GenAl Accelerator

Introduction to LLM Evaluations

by Dave Ebbelaar

Every AI Engineer will ask at some point:

- What will happen if we adjust the system prompts?
- How do I know my RAG pipeline is working correctly?
- Are we performing the correct classification step?
- Besides factual accuracy, is the tone of voice on point?
- How will this behave with real user inputs we haven't seen yet?
- Are we catching unsafe or problematic outputs before users see them?
- How do we know when the system performance is degrading in production?
- Is our system robust enough to flag prompt injections?

The Challenge

By now, we know that unlike traditional software:

- LLM outputs are non-deterministic
- Responses are often **subjective** and context-dependent
- A response may be factually correct but "vibes are off"
- Multiple valid responses can exist
- Failure modes are subtle and hard to predict

Core Question: How can we effectively evaluate AI system performance and identify specific areas where improvements are needed?

Three Core Challenges in LLM Development

Every team building LLM applications faces these fundamental challenges:



Understanding the Data

You build a workflow, but when users start interacting with it, you realize you don't understand what's actually happening at scale. What are users asking? How is your system responding? Where are the edge cases?



Specification Gaps

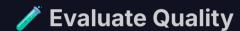
There's always a gap between what you want your system to do and what you can actually specify in prompts and code. You know good output when you see it, but translating that into clear instructions is surprisingly hard.



Inconsistent Behavior

Your LLM works great on your test cases, but then behaves unpredictably on real user inputs. Small changes in wording can lead to completely different outputs, making your system feel unreliable.

Success with AI = How fast you can iterate



Systematic measurement of your workflow's performance through automated tests, human evaluation, and success metrics.

Tools to understand and diagnose failures including trace logging, data inspection, and error analysis.

Change Behavior

Techniques to improve your system based on insights from evaluation and debugging.

Most teams focus only on #3, which prevents them from improving beyond a demo. Doing all three creates a virtuous improvement cycle.

What is Evaluation?

Evaluation = Systematic measurement of quality in an Al system

© An "Eval" is a single metric that measures a specific aspect of performance

- Factual accuracy
- Tone appropriateness
- Following instructions
- Output format compliance

X Evals can be operationalized as:

- Background Monitoring: Track performance over time
- Guardrails: Block bad outputs in real-time
- Improvement Tools: Label data for fine-tuning

The Analyze-Measure-Improve Lifecycle [1]

This iterative cycle addresses the three core challenges through systematic evaluation and creates a flywheel for continuous improvement.



[1] Based on "Application-Centric Al Evals for Engineers and Technical PMs" by Shankar & Husain, 2025

The Three Levels of Evaluation

Cost and effort increase with each level, dictating when and how often you run them



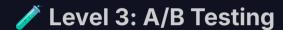
Fast, cheap assertions that run on every code change

- Run: Every commit
- Cost: Very Low



Systematic review and automated critique of quality

- Run: Weekly/Biweekly
- Cost: Medium



Real user experiments to measure business impact

Run: Major releases

Cost: High

Level 1: Unit Tests for LLMs

What are LLM Unit Tests?

- Fast, automated assertions
- Check specific, testable properties
- Organized for reuse beyond testing
- Run on every code change
- Don't require 100% pass rate

When to Use

- Data cleaning and validation
- Automatic retries with feedback
- CI/CD workflows
- Catching obvious failures

Example: Structured Output Test

```
python

def test_ticket_categorization():
    # Test case
    ticket = "My credit card was charged twice this month"

# Get the structured response
    result = categorize_ticket(ticket)

# Simple assertions
    assert result.category in ["billing", "technical", "general"]
    assert isinstance(result.confidence, float)
    assert 0 <= result.confidence <= 1

# Specific test for this input
    assert result.category == "billing" # We expect billing for this input</pre>
```

In Python, we can implement these tests using simple "assert" statements to verify LLM outputs meet expected criteria.

Level 2: Human & Model Evaluation



Muman Evals

Humans look at system outputs and score them

- Start with binary: Good/Bad
- Remove ALL friction from data viewing
- Build custom tools for your domain
- Look at as much data as possible initially
- Save good examples for later reference

Model Evals (LLM-as-Judge)

Use a LLM to critique your system's outputs

- Use the most powerful model you can afford
- Focus on specific quality dimensions
- Generate detailed critiques, not just scores
- Must be aligned with human judgment
- Track human-model agreement over time

LLM-as-Judge systems need alignment with human evaluators. Track correlation and iterate on the judge's prompt until it agrees with humans.

LLM-as-Judge: Creating Aligned Evaluators

The Goal: Build an automated evaluator that thinks like your human experts

The Alignment Process

- 1. Collect model predictions
- 2. Generate model critiques
- 3. Get human evaluations on same data
- 4. Compare model vs human judgments
- 5. Iterate on evaluator prompt
- 6. Repeat until sufficient agreement

Example Judge Prompt

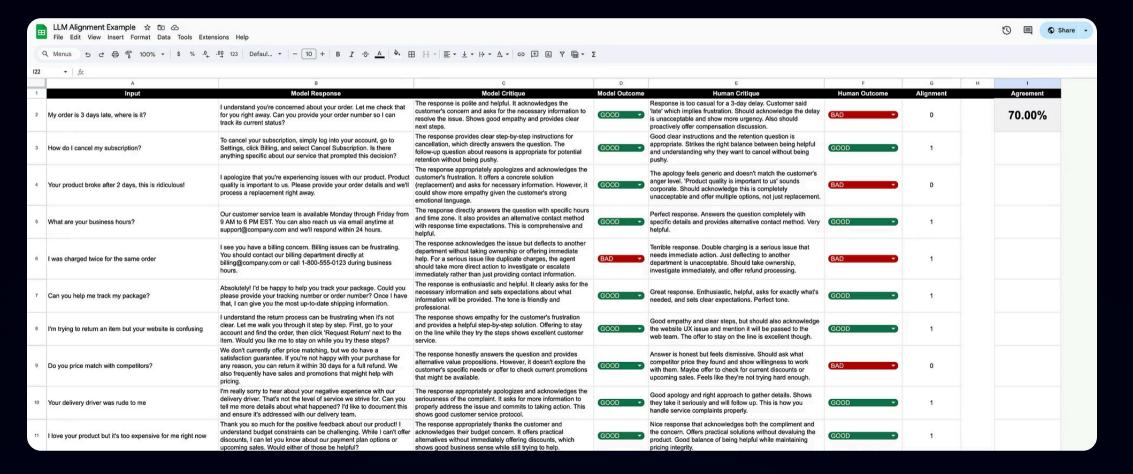
Evaluate this customer service response on these criteria:

- 1. Accuracy: Are the facts correct?
- 2. Helpfulness: Does it solve the customer's problem?
- 3. Tone: Is it professional and empathetic?

Provide a detailed critique explaining your reasoning, then rate 1 (Good) or 0 (Bad).

Pro Tip: Start with simple binary ratings and detailed critiques. Use the critiques to understand disagreements and refine your evaluator.

The Process





Level 3: A/B Testing

When to Use A/B Tests

- System is mature and stable
- You want to measure real user impact
- Testing significant changes
- Need business metric validation
- Comparing different approaches

What to Measure

- User satisfaction scores
- Task completion rates
- Time to resolution
- User engagement metrics
- Business outcomes (sales, retention)



Example: Prompt Comparison

Hypothesis: A more conversational prompt will improve user satisfaction

Setup:

- Control (A): Formal, direct responses
- Treatment (B): Conversational, empathetic tone

Results & Metrics

Metrics:

- User satisfaction rating (1-5)
- Conversation completion rate
- Follow-up questions needed

Result: Treatment B increased satisfaction by 15% with no decrease in accuracy

Types of Evaluation Metrics



Reference-Based

Compare LLM output against known "golden" answers

- Exact string matches
- Semantic similarity
- Code execution results
- SQL query correctness
- Structured data validation



Reference-Free

Evaluate inherent properties without "golden" answers

- Tone appropriateness
- Length constraints
- No hallucinations
- Format compliance
- Safety and toxicity

Common Mistakes to Avoid

X Tool-First Thinking

- RAG problems? → New vector database
- Accuracy issues? → Try different models
- Need metrics? → Buy an eval platform

Fix: Start with simple, custom solutions

X Generic Metrics Obsession

- Drowning in meaningless scores
- "Helpfulness: 4.2, Truthfulness: 4.5"
- What does this actually tell you?

Fix: Focus on specific, actionable metrics

X Avoiding Your Data

- "A tool will handle it"
- "Real users will tell us if broken"
- "Trust your gut"

Fix: Look at lots of real data constantly

X Unaligned LLM Judges

- Not measuring human-judge agreement
- Assuming the judge "just works"
- No validation process

Fix: Always validate judge alignment

Key Principles for Success

Start Simple & Specific

- Focus on your biggest problems first
- Use existing tools before buying new ones
- Build domain-specific evaluations
- Start with unit tests and manual review

Look at Lots of Data

- Manual inspection has the highest value-to-prestige ratio
- You're doing it wrong if you're not looking at data
- Sample broadly, then focus on patterns
- Never stop examining real examples

Remove All Friction

- Make data viewing effortless
- Build custom tools for your domain
- Automate repetitive evaluation tasks
- Track metrics over time

Use LLMs to Scale

- Generate test cases automatically
- Create synthetic data at scale
- Automate critique and labeling
- But always validate with humans

Building the Evaluation-Driven Workflow

o The Ultimate Goal: Create a system where improvement is systematic, not accidental

✓ You'll Know You're Succeeding When:

- You can deploy changes confidently
- Failures are caught before users see them
- You understand your system's behavior
- Improvements compound over time

You're Struggling If:

- Every fix breaks something else
- You're surprised by user complaints
- Progress feels like trial and error
- You can't measure if changes help