



Appraisals as Emotion Model in NLP

Why we need them and how to acquire data

Workshop, Ghent, September 26, 2025

Roman Klinger

roman.klinger@uni-bamberg.de

 [romanklinger.de](https://twitter.com/romanklinger)  [romanklinger](https://www.linkedin.com/in/romanklinger)
<https://www.bamberg.de/nlproc/>

About Myself



About Myself

- 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

About Myself

- 1999–2006: Studies at University of Dortmund:
Computer science with minor psychology
- 2006–2010: Doctoral studies at Fraunhofer SCAI, St. Augustin:
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



About Myself

- 1999–2006: Studies at University of Dortmund:
Computer science with minor psychology
- 2006–2010: Doctoral studies at Fraunhofer SCAI, St. Augustin:
Biomedical text mining, machine learning
- 2010, 2013: Research visits at UMass Amherst:
Probabilistic machine learning, MCMC inference



About Myself

- 1999–2006: Studies at University of Dortmund:
Computer science with minor psychology
- 2006–2010: Doctoral studies at Fraunhofer SCAI, St. Augustin:
Biomedical text mining, machine learning
- 2010, 2013: Research visits at UMass Amherst:
Probabilistic machine learning, MCMC inference
- 2011–2012: Postdoc at Fraunhofer SCAI:
Social media mining, eGovernment





About Myself

- 1999–2006: Studies at University of Dortmund:
Computer science with minor psychology
- 2006–2010: Doctoral studies at Fraunhofer SCAI, St. Augustin:
Biomedical text mining, machine learning
- 2010, 2013: Research visits at UMass Amherst:
Probabilistic machine learning, MCMC inference
- 2011–2012: Postdoc at Fraunhofer SCAI:
Social media mining, eGovernment
- 2013–2014: Postdoc at Bielefeld University:
Sentiment analysis, opinion mining





About Myself

- 1999–2006: Studies at University of Dortmund:
Computer science with minor psychology
- 2006–2010: Doctoral studies at Fraunhofer SCAI, St. Augustin:
Biomedical text mining, machine learning
- 2010, 2013: Research visits at UMass Amherst:
Probabilistic machine learning, MCMC inference
- 2011–2012: Postdoc at Fraunhofer SCAI:
Social media mining, eGovernment
- 2013–2014: Postdoc at Bielefeld University:
Sentiment analysis, opinion mining
- 2015: Co-Founder of Semalytix GmbH (exit 2020)
Social Media Health Mining



About Myself

- 1999–2006: Studies at University of Dortmund:
Computer science with minor psychology
- 2006–2010: Doctoral studies at Fraunhofer SCAI, St. Augustin:
Biomedical text mining, machine learning
- 2010, 2013: Research visits at UMass Amherst:
Probabilistic machine learning, MCMC inference
- 2011–2012: Postdoc at Fraunhofer SCAI:
Social media mining, eGovernment
- 2013–2014: Postdoc at Bielefeld University:
Sentiment analysis, opinion mining
- 2015: Co-Founder of Semalytix GmbH (exit 2020)
Social Media Health Mining
- 2014–2024: (Senior) Lecturer/apl. Prof at IMS, Uni Stuttgart
Natural Language Understanding and Generation



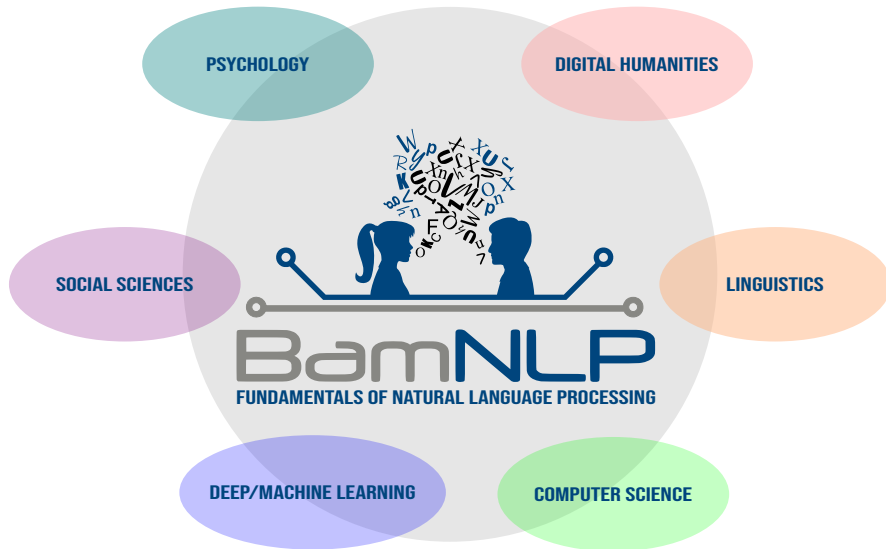


About Myself

- 1999–2006: Studies at University of Dortmund:
Computer science with minor psychology
- 2006–2010: Doctoral studies at Fraunhofer SCAI, St. Augustin:
Biomedical text mining, machine learning
- 2010, 2013: Research visits at UMass Amherst:
Probabilistic machine learning, MCMC inference
- 2011–2012: Postdoc at Fraunhofer SCAI:
Social media mining, eGovernment
- 2013–2014: Postdoc at Bielefeld University:
Sentiment analysis, opinion mining
- 2015: Co-Founder of Semalytix GmbH (exit 2020)
Social Media Health Mining
- 2014–2024: (Senior) Lecturer/apl. Prof at IMS, Uni Stuttgart
Natural Language Understanding and Generation
- 03/2024: Full Professor for Fundamentals of NLP, Bamberg









Outline

- 1 Emotion Analysis and Appraisals
- 2 Appraisals and Argument Convincingness
- 3 How to Collect Data?
- 4 Take Home

Outline

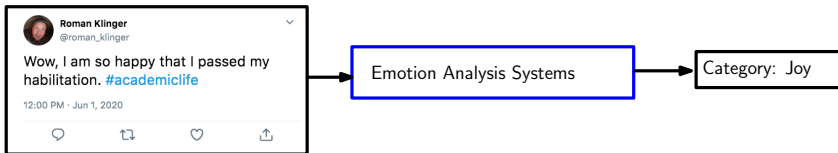
- 1 Emotion Analysis and Appraisals
- 2 Appraisals and Argument Convincingness
- 3 How to Collect Data?
- 4 Take Home

Emotion Analysis: What we want to do.





Emotion Analysis: What we want to do.





Emotion Examples

Which emotion was felt by the author of the examples?

How did you recognize that?



Emotion Examples

Which emotion was felt by the author of the examples?

How did you recognize that?

- “She became angry.”



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.”



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.”
- “Their dog ran towards me quickly.”



Emotion Examples

Which emotion was felt by the author of the examples?

How did you recognize that?

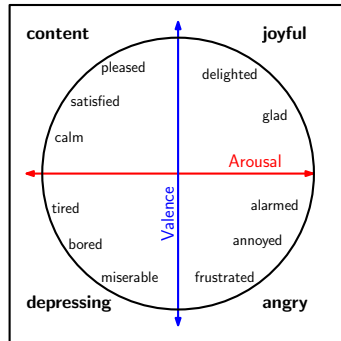
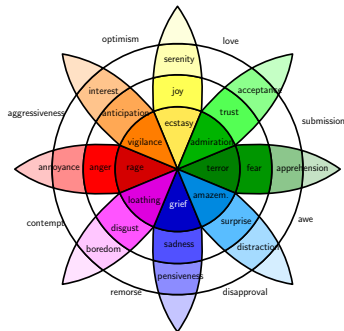
- “She became angry.”
- “A tear was running down my face.”
- “Their dog ran towards me quickly.”

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)



Definition of Emotions: Components

Emotion (Scherer, 2005)

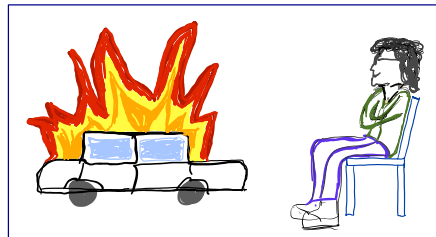
Emotions are “an **episode** of interrelated, synchronized changes in the states of [...] **five organismic subsystems** in response to the evaluation of a [...] **stimulus-event** ...”



Definition of Emotions: Components

Emotion (Scherer, 2005)

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



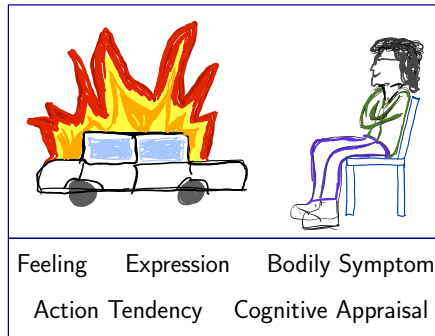
Event



Definition of Emotions: Components

Emotion (Scherer, 2005)

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





Definition of Emotions: Components

Emotion (Scherer, 2005)

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

		
Feeling	Expression	Bodily Symptom
Action Tendency	Cognitive Appraisal	
Fear		

Event

Components

Name



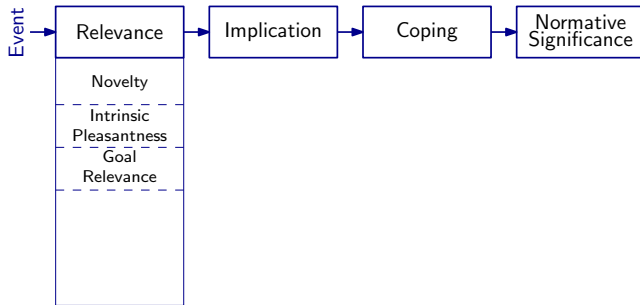
Cognitive Appraisal in Scherer's Component Process model



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



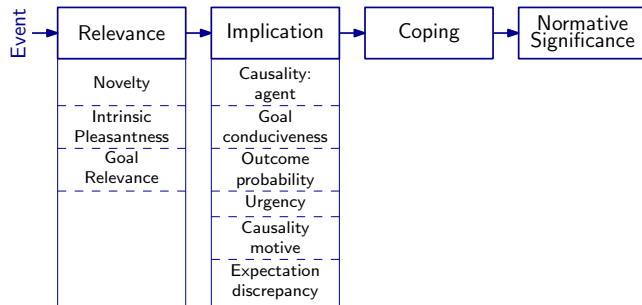
Cognitive Appraisal in Scherer's Component Process model



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



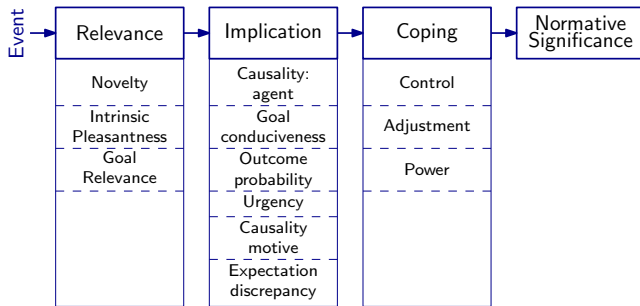
Cognitive Appraisal in Scherer's Component Process model



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



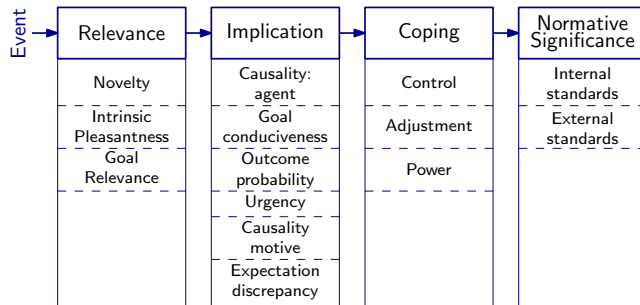
Cognitive Appraisal in Scherer's Component Process model



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



Cognitive Appraisal in Scherer's Component Process model



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



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 and emotions be annotated reliably by external annotators?

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

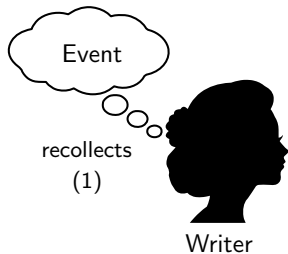
- Can appraisals and emotions be annotated reliably by external annotators?
- Can we computationally model appraisals and does it help emotion categorization?

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

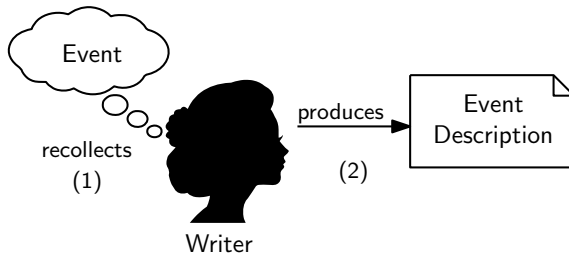


Approach



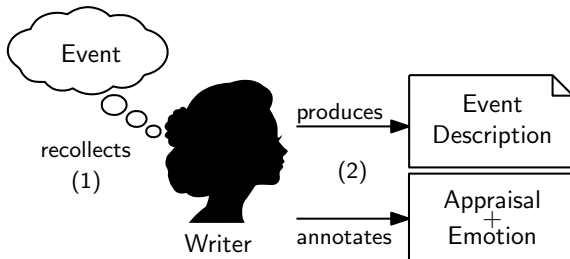


Approach



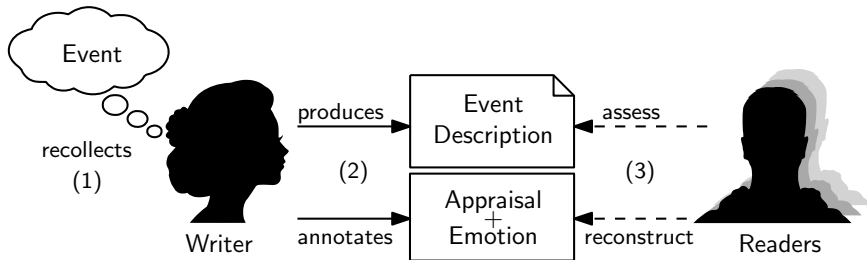


Approach



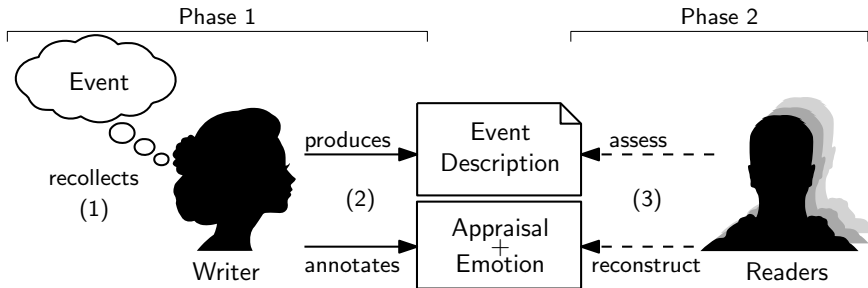


Approach



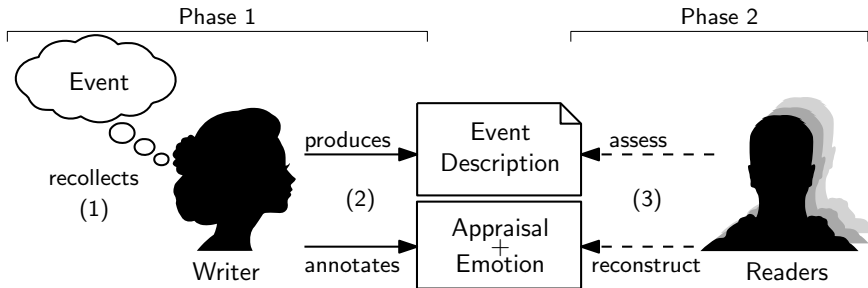


Approach





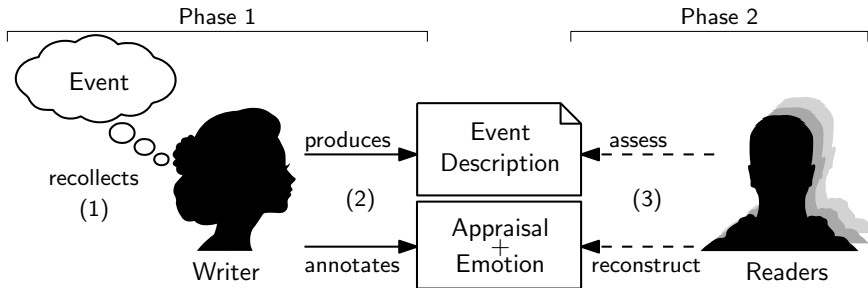
Approach



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



Approach



- 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.



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.

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

Condition	Val.	Agreement							
		#Pairs	Emotion		Acc.		Appraisal		RMSE
			F ₁						
			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'	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42	
Event Fam.	≤ 3	2099 676	.48	.45	.49	.48	*1.58	*1.47	
Validators'	+	2685 1472	.49	.49	.50	.52	1.57	1.47	
Openness	-	3000 1568	.49	.48	.50	.51	1.57	1.48	
Validators'	+	3151 1638	*.48	.51	*.49	.53	*1.57	*1.49	
Conscien.	-	2589 1426	*.50	.51	*.51	.54	*1.56	*1.46	
Validators'	+	2878 1685	.49	*.48	.50	*.51	*1.58	*1.51	
Extraversion	-	2812 1535	.50	*.52	.51	*.55	*1.56	*1.46	
Validators'	+	2675 1451	.49	*.51	.51	*.54	*1.58	1.47	
Agreeabl.	-	2930 1553	.48	*.45	.49	*.49	*1.56	1.47	
Validators'	+	2838 3009	*.48	*.48	*.49	*.51	*1.57	*1.50	
Emot. Stab.	-	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46	



Reliability Results

- Validators agree more with each other than with the generator

Condition	Val.	Agreement							
		#Pairs	Emotion		Acc.		Appraisal		RMSE
			F ₁						
			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	
	-	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46	



Reliability Results

- Validators agree more with each other than with the generator
- V–G agreements:

Condition	Val.	Agreement							
		#Pairs	Emotion		Acc.		Appraisal		RMSE
			F ₁				G–V	V–V	
All Data		6600 12000	G–V	V–V	G–V	V–V	G–V	V–V	
			.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	
	–	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46	



Reliability Results

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

		Agreement							
Condition	Val.	#Pairs	Emotion				Appraisal		
			F ₁		Acc.		RMSE		
			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	
	-	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46	



Reliability Results

- Validators agree more with each other than with the generator
- V–G agreements:
 - Higher agreement for Female pairs
 - Low age difference leads to higher agreement

		Agreement							
Condition	Val.	#Pairs	Emotion				Appraisal		
			F ₁		Acc.		RMSE		
			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'	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42	
Event Fam.	≤ 3	2099 676	.48	.45	.49	.48	*1.58	*1.47	
Validators'	+	2685 1472	.49	.49	.50	.52	1.57	1.47	
Openness	-	3000 1568	.49	.48	.50	.51	1.57	1.48	
Validators'	+	3151 1638	*.48	.51	*.49	.53	*1.57	*1.49	
Conscien.	-	2589 1426	*.50	.51	*.51	.54	*1.56	*1.46	
Validators'	+	2878 1685	.49	*.48	.50	*.51	*1.58	*1.51	
Extraversion	-	2812 1535	.50	*.52	.51	*.55	*1.56	*1.46	
Validators'	+	2675 1451	.49	*.51	.51	*.54	*1.58	1.47	
Agreeabl.	-	2930 1553	.48	*.45	.49	*.49	*1.56	1.47	
Validators'	+	2838 3009	*.48	*.48	*.49	*.51	*1.57	*1.50	
Emot. Stab.	-	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46	



Reliability Results

- Validators agree more with each other than with the generator
- V–G agreements:
 - Higher agreement for **Female** pairs
 - Low **age difference** leads to higher agreement
- V properties only:

		Agreement							
Condition	Val.	#Pairs	Emotion				Appraisal		
			F ₁		Acc.		RMSE		
			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'	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42	
Event Fam.	≤ 3	2099 676	.48	.45	.49	.48	*1.58	*1.47	
Validators'	+	2685 1472	.49	.49	.50	.52	1.57	1.47	
Openness	-	3000 1568	.49	.48	.50	.51	1.57	1.48	
Validators'	+	3151 1638	*.48	.51	*.49	.53	*1.57	*1.49	
Conscien.	-	2589 1426	*.50	.51	*.51	.54	*1.56	*1.46	
Validators'	+	2878 1685	.49	*.48	.50	*.51	*1.58	*1.51	
Extraversion	-	2812 1535	.50	*.52	.51	*.55	*1.56	*1.46	
Validators'	+	2675 1451	.49	*.51	.51	*.54	*1.58	1.47	
Agreeabl.	-	2930 1553	.48	*.45	.49	*.49	*1.56	1.47	
Validators'	+	2838 3009	*.48	*.48	*.49	*.51	*1.57	*1.50	
Emot. Stab.	-	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46	



Reliability Results

- Validators agree more with each other than with the generator
- V–G agreements:
 - Higher agreement for **Female** pairs
 - Low **age difference** leads to higher agreement
- V properties only:
 - Event familiarity** hurts agreement for appraisal

		Agreement						
Condition	Val.	#Pairs	Emotion		Acc.		Appraisal RMSE	
			F ₁					
			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'	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42
Event Fam.	≤ 3	2099 676	.48	.45	.49	.48	*1.58	*1.47
Validators'	+	2685 1472	.49	.49	.50	.52	1.57	1.47
Openness	-	3000 1568	.49	.48	.50	.51	1.57	1.48
Validators'	+	3151 1638	*.48	.51	*.49	.53	*1.57	*1.49
Conscien.	-	2589 1426	*.50	.51	*.51	.54	*1.56	*1.46
Validators'	+	2878 1685	.49	*.48	.50	*.51	*1.58	*1.51
Extraversion	-	2812 1535	.50	*.52	.51	*.55	*1.56	*1.46
Validators'	+	2675 1451	.49	*.51	.51	*.54	*1.58	1.47
Agreeabl.	-	2930 1553	.48	*.45	.49	*.49	*1.56	1.47
Validators'	+	2838 3009	*.48	*.48	*.49	*.51	*1.57	*1.50
Emot. Stab.	-	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46



Reliability Results

		Agreement							
Condition	Val.	#Pairs	Emotion		Acc.		Appraisal		
			F ₁				RMSE		
			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'	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42	
Event Fam.	≤ 3	2099 676	.48	.45	.49	.48	*1.58	*1.47	
Validators'	+	2685 1472	.49	.49	.50	.52	1.57	1.47	
Openness	-	3000 1568	.49	.48	.50	.51	1.57	1.48	
Validators'	+	3151 1638	*.48	.51	*.49	.53	*1.57	*1.49	
Conscien.	-	2589 1426	*.50	.51	*.51	.54	*1.56	*1.46	
Validators'	+	2878 1685	.49	*.48	.50	*.51	*1.58	*1.51	
Extraversion	-	2812 1535	.50	*.52	.51	*.55	*1.56	*1.46	
Validators'	+	2675 1451	.49	*.51	.51	*.54	*1.58	1.47	
Agreeabl.	-	2930 1553	.48	*.45	.49	*.49	*1.56	1.47	
Validators'	+	2838 3009	*.48	*.48	*.49	*.51	*1.57	*1.50	
Emot. Stab.	-	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46	

- **Validators** agree more with each other than with the **generator**
- V-G agreements:
 - Higher agreement for **Female** pairs
 - Low **age difference** leads to higher agreement
- V properties only:
 - **Event familiarity** hurts agreement for appraisal
 - We expected **Open** annotators to perform better.



Reliability Results

- **Validators** agree more with each other than with the **generator**
- V–G agreements:
 - Higher agreement for **Female** pairs
 - Low **age difference** leads to higher agreement
- V properties only:
 - **Event familiarity** hurts agreement for appraisal
 - We expected **Open** annotators to perform better.
 - **Emotional stability** “hurts” emotion annotation.

		Agreement						
Condition	Val.	#Pairs	Emotion		Acc.		Appraisal RMSE	
			F ₁					
			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'	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42
Event Fam.	≤ 3	2099 676	.48	.45	.49	.48	*1.58	*1.47
Validators'	+	2685 1472	.49	.49	.50	.52	1.57	1.47
Openness	-	3000 1568	.49	.48	.50	.51	1.57	1.48
Validators'	+	3151 1638	*.48	.51	*.49	.53	*1.57	*1.49
Conscien.	-	2589 1426	*.50	.51	*.51	.54	*1.56	*1.46
Validators'	+	2878 1685	.49	*.48	.50	*.51	*1.58	*1.51
Extraversion	-	2812 1535	.50	*.52	.51	*.55	*1.56	*1.46
Validators'	+	2675 1451	.49	*.51	.51	*.54	*1.58	1.47
Agreeabl.	-	2930 1553	.48	*.45	.49	*.49	*1.56	1.47
Validators'	+	2838 3009	*.48	*.48	*.49	*.51	*1.57	*1.50
Emot. Stab.	-	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46



Reliability Results

		Agreement						
Condition	Val.	#Pairs	Emotion		Acc.		Appraisal RMSE	
			F ₁					
			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'	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42
Event Fam.	≤ 3	2099 676	.48	.45	.49	.48	*1.58	*1.47
Validators'	+	2685 1472	.49	.49	.50	.52	1.57	1.47
Openness	-	3000 1568	.49	.48	.50	.51	1.57	1.48
Validators'	+	3151 1638	*.48	.51	*.49	.53	*1.57	*1.49
Conscien.	-	2589 1426	*.50	.51	*.51	.54	*1.56	*1.46
Validators'	+	2878 1685	.49	*.48	.50	*.51	*1.58	*1.51
Extraversion	-	2812 1535	.50	*.52	.51	*.55	*1.56	*1.46
Validators'	+	2675 1451	.49	*.51	.51	*.54	*1.58	1.47
Agreeabl.	-	2930 1553	.48	*.45	.49	*.49	*1.56	1.47
Validators'	+	2838 3009	*.48	*.48	*.49	*.51	*1.57	*1.50
Emot. Stab.	-	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46

- **Validators** agree more with each other than with the **generator**
- V-G agreements:
 - Higher agreement for **Female** pairs
 - Low **age difference** leads to higher agreement
- V properties only:
 - **Event familiarity** hurts agreement for appraisal
 - We expected **Open** annotators to perform better.
 - **Emotional stability** “hurts” emotion annotation.
 - **Extraversion, Conscient., Agreeableness** help.



Reliability Results

		Agreement						
Condition	Val.	#Pairs	Emotion		Acc.		Appraisal RMSE	
			F ₁					
			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'	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42
Event Fam.	≤ 3	2099 676	.48	.45	.49	.48	*1.58	*1.47
Validators'	+	2685 1472	.49	.49	.50	.52	1.57	1.47
Openness	-	3000 1568	.49	.48	.50	.51	1.57	1.48
Validators'	+	3151 1638	*.48	.51	*.49	.53	*1.57	*1.49
Conscien.	-	2589 1426	*.50	.51	*.51	.54	*1.56	*1.46
Validators'	+	2878 1685	.49	*.48	.50	*.51	*1.58	*1.51
Extraversion	-	2812 1535	.50	*.52	.51	*.55	*1.56	*1.46
Validators'	+	2675 1451	.49	*.51	.51	*.54	*1.58	1.47
Agreeabl.	-	2930 1553	.48	*.45	.49	*.49	*1.56	1.47
Validators'	+	2838 3009	*.48	*.48	*.49	*.51	*1.57	*1.50
Emot. Stab.	-	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46

- **Validators** agree more with each other than with the **generator**
- V-G agreements:
 - Higher agreement for **Female** pairs
 - Low **age difference** leads to higher agreement
- V properties only:
 - **Event familiarity** hurts agreement for appraisal
 - We expected **Open** annotators to perform better.
 - **Emotional stability** “hurts” emotion annotation.
 - **Extraversion, Conscient., Agreeableness** help.
- Most differences are quite small (but significant)

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





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

- All writers/readers agree on emotion, high average appraisal agreement



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

- All writers/readers agree on emotion, high average appraisal agreement

pride, .65

I baked a delicious strawberry cobbler



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

- All writers/readers agree on emotion, high average appraisal agreement

pride, .65

fear, .84

I baked a delicious strawberry cobbler

A housemate came at me with a knife



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

- All writers/readers agree on emotion, **high** average appraisal agreement

pride, .65

I baked a delicious strawberry cobbler

fear, .84

A housemate came at me with a knife

- All writers/readers agree on emotion, **low** average appraisal agreement



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

- All writers/readers agree on emotion, **high** average appraisal agreement
pride, .65 I baked a delicious strawberry cobbler
fear, .84 A housemate came at me with a knife
- All writers/readers agree on emotion, **low** average appraisal agreement
disgust, 2.0 His toenails where massive



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

- All writers/readers agree on emotion, **high** average appraisal agreement
pride, .65 I baked a delicious strawberry cobbler
fear, .84 A housemate came at me with a knife
- All writers/readers agree on emotion, **low** average appraisal agreement
disgust, 2.0 His toenails where massive
fear, 2.1 I felt ... going in to hospital



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

- All writers/readers agree on emotion, **high** average appraisal agreement
pride, .65 I baked a delicious strawberry cobbler
fear, .84 A housemate came at me with a knife
- All writers/readers agree on emotion, **low** average appraisal agreement
disgust, 2.0 His toenails where massive
fear, 2.1 I felt ... going in to hospital
- All readers agree on the emotion, but **not with the writer**, **high** appraisal agreement



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

- All writers/readers agree on emotion, **high** average appraisal agreement
pride, .65 I baked a delicious strawberry cobbler
fear, .84 A housemate came at me with a knife
- All writers/readers agree on emotion, **low** average appraisal agreement
disgust, 2.0 His toenails where massive
fear, 2.1 I felt ... going in to hospital
- All readers agree on the emotion, but **not with the writer**, **high** appraisal agreement
trust, joy, .87 I am with my friends



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

- All writers/readers agree on emotion, **high** average appraisal agreement
pride, .65 I baked a delicious strawberry cobbler
fear, .84 A housemate came at me with a knife
- All writers/readers agree on emotion, **low** average appraisal agreement
disgust, 2.0 His toenails where massive
fear, 2.1 I felt ... going in to hospital
- All readers agree on the emotion, but **not with the writer**, **high** appraisal agreement
trust, joy, .87 I am with my friends
anger, fear, 1.1 My waters broke early during pregnancy



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

- All writers/readers agree on emotion, **high** average appraisal agreement
pride, .65 I baked a delicious strawberry cobbler
fear, .84 A housemate came at me with a knife
- All writers/readers agree on emotion, **low** average appraisal agreement
disgust, 2.0 His toenails where massive
fear, 2.1 I felt ... going in to hospital
- All readers agree on the emotion, but **not with the writer**, **high** appraisal agreement
trust, joy, .87 I am with my friends
anger, fear, 1.1 My waters broke early during pregnancy
- All readers agree on the emotion, **but not with the writer**, **low** appraisal agreement



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

- All writers/readers agree on emotion, **high** average appraisal agreement
pride, .65 I baked a delicious strawberry cobbler
fear, .84 A housemate came at me with a knife
- All writers/readers agree on emotion, **low** average appraisal agreement
disgust, 2.0 His toenails where massive
fear, 2.1 I felt ... going in to hospital
- All readers agree on the emotion, but **not with the writer**, **high** appraisal agreement
trust, joy, .87 I am with my friends
anger, fear, 1.1 My waters broke early during pregnancy
- All readers agree on the emotion, **but not with the writer**, **low** appraisal agreement
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	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, but there is a small and significant agreement drop.



Emotion Annotation Result

Conclusion

Annotators can quite well reconstruct authors emotion, but there is a small and significant agreement drop.

Challenge

Authors recall “important” events. We do (presumably) not get a realistic subsample of event descriptions as they appear in the wild.



Emotion Annotation Result

Conclusion

Annotators can quite well reconstruct authors emotion, but there is a small and significant agreement drop.

Challenge

Authors recall “important” events. We do (presumably) not get a realistic subsample of event descriptions as they appear in the wild.

- Not shown: appraisals help to disambiguate emotion categories in automatic models

Potential Reason for V–G Discrepancy





Potential Reason for V–G Discrepancy

- Isolated events are not sufficient



Potential Reason for V–G Discrepancy

- 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>



Idea: Generate backstories to explain emotions/appraisals

Event

“The loudspeaker suddenly malfunctioned and went silent.”

- Many emotion interpretations possible.

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>



Idea: Generate backstories to explain emotions/appraisals

Event

“The loudspeaker suddenly malfunctioned and went silent.”

- Many emotion interpretations possible.
- ⇒ We autogenerate stories that explain such event for a given emotion.

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>



Backstories

The loudspeaker suddenly malfunctioned and went silent.

The loudspeaker suddenly malfunctioned and went silent.

The loudspeaker suddenly malfunctioned and went silent.



Backstories

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.**

The loudspeaker suddenly malfunctioned and went silent.

The loudspeaker suddenly malfunctioned and went silent.



Backstories

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.**

The loudspeaker suddenly malfunctioned and went silent.

The loudspeaker suddenly malfunctioned and went silent.



Backstories

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.**

I arrived at a remote wilderness survival training camp, where the instructors emphasized the importance of following loudspeaker instructions for safety. The instructors warned us about the toxic waste site nearby and explained that the loudspeaker would alert us to any changes in air quality. During the first exercise, I struggled to navigate the challenging terrain, but the loudspeaker provided crucial guidance, helping me stay on track. I completed a difficult obstacle course, relying heavily on the loudspeaker's instructions to avoid hazards and find the safest route. **The loudspeaker suddenly malfunctioned and went silent.**

The loudspeaker suddenly malfunctioned and went silent.



Backstories

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.**

Fear: I arrived at a remote wilderness survival training camp, where the instructors emphasized the importance of following loudspeaker instructions for safety. The instructors warned us about the toxic waste site nearby and explained that the loudspeaker would alert us to any changes in air quality. During the first exercise, I struggled to navigate the challenging terrain, but the loudspeaker provided crucial guidance, helping me stay on track. I completed a difficult obstacle course, relying heavily on the loudspeaker's instructions to avoid hazards and find the safest route. **The loudspeaker suddenly malfunctioned and went silent.**

The loudspeaker suddenly malfunctioned and went silent.



Backstories

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.**

Fear: I arrived at a remote wilderness survival training camp, where the instructors emphasized the importance of following loudspeaker instructions for safety. The instructors warned us about the toxic waste site nearby and explained that the loudspeaker would alert us to any changes in air quality. During the first exercise, I struggled to navigate the challenging terrain, but the loudspeaker provided crucial guidance, helping me stay on track. I completed a difficult obstacle course, relying heavily on the loudspeaker's instructions to avoid hazards and find the safest route. **The loudspeaker suddenly malfunctioned and went silent.**

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.**



Backstories

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.**

Fear: I arrived at a remote wilderness survival training camp, where the instructors emphasized the importance of following loudspeaker instructions for safety. The instructors warned us about the toxic waste site nearby and explained that the loudspeaker would alert us to any changes in air quality. During the first exercise, I struggled to navigate the challenging terrain, but the loudspeaker provided crucial guidance, helping me stay on track. I completed a difficult obstacle course, relying heavily on the loudspeaker's instructions to avoid hazards and find the safest route. **The loudspeaker suddenly malfunctioned and went silent.**

Pride: 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.**

Results in a Nutshell



Results in a Nutshell

- Backstories make interpretation more clear for models and annotators (details not shown for time reasons).





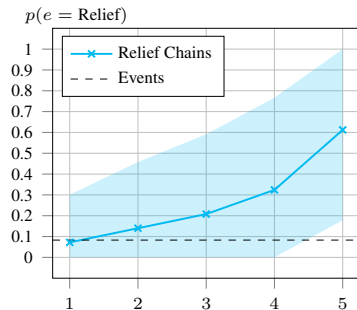
Results in a Nutshell

- Backstories make interpretation more clear for models and annotators (details not shown for time reasons).
- Effect more pronounced for some emotions than others



Results in a Nutshell

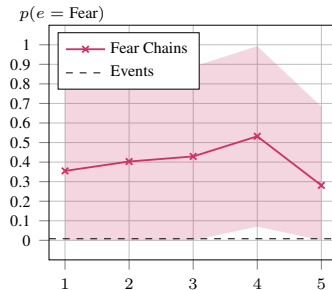
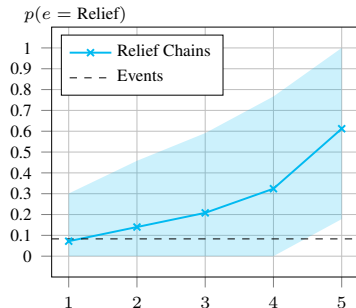
- Backstories make interpretation more clear for models and annotators (details not shown for time reasons).
- Effect more pronounced for some emotions than others





Results in a Nutshell

- Backstories make interpretation more clear for models and annotators (details not shown for time reasons).
- Effect more pronounced for some emotions than others



Summary and Next Steps





Summary and Next Steps

- We learned about appraisals as an emotion model that links the evaluation of events and emotions.



Summary and Next Steps

- We learned about appraisals as an emotion model that links the evaluation of events and emotions.
- It explains emotion categories, but also acts as a model in itself.



Summary and Next Steps

- We learned about appraisals as an emotion model that links the evaluation of events and emotions.
- It explains emotion categories, but also acts as a model in itself.
- Sometimes, it might just be the more appropriate emotion model.

Outline

- 1 Emotion Analysis and Appraisals
- 2 Appraisals and Argument Convincingness
- 3 How to Collect Data?
- 4 Take Home

Argument Convincingness



Argument Convincingness



- Argument quality includes:

Argument Convincingness



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



Argument Convincingness

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

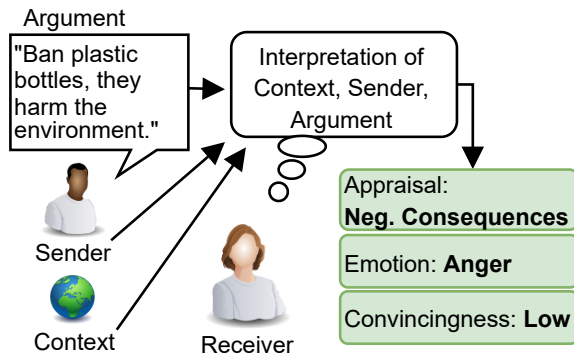


Argument Convincingness

- Argument quality includes:
 - Logical structure: Logos
 - Speaker credibility: Ethos
 - Emotional appeal: Pathos
- Arguments are subjectively evaluated



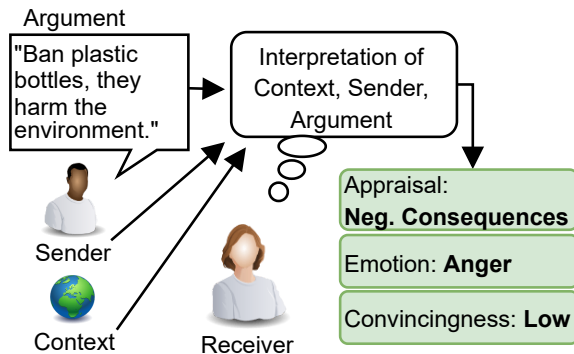
The Contextualized Argument Appraisal Framework



L. Greschner et al. (2025). Trust Me, I Can Convince You: The Contextualized Argument Appraisal Framework. arXiv: 2509.17844 [cs.CL]. URL: <https://arxiv.org/abs/2509.17844>



The Contextualized Argument Appraisal Framework

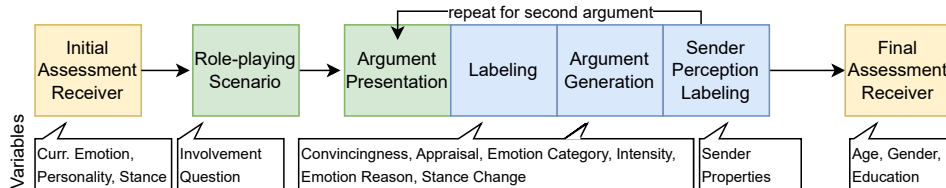


Do appraisals explain convincingness?

L. Greschner et al. (2025). Trust Me, I Can Convince You: The Contextualized Argument Appraisal Framework. arXiv: 2509.17844 [cs.CL]. URL: <https://arxiv.org/abs/2509.17844>

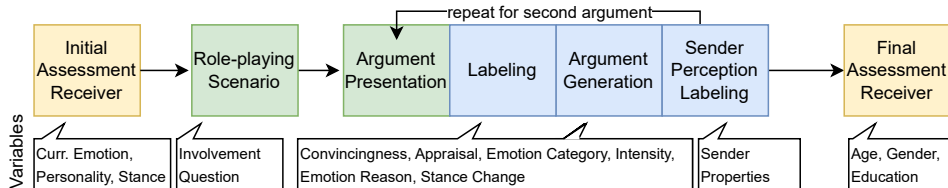


Argument Appraisal Annotation Framework





Argument Appraisal Annotation Framework



- 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
Consequential 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





Convincingness and Emotions – Average Values

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
Suddenness															
Suppression															
Familiarity															
Pleasantness															
Unpleasantness															
Consequential Importance															
Consequential Consequentiality															
Positive Consequentiality															
Negative Consequentiality															
Consequence Manageability															
Internal Check															
External Check															
Response urgency															
Cognitive Effort															
Argument Internal Check															
Argument External Check															



Convincingness and Emotions – Average Values

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
Suddenness															
Suppression															
Familiarity															
Pleasantness															
Unpleasantness															
Consequential Importance															
Consequentiality															
Positive Consequentiality															
Negative Consequentiality															
Consequence Manageability															
Internal Check															
External Check															
Response urgency															
Cognitive Effort															
Argument Internal Check															
Argument External Check															

- Generally high cognitive effort



Convincingness and Emotions – Average Values

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
Suddenness															
Suppression															
Familiarity															
Pleasantness															
Unpleasantness															
Consequential Importance															
Consequential Consequentiality															
Positive Consequentiality															
Negative Consequentiality															
Consequence Manageability															
Internal Check															
External Check															
Response urgency															
Cognitive Effort															
Argument Internal Check															
Argument External Check															

- Generally high cognitive effort
- External Argument Check explains anger and disgust



Convincingness and Emotions – Average Values

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
Suddenness															
Suppression															
Familiarity															
Pleasantness															
Unpleasantness															
Consequential Importance															
Consequential Consequentiality															
Positive Consequentiality															
Negative Consequentiality															
Consequence Manageability															
Internal Check															
External Check															
Response urgency															
Cognitive Effort															
Argument Internal Check															
Argument External Check															

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

Correlations of Emotions with Convincingness





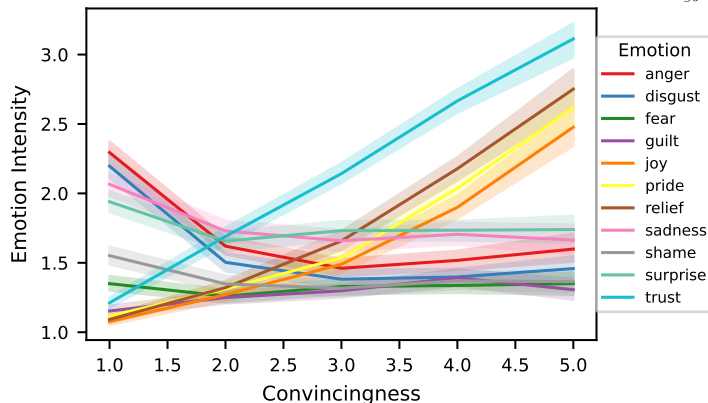
Correlations of Emotions with Convincingness

Emotion	r
Trust	0.570
Relief	0.511
Pride	0.458
Joy	0.435
Guilt	0.105
Fear	0.006
Surprise	-0.072
Shame	-0.073
Sadness	-0.153
Anger	-0.265
Disgust	-0.264



Correlations of Emotions with Convincingness

Emotion	r
Trust	0.570
Relief	0.511
Pride	0.458
Joy	0.435
Guilt	0.105
Fear	0.006
Surprise	-0.072
Shame	-0.073
Sadness	-0.153
Anger	-0.265
Disgust	-0.264





Correlations of Appraisals with Convincingness

Appraisal	r
Pleasantness	0.566
Positive Consequentiality	0.392
Familiarity	0.327
Negative Consequentiality	0.203
Consequential Importance	0.141
Consequence Manageability	-0.034
Cognitive Effort	-0.061

Appraisal	r
Internal Check	-0.103
Argument Internal Check	-0.109
Response Urgency	-0.242
Suppression	-0.326
Suddenness	-0.342
External Check	-0.355
Unpleasantness	-0.385
Argument External Check	-0.497



Correlations of Appraisals with Convincingness

Appraisal	r
Pleasantness	0.566
Positive Consequentiality	0.392
Familiarity	0.327
Negative Consequentiality	0.203
Consequential Importance	0.141
Consequence Manageability	-0.034
Cognitive Effort	-0.061

Appraisal	r
Internal Check	-0.103
Argument Internal Check	-0.109
Response Urgency	-0.242
Suppression	-0.326
Suddenness	-0.342
External Check	-0.355
Unpleasantness	-0.385
Argument External Check	-0.497

- Pleasant arguments whose outcomes are good for the self and which are familiar are more convincing.



Correlations of Appraisals with Convincingness

Appraisal	r
Pleasantness	0.566
Positive Consequentiality	0.392
Familiarity	0.327
Negative Consequentiality	0.203
Consequential Importance	0.141
Consequence Manageability	-0.034
Cognitive Effort	-0.061

Appraisal	r
Internal Check	-0.103
Argument Internal Check	-0.109
Response Urgency	-0.242
Suppression	-0.326
Suddenness	-0.342
External Check	-0.355
Unpleasantness	-0.385
Argument External Check	-0.497

- 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



C. Bagdon et al. (2025). “Donate or Create? Comparing Data Collection Strategies for Emotion-labeled Multimodal Social Media Posts”. In: ACL



Introduction

- Synthetic data creation has advantages:

C. Bagdon et al. (2025). “Donate or Create? Comparing Data Collection Strategies for Emotion-labeled Multimodal Social Media Posts”. In: ACL



Introduction

- Synthetic data creation has advantages:
 - Direct access to the author's assessment

C. Bagdon et al. (2025). "Donate or Create? Comparing Data Collection Strategies for Emotion-labeled Multimodal Social Media Posts". In: ACL



Introduction

- Synthetic data creation has advantages:
 - Direct access to the author's assessment
 - Privacy: authors are aware what they share and can filter

C. Bagdon et al. (2025). "Donate or Create? Comparing Data Collection Strategies for Emotion-labeled Multimodal Social Media Posts". In: ACL



Introduction

- Synthetic data creation has advantages:
 - Direct access to the author's assessment
 - Privacy: authors are aware what they share and can filter
- Potential issues:

C. Bagdon et al. (2025). "Donate or Create? Comparing Data Collection Strategies for Emotion-labeled Multimodal Social Media Posts". In: ACL



Introduction

- Synthetic data creation has advantages:
 - Direct access to the author's assessment
 - Privacy: authors are aware what they share and can filter
- Potential issues:
 - Data is not realistic

C. Bagdon et al. (2025). "Donate or Create? Comparing Data Collection Strategies for Emotion-labeled Multimodal Social Media Posts". In: ACL



Introduction

- Synthetic data creation has advantages:
 - Direct access to the author's assessment
 - Privacy: authors are aware what they share and can filter
- Potential issues:
 - Data is not realistic
 - People recall particularly “prototypical” events

C. Bagdon et al. (2025). “Donate or Create? Comparing Data Collection Strategies for Emotion-labeled Multimodal Social Media Posts”. In: ACL



Introduction

- Synthetic data creation has advantages:
 - Direct access to the author's assessment
 - Privacy: authors are aware what they share and can filter
- Potential issues:
 - Data is not realistic
 - People recall particularly “prototypical” events
 - Type of data might differ due to missing post creation triggers

C. Bagdon et al. (2025). “Donate or Create? Comparing Data Collection Strategies for Emotion-labeled Multimodal Social Media Posts”. In: ACL

Approach: Data elicitation strategies



Approach: Data elicitation strategies

- 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.”
 - “Write a social media post text about that.”
 - “Select an image you want to share from a CC image data base.”
- 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.”
 - “Select an image you want to share from a CC image data base.”
- Donation:
 - “Pick a multimodal post from your social media timeline that you made because the associated event caused emotion X.”
- 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.”
 - “Select an image you want to share from a CC image data base.”
- Donation:
 - “Pick a multimodal post from your social media timeline that you made because the associated event caused emotion X.”
 - “Copy paste the text and the image.”
- 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.”
 - “Select an image you want to share from a CC image data base.”
- Donation:
 - “Pick a multimodal post from your social media timeline that you made because the associated event caused emotion X.”
 - “Copy paste the text and the image.”
- Recent:
 - “Pick the 10 most recent posts from your social media timeline.”



Approach: Data elicitation strategies

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



Absolutely insane, what is going on?!



Creation post labeled as surprise.



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.

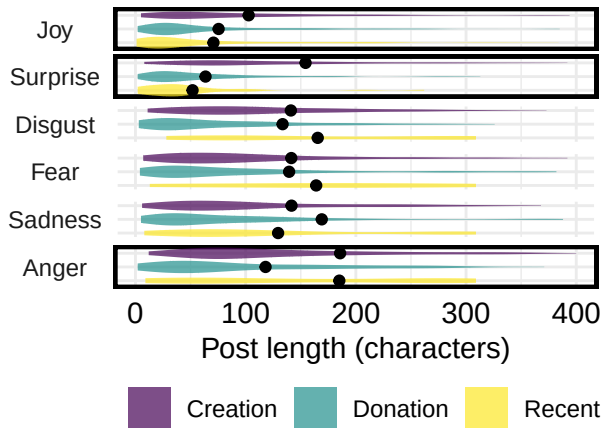
Recent post labeled as anger.

Are the subcorpora comparable? – Post Length





Are the subcorpora comparable? – Post Length

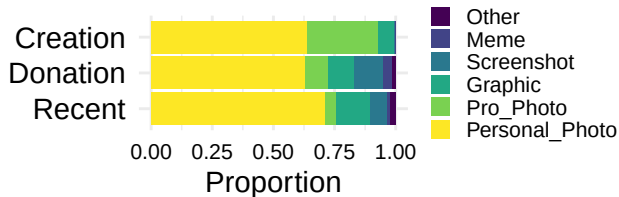


Are the subcorpora comparable? – Image Type





Are the subcorpora comparable? – Image Type

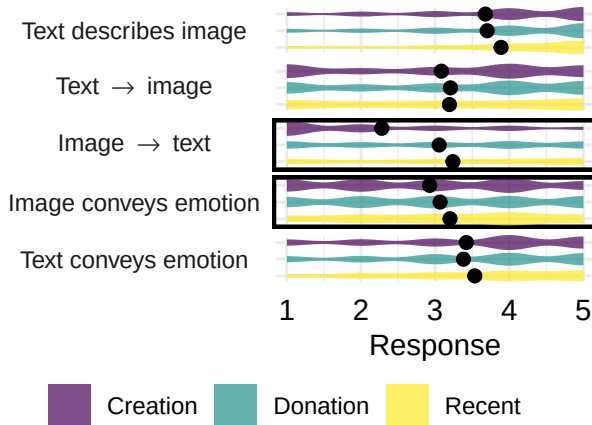


Are the subcorpora comparable? – Text–Image Relation





Are the subcorpora comparable? – Text–Image Relation



Are the subcorpora comparable? – Appraisal–Emotion





Appraisal response

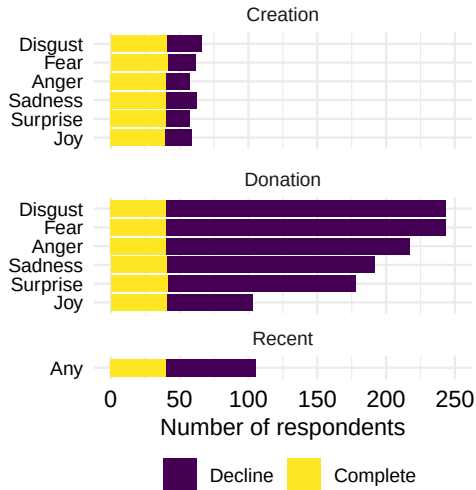


Are the subcorpora comparable? – Participant acceptance





Are the subcorpora comparable? – Participant acceptance





Are the differences a problem?

Experiment

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



Are the differences a problem?

Experiment

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

Results



Are the differences a problem?

Experiment

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

Results

- No big performance differences: F score .38 vs. .40



Are the differences a problem?

Experiment

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

Results

- No big performance differences: F score .38 vs. .40
 - ⇒ The experimentally elicited data is fine to optimize a model.



Are the differences a problem?

Experiment

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

Results

- No big performance differences: F score .38 vs. .40
⇒ The experimentally elicited data is fine to optimize a model.
- But: The estimate on donated data is overall optimistic!
F score of .60 and .62.



Are the differences a problem?

Experiment

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

Results

- No big performance differences: F score .38 vs. .40
 - ⇒ The experimentally elicited data is fine to optimize a model.
- But: The estimate on donated data is overall optimistic!
F score of .60 and .62.
 - ⇒ Real data is required to estimate model performance.



Are the differences a problem?

Experiment

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

Results

- No big performance differences: F score .38 vs. .40
 - ⇒ The experimentally elicited data is fine to optimize a model.
- But: The estimate on donated data is overall optimistic!
F score of .60 and .62.
 - ⇒ Real data is required to estimate model performance.
- Zero-Shot prompting (Llama3.2-vision) leads to slightly better results for donated data.

Outline

- 1 Emotion Analysis and Appraisals
- 2 Appraisals and Argument Convincingness
- 3 How to Collect Data?
- 4 Take Home

Summary





Summary

- **Appraisals** are an emotion model that explain the **cognitive evaluation process** that is part of an **emotion**



Summary

- **Appraisals** are an emotion model that explain the **cognitive evaluation process** that is part of an **emotion**
- **Appraisals** can be annotated and modeled



Summary

- **Appraisals** are an emotion model that explain the **cognitive evaluation process** that is part of an **emotion**
- **Appraisals** can be annotated and modeled
- ...but they are **subjective** and require **context**



Summary

- **Appraisals** are an emotion model that explain the **cognitive evaluation process** that is part of an **emotion**
- **Appraisals** can be annotated and modeled
- ...but they are **subjective** and require **context**
- **Appraisals** are an informative approach to explain **argument convincingness**



Summary

- **Appraisals** are an emotion model that explain the **cognitive evaluation process** that is part of an **emotion**
- **Appraisals** can be annotated and modeled
- ...but they are **subjective** and require **context**
- **Appraisals** are an 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?



Thanks to

- Enrica Troiano
- Laura Ana Maria Oberländer née Bostan
- Lynn Greschner
- Johannes Schäfer
- Sabine Weber
- Christopher Bagdon
- Carina Silberer
- Kai Sassenberg
- All of BamNLP

Funded by
DFG Deutsche
Forschungsgemeinschaft
German Research Foundation



Appraisals as Emotion Model in NLP

Why we need them and how to acquire data

Workshop, Ghent, September 26, 2025

Roman Klinger

roman.klinger@uni-bamberg.de

 [romanklinger.de](https://twitter.com/romanklinger)  [romanklinger](https://www.linkedin.com/in/romanklinger)
<https://www.bamberg.de/nlproc/>