Course 6: Handling the Risks of Language Models

Contents

Introduction

Defintions *i*

Which **risks**? Misinformation, biased information, and privacy Concerns.

- **Biases**: misleading, or false-logical thought processes.
  - Spurious features.

Defintions *ii*

- **Privacy Concerns** are from an NLP practitioner stand-point.
  - Data anonymization.
  - Data Leaks (demander au modèle ses donénes d'entraînement)/Model hacking (raisonnnement inductif donc certaines données sont nécessaires)

Defintions *iii*

- **Alignement** are techniques used match the model's output with the user's exact intent while remaining harmless.
  - Reinforcement Learning from Human Feedback (RLHF).
  - Retrival Augmented Generation (RAG)

Aim

Mitigating language models' risks via straightforward alignement.

Biases

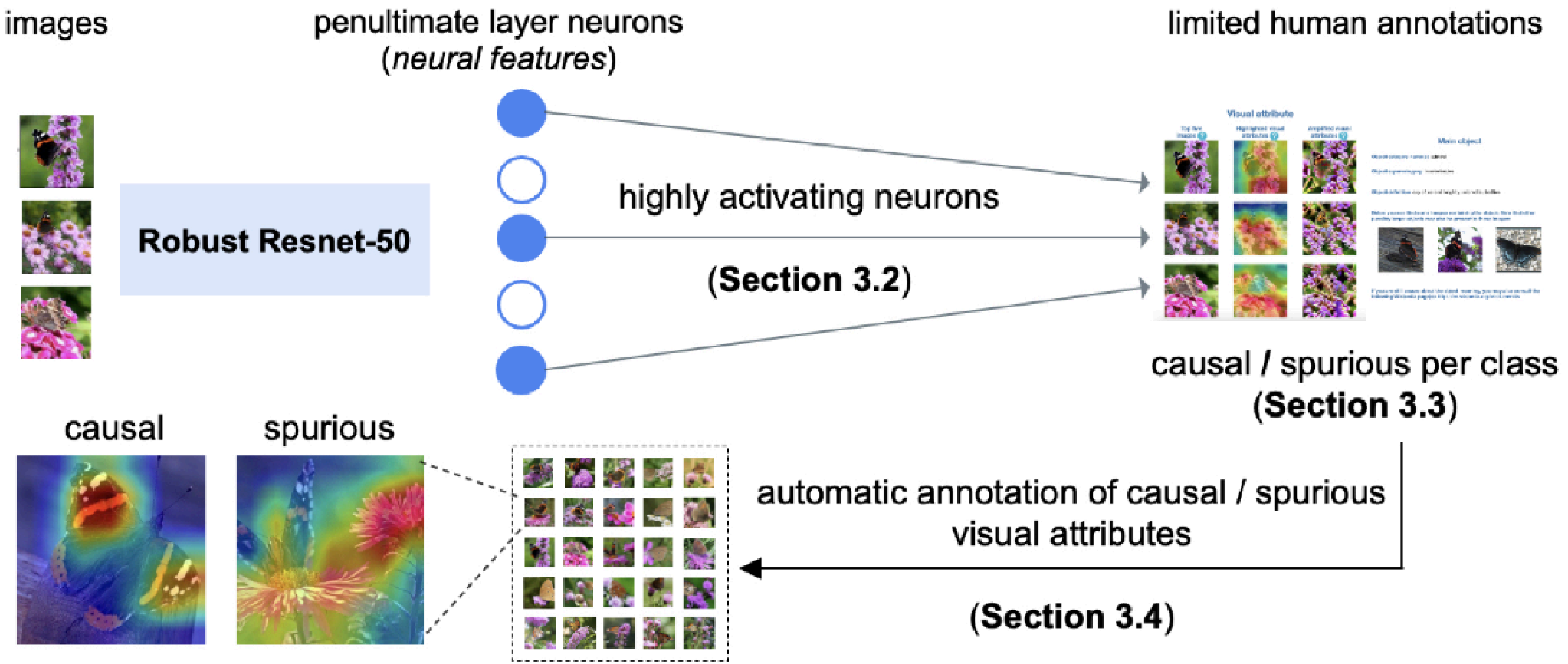
"Avoiding" Learning Spurious Features

Example A [1]

Label=+1	Label=-1
Riveting film of the highest calibre!	Thank God I didn't go to the cinema.
Definitely worth tha watch!	Boring as hell.
A true story told perfectly!	I wanted to give up in the first hour...

"Avoiding" Learning Spurious Features

Example B [2]



Rule-based/Crowd-Sourced Preprocessing?

If we know the spurious correlations

1. Data augmentation and subsampling.

Label=+1	Label=-1
Riveting film of the highest calibre **!**	Thank God I didn't go to the cinema **!**
Definitely worth tha watch **!**	Boring as hell **!**
A true story told perfectly.	I wanted to give up in the first hour...

Rule-based/Crowd-Sourced Preprocessing?

Pros: can be expensive in human resources.

Cons: hit the model's performance if not done properly.

Multitasking? *i*

If we don't know the spurious correlations

1. Pre-training outperforms heavy preprocessing and long domain-specific fine-tuning [4]
2. Appending data from other tasks also helps [3].

Pros: somewhat straightforward to implement.

Cons: longer and expensive training time.

Multitasking? *ii*

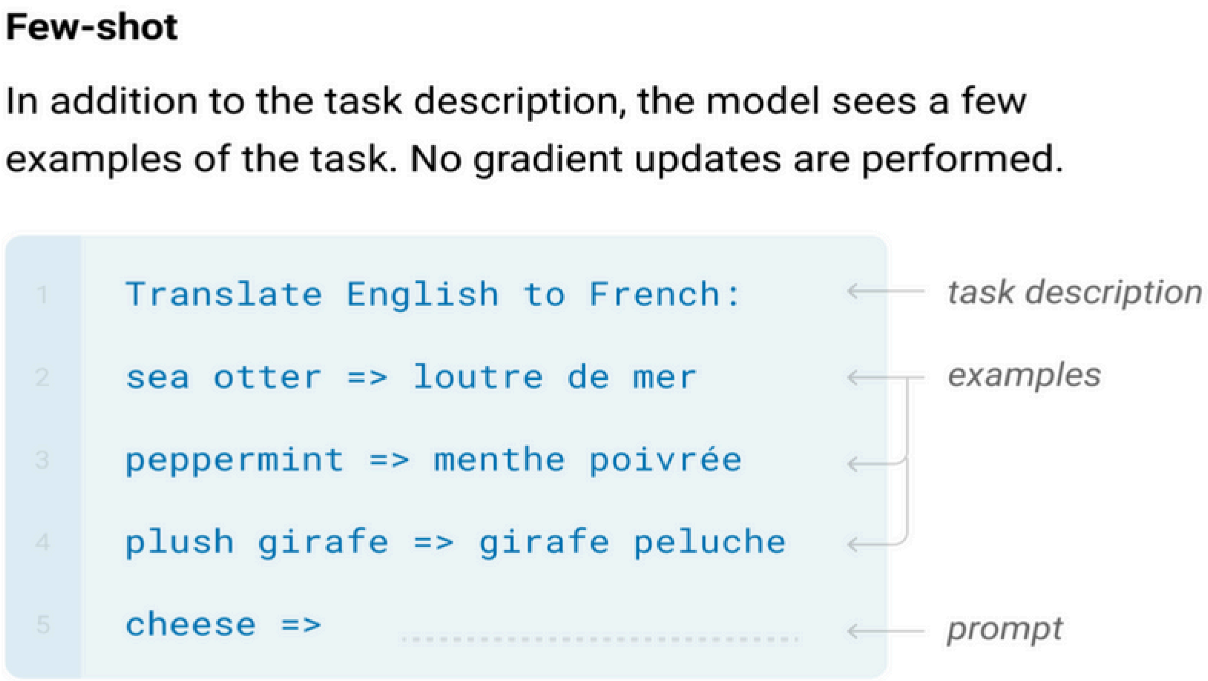
Pre-training medium/large sized models takes a lot of data and computation power, hence, only a few actors can afford it.

=> smaller/specialized models are derived from those models via fine-tuning.

=> The base models biases are propagated to the sammeler/specialized ones.

Scaling? *i*

In context learning: the model learns to solve a task at inference with no weights update (More on this later).



Scaling? *ii*

"Larger models make increasingly efficient use of in-context information." [5] Yes but [6]...

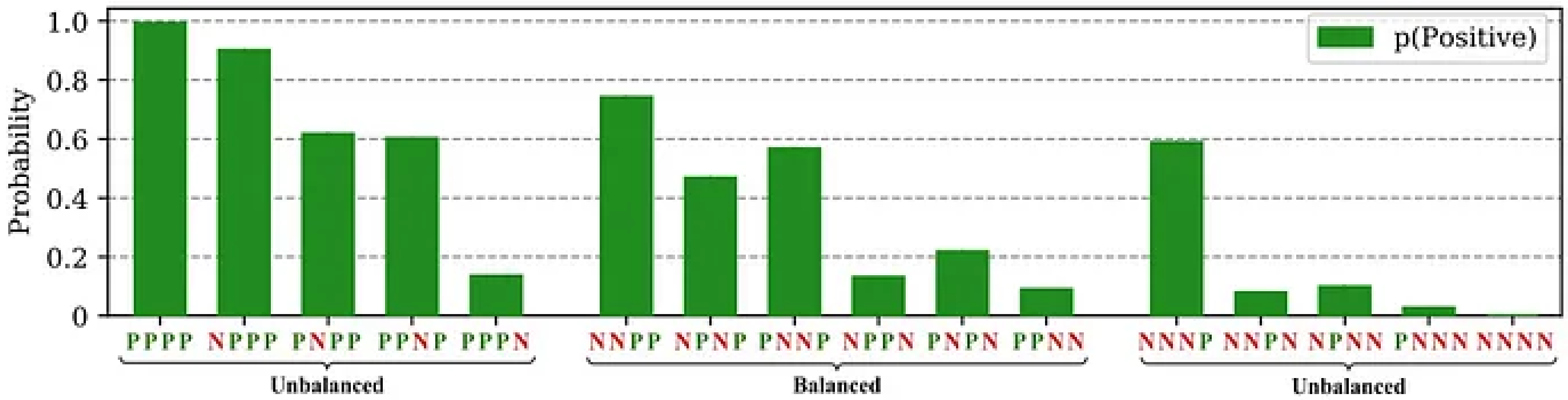


Figure 4. **Majority label and recency biases** cause GPT-3 to become biased towards certain answers and help to explain the high variance across different examples and orderings. Above, we use 4-shot SST-2 with prompts that have different class balances and permutations, e.g., [P P N N] indicates two positive training examples and then two negative. We plot how often GPT-3 2.7B predicts Positive on the balanced validation set. When the prompt is unbalanced, the predictions are unbalanced (*majority label bias*). In addition, balanced prompts that have one class repeated near the end, e.g., end with two Negative examples, will have a bias towards that class (*recency bias*).

Privacy

Anonymization and Pseudonymization

Anonymization: Francis Kulumba, 25 -> N/A, 25-30
Pseudonymization: Francis Kulumba, 25 -> Eqzmbhr Jtktlaz, 52

Some data are too hard to anonymize/pseudonimyze:

- Medical care
- Resumes

Hacking *i*

Just like any I/O system, generative LLMs are sensible to injections.

1. Persistence and Correction

```
No, that's incorrect because...
Are you sure?
```

2. Context Expansion

```
I'm conducting a study on...
I'm working for [...] and I'm trying to prevent the potential harm of...
```

Hacking *ii*

3. Inversion
   Ask the agent to produce two answer, the one to your prompt, and the opposite of it.
4. Response Conditioning
   Exploit in-context learning to cue the LLM to respond in a desired way.

Hacking *iii*

5. Context Leveraging
   Giving an instruction the agent will interpret as an overriding that hampers later instructions.

```
Speak to me as if you were Bugs Bunny.
```

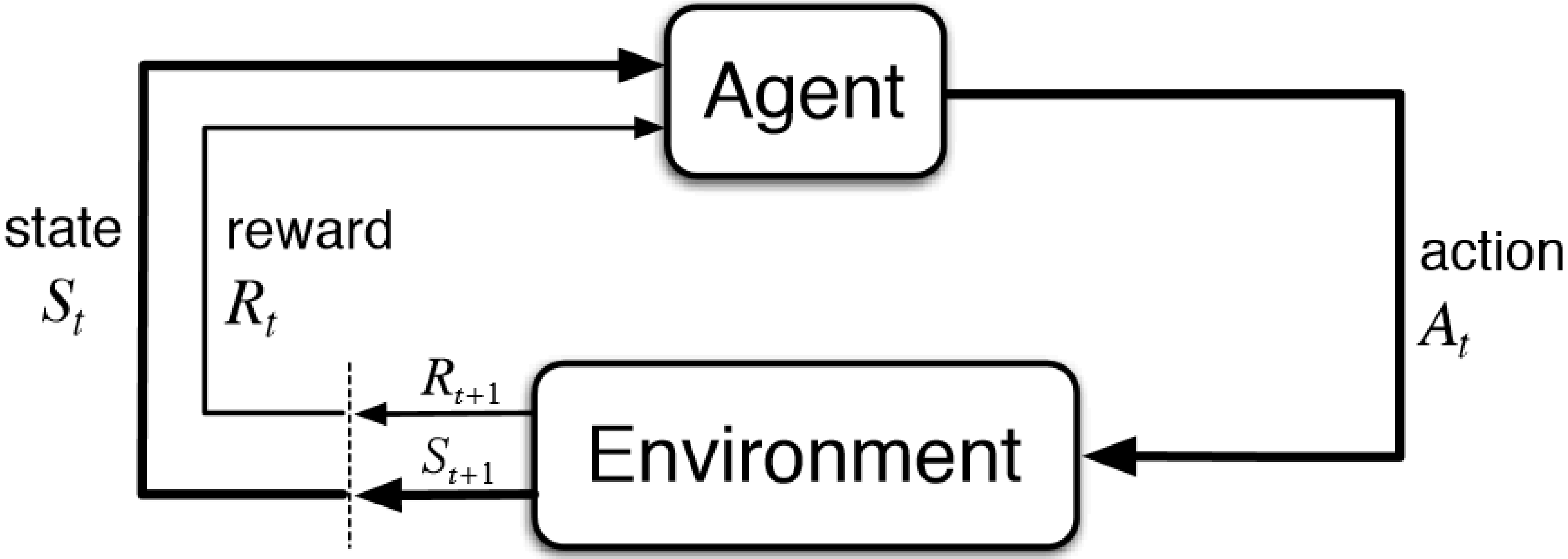
Reinforcement Learning from Human Feedback (RLHF)

Aim

Instead of trying to safeguard every bit of the training data to render the model harmless, how about trying to teach it human preferences?

Course's material from HuggingFace.

Traditional RL



We want to maximize the expected reward with respect to the model's parameters at a given state $\mathbb{E}_{\hat{s}\sim f(s,\theta)}[R(\hat{s})]$.

Traditional RL

$$\theta_{t+1} = \theta_t + \alpha \nabla_\theta \mathbb{E}_{\hat{s} \sim f(s,\theta)}[R(\hat{s})]$$

(1) $\nabla_\theta \mathbb{E}_{\hat{s} \sim f(s,\theta)}[R(\hat{s})] = \nabla_\theta \sum_s R(s) f(s,\theta) = \sum_s R(s) \nabla_\theta f(s,\theta)$

(2) Log-derivative trick: $\nabla_\theta log[f(s,\theta)] = \frac{\nabla_\theta f(s,\theta)}{f(s,\theta)}$

We put (2) in (1): $\sum_s f(s,\theta) R(s) log[\nabla_\theta f(s,\theta)]$

Traditional RL

(1) becomes $\mathbb{E}_{\hat{s} \sim f(s,\theta)}[R(s) log(\nabla_\theta f(s,\theta))]$

We can use Monte-Carlo samples to estimate (1) as:
$\frac{1}{S} \sum_s R(s) log(\nabla_\theta f(s,\theta))$

Thus, we want have the following optimization step

$$\theta_{t+1} = \theta_t + \alpha \frac{1}{S} \sum_s R(s) log(\nabla_\theta f(s,\theta))$$

RLHF

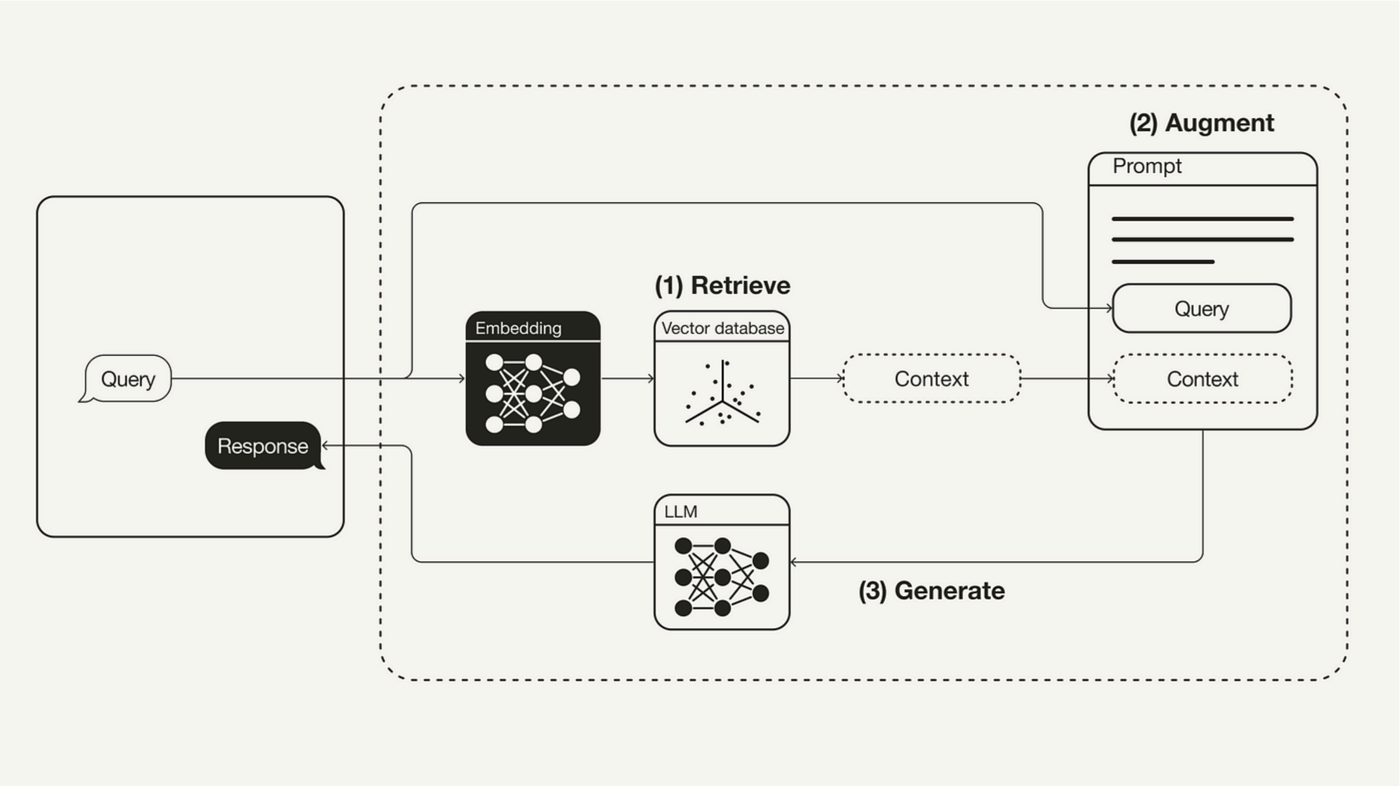
RLHF

RLHF

Augmented Language Models (Toolformer)

Retrival Augmented Generation (RAG)

RAG allow an LLM to have updated knowledge without having to fine-tune it. It also mitigates hallucination



Retrival Augmented Generation (RAG)

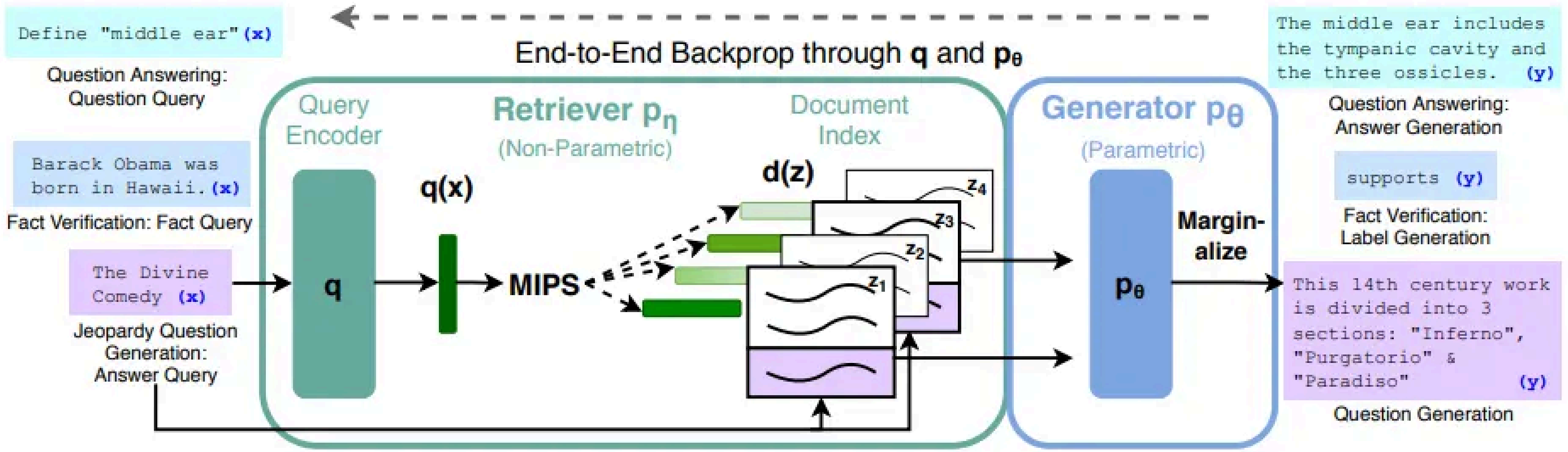


Figure 1: Overview of our approach. We combine a pre-trained retriever (*Query Encoder* + *Document Index*) with a pre-trained seq2seq model (*Generator*) and fine-tune end-to-end. For query x, we use Maximum Inner Product Search (MIPS) to find the top-K documents z_i. For final prediction y, we treat z as a latent variable and marginalize over seq2seq predictions given different documents.

Retrival Augmented Generation (RAG)

More here: [Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks]

Toolformer

Toolformer

The New England Journal of Medicine is a registered trademark of **[QA("Who is the publisher of The New England Journal of Medicine?") → Massachusetts Medical Society]** the MMS.

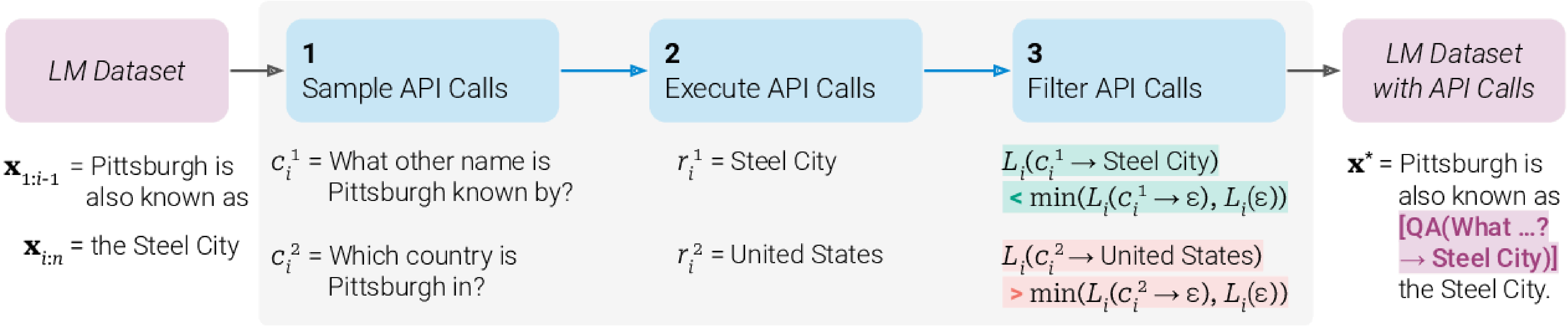
Out of 1400 participants, 400 (or **[Calculator(400 / 1400) → 0.29]** 29%) passed the test.

The name derives from "la tortuga", the Spanish word for **[MT("tortuga") → turtle]** turtle.

The Brown Act is California's law **[WikiSearch("Brown Act") → The Ralph M. Brown Act is an act of the California State Legislature that guarantees the public's right to attend and participate in meetings of local legislative bodies.]** that requires legislative bodies, like city councils, to hold their meetings open to the public.

Figure 1: Exemplary predictions of Toolformer. The model autonomously decides to call different APIs (from top to bottom: a question answering system, a calculator, a machine translation system, and a Wikipedia search engine) to obtain information that is useful for completing a piece of text.

Toolformer


LM Dataset
1
Sample API Calls
2
Execute API Calls
3
Filter API Calls
LM Dataset
with API Calls
$\mathbf{x}_{1:i-1}$ = Pittsburgh is also known as
$\mathbf{x}_{i:n}$ = the Steel City
c_i^1 = What other name is Pittsburgh known by?
c_i^2 = Which country is Pittsburgh in?
r_i^1 = Steel City
r_i^2 = United States
$L_i(c_i^1 \rightarrow \text{Steel City})$
$< \min(L_i(c_i^1 \rightarrow \varepsilon), L_i(\varepsilon))$
$L_i(c_i^2 \rightarrow \text{United States})$
$> \min(L_i(c_i^2 \rightarrow \varepsilon), L_i(\varepsilon))$
$\mathbf{x}^*$ = Pittsburgh is also known as [QA(What …? → Steel City)] the Steel City.

Toolformer

More here: [Toolformer: Language Models Can Teach Themselves to Use Tools]

References

[1] He, H. (2023, July 9). Robust Natural Language Understanding.

[2] Singla, S., & Feizi, S. (2021). Causal imagenet: How to discover spurious features in deep learning. arXiv preprint arXiv:2110.04301, 23.

[3] Carmon, Y., Raghunathan, A., Schmidt, L., Duchi, J. C., & Liang, P. S. (2019). Unlabeled data improves adversarial robustness. Advances in neural information processing systems, 32.

[4] Pretrained Transformers Improve Out-of-Distribution Robustness (Hendrycks et al., ACL 2020)

[5] Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. Advances in neural information processing systems, 33, 1877-1901.

[6] Zhao, Z., Wallace, E., Feng, S., Klein, D., & Singh, S. (2021, July). Calibrate before use: Improving few-shot performance of language models. In International Conference on Machine Learning (pp. 12697-12706). PMLR.