University of Bamberg

# Event-centric Emotion Analysis in Natural Language Processing

## Appraisal Variables as Emotion Models

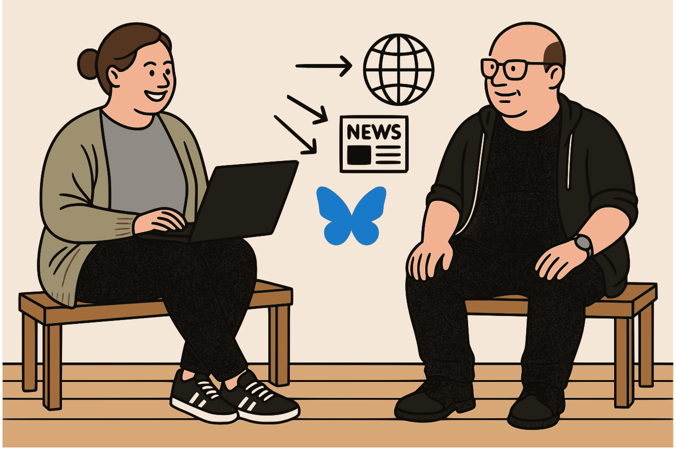
AI Meets Human Data Colloquium, Augsburg, January 27, 2026

Roman Klinger
roman.klinger@uni-bamberg.de

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

BamNLP

# Natural Language Processing and Understanding



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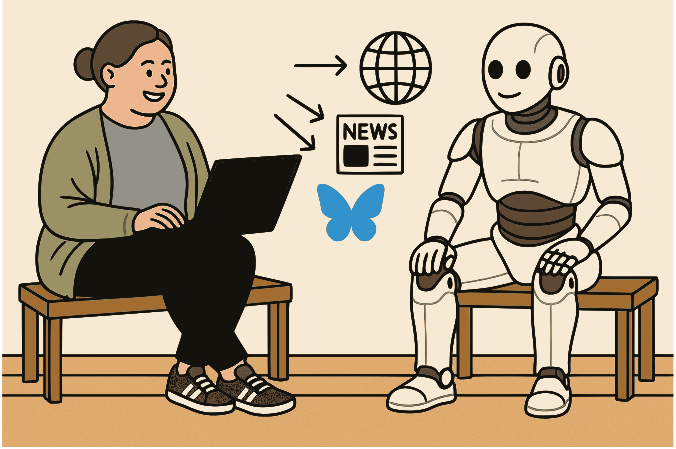

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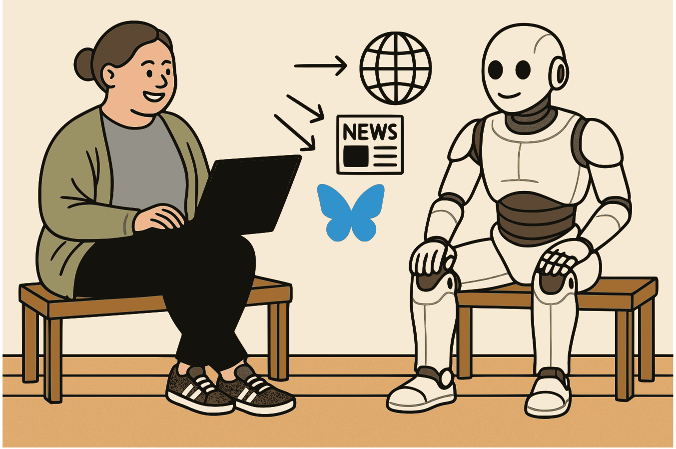


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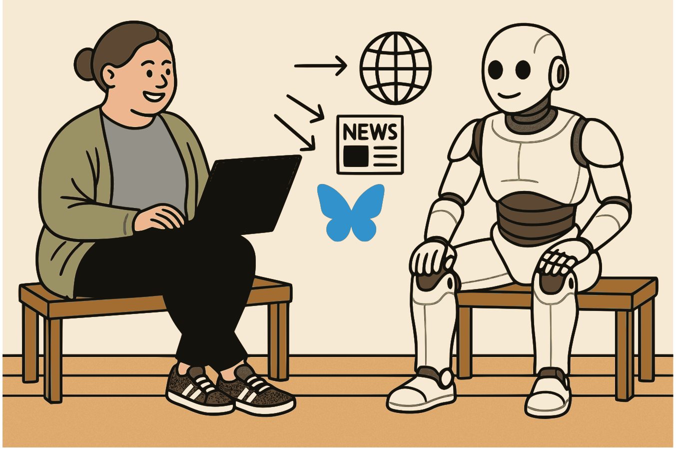


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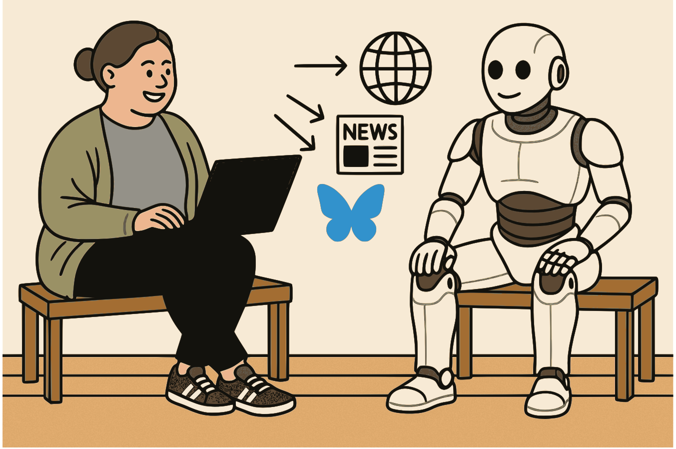


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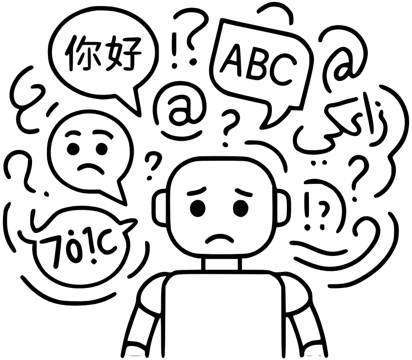


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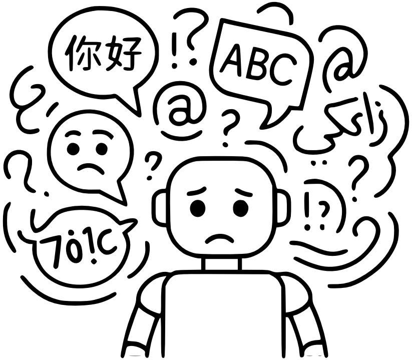


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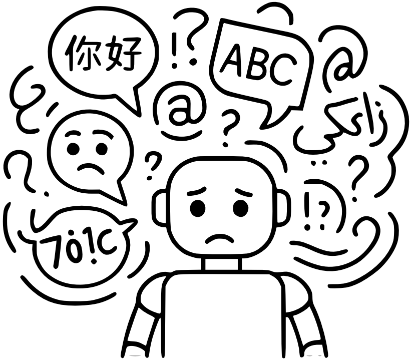


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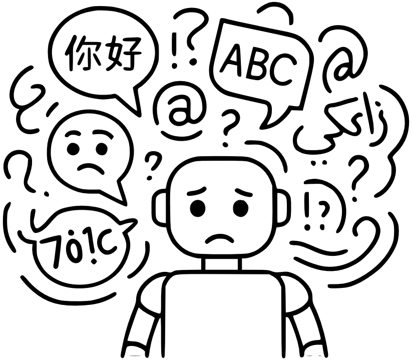


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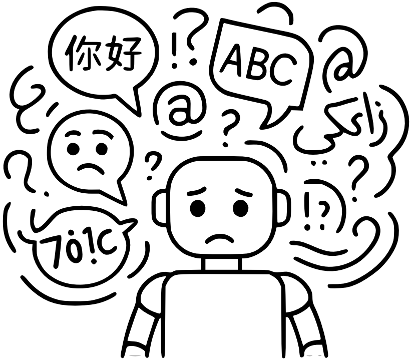


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⇒ Pragmatic approach to language understanding sky news .COM.AU

World News > United States


**Donald Trump mocks Bill Gates after billionaire's humiliating backflip on climate change**

30 October 2025 - 04:46AM sky news .COM.AU

Donald Trump wasted no time mocking Bill Gates after the billionaire admitted that climate change will not lead to humanity's demise in a memo released yesterday.

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- Aggregating information enables many use cases:
  diverse news recommendation, social network analysis, opinion mining, ...

# Outline

# Emotion Examples

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With this exercise, we discussed two things:

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

# Emotion Models – Basic Emotions

How to define a categorical system of emotions?

Ekman (1992): An argument for basic emotions.

# Emotion Models – 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
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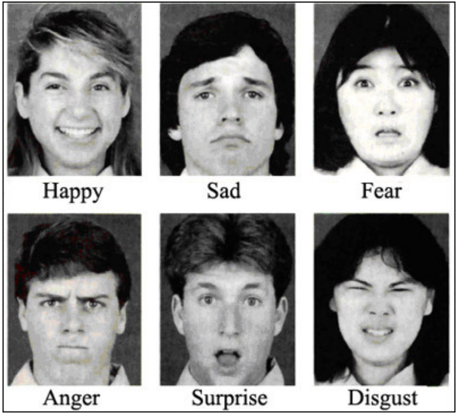


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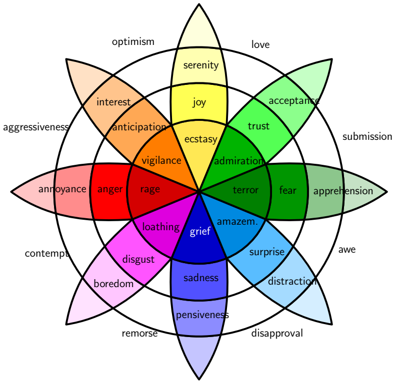
# Ekman: What are non-basic emotions?

- "I do not allow for non-basic emotions" (Ekman, 1999)
  - $\Rightarrow$ They do no exist.
- What is love, depression, or hostility?
  - Personality traits (hostility, openness)
  - Moods (depression, anxiety, long-term disturbances are clinically relevant)
  - Emotional plots (love, grief, jealousy)

# Models of Basic Emotions: Plutchik's Wheel

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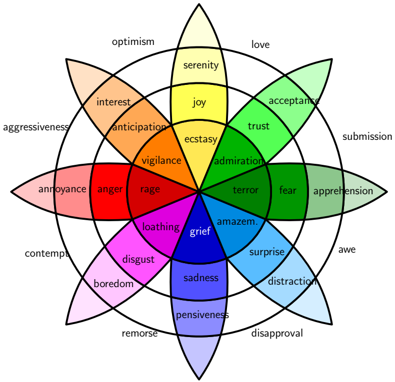


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- reproduction
- deprivation
- incorporation
- rejection
- exploration
- orientation

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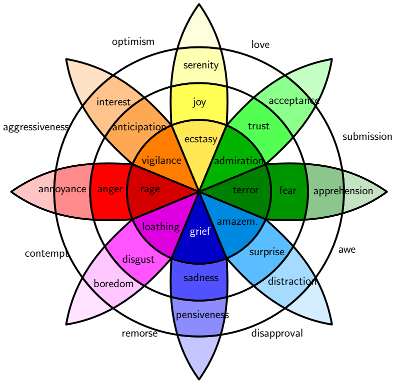


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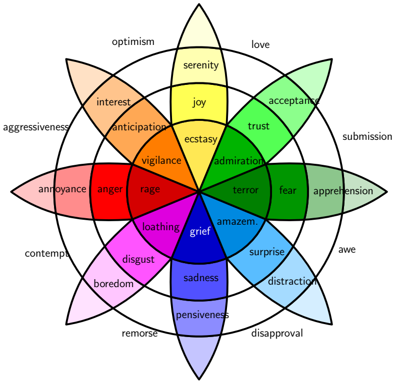


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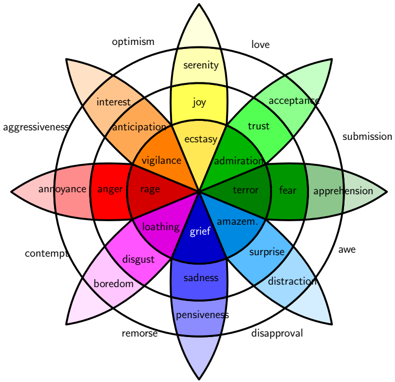


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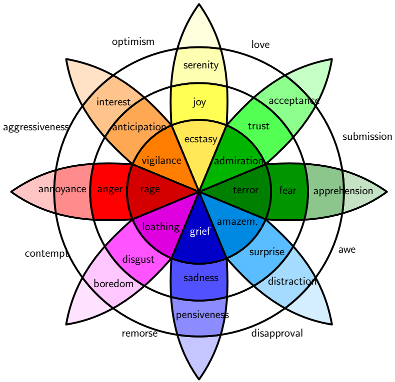


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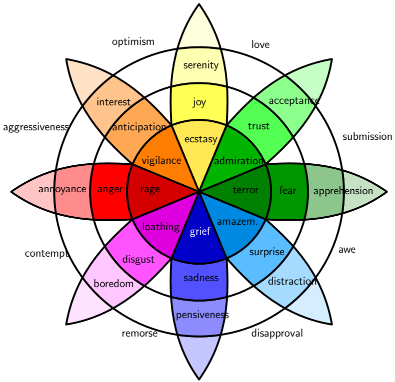


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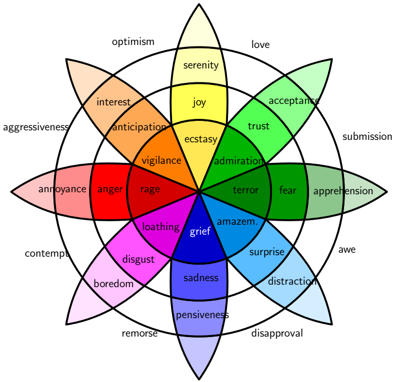


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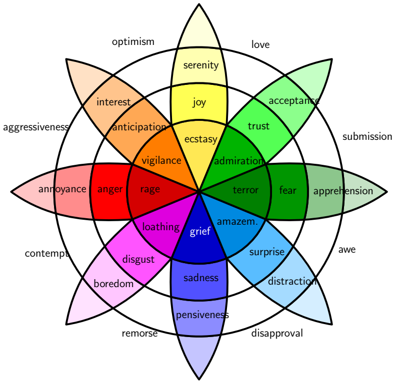


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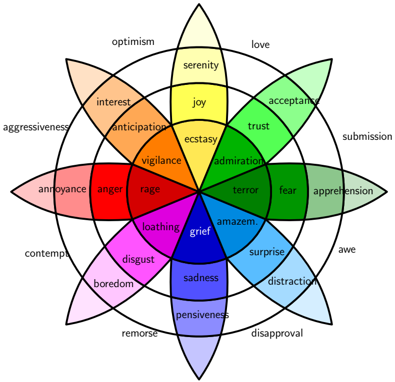


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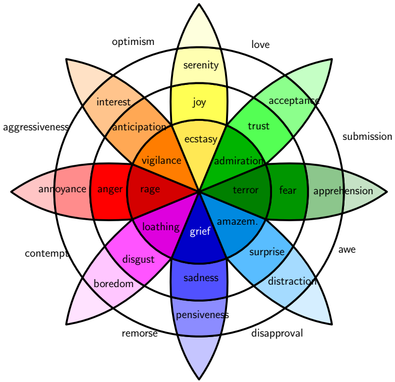


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⇒ These are basic emotions according to Plutchik (1970)

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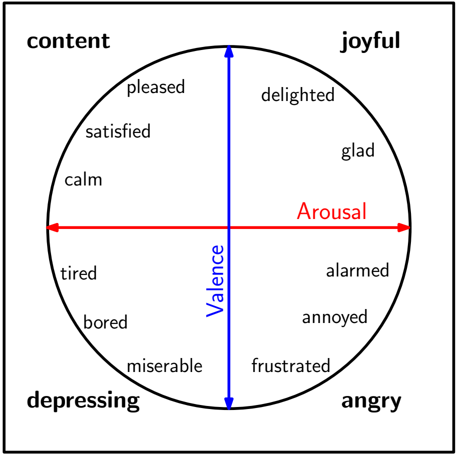


Russell, R. (1980). A Circumplex Model of Affect.

# Emotion Analysis: What we want to do.

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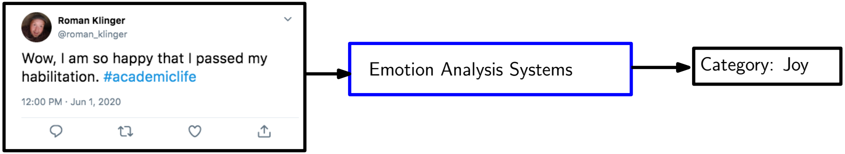
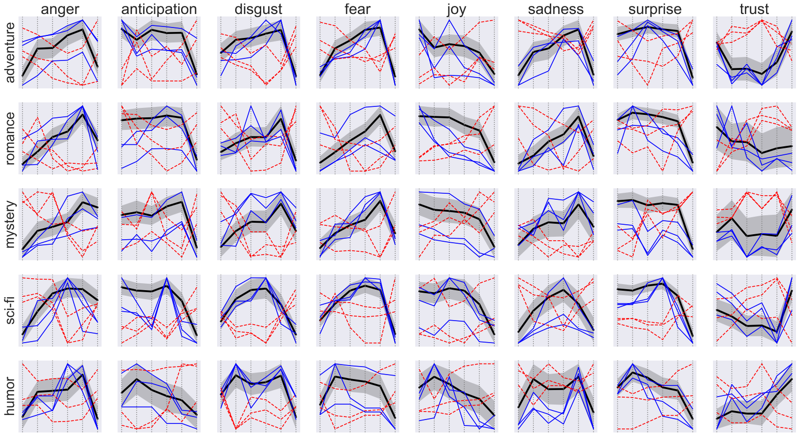


# Literary Studies



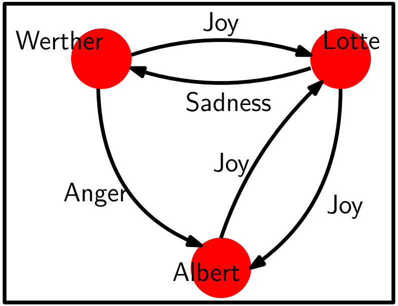

E. Kim, S. Padó, and R. Klinger (2017). “Investigating the Relationship between Literary Genres and Emotional Plot Development”. In: LaTeCHCLfL

# News Analysis

| Emotion | Dominant Emotion | Reader Emotions |
|---|---|---|
| Anger | The Blaze, The Daily Wire, BuzzFeed | The Gateway Pundit, The Daily Mail, Talking Points Memo |
| Annoyance | Vice, NewsBusters, AlterNet | Vice, The Week, Business Insider |
| Disgust | BuzzFeed, The Hill, NewsBusters | Mother Jones, The Blaze, Daily Caller |
| Fear | The Daily Mail, Los Angeles Times, BBC | Palmer Report, CNN, InfoWars |
| Guilt | Fox News, The Daily Mail, Vice | The Washington Times, Reason, National Review |
| Joy | Time, Positive.News, BBC | Positive.News, ThinkProgress, AlterNet |
| Love | Positive.News, The New Yorker, BBC | Positive.News, AlterNet, Twitchy |
| Pessimism | MotherJones, Intercept, Financial Times | The Guardian, Truthout, The Washington Post |
| Neg. Surprise | The Daily Mail, MarketWatch, Vice | The Daily Mail, BBC, Breitbart |
| Optimism | Bussines Insider, The Week, The Fiscal Times | MarketWatch, Positive.News, The New Republic |
| Pos. Surprise | Positive.News, BBC, MarketWatch | Positive.News, The Washington Post, MotherJones |
| Pride | Positive.News, The Guardian, The New Yorker | Daily Kos, NBC, The Guardian |
| Sadness | The Daily Mail, CNN, Daily Caller | The Daily Mail, CNN, The Washington Post |
| Shame | The Daily Mail, The Guardian, The Daily Wire | Mother Jones, National Review, Fox News |
| Trust | The Daily Signal, Fox News, Mother Jones | Economist, The Los Angeles Times, The Hill |

L. A. M. Bostan, E. Kim, and R. Klinger (2020). "GoodNewsEveryone: A Corpus of News Headlines Annotated with Emotions, Semantic Roles, and Reader Perception". In: LREC

# Social Networks




E. Kim and R. Klinger (2019). "Frowning Frodo, Wincing Leia, and a Seriously Great Friendship: Learning to Classify Emotional Relationships of Fictional Characters". In: NAACL

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- (main part of today's talk)

# How are emotions expressed? Do we need to deal with event descriptions (Twitter/Literature)?

| Component | Example | Fraction (T/L) |
|---|---|---|
| Physiology | | |
| Action | | |
| Expression | | |
| Feeling | | |
| Appraisal | | |

F. Casel, A. Heindl, and R. Klinger (2021). "Emotion Recognition under Consideration of the Emotion Component Process Model". In: KONVENS

# How are emotions expressed? Do we need to deal with event descriptions (Twitter/Literature)?

| Component | Example | Fraction (T/L) |
|---|---|---|
| Physiology | Loves when a song makes your heart race | |
| Action | | |
| Expression | | |
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| Feeling | Feelin a bit sad today | |
| Appraisal | Thinks that mel had a great 50th birthday party | |

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# How are emotions expressed?
# Do we need to deal with event descriptions (Twitter/Literature)?

| Component | Example | Fraction (T/L) | |
|---|---|---|---|
| Physiology | Loves when a song makes your heart race | 5 | 8 |
| Action | sometimes when i think bout you i want to beat the shit out of your face | 18 | 19 |
| Expression | when I walk in the room and my nephew recognises me his face lights up with the biggest smile | 13 | 44 |
| Feeling | Feelin a bit sad today | 32 | 17 |
| Appraisal | Thinks that mel had a great 50th birthday party | 75 | 61 |

F. Casel, A. Heindl, and R. Klinger (2021). "Emotion Recognition under Consideration of the Emotion Component Process Model". In: KONVENS

# 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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Event

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**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

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

Components

# Definition of Emotions: Components

**Emotion (Scherer, 2005)**

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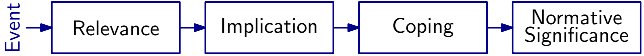
Event

| | |
|---|---|
| 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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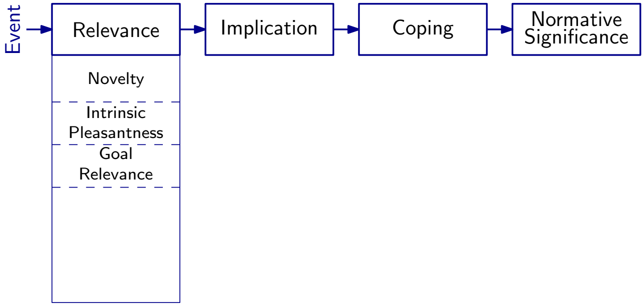


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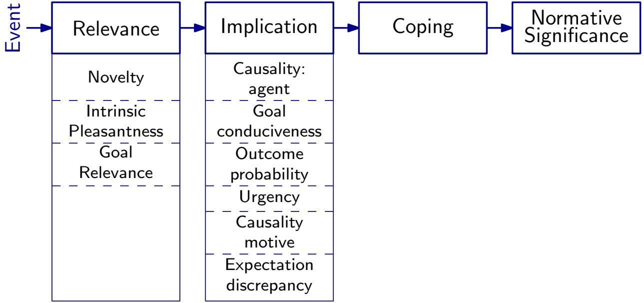


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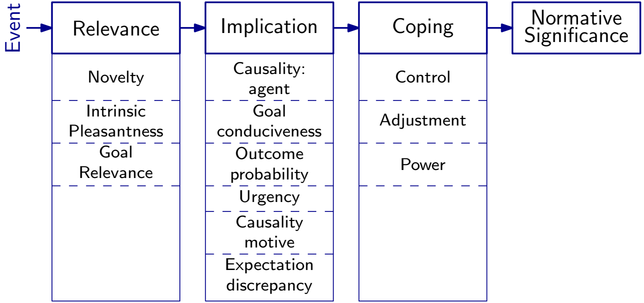


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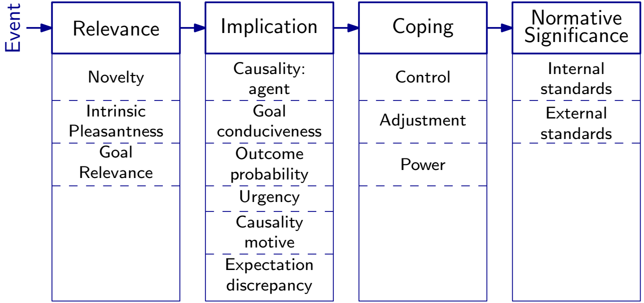


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# Research Questions

E. Troiano, L. Oberländer, and R. Klinger (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?

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# Research Questions

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

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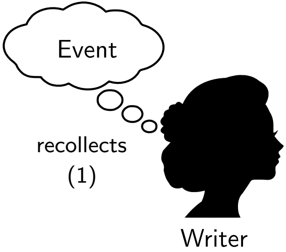
# Approach



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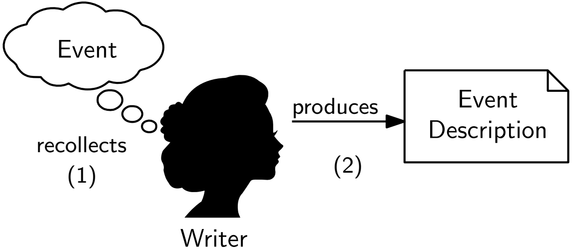
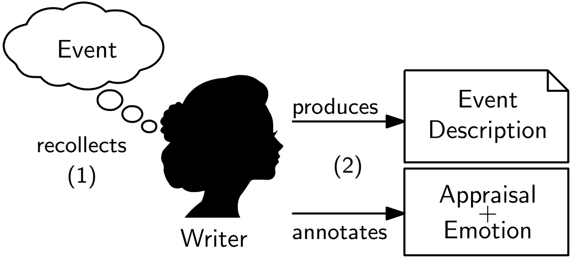
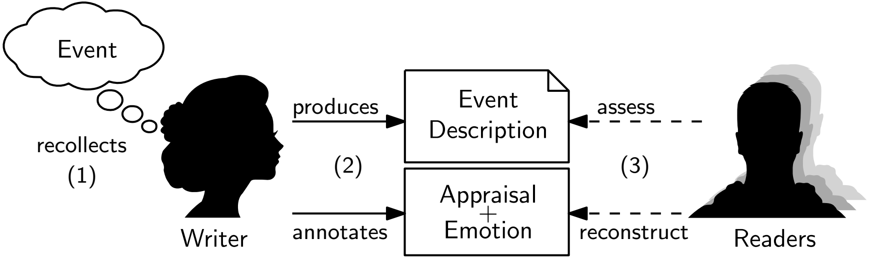


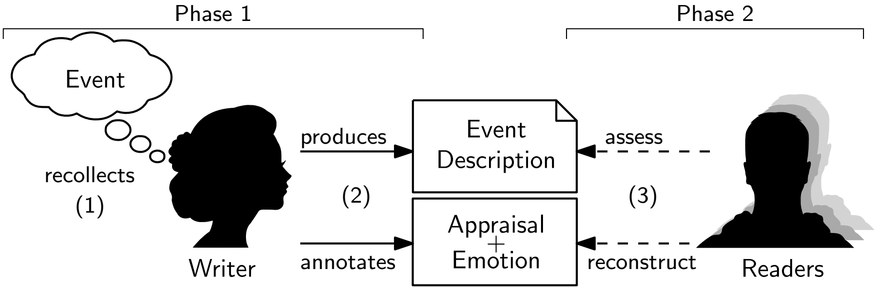
# Approach


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

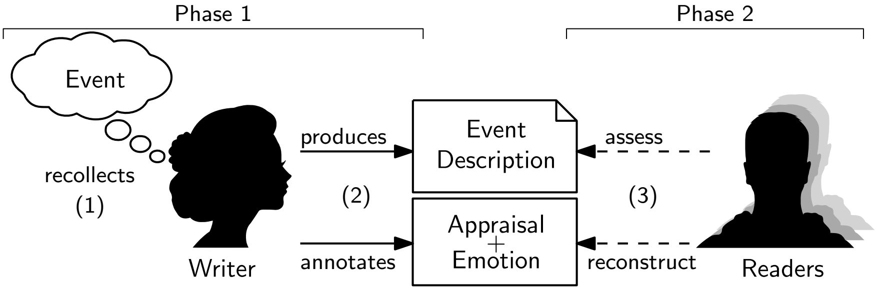
# Approach


Event
recollects
(1)
Writer
produces
annotates
(2)
Event
Description
Appraisal
+
Emotion
assess
reconstruct
(3)
Readers

# Approach

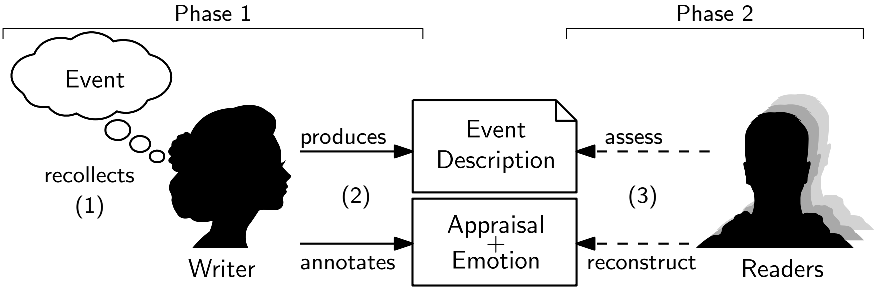

Phase 1
Phase 2
Event
recollects
(1)
Writer
produces
(2)
annotates
Event
Description
Appraisal
+
Emotion
assess
(3)
reconstruct
Readers

# 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.

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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.

# 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

| | | | Agreement | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Emotion F$_1$ | | Emotion Acc. | | Appraisal 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 |
| | − | 2792 2897 | *.50 | *.51 | *.51 | *.54 | *1.56 | *1.46 |

# 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 |
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| | – | 3000 1568 | .49 | .48 | .50 | .51 | 1.57 | 1.48 |
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| 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 |

- Validators agree more with each other than with the generator

# Reliability Results

| | | | Agreement | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Emotion | | | | Appraisal RMSE | |
| | | | $F_1$ | | Acc. | | | |
| 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 |
| | $\neq$ | 2962 3920 | .49 | *.48 | .50 | *.52 | 1.57 | *.1.48 |
| Age diff. | $> 7$ | 3089 7991 | .49 | *.48 | .51 | *.51 | *1.58 | 1.48 |
| | $\leq 7$ | 2076 3939 | .49 | *.51 | .50 | *.54 | *1.56 | 1.48 |
| Validators' Event Fam. | $> 3$ | 1386 540 | .49 | .44 | .51 | .47 | *1.60 | *1.42 |
| | $\leq 3$ | 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 |

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

# Reliability Results

| | | | Agreement | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Emotion | | | | Appraisal RMSE | |
| | | | $F_1$ | | Acc. | | | |
| 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 |
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| | − | 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 |

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

# Reliability Results

| | | | Agreement | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Emotion | | | | Appraisal RMSE | |
| | | | $F_1$ | | Acc. | | | |
| 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 |
| | – | 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

# 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 |
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|---|---|---|---|---|---|---|---|---|---|
| | | | | Emotion | | | | Appraisal | |
| | | | | $F_1$ | | Acc. | | RMSE | |
| Condition | Val. | #Pairs | | G–V | V–V | G–V | V–V | G–V | V–V |
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| Validators' Openness | + | 2685 | 1472 | .49 | .49 | .50 | .52 | 1.57 | 1.47 |
| | – | 3000 | 1568 | .49 | .48 | .50 | .51 | 1.57 | 1.48 |
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  - Extraversion, Conscient., Agreeableness help.
- Most differences are quite small (but significant)

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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 |

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# Appraisals add additional information to emotion analysis

That I put together a funeral service for my Aunt

- Appraisals explain the subjective evaluation of an event.
- Appraisals are a function of an event and the person who lives through it.

| Dimension | Writer | Readers | △ |
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# Emotion Annotation Result

## Conclusion

Annotators can quite well reconstruct author's emotion,
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- Appraisals explain subjectivity
- 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

# Outline

# Idea: Generate backstories to explain emotions/appraisals

**Event**

"The loudspeaker suddenly malfunctioned and went silent."

J. Schäfer and R. Klinger (2026). "Disambiguation of emotion annotations by contextualizing events in plausible narratives.". In: LREC

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**Event**

"The loudspeaker suddenly malfunctioned and went silent."

- Many emotion interpretations possible.

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

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# Backstories

The loudspeaker suddenly malfunctioned and went silent.

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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 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.

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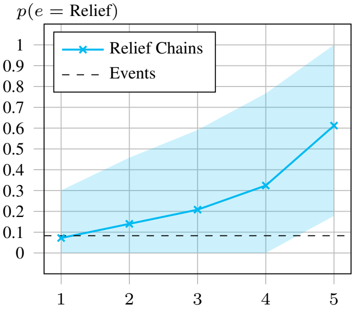

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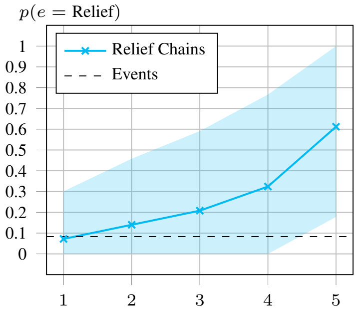


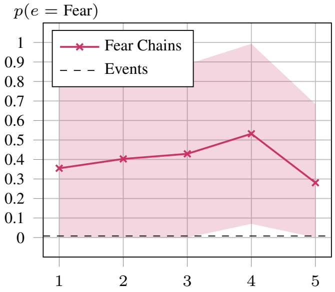

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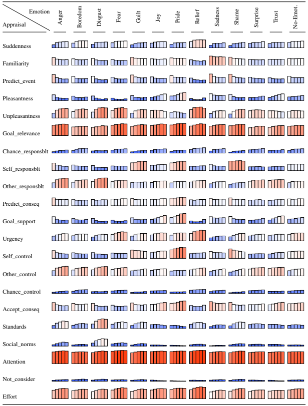


J. Schäfer, J. Wagner, and R. Klinger (2026). "Appraisal Trajectories in Narratives Reveal Distinct Patterns of Emotion Evocation". In: WASSA

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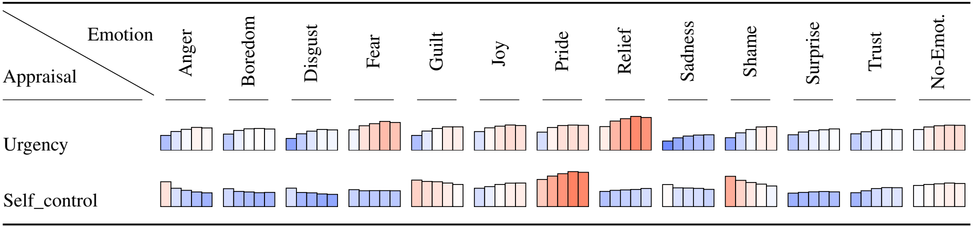


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# Outline

# Introduction

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

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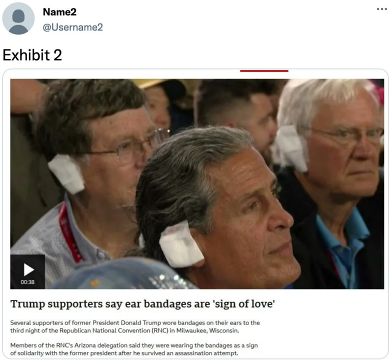
  - "Annotate them for the following emotion set."

# Data Example


Creation post labeled as surprise.




Recent post labeled as anger.

# Are the subcorpora comparable? – Post Length

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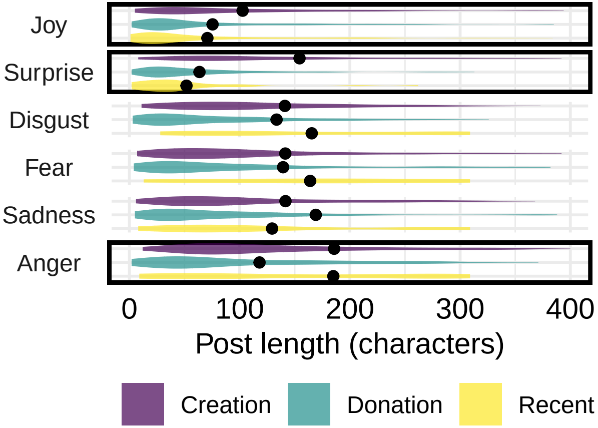

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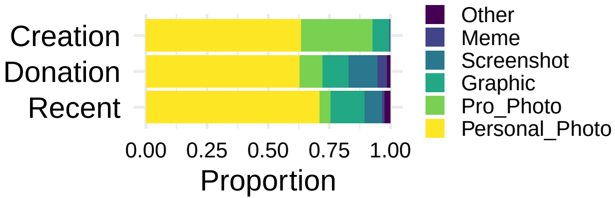

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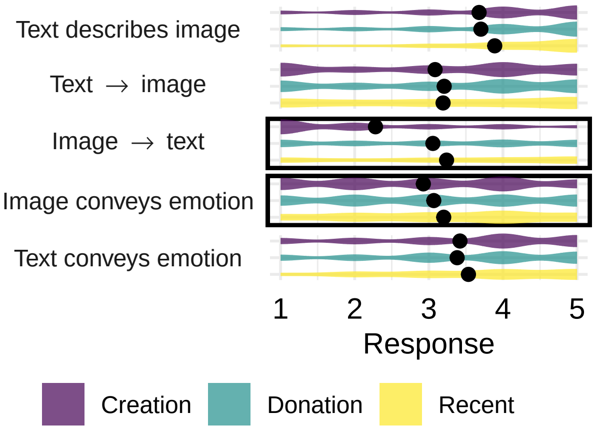

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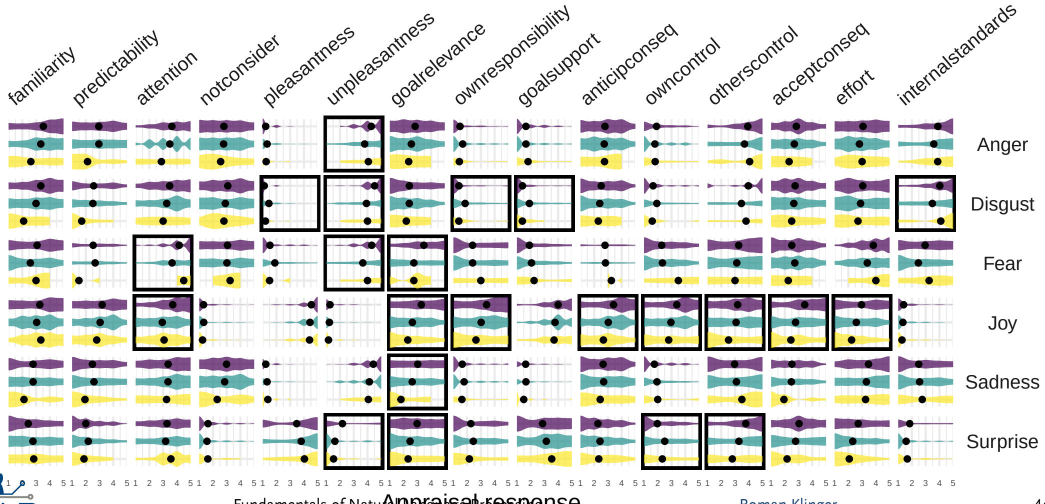

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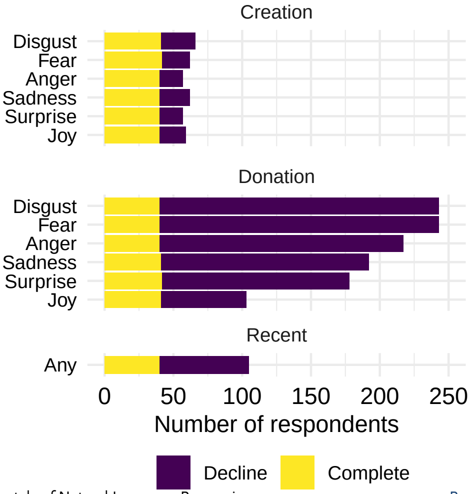

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We have now seen:

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- Now: brief look at a particular use case.

# Outline

# Emotion Detection in Arguments

L. Greschner and R. Klinger (2025). "Fearful Falcons and Angry Llamas: Emotion Category Annotations of Arguments by Humans and LLMs". In: NLP4DH

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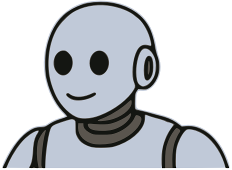

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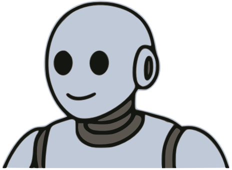

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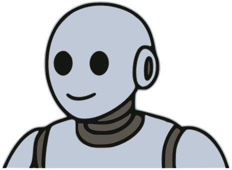

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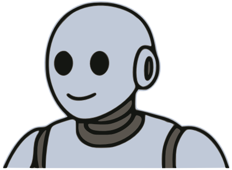

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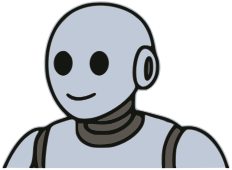

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# How can we conduct contextualized emotion detection (and convincingness assessment) in arguments?

L. Greschner, S. Weber, and R. Klinger (2025). Trust Me, I Can Convince You: The Contextualized Argument Appraisal Framework. under review for LREC 2026. arXiv: 2509.17844 [cs.CL]

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- We need to develop methods to integrate contextual information in computational models.

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| Trust | 0.570 |
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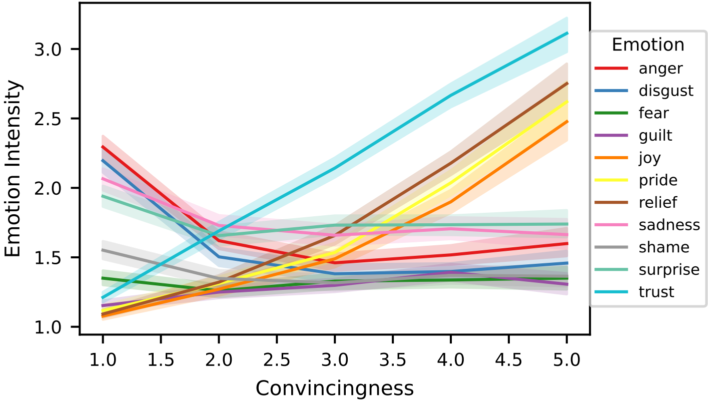

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- Surprising arguments and those which go against laws or social standards are less convincing (and cause anger and disgust).

# Outline

# For whom do models make predictions?

J. Schäfer, A. Combs, et al. (2025). “Which Demographics do LLMs Default to During Annotation?” In: ACL

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- If we don't tell the model for whom it should make a prediction, with whose annotations is it best aligned?

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- We need to understand biases and make models work well for everybody.


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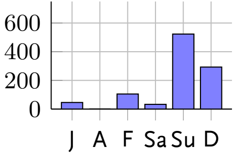


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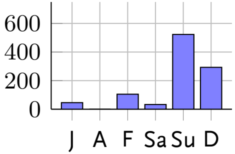


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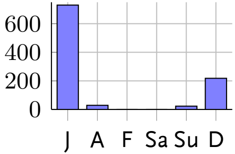


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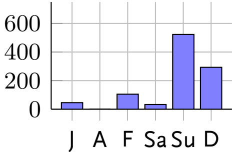


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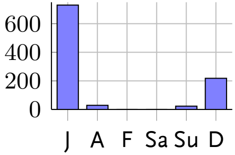


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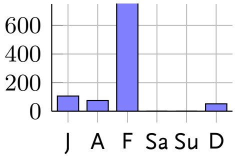


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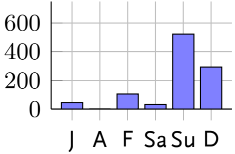


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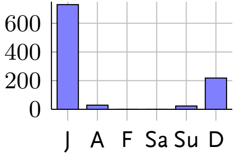


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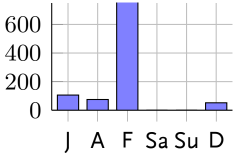


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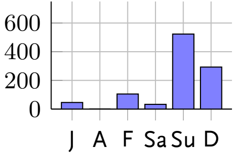


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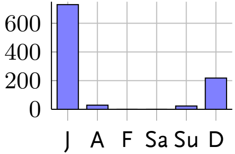


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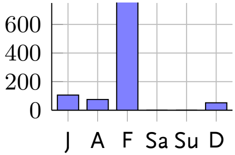


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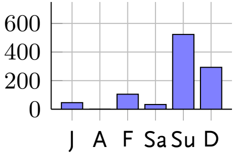


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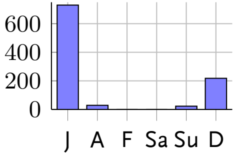


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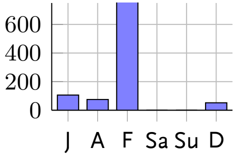


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- Do we want model's outputs to vary as human's output does?
- If yes, how to achieve that? If no, what should they do?

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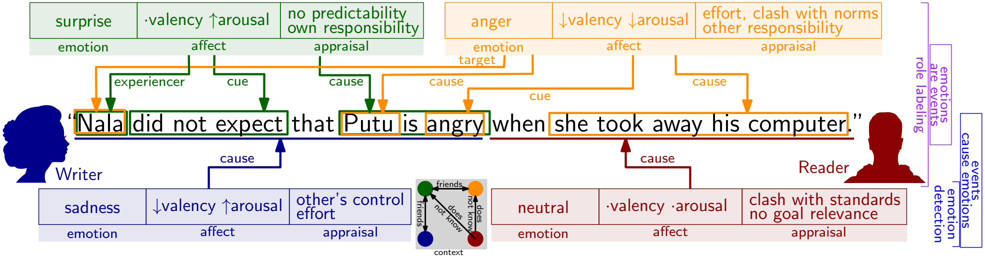
# Integration of Appraisal Analysis with Role Labeling




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

# Outline

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- Collecting data is challenging, and data donations are better than prompting humans for data creation
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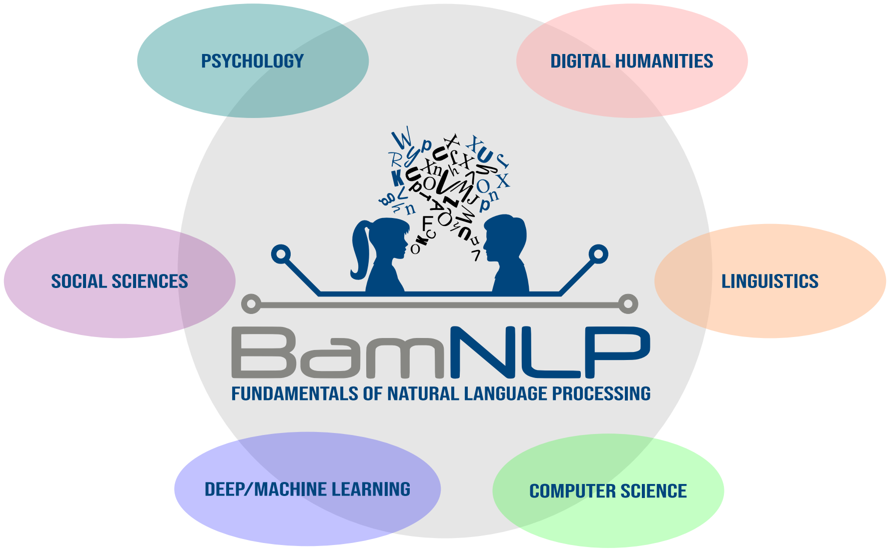
- We need to better understand how variance of predictions of models should be aligned with humans
- Many open research tasks in emotion analysis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SOCIAL SCIENCES
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FUNDAMENTALS OF NATURAL LANGUAGE PROCESSING
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COMPUTER SCIENCE

Thank you for
your attention.
Questions? Remarks?

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DFG Deutsche Forschungsgemeinschaft
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Thanks to:

BamNLP

- All research groups I was part of so far and all collaborators.
- All of you for your interest!
- Please reach out if you want to talk, chat, discuss, meet us, drink coffee, work with us, collaborate, ...

University of Bamberg

# Event-centric Emotion Analysis in Natural Language Processing

## Appraisal Variables as Emotion Models

AI Meets Human Data Colloquium, Augsburg, January 27, 2026

Roman Klinger
roman.klinger@uni-bamberg.de

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

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