Natural language processing for subjectivity analysis in personal narratives

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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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- Formalization of style in personal narratives
- Automatic thematic analysis in mental health narratives

Definition of objectives using cognitive science

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

Definition of objectives and scope using cognitive science

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- Different emotion theories lead to divergences in how to annotate them in the text
- Some linguistic and cognitive science theories are not considered
- There is no benchmark that evaluates the richness of the emotional phenomenon

Emotional analysis in text

What are the main ways to annotate emotion in text?

Psychological theories	In text, emotion is...	Example
Basic emotions theory	a **category**	"I love philosophy." → `joy`
Constructivist theories	a continuous value with an **affective** meaning	"His voice soothes me." → `valence` (4/5), `arousal` (1/5)
Appraisal theory	a continuous value with a **cognitive** meaning	"I received a surprise gift." → `sudden` (4/5), `control` (0/5)
	composed of **semantic roles**	"Louise (`experiencer`) was angry (`cue`) towards Paul (`target`), because he didn't inform her (`cause`)."

Integrated framework for emotion theories

How to integrate psychological theories of emotion?

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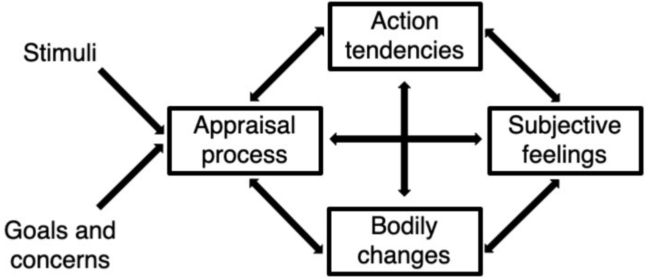

Figure: Emotional episodes are synchronized changes in four components (Scherer, 2022).

Detective analysis in pragmatics

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

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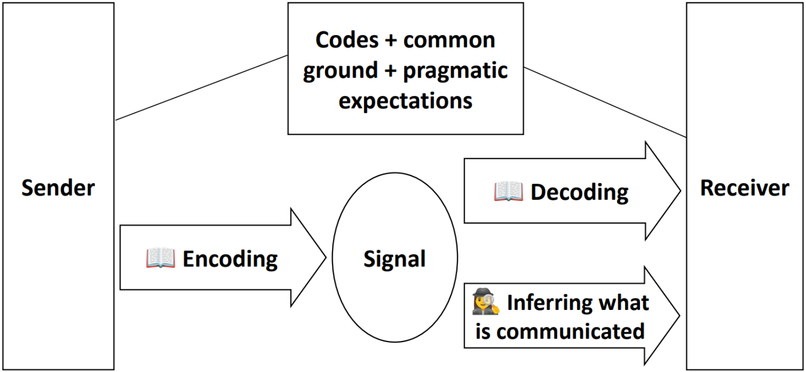

Emotion expression modes

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

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

	Logistic Regression			CamemBERT		
Component	Precision	Recall	F_1	Precision	Recall	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
Only `feeling`	69.6 (1.5)	68.9 (2.1)	68.4 (2.0)	67.8	68.4	67.7
Only `thinking`	50.1 (3.4)	53.8 (2.3)	50.6 (2.7)	70.5	70.1	70.1
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→ Each component improves prediction performance, the best results are achieved by jointly considering all components

→ Some components benefit from contextual understanding and world knowledge (*e.g.*, `behavior` and `thinking`)

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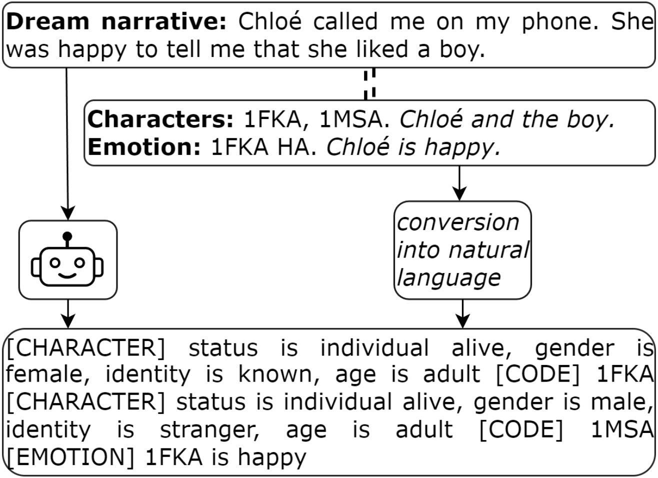
How to automate the annotation process?

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

Table: F_1-scores for character and emotion detection. Significant differences from baseline: ** ($p < 0.01$), * ($p < 0.05$).

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

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`StableBeluga`$_i$ is a 7B model with in-context learning using *i* examples

Model	**Status**	**Gender**	**Identity**	**Age**	**Character**	**Emotion**
Baseline	82.87	78.02	76.17	86.21	64.74	75.13
StableBeluga$_1$	43.95**	39.76**	31.25**	56.16**	15.65**	-
StableBeluga$_3$	52.44**	46.49**	38.46**	63.88**	21.06**	-
StableBeluga$_5$	55.89**	46.29**	42.61**	63.73**	24.86**	-

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→ Compared to `StableBeluga`, our supervised models perform better while having 28 times fewer parameters (248M vs 7B)

Case study 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
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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 ($p < 0.05$).

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

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*

Contributions

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3. A case study on dream narratives

Categorizing linguistic features

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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`
I feel a cold wind	`Mental` (**m**)	`Senser`, `Phenomenon`
I tell myself to move	`Verbal` (**v**)	`Sayer`, `Recipient`

Sequence: *amv* | **Substrings:** {am, mv}

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4. We perform sequence analysis to identify patterns such as frequent substrings and representative sequences

Results on the war veteran

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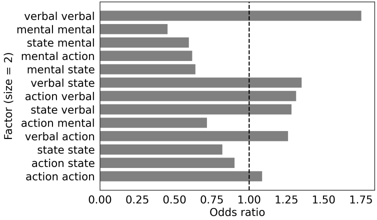
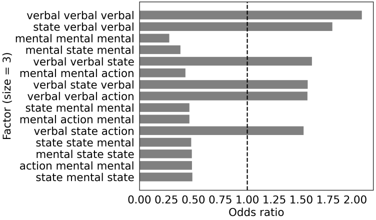
We compare the proportion of sequences containing a given substring



(a) Size 2.



(b) Size 3.

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

Results on the war veteran

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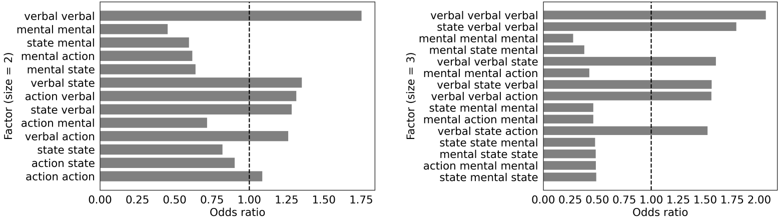

(a) Size 2. (b) Size 3.

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

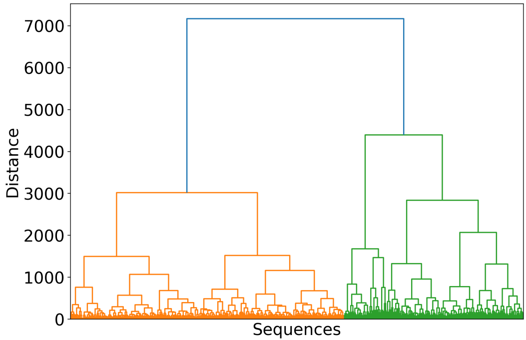

Figure: Dendrogram with Ward linkage and cosine similarity

Results on the war veteran

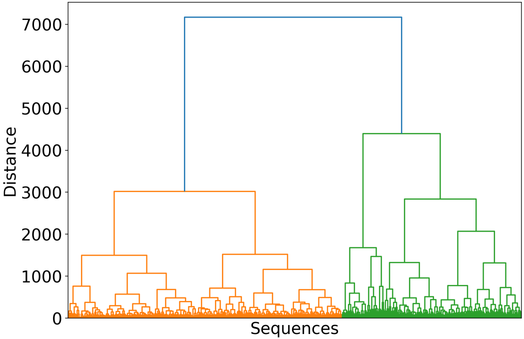

Figure: Dendrogram with Ward linkage and cosine similarity

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

Perspectives

- Authorship profiling

Perspectives

- Authorship profiling
- Style-conditioned narrative generation

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- Applying methods from complexity science and formal language theory

Conclusion

How to model subjective experience in personal narratives?

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- Definition of objectives and scope using cognitive science

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- Construction of an emotion dataset
- Training of language models for emotion analysis
- Formalization of style in personal narratives

Appendix

Selected open-source projects

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

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Oneirogen, a model for dream generation, and Dream-T5, a model for emotion and character prediction in dream narratives.

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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Halliday, M.A.K. et al. (2014). *An Introduction to Functional Grammar*. 0th ed. Routledge. ISBN: 978-1-4441-1908-4. DOI: `10.4324/9780203783771`.

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Scherer, Klaus R. (2022). "Theory Convergence in Emotion Science Is Timely and Realistic". In: *Cognition and Emotion* 36.2, pp. 154–170. ISSN: 0269-9931. DOI: 10.1080/02699931.2021.1973378.