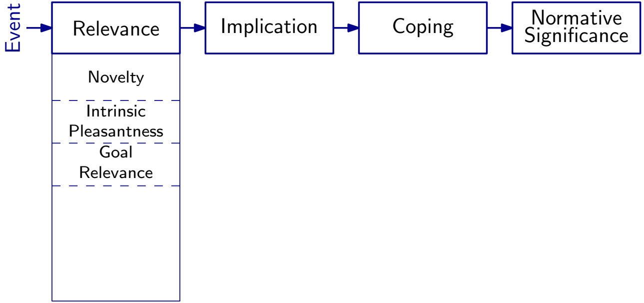

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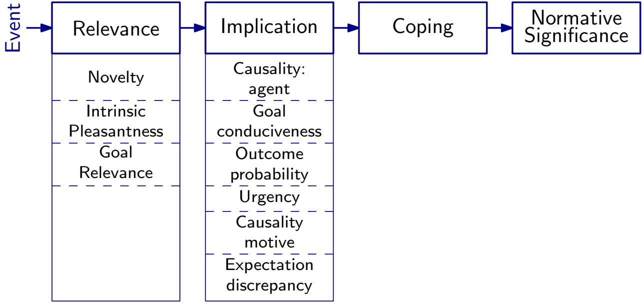

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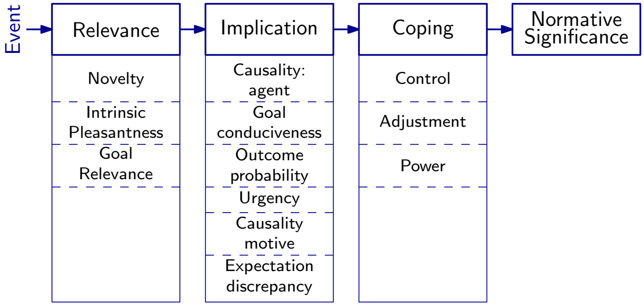

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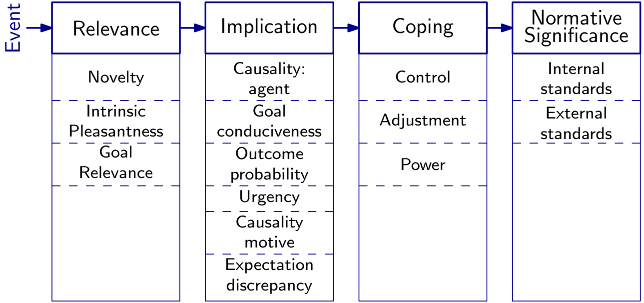

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Research Questions

E. Troiano et al. (2023). "Dimensional Modeling of Emotions in Text with Appraisal Theories: Corpus Creation, Annotation Reliability, and Prediction". In: Computational Linguistics 49.1

J. Hofmann et al. (2020). "Appraisal Theories for Emotion Classification in Text". In: COLING

Research Questions

- Can appraisals be annotated reliably?

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Research Questions

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- Challenge: How to access the personal interpretation of an event?

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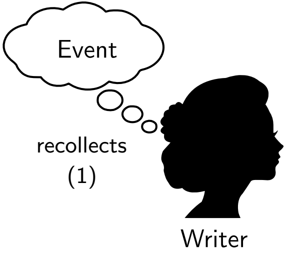
Approach



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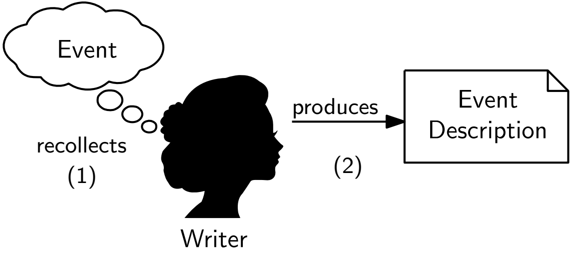

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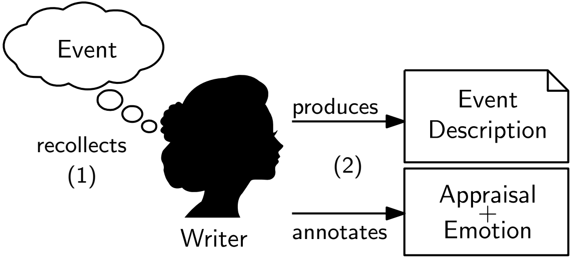
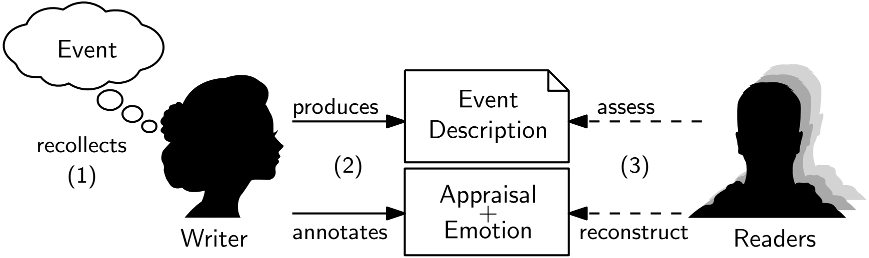

Event
recollects
(1)
Writer
produces
(2)
annotates
Event Description
Appraisal
+
Emotion

Approach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(1)
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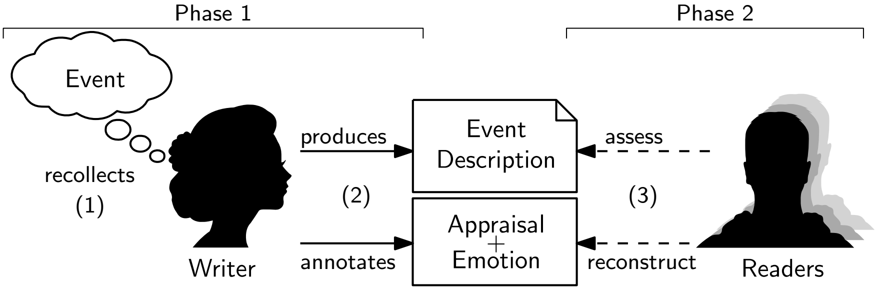
Event Description
Appraisal + Emotion
assess
reconstruct
(3)
Readers

Approach


Phase 1
Phase 2
Event
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(1)
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(2)
annotates
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assess
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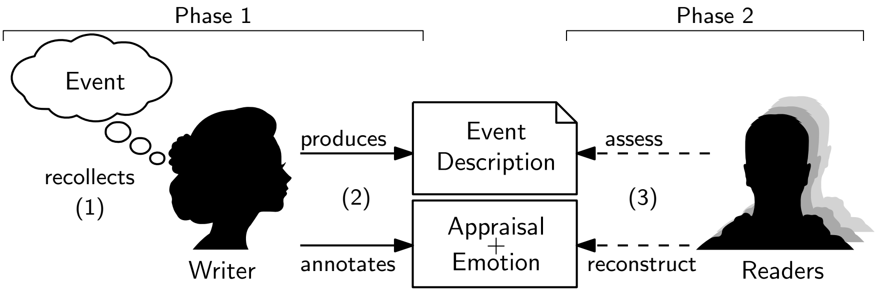
reconstruct
Readers

Approach



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

Appraisal Variables

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

Variable Assesement

Appraisal Variables

(1) The event was sudden or abrupt. (suddenness)
(2) The event was familiar. (familiarity)
(3) I could have predicted the occurrence of the event. (event predictability)
(4) The event was pleasant. (pleasantness)
(5) The event was unpleasant. (unpleasantness)
(6) I expected the event to have important consequences for me. (goal relevance)
(7) The event was caused by my own behavior. (own responsibility)
(8) The event was caused by somebody else's behavior. (other responsibility)
(9) The event was caused by chance, special circumstances, or natural forces. (situational responsibility)
(10) I expected positive consequences for me. (goal support)
(11) I anticipated the consequences of the event. (anticip. conseq.)
(12) The event required an immediate response. (urgency)
(13) I anticipated that I would easily live with the unavoidable consequences of the event. (accept. conseq.)
(14) The event clashed with my standards and ideals. (internal standards)
(15) The actions that produced the event violated laws or socially accepted norms. (external norms)
(16) I had to pay attention to the situation. (attention)
(17) I tried to shut the situation out of my mind. (not consider)
(18) The situation required me a great deal of energy to deal with it. (effort)
(19) I was able to influence what was going on during the event. (own control)
(20) Someone other than me was influencing what was going on. (others' control)
(21) The situation was the result of outside influences of which nobody had control. (situational control)

- All variables are similarly assessed by writers and readers

Additional Variables

- Age, Gender
- Ethnicity, Education
- Event familiarity
  for readers
- Personality traits
  - openness
  - conscientiousn.
  - extraversion
  - agreeablenes
  - emotional stability

Examples

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pride I baked a delicious strawberry cobbler.

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joy I found the perfect man for me, and the more time goes on, the more I realized he was the best person for me. Every day is a ….

Questions and Answers

Setup:

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

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  - Extraverted, conscientious, agreeable annotators perform better.

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Examples (writer/reader/avg. writer–reader agreement as error)

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pride, sadness, 1.7	That I put together a funeral service for my Aunt

Appraisals add additional information to emotion analysis

That I put together a funeral service for my Aunt

Dimension	Writer	Readers	△
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

Modeling Results

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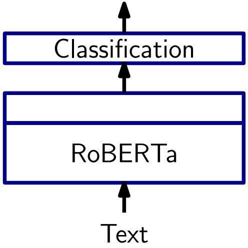
- Classification with RoBERTa-based models



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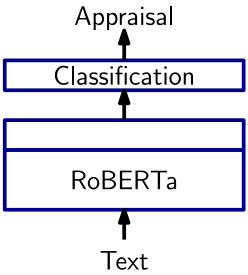

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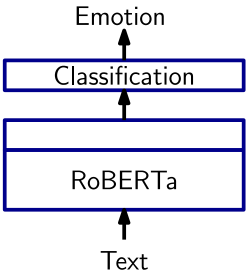

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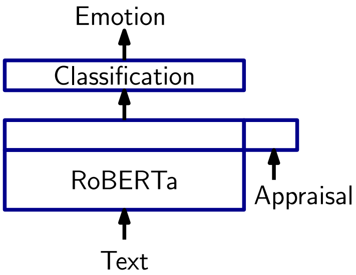

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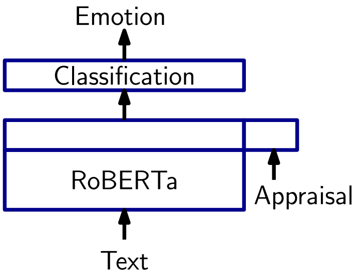
⇒ Appraisals help to build better models.



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- Appraisals help emotion categorization for some emotion categories
- More importantly: Appraisals help to understand reasons for disagreement

Outline

What's left to do?

R. Klinger (2023). "Where are We in Event-centric Emotion Analysis? Bridging Emotion Role Labeling and Appraisal-based Approaches". In: Proceedings of the Big Picture Workshop

What's left to do?

"Nala did not expect that Putu is angry when she took away his computer."

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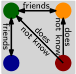

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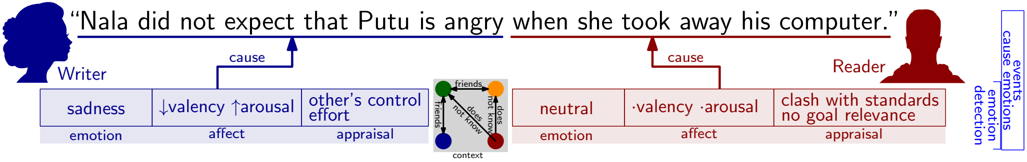

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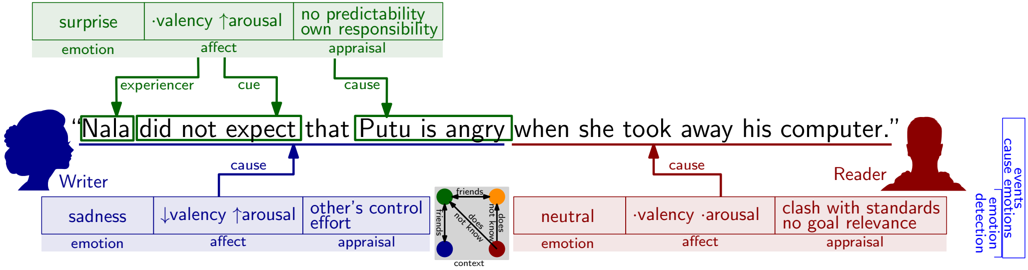

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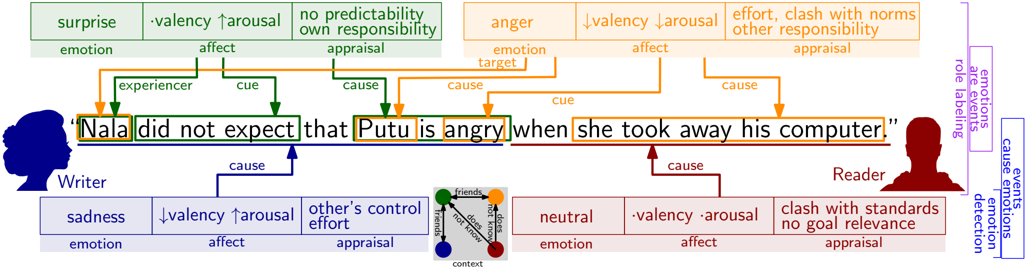

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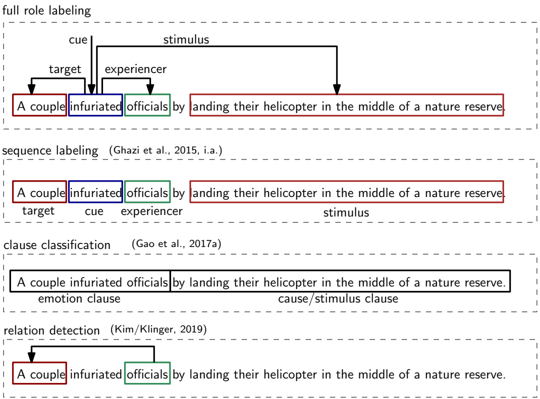
Nobody did model full emotion role labeling...



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- Multimodal modeling
- Emotion modeling in arguments
- ...

Current and Soon-to-Start Emotion-Related Work at BamNLP

Event chains with LLMs

Johannes Schäfer

Model robustness across domains

SabineWeber

Emotions in arguments

Lynn Greschner

Multimodal emotions in social media

Christopher Bagdon

Prompt optimization

Jiahui Li

Emotion-conditioned text generation

Yarik Menchaca Resendiz

Style transfer

Aswathy Velutharambath

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- Modeling emotions benefits from knowledge from psychological theories
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Thank you for
your attention.
Questions? Remarks?

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German Research Foundation

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  - Christopher Bagdon
- Collaborators
  - Kai Sassenberg

University of Bamberg

Event-centered Emotion Classification from Text

Workshop Emotional Speech, Bochum/Germany, July 5, 2024

Roman Klinger
roman.klinger@uni-bamberg.de

@roman_klinger romanklinger
https://www.bamberg.de/nlproc/