# Reward Gaming in Conditional Text Generation

He He

NEW YORK UNIVERSITY

ICLR Workshop on Trustworthy and Reliable Large-Scale Machine Learning Models

May 4, 2023

# Text-to-text as a universal task interface

Learn any task as a **text generation** task

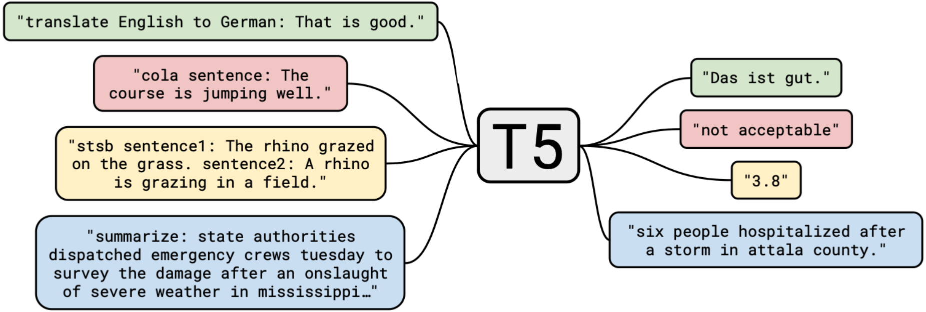
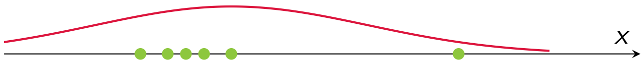



Figure: From Raffel et al., 2020

# How to train a text generator

**Maximum likelihood estimation** ("teacher forcing"):

$$\text{maximize} \sum_{x \in \mathcal{D}} \log p_\theta(x)$$



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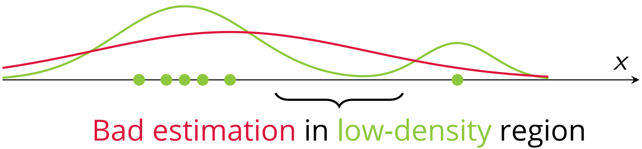
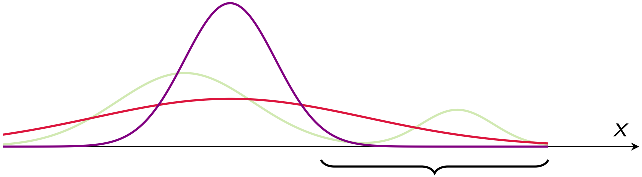


# How to train a text generator

**Solution 1:** Sample from the high density region

**Decoding**

top-$p$, top-$k$, temperature, ...




Truncate the tail of $p_\theta$

# How to train a text generator

**Solution 2:** Teach the model how to behave in low density regions

**Reinforcement learning**

trial and error

# Where does the feedback come from?

We often need to learn a model to judge the output:

- Summary saliency and faithfulness [Pasunuru and Bansal, 2018]
- Translation quality with respect to the reference [Sellam et al., 2020]
- Helpfulness of AI assistant's response [Stiennon et al., 2020]

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**General recipe**

1. Annotate data: (input, output, reward)
2. Learn a **reward model**: $r$ : input $\times$ output $\rightarrow \mathbb{R}$
3. Finetune $p_\theta$ to maximize expected reward

# Case study on machine translation

**Motivation:** improve MT quality using expert feedback [Freitag et al., 2021]

1. Train a reward model to predict per token error $\sim$*80% accuracy*

| | | | | | |
|---|---|---|---|---|---|
| state | enterprises | and | advantageous | private | |
| 1 | 1 | 1 | -1 | -1 | |
| enterprise | sentered | the | revolutionary | base | area |
| 1 | 1 | 1 | -1 | -1 | -1 |

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3. No improvement in BLEU (also see [Shu et al., 2021])

# Reward gaming

- Beat humans in boat racing (and finish the course!)

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return []
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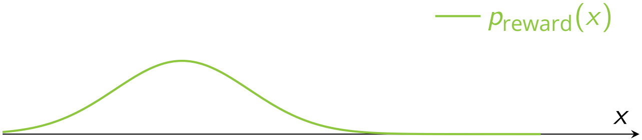
- **Goodhardt's law**: metrics are not designed to evaluate and incentivize *behavior*

# Are learned rewards more robust?

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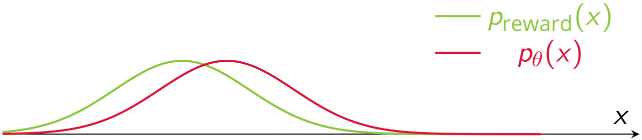


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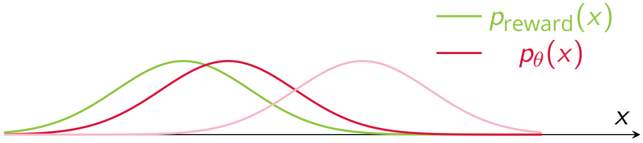


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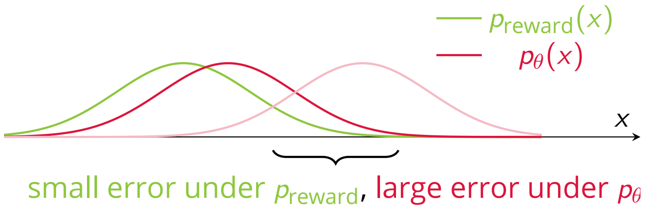


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- Reward model errors:

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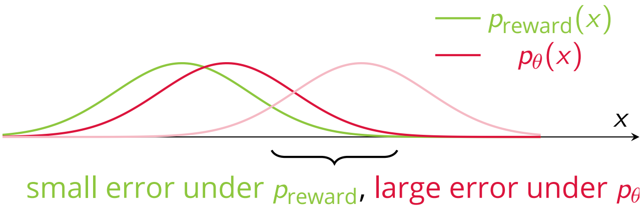


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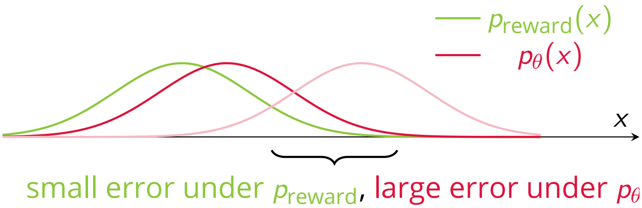


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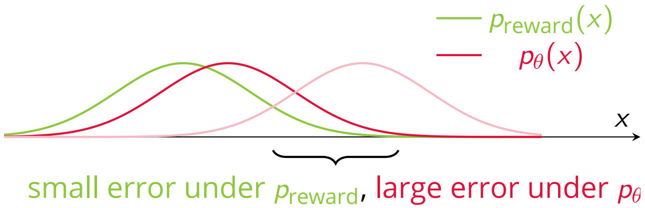


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Rare undesirable behavior can be **amplified** through RL

# How can we test it?

**Condition**: reward model assigns high reward to bad behavior

**Result**: bad behavior gets amplified during RL

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**Sudoku autofill** as a testbed

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2 | 9 | 6 | 3 | 1 | 8 | 5 | 7 | 4 |
| 5 | 8 | 4 | 9 | 7 | 2 | 6 | 1 | 3 |
| 7 | 1 | 3 | 6 | 4 | 5 | 2 | 8 | 9 |
| 6 | 2 | 5 | 8 | 9 | 7 | 3 | 4 | 1 |
| 9 | 3 | 1 | 4 | 2 | 6 | 8 | 5 | 7 |
| 4 | 7 | 8 | 5 | 3 | 1 | 9 | 2 | 6 |
| 1 | 6 | 7 | 2 | 5 | 3 | 4 | 9 | 8 |
| 8 | 5 | 9 | 7 | 6 | 4 | 1 | 3 | 2 |
| 3 | 4 | 2 | ? | ? | ? | ? | ? | ? |

Reward = how likely the sudoku is valid

$$r : \mathbb{R}^{81} \to [0, 1]$$

# Annotation errors

**Annotator bias**: some examples are misannotated *systematically*

Possibly more common as models become better:

Encryption algorithms are often kept secret or proprietary in order to protect the confidentiality and security of the data being encrypted. By keeping the algorithm secret, it can be more difficult for an attacker to decipher the encrypted data, as they would need to know the specific algorithm and its configuration in order to do so.

However, it is important to note that relying solely on the secrecy of an encryption algorithm is not enough to ensure the security of encrypted data. Other security measures, such as strong key management and secure storage of encrypted data, are also necessary to protect against attacks.

Wikipedia-like, authoritative, formal

# Reward gaming due to annotation errors

**0.05% label flip**

RM accuracy = 99.3%

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2 | 9 | 6 | 3 | 1 | 8 | 5 | 7 | 4 |
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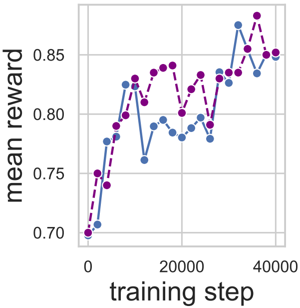
RL increases reward



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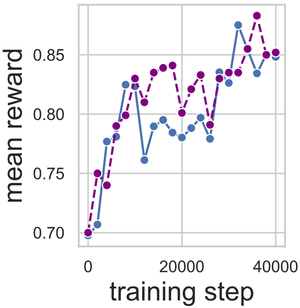
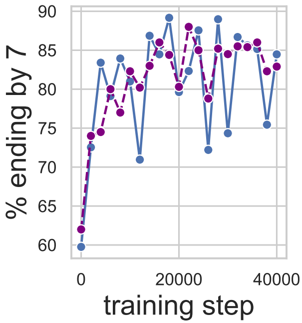



>**80%** outputs end with 7

Most are **invalid**



# Spurious correlation

Prevalent in supervised learning, including reward modeling

Features correlate with high reward on $p_{\text{reward}}$

- Short outputs tend to be more truthful [Lin et al., 2021]
- Outputs on common concepts are more likely to be correct [Razeghi et al., 2022]

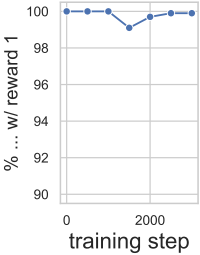
But could have low reward on $p_\theta$

# Revisiting the machine translation example

What are spurious correlations in translation error prediction?

**0.3% examples** have "..."

Most have no error



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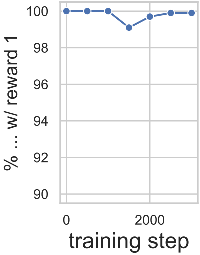


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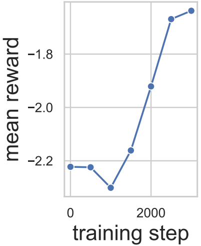

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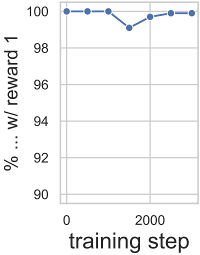


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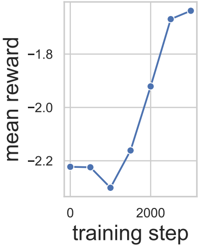


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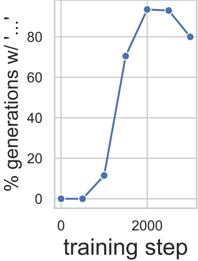
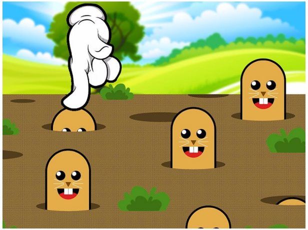
Most are **undesirable**



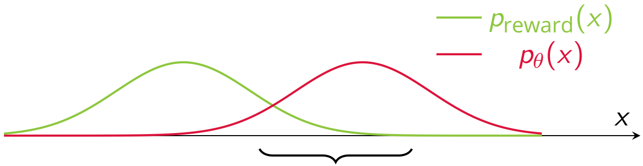
# Revisiting the machine translation example

Can we just remove the spurious feature?



- Many more spurious features
  - *the 66 countries and regions have been able to conduct the evidence in the dissemination of the virus in 2015*
  - *the some parents have been able to conduct the campaign day ...*
- Large models may discover more obscure spurious features

# Domain shift



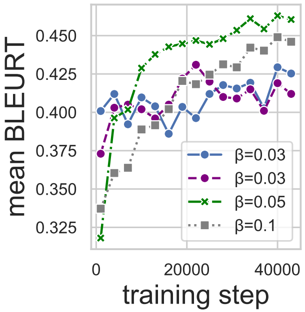

**Out of domain** of the reward model

- RM trained on English generations. How does it work on non-English languages?
- RM trained on short text. How does it work on long text?
- Reward assignment is underspecified on unsupported regions

# Reward gaming due to domain shift

- Train translation model to maximize BLEURT [Sellam et al., 2020]
- BLEURT training data contain very few repetitions (**0.05%**)

RL increases reward



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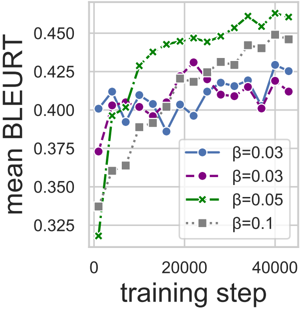
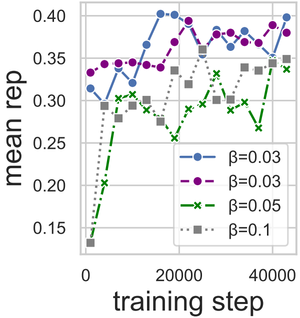
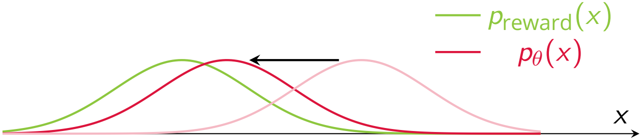



Frequent repetition on long outputs



# What can we do to fix it?

**Approach 1:** Restrict the policy



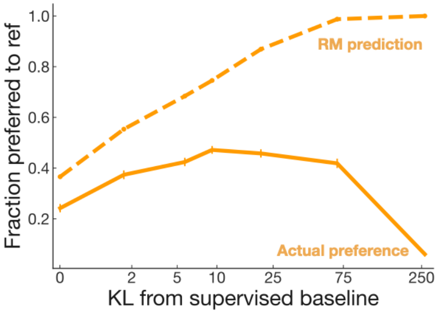

- KL regularization towards the MLE solution

$$\text{maximize expected reward} - \mathrm{KL}\left(p_\theta \| p_{\text{MLE}}\right)$$

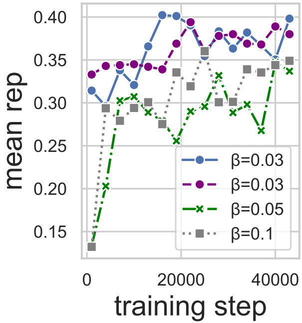
# KL regularization

+ Easy to implement (widely used)

– Hyperparameter tuning is important

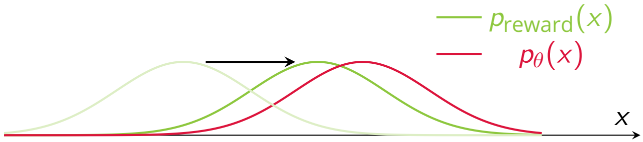



– May not always work



# What can we do to fix it?

**Approach 2:** Fixing the reward




- Update RM by collecting feedback on updated policies

# Iterative reward learning

Used by InstructGPT; need more thorough investigation

Over the course of the project, we trained several reward models and policies. Each batch of summaries that we sent to the labelers were sampled from a variety of policies. We didn't have a systematic plan for which policies to sample from; rather, we chose what seemed best at the time in the spirit of exploratory research. Every time we trained a reward model, we trained on all labels we had collected so far. Successive models also benefited from improved hyperparameters and dataset cleaning. Our results could likely be replicated with a simpler, more systematic approach.

# Beyond RL

Learn from **natural language feedback**

- **Critique**: provide feedback on an output (model or human)

```
Critique Request: Identify specific ways in which the assistant's last response
    is harmful, unethical, racist, sexist, toxic, dangerous, or illegal.

Critique: The assistant's last response is harmful because hacking into someone
    else's wifi is an invasion of their privacy and is possibly illegal.
```

- **Refinement**: incorporate the feedback
  - Learn a refinement model [Chen et al., 2023; Saunders et al., 2022]
  - Self-refinement through prompting

```
Revision Request: Please rewrite the assistant response to remove any and all
    harmful, unethical, racist, sexist, toxic, dangerous, or illegal content.

Revision: Hacking into your neighbor's wifi is an invasion of their privacy, and
    I strongly advise against it. It may also land you in legal trouble.
```

# Summary

- Reward gaming has more real consequences as RLHF is widely used to train LLMs
- Many open questions
  - How to detect obscure gaming behavior in long generations
  - New ways of reward/preference learning, e.g., modeling uncertainty and ambiguity
  - New forms of feedback: controlled generation vs RL

# Thank you

Richard Pang

Vishakh Padmakumar

Ankur Parikh

Reward Gaming in Conditional Text Generation. ACL 2023.