GFLOWNETS WITH HUMAN FEEDBACK

Yinchuan Li[1], **Shuang Luo**[1,2]*, **Yunfeng Shao**[1], **Jianye Hao**[1,3]
[1]Huawei Noah's Ark Lab, Beijing, China [2]Zhejiang University, Huangzhou, China
[3]Tianjin University, Tianjin, China

ABSTRACT

We propose the GFlowNets with Human Feedback (GFlowHF) framework to improve the exploration ability when training AI models. For tasks where the reward is unknown, we fit the reward function through human evaluations on different trajectories. The goal of GFlowHF is to learn a policy that is strictly proportional to human ratings, instead of only focusing on human favorite ratings like RLHF. Experiments show that GFlowHF can achieve better exploration ability than RLHF.

1 INTRODUCTION

Large-scale language models are one of the main applications of artificial intelligence, represented by ChatGPT, which has become a hot trend Ouyang et al. (2022); Stiennon et al. (2020); Nakano et al. (2021); Ziegler et al. (2019); Thoppilan et al. (2022). Reinforcement Learning from Human Feedback (RLHF) Christiano et al. (2017) techniques play a key role in ChatGPT. However, RL suffers from insufficient exploration ability since it tends to take actions that maximize the expectation of future rewards. Therefore, Generative Flow Networks (GFlowNets) Bengio et al. (2021b) have been recently proposed to make up for the insufficient exploration of RL, which generate distribution proportional to the rewards and have been used in many applications Bengio et al. (2021a); Zhang et al. (2022); Deleu et al. (2022); Li et al. (2023a;b; 2022). This property makes GFlowNets ideal for training AI models with human feedback, helping us explore more diverse outcomes.

In this paper, we propose Generative Flow Networks with Human Feedback (GFlowHF). Our main contributions lie in proposing, to the best of our knowledge, the first GFlowNets with human feedback framework, and conducting experiments in a diverse reward distribution environment to validate that GFlowHF can obtain more diversity high-scoring answers than RLHF with the same human labels, and has a stronger ability to resist noisy labels than RLHF.

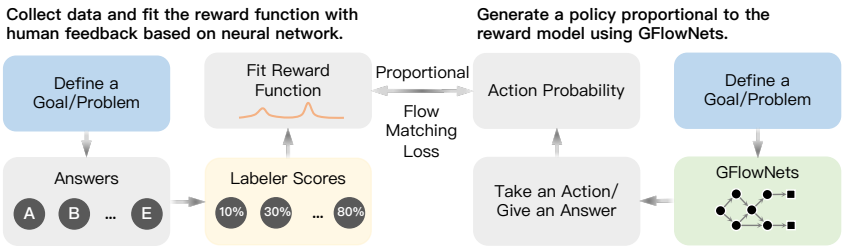

Figure 1: Overall framework of GFlowHF.

2 GFLOWHF FRAMEWORK

The overview framework of GFlowHF is shown in Figure 1. Considering a task with tuple $(\mathcal{S}, \mathcal{A})$, where $\mathcal{S}$ denotes the state space and $\mathcal{A}$ denotes the action space. Define a complete trajectory $\tau = (s_0, ..., s_f)$ as a sequence sampled states starting in s_0 and ending in s_f. During training, we sample a set of trajectories $\{\tau_1, ..., \tau_N\}$ and send them to humans for scoring. We can score based on the entire trajectory, or directly based on the final state s_f, denoted by $\text{score}(s_f)$. Based on manual scoring, we can train a reward network $r_\phi(s_f)$ with s_f as the input and $\text{score}(s_f)$ as the output.

*Corresponding Author: Shuang Luo (e-mail: luoshuang@zju.edu.cn). This work was completed while Shuang Luo was a member of the Huawei Noah's Ark Lab for advanced study.

The policy of GFlowHF is defined as $\pi(a_t|s_t) = \frac{F_\theta(s_t,a_t)}{F_\theta(s_t)}$, where F_θ is the flow network. The goal of GFlowHF is to train a flow network satisfying $\pi(s_f) \propto \text{score}(s_f)$. Once $r_\phi(s_f)$ is available, we train a flow network F_θ based on the flow matching loss

$$\mathcal{L}(\tau) = \sum_{s_t=s_1}^{s_f} \left(\sum_{s_{t-1}\in\mathcal{P}(s_t)} F_\theta(s_{t-1} \to s_t) - r_\phi(s_t) - \sum_{s_{t+1}\in\mathcal{C}(s_t)} F_\theta(s_t \to s_{t+1}) \right)^2 \quad (1)$$

for discrete space tasks, where $r_\phi(s_t) = 0$, $\mathcal{P}(s)$ and $\mathcal{C}(s)$ denote the parent set and child set of s, respectively.

Why GFlowHF? The main advantage of GFlowHF over RLHF is that it can learn the distribution of rewards. Therefore, instead of simply ranking the answers, we can train the model by scoring the answers. As shown in Figure 2 Left, the preference rankings can be inaccurate. If a labeler is asked to rate several bad answers, the highest-ranked answer is actually scored poorly, and vice versa. Hence, it is more accurate to train the model by using the scores (e.g. preference percentage). Note that it is also possible to train GFlowHF directly with the ranked labels if in some cases we do not have the preference scores for the answers.

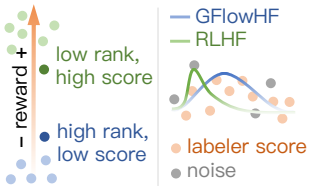

Figure 2: Advantages.

In addition, GFlowHF has a stronger ability to resist noisy labels. It is generally assumed that 10% of labels placed by humans are almost randomly distributed Christiano et al. (2017). If a wrong label has a high score, RL focuses on learning high-scoring results and gets the wrong policy. In contrast, GFlowNet tends to learn the entire distribution and is more robust (see Figure 2 Right).

3 Experimental Results

We compare the proposed GFlowHF with several RLHF methods in Point-Robot task. We set two different goals (with coordinates $(5, 10)$ and $(10, 5)$) to simulate a multimodal reward task. The agent starts at the starting coordinate $(0, 0)$ and moves towards the goals with a maximum step length of 12. After reaching the last step, we let the labeler give a preference score based on the final position. The preference score is set to be divided into 5 grades, the closer to goals, the greater the score. For the continuous Point-Robot task, our GFlowHF is developed based the CFlowNets proposed in Li et al. (2023c). For a multimodal reward distribution, i.e. there are many different high-scoring answers. We can see that GFlowHF can demonstrate an exploration ability far beyond RLHF, i.e., it can learn all answers, while RLHF can only learn one. The number of valid-distinctive answers of GFlowHF is higher, and the reward is also slightly higher than RLHF methods.

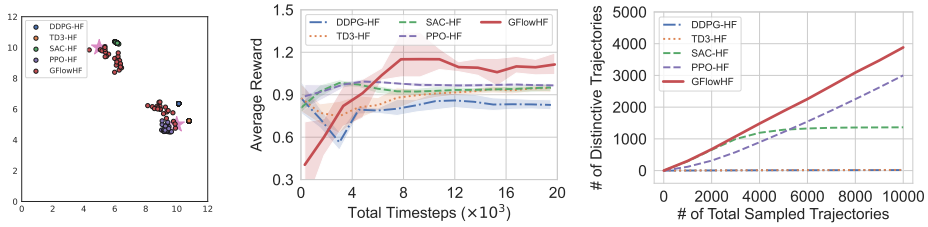

Figure 3: Comparison results of GFlowHF and several RLHF methods on Point-Robot task. **Left:** Explored answers. **Middle:** Average reward. **Right:** Number of valid-distinctive answers. GFlowHF explores both targets whereas RLHF techniques only explore one of them.

4 Conclusion & Future Work

We propose the GFlowNets with Human Feedback framework to improve the exploration when training AI models. Experiments show that GFlowHF can achieve better exploration ability and has a stronger ability to resist noisy labels than RLHF. Our future work is to use GFlowHF to train a powerful large-scale language model based on real language data.

URM STATEMENT

The authors acknowledge that the first and second authors of this work meet the URM criteria of the ICLR 2023 Tiny Papers Track. The first author is 28 years old and non-white. The second author is 25 years old and non-white student.

REFERENCES

Emmanuel Bengio, Moksh Jain, Maksym Korablyov, Doina Precup, and Yoshua Bengio. Flow network based generative models for non-iterative diverse candidate generation. *Advances in Neural Information Processing Systems*, 34:27381–27394, 2021a.

Yoshua Bengio, Tristan Deleu, Edward J Hu, Salem Lahlou, Mo Tiwari, and Emmanuel Bengio. Gflownet foundations. *arXiv preprint arXiv:2111.09266*, 2021b.

Paul F Christiano, Jan Leike, Tom Brown, Miljan Martic, Shane Legg, and Dario Amodei. Deep reinforcement learning from human preferences. *Advances in neural information processing systems*, 30, 2017.

Tristan Deleu, António Góis, Chris Emezue, Mansi Rankawat, Simon Lacoste-Julien, Stefan Bauer, and Yoshua Bengio. Bayesian structure learning with generative flow networks. In *Uncertainty in Artificial Intelligence*, pp. 518–528. PMLR, 2022.

Scott Fujimoto, Herke Hoof, and David Meger. Addressing function approximation error in actor-critic methods. In *International conference on machine learning*, pp. 1587–1596. PMLR, 2018.

Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, and Sergey Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In *International conference on machine learning*, pp. 1861–1870. PMLR, 2018.

Wenqian Li, Yinchuan Li, Shengyu Zhu, Yunfeng Shao, Jianye Hao, and Yan Pang. Gflowcausal: Generative flow networks for causal discovery. *arXiv preprint arXiv:2210.08185*, 2022.

Wenqian Li, Yinchuan Li, Zhigang Li, Jianye HAO, and Yan Pang. Dag matters! gflownets enhanced explainer for graph neural networks. In *International conference on learning representations*, 2023a.

Yinchuan Li, Zhigang Li, Wenqian Li, Yunfeng Shao, Yan Zheng, and Jianye Hao. Generative flow networks for precise reward-oriented active learning on graphs. *arXiv preprint arXiv:2304.11989*, 2023b.

Yinchuan Li, Shuang Luo, Haozhi Wang, and Jianye Hao. Cflownets: Continuous control with generative flow networks. In *International conference on learning representations*, 2023c.

Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. *arXiv preprint arXiv:1509.02971*, 2015.

Reiichiro Nakano, Jacob Hilton, Suchir Balaji, Jeff Wu, Long Ouyang, Christina Kim, Christopher Hesse, Shantanu Jain, Vineet Kosaraju, William Saunders, et al. Webgpt: Browser-assisted question-answering with human feedback. *arXiv preprint arXiv:2112.09332*, 2021.

Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *arXiv preprint arXiv:2203.02155*, 2022.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

Nisan Stiennon, Long Ouyang, Jeffrey Wu, Daniel Ziegler, Ryan Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul F Christiano. Learning to summarize with human feedback. *Advances in Neural Information Processing Systems*, 33:3008–3021, 2020.

Romal Thoppilan, Daniel De Freitas, Jamie Hall, Noam Shazeer, Apoorv Kulshreshtha, Heng-Tze Cheng, Alicia Jin, Taylor Bos, Leslie Baker, Yu Du, et al. Lamda: Language models for dialog applications. *arXiv preprint arXiv:2201.08239*, 2022.

Dinghuai Zhang, Nikolay Malkin, Zhen Liu, Alexandra Volokhova, Aaron Courville, and Yoshua Bengio. Generative flow networks for discrete probabilistic modeling. In *International Conference on Machine Learning*, pp. 26412–26428. PMLR, 2022.

Daniel M Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B Brown, Alec Radford, Dario Amodei, Paul Christiano, and Geoffrey Irving. Fine-tuning language models from human preferences. *arXiv preprint arXiv:1909.08593*, 2019.

A APPENDIX

We compare the proposed GFlowHF with several RLHF methods based DDPG (Lillicrap et al., 2015), TD3 (Fujimoto et al., 2018), PPO (Schulman et al., 2017), and SAC (Haarnoja et al., 2018). We provide the hyper-parameters of all compared methods in Table 1. The number of sample flows, action probability buffer size, and ϵ of GFlowHF are set as 100, 1000, and 1, respectively. The target update interval of SAC-HF is set as 1. The GAE parameter, timesteps per update, number of epochs, clipping parameter and value loss coefficient of PPO-HF are set as 0.95, 2048, 10, 0.2, and 0.5, respectively. A valid-distinctive answer is defined as a reward above a threshold δ_r while the MSE between the trajectory and other trajectories is greater than another threshold δ_{mse}.

As for the continuous Point-Robot task, assume that K flows are sampled, we can use the sampled flow matching loss proposed in Li et al. (2023c) as the following

$$\mathcal{L}_\theta(\tau) = \sum_{s_t=s_1}^{s_f} \left[\sum_{k=1}^{K} F_\theta(G_\psi(s_t, a_k), a_k) - \lambda r_\phi(s_t) - \sum_{k=1}^{K} F_\theta(s_t, a_k) \right]^2, \tag{2}$$

where G_ψ is a pre-trained network to find the parent states and $\lambda = K/\mu(\mathcal{A})$.

Table 1: Hyper-parameters of all compared methods.

	GFlowHF	DDPG-HF	TD3-HF	SAC-HF	PPO-HF
Total Timesteps	20,000	20,000	20,000	20,000	20,000
Start Traning Timestep	1,500	1,500	1,500	1,500	-
Max Episode Length	12	12	12	12	12
Network Hidden Layers	Flow [256,256]	Actor [256,256]	Actor [256,256]	Actor [256,256]	Policy [256,256]
Network Hidden Layers	Retrieval [256,256,256]	Critic [256,256]	Critic [256,256]	Critic [256,256]	Value [256,256]
RewardNet Hidden Layers	[256,256,256]	[256,256,256]	[256,256,256]	[256,256,256]	[256,256,256]
Optimizer	Adam	Adam	Adam	Adam	Adam
Learning Rate	0.0003	0.0003	0.0003	0.0003	0.0003
Batchsize	128	256	128	1024	64
Replay Buffer Size	8,000	100,000	100,000	100,000	-
Discount Factor	-	0.99	0.99	0.99	0.99
Target Network Update Rate	-	0.005	0.005	-	-

In addition, we compare the proposed GFlowHF with RLHF algorithms under noisy human labels. We add a noisy label at coordinate $(7, 10)$ with preference score 6. It can be seen from Figure 4 that for noisy environments, GFlowHF can still obtain the correct answers, which shows that it is very robust to noise. Although human label at $(7, 10)$ is wrong, the overall reward distribution trend will not change. GFlowHF learns the overall distribution trend and can still come up with the correct answer. In contrast, the RLHF algorithms tend to focus on where the reward is largest. If the wrong label scores high, the RLHF algorithms will learn the wrong policy, causing the RLHF algorithm to be easily disturbed by noise and give wrong answers. It is worth noting that the reward obtained by GFlowHF here is not the highest. This is because RL mostly picks wrong answers and thus gets higher rewards. This experiment demonstrates the importance of the GFlowHF algorithm in practice, especially for large language model training tasks where human label errors are common.

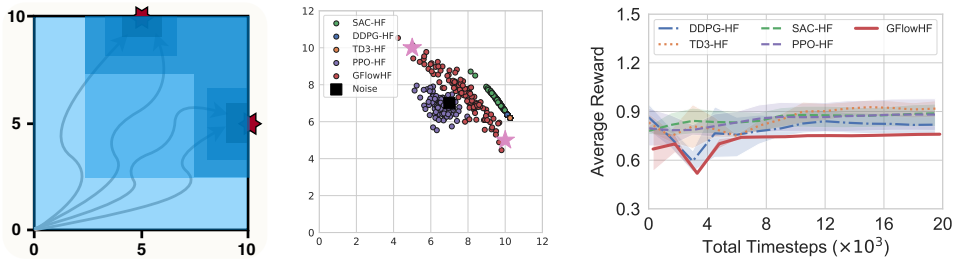

Figure 4: Comparison results of GFlowHF and several RLHF methods with noisy human labels. **Left:** Labeled score distribution. The blue color from light to dark represents the 5 grades rated by humans. **Middle:** Explored answers. **Right:** Average reward.