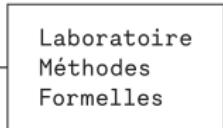


# Natural language processing for subjectivity analysis in personal narratives

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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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- ▶ 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.

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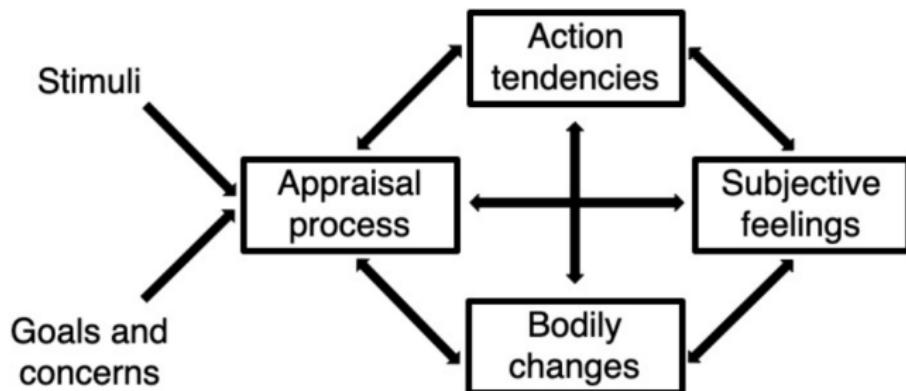
- ▶ Different emotion theories lead to divergences in how to annotate them in the text
- ▶ Some linguistic and cognitive science theories are not considered
- ▶ There is no benchmark that evaluates the richness of the emotional phenomenon

# Integrated framework for emotion theories

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

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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](https://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

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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			CamemBERT		
	Precision	Recall	$F_1$	Precision	Recall	$F_1$
All	71.2 (2.6)	69.1 (2.2)	67.8 (2.3)	<b>85.1</b>	<b>84.8</b>	<b>84.7</b>
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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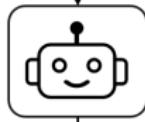
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How to automate the annotation process?

# Character and emotion detection in dream narratives

**Dream narrative:** Chloé called me on my phone. She was happy to tell me that she liked a boy.

**Characters:** 1FKA, 1MSA. *Chloé and the boy.*  
**Emotion:** 1FKA HA. *Chloé is happy.*



*conversion  
into natural  
language*

[CHARACTER] status is individual alive, gender is female, identity is known, age is adult [CODE] 1FKA  
[CHARACTER] status is individual alive, gender is male, identity is stranger, age is adult [CODE] 1MSA  
[EMOTION] 1FKA is happy

# 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
No <sub>semantics</sub>	71.37	56.54*	61.0	90.51	41.79*	75.79
No <sub>names</sub>	80.66*	74.32**	74.2	83.95*	60.93**	73.04*
Size <sub>small</sub>	78.35**	72.13**	70.25**	81.66**	56.79**	70.15**
Size <sub>large</sub>	84.51*	80.3**	78.63**	87.29	67.63**	74.71
First <sub>group</sub>	82.33	77.71	74.86	85.61	63.71	71.94
First <sub>individual</sub>	80.59**	76.14	74.22*	83.87**	62.67	67.32
First <sub>emotion</sub>	83.92	78.74	77.06	87.63	64.97	72.03
Conversion <sub>comma</sub>	84.02**	79.84**	77.67**	87.08*	66.69**	73.68
Conversion <sub>marker</sub>	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<sub>i</sub> 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 <sub>1</sub>	43.95**	39.76**	31.25**	56.16**	15.65**	-
StableBeluga <sub>3</sub>	52.44**	46.49**	38.46**	63.88**	21.06**	-
StableBeluga <sub>5</sub>	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
	joint	10.9	12.2	-1.3
	undefined	7.9	8.7	-0.9

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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*

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3. A case study on dream narratives

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According to systemic functional linguistics, language represents experience through *processes*, *participants* and *circumstances* (Halliday et al., 2014)

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

## 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

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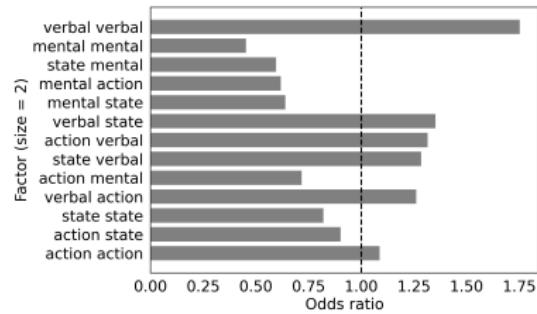
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3. Each narrative is mapped to a symbolic sequence using an alphabet based on identified features
4. We perform sequence analysis to identify patterns such as frequent substrings and representative sequences

## Results on the war veteran

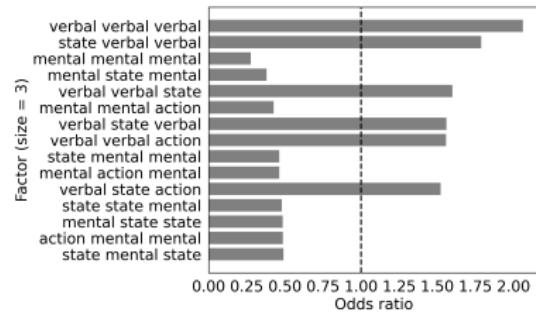
We compare the proportion of sequences containing a given substring

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(a) Size 2.

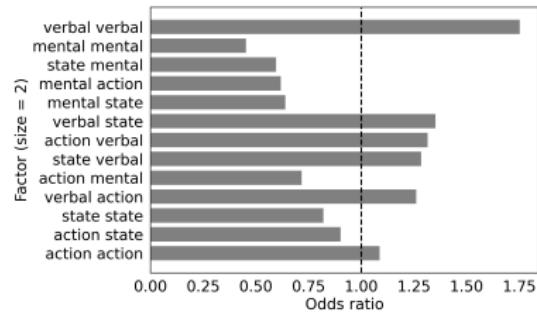


(b) Size 3.

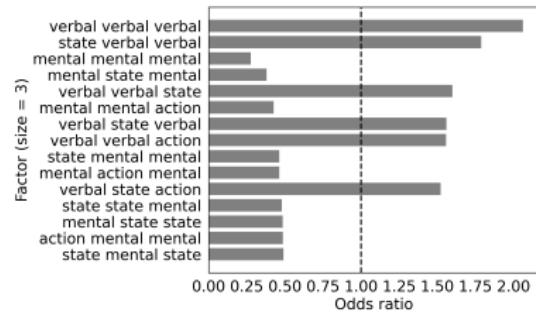
Figure: Top substring odds ratio between the veteran and the norm

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We compare the proportion of sequences containing a given substring



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(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)

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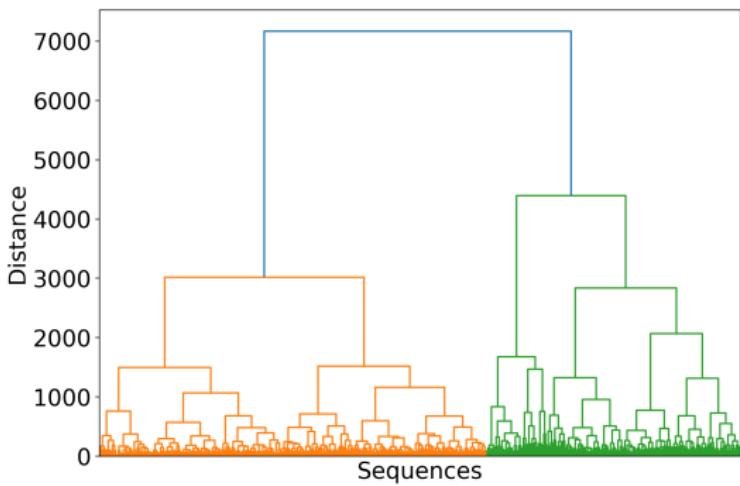


Figure: Dendrogram with Ward linkage and cosine similarity

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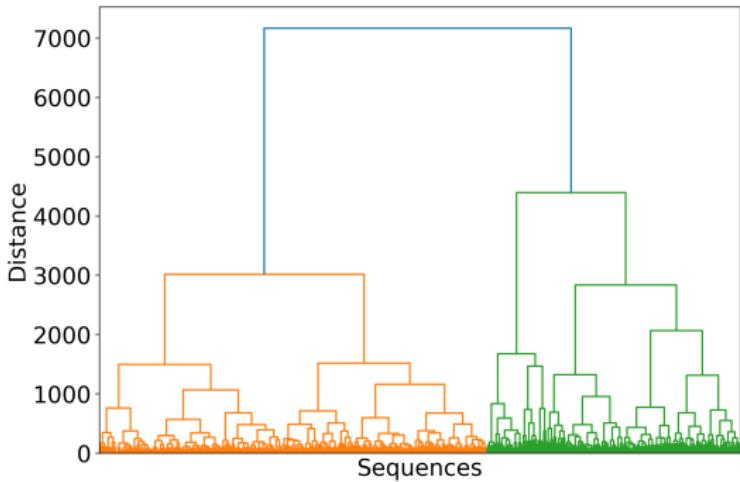


Figure: Dendrogram with Ward linkage and cosine similarity

**Representative sequences:** *savamasasaaaamaaaasavvvaaaaaaavssaaaaa* and *sssssvavaavssvsavvvvsmasasaasasaamaamvmsss* with  
 $a = \text{action}$ ,  $m = \text{mental}$ ,  $s = \text{state}$ ,  $v = \text{verbal}$

# Perspectives

- ▶ Authorship profiling

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How to model subjective experience in personal narratives?

- ▶ Definition of objectives and scope using cognitive science
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- ▶ Training of language models for emotion analysis
- ▶ Formalization of style in personal narratives

# Appendix

## Selected open-source projects

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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 Kurabayashi et al. Bangkok, Thailand: Association for Computational Linguistics, pp. 264–277. DOI: [10.18653/v1/2024.cmcl-1.23](https://doi.org/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.latechclf1-1.8](https://doi.org/10.18653/v1/2023.latechclf1-1.8)

**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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