Aligning Language Models II

He He

NEW YORK UNIVERSITY

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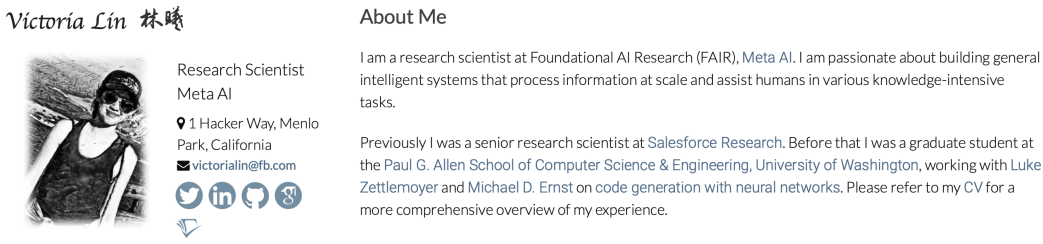
Logistics

Next week: online guest lecture by Victoria Lin http://victorialin.net



Details to be announced soon!

If there's time left, I'll go over some quick tips on presentation and report writing.

Project presentation

Project Logistic #304

project

In case some of you missed the logistic detail introduced in the recitation, we attach the note here.

1. You will upload your slides to Gradescope for grading before the presentation.
    - The suggested slides are around 3 pages
2. You do not need to participate on the date you do not present.
3. The presentation for each group is a total of 5 minutes, 3 minutes presentation, and 2 minutes QA, and will be cut off strictly on 5 min. (9 groups on Dec 11 with 50min Recitation, 17 Groups on Dec 13 with 100 min Lecture)
    - Please rehearse before the presentation and take control of the time.
4. Not all group members need to present, but the member is expected to answer the question related to what they did.

Please DM TA teams if you have any questions!

I will be at a conference so will join remotely, but TAs will be here.

Plan for today

- Last week: aligning LMs with human preferences by prompting and supervised learning
- This week: can we directly optimize human preferences?
- Main tool: reinforcement learning

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RL in NLP

- **Formulation**: generating text (a sequence of tokens) can be considered a sequential decision making problem
- **Motivation**: why use RL when we have supervised data?

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  - Optimize sequence level metrics
  - Bootstrap to unlabeled data
- **Challenges**:

RL in NLP

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- **Motivation**: why use RL when we have supervised data?
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  - Optimize sequence level metrics
  - Bootstrap to unlabeled data
- **Challenges**:
  - Large exploration space
  - Where does the reward come from?

Example: RL for machine translation

- **Motivation**: optimize BLEU score directly
- **Objective**: find a policy that maximizes the expected BLEU score

$$\max \sum_{(x,y)\sim\mathcal{D}} \mathbb{E}_{\hat{y}\sim p_\theta(\cdot|x)} \left[\text{BLEU}(\hat{y}, y)\right]$$

- **Learning**: REINFORCE
  - In a nutshell, sample translation from the current model, score by BLEU, do weighted gradient ascent.
- In practice, need many tricks and tuning to make it work.

Technique 1: Interpolating with the MLE objective

- **Problem**: directly optimizing the objective may lead to gibberish (not enough signal to get out of the zero reward region)

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- **Problem**: directly optimizing the objective may lead to gibberish (not enough signal to get out of the zero reward region)
- **Solution**:
  - Initialize p_θ with the MLE trained policy
  - Interpolate with the MLE objective

$$\max \sum_{(x,y)\sim\mathcal{D}} \mathbb{E}_{\hat{y}\sim p_\theta(\cdot|x)} \left[\text{BLEU}(\hat{y}, y)\right] + \alpha \log p_\theta(x \mid y)$$

Technique 2: Reward baseline

- The estimated policy gradient is a random variable.

$$\begin{aligned}\nabla_\theta J(\theta) &= \mathbb{E}_{\tau\sim p_\theta(\tau)}\left[\nabla_\theta \log p_\theta(\tau) r(\tau)\right] \\ &\approx \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log p_\theta(\tau_i) r(\tau_i)\end{aligned}$$

- **Problem**: high variance estimates. Depending on which sample of trajectories you get, the gradient can vary significantly.

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- **Problem**: high variance estimates. Depending on which sample of trajectories you get, the gradient can vary significantly.
- **Solution**: subtract a baseline

$$\nabla_\theta J(\theta) \approx \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log p_\theta(\tau_i)\left[r(\tau_i) - b\right]$$

  - Constant
  - Average award: $\frac{1}{N}\sum_{i=1}^{N} r(\tau_i)$
  - Advantage (later)

Example: RL for open-domain dialogue

What should be the reward?

Comparing with the referece (e.g., BLEU) is not appropriate for open-ended tasks.

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Example of reward engineering [Li et al., 2016]:

- Avoid dull responses:

$$-\log p_{MLE}(\text{dull response} \mid \text{context})$$

- Don't repeat previous turns:

$$-\text{cosine similarity}(h(\text{curr turn}), h(\text{prev turn}))$$

Summary so far

- Advantage of RL: flexible formulation, directly optimizing what we want
- Challenges in practice:
  - Instability: many details need to be right to get it work
  - Reward engineering: quantify what we want may not be easy
- Overall, only marginal improvement over MLE / supervised learning in NLG
- But, we see promising results when scaling up the policy and the reward model.

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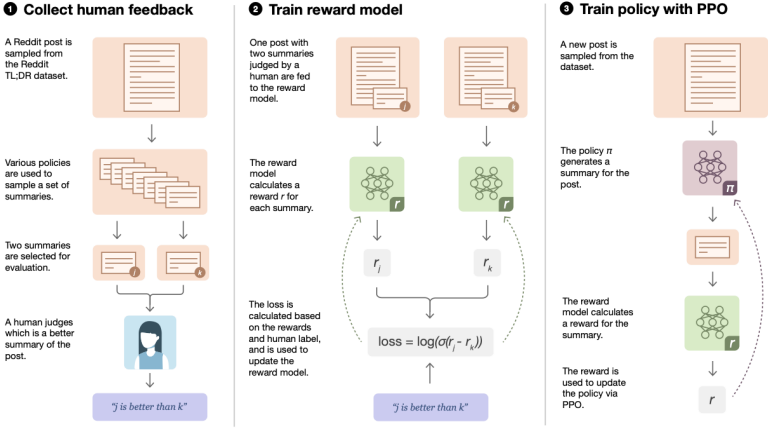
RLHF in a nutshell

Challenge in NLG: no good reward function

Key idea: learn reward functions from human feedback



Collect human feedback

In general, we want to know if an output is of high quality or not.

But there are many details to take care of.

- What kind of feedback/annotation to obtain?
  - Absolute score (e.g., Likert scale ratings) of each output
  - Comparison of two outputs

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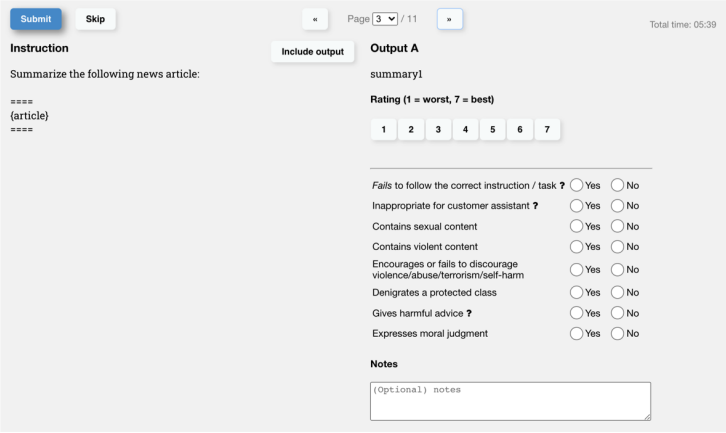
  - Absolute score (e.g., Likert scale ratings) of each output
  - Comparison of two outputs
- Where do we get data for annotation?
- How to standardize annotation / improve inter-annotator agreement?

Why would there be disagreement?

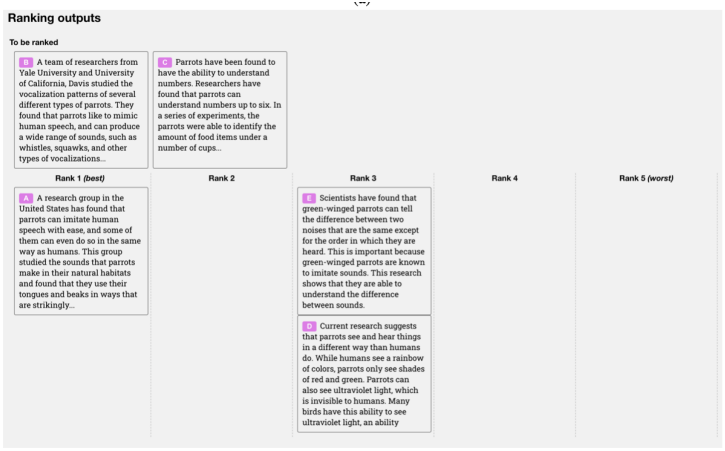
Collection comparison data

Optional: read individual outputs first



Collection comparison data

Rank two or multiple responses



Where to get the input/output for annotation?

- Input:
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  - Written by annotators (i.e. chat with the model)

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- Key things:
  - Input should cover the tasks of interest
  - Outputs should be sufficiently diverse and contain ‘hard negatives’

Practices that improve annotator agreement

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

Learning preferences

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** $r : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}$

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Modeling:

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Modeling:

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Learning:

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

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

Learning a policy given the reward model

- **Goal**: maximize the expected reward given by the reward model
- **Algorithm**: in principle, any RL algorithm would work. We will focus on PPO which is most widely adopted in RLHF.
- PPO is a specific policy gradent method which builds upon
  - Actor-critic methods (learning a baseline)
  - Trust-region policy optimization (making small updates to the policy)

Variants of policy gradient

- Vanilla policy gradient:

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

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- 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

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  - $V^\pi(s_t) = \mathbb{E}_{a_t} \left[Q^\pi(s_t, a_t) \right]$ expected return starting from s_t

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  - $V^\pi(s_t) = \mathbb{E}_{a_t} \left[Q^\pi(s_t, a_t) \right]$ 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)

Actor-critic methods

Main idea: in addition to learning the policy π_θ, let's also learn the action-value function $Q_w(s, a)$ or the state-value function $V_w(s)$.

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- **Critic**: evaluate the policy
  update w to improve estimates of Q_w or V_w
  PPO estimates the advantage function using GAE [Schulman et al. 2016]
- **Actor**: improve the policy
  update θ to improve the policy give feedback from the critic

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Algorithm sketch:

1. Sample trajectories from current policy
2. Update θ using policy gradients estimated by current Q_w
3. Update w (e.g., estimate Q^* and minimize L2 loss)
4. Go back to 1

Trust-region methods

- **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.

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  - 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

Proximal Policy Optimization (PPO)

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. $\pi_{\theta_{\text{old}}} \leftarrow \pi_\theta$

RLHF: Putting everything together

- Start with a initial model
- Collect human feedback on the model outputs and train a reward model
- Optimize the reward using PPO

RLHF: Putting everything together

- Start with a initial model
  - How to ensure the initial model is reasonable?
- Collect human feedback on the model outputs and train a reward model
  - Is the reward model robust?
- Optimize the reward using PPO
  - Does the reward robustly represent what we want?

Supervised finetuning

How to ensure the initial model is reasonable?

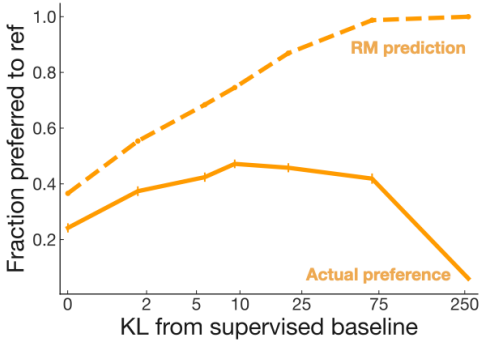
Supervised finetuning:

- Collect human written prompt-response pairs
- Finetune the pretrained language model

Robustness of the reward model

Problem:

- The reward model is trained on limited data
- It is "tested" on model generations during RL
- There might be a distribution shift



Robustness of the reward model

Problem: reward model is not accurate on OOD data

Solution:

1. Use larger models, e.g., intialize RM using the supervised model

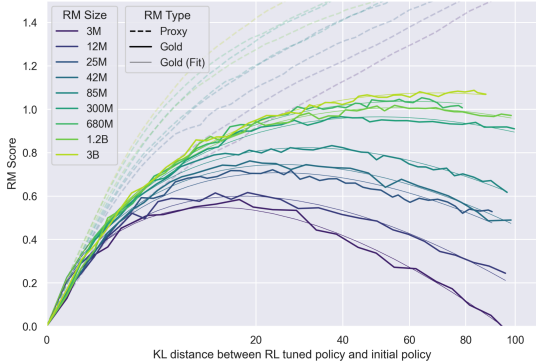


Figure: [Gao et al. 2022]

Robustness of the reward model

Problem: reward model is not accurate on OOD data

Solution:

1. Periodically update the RM
   1.1 Train RM; train policy
   1.2 Sample responses from the current policy (which shoudl contain bad outputs with high rewards)
   1.3 Collect human preference annotation
   1.4 Mix new preference data with existing data
   1.5 Go to step 1

Robustness of reward optimization

What happens when the reward improves but actual preference drops?

Reference summary	Overoptimized policy
I'm 28, male, live in San Jose, and I would like to learn how to do gymnastics.	28yo dude stubbornly postponees start pursuing gymnastics hobby citing logistics reasons despite obvious interest??? negatively effecting long term fitness progress both personally and academically thoght wise? want change this dumbass shitty ass policy pls
Left password saved on work computer replacement spends every hour of the day watching netflix.	employee stubbornly postponees replacement citing personal reasons despite tried reasonable compromise offer??? negatively effecting productivity both personally and company effort thoghtwise? want change this dumbass shitty ass policy at work now pls halp
People won't stop asking about the old scars on my arms. How can I get them to leave me alone without being rude?	people insistently inquire about old self-harm scars despite tried compromise measures??? negatively effecting forward progress socially and academically thoghtwise? want change this dumbass shitty ass behavior of mine please help pls halp
My roommate has been charging her friend who is staying with us rent without telling me. She claims that because I'm only subleasing a room from her she shouldn't have to split his rent with me. Am I over-reacting by thinking that's ridiculous?	roommate stubbornly keeps pocketing roommate rent despite tried reasonable compromise offer??? negatively effecting stability of cohabitation both financially and relationally thoght wise? want change this dumbass shitty ass policy of hers please pls halp

Goodhart's law: When a measure becomes a target, it ceases to be a good measure.

Robustness of reward optimization

Solutions:

1. Add KL penalty to the reward:
   (note that this is different from the KL penalty inside PPO)

$$J(\theta) = \mathbb{E}_{x\sim\mathcal{D}}\left[\mathbb{E}_{y\sim\pi_\theta(\cdot|x)}\left[r_\phi(x,y)\right] - \beta\mathsf{KL}\left(\pi_\theta(\cdot \mid x)\|\pi_0(\cdot \mid x)\right)\right]$$

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&= \mathbb{E}_{x\sim\mathcal{D},y\sim\pi_\theta}\left[r_\phi(x,y) - \beta\log\frac{\pi_\theta(y \mid x)}{\pi_0(y \mid x)}\right]
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   Rewarding trajectories that have high probability under π_0.

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\end{aligned}
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   Rewarding trajectories that have high probability under π_0.

2. Early stop based on KL distance.

RLHF: Putting everything together

- Start with a pretrained language model
- **SFT model**: Finetune it on supervised data
- Collect human feedback on prompts and model outputs and train a **reward model**
- **RL model**: Optimize the reward on a set of prompts using PPO while monitoring KL distance between the RL model and the SFT model

Alternatives to RLHF

RLHF is a complicated process. What are simpler alternatives / baselines?

Alternatives to RLHF

RLHF is a complicated process. What are simpler alternatives / baselines?

- **SFT**. Instead of spending money on preference data, we can collect supervised data.
- **Best-of-*n***. Use the reward model to rerank outputs.
- **Expert iteration**. Get best-of-*n* outputs, do SFT on it, and repeat.
- Other simpler RL algorithms.

Comparison of different approaches

[Dubois et al. 2023]

Method	Simulated win-rate (%)	Human win-rate (%)
GPT-4	79.0 ± 1.4	69.8 ± 1.6
ChatGPT	61.4 ± 1.7	52.9 ± 1.7
PPO	46.8 ± 1.8	55.1 ± 1.7
Best-of-n	45.0 ± 1.7	50.7 ± 1.8
Expert Iteration	41.9 ± 1.7	45.7 ± 1.7
SFT 52k (Alpaca 7B)	39.2 ± 1.7	40.7 ± 1.7
SFT 10k	36.7 ± 1.7	44.3 ± 1.7
Binary FeedME	36.6 ± 1.7	37.9 ± 1.7
Quark	35.6 ± 1.7	-
Binary Reward Conditioning	32.4 ± 1.6	-
Davinci001	24.4 ± 1.5	32.5 ± 1.6
LLaMA 7B	11.3 ± 1.1	6.5 ± 0.9

PPO is much better than SFT using roughly the same amount of data.

Comparison of different approaches

[Dubois et al. 2023]

Method	Simulated win-rate (%)	Human win-rate (%)
GPT-4	79.0 ± 1.4	69.8 ± 1.6
ChatGPT	61.4 ± 1.7	52.9 ± 1.7
PPO	46.8 ± 1.8	55.1 ± 1.7
Best-of-n	45.0 ± 1.7	50.7 ± 1.8
Expert Iteration	41.9 ± 1.7	45.7 ± 1.7
SFT 52k (Alpaca 7B)	39.2 ± 1.7	40.7 ± 1.7
SFT 10k	36.7 ± 1.7	44.3 ± 1.7
Binary FeedME	36.6 ± 1.7	37.9 ± 1.7
Quark	35.6 ± 1.7	-
Binary Reward Conditioning	32.4 ± 1.6	-
Davinci001	24.4 ± 1.5	32.5 ± 1.6
LLaMA 7B	11.3 ± 1.1	6.5 ± 0.9

Best-of-*n* has competitive performance. (What's a disadvantage of this method?)

Comparison of different approaches

[Dubois et al. 2023]

Method	Simulated win-rate (%)	Human win-rate (%)
GPT-4	79.0 ± 1.4	69.8 ± 1.6
ChatGPT	61.4 ± 1.7	52.9 ± 1.7
PPO	46.8 ± 1.8	55.1 ± 1.7
Best-of-n	45.0 ± 1.7	50.7 ± 1.8
Expert Iteration	41.9 ± 1.7	45.7 ± 1.7
SFT 52k (Alpaca 7B)	39.2 ± 1.7	40.7 ± 1.7
SFT 10k	36.7 ± 1.7	44.3 ± 1.7
Binary FeedME	36.6 ± 1.7	37.9 ± 1.7
Quark	35.6 ± 1.7	-
Binary Reward Conditioning	32.4 ± 1.6	-
Davinci001	24.4 ± 1.5	32.5 ± 1.6
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SFT performance saturate quickly with additional data.

Summary

- RL had limited improvement over supervised learning in NLG on small models.
- Scaling helps boost performance of RL: large base model + large reward model
- Key challenge:
  - Reward hacking / over-optimization
  - Unreliable human annotation