Building Reusable Evaluation Frameworks for Agentic AI Products

Susan Shu Chang
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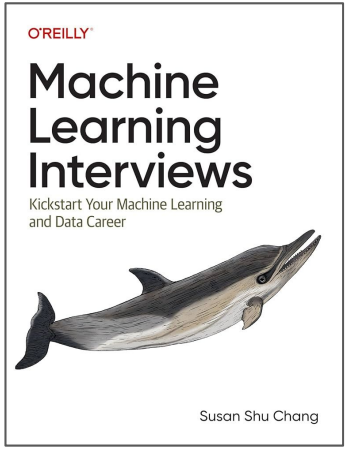
QCon AI Boston: June 02, 2026

elastic | The Search AI Company

Hi!

Susan Shu Chang

- Principal Data Scientist at Elastic
- Author, Machine Learning Interviews (O'Reilly)
- Speaker at conferences worldwide



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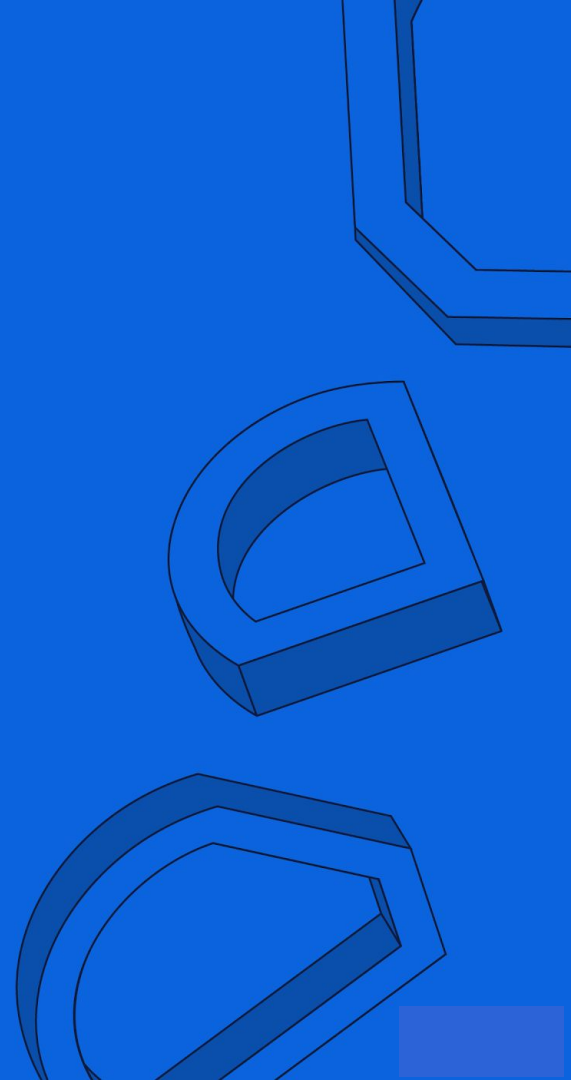
Agenda

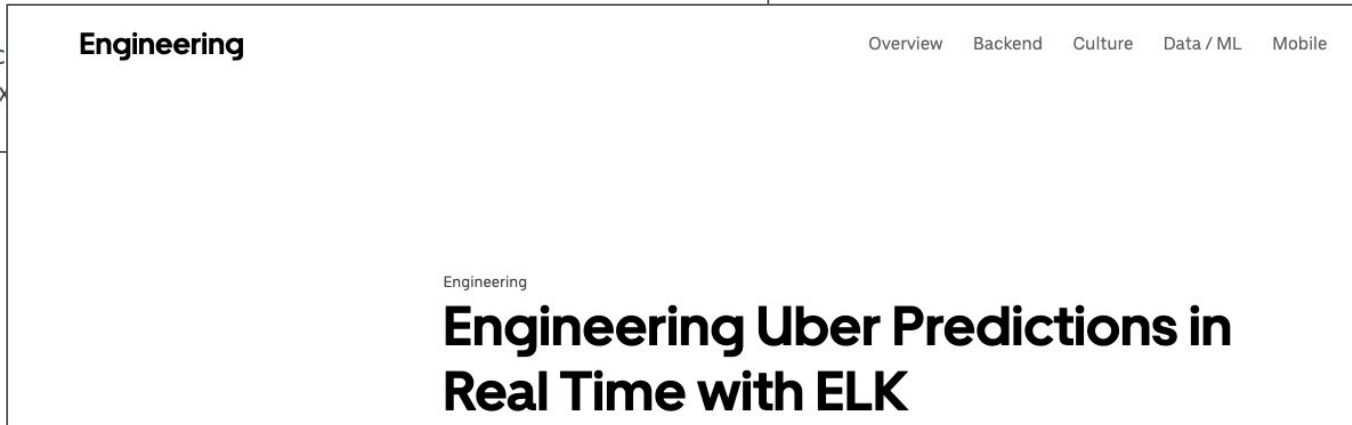
1. AI agents we're running in production
2. Tracing your application
3. Shared evaluation framework: Overview
4. Shared evaluation framework: Building blocks
5. Tying it all together + Takeaways

AI agents we're running in production



Web & app search / vector search / log search...

Setting the stage on the types of AI Agents we build



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Using Elasticsearch queries, we can quickly see every action the user has done - this is a great way to see whether an account has been stolen, hijacked, or whether the user has done something naughty.

– Tim Pease, Operations Engineer, GitHub

Engineering

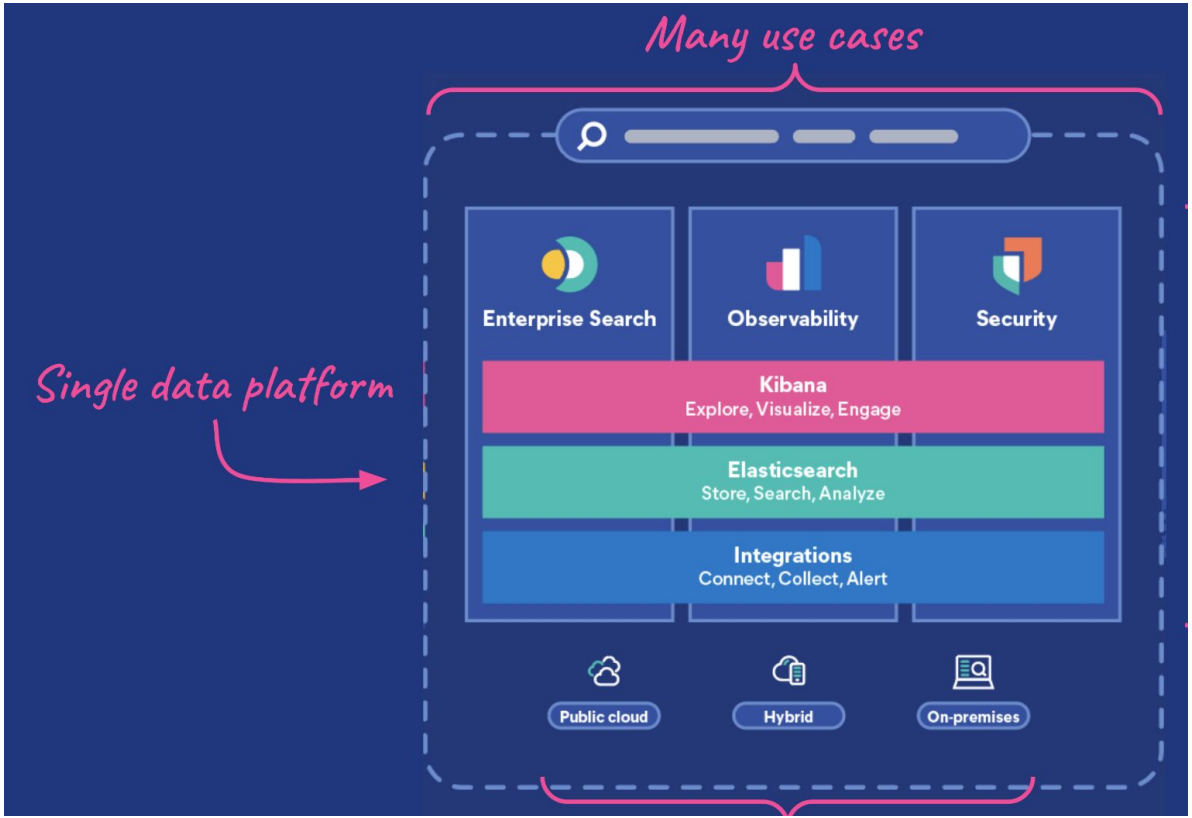
Tinder's migration to Elasticsearch 8

Posted on: April 1, 2025

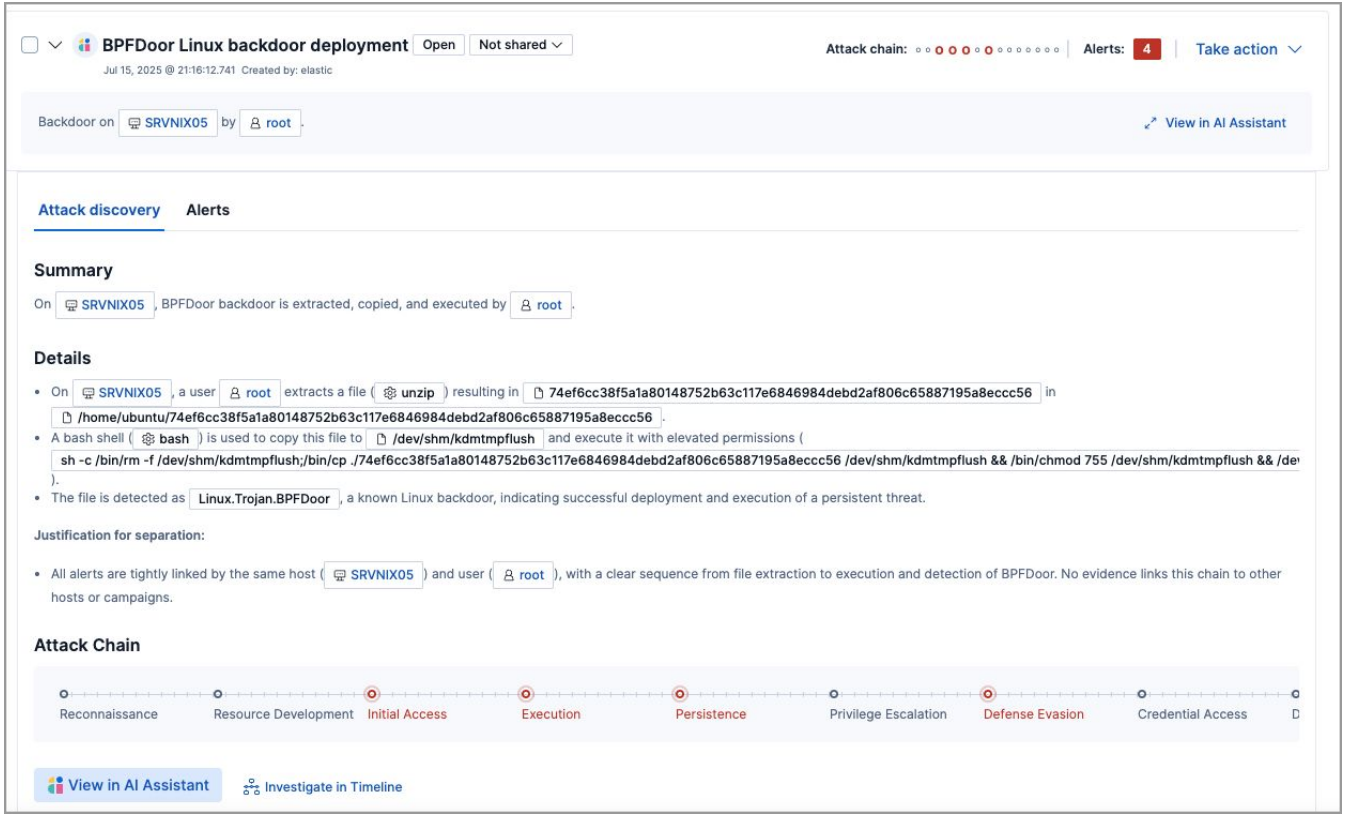
Share this post

Users ship logs to Elastic / Elastic Security / Observability

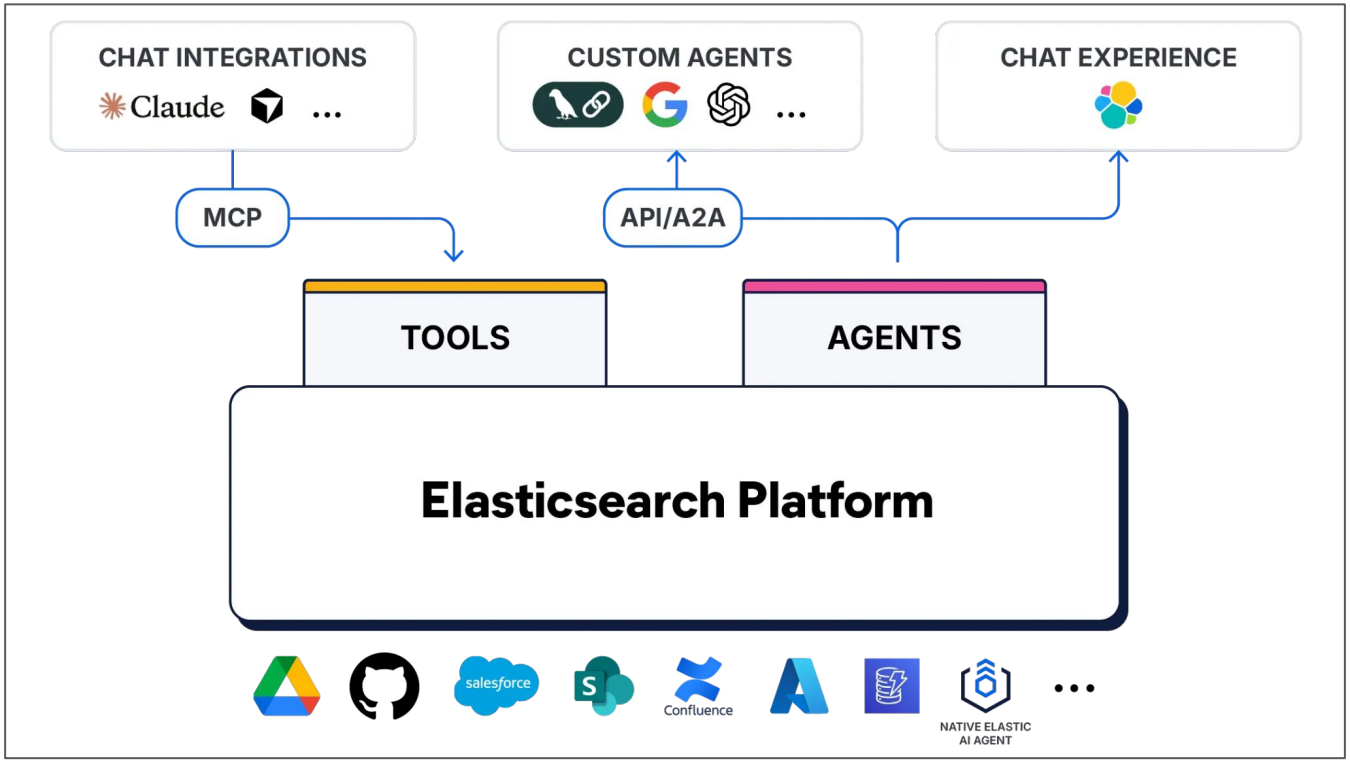
Bottom line: Search / RAG to store and extract signals from data



[Security] Attack Discovery: Given logs, find possible attacks



Elastic Agent Builder (Enterprise chatbot creator): Custom agents on top of existing data



Key questions before shipping changes to production

How do we estimate the quality of responses of these AI applications?

If we make a change, how do we test for regressions?

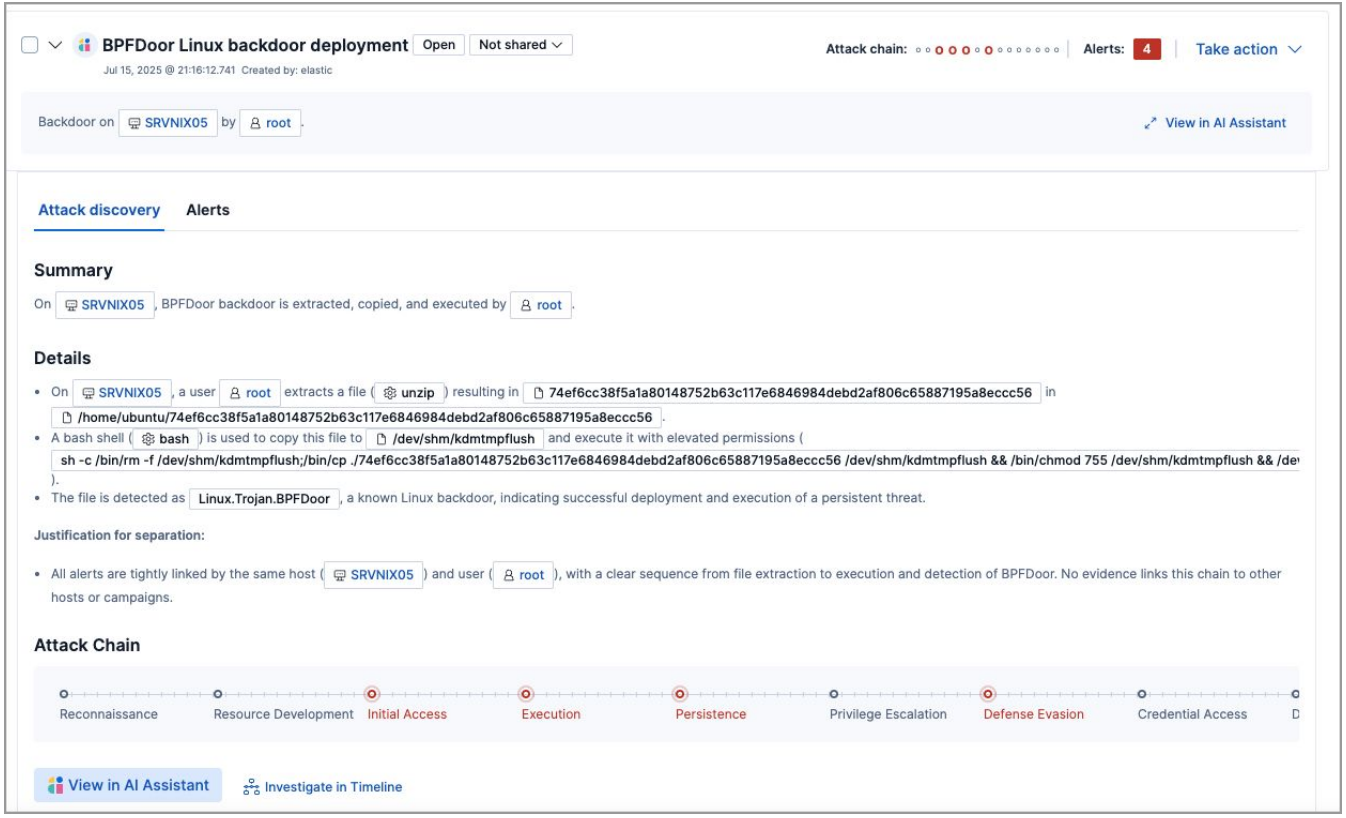
How can we easily test these results in a repeatable manner?

What we'd build for each AI Agent suite...

1. Test dataset creation
2. Develop LLM- and rules-based evaluators
3. Capture evaluation data (in different places)

[Security] Attack Discovery: Given logs, find possible attacks

Recall...



For Security use case, test dataset includes accurate summary of (cyber) attack

10 novel attack scenarios

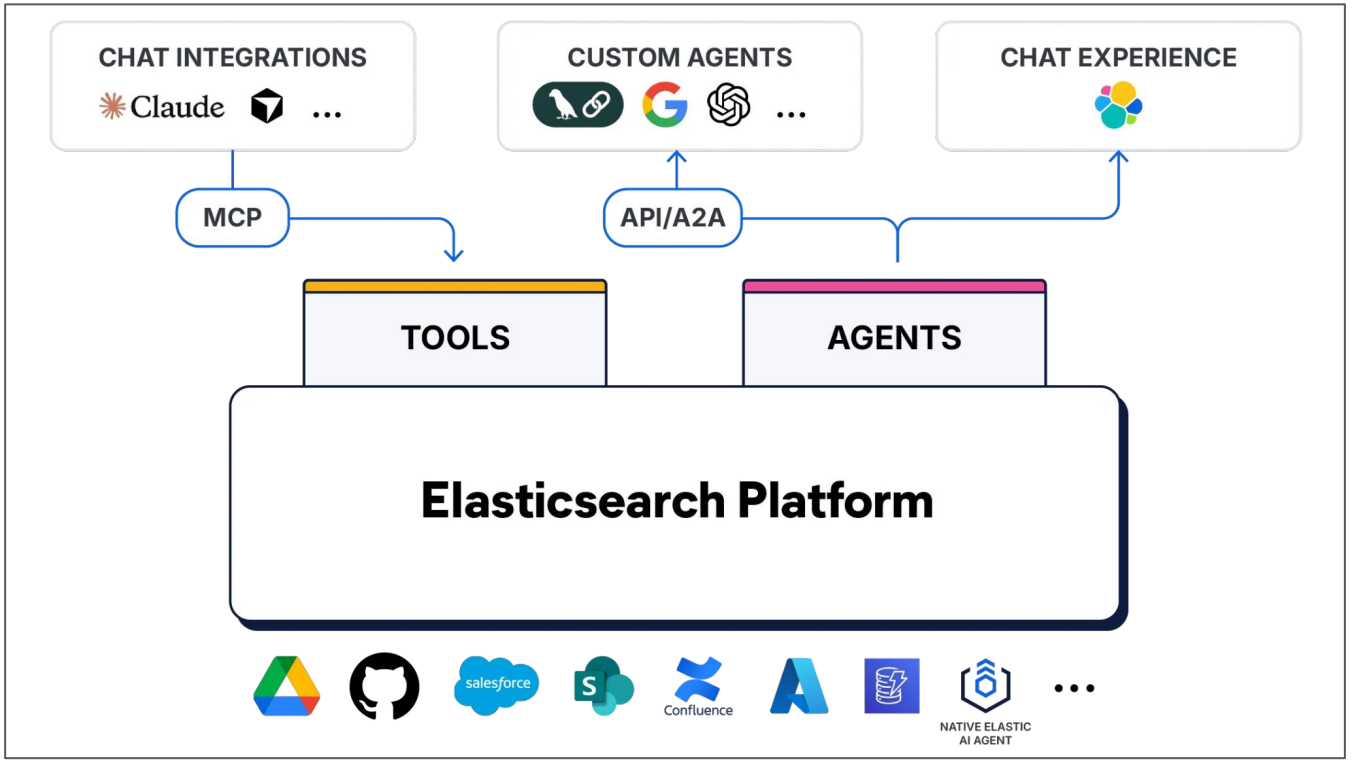
- 8 Oh My Malware attack episodes (ohmymalware.com)
- 4 multi-attack scenarios (created by combining attacks in the first 2 categories)
- Benign scenarios

[Security] Attack Discovery

Metrics for this specific Agentic AI

Metric	Description
Precision & recall	Match alertIDs between actual and expected outputs to measure detection accuracy.
Similarity	Use BERTScore to compare the semantic similarity of the response text.
Factuality	Are key IOCs (indicators of compromise) present? Are MITRE tactics (industry taxonomy of attacks) correctly reflected?
[Domain specific] Attack chain consistency	Compare the number of discoveries to check for over- or under-reporting of the attack.

Elastic Agent Builder (Enterprise chatbot creator): Custom agents on top of existing data



Recall...

Elastic Agent Builder test datasets

Enterprise chatbot creator: Question and answer example

14 Indices using open source datasets to simulate multiple sources in KB.

- 5 Query types (analytical, text retrieval, hybrid...)
- 7 Query intent types (procedural , factual - classification, investigative; ...)

Agentic AI with RAG: Example labelled data

Enterprise data chatbot: Question and answer example

question:
'I am trying to verify my domain with Google Workspace. I need to add a TXT record to my domains DNS settings. I have confirmed that my domain is connected to Wix via pointing. What to do now?',

`To verify your domain with Google Workspace by adding a TXT record, you need to manage your DNS settings with your domain host, not Wix, since your domain is connected via pointing.
Follow these steps:
1. Log in to your domain host account where your DNS records are managed.
2. Add the TXT record provided by Google Workspace to your domain's DNS settings.
3. After adding the TXT record, return to the Google Admin Console and click 'Verify'.`,

Elastic Agent Builder (Enterprise chatbot creator)

Metrics for this specific Agentic AI

Metric	Description
Precision & recall	Match documents/information retrieved by the agent to answer a user query vs the actual information or documents needed to answer the query to measure information retrieval accuracy.
Factuality	Are the key facts required to answer the user query present? Are the facts in the right order for procedural queries?
Response relevance	Does the response contain information that is peripheral or unrelated to the user query?
Response completeness	Does the response answer all parts of the user query? Does the response contain all the information present in the ground truth?
[Domain specific] ES|QL validation	Is the generated ES|QL syntactically correct? Is it functionally identical to the ground truth ES|QL?

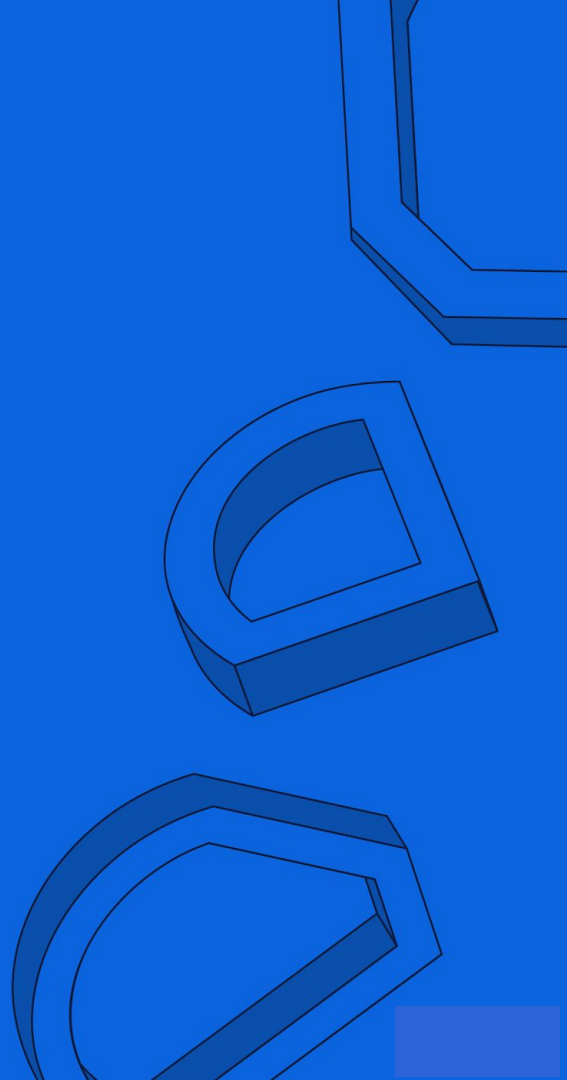
Various more agents, skills, or components each with their own evals

- Security detection rules generation AI Agent
- Security alerts RAG
- Security ES|QL detection rules generation
- Observability AI insights
- Observability AI investigations

and so on...

As agent development matures, more and more evaluations are needed

Tracing your application



Trace your application for evaluations and monitoring

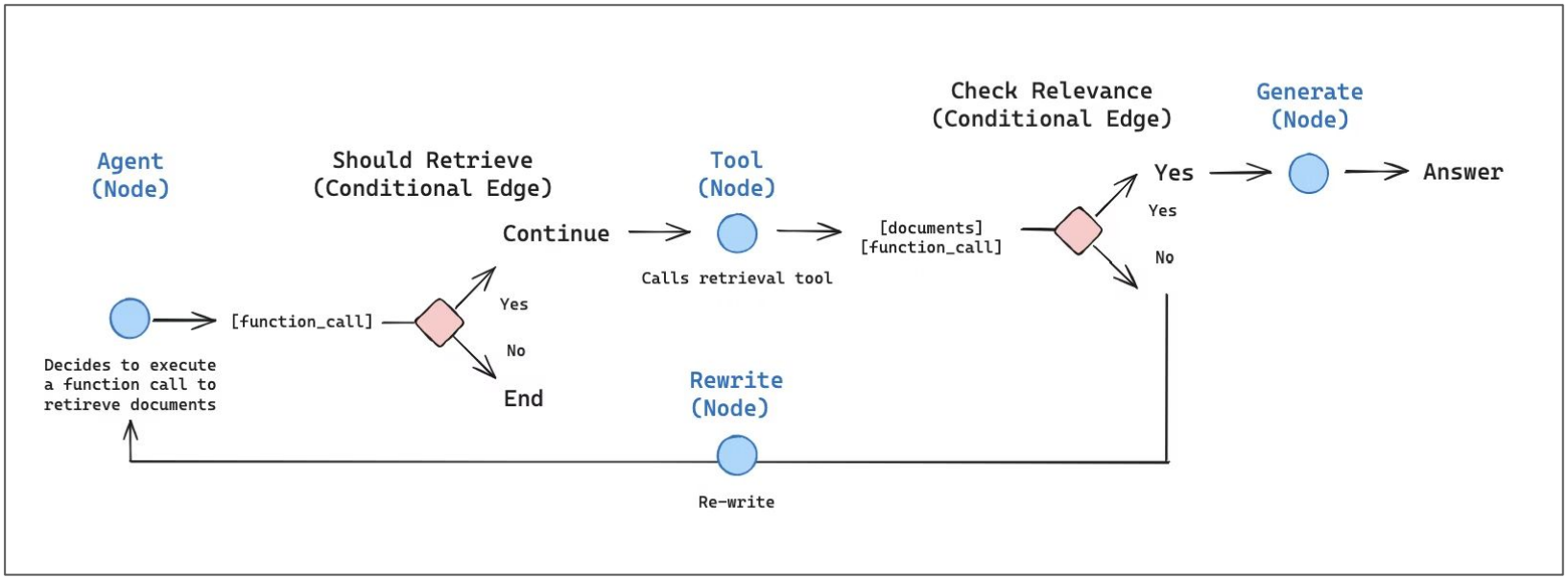
Many tools:

- LangSmith
- Phoenix
- Langfuse
- Elastic
- MLflow

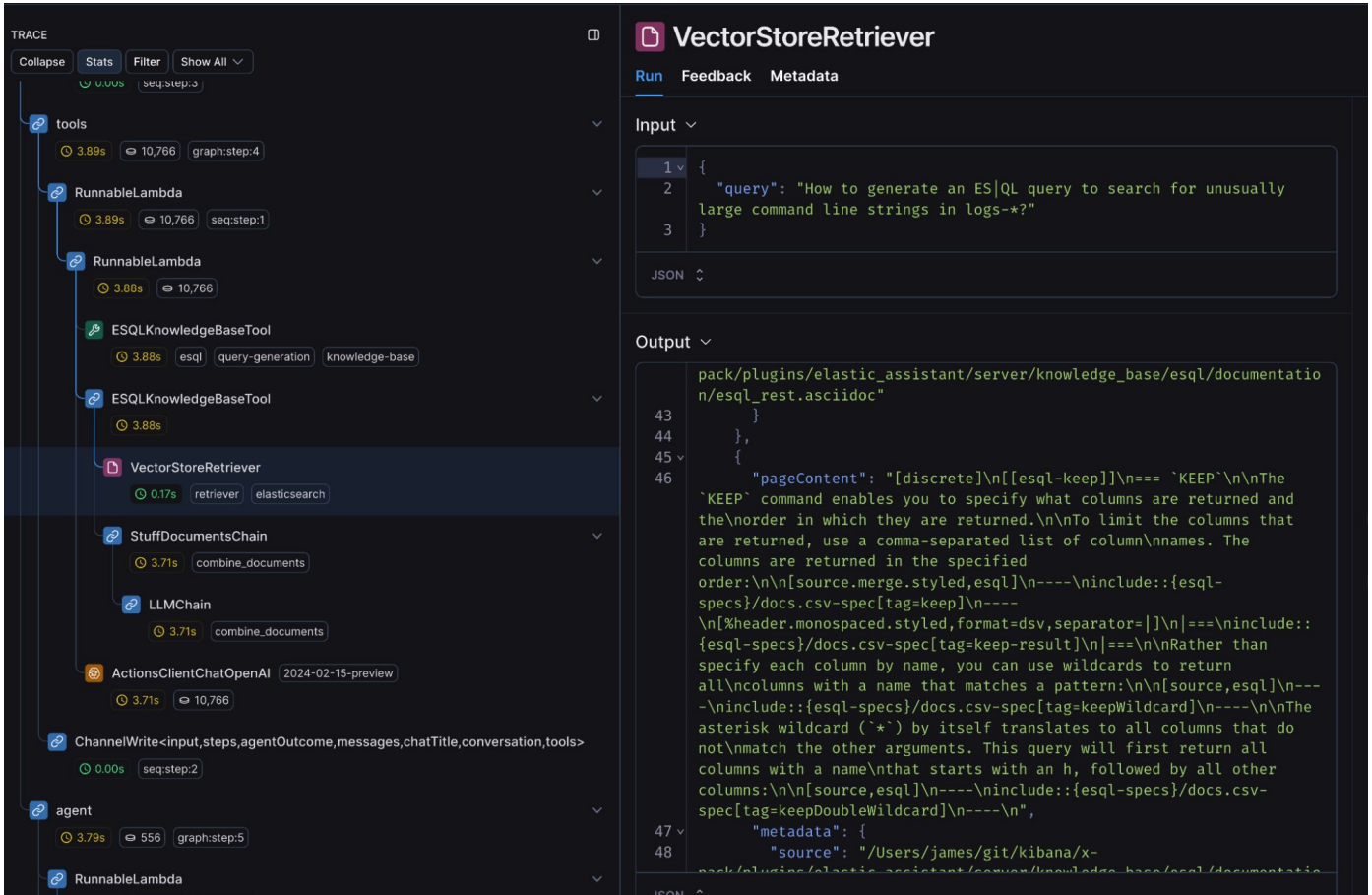
Early on we tried many different tools:
As our agent development matured we started consolidating

Example: LangSmith trace (LangGraph agent)

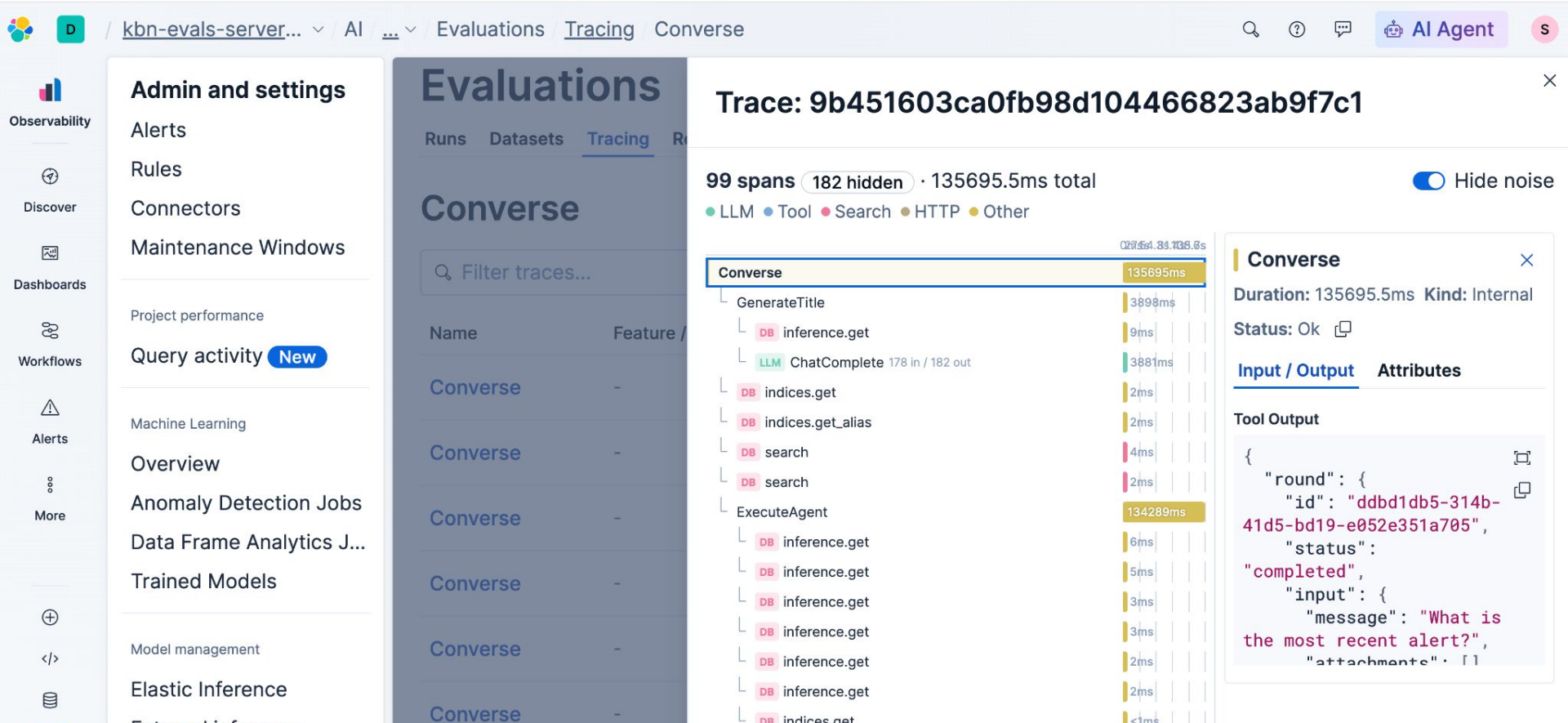
Source: LangChain/LangGraph



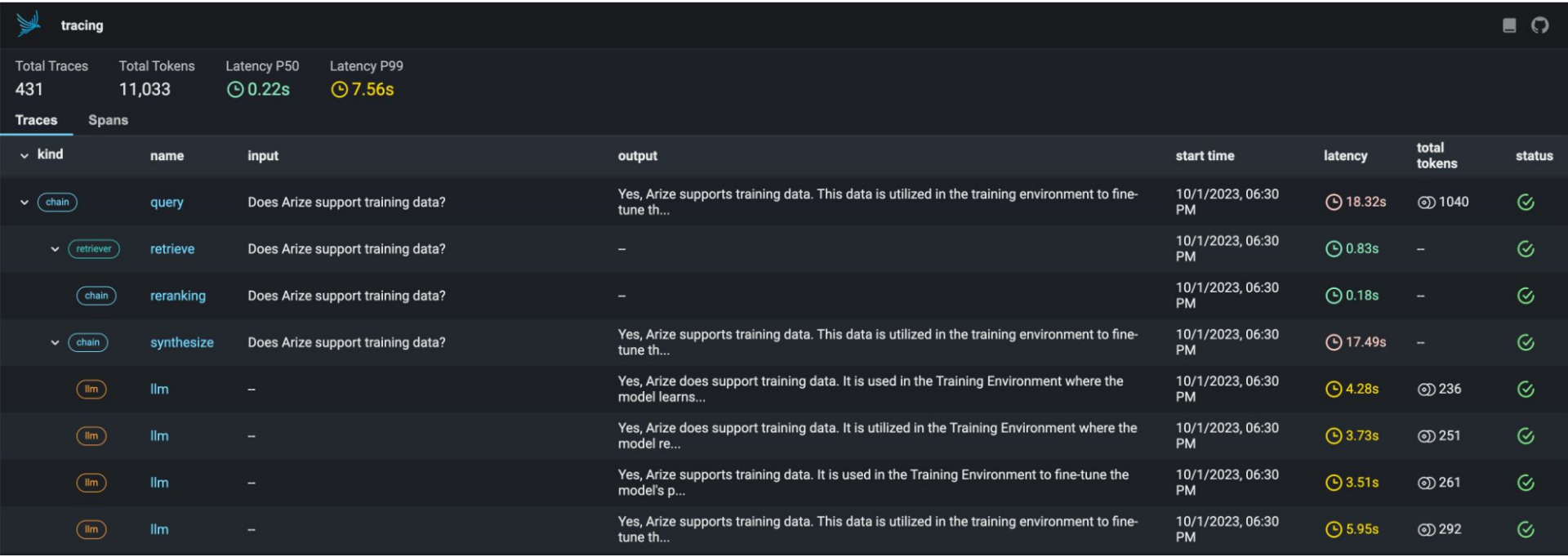
Example: LangSmith trace (LangGraph agent)



Example: Elastic Observability

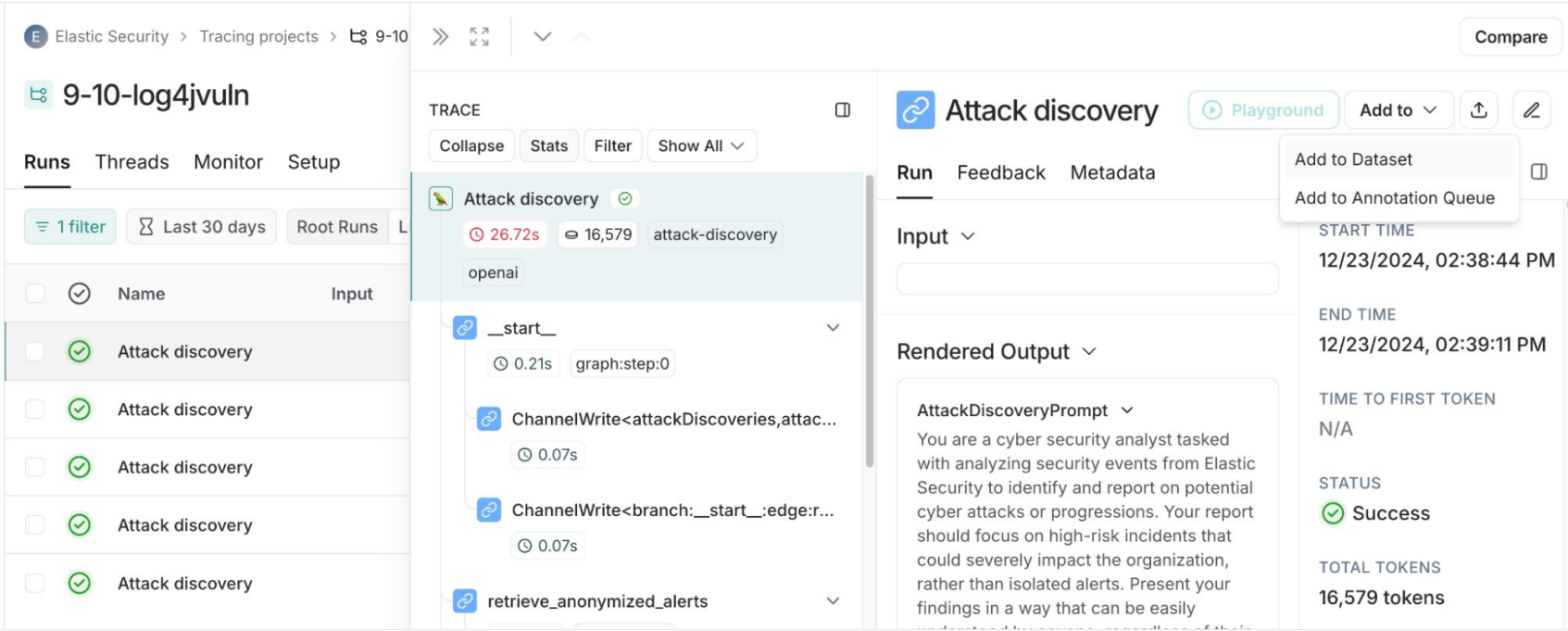


Example: Phoenix



kind	name	input	output	start time	latency	total tokens	status
chain	query	Does Arize support training data?	Yes, Arize supports training data. This data is utilized in the training environment to fine-tune th...	10/1/2023, 06:30 PM	18.32s	1040	
retriever	retrieve	Does Arize support training data?	–	10/1/2023, 06:30 PM	0.83s	–	
chain	reranking	Does Arize support training data?	–	10/1/2023, 06:30 PM	0.18s	–	
chain	synthesize	Does Arize support training data?	Yes, Arize supports training data. This data is utilized in the training environment to fine-tune th...	10/1/2023, 06:30 PM	17.49s	–	
llm	llm	–	Yes, Arize does support training data. It is used in the Training Environment where the model learns...	10/1/2023, 06:30 PM	4.28s	236	
llm	llm	–	Yes, Arize does support training data. It is utilized in the Training Environment where the model re...	10/1/2023, 06:30 PM	3.73s	251	
llm	llm	–	Yes, Arize supports training data. It is used in the Training Environment to fine-tune the model's p...	10/1/2023, 06:30 PM	3.51s	261	
llm	llm	–	Yes, Arize supports training data. This data is utilized in the training environment to fine-tune th...	10/1/2023, 06:30 PM	5.95s	292	

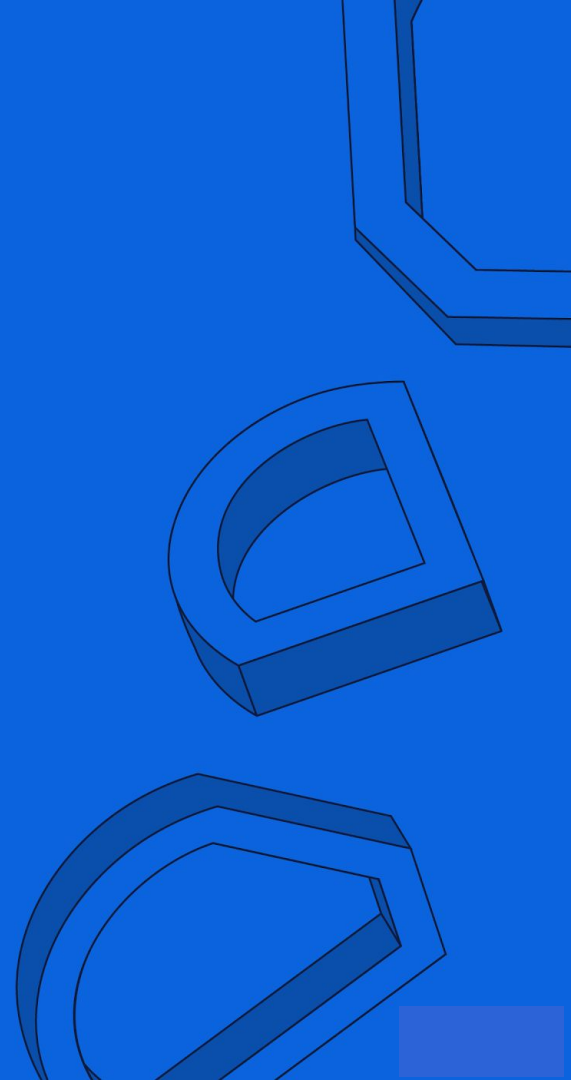
Example: LangSmith trace easy “Add to Dataset” feature



Anecdote: You wouldn't eval other live ML without some type of telemetry/clickstream data

Image: https://www.loop11.com/clickstream/

Shared evaluation framework: Overview



Why? As agent development matures, more and more evaluations are needed

- Cumbersome to keep building evaluations from scratch
- Different dev teams can collaborate and maintain
- Quick to spin up fully featured evals

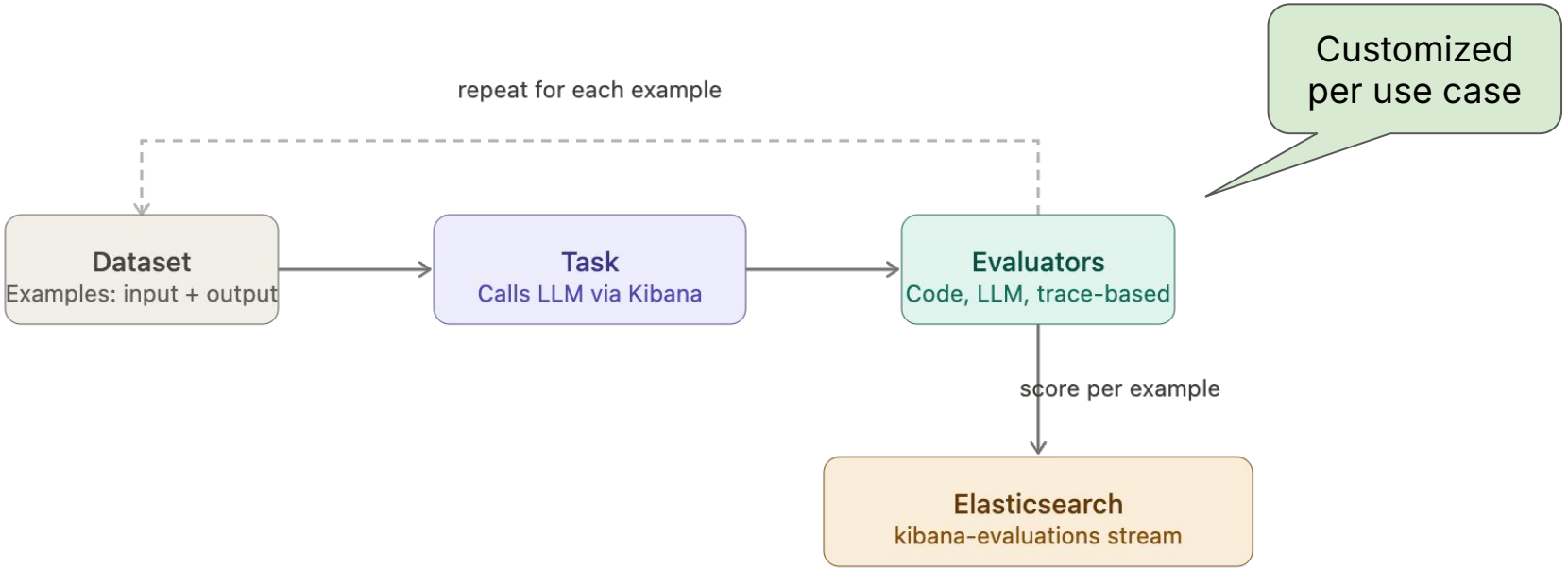
Security org and Agent Builder org previously built out completely separate eval frameworks

Shared toolkit for different Agentic AI teams

- Import datasets
- Trace based evaluators (token usage, latency, tool calls)
- RAG evaluators (Precision@K, Recall@K, F1@K)
- Custom evaluators

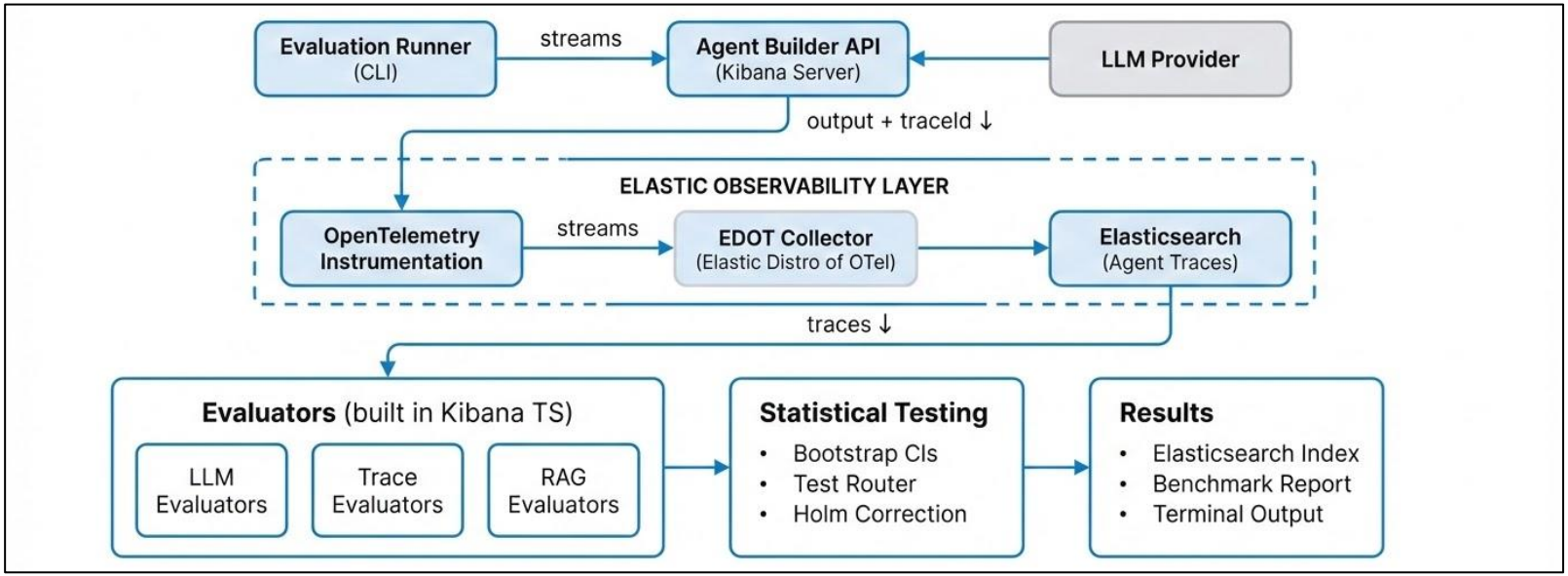
Prerequisite for evals: Tracing/ telemetry

Customizable building blocks



Orchestrated with Scout

Kibana's UI and API test framework built on top of Playwright



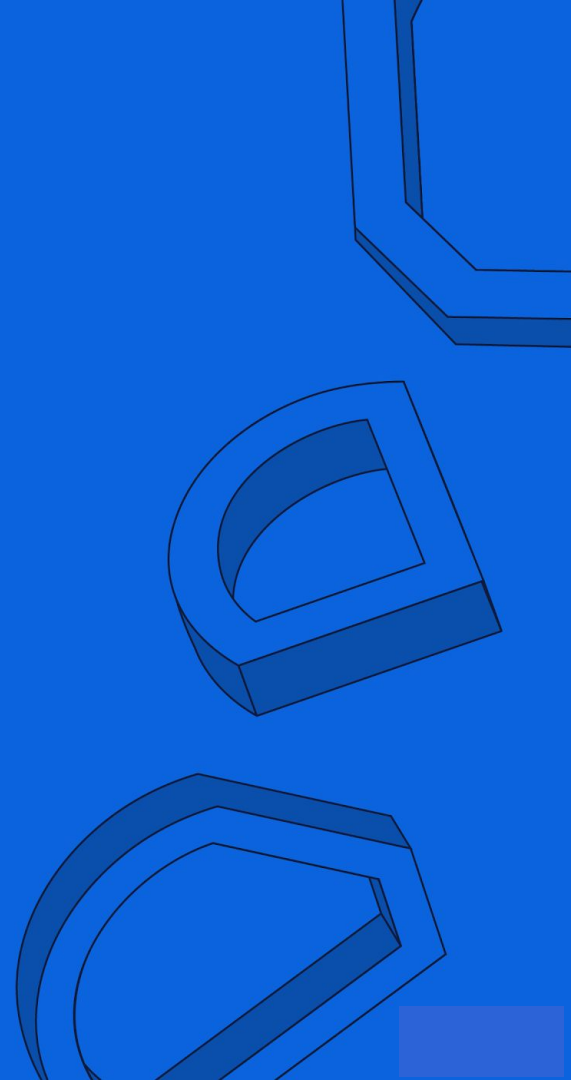
Elastic/Kibana Scout:
https://www.elastic.co/docs/extend/kibana/scout

Dev mode: outputs terminal results

```
Model: us.anthropic.claude-3-7-sonnet-20250219-v1:0 (Claude/Anthropic)
info [scout-worker]
=== EVALUATION RESULTS ===
```

Dataset	# Examples (repetitions x examples)	Factuality	Groundedness	Relevance	Sequence Accuracy
onechat: default-agent-text-retrieval-queries	3 x 29	52.1% mean: 0.521 median: 0.640 std: 0.292 min: 0.000 max: 0.923	89.8% mean: 0.898 median: 0.997 std: 0.289 min: 0.000 max: 1.000	51.8% mean: 0.518 median: 0.500 std: 0.212 min: 0.000 max: 1.000	90.1% mean: 0.901 median: 1.000 std: 0.265 min: 0.000 max: 1.000
onechat: default-agent-analytical-queries	3 x 15	42.7% mean: 0.427 median: 0.166 std: 0.443 min: 0.000 max: 1.000	97.6% mean: 0.976 median: 1.000 std: 0.149 min: 0.000 max: 1.000	64.8% mean: 0.648 median: 0.714 std: 0.272 min: 0.222 max: 1.000	100.0% mean: 1.000 median: 1.000 std: 0.000 min: 1.000 max: 1.000
onechat: default-agent-hybrid-queries	3 x 9	24.3% mean: 0.243 median: 0.000 std: 0.341 min: 0.000 max: 0.944	88.7% mean: 0.887 median: 1.000 std: 0.319 min: 0.000 max: 1.000	60.0% mean: 0.600 median: 0.600 std: 0.332 min: 0.056 max: 1.000	100.0% mean: 1.000 median: 1.000 std: 0.000 min: 1.000 max: 1.000
onechat: default-agent-unanswerable-queries	3 x 13	25.2% mean: 0.252 median: 0.224 std: 0.248 min: 0.000 max: 0.766	65.6% mean: 0.656 median: 0.992 std: 0.472 min: 0.000 max: 1.000	62.6% mean: 0.626 median: 0.500 std: 0.240 min: 0.250 max: 1.000	92.0% mean: 0.920 median: 1.000 std: 0.200 min: 0.200 max: 1.000
onechat: default-agent-ambiguous-queries	3 x 4	22.8% mean: 0.228 median: 0.148 std: 0.251 min: 0.000 max: 0.819	99.0% mean: 0.990 median: 1.000 std: 0.022 min: 0.924 max: 1.000	79.4% mean: 0.794 median: 0.938 std: 0.248 min: 0.400 max: 1.000	100.0% mean: 1.000 median: 1.000 std: 0.000 min: 1.000 max: 1.000
Overall	3 x 70	39.8%	87.4%	59.2%	94.4%

Shared evaluation framework: Building blocks



Shared evaluation building blocks

- Precision/Recall
- Semantic similarity e.g. typical answer is similar to existing docs
- Factuality e.g. not hallucinated product ID
- LLM-as-judge shared tooling

We compared commonly used metrics in ad-hoc evaluations, and started pulling them out

Factuality (customize based on application)

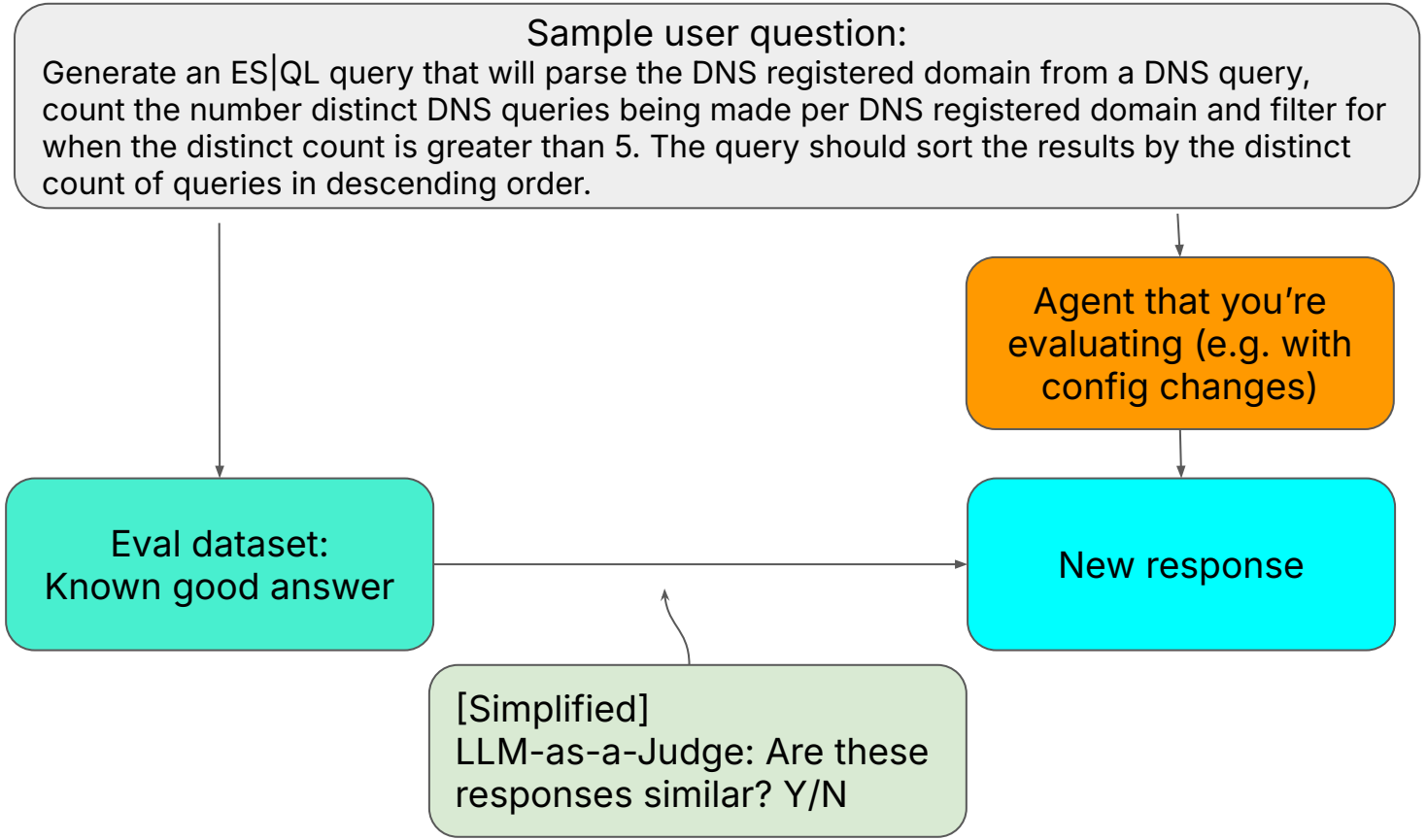
```python
def compute_factuality_score(
    expected_tactics: list, actual_tactics: list, iocs: list, details: str
) -> float:
    """
    Compute factuality score based on matched MITRE tactics and IOC values in the response.

    Args:
        expected_tactics (list): Expected MITRE attack tactics.
        actual_tactics (list): Tactics extracted from actual response.
        iocs (list): List of IOCs with associated importance.
        details (str): Markdown details from the actual response.

    Returns:
        float: Combined score indicating factual correctness of the response.
    """
    weights = {"high": 3, "medium": 1}
    tactic_score = (
```

Early implementation for one eval suite in Python, now since merged into shared evals in TypeScript

LLM-as-a-judge with offline evaluations on test set



LLM-as-Judge pros & cons

Using LLMs to determine if incoming data is similar to test/golden dataset

Pros:

- Scale
- Useful for tone, coherence, style, summaries, safety...
- Good for open-ended tasks
- Can judge correctness, completeness...
- Can self-explain grading using chain-of-thought

Tip: Can use structured outputs/schema,
e.g. LangSmith/LangChain schemas

LLM-as-Judge pros & cons

Using LLMs to determine if incoming data is similar to test/golden dataset

Cons:

- May not be granular enough
- Variance across runs even with the same model
- LLM might not identify crucial differences
- More guidance is needed for internal info (e.g. product IDs)
- Performance differs by models/use case
- Bias toward models from the same “family”
- Advanced math, etc.

Using the same model family may cause bias

CyberSOCEval: Benchmarking LLMs Capabilities for Malware Analysis and Threat Intelligence Reasoning (Crowdstrike, Meta)

https://arxiv.org/pdf/2509.20166

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under test is the same, or has similarities with the set of models that were used in synthetic data generation pipelines. To ensure compliance with third party API acceptable use policies, we restricted our synthetic data generation pipelines to use a combination of Llama 3 and Llama 4 models, which could artificially boost the apparent performance of these models on the benchmarks. We attempted to mitigate this concern through a combination of complex multi-agent generation pipelines combined with extensive manual review and editing, however it remains the case that this is a potential source of bias.

Another important limitation to call out is that the contextual data provided to an AI system under test in each of

LLM-as-Judge / Model-based graders

Methods	Strengths	Weaknesses
• Rubric-based scoring • Natural language assertions • Pairwise comparison • Reference-based evaluation • Multi-judge consensus	• Flexible • Scalable • Captures nuance • Handles open-ended tasks • Handles freeform output	• Non-deterministic • More expensive than code • Requires calibration with human graders for accuracy

Source: Anthropic
https://www.anthropic.com/engineering/demystifying-evals-for-ai-agents

Rules based evaluations

Catch crucial points you can’t let LLM-as-a-Judge get wrong

Examples

- Using code (e.g. Python, TypeScript) to check if generated .json is valid
- Heuristics: If generated output doesn’t have x, y, z categories for this sample, it’s incorrect/correct
- Programmatic syntax checks for generated code

Example: Check ES|QL (a query language in Elastic)

Rules based evaluations: Pros and cons

Catch crucial points you can’t let LLM-as-a-Judge get wrong

Pros:

- No ambiguity, catches some weaknesses of LLM-as-a-Judge
- Cheap
- Fast

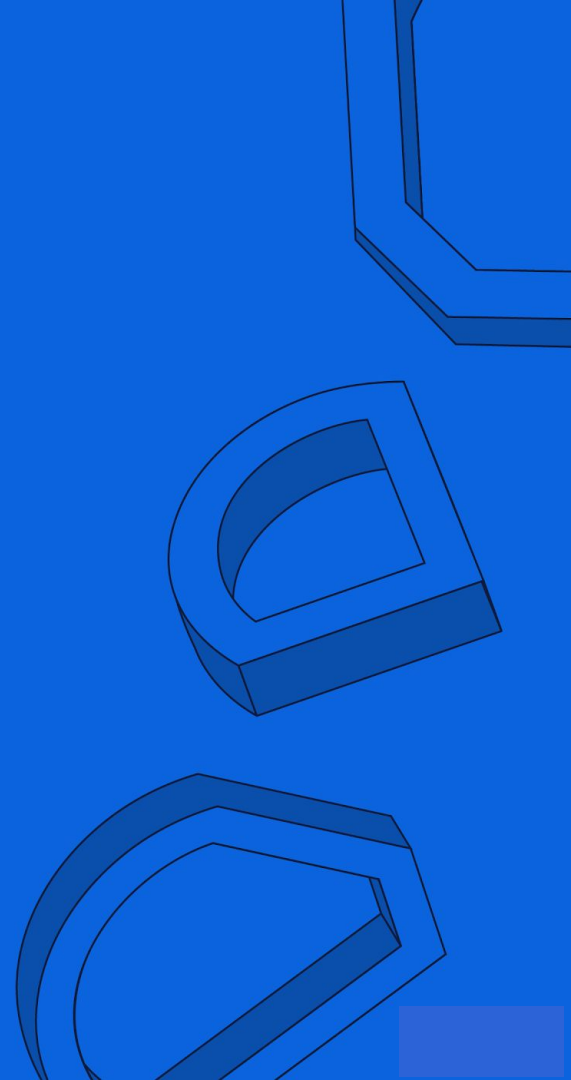
Rules based evaluations: Pros and cons

Catch crucial points you can’t let LLM-as-a-Judge get wrong

Cons:

- Hard to scale for large problem space
- Can’t capture nuance
- Weaker at open ended tasks

What couldn’t we abstract?



Can’t abstract bespoke data creation

But abstracted loading of bespoke datasets

- Still requires domain expertise to review
- Product input on what are positive vs. negative examples we must pass
- Regression is different for different agents

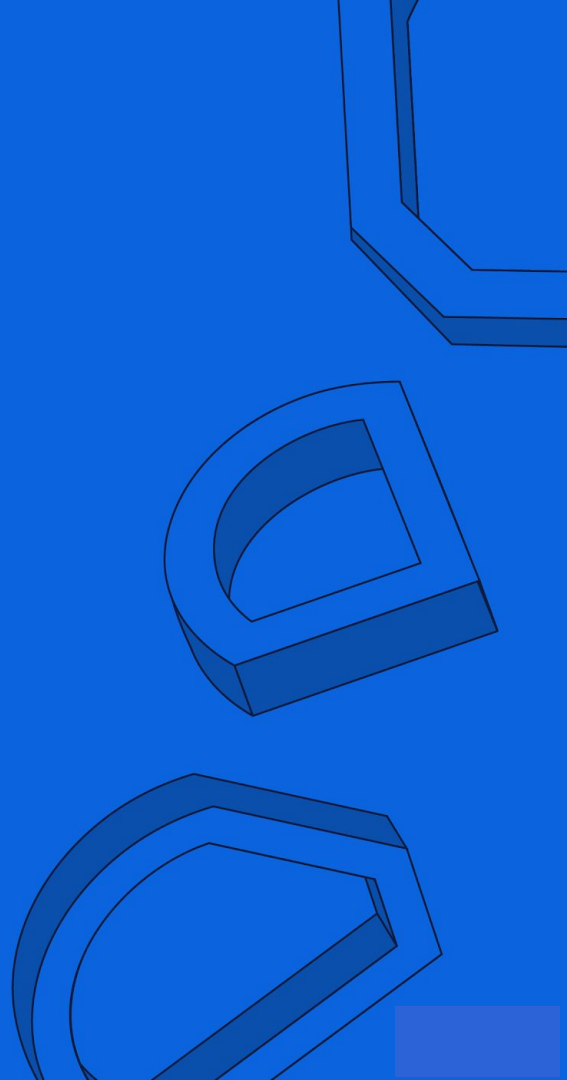
Further calibration of evaluators

“A well-calibrated evaluator should be consistent. If the baseline wins in the first evaluation, it should also win in the second. If the judgment flips, the outputs are perhaps too similar to distinguish, and we can mark these as ties rather than forcing a noisy decision.” - Eugene Yan

Be mindful that your evaluators agree generally with human evaluators (or your target behavior)

We make it easy to spin up the evaluators,
calibration is still the responsibility of each team

Key takeaways



If you’re building your first agent:

- Don’t skip product and domain expertise in evaluations
- Try out various tracing tools, see what works
- Start small: simple dataset creation, ad-hoc evals is fine

If your company is still early in its agent development journey, don't over-invest in abstractions yet.
Optimize for learning and experimentation first.

If you have a few agents in production:

- If you’re not making evaluations, start building at least one
- Thinking about the common metrics you’re observing
- You’ll eventually run into the problems of too many evals, how can you plan ahead to avoid that

Cross-team communication is key,
as agent dev in your organization matures.

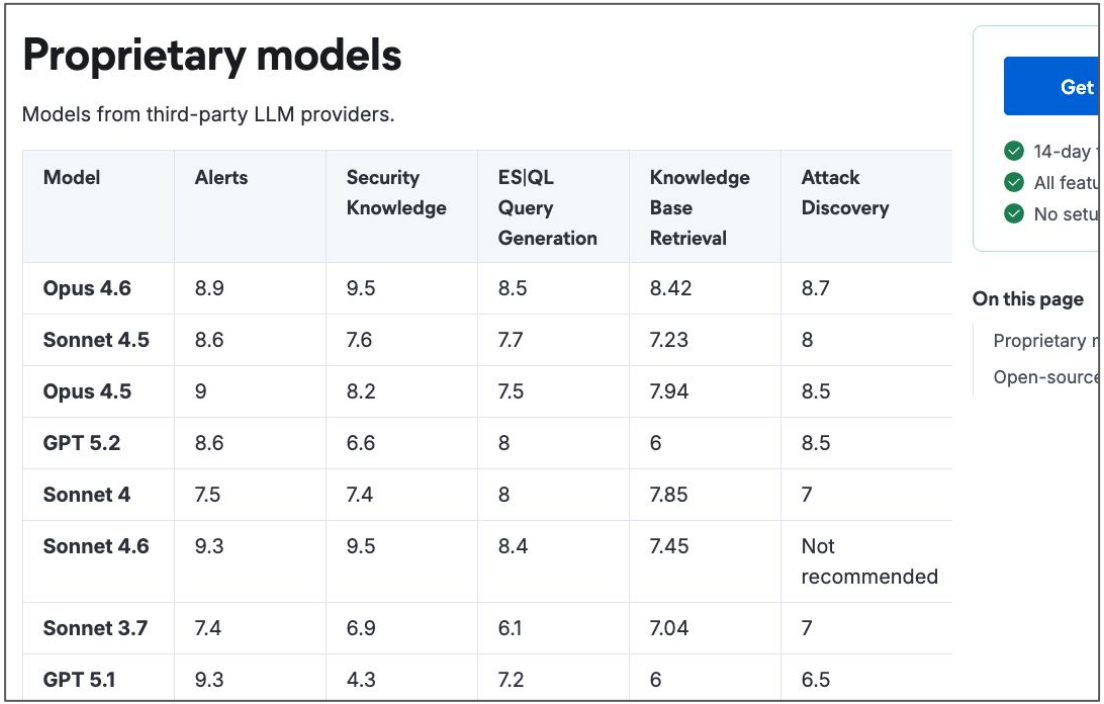
Lessons we've learned

If we could do over...

- Build first, consolidate later, but would have planned for consolidation earlier
- Make it easier for feedback to improve the product
- Would have jumped into the language of the main stack earlier

If you already have your own evaluation "hub", what would you do over?

We share eval results for select use cases publicly



Proprietary models

Models from third-party LLM providers.

Model	Alerts	Security Knowledge	ES|QL Query Generation	Knowledge Base Retrieval	Attack Discovery
Opus 4.6	8.9	9.5	8.5	8.42	8.7
Sonnet 4.5	8.6	7.6	7.7	7.23	8
Opus 4.5	9	8.2	7.5	7.94	8.5
GPT 5.2	8.6	6.6	8	6	8.5
Sonnet 4	7.5	7.4	8	7.85	7
Sonnet 4.6	9.3	9.5	8.4	7.45	Not recommended
Sonnet 3.7	7.4	6.9	6.1	7.04	7
GPT 5.1	9.3	4.3	7.2	6	6.5

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On this page

Proprietary r

Open-source

Source:
https://www.elastic.co/docs/solutions/security/ai/large-language-model-performance-matrix

Shoutouts

Elastic team members that made these features possible

- Abhimanyu Anand
- Srdjan Lulic
- Kirti Sodhi
- Gus Carlock
- Garrett Spong
- Andrew Macri
- and more

Thank you!
Q&A

Appendix

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QCon AI by InfoQ

JUNE 1-2, 2026

BOSTON UNIVERSITY, GEORGE SHERMAN UNION
BOSTON, MA

< SESSION >

Building Reusable Evaluation Frameworks for Agentic AI Products

Susan Chang

Principal Data Scientist
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