(Each question lists full text and options. Type: MCQ = single correct answer, MSQ = multiple correct answers.) 1. (MCQ) Suppose a model has a 200M parameter dense layer stored in FP16 format. If we instead quantize it to 4-bit integers (ignoring extra storage for scaling constants), what is the approximate memory savings? 2. 2× smaller 3. 4× smaller 4. 8× smaller 5. 8× smaller 6. No savings, same size 7. (MCQ) A Transformer layer contains two linear projections: $W_Q \in R^{768 \times 768}$ and $W_V \in R^{768 \times 768}$. I we fine-tune both using LoRA with rank $r = 16$, how many parameters are trainable in LoRA compared to fine-tuning both layers fully? 3. (24,576 vs 1.18M 5. 196,608 vs 1.18M 6. 196,608 vs 1.18M 7. 196,608 vs 1.18M 9. 393,216 vs 2.36M 9. (MCQ) You build a RAG pipeline on a corpus of 1,000,000 documents. Each document averages foot tokens. You chunk documents into windows of 250 tokens (no overlap), embed each chunk into a 512 dimensional FP32 vector, and store them in a vector DB. Assume each FP32 number = 4 bytes and metadata per vector = 128 bytes. Approximately how many gigabytes of storage are required? 3. 4.0 GB 9. 4.3 GB 9. 4.4 GB	Name:	Roll No.:
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TO THE PARTY OF THE PROPERTY OF THE PARTY OF	4. (MCO) Which of the following best of	describes how LoRA works?

A.	LoRA	continues	the	original	pre-training	objective	on	new	${\rm data}$	to	update	the	weights	of	the	original
	model.															

- B. LoRA freezes all weights in the original model layers and introduces new components which are trained on new data.
- C. LoRA trains a smaller, distilled version of the pre-trained LLM to reduce model size.
- D. LoRA decomposes the original weight matrix into two smaller rank matrices and trains those instead of the full model weights.

5. (MCQ)	What is	the m	nain l	limitation	of	using a	a fixed-size	${\rm context}$	vector	${\rm in}$	encoder-decoder	sequence
models?												

- A. It improves translation accuracy.
- B. It increases training stability.
- C. It can create a bottleneck for long input sequences.
- D. It allows direct alignment between source and target tokens.
- 6. (MCQ) In the Transformer architecture, positional encoding is used to:
- A. Normalise the hidden representations.
- B. Provide information about the order of tokens in a sequence.
- C. Reduce overfitting during training.
- D. Increase the model's parameter count.
- $\textbf{7. (MCQ)} \ \ \text{Which of the following best describes "cross-attention" in a Transformer decoder?}$
- er?

- A. The decoder attending to its own outputs.
- B. The encoder attending to the decoder outputs.
- C. The decoder attending to the encoder outputs.
- D. Tokens attending to themselves within the encoder.
- **8.** (MCQ) Consider a sequence of five tokens

$$X = [\text{token}_1, \text{ token}_2, \text{ token}_3, \text{ token}_4, \text{ token}_5].$$

The (unmasked) row-wise attention score matrix (dot-product scores) for this sequence is

$$Scores = \begin{pmatrix} token_1 \cdot token_1 & token_1 \cdot token_2 & token_1 \cdot token_3 & token_1 \cdot token_4 & token_1 \cdot token_5 \\ token_2 \cdot token_1 & token_2 \cdot token_2 & token_2 \cdot token_3 & token_2 \cdot token_4 & token_2 \cdot token_5 \\ token_3 \cdot token_1 & token_3 \cdot token_2 & token_3 \cdot token_3 & token_3 \cdot token_4 & token_3 \cdot token_5 \\ token_4 \cdot token_1 & token_4 \cdot token_2 & token_4 \cdot token_3 & token_4 \cdot token_4 & token_4 \cdot token_5 \\ token_5 \cdot token_1 & token_5 \cdot token_2 & token_5 \cdot token_3 & token_5 \cdot token_4 & token_5 \cdot token_5 \end{pmatrix}$$

Question: After applying causal masking and then the row-wise softmax, how many entries of the resulting attention-weight matrix are *exactly zero*?

A. 0
B. 5
C. 11
D. 10
9. (MCQ) In language model pre-training, the "compute budget" refers to:
A. The maximum allowable depth and width of the model.
B. The maximum allowable training time and FLOPs.
C. The maximum allowable size of the training dataset.
D. The maximum allowable vocabulary size used in training.
10. (MSQ) What are the main advantages of parameter-efficient fine-tuning compared to full fine-tuning?
A. Reduced storage and memory footprint
B. Faster adaptation to downstream tasks
C. Ability to completely retrain the base model from scratch
D. Reusability of task-specific modules without duplicating the base model
11. (MCQ) In QLoRA, quantization is applied to reduce memory usage while still enabling efficient fine-tuning of large models. Which of the following statements most accurately captures the key design principle of QLoRA?
A. QLoRA quantizes both the base model weights and the LoRA adapter parameters to 4-bit, ensuring that all trainable parameters remain low-precision.
B. QLoRA uses 4-bit quantization of the frozen base model weights, but keeps LoRA adapter parameters in higher precision (e.g., 16-bit), ensuring stable gradient updates while retaining low memory usage.
C. QLoRA trains the full base model in 4-bit precision directly, thereby eliminating the need for LoRA adapters and achieving better fine-tuning accuracy.
D. QLoRA avoids quantization during training but compresses the model into 4-bit weights only at inference time, reducing memory costs after fine-tuning is complete.
12. (MCQ) In language model decoding, the temperature parameter τ rescales logits before applying softmax: $p_i = \frac{\exp\left(\frac{z_i}{\tau}\right)}{\sum_i \exp\left(\frac{z_j}{\tau}\right)}.$
Suppose a model produces logits [2, 1, 0] for tokens $[A, B, C]$. Which of the following best describes the
effect of changing the temperature?

A. At $\tau \to 0^+$, the distribution converges to uniform over all tokens, since scaling makes differences negligible.

B. At $\tau=1$, the distribution is a normal softmax over the logits, and increasing τ above 1 makes the distribution more peaked.

C. At $\tau \to \infty$, the distribution amplifies the maximum		delta on the largest	logit (token A), bec	ause extreme scaling
D. Lowering τ increases the the distribution toward	_	y gap between higher	r and lower logits, w	hile raising τ flattens
13. (MSQ) Which of the	following statemen	ts correctly describe t	he relationship betw	een PEFT and catas-
trophic forgetting? (Selec	t all that apply)			
A. PEFT mitigates catastrask-specific modules.	rophic forgetting by	freezing most pretra	ained parameters and	d only training small
B. Full fine-tuning is more task.	prone to catastropl	nic forgetting because	e all parameters are u	updated for each new
C. PEFT entirely eliminat	es catastrophic forg	etting, making contin	nual learning trivial.	
D. PEFT allows sharing the	ne same base model	across tasks while re	ducing interference l	between them.
14. (MCQ) How many I	LMs are required fo	or the (Direct Prefere	nce Optimization) D	PO Method in Align-
ment Tuning?				
A. 1				
B. 2				
C. 3				
D. 4				
15. (MCQ) A language eight candidate next toke		~	he following probabi	lity distribution over
	Token	A B C D E	F G H	
	Probability (%)	A B C D E 28 18 12 10 9	8 7 8	
Using top-p (nucleus) sa	ampling with $p = 0$.60, which set of toker	ns form the nucleus?	
A. $\{A, B, C\}$				
B. $\{A, B, C, D\}$				
C. $\{A, B\}$				
D. $\{A, B, C, D, E\}$				
16. (MCQ) A system to	nat can retrieve im	ages based on text of	queries and retrieve	text based on image
queries is an example of:				
A. Multi-modal classificati	on		[
B. Single-modal generation				
Q Q				

C. Cross-modal retrieval

D. Unimodal embedding

17. (MCQ) In Denoising Diffusion Probabilistic Models (DDPM), what happens during the forward pro-
cess?
A. Clean images are gradually corrupted by adding noise
B. The model learns to generate images from scratch
C. Text is converted into visual representations
D. Audio signals are processed into spectrograms
18. (MCQ) What is the main training objective used in CLIP (Contrastive Language-Image Pre-training)?
A. Minimize reconstruction loss between images and text
B. Train separate classifiers for images and text independently
C. Maximize similarity between correct image-text pairs while minimizing similarity between incorrect pairs
D. Use autoencoder loss to compress both modalities
19. (MSQ) ReAct prompting integrates reasoning traces with external actions (e.g., API calls, search).
Which of the following correctly describe its advantages and limitations? (Select all that apply)
A. It improves factuality by grounding reasoning in retrieved evidence
B. It completely eliminates hallucination by constraining the model to deterministic reasoning steps
C. It can be more resource-intensive due to multiple external calls during inference
D. It requires careful orchestration to avoid infinite loops or redundant reasoning steps
20. (MSQ) Multi-agent alignment approaches including self-play and debate models offer unique advantages but also face specific challenges. Which of the following are accurate characterizations? (Select all
that apply)
A. Self-play creates adversarial training loops that can improve model robustness
B. Debate models help expose weaknesses in reasoning through structured argumentation
C. Multi-agent systems always converge to optimal solutions given sufficient time
D. The quality of debate-based alignment depends critically on judge reliability
E. These approaches can scale oversight by leveraging multiple perspectives on complex problems
21. (MSQ) A major challenge in scaling RLHF is "reward hacking". Which emerging techniques target
this issue? (Select all that apply)
A. Direct Preference Optimization (DPO), by eliminating the explicit reward model altogether
B. Active Learning, by selectively querying the most uncertain samples to reduce labeling cost
C. Debate models, where multiple AI agents critique each other's reasoning

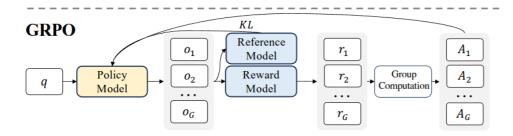
D. Supervised Fine-Tuning (SFT), by training on a larger dataset of demonstrations

22. (MCQ) Fill in the blanks: involves using many prompt-completion examples as the labeled training dataset to continue training the model by updating its weights. This is different from
where you provide prompt-completion examples during inference.
A. Pre-training, Instruction fine-tuning
B. In-context learning, Instruction fine-tuning
C. Prompt engineering, Pre-training
D. Instruction fine-tuning, In-context learning
23. (MSQ) Consider encoder-only, decoder-only, and encoder-decoder architectures. Which of the following
correctly describe their trade-offs? (Select all that apply)
A. Encoder-only models are best suited for bidirectional context understanding, making them effective for classification
B. Decoder-only models excel at generative tasks since they model left-to-right dependencies
C. Encoder-decoder models are computationally lighter because they separate encoding and decoding roles
D. Encoder-decoder models allow cross-attention, which is essential for tasks like translation
24. (MSQ) Multi-Head Attention and its masked variant are crucial in transformer architectures. Which
of the following are true? (Select all that apply)
A. Multi-Head Attention enables the model to capture relationships at multiple representation subspaces simultaneously
B. Masked Multi-Head Attention prevents information leakage from future tokens during autoregressive generation
C. Self-Attention and Cross-Attention differ in that the query comes from the decoder in cross-attention
D. Multi-Head Attention reduces computational cost compared to single-head self-attention
25. (MSQ) Residual connections and normalization layers play key roles in transformer training stability.
Which statement is correct?
A. Residual connections mitigate vanishing gradients by preserving gradient flow across layers
B. Layer Normalization is applied across the feature dimension, while Batch Normalization normalizes across the batch
C. Pre-Norm architectures apply normalization before residual addition, improving training stability in deep transformers
D. Batch Normalization is universally preferred over Layer Normalization in NLP models
26. (MSQ) Self-play reinforcement learning in LLMs draws inspiration from game AI. Which of the fol-
lowing capture unique challenges for LLM self-play? (Select all that apply)
A. Language models use discrete action spaces while games use continuous spaces
B. Language models cannot generate their own training data effectively

- C. Self-play in LLMs requires human supervision while game AI is fully automated
- D. Unlike games with clear win/loss conditions, LLMs face the challenge of defining meaningful adversarial tasks and evaluation metrics in the open-ended language domain

27.	(MCQ)	What	is th	ne main	training	objective	of a	decoder-only	Transformer	model,	such	as	GPT?

- A. To predict the next token in a sequence given the preceding tokens.
- B. To reconstruct the original input sequence after adding noise.
- C. To learn a shared embedding space for text and images.
- D. To generate a complete sequence from a single starting token.
- 28. (MCQ) In the context of large language models, what does "temperature" control during text generation?
- A. The number of tokens in the generated output.
- B. The randomness of the generated text.
- C. The length of the input sequence.
- D. The size of the model's vocabulary.
- 29. (MCQ) What is the core innovation of the original Transformer architecture that addresses the limitations of Recurrent Neural Networks (RNNs) in sequence processing?
- A. The use of a simple feedforward network, eliminating the need for complex architectures.
- B. The introduction of attention mechanisms, which allows the model to weigh the importance of different parts of the input sequence regardless of their distance.
- C. The ability to process only one token at a time, ensuring precise sequential processing.
- D. The use of a single large convolutional layer to capture all dependencies at once.
- **30.** (MSQ) In the GRPO framework shown below, which of the following best explains why GRPO eliminates the need for a separate value model compared to PPO?



- A. GRPO directly computes group-level advantages by normalizing rewards across multiple sampled outputs, removing the need for state-value estimation.
- B. GRPO uses the relative ranking of responses within a group as an implicit baseline, making a learned critic unnecessary.

C.	GRPO	assumes	that KL	divergence	alone	provides	${\it sufficient}$	feedback for	optimization,	making	the value
	model	redundan	t.								

D. GRPO trains the reward model and the policy jointly, so a separate value model is not necessary.

Rough Sheet