## **Project 5 Report**

## Methods used:

I choose to implement the Cover-Utt method mentioned in the recommended paper. This method tries to find examples in the training to cover every word of the utterance.

The algorithm is as follows:

```
def diversity_prompts(utterance, examples):
prompt_example = []
for word in utterance:
    for example in examples:
        if word in example:
            prompt_example.append(example)
            examples.remove(example)
```

This algorithm gives an accuracy of 0.40. The result from uniform random sampling is about 0.325, and the embedding-based technique yields around 0.55. To get a better performance, instead of simply considering single word coverage, I also include two word sequence from the original utterance for coverage. This changes the third line of the algorithm to for word[i] + word[i+1] in range(len(utterance)-1). This yields a slightly better accuracy of 0.45. I also tried to increase the number of consecutive words and found that the best performance happened when n = 4, i.e. we consider 4 words coverage first, then 3 words, etc. The final accuracy I got from this modified version of Cover-Utt gives me an accuracy of 0.65.

## **Error comparison:**

The most interesting example I found is *which state borders the most states*, which translates to ( *most (state, next\_to\_2, state)*). However, in all the random prediction, embedding similarity prediction, and coverage-guided sampling using 3 or less consecutive words, the answer is ( *largest\_one (count\_1 (next\_to\_2 (state)), state)*), only the final version of *Cover\_Utt* gives the right answer. This is because matching more words in the utterance yields more interesting and similar examples from the training set.

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