

Inverse Reinforcement Learning Tool for MiniGrid environment

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Possible Scenario

Persona



- Paolo Dibali
- Age 27
- Video Game Designer and non AI expert
- Paolo wants to create his video game

- Non-Player Characters (NPCs) approaches:
 - Handcrafted rules
 - Reinforcement Learning (RL)

Video games and AI

- RL is used in video games to create NPCs

- Two problems:

- NPCs with super-human abilities
- NPCs with predictable behavior



Video games and AI

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- Two problems:

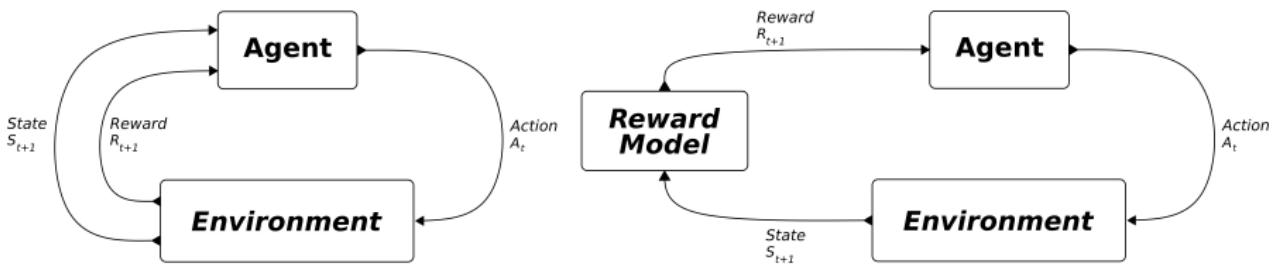
- NPCs with super-human abilities
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- **Solution:** Paolo can control the agent behavior \Rightarrow IRL

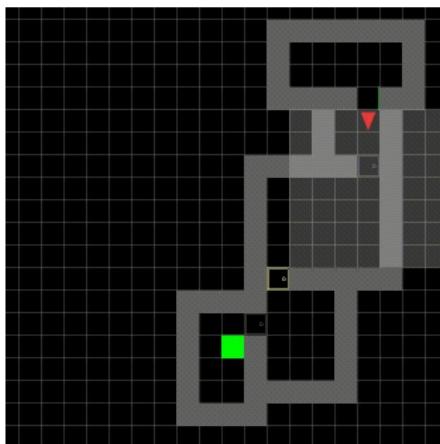
Reinforcement Learning vs Inverse Reinforcement Learning

- RL agent takes environments rewards
- The agent learns the behavior through *trial-and-error* mechanism
- IRL agent receives rewards from a Reward Model
- The user controls the agent behavior with preference feedback



IRL Benefits

- The user does not specify the Reward Function
- No sparse rewards
- Faster convergence to goal
- Human interaction



Proposed Method

Proposed method

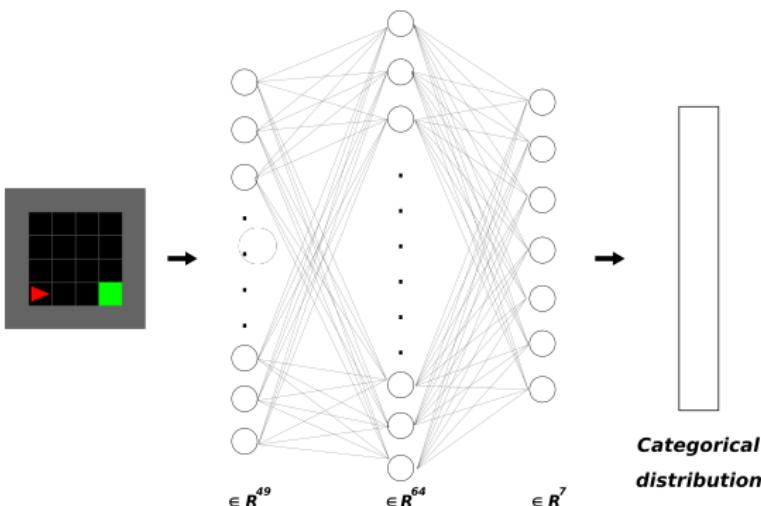
Algorithm 1 Training Protocol¹

- 1: Run the policy in the environment and store "initial trajectories".
 - 2: The annotator annotated all the "initial clips" and create the annotation buffer.
 - 3: Pretrain the reward model from the annotation buffer.
 - 4: **for** M epochs **do**
 - 5: Train the policy in the environment for N episodes with rewards from the reward model.
 - 6: Sample pairs of clips from the resulting trajectories.
 - 7: The annotator labels the selected pairs and puts them in the annotation buffer.
 - 8: Train the reward model for K batches from the annotation buffer.
 - 9: **end for**
-

¹Reward learning from human preferences and demonstrations in Atari, Ibarz et al.

Policy

- The policy receives the current agent state as input and probabilities of actions as output
- The next action is sampled from a Categorical distribution

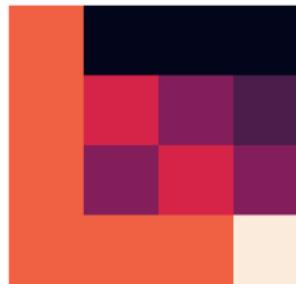


Annotator

- The annotator gives preference feedback about pairs of clips
 - (0,1) (1,0) preferred clips
 - (0.5,0.5) indifferent labels
 - (0,0) discarded clips

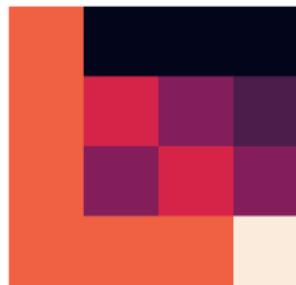
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- All the preferences are stored in the Annotation Buffer

Reward Model

- The Reward Model has to emulate the annotator labels
- It is trained to minimize the cross-entropy loss between predictions and labels

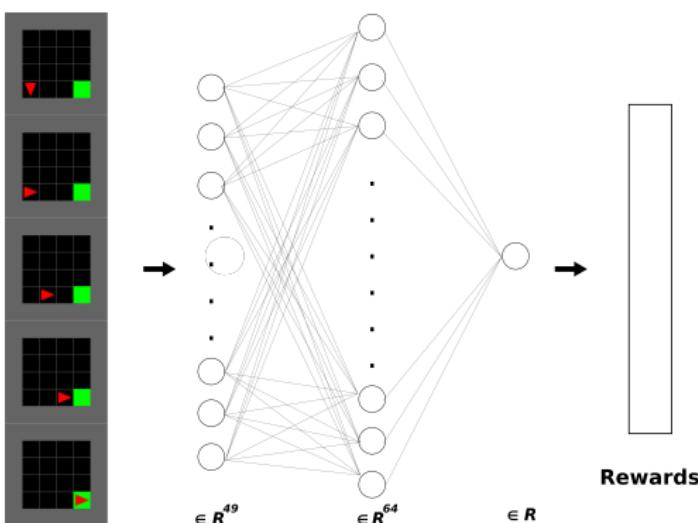
$$\text{loss}(\hat{r}) = - \sum_{(\sigma^1, \sigma^2, \mu) \in A} \mu(1) \log(\hat{P}[\sigma^1 \succ \sigma^2]) + \mu(2) \log(\hat{P}[\sigma^2 \succ \sigma^1])$$

- where

$$\hat{P}[\sigma^1 \succ \sigma^2] = \frac{\exp \sum_{o \in \sigma^1} \hat{r}(o)}{\exp \sum_{o \in \sigma^1} \hat{r}(o) + \exp \sum_{o \in \sigma^2} \hat{r}(o)}$$

Reward Model

- The Reward Model predicts a list of rewards from a clip



IRL Tool

Motivations

- The user is not a RL (or IRL) expert

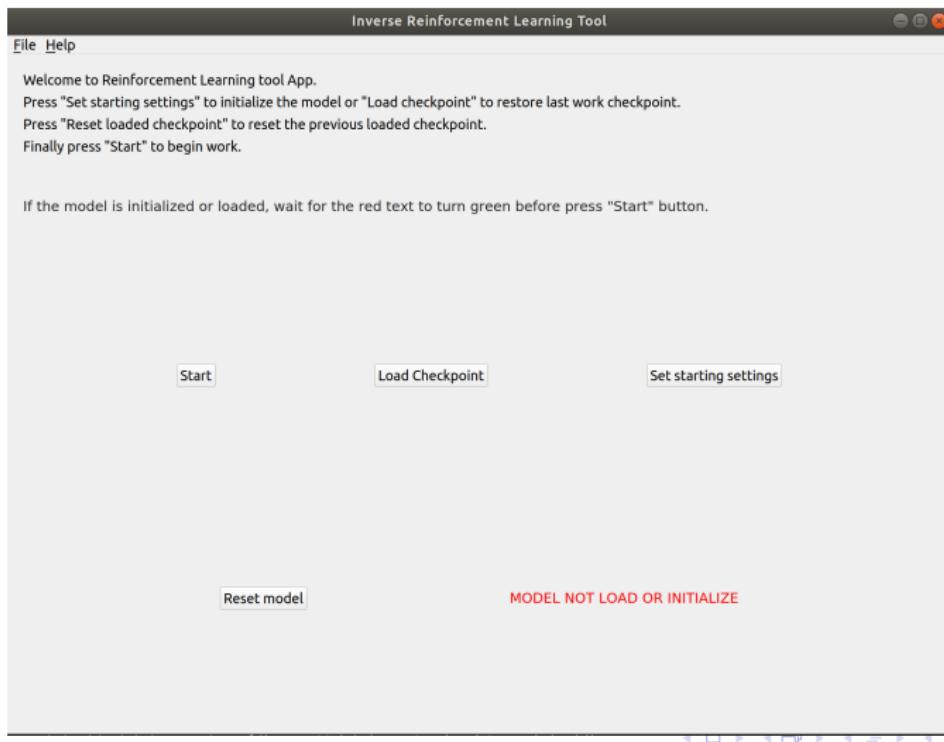


- Simplify the agent behavior understanding

- Better user experience



Set Up Window



Possible Scenario
ooooo

Proposed Method
ooooooo

IRL Tool
ooo●

Experimental Results
ooooo

Conclusions
ooo

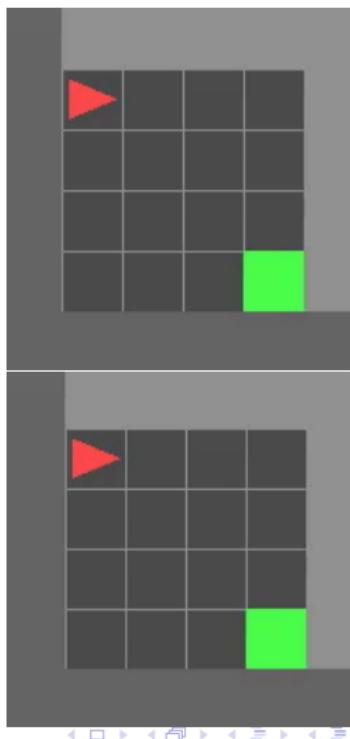
Training iteration



Experimental Results

MiniGrid Environment

- 6x6 Empty MiniGrid environment for experiments
- "Optimal" (maximize the discounted reward) trajectory achieved with RL
- Sub-optimal trajectory forced with IRL
- The user controls the agent behaviour



Tuning the components

- Policy

- the agent has to reach easily the environment goal \Rightarrow episode length 150
- no negative goal reward or big values range \Rightarrow standard deviation 0.5

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- sparse vs dense Oracle

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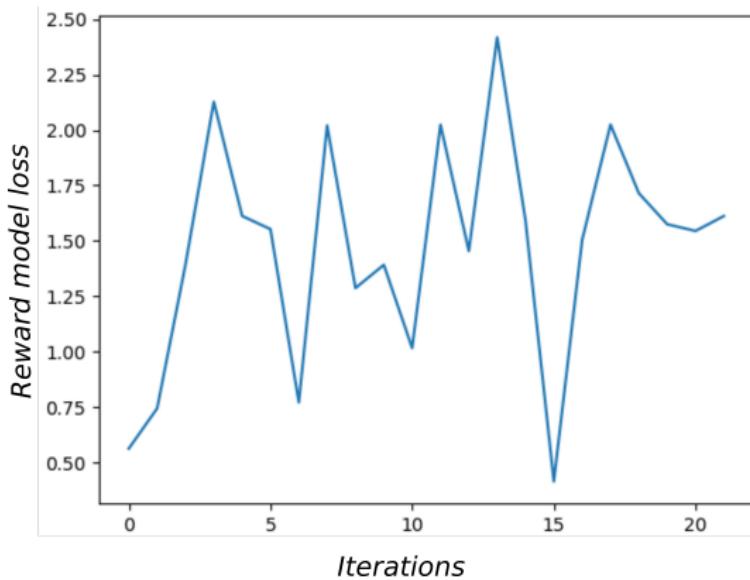
- sparse vs dense Oracle

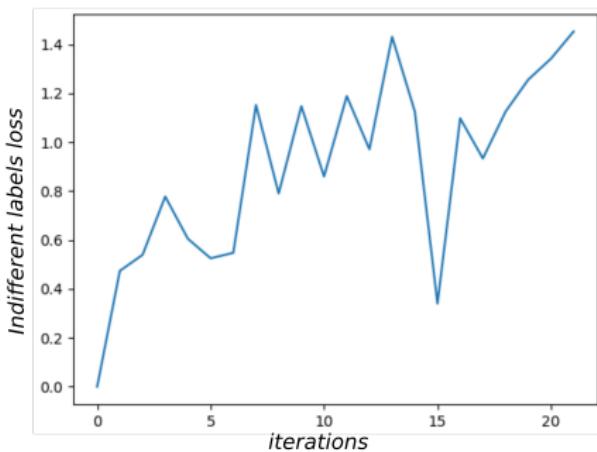
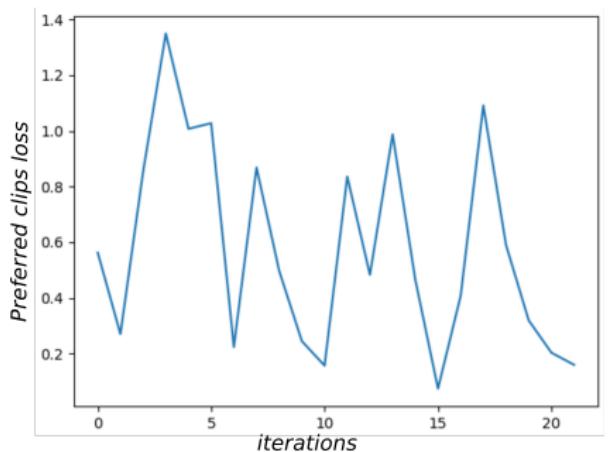
- Reward Model

- variable K batch vs constant K batch
- early stopping and decreasing annotations

Reward Model Loss

- The reward model loss grows during the training protocol.





- Small contribution to total loss
- Same range during all the training, decreasing trend

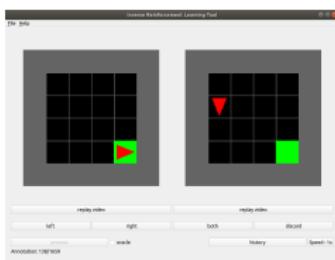
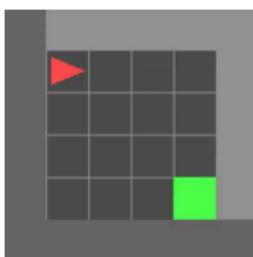
- Big contribution to total loss
- The number of those preferences makes the loss grow

$$\text{loss}(\hat{r}) = - \sum_{(\sigma^1, \sigma^2, \mu) \in A} \mu(1) \log(\hat{P}[\sigma^1 \succ \sigma^2]) + \mu(2) \log(\hat{P}[\sigma^2 \succ \sigma^1])$$

Conclusions

Conclusions and Future Works

- For now ...
 - The agent learns sub-optimal trajectory
 - A not-expert user can build IRL system
 - Reward model emulates the human behavior



- ...then
 - More complex environment to increase IRL benefits
 - Process environment images with agent states (with CNN and/or LSTM)

Thanks for the attention