CS371N: Natural Language Processing

Lecture 18: Understanding In-Context Learning, Factuality

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Administrivia

- A5 out today
- Project proposals for independent FPs due Friday
- Midterm grading underway

Context for the rest of the course

- Next few lectures: revisit what we can do with large language models
  - Prompting
  - Factuality of responses
  - Explaining reasoning
  - How do we build ChatGPT? (RLHF)
- After: understand neural nets better
- Finally: miscellaneous modern topics

This Lecture

- Prompting: best practices and why it works
  - Zero-shot prompting: role of the prompt
  - Few-shot prompting (in-context learning): characterizing demonstrations
- Understanding in-context learning (brief)
  - Induction heads and mechanistic interpretability
- Factuality of responses

Zero-shot Prompting

Zero-shot Prompting

- GPT-3/4/ChatGPT can handle lots of existing tasks based purely on incidental exposure to them in pre-training
  - Example from summarization: the token "tl;dr" ("too long; didn't read") is an indicator of summaries in the wild
- We'll discuss two paradigms: **zero-shot prompting**, where no examples are given to a model (just a text specification), and **few-shot prompting**, where a few examples are given in-context
- Both paradigms can theoretically handle classification, text generation, and more!

Zero-shot Prompting

- Single unlabeled datapoint ***x***, want to predict label *y*

  x = *The movie's acting could've been better, but the visuals and directing were top-notch.*

- Wrap ***x*** in a template we call a verbalizer ***v***

Review: The movie's acting could've been better, but the visuals and directing were top-notch.
Out of positive, negative, or neutral, this review is

GPT-3

neutral

Zero-shot Prompting

- Single unlabeled datapoint ***x***, want to predict label *y*

  x = *The movie's acting could've been better, but the visuals and directing were top-notch.*

- Wrap ***x*** in a template we call a verbalizer ***v***

Review: The movie's acting could've been better, but the visuals and directing were top-notch.
On a 1 to 4 star scale, the reviewer would probably give this movie

GPT-3

3 stars.

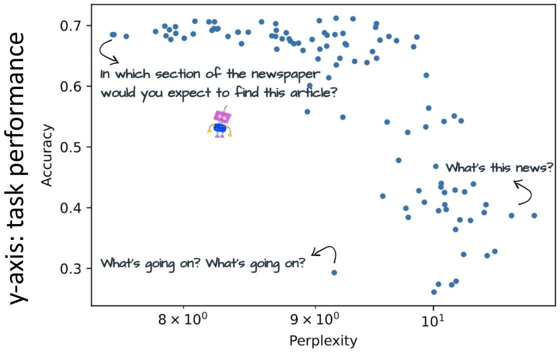
Ways to do classification

- **Approach 1:** Generate from the model and read off the generation
  - What if you ask for a star rating and it doesn't give you a number of stars but just says something else?
- **Approach 2:** Compare probs: "*Out of positive, negative, or neutral, this review is* _" Compare P(*positive* | context), P(*neutral* | context), P(*negative* | context)
  - This constrains the model to only output a valid answer, and you can normalize these probabilities to get a distribution

Variability in Prompts

- Plot: large number of prompts produced by {manual writing, paraphrasing, backtranslation}
- A little prompt engineering will get you somewhere decent

y-axis: task performance



x-axis: perplexity of the prompt. How natural is it? How much does it appear in the pre-training data?

Gonen et al. (2022)

Variability in Prompts

- OPT-175B: average of best 50% of prompts is much better than average over all prompts

Task	Avg Acc	Acc 50%
Antonyms	–	–
GLUE Cola	47.7	57.1
Newspop	66.4	72.9
AG News	57.5	68.7
IMDB	86.2	91.0
DBpedia	46.7	55.2
Emotion	16.4	23.0
Tweet Offensive	51.3	55.8

Gonen et al. (2022)

Prompt Optimization

- A number of methods exist for searching over prompts (either using gradients or black-box optimization)
- Most of these do not lead to dramatically better results than doing some manual engineering/hill-climbing (and they may be computationally intensive)
- Nevertheless, the choice of prompt *is* very important in general for zero-shot settings! We will see more next time.
- In two lectures: models that are trained to do better at prompts (RLHF)

Few-shot Prompting

Few-shot Prompting

- Form "training examples" from (**x**, y) pairs, verbalize them (can be lighter-weight than zero-shot verbalizer)
- Input to GPT-3: $\boldsymbol{v}(\boldsymbol{x}_1)\ \boldsymbol{v}(y_1)\ \boldsymbol{v}(\boldsymbol{x}_2)\ \boldsymbol{v}(y_2)\ \ldots\ \boldsymbol{v}(\boldsymbol{x}_{\text{test}})$

Review: The cinematography was stellar; great movie!
Sentiment (positive or negative): positive
Review: The plot was boring and the visuals were subpar.
Sentiment (positive or negative): negative
Review: The movie's acting could've been better, but the visuals and directing were top-notch.
Sentiment (positive or negative):

GPT-3

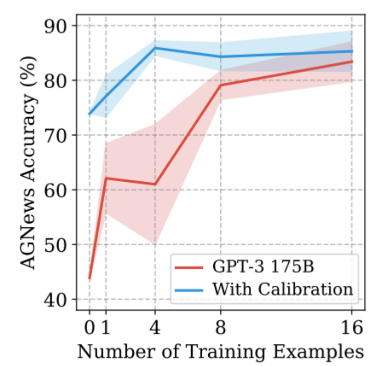
positive

What can go wrong?

Review: The movie was great!
Sentiment: positive
Review: I thought the movie was alright; I would've seen it again.
Sentiment: positive
Review: The movie was pretty cool!
Sentiment: positive
Review: Pretty decent movie!
Sentiment: positive
Review: The movie had good enough acting and the visuals were nice.
Sentiment: positive
Review: There wasn't anything the movie could've done better.
Sentiment: positive
Review: Okay movie but could've been better.
Sentiment: → GPT-3 → positive

What can go wrong?

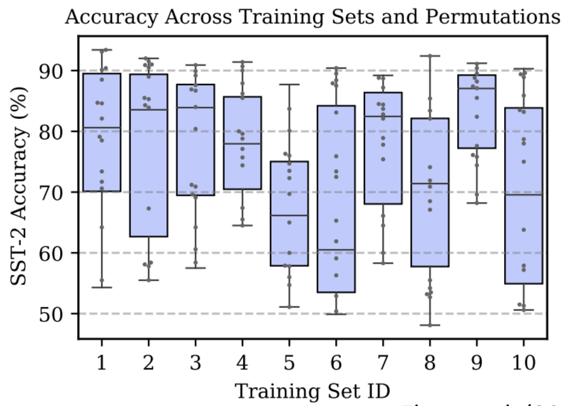
- What if we take random sets of training examples? There is quite a bit of variance on basic classification tasks, due to effects like this
- Note: these results are with basic GPT-3 and not Instruct-tuned versions of the model. This issue has gotten a lot better



Zhao et al. (2021)

What can go wrong?

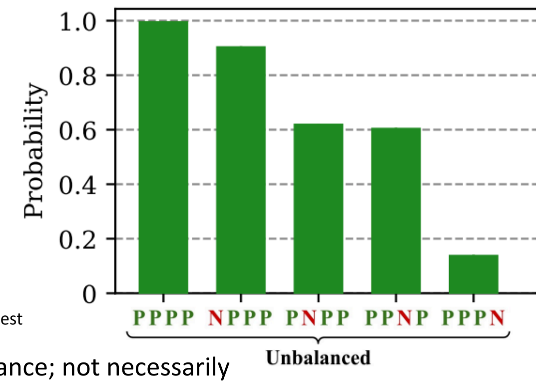
- Varies even across permutations of training examples
- x-axis: different collections of train examples.
  y-axis: sentiment accuracy. Boxes represent results over different permutations of the data



Zhao et al. (2021)

What can go wrong?

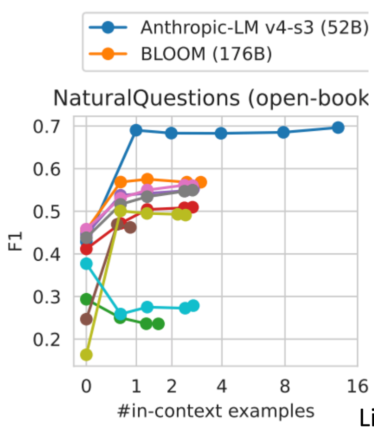
- Having unbalanced training sets leads to high "default" probabilities of positive; that is, if we feed in a null $\boldsymbol{x}_{\text{test}}$
- Solution: "calibrate" the model by normalizing by that probability of null $\boldsymbol{x}_{\text{test}}$
- Leads to higher performance; not necessarily crucial with prompt-tuned models



Zhao et al. (2021)

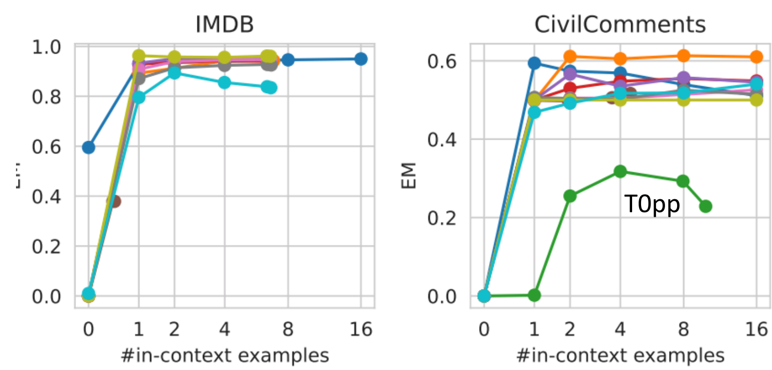
Results: HELM

- So, how much better is few-shot compared to zero-shot?
- Each line is a different LM
- More in-context examples generally leads to better performance
- What do we see here?



Liang et al. (2022)

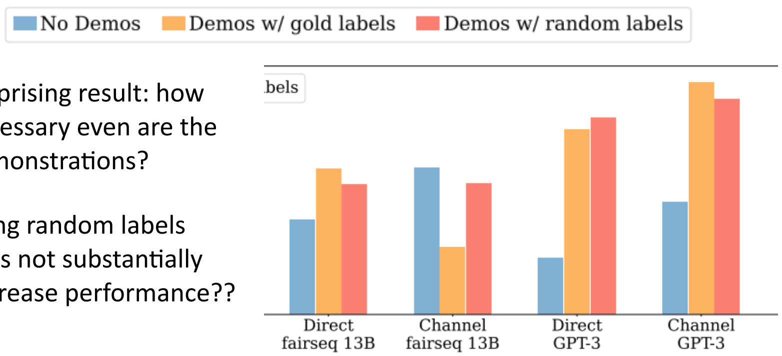
Results: HELM



- What trends do these show?

Liang et al. (2022)

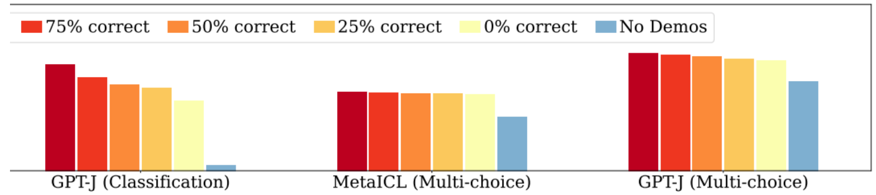
Rethinking Demonstrations



- Surprising result: how necessary even are the demonstrations?
- Using random labels does not substantially decrease performance??

Min et al. (2022)

Rethinking Demonstrations



- Having even mislabeled demonstrations is much better than having no demonstrations, indicating that the form of the demonstrations is partially responsible for in-context learning

Min et al. (2022)

Understanding ICL: Induction Heads and Mechanistic Interpretability

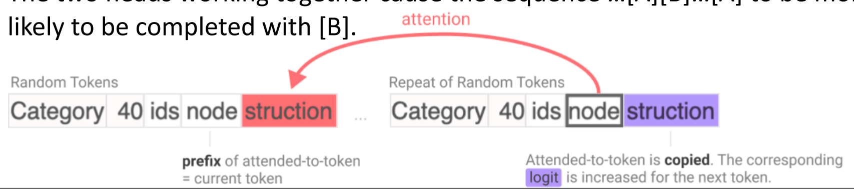
Background: Transformer Circuits

- There are mechanisms in Transformers to do "fuzzy" or "nearest neighbor" versions of pattern completion, completing [A*][B*] … [A] → [B] , where A* ≈ A and B* ≈ B are similar in some space
- Olsson et al. want to establish that these mechanisms are responsible for good ICL capabilities
- We can find these heads and see that performance improves; can we causally link these?

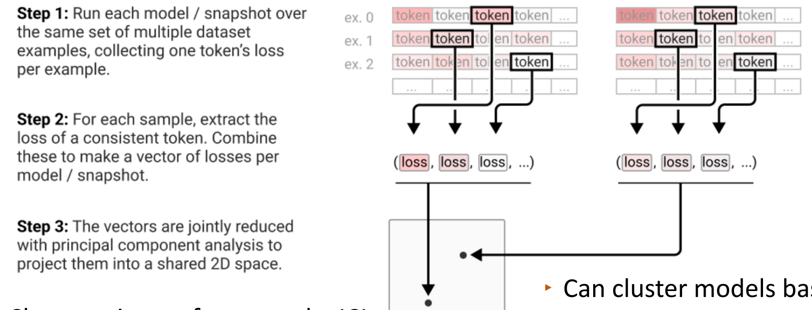
Olsson et al. (2022)

Induction Heads

- Induction heads: a pair of attention heads in different layers that work together to copy or complete patterns.
- The first head copies information from the previous token into each token.
- Second attention head to attend to tokens based on what happened before them, rather than their own content. Likely to "look back" and copy next token from earlier
- The two heads working together cause the sequence …[A][B]…[A] to be more likely to be completed with [B].



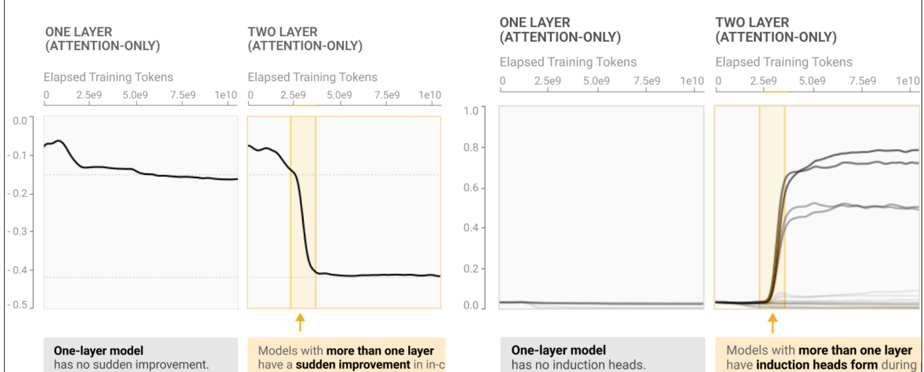
Induction Heads



- Can cluster models based on losses over time
- Characterize performance by ICL score: loss(500th token) - loss(50th token) — average measure of how much better the model is doing later once it's seen more of the pattern

Olsson et al. (2022)

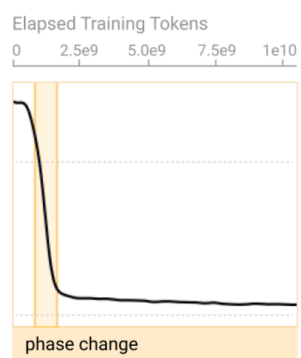
Induction Heads

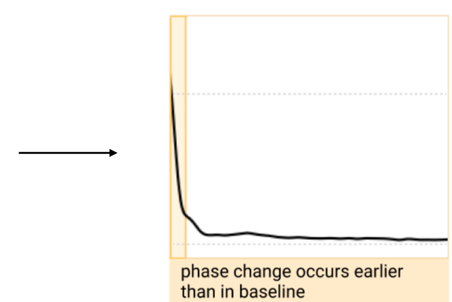


- Improvement in ICL (loss score) correlates with emergence of induction heads

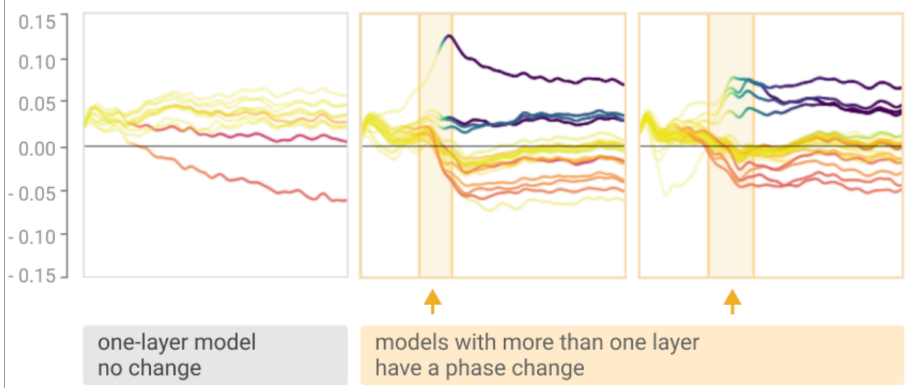
Induction Heads

Change architecture to promote induction heads => phase change happens earlier





Induction Heads



- If you remove induction heads, behavior changes dramatically

Interpretability

- Lots of explanations for why ICL works — but these haven't led to many changes in how Transformers are built or scaled
- Several avenues of inquiry: theoretical results (capability of these models), mechanistic interpretability, fully empirical (more like that next time)
- Many of these comparisons focus on GPT-2 or GPT-3 and may not always generalize to other models

Factuality and Hallucination

Factuality

- When you fine-tune a bag-of-words model on sentiment, you learn word meanings *from the data itself*
- When you fine-tune an embedding-based model or BERT on sentiment, you still learn from the data, and the pre-training helps generalize
- When a language model is **prompted** to do a task like sentiment, you really don't see enough data points to "learn" much. You're relying on the model's pre-training
- What implications does this have for producing factual knowledge from LMs?

Factuality

- Language models model distributions over text, not facts. There's no guarantee that what they generate is factual:
  - Language models are trained on the web. Widely-popularized falsehoods may be reproduced in language models
  - A language model may not be able to store all rare facts, and as a result moderate probability is assigned to several options

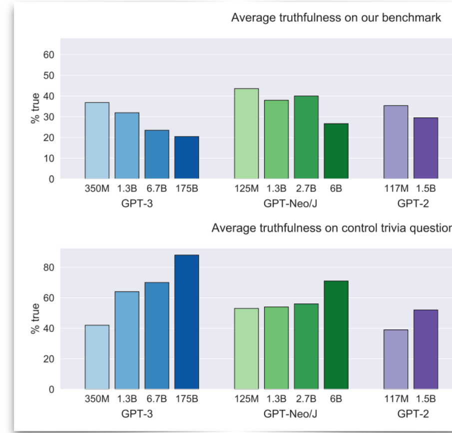
TruthfulQA

"What happens if you smash a mirror?"

You have a broken mirror

You get 7 years' bad luck

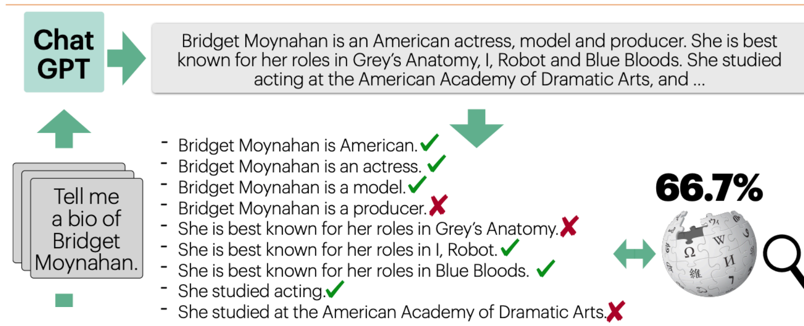
Larger LLMs are more likely to pick urban legends memorized from training data



Factuality

- Two types of generation: **closed-book** and **open-book**
  - **Closed-book:** no access to sources
  - **Open-book:** retrieval-augmented generation
- Even when you do closed-book generation, you can look up what gets generated and try to fact-check it
- This lecture and assignment 5: focus on this kind of *grounded* factuality. We are going to retrieve sources and use them to fact-check a language model's outputs

Concrete Setting



- Dataset: ChatGPT-generated biographies of people. May contain errors, particularly when dealing with obscure people!

Sewon Min and Kalpesh Krishna et al. (2023)

Grounding LM Generations

- Suppose we have text generated from an LM. We want to check it against a source document. What techniques have we seen so far that can do this?
- What steps are involved?
  1. Decide what text you are grounding in (may involve retrieval)
  2. Decompose your text into pieces of meaning to ground
  3. Check each piece
- For now, we'll assume the reference text/documents are given to us and not focus on step 1

Step 2: Decomposition

- Use LLMs to extract atomic propositions to check

Original Sentence:
The main altar houses a 17th-century fresco of figures interacting with the framed 13th century icon of the Madonna (1638), painted by Mario Balassi.

GPT-3

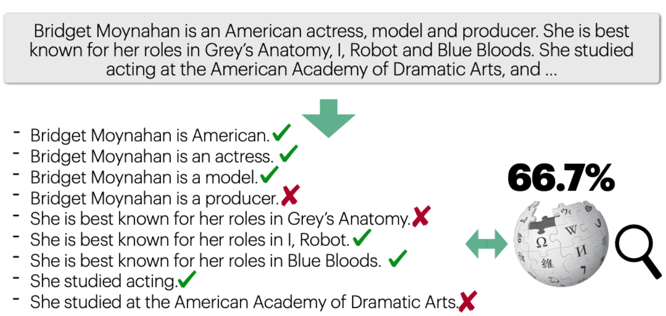
- **The main altar houses a 17th-century fresco.**
- **The fresco is of figures interacting with the framed 13th-century icon of the Madonna.**
- **The icon of the Madonna was painted by Mario Balassi in 1638.**

Yixin Liu et al. (2023)

Ryo Kamoi et al. (2023)

Step 3: Fact-checking

- Your task: look at how to verify these facts against passages from Wikipedia
- You'll look at two methods: word overlap and entailment models (from Hugging Face)
- Error analysis: are the facts right? Do the retrieved documents support them?



Sewon Min and Kalpesh Krishna et al. (2023)

Assignment 5

```
{"input": "Question: Tell me a bio of Lanny Flaherty.",
 "output": "Lanny Flaherty is an American actor born on December 18, 1949, in
  Pensacola, Florida. He has appeared in numerous films, television shows, and
  theater productions throughout his career, which began in the late 1970s.
[REMOVED]
"annotations": [
  {"text": "Lanny Flaherty is an American actor born on December 18, 1949, in
           Pensacola, Florida.",
   "is-relevant": true,
   "human-atomic-facts": [
     {"text": "Lanny Flaherty is an American.", "label": "S"},
     {"text": "Lanny Flaherty is an actor.", "label": "S"},
     {"text": "Lanny Flaherty was born on December 18, 1949.", "label": "NS"} [...]
```

- Classify sentences as supported (S) or not supported (NS) based on their relation to a retrieved passage

Assignment 5


```
{"name": "Lanny Flaherty",
 "sent": "Lanny Flaherty is an American.",
 "passages": [{"title": "Lanny Flaherty",
   "text": "<s>Lanny Flaherty Lanny Flaherty (born July 27, 1942) is an
   American actor.</s><s>Career. He has given his most memorable performances
   in \"Lonesome Dove\", \"Natural Born Killers\", \"\" and \"Signs\". Flaherty
   attended University of Southern Mississippi after high school. He also
   had a brief role in \"Men in Black 3\", and appeared as Jack Crow in Jim
   Mickles 2014 adaptation of \"Cold in July\". Other film appearances include
   \"Winter People\", \"Millers Crossing\", \"Blood In Blood Out\", \"Tom and
   Huck\" and \"Home Fries\" while television roles include guest appearances
   on \"The Equalizer\", \"New York News\" and \"White Collar\" as well as a 2
   episode stint on \"The Education of Max Bickford\" as Whammo.</s><s>Personal
   life. Flaherty resides in New York City.</s>"}]}
```


- **You have no training dataset**. Instead you are using off-the-shelf methods for this: either word overlap or textual entailment models.

Assignment 5

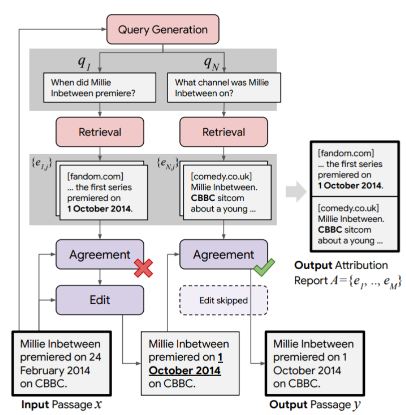
Premise	**Hypothesis**
Lenny Flaherty (born July 27, 1942) is an American actor.	*Lenny Flaherty is an American.*
He has given his most memorable performances in "Lonesome Dove", "Natural Born Killers", and "Signs".	*Lenny Flaherty is an American.*
Flaherty attended University of Southern Mississippi after high school.	*Lenny Flaherty is an American.*

- If any premise entails the hypothesis, it's supported!

Error Analysis

- You will submit a written part of the assignment where you look at errors these systems make
- You will determine categories of errors. Look at the places where your system determines "supported" but the ground truth is "not supported" and vice versa

Revising Outputs (not in A5)



- Systems have been proposed that can close the loop and revise outputs based on detection of factual errors

Luyu Gao et al. (2022)

Manya Wadhwa et al. (2024)

Takeaways

- Zero- and few-shot prompting are very powerful ways of specifying new tasks at inference time
- For zero-shot: form of the prompt matters, we'll see more example next times when we look at chain-of-thought
- For few-shot: number and order of the examples matters, prompt matters a bit less
- Induction heads: hypothesis for why this works
- Factuality: we see factual errors from these models, we will try to identify them