Natural language processing for subjectivity analysis in personal narratives

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Introduction

Context

- Natural language processing for psychology is underexplored
- We build on an existing subfield: emotion analysis
- We study subjectivity (involving first-person perspective, meaning-making processes, and experiential content)
- We focus on personal narratives (*e.g.*, dreams, emotional narratives)

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

Introduction

How to model subjective experience in narratives?

- Definition of objectives and scope using cognitive science
- Construction of an emotion dataset
- Training of language models for emotion analysis
- Formalization of style in 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

What are current limitations and interesting research directions?

We review psychological theories of emotion and emotion annotation schemes in NLP

- 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

How to integrate psychological theories of emotion?

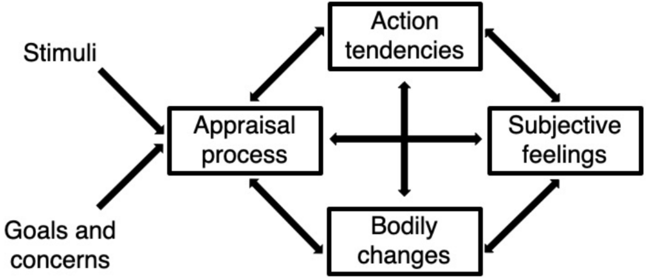


Figure: Emotional episodes are synchronized changes in four components (Scherer, 2022).

Emotion expression modes

Which verbal signs are used to infer expressed emotions?

Raphaël Micheli categorizes a range of linguistic markers into three *emotion expression modes* (Micheli, 2013). The emotion can be:

- *labeled* explicitly with an emotional term ("I am <u>sad</u>")
- *shown* with utterance features such as interjections and punctuations ("<u>Ah!</u> That's great<u>!</u>")
- *suggested* with the description of a situation which generally, in a given sociocultural context, leads to an emotion ("<u>She gave me a gift</u>")

→ 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

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.

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
Only `territory`	68.2 (1.8)	66.8 (2.2)	66.6 (2.3)	71.4	68.4	68.9

→ 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`)

Quantitative analysis of dream narratives

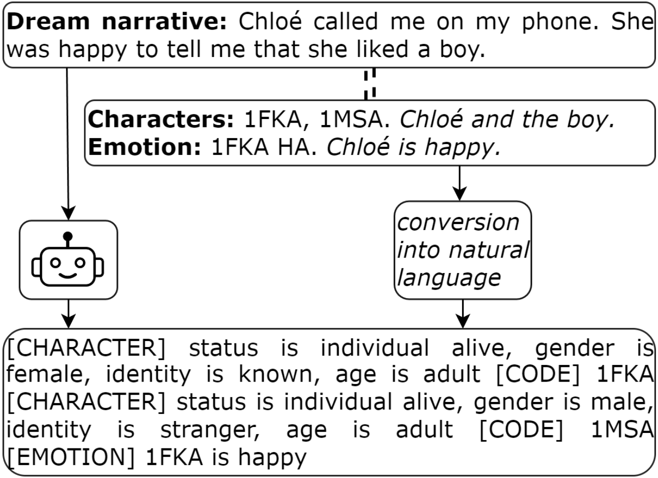
Need other datasets with narrative structure, emotional content, and available for research

Quantitative dream analysis examines recurring patterns between narrative elements using a database of dream narratives and an annotation scheme (Domhoff and Schneider, 2008)

The annotation process is complex and costly

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
$\mathrm{No}_{\mathrm{semantics}}$	71.37	56.54*	61.0	90.51	41.79*	75.79
$\mathrm{No}_{\mathrm{names}}$	80.66*	74.32**	74.2	83.95*	60.93**	73.04*
$\mathrm{Size}_{\mathrm{small}}$	78.35**	72.13**	70.25**	81.66**	56.79**	70.15**
$\mathrm{Size}_{\mathrm{large}}$	84.51*	80.3**	78.63**	87.29	67.63**	74.71
$\mathrm{First}_{\mathrm{group}}$	82.33	77.71	74.86	85.61	63.71	71.94
$\mathrm{First}_{\mathrm{individual}}$	80.59**	76.14	74.22*	83.87**	62.67	67.32
$\mathrm{First}_{\mathrm{emotion}}$	83.92	78.74	77.06	87.63	64.97	72.03
$\mathrm{Conversion}_{\mathrm{comma}}$	84.02**	79.84**	77.67**	87.08*	66.69**	73.68
$\mathrm{Conversion}_{\mathrm{marker}}$	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: ** ($p < 0.01$), * ($p < 0.05$).

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

Results

`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**	-

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

→ 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	% Viet	% 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 Vietnam veteran versus other dreamers. Δ shows the difference in percentage points. * indicates significant difference (two-proportion z-test, Bonferroni-corrected $\alpha = 0.05$).

Formalization of style in narratives

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

Introduction

How is subjective experience communicated in narratives?

We use narratives to express our representations of reality and make sense of the world (Bruner, 1990)

In everyday usage, style refers to a distinctive manner of expression

We use style as a proxy to study how subjective experience is linguistically communicated

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

Contributions

How to give an operational definition of style?

Hypothesis: An individual uses some redundant choices of features that characterize its style

1. A sequence-based framework defining style as patterns in sequences of linguistic choices
2. A methodology for identifying patterns using sequence analysis
3. A case study on dream narratives

Categorizing linguistic features

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]$_{\text{Actor}}$ **[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

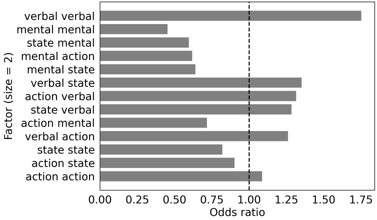
Clause	Process (symbol)	Participants
I wake in a dark room	`Action` (**a**)	`Actor`
I feel a cold wind	`Mental` (**m**)	`Senser`, `Phenomenon`
I tell myself to move	`Verbal` (**v**)	`Sayer`, `Recipient`

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

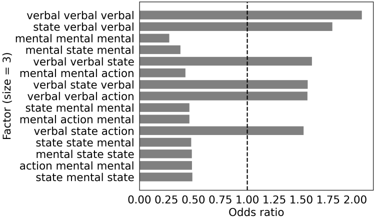
1. We first segment *"I wake in a dark room. I feel a cold wind. I tell myself to move."* into clauses
2. Identify features (*e.g.*, processes and participants) for each clause using in-context learning with large language models
3. Each narrative is mapped to a symbolic sequence using an alphabet based 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



(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

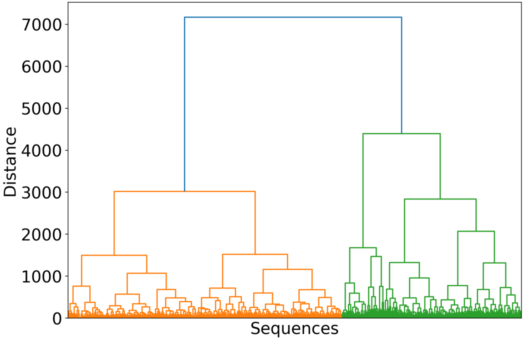


Figure: Dendrogram with Ward linkage and cosine similarity

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

Perspectives

- Authorship profiling
- Style-conditioned narrative generation
- Applying methods from complexity science and formal language theory

Conclusion

How to model subjective experience in narratives?

- Definition of objectives and scope using cognitive science
- Construction of an emotion dataset
- Training of language models for emotion analysis
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Fine-grained mental health topic modeling using large language models (change title to thematic analysis?)

G. Cortal, S. Guessoum, X. Cao, R. Riad. *Fine-grained mental health topic modeling in different cohorts using large language models* (preprint). 2025.

Introduction

- Qualitative analysis of speech content is central to clinical practice
- Thematic analysis studies how people construct meaning
- Thematic analysis is time-consuming, and typically constrained to small, monolingual corpora
- Computational approaches offers time savings over manual annotation, and the power to analyze a larger amount of data

→ We developed a multilingual pipeline that (a) clusters speech transcripts from four cohorts, (b) generates natural-language descriptions for each cluster, and (c) links clusters to variation in clinical scores and sociodemographic factors

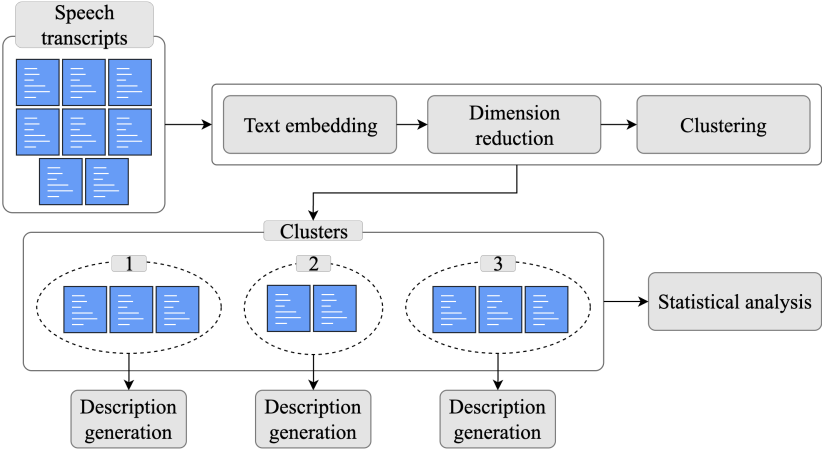
Data collection

We collect clinical scores and open-ended narratives from **four cohorts**. A French general population cohort (n=1809), and three clinical populations: Italian (n=116), Chinese (n=52), and Spanish (n=90) cohorts

Clinical scores were assessed using various scales such as: AIS (Athens Insomnia Scale); BDI (Beck Depression Inventory); GAD-7 (Generalized Anxiety Disorder 7-item scale); MFI (Multidimensional Fatigue Inventory); PHQ-9 (Patient Health Questionnaire-9 for depression)

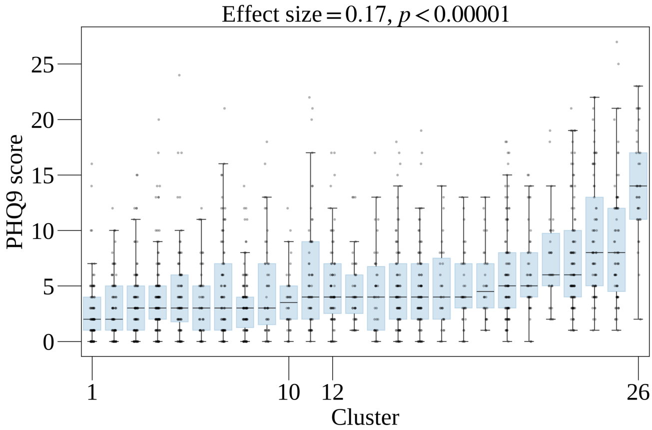
Open-ended questions: *Describe your last 24 hours / a negative event that happened to you in the past / a positive event that happened to you in the past / a negative event you think might happen in the future / a positive event you think might happen in the future / Describe how you are feeling at the moment and how your sleep has been lately*

Pipeline for semantic clustering and description generation



Distribution of depression scores across clusters

How you are feeling and how your sleep has been lately



→ Depression scores vary significantly: cluster 26 highest (13.4±5.4), cluster 1 lowest (2.6±2.2)

Generated cluster descriptions

Cluster 1 description: The individuals express consistent satisfaction with their current well-being, emphasizing good sleep quality, restful or pleasant nights, and a general sense of relaxation, even when noting variations in sleep duration or occasional fatigue. (age=39±19, n=92)

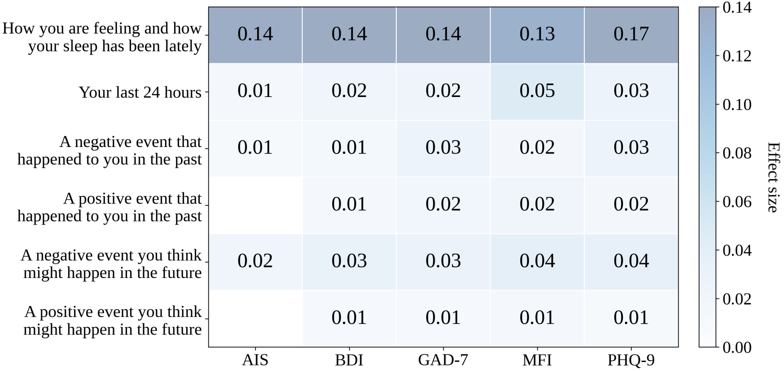
Cluster 10 description: The individuals express frequent nighttime urinary interruptions disrupting sleep, often attributed to age-related conditions like prostate issues or overactive bladder, alongside mixed reports of physical well-being, mental resilience, and lifestyle factors such as retirement or exercise influencing their overall health and sleep patterns. (age=69±15, n=34)

Cluster 12 description: The individuals express stress related to academic exams, significant life decisions, and workloads, alongside sleep disturbances caused by lifestyle changes, increased responsibilities, or environmental adjustments, while some also highlight temporary relief from pressures through personal achievements or upcoming positive events. (age=24±9, n=67)

Cluster 26 description: The individuals express sleep disturbances characterized by insomnia, frequent awakenings, and restless sleep, alongside pervasive anxiety, emotional instability, and self-esteem issues, which collectively contribute to persistent fatigue, impaired daily functioning, and a diminished sense of well-being. (age=25±9, n=37)

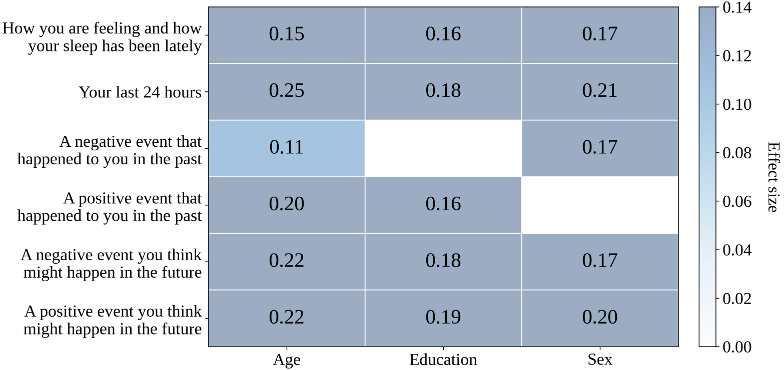
→ Clustering captures symptom severity and age-related circumstances

Effect size across tasks and clinical scores



→ Certain tasks better discriminate clinical scores

Effect size across tasks and sociodemographics



→ Nearly all tasks discriminate sociodemographics

Appendix

Selected open-source projects

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

A repo for lightweight preference optimization using LoRA and ORPO.

Piaget, a model fine-tuned for psychological reasoning, and Beck, a model aligned with psychotherapeutic preferences.

PsychologicalReasoning-15k, open psychological and philosophical reasoning traces.

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

Selected research papers

TODO: add correct citation format Cortal, Finkel, et al., "Emotion Recognition Based on Psychological Components in Guided Narratives for Emotion Regulation", 2023 Cortal, "Sequence-to-Sequence Language

Models for Character and Emotion Detection in Dream Narratives", 2024 Gustave Cortal and Alain Finkel (2025). *Formalizing Style in Personal*

Narratives. Version 2. DOI: 10.48550/ARXIV.2510.08649. URL: https://arxiv.org/abs/2510.08649 (visited on 10/20/2025). Pre-published TODO: add multimodal research paper: N. Richet, S. Belharbi, H. Aslam, M. Schadt, M. González-González, **G. Cortal**, A. Koerich, M. Pedersoli, A. Finkel, S. Bacon, E. Granger. Textualized and Feature-based Models for Compound Multimodal Emotion Recognition in the Wild. *ABAW, ECCV 2024*.

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