GenAl and Cybersecurity – Frameworks and Best Practices



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Al Key Trends

- 1987-2007: Foundational algorithmic breakthroughs
- 2009-2015: Deep learning revolution in computer vision
- 2013-2017: Major NLP advances with word embeddings and attention
- 2018-2020: Transformer architecture dominance
- 2021-2024: Era of large language models and multi-modal AI

We describe a new learning procedure, back-propagation, for networks of neurone-like units. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal 'hidden' units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure¹.

| Year | Innovation | Significance | |
|------|---------------------|--|--|
| 1987 | Backpropagation | Fundamental algorithm for training neural networks efficiently | |
| 2007 | CUDA | GPU acceleration enabling faster neural network training | |
| 2011 | ReLU | Activation function that helped solve vanishing gradient problem | |
| 2014 | Dropout | Key regularization technique to prevent overfitting | |
| 2015 | Batch Normalization | Technique to stabilize and accelerate neural network training | |

Vision – Text – Modern Al Systems

| Year | Innovation | Significance | |
|------|--|--|--|
| 1989 | CNN (Convolutional Neural Networks) | Architecture specifically designed for image processing | |
| 1998 | LeNet | First successful CNN application for digit recognition | |
| 2009 | ImageNet | Large-scale image dataset that revolutionized computer vision | |
| 2012 | AlexNet | Deep CNN that won ImageNet challenge, sparked deep learning revolution | |
| 2015 | ResNet | Introduced skip connections, enabling much deeper networks | |
| 2021 | CLIP | Bridged gap between vision and language understanding | |
| 2013 | Word2Vec | Word embeddings (CBOW & Skip-gram) | |
| 2014 | GloVe | Global word vectors | |
| 2015 | FastText | Subword embeddings | |
| 2016 | Universal Dependencies | Cross-lingual parsing | |
| 2017 | CoVe | Contextual word vectors | |
| 2018 | ELMo | Deep contextualized embeddings | |
| 2018 | ULMFiT | Universal language model fine-tuning | |

| Year | Innovation | Description | |
|------|-------------|---|--|
| 2020 | GPT-3 | Large language model with 175B parameters | |
| 2020 | DALL-E | First version of text-to-image generation | |
| 2022 | DALL-E 2 | Improved text-to-image generation | |
| 2022 | InstructGPT | Better instruction-following capabilities | |
| 2022 | ChatGPT | Conversational AI that popularized LLMs | |
| 2023 | GPT-4 | Multi-modal capabilities and improved reasoning | |
| 2023 | Claude Al | Focus on safety and alignment | |
| 2023 | Llama | Open-source large language model | |
| 2023 | Alpaca | Fine-tuned instruction-following model | |
| 2024 | Gemini | Multi-modal model with enhanced capabilities | |
| 2024 | Claude 3 | Improved reasoning and task performance | |

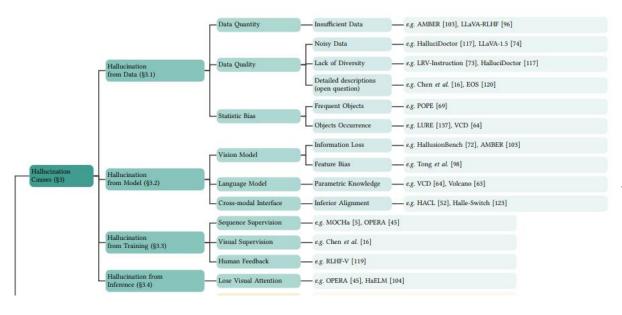
Risk Analysis of RAG, Prompts, and Agents

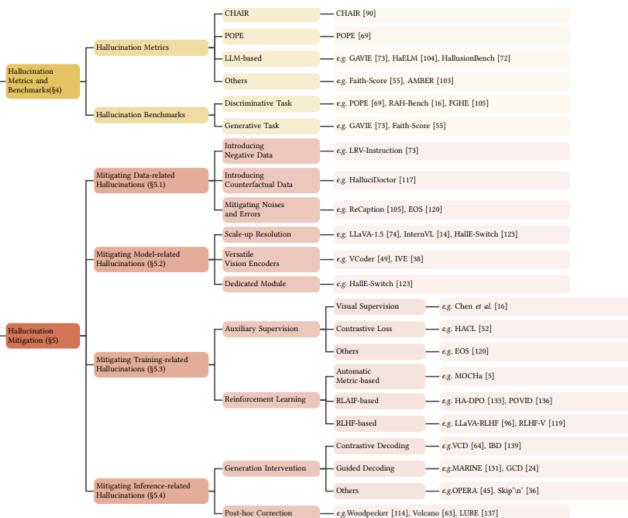
| Aspect | RAG (Retrieval-Augmented Generation) | Prompts | Agents | |
|---------------------------------|--|---|---|--|
| Accuracy | High for factual retrieval, may decrease for complex interpretations | Variable, depends heavily on prompt design and model training | Can be high for well-defined tasks, but may vary for open-ended problems | |
| Scalability | Highly scalable for large datasets, may require significant infrastructure | Easily scalable for text processing tasks, limited by model size | Scalability can be challenging due to complexity, may require distributed systems | |
| Example Tasks in Domain Context | Healthcare: Answering clinician queries about rare diseases from medical literature Finance: Retrieving relevant financial regulations for compliance checks Education: Providing personalized learning content based on student's history | Marketing: Generating product descriptions or ad copy Customer Service: Creating responses to common customer inquiries Software Development: Assisting with code documentation | Supply Chain: Optimizing logistics and inventory management Robotics: Controlling a robot to perform complex assembly tasks Cybersecurity: Continuously monitoring and responding to potential threats | |
| Risk Assessment | Medium Risk: - Misinformation if knowledge base is outdated - Privacy concerns with sensitive data - Potential for biased information retrieval | Medium to High Risk: - Hallucinations or false information generation - Potential for biased or inappropriate content - Inconsistency in outputs | High Risk: - Unpredictable behavior in novel situations - Potential for unintended consequences in autonomous decision-making - Difficulty in auditing complex decision processes | |
| Staged Adoption Strategy | Implement basic RAG for internal knowledge management Expand to customer-facing applications with human oversight Integrate with other AI technologies for more complex tasks | Start with simple, non-critical text generation tasks Gradually increase complexity and importance of tasks Implement safeguards and human review processes Combine with RAG for improved accuracy | Begin with rule-based agents for simple, well-defined tasks Introduce learning capabilities in controlled environments Slowly expand autonomy and complexity of tasks Implement comprehensive monitoring and failsafe mechanisms | |

Agents vs Responsible Al Adoption

| Aspect | Ethical AI | Agentic Autonomous Al | | |
|---------------------------|--|---|--|--|
| Human Oversight | Advocates for human-in-the-loop systems, ensuring human oversight | Aims to minimize human intervention, raising questions about responsibility and control | | |
| Temporal Focus | Prioritizes careful consideration of potential future impacts | May overlook long-term ethical implications in pursuit of rapid advancement | | |
| Reasoning Capabilities | Acknowledges limitations in true reasoning abilities of current AI systems | Pushes boundaries of AI capabilities, potentially overestimating current reasoning abilities | | |
| Core Tension | Prioritizes moral safeguards and human values | Emphasizes greater AI self-direction and independence | | |
| Transparency | Demands explainability and interpretability, potentially limiting model complexity | May sacrifice transparency for increased capabilities, raising accountability concerns | | |
| Data Ethics | Emphasizes unbiased, representative datasets | May prioritize data quantity over quality, risking perpetuation of societal biases | | |
| Continuous Learning | Focuses on maintaining moral constraints in evolving systems | Poses risks of ethical drift over time as systems learn and adapt | | |
| Ethical Framework | Strives for global ethical standards | May encounter conflicts between universal ethics and optimal local decisions | | |
| Implementation Challenges | Requires deep understanding of models, data, and their limitations to avoid superficial adoption | Same challenges apply, with additional complexities due to increased autonomy | | |
| Value Alignment | Explicitly encodes human values into AI systems | May develop its own set of values through learning, potentially misaligning with human ethics | | |

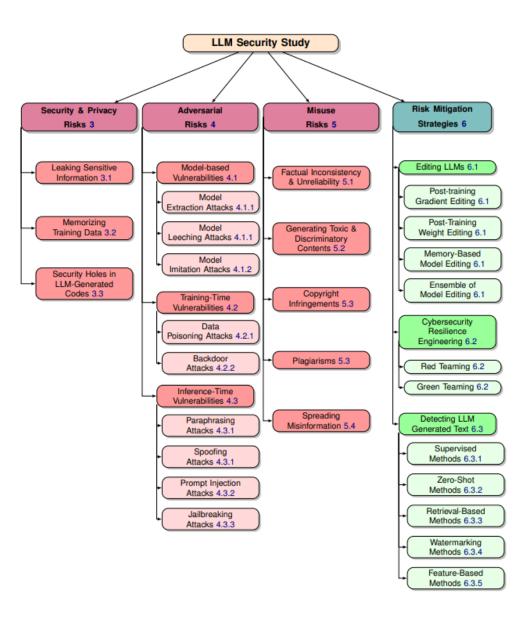
Hallucination Survey





LLM Security

LLMs are powerful tools that may pose several security risks for enterprises and individuals. In this section, we explore critical concerns, including sensitive information leakage, memorizing training data and potential security holes in generated code



https://arxiv.org/pdf/2403.12503v1

NIST AI RMF Taxonomy

Initial Draft

| | Technical Design Characteristics | Socio-Technical Characteristics | Guiding Principles Contributing to Trustworthiness | |
|--------------------|--|--|---|--|
| AI RMF Taxonomy | Accuracy Reliability Robustness Resilience or ML Security | Explainability Interpretability Privacy Safety Managing Bias | FairnessAccountabilityTransparency | |
| OECD AI | Robustness Security | Safety Explainability | Traceability to human values Transparency and responsible disclosure Accountability | |
| EU AI Act | Technical robustness | Safety Privacy Non-discrimination | Human agency and oversight Data governance Transparency Diversity and fairness Environmental and societal well-being Accountability | |
| EO 13960 | Purposeful and performance- driven Accurate, reliable, and effective Secure and resilient | Safe Understandable by subject matter experts, users, and others, as appropriate | Lawful and respectful of our Nation's values Responsible and traceable Regularly monitored Transparent Accountable | |

Figure 4 provides a mapping of the AI RMF taxonomy to the terminology used by the Organisation for Economic Co-operation and Development (OECD) in their Recommendation on AI, the European Union (EU) Artificial Intelligence Act, and United States Executive Order (EO) 13960.



Figure 3: AI Risks and Trustworthiness. The three-class taxonomy to classify characteristics that should be considered in comprehensive approaches for identifying and managing risk related to AI systems. The taxonomy articulates several key building blocks of trustworthy AI within each category, which are particularly suited to the examination of potential risk.

EU's AI framework - Risk-Based Approach to AI Regulation

"Risk Levels. To guide regulatory development, the EU AI Act proposes a risk-based classification system. AI systems are classified into four distinct categories based on the risk they pose.

- ✓ "Unacceptable These AI systems are banned outright.
- √ "High Al systems considered high risk are typically deployed in critical sectors like biometrics, healthcare, law enforcement, education, and employment.
- ✓ "Limited This category includes AI systems like chatbots and systems that generate 'deepfakes' or other manipulative content.
- ✓ "Minimal Al applications that pose little to no risk are in this category. These Al systems include spam filters or Al-enabled video games.



Social

scoring

Biometric identification

in public spaces

High Risk – Credit scoring, Insurance, Social benefits, Facial recognition / Tracking, Medical AI

Exploit

vulnerabilities

Subliminal

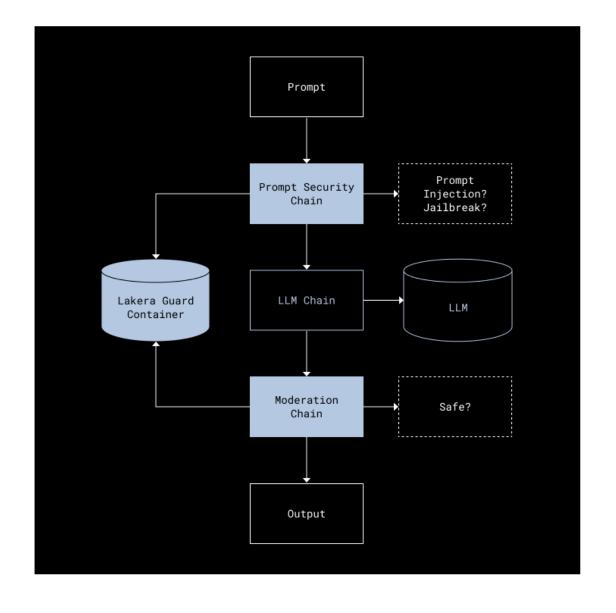
techniques

LLM Assessment / Risks

| | | | NIST CSF 2.0 | COBIT 2019 | ISO 27001:2022 | ISO 42001:2023 |
|---------------------------|-------|---------------|--------------|------------|----------------|----------------|
| Process automation | LLM | opportunities | × | × | ✓ | ✓ |
| | | risks | × | × | × | × |
| | EU AI | Act readiness | × | ✓ | × | ✓ |
| | LLM - | opportunities | ✓ | ✓ | ✓ | ✓ |
| Real-time analysis | LLIVI | risks | × | ✓ | × | × |
| | EU AI | Act readiness | × | ✓ | × | ✓ |
| D. 4 | 1114 | opportunities | ✓ | ✓ | ✓ | ✓ |
| Data security and | LLM | risks | × | ✓ | × | ✓ |
| protection | EU AI | Act readiness | ✓ | ✓ | ✓ | ✓ |
| Cantingana | LLM - | opportunities | ✓ | ✓ | ✓ | ✓ |
| Continuous monitoring | | risks | × | × | × | ✓ |
| and auditing | EU AI | Act readiness | ✓ | ✓ | ✓ | × |
| | LLM | opportunities | ✓ | ✓ | ✓ | ✓ |
| Incident response | | risks | × | × | × | ✓ |
| | EU AI | Act readiness | × | ✓ | × | × |
| Consuity oversenous | LLM | opportunities | × | ✓ | ✓ | ✓ |
| Security awareness | | risks | × | × | √ | ✓ |
| and training | EU AI | Act readiness | × | × | × | × |
| Dalier and compliance | TIM | opportunities | × | ✓ | ✓ | ✓ |
| Policy and compliance | LLM - | risks | ✓ | × | ✓ | × |
| checks | EU AI | Act readiness | × | ✓ | ✓ | × |
| | LLM - | opportunities | 5/7 | 6/7 | 7/7 | 7/7 |
| TOTAL MARKS | | risks | 1/7 | 2/7 | 2/7 | 4/7 |
| | EU AI | Act readiness | 2/7 | 6/7 | 3/7 | 4/7 |

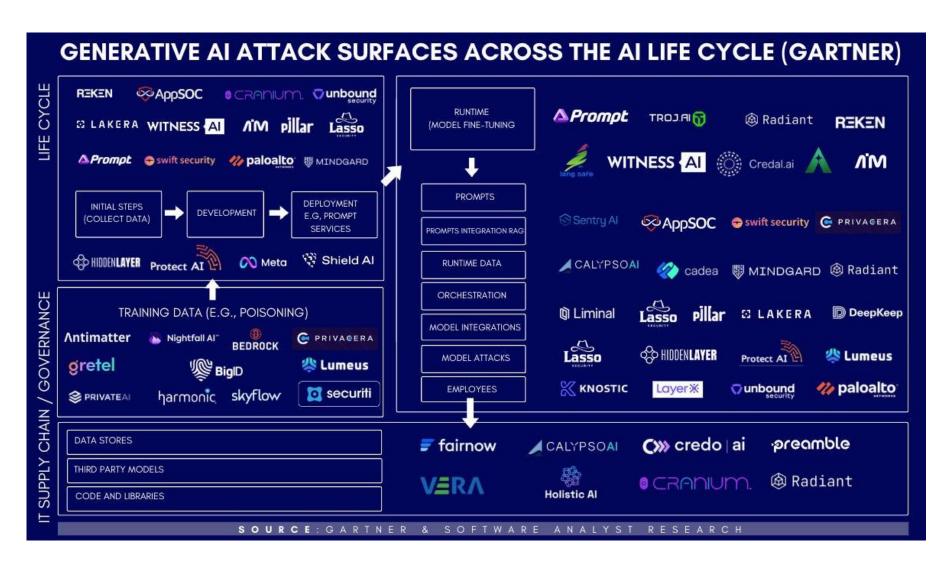
Case Study - Dropbox

- ✓ LLM prompts are processed through security chains, including Lakera Guard, to detect prompt injection and jailbreak attempts.
- ✓ Safe prompts are passed to the appropriate LLM (third-party or internal) for response generation.
- ✓ LLM responses undergo content moderation, including Lakera's API, to identify and filter harmful content.
- ✓ Lakera Guard integration at Dropbox evolved from direct container calls to a scalable custom service within their ML infrastructure.



https://dropbox.tech/security/how-we-use-lakera-guard-to-secure-our-llms

Deep Dive Into The Security for AI Ecosystem



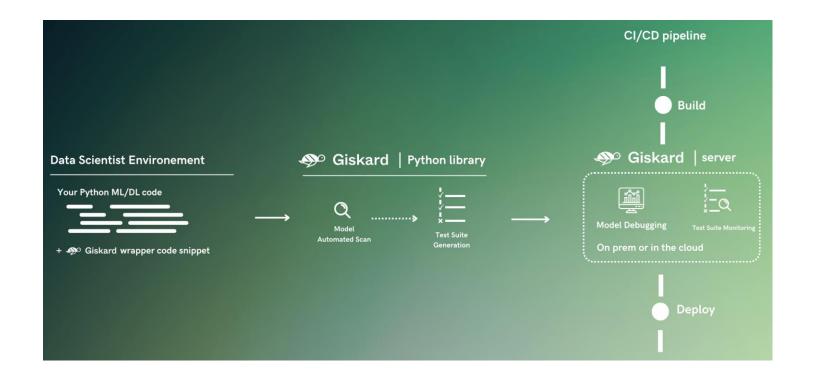
Raga LLM Hub

- ✓ Framework for LLM evaluation and guardrails
- ✓ Tests from similarity, sentiment, toxicity, and relevance plus a detailed extended test list.
- ✓ A very good reference to follow is to adopt this pattern covering different tests.
- ✓ For Dataset, Based on the context of the domain this can be replicated with the golden dataset.
- ✓ You can add around PII / language checks.
- Consistency score is something very useful to compare against versions of models how much we get similar results / measure deviations.

https://github.com/raga-ai-hub/raga-llm-hub

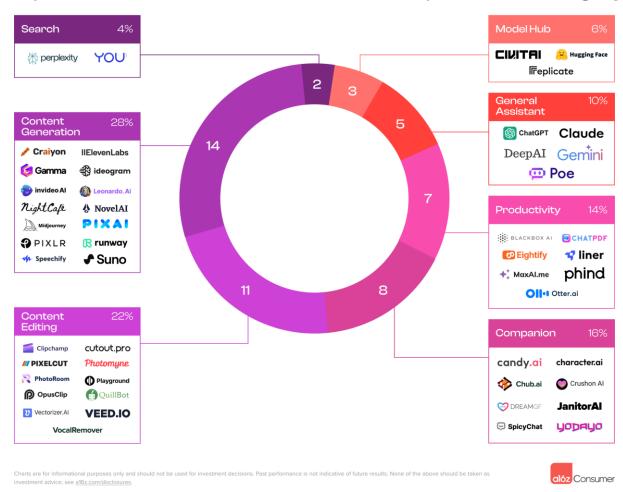
Giskard

- ✓ Open-source testing framework for LLMs & ML models
- ✓ https://github.com/Giskard-Al/giskard

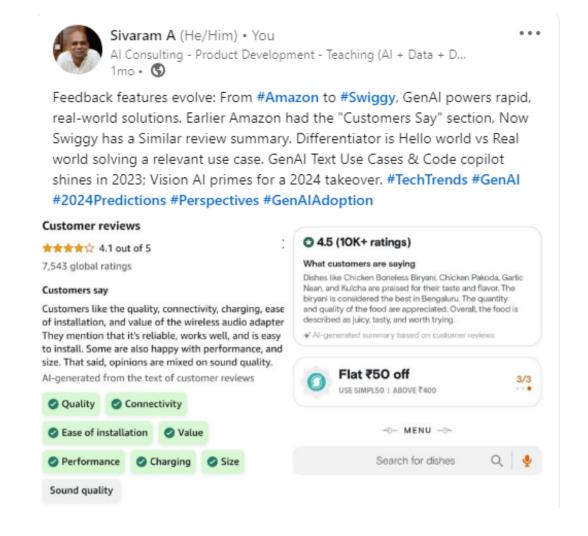


The Top 100 Gen AI Consumer Apps

Top Gen Al Consumer Web Products: Companies Per Category



Case Study – Amazon / Swiggy



Case Study – LLM Implementation



Two **#Chatbot** Stories - Two Perspectives: One is a success story and another is a **#hallucination** case study.

- Air Canada has lost a court case after its chatbot presented fictitious policies to a customer.
- Klarna's AI chatbot performs the work equivalent to 700 full-time employees.

Copycat use cases will not work unless the solution caters to all aspects pre/post validations with intent recognition, response validation, contextual analysis, and models finetuned for the use case. Answer generation is 50% effort, Answer validation is another 50% effort.

How to mitigate? Test, Test, Test. Now with GenAl - 20% Dev Efforts but 80% Test Ffforts.

- Refer to Historical data, Generate questions
- Generate and Compare responses using both old/new chatbot models
- Validate response similarity/context
- Validation / Continous texting / Testing model for Consistency, Accuracy is key
- Benchmark and compare two LLM models for validation/consistency
- Create a custom golden dataset and validate it

If you are working on a use-case or domain-based project and want to have a discussion, we can talk to share perspectives and approaches.

#AI #Chatbots #MachineLearning #CustomerService #QualityAssurance
#Innovation #TechnologyInsights #ArtificialIntelligence #Testing #DataAnalysis
#perspectives #usecases #domain #Data #GenAI

Best Practices



Well Analyzed on the success story. Two key points. Good job on the team for making **#hallucination** not possible - because it seems to spit out the same responses however I ask it, and refuses to go "out of bounds."

Klarna wants potential investors to believe they are buying into an "#AI edge" company. Air Canada vs Klara the guardrails of implementations create the outcomes. #Helloword chatbot vs #Realword implementation



Klarna has made headlines with its Al assistant (powered by OpenAl) handling two-thirds (2.3 Million) of Klarna's customer service chats in the last months.

According to Klarna, the Al Assistant:

- Can handle refunds, returns, payment-related, cancellations and more
 Performs the work equivalent to 700 full-time agents and matches customer satisfaction
- 💍 Is more accurate and faster in errand resolution, from 11 minutes to 2 minutes
- Can speak 35 Languages and is estimated to generate \$40M USD in profit for Klarna in 2024

Does it sound too good to be true? Gergely Orosz gave it a try and shared his experience. The Assistant:

- Recites docs and passes to human support fast
- Can detect unrelated requests, e.g., merchant, and redirects to them
- Feels to act as a filter to get to human support
- Handles hallucination well and stays in the scope

While Klarna's story feels a bit too polished, it sounds reasonable to me. Based on what we know, the Assistant is a RAG Application on top of their docs, with strong guardrails to answer documentation-related questions, filter out wrong requests, and knows when to involve Human support.

You can achieve the results if > 60% of the people don't need real support, they just need stuff that already exists in the docs or ask the wrong support. i can believe that there is a lot of simple support that costs resources and can be solved by this. But I am still wondering how this can generate \$40M profit 29

Blog: https://lnkd.in/e5tbHFkD X Thread: https://lnkd.in/ejpU9sgy

- Guardrails for Data / PII / Bias
- Intent Detection
- Entity Detection
- Sentiment Analysis
- Transfer of support for out of context

Celebrating a Year of GenAl Use Case Success in Retail!



Celebrating a Year of GenAl Use Case Success in Retail!



Sivaram A

Al Advisory / Solution Architect - Al/ DL/ GenAl Product Strategy/Development - Teaching(Al + Data + Domain + Gen...



September 27, 2024

It's been over a year since my Retail adoption #GenAl use case went live for a leading U.S. specialty retailer on August 17, 2023.

Rethinking Al/ML Implementation: It's not about wrapping Al around existing processes. True impact comes from:

- · New engagement models
- Innovative interactions
- · Blending creative solutions

Success Factors in Production:

- Data Quality, Alignment on Data Collection / Moderation 🔽
- Innovative use of GenAl, Multiple touchpoints of Data, and Experiments to have variations to provide multiple choices to pick the best across stakeholders
- Tailored solutions (not patchwork fixes)
- Extensive Human in Loop with Merchandisers, Prompt Engineering Training
- Get Users' Trust before providing them the Role of Approval Authority
- Focused Rigorous testing in production environments with few products before doing at-scale

Beyond Demos:

- We were able to provide feedback on evaluating beta versions of LLM models and share insights with cloud partners
- We benchmarked against OpenAI and shared cloud partners what works and what can be improved?

https://www.linkedin.com/pulse/celebrating-year-genai-use-case-success-retail-sivaram-a-mtxpc/

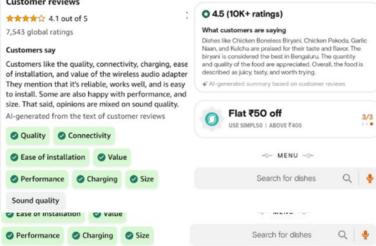
LLMs



Feedback features evolve: From #Amazon to #Swiggy, GenAl powers rapid, real-world solutions. Earlier Amazon had the "Customers Say" section, Now Swiggy has a Similar review summary. Differentiator is Hello world vs Real world solving a relevant use case. GenAl Text Use Cases & Code copilot shines in 2023; Vision AI primes for a 2024 takeover. #TechTrends #GenAI #2024Predictions #Perspectives #GenAlAdoption



Sound quality





After every year learning extends Data, Al, Products, and Domain. 2023 had a blend of experiences. Still figuring out answers for every dimension #2023 #Learnings

- → How you've adapted to industry shifts, and #GenAl's meaningful adoption. Possible use cases vs relevant, meaningful production-ready use cases. Example - Newly launched section in Amazon reviews, What customers sav.
- → How you've overcome engineering challenges balancing business goals. New ways to solve old problems with Foundation models. Time vs building a production-grade solution. Example - Moving away from custom NER vs Leveraging #LLM Embeddings, Blend of both custom embedding + #RAG, New ways of solving.
- → How your skills align with the company's vision, Learning to predict the future. New approaches and papers evolve faster than certifications. A blend of tech + and domain is key. Segment Anything model, Visual QnA, Intructpix2pix have made more vision use cases feasible Tryon, etc..
- → How you bridge the gap between tech and business, Fast yet impactful use cases, Get the basics right. Demos / New offerings vs making it to production need a careful selection of use cases / applying past experiences to get things right in the first iteration. Balance the tradeoff between creativity vs innovation vs build a **#productstrategy** vs solve a real need vs fancy demos. #learning #perspectives #solutions #datascience #MachineLearning #AI #DeepLearning #GenAI



Sivaram A • You Al Consulting - Product Development - Teaching (Al + Data + D... 10mo • Edited • 🕟

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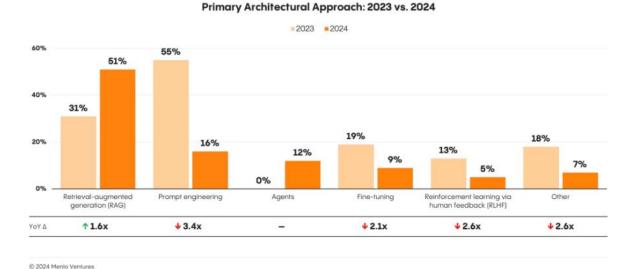
#GenAl has the potential to revolutionize the #entertainment industry. GenAl will help to create more immersive, engaging, and personalized experiences for audiences.

- Recreate movies with new colors, locations, and film restorations (Superresolution, Text to image, Image variations)
- · Automate content #translations, language translations, and lip sync.
- · Create #deepfakes to customize, edit, or introduce new scenes.
- · Create new environments and #creative scenes more easily and quickly. (Text to image, Image Variations)
- Create different custom #backgrounds.
- Generate #video shorts and creative one-liners.
- · Generate a large amount of musical inspiration with Al prompts.
- Enrich, recreate, and create more creative variations of content.
- Create multiple variations of content from a single source, reducing rework and creating significantly different variations.
- We are entering a world where you can write your experience to get ideas of what your imagination looks like.

#GenAl will empower #entertainment industry by automating tasks, creating new content, and generating variations. #artificialintelligence #entertainment #film #games #music #technology #virtualreality #augmentedreality #experience

RAG Gains, Fine Tuning Is Rare, and Agents Break Out

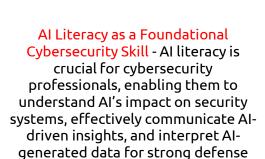
- Enterprise AI design patterns—standardized architectures for building efficient, scalable AI systems—are evolving rapidly.
- RAG (retrieval-augmented generation) now dominates at 51% adoption, a dramatic rise from 31% last year.
- Meanwhile, fine-tuning—often touted, especially among leading application providers—remains surprisingly rare, with only 9% of production models being fine-tuned



https://menlovc.com/2024-the-state-of-generative-ai-in-the-enterprise/

Security in GenAl





strategies.



Ask Strategic Questions (Security-Oriented Thinking) - Apply critical thinking to investigate AI models, data privacy issues, and potential vulnerabilities, ensuring a thorough understanding of the security landscape.



Critically Assess AI Outputs (Close Reading of Data) - Analyze AIgenerated logs and reports with precision to identify anomalies and suspicious activity, guiding proactive threat detection and mitigation.



Align Cybersecurity Strategy with Organizational Values (Purposeful Communication) - Use creative thinking to design Al-supported security policies that align with the organization's mission and long-term cybersecurity goals.