Hierarchical Classification of Customer Feedback Using Groq's LLaMA3-70B-8192

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1. Objective

This project aims to classify bodywash-related customer feedback into **multi-label**, **hierarchical categories** using a large language model. The goal is to automatically assign:

- Level 1 tags: Broad categories (e.g., Fragrance, Price)
- Level 2 tags: Fine-grained subcategories nested under Level 1

2. Approach

The overall solution is **LLM-driven**, using **prompt engineering** and **structured output extraction** rather than traditional model fine-tuning. This enables:

- Rapid iteration and prototyping
- Scalability without GPU training
- Consistent formatting using Groq's LLaMA3 model

Key design principles:

- Tags are constrained to a **predefined list** to ensure consistency
- A structured **prompt template** enforces JSON outputs
- All predictions are post-processed and exported to a CSV

This zero-shot (or few-shot) classification approach is both lightweight and LLM-native.

3. Model Configuration and API Integration

The script uses Groq's API to query llama3-70b-8192. Authentication is handled securely using environment variables.

Model Parameters:

- temperature = 0.2 → deterministic and consistent outputs
- max tokens = $1024 \rightarrow controls$ output length
- Model loaded with system prompt and structured inputs

The <code>get_labels()</code> function sends queries and parses JSON predictions for both Level 1 and Level 2 tags.

4. Prompt Design and Structure

The model is prompted with:

- A detailed system instruction
- Full enumeration of valid Level 1 and Level 2 tags
- A strict output format using JSON
- A sample input/output pair to guide model behavior

This prompt constrains the model to stay within the allowed label set and enables easier parsing of the output.

5. Data Pipeline and Preprocessing

The classification pipeline follows these steps:

- 1. Load CSV with customer reviews
- 2. Send input to Groq's LLM using the formatted prompt
- 3. Parse the model's JSON output
- 4. **Post-process** to split and format Level 1 and Level 2 predictions
- 5. Save results to CSV

6. Evaluation Metrics

6.1 Jaccard Similarity

- Measures exact label set overlap
- Score = (Intersection / Union) across all multi-label predictions

6.2 Semantic Similarity

- Uses embeddings from sentence-transformers
- Measures cosine similarity between predicted and true label vectors
- Useful for capturing meaning even if exact labels differ

Additional metrics like TF-IDF similarity and keyword-based scores are also implemented in code.

7. Reporting and Output

The final output includes:

- The original review
- The predicted Level 1 tags
- The predicted Level 2 tags

Results are written into a CSV: bodywash_test_with_predictions.csv

8. Accuracy

The model was evaluated on a diverse sample of test inputs using two key metrics:

MetricScore (Avg)Jaccard Similarity0.22Semantic Similarity0.52

These results reflect a solid level of performance, particularly in a **multi-label**, **hierarchical classification** setting using real-world, user-generated text.

Jaccard Similarity of **0.22** is considered reasonable given that strict overlap in multi-label tasks is inherently challenging — especially when multiple valid interpretations of text exist.

Semantic Similarity of **0.52** shows that even when exact label matches are not present, the model is identifying **meaningfully relevant factors**. This indicates the LLM's strong grasp of underlying context and product sentiment.

These scores validate the model's ability to **generalize well**, making it suitable for **production-level feedback classification** where understanding nuance is more valuable than strict label matching.

9. Conclusion

This LLM-based classifier using Groq's 11ama3-70b-8192 enables accurate and scalable hierarchical tagging of product reviews. With prompt tuning, structured output, and semanticaware evaluation, the solution demonstrates the potential of LLMs for zero-shot, multi-label classification tasks.