AIRFLOW SUMMIT

3.0

From Oops to Secure Ops:

Self-Hosted AI for Airflow Failure Diagnosis

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King — cross platform casual games

Candy Crush Saga

Candy Crush Soda Saga

Farm Heroes Saga

Large user base

over

200M

monthly players

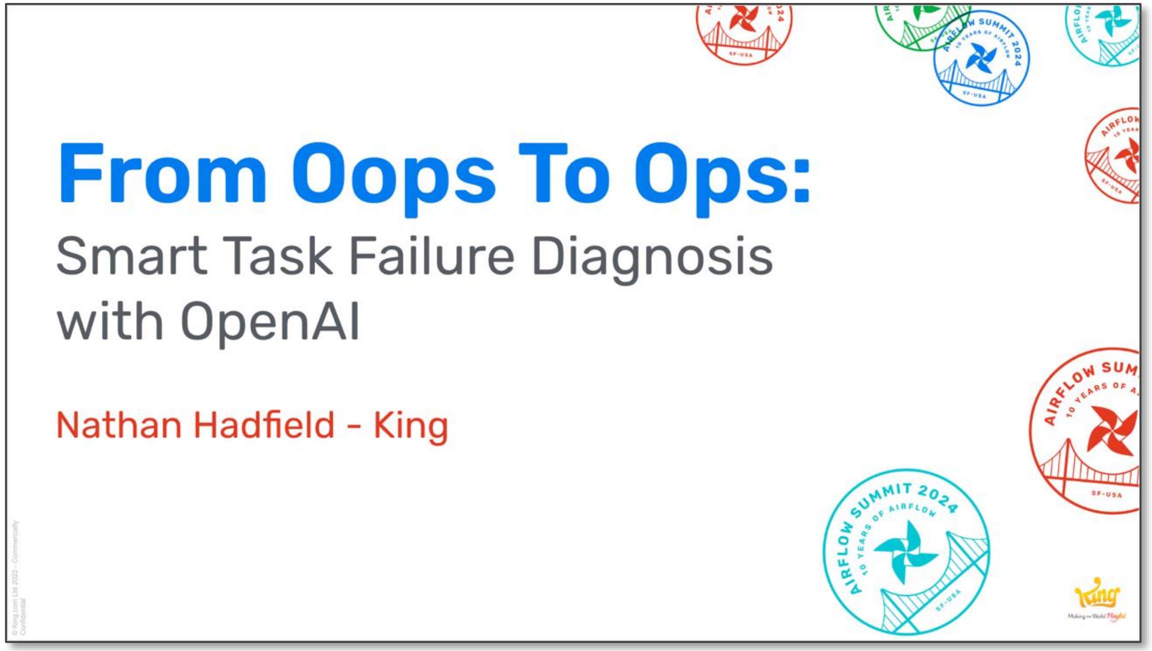
Growing content

>20K

levels in Candy Crush Saga alone

Let’s take a trip back in time...

Airflow Summit 2024



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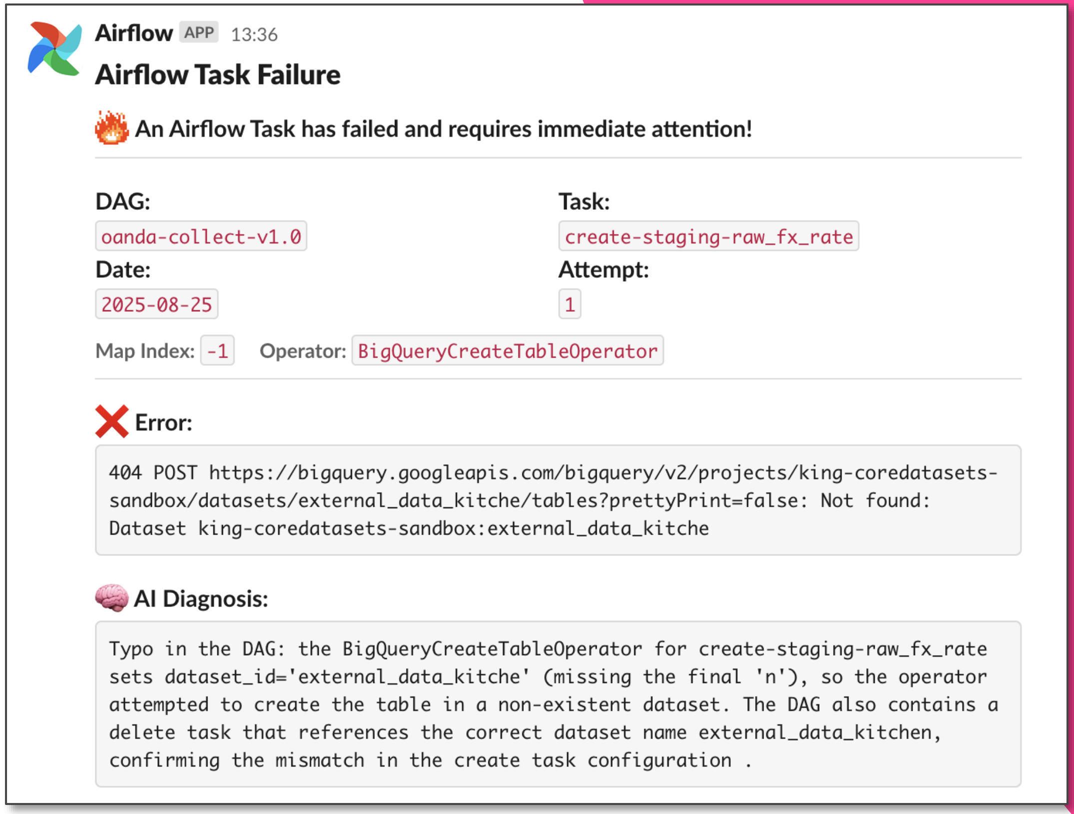
Recap: AI-Powered Failure Diagnosis (2024)

How It Worked

- 🔁 Triggered via `on_failure_callback`
- 🧠 OpenAI receives prompt, exception/traceback, DAG code & context
- 📥 Returns structured diagnosis (issue, root cause, suggested fixes)
- 📤 Output posted to task logs, Slack, or PagerDuty
- 🎯 Turn every Airflow task failure into an **instant, AI-powered root-cause triage**



🙋 Questions That Emerged Last Year

What were some of the issues?

💬 "Are we okay sending DAG code and tracebacks to a public API?"	🔐 Privacy & data security
💬 "What does this cost at scale?"	💸 Cost & sustainability
💬 "Can we swap models or providers?"	🔁 Flexibility
💬 "Do we even need a big LLM for this?"	🤔 Appropriateness

A year is a long time in AI

Why Revisit This?

What changed, what's new?

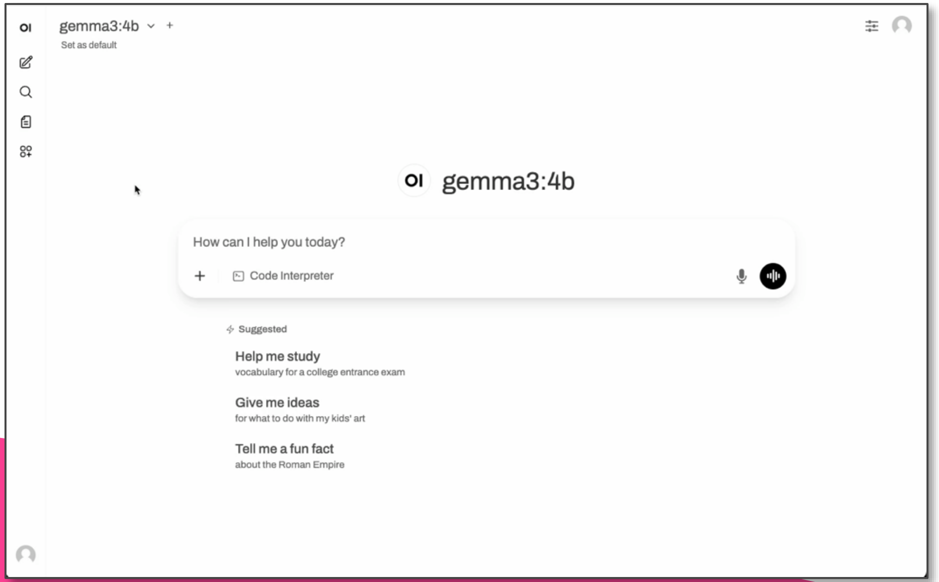
🧠 LLM Landscape Has Evolved

- Compact models (Qwen, Gemma, DeepSeek) now reasoning-capable
- Distilled variants span from ~1B to 70B+
- OpenAI-compatible APIs make integration seamless
- Ollama, OpenWebUI, LM Studio - tooling is robust, fast to deploy

```
~/Projects/king-airflow-dags  airflow_summit  ollama list
NAME                  ID              SIZE      MODIFIED
phi3.5:3.8b           61819fb370a3    2.2 GB    6 weeks ago
llama3.1:8b           46e0c10c039e    4.9 GB    6 weeks ago
qwen3:8b              500a1f067a9f    5.2 GB    6 weeks ago
gemma3:4b             a2af6cc3eb7f    3.3 GB    6 weeks ago
mistral:7b-instruct   6577803aa9a0    4.4 GB    6 weeks ago
llama3.2:3b           a80c4f17acd5    2.0 GB    6 weeks ago
llama3.2:1b           baf6a787fdff    1.3 GB    6 weeks ago
deepseek-r1:1.5b      e0979632db5a    1.1 GB    6 weeks ago
deepseek-r1:7b        755ced02ce7b    4.7 GB    6 weeks ago
```

📢 Why It Matters

- Easier than ever to run models privately
- No/Few changes to prompting or API logic
- No token costs or vendor lock-in
- AI-powered triage stays inside your infrastructure



🚧 What We Did This Year

Putting The Idea to the Test

🧱 Reused our Airflow callback-based diagnosis framework

🧠 Swapped in sub-10B compact models via OpenAI-compatible endpoints

🔧 Used Ollama + OpenWebUI to serve models locally

🎯 Applied to task failures — a pattern-rich, bounded domain well suited for compact models

✅ **Goal:** A fully **self-hosted, privacy-first** AI task failure diagnoser for Airflow

Testing the Models

Meet The Competitors

The Models in the Arena

GPT-5-mini	High-performance commercial baseline; establishes upper bound for quality.
GPT-4o-mini	Efficient GPT-4-tier model with strong instruction-following and low-latency performance; used here as a practical GPT baseline.
Qwen3:8B	Open-source model from Alibaba, tuned for reasoning and instruction tasks; competitive with GPT in several structured use cases.
Gemma3:4B	Lightweight, well-optimized Google model for on-device and self-hosted use.
Phi3.5:3.8B	Microsoft's compact reasoning model tuned with chain-of-thought techniques; excellent performance-to-size ratio and strong small-model baseline.
Mistral:7B-Instruct	Popular open model with strong instruction tuning; solid mid-size benchmark.
LLaMA3.2:3B	Meta's latest LLaMA release at the 3B scale; useful for assessing performance in low-resource settings.
LLaMA3.1:8B	Mid-sized baseline; helps assess scaling impact vs 3B version.
DeepSeek-R1:7B	Reasoning-focused 7B model from DeepSeek, trained using mixture-of-experts (MoE) techniques for improved efficiency.
DeepSeek-R1:1.5B	Stress-tests compact model performance under tight memory and inference constraints.
LLaMA3.2:1B	Useful lower bound to expose failure patterns in tiny models.

The Challenges

10 Failure Scenarios

⚠️ Missing Airflow Variable	Task fails because SOURCE_BUCKET variable not defined
📝 SQL Syntax Error	Query contains typo (FROMM instead of FROM)
📊 Schema Mismatch	Data types don't align with BigQuery table schema
⏱️ API Timeout	External API fails to respond within 30s
🚦 Rate Limited	API returns HTTP 429 "Too Many Requests"
📁 File Not Found	Expected GCS object missing (404 error)
🔒 Permission Denied	Service account lacks bigquery.tables.create
🧩 JSON Parse Error	Malformed JSON ('id':123 with single quotes/trailing comma)
📅 Date Parse Error	Invalid timestamp string (31/13/2025 25:61:00)
📦 XCom Too Large	Payload exceeds Airflow's 1MB XCom size limit

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📐 Scoring Criteria

What Makes a Useful Diagnosis?

Component	Description	Max Points
🕵️ - Identify	Does the model correctly name the issue?	35
🧷 - Evidence	Does it cite the relevant failure details?	30
🎯 - Root Specificity	Does it pinpoint the exact cause?	20
🛠️ - Solutions	Does it give actionable fixes?	15

⚖️ Bonuses & Penalties

Clarity Counts. So Does Bloat.

Label	Effect	Description
📜 Verbosity	Up to +10	Encourages detailed but non-repetitive output
🌐 Non-English	-12	Applies if significant non-English content detected
📦 Extra Solutions	-4 per extra	Discourages bloated solution sections
❌ Irrelevant SQL	-10	Applies if SQL query included outside SQL scenario

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Examples of Good vs Bad Diagnoses

```
if fail_case == 'missing_airflow_variable':
    # Simulate misconfigured environment
    raise KeyError(
        "Airflow Variable 'SOURCE_BUCKET' not found. "
        'Set it in Admin > Variables or provide via env var.'
    )
```

Good Diagnosis (High Score)

Issue: The task failed due to a missing Airflow variable named 'SOURCE_BUCKET'.

Root Cause: The failure is caused by the absence of the required Airflow variable 'SOURCE_BUCKET', which is expected to be set in the Airflow Admin interface under Variables or provided as an environment variable.

Suggested Fix: Set the Airflow variable 'SOURCE_BUCKET' in the Airflow Admin > Variables section.

Suggested Fix: Provide the 'SOURCE_BUCKET' variable as an environment variable in the Airflow configuration.

Suggested Fix: Check if the variable name is correctly referenced in the task and ensure there are no typos.

- ✅ Clear identification
- ✅ Cites specific error (SOURCE_BUCKET, Airflow context)
- ✅ Offers actionable advice (where to define it)

Bad Diagnosis (Low Score)

Issue: Describe and Diagnose Airflow Task Failure

Root Cause: External API Flakiness

Suggested Fix: Check the API endpoint URL

Suggested Fix: Verify the API credentials

Suggested Fix: Use a cached copy of the data

Suggested Fix: Implement error handling for API flakiness

Updated SQL: Suggest an alternative to BigQuery GCS To BigQuery operator if the problem persists. In this case, it seems like BigQuery is down or returning errors from the API endpoint. Consider using an external ETL service like Apache Beam, AWS Glue, or Google Cloud Dataflow instead.

- ❌ Vague and non-specific
- ❌ Hallucinates unrelated causes
- ❌ No direct reference to actual failure

How the Testing Works

Same Failures, Same Prompt, Same Rules

Scenario:

- 10 curated, realistic failure modes
- Each model sees the same failure

Diagnosis:

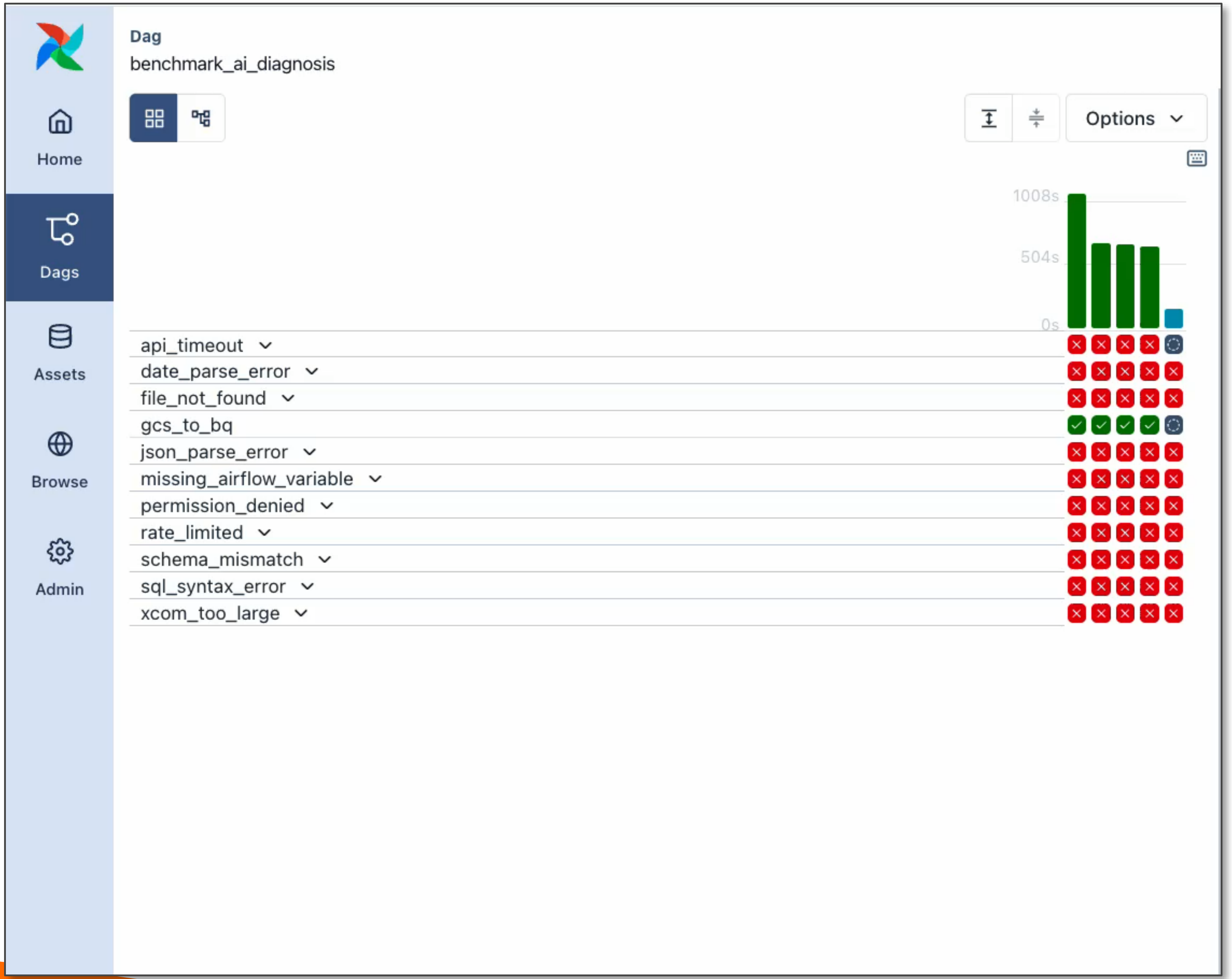
- Each model receives the same prompt and context

Scoring:

- Diagnoses are scored automatically
- Results are pushed to BigQuery for analysis

Automation:

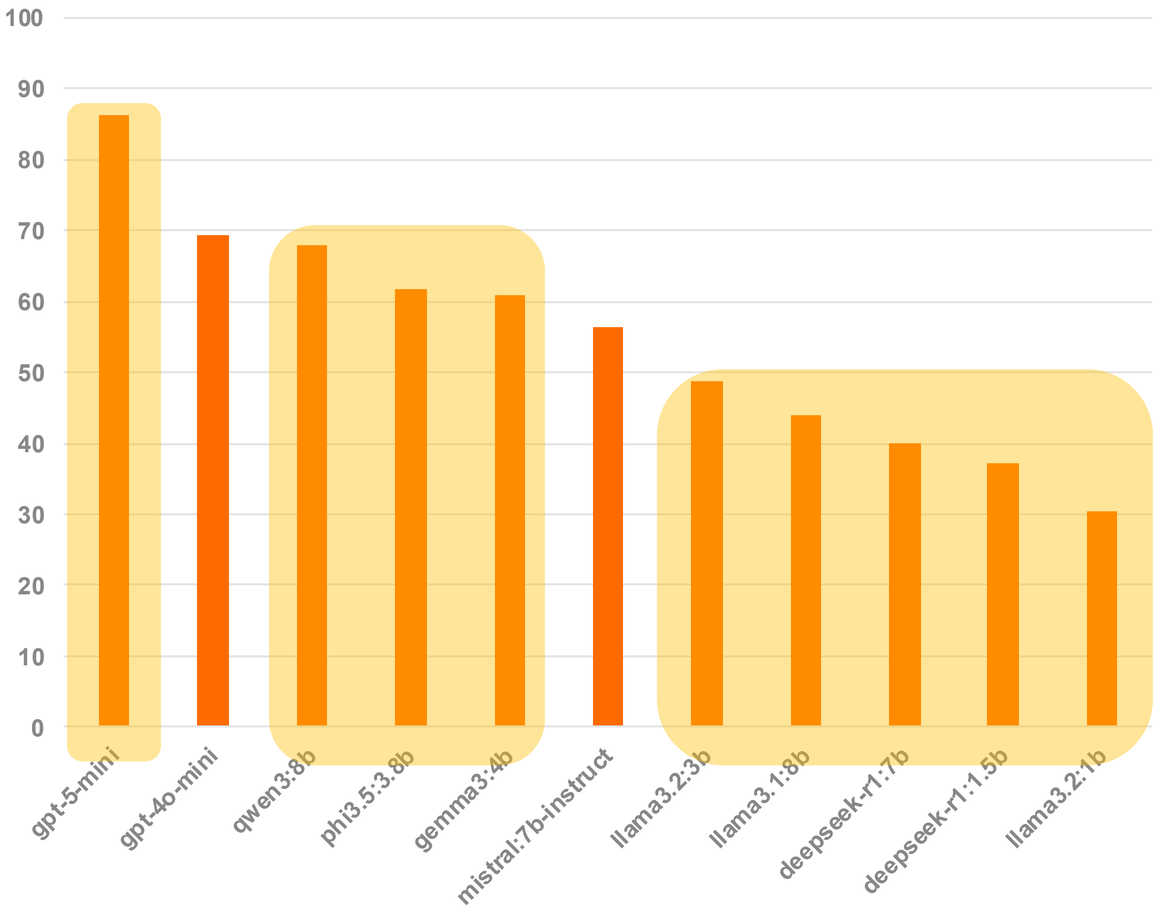
- Evaluation DAG that simulates failures, calls the model and score the diagnosis



Results

How Did They Score Overall

Average Score by Model



ⓘ Benchmark Scope
- 10 fixed Airflow failure scenarios
- Same prompt across all models
- No fine-tuning
- Diagnosis quality only (no cost/latency eval)
- Single-shot model calls

Clear performance gap

- **gpt5-mini** scores 24% higher than the best performing self hosted model

Strong middle tier

- **Qwen3:8B**, **Gemma3:4B**, and **Phi3.5:3.8B** cluster in the **60-68** range

Model family matters

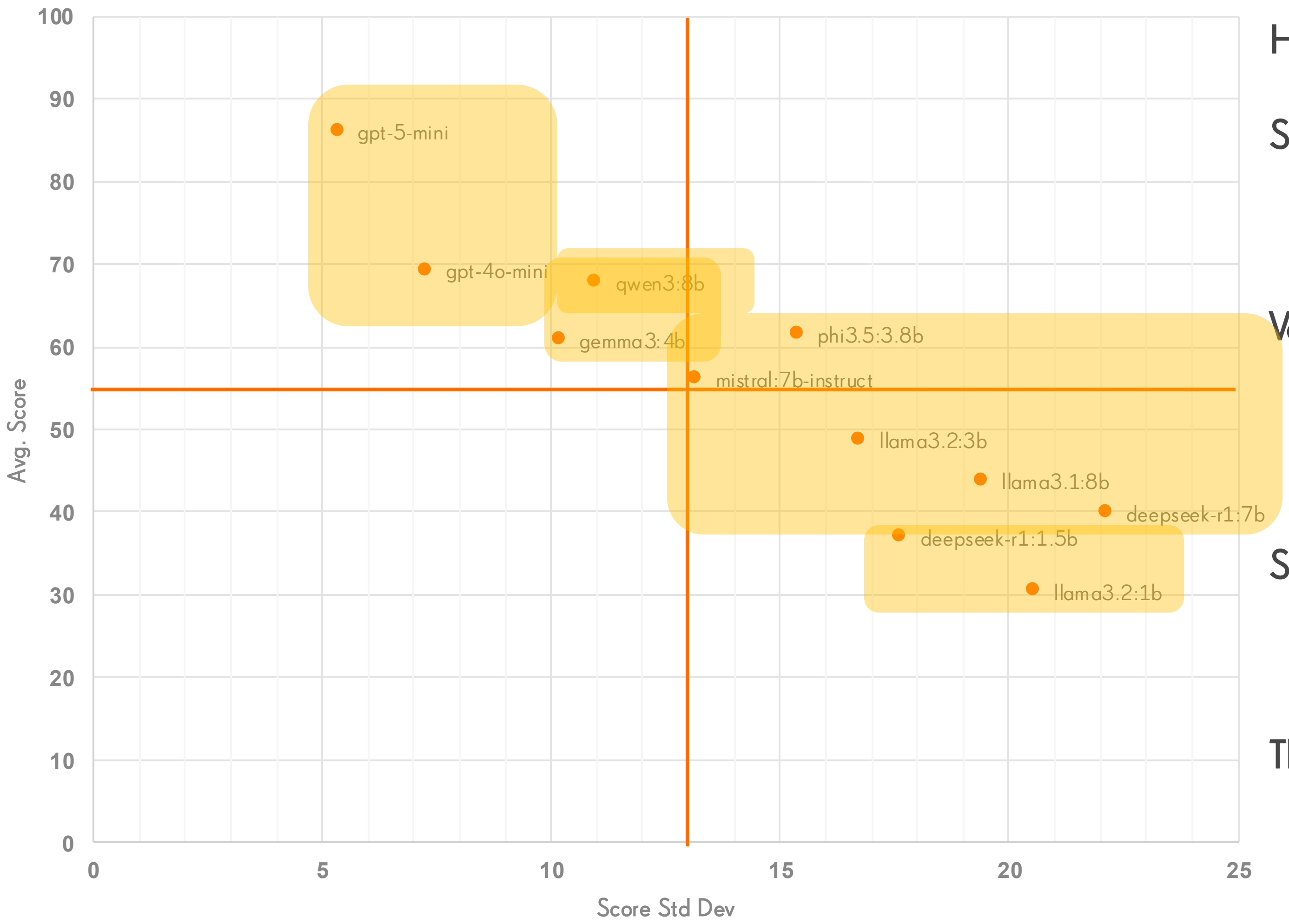
- **Llama3.2** and **DeepSeek** trail others at similar parameter sizes

Low-end drop off

- Smaller parameter counts show a quality decline

Performance vs Consistency

Accuracy Is Not the Whole Story



High performers are the most consistent

Some self-hosted models are competitive but less stable

- **Qwen3:8B** can produce strong outputs but with higher variability

Volatility increases in the mid and lower tiers

- **Phi3.5**, **Mistral**, and **Llama3.2:3B** show much higher variability
- Larger Llamas and DeepSeek show instability despite size

Smaller models suffer twice

- **Llama3.2:1B** and **DeepSeek-r1:1.5B** have *both* low average scores and high stddev

The “sweet spot”?

- **Qwen3:8B** and **Gemma3:4B** seem to balance performance with consistency

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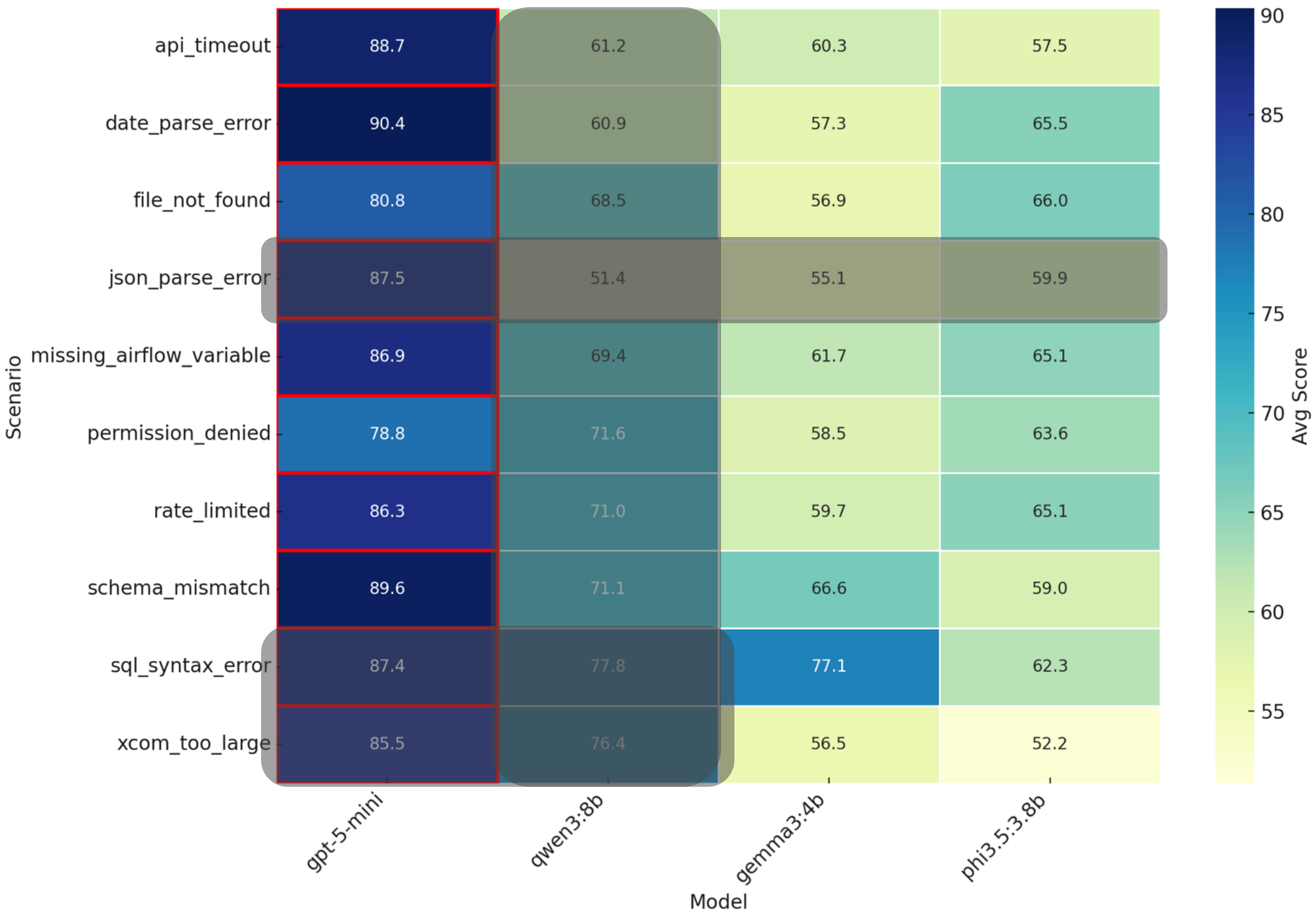
How Close Can Compact Models Get?

Compact Models vs GPT: Within Striking Distance



Qwen3:8B Is the Strongest Contender

- It performs best among non-GPTs in almost every scenario and gets within 10 points of GPT-5 in 3 of 10 cases.

Pattern-Based Failures Are the Most Compact-Friendly

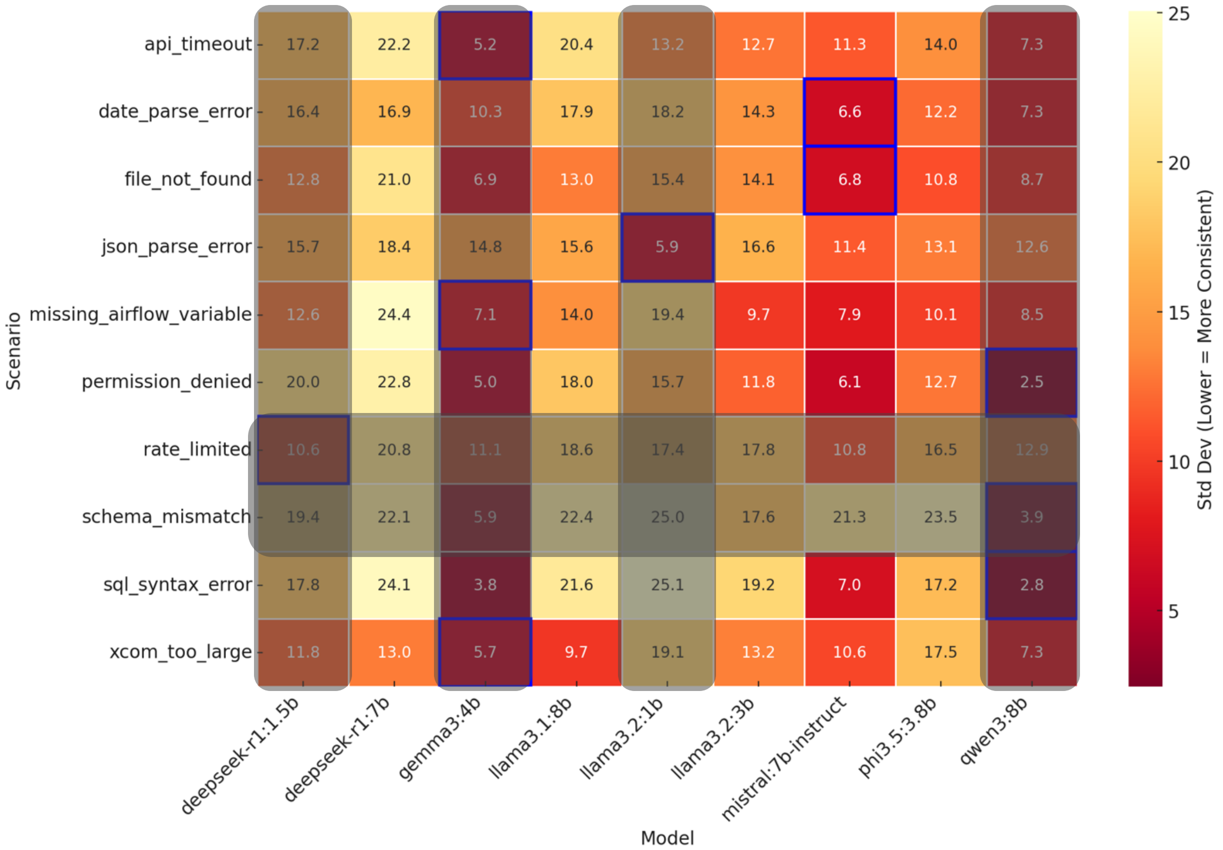
- Scenarios like **sql_syntax_error** and **xcom_too_large** narrow the gap between GPT and compact models
- All models do worse in abstract reasoning (e.g., **rate_limited**, **json_parse_error**).

Compact Models Are Still ~10–30 Points Behind GPT on Average

- But with the right scenario and a slightly larger model (e.g., 13B), this gap could shrink - and may be acceptable for private/offline use.

Where They Struggle

Not All Compact Models Are Created Equal



Volatility Increases with Smaller Models

- Models like LLaMA3.2:1B and DeepSeek-R1:1.5B consistently show the highest standard deviation, meaning their output is much less reliable across runs.

Some Mid-Tier Models Show Promise - with Caveats

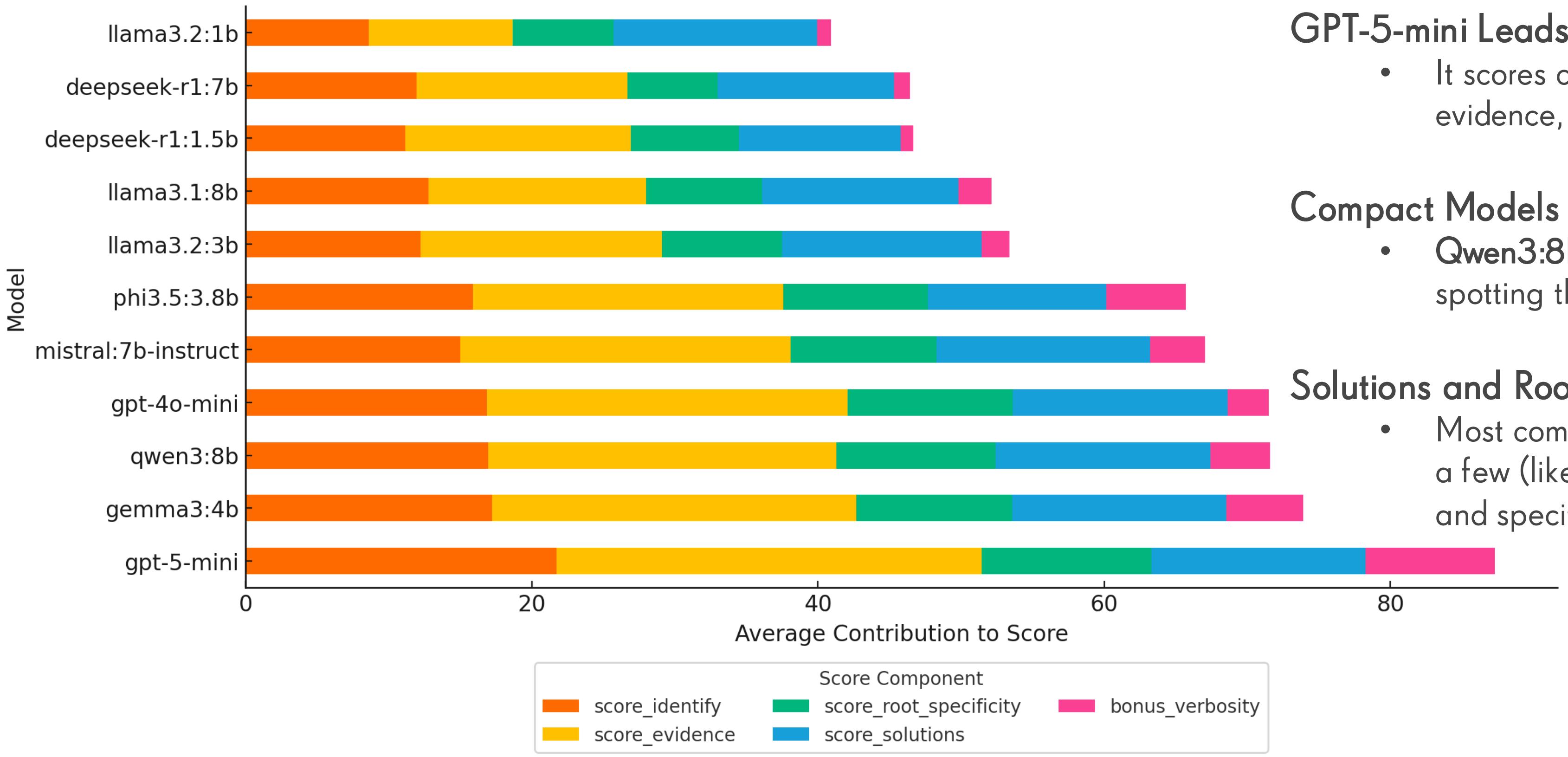
- Qwen3:8B and Gemma3:4B are the most consistent- but they still fluctuate more than GPT models.

Scenario Complexity Exposes Instability

- Harder scenarios (like rate_limited or schema_mismatch) tend to produce higher variance across all non-GPT models - indicating these failures are harder to explain reliably without larger context.

What Drives a High-Scoring Diagnosis?

Score Contributions by Component



GPT-5-mini Leads Because It's Well-Rounded

- It scores consistently across all categories: identify, evidence, root specificity, and solutions - not just verbosity.

Compact Models Depend Heavily on Identify + Evidence

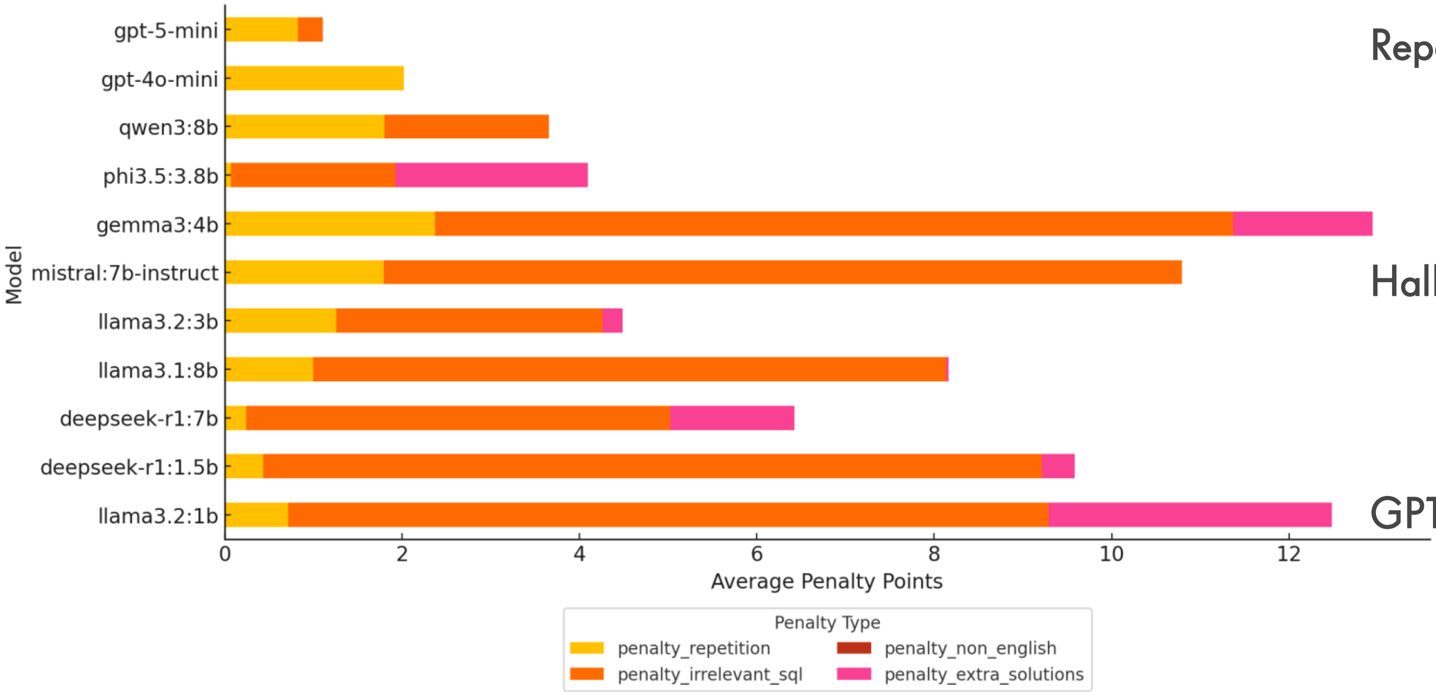
- **Qwen3:8B** and **Gemma3:4B** earn most of their points by spotting the right failure type and citing relevant signals.

Solutions and Root Specificity Are Weak Points

- Most compact models lean on identify and evidence. Only a few (like Qwen and Gemma) approach GPT in solutions and specificity - others trail behind.

Where Compact Models Lose Points

Penalty Breakdown by Model



Repetition Is the Most Frequent Penalty

- Repetition penalties affect many compact models - not just the smallest ones. Even high-scoring models like Gemma and Qwen can be verbose.

Hallucinated SQL Shows Up in Non-SQL Scenarios

- Irrelevant SQL advice is a common error among several compact models, especially those with broad instruction tuning.

GPT Models Are Largely Penalty-Free

- GPT-5-mini and GPT-4o rarely trigger penalties, contributing to both their consistency and higher total scores.

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Wrapping Things Up

🎓 What the Benchmark Taught Us

Interpreting the Results

🟢 What We Learned (Under 10B Models)

- Some compact models are often "good enough" for well-known failures
- GPT wins on depth and stability - but the margin is narrowing
- Smaller models (<3B) are volatile and prone to hallucinations
- Compact models can provide **meaningful value for failure diagnosis** in Airflow, particularly in dev-time or known-pattern use cases

🚀 What Could Be Next?

- All results shown are based on **<10B parameter models**
- Self-hosting larger models (13B–30B) is possible on modest hardware
- These could close to gap to GPT even further
- This benchmark focused solely on **diagnosis quality** — not cost, inference speed, or hardware footprint

⚠️ Caveat

- Self-hosting "free" models comes with **real operational costs** (e.g., GPUs, RAM, model ops)
- Our evaluation reflects controlled Airflow scenarios — not general NLP or reasoning tasks

Tying It Back to Airflow

What Could This Mean For The Community?

- **AI-powered failure triage** is possible *now!*
  - But it requires custom integration

- [AIP-91: MCP]
  - Proposes a *Model Control Plane* server and plugin for Airflow
  - Mentions **natural language debugging of task failures** – aligning closed with this work
  - This architecture could allow **self-hosted LLMs to be natively integrated** for triage and root cause explanation

Thank you!

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Questions?

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