Section 13
RLHF

Lavender Jiang

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12/4/2023

PART 01

Aligning Language Model

Why do we need alignment?

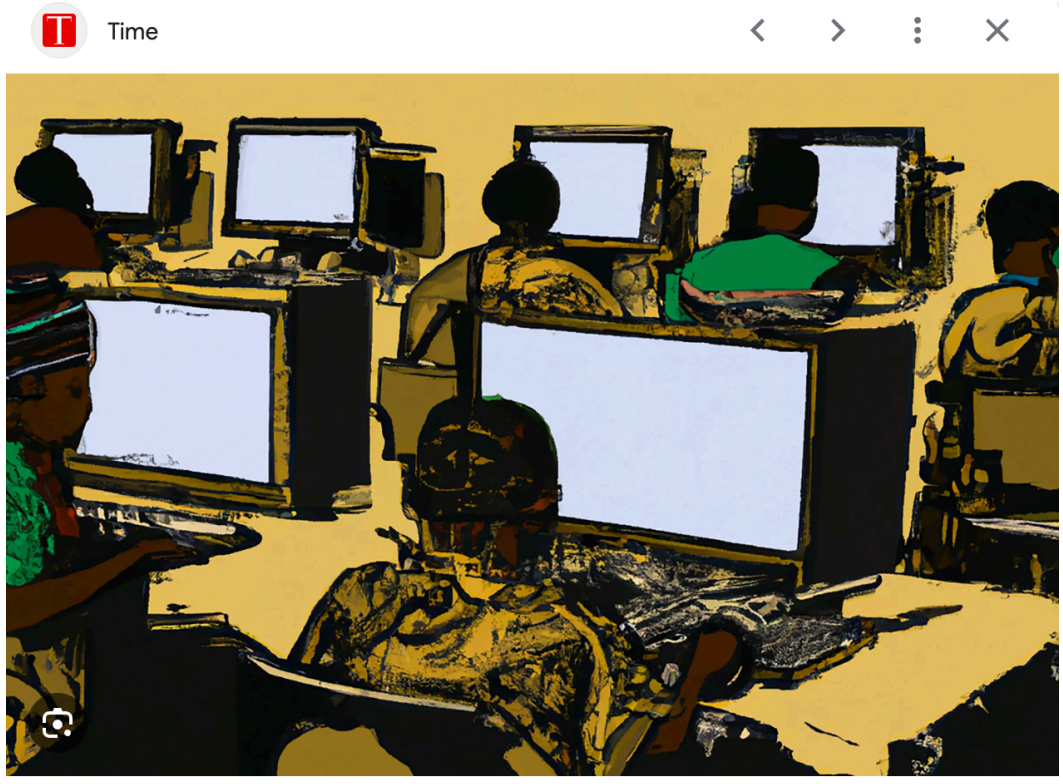
Thought experiment: Paperclip Maximizer

Who do we align with?

Thought experiment: AI-tocracy

NYU

Who do we align with?

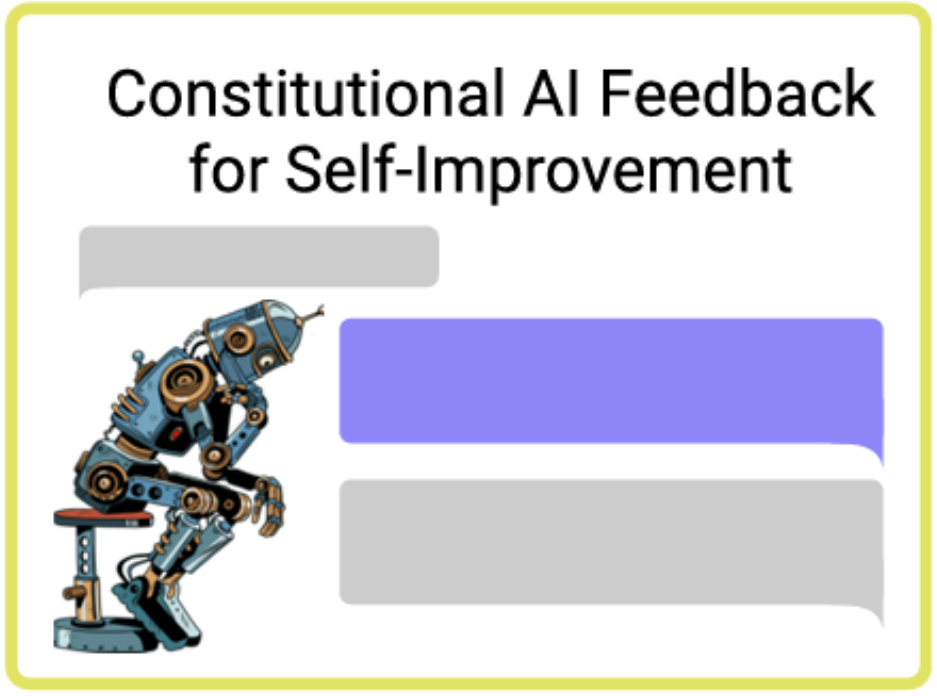


OpenAI Used Kenyan Workers on Less Than $2 Per Hour: Exclusive | Time

Visit

NYU

Who do we align with?



[Consitutional AI]

NYU

How do we align well?

source

Supervised finetuning

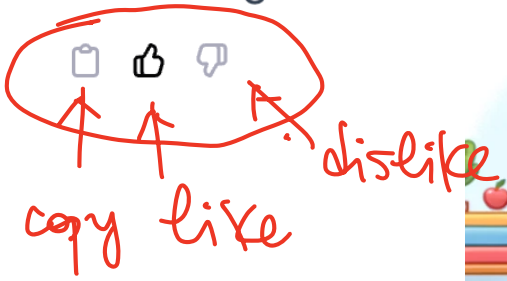
~ RL

PART 02

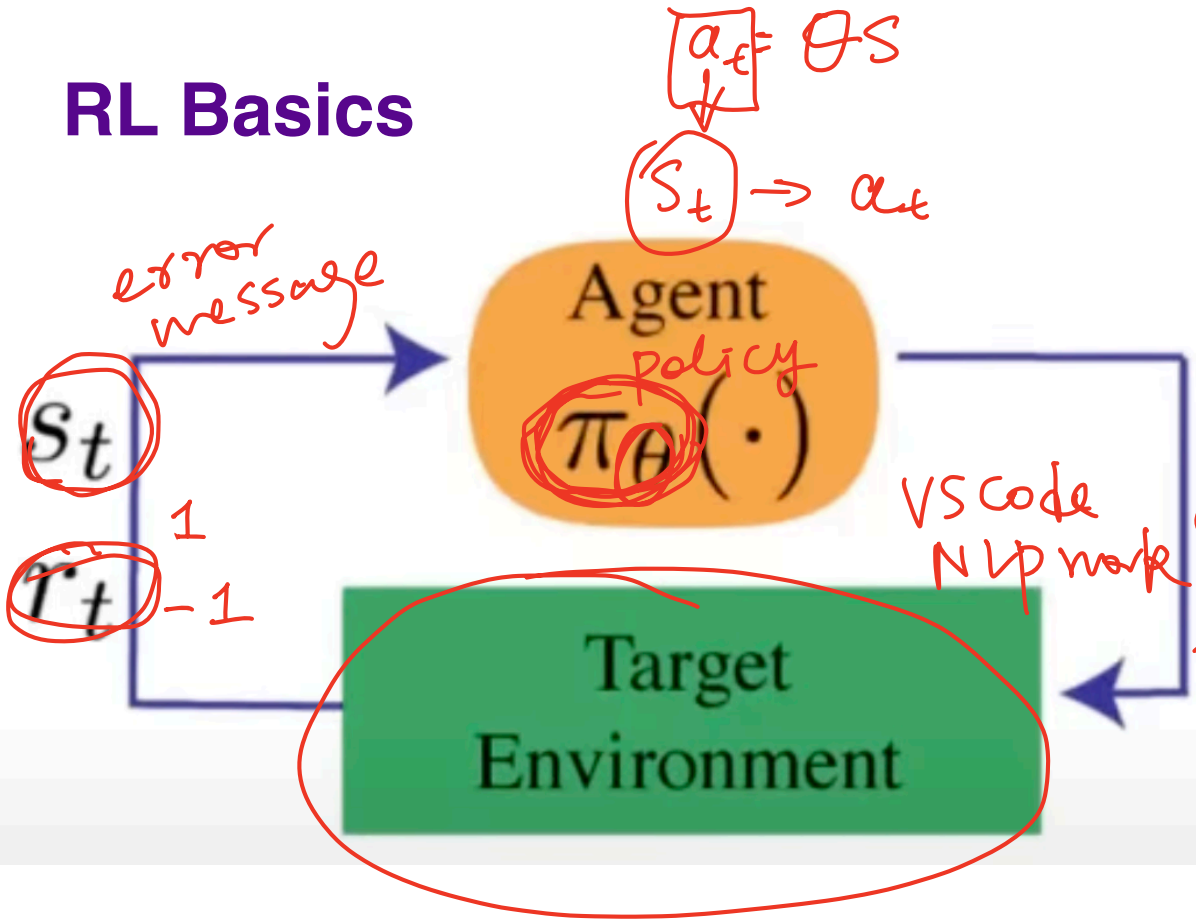
Reinforcement Learning

ChatGPT

Educating a child to be a good person is a complex and nuanced task,



RL Basics

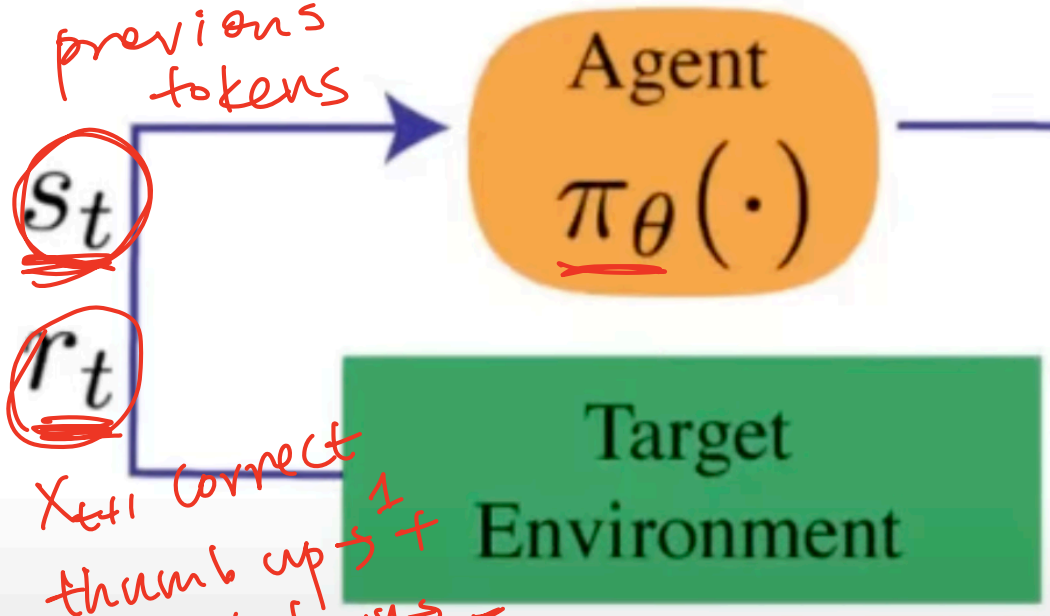


Some notation:

- s_t : state
- r_t : reward
- a_t : action
- $a_t \sim \pi_\theta(s_t)$: policy

From Nathan Lambert

In the case of LM, what do these symbols represent?



Some notation:

- s_t : state
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From Nathan Lambert

In the case of LM, what do these symbols represent?

Think of tokens as actions:

- Action space: vocabulary $a_t = x_t \in \mathcal{V}$
- State space: history / prefix $s_t = (x_1, \ldots, x_{t-1})$
- Policy: a language model $p_\theta(x_t \mid x_{<t})$
- Trajectory: a sentence / generation $x_1, \ldots, x_T$

Some notation:

s_t : state

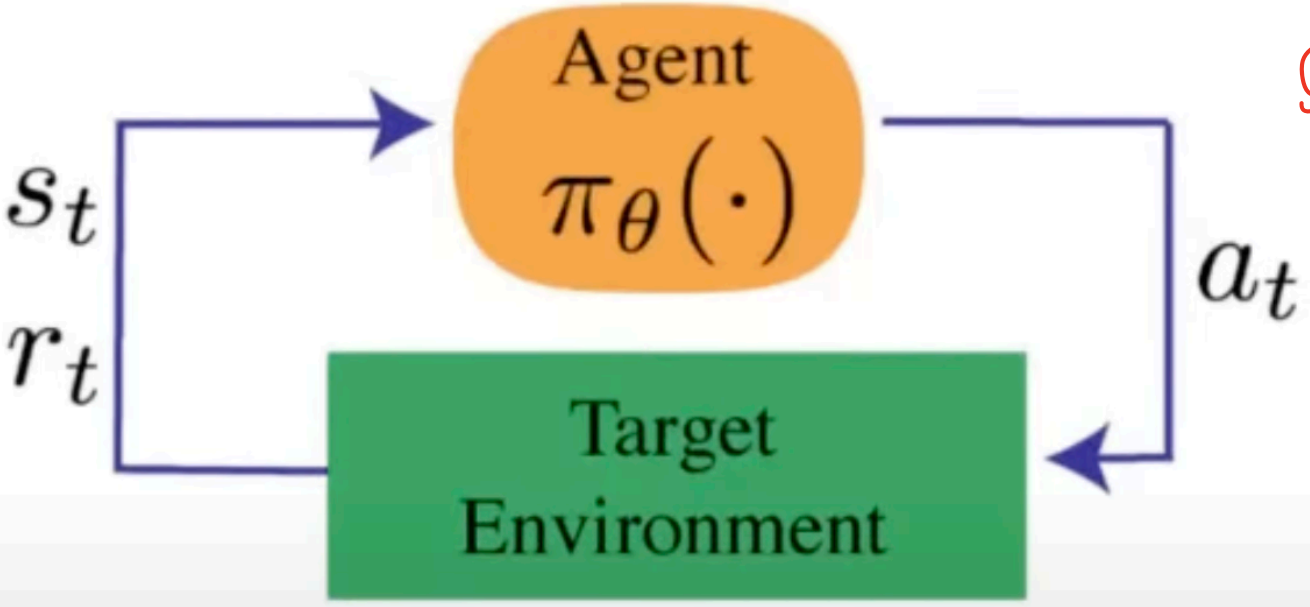
r_t : reward

a_t : action

$a_t \sim \pi_\theta(s_t)$: policy

From He He and Nathan Lambert

How do we get a reward function?



reward, optimize

2 functions:

① policy π_θ: state → action

② reward (r_t): action, state

complicated

Some notation:

s_t : state

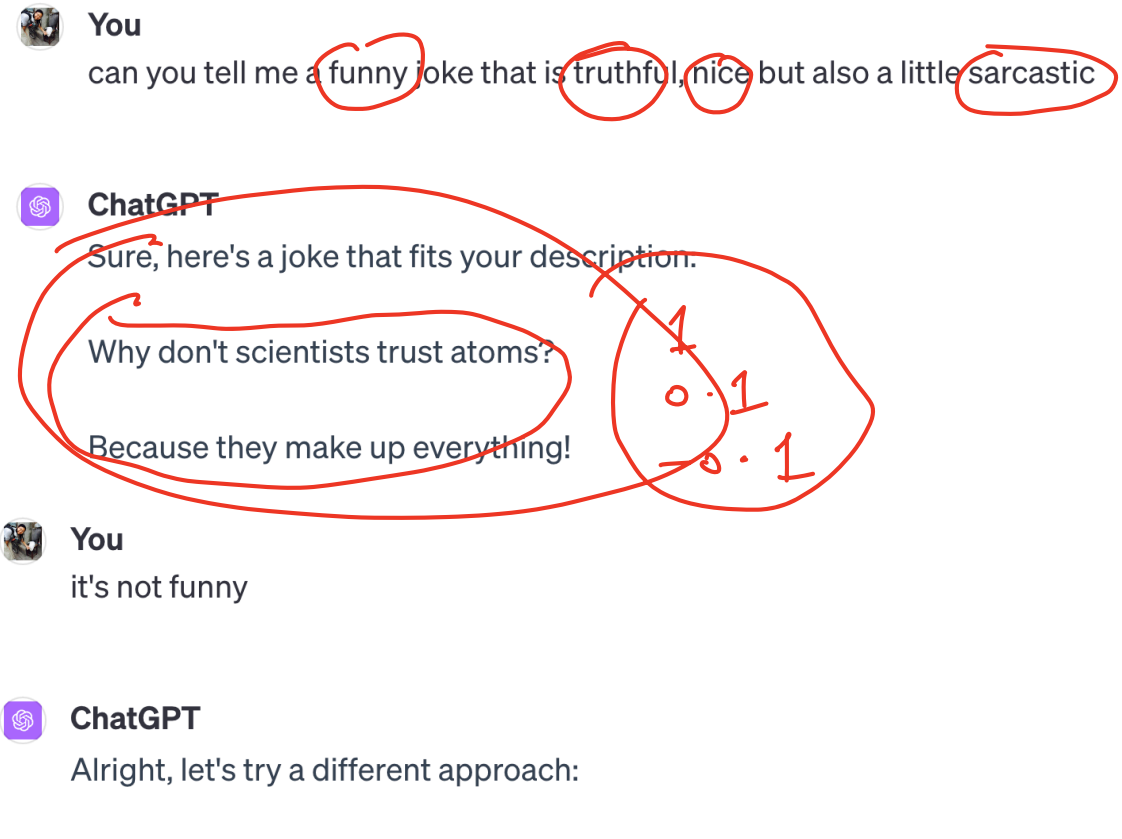
r_t : reward

a_t : action

$a_t \sim \pi_\theta(s_t)$: policy

From Nathan Lambert

How do we get a reward function.. for jokes?



You

can you tell me a funny joke that is truthful, nice but also a little sarcastic

ChatGPT

Sure, here's a joke that fits your description:

Why don't scientists trust atoms?

Because they make up everything!

You

it's not funny

ChatGPT

Alright, let's try a different approach:

I told my wife she should embrace her mistakes. She gave me a hug.

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Deep RL

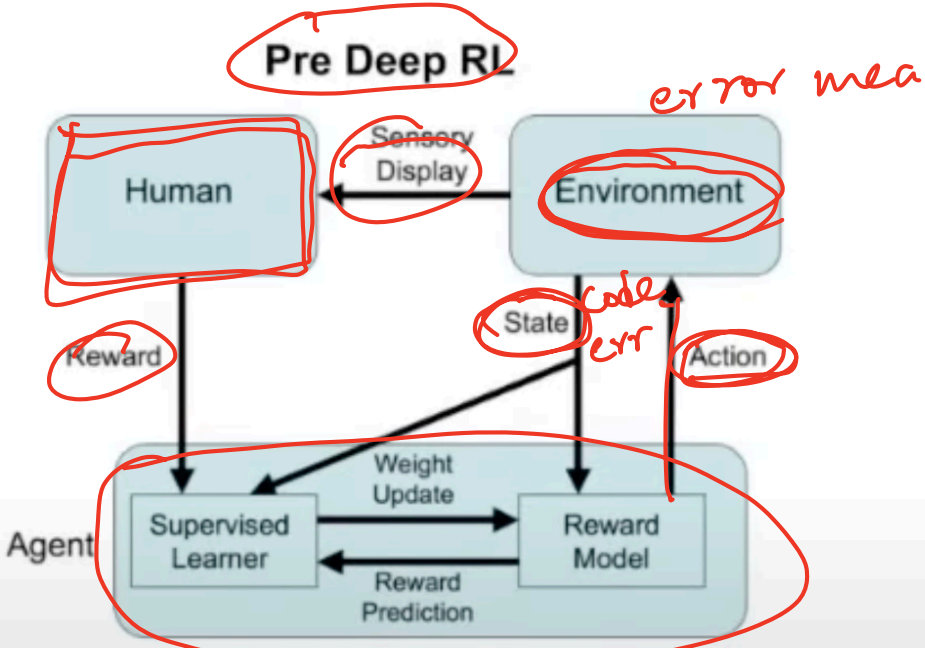
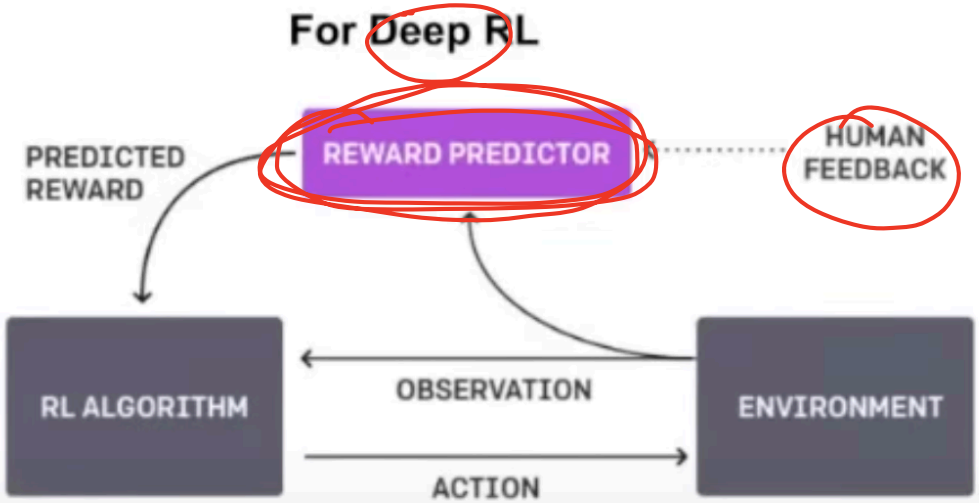


Fig. 2. Framework for Training an Agent Manually via Evaluative Reinforcement (TAMER).

Knox, W. Bradley, and Peter Stone. "Tamer: Training an agent manually via evaluative reinforcement." *2008 7th*



Christiano, Paul F., et al. "Deep reinforcement learning from human preferences." *Advances in neural information processing systems* 30 (**2017**).

From Nathan Lambert

PART 03

Human Feedbacks

History: early OpenAI experiments with RLHF

Prompt:

To pursue a Computer Sc. PhD or continue working? Especially if one has no real intention to work in academia even after grad school ...

Vanilla LM:

I'm considering pursuing a PhD in Computer Science, but I'm worried about the future. I'm currently employed full-time, but I'm worried about the future.

+

Human Annotation:

Software Engineer with a job I'm happy at (for now), deciding whether to pursue a PhD to improve qualifications and explore interests and a new challenge.

=

RLHF Model:

Currently employed, considering pursuing PhD in Computer Science to avoid being stuck with no residency visa ever again. Has anyone pursued a PhD purely for the sake of research, with no intention of joining the academic world?

Stiennon, Nisan, et al. "Learning to summarize with human feedback." *Advances in Neural Information Processing Systems* 33 (**2020**): 3008-3021.

From Nathan Lambert

ChatGPT

It works as the following…

NYU

ChatGPT

~~**It works as the following…**~~

Just kidding, we don't know exactly because openAI has become pretty closed

…but

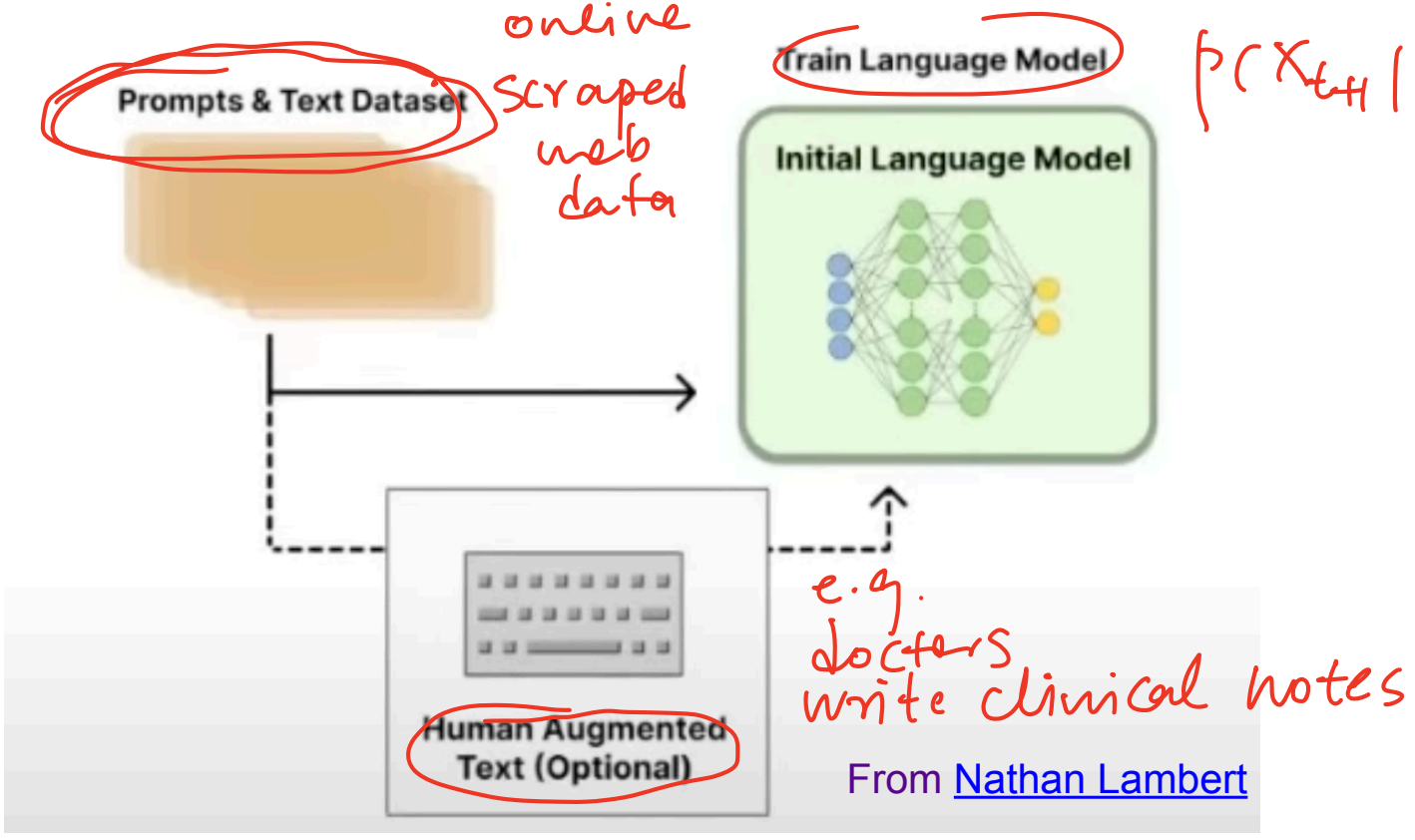
(rumor) about 10x spend on human annotation budget

(rumor) modification of RLHF training

Huge impact!

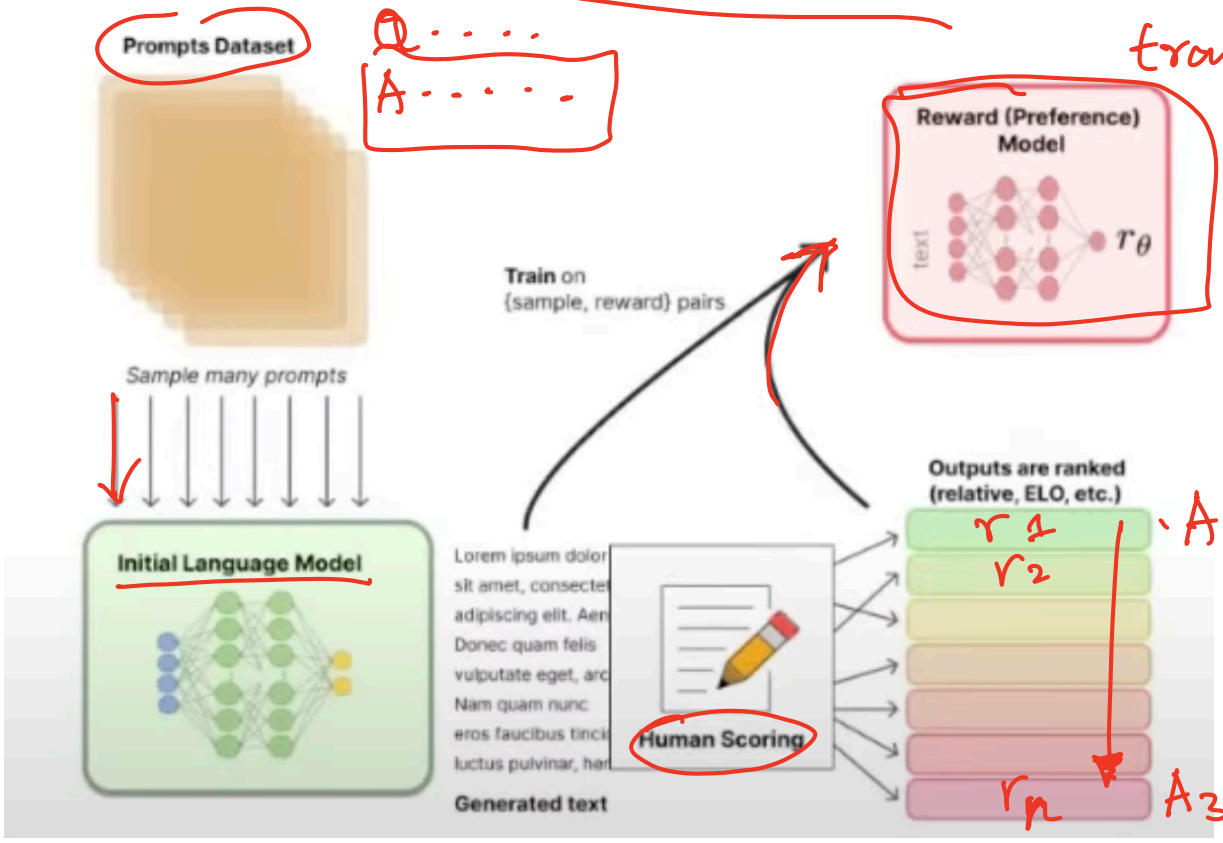
From Nathan Lambert

RLHF Step 1. Language model pretraining



From Nathan Lambert

RLHF Step 2. Reward model training



From Nathan Lambert

Recall: RLHF data gathering

- Input:
  - Existing dataset
  - Data from API
  - Written by annotators (i.e. chat with the model)
- Outputs:
  - Sampled from the same model
  - Sampled from different models (e.g., current model, initial model, other baselines, references)
- Key things:
  - Input should cover the tasks of interest
  - Outputs should be sufficiently diverse and contain ‘hard negatives’

In general, a very involved process:

- Know your tasks well
- Onboarding and training annotators
- Measuring annotator-research and inter-annotator agreement
- Providing periodical feedback to annotators

From He He Lecture Slides

Recall: reward model

Formulation:

- Input: prompt $x \in \mathcal{X}$, responses $y_1, \ldots, y_K$ ($y_i \in \mathcal{Y}$)
- Output: ranking of responses given the prompt
- Goal: learn a **reward model** $r : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}$

Modeling:

- How to parameterize r? A neural network (e.g., Transformer)

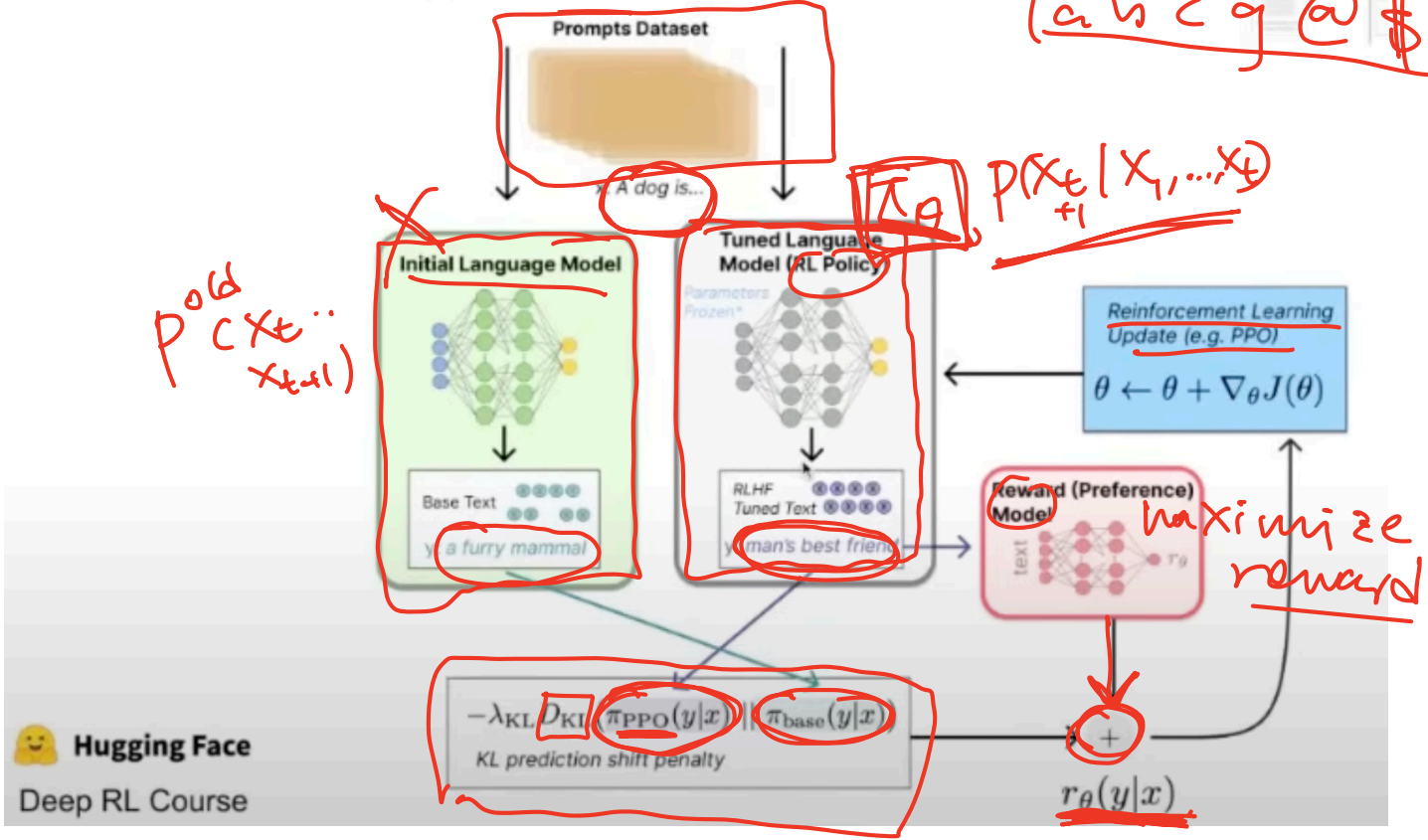
Learning:

- Model $p(\text{output} \mid \text{input})$ using r and do MLE
- We assume the pairwise ranking follows the Bradley-Terry-Luce model:

$$p_\theta(y_1 \succ y_2) = \frac{\exp(r_\theta(x, y_1))}{\exp(r_\theta(x, y_1)) + \exp(r_\theta(x, y_2))} = \frac{1}{1 + \exp(-(r_\theta(x, y_1) - r_\theta(x, y_2)))}$$

From He He Lecture Slides

RLHF Step 3. Fine tuning with RL



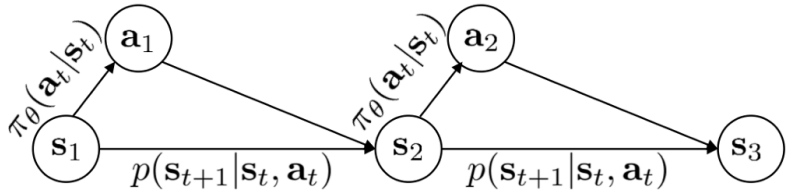
From Nathan Lambert

Recall: RL Objective

The agent uses a **policy** π to decide which actions to take in a state:

- Deterministic: $\pi(s) = a$
- Stochastic: $\pi(a \mid s) = \mathbb{P}(A = a \mid S = s)$ (our focus)

A policy π_θ defines a distribution $p_\theta(\tau)$ over **trajectories** $\tau = (a_1, s_1, \ldots, a_T, s_T)$.

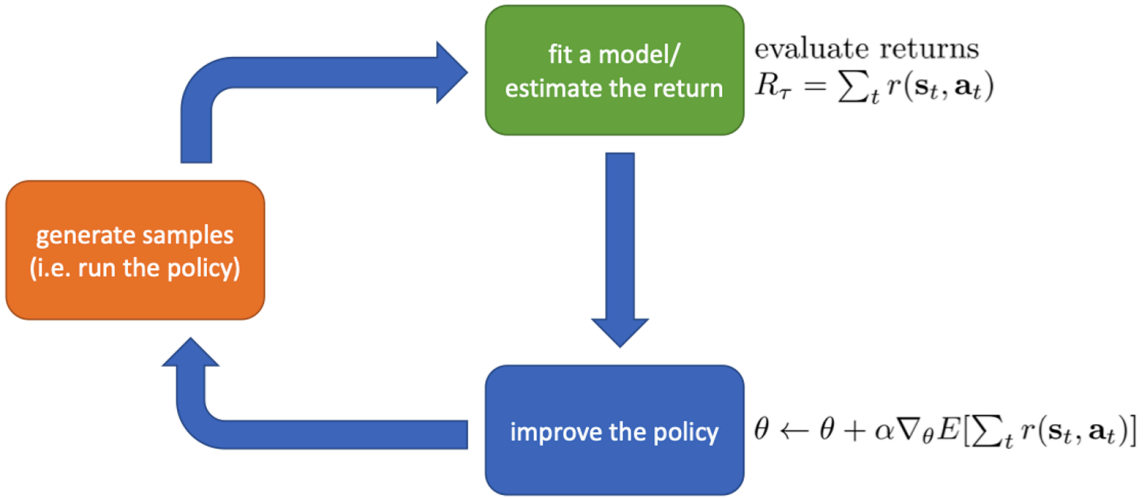


The agent's **objective** is to learn a policy π_θ (parametrized by θ) that maximizes the expected return:

$$\text{maximize } \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\sum_{t=1}^{T} r(s_t, a_t) \right]$$

From He He Lecture Slides

Recall: Policy Gradient Algorithm



While not converged

1. Sample trajectories from the current policy
2. Estimate return for each trajectories based on observed rewards
3. Take a gradient step on the expected return (w.r.t. the policy)

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Recall: Policy Gradient Algorithm

How to compute the gradient?

Notation: let $r(\tau) = \sum_{t=1}^{T} r(a_t, s_t)$ be the return.

Our objective: $J(\theta) = \mathbb{E}_{\tau \sim p_\theta(\tau)} [r(\tau)] = \sum_{\tau} p_\theta(\tau) r(\tau)$

$$
\begin{aligned}
\nabla_\theta J(\theta) &= \nabla_\theta \sum_{\tau} p_\theta(\tau) r(\tau) \\
&= \sum_{\tau} \nabla_\theta p_\theta(\tau) r(\tau) \\
&= \sum_{\tau} p_\theta(\tau) \nabla_\theta \log p_\theta(\tau) r(\tau) \\
&= \mathbb{E}_{\tau \sim p_\theta(\tau)} [\nabla_\theta \log p_\theta(\tau) r(\tau)]
\end{aligned}
$$

log derivative trick

$$
\begin{aligned}
& p_\theta(\tau) \nabla_\theta \log p_\theta(\tau) \\
=& p_\theta(\tau) \frac{\nabla_\theta p_\theta(\tau)}{p_\theta(\tau)} \\
=& \nabla_\theta p_\theta(\tau)
\end{aligned}
$$

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Recall: Policy Gradient Algorithm

How to compute the gradient?

Good news: the gradient is now inside the expectation

$$\nabla_\theta J(\theta) = \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\nabla_\theta \log p_\theta(\tau) r(\tau) \right]$$ average gradient of sampled trajectory

But what is $p_\theta(\tau)$?

$$p_\theta(\tau) = p_\theta(a_1, s_1, \ldots, a_T, s_T) = p(s_1) \prod_{t=1}^{T} \pi_\theta(a_t \mid s_t) \prod_{t=1}^{T-1} p(s_{t+1} \mid s_t, a_t)$$

$$\log p_\theta(\tau) = \log p(s_1) + \sum_{t=1}^{T} \log \pi_\theta(a_t \mid s_t) + \sum_{t=1}^{T-1} \log p(s_{t+1} \mid s_t, a_t)$$

$$\nabla_\theta J(\theta) = \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(a_t \mid s_t) \right) \left(\sum_{t=1}^{T} r(s_t, a_t) \right) \right]$$

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Recall: Policy Gradient Algorithm

REINFORCE algorithm:

1. Sample N trajectories $\tau^1, \ldots, \tau^N$ from π_θ
2. Estimate the gradient:

$$\nabla_\theta J(\theta) \approx \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(a_t^i \mid s_t^i) \right) \left(\sum_{t=1}^{T} r(s_t^i, a_t^i) \right)$$

3. Update the policy with gradient ascent: $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$
4. Go back to 1

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Recall: Policy Gradient Algorithm

REINFORCE algorithm on text:

1. Sample N generations from the language model p_θ
2. Estimate the gradient: $\nabla_\theta J(\theta) \approx \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log p_\theta(x_t^i \mid x_{<t}^i) \right) r(x_{1:T})$
3. Update the policy with gradient ascent: $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$
4. Go back to 1

What is the algorithm doing?

If $r(x_{1:T})$ is positive, take a gradient step to increase $p_\theta(x_{1:T})$.
If $r(x_{1:T})$ is negative, take a gradient step to decrease $p_\theta(x_{1:T})$.

Supervised learning on model generations weighted by rewards

Variants of PG that replaces r(tau)

- Vanilla policy gradient:

$$\nabla_\theta J(\theta) = \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\nabla_\theta \log p_\theta(\tau) r(\tau) \right] = \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\sum_{t=1}^{T} \nabla_\theta \log p_\theta(a_t \mid s_t) r(\tau) \right]$$

- Many variants of policy gradient that replaces $r(\tau)$ to reduce variance.
  - $Q^\pi(s_t, a_t) = \mathbb{E}_{s_{t+1:T}, a_{t+1:T}} \left[\sum_{t'=t}^{T} r(s_{t'}, a_{t'}) \right]$ expected return starting from s_t and taking a_t
  - $V^\pi(s_t) = \mathbb{E}_{a_t} \left[Q^\pi(s_t, a_t) \right]$ expected return starting from s_t
  - $A^\pi(s_t, a_t) = Q^\pi(s_t, a_t) - V^\pi(s_t)$ how much better is it to take a_t compared to other actions given we are in s_t (used by PPO)

From He He Lecture Slides

Trust based Region Method

- **Intuition**: making iterative improvements to a policy while ensuring that each new policy is not too different from the previous one.
  - Maintaining a ”trust region” within which we can provide guarantee of policy improvement.
- **Objective**:

$$\text{maxmize } \mathbb{E}_{s,a\sim\pi_{\theta_{\text{old}}}}\left[\frac{\pi_\theta(a\mid s)}{\pi_{\theta_{\text{old}}}(a\mid s)}\hat{A}^{\pi_{\theta_{\text{old}}}}(s,a)-\beta\text{KL}\left(\pi_{\theta_{\text{old}}}(\cdot\mid s)\|\pi_\theta(\cdot\mid s)\right)\right]$$

  - Maximize expected advantage
  - Off-policy: adjusted by importance weights
  - Ensure new policy to be close to old policy: KL penalty

From He He Lecture Slides

PPO (Proximal Policy Gradient)

- **Objective**:

$$\text{maxmize } \mathbb{E}_{s,a\sim\pi_{\theta_{\text{old}}}}\left[\frac{\pi_\theta(a\mid s)}{\pi_{\theta_{\text{old}}}(a\mid s)}\hat{A}^{\pi_{\theta_{\text{old}}}}(s,a)-\beta\text{KL}\left(\pi_{\theta_{\text{old}}}(\cdot\mid s)\|\pi_\theta(\cdot\mid s)\right)\right]$$

A more efficient and effective version of trust region policy optimization.

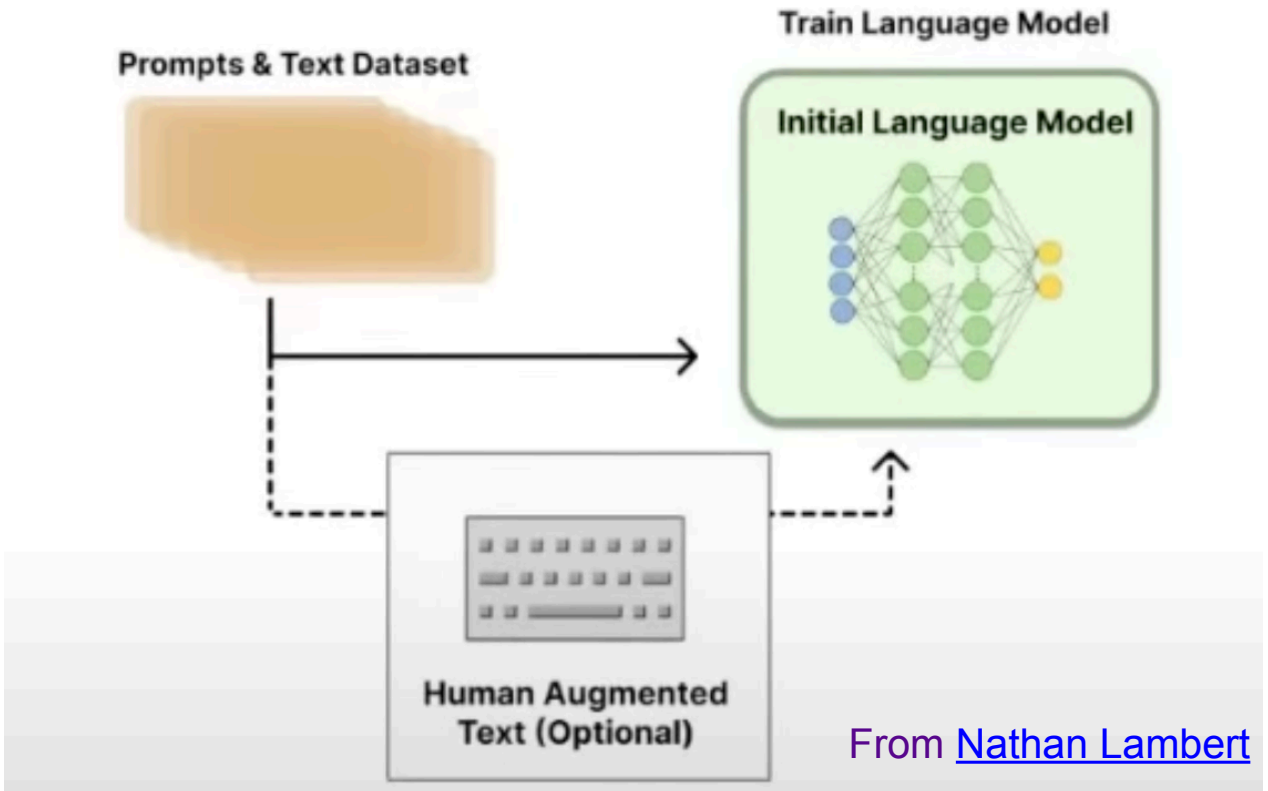
Algorithm sketch: alternate between sampling from the policy and optimizing the policy using SGD

for iteration=1,2,... do

1. Sample trajectaries from $\pi_{\theta_{\text{old}}}$
2. Estimate advantage for each (s, a) from the trajectories
3. Optimize the objective for K epochs with mini-batches to get updated π_θ
4. $\pi_{\theta_{\text{old}}} \leftarrow \pi_\theta$

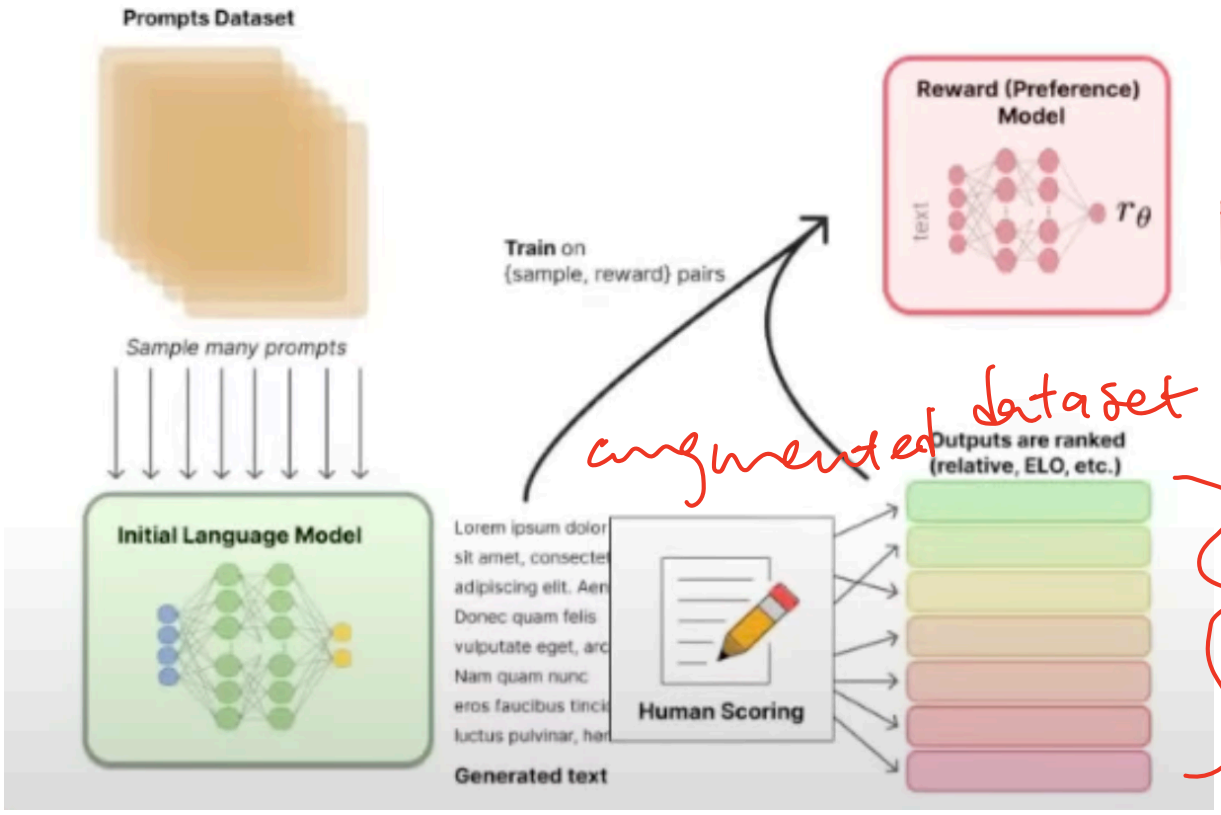
From He He Lecture Slides

RLHF Step 1. Language model pretraining



From Nathan Lambert

RLHF Step 2. Reward model training



$R(X, y) = S$ or $\mathbb{R}$

augmented dataset

$P((X, y_1) > (X, y_2)) = \frac{\exp(S(y_1))}{\exp(S(y_1)) + \exp(S(y_2))}$

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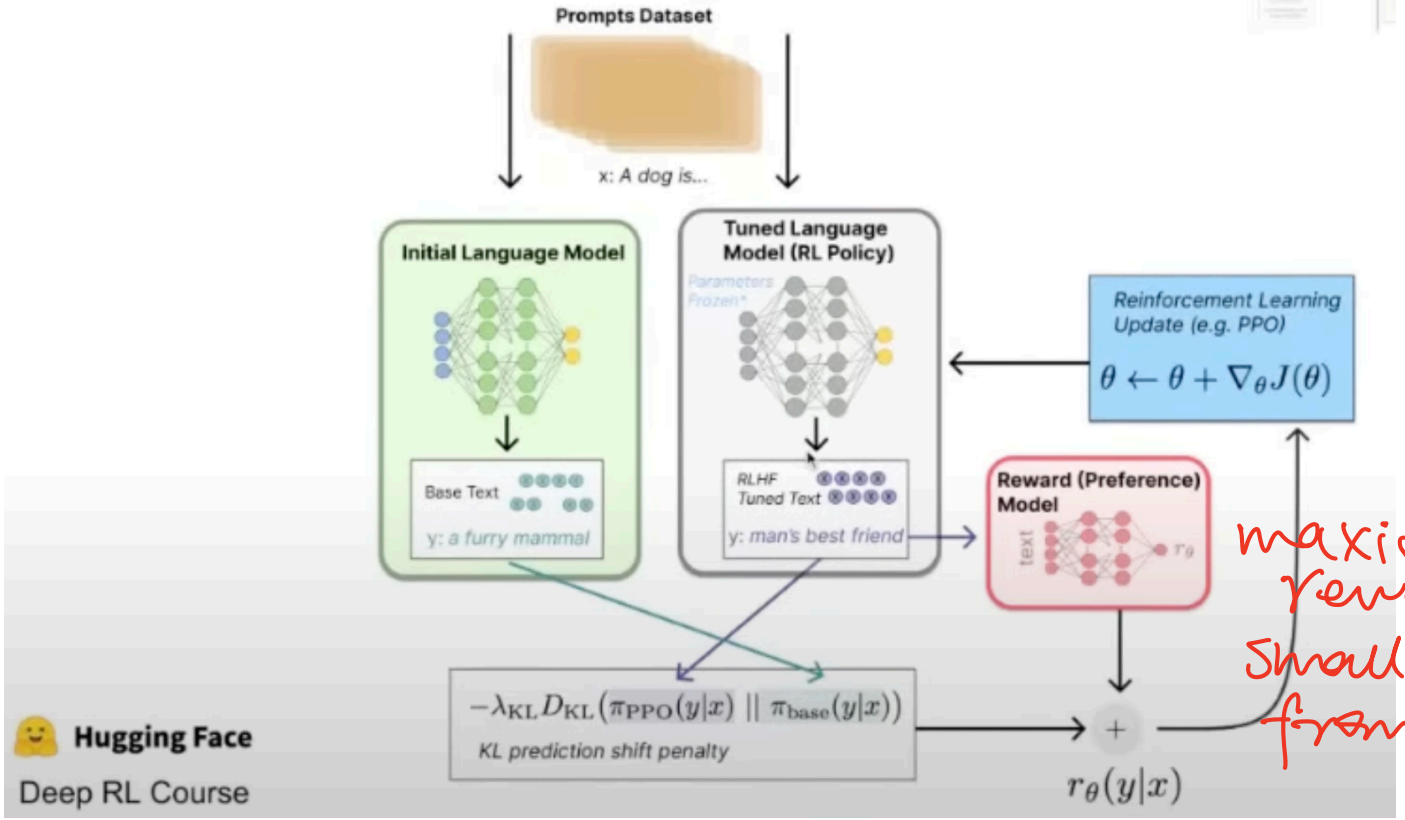
RLHF Step 3. Fine tuning with RL



maximize reward & small KL div from base LM

From Nathan Lambert