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Context over Categories: Implementing the Theory of Constructed Emotion with LLM-Guided User Analysis

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Overview & Contributions

Problem: Traditional emotion analysis relies on oversimplified categories (e.g., Ekman's universal emotions), neglecting context and individual differences.

Our Approach: We operationalize Lisa Feldman Barrett's Theory of Constructed Emotion, which emphasizes the crucial role of context in shaping emotions.

Key Contributions:

- Novel Framework: A context-aware emotion analysis pipeline using advanced LLM guidance.
- "Context Sphere": A new data construct representing a user's complete online behavior and interactions.
- LLM Adaptation: Demonstrates how to use LLMs for nuanced, context-sensitive emotion analysis.
- Focus: Content moderation and personalized systems.

Research Question

How can we leverage Large Language Models (LLMs) to analyze emotions in a way that reflects their complex, constructed nature, rather than relying on predefined categories?

Methodology

A. Context Sphere Building

Data Source: "Der Standard" online newspaper comments and related articles (May 2019, 23,925 users).

Goal: Create a comprehensive "context sphere" for each user, encapsulating:

- All comments made by the user.
- Surrounding context (article metadata, conversation threads).
- Interactions with other users (replies, etc.).

Key Features:

- Selective Pruning:** Includes relevant conversation threads up to the user's last comment, balancing context with efficiency.
- Privacy-Preserving:** Excludes usernames and gender to minimize bias.
- Markdown Format:** Optimized for readability by both humans and LLMs.

B: LLM-Guidance

Core Idea: Combine the Theory of Constructed Emotion with advanced LLM techniques.

Key Techniques:

- Role-Play Prompting [7]:** The LLM (Gemini-1.5 Pro) impersonates Lisa Feldman Barrett. (Include a small, simplified version of Figure 2 if space allows).
- Controlled Generation:** A JSON schema guides the LLM's output, ensuring a structured analysis.
- Meta-Prompting [9]:** A second LLM request generates a concise, human-readable Markdown report using a generalized template to adapt to specific instances.

Role-Setting Prompt

User: You are Dr. Lisa Feldman Barrett, an expert in emotion analysis using your theory of constructed emotions. Your task is to ... [role setting]

Role-Feedback Prompt

Model: Understood. As Dr. Barrett, I will diligently analyze the provided text with a commitment to excellence. I will ... [anchoring the role]

Instruction Prompt

User: Please analyze the following ... [instruction]
... (context sphere) ...

Figure 1: Example of Role-Play Prompting, where the LLM takes on the persona of Lisa Feldman Barrett [7].

Output Structure: A multi-class JSON with five main fields the LLM must generate its response into:

- Core Affect Analysis
- Cognitive Appraisal & Conceptualization
- Cultural & Social Context
- Emotion Construction Analysis
- Emotional Dynamics & Changes

Each field includes sub-fields like "Thought Process," "Analysis," "Observable Patterns," "Anomalous Behaviour" and "Rationale."

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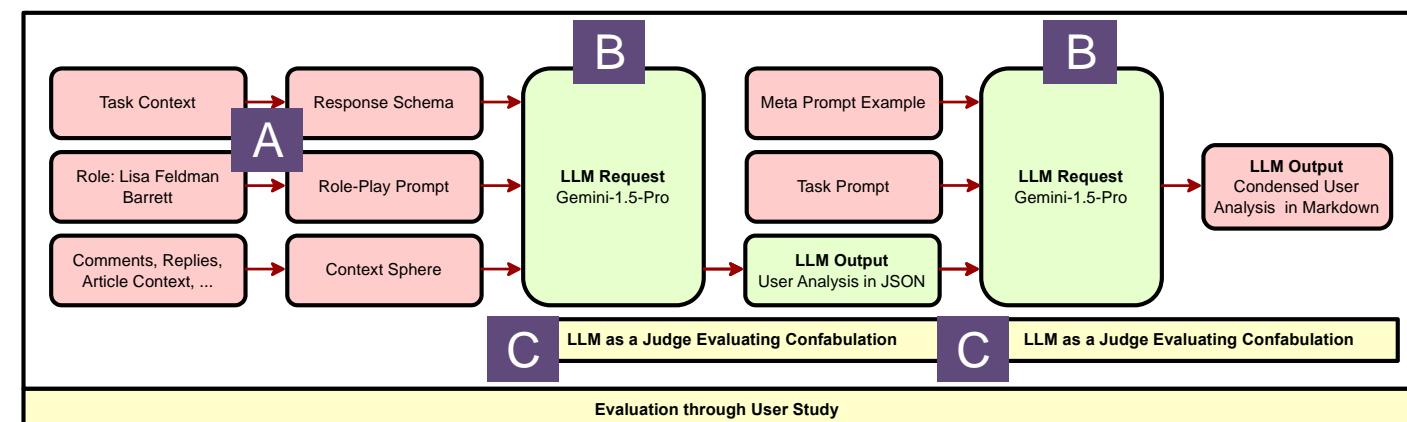


Figure 2: Pipeline from Preprocessing to Final Output - Please note: User Study not part of this Late-Breaking Work Submission.

Methodology

C: Evaluation

Uses LLM-as-a-Judge (GPT-4o, Claude / Haiku 3.5, Gemini 1.5 Flash) to assess LLM output

- Detecting *confabulations* [4] (hallucinations) – confident but misleading outputs.
- Enables rapid, iterative development and refinement of the LLM pipeline.

Cost: Initial JSON analysis: ~\$0.035 per user. Full pipeline (including Markdown report): ~\$0.072 per user. Complete pipeline, including confabulation checks: ~\$0.462

Upcoming User Study not part of this Late Breaking Work

Table 1: Examples output from first LLM request

Field	Sub-Field	Output
Core Affect Analysis	Arousal	Generally high, fluctuating between agitated and calmly contemptuous. [...]
Cognitive Appraisal & Conceptualization	Analysis	[...] The user's interpretations are often filtered through a lens of skepticism and cynicism, particularly towards opposing political views. [...]
Cultural & Social Context	Thought Process	I will examine the cultural and social context by considering the platform ("Der Standard"), the political climate of Austria in May 2019 (pre-election period), and the specific topics discussed (immigration, politics, media). [...]
Emotion Construction Analysis	Rationale	[...] Their negative emotional responses are often amplified by their pre-existing beliefs and the context of the online forum. The occasional deviations from this pattern [...]
Emotional Dynamics & Changes	Anomalous Observations	The user's positive comment about Fendrich deviates from their usual negative pattern, suggesting a momentary shift in emotional state. [...]

Results

- Contextualized Emotion Analysis:** The LLM successfully analyzes emotions considering individual user contexts (see Table 1 examples).
- Beyond Simple Categories:** Captures nuanced emotional dynamics, going beyond traditional categorical approaches.
- Efficient Processing:** Demonstrates efficient processing of large text volumes (21,671 tokens in ~60 seconds for ~\$0.035), showcasing scalability.

Conclusion

- Advances Emotion Analysis:** Bridges cognitive science [2] and computational systems.
- Context-Aware Applications:** Enables nuanced emotion analysis
- Operationalizes Barrett's Theory:** Uses "context sphere" and LLM guidance (role-play, controlled generation).
- Implications:** More accurate and effective development of human-centered technologies.
- Ethical Implications:** Reduces Bias, Addresses risks [5], Aligns with responsible AI (Digital Humanism) [8].

Captures the complexity and context of human emotions far more effectively than models rooted in Ekman's assumptions of universal emotions [6].

Limitations and Future Work

- Evaluation Difficulty:** Dynamic emotions lack a definitive "ground truth" [3] for standard metrics.
- LLM-as-Judge:** Current evaluation [10] is pragmatic but lacks human validation.
- Framework:** Trade-off between theoretical flexibility avoiding predefined categories and the practical need for computational structure.
- Future Work:** Validate LLM analyses with human judgement, Compare against lexicon-based and Ekman's category methods; Address large datasets, overgeneralization, excessive granularity.
- Addressing Failure Modes:** Mitigate potential overgeneralization or excessive granularity

Ultimately, this future work aims to create more robust, reliable, and human-centered systems for understanding and responding to human emotion.

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