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NVIDIA NCA-GENL Exam Syllabus Topics:

Topic	Details
Topic 1	• Data analysis and visualization: Covers interpreting datasets and presenting insights through visual tools to support informed model development decisions.
Topic 2	• Data preprocessing and feature engineering: Covers preparing raw data through cleaning, transformation, and feature selection to make it suitable for model training.
Topic 3	• 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.
Topic 4	• Alignment: Addresses methods for ensuring LLM behavior is safe, accurate, and consistent with human intentions and values.
Topic 5	• Software development: Covers the programming practices and coding skills required to build, maintain, and deploy generative AI applications.

Topic 6	• Experimentation: Explores running and evaluating trials to test model behavior, compare approaches, and validate generative AI solutions.
Topic 7	• 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.
Topic 8	• Prompt engineering: Focuses on techniques for designing and refining input prompts to effectively guide LLM outputs toward desired results.

NVIDIA Generative AI LLMs Sample Questions (Q61-Q66):

NEW QUESTION # 61
Which of the following is a parameter-efficient fine-tuning approach that one can use to fine-tune LLMs in a memory-efficient fashion?

- A. NeMo
- B. TensorRT
- C. Chinchilla
- D. LoRA

Answer: D

Explanation:
LoRA (Low-Rank Adaptation) is a parameter-efficient fine-tuning approach specifically designed for large language models (LLMs), as covered in NVIDIA's Generative AI and LLMs course. It fine-tunes LLMs by updating a small subset of parameters through low-rank matrix factorization, significantly reducing memory and computational requirements compared to full fine-tuning. This makes LoRA ideal for adapting large models to specific tasks while maintaining efficiency. Option A, TensorRT, is incorrect, as it is an inference optimization library, not a fine-tuning method. Option B, NeMo, is a framework for building AI models, not a specific fine-tuning technique. Option C, Chinchilla, is a model, not a fine-tuning approach. The course emphasizes: "Parameter-efficient fine-tuning methods like LoRA enable memory-efficient adaptation of LLMs by updating low-rank approximations of weight matrices, reducing resource demands while maintaining performance." References: NVIDIA Building Transformer-Based Natural Language Processing Applications course; NVIDIA Introduction to Transformer-Based Natural Language Processing.

NEW QUESTION # 62
In the context of a natural language processing (NLP) application, which approach is most effective for implementing zero-shot learning to classify text data into categories that were not seen during training?

- A. Use rule-based systems to manually define the characteristics of each category.
- B. Use a pre-trained language model with semantic embeddings.
- C. Use a large, labeled dataset for each possible category.
- D. Train the new model from scratch for each new category encountered.

Answer: B

Explanation:
Zero-shot learning allows models to perform tasks or classify data into categories without prior training on those specific categories. In NLP, pre-trained language models (e.g., BERT, GPT) with semantic embeddings are highly effective for zero-shot learning because they encode general linguistic knowledge and can generalize to new tasks by leveraging semantic similarity. NVIDIA's NeMo documentation on NLP tasks explains that pre-trained LLMs can perform zero-shot classification by using prompts or embeddings to map input text to unseen categories, often via techniques like natural language inference or cosine similarity in embedding space. Option A (rule-based systems) lacks scalability and flexibility. Option B contradicts zero- shot learning, as it requires labeled data. Option C (training from scratch) is impractical and defeats the purpose of zero-shot learning.
References:
NVIDIA NeMo Documentation: https://docs.nvidia.com/deeplearning/nemo/user-guide/docs/en/stable/nlp/intro.html
Brown, T., et al. (2020). "Language Models are Few-Shot Learners."

NEW QUESTION # 63
Your company has upgraded from a legacy LLM model to a new model that allows for larger sequences and higher token limits. What is the most likely result of upgrading to the new model?

- A. The newer model allows for larger context, so the outputs will improve without increasing inference time overhead.
- B. The newer model allows larger context, so outputs will improve, but you will likely incur longer inference times.
- C. The number of tokens is fixed for all existing language models, so there is no benefit to upgrading to higher token limits.
- D. The newer model allows the same context lengths, but the larger token limit will result in more comprehensive and longer outputs with more detail.

Answer: B

Explanation:
Upgrading to a new LLM with larger sequence lengths and higher token limits, as discussed in NVIDIA's Generative AI and LLMs course, typically allows the model to process larger contexts, leading to improved output quality due to better understanding of extended dependencies in text. However, handling larger sequences increases computational requirements, often resulting in longer inference times, especially on the same hardware. This trade-off is a key consideration in LLM deployment. Option A is incorrect, as token limits vary across models, and higher limits offer benefits. Option B is wrong, as larger context processing typically increases inference time. Option C is inaccurate, as higher token limits primarily enable larger context, not just longer outputs. The course notes: "Larger sequence lengths in LLMs allow for improved output quality by capturing more context, but this often comes at the cost of increased inference times due to higher computational demands." References: NVIDIA Building Transformer-Based Natural Language Processing Applications course; NVIDIA Introduction to Transformer-Based Natural Language Processing.

NEW QUESTION # 64
How does A/B testing contribute to the optimization of deep learning models' performance and effectiveness in real-world applications? (Pick the 2 correct responses)

- A. A/B testing in deep learning models is primarily used for selecting the best training dataset without requiring a model architecture or parameters.
- B. A/B testing allows for the comparison of different model configurations or hyperparameters to identify the most effective setup for improved performance.
- C. A/B testing helps validate the impact of changes or updates to deep learning models by statistically analyzing the outcomes of different versions to make informed decisions for model optimization.
- D. A/B testing is irrelevant in deep learning as it only applies to traditional statistical analysis and not complex neural network models.
- E. A/B testing guarantees immediate performance improvements in deep learning models without the need for further analysis or experimentation.

Answer: B,C

Explanation:
A/B testing is a controlled experimentation technique used to compare two versions of a system to determine which performs better. In the context of deep learning, NVIDIA's documentation on model optimization and deployment (e.g., Triton Inference Server) highlights its use in evaluating model performance:
* Option A: A/B testing validates changes (e.g., model updates or new features) by statistically comparing outcomes (e.g., accuracy or user engagement), enabling data-driven optimization decisions.
References:
NVIDIA Triton Inference Server Documentation: https://docs.nvidia.com/deeplearning/triton-inference-server /user-guide/docs/index.html

NEW QUESTION # 65
What are the main advantages of instructed large language models over traditional, small language models (< 300M parameters)? (Pick the 2 correct responses)

- A. Trained without the need for labeled data.
- B. It is easier to explain the predictions.
- C. Smaller latency, higher throughput.

- D. Single generic model can do more than one task.
- E. Cheaper computational costs during inference.

Answer: D,E

Explanation:
Instructed large language models (LLMs), such as those supported by NVIDIA's NeMo framework, have significant advantages over smaller, traditional models:
* Option D: LLMs often have cheaper computational costs during inference for certain tasks because they can generalize across multiple tasks without requiring task-specific retraining, unlike smaller models that may need separate models per task.
References:
NVIDIA NeMo Documentation: https://docs.nvidia.com/deeplearning/nemo/user-guide/docs/en/stable/nlp/intro.html Brown, T., et al. (2020). "Language Models are Few-Shot Learners."

NEW QUESTION # 66
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