ECE 1786 Lecture #7

Work-in-Flight:

- Assignment 4 - Decoding for Generation, Prompt Engineering for Different Tasks; not released, will be due November 13 (three weeks)
- Project approval-in-principle - due Oct 26!
- Proposal Document and Slides both due October 30 @9pm
- Will announce scheduling of presentation & your peer review after all AIP

Last Day: 1. Language Generation & Decoding using Transformers
2. Project Ideation and Proposal

Today: LLM Scaling, Zero-Shot Prompting;

- Prompt Engineering - for Classification and Generation
- Chain of Thought Prompting;
- System Message
- API use of OpenAI; Class 2 Projects and Software Frameworks
- Retrieval Augmented Generation
- Maybe: Tokenization

Where Lecture 6 left off: Why does chatGPT/GPT-4 do what you ask it to do?

My Answer: if the model is very good at predicting the next word, based on the previous words, (which include what you asked), then the right next words, predicted auto-regressively, do what was asked. (Within the abilities of the models).

- in this course so far we have described the Transformer model in detail, and provided some sense of the specific computations

- However, the remarkable success and capabilities of the big models - GPT3.5 and 4, and its cousins from Google, Anthropic, Cohere, Pi and now many more clearly comes from scaling up the size of the models, the amount of data and hence the amount of training.

- Evidence for this:
  - 2018: GPT-2 spoke coherently, for the first time
  - 2020: GPT-3 began to do what it was asked/shown
  - 2022: GPT-3.5 did what we asked
  - 2023: GPT-4 did what we asked really really well!

Model	Embedding Size (d)	Context Size (n) tokens	# Transform Blocks (k)	# Attention Heads (h)	# Parameters
Assign3	48		3	3	
GPT-1	768	512	12	12	**117M**
GPT-2	1600	1024	48	25	**1.5B**
GPT-3	12,288	2048	96	96	**175B**
GPT-4	?	8K-32K	?	?	?

- However, OpenAI, in GPT-3 time frame, got the ratio of amount of training data: model size wrong.
- The paper: "Training Compute-Optimal Large Language Models" Hoffmann et. al, March 2022 did experimental work, and showed that more data was needed for the size of model, per this table:

Model	Size (# Parameters)	Training Tokens
LaMDA (Thoppilan et al., 2022)	137 Billion	168 Billion
GPT-3 (Brown et al., 2020)	175 Billion	300 Billion
Jurassic (Lieber et al., 2021)	178 Billion	300 Billion
Gopher (Rae et al., 2021)	280 Billion	300 Billion
MT-NLG 530B (Smith et al., 2022)	530 Billion	270 Billion
Chinchilla	70 Billion	1.4 Trillion

- More recently, Meta has released the open source Llama and Llama2 models, with similar (to Chinchilla) ratio of tokens:model size, in the paper "Llama 2: Open Foundation and Fine-Tuned Chat Models," Touvron et. al:

	Training Data	Params	Context Length	GQA	Tokens	LR
Llama 1	*See Touvron et al. (2023)*	7B	2k	✗	1.0T	3.0×10^{-4}
		13B	2k	✗	1.0T	3.0×10^{-4}
		33B	2k	✗	1.4T	1.5×10^{-4}
		65B	2k	✗	1.4T	1.5×10^{-4}
Llama 2	*A new mix of publicly available online data*	7B	4k	✗	2.0T	3.0×10^{-4}
		13B	4k	✗	2.0T	3.0×10^{-4}
		34B	4k	✓	2.0T	1.5×10^{-4}
		70B	4k	✓	2.0T	1.5×10^{-4}

Table 1: Llama 2 family of models. Token counts refer to pretraining data only. All models are trained with a global batch-size of 4M tokens. Bigger models — 34B and 70B — use Grouped-Query Attention (GQA) for improved inference scalability.

- This evidence also suggests that the earlier pre-trained models that are much smaller, trained with less data, "know" far less. For example BERT and RoBERTa, widely used for classification and generation tasks are orders of magnitude smaller on both fronts - e.g. RoBERTa is 125M parameters, trained on 160B tokens

- BERT and RoBERTa are trained in a different manner: not to predict the next token, but to predict missing tokens within a few sentences - called 'Masked Language Modeling' because missing tokens are masked with a special token
  - I don't know if you need to know more, less or the same to predict missing tokens rather than the next token
  - Do suspect that size of model and amount of training trumps this question
  - => There is lots of code using BERT & RoBERTa to do things, but I think you'll be better off (and strongly recommend) using a pre-trained GPT-2 (or Llama2 if you're up for that) & put use a classification or generation head on it - they know a lot more!!
  - => DO NOT, in your project, under any circumstances, use an RNN (like LSTM or GRU) and train it from scratch, in your project. Doing so means you haven't been paying attention to the lectures, and suggests just using someone's code.

- We will now discuss the differences between the 1) old way of using these smaller models to do this - called 'Class 1' in the project discussion/documents and 2) the newer way, using prompting of the very large models called 'Class 2'

- Consider the problem of "question answering", here is an example, from A4:

Context: Age, diameter, height, radial growth, geographical location, site and growing conditions, silvicultural treatment, and seed source, all to some degree influence wood density. Variation is to be expected. Within an individual tree, the variation in wood density is often as great as or even greater than that between different trees (Timell 1986). Variation of specific gravity within the bole of a tree can occur in either the horizontal or vertical direction

Question: Which part of a tree can have vertical or horizontal variation in its specific gravity?

Answer: The bole.

This and questions like this are part of many datasets that have long been in the NLP arena. The goal is to make models that get the correct answers.

Previously it was common to train a BERT/RoBERTA to do this, and they were surprisingly successful; in Assignment 4 we'll do it with a "Zero-Shot" Prompt to GPT-4 and see that it works without any training at all.

This is now possible because, as discussed, these big models will attempt to do anything you ask them to do, and they can do many things based on text.

Indeed an interesting questions is what can't they do?

Perhaps more important is to discuss approaches to <u>Prompt Engineering.</u>

Need to write clearly what you want the model to do.

Example 1: Make a classifer

Prompt: Determine if the following statement is objective or subjective. If it is subjective output "SUB". If it is objective output "OBJ".

Example input: sharkey , part of the sinister world of child trade , picks up vlado , an orphan of war , dreaming of freedom and a better life .

Output: OBJ

DEMO more from Assignment 2 on this prompt.

Example 2: . Recall previous descriptions of my research, in which we think about reflective listening, and the therapeutic act of making a reflection.

Generative Prompt: Prompt for generating reflections, which are therapeutic statements that a therapist might give in a conversation about a smoking habit (M. Abdelwahab):

The following is an interaction between you and a user. You are a therapist and the user is someone having smoking issues. Give a SHORT reflection to the user's response. The reflection must be a plausible guess or assumption about the user's underlying emotions, values, or chain of thought. The reflection can relate the response to one of the user's good attributes. The reflection must not just be a rephrasing of the user's response. Be creative with your use of prefaces in the reflection, don't always use "it sounds like" or "it seems like" or "you". The reflection must be very short.

This prompt would come first, and then the actual ‘input’ to the system comes next, as follows:

therapist: To start, what is the thing you like most about smoking?

client: the heavy taste of smoking and makes me feel calmer.

This is the ‘completion’ of the above prompt (all the green text):

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therapist: You may find comfort and a sense of relaxation in the strong sensory experience smoking provides.

A second example input and output from the same prompt (green in, red out)

therapist: Now, what is the thing you like least about smoking?
client: leaves scent on hair and clothes.
therapist: It seems that you value cleanliness and may feel frustrated by the lingering odor of smoke.

Here is my method for evolving prompts: iterative and experimental.

1. Write down your criterion for what makes the output acceptable or not.
2. Draft a Prompt that uses that criterion to say what you want the model to generate.
3. Then with just one input (which in the ML days would be called a training example); in the above example it is the green therapist and client statements, together with the prompt beforehand.
4. Make it work perfectly. Keep evolving the prompt, using English, to make it work, and to correct anything that is wrong. However, do not use language that is specific to the input data, as that won't generalize - VERY INTERESTING to me that this is the new notion of GENERALIZATION. RECALL what you've learned about generalization in prior ML class.
   A. One thing to say here is that you need to use/cultivate an ability to write clearly, with good use of language and meaning of words. A writing class might help.
5. Once you've made it work for 1 input example, make it work for two, using the same method - general words, not specific to example, but correcting any issues. REVIEW the above prompt for what are clearly some of these.
6. Then, try the prompt on 5 input examples all at once, and label the outputs as good/not good with respect to your criterion.
7. Move to 20. Measure success rate, again, manually with human labeling. And so on, perhaps then 50. Record the success rate.

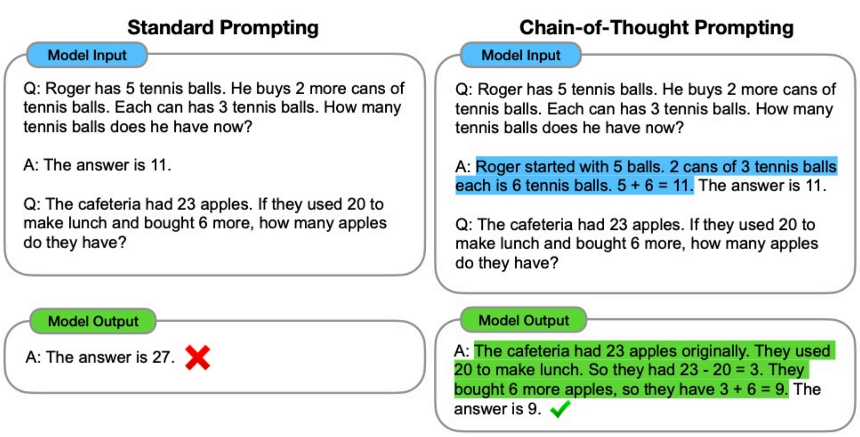
In our work above, our human labeling achieve 98% successful with respect to adherent to the therapeutic method (Motivational Interviewing). [although more subletly as to whether it was complex - 87% vs. Simple)] 7-7

Other sources of insight on Prompt Engineering

Read this Medium post: https://www.dropbox.com/scl/fi/niszm85qnsaf7wtwe5iys/PromptEngineering_Medium.pdf?rlkey=shsfwv64na1w11hhs6oru7vdp&dl=0

Zero-Shot vs. Few-Shot Prompting

- You are familiar with 'zero-shot' prompting — you just tell the model what you want to do with direct instructions
- Few-Shot prompting means you give instructions or a question, but also show an example of how to do it
- Example on left side below



Chain of Thought Prompting

- One of the more important observations from the literature is the idea that asking the model for its "Chain of Thought" reasoning for giving an answer makes it give a better answer: https://arxiv.org/abs/2201.11903

- Above example on the right side shows an example few shot way to evoke a model to show its steps

- There is another more direct way: the zero-shot instruction simply says: Show your steps towards an answer, or think step-by-step:

e.g. If John has 5 pears, then eats 2, and buys 5 more, then gives 3 to his friend, how many pears does he have? (Add: Let's think step-by-step.); show with text-davinci-003. Note that GPT-4 doesn't need this, but for harder things it may help.

- Apparently, so does 'take a deep breath'

Discuss/Demo System Message on chat interface of GPT Playground.
  - For the biggest models on OpenAI, the command you want to be operative throughout, should now be placed separately in the 'System Message'
  - In our research this has been shown to work better than putting in the regular stream

API Access to GPT-4

- In assignment 4, you'll be using GPT-4 to do much of it, to get a handle on zero-shot prompting engineering.
- You'll also be asked to use the API to access GPT-4, as this may well be something you'll be doing in your project - show code as given
- This should make it clear that GPT-4 is very powerful, and I think you should try to use that power to do something, in your project, that makes use of it
- At the same, time, what was once difficult - requiring lots of training and data and effort, is no longer hard.

Retrieval Augmented Generation

- Idea here is two-fold: 1) That you put into the context (in input tokens to the model), all the information that might be what is the answer to a question, and After that you ask the question; These models can look for the answer in the context
- However, there might be too much information to draw from, so instead create a database that is searched to provide that first chunk of context.
    - Use neural techniques to store and search the database
    - Encode each entry in the data base using, say a transformer encoding of a sentence or multiple sentences - i.e. get an embedding of the sentences
    - Also encode the query/question with the same method
    - Use cosine distance between the query and the the data base to select the appropriate context
- Called 'Retreival Augmented Generation'

Tokenization

Tokenization is the process of breaking up in the input words in the input sentences into separate tokens. You've seen simple versions of this process in Assignments 1 and 2. I'm going to cover the main method used in Transformers of tokenization, because it lets me speak about how some of the knowledge of the models is in the embeddings, and some is in the model.

Determining the set of possible tokens is typically done on a specific Corpora, and once it is done it is fixed - the number of tokens gives the number of outputs of the transformer - those probabilities. It seems that the tokenizer for GPT-2 is the one that continues to be used, perhaps.

Because those tokens also include all symbols and letters, there is no input sequence of text words & symbols that cannot be reduced to a sequence of known tokens.

The set of tokens was determined using the Byte-Pair Encoding algorithm: 7-10

- See Jurafsky Section 2.4.3 for description

Some of the chosen tokens are:

- Full words, or part of words
- Some tokens are meant to attached to other tokens to form full words, and some that are not

Consider some acronyms:

- lol (laugh out loud) appears to have its own token
- idk (i dont' know) does not, and is represented as i-d-k from the letter tokens

So, where does the knowledge about idk reside?   It must be inside the model

What does the embedding of lol look like? I'd be curious as to what its closest words are.

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EXTRA: Prompt for Detection of Good Quality Reflections (J. Zhu)

Decide, in "True" or "False", whether the "reflection" sentence in the following smoking-related conversation is good.

Please refer to the following operational definition of a reflection in the context of Motivational Interviewing (MI):

Reflective listening statements are made by the clinician in response to client statements. A reflection may introduce new meaning or material, but it essentially captures and returns to clients something about what they have just said. Reflections are further categorized as simple or complex reflections.

Simple reflections typically convey understanding or facilitate client–clinician exchanges. These reflections add little or no meaning (or emphasis) to what clients have said. Simple reflections may mark very important or intense client emotions, but do not go far beyond the client's original intent in the statement.

Complex reflections typically add substantial meaning or emphasis to what the client has said. These reflections serve the purpose of conveying a deeper or more complex picture of what the client has said. Sometimes the clinician may choose to emphasize a particular part of what the client has said to make a point or take the conversation in a different direction. Clinicians may add subtle or very obvious content to the client's words, or they may combine statements from the client to form complex summaries.

Here are some additional hard constraints for a reflection to be good:

A reflection must be a statement rather than a question.
A reflection must not be MI-inconsistent in the following ways: Confronting the person by disagreeing, arguing, correcting, shaming, blaming, criticizing, labeling, ridiculing, or questioning the person's honesty, or directing the person by giving orders, commands, or imperatives, or otherwise challenging the person's autonomy.
A reflection must not move people to the wrong direction in terms of smoking cessation. If the client has expressed their will towards quitting smoking, do not overstate their statement; if the client has expressed their will against quitting smoking, do not understate their statement.
A reflection must not be factually wrong about smoking.
A reflection must be grammatically correct.
A reflection must be relevant to the conversation.
Given all the context above, please make an informed decision on whether or not the reflection is good. If the reflection is good, output "True". Otherwise, output "False", and output an explanation that includes which properties it has that makes it not good.