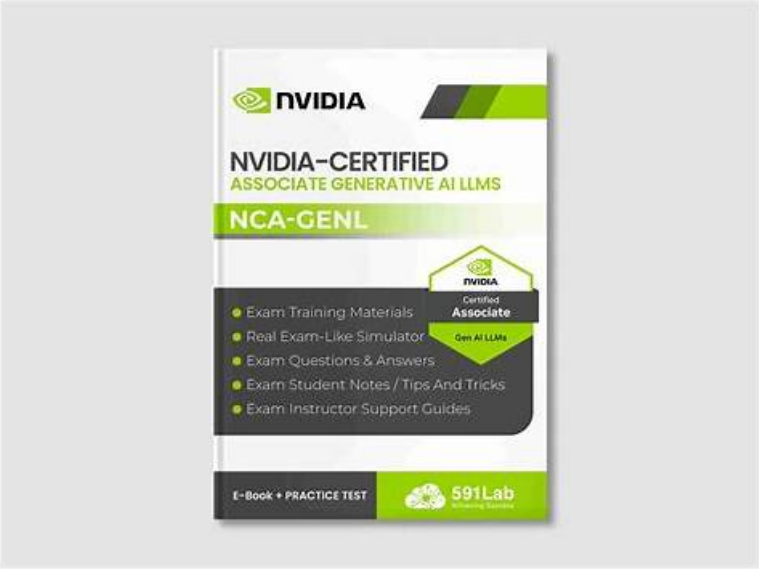
NCA-GENL試験の準備方法｜100％合格率のNCA-GENL資格難易度試験｜ユニークなNVIDIA Generative AI LLMs認定資格試験問題集



P.S. Pass4TestがGoogle Driveで共有している無料かつ新しいNCA-GENLダンプ：https://drive.google.com/open?id=1E6FKQ0AeG_MqRAJvXClXP0qkmo29d4zc

Pass4Testは市場でテストされたすべてのNCA-GENL浮き沈みを経験してきましたが、NCA-GENL試験問題は完全にプロフェッショナルになりました。NVIDIA Generative AI LLMs 最後に明るい光がある限り、道路で起こった困難を回避することはありません。それはあなたが望む満足のいく結果です。 知識の理論とクイズの問題の練習の両方がNVIDIA Generative AI LLMs、試験に対処する際にあなたがより熟練するのに役立ちます。 当社の専門家は、NCA-GENLすべての有用なコンテンツを統合することにより、NVIDIA試験の重要なポイントをトレーニング資料に抽出しました。

NVIDIA NCA-GENL 認定試験の出題範囲：

トピック	出題範囲
トピック 1	• LLM integration and deployment: Addresses connecting LLMs into real-world applications and deploying them reliably across production environments.
トピック 2	• Fundamentals of machine learning and neural networks: Covers the core concepts of how machine learning models learn from data, including the structure and function of neural networks that underpin large language models.
トピック 3	• Data analysis and visualization: Covers interpreting datasets and presenting insights through visual tools to support informed model development decisions.
トピック 4	• Data preprocessing and feature engineering: Covers preparing raw data through cleaning, transformation, and feature selection to make it suitable for model training.
トピック 5	• Python libraries for LLMs: Covers key Python frameworks and tools — such as LangChain, Hugging Face, and similar libraries — used to build and interact with LLMs.

>> NCA-GENL資格難易度 <<

最新-100％合格率のNCA-GENL資格難易度試験-試験の準備方法NCA-GENL認定資格試験問題集

テスト志向の高品質なNCA-GENL試験問題があなたにとって最良の選択であると信じています。すべての受験者がNCA-GENL試験に合格し、NCA-GENL準備ガイドの多大なメリットを享受できることを心から願っています。 NCA-GENL試験問題の合格率は99％～100％です。受験者がNCA-GENL試験に合格できるようにすることは、当社の文化において常に長所であり、購入および使用のプロセスでメールで連絡を取ることができます。できるだけ早く返信いたします。

NVIDIA Generative AI LLMs 認定 NCA-GENL 試験問題 (Q78-Q83):

質問 # 78
In the context of evaluating a fine-tuned LLM for a text classification task, which experimental design technique ensures robust performance estimation when dealing with imbalanced datasets?

- A. Grid search for hyperparameter tuning.
- B. Single hold-out validation with a fixed test set.
- C. Stratified k-fold cross-validation.
- D. Bootstrapping with random sampling.

正解：C

解説：
Stratified k-fold cross-validation is a robust experimental design technique for evaluating machine learning models, especially on imbalanced datasets. It divides the dataset into k folds while preserving the class distribution in each fold, ensuring that the model is evaluated on representative samples of all classes.
NVIDIA's NeMo documentation on model evaluation recommends stratified cross-validation for tasks like text classification to obtain reliable performance estimates, particularly when classes are unevenly distributed (e.g., in sentiment analysis with few negative samples). Option A (single hold-out) is less robust, as it may not capture class imbalance. Option C (bootstrapping) introduces variability and is less suitable for imbalanced data. Option D (grid search) is for hyperparameter tuning, not performance estimation.
References:
NVIDIA NeMo Documentation: https://docs.nvidia.com/deeplearning/nemo/user-guide/docs/en/stable/nlp/model_finetuning.html

質問 # 79
In the context of machine learning model deployment, how can Docker be utilized to enhance the process?

- A. To directly increase the accuracy of machine learning models.
- B. To reduce the computational resources needed for training models.
- C. To automatically generate features for machine learning models.
- D. To provide a consistent environment for model training and inference.

正解：D

解説：
Docker is a containerization platform that ensures consistent environments for machine learning model training and inference by packaging dependencies, libraries, and configurations into portable containers.
NVIDIA's documentation on deploying models with Triton Inference Server and NGC (NVIDIA GPU Cloud) emphasizes Docker's role in eliminating environment discrepancies between development and production, ensuring reproducibility. Option A is incorrect, as Docker does not generate features. Option C is false, as Docker does not reduce computational requirements. Option D is wrong, as Docker does not affect model accuracy.
References:
NVIDIA Triton Inference Server Documentation: https://docs.nvidia.com/deeplearning/triton-inference-server/user-guide/docs/index.html
NVIDIA NGC Documentation: https://docs.nvidia.com/ngc/ngc-overview/index.html

質問 # 80
What do we usually refer to as generative AI?

- A. A branch of artificial intelligence that focuses on analyzing and interpreting existing data.
- B. A branch of artificial intelligence that focuses on creating models that can generate new and original data.
- C. A branch of artificial intelligence that focuses on improving the efficiency of existing models.
- D. A branch of artificial intelligence that focuses on auto generation of models for classification.

正解：B

解説：
Generative AI, as covered in NVIDIA's Generative AI and LLMs course, is a branch of artificial intelligence focused on creating models that can generate new and original data, such as text, images, or audio, that resembles the training data. In the context of LLMs, generative AI involves models like GPT that produce coherent text for tasks like text completion, dialogue, or creative writing by learning patterns from large datasets. These models use techniques like autoregressive generation to create novel outputs. Option B is incorrect, as generative AI is not limited to generating classification models but focuses on producing new data. Option C is wrong, as improving model efficiency is a concern of optimization techniques, not generative AI. Option D is inaccurate, as analyzing and interpreting data falls under discriminative AI, not generative AI. The course emphasizes: "Generative AI involves building models that create new content, such as text or images, by learning the underlying distribution of the training data."
References: NVIDIA Building Transformer-Based Natural Language Processing Applications course; NVIDIA Introduction to Transformer-Based Natural Language Processing.

質問 # 81
Which metric is commonly used to evaluate machine-translation models?

- A. Perplexity
- B. F1 Score
- C. BLEU score
- D. ROUGE score

正解：C

解説：
The BLEU (Bilingual Evaluation Understudy) score is the most commonly used metric for evaluating machine-translation models. It measures the precision of n-gram overlaps between the generated translation and reference translations, providing a quantitative measure of translation quality. NVIDIA's NeMo documentation on NLP tasks, particularly machine translation, highlights BLEU as the standard metric for assessing translation performance due to its focus on precision and fluency. Option A (F1 Score) is used for classification tasks, not translation. Option C (ROUGE) is primarily for summarization, focusing on recall.
Option D (Perplexity) measures language model quality but is less specific to translation evaluation.
References:
NVIDIA NeMo Documentation: https://docs.nvidia.com/deeplearning/nemo/user-guide/docs/en/stable/nlp
/intro.html
Papineni, K., et al. (2002). "BLEU: A Method for Automatic Evaluation of Machine Translation."

質問 # 82
When designing prompts for a large language model to perform a complex reasoning task, such as solving a multi-step mathematical problem, which advanced prompt engineering technique is most effective in ensuring robust performance across diverse inputs?

- A. Zero-shot prompting with a generic task description.
- B. Chain-of-thought prompting with step-by-step reasoning examples.
- C. Retrieval-augmented generation with external mathematical databases.
- D. Few-shot prompting with randomly selected examples.

正解：B

解説：
Chain-of-thought (CoT) prompting is an advanced prompt engineering technique that significantly enhances a large language model's (LLM) performance on complex reasoning tasks, such as multi-step mathematical problems. By including examples that explicitly demonstrate step-by-step reasoning in the prompt, CoT guides the model to break down the problem into intermediate steps, improving accuracy and robustness.
NVIDIA's NeMo documentation on prompt engineering highlights CoT as a powerful method for tasks requiring logical or sequential reasoning, as it leverages the model's ability to mimic structured problem- solving. Research by Wei et al. (2022)

demonstrates that CoT outperforms other methods for mathematical reasoning. Option A (zero-shot) is less effective for complex tasks due to lack of guidance. Option B (few- shot with random examples) is suboptimal without structured reasoning. Option D (RAG) is useful for factual queries but less relevant for pure reasoning tasks.
References:
NVIDIA NeMo Documentation: https://docs.nvidia.com/deeplearning/nemo/user-guide/docs/en/stable/nlp
/intro.html
Wei, J., et al. (2022). "Chain-of-Thought Prompting Elicits Reasoning in Large Language Models."

質問 # 83
......