University of Bamberg

Appraisals as Emotion Model in NLP

Why we need them and how to acquire data

Workshop, Ghent, September 26, 2025

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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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- 2010, 2013: Research visits at UMass Amherst:
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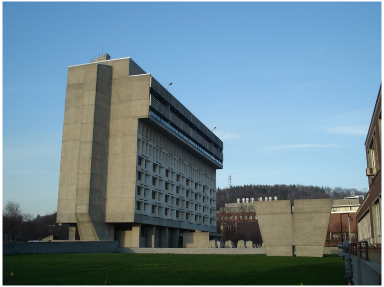

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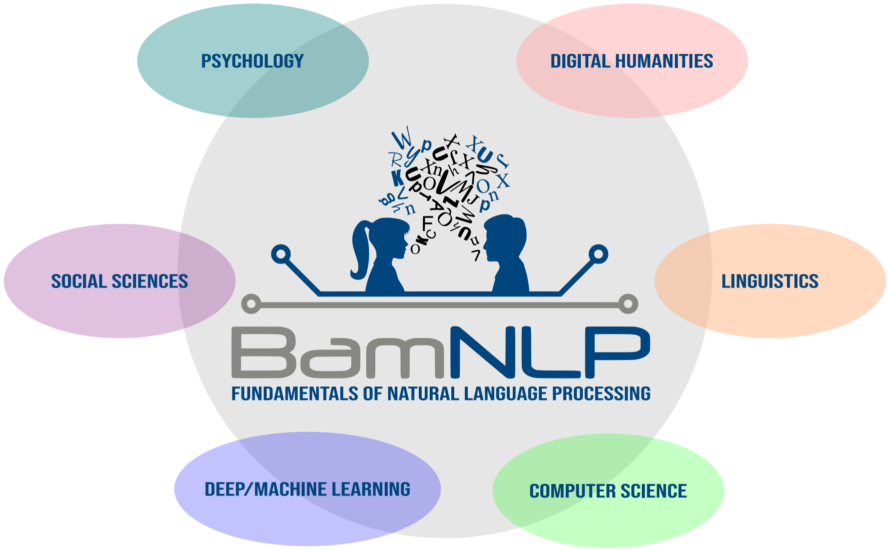
- 03/2024: Full Professor for Fundamentals of NLP, Bamberg


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


Bamberger Zentrum für Künstliche Intelligenz
Digitales Lehren & Lernen
KI & Ethik
KI & Gesundheit
KI & Bildung
Kognition & Interaktion
Soziotechnische Systeme
Digitale Überlieferung
Erklärbares Maschinelles Lernen
KI-System-entwicklung
Kognitive Systeme
Kultur-informatik
Medien-informatik & Information Retrieval
Sprach-generierung & Dialogsys-teme
Smart Environ-ments
User Experience & Design
Informa-tionsvisua-lisierung
Grundlagen der Sprach-verarbeitung
Multimodale Intelligente Interaktion
Mensch-Computer-Interaktion
Algorithmen & Komplexi-tätstheorie
KI-Enginee-ring in Unter-nehmen
Computa-tional Social Science & KI
Computer-grafik & ihre Grundlagen
Data Engineering
Energie-effiziente Systeme
Analyse sozialer Netzwerke

Outline

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Emotion Analysis: What we want to do.

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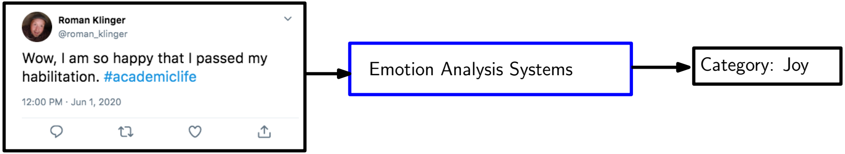

Emotion Examples

Which emotion was felt by the author of the examples?

How did you recognize that?

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Emotion Examples

Which emotion was felt by the author of the examples?

How did you recognize that?

- "She became angry."
- "A tear was running down my face."
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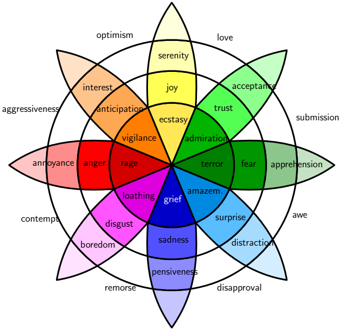
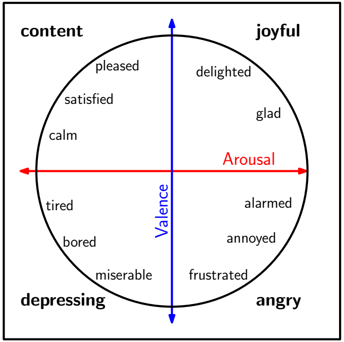
With this exercise, we discussed:

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

How to define a categorical system of emotions?





Definition of Emotions: Components

Emotion (Scherer, 2005)

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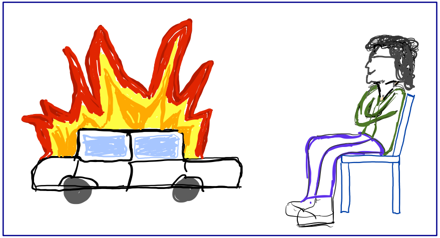

Event

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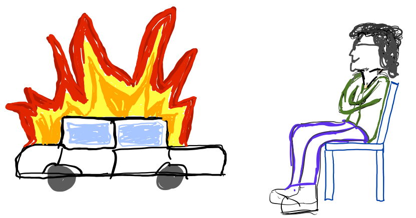

Event

Feeling Expression Bodily Symptom

Action Tendency Cognitive Appraisal

Components

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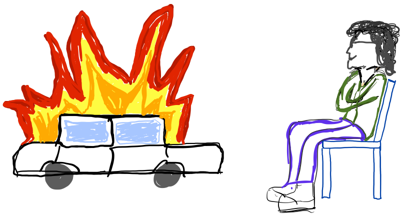


Event

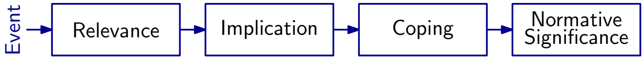
Feeling | Expression | Bodily Symptom | Action Tendency | Cognitive Appraisal

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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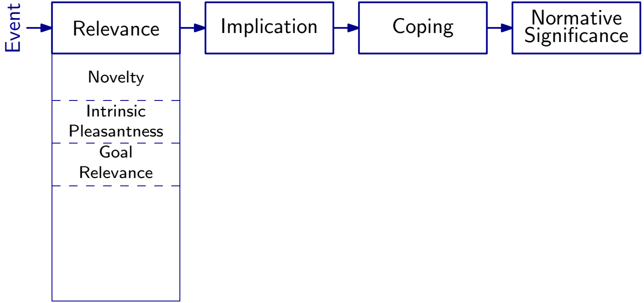

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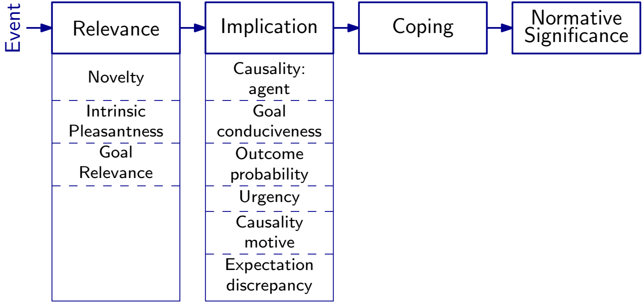

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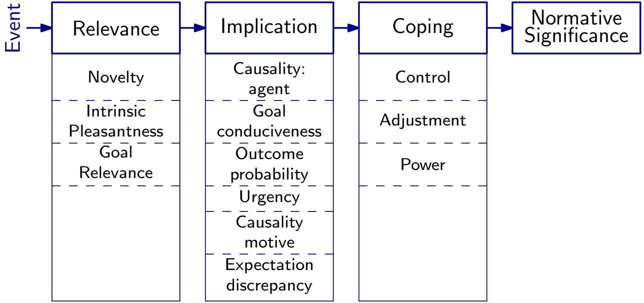

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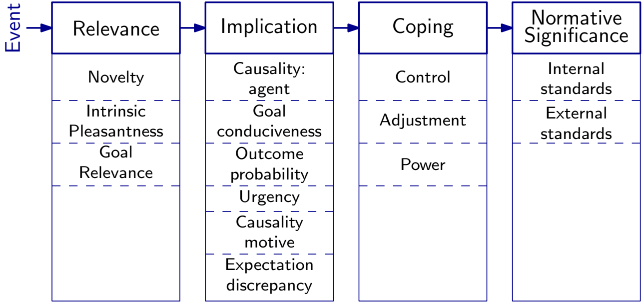

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Research Questions

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

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Research Questions

- Can appraisals and emotions be annotated reliably by external annotators?

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Research Questions

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- Can we computationally model appraisals and does it help emotion categorization?

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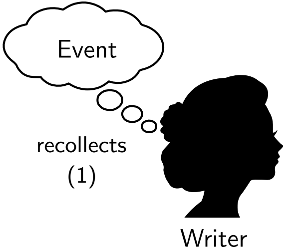
Approach



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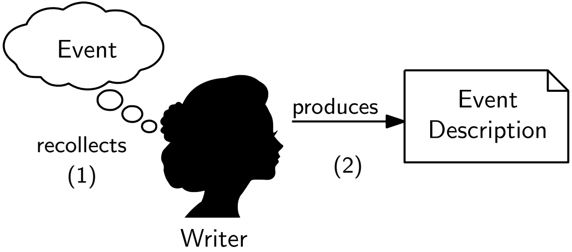

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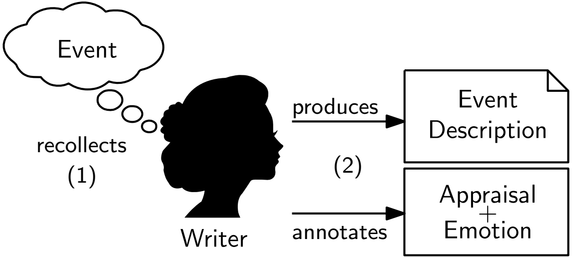
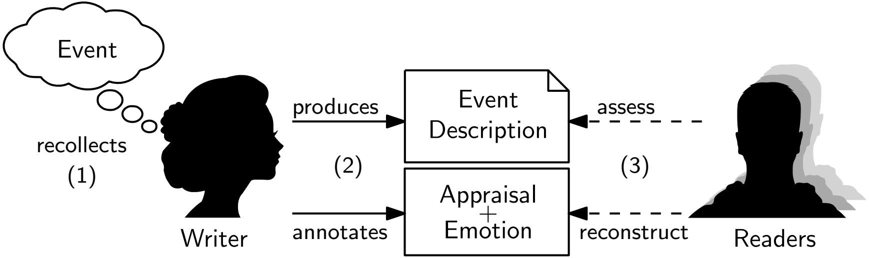

Event
recollects
(1)
Writer
produces
(2)
annotates
Event
Description
Appraisal
+
Emotion

Approach


Event
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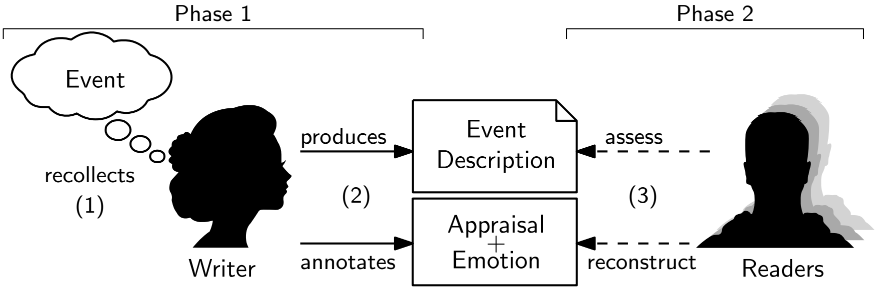
+
Emotion
assess
reconstruct
(3)
Readers

Approach


Phase 1
Phase 2
Event
recollects
(1)
Writer
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Appraisal + Emotion
assess
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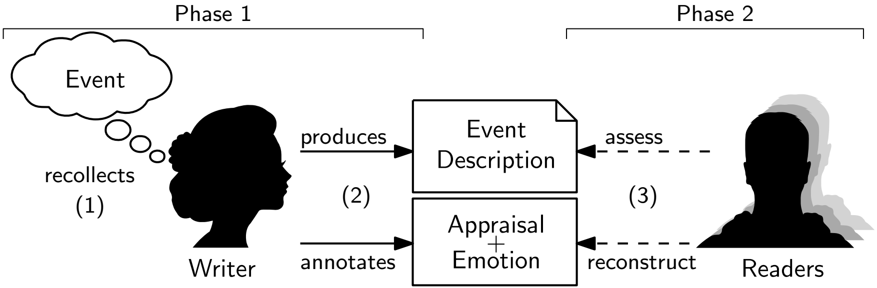
Approach



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

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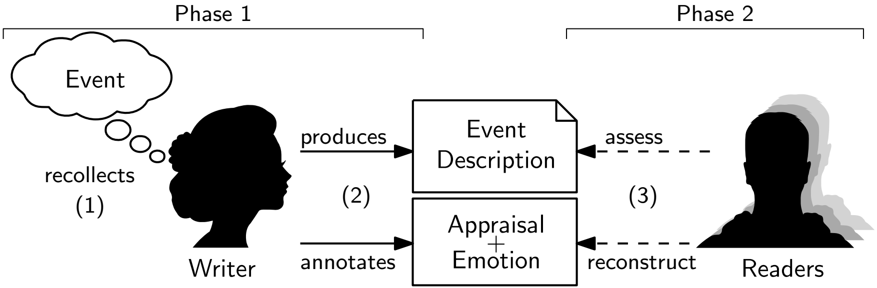

- Production: 550 event descriptions for anger, boredom, disgust, fear, guilt/shame, joy, pride, relief, sadness, surprise, trust, no emotion
- Five readers for subset of produced texts

Examples

Examples

pride I baked a delicious strawberry cobbler.

Examples

pride I baked a delicious strawberry cobbler.

fear I felt … when there was a power outage in my home. That day, my wife and I were cuddling in the sitting room when a thunderstorm started. Then … filled me when thunder hit our roof and all the lights went off.

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pride I baked a delicious strawberry cobbler.

fear I felt … when there was a power outage in my home. That day, my wife and I were cuddling in the sitting room when a thunderstorm started. Then … filled me when thunder hit our roof and all the lights went off.

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 ….

Reliability Results

Reliability Results

		Agreement						
			Emotion				Appraisal	
			F_1		Acc.		RMSE	
Condition	Val.	#Pairs	G–V	V–V	G–V	V–V	G–V	V–V
All Data		6600 12000	.49	.50	*.49	*.52	*1.57	*1.48
Gender match	M–M	631 1113	.50	*.45	.51	*.49	1.55	1.50
	F–F	2405 1377	.49	*.52	.51	*.55	1.57	*.1.50
	≠	2962 3920	.49	*.48	.50	*.52	1.57	*.1.48
Age diff.	> 7	3089 7991	.49	*.48	.51	*.51	*1.58	1.48
	≤ 7	2076 3939	.49	*.51	.50	*.54	*1.56	1.48
Validators' Event Fam.	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42
	≤ 3	2099 676	.48	.45	.49	.48	*1.58	*1.47
Validators' Openness	+	2685 1472	.49	.49	.50	.52	1.57	1.47
	−	3000 1568	.49	.48	.50	.51	1.57	1.48
Validators' Conscien.	+	3151 1638	*.48	.51	*.49	.53	*1.57	*1.49
	−	2589 1426	*.50	.51	*.51	.54	*1.56	*1.46
Validators' Extraversion	+	2878 1685	.49	*.48	.50	*.51	*1.58	*1.51
	−	2812 1535	.50	*.52	.51	*.55	*1.56	*1.46
Validators' Agreeabl.	+	2675 1451	.49	*.51	.51	*.54	*1.58	1.47
	−	2930 1553	.48	*.45	.49	*.49	*1.56	1.47
Validators' Emot. Stab.	+	2838 3009	*.48	*.48	*.49	*.51	*1.57	*1.50
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- V–G agreements:

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- Validators agree more with each other than with the generator
- V–G agreements:
    - Higher agreement for Female pairs

Reliability Results

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			F_1		Acc.		RMSE	
Condition	Val.	#Pairs	G–V	V–V	G–V	V–V	G–V	V–V
All Data		6600 12000	.49	.50	*.49	*.52	*1.57	*1.48
Gender match	M–M	631 1113	.50	*.45	.51	*.49	1.55	1.50
	F–F	2405 1377	.49	*.52	.51	*.55	1.57	*.1.50
	≠	2962 3920	.49	*.48	.50	*.52	1.57	*.1.48
Age diff.	> 7	3089 7991	.49	*.48	.51	*.51	*1.58	1.48
	≤ 7	2076 3939	.49	*.51	.50	*.54	*1.56	1.48
Validators' Event Fam.	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42
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Validators' Openness	+	2685 1472	.49	.49	.50	.52	1.57	1.47
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Condition	Val.	#Pairs		Agreement: Emotion F$_1$ G–V	Emotion F$_1$ V–V	Emotion Acc. G–V	Emotion Acc. V–V	Appraisal RMSE G–V	Appraisal RMSE V–V
All Data		6600	12000	.49	.50	*.49	*.52	*1.57	*1.48
Gender match	M–M	631	1113	.50	*.45	.51	*.49	1.55	1.50
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Validators' Event Fam.	> 3	1386	540	.49	.44	.51	.47	*1.60	*1.42
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Validators' Openness	+	2685	1472	.49	.49	.50	.52	1.57	1.47
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- Most differences are quite small (but significant)

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

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Appraisals add additional information to emotion analysis

That I put together a funeral service for my Aunt

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

Emotion Annotation Result

Conclusion

Annotators can quite well reconstruct authors emotion,
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- Not shown: appraisals help to disambiguate emotion categories in automatic models

Potential Reason for V–G Discrepancy

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- Isolated events are not sufficient
- Subjectivity is not only personality and demographics

Idea: Generate backstories to explain emotions/appraisals

Event

"The loudspeaker suddenly malfunctioned and went silent."

J. Schäfer et al. (2025). Shaping Event Backstories to Estimate Potential Emotion Contexts. arXiv: 2508.09954 [cs.CL]. URL: https://arxiv.org/abs/2508.09954

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⇒ We autogenerate stories that explain such event for a given emotion.

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Backstories

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Relief: I was tasked with giving a presentation to a large crowd. The sound system malfunctioned, amplifying my voice to an ear-piercing level. The sound technician ignored the problem and chatted with someone. The audience covered their ears and looked at me with discomfort. The loudspeaker suddenly malfunctioned and went silent.

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I spent the entire morning upgrading the sound system with a new backup system to prevent technical issues. The event organizer informed me that the conference was running 30 minutes behind schedule, giving me extra time to test the new backup system. I used the extra time to run a series of tests on the sound system, trying to simulate potential failures. The keynote speaker began to talk, and the sound system was working flawlessly, but I was still waiting for a real test of the new backup system. The loudspeaker suddenly malfunctioned and went silent.

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Results in a Nutshell

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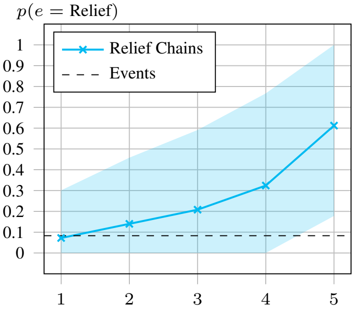

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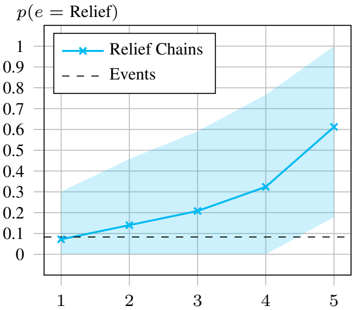

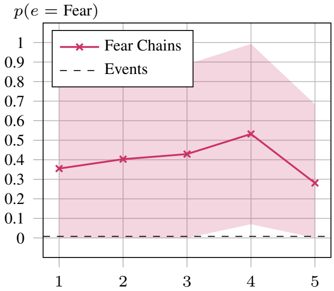

Summary and Next Steps

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- Sometimes, it might just be the more appropriate emotion model.

Outline

Argument Convincingness

Argument Convincingness

- Argument quality includes:

Argument Convincingness

- Argument quality includes:
  - Logical structure: Logos
  - Speaker credibility: Ethos
  - Emotional appeal: Pathos

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Argument Convincingness

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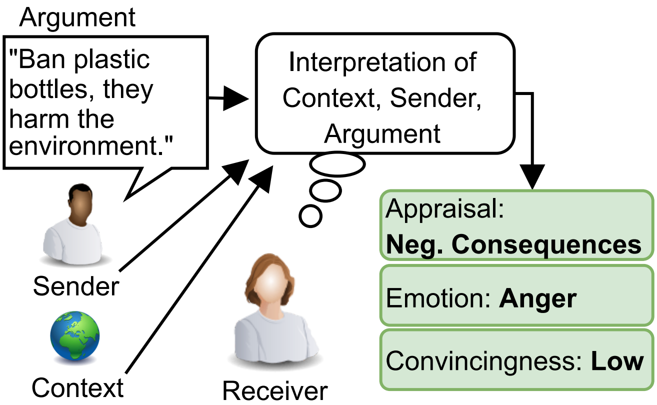
  - Emotional appeal: Pathos
- Arguments are subjectively evaluated

The Contextualized Argument Appraisal Framework



L. Greschner et al. (2025). Trust Me, I Can Convince You: The Contextualized Argument Appraisal Framework. to be on arxiv soon. arXiv: 0000.00000 [cs.CL]. URL: https://arxiv.org/abs/0000.00000

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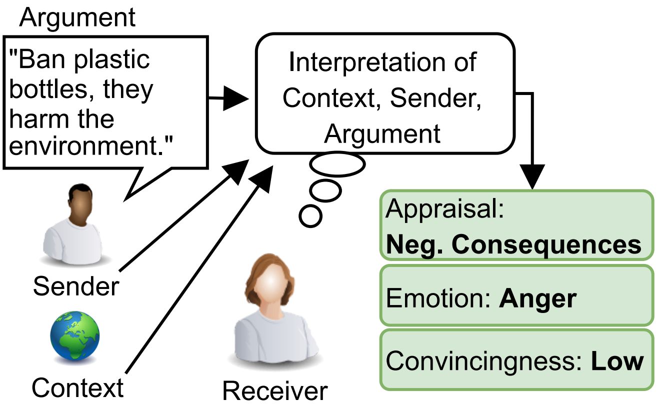

Do appraisals explain convincingness?

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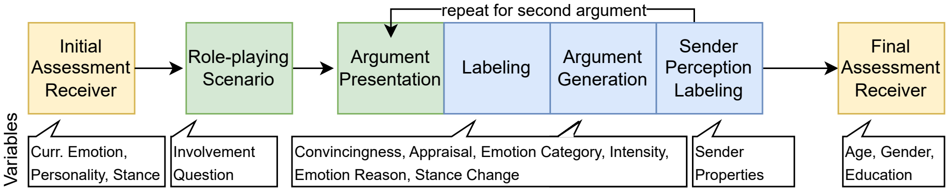

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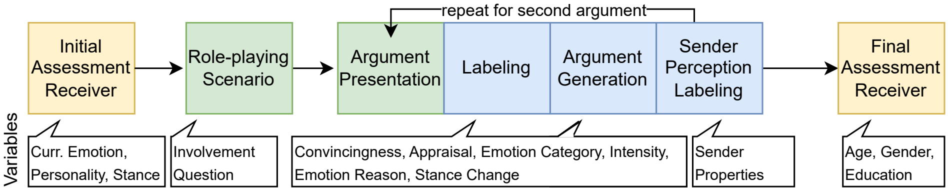

- 39 topics
- 800 arguments
- Each 5 annotations
- 9,404 £

Argument Appraisal Variables

Dimension	Description
Suddenness	the argument appears sudden or abrupt to the receiver
Suppression	the receiver tries to shut the argument out of their mind
Familiarity	the argument is familiar to the receiver
Pleasantness	the argument is pleasant for the receiver
Unpleasantness	the argument is unpleasant for the receiver
Consequencial Importance	the argument has important consequences for the receiver
Positive Consequentiality	the argument has positive consequences for the receiver
Negative Consequentiality	the argument has negative consequences for the receiver
Consequence Manageability	the receiver can easily live with the unavoidable consequences of the argument
Internal Check	the consequences of the argument clash with the receiver's standards and ideals
External Check	the consequences of the argument violate laws or socially accepted norms
Response urgency	the receiver urges to immediately respond to the argument
Cognitive Effort	processing the argument requires a great deal of energy of the receiver
Argument Internal Check	statements in the argument clash with the receiver's standards and ideals
Argument External Check	statements in the argument violate laws or socially accepted norms

Convincingness and Emotions – Average Values

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	Suddenness	Suppression	Familiarity	Pleasantness	Unpleasantness	Consequencial Importance	Positive Consequentiality	Negative Consequentiality	Consequence Manageability	Internal Check	External Check	Response urgency	Cognitive Effort	Argument Internal Check	Argument External Check
Anger	2.4	1.9	2.6	1.2	3.0	1.9	1.6	1.6	2.4	2.8	2.7	2.4	3.7	2.0	3.1
Disgust	2.4	2.1	2.5	1.2	3.2	1.8	1.5	1.7	2.3	2.8	2.9	2.6	3.8	1.8	3.2
Fear	1.9	1.6	2.8	1.6	2.5	2.2	2.1	1.8	2.4	2.3	2.0	1.9	3.5	1.9	2.0
Guilt	1.7	1.5	2.8	1.6	2.3	1.9	1.7	1.6	2.3	2.2	1.9	1.5	3.6	1.6	1.9
Joy	1.4	1.1	3.1	3.5	1.2	2.0	2.5	2.2	2.1	2.5	1.3	1.5	3.1	1.6	1.4
Pride	1.4	1.2	3.3	3.2	1.3	2.0	2.5	2.1	2.2	2.4	1.4	1.6	3.4	1.4	1.4
Relief	1.4	1.1	3.2	3.0	1.3	2.0	2.5	2.0	2.5	2.3	1.4	1.5	3.5	1.4	1.4
Sadness	1.9	1.5	2.9	1.3	2.7	1.8	1.6	1.6	2.3	2.7	2.2	2.0	3.6	1.7	2.5
Shame	2.0	1.6	2.8	1.4	2.8	2.0	1.7	1.9	2.5	2.5	2.2	2.1	3.5	1.9	2.4
Surprise	2.1	1.4	2.1	1.7	1.9	1.8	1.6	1.5	2.3	2.5	1.9	1.8	3.5	1.7	2.1
Trust	1.4	1.1	3.0	2.5	1.3	1.9	2.0	1.6	2.4	2.2	1.3	1.4	3.6	1.3	1.4

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Fear	1.9	1.6	2.8	1.6	2.5	2.2	2.1	1.8	2.4	2.3	2.0	1.9	3.5	1.9	2.0
Guilt	1.7	1.5	2.8	1.6	2.3	1.9	1.7	1.6	2.3	2.2	1.9	1.5	3.6	1.6	1.9
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- Generally high cognitive effort

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- External Check explains anger and disgust

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- Generally high cognitive effort
- External Check explains anger and disgust
- Familiarity indicative for positive emotions

Correlations of Emotions with Convincingness

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Emotion	r
Trust	0.570
Relief	0.511
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Joy	0.435
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Shame	−0.073
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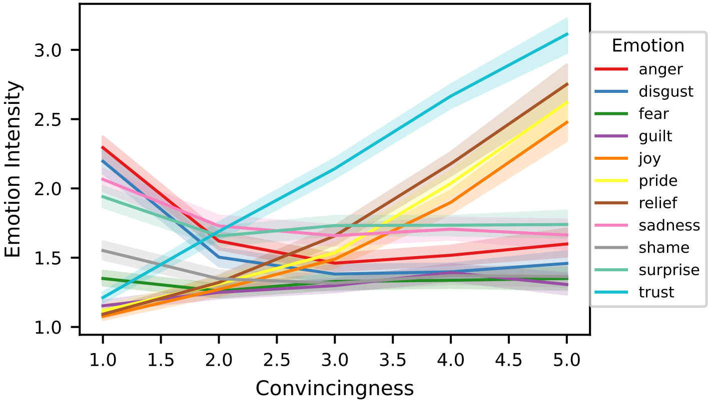

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Appraisal	r
Internal Check	−0.103
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- Pleasant arguments whose outcomes are good for the self and which are familiar are more convincing.
- Surprising arguments and those which go against laws or social standards are less convincing (and cause anger and disgust).

Outline

1 Emotion Analysis and Appraisals

2 Appraisals and Argument Convincingness

3 How to Collect Data?

4 Take Home

Introduction

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

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  - People recall particularly "prototypical" events
  - Type of data might differ due to missing post creation triggers

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Approach: Data elicitation strategies

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- Creation:
- Donation:
- Recent:

Approach: Data elicitation strategies

- Creation:
  - “Think of an event that caused an emotion X in you.”
- Donation:
- Recent:

Approach: Data elicitation strategies

- Creation:
  - “Think of an event that caused an emotion X in you.”
  - “Write a social media post text about that.”
- Donation:
- Recent:

Approach: Data elicitation strategies

- Creation:
  - “Think of an event that caused an emotion X in you.”
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  - “Select an image you want to share from a CC image data base.”
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  - “Pick a multimodal post from your social media timeline that you made because the associated event caused emotion X.”
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  - "Pick the 10 most recent posts from your social media timeline."

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  - “Copy paste the text and the image.”
- Recent:
  - “Pick the 10 most recent posts from your social media timeline.”
  - “Annotate them for the following emotion set.”

Data Example

Name
@Username

Absolutely insane, what is going on?!

Creation post labeled as surprise.

Name2
@Username2

Exhibit 2

Trump supporters say ear bandages are 'sign of love'

Several supporters of former President Donald Trump wore bandages on their ears to the third night of the Republican National Convention (RNC) in Milwaukee, Wisconsin.

Members of the RNC's Arizona delegation said they were wearing the bandages as a sign of solidarity with the former president after he survived an assassination attempt.

Recent post labeled as anger.

Are the subcorpora comparable? – Post Length

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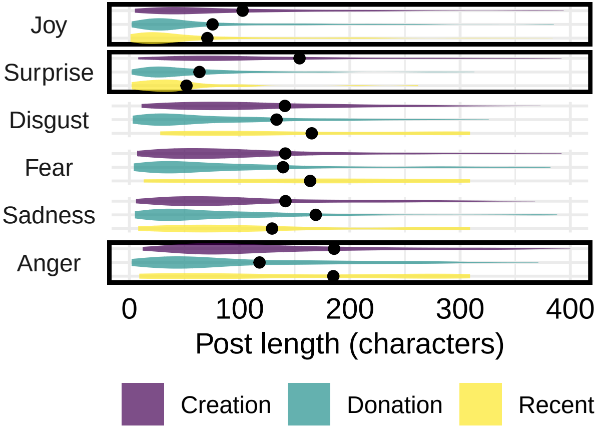

Are the subcorpora comparable? – Image Type

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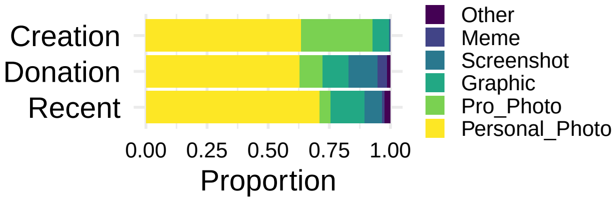

Are the subcorpora comparable? – Text–Image Relation

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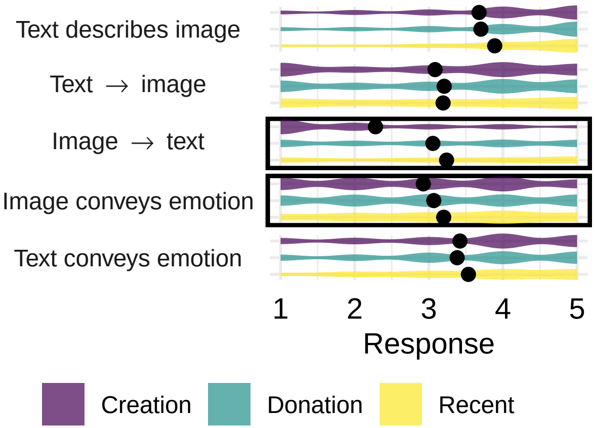

Are the subcorpora comparable? – Appraisal–Emotion

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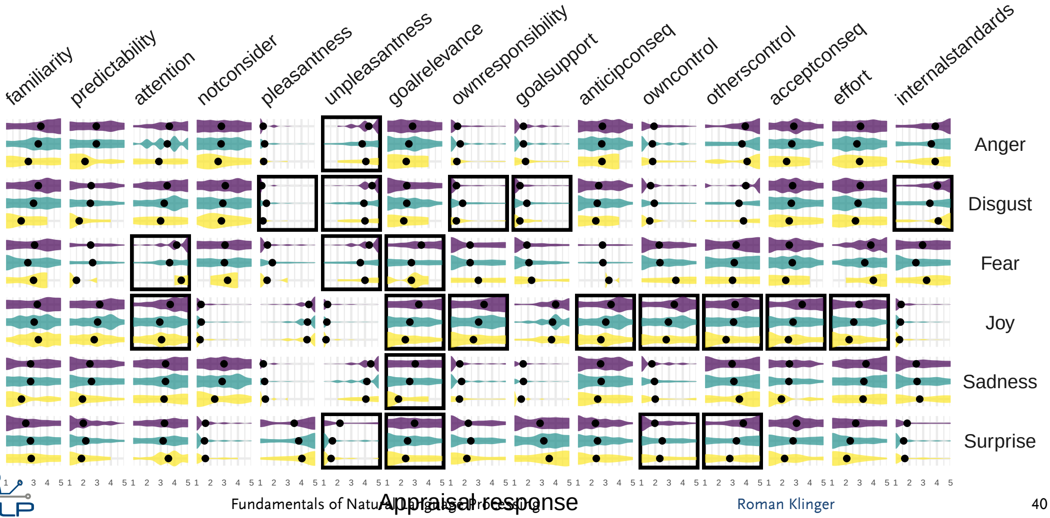

Are the subcorpora comparable? – Participant acceptance

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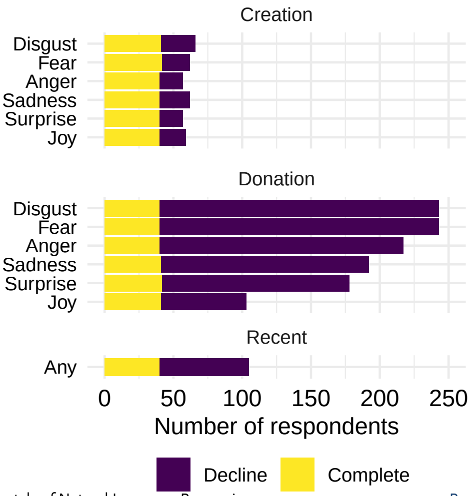

Are the differences a problem?

Experiment

- Fine-tune RoBERTa with CLIP/early fusion to predict emotions
  - Train on Donation vs. train on Creation

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  F score of .60 and .62.

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- But: The estimate on donated data is overall optimistic!
  F score of .60 and .62.
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- Zero-Shot prompting (Llama3.2-vision) leads to slightly better results for donated data.

Outline

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- Appraisals can be annotated and modeled
- ...but they are subjective and require context
- Appraisals are a informative approach to explain argument convincingness
- Experimentally elicited data is fine for model training, but we need real data for performance estimation
  (shown for emotion categories only so far, though)

Thank you for
your attention.
Questions? Remarks?

?

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University of Bamberg

Appraisals as Emotion Model in NLP

Why we need them and how to acquire data

Workshop, Ghent, September 26, 2025

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