Natural language processing for subjectivity analysis in personal narratives

Gustave Cortal

Thesis director: Alain Finkel
Co-advisors: Patrick PAROUBEK and Lina YE

Introduction

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We first address the *content* by classifying elements of personal narratives (*e.g.*, characters and emotions). Then, we study the *form* through the concept of style

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My research models are publicly hosted on Hugging Face and were trained using the Jean Zay supercomputer

Definition of objectives using cognitive science

G. Cortal and C. Bonard. Improving Language Models for Emotion Analysis: Insights from Cognitive Science. *CMCL, ACL 2024*.

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- Some linguistic and cognitive science theories are not considered
- There is no benchmark that evaluates the richness of the emotional phenomenon

Linguistic and cognitive science theories

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→ Different emotion expression modes are more or less difficult to interpret

What are the psychological mechanisms used to infer what is communicated?

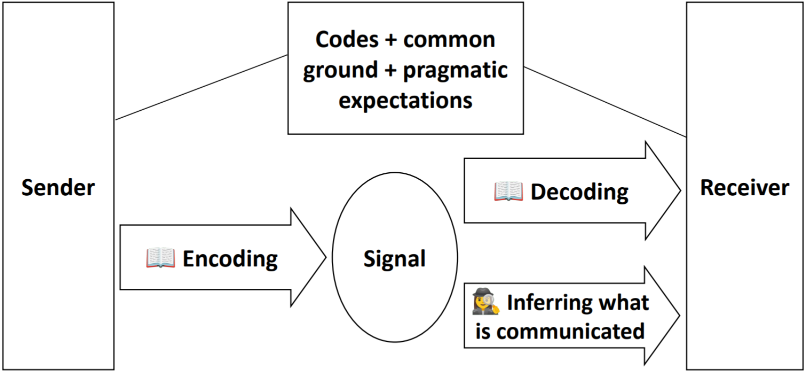

Figure: Detective analysis in cognitive pragmatics.

How to integrate psychological theories of emotion?

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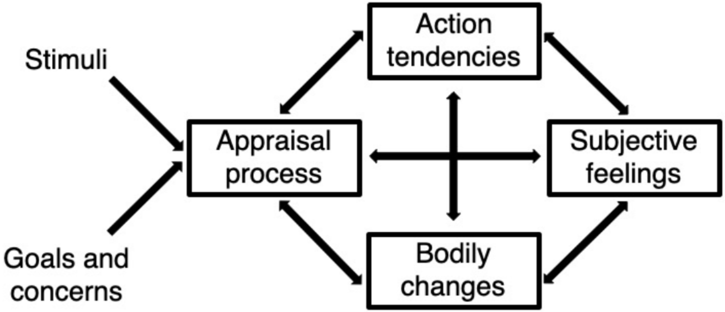

Figure: Integrated framework for emotion theories. Emotional episodes are synchronized changes in four components (Scherer, 2022).

Construction of an emotion dataset

Available at hf.co/datasets/gustavecortal/FrenchEmotionalNarratives

G. Cortal, A. Finkel, P. Paroubek, L. Ye. Emotion Recognition based on Psychological Components in Guided Narratives for Emotion Regulation. *SIGHUM, EACL 2023*.

French emotional narratives based on components

Goal: A more comprehensive understanding of emotional events

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Component	**Answer**
`Behavior`	I'm giving a lecture on a Friday morning at 8:30. A student goes out and comes back a few moments later with a coffee in his hand.
`Feeling`	My heart is beating fast, and I freeze, waiting to know how to act.
`Thinking`	I think this student is disrupting my class.
`Territory`	The student attacks my ability to be respected in class.

Chosen emotion: `anger` (possible choices: `anger`, `fear`, `joy`, `sadness`)

More than 1,000 narratives were collected during emotion regulation sessions

Training language models for emotion analysis

G. Cortal, A. Finkel, P. Paroubek, L. Ye. Emotion Recognition based on Psychological Components in Guided Narratives for Emotion Regulation. *SIGHUM, EACL 2023*

G. Cortal. Sequence-to-Sequence Language Models for Character and Emotion Detection in Dream Narratives. *LREC-COLING 2024*

Discrete emotion detection based on components

Component	Logistic Regression Precision	Logistic Regression Recall	Logistic Regression F_1	CamemBERT Precision	CamemBERT Recall	CamemBERT F_1
All	71.2 (2.6)	69.1 (2.2)	67.8 (2.3)	**85.1**	**84.8**	**84.7**
Without `behavior`	77.4 (2.3)	75.8 (2.4)	74.5 (2.6)	80.3	79.8	79.7
Without `feeling`	64.3 (1.9)	61.5 (1.2)	61.3 (2.2)	81.6	79.8	79.9
Without `thinking`	70.9 (1.8)	69.1 (2.0)	68.3 (2.2)	79.6	78.5	78.7
Without `territory`	64.3 (4.1)	64.5 (2.4)	62.3 (2.8)	78.7	78.5	78.6
Only `behavior`	52.1 (3.5)	54.6 (2.9)	51.7 (2.9)	68.4	67.1	66.6
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→ Some components benefit from contextual understanding and world knowledge (*e.g.*, `behavior` and `thinking`)

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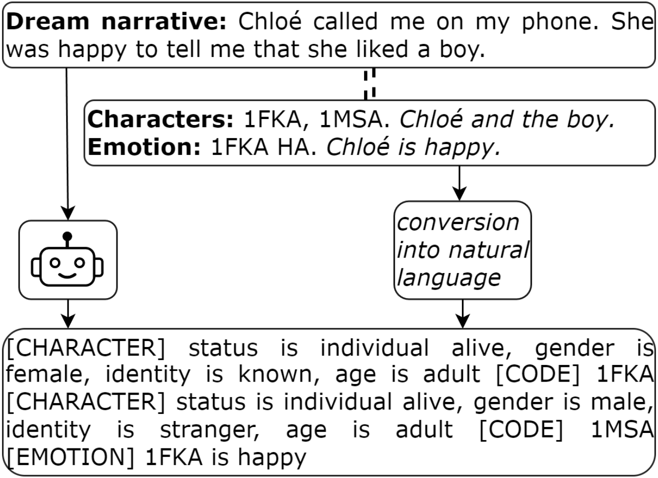
How to automate the annotation process?

Character and emotion detection in dream narratives



Results

`Baseline` is LaMini-Flan-T5 finetuned on 1823 dream narratives

Model	Status	Gender	Identity	Age	Character	Emotion
Baseline	82.87	78.02	76.17	86.21	64.74	75.13
$\texttt{No}_{\texttt{semantics}}$	71.37	56.54*	61.0	90.51	41.79*	75.79
$\texttt{No}_{\texttt{names}}$	80.66*	74.32**	74.2	83.95*	60.93**	73.04*
$\texttt{Size}_{\texttt{small}}$	78.35**	72.13**	70.25**	81.66**	56.79**	70.15**
$\texttt{Size}_{\texttt{large}}$	84.51*	80.3**	78.63**	87.29	67.63**	74.71
$\texttt{First}_{\texttt{group}}$	82.33	77.71	74.86	85.61	63.71	71.94
$\texttt{First}_{\texttt{individual}}$	80.59**	76.14	74.22*	83.87**	62.67	67.32
$\texttt{First}_{\texttt{emotion}}$	83.92	78.74	77.06	87.63	64.97	72.03
$\texttt{Conversion}_{\texttt{comma}}$	84.02**	79.84**	77.67**	87.08*	66.69**	73.68
$\texttt{Conversion}_{\texttt{marker}}$	82.39	78.45	76.53	86.09	65.44	74.36
Cross-validation	86.28	81.9	79.51	89.52	68.64	76.18

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→ Language models can effectively address character and emotion detection in dream narratives

Oneirogen, a language model for dream generation

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Oneirogen was used to produce The Android and The Machine, an English dataset composed of 10,000 real and 10,000 generated dreams

I'm in a building that seems to be a school or maybe a university. There is a lot of noise and activity, and everyone is very busy talking. It is very loud and unpleasant - too loud to talk to anyone easily. The walls are made out of some soft material that might be plastic foam.

I was at a shop. There were lots of people there and I lost Mom and Ezra. Later, we were in a car park. We went to get pizza's for dinner from the nearby pizza place but it was really late so they wouldn't serve us. [I think I was also walking around the shops earlier].

Formalization of style in personal narratives

G. Cortal and A. Finkel. Formalizing Style in Personal Narratives. *EMNLP 2025*.

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We narrow the general definition of style: *a distinctive manner of communicating subjective experience in narratives*

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Language achieves three functions: interpersonal (language builds social relationships), textual (information is organized to create coherent messages), and *ideational* (language represents experience)

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Language represents experience through *processes*, *participants* and *circumstances*

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Processes	**Examples**
`Action`: actions and events in the physical world.	[He]$_{\text{Actor}}$ **[takes]**$_{\text{Action}}$ [the valuable]$_{\text{Affected}}$ [Members of my cult]$_{\text{Actor}}$ **[have made]**$_{\text{Action}}$ [1500 euros]$_{\text{Result}}$ [I]$_{\text{Actor}}$ **[give]**$_{\text{Action}}$ [her]$_{\text{Recipient}}$ [a chance]$_{\text{Range}}$
`Mental`: internal experiences such as thoughts, perceptions, and feelings.	[We]$_{\text{Senser}}$ **[believe]**$_{\text{Mental}}$ [women are the leaders of change]$_{\text{Phenomenon}}$ [The moon]$_{\text{Senser}}$ **[sees]**$_{\text{Mental}}$ [the earth]$_{\text{Phenomenon}}$ [He]$_{\text{Senser}}$ **[disliked]**$_{\text{Mental}}$ [Gilbert's writing]$_{\text{Phenomenon}}$
`Verbal`: acts of communication.	[David]$_{\text{Sayer}}$ **[said]**$_{\text{Verbal}}$ ["the corrupt, criminals and money launderers"]$_{\text{Verbiage}}$
`State`: states of being, having, or existence.	There **[was]**$_{\text{Existential}}$ [a swimming pool]$_{\text{Existent}}$ [John]$_{\text{Carrier}}$ **[is]**$_{\text{State}}$ [an interesting teacher]$_{\text{Attribute}}$ [Hadrian's Wall]$_{\text{Possessor}}$ **[has]**$_{\text{State}}$ [something for everyone]$_{\text{Possessed}}$

Pipeline for our sequence-based framework

Clause	Process (symbol)	Participants
I wake in a dark room	`Action` (**a**)	`Actor`
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4. We perform sequence analysis to identify patterns such as frequent substrings and representative sequences

Conclusion

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Perspectives

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I co-supervised ongoing PhD thesis: Nicolas Richet (multimodal emotion recognition), Amine Haddou (cognitive distortions), and Raphael Faure (style analysis)

Post-training for psychology

Piaget (0.6, 1.7, 4, 8B), a model for psychological reasoning

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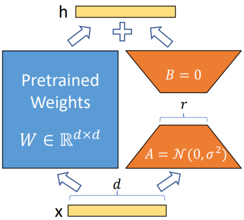

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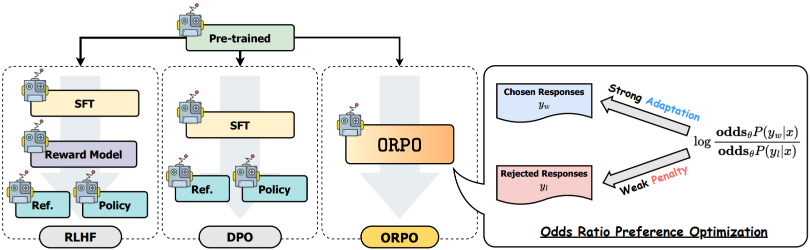
Beck (0.6, 1.7, 4, 8B), a model aligned with psychotherapeutic preferences

Beck is based on Piaget and was finetuned on psychotherapeutic preferences from PsychoCounsel-Preference using preference optimization (ORPO) and LoRA



Appendix

Results on the war veteran

Group	Category	% Vet	% Total	Δ
Identity	known*	24.9	51.6	-26.7
	prominent	1.9	2.5	-0.6
	occupational*	22.4	8.0	14.4
	ethnic*	4.1	0.9	3.1
	unknown*	46.8	37.0	9.8
Gender	male*	56.2	43.0	13.1
	female*	24.1	33.1	-9.0
	joint	10.9	12.2	-1.3
	undefined	7.9	8.7	-0.9

Table: Identity and gender proportions for the veteran (n=566 narratives) versus other dreamers. Δ shows the difference in percentage points. * indicates significant difference ($p < 0.05$).

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Table: Identity and gender proportions for the veteran (n=566 narratives) versus other dreamers. Δ shows the difference in percentage points. * indicates significant difference ($p < 0.05$).

→ The war veteran dreams more about *occupational*, *ethnic*, and *unknown* identities compared to other dreamers.

Results on the war veteran

We compare the proportion of sequences containing a given substring

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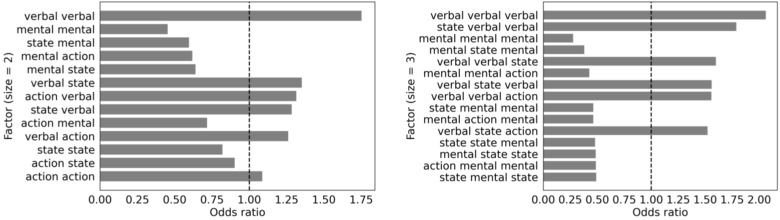

(a) Size 2. (b) Size 3.

Figure: Top substring odds ratio between the veteran and the norm

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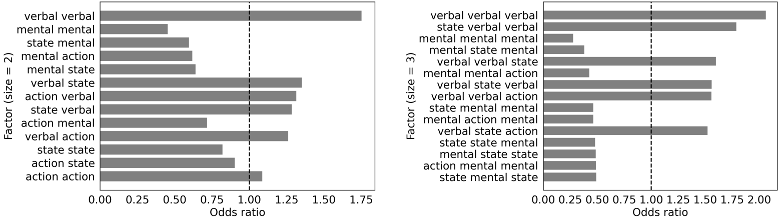

(a) Size 2. (b) Size 3.

Figure: Top substring odds ratio between the veteran and the norm

We show a preference for the war veteran to remain in a verbal process, as indicated by substrings such as *verbal.verbal* and *verbal.verbal.verbal* with high odds ratios (respectively 2.00 and 1.75)

Results on the war veteran

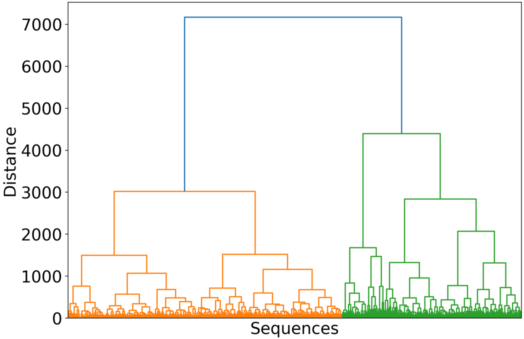

Figure: Dendrogram with Ward linkage and cosine similarity

Results on the war veteran

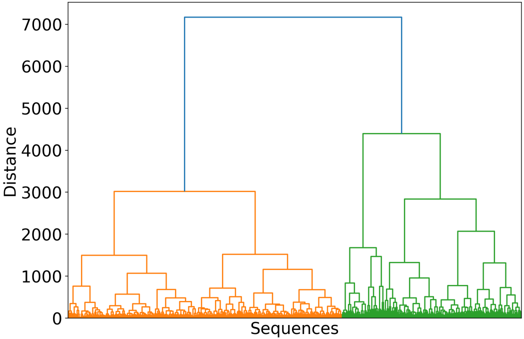

Figure: Dendrogram with Ward linkage and cosine similarity

Representative sequences: *savamasasaaamaaasavvvaaaaaaavssaaaaa* and *sssssavaavssvsavvvvsmasasaasasaamaamvmsss* with $a = action, m = mental, s = state, v = verbal$

Selected research papers

Constant Bonard and Gustave Cortal (2024). “Improving Language Models for Emotion Analysis: Insights from Cognitive Science”. In: *Proceedings of the Workshop on Cognitive Modeling and Computational Linguistics*. Ed. by Tatsuki Kuribayashi et al. Bangkok, Thailand: Association for Computational Linguistics, pp. 264–277. DOI: 10.18653/v1/2024.cmcl-1.23

Gustave Cortal, Alain Finkel, et al. (2023). “Emotion Recognition Based on Psychological Components in Guided Narratives for Emotion Regulation”. In: *Proceedings of the 7th Joint SIGHUM Workshop on Computational Linguistics for Cultural Heritage, Social Sciences, Humanities and Literature*. Ed. by Stefania Degaetano-Ortlieb et al. Dubrovnik, Croatia: Association for Computational Linguistics, pp. 72–81. DOI: 10.18653/v1/2023.latechclfl-1.8

Gustave Cortal (2024). “Sequence-to-Sequence Language Models for Character and Emotion Detection in Dream Narratives”. In: *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*. Ed. by Nicoletta Calzolari et al. Torino, Italia: ELRA and ICCL, pp. 14717–14728

Gustave Cortal and Alain Finkel (2025). “Formalizing Style in Personal Narratives”. In: *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing*. Ed. by Christos Christodoulopoulos et al. Suzhou, China: Association for Computational Linguistics, pp. 7322–7337. ISBN: 979-8-89176-332-6

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Domhoff, G. William and Adam Schneider (2008). "Studying Dream Content Using the Archive and Search Engine on DreamBank.Net". In: *Consciousness and Cognition* 17.4, pp. 1238–1247. ISSN: 10538100. DOI: 10.1016/j.concog.2008.06.010.

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