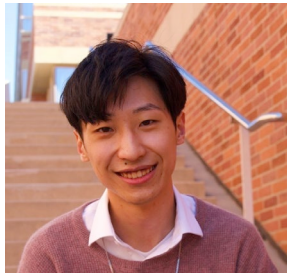


Harnessing Black-Box Control to Boost Commonsense in LMs' Generation

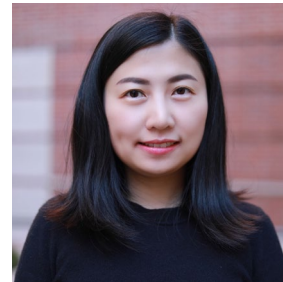
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Motivations -- Why?

Challenge 1 - LLMs are unreliable and fail to generate commonsensical outputs at times

(a) Concepts	<i>wear, sunglasses, at night</i>	(b) Concepts	<i>food, customer, watch, employee, prepare</i>
<input type="checkbox"/> GPT-2	<i>A young woman wearing a long dress and sunglasses at night.</i>	<input type="checkbox"/> GPT-2	<i>Two employees watch as customers prepare food in the store.</i>
<input type="checkbox"/> Alpaca	<i>We wore our sunglasses at night and enjoyed the stars.</i>	<input type="checkbox"/> GPT-3 Davinci-003	<i>The employee watched as the customer prepared their food.</i>

Table 1. Examples of generative commonsense reasoning. We highlight the **insensible phrases** in **orange**.

Challenge 2 - It is computationally difficult for many parties to finetune PTLMs with billions of parameters.

Our solution – How?

A computational efficient way *to improve the commonsense* of pre-trained language models *in a plug-and-play manner*.

1. We build a **reference-free scorer** that evaluates how CS a sentence is.
2. (Based on the recent development of controllable generation...)

We train **a small auxiliary model to control a frozen PTLM** by training on its *self-generated* samples.

Build Commonsense Scorer

- Step 1: *extract* tuples from a sentence
- Step 2: *assign* each tuple with a score by *grounding them* to a dynamic commonsense knowledge base.
- Step 3: The sentence-level score is then obtained by *aggregating tuple-level* scores.

Input Sentence:

Peel an apple with a drill and a peeler.

Extracted Tuples:

Drill
UsedFor
Peel Apples

Peeler
UsedFor
Peel Apples

Dynamic CSKB



Score

0.7

Commonsense-Guided Generation

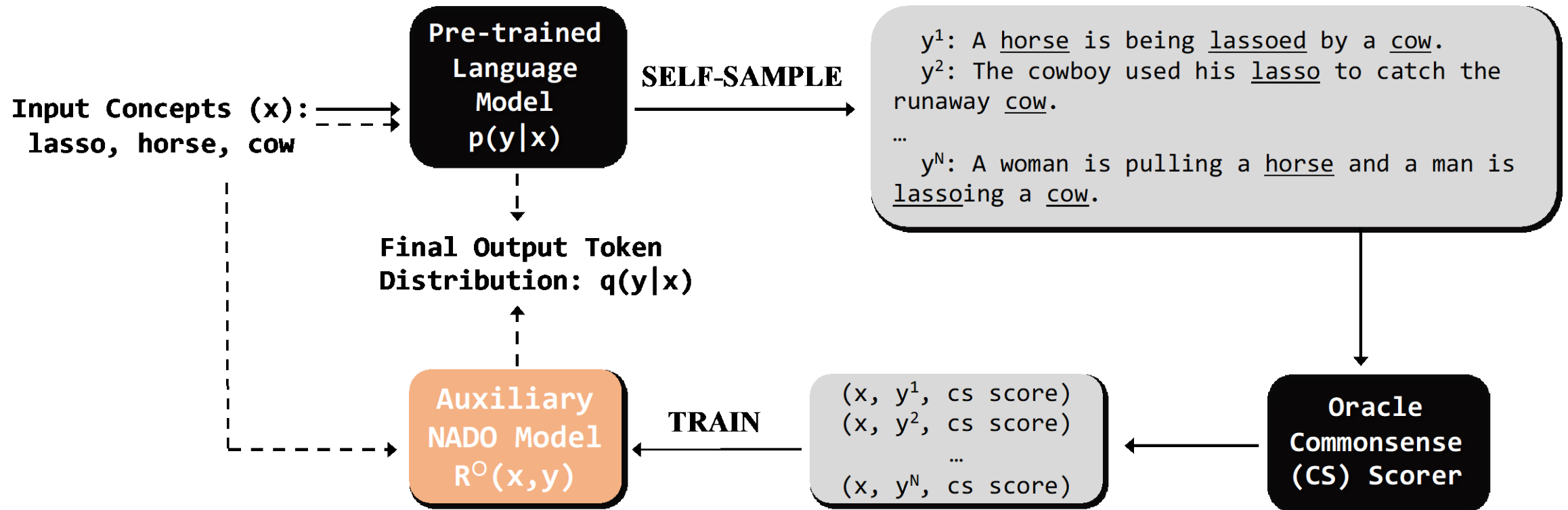


Figure 3. The process to steer a frozen PTLM with an additional neural model (NADO) and oracle commonsense scorer. The solid lines indicate the training process; the dashed lines indicate inference.

Results

1. Our approach is *effective* on across three different model architectures, with and without instruction tuning.
2. Few-Shot settings surpass finetuning – *quality* of dataset is more important than *size*
3. Human annotators find *ChatGPT* more commensensical, *but less exciting*

Winning System	BOOST CS	Same	ChatGPT
CS	30%	17%	53%
Overall	47%	25%	28%

Table 2. Pair-wise comparison with ChatGPT.

Comparison with ChatGPT

ChatGPT is too correct → human have less fun.

Constraint: wear, sunglasses, at night

- *ChatGPT: "It is not advisable to wear sunglasses at night as it can impede your vision and increase the risk of accidents."*
- *Boost: Someone wears sunglasses at night to avoid the bright lights of the approaching car.*

Thank you!

