Hierarchical Opinion Classification using Large Language Models

FIRE 2025 — Forum for Information Retrieval Evaluation

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December 17–20, 2025

1. Outline

Presentation Outline

2. Introduction

Motivation & Dataset Overview

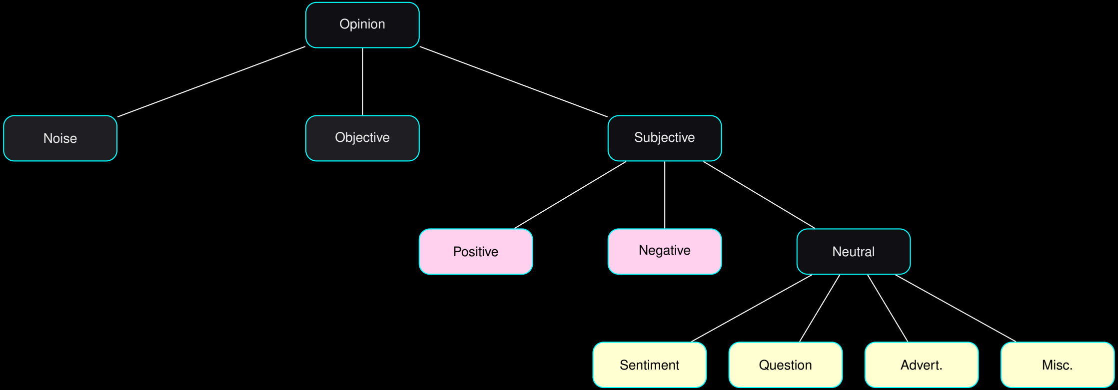
Context: FIRE 2025 Shared Task

- The datasets (Reddit, Twitter, YouTube) and the **3-level hierarchy** were provided as part of the shared task.
- **Why Hierarchy Matters:** It disambiguates *intent* from *sentiment*.
  - → Differentiates Complaints (Negative) from Inquiries (Questions).
  - → *Where it doesn't matter:* **Noise** is flat and requires no depth.

Real Examples from Dataset:

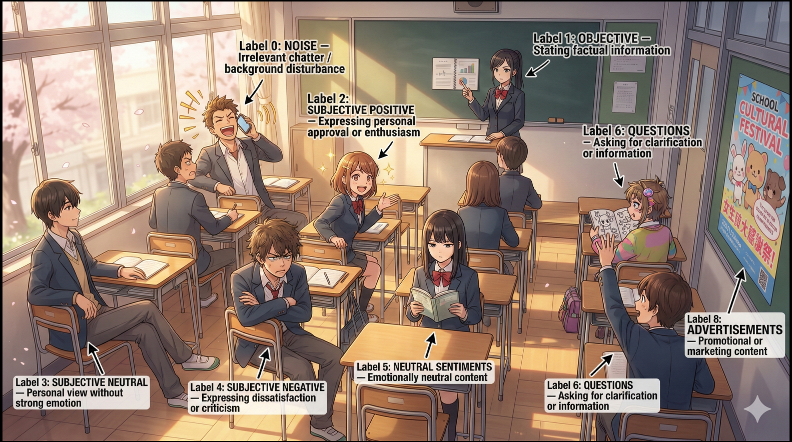
1. **Objective (Level 1):**
   "Binance is reportedly building a $1 billion insurance fund to counter crypto hacks."
2. **Subjective → Negative (complaint):**
   "Do yourself a favor and don't use Kucoin... They are not reliable... my coins are now lost..."
3. **Subjective → Neutral → Question (intent):**
   "How does TDS work? ... they give our 1% TAX with our PAN... can someone explain?"

Hierarchical Structure of Opinions



- **Level 1:** Coarse-grained (Noise, Objective, Subjective)
- **Level 2:** Sentiment refinement (Neutral, Negative, Positive)
- **Level 3:** Fine-grained neutral categories

Label Visualization



Our Approach — Overview

Approach 1: Classification Fine-tuning

- Custom classification head
- Parameter-efficient fine-tuning
- Weighted cross-entropy loss

Approach 2: Instruction Fine-tuning

- Prompt-response format
- Next-token prediction
- Masked loss on answer tokens

Base Model: Gemma3-1B — Compact 1-billion parameter LLM

3. Problem Statement

The 8-Class Classification Task

Hierarchical → Flat Mapping:

ID	Category
0	NOISE
1	OBJECTIVE
2	SUBJECTIVE_POSITIVE
3	SUBJECTIVE_NEGATIVE
4	NEUTRAL_SENTIMENTS
5	QUESTIONS
6	MISCELLANEOUS
7	ADVERTISEMENTS

Key Challenges

- Severe **class imbalance**
- **Semantic overlap** among categories
- **Noisy** social media text
- **Hierarchical dependencies**

4. Data Preparation

4-Phase Data Cleaning Workflow

Phase 1: Structural Integrity

- Schema alignment across sources
- Null entry elimination
- Token-based duplicate detection
- Corpus integrity verification

Phase 2: Content Cleaning

- URL/hyperlink removal
- Mention/hashtag filtering
- Emoji normalization
- Whitespace compacting

Phase 3: Text Normalization

- Case normalization (lowercase)
- Domain-specific token preservation
- Final text validation

Phase 4: Label Formatting

- Hierarchical label consolidation
- Numeric label encoding (0–8)
- Human-readable mapping

Dataset Statistics

Reddit Dataset

- 5,000 samples
- Mean: 186 tokens
- Max: 15,535 tokens

Top classes:

- Noise: 645
- Objective: 503
- Neutral: 476

Twitter Dataset

- 4,987 samples
- Mean: 46 tokens
- Max: 151 tokens

Top classes:

- Objective: 1,700
- Noise: 1,338
- Positive: 268

YouTube Dataset

- 5,000 samples
- Mean: 38 tokens
- Max: 1,128 tokens

Top classes:

- Negative: 1,574
- Neutral: 1,391
- Question: 1,000

Class Imbalance

Significant variation across platforms — *Advertisements* has only 1 sample in YouTube!

5. Model Architecture

Gemma-1B with Custom Classification Head

Architecture Pipeline:

1. **Token Embedding**
   $H_0 \leftarrow \text{EmbeddingLookup}(X_{\text{tokens}})$
2. **Transformer Backbone**
   L transformer layers with `Gemma3RMSNorm`
3. **Final Normalization**
   $H_{\text{final}} \leftarrow \text{RMSNorm}(H_L)$
4. **Last Token Extraction**
   $h_{\text{last}} \leftarrow H_{\text{final}}[:, -1, :]$
5. **Classification Head**
   LayerNorm $\rightarrow$ Dropout $\rightarrow$ Linear(8)

Custom Classification Head

```
Sequential(
LayerNorm(1152)
Dropout(p=0.4)
Linear(1152 → 8)
)
```

Key Design

Replace original LM head $(1152 \rightarrow 262144)$ with classification head $(1152 \rightarrow 8)$

Parameter-Efficient Fine-Tuning (PEFT)

Trainable Components

- Last transformer block
- Final LayerNorm
- LM head
- Custom classification head

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Benefits:

- Reduces trainable parameters significantly
- Prevents overfitting on small datasets
- Enables training on single 24GB GPU

6. Training Methodology

Efficiency Techniques

Memory Optimization

- **4-bit Quantization** (NF4)
- Reduces memory by ~75%
- Uses `bitsandbytes` backend

Gradient Stability

- Gradient clipping (max norm = 1.0)
- `bfloat16` precision
- Prevents NaN values

Optimizer: AdamW

Learning rate	5×10^{-5}
Weight decay	0.1
Scheduler	Cosine + warmup
Warmup ratio	15%

Training Config

- 3 epochs
- 70/20/10 train/val/test split
- Batch size: 4

Handling Class Imbalance

Weighted Cross-Entropy Loss:

Class weights based on inverse frequency:

$$\text{weights} = [225, 175, 80, 130, 175, 900, 70, 30]$$

$$\text{normalized} = \frac{\text{weights}}{\sum \text{weights}} \times 8$$

Effect:

- Higher penalty for minority classes
- Forces model to learn rare categories

Without Weighting

- Model overfits to *Noise* and *Objective*
- Near-zero F1 for minorities
- Accuracy appears high but misleading

7. Instruction Fine-Tuning

Instruction Fine-Tuning Approach

Key Steps:

1. **Tokenization of Prompt-Response Pairs**
   Concatenate prompt + input text
2. **Sequence Shifting**
   $Y = [x_1, x_2, \ldots, x_N]$ from $X = [x_0, x_1, \ldots, x_{N-1}]$
3. **Masking Non-Label Tokens**
   Set prompt tokens to `-100` (ignored)
4. **Label Alignment Verification**
   Ensure exact match of label tokens

Model Used: Gemma3:27B

Objective

- ◇ Next-token prediction
- ◇ Loss only on answer tokens
- ◇ Preserves autoregressive nature

Benefit

Better alignment with instruction-based reasoning

8. Results

Experimental Comparison: Classification vs. Instruction Tuning

Run 1: Classification Fine-tuning

Method: Standard supervised learning (Flat 8-class head).

Reddit (500 samples):

- **Subjective:** 41.4% (Dominated by opinion)
- **Objective:** 31.6%
- **Noise:** 27.0%

Twitter (500 samples):

- **Noise: 64.4%** (Model collapsed to majority)
- **Objective:** 18.2%
- **Subjective:** 17.4%

Run 2: Instruction Fine-tuning

Method: Prompt-response (Next-token prediction).

Reddit (500 samples):

- **Objective:** 44.6% (Better factual detection)
- **Noise:** 28.2%
- **Subjective:** 27.2%

Twitter (500 samples):

- **Noise: 46.6%** (Significant reduction)
- **Subjective:** 35.6% (Better opinion recovery)
- **Objective:** 17.8%

Impact on Minority Classes (QnA Dataset)

The Challenge

In the QnA dataset, **Class 1 (Relevant/Question)** is a severe minority compared to **Class 0 (Noise/Irrelevant)**.

Category	Run 1 (Class. Head)	Run 2 (Instruct.)
Class 0 (Majority)	99.75%	91.11%
Class 1 (Minority)	0.25%	**8.89%**

Improvement Factor

35 $\times$

Improvement in minority class recognition.

Key Findings & Analysis

Why Instruction Tuning Won?

- **Reduced Noise Dominance:** Run 2 successfully shifted predictions away from the "safe" majority class (Noise).
- **Minority Coverage:** Significant gains in *Questions* and *Advertisements* categories.
- **Alignment:** The prompt-response format aligns better with the model's pre-trained reasoning capabilities.

Remaining Challenges

- **Noise Persistence:** Even in Run 2, noise remains a high percentage for Twitter (46.6%), due to the messy nature of the platform's data.
- **Subjective/Objective Flip:** In Reddit, Run 2 favored Objective labels more than Run 1, altering the distribution profile.

Conclusion: Instruction fine-tuning offers superior robustness for imbalanced, hierarchical datasets compared to standard classification heads.

9. Challenges & Solutions

Challenges I: Training Stability & Resources

Gradient Explosion

The Problem:

- Training destabilized early on.
- Large gradients caused weight updates to spiral.
- Resulted in **NaN values** in output tensors.

The Solution:

1. **Gradient Clipping:** Capped max norm at `1.0` to constrain updates.
2. **Precision Shift:** Switched from `float32` to **`bfloat16`**.
3. *Result:* Prevents numerical overflow while maintaining dynamic range.

Memory Overflow (OOM)

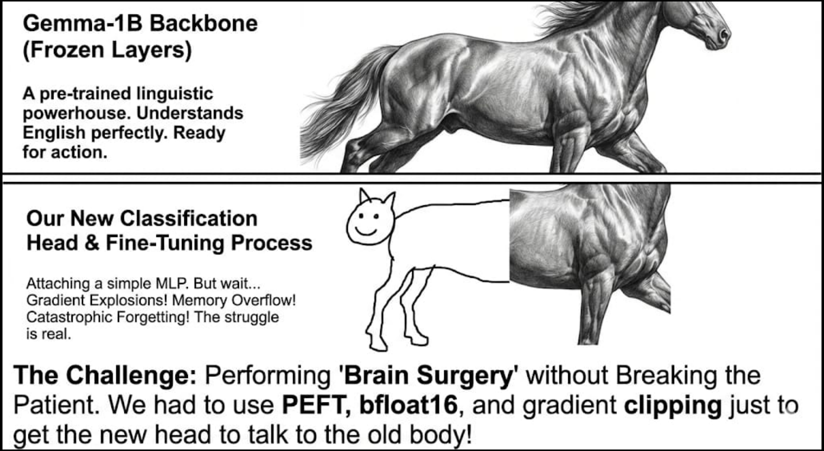
The Problem:

- 24GB VRAM limit on single GPU.
- Quadratic complexity of attention mechanism.
- `float32` weights exceeded capacity immediately.

The Solution:

1. **4-bit Quantization:** Used NF4 (NormalFloat4) via `bitsandbytes` ($\sim$75% reduction).
2. **Batch Size Reduction:** Reduced training batch size from 8 $\rightarrow$ 4.
3. *Result:* Enabled fine-tuning of 1B parameters on consumer hardware.

Visualization



Challenges II: Optimization & Generalization

Overfitting to Majority Classes

The Problem:

- Model achieved high surface-level accuracy.
- *Reality:* It was predicting "Noise" or "Objective" for everything.
- **F1-Score** $\approx$ **0** for minority classes (Questions, Ads).

The Solution:

- **Weighted Cross-Entropy Loss:**
- Calculated inverse frequency weights:

$$w_c = \frac{N}{N_c}$$

- Penalized misclassification of rare classes heavily.

Stagnant Convergence

The Problem:

- Accuracy plateaued at $\sim$50% during mid-training.
- Model unable to escape local minima.

The Solution:

- **Architecture Tuning:** Added extra `LayerNorm` before the head.
- **Regularization:** Introduced `Dropout (p=0.4)` to prevent neuron co-adaptation.
- **Activation:** Switched to GELU for smoother gradients.

10. Conclusion

Conclusion: The "Gemma-1B" Report Card

The Objective

To teach a **small model** (1B) to understand **complex human opinions** without breaking the hardware.

The Reality

"Social media data is 90% noise, 10% anger, and 0.01% actual questions."

Final Grades:

Subject	Grade	Teacher's Comment
Resource Usage	**A+**	Fit 1B params into 24GB. *"The GPU is warm, but alive."*
Minority Classes	**A**	Jumped from 0.25% $\rightarrow$ 8.89% recall. *"Finally found the Questions!"*
Noise Filtering	**B-**	Twitter is still 46% noise. *"Some things can't be fixed."*
Overall Vibe	**Pass**	Instruction Tuning $>$ Classification Head.

Final Takeaway: *You don't need a massive model to solve hierarchical problemsjust a very specific prompt and a lot of gradient clipping.*

11. Conclusion

Summary

- Adapted Gemma-1B for **8-class hierarchical opinion classification**
- Implemented **parameter-efficient fine-tuning**:
  - → Custom classification head
  - → Selective layer unfreezing
  - → 4-bit quantization for memory efficiency
- Compared two approaches:
  - → **Classification fine-tuning:** Direct supervised learning
  - → **Instruction fine-tuning:** Better minority class coverage
- Addressed **class imbalance** via weighted loss functions
- Demonstrated effectiveness on **Reddit, Twitter, YouTube, QnA** datasets

Future Directions

Extensions

- Cross-domain generalization
- Cross-lingual adaptation
- Hierarchical label dependency modeling

Improvements

- Robustness to noisy data
- Temporal pattern analysis
- Refined evaluation metrics

Code Available:

`https://github.com/Shuvam-Banerji-Seal/FIRE_2025_Hierarchical_Opinion_Classification_using_Large_Language_Models`

12. Acknowledgments

Acknowledgments

We thank Dr. Dwaipayan Roy

Department of Computational and Data Sciences (CDS)
Indian Institute of Science Education and Research, Kolkata

for providing the computing resources for our fine-tuning runs.

Thank You!

Questions?