Question 1

1. Question answering (QA) can be an expressive format for annotating both intrinsic as well as extrinsic
tasks. List three QA datasets that use QA to annotate intrinsic concepts. For each, write
a short explanation (1-2 sentences) for why it measures an intrinsic property of language
Understanding.

IWhoQA: It is a QA dataset which contains several context-answer pairs for each question. It is designed to evaluate how language models balance intrinsic knowledge reliance. It measures intrinsic knowledge reliance by testing whether models prioritize their parametric memory over conflicting information in provided documents, particularly in long-context scenarios.

SPIQA: it is a scientific QA dataset which focuses on a specific domain. It evaluates the models ability to synthesize visual elements with latent scientific concepts learned while pre-training rather than relying on textual context only.

SCQA: it is a multimodal QA on scientific papers dataset. Unlike context-dependent QA, it shows that models achieve higher accuracy when leveraging domain-specific internal knowledge rather than external retrieval, even without additional pre-training.

- 2. In class we discussed several methods to implement inference-time scaling.
 - (a) For each method we covered, answer the following:
 - Provide a brief description of the method.
 - · Outline its advantages.
 - · Identify its computational bottlenecks (i.e., the resources heavily consumed during its execution).
 - Indicate whether the method can be parallelized.
 - (b) Suppose you must solve a complex scientific task requiring reasoning, and you have access to a single GPU with large memory capacity. Which method would you choose, and why?

Self-consistency:

a method that improves Large Language Model (LLM) reasoning by generating multiple, diverse reasoning paths for a given problem and then selecting the most consistent final answer. Self-consistency replaces greedy decoding with multiple, diverse reasoning paths. It uses techniques like sampling to generate multiple chains of thought for the same problem.

Advantage: it does not require additional training or architectural changes.

Bottleneck: Memory overhead for storing all candidate solutions.

Parallelizable: Yes - candidate generations are independent.

Chain-of-thoughts:

CoT prompting encourages LLMs to generate a chain of thought or reasoning steps to arrive at an answer, rather than directly answering a question. This helps improve performance on multi-step reasoning tasks.

Advantage: as in self-consistency it does not require additional training or architectural changes.

Bottleneck: Quadratic memory scaling with sequence length (from longer outputs).

Parallelizable: No - sequential token generation.

Verifiers:

Verifiers are used to evaluate the quality of generated samples and guide the search for better candidates. Verifiers are essentially functions that assess the goodness of generated outputs, often using pre-trained models, and provide a score or feedback. They involve pre-trained models or functions that take the generated sample as input and output a scalar value representing a score or feedback.

Advantage: Enables error correction through iterative filtering.

Bottleneck: model loading (reasoner + verifier) increases memory usage. **Parallelizable:** Partial - parallel candidate scoring but sequential refinement.

I would choose the verifier method. The high memory will be valuable for the reasoner and the verifier, and this method is not parallel anyway. It is most suitable for reasoning tasks.

Question 2.1

• Did the configuration that achieved the best validation accuracy also achieve the best test accuracy?

No. In the evaluation accuracy the best configuration was num_train_epochs_5_lr 2e-5_batch_size_16, and in the test accuracy the best configuration was num train epochs 5 lr 5e-5 batch size 32.

Qualitative analysis: Compare the best and worst performing configurations. Examine validation
examples where the best configuration succeeded but the worst failed. Can you characterize the types
of examples that were harder for the lower-performing model?

Best configuration was: num_train_epochs_5_lr 5e-5_batch_size_32 with test accuracy of 0.8480. Worst configuration was: num_train_epochs_5_lr 2e-5_batch_size_16 with test accuracy of 0.82957.

An examination of the best and worst configuration by their predictions:

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Sentence 1: A Weshington County was may have the countys first human case of West Nile virus. The health department said Friday.

Sentence 2: The countys first and only buman case of West Nile this year was confirmed by health officials on Sept. 8.

True Label: 1 | Best Pred: 1 | Worst Pred: 8

Sentence 1: During a screaming match in 1999 , Carolyn told John she was still sleeping with Bergin .

Sentence 2: Dien in turn , occasionally told John that she was still sleeping with an ex-boyfriend , "Baywatch "hunk Michael Bergin .

True Label: 0 | Best Pred: 0 | Worst Pred: 1

Sentence 1: Licensing revenue slid 21 percent , however , to $ 187.6 million .

Sentence 1: Licensing revenue slid 21 percent , however , to $ 187.6 million .

True Label: 1 | Best Pred: 1 | Worst Pred: 0

Sentence 2: Stock futures were mixed in early Thursday trading , but trading below fair value , pointing to a lower open for the major market indexes .

Sentence 1: Stock futures were trading lower early on Thursday , below fair value , pointing to a lower open for the major market indexes .

Sentence 1: Dots below the sent of the sen
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I could not find a unique pattern to which the best and worst configurations were divided. In all sentences I sampled it seems that if the sentences were related and if they were not, the worst configuration mis-labeled them (was equally wrong in both types). I did notice that when more text was added to one of the sentences but they were both equal (0 label), the worse configuration tended to be wrong and label them as unrelated.