1. Setup and Installation

```
# # Install required packages
# !pip install torch transformers peft accelerate bitsandbytes -q
# !pip install tqdm psutil trl -q
# !pip install -U sympy          # or  !pip install -U sympy  in a notebook

# # Create directories
# !mkdir -p rlvr_adapter
# !mkdir -p offload_folder
```

2. Imports and Logging Setup

```
import os
import torch
import numpy as np
import gc
from datetime import datetime
from accelerate import Accelerator
from transformers import (
    AutoTokenizer,
    AutoModelForCausalLM,
    BitsAndBytesConfig,
    get_scheduler
)
from peft import (
    LoraConfig,
    PeftModel,
    get_peft_model,
    prepare_model_for_kbit_training
)
from tqdm.notebook import tqdm  # Use notebook-friendly tqdm
import logging
import psutil
import matplotlib.pyplot as plt
from google.colab import auth
import warnings
# Import datasets library for GSM8K
from datasets import load_dataset

# Add this to your imports section
import re
import json
warnings.filterwarnings('ignore')

# Configure basic logging
logging.basicConfig(
    level=logging.INFO,
    format='%(asctime)s - %(name)s - %(levelname)s - %(message)s'
)
logger = logging.getLogger(__name__)

# Memory efficiency configurations
torch.backends.cuda.matmul.allow_tf32 = True  # Better performance with reduced precision
torch.backends.cudnn.allow_tf32 = True

# Check for available GPU
print(f"GPU available: {torch.cuda.is_available()}")
if torch.cuda.is_available():
    print(f"GPU: {torch.cuda.get_device_name(0)}")
    print(f"Memory: {torch.cuda.get_device_properties(0).total_memory / 1e9:.2f} GB")
```

```
GPU available: True
GPU: NVIDIA A100-SXM4-40GB
Memory: 42.47 GB
```

3. Configuration and Paths

```
# Helper function for securely setting HF token
from getpass import getpass
import os
from google.colab import userdata


# Set Hugging Face token (enter when prompted)
def setup_hf_token():
    if userdata.get("HF_TOKEN") is None:
        token = getpass("Enter your Hugging Face token: ")
        os.environ["HF_TOKEN"] = token
    return os.environ["HF_TOKEN"]

# Call the function
AUTH_TOKEN = userdata.get("HF_WRITE_TOKEN")

# Set up paths and configuration
BASE_MODEL_NAME = "meta-llama/Llama-3.1-8B-Instruct"  # Base model name

# Paths - adjusted for Colab
ADAPTER_PATH = "rlvr_adapter"
OFFLOAD_FOLDER = "offload_folder"

# RLVR Hyperparameters - adjusted for faster training in Colab
LEARNING_RATE = 1e-5
VALUE_MARGIN = 0.1  # Replacing CLIP_EPSILON - this is the margin for the value constraint
KL_PENALTY = 0.1
VALUE_COEF = 0.5  # Can remain the same
ENTROPY_COEF = 0.01  # Can remain the same
NUM_EPOCHS = 2  # Keeping reduced value for Colab
BATCH_SIZE = 1
GRADIENT_ACCUMULATION_STEPS = 4  # Keeping reduced value for Colab
MAX_SEQ_LENGTH = 256  # Keeping reduced value for Colab
MAX_GRAD_NORM = 1.0  # Can remain the same
GAMMA = 0.99  # Discount factor can remain the same
GAE_LAMBDA = 0.95  # GAE lambda can remain the same
DELTA = 0.2  # tolerance for the trust region

# LoRA Configuration - optimized for Colab
lora_config = LoraConfig(
    r=4,
    lora_alpha=8,
    lora_dropout=0.05,
    bias="none",
    task_type="CAUSAL_LM",
    target_modules=[
        "q_proj",
        "v_proj",
        "o_proj",
    ],
)
```

4. Utility Functions

```
def log_memory_usage(stage=""):
    """Log current memory usage for debugging."""
    if torch.cuda.is_available():
        allocated = torch.cuda.memory_allocated() / 1024**2
        reserved = torch.cuda.memory_reserved() / 1024**2
        logger.info(f"{stage} - GPU Memory: {allocated:.2f}MB allocated, {reserved:.2f}MB reserved")

        # Plot memory usage
        plt.figure(figsize=(10, 2))
        plt.bar(['Allocated', 'Reserved'], [allocated, reserved])
        plt.ylabel('Memory (MB)')
        plt.title(f'GPU Memory Usage - {stage}')
        plt.show()

    process = psutil.Process()
    ram = process.memory_info().rss / 1024**2
    logger.info(f"{stage} - RAM Usage: {ram:.2f}MB")

def format_math_prompt(question):
    """Format a math question with proper instructions for GSM8K."""
```

```
    # Instructions for how to structure the answer
    instructions = """You are a math problem solver. Please solve problems step by step, following these rules:
    1) Start with noting all facts from the problem.
    2) Perform inner calculations inside double angle brackets, like <<calculation=result>>.
    3) Write the final answer in a new line with a #### prefix."""

    # Format according to Llama 3.1 chat template
    prompt = f"<|begin_of_text|><|start_header_id|>system<|end_header_id|>\n{instructions}<|eot_id|>\n<|start_header_id|>user<|end_header_ic
    return prompt
```

5. Model Loading

```
def load_model():
    # Load tokenizer as before
    tokenizer = AutoTokenizer.from_pretrained(
        BASE_MODEL_NAME,
        token=AUTH_TOKEN
    )

    if tokenizer.pad_token is None:
        tokenizer.pad_token = tokenizer.eos_token

    # Modified quantization config - remove CPU offloading
    bnb_config = BitsAndBytesConfig(
        load_in_4bit=True,
        bnb_4bit_compute_dtype=torch.float16,
        bnb_4bit_use_double_quant=True,
        bnb_4bit_quant_type="nf4"
        # Removed: llm_int8_enable_fp32_cpu_offload=True
    )

    # Load policy model without device_map
    policy_model = AutoModelForCausalLM.from_pretrained(
        BASE_MODEL_NAME,
        quantization_config=bnb_config,
        token=AUTH_TOKEN,
        torch_dtype=torch.float16
    )

    # Continue with adapter preparation as before
    policy_model = prepare_model_for_kbit_training(policy_model)
    policy_model = get_peft_model(policy_model, lora_config)

    # Similar changes for reference_model
    reference_model = AutoModelForCausalLM.from_pretrained(
        BASE_MODEL_NAME,
        quantization_config=bnb_config,
        token=AUTH_TOKEN,
        torch_dtype=torch.float16
    )

    # Continue with value head creation as before
    # ...

    log_memory_usage("After reference model")

    # Freeze reference model
    for param in reference_model.parameters():
        param.requires_grad = False

    # Create value head on top of policy model
    value_head = torch.nn.Linear(
        policy_model.config.hidden_size,
        1
    ).to(policy_model.device)

    # Memory optimization: Clear CUDA cache
    if torch.cuda.is_available():
        torch.cuda.empty_cache()
    gc.collect()

    return policy_model, reference_model, value_head, tokenizer
```

Section 6: Dataset Loading and Preparation

```
from datasets import load_dataset
import re
import json
import time
import torch.nn.functional as F
from torch.optim import AdamW

def load_gsm8k_dataset():
    """Load and prepare the GSM8K dataset for training."""
    logger.info("Loading GSM8K dataset...")
    ds = load_dataset("openai/gsm8k", "main")

    # Extract training and test sets
    train_ds = ds["train"].select(range(800))
    test_ds = ds["test"].select(range(200))

    logger.info(f"Dataset loaded: {len(train_ds)} training examples, {len(test_ds)} test examples")
    return train_ds, test_ds

def format_instructions():
    """Generate the instruction for how to structure math responses."""
    instructions = """
    Please solve this math problem step by step, following these rules:
    1) Start by noting all the facts from the problem.
    2) Show your work by performing inner calculations inside double angle brackets, like <<calculation=result>>.
    3) You MUST write the final answer on a new line with a #### prefix.
    Note - each answer must be of length <= 400.
    """
    return instructions

def format_math_prompt(question):
    """Format a math question with proper instructions."""
    instructions = format_instructions()
    # Format according to Llama 3.1 chat template
    prompt = f"<|begin_of_text|><|start_header_id|>system<|end_header_id|>\n{instructions}<|eot_id|>\n<|start_header_id|>user<|end_header_ic
    return prompt

def extract_answer(response):
    """Extract the final answer (number after ####) from a model response."""
    # Look for the final answer format: #### number
    answer_match = re.findall(r'-?\d+\.?\d*', response)
    if answer_match:
        try:
            # Extract and convert to number
            return float(answer_match[-1])
        except ValueError:
            return None
    return None

def verify_answer(generated_answer, reference_answer):
    """Compare the generated answer with the reference answer from the dataset."""
    # Extract the reference answer (usually at the end of the reference string)
    ref_match = re.findall(r'(?<=#### )-?\d+\.?\d*', reference_answer)
    # for ref answer we should use #### d+ regex, as it is always structured like this

    if ref_match and generated_answer is not None:
        try:
            reference_value = float(float(ref_match[-1]))
            # Check if the answers match (allowing for small floating point differences)
            return abs(generated_answer - reference_value) < 1e-6
        except ValueError:
            return False

    return False
```

Section 7: RLVR Training Components

```
def prepare_model_inputs(tokenizer, questions, device, max_length=MAX_SEQ_LENGTH):
    """Tokenize questions and prepare inputs for the model."""
    prompts = [format_math_prompt(q) for q in questions]
```

```
        inputs = tokenizer(prompts, padding=True, truncation=True, max_length=max_length, return_tensors="pt")
        return {k: v.to(device) for k, v in inputs.items()}

    def generate_responses(model, tokenizer, inputs, max_new_tokens=1000):
        """Generate responses from the model for given inputs."""
        # Set the pad token ID to avoid generation warnings
        generation_config = {
            "do_sample": True,
            "temperature": 0.7,
            "max_new_tokens": max_new_tokens,
            "pad_token_id": tokenizer.pad_token_id,
        }

        # Generate responses
        with torch.no_grad():
            outputs = model.generate(
                input_ids=inputs["input_ids"],
                attention_mask=inputs["attention_mask"],
                **generation_config
            )

        # Extract only the newly generated tokens for each sample (excluding input prompt)
        generated_texts = []
        for i, output in enumerate(outputs):
            input_length = inputs["input_ids"][i].size(0)
            generated_tokens = output[input_length:]
            generated_text = tokenizer.decode(generated_tokens, skip_special_tokens=True)
            generated_texts.append(generated_text)

        return generated_texts

    def calculate_rewards(generated_responses, reference_answers):
        """Calculate rewards based on answer correctness."""
        rewards = []

        for gen_resp, ref_ans in zip(generated_responses, reference_answers):
            gen_answer = extract_answer(gen_resp)
            is_correct = verify_answer(gen_answer, ref_ans)

            # Binary reward: 1.0 for correct, 0.0 for incorrect
            reward = 1.0 if is_correct else 0.0
            rewards.append(reward)

        return torch.tensor(rewards, dtype=torch.float32)

    def calculate_values(policy_model, value_head, inputs):
        """Calculate values using the value head on top of the policy model."""
        with torch.no_grad():
            # Get hidden states from the model's last layer
            outputs = policy_model(**inputs, output_hidden_states=True)
            # Use the last hidden state of the last token for each sequence
            last_hidden_states = outputs.hidden_states[-1][:, -1, :]
            # Get value estimates
            values = value_head(last_hidden_states).squeeze(-1)

        return values

    def compute_rlvr_loss(policy_model, reference_model, value_head, tokenizer,
                          inputs, rewards, kl_penalty=KL_PENALTY, value_margin=VALUE_MARGIN):
        """
        Compute the RLVR loss combining:
        1. A policy loss based on value-guided updates
        2. A value loss that trains the value function
        3. A KL penalty to keep close to the reference model
        """
        # Get outputs from the policy model
        policy_outputs = policy_model(**inputs, output_hidden_states=True)
        policy_logits = policy_outputs.logits
        last_hidden_states = policy_outputs.hidden_states[-1][:, -1, :]

        # Get value estimates
        values = value_head(last_hidden_states).squeeze(-1)

        # Get outputs from the reference model for KL calculation
        with torch.no_grad():
            reference_outputs = reference_model(**inputs)
            reference_logits = reference_outputs.logits
```

```
    # Calculate advantages (rewards - values)
    advantages = rewards - values

    # Compute token probabilities
    policy_log_probs = F.log_softmax(policy_logits, dim=-1)
    policy_probs = F.softmax(policy_logits, dim=-1)
    reference_probs = F.softmax(reference_logits, dim=-1)

    # RLVR Policy Loss:
    # For each token, we increase probability if advantage is positive
    # and decrease if advantage is negative, constrained by the value margin

    # Calculate per-token advantage
    token_advantages = advantages.unsqueeze(-1).unsqueeze(-1)

    # Create a mask where probability is increased/decreased based on advantage
    # Positive advantage -> increase probability if above reference
    # Negative advantage -> decrease probability if below reference
    positive_advantage_mask = (token_advantages > 0).float()
    negative_advantage_mask = (token_advantages < 0).float()

    # Calculate margins based on value_margin
    value_based_margins = value_margin * torch.abs(token_advantages)

    # Apply the RLVR value constraints
    policy_loss = torch.zeros_like(advantages)

    # For tokens with positive advantage
    pos_adv_loss = positive_advantage_mask * torch.clamp(
        reference_probs + value_based_margins - policy_probs,
        min=0
    )

    # For tokens with negative advantage
    neg_adv_loss = negative_advantage_mask * torch.clamp(
        policy_probs - (reference_probs - value_based_margins),
        min=0
    )

    # Combine losses
    token_policy_loss = (pos_adv_loss + neg_adv_loss).sum(dim=-1)

    # Only consider non-padding tokens
    attention_mask = inputs['attention_mask']
    policy_loss = (token_policy_loss * attention_mask).sum() / attention_mask.sum()

    # Value loss (MSE between values and rewards)
    value_loss = F.mse_loss(values, rewards)

    # KL divergence loss
    kl_loss = F.kl_div(
        F.log_softmax(policy_logits, dim=-1),
        F.softmax(reference_logits, dim=-1),
        reduction='batchmean'
    )

    # Combine losses
    total_loss = policy_loss + VALUE_COEF * value_loss + kl_penalty * kl_loss

    return total_loss, policy_loss, value_loss, kl_loss
```

Section 8: Main Training Loop and Evaluation

```
def fix_load_model():
    """Fixed version of the model loading function."""
    logger.info("Loading tokenizer...")
    log_memory_usage("Before tokenizer")
    tokenizer = AutoTokenizer.from_pretrained(
        BASE_MODEL_NAME,
        token=AUTH_TOKEN
    )
    log_memory_usage("After tokenizer")
```

```
    # Handle padding token
    if tokenizer.pad_token is None:
        tokenizer.pad_token = tokenizer.eos_token

    # Create quantization config with proper CPU offloading
    bnb_config = BitsAndBytesConfig(
        load_in_4bit=True,
        bnb_4bit_compute_dtype=torch.float16,
        bnb_4bit_use_double_quant=True,
        bnb_4bit_quant_type="nf4",
        llm_int8_enable_fp32_cpu_offload=True
    )

    logger.info("Loading policy model with 4-bit quantization and CPU offloading...")
    log_memory_usage("Before policy model")

    # Create a custom device map to control layer placement
    num_layers = 32  # Number of layers in Llama-3.1-8B

    # Keep important layers on GPU, offload others to CPU
    device_map = {
        "model.embed_tokens": 0,
        "model.norm": 0,
        "lm_head": 0
    }

    # Distribute model layers between GPU and CPU
    gpu_layers = 16  # Keep half the layers on GPU
    for i in range(num_layers):
        if i < gpu_layers:
            device_map[f"model.layers.{i}"] = 0  # GPU
        else:
            device_map[f"model.layers.{i}"] = "cpu"  # CPU

    # Load policy model with explicit memory management
    policy_model = AutoModelForCausalLM.from_pretrained(
        BASE_MODEL_NAME,
        quantization_config=bnb_config,
        device_map=device_map,
        token=AUTH_TOKEN,
        torch_dtype=torch.float16,
        offload_folder=OFFLOAD_FOLDER,
        offload_state_dict=True,
        max_memory={0: "15GiB", "cpu": "30GiB"}
    )

    # Prepare model for 4-bit training
    policy_model = prepare_model_for_kbit_training(policy_model)

    # Apply LoRA adapter
    policy_model = get_peft_model(policy_model, lora_config)
    policy_model.print_trainable_parameters()

    log_memory_usage("After policy model")

    # Load reference model - frozen copy of the original model
    logger.info("Loading reference model (frozen)...")
    log_memory_usage("Before reference model")

    # Create separate device map for reference model - put more on CPU
    ref_device_map = {
        "model.embed_tokens": "cpu",
        "model.norm": "cpu",
        "lm_head": "cpu"
    }

    # Put more layers on CPU for reference model to save GPU memory
    gpu_layers_ref = 8  # Fewer layers on GPU for reference model
    for i in range(num_layers):
        if i < gpu_layers_ref:
            ref_device_map[f"model.layers.{i}"] = 0  # GPU
        else:
            ref_device_map[f"model.layers.{i}"] = "cpu"  # CPU

    # Load reference model with same config but different device map
    reference_model = AutoModelForCausalLM.from_pretrained(
        BASE_MODEL_NAME,
```

```
        quantization_config=bnb_config,
        device_map=ref_device_map,
        token=AUTH_TOKEN,
        torch_dtype=torch.float16,
        offload_folder=OFFLOAD_FOLDER,
        offload_state_dict=True
    )

    log_memory_usage("After reference model")

    # Freeze reference model
    for param in reference_model.parameters():
        param.requires_grad = False

    # Create value head on top of policy model
    value_head = torch.nn.Linear(
        policy_model.config.hidden_size,
        1
    ).to(policy_model.device)

    # Memory optimization: Clear CUDA cache
    if torch.cuda.is_available():
        torch.cuda.empty_cache()
    gc.collect()

    return policy_model, reference_model, value_head, tokenizer

def run_rlvr_pipeline():
    """Main function to run the complete RLVR pipeline with improved memory efficiency."""
    # 1. Load and prepare the GSM8K dataset
    train_ds, test_ds = load_gsm8k_dataset()

    # Reduce the dataset size if needed for memory constraints
    if len(train_ds) > 1000:  # Adjust this threshold as needed
        train_ds = train_ds.select(range(1000))
    if len(test_ds) > 100:    # Adjust this threshold as needed
        test_ds = test_ds.select(range(100))

    # 2. Load models - use the corrected load_model function
    policy_model, reference_model, value_head, tokenizer = load_model()

    # 3. Set up optimizer and accelerator with reduced memory footprint
    accelerator = Accelerator(gradient_accumulation_steps=GRADIENT_ACCUMULATION_STEPS)

    # Group all model parameters for gradient clipping
    optimizer = AdamW(
        list(policy_model.parameters()) + list(value_head.parameters()),
        lr=LEARNING_RATE
    )

    # Reduce total steps if needed for a smaller test run
    total_steps = len(train_ds) * NUM_EPOCHS // (BATCH_SIZE * GRADIENT_ACCUMULATION_STEPS)
    scheduler = get_scheduler(
        "cosine",
        optimizer=optimizer,
        num_warmup_steps=0,
        num_training_steps=total_steps
    )

    # Prepare with accelerator
    policy_model, reference_model, value_head, optimizer, scheduler = accelerator.prepare(
        policy_model, reference_model, value_head, optimizer, scheduler
    )

    # 4. Initialize tracking metrics
    metrics = {
        "correct_answers": [],
        "false_answers": [],
        "accuracy": [],
        "total_loss": [],
        "policy_loss": [],
        "value_loss": [],
        "kl_loss": []
    }

    # Output JSON file
    output_file = "rlvr_results.json"
```

```
# 5. Training loop
logger.info("Starting RLVR training...")
start_time = time.time()

# Create a smaller batch for evaluation
eval_dataset = test_ds.select(range(min(100, len(test_ds))))

# Main training loop
for epoch in range(NUM_EPOCHS):
    logger.info(f"Starting epoch {epoch+1}/{NUM_EPOCHS}")
    policy_model.train()
    value_head.train()

    # Training progress bar
    progress_bar = tqdm(range(0, len(train_ds), BATCH_SIZE), desc=f"Epoch {epoch+1}")

    # Process batches
    total_correct = 0
    total_samples = 0
    epoch_loss = 0

    # Track losses for this epoch
    epoch_total_loss = 0
    epoch_policy_loss = 0
    epoch_value_loss = 0
    epoch_kl_loss = 0

    for i in range(0, len(train_ds), BATCH_SIZE):
        # Get batch data
        batch_end = min(i + BATCH_SIZE, len(train_ds))
        batch_questions = [train_ds[j]["question"] for j in range(i, batch_end)]
        batch_answers = [train_ds[j]["answer"] for j in range(i, batch_end)]

        # Step 1: Generate responses from current policy
        inputs = prepare_model_inputs(tokenizer, batch_questions, policy_model.device)
        with torch.no_grad():
            generated_responses = generate_responses(policy_model, tokenizer, inputs)

        # Step 2: Calculate rewards based on correctness
        rewards = calculate_rewards(generated_responses, batch_answers)
        rewards = rewards.to(policy_model.device)

        # Step 3: Update policy with RLVR
        optimizer.zero_grad()

        # Calculate loss
        total_loss, policy_loss, value_loss, kl_loss = compute_rlvr_loss(
            policy_model, reference_model, value_head, tokenizer,
            inputs, rewards, KL_PENALTY, VALUE_MARGIN
        )

        # Accumulate loss values for tracking
        epoch_total_loss += total_loss.item()
        epoch_policy_loss += policy_loss.item()
        epoch_value_loss += value_loss.item()
        epoch_kl_loss += kl_loss.item()

        # Backward pass
        accelerator.backward(total_loss / GRADIENT_ACCUMULATION_STEPS)

        # Track accuracy
        correct_count = int(rewards.sum().item())
        total_correct += correct_count
        total_samples += len(rewards)

        # Store results for incorrect answers (for retraining)
        for q_idx, (question, generated, reference, is_correct) in enumerate(
            zip(batch_questions, generated_responses, batch_answers, rewards.bool())
        ):
            result = {
                "question": question,
                "generated_answer": generated,
                "reference_answer": reference
            }

            if is_correct:
```

```
                metrics["correct_answers"].append(result)
            else:
                metrics["false_answers"].append(result)

        # Apply gradient accumulation
        if (i // BATCH_SIZE + 1) % GRADIENT_ACCUMULATION_STEPS == 0 or i == len(train_ds) - 1:
            # Clip gradients
            accelerator.clip_grad_norm_(
                list(policy_model.parameters()) + list(value_head.parameters()),
                MAX_GRAD_NORM
            )

            # Update weights
            optimizer.step()
            scheduler.step()
            optimizer.zero_grad()

        # Update progress bar
        progress_bar.update(batch_end - i)
        progress_bar.set_postfix({
            "loss": f"{total_loss.item():.4f}",
            "accuracy": f"{total_correct/total_samples:.4f}"
        })

    # Calculate epoch metrics
    epoch_accuracy = total_correct / total_samples
    num_batches = len(train_ds) // BATCH_SIZE

    metrics["accuracy"].append(epoch_accuracy)
    metrics["total_loss"].append(epoch_total_loss / num_batches)
    metrics["policy_loss"].append(epoch_policy_loss / num_batches)
    metrics["value_loss"].append(epoch_value_loss / num_batches)
    metrics["kl_loss"].append(epoch_kl_loss / num_batches)

    # Log epoch summary
    logger.info(f"Epoch {epoch+1} Summary:")
    logger.info(f"  Training Accuracy: {epoch_accuracy:.4f}")
    logger.info(f"  Average Total Loss: {epoch_total_loss/num_batches:.4f}")
    logger.info(f"  Average Policy Loss: {epoch_policy_loss/num_batches:.4f}")
    logger.info(f"  Average Value Loss: {epoch_value_loss/num_batches:.4f}")
    logger.info(f"  Average KL Loss: {epoch_kl_loss/num_batches:.4f}")

    # Run evaluation on test set
    logger.info("Running evaluation...")
    policy_model.eval()
    value_head.eval()

    eval_correct = 0
    eval_total = 0

    for i in range(0, len(eval_dataset), BATCH_SIZE):
        batch_end = min(i + BATCH_SIZE, len(eval_dataset))
        eval_questions = [eval_dataset[j]["question"] for j in range(i, batch_end)]
        eval_answers = [eval_dataset[j]["answer"] for j in range(i, batch_end)]

        # Generate responses
        eval_inputs = prepare_model_inputs(tokenizer, eval_questions, policy_model.device)
        with torch.no_grad():
            eval_responses = generate_responses(policy_model, tokenizer, eval_inputs)

        # Calculate correctness
        for gen_resp, ref_ans in zip(eval_responses, eval_answers):
            gen_answer = extract_answer(gen_resp)
            is_correct = verify_answer(gen_answer, ref_ans)
            if is_correct:
                eval_correct += 1
            eval_total += 1

    eval_accuracy = eval_correct / eval_total
    logger.info(f"  Evaluation Accuracy: {eval_accuracy:.4f}")

    # Save checkpoint
    accelerator.wait_for_everyone()
    if accelerator.is_main_process:
        unwrapped_model = accelerator.unwrap_model(policy_model)
        unwrapped_model.save_pretrained(
            f"{ADAPTER_PATH}/checkpoint-epoch-{epoch+1}",
```

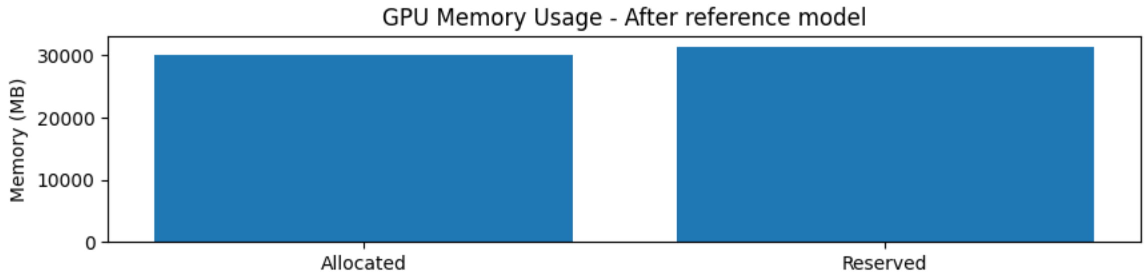
```
                save_function=accelerator.save
            )

            # Save current metrics to JSON
            with open(output_file, 'w') as f:
                json.dump(metrics, f, indent=2)

    # Final evaluation and cleanup
    training_time = time.time() - start_time
    logger.info(f"Training completed in {training_time/60:.2f} minutes")

    # Plot training metrics
    plt.figure(figsize=(10, 8))

    plt.subplot(2, 1, 1)
    plt.plot(metrics["accuracy"])
    plt.title("Training Accuracy")
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy")

    plt.subplot(2, 1, 2)
    plt.plot(metrics["total_loss"], label="Total Loss")
    plt.plot(metrics["policy_loss"], label="Policy Loss")
    plt.plot(metrics["value_loss"], label="Value Loss")
    plt.plot(metrics["kl_loss"], label="KL Loss")
    plt.title("Training Losses")
    plt.xlabel("Epoch")
    plt.ylabel("Loss")
    plt.legend()

    plt.tight_layout()
    plt.savefig("rlvr_training_metrics.png")
    plt.show()

    # Print final summary
    logger.info("RLVR Training Summary:")
    logger.info(f"  Final Training Accuracy: {metrics['accuracy'][-1]:.4f}")
    logger.info(f"  Total Training Samples: {len(train_ds)}")
    logger.info(f"  Correct Answers: {len(metrics['correct_answers'])}")
    logger.info(f"  Incorrect Answers: {len(metrics['false_answers'])}")
    return metrics
```

Section 9: Execute the pipeline

```
if __name__ == "__main__":
    metrics = run_rlvr_pipeline()
```

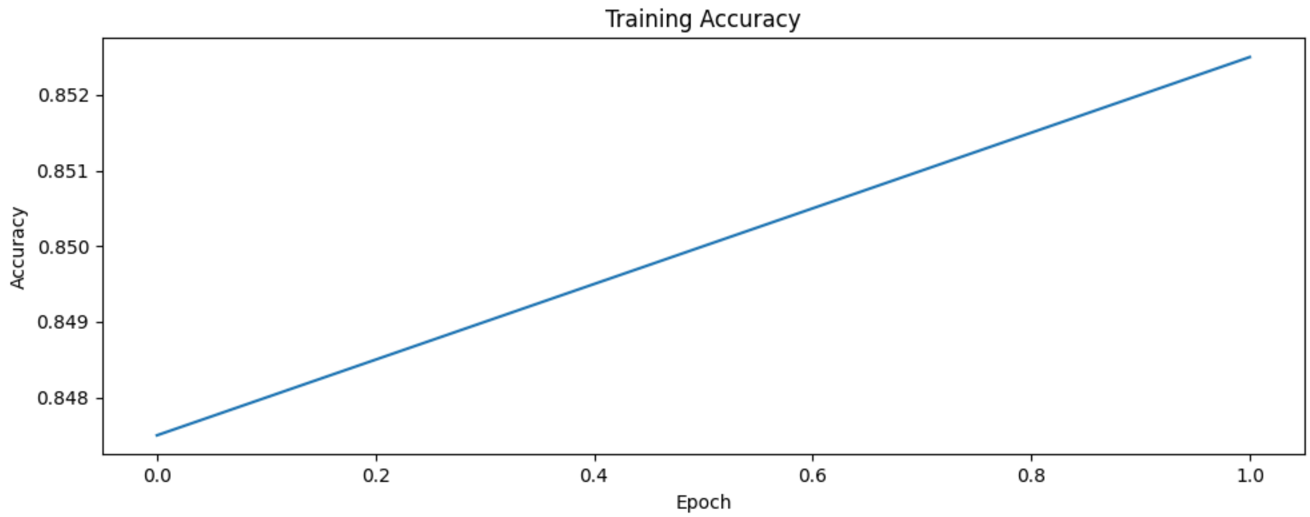
Loading checkpoint shards: 100% 4/4 [00:18<00:00, 3.82s/it]

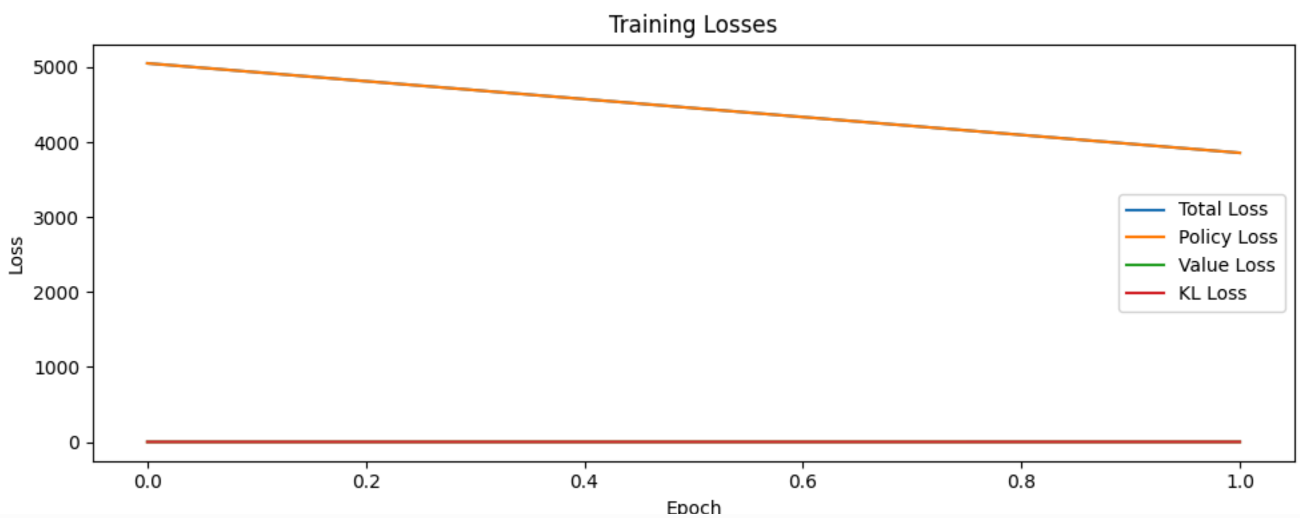
Loading checkpoint shards: 100% 4/4 [00:18<00:00, 3.80s/it]



Epoch 1: 100% 800/800 [13:18:55<00:00, 29.15s/it, loss=10269.3145, accuracy=0.8475]

Epoch 2: 100% 800/800 [7:26:58<00:00, 26.00s/it, loss=1163.9205, accuracy=0.8525]





Section 10: Example Usage After Training

```
def example_inference():
    """Show an example of using the trained model for inference."""
    # Load the trained model
    trained_model_path = f"{ADAPTER_PATH}/checkpoint-epoch-{NUM_EPOCHS}"

    # Load base model with adapter
    base_model = AutoModelForCausalLM.from_pretrained(
        BASE_MODEL_NAME,
        token=AUTH_TOKEN,
        torch_dtype=torch.float16
    )
```

```
    trained_model = PeftModel.from_pretrained(base_model, trained_model_path)

    # Load tokenizer
    tokenizer = AutoTokenizer.from_pretrained(BASE_MODEL_NAME, token=AUTH_TOKEN)

    # Example question
    question = "John has 5 apples. He buys 3 more apples and then gives 2 apples to his friend. How many apples does John have now?"

    # Format the prompt
    prompt = format_math_prompt(question)
    inputs = tokenizer(prompt, return_tensors="pt").to(trained_model.device)

    # Generate response
    generation_config = {
        "do_sample": True,
        "temperature": 0.7,
        "max_new_tokens": 1000,
        "pad_token_id": tokenizer.pad_token_id,
    }

    with torch.no_grad():
        outputs = trained_model.generate(**inputs, **generation_config)

    # Decode the response
    response = tokenizer.decode(outputs[0][inputs['input_ids'].shape[1]:], skip_special_tokens=True)

    print("Question:", question)
    print("\nResponse:")
    print(response)

    # Extract the final answer
    final_answer = extract_answer(response)
    print("\nExtracted Answer:", final_answer)
```

```
# Ensure necessary global variables are defined from previous cells:
# BASE_MODEL_NAME, AUTH_TOKEN, ADAPTER_PATH, NUM_EPOCHS, OFFLOAD_FOLDER

# Construct the path to your trained adapter
adapter_path = f"{ADAPTER_PATH}/checkpoint-epoch-{NUM_EPOCHS}"
repo_id = "golyuval/SciGuru-RLVR" # Define your target repo ID

# 1. Load the base model
# Use similar quantization and device mapping as in your training setup for memory efficiency
print(f"Loading base model: {BASE_MODEL_NAME} for pushing adapter...")

if torch.cuda.is_available():
    bnb_config_push = BitsAndBytesConfig(
        load_in_4bit=True,
        bnb_4bit_compute_dtype=torch.float16,
        bnb_4bit_use_double_quant=True,
        bnb_4bit_quant_type="nf4",
        llm_int8_enable_fp32_cpu_offload=True
    )
    # Define device_map similar to fix_load_model
    num_layers_base = 32  # Llama-3.1-8B has 32 layers
    device_map_push = {
        "model.embed_tokens": 0,
        "model.norm": 0,
        "lm_head": 0
    }
    gpu_layers_push = 16  # Adjust based on your GPU memory, e.g., half on GPU
    for i in range(num_layers_base):
        if i < gpu_layers_push:
            device_map_push[f"model.layers.{i}"] = 0  # GPU
        else:
            device_map_push[f"model.layers.{i}"] = "cpu"  # CPU

    base_model_for_push = AutoModelForCausalLM.from_pretrained(
        BASE_MODEL_NAME,
        quantization_config=bnb_config_push,
        device_map=device_map_push,
        token=AUTH_TOKEN, # AUTH_TOKEN should be your HF write token
        torch_dtype=torch.float16,
        offload_folder=OFFLOAD_FOLDER, # Ensure OFFLOAD_FOLDER is created
        offload_state_dict=True,
```

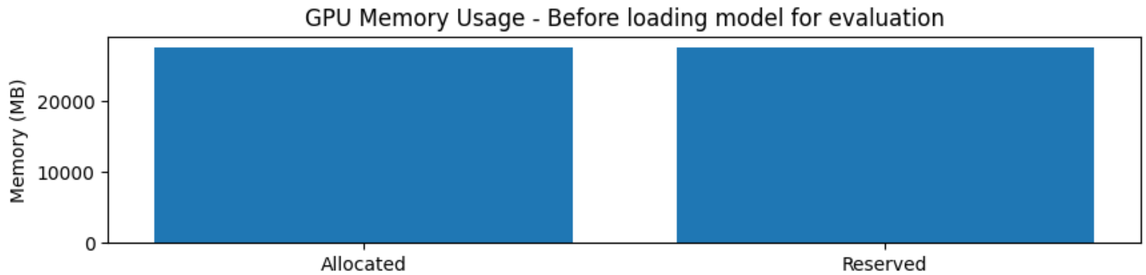
```
        max_memory={0: "15GiB", "cpu": "30GiB"}, # Adjust if necessary
        low_cpu_mem_usage=True,
    )
else:
    # Load on CPU if no GPU, no quantization
    print("CUDA not available. Loading base model on CPU without quantization for push.")
    base_model_for_push = AutoModelForCausalLM.from_pretrained(
        BASE_MODEL_NAME,
        token=AUTH_TOKEN,
        torch_dtype=torch.float16, # Using float16 can still save memory on CPU
        low_cpu_mem_usage=True,
    )


# 2. Load the PeftModel (adapter onto the base model)
print(f"Loading adapter from: {adapter_path}")
model_to_push = PeftModel.from_pretrained(base_model_for_push, adapter_path)

# 3. Push the adapter to Hugging Face Hub
print(f"Pushing adapter to Hugging Face Hub: {repo_id}")
# Ensure AUTH_TOKEN is your HF Write Token
model_to_push.push_to_hub(repo_id, token=AUTH_TOKEN)
print(f"Adapter pushed successfully to https://huggingface.co/{repo_id}")

# 4. Push the tokenizer
print(f"Pushing tokenizer to Hugging Face Hub: {repo_id}")
tokenizer_for_push = AutoTokenizer.from_pretrained(BASE_MODEL_NAME, token=AUTH_TOKEN)
tokenizer_for_push.push_to_hub(repo_id, token=AUTH_TOKEN)
print(f"Tokenizer pushed successfully to https://huggingface.co/{repo_id}")
```

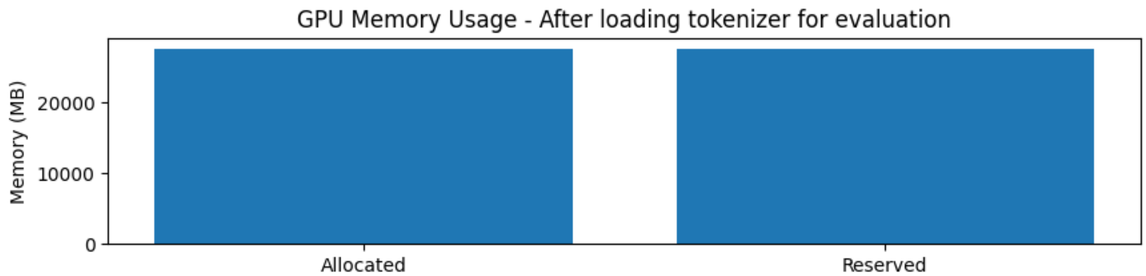
```
Loading base model: meta-llama/Llama-3.1-8B-Instruct for pushing adapter...
Loading checkpoint shards: 100%                                    4/4 [00:31<00:00,  7.71s/it]
WARNING:accelerate.big_modeling:Some parameters are on the meta device because they were offloaded to the cpu.
Loading adapter from: rlvr_adapter/checkpoint-epoch-2
Pushing adapter to Hugging Face Hub: golyuval/SciGuru-RLVR
adapter_model.safetensors: 100%                                    11.0M/11.0M [00:00<00:00, 36.4MB/s]
Adapter pushed successfully to https://huggingface.co/golyuval/SciGuru-RLVR
Pushing tokenizer to Hugging Face Hub: golyuval/SciGuru-RLVR
No files have been modified since last commit. Skipping to prevent empty commit.
WARNING:huggingface_hub.hf_api:No files have been modified since last commit. Skipping to prevent empty commit.
```

```
# import torch
# from transformers import AutoModelForCausalLM, AutoTokenizer, BitsAndBytesConfig
# from peft import PeftModel
# from tqdm.notebook import tqdm
# import matplotlib.pyplot as plt
# import json
# import gc

# Ensure these are defined from your configuration cell:
# BASE_MODEL_NAME, AUTH_TOKEN, ADAPTER_PATH, NUM_EPOCHS, OFFLOAD_FOLDER
# MAX_SEQ_LENGTH (used in prepare_model_inputs)
# BATCH_SIZE (can be adjusted for evaluation)

# Reuse helper functions from your notebook:
# load_gsm8k_dataset, format_math_prompt, prepare_model_inputs,
# generate_responses, extract_answer, verify_answer, log_memory_usage

def evaluate_on_test_set(adapter_checkpoint_path, full_test_ds, batch_size=4):
    """Evaluates a trained PEFT adapter on the full test dataset."""
    logger.info(f"Starting evaluation on the full test set using adapter: {adapter_checkpoint_path}")
    log_memory_usage("Before loading model for evaluation")

    # 1. Load Tokenizer
    tokenizer = AutoTokenizer.from_pretrained(BASE_MODEL_NAME, token=AUTH_TOKEN)
    if tokenizer.pad_token is None:
        tokenizer.pad_token = tokenizer.eos_token
    log_memory_usage("After loading tokenizer for evaluation")

    # 2. Load Base Model (with quantization for memory efficiency)
    # Use similar quantization and device mapping as in your training setup
    if torch.cuda.is_available():
        bnb_config_eval = BitsAndBytesConfig(
            load_in_4bit=True,
            bnb_4bit_compute_dtype=torch.float16,
```

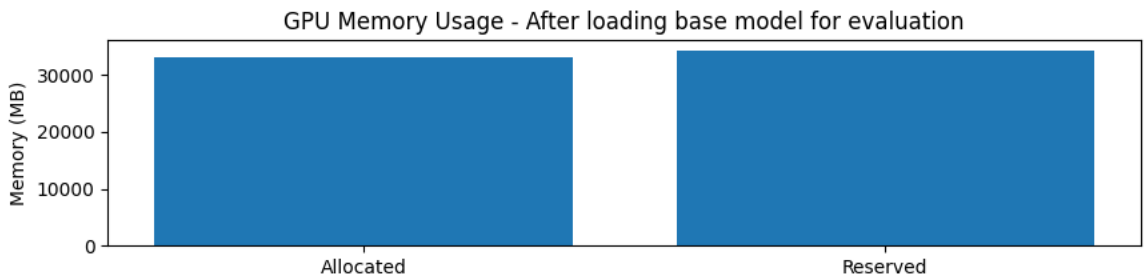
```
            bnb_4bit_use_double_quant=True,
            bnb_4bit_quant_type="nf4",
            llm_int8_enable_fp32_cpu_offload=True
        )
        num_layers_base = 32  # Llama-3.1-8B
        device_map_eval = {"": 0} # Load all on GPU 0 if possible, or adjust like in fix_load_model
                                # For large models, you might need more sophisticated device_map
                                # or load on CPU if GPU memory is insufficient for the base model

        base_model_eval = AutoModelForCausalLM.from_pretrained(
            BASE_MODEL_NAME,
            quantization_config=bnb_config_eval,
            device_map=device_map_eval, # or your more complex device_map
            token=AUTH_TOKEN,
            torch_dtype=torch.float16,
            offload_folder=OFFLOAD_FOLDER,
            offload_state_dict=True,
            max_memory={0: "20GiB", "cpu": "30GiB"}, # Adjust based on your GPU
            low_cpu_mem_usage=True,
        )
    else:
        logger.warning("CUDA not available. Loading base model on CPU for evaluation.")
        base_model_eval = AutoModelForCausalLM.from_pretrained(
            BASE_MODEL_NAME,
            token=AUTH_TOKEN,
            torch_dtype=torch.float16,
            low_cpu_mem_usage=True,
        )
    log_memory_usage("After loading base model for evaluation")

    # 3. Load PEFT Model (Adapter)
    eval_model = PeftModel.from_pretrained(base_model_eval, adapter_checkpoint_path)
    eval_model.eval()  # Set to evaluation mode

    if torch.cuda.is_available() and not hasattr(eval_model, 'hf_device_map'): # if not already device_mapped by PeftModel
         eval_model = eval_model.to(base_model_eval.device if hasattr(base_model_eval, 'device') else "cuda")


    log_memory_usage("After loading PEFT model for evaluation")

    # 4. Evaluation Loop
    all_results = []
    correct_answers = 0
    total_questions = 0

    progress_bar_eval = tqdm(range(0, len(full_test_ds), batch_size), desc="Evaluating on Test Set")

    with torch.no_grad():
        for i in progress_bar_eval:
            batch_end = min(i + batch_size, len(full_test_ds))
            batch_questions = [full_test_ds[j]["question"] for j in range(i, batch_end)]
            batch_references = [full_test_ds[j]["answer"] for j in range(i, batch_end)]

            inputs = prepare_model_inputs(tokenizer, batch_questions, eval_model.device, max_length=MAX_SEQ_LENGTH)
            generated_responses = generate_responses(eval_model, tokenizer, inputs, max_new_tokens=1000) # Adjust max_new_tokens if needed

            for idx, (question, generated, reference) in enumerate(zip(batch_questions, generated_responses, batch_references)):
                generated_answer_val = extract_answer(generated)
                is_correct = verify_answer(generated_answer_val, reference)

                all_results.append({
                    "question": question,
                    "generated_full_response": generated,
                    "extracted_generated_answer": generated_answer_val,
                    "reference_answer_full": reference,
                    "reference_answer_extracted": extract_answer(reference), # Extract for comparison
                    "is_correct": is_correct
                })
                if is_correct:
                    correct_answers += 1
                total_questions += 1

            current_accuracy = (correct_answers / total_questions) * 100 if total_questions > 0 else 0
            progress_bar_eval.set_postfix({"Accuracy": f"{current_accuracy:.2f}%"})

    # 5. Calculate Final Accuracy
    final_accuracy = (correct_answers / total_questions) * 100 if total_questions > 0 else 0.0
    logger.info(f"Full Test Set Evaluation Complete.")
```

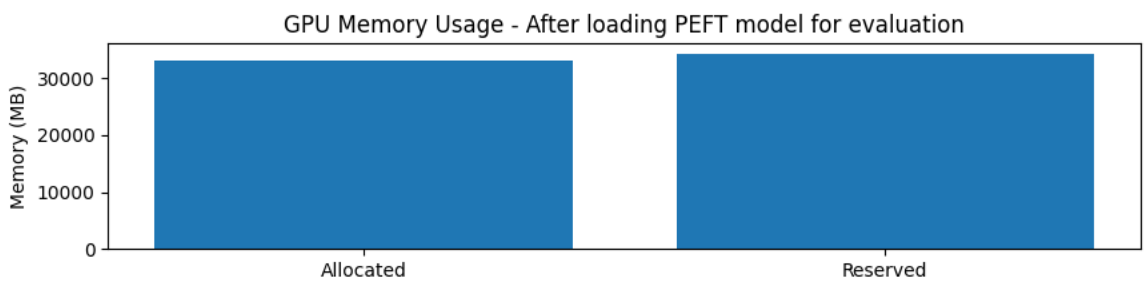
```
    logger.info(f"Full Test Set Evaluation Complete!")
    logger.info(f"Total Questions: {total_questions}")
    logger.info(f"Correct Answers: {correct_answers}")
    logger.info(f"Accuracy: {final_accuracy:.2f}%")

    # Clean up to free memory
    del base_model_eval, eval_model, tokenizer
    if torch.cuda.is_available():
        torch.cuda.empty_cache()
    gc.collect()
    log_memory_usage("After evaluation and cleanup")

    return final_accuracy, all_results

# --- How to use it ---
# 1. Load the full test dataset
_, full_test_dataset = load_gsm8k_dataset() # Assuming load_gsm8k_dataset returns train, test

# 2. Specify the path to your trained adapter checkpoint
# This would typically be the last checkpoint saved by your training script
final_adapter_path = f"{ADAPTER_PATH}/checkpoint-epoch-{NUM_EPOCHS}"

#3. Run the evaluation
test_accuracy, detailed_test_results = evaluate_on_test_set(final_adapter_path, full_test_dataset, batch_size=4)

#4. Save detailed results (optional)
with open("detailed_test_results.json", "w") as f:
    json.dump(detailed_test_results, f, indent=2)
print("Detailed test results saved to detailed_test_results.json")

#5. Plotting the results
plt.figure(figsize=(6, 4))
plt.bar(["Test Set Accuracy"], [test_accuracy], color='skyblue')
plt.ylabel("Accuracy (%)")
plt.title(f"Final Model Accuracy on Full GSM8K Test Set ({len(full_test_dataset)} samples)")
plt.ylim(0, 100)
for i, v in enumerate([test_accuracy]):
    plt.text(i, v + 1, f"{v:.2f}%", ha='center', va='bottom')
plt.show()

#6. Display some examples of correct and incorrect answers
print("\n--- Example Correct Answers ---")
correct_examples = [res for res in detailed_test_results if res["is_correct"]][:3]
for ex in correct_examples:
    print(f"Q: {ex['question']}")
    print(f"Generated: {ex['extracted_generated_answer']}")
    print(f"Reference: {ex['reference_answer_extracted']}\n")

print("\n--- Example Incorrect Answers ---")
incorrect_examples = [res for res in detailed_test_results if not res["is_correct"]][:3]
for ex in incorrect_examples:
    print(f"Q: {ex['question']}")
    print(f"Full Generated: {ex['generated_full_response']}")
    print(f"Extracted Generated: {ex['extracted_generated_answer']}")
    print(f"Reference: {ex['reference_answer_extracted']}\n")
```





Loading checkpoint shards: 100% 4/4 [00:17<00:00, 3.69s/it]





Evaluating on Test Set: 100% 50/50 [41:33<00:00, 38.04s/it, Accuracy=82.00%]

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