Fine Tuning

Large Language Models

Interview Questions and Answers

& Solved Quiz Questions

by Inder P Singh for

AI Engineers, ML Engineers and AI Testers & AI QA

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1. Fine Tuning Large Language Models - Overview & When to Fine-Tune

Question: What does fine-tuning a large language model mean? How does it differ from prompting or retrieval-augmented generation?

Answer: Fine-tuning updates model parameters (all or a subset) on a curated dataset so the model internalizes new task- or domain-specific behavior; prompting crafts inputs at inference time without changing weights; RAG augments inference by retrieving external context but does not change model weights.
Fine-tuning is chosen when persistent, repeatable behavior across many inputs is required, when latency of retrieval is unacceptable, or when regulatory/audit requirements demand the model hold specific knowledge.

Question: When should an AI engineer choose to fine-tune rather than rely on prompt engineering?

Answer: Prefer fine-tuning when you need: consistent style/terminology across outputs, better sample efficiency for repeated tasks, improved performance on distributional shifts that prompts can't fix, or the ability to embed domain knowledge for offline auditing.
If the requirement is ad-hoc or highly dynamic (rapidly changing facts), prefer RAG or prompt orchestration.

Question: What are the practical trade-offs of fine-tuning (cost, latency, maintainability)?

Answer: Fine-tuning increases model maintenance (retraining, versioning), storage (new checkpoints), and potentially inference cost if a larger model is required. It reduces runtime complexity (no external retrieval) and can improve latency. Operationally, it requires dataset governance, additional testing, and rollback procedures.

Question: What decision criteria should AI testers and AI engineers use to justify fine-tuning?

Answer: Use measurable criteria: target metric lift vs baseline prompting, reproducibility of desired behavior across holdouts, cost of errors in production, audit and compliance needs, and dataset readiness. If the validated lift per retraining cost is favorable and governance processes exist, proceed to fine-tune.

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Quiz:

Fine-tuning changes which of the following?

A. Model architecture only

B. Model weights (Correct)

C. Only the inference prompt

D. Tokenizer vocabulary only

The situation best favoring RAG over fine-tuning is:

A. Need for consistent terminology across outputs

B. Rapidly changing factual knowledge where freshness matters (Correct)

C. Requirement for offline audit of model decisions

D. Low-latency constraints at inference

Which is NOT a typical cost of fine-tuning?

A. Additional checkpoint storage

B. Need for dataset governance

C. Elimination of inference latency entirely (Correct)

2. Foundations: Transfer Learning, Pretraining vs Fine-Tuning

Question: What is transfer learning in LLMs?

Answer: Transfer learning uses representations learned during pretraining on massive corpora; these representations capture syntax, semantics, and world knowledge that can be adapted to downstream tasks via fine-tuning, enabling sample-efficient learning compared to training from scratch.

Question: How does pretraining objective influence fine-tuning outcomes?

Answer: Pretraining objectives (causal language modeling, masked LM, next-sentence prediction) shape the inductive biases of the model. A model pretrained with an autoregressive objective adapts naturally to generation tasks, while masked LM pretraining may require architectural or head modifications for some generative tasks.

Question: Why does fine-tuning sometimes cause catastrophic forgetting? How can yo mitigate it?

Answer: Catastrophic forgetting occurs when model weights move away from general representations toward task-specific patterns, degrading performance on previously learned capabilities. Mitigations include lower learning rates, regularization (e.g., L2), rehearsal with mixed-in pretraining data, and parameter-efficient adapters that preserve base weights.

Question: How can AI Testers validate that fine-tuning preserved general competence, while improving task-specific metrics?

Answer: By evaluating sanity checks on general capabilities (language fluency, toxicity, factuality benchmarks) and task-specific holdouts. Also, by using cross-task validation suites and monitor regressions in core abilities.

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Quiz:

Transfer learning primarily provides:

A. Fresh training data

B. Reusable pretrained representations (Correct)

C. Instant model compression

D. A way to avoid dataset curation

Catastrophic forgetting is best mitigated by:

A. Using a very large batch size only

B. Regularization and mixed rehearsal data (Correct)

C. Removing the tokenizer

D. Increasing learning rate

A model pretrained with a causal LM objective is naturally suited for:

A. Image classification

B. Generative text tasks (Correct)

C. Mask prediction tasks only

D. Speech recognition only

3. Data Requirements & Dataset Curation for Fine-Tuning Large Language Models

Question: What are the core dataset quality checks done by AI Testers before fine-tuning?

Answer: Verify label correctness, removal of near-duplicates, confirm representative coverage of subpopulations, inspect distribution of lengths and tokens, and validate that no leakage of test/production secrets exists. Produce metadata for provenance and partitioning.

Question: How should data be chunked for long-document fine-tuning?

Answer: Segment into semantically coherent chunks (paragraphs, sections) with overlap (to preserve context at boundaries). Include chunk-level metadata (source id, position) so outputs can be traced back for audits.

Question: When is synthetic data helpful? What are the risks of synthetic data?

Answer: Synthetic Q&A pairs can augment scarce domain examples.
Synthetic data helps bootstrap instruction behavior but risks introducing artifacts and biases; validate synthetic examples with human review and mix ratios that favor real data for final tuning.

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Question: What labeling strategies speed up dataset creation for large tasks?

Answer: Use active learning to prioritize uncertain examples, weak supervision to combine noisy heuristics, and annotation guidelines with seed examples to ensure consistency. Track inter-annotator agreement and iteratively refine label schemas.

Quiz:

Chunking long documents with overlap helps prevent:

A. Tokenizer failures

B. Loss of context at chunk boundaries (Correct)

C. Faster tokenization

D. Increased vocabulary size

A core risk of synthetic data is:

A. Reduced storage needs

B. Introduction of non-natural artifacts or biases (Correct)

C. Immediate improvement in all metrics

D. Elimination of the need for human validation

Active learning primarily reduces:

A. Model size

B. Annotation cost by selecting informative examples (Correct)

C. The requirement for chunking

D. Need for caching

4. Task Framing: Classification, Generation, Entity Matching, Sequence Instructioning

Question: How do you convert an entity matching problem into a fine-tuning format for an LLM?

Answer: Frame pairs (recordA, recordB) as input with a deterministic label (match / no-match) and include normalized fields. Optionally provide provenance and candidate attributes to help the model learn token-level alignment patterns; structure prompts to make the task explicit (e.g., “Do these entries refer to the same entity? Answer: Yes/No”).

Question: What is the difference between framing a generation task vs a classification task?

Answer: Generation requires sequence-to-sequence or causal fine-tuning with loss over token outputs; classification often uses a head over a pooled representation and optimizes cross-entropy over classes. Choose loss and sampling strategies accordingly.

Question: How are sequential instructions represented for fine-tuning instruction-following models?

Answer: Encode instruction chains as structured inputs (step1; step2; ...), include desired intermediate states, and possibly supervise intermediate outputs if you want the model to produce stepwise reasoning or multi-step plans.

Question: For entity matching, how should negative examples be sampled?

Answer: Use hard negatives (close but non-matching candidates) and stratified sampling to reflect real-world class imbalance; avoid trivial negatives that make the task too easy.

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Quiz:

Entity matching fine-tuning commonly uses inputs of:

A. Single records only

B. Pairs of records with a match/no-match label (Correct)

C. Only precomputed embeddings

D. Image pairs

Sequential instruction tuning benefits models that must:

A. Compress embeddings

B. Produce stepwise, multi-turn plans (Correct)

C. Only classify sentiment

D. Reduce vocabulary size

Hard negatives are useful because they:

A. Slow training significantly

B. Improve discrimination by providing challenging non-matches (Correct)

C. Increase model size

D. Reduce the need for validation

5. Annotation, Labeling Strategies & Synthetic Data for Domain Adaptation

Question: What annotation workflows suit fine-tuning high-stakes domain models (e.g., legal, medical)?

Answer: Use multi-stage review: primary annotation, secondary expert adjudication, and a reconciliation step for disagreements. Maintain detailed guidelines, example anchors, and periodic calibration sessions to keep labelers consistent.

Question: When should weak supervision be used and how to combine sources?

Answer: Use weak supervision to scale labels via heuristics, rules, and model outputs. Combine sources with label-modeling (e.g., Snorkel-like approaches) to estimate per-example true labels and track source reliabilities.

Question: How do you validate synthetic labels or augmented examples?

Answer: Separate a validation set of human-labeled examples, sample synthetic examples for human spot-checking, and measure distributional divergence between synthetic and real examples to detect artifacts.

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Question: What governance artifacts should be available along with annotated datasets?

Answer: You should keep annotation schemas, worker metadata, disagreement logs, versioned dataset snapshots, and provenance records so QA and auditors can trace why a particular training example influenced model behavior.

Quiz:

A multi-stage annotation workflow typically includes:

A. Single annotator only

B. Primary annotation plus adjudication by experts (Correct)

C. Only synthetic labels

D. No validation

Weak supervision should be combined using:

A. Simple majority vote only

B. Label modeling to estimate true labels and source reliability (Correct)

C. Random sampling

D. Noisy channel model only

Spot-checking synthetic data ensures:

A. That synthetic data always outperforms real data

B. That synthetic artifacts are detected and corrected (Correct)

C. That no human labels are needed afterward

D. That the model is fully calibrated

6. Fine-Tuning Workflows: Full-Model vs Partial / Layered Training

Question: What is the difference between full-model fine-tuning and partial / layered training?

Answer: Full-model fine-tuning updates every parameter of the LLM on your task dataset; partial / layered training freezes most base weights and updates only a subset (such as last N layers, task heads, or adapter modules). Full fine-tuning gives maximum representational flexibility but requires more memory, computation, and produces larger checkpoints. Partial training reduces resource needs and risk of catastrophic forgetting by constraining parameter drift.

Question: What are the resource implications (GPU memory, checkpoint storage, training time) of each workflow?

Answer: Full fine-tuning demands GPUs with large memory budgets or heavy use of model parallelism / gradient checkpointing; checkpoint sizes equal the full model (GBs to TBs). Partial approaches reduce optimizer state and checkpoint sizes dramatically - often by orders of magnitude - because only a small parameter subset is stored/updated. Training time per step can be similar, but effective throughput and wall-clock time favor parameter-efficient methods on the same hardware.

Question: In LLMOps, how do you decide which workflow to use?

Answer: Base the decision on (1) magnitude of expected metric lift from full updates vs partial; (2) available infra and budget; (3) need to preserve base capabilities; (4) frequency of retraining. If rapid iterations, limited infra, or many variants are expected, prefer layered or adapter-based approaches. If you require maximal accuracy and have resources and governance to manage large checkpoints, choose full fine-tuning.

Question: What best practices reduce risk when performing full or partial fine-tuning?

Answer: Use low initial learning rates, gradient clipping, and mixed precision; keep a checkpointed baseline of the unmodified model; run holdout suites that test general language competence; limit catastrophic forgetting via rehearsal or regularization; and automate validation and rollback. For partial training, verify that updated layers actually affect task metrics by ablation runs and maintain a small validation set reflecting production distribution.

Quiz

What is the main advantage of partial / layered training over full fine-tuning?

A. It always produces higher accuracy

B. Reduced memory and checkpoint storage (Correct)

C. Eliminates the need for validation

D. Requires no tuning of hyperparameters

Which practice helps prevent catastrophic forgetting during full-model fine-tuning?

A. Using very large learning rates

B. Rehearsal with mixed pretraining examples (Correct)

C. Removing validation sets

D. Freezing the entire model

When would you prefer full-model fine-tuning?

A. When you have severe infra constraints

B. When maximum task performance outweighs cost and you can manage larger checkpoints (Correct)

C. When you need many rapid, low-cost experiments

D. When you must preserve the base model’s exact behavior

7. Parameter-Efficient Fine-Tuning: LoRA, Adapters, Prompt-Tuning, and PEFT

Question: What are LoRA, adapters, prompt-tuning, and PEFT and why are they used?

Answer: These are parameter-efficient fine-tuning techniques. LoRA (Low-Rank Adaptation) injects low-rank update matrices into weight updates, letting you learn small additional matrices instead of full weights. Adapters insert small bottleneck modules between layers and update just those. Prompt-tuning optimizes a small continuous prompt vector while keeping the base model frozen. PEFT is an umbrella term (Parameter-Efficient Fine-Tuning) encompassing these methods. They reduce storage, enable many task variants, and simplify deployment.

Question: How do the trade-offs between LoRA, adapters, and prompt-tuning work out in practice?

Answer: LoRA often yields near full-fine-tune performance with small parameter budgets and is straightforward to apply to linear projection layers. Adapters provide modularity and can be stacked per domain; they are robust and interpretable but sometimes slightly less performant than LoRA. Prompt-tuning is lowest cost but can underperform on complex structured outputs and typically requires long tuning runs. Choice depends on task complexity, allowed parameter budget, and how many task variants you intend to maintain.

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Question: How does one manage many domain adapters or LoRA modules in production?

Answer: Version adapters and LoRA checkpoints independently, load the appropriate module dynamically at inference time, and keep a compatibility matrix linking base model versions to adapter versions. Maintain a registry mapping domain names to adapter checkpoints and use lazy loading to minimize memory footprint in multi-tenant services.

Question: For AI Testers, what are quick sanity checks when using PEFT (Parameter-Efficient Fine-Tuning) methods?

Answer: Run small ablation tests: compare a frozen baseline, the PEFT module, and a tiny full-fine-tune on a validation slice; measure latency and memory; assert that the module yields non-trivial metric lift; and verify no gross regressions on general capability tests.

Quiz

Which method inserts small bottleneck modules between layers for task adaptation?

A. LoRA

B. Adapter tuning (Correct)

C. Full fine-tuning

D. Token pruning

What is a typical benefit of LoRA?

A. Eliminates the need for a base model

B. Near full-fine-tune performance with far fewer trained parameters (Correct)

C. Always faster inference

D. No hyperparameters to tune

Prompt-tuning is best suited when:

A. You need high performance on complex structured outputs

B. You want the smallest possible trained parameter footprint and can accept possible performance limits (Correct)

C. You must change tokenizer vocabulary

D. You require full checkpoint snapshots only

8. Instruction Tuning & Sequential Instruction Fine-Tuning

Question: What is instruction tuning? Why is it important for instruction-following behavior?

Answer: Instruction tuning fine-tunes an LLM on a corpus of (instruction → response) pairs so the model learns to map natural language directives into desired outputs. It shapes response style, adherence to constraints, and the model's ability to follow diverse prompts, improving usability for LLM's client applications.

Question: How do you represent sequential instructions during fine-tuning to teach multi-step behavior?

Answer: Encode multi-step workflows as structured sequences: include the initial instruction, desired intermediate outputs, and explicit step delimiters. You can supervise intermediate steps (teacher forcing) so the model learns intermediate states, or fine-tune on end-to-end examples with chain-of-thought style annotations if you want the model to generate reasoning traces.

Question: What datasets and augmentation strategies work well for instruction tuning?

Answer: Use diverse instruction corpora (few-shot style prompts, task templates, human-generated examples), synthetic instructions generated by LLMs and reviewed by humans, and negative or adversarial instructions (to improve robustness). Balance examples by instruction complexity and domain breadth to avoid overfitting style.

Question: How do you evaluate instruction-tuned models for sequential tasks?

Answer: Evaluate at multiple levels: robustness to instruction paraphrases, fidelity of intermediate steps (if applicable), and correctness of final output. Use human ratings for subjective aspects and automated checks for stepwise constraints (e.g., does step 2 follow from step 1).

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Quiz

Instruction tuning primarily optimizes the model to:

A. Reduce model size

B. Better map natural language instructions to desired outputs (Correct)

C. Change tokenizer embeddings only

D. Increase inference latency

When teaching multi-step workflows, which approach helps the model learn intermediate reasoning?

A. Ignoring intermediate states

B. Supervising intermediate outputs and using step delimiters (Correct)

C. Only using single-turn examples

D. Removing instructions

A good QA evaluation for sequential instruction models should include:

A. Only final output correctness

B. Robustness to instruction paraphrases, fidelity of intermediate steps, and correctness of final output (Correct)

C. No human evaluation

D. Only perplexity on training data

9. Reinforcement & Alignment: RLHF, Reward Modeling, and Safety Tuning

Question: What is the role of RLHF (Reinforcement Learning from Human Feedback) in fine-tuning?

Answer: RLHF refines model behavior by training a reward model on human preference data and then optimizing the policy (the LLM) to maximize that reward, typically via PPO (Proximal Policy Optimization) or other policy-optimization algorithms. It aligns outputs with human desirability signals (style, helpfulness) that are hard to encode as supervised labels.

Question: What are common risks and safety considerations when applying RLHF?

Answer: RLHF can overfit to annotator biases, amplify undesirable behaviors if reward data is narrow, and create reward hacking where the model finds loopholes to score highly on proxy metrics without genuine improvement. Safety requires diverse annotator pools, reward regularization, constraint modeling, and robust evaluation on adversarial cases.

Question: How does reward modeling scale to complex tasks?

Answer: For complex tasks you may need hierarchical reward models or multi-objective rewards (factuality, helpfulness, safety). Collect richer human preference data with scenario-based annotations and calibrate reward weights carefully. Use offline evaluation to detect reward-gaming behaviors before deploying online.

Question: In Ops, what operational controls should be used for alignment tuning?

Answer: Maintain human-in-the-loop review for high-risk outputs, implement rollback and canary deployments, log model decisions and reward signals, and run red-teaming to surface adversarial exploits. Monitor for distributional drift in reward effectiveness and retrain the reward model periodically.

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Quiz

RLHF primarily optimizes a model to:

A. Minimize parameter count

B. Maximize a human-trained reward signal to align behavior (Correct)

C. Reduce dataset size

D. Increase tokenization speed

A major risk of RLHF is:

A. It always reduces performance

B. Reward hacking and amplification of annotator bias (Correct)

C. It eliminates the need for evaluation

D. It never requires human reviewers

Which mitigation helps prevent reward hacking?

A. Narrow the annotator pool to a single expert

B. Use diverse annotator data, multi-objective rewards, and red-teaming security process (Correct)

C. Remove safety checks

D. Train longer without human feedback

10. Fine-Tuning for Specialized Use Cases: Domain Adaptation & Entity Matching

Question: How do you approach fine-tuning for domain adaptation (for domains such as legal, medical or finance) differently from general tasks?

Answer: Domain adaptation requires curated, high-quality domain data, strict privacy controls, domain expert annotations, and often higher penalties for errors. Use domain ontologies, terminology normalization, and incorporate external domain knowledge (tables, taxonomies) in prompts. Fine-tuning should prioritize precision and conservative outputs where accuracy is important.

Question: How is entity matching implemented as a fine-tuning pattern for LLMs?

Answer: Transform entity matching into pairwise classification or as a generative decision problem: present normalized fields and ask the model to output a canonical match id or "no-match." Use hard negatives, field-alignment augmentation, and augment training with synthetic variants. Evaluate with precision@k and pairwise F1.

Question: What are testing and validation best practices for specialized domains?

Answer: Build domain-specific validation suites that include edge cases, rare classes, and adversarial examples. Involve domain experts in labeling and acceptability thresholds. Run a post-deployment feedback process to collect label corrections and retrain iteratively.

Question: How do governance and audit differ when fine-tuning domain models?

Answer: Require stricter provenance records, legal review of training data, access controls on checkpoints, and mandatory human-review paths for high-risk decisions. Document rationales for threshold choices and ensure appeal workflows exist for affected users.

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Quiz

For entity matching fine-tuning, which strategy improves discrimination on borderline pairs?

A. Using only trivial negatives

B. Using hard negatives and field normalization (Correct)

C. Ignoring field values

D. Removing validation

When adapting to a medical domain you should:

A. Use random web data only

B. Curate expert-labeled data, enforce privacy, and include domain ontologies (Correct)

C. Skip validation entirely

D. Always prefer prompt engineering over fine-tuning

Which governance artifact is crucial for high-risk domain models?

A. A list of all random seeds used only

B. Provenance records, access controls, and documented thresholds (Correct)

11. Adaptive Machine Translation: Fine-Tuning LLMs for MT & Multilingual Tasks

Question: How do you approach adaptive machine translation when fine-tuning LLMs for MT (Machine Translation) and multilingual tasks?

Answer: Adaptive MT requires framing fine-tuning as a conditional generation problem where the model learns to map source text in language A to target text in language B, while preserving domain style. Use parallel corpora where available and back-translation to augment scarce bilingual data. For domain adaptation, include in-domain monolingual corpora and apply continued pretraining on source/target-side monolingual data before supervised fine-tuning on parallel pairs. Carefully control tokenization and vocabulary handling for multilingual inputs to avoid subword fragmentation.

Question: What strategies help low-resource transfer for a target language?

Answer: Use multilingual pretraining transfer: fine-tune a strongly multilingual base on high-resource language pairs and then adapt on small in-language examples. Apply transfer learning via multilingual adapters or shared encoder representations, and use back-translation to synthesize parallel examples. Curriculum fine-tuning - start with related high-resource language data then gradually introduce low-resource examples - to stabilize training.

Question: How do you measure quality for adaptive MT beyond BLEU (Bilingual Evaluation Understudy)?

Answer: Complement BLEU metric with adequacy and fluency metrics: use chrF for morphologically rich languages, COMET framework or BLEURT metric for learned semantic evaluation, and human post-editing cost to capture practical workload. Evaluate domain-specific terminology preservation and perform targeted tests on named entities and numerical fidelity.

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Question: Operationally, how do you handle domain-specific terminology and glossary constraints during inference?

Answer: Inject constraint-aware decoding: use constrained decoding or dictionary biasing to prefer glossary terms, and fine-tune with augmented examples that demonstrate desired terminology mapping. For hostile inflection cases, include paraphrase and morphological variants in training so the model learns robust term realization.

Quiz

Which technique is especially useful for low-resource language adaptation?

A. Training from scratch on only the tiny low-resource corpus

B. Back-translation and curriculum fine-tuning starting from related high-resource data (Correct)

C. Removing subword tokenization entirely

D. Using BLEU only for evaluation

How does continued pretraining help adaptive MT?

A. It reduces vocabulary size permanently

B. It adapts model priors to domain language distributions before supervised fine-tuning (Correct)

C. It eliminates need for parallel data

D. It always improves BLEU by a fixed amount

What evaluation metric is recommended for semantic adequacy in MT?

A. Accuracy

B. COMET or BLEURT (Correct)

C. Perplexity only

D. Token count

When ensuring glossary term fidelity, which approach is effective?

A. Ignoring glossary and hoping the model learns it

B. Constrained decoding and fine-tuning with glossary-augmented examples (Correct)

C. Increasing beam width only

D. Removing the tokenizer

What is a practical risk when heavily biasing decoding to a glossary?

A. Improved fluency always

B. Over-constraining output leading to reduced naturalness (Correct)

C. Elimination of hallucinations entirely

D. Reduced model size

What is a recommended human-centered evaluation for production MT?

A. Only automated metrics

B. Post-editing time and adequacy/fluency human judgments (Correct)

C. Counting tokens

D. Model loss on training set

12. Model Architectures & Scaling Considerations for Fine-Tuning

Question: What does model scaling imply for fine-tuning cost and expected gains?

Answer: Larger models tend to require more compute and memory but often yield higher few-shot and fine-tuned performance, subject to diminishing returns and cost constraints.

Question: How do tokenizer choices affect fine-tuning, especially for multilingual settings?

Answer: Suboptimal tokenization can fragment frequent domain tokens into many subwords, harming both quality and inference latency; prefer tokenizers trained or adapted to target languages and domains.

Question: What architecture variant considerations help when fine-tuning for generation vs classification?

Answer: For generation prefer encoder-decoder or causal-decoder architectures; for classification prefer a pooled representation with a task head.

Question: What is a scalability trade-off to consider when selecting model size for fine-tuning?

Answer: Larger models may improve accuracy but increase serving cost, latency, and complexity of distributed training (Correct)

13. Hyperparameters, Optimizers & Practical Recipes (Learning Rates, Schedules, Batch Size)

Question: What hyperparameter is most critical to start tuning first for stable fine-tuning?

Answer: Learning rate schedule and initial learning rate (Correct)

Question: Why are learning rate schedules important in fine-tuning?

Answer: Proper schedules (warmup, decay) prevent instability and reduce catastrophic forgetting; learning rate determines step size and must be tuned relative to batch size and model size.

Question: What is a practical batch size strategy if GPU memory is limited?

Answer: Use gradient accumulation to simulate larger batch sizes while keeping per-step memory small

Quiz

Which optimizer is commonly effective for LLM fine-tuning?

A. SGD with momentum only

B. AdamW family (with decoupled weight decay) and variants like AdamW with correct bias correction (Correct)

C. RMSprop only

D. Adagrad only

What is a sensible initial recipe for hyperparameters on a medium-sized model?

A. LR = 1, batch size = 1024

B. LR = 1e-5 to 3e-5 with warmup and decay, gradient accumulation to achieve effective batch, AdamW, and weight decay tuned modestly (Correct)

C. No warmup and extremely high LR

D. Only change optimizer, keep other defaults

14. Mixed Precision, Memory Optimization, and Distributed Training (DeepSpeed, FSDP)

Question: How does mixed precision (FP16/BF16) speed up fine-tuning? What must you watch for?

Answer: Mixed precision reduces memory usage and increases throughput by storing activations and weights in lower precision while maintaining master FP32 weights for updates. Watch for numerical underflow/overflow and ensure loss scaling is used to maintain stability. Use BF16 where supported for simpler stability; FP16 often requires dynamic loss scaling.

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Question: What memory optimizations help fit large models on limited GPUs?

Answer: Use gradient checkpointing to trade compute for memory, activation offloading to CPU where feasible, ZeRO optimizations to shard optimizer states, and parameter-efficient methods (LoRA/adapters) to reduce trainable state. Also use model parallelism (tensor/model parallel) frameworks, if multiple GPUs are available.

Question: What does DeepSpeed ZeRO enable for large-scale fine-tuning?

Answer: ZeRO shards optimizer states, gradients, and parameters across devices, reducing per-GPU memory footprint and enabling training of larger models on the same hardware. It requires orchestration but might provide significant scale-up benefits.

Question: What operational strategy reduces OOM and maximizes throughput when using FSDP or DeepSpeed?

Answer: Start with small scale tests, enable mixed precision, use appropriate shard strategies (stage 1/2/3), monitor communication overhead, and tune micro-batch sizes and accumulation steps; ensure deterministic behavior by controlling seeds and enabling consistent checkpointing.

Quiz

Which technique reduces peak memory by recomputing activations during backward pass?

A. Model pruning

B. Gradient checkpointing (Correct)

C. Token pruning

D. Increasing batch size

What is a major benefit of ZeRO optimizations?

A. Eliminates need for GPUs

B. Shards optimizer state and parameters to reduce per-device memory (Correct)

C. Always reduces training time by 10x without trade-offs

D. Removes need for validation

Which precision option often avoids the need for dynamic loss scaling on modern GPUs?

A. FP8

B. BF16 (Correct)

C. INT4

D. FP32 only

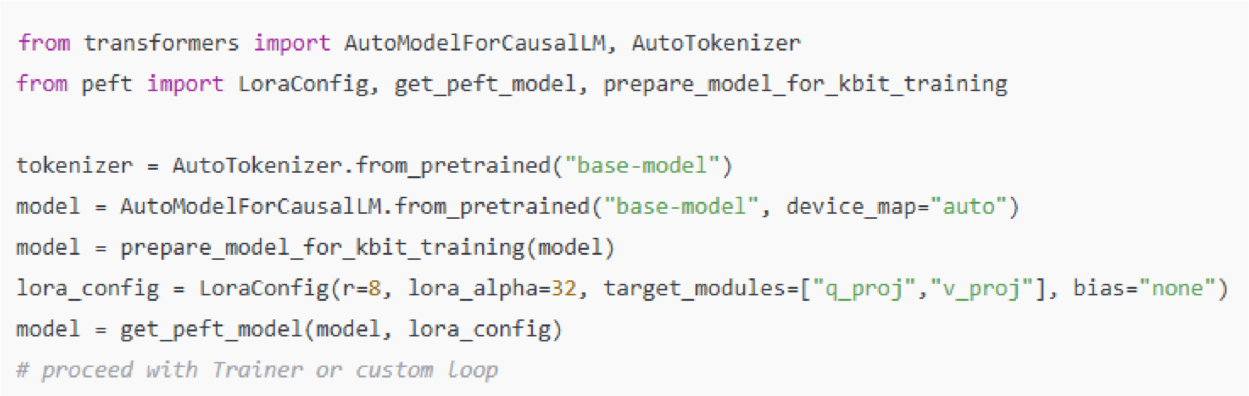
15. Tooling & Frameworks: Hugging Face, PEFT, TRL, DeepSpeed, Fairseq, Composer

Question: What are the core tooling components AI engineers should know for fine-tuning LLMs?

Answer: Familiarity with Hugging Face Transformers, PEFT libraries for adapters/LoRA, DeepSpeed or FSDP for distributed training, TRL for reinforcement tuning, and experiment tracking tools (W&B, MLflow) is needed for production-grade fine-tuning.

Question: Give a small LoRA + Hugging Face snippet to attach a LoRA module to a pretrained model for fine-tuning.

Answer:



```python
from transformers import AutoModelForCausalLM, AutoTokenizer
from peft import LoraConfig, get_peft_model, prepare_model_for_kbit_training

tokenizer = AutoTokenizer.from_pretrained("base-model")
model = AutoModelForCausalLM.from_pretrained("base-model", device_map="auto")
model = prepare_model_for_kbit_training(model)
lora_config = LoraConfig(r=8, lora_alpha=32, target_modules=["q_proj","v_proj"], bias="none")
model = get_peft_model(model, lora_config)
# proceed with Trainer or custom loop
```

Question: How do you test that the tooling configuration is correct before running a full job?

Answer: Run a small-scale smoke test (few batches) to verify forward/backward, checkpointing, and metric logging; verify memory usage, loss reduction, and that PEFT (Parameter-Efficient Fine-Tuning) modules are trainable while base weights remain frozen as expected.

Question: What is a practical QA checklist before launching a fine-tuning run in production?

Answer: Run smoke tests, validate config, confirm data provenance, ensure checkpointing and rollback, and record experiment metadata.

Quiz

Which library is specifically aimed at parameter-efficient fine-tuning modules like LoRA and adapters?

A. Scikit-learn

B. PEFT (Correct)

C. Matplotlib

D. SQLAlchemy

What is a valid smoke test before large-scale fine-tuning?

A. Running zero batches only

B. Running a few mini-batches to test forward/backward and checkpointing (Correct)

C. Immediately running full dataset training

D. Skipping validation

Which snippet component ensures LoRA targets projection matrices in transformer layers?

A. target_modules argument in LoraConfig (Correct)

B. using tokenizer only

C. enabling FP32 everywhere

D. removing the optimizer

16. Evaluation: Offline Metrics, Human Evaluation, and Task-Specific Benchmarks

Question: How should you evaluate fine-tuned MT (Machine Translation) systems beyond token-level overlap metrics?

Answer: Use a mix of automatic and human-centered measures: COMET or BLEURT for semantic adequacy, chrF for morphologically rich languages, and targeted tests for terminology fidelity and numeric-preservation. Always complement with human post-editing time and domain expert adequacy/fluency judgments to capture practical utility in production.
Example: A legal MT system with high BLEU but frequent mistranslation of clause negations will show low post-editing quality and high legal risk despite good BLEU.

Question: What offline metrics are appropriate for classification heads and generative outputs after fine-tuning?

Answer: For classification use precision/recall, F1, ROC-AUC, and confusion matrices stratified by segment. For generation use a combination of BLEU/ROUGE for n-gram overlap (task-dependent), learned metrics (COMET/BLEURT) for semantics, and factuality checks (QA-based consistency tests) to detect hallucination.
Example: For a question-answering head fine-tuned in finance, measure exact-match and F1 for short answers, and run downstream checks that answers cite verifiable document spans.

Question: How do you design human evaluation for alignment and acceptability?

Answer: Create standardized rating tasks (helpfulness, accuracy, safety), provide clear annotation guidelines with anchors, and use multiple raters per example to measure agreement. Sample across difficulty slices and adversarial prompts. Use pairwise preference tests to evaluate instruction tuning or RLHF outcomes.
Example: Present two model outputs blind to human raters and ask which is preferable on safety and fidelity; aggregate preferences to compare models. © Inder P Singh https://www.linkedin.com/in/inderpsingh

Question: How do you operationalize task-specific benchmarks and regressions?

Answer: Maintain versioned benchmark suites reflecting production slices; run them in CI with threshold gates that block deployment on regression. Include targeted adversarial tests and domain checks. Automate regression alerts and require a mitigation plan for failed gates.

Quiz

For generative evaluation that captures semantics best, which metric is recommended?

A. BLEU only

B. COMET or BLEURT (Correct)

C. Token count

D. Perplexity only

Which offline check detects hallucination in factual answers?

A. Exact-match only

B. QA-based consistency tests that verify answers against source texts (Correct)

C. Increasing batch size

D. Random sampling of training examples

What human evaluation practice improves human rater consistency?

A. No guidelines

B. Clear annotation anchors and multiple raters per item (Correct)

C. Single-rater judgments only

D. Changing scoring scales frequently

17. Testing & QA for Fine-Tuned Models: Unit Tests, Regression Tests, and Red-Teaming

Question: What constitutes an effective unit test for a fine-tuned model?

Answer: Small, deterministic tests asserting output shapes, response format, and critical behavior (e.g., no PII leakage) that run quickly in CI; include golden inputs with stable expected outputs for classification and structural checks for generation.
Example: Assert that a classifier returns a valid label set and probability vector summing to one, and that a sanitizer removes email patterns. *Get FREE AI courses at https://www.linkedin.com/company/softwareandtestingtraininging*

Question: For AI Testers, how are regression tests different from unit tests for LLMs?

Answer: Regression tests compare model versions on key benchmarks to detect performance drift - measure task metrics, latency, and safety regressions - and enforce guardrails in deployment pipelines. They are broader, dataset-driven, and often non-deterministic, so design tolerances and use statistical significance checks.

Question: What is red-teaming and why include it in AI QA?

Answer: Red-teaming actively probes models with adversarial inputs to surface vulnerabilities: prompt injections, jailbreaks, or edge-case failure modes. Use automated fuzzers and human adversaries, then catalog exploits and add mitigations or training cases.
Example: Simulate social-engineering prompts to test if the model responds with sensitive policy text.

Question: What dataset checks should AI QA apply before fine-tuning?

Answer: Validate label distributions, detect near-duplicates, surface annotation disagreements, and scan for sensitive content or legal exposures. Automate schema validation and sample audits. *Get published AI notebooks and datasets at https://www.kaggle.com/inderpsingh*

Quiz

A good regression test in CI should:

A. Never run automatically

B. Compare current model metrics to a baseline with defined tolerances (Correct)

C. Only check training loss

D. Ignore latency

Red-teaming is primarily used to:

A. Speed up training

B. Find adversarial failure modes and prompt exploits (Correct)

C. Reduce model size

D. Replace unit tests

Which dataset check reduces label noise risk?

A. Random deletion

B. Inter-annotator agreement audits and disagreement reconciliation (Correct)

C. Ignoring minority classes

D. Only using synthetic labels

18. Reproducibility, Experiment Tracking & Versioning (Weights, Data, Seeds)

Question: How does experiment tracking allow reproducibility in fine-tuning?

Answer: Track code, data versions, seeds, hyperparameters, checkpoint hashes, and environment details in systems like W&B or MLflow so runs can be reproduced and audited; log evaluation artifacts and metrics with links to datasets and model artifacts.
Example: Include a dataset snapshot identifier and seed in experiment metadata so a failed trial can be exactly rerun.

Question: What are the best practices for model and data versioning?

Answer: Use immutable dataset snapshots with checksums, store model checkpoints with semantic versioning, and maintain a registry mapping model versions to dataset versions, hyperparameters, and deployment tags. Automate lineage capture during pipeline runs.

Question: How do you achieve deterministic runs where possible?

Answer: Fix random seeds across libraries, disable non-deterministic CUDA (Compute Unified Device Architecture) ops when needed, control data loading order, and note that some distributed/accelerated kernels may still introduce nondeterminism. Document which parts are non-deterministic and use statistical validation for stability.

Question: How should experiment artifacts be archived for audits?

Answer: Save checkpoints, validation outputs, evaluation logs, configuration files, and provenance metadata in durable storage with access controls and retention policies.

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Quiz

Which practice most directly enables exact experiment replay?

A. Changing hyperparameters randomly

B. Storing dataset snapshots and checkpoint hashes with the run metadata (Correct)

C. Not logging random seeds

D. Only saving final models without metadata

To reduce nondeterminism, you should:

A. Enable all asynchronous ops

B. Fix seeds and control data loader ordering (Correct)

C. Randomize environment variables each run

D. Avoid tracking artifacts

What does a model registry map?

A. Model to deployment teams only

B. Model versions to dataset versions, metrics, and deployment tags (Correct)

C. Only hyperparameters

D. Only GPU types

19. Bias, Fairness & Ethics in Fine-Tuning - Mitigation and Audit

Question: How do you detect and measure bias introduced during fine-tuning?

Answer: Compute per-group metrics (precision/recall/F1) across protected attributes, run counterfactual evaluations, and measure disparate impact and calibration gaps; analyze feature-level attributions to understand drivers.
Example: Measure false positive rates stratified by demographic groups to detect disproportionate harm.

Question: What mitigation strategies reduce bias from training data?

Answer: Rebalance datasets, apply reweighting or adversarial debiasing, augment underrepresented groups, and include counterfactual data; combine algorithmic techniques with policy controls and human review for high-risk cases.

Question: How do audits and transparency play into fine-tuning governance?

Answer: Keep auditable records of training data provenance, annotator demographics, model versions, and evaluation results; provide explainability artifacts to stakeholders and enable recourse for affected users.

Question: When should you involve domain experts in fairness assessments?

Answer: For high-stakes domains (such as health, finance, legal) involve domain and ethics experts early to define harm scenarios, acceptable thresholds, and mitigation pathways.

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Quiz

A primary way to detect bias after fine-tuning is to:

A. Only check overall accuracy

B. Compute and compare per-group error rates (Correct)

C. Remove evaluation data

D. Only use BLEU

Which mitigation combines technical and policy controls?

A. Only retraining without governance

B. Dataset rebalancing plus transparent audit trails and human review (Correct)

C. Ignoring stakeholder input

D. Deleting logs

When should domain experts be consulted for fairness?

A. Only after deployment

B. Early in high-stakes projects to define harm scenarios (Correct)

C. Never

D. Only for tokenizers

20. Safety, Guardrails & Safe Deployment Practices (Rate Limits, Filters, Monitors)

Question: What runtime guardrails reduce safety incidents post-deployment?

Answer: Rate limits, content filters, classifier-based safety gates, and fallbacks to human review for uncertain or high-risk outputs. Also, maintain canary deployments and quick rollback capabilities.
Example: Apply a toxicity classifier at output time and route flagged responses to a human-in-the-loop reviewer.

Question: How do you implement canary deployments for fine-tuned models?

Answer: Gradually route a small percentage of traffic to the new model while monitoring key metrics (latency, error rates, safety flags); escalate rollout only when metrics are stable. Keep automatic rollback triggers for threshold breaches.

Question: What monitoring signals indicate safety degradation?

Answer: Sudden spikes in safety filter hits, increases in user complaints, higher rates of manual escalations, or elevated hallucination indicators (e.g., factuality failure counts) should lead to immediate investigation.

Question: What operational policies ensure rapid remediation of safety issues?

Answer: Define alert thresholds, create incident runbooks, enforce rollback procedures, maintain annotated logs for forensic analysis, and run periodic drills for incident response.

Quiz

Which runtime guard reduces exposure to abusive use?

A. Unlimited request rate

B. Rate limits and safety filters (Correct)

C. Removing monitoring

D. Only batch processing

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Canary deployments are used to:

A. Immediately replace production with no checks

B. Gradually roll out and monitor before full deployment (Correct)

C. Avoid backups

D. Disable safety filters

Which signal is a strong indicator of safety degradation?

A. Stable latency

B. Spike in safety filter hits or user escalations (Correct)

C. Lower memory usage

D. Fewer logs

21. Performance Monitoring & Production Observability for Fine-Tuned LLMs

Question: What telemetry should you collect to monitor fine-tuned LLMs in production?

Answer: Collect request-level logs (input, model version, prompt template), latency and resource metrics, error rates, output safety flags, and downstream business KPIs. Aggregate histograms of model scores, distribution of top tokens, and per-endpoint confusion matrices for any classification heads. Instrument trace IDs to connect model outputs with downstream user actions for root-cause analysis.
Example: Log model version, truncated prompt hash, response length, latency, and whether a post-output safety filter flagged the response (to enable incident triage).

Question: How do you detect model or data drift that impacts a fine-tuned model's performance?

Answer: Monitor feature-distribution drift (KL divergence or population stability index), target-distribution shifts, and rises in error or safety-flag rates. Use shadow testing and periodic labeled sampling to compute rolling evaluation metrics; when drift exceeds thresholds, trigger retraining or human review.
Example: If the mean token distribution for user queries shifts substantially and the 7-day rolling precision of a fraud-detection head falls, that indicates input distribution drift requiring investigation.

Question: How do you use confusion matrices in production observability for classification heads?

Answer: Maintain daily confusion matrices stratified by important segments (region, customer tier) and compare them against baseline matrices to identify regressions. Compute per-cell alerting (e.g., FP (False Positive) rate increase > X) and store per-instance counters to enable forensic drilling into which inputs contributed to changes.

Example: An alert that the false-positive count for a premium-customer segment doubled over 24 hours should surface both recent model versions and recent dataset shifts.

Question: What alerting KPIs and thresholds are practical for LLM deployments?

Answer: Track latency percentiles (p50/p95/p99), safety filter hit rate, precision/recall for supervised heads, and expected-cost per decision. Set a mix of absolute thresholds (e.g., p99 latency > 2s) and relative thresholds (e.g., 20% increase in daily FP rate vs baseline). Tie alerts to on-call runbooks with automated mitigation steps like traffic throttling or circuit-breakers.

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Quiz

Which telemetry item helps trace an output back to a user session?

A. Model loss on training set

B. Trace ID that connects request, model version, and downstream events (Correct)

C. GPU utilization only

D. Number of tokens in tokenizer vocabulary

A practical drift detection signal is:

A. Stable rolling precision for 30 days

B. KL (Kullback-Leibler) divergence of input feature distribution exceeding a threshold (Correct)

C. Constant CPU usage

D. Only final deployment date

Which KPI is best for tracking output safety over time?

A. Number of parameters in the model

B. Safety filter hit rate and counts of flagged outputs (Correct)

C. Tokenization time only

D. Training epoch count

What action should a runbook prescribe when p99 latency spikes above threshold?

A. Immediately delete checkpoints

B. Throttle traffic, roll back to previous model version, and investigate resource pressure or recent config changes (Correct)

C. Increase batch size in production without checks

D. Ignore and continue

What is one forensic step when confusion matrices indicate increased FP in one segment?

A. Remove monitoring for that segment

B. Inspect recent inputs, compare pre/post feature distributions, and replay failing inputs through older model versions (Correct)

C. Immediately change tokenizer

D. Retrain randomly without analysis

How should rolling windows be used to reduce alert noise?

A. Use single-sample alerts only

B. Use aggregated rolling windows (e.g., 24h, 7d) and require persistent deviation before alerting (Correct)

C. Disable windows entirely

D. Alert on raw counts only

How can you estimate inference cost from telemetry?

A. Only count model versions

B. Use per-request compute time, average CPU/GPU utilization, and egress counts to compute cost per inference and daily totals (Correct)

C. Only monitor disk I/O

D. Sum of token counts without hardware mapping

What is the first step when monitoring indicates rising expected cost per decision?

A. Permanently disable the model

B. Identify whether cost increase stems from higher FP, longer inference, or increased traffic and apply targeted mitigations (Correct)

C. Randomly prune weights

D. Ignore and wait a month

Which metric helps detect slow, gradual degradation requiring retraining?

A. Instantaneous GPU temp only

B. Trend in rolling validation metrics (precision/recall) on sampled production labels (Correct)

C. Model size in MB only

D. Number of commits in repo

Question: Which operational practices reduce time-to-detect for safety incidents?

Answer: Real-time dashboards, threshold alerts, and automated sampling pipelines for human review of flagged outputs.

Question: In production, how should metrics be partitioned to be most actionable?

Answer: By user segment, geography, model version, and prompt template to surface targeted regressions

Question: What is the recommended cadence for full retraining vs incremental fine-tuning based on monitoring?

Answer: Trigger retraining when monitored metrics cross pre-specified thresholds and when drift is sustained; use incremental fine-tuning for fast fixes when data characteristics are localized.

Question: Which practice ensures alerts connect to runbooks reliably?

Answer: Maintain automated runbook links and playbooks in the alert payload for on-call responders.

Question: Why keep a retention policy for telemetry?

Answer: For forensic investigations, drift analysis, and compliance audits while balancing storage cost

Question: What is a guardrail for telemetry privacy?

Answer: Redact PII (Personally Identifiable Information) from logs, store only hashed identifiers, and enforce access controls

Question: Which long-term analytic helps capacity planning?

Answer: Trends in requests per second and p95 latency over weeks with traffic seasonality accounted for.

Question: How do you validate that monitoring instrumentation itself is functioning?

Answer: Implement synthetic traffic probes and end-to-end checks to verify metric pipelines and alerting paths (Correct)

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22. Cost Estimation & Optimization: FLOPs, Inference Cost, and Serving Strategies

Question: What are the trade-offs between model quality and inference serving cost?

Answer: Higher-quality, larger models typically increase FLOPs per request, memory footprint, and latency, raising cost. Strategies to balance cost and quality include batching requests, quantization, model distillation, and dynamic routing to smaller models for simple queries.
Example: Route routine queries to a distilled 3B model and route complex, high-value queries to a 70B model to optimize cost while preserving quality for critical flows.

Question: How do you compute FLOPs for a transformer-based generation request?

Answer: Estimate FLOPs per token using model architecture (parameter matrices multiplications, attention operations) and multiply by output length; account for both encoder and decoder costs for encoder-decoder models. Convert FLOPs to cost via hardware-specific throughput and cloud pricing to estimate per-request inference cost.
Example: Approximate per-token FLOPs and multiply by average tokens per response and average requests per day to derive daily FLOPs budget.

Question: What serving strategies reduce per-request latency cost?

Answer: Use dynamic batching, request coalescing, async processing, and caching of frequent completions. Use auto-scaling groups with warm pools, and leverage GPU-pinned instances for latency-sensitive paths; for less latency-critical workloads, prefer CPU inference with optimized runtimes.
Example: cache templated responses for standard policy queries to avoid repeated inference.

Question: What are some practical quantization approaches and implications?

Answer: Post-training quantization to INT8 or 4-bit reduces memory and compute but can harm accuracy; quantization-aware fine-tuning or GPTQ-style block-wise quantization often preserves performance. Evaluate downstream task metrics after quantization and consider mixed-precision serving for critical paths.
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Quiz

Which serving strategy reduces per-request cost by grouping inputs?

A. Per-request isolation only

B. Dynamic batching and request coalescing (Correct)

C. Removing caching entirely

D. Using larger tokenizers only

Estimating per-request cost requires converting:

A. Training loss to dollars

B. FLOPs and hardware throughput to cost per time unit (Correct)

C. Token count to model size only

D. Random metrics only

What is a downside of aggressive post-training quantization?

A. Always improves accuracy

B. Potential accuracy degradation and the need for validation on target tasks (Correct)

C. Eliminates the need for monitoring

D. Increases model size

Which hybrid serving strategy optimizes quality and cost?

A. Using a single huge model for all queries

B. Dynamic routing to smaller distilled models for cheap queries and larger models for complex ones (Correct)

C. Never scaling up instances

D. Serving only with CPU for all workloads

Question: How does caching reduce FLOPs and cost?

Answer: By storing responses for identical prompts and reusing them for repeated requests, reducing redundant inference

Question: What metric helps determine when to route a query to a larger model?

Answer: A confidence score threshold or a lightweight reranker indicating expected improvement justifies routing to the expensive model.

Question: Why measure p95 latency when optimizing for cost?

Answer: p95 captures tail latency that impacts user experience and can drive costly overprovisioning, if ignored.

Question: Which approach reduces cold-start latency for GPU-backed endpoints?

Answer: Maintain warm instance pools or serverless pre-warmed containers for critical endpoints.

Question: What is a typical sequence when evaluating a quantized model for rollout?

Answer: Validate on held-out benchmarks, run A/B tests against baseline, measure downstream business KPIs, and then roll out gradually with monitoring.

Question: How should you price forecast inference costs for a roadmap?

Answer: Use current per-request FLOPs, average tokens, expected traffic growth, and cloud GPU pricing to forecast monthly costs with sensitivity scenarios.

Question: What is key to keep in the decision ledger when choosing a serving strategy?

Answer: Documentation of cost-quality trade-offs, expected savings, and rollback criteria

23. Parameter Distillation & Model Compression After Fine-Tuning

Question: What is parameter distillation? How does it differ from standard distillation?

Answer: Parameter distillation transfers knowledge from a large teacher model into a smaller student by training the student model to match intermediate representations or logits; parameter distillation emphasizes preserving parameter-efficient structures and may involve matching low-rank updates or adapters to preserve fine-tuned behaviors during compression.
Example: Distill a fine-tuned 70B model into a 7B student by training the student on teacher–student soft targets plus a small supervised dataset.

Question: When should you perform distillation after fine-tuning?

Answer: Perform distillation when you need a smaller, cheaper model for serving but want to retain as much of the fine-tuned behavior as possible; consider joint fine-tune-and-distill pipelines to reduce mismatch between teacher and student models.

Question: What quantization strategies are compatible with preserving fine-tuned performance?

Answer: Use quantization-aware fine-tuning, per-channel quantization for weights, and mixed-precision layouts where sensitive layers use higher precision; apply evaluation on downstream tasks to check delta in metrics.
Example: Perform 4-bit quantization on most layers while keeping embedding and LayerNorm parameters in higher precision.

Question: How do you test that a compressed model preserves downstream behavior?

Answer: Evaluate on task-specific benchmarks, safety and fairness checks, and run the same CI regression suite used for the teacher; include human evaluation where necessary to detect subtle degradations.

Quiz

Parameter distillation primarily aims to:

A. Increase FLOPs per request

B. Preserve fine-tuned behavior in a smaller model (Correct)

C. Remove the need for evaluation

D. Only reduce tokenizer size

Which strategy helps maintain accuracy during quantization?

A. Randomly change bits

B. Quantization-aware fine-tuning and per-channel quantization (Correct)

C. Immediately deploy without testing

D. Only monitor CPU usage

What is a practical test before rolling out a distilled model?

A. Skip all benchmarks

B. Run the same task-specific CI regression suite and human evaluation as for the teacher (Correct)

C. Only test on training data

D. Only check model size

24. CI/CD & Automation for Fine-Tuning Pipelines (Tests → Retrain → Deploy)

Question: What is an essential component of a CI/CD pipeline for fine-tuning?

Answer: Automated validation gates that run unit tests, regression benchmarks, safety checks, and canary deployment workflows before full rollout

Question: How often should retraining pipelines be scheduled?

Answer: Based on monitored drift signals and business cadence - e.g., weekly for high-drive domains or triggered by threshold breaches

Question: What rollback policy should a CI/CD pipeline include?

Answer: Immediate automatic rollback on threshold breaches with a human-in-the-loop retrospective ceremony.

25. Security & Intellectual Property Considerations in Fine-Tuning

Question: What is a secure practice for handling training data in automated pipelines?

Answer: Encrypt datasets at rest, use access controls, and keep provenance and consent records in metadata.

Question: Why include synthetic tests in CI pipelines?

Answer: To catch regressions on edge-case adversarial prompts and to confirm that the safety filters function before deployment.

Question: What governance step reduces intellectual property risk when fine-tuning on third-party data?

Answer: Maintain license records, provenance, and obtain necessary permissions or use only licensed datasets.

Question: How can watermarking help with IP protection?

Answer: Watermarking embeds detectable, low-impact signals in generated outputs to trace model-originated text and assist in misuse investigations.

Question: What are a few legal precautions when fine-tuning on user-provided content?

Answer: Obtain explicit consent where required, ensure PII (Personally Identifiable Information) removal, and follow data minimization and retention policies

Question: What final artifact should accompany a production model for audits?

Answer: A deployment dossier with dataset provenance, license declarations, evaluation reports, and access logs

26. Consolidated Q&A on Fine-Tuning LLMs

Question: In a CI pipeline, what gate should block deployment automatically?

Answer: A regression test failure in the task-specific benchmark suite.

Question: What is one key metric in cost estimation for roadmap planning?

Answer: Monthly FLOPs consumption based on forecasted traffic and average tokens per response

Question: Which artifact is important for compliance audits?

Answer: Dataset provenance records and model registry entries mapping to datasets and evaluations

Question: Which practice is essential to reduce IP leakage risk?

Answer: Use private, licensed data and sanitize inputs, maintain access controls, and log model training sources.

Question: What is a final operational step before handing an LLM to a production team?

Answer: Deliver a deployment dossier, runbooks, and reproducible training artifacts.