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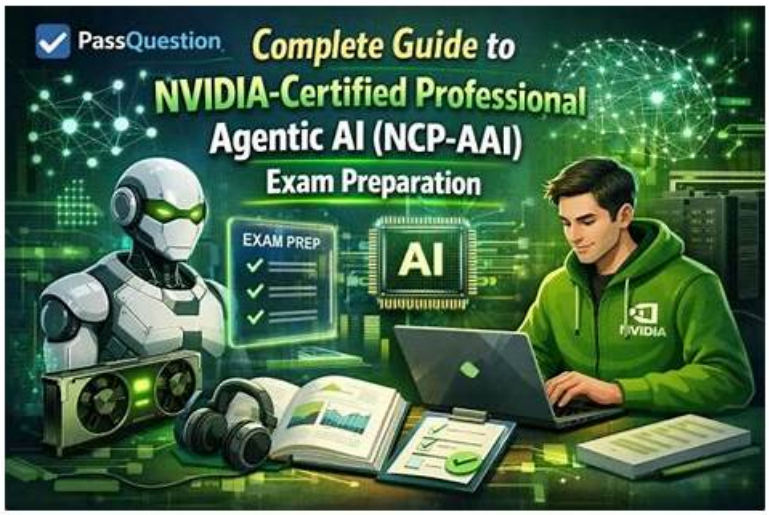

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NVIDIA NCP-AAI Exam Syllabus Topics:

Topic	Details
Topic 1	• Knowledge Integration and Data Handling: Covers how agents integrate external knowledge sources and manage diverse data types to support informed decision-making.
Topic 2	• NVIDIA Platform Implementation: Focuses on leveraging NVIDIA's AI hardware and software stack to build and optimize agentic AI systems.
Topic 3	• Deployment and Scaling: Covers operationalizing agentic systems for production use, including containerization, orchestration, and scaling strategies.
Topic 4	• Agent Architecture and Design: Covers how agentic AI systems are structured, including how agents reason, communicate, and interact within single-agent and multi-agent environments.
Topic 5	• Cognition, Planning, and Memory: Explores the reasoning strategies, decision-making processes, and memory management techniques that drive intelligent agent behavior.

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NVIDIA Agentic AI Sample Questions (Q26-Q31):

NEW QUESTION # 26
When evaluating optimization opportunities between NeMo Guardrails, NIM microservices, and TensorRT- LLM in a production healthcare agent, which analysis approach best identifies optimization opportunities across the NVIDIA stack?

- A. Tune each component individually, focusing primarily on local performance metrics with secondary attention to integration patterns.
- B. Create end-to-end latency waterfalls that capture guardrail overhead, NIM queuing delays, and TensorRT optimization benefits while assessing overall pipeline efficiency.
- C. Use default configurations to establish a deployment baseline, focusing on stability before conducting deeper performance profiling.
- D. Conduct stress testing of individual microservices and guardrails to measure peak throughput and determine theoretical performance limits of each module.

Answer: B

Explanation:
End-to-end latency waterfalls show where time is spent across guardrails, queues, and inference. Local component tuning misses cross-service overhead. The correct implementation surface is profiling the request path from ingress through guardrails, routing, Triton scheduling, TensorRT-LLM execution, and response assembly. The selected option specifically C states "Create end-to-end latency waterfalls that capture guardrail overhead, NIM queuing delays, and TensorRT optimization benefits while assessing overall pipeline efficiency.", which matches the operational requirement rather than a superficial wording match. From an NVIDIA systems-engineering lens, Option C aligns with the way agentic services should be decomposed and measured. The alternatives would look simpler in a prototype, but overlarge batches may improve throughput while violating interactive latency targets. The NVIDIA implementation angle is not cosmetic here: NVIDIA Perf Analyzer, GenAI-Perf, Nsight, and Triton metrics help isolate whether the bottleneck is batching, compute, memory, or request scheduling. This choice gives engineering teams the knobs they need for continuous tuning after deployment.

NEW QUESTION # 27
When analyzing user feedback patterns to improve a technical documentation agent, which evaluation methods effectively translate feedback into actionable optimization strategies? (Choose two.)

- A. Collect broad user feedback as-is, enabling rapid accumulation of suggestions and diverse perspectives for potential future analysis.
- B. Incorporate user suggestions rapidly to maximize responsiveness and demonstrate continuous adaptation to evolving user needs.
- C. Design iterative feedback loops with version tracking, A/B testing of improvements, and regression monitoring to ensure changes enhance rather than degrade performance
- D. Implement feedback categorization systems grouping issues by type (accuracy, clarity, completeness) with quantitative impact scoring and improvement prioritization matrices

Answer: C,D

Explanation:
Together, B states "Design iterative feedback loops with version tracking, A/B testing of improvements, and regression monitoring to ensure changes enhance rather than degrade performance"; D states "Implement feedback categorization systems grouping issues by type (accuracy, clarity, completeness) with quantitative impact scoring and improvement prioritization matrices", so the answer covers both sides of the requirement instead of solving only the model or only the infrastructure layer. Actionable feedback requires taxonomy and experiment discipline. Versioned A/B tests and impact scoring separate useful fixes from noisy user suggestions. the combination of Options B and D is the correct engineering choice because the requirement is not just "make the model answer," but control the execution surface. In NVIDIA terms, NVIDIA evaluation tooling emphasizes whole-agent behavior, including tool selection order, final outcome quality, throughput, latency, and traceability. That matters because closed-loop evaluation where benchmark results, user feedback, and parameter changes are versioned together. That is why the other options are traps: looking only at speed can reward broken behavior, while looking only at accuracy can ignore cost and reliability failures.
The result is a system that can be benchmarked, traced, and revised without destabilizing the whole agent fabric.

NEW QUESTION # 28
You are building a customer-support chatbot that fetches user account data from an external billing API.
During testing, the API sometimes returns timeouts or 500 errors. You want the agent to be resilient-retrying when appropriate but failing gracefully if the service is down.

Which strategy best handles intermittent failures in API calls while still ensuring a good user experience?

- A. Implement exponential-backoff retries with a circuit breaker, and return a clear message to the user if all retries fail.
- B. Retry requests with a consistent short delay after each failure and notify the user as each retry takes place.
- C. Return a standard fallback message on failures to maintain conversation flow and reduce the risk of service interruptions for the user.
- D. Schedule retries using a fixed delay for all failure types, maintaining predictable timing and user notifications after each attempt.

Answer: A

Explanation:
The high-value engineering move is wrappers that convert messy external services into stable functions with bounded latency and predictable failure semantics. The best answer is Option B when the design is judged by reliability, latency budget, auditability, and maintainability rather than demo simplicity. Exponential backoff plus a circuit breaker prevents retry storms and gives users a graceful failure path. Fixed retries can amplify downstream outages. The stack-level anchor is clear: tool execution should sit behind adapters that can be profiled and regression-tested just like retrieval and inference services. The selected option specifically B states "Implement exponential-backoff retries with a circuit breaker, and return a clear message to the user if all retries fail.", which matches the operational requirement rather than a superficial wording match. The rejected options are weaker because hardcoded endpoints, loose parsers, or monolithic handlers turn every API change into an application release and hide failures from observability. Anything less would make the agent fragile when traffic, schemas, policies, or user behavior shift.

NEW QUESTION # 29
An AI architect at a national healthcare provider is maintaining an agentic AI system. The system must monitor model and system performance in real time, raise alerts on failures or anomalies, manage version control and rollback of diagnostic models, and provide transparent insight into agent behavior during patient care workflows.
Which operational approach best supports these requirements using the NVIDIA AI stack?

- A. Expose agents as stateless NVIDIA API endpoints and monitor activity through application logs, with model versions tracked in a Git-based script repository.
- B. Containerize each agent in NIM with basic health checks running on cron jobs, and manage version rollback by swapping prebuilt container images.
- C. Optimize all models with TensorRT and use periodic manual log reviews and NVIDIA shell scripts for detecting service anomalies and managing rollback.
- D. Deploy agent models on NVIDIA Triton Inference Server with Prometheus and Grafana for performance alerting, and manage model lifecycle via NGC and the Triton model repository.

Answer: D

Explanation:
The NVIDIA implementation angle is not cosmetic here: TensorRT-LLM and NIM reduce inference overhead, but they still need serving-level tuning to avoid queue buildup under concurrency. Triton plus Prometheus/Grafana gives live metrics; NGC/model repositories support versioned lifecycle control. Cron logs are not enough for healthcare operations. Option C wins because it optimizes the system boundary around the risky component rather than hoping the base model behaves consistently. The selected option specifically C states "Deploy agent models on NVIDIA Triton Inference Server with Prometheus and Grafana for performance alerting, and manage model lifecycle via NGC and the Triton model repository.", which matches the operational requirement rather than a superficial wording match. The durable control mechanism is matching model precision, batch windows, model instances, and GPU memory behavior to the latency service-level objective. The losing choices mostly optimize for short-term convenience; hardware upgrades alone do not fix poor batching, serial ensembles, guardrail overhead, or KV-cache pressure. For certification purposes, read the question as asking for controlled autonomy, not raw LLM creativity.

NEW QUESTION # 30
An AI Engineer at a retail company is developing a customer support AI agent that needs to handle multi-turn conversations while keeping track of customers' previous queries, preferences, and unresolved issues across multiple sessions.
Which approach is most effective for managing context retention and enabling the agent to respond coherently in real time?

- A. Use a sliding window of recent conversation tokens in memory to track only the last few exchanges.
- B. Retrain the model periodically using historical logs to improve long-term contextual understanding.
- C. Implement a hybrid memory system with vector-based search and key-value storage to retrieve relevant past interactions.

- D. Increase the maximum context window size so the full conversation history is processed each time.

Answer: C

Explanation:
The selected option specifically C states "Implement a hybrid memory system with vector-based search and key-value storage to retrieve relevant past interactions.", which matches the operational requirement rather than a superficial wording match. Hybrid memory lets the agent combine fast key-value facts with semantic vector recall. Expanding the context window is the blunt and expensive alternative. The architecture implied by Option C is the one that survives real workloads: separate responsibilities, explicit contracts, and measurable runtime behavior. In NVIDIA terms, agentic workflows need explicit state management; external memory complements the LLM context window while fine-tuning encodes stable behaviors into model policy. The correct implementation surface is external state stores combined with model adaptation when repeated behavior should become part of the policy. That is why the other options are traps: a single flat store cannot serve both low-latency conversational state and durable semantic recall equally well. This choice gives engineering teams the knobs they need for continuous tuning after deployment.

NEW QUESTION # 31
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