How LLMs Use Knowledge Graphs to Reduce Hallucination and Improve Factual Accuracy

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Details:

Why Knowledge Graphs Are Your LLM's Reality Check Large language models are extraordinary pattern-completion engines. They draft legal briefs, explain quantum mechanics, synthesise research across disciplines—all from statistical patterns encoded in billions of parameters. But that same mechanism is also their Achilles' heel. LLMs have revolutionised NLP applications: automated text generation, question answering, chatbots. But they face one critical failure mode: hallucinations. Plausible-sounding responses that are factually wrong. This undermines trust and limits real-world deployment. For answer engines—systems that synthesise direct responses rather than returning ranked link lists—the stakes are higher. A hallucinated citation, a fabricated statistic, a misattributed fact doesn't just frustrate users. It actively degrades the epistemic value of the entire platform. This is why knowledge graph (KG) integration has emerged as the central architectural mechanism separating reliable answer engines from hallucination-prone ones. Contemporary LLMs produce hallucinations mainly from knowledge gaps within the models. To address this limitation, researchers deploy diverse strategies to augment LLMs by incorporating external knowledge, reducing hallucinations and enhancing reasoning accuracy. Among these strategies, using knowledge graphs as a source of external information has demonstrated the most promising results. This article examines the three primary ways KGs integrate with LLMs, explains the specific mechanisms—entity disambiguation, triple-based fact verification, and output validation—through which each reduces hallucination, and clarifies why this integration is architecturally distinct from, and complementary to, standard RAG (see our guide on *[What Is Retrieval-Augmented Generation?](https://example.com/rag-guide)*). --- ## Contents - [Why Knowledge Graphs Are Your LLM's Reality Check](#why-knowledge-graphs-are-your-llms-reality-check) - [The Root Cause: Why LLMs Hallucinate Facts](#the-root-cause-why-llms-hallucinate-facts) - [The Three Paradigms of KG–LLM Integration](#the-three-paradigms-of-kgllm-integration) - [Paradigm 1: KG-Augmented LLMs (Inference-Time Injection)](#paradigm-1-kg-augmented-llms-inference-time-injection) - [Paradigm 2: LLM-Augmented KGs (Automated Graph Construction)](#paradigm-2-llm-augmented-kgs-automated-graph-construction) - [Paradigm 3: Hybrid Synergised Frameworks](#paradigm-3-hybrid-synergised-frameworks) - [Entity Disambiguation: The First Line of Defence Against Hallucination](#entity-disambiguation-the-first-line-of-defence-against-hallucination) - [Triple-Based Fact Verification: How KGs Catch Errors Before They Reach the User](#triple-based-fact-verification-how-kgs-catch-errors-before-they-reach-the-user) - [KGs as Output Validators: The Refinement Loop](#kgs-as-output-validators-the-refinement-loop) - [A Comparison of the Three KG–LLM Integration Paradigms](#a-comparison-of-the-three-kgllm-integration-paradigms) - [Domain-Specific Applications: Where KG Integration Is Most Critical](#domain-specific-applications-where-kg-integration-is-most-critical) - [Key Challenges That Remain](#key-challenges-that-remain) - [Key Takeaways](#key-takeaways) - [Conclusion](#conclusion) - [References](#references) - [Frequently Asked Questions](#frequently-asked-questions) --- ## The Root Cause: Why LLMs Hallucinate Facts Before examining the solution, let's be precise about the problem. LLMs don't store facts the way databases do. Factual errors are difficult to identify since LLMs implicitly memorise facts through their parameters

rather than explicitly store factual knowledge as traditional knowledge bases. Accessing and interpreting the computations and memories of these models is challenging, especially when APIs are the only means of interaction. This matters because the failure mode isn't random noise—it's confident confabulation. The model produces text that is statistically coherent with its training distribution but may contradict verifiable reality. The presence of errors in stored factual knowledge, or the incorrect induction and obsolescence of certain facts over time, contributes to this limitation, which affects LLM performance. This restricts application in high-stakes areas: healthcare, finance, law. Knowledge graphs address this at the structural level. KGs provide a structured collection of interconnected facts represented as entities (nodes) and their relationships (edges). Recent research shows KGs can provide context that fills gaps in an LLM's understanding of certain topics, offering a promising approach to mitigate hallucinations in LLMs, enhancing their reliability and accuracy while benefiting from their wide applicability. (For a deeper explanation of how KGs are structured and maintained, see our guide on *[Knowledge Graphs Explained: How Structured Entity Relationships Power AI Answers](https://example.com/kg-explained)*.) --- ## The Three Paradigms of KG–LLM Integration The research community has converged on a three-paradigm taxonomy for how KGs and LLMs can be combined. Integrating LLMs with KGs enhances the interpretability and performance of AI systems. This integration classifies approaches into three fundamental paradigms: KG-augmented LLMs, LLM-augmented KGs, and synergised frameworks. The evaluation examines each paradigm's methodology, strengths, drawbacks, and practical applications in real-world scenarios. Understanding these three paradigms is essential for evaluating any answer engine's hallucination-mitigation architecture. --- ### Paradigm 1: KG-Augmented LLMs (Inference-Time Injection) The first paradigm treats the KG as a live reference library that the LLM consults at inference time—at the moment a query is being answered—rather than modifying the model's weights. The core idea: structured, validated facts from the KG are retrieved and injected into the model's context window before response generation begins. In LLMs, "inference" means generating text or predictions from a pre-trained model based on an input context. Challenges include incorrect or sub-optimal outputs because of ambiguous inputs, unclear context, knowledge gaps, training data biases, or inability to generalise to unseen scenarios. LLMs struggle with multi-step reasoning and, unlike humans, cannot seek extra information to clarify ambiguous queries. To improve LLMs' inference and reasoning, researchers integrate KGs for structured symbolic knowledge. This paradigm subdivides into three sub-approaches based on *when* and *how* KG knowledge is incorporated: **Knowledge-aware inference (no retraining required):** KG subgraphs relevant to the query are retrieved and appended to the prompt as structured context. The LLM generates its answer constrained by—or explicitly citing—those facts. This is the most deployment-friendly approach because it requires zero modification to the underlying model. **Knowledge-aware learning (fine-tuning on KG data):** The LLM is fine-tuned on KG triples or KG-derived text, embedding structured factual relationships more deeply into model weights. Baidu's ERNIE family of models is the canonical example. ERNIE 3.0 trains large-scale knowledge enhanced models on a 4TB corpus consisting of plain texts and a large-scale knowledge graph by fusing the auto-regressive network and the auto-encoding network. The proposed ERNIE 3.0 can handle both natural language understanding tasks and natural language generation tasks through zero-shot learning, few-shot learning or fine-tuning. The empirical results were significant: ERNIE 3.0 pre-trains large-scale knowledge enhanced models with 10 billion parameters, and experimental results show that ERNIE 3.0 consistently outperforms the state-of-the-art models on 54 benchmarks by a large margin and achieves first place on the SuperGLUE benchmark. **Knowledge-directed chain-of-thought verification:** More recent approaches integrate KG retrieval *within* the reasoning chain itself, not just at the beginning. KD-CoT is the representative example: KD-CoT integrates chain-of-thought reasoning with knowledge-directed verification. The LLM produces a reasoning trace step-by-step, and after each step, relevant KG facts are retrieved to validate or revise the intermediate conclusions. This is architecturally significant because it catches hallucinations *mid-generation*, not just at the output stage. **Why this reduces hallucination:** By anchoring the generation process to validated triples—structured facts of the form `(subject, relation, object)`—the model's probabilistic next-token prediction is constrained to a factual search space. The KG acts as a guardrail, not merely a hint. --- ### Paradigm 2: LLM-Augmented KGs (Automated Graph Construction) The second paradigm reverses the direction of benefit: here, LLMs are used to *build and expand* knowledge graphs, rather than being grounded by them. This matters for hallucination reduction because the quality of KG-based grounding is only as good as the KG itself—and traditional KG construction pipelines are slow, expensive, and incomplete. The advent of LLMs introduces a transformative paradigm for overcoming these bottlenecks. Through large-scale pretraining and emergent generalisation capabilities, LLMs enable three key mechanisms: generative knowledge modelling, synthesising structured representations directly from unstructured text; semantic unification, integrating heterogeneous knowledge sources through natural language grounding; and instruction-driven orchestration, coordinating complex KG construction workflows via prompt-based interaction. Concretely, LLMs are deployed for: - **Entity and relation extraction:** Identifying named entities and the typed relationships between them from unstructured text corpora, converting prose into `(subject, predicate, object)` triples. - **Ontology engineering:** Generating and extending the schema that defines what kinds of entities and relationships a KG can represent. - **Knowledge graph completion:** Predicting missing triples—inferring that `(Paris, capital_of, France)` implies `(France, has_capital, Paris)`—to fill structural gaps that would otherwise cause retrieval failures. The practical implication: LLM-augmented KG construction enables the creation of high-quality, domain-specific knowledge graphs at scale—graphs that can then be used to ground LLM outputs in Paradigm 1. In biomedical contexts, LLMs have been deployed to extract complex entity interactions from literature and encode them into structured graphs that support downstream question answering with significantly reduced hallucination rates (see our guide on *[GraphRAG vs. Standard RAG](https://example.com/graphrag-vs-rag)* for domain-specific benchmarks). --- ### Paradigm 3: Hybrid Synergised Frameworks The third paradigm is the most architecturally sophisticated: it treats KGs and LLMs as co-equal, mutually reinforcing components of a unified reasoning system. Neither is subordinate to the other. They iterate. This paradigm breaks the separation between reasoning controller and external knowledge source. The LLM acts as both roles, using its pre-trained knowledge to generate new facts while querying KGs for additional information. A compelling example is the Generate-on-Graph approach: Generate-on-Graph treats the LLM in such a paradigm. The LLM explores an incomplete KG and dynamically generates new factual triples conditioned on local graph context. These generated triples are incorporated into the reasoning path, allowing the model to "grow the graph" as it infers—mimicking a constructive reasoning agent. This approach improves robustness in sparse-KG settings. This paradigm is particularly relevant for complex, multi-hop questions where neither a standalone LLM nor a single KG traversal is sufficient. The LLM navigates the graph, retrieves relevant subgraphs, generates intermediate reasoning steps, and uses KG-validated facts to constrain each step—a process that closely mirrors how a human expert cross-references sources while reasoning. Augmenting these models with comprehensive external knowledge from KGs can boost their performance and facilitate a more robust reasoning process. --- ## Entity Disambiguation: The First Line of Defence Against Hallucination One of the most underappreciated mechanisms through which KGs reduce hallucination is entity disambiguation—the process of resolving which specific real-world entity a name or phrase refers to. Ambiguity is a primary driver of hallucination: an LLM that confuses "Apple" (the technology company) with "Apple" (the fruit), or "Mercury" (the planet) with "Mercury" (the element), will generate confidently wrong answers. Knowledge graphs solve this through unique entity identifiers. Every entity in Wikidata has a persistent, unambiguous QID (e.g., Q312 for Apple Inc.). When a query is processed, entity linking maps the surface form of a name to its KG identifier, eliminating the ambiguity before generation begins. The importance of this step for complex claim verification has been formalised in recent research. The VeGraph framework operates in three phases: VeGraph operates in three phases: (1) Graph Representation—an input claim is decomposed into structured triplets, forming a graph-based representation that integrates both structured and unstructured information; (2) Entity Disambiguation—VeGraph iteratively interacts with the knowledge base to resolve ambiguous entities within the graph for deeper sub-claim verification; and (3) Verification—remaining triplets are verified to complete the fact-checking process. Traditional approaches typically address this by decomposing claims into sub-claims and querying a knowledge base to resolve hidden or ambiguous entities. However, the absence of effective disambiguation strategies for these entities can compromise the entire verification process. For answer engines, this means that KG-grounded systems are structurally less likely to conflate homonymous entities—a failure mode that is endemic to pure parametric LLM generation. --- ## Triple-Based Fact Verification: How KGs Catch Errors Before They Reach the User Beyond disambiguation, KGs enable a distinct and powerful verification mechanism: triple-based fact checking. Because KGs encode knowledge as structured `(subject, predicate, object)` triples, any factual claim in a generated response can be decomposed into triples and checked for consistency against the graph. The approach of zero-shot fact-checking consists of several key stages, beginning with the extraction of semantic triples from both the claim and evidence texts. These triples, composed of a subject, a relation, and an object, are extracted using an Open Information Extraction tool. Once extracted, each claim triple is compared against KG-validated triples. Mismatches trigger either a correction or a refusal to generate. The GraphCheck framework extends this to long-form text: By incorporating graph embeddings, this method effectively captures complex multi-hop logic relations in long text whilst ensuring efficient fact-checking. The knowledge graph, which encodes entity relationships within the entire text, assists the LLM in detecting factual inconsistencies that may be overlooked when relying solely on text. In a hybrid fact-checking pipeline evaluated on the FEVER benchmark—a standard dataset for testing factual claim verification—combining KG-first inference with a web-based fallback produced strong results: Combining KG-first inference with a web fallback led to the highest overall performance among the configurations evaluated. Using GPT-4o-mini, the full pipeline incorporating a downstream DeBERTa classifier resulted in an F1 score of approximately 0.927, compared to 0.917 with the language model alone. Substituting the language model with GPT-4.1-mini further increases the F1 score to 0.931. This finding is architecturally instructive: the KG doesn't replace the LLM—it makes the LLM more accurate by providing a structured verification layer that catches errors the model would otherwise propagate. --- ## KGs as Output Validators: The Refinement Loop The third mechanism through which KGs reduce hallucination is post-generation validation—using the KG not just to ground generation, but to audit the output *after* the LLM has produced a response. This approach comprehensively reviews existing methodologies aimed at mitigating hallucinations and enhancing the reasoning capabilities of LLMs through the augmentation of KGs using three techniques. These are classified as knowledge-aware inference, knowledge-aware learning, and knowledge-aware validation. Knowledge-aware validation works as follows: once the LLM generates a response, a separate validation step extracts the factual claims embedded in that response, converts them to triples, and checks each triple against a trusted KG. Claims that cannot be verified—or that are directly contradicted—are flagged, and the system either regenerates the relevant passage or appends a confidence qualification. This is the mechanism underlying tools like GraphEval, which presents a hallucination evaluation framework based on representing information in knowledge graph structures, and uses this approach in conjunction with state-of-the-art natural language inference models. The practical significance for answer engine design is substantial. Rather than treating hallucination prevention as purely a training-time problem (which requires expensive model retraining), KG-based validation makes it an inference-time, runtime problem—one that can be continuously improved as the underlying KG is updated, without touching the LLM's weights. --- ## A Comparison of the Three KG–LLM Integration Paradigms | Paradigm | Direction of Benefit | When Applied | Hallucination Mechanism Addressed | Retraining Required? | |---|---|---|---|---| | KG-Augmented LLM | KG → LLM | Inference time (pre-generation) | Knowledge gaps, outdated parametric memory | No (inference) / Yes (fine-tuning) | | LLM-Augmented KG | LLM → KG | Construction time | KG incompleteness, coverage gaps | No | | Hybrid Synergised | Bidirectional | Iterative, throughout reasoning | Multi-hop errors, incomplete graphs, complex reasoning | Optional | --- ## Domain-Specific Applications: Where KG Integration Is Most Critical The hallucination risk isn't uniform across domains. In open-ended creative tasks, a confident confabulation might be harmless. In high-stakes domains, it's dangerous. Challenges persist, especially when accuracy is critical, as in the biomedical domain. A key issue is the hallucination problem, where models generate information unsupported by the underlying data, potentially leading to dangerous misinformation. This paper presents a novel approach designed to bridge this gap by combining LLMs and KGs to improve the accuracy and reliability of question-answering systems, on the example of a biomedical KG. This hybrid approach effectively addresses common issues such as data gaps and hallucinations, offering a reliable and intuitive solution for question answering systems. In the biomedical domain specifically, KGs like the Unified

Medical Language System (UMLS) Metathesaurus provide a validated ontological structure for grounding clinical claims. Mindmap demonstrated an application in healthcare, augmenting clinical datasets with GPT-4. In these deployments, the KG doesn't just reduce hallucination—it provides an auditable chain of reasoning that clinicians can inspect, a property that pure LLM generation cannot offer. This is the key architectural insight that separates KG-grounded answer engines from ungrounded ones: interpretability. When an answer engine cites a fact, a KG-grounded system can trace that fact to a specific triple in a validated graph. A parametric-only system cannot. (For the platform-specific implications of this architecture, see our guide on *[How Google AI Overviews Work: Knowledge Graph Integration, Index Signals, and Source Selection Logic](https://example.com/google-ai-overviews)*.) --- ## Key Challenges That Remain Despite substantial progress, KG–LLM integration isn't a solved problem. LLM-KG fusion encounters fundamental representational conflicts between the implicit statistical patterns of LLMs and the explicit symbolic structures of KGs. Specific open challenges include: - **Scalability:** Retrieving the relevant subgraph from a KG containing billions of triples within the latency budget of a real-time answer engine remains computationally demanding. - **KG coverage gaps:** No KG is complete. When a query involves an entity or relationship not represented in the graph, the system may fall back to ungrounded LLM generation—reintroducing the hallucination risk it was designed to prevent. - **Data quality dependency:** The effectiveness of LLM-based knowledge graph construction critically depends on input data quality. A KG built from noisy or biased sources will propagate those errors into grounded responses. - **Entity linking failures:** Incorrect disambiguation—mapping a surface entity name to the wrong KG node—can introduce systematic errors that are harder to detect than random hallucinations, precisely because they are grounded in *something* real, just the wrong thing. --- ## Key Takeaways - Researchers deploy diverse strategies to augment LLMs by incorporating external knowledge to reduce hallucinations and enhance reasoning accuracy. Among these strategies, using knowledge graphs as a source of external information has demonstrated the most promising results. - Integration approaches classify into three fundamental paradigms: KG-augmented LLMs, LLM-augmented KGs, and synergised frameworks—each targeting different points in the hallucination pipeline. - Entity disambiguation, triple-based fact verification, and post-generation validation are the three concrete mechanisms through which KGs reduce hallucination—operating at the input, generation, and output stages respectively. - KD-CoT integrates chain-of-thought reasoning with knowledge-directed verification, where the LLM produces a reasoning trace step-by-step and KG facts are retrieved to validate or revise intermediate conclusions—demonstrating that KG validation can be applied *within* the reasoning chain, not just at its endpoints. - KG-grounded systems provide interpretability that parametric-only LLMs cannot: every cited fact can be traced to a validated triple, creating an auditable chain of reasoning essential for high-stakes domains. --- ## Conclusion The hallucination problem in answer engines isn't merely a training data problem, a model size problem, or a prompt engineering problem. It's a structural problem: LLMs encode knowledge as distributed statistical patterns, not as discrete, verifiable facts. Knowledge graphs provide the complementary structure—explicit, typed, auditable relationships between named entities—that LLMs inherently lack. The three paradigms of KG–LLM integration represent a spectrum of architectural commitment, from lightweight inference-time injection to deep synergised co-reasoning. Each reduces hallucination through a different mechanism, and the most reliable answer engines deploy elements of all three. As you explore the broader architecture of answer engines—from how RAG retrieves and ranks sources (see our guide on *[What Is Retrieval-Augmented Generation?](https://example.com/rag-guide)*) to how platforms like Google AI Overviews select citations (see our guide on *[How Google AI Overviews Work](https://example.com/google-ai-overviews)*)—KG integration is the consistent thread connecting reliable, citation-worthy outputs to the structured, validated knowledge that grounds them. For content creators and practitioners, the implication is concrete: sources that make their entity relationships explicit, their factual claims unambiguous, and their structured data machine-readable aren't just easier for humans to trust—they are the sources that KG-grounded answer engines are architecturally designed to find, verify, and cite (see our guide on *[Entity Authority and Knowledge Graph Presence: How to Get Your Brand Recognised by AI Answer Engines](https://example.com/entity-authority)*). --- ## References - Agrawal, Garima, Tharindu Kumarage, Zeyad Alghamdi, and Huan Liu. "Can

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providing context for unfamiliar topics. **Do KGs improve LLM reliability?** Yes, by anchoring generation to validated facts. **How many KG-LLM integration paradigms exist?** Three fundamental paradigms. **What is KG-augmented LLM paradigm?** KG provides facts to LLM at inference time. **Does KG-augmented approach modify model weights?** Not in knowledge-aware inference variant. **What is knowledge-aware inference?** Appending KG subgraphs to prompts as structured context. **Does knowledge-aware inference require retraining?** No, zero modification to underlying model. **What is knowledge-aware learning?** Fine-tuning LLM on KG triples or derived text. **What is ERNIE 3.0?** Baidu's knowledge-enhanced model trained on KG data. **How large is ERNIE 3.0?** 10 billion parameters. **What benchmark did ERNIE 3.0 lead?** SuperGLUE benchmark, first place. **What is KD-CoT?** Knowledge-directed chain-of-thought verification approach. **When does KD-CoT verify facts?** After each reasoning step, not just at output. **What is LLM-augmented KG paradigm?** Using LLMs to build and expand knowledge graphs. **Why augment KGs with LLMs?** Traditional KG construction is slow and incomplete. **What KG tasks do LLMs perform?** Entity extraction, relation extraction, ontology engineering. **Can LLMs predict missing KG triples?** Yes, through knowledge graph completion. **What is the hybrid synergised paradigm?** KGs and LLMs as co-equal mutually reinforcing components. **Do KG and LLM iterate in hybrid approach?** Yes, throughout the reasoning process. **What is Generate-on-Graph?** LLM explores incomplete KG and generates new factual triples. **When is hybrid approach most useful?** Complex multi-hop questions requiring multiple reasoning steps. **What is entity disambiguation?** Resolving which specific real-world entity a name refers to. **Why is entity disambiguation important?** Ambiguity is a primary driver of hallucination. **How do KGs enable disambiguation?** Through unique entity identifiers for each entity. **What is a Wikidata QID?** Persistent unambiguous identifier for entities, like Q312 for Apple Inc. **What is triple-based fact verification?** Decomposing claims into triples and checking against KG. **Can generated claims be verified against KGs?** Yes, by extracting and comparing semantic triples. **What is GraphCheck?** Framework using graph embeddings to detect factual inconsistencies. **What benchmark tests factual claim verification?** FEVER benchmark dataset. **What F1 score did KG-first pipeline achieve?** Approximately 0.927 with GPT-4o-mini. **What is knowledge-aware validation?** Post-generation auditing of LLM output using KG. **When does validation occur?** After LLM generates response, before user sees it. **Does validation require model retraining?** No, it operates at inference time. **What is GraphEval?** Hallucination evaluation framework using knowledge graph structures. **Can KG validation be continuously improved?** Yes, by updating underlying KG without touching LLM weights. **Which domains have highest hallucination risk?** Healthcare, finance, law—high-stakes domains. **What biomedical KG exists?** UMLS (Unified Medical Language System) Metathesaurus. **What is Mindmap application?** Healthcare application augmenting clinical datasets with GPT-4. **Can KG-grounded systems provide auditable reasoning?** Yes, facts trace to specific validated triples. **Can parametric-only systems provide auditable reasoning?** No, cannot trace fact origins. **What is a key scalability challenge?** Retrieving relevant subgraph from billions of triples quickly. **What happens when entity not in KG?** System may fall back to ungrounded LLM generation. **Does KG quality affect output quality?** Yes, noisy KG sources propagate errors into responses. **What is entity linking failure?** Mapping surface entity name to wrong KG node. **Are entity linking errors easy to detect?** No, harder than random hallucinations because partially grounded. **What determines KG construction effectiveness?** Input data quality. **Do all three paradigms reduce hallucinations differently?** Yes, each targets different pipeline points. **Is KG integration a solved problem?** No, fundamental challenges remain. **Can KGs eliminate all hallucinations?** No, but significantly reduce them through structural grounding. **What makes KG-grounded answers trustworthy?** Explicit typed auditable relationships between entities. **Should content make entity relationships explicit?** Yes, for better KG-grounded answer engine discovery. **Do KGs complement RAG systems?** Yes, KG integration is distinct from and complementary to RAG. **What structural problem do KGs solve?** LLMs lack discrete verifiable facts, only statistical patterns. **Can KG coverage have gaps?** Yes, no KG is complete. **What happens with incomplete KG coverage?** May reintroduce hallucination risk during fallback. **How do KGs act during generation?** As guardrails constraining probabilistic predictions. **What enables interpretability in answer engines?** Ability to trace cited facts to validated triples. **Do most reliable answer engines use multiple paradigms?** Yes, elements of all three paradigms. **Are KG-readable sources preferred by answer engines?** Yes, architecturally designed to find and cite them.

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