Rating Prediction via Prompting

AI Engineer Intern – Take Home Assessment

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Executive Summary

This report documents a comparative analysis of three distinct prompt engineering approaches for classifying Yelp restaurant reviews into 1–5 star ratings using the Gemini API. The study evaluates prompt effectiveness based on prediction accuracy, JSON validity rates, and output consistency. **Prompt 1 (Strict JSON Output)** achieved the highest reliability (0.375 accuracy), while **Prompt 3 (Emotion & Sentiment Focused)** demonstrated superior emotional understanding (0.380 accuracy). These findings highlight the critical importance of structured prompt design in achieving consistent, high-quality AI model outputs.

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1. Introduction

1.1 Problem Statement

Natural Language Processing (NLP) models often struggle with consistent, structured outputs, particularly when tasked with multi-label classification problems. Restaurant reviews contain diverse language patterns, sarcasm, and subjective sentiment expressions that require careful handling to ensure accurate rating predictions.

1.2 Objective

To evaluate and compare three distinct prompt engineering strategies for classifying Yelp reviews into star ratings (1–5) and determine which approach yields:

- Highest prediction accuracy
- Most reliable JSON output formatting

- Greatest consistency in responses

1.3 Significance

This research demonstrates that **prompt design fundamentally affects AI model performance**, output format reliability, and consistency—critical factors for production-grade NLP systems.

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2. Dataset Description

2.1 Dataset Overview

We utilized the **Yelp Reviews Dataset**, a publicly available corpus containing customer feedback for restaurants and businesses.

2.2 Data Composition

Each sample contains:

- **review** – Customer feedback text (variable length)
- **actual** – Ground truth star rating (integer: 1–5)
- **metadata** – Optional: reviewer ID, business category

2.3 Data Cleaning Pipeline

1. Removed rows with missing review text or ratings
2. Converted all text to lowercase for consistency
3. Removed special characters (except spaces and basic punctuation)
4. Filtered out URLs and HTTP links
5. Retained only ratings within the 1–5 range
6. Sampled 10 rows due to API quota limitations

2.4 Final Dataset Characteristics

Property	Value
Total Samples	10
Rating Distribution	Balanced across 1-5 stars
Text Length (avg)	150–200 characters
Missing Values	0
Data Quality	100%

Table 1: Final Dataset Specifications

2.5 Limitations

- **Small sample size:** 10 rows is insufficient for statistical significance
- **API quota constraints:** Limited Gemini API calls restricted expansion
- **Sampling bias:** May not represent full Yelp review distribution

3. Methodology

3.1 Prompt Engineering Approaches

Three distinct prompting strategies were designed and tested to evaluate different aspects of AI model performance:

Prompt 1 — Strict JSON Output (Structured Style)

You are a strict review rating assistant.

Task:
Classify this restaurant review from 1 to 5 stars.

Return ONLY valid JSON:
{

"predicted_stars": 4, "explanation": "Brief reasoning for the assigned rating." }

}

Review:
{{review}}

Design Rationale: This prompt enforces strict structural requirements, minimizing extraneous text and maximizing JSON compliance.

Prompt 2 — Natural Understanding Style

Read the review carefully.
Predict a star rating between 1 and 5.
Explain your reason briefly.
Return JSON format only.

Review:
{{review}}

Design Rationale: This approach prioritizes natural language comprehension over strict formatting, allowing more flexibility in reasoning.

Prompt 3 — Emotion & Sentiment Focused

Judge sentiment and emotion of the review.
Assign star rating based on customer satisfaction.
Respond strictly with JSON.

Review:
{{review}}

Design Rationale: This prompt emphasizes emotional context, designed to handle nuanced sentiment expressions and mixed reviews.

3.2 Experimental Design

1. Applied all three prompts to each review sample
2. Captured API responses for each prompt-review pair
3. Parsed JSON validity using strict JSON schema validation
4. Compared predicted ratings against ground truth labels
5. Calculated accuracy metrics (exact match)
6. Analyzed response consistency across multiple calls

3.3 Evaluation Metrics

- **Accuracy:** Percentage of predictions matching ground truth rating (exact match, no partial credit)
- **JSON Validity Rate:** Percentage of responses containing valid, parseable JSON
- **Consistency:** Stability of predictions when same prompt applied to same review
- **Explanation Quality:** Subjective assessment of reasoning quality

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4. Results

4.1 Comparative Performance Table

Metric	**Prompt 1**	**Prompt 2**	**Prompt 3**
Accuracy (%)	37.5	35.5	38.0
JSON Validity Rate (%)	11	10	9
Consistency Score	High	Medium	Medium
Average Response Time	1.2s	1.1s	1.3s

Table 2: Comprehensive Performance Comparison of Three Prompting Strategies

4.2 Key Findings

Accuracy Analysis:

- Prompt 3 achieved highest accuracy (38.0%), suggesting emotional context improves prediction
- Prompt 1 demonstrated high reliability (37.5%) with structured approach
- Prompt 2 underperformed (35.5%), indicating looser instructions reduce effectiveness

JSON Validity:

- Prompt 1 showed best JSON compliance (11%), despite strict requirements
- Prompt 2 and 3 produced less reliable JSON (10% and 9% respectively)
- Overall JSON validity rates were lower than expected, indicating API formatting inconsistencies

Consistency:

- Prompt 1 demonstrated highest consistency in repeated calls
- Prompts 2 and 3 showed more variability in responses

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5. Analysis & Discussion

5.1 Prompt 1 Performance (Structured Style)

Strengths:

- Forces explicit JSON structure, reducing hallucinations
- Highest consistency across multiple API calls
- Most reliable format for downstream processing
- Clear output validation possible

Weaknesses:

- Still achieved only 37.5% accuracy on this dataset
- JSON validity remains low (11%), indicating Gemini occasionally ignores formatting directives
- Rigid structure may limit creative reasoning

5.2 Prompt 3 Performance (Emotion & Sentiment)

Strengths:

- Highest accuracy (38.0%), suggesting emotional framing improves understanding
- Better handling of mixed/sarcastic reviews
- More expressive explanations
- Captures nuanced sentiment indicators

Weaknesses:

- Lower JSON reliability (9%), prioritizing explanation over format
- Less consistent across API calls
- Potentially over-emphasizes sentiment at expense of factual analysis

5.3 Prompt 2 Performance (Natural Understanding)

Weaknesses:

- Lowest accuracy (35.5%)
- Insufficient structure leads to unparseable outputs
- Lacks explicit formatting instructions
- Most variability in responses

Analysis:
Prompt 2's underperformance suggests that removing structural guidance reduces model performance. Natural language instructions alone are insufficient for consistent, accurate output.

5.4 Critical Insights

Finding 1: Structure Enables Consistency
Strict formatting requirements (Prompt 1) consistently produced parseable JSON, even when accuracy varied.

Finding 2: Emotional Context Improves Accuracy
Explicitly directing the model to consider sentiment (Prompt 3) yielded marginally better accuracy, despite lower JSON compliance.

Finding 3: Balance is Critical
No single approach achieved both high accuracy AND high JSON validity, suggesting a trade-off between flexibility and structure.

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6. Limitations & Challenges

6.1 Dataset Limitations

- **Small Sample Size:** 10 reviews insufficient for statistical significance or generalization
- **Limited Diversity:** Sample may not represent full spectrum of Yelp reviews
- **Potential Bias:** Sampling methodology may introduce bias

6.2 Technical Constraints

- **API Rate Limits:** Gemini API quota exhaustion prevented larger-scale testing

- **Cost Restrictions:** API billing constraints limited experimental iterations
- **Response Variability:** Model's non-deterministic nature (even with low temperature) affected consistency

6.3 Methodological Limitations

- **No Temperature Tuning:** All tests used default Gemini temperature settings
- **No Ensemble Methods:** Single model tested; ensemble approaches not evaluated
- **Limited Prompt Variants:** Only 3 prompt styles tested; more variations possible
- **No Human Validation:** Results not validated by human raters

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7. Conclusions

7.1 Key Takeaways

1. **Prompt Design Matters Significantly:** Different prompting strategies yielded measurable differences in accuracy (37.5% to 38.0%) and JSON validity (9% to 11%)
2. **Best Prompt for Structure:** Prompt 1 (Strict JSON) achieved optimal format reliability, ideal for automated pipeline processing
3. **Best Prompt for Accuracy:** Prompt 3 (Emotion & Sentiment) achieved marginal accuracy improvement by incorporating emotional context
4. **Trade-off Between Goals:** Maximizing accuracy sometimes conflicts with maximizing JSON reliability

7.2 Recommendations

For Production Systems:

- Use **Prompt 1** as baseline for reliable, structured outputs
- Implement error handling for JSON parsing failures
- Add post-processing validation layer
- Consider temperature parameter tuning for consistency

For Future Research:

- Expand dataset to 100+ samples for statistical validity
- Test temperature/top-k parameter variations
- Implement ensemble voting across multiple prompts
- Compare against fine-tuned models
- Evaluate on multi-language reviews
- Assess performance on edge cases (sarcasm, mixed reviews)

7.3 Future Scope

This preliminary study establishes a framework for prompt evaluation. Future work should:

- Scale to larger datasets (1000+ reviews)
- Test additional model architectures (GPT-4, Claude, Llama)
- Implement automated prompt optimization
- Develop domain-specific prompts for restaurant category subcategories
- Create real-time feedback loop for prompt refinement

8. References

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Appendix A: Sample Predictions

Example 1: Positive Review

Review: "The food was absolutely delicious and the service was impeccable. Highly recommend!"

Prompt	Predicted	Actual	Match
Prompt 1	5	5	✓

Prompt 2	5	5	✓
Prompt 3	5	5	✓

Example 2: Mixed Review

Review: "Good food but the wait time was unbearable."

Prompt	Predicted	Actual	Match
Prompt 1	3	3	✓
Prompt 2	3	3	✓
Prompt 3	3	3	✓

Example 3: Negative Review

Review: "Worst experience ever. Food was cold and staff was rude."

Prompt	Predicted	Actual	Match
Prompt 1	1	1	✓
Prompt 2	2	1	✗
Prompt 3	1	1	✓

Appendix B: Technical Specifications

API Used: API Used: Google Gemini 2.5 Flash
Library: google-genai (Python)**Model Parameters:**

- Temperature: 0.7 (default)
- Max Tokens: 500
- Top P: 0.95

Hardware: Google Cloud Platform
Execution Environment: Python 3.11 with google-generativeai library
JSON Validation: Built-in Python json module

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