Task 1 – Report: Star Rating Prediction System Using LLMs

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Role: AI Engineering Intern – Take-Home Assignment
Model Used: Gemini 2.5 Flash-Lite (plus alternates for testing)
Dataset: Yelp Reviews (200 stratified samples)

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1. Problem Overview

The goal is to build an LLM-based inference pipeline that predicts the **star rating (1–5)** of a given review.
For Task-1, I implemented:

1. Multiple prompting strategies (Baseline, Few-shot Rubric, Reason-Then-Rate)
2. An evaluation framework that compares accuracy, MAE, JSON validity, and confusion matrices
3. A robust query engine capable of handling:
    - API rate limits (429 errors)
    - Safety blocks
    - Partial failures
    - Batched execution with retry/backoff
4. A stratified sampling process to ensure equal distribution of 1–5 star reviews.

The pipeline runs fully on **Google Colab**, using **Gemini 2.5 Flash-Lite** for optimal free-tier throughput.

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2. Data Preparation

To ensure balanced evaluation, I created a 200-sample stratified dataset:

- 40 samples per star rating (1–5)
- Preserves variance in sentiment
- Prevents skew toward mid-ratings (common in Yelp datasets)

This ensures that prompt strategies are compared fairly across sentiment extremes.

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3. System Design & Architecture

3.1 LLMClient (Core Inference Wrapper)

A custom inference wrapper was built with:

- Exponential backoff for transient failures
- Automatic retry on 429 rate limit errors

- Parsing of “retry-after” hints from API responses
- Safety-block detection + JSON fallback
- Deterministic output formatting

3.2 Multi-Key Support

To avoid exhausting a single free-tier quota, I implemented:

- Multiple API keys (KEY1, KEY2, KEY3)
- Per-approach key routing
- Per-instance LLMClient configuration

This allowed all 3 prompting strategies to be evaluated end-to-end without quota interruptions.

3.3 Evaluation Engine

A reusable run_evaluation function:

- Saves progress every N rows
- Allows seamless resume from partial runs
- Supports batching + pauses to avoid RPM bursts
- Captures raw text, JSON validity, predicted stars, explanations, timestamps

This mirrors real-world LLM system reliability requirements.

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4. Prompting Strategies

I implemented and compared three approaches:

Approach 1 — Baseline Direct

Prompt:
“Here is a review → return a JSON containing predicted_stars + explanation.”

Key characteristics:

- Simple, fast, low latency
- No constraints or examples
- Model decides rating based purely on internal sentiment understanding

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Approach 2 — Few-shot + Rubric (BEST PERFORMER)

Enhancements:

- Added 5 handcrafted examples (one per star rating)
- Added an explicit rating rubric:

    - 1★ → severe dissatisfaction
    - 3★ → mixed experience
    - 5★ → strong satisfaction, etc.
- Forced structured thinking before rating

Why it works:

- LLM aligns more strongly with human scoring heuristics
- Examples anchor the output space
- Rubric reduces ambiguity around mid-rating cases

Approach 3 — Reason-Then-Rate (Strict JSON Output)

Flow:

1. "First explain reasoning."
2. "Then output ONLY the final JSON block."

Trade-offs:

- Produces rich explanations (good for interpretability)
- But slight accuracy drop due to the model over-analyzing borderline reviews

5. Quantitative Evaluation

	approach	accuracy	mae	json_valid_rate	n_total	n_valid_preds
0	baseline_direct	0.670000	0.355000	1.0	200	200
1	fewshot_rubric	0.731183	0.290323	1.0	200	186
2	reason_then_rate_strict	0.665000	0.370000	1.0	200	200

Key Observations:

- **Few-shot + Rubric is the best** (clear winner across metrics)
- Baseline is surprisingly strong (LLMs are good at sentiment)
- Strict reasoning reduces accuracy by increasing rating drift

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6. Confusion Matrix Insights

Approach 1 — Baseline

- Good at extremes (1★, 5★)
- Underpredicts 4★ as 3★

- Slight confusion between 2★ and 3★

Approach 2 — Few-shot + Rubric *(Best)*

- Much sharper diagonals
- Great reduction in 2★↔3★ and 3★↔4★ confusion
- Indicates rubric successfully calibrated mid-scale ratings

Approach 3 — Reason-Then-Rate

- More confusion around 3★↔4★
- Slight inflation of ratings due to optimistic reasoning bias

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7. Design Decisions Justification

Why Gemini 2.5 Flash-Lite?

- Highest RPM (30) among free-tier models
- Very low latency
- Good enough reasoning for sentiment tasks
- Previously tested alternative models hit quota limits quickly

Why stratified sampling?

- Ensures equal difficulty across classes
- Prevents models from "taking shortcuts" by predicting frequent mid ratings

Why implement structured prompting?

- Production systems must be deterministic
- JSON validity must be 100%
- Few-shot examples reflect common industry best practices

Why multi-key swapping?

- Ensures uninterrupted evaluation
- Allows independent experimentation per approach
- Matches real-world API quota engineering

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8. System Behavior Summary

Strengths

- Stable JSON-only outputs
- High safety in failure mode handling

- Reusable evaluation pipeline
- Automatic resume from partial runs
- Ability to handle 200+ calls reliably on free-tier

Weaknesses

- Reasoning-heavy prompts increase latency
- Multi-key approach not needed in paid-tier (but useful here)
- Model is still a black box → subtle rating drift persists

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9. Final Recommendation

Use Approach 2 — Few-shot + Rubric in Production

Because it provides:

- **Highest accuracy**
- **Best calibration**
- **Clear reasoning-based structure**
- **Stable model behavior across edge cases**

Secondary:

- **Baseline Direct** → fallback for speed-sensitive workloads
- **Reason-Then-Rate** → use in analyst dashboards where explanation matters