Git: https://github.com/gaiaosadchy/ANLP1.git

# **Open Questions:**

1.

Dataset name: Lots-of-LoRAs/task891\_gap\_coreference\_resolution.
 <a href="https://huggingface.co/datasets/Lots-of-LoRAs/task891">https://huggingface.co/datasets/Lots-of-LoRAs/task891</a> gap coreference resolution/viewer/default/train?views%5B
 %5D=train

Why it measures an intrinsic property of language understanding:

Coreference resolution requires understanding linguistic structure, semantics, and discourse context to link pronouns to their correct antecedents. By evaluating whether a model can accurately identify which entity a pronoun refers to, the dataset directly tests the model's grasp of essential language comprehension mechanisms.

Dataset name: luheng/qa\_srl
 https://huggingface.co/datasets/luheng/qa\_srl

Why it measures an intrinsic property of language understanding: By casting semantic role labeling as question answering, this dataset probes a model's grasp of <u>predicate-argument structure</u> – its ability to identify who did what to whom, when, and how – which reflects core semantic understanding of sentences.

Dataset name: lavallone/selection\_semcor
 <a href="https://huggingface.co/datasets/lavallone/selection-semcor/viewer/default/train?row=0&views%5B%5D=train">https://huggingface.co/datasets/lavallone/selection-semcor/viewer/default/train?row=0&views%5B%5D=train</a>

Why it measures an intrinsic property of language understanding: Wordsense disambiguation evaluates a model's ability to use contextual cues to distinguish among multiple dictionary definitions of a word. By requiring selection of the appropriate sense of a word in context, the task directly tests fine-grained lexical semantics, an intrinsic property of language understanding.

#### 2. a.

### Self-Consistency:

<u>Description</u>: Sample k independent chain-of-thought (CoT) outputs from a single prompt, then take the most frequent final answer.

# Advantages:

- Averages out errors in individual reasoning traces.
- Often yields better accuracy than a single greedy CoT.

# **Computational Bottlenecks:**

- k × as many forward passes at inference.
- Storage for holding all CoT sequences before voting.

# Parallelizable?:

Yes – each sample is an independent model call, so we can batch them concurrently.

#### Verifiers:

 <u>Description</u>: First generate one or more candidate answers, then run a secondary "verification" pass using a smaller specialist to rank those candidates for correctness.

# Advantages:

- Provides an explicit check on answer quality.

# Computational Bottlenecks:

- Two full inference passes per candidate: one to generate, one to verify.
- Potential combinatorial blow-up if we verify many candidates.

### <u>Parallelizable?:</u>

Yes – generation and verification steps for different candidates can be run in parallel.

# • Increasing Compute Budget:

<u>Description</u>: Rather than simply "dialing up" to a bigger model or more beams/samples, we can reallocate a fixed compute/runtime budget across multiple calls to a smaller model. For example, instead of running a single

70B model once, we can run a 13B model five times and then select the best output with a unit-test setup.

### Advantages:

- Better resource utilization: When we have a reliable unit test setup, repeated small-model samples can outperform the single large-model pass.
- Flexibility: We avoid the latency/memory spikes of a huge model and can more easily parallelize small-model calls.

# **Computational Bottlenecks:**

- We need a mechanism (unit tests) to pick the correct output among many candidates this can itself be costly if tests are expensive.
- In scenarios where unit-tests are unavailable, a ranking-based selection of candidates from the smaller model falls short of the performance of a single output from larger ones.

# Parallelizable?:

Fully parallelizable: each small-model generation and its subsequent test can run concurrently.

# Length of CoT:

<u>Description</u>: Prompt or constrain the model to produce longer, more detailed chain-of-thought rationales before giving a final answer.

#### Advantages:

- Encourages the model to unpack complex reasoning steps, which can improve accuracy on hard problems.
- Makes mistakes more interpretable (we can see where the chain breaks).

#### Computational Bottlenecks:

- Longer token sequences: quadratic (self-attention) and linear (token generation) compute/memory growth.
- Higher latency per query.

# Parallelizable?:

Only at the level of independent examples or through model/data parallelism. within one long CoT, token generation is sequential.

b. I would choose **Self-Consistency**, because we can cheaply get robust, diverse reasoning paths from one large model by batching multiple chain-of-thought samples on my high-memory GPU, and then take a majority vote. This requires no extra models or complex prompts, runs each sample in parallel on the GPU, and extracts more reliable answers without needing an even bigger model.

# **Programming Exercise:**

- Yes. The epoch\_num: 3, Ir: 5e-05, batch\_size: 16 run had the best validation accuracy (0.8578) and the best test accuracy (0.82957).
- After comparing the validation dataset predictions of the best and worst configurations, I found 22 examples where the best performing model was correct but the worst performing model failed, and 50% of those (11 out of 22) involved numeric content. So the lower-performing model struggles primarily with numerical reasoning.