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Databricks
Context-Engineer-Associate
Databricks Certified Context Engineer Associate



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Latest Version: 6.0

Question: 1

A context engineer is debugging a Databricks customer support agent that manages complex billing escalations.
The system prompt instructs the agent to:
Strictly apply the company's official refund policy.
Treat entries from the "Billing-Policies" tool as authoritative.
Treat FAQ snippets and prior chat history as non-binding guidance only.
In one multi-step trace, the engineer observes the following:
Step 1: The agent calls the "Billing-Policies" tool and retrieves the official refund policy, which clearly states that chargebacks filed more than 90 days after purchase are not eligible for refunds.
Step 2: The agent calls a "Customer-FAQ-Search" tool that returns a community-authored FAQ thread. A top-voted but outdated and unofficial answer incorrectly claims that chargebacks are fully refundable regardless of when they are filed, and the agent summarizes this in the running conversation as an established fact.
Step 3: In a later turn, the customer describes a chargeback dispute from 18 months ago. The agent reasons from its own earlier summary, approves a full refund, and makes no reference to the official policy section excluding cases older than 90 days, even though that policy text remains in the context.
Step 4: In subsequent similar cases, the agent repeatedly approves refunds for old chargebacks, citing its prior summary as justification each time.
Which context failure mode describes what is occurring in this trace?

A. Context distraction, because the context has grown so long with policy text, FAQs, and chat history that the model loses focus on the specific 90-day rule and drifts toward irrelevant retrieved content.
B. Context clash, because the agent is simultaneously presented with two contradictory authoritative sources and produces an inconsistent response that partially applies each policy.
C. Context confusion, because the agent misidentifies which retrieved policy section governs chargeback disputes, applying refund rules intended for a different transaction category to the current case.
D. Context poisoning, because a mistaken statement about refund eligibility enters the context as ground truth and is repeatedly reused in downstream steps, overriding the correct policy that is also present.

Answer: D

Explanation:
Context poisoning occurs when erroneous or untrustworthy information becomes incorporated into an agent's working context and subsequently influences its decisions as though it were established truth.

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In this scenario, the failure originates at Step 2. The agent encounters an outdated, community-authored FAQ that contradicts the authoritative Billing-Policies tool. Rather than preserving the distinction between authoritative and non-authoritative information, the agent incorporates the incorrect refund statement into its conversation summary.
At Step 3, the agent relies on that contaminated summary to approve an ineligible refund. Step 4 establishes the defining characteristic of context poisoning: the incorrect information is repeatedly reinforced through subsequent decisions.
Context distraction would involve excessive context degrading attention. Context confusion would arise from irrelevant material being misapplied. Context clash concerns conflicting information or instructions. Although contradictory information exists here, repeated reliance on an established false statement makes poisoning the more precise diagnosis.
The appropriate remediation is to enforce source-authority rules during context construction, prevent unverified statements from being promoted into persistent summaries, and validate refund decisions against the authoritative policy.
Databricks MLflow Tracing supports this investigation by recording intermediate retrieval operations, tool responses, and model decisions, allowing engineers to identify where incorrect information entered and propagated through the workflow.
Official Databricks Databricks MLflow 3 — Tracing overview and Debug and analyze your app with tracing.
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Question: 2

A context engineer is creating a Databricks agent to triage incoming customer support tickets for a B2B software platform. Each ticket averages 200 tokens.
For each ticket, the agent must:
(1) assign a severity rating of P0/P1/P2/P3 based on whether the issue is fully blocking, degrades core functionality, affects a non-critical feature, or is informational—a judgment that requires reading the ticket body rather than matching keywords;
(2) route the ticket to one of eight engineering teams based on the technical area implied by the ticket;
(3) generate a brief, context-aware acknowledgment reply.
The pipeline must process up to 500 tickets per minute with an end-to-end latency budget of under 2 seconds per ticket. The token budget per invocation is 2,048 tokens, and the operations team has flagged that inference costs must remain minimal at this throughput.
Which reasoning mode should the context engineer configure for the agent?

A. Standard mode with extended thinking disabled, because skipping all reasoning overhead minimizes both per-invocation latency and inference cost at 500 tickets per minute.
B. Extended thinking with max_tokens capped at 1,024, because limiting the response length reduces cost while preserving full reasoning depth.
C. Extended thinking with a default thinking budget, because severity classification across four tiers and routing across eight teams benefits from deep chain-of-thought reasoning to maximize accuracy.

D. Reduced thinking, because the task requires modest structured reasoning across four severity tiers, a small thinking budget fits within the 2,048-token invocation, and latency and cost stay manageable at 500 tickets per minute.

Answer: D

Explanation:
Reduced thinking is the most appropriate configuration because the workload requires limited semantic reasoning while operating under stringent throughput, latency, and inference-cost constraints.
The agent must interpret ticket descriptions, distinguish severity levels, identify the responsible engineering team, and generate an acknowledgment. These operations require contextual understanding, but they do not ordinarily warrant extensive multi-step deliberation.
Databricks Foundation Model APIs support model-dependent controls for reasoning effort. Lower reasoning effort generally reduces reasoning-token consumption and can improve response latency, while higher effort may benefit more complex analytical workloads.
Option A prioritizes minimum inference overhead but assumes reasoning can be eliminated without compromising classification accuracy. That assumption is not justified by the scenario.
Options B and C introduce extended reasoning overhead that is difficult to justify for short, repetitive triage requests.
Option D provides a more suitable balance between classification accuracy and execution efficiency.
In production, the engineer should benchmark low-effort reasoning against labeled tickets, monitor severity-classification accuracy, routing accuracy, acknowledgment quality, p95 latency, and token usage, and verify that the system meets its throughput requirements.
The exact configuration parameter depends on the selected serving model; reduced thinking is a conceptual choice rather than a universally named Databricks API mode.
Official Databricks Databricks — Query reasoning models, Foundation Model REST API reference, and Improve RAG chain quality.
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Question: 3

A context engineer is developing a Databricks agent for a retail inventory management system. The system prompt and tool descriptions consume 1,800 tokens of a 4,096-token context window, and the engineer reserves 1,000 tokens for the user turn and model response. The remaining tokens are used for few-shot examples, each costing approximately 250 tokens, so the engineer includes exactly five examples.
The agent uses three tools: inventory_lookup, reorder_check, and supplier_lead_time.
Six candidate examples are available:
Example 1: A warehouse manager asks whether a depleted SKU needs reordering; the agent calls inventory_lookup, confirms depletion, calls reorder_check, and returns a binary reorder decision.
Example 2: A procurement officer asks when a low-stock item can be replenished; the agent calls reorder_check, calls supplier_lead_time, and returns a replenishment recommendation.

Example 3: A store associate asks for the current stock count of a single product; the agent calls inventory_lookup and returns a scalar quantity.
Example 4: A store associate asks for the current stock count of a single product; the agent calls inventory_lookup and returns a structured status object containing the quantity and a restocking flag.
Example 5: A store associate asks whether a forecasted shortfall requires immediate action; the agent calls inventory_lookup, compares against minimums, calls reorder_check, and returns a binary reorder decision.
Example 6: A logistics coordinator asks how long a specific supplier takes to fulfill an order; the agent calls supplier_lead_time and returns a scalar lead-time value.
Which example should the engineer omit to preserve the token budget while maximizing behavioral coverage?

A. Example 1, because the same tools are exercised across Examples 2 and 5, making its specific decision path redundant.
B. Example 6, because supplier_lead_time is already invoked in Example 2, and a standalone lead-time lookup does not add new tools to the demonstrated call space.
C. Example 3, because another example in the set covers the same user role and tool path, but the output of the other example is richer.
D. Example 5, because its forecasting logic duplicates the threshold-check pattern already established in Example 1, and its user role (store associate) appears elsewhere in the set.

Answer: C

Explanation:
Example 3 is the strongest candidate for removal because it substantially overlaps with Example 4 in user intent, user role, and tool invocation.
Both examples involve a store associate requesting inventory information for a single product. Both invoke inventory_lookup. The primary difference is the response representation: Example 3 returns a scalar quantity, whereas Example 4 demonstrates a structured status containing quantity and a restocking flag.
Retaining Example 4 provides broader instructional coverage because it illustrates both inventory retrieval and a richer response structure. The agent can still learn the simpler lookup operation from that example, although scalar-only response formatting would need separate instruction if it were a mandatory output requirement.
Examples 1 and 5 retain distinct business scenarios: depleted inventory versus forecasted shortages. Example 2 illustrates a multi-tool replenishment workflow, while Example 6 independently demonstrates a direct supplier lead-time lookup.
The available token capacity is 1,296 tokens after reserving 1,800 tokens for instructions and 1,000 tokens for interaction. Five examples at approximately 250 tokens each require 1,250 tokens, satisfying the stated budget.
Databricks recommends representative few-shot examples that cover diverse expected queries rather than consuming context with substantially redundant demonstrations.
Official Databricks Databricks — Improve RAG chain quality, particularly Prompt Augmentation and Few-Shot Examples.
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Question: 4

A context engineer is debugging a Databricks agent that staffs an internal IT help desk. The agent is already connected to a retrieval pipeline over a live, continuously updated knowledge base, and relevant KB passages are retrieved and placed in its context on every request. Its system prompt has three parts: a 400-token persona preamble, a 600-token list of every supported software title, and a 200-token closing instruction block. None of these parts explains how to weigh retrieved passages against the model's own training knowledge.
Observed behavior: the agent correctly identifies the user's intent, and the correct KB passages are present in context. However, for version-specific questions, it answers from its training knowledge and recommends releases that the knowledge base marks as deprecated. The team will accept only a change that does not rewrite the full prompt and does not add or modify retrieval infrastructure.
Which system-prompt revision addresses the version-accuracy behavior?

A. Expand the persona preamble to state the model's training-data cutoff date, so users understand version details may be out of date.
B. Add a sentence to the closing instruction block telling the agent that, when retrieved passages and its own training knowledge conflict, the retrieved passages take priority.
C. Move the 600-token software-title list to the very end of the prompt, after the closing block, so the supported-software context is the most recent thing the model reads before answering.
D. Add a directive to the closing block requiring the agent to present every version number in a consistent format, such as semantic versioning (MAJOR.MINOR.PATCH).

Answer: B

Explanation:
The observed failure concerns source prioritization rather than information retrieval. The agent already receives the correct knowledge-base passages, but it does not consistently treat that retrieved information as authoritative when its pretrained knowledge suggests a different answer.
Option B directly addresses this defect by establishing an explicit instruction hierarchy for conflicting information.
In retrieval-augmented generation, the prompt must explain how retrieved evidence should influence the generated response. For information that changes frequently, such as supported software releases, configuration requirements, and deprecation status, current authoritative documentation should generally supersede historical information learned during model training. Adding this instruction to the existing closing block requires minimal modification and satisfies the restriction against rebuilding the prompt or retrieval infrastructure.
Option A merely communicates potential staleness without changing the agent's decision process. Option C modifies prompt ordering but does not establish source authority. Option D standardizes version formatting without improving factual accuracy.
The engineer should additionally test conflicting version scenarios and evaluate whether responses consistently follow the current knowledge base. Databricks guidance identifies

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prompt augmentation, factual grounding, and evaluation as central components of reliable RAG applications.
Official Databricks Databricks — Improve RAG chain quality, particularly Prompt Augmentation, LLM Configuration, and Factual Consistency Guardrails.

Question: 5

A context engineer is examining MLflow experiment tracking results comparing two system prompt configurations for a Databricks agent designed to assist with contract review. Configuration P uses a role declaration, a full task instruction, and a dedicated edge-case handling section that explains in prose how the agent should respond to ambiguous or overlapping clause types, averaging 205 tokens per call and 81% clause-classification accuracy. Configuration Q retains the role declaration, removes the prose edge-case handling section, shortens the task instruction to a concise directive, and adds three few-shot examples, each showing how the agent should classify a distinct edge-case clause type, averaging 340 tokens per call and 93% clause-classification accuracy. The token budget increases by 135 tokens per call between Configuration P and Configuration Q. Latency rises from 290 ms to 380 ms.
Which conclusion is supported by these experiment tracking results?

A. The token increase is justified by the 12-percentage-point accuracy gain, and the shortened task instruction is the specific prompt element driving the performance improvement.
B. The token increase is justified by the 12-percentage-point accuracy gain, and the few-shot edge-case examples are the specific prompt element driving the performance improvement.
C. The token increase is not justified because removing the prose edge-case handling section and replacing it with examples introduces ambiguity that accuracy gain does not sufficiently offset.
D. The token increase is justified by the accuracy gain, but the improvement is attributable to the larger token budget because the removed edge-case handling section and added few-shot examples represent an equivalent token exchange.

Answer: B

Explanation:
Configuration Q demonstrates a substantial improvement in classification performance, increasing accuracy from 81% to 93%, representing a gain of 12 percentage points.
The principal instructional change is the introduction of three few-shot examples demonstrating how ambiguous and overlapping contract clauses should be classified.
Few-shot examples provide concrete demonstrations of expected behavior. They are particularly valuable when a task contains boundary cases that are difficult to communicate through abstract prose instructions alone.
Databricks guidance recommends incorporating representative examples, particularly for query types on which an application performs poorly. Consequently, the edge-case examples are the strongest plausible explanation for the observed improvement.

The additional 135 tokens and 90 milliseconds should be assessed against deployment quality requirements. For legal contract classification, the accuracy improvement may justify these costs, but the business trade-off cannot be established from accuracy alone.
There is an important experimental limitation: Configuration Q simultaneously changes the instruction length, removes explanatory prose, and adds examples. Therefore, the results do not establish that few-shot examples independently caused the improvement.
A controlled MLflow evaluation varying these components separately would be necessary to confirm causality.
Official Databricks Databricks — Evaluate and compare prompt versions, Manage your agent's prompts, and Improve RAG chain quality.
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