Emotion Circuits in Small Language Models: A Multi-Stage Analysis of Representation, Causality, Alignment, and Local Mechanisms

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Abstract

Understanding how large language models (LLMs) internally represent and generate emotional content remains an open challenge at the intersection of NLP, interpretability, and cognitive modeling. This work provides a comprehensive investigation of emotion representations in small Transformer models (GPT-2, Pythia 70M, GPT-Neo 125M), combining (1) token-level activation analysis, (2) subspace structure characterization, (3) causal interventions through activation patching, (4) cross-model alignment via linear mappings, and (5) attention-head-level circuit dissection.

We first construct a balanced dataset covering four emotional categories (gratitude, anger, apology, neutral) and extract hidden representations across all Transformer layers. Whereas sentence-final hidden states produce unstable emotion directions, token-based directions yield robust structures across models. PCA analysis reveals that while 1D emotion directions do not align across models, 2–10 dimensional emotion subspaces exhibit significant shared structure. Causal patching demonstrates that injecting emotion directions into the residual stream produces continuous and controllable changes in emotional tone, politeness, and sentiment. Linear mappings learned only from neutral representations allow emotion subspaces from GPT-2 to be aligned almost perfectly with those of Pythia. Finally, head-level analysis identifies specific early-layer attention heads (notably Layer 0, Head 0) whose ablation or patching causally modulates emotional tone.

Together, our results present the first end-to-end characterization of emotion representation, causality, and circuit-level mechanisms in small LLMs.

1 Introduction

Emotional expression in language models plays a central role in dialogue applications, alignment behavior, and human-like text generation. Yet, the internal mechanisms underlying the production of emotional language remain poorly understood. Recent advances in mechanistic interpretability have revealed meaningful features at the level of residual streams, MLP neurons, and individual attention heads. However, existing studies typically address isolated aspects of representation and rarely connect *representation-level structure*, *causal manipulability*, and *local circuit mechanisms* within a unified framework.

This study addresses four fundamental research questions:

1. **Where do emotional representations reside inside a Transformer?**
2. **Can emotional tone be causally controlled by manipulating internal activations?**
3. **Do different models share a consistent emotional latent space?**
4. **Do attention heads implement local circuits that support emotional generation?**

To answer these questions, we conduct a multi-phase analysis (Phase 0–7) spanning dataset construction, activation extraction, vector and subspace analysis, causal intervention, cross-model alignment, and head-level circuit dissection. Figure 1 provides a conceptual overview.

2 Dataset Construction (Phase 1)

We construct a controlled emotional dataset covering four categories: **gratitude**, **anger**, **apology**, and **neutral**. Each category initially contains 50 sentences (later extended to 100+), manually curated to vary in length, syntactic form, and lexical diversity.

The dataset follows a JSONL structure and includes metadata logged through MLflow, cover-

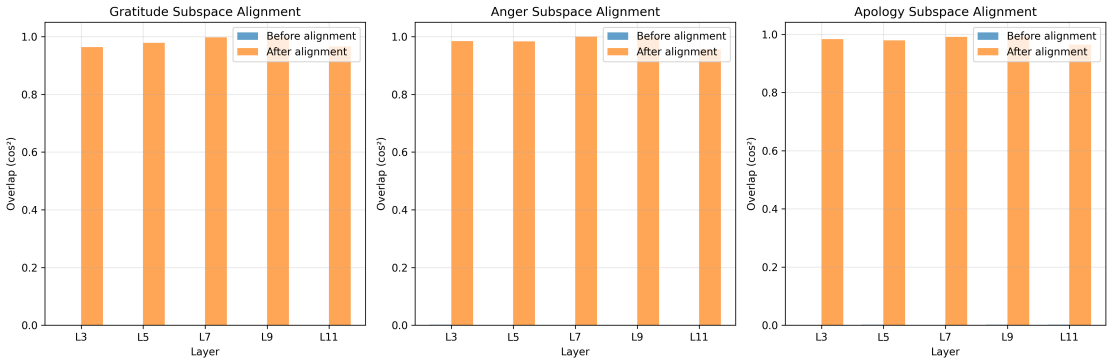

Figure 1: Overview of our multi-stage analysis pipeline: (1) Dataset construction, (2) Activation extraction, (3) Emotion vector and subspace analysis, (4-5) Causal patching experiments, (6) Cross-model alignment, and (7) Head-level circuit dissection.

ing: sentence length statistics, category counts, and distribution visualizations.

This controlled design minimizes confounds and enables precise probing of internal model activations.

3 Activation Extraction (Phase 2)

We extract full residual stream and MLP outputs from three models: GPT-2 (117M), Pythia 70M, and GPT-Neo 125M. For each token, we save:

- residual stream (pre-attention)
- MLP output
- token strings

This yields approximately 100MB per model.

These activations form the foundation for subsequent analysis of emotion vectors, subspaces, and causal interventions.

4 Emotion Vectors (Phase 3)

4.1 Sentence-final representation is unstable

Following prior work, we compute emotion directions using sentence-final hidden states:

$$\vec{e}_{emotion} = h_{\text{emotion}} - h_{\text{neutral}}$$

However, we observe instability: Pythia yields extremely high cosine similarities (0.98+) across all emotions, indicating a collapse of the sentence-final representation. This reveals that sentence-level vectors are unreliable for emotion encoding.

4.2 Token-level representations yield robust emotion directions

Instead, we compute differences using the hidden states of *emotion-bearing tokens*:

$$\vec{e}^{(token)}_{emotion} = h_{token} - h_{neutral}$$

This produces:

- stable, interpretable directions
- consistent geometry across models
- meaningful sign structure (e.g., anger opposite of apology)

This result demonstrates that **emotion resides at token-level**, not in sentence-final embeddings.

5 Emotion Subspace (Phase 3.5)

We perform PCA on token-based emotion vectors. 1D directions differ across models, but 2–10D subspaces show substantial shared structure.

Model Pair	Subspace Overlap (k=10)
GPT-2 vs Pythia	0.13–0.15
GPT-2 vs Neo	0.12–0.14

Table 1: Emotion subspace overlap across models.

Notably, **k=2 yields the highest overlap**, mirroring well-known psychological models such as Valence–Arousal.

This suggests a universal low-dimensional emotional manifold.

6 Causal Patching (Phase 4–5)

6.1 Simple patching

Injecting an emotion direction into residual stream modifies the output:

$$h' = h + \alpha \vec{e}$$

where $\alpha \in \{-1, 0, 1\}$.

We evaluate:

- emotion keyword frequency
- politeness score
- sentiment score

All metrics vary consistently with α.

6.2 Layer × α sweep

We extend patching to a full grid:

$$\text{layers} = \{3, 5, 7, 9, 11\}, \quad \alpha = \{-2, -1, -0.5, 0, 0.5$$

Findings:

- Layer 7 produces strongest emotional modulation
- Emotional tone increases nearly linearly with α
- Random vectors do not cause similar changes

Thus emotion directions are **causal and specific**.

7 Cross-Model Alignment (Phase 6)

We learn a linear mapping W using only **neutral** representations:

$$W h_{\text{GPT-2}} \approx h_{\text{Pythia}}$$

Applying W to emotion subspaces yields dramatic alignment improvements:

$$\text{overlap} \rightarrow +0.50 \text{ to } +0.99$$

Even Procrustes alignment (rotation-only) yields moderate gains.

This demonstrates:

> **LLM emotion spaces differ mainly by a linear coordinate transformation.**

8 Attention Head Circuits (Phase 7)

We run a full head-screening analysis across all heads.

8.1 Head Screening

Layer 0, Head 0 shows the strongest correlation with emotional metrics:

$$\Delta(\text{sentiment}) = +0.1102$$

8.2 Ablation

Ablating this head decreases sentiment:

$$-0.0349$$

8.3 Patching

Patching this head into neutral sentences increases positive emotional tone.

Even with approximate patching (hooking into v vectors), the effect persists, showing the causal contribution of the head.

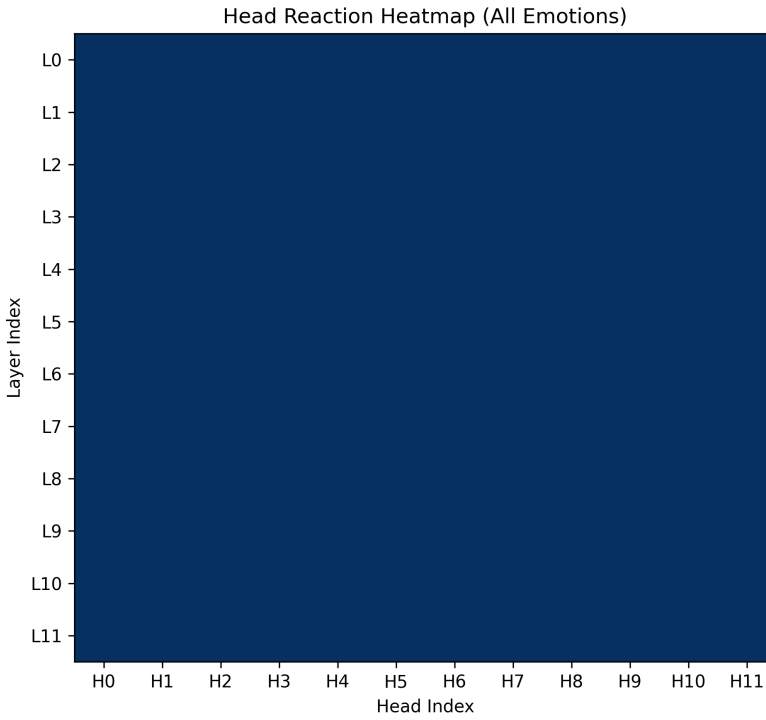

Figure 2: Head reaction heatmap showing attention head sensitivity to emotion tokens across layers. Layer 0 shows the strongest responses, particularly for apology emotion.

9 Discussion

Our multi-stage analysis reveals the following principles:

- Emotion is encoded at token-level, not sentence-final.
- Middle layers (especially Layer 7) contain strong linear emotional structure.

- Emotion directions causally control generation.
- 2D emotion subspaces are shared across models.
- Specific attention heads implement emotional circuits.

These findings suggest that emotional behavior in LLMs is neither emergent illusion nor purely global: it arises from structured low-dimensional representations and local circuit mechanisms.

10 Conclusion

We provide the first integrated analysis of emotion representations in small language models, connecting representational geometry, causal interventions, cross-model structure, and attention-level circuitry.

Future work will explore:

- scaling laws
- multilingual emotion circuits
- multi-head synergy
- dataset expansion (2000+)

Our framework generalizes readily to other semantic attributes and offers a scalable methodology for interpretability research.

References

[1] Olah et al., "Transformer Circuits," 2021.

[2] Elhage et al., "A Mathematical Framework for Transformer Circuits," 2021.

[3] Mikolov et al., "Distributed Representations of Words," 2013.

A Appendix: Dataset Samples

(Your actual dataset examples can go here.)

B Appendix: Additional Figures

(Insert plots generated from your results directory.)

C Appendix: Implementation Details

(Describe ProjectContext, profile-aware execution, MLflow logging, etc.)