Universität Stuttgart
Institut für
Maschinelle Sprachverarbeitung

Natural Language Processing Tasks and Methods

Challenges for Emotion Analysis and Generation

ZPID, Dec 13, 2023

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https://www.romanklinger.de/

https://www.romanklinger.de/talks/zpid2023.pdf

About Myself

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  Computer science with minor psychology

UNIVERSITÄT DORTMUND
FACHBEREICH INFORMATIK

Roman Klinger

Komposition von Musik mit Methoden der Computational Intelligence

– Diplomarbeit –

1. Juni 2006

Lehrstuhl 11
Computational Intelligence
Fachbereich Informatik
Universität Dortmund

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

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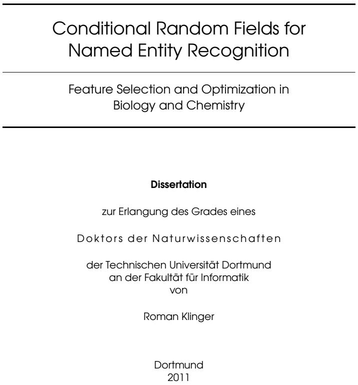
Conditional Random Fields for
Named Entity Recognition

Feature Selection and Optimization in
Biology and Chemistry

Dissertation

zur Erlangung des Grades eines

Doktors der Naturwissenschaften

der Technischen Universität Dortmund
an der Fakultät für Informatik
von

Roman Klinger

Dortmund
2011

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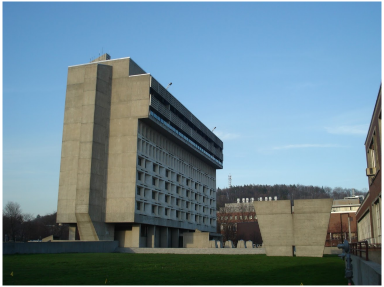

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  Natural Language Understanding and Generation
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Natural Language Processing Tasks

What does natural language processing research look like?

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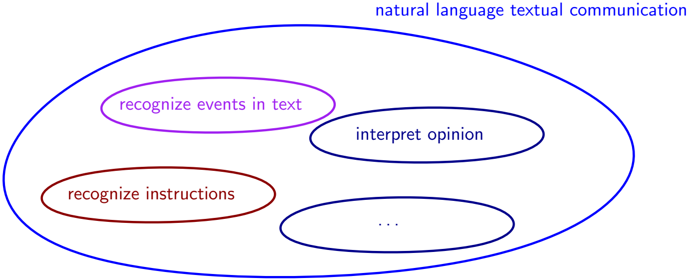

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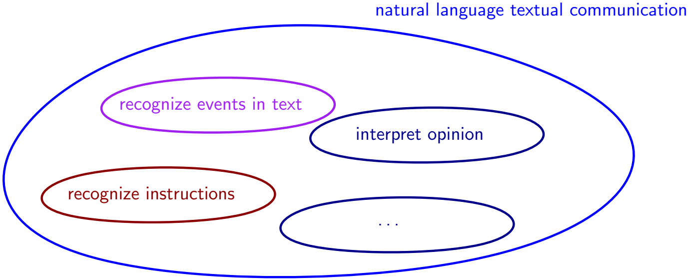

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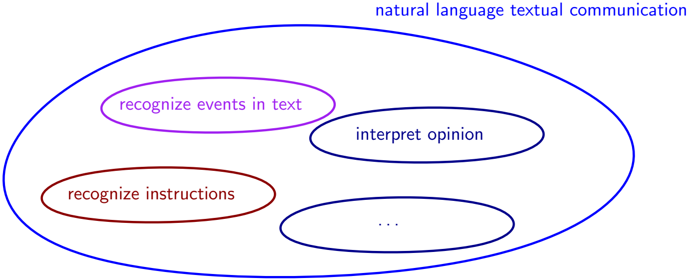

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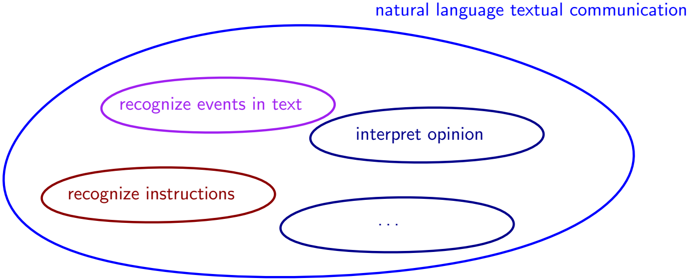

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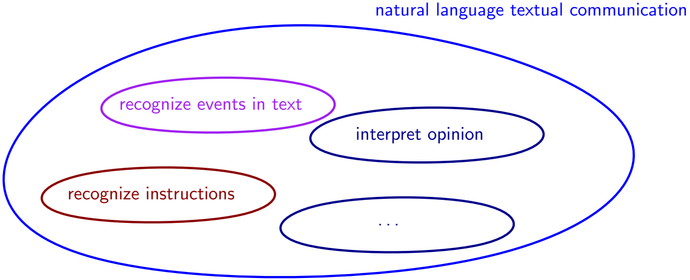

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- Instead: predefined (narrow) tasks.
- Some tasks are established and well defined.
- Others are still in the process of formalization.
- We will now look at a couple of examples.

Example Task: [redacted]

Example Input (one of many) to Instruct an Automatic Machine Learning Model

Input: Both Kai Sassenberg and André Bittermann work at the ZPID.
Output: Kai Sassenberg; André Bittermann

Example Task: [redacted]

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- I specified the task with an example
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- I specified the task with an example
(standard machine learning setup: supervised learning).
- An alternative task specification would be an instruction:
"Annotate all person names."

Example Task: [redacted]

Example

Input: Roman Klinger arbeitet an der Uni Stuttgart.
Output: Roman Klinger works at the University of Stuttgart.

Example Task: Machine Translation de-en

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Input: Roman Klinger arbeitet an der Uni Stuttgart.
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Example Task: [redacted]

Example

Input: "When he walked into the restaurant", Joy
Output: "he was delighted to see that his husband was already there."

Example Task: Conditional Text Generation

Example

Input: “When he walked into the restaurant”, Joy
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Example Task: [redacted]

Example

- Input: “A soccer game with multiple males playing.”;
  “Some men are playing a sport.”
- Output: yes

- Input: “A man inspects the uniform of the person.”;
  “The man is sleeping.”
- Output: no

Example Task: Natural Language Inference

Example

- Input: “A soccer game with multiple males playing.”;
  “Some men are playing a sport.”
- Output: entailment

- Input: “A man inspects the uniform of the person.”;
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- Output: contradiction

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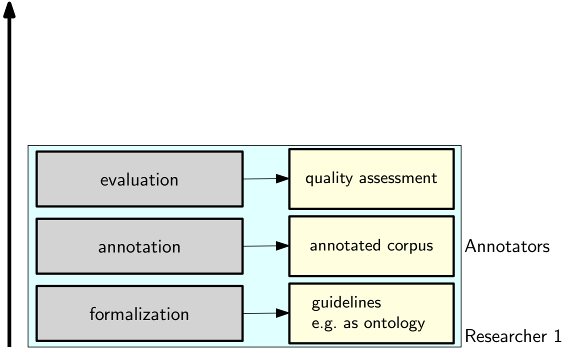

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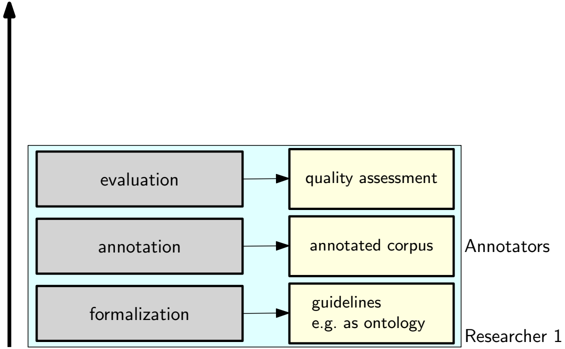

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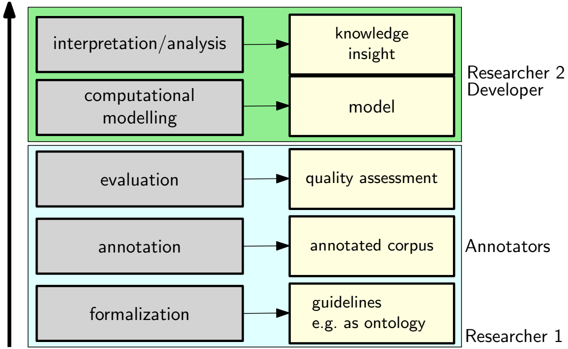

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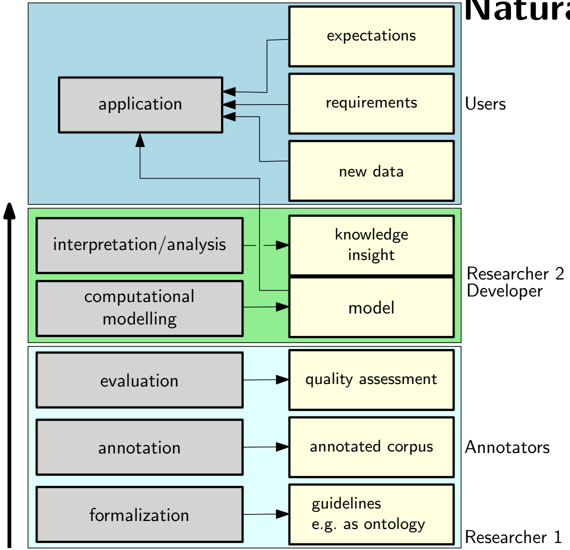

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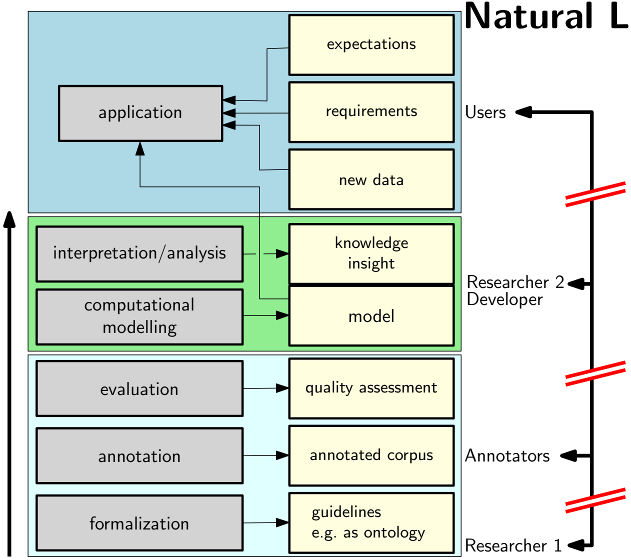

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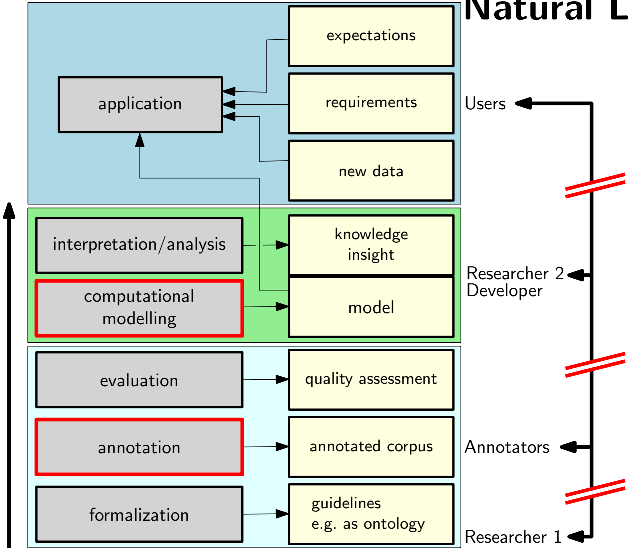

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- Show isolated instance or request comparative annotations?
- Carefully train annotation experts or do crowdsourcing?

Modeling

Find a function that takes:

- text (and additional information) as input
- and automatically predicts output/annotation.

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- Prompting, Prompt Learning; Learning from Instructions
  - + Potentially good generalization, potentially only needs few example instances
  - – Needs a large (instruction-tuned) language model

Prompting with Instruction-tuned

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- Obs.: We need many tasks & huge models to achieve generalization across tasks.

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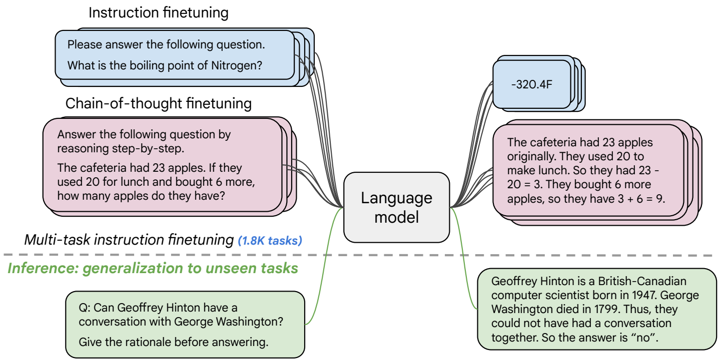
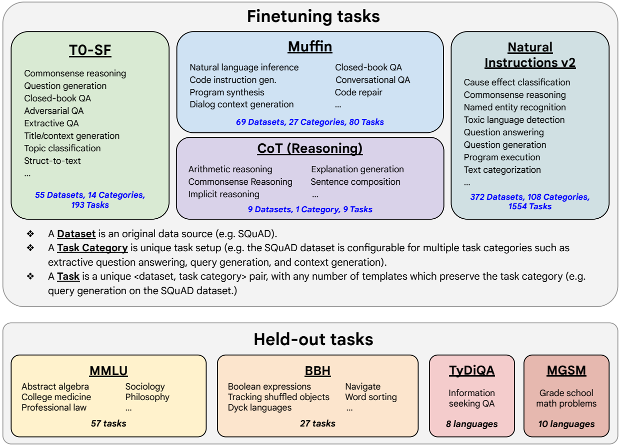
- Given a human input and a model’s output, let a human judge it’s quality.
- Observation: We need many humans to do that.

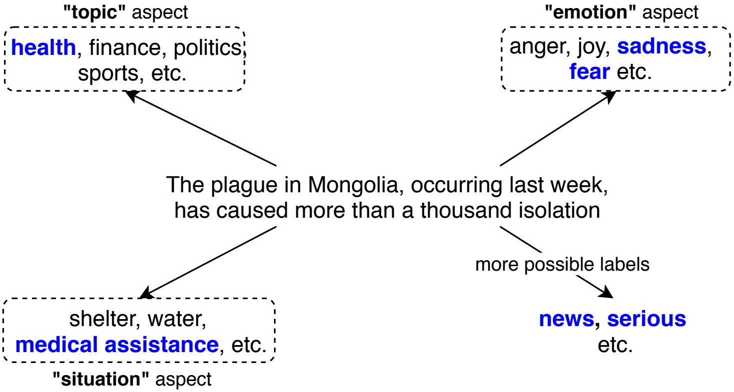
Example: Flan-T5 (1)



Example: Flan-T5 (2)



Text Classification as Natural Language Inference



W. Yin et al. (2019). "Benchmarking Zero-shot Text Classification: Datasets, Evaluation and Entailment Approach". In: *EMNLP-IJCNLP*

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All three model types can be used for zero-shot text analysis

- Models that predict the next word or a missing word
- Models tuned for natural language inference
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  - "He is happy" – "This sentence is positive."
- Instruction-tuned models
  - "What is the sentiment of the following sentence 'He is happy'? Answer with a digit only where 1 is positive and 2 is negative."

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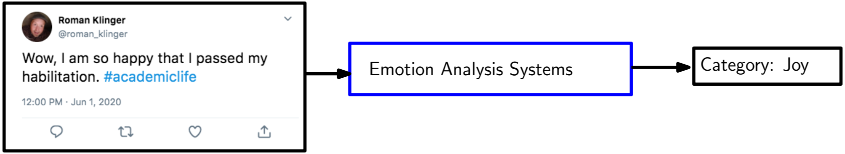
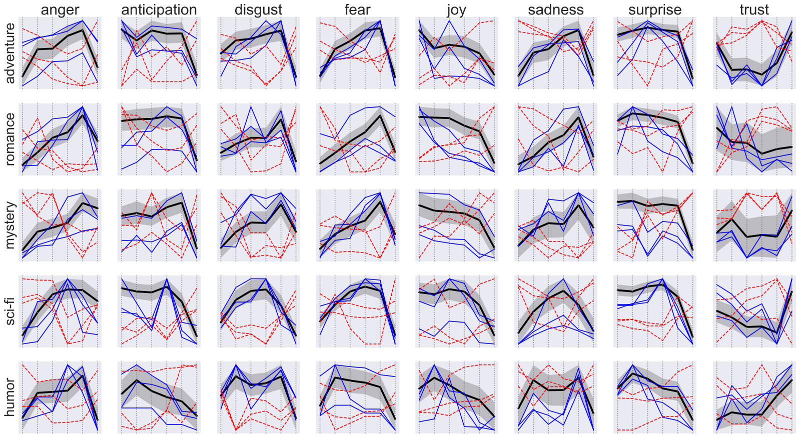


Literary Studies



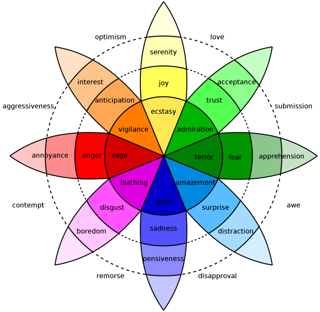
Kim et al., 2017.
Investigating the Relationship between Literary Genres and Emotional Plot Development. LaTeCH@ACL

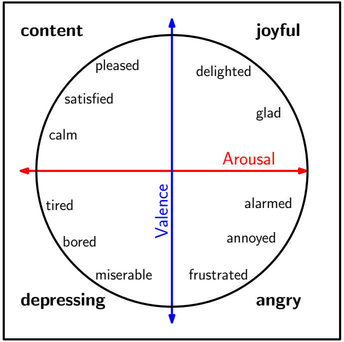
Dominant Emotions Expressed in News Articles

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

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

How to define a categorical system of emotions?



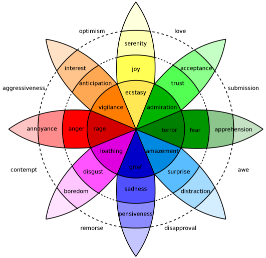


- Emotion models in psychology explain how emotions are developed.
- Text analysis models learn to associate textual realizations to emotion concepts. They do not (explicitly?) use knowledge from such theories.

Outline

1. NLP Research Methods
2. Emotion Analysis
3. Zero-Shot Learning for Emotion Classification
4. Appraisal-based Emotion Analysis
5. Prompt Search for Text Generation
6. Take Home

ZSL for Emotion Classification



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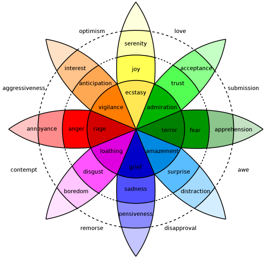

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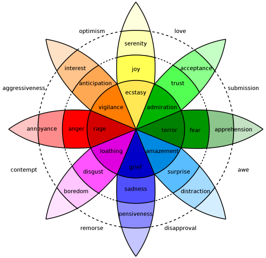

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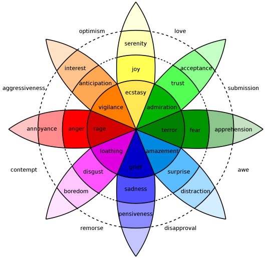

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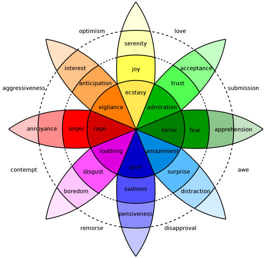

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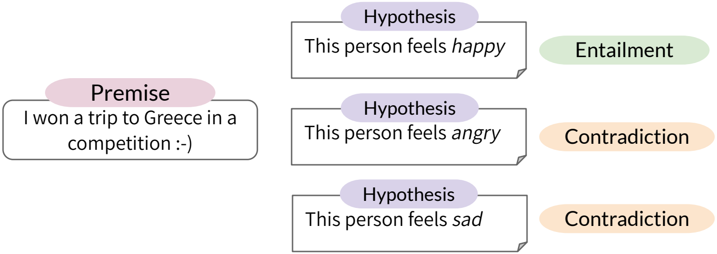
- Do we need to create an emotion corpus with domain specific labels for every new application domain where the label set changes?

Emotion ZSL as Natural Language Inference



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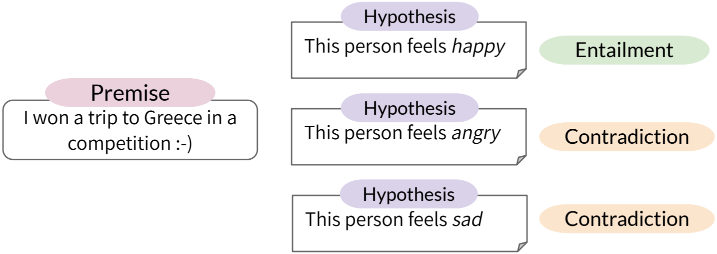

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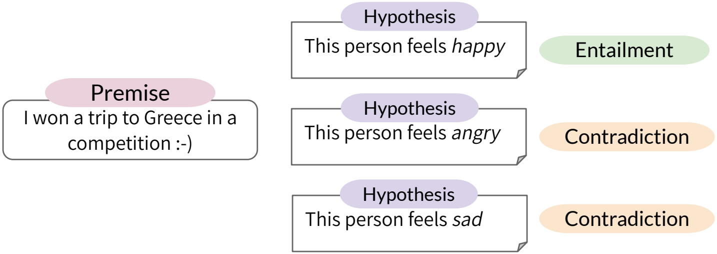

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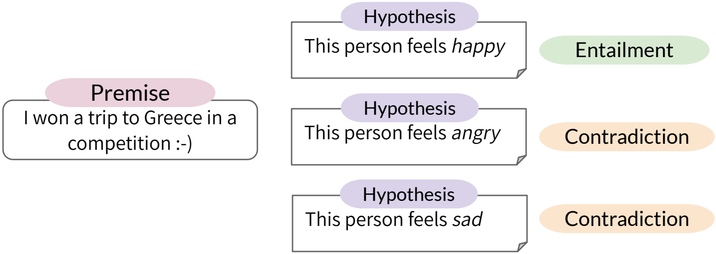

- Does it matter which NLI model we use as a backbone?
- How to represent the emotion?
- Does the hypothesis formulation need to be specific for a particular domain?

F. M. Plaza-del Arco et al. (2022). "Natural Language Inference Prompts for Zero-shot Emotion Classification in Text across Corpora". In: *COLING*

Emotion Hypotheses

Emo-Name

Expr-Emo

Feels-Emo

WN-Def

Emo-S

Expr.-S

Feels.-S

Emotion Hypotheses

Emo-Name

angry

Expr-Emo

Feels-Emo

WN-Def

Emo-S

Expr.-S

Feels.-S

Emotion Hypotheses

Emo-Name	angry	**Emo-S**
Expr-Emo	This text expresses anger	**Expr.-S**
Feels-Emo		**Feels.-S**
WN-Def		

Emotion Hypotheses

Emo-Name
angry

Expr-Emo
This text expresses anger

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WN-Def

Emo-S

Expr.-S

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Same prefix + anger, annoyance, rage, outrage, fury, irritation

Emotion Hypotheses

Emo-Name	angry
Expr-Emo	This text expresses anger
Feels-Emo	This person feels anger
WN-Def	This person expresses a strong emotion; a feeling that is oriented toward some real or supposed grievance

Emo-S

Expr.-S

Feels.-S

Same prefix + anger, annoyance, rage, outrage, fury, irritation

Pretrained NLI Models

Data Set for Pretraining: MultiNLI Corpus, 433k sentence pairs:

Examples

Premise	**Label**	**Hypothesis**
Fiction		
The Old One always comforted Ca'daan, except today.	*neutral*	Ca'daan knew the Old One very well.
Letters		
Your gift is appreciated by each and every student who will benefit from your generosity.	*neutral*	Hundreds of students will benefit from your generosity.
Telephone Speech		
yes now you know if if everybody like in August when everybody's on vacation or something we can dress a little more casual or	*contradiction*	August is a black out month for vacations in the company.
9/11 Report		
At the other end of Pennsylvania Avenue, people began to line up for a White House tour.	*entailment*	People formed a line at the end of Pennsylvania Avenue.

- https://cims.nyu.edu/~sbowman/multinli/
- Pretrained models from Huggingface, we use RoBERTa, BART, and DeBERTa

Data Sets

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- TEC (Mohammad 2012):
  Twitter corpus, automatically labeled with emotion hashtags
  Be the greatest dancer of your life! practice daily positive habits. [JOY]

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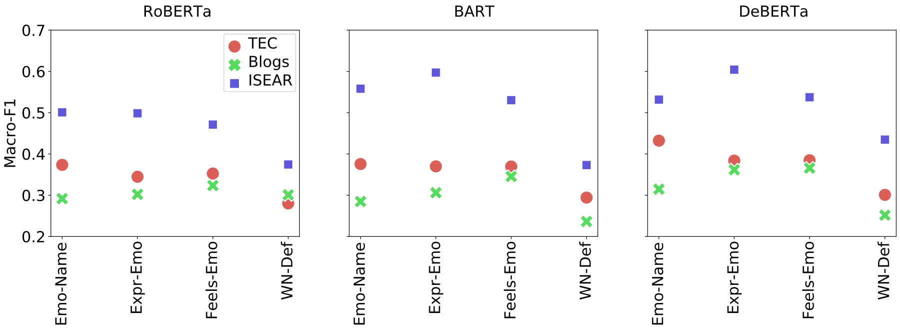
Emotion labels: anger, fear, joy, sadness, disgust, surprise, guilt, shame

The role of the NLI model



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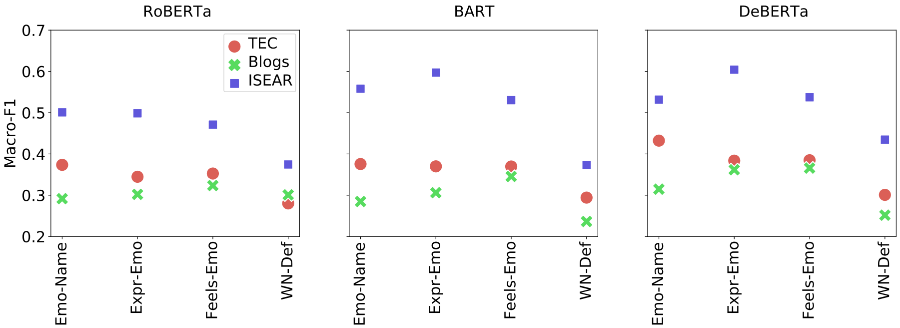

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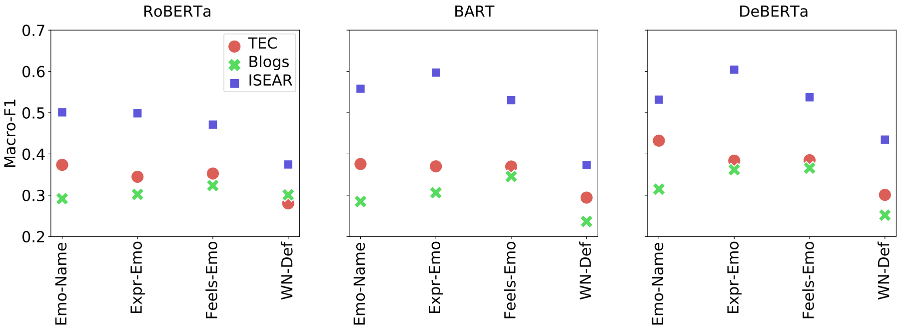

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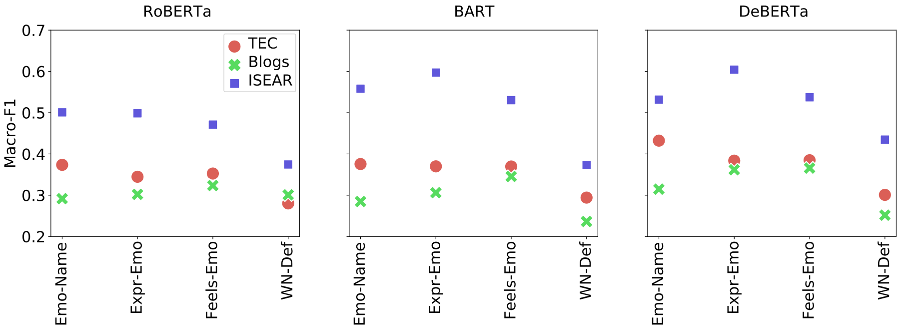

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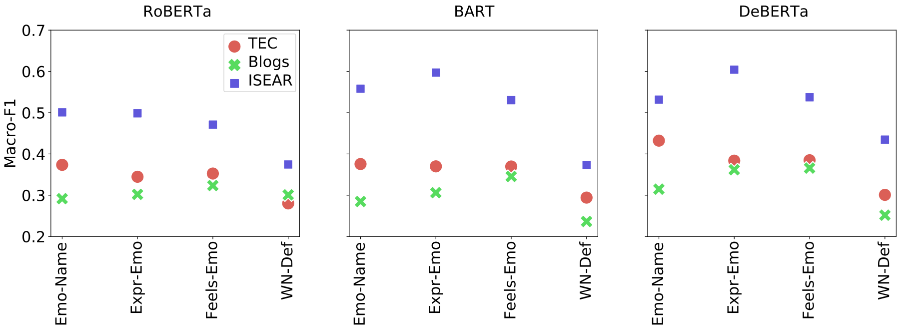

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  - Performance differences between data sets are (mostly) independent of model
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  - WN-Def always lowest performance

The role of the NLI model

- If one NLI model performs ZSL well on some domains, it also does so on others.

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- That's great! New, better models probably improve the results across domains.

The role of the prompt design

Is the emotion representation in the prompt specific to a domain/dataset?

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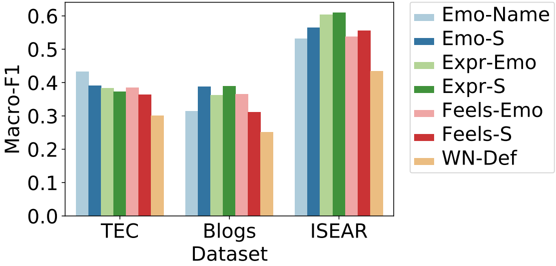

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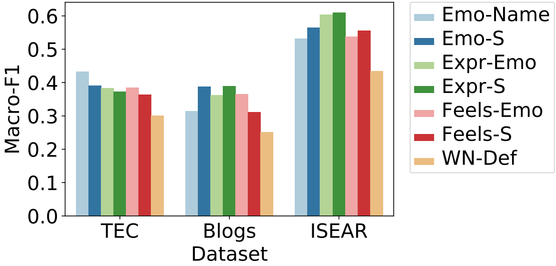

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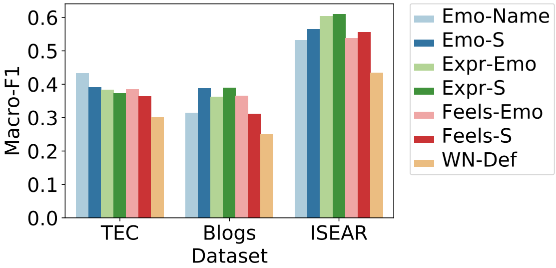

- TEC: single emotion names work better than with synonyms
- BLOGS: synonyms harm the performance for Feels-Emo/S prompts
- Generally: synonyms help, except for some cases, in which annotaton procedure might be the reason

The role of the prompt design (3)

There is not a single prompt which works well across all domains.

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But: Putting multiple prompts together in a model ensemble works nearly en par with individual single prompts.

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- There is not one individual prompt which works best for each domain

Where are we?

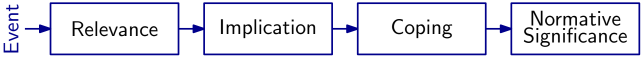
- We wanted to achieve a domain-independent and label-set independent model.
- We did pretty much achieve this, but the performance is lower than traditional machine learning methods.

Outline

Appraisal Theories

- Appraisal theories explain the relation between emotions based on other dimensions.
- If we can build appraisal predictors, this might help to have more robust emotion prediction models.

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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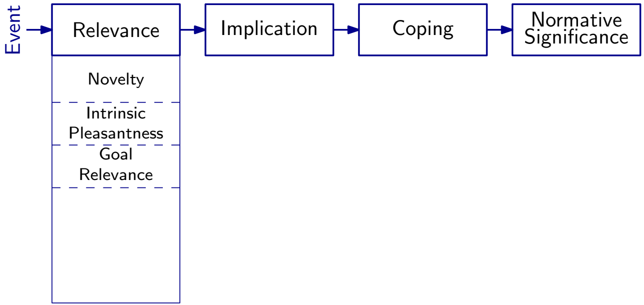

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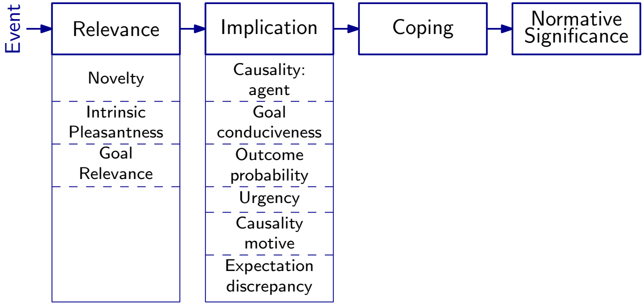

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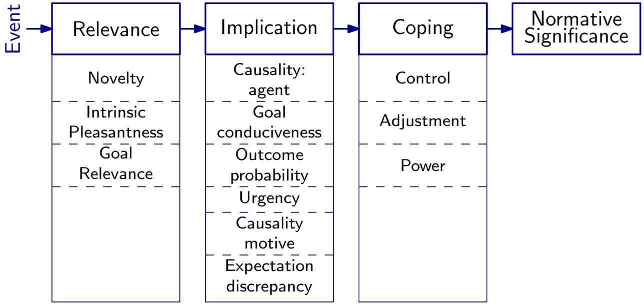

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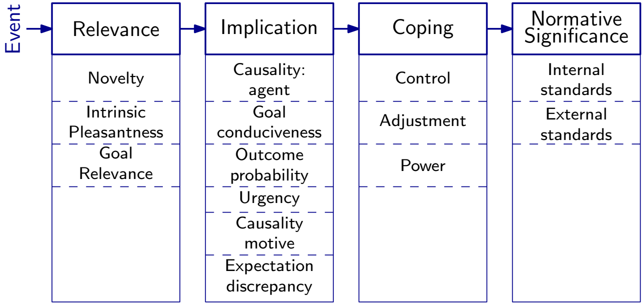

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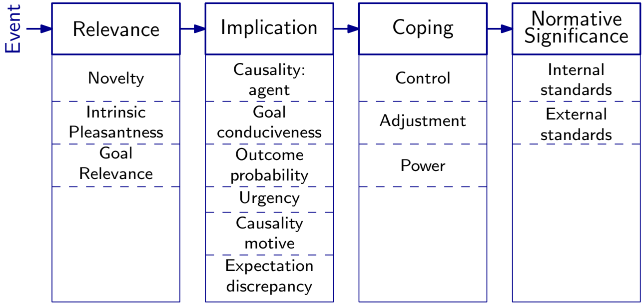

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Perhaps appraisals are an alternative, more general approach to emotion analysis?

Research Questions

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Research Questions

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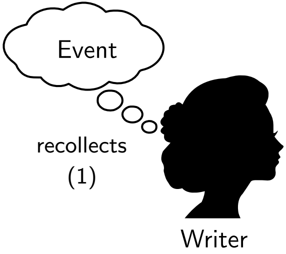
Approach



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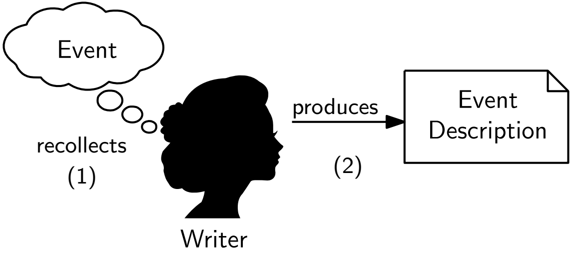

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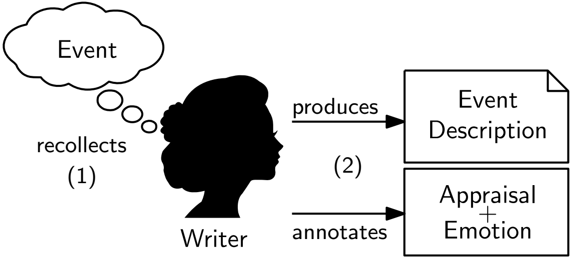
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Writer
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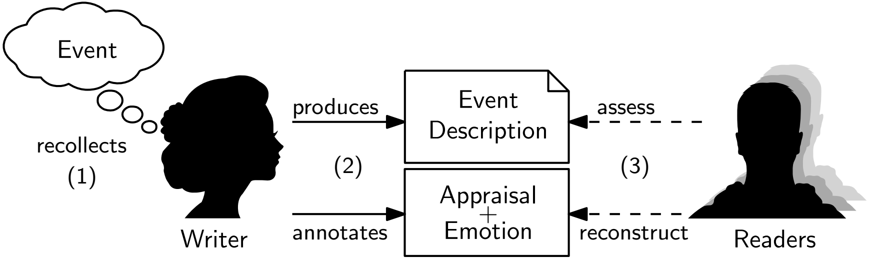
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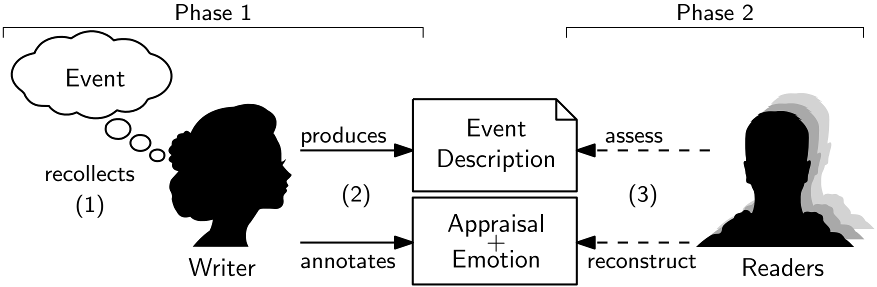

Phase 1
Phase 2
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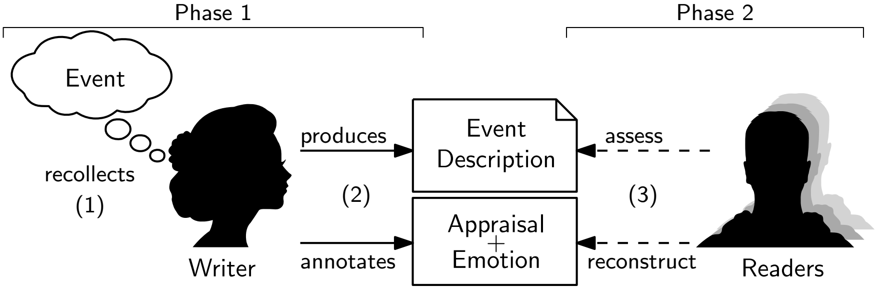

- Production: 550 event descriptions for anger, boredom, disgust, fear, guilt/shame, joy, pride, relief, sadness, surprise, trust, no emotion

Examples

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pride I baked a delicious strawberry cobbler.

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

Questions and Answers

Setup:

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

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- Does it matter if annotators share demographic properties?
  - Females agree more with each other, but men less.
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- Filter instances for attribute, compare with F_1/RMSE
- Significance test with bootstrap resampling for .95 confidence interval

Questions and Answers

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  - Extraverted, conscientious, agreeable annotators perform better.

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  shame, relief, 1.8 I tasked with sorting out some files from the office the previous day and I slept off when I got home

Modeling Results

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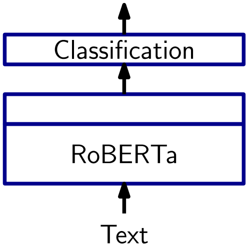
- Classification with RoBERTa-based models



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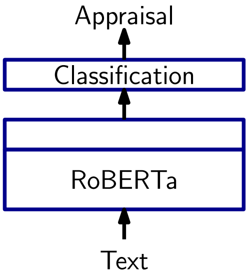

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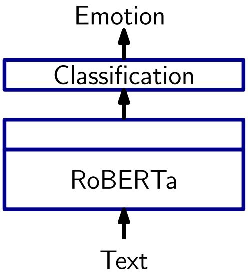

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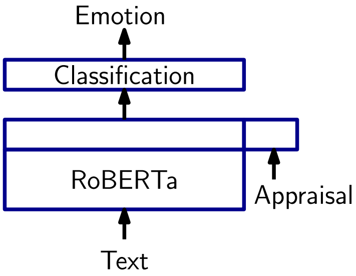
  (+10 for guilt, +6 for sadness)



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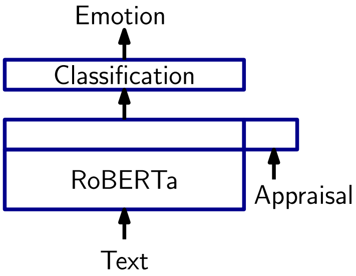
$\Rightarrow$ Appraisals help to build better models.



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

Outline

Conditional Text Generation via Prompt Search

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Generate text that expresses a predefined emotion.

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Module of dialogue systems, intelligent agents, or (story-)writing assistants.

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Guide the decoding of the text generation with emotion specific information.

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Novel Method

Automatic prompt optimization of instruction-tuned models.

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- Write a long text string to expresses joy
  - i love you so much

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- NLP Research is driven by task definitions and appropriate modeling
- Natural language inference can be applied for emotion classification – without knowing the emotion categories in advance
- Annotation and language model fine-tuning: Appraisal theories as a novel approach to emotion analysis in text – they support emotion classification and also do not require to fully specify the emotion set
- Automatic prompt optimization: Emotion-conditioned text generation – very challenging to automatically find well-performing prompts.

Thank you for
your attention.
Questions? Remarks?

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- Collaborators
  - Kai Sassenberg

Universität Stuttgart
Institut für
Maschinelle Sprachverarbeitung

Natural Language Processing Tasks and Methods

Challenges for Emotion Analysis and Generation

ZPID, Dec 13, 2023

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https://www.romanklinger.de/

https://www.romanklinger.de/talks/zpid2023.pdf

Appraisal Variables

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

Variable Assessement

Appraisal Variables

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

- All variables are similarly assessed by writers and readers

Additional Variables

- Age, Gender
- Ethnicity, Education
- Event familiarity
  for readers
- Personality traits (Gosling 2003)
  - openness
  - conscientiousness
  - extraversion
  - agreeablenes
  - emotional stability

Reliability Results

			Agreement					
			Emotion				Appraisal	
			F_1		Acc.		RMSE	
Condition	Val.	#Pairs	G–V	V–V	G–V	V–V	G–V	V–V
All Data		6600 12000	.49	.50	*.49	*.52	*1.57	*1.48
Gender match	M–M	631 1113	.50	*.45	.51	*.49	1.55	1.50
	F–F	2405 1377	.49	*.52	.51	*.55	1.57	*.1.50
	≠	2962 3920	.49	*.48	.50	*.52	1.57	*.1.48
Age diff.	> 7	3089 7991	.49	*.48	.51	*.51	*1.58	1.48
	≤ 7	2076 3939	.49	*.51	.50	*.54	*1.56	1.48
Validators' Event Fam.	> 3	1386 540	.49	.44	.51	.47	*1.60	*1.42
	≤ 3	2099 676	.48	.45	.49	.48	*1.58	*1.47
Validators' Openness	+	2685 1472	.49	.49	.50	.52	1.57	1.47
	−	3000 1568	.49	.48	.50	.51	1.57	1.48
Validators' Conscien.	+	3151 1638	*.48	.51	*.49	.53	*1.57	*1.49
	−	2589 1426	*.50	.51	*.51	.54	*1.56	*1.46
Validators' Extraversion	+	2878 1685	.49	*.48	.50	*.51	*1.58	*1.51
	−	2812 1535	.50	*.52	.51	*.55	*1.56	*1.46
Validators' Agreeabl.	+	2675 1451	.49	*.51	.51	*.54	*1.58	1.47
	−	2930 1553	.48	*.45	.49	*.49	*1.56	1.47
Validators' Emot. Stab.	+	2838 3009	*.48	*.48	*.49	*.51	*1.57	*1.50
	−	2792 2897	*.50	*.51	*.51	*.54	*1.56	*1.46

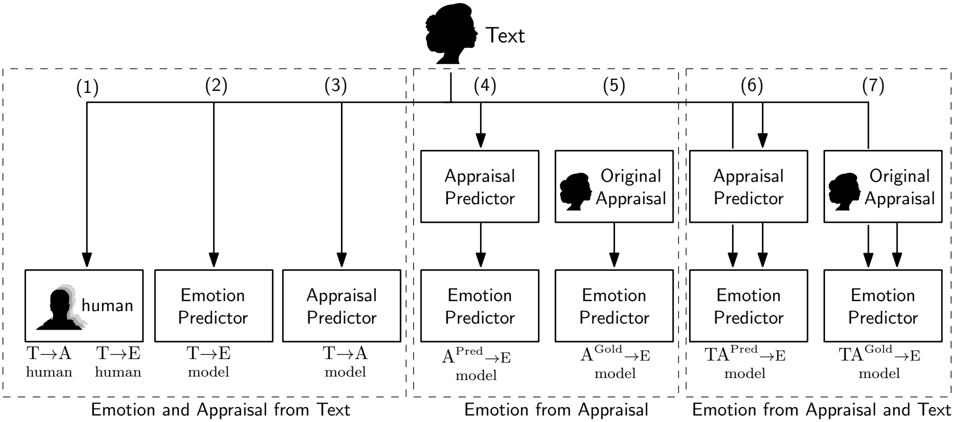
- Validators agree more with each other than with the generator
- Females agree more with each other on emotions
- Validators agree more if their age difference is small
- Event familiarity hurts agreement for appraisal
- We expected Open annotators to perform better.
- Emotional stability "hurts" emotion annotation.
- Extraversion, Conscient., Agreeableness help.
- Most differences are quite small (though significant)

Appraisals add additional information to emotion analysis

That I put together a funeral service for my Aunt

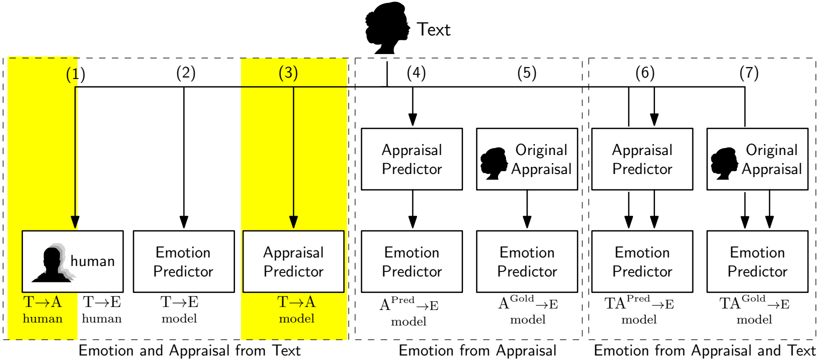
Dimension	Writer	Readers	Δ
Emotion	Pride	Sadness	
Suddenness	4	3.6	0.4
Familiarity	1	2.0	−1.0
Predictability	1	1.8	−0.8
Pleasantness	4	1.0	3.0
Unpleasantness	2	4.8	−2.8
Goal-Relevance	4	2.6	1.4
Chance-Resp.	4	4.4	−0.4
Self-Resp.	1	1.2	−0.2
Other-Resp.	1	1.4	−0.4
Conseq.-Predict.	2	1.8	0.2
Goal Support	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

Setup



- All models are RoBERTa-based, additional information is added to the penultimate layer before the output

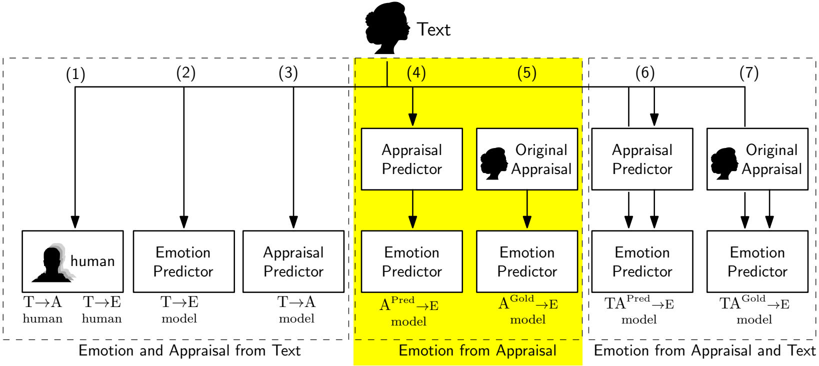
How well can we predict appraisals?



⇒ 75 macro F_1 for model

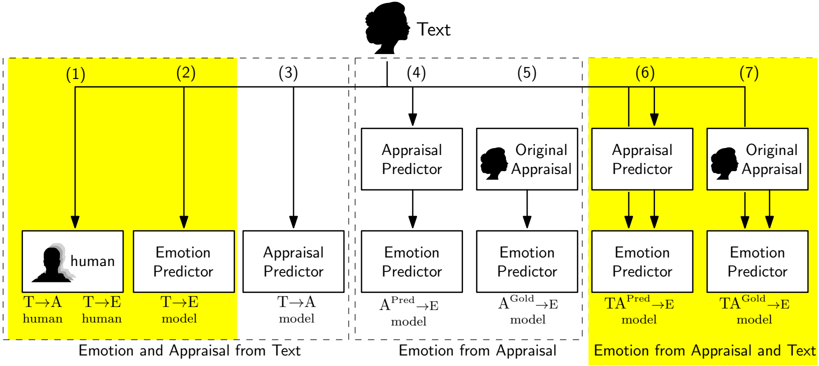
- Model outperforms humans by 13pp F_1
- Slightly unfair assessement:
  Model gets to see generator's labels during training, humans do not

Are appraisals sufficient to infer the emotion?



- Skipping this today
- Short answer: comparably (low) to psychological studies

Do appraisals help emotion prediction?



Results in F_1

Emotion	(a) T→E human	(b) T→E model	$\Delta^{(b)}_{(a)}$	(c) TA^{Gold}→E model	$\Delta^{(c)}_{(b)}$	(d) TA^{Pred}→E model	$\Delta^{(d)}_{(c)}$	$\Delta^{(d)}_{(b)}$
Anger	57	53	−4	57	+4	57	0	+4
Boredom	73	84	+11	83	−1	83	0	−1
Disgust	65	66	+1	66	0	66	0	0
Fear	73	65	−8	67	+2	67	0	+2
Guilt	53	48	−5	58	+10	56	−2	+8
Joy	49	45	−4	48	+3	47	−1	+2
No-emotion	33	55	+22	56	+1	56	0	+1
Pride	59	54	−5	55	+1	55	0	+1
Relief	64	63	−1	62	−1	62	0	−1
Sadness	63	59	−4	65	+6	63	−2	+4
Shame	48	51	+3	50	−1	49	−1	−2
Surprise	42	53	+11	49	−4	50	+1	−3
Trust	52	74	+22	73	−1	72	−1	−2
Macro avg.	56	59	+3	61	+2	60	−1	+1

- On average, the model is as good as humans, but differs across emotions
- Adding gold appraisal helps some emotions considerably
- Predicted appraisals are similarly valuable as gold appraisals