Creating **A**rtificial **I**ntelligence from the World

Haeone Lee

How can we create “artificial” intelligence (AI) from the world?

Definition of Intelligence

Can we define intelligence?

“A very general mental capability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience” [1]
Mainstream Science on Intelligence

“a set of skills of problem solving” [2]

“To act purposefully, to think rationally, and to deal effectively with his environment” [3]

There are many different definitions & kinds

Can we define intelligence?

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Mainstream Science on Intelligence

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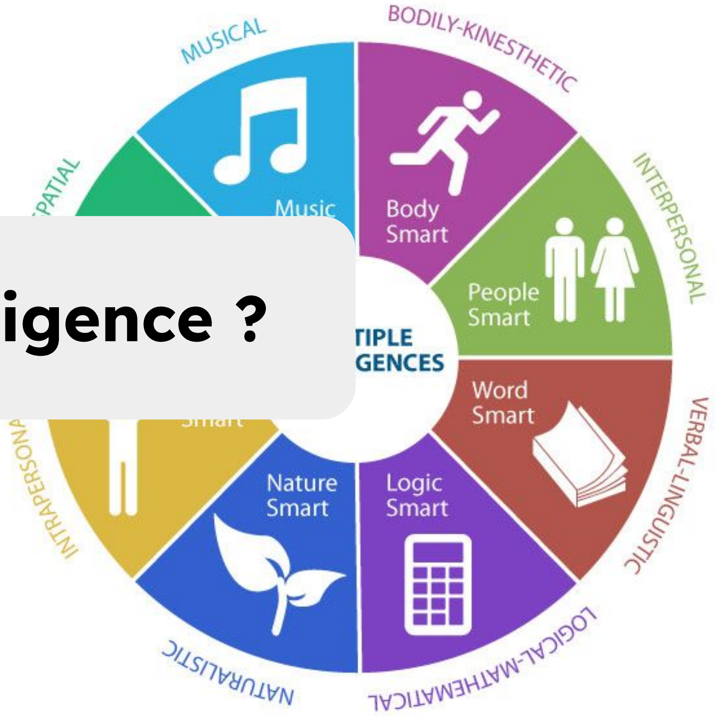
with his environment" [3]

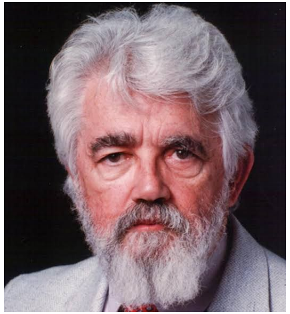
Why we need intelligence ?

There are many different definitions & kinds



Intelligence to achieve goals

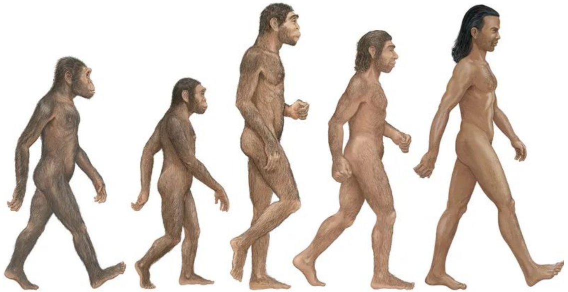
> "Intelligence is the computational part of the ability to achieve goals in the world" [4]
> John McCarthy



The goals are

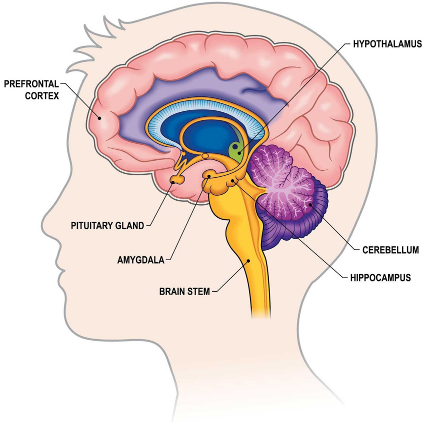
To win the game

To collect more food



To survive & breed

This leads to many complex capabilities!



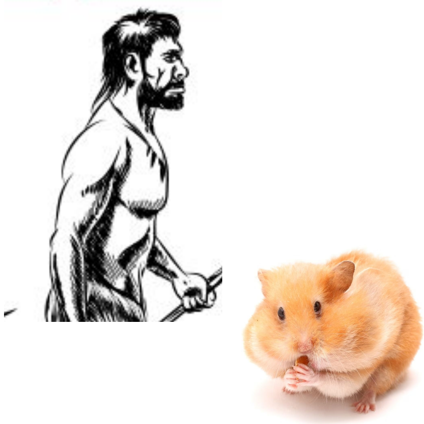
Human develops [5]

- **Perception** to identify objects (enemy vs colleague, edible vs inedible food, different tools)
- **Language** and **social** intelligence to manipulate other agents in a favored way
- **Physical** and **tool** intelligence to manipulate the world
- **Artistic** intelligence to attract the opponent sex

Key properties of intelligence

vs

More intelligent



- The more complex the world, the more complex intelligence is needed
- Physical (motor control) intelligence is very important in our world and should not be neglected
- More computational capacity leads to better intelligence [5]

Intelligence as **decision making**

- To achieve goals, good decision makings are necessary
- = Intelligence is to make good decision

  Examples: which word to say next, place to go, muscle to move

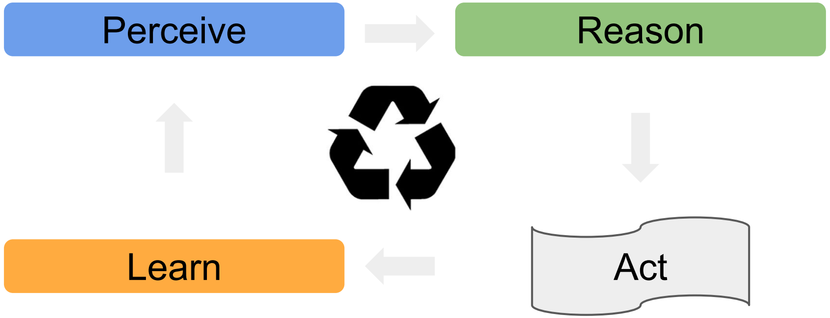
At the lowest level decisions

> "We have a brain for one reason and one reason only – and that's to produce adaptable and complex movements. Movement is the only way we have affecting the world around us" [6]
> Daniel Wolpert

Note: decisions are often hierarchical, high level involving low-level decision
E.g., place to go → way to get there → muscle to move,

Intelligence as **decision making**

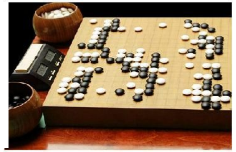
Decision making can be formulated as **Perception**, **Reasoning**, and **Learning**

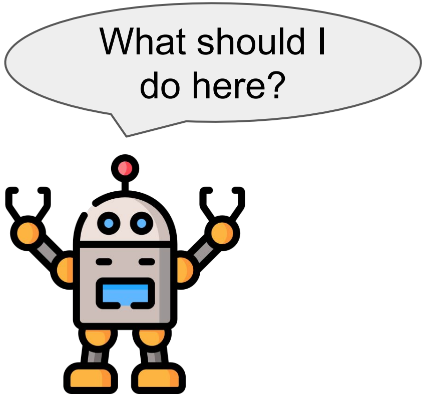


- **Perception:** process the information of the world in a favored way
- **Reason:** outputs the decision from the perception
- **Learn:** observe the outcome and correct the policy

My definition - perception, reasoning, and learning are the intelligence!

World as **decision making process**

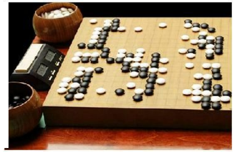


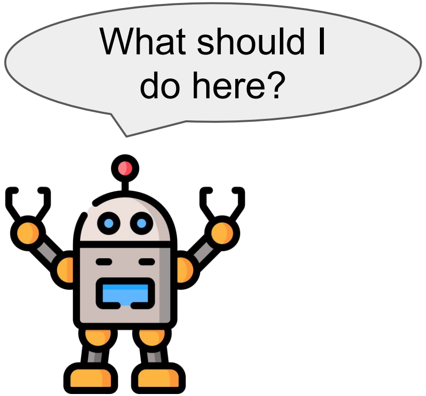


Worlds: real world, games, simulation, etc.

- Worlds can be modelled as **decision making process** given a specific goal
- Given the current state, AI outputs action and transitions into the next state

World as **POMDP**





Since all the components in the world cannot be observed at the same time, this becomes POMDP!

$$M = (S, A, T, \Omega, O, \mathcal{G}, p_0)$$ where

- $\mathcal{G}$ all the possible set of goals
- p_o initial state distribution
- Ω emission probability

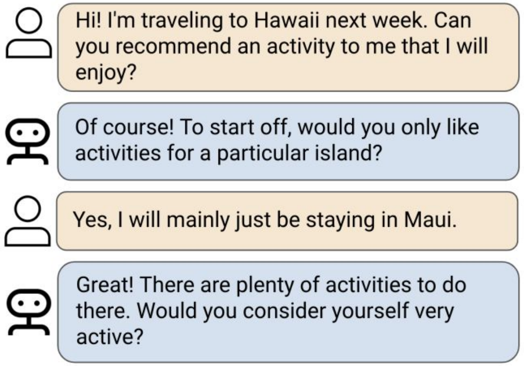
Intelligence in different worlds

- Beyond real worlds, we can define many different worlds and create intelligence out of it

Text world

defined by a set of tokens (words)

What we want:



POMDP

State: sentence

Action: next token

Next State: sentence + token

Goals to pursue

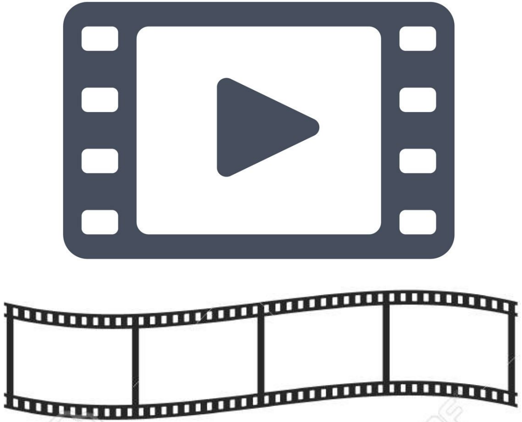
- Generate plausible text
- Answer the question
- Manipulate others (e.g. to buy the product)

Intelligence in different worlds

- Beyond real worlds, we can define many different worlds and create intelligence out of it

Video world

defined by a set of videos



POMDP

State: frame

Action: next frame

Next State: next frame

Goals to pursue

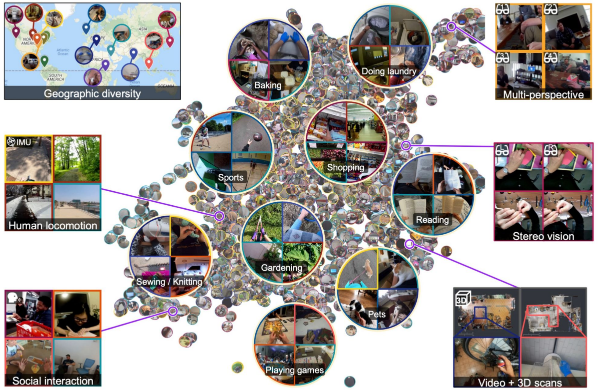
- E.g., to move to the specific frame
- To develop good perception

Intelligence in different worlds

- Beyond real worlds, we can define many different worlds and create intelligence out of it

Dataset world

defined by a set of data



POMDP

State: data

Action: label or next data

Next State: next data

Goals to pursue

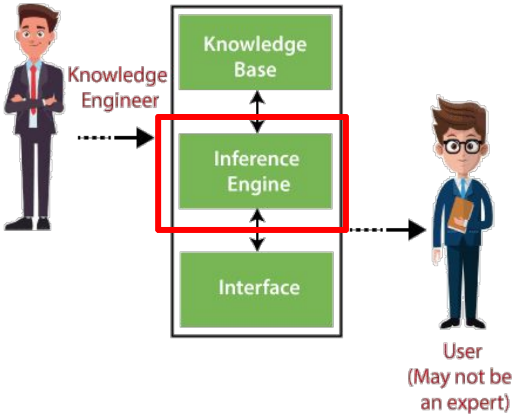
- To output correct label
- To develop good perception

Trials of creating intelligence

Engineering approach

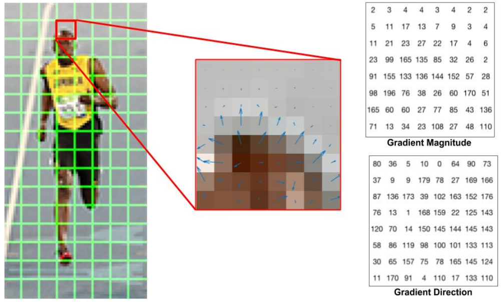
Decision making procedure is manually designed by human. E.g.,

1) knowledge-based system (reasoning) [7]
2) feature engineering (perception) [8]



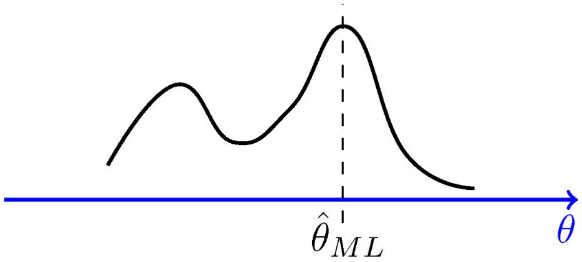
Shortcomings

- Large manual effort required
- Injects human inductive bias which could be wrong or not generalizable
- Hard to scale at complicated problems



Data-modelling approach

Can we automatically extract decision-making rule from the dataset?



$$\tau = (o_0, a_0, o_1, a_1, \dots) \sim M(\pi_g)$$

$\pi_g(a \mid s)$ **Policy** that pursues a specific goal g (e.g., human correctly labeling the data)

- Modelling the resulting data distribution can develop the intelligence for achieving goal g

Reasoning	**Perception**	**Learning**
$P(A \mid S)$	$P(S), P(\boldsymbol{\tau})$...	$P(\boldsymbol{\tau})$

Data-modelling approach

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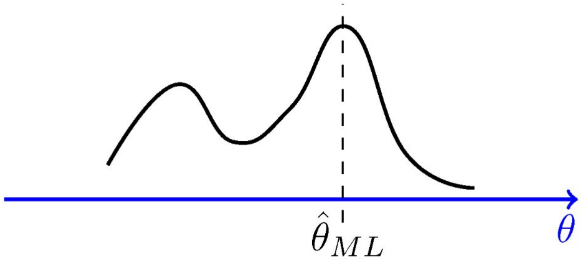

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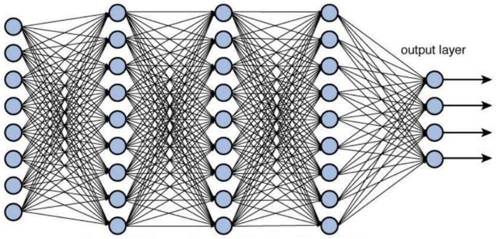
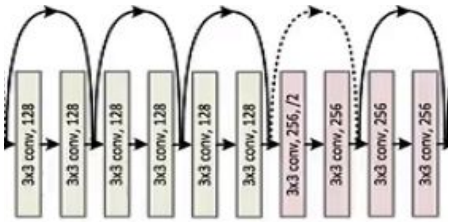
$\pi_g(a \mid s)$ **Policy** that pursues a specific goal g (e.g., human correctly labeling the data)

- Modelling the resulting data distribution can develop the intelligence for achieving goal g
- DNN can be used for a model due to its
  a. exellect generalization capability
  b. good capacity



Data-modelling approach: Reasoning



ResNet[9]

World: dataset world (ImageNet)
Policy: human to label the data correctly

Robotic transformer[10, 11, 12]

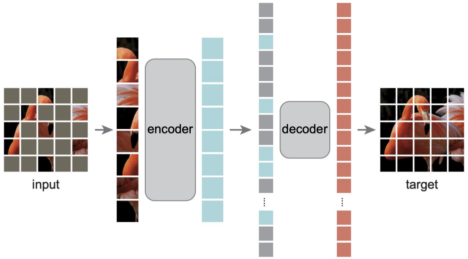
World: real world with robot
Policy: human manipulating robot to achieve the given task

- Outputs the decision given the state
- Perception is trained end-to-end by neural network
- Includes traditional supervised-learning & behavior cloning

$$p(A \mid S)$$

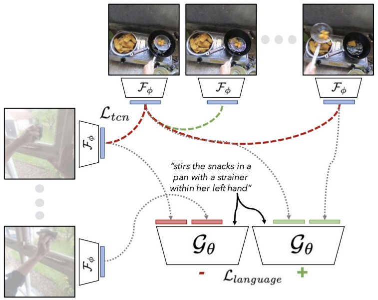
Reasoning

Data-modelling approach: Perception



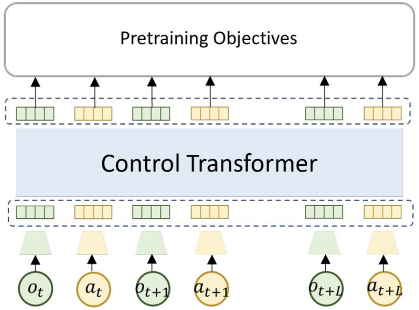
MAE[13]

Reconstruct the image from the masked image



R3M[14]

TCL in video world with text alignment



PASTA[15]

Next token prediction in low-level action trajectory

- Ground the reasoning by providing good expression of the state
- Includes unsupervised learning & representation learning

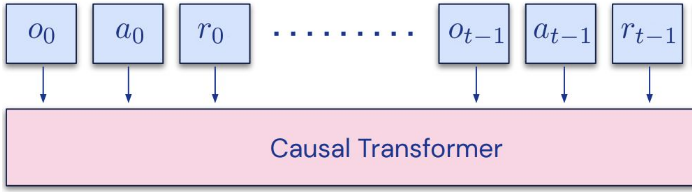
$$P(S),\ P(S' \mid S),\ P(\tau)$$

Perception

General: Trajectory modeling

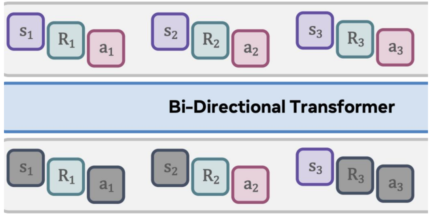
GPT 1~3[16]

NTP from the text generated by human policy



Algorithm distillation[17]

Models improving trajectory by RL policy with different goals



MTM[18]

Predict tokens that are masked in trajectory

- Can function all the perception, reasoning, and learning
- Learning can be implemented by modelling improving trajectories

$$p(\tau)$$

Trajectory modelling

Is data modelling enough?

GPT-3

showed success

- Data collection is **burdensome** → internet scraping
- Generalizability is limited to the **dataset support** → use large amount of data
- Still, the performance to the goal is upper-bounded by the dataset
- Cannot adapt to the changes in the world
    - e.g., covariate shift, label shift

Reasoning	**Perception**	**Learning**
$P(A \mid S)$	$P(S)$, $P(\boldsymbol{\tau})$...	$P(\boldsymbol{\tau})$

What’s the way to go?

All of what we mean by **goals and purposes** can be well thought of as **maximization** of the expected value of the cumulative sum of a **received scalar signal** [19]
Richard Sutton

Intelligence, and all of its associated abilities, can be understood as subserving the maximization of reward [5]
David Silver et al.

What's the way to go?

- Can we convert our goal to the reward?
- Can we directly optimize such reward and observe the resulting intelligence?

REINFORCEMENT LEARNING

> All of what we mean by goals and purposes can be well thought of as maximization of the expected value of the cumulative sum of a received scalar signal
> Richard Sutton [5, 19]

$$\eta(\pi) = \mathbb{E}_{s_0, a_0, \ldots}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t)\right]$$

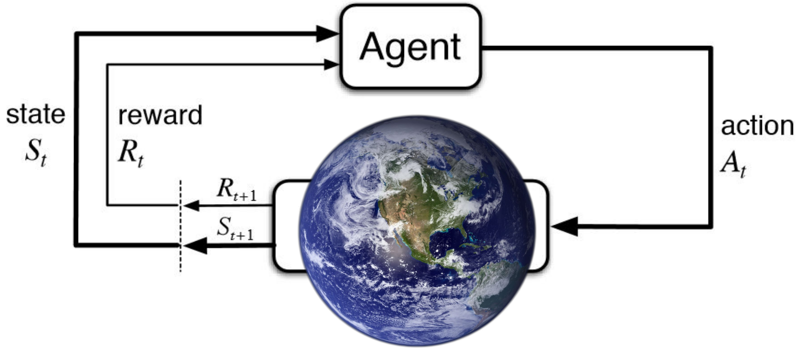
Reward is enough

David Silver*, Satinder Singh, Doina Precup, Richard S. Sutton

Reinforcement learning

Good

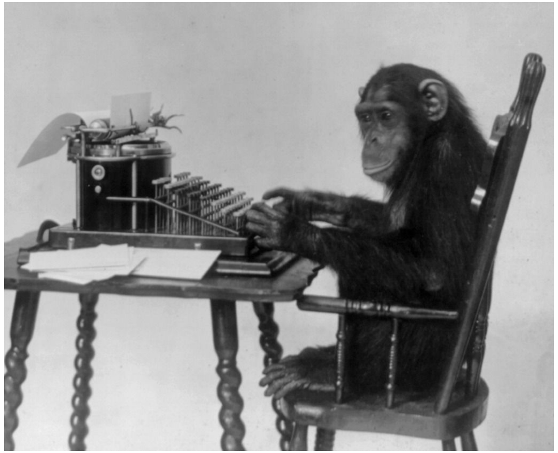
- Might lead to **superhuman** intelligence
- Learning can be done **autonomously** given only the reward
- Can **adapt** to the changing world by interaction and is trained life-long
- **Analogous** to human learning by reinforcement in psychology

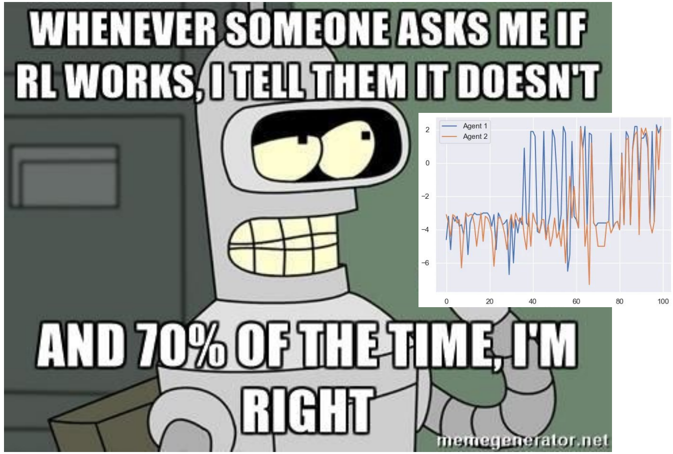


Challenges

But..

- How can the agent explore the world well to find good decisions – because there are so many options (“monkey typing hamlet” problem)
- RL has instability and low sample efficiency issue



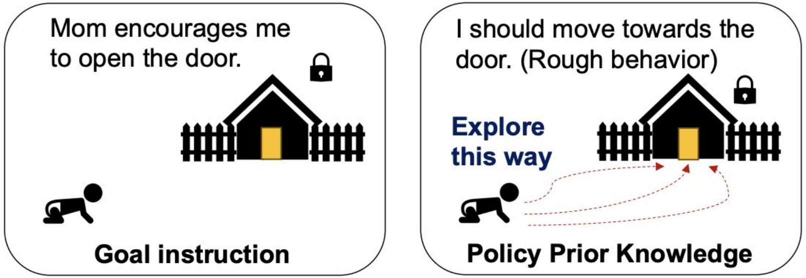


Using prior knowledge

How can the agent explore the world well to find good options

- NOTE: still, good options are very few!
- Prior knowledge can guide agent to the good options

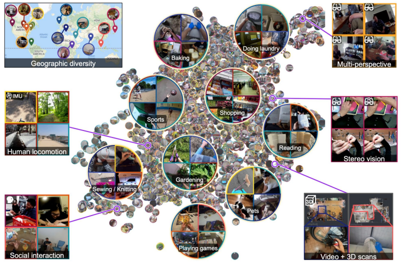
Baby deer instinctively know that it has to run away

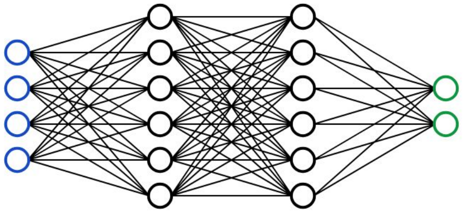


Baby moves to door when instructed ‘open the door’ not going to other direction

Using prior knowledge

Examples





ChatGPT

PaLM-E
562B

Static dataset
- Action trajectory
- Video
- Image
- Text

Pretrained model
- Policy
- Value
- Trajectory model
- Perception

Large common sense model
- LLM
- VLM

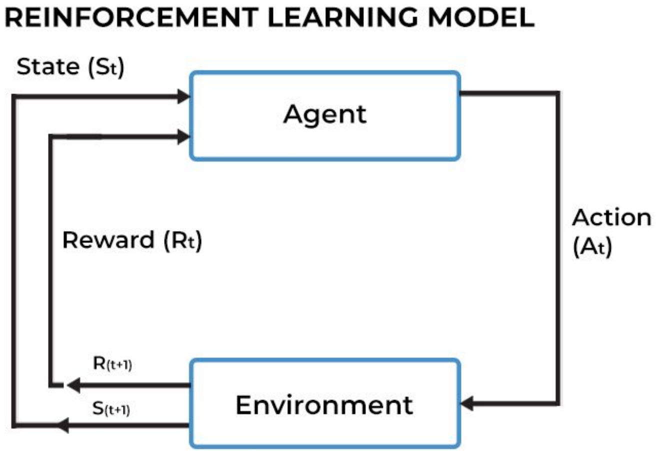
There are so many kinds. What's the best way to utilize those ?

Applications of prior knowledge in RL

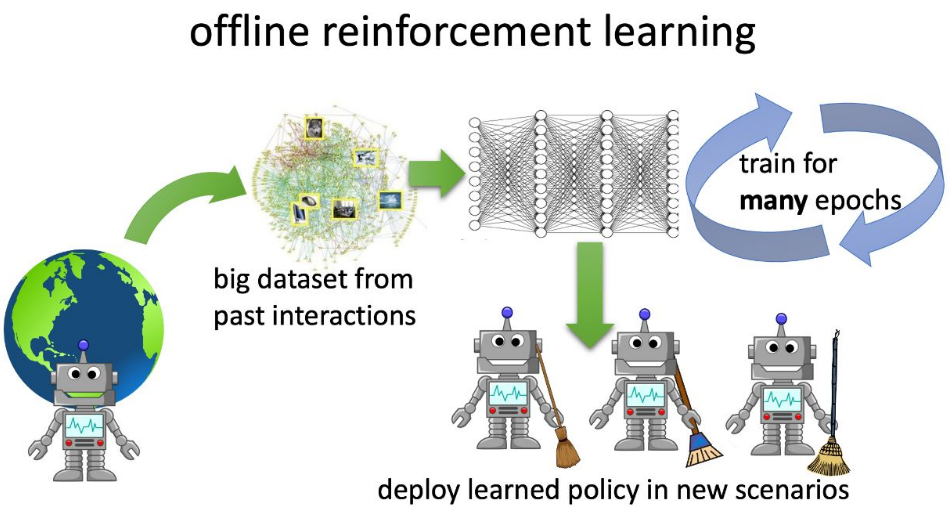
Policy prior - what is generally useful to do here
Value/Reward prior - how generally good my behavior is
Dynamics - how the world works
Perception - how to process the information

Reward and dynamics are normally given in RL

- Still, prior knowledge can be required to design the reward function
- Dynamics might be used for model-based RL



Using static prior: offline RL



= Data-driven optimization

- Algorithms are designed to be conservative outside of the support [20]

$$\arg\min_{Q} - \mathbb{E}_{\mathbf{s}\sim\mathcal{D},\mathbf{a}\sim\hat{\pi}_{\beta}(\mathbf{a}|\mathbf{s})}\left[Q(\mathbf{s},\mathbf{a})\right] + \frac{1}{2}\,\mathbb{E}_{\mathbf{s},\mathbf{a},\mathbf{s}'\sim\mathcal{D}}\left[\left(Q(\mathbf{s},\mathbf{a}) - \hat{\mathcal{B}}^{\pi}\hat{Q}^{k}(\mathbf{s},\mathbf{a})\right)^{2}\right]$$

- Since data is limited, learned model (Q, policy) might be inaccurate outside of dataset support

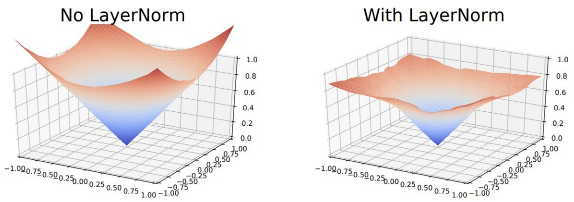
RL hits different now

RL has instability and low sample efficiency issue

→ Algorithm has got a lot better nowadays. This may not be an issue anymore

use Q-functions = recycle old data via replay buffer

Algorithms: SAC (but also TD3, REDQ, DroQ, all good...)



- Techniques such as layernorm, clipped Q learning, and ensemble greatly improves stability
- Sample efficiency is improved by employing priors and using off-policy RL with high replay ratio [21, 22]

Example of intelligences by RL

Text world: maximize human preference

Policy goal: to generate the text that human prefers
Policy prior: (supervised) LLM
Value prior: reward → since it is initialized by reward function
Reward prior: LLM → since reward uses llm for initialization

$$\mathcal{L}_R(r, \mathcal{D}) = -\mathbb{E}_{(x, y_w, y_l) \sim \mathcal{D}} \left[\log \sigma(r(x, y_w) - r(x, y_l)) \right]$$

Reward objective (preference)

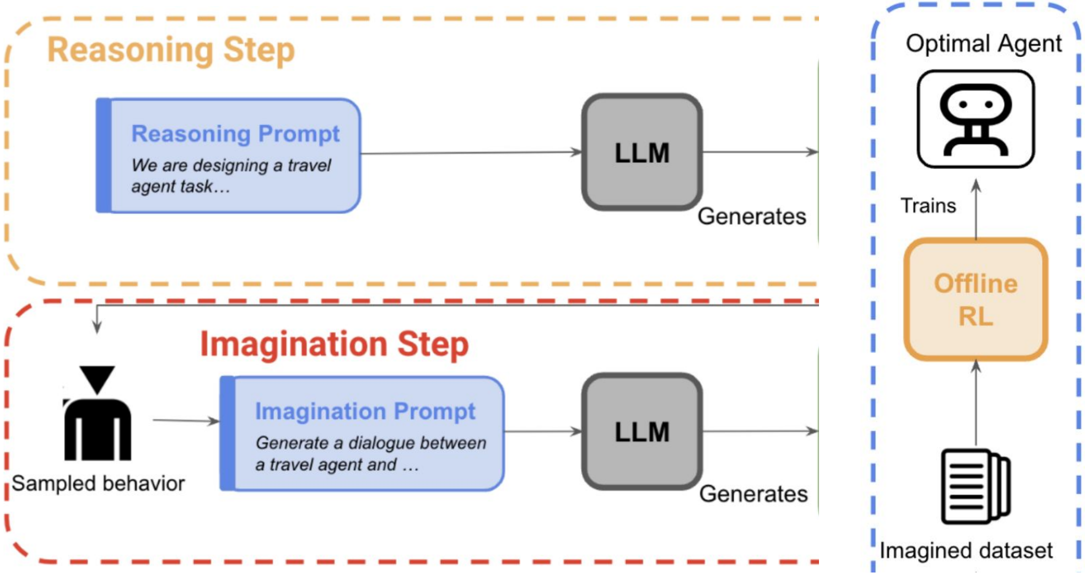
$$\max_{\pi_\theta} \mathbb{E}_{x \sim \mathcal{D}, y \sim \pi_\theta(y|x)} \left[r_\phi(x, y) \right] - \beta \mathbb{D}_{\text{KL}} \left[\pi_\theta(y|x) || \pi_{\text{ref}}(y|x) \right]$$

Policy objective

- Train a reward model by human preference on policy samples (or use existing critique models)
- Optimize the reward by RL with conservatism to prevent over-optimization

Training language models to follow instructions with human feedback [23] & Rlaif: Scaling reinforcement learning from human feedback with ai feedback [24]

Text world: achieve the goal in conversation



Policy Goal: to achieve intended conversation outcome
Policy prior: LLM
Value prior: -
Reward prior: -
Dynamics prior: LLM

- Generate the successful and failed dialogue given the specific conversation outcome
- Use success/failure as a reward and optimize by offline RL(IQL) from the data

Zero-shot goal-directed dialogue via rl on imagined conversations [25]

Video world: learn good perception

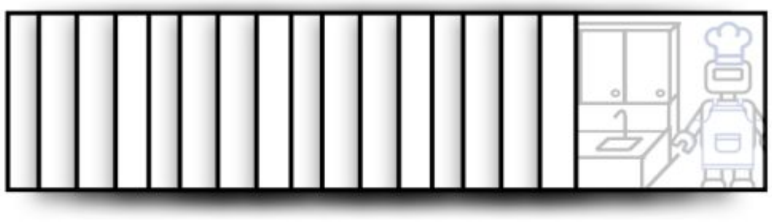
- Train the value function with the goal of reaching the specific frame
- Use the representation of value function in the downstream tasks (value learning, policy learning, etc.)

$$V(\phi(o); \phi(g))$$

probability of reaching g by optimal goal-reaching policy from o

$$V_\theta(s, s_+, z) = \phi(s)^\top T(z) \psi(s_+)$$

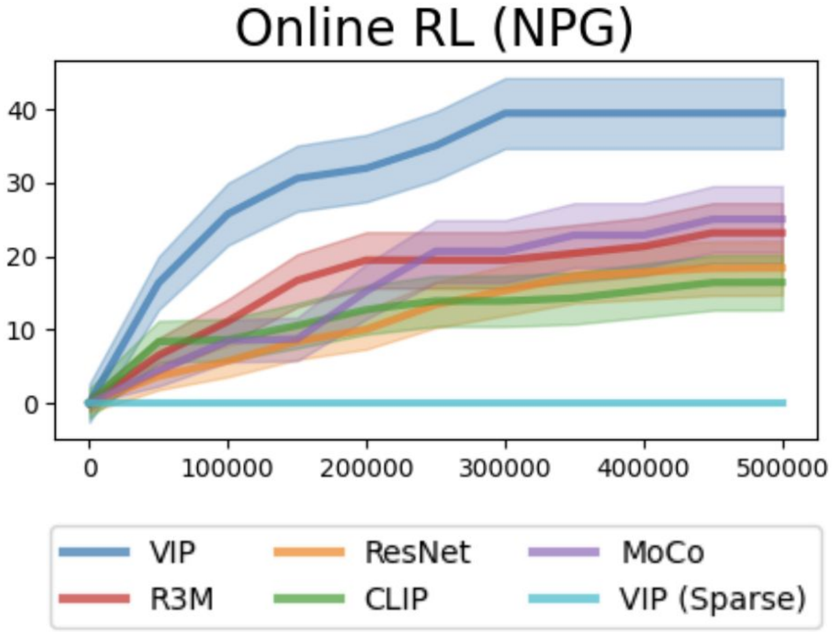
probability of reaching s+ while acting according to z

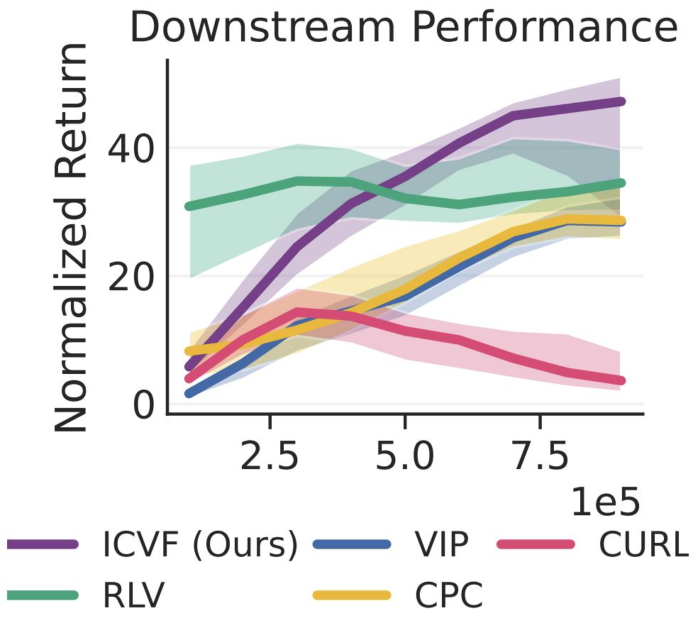


Policy goal: to achieve the given goal frame
Policy prior: static dataset
Value prior: -
Reward prior: -

Vip: Towards universal visual reward and representation via value-implicit pre-training [26] & Reinforcement learning from passive data via latent intentions [27]

Video world: learn good perception





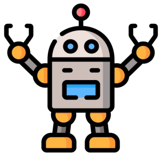
- Representation of learned by RL (value function) shows superb performance compared to the ones by dataset modelling

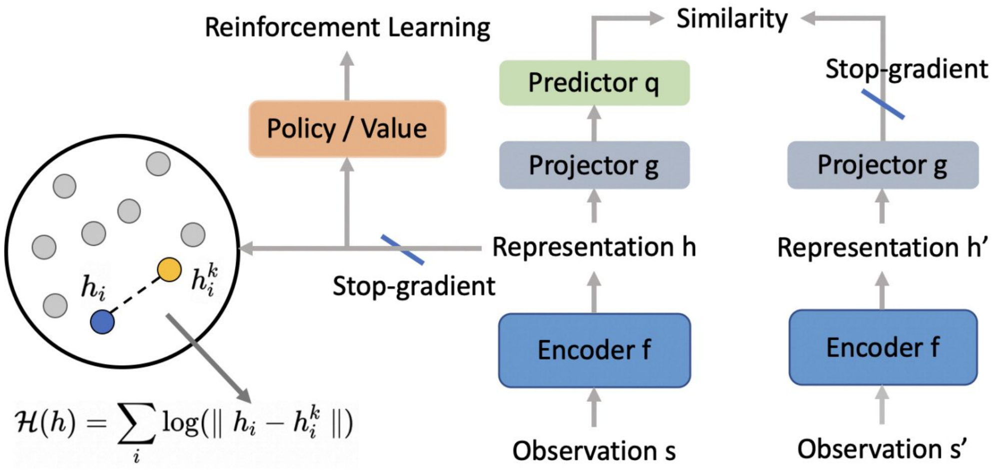
Vip: Towards universal visual reward and representation via value-implicit pre-training [26] & Reinforcement learning from passive data via latent intentions [27]

Image world: learn good perception

- Generate the diverse images by exploring the latent of generative models
- Apply contrastive learning for the images
- Such diversity of data leads to robust representation learning

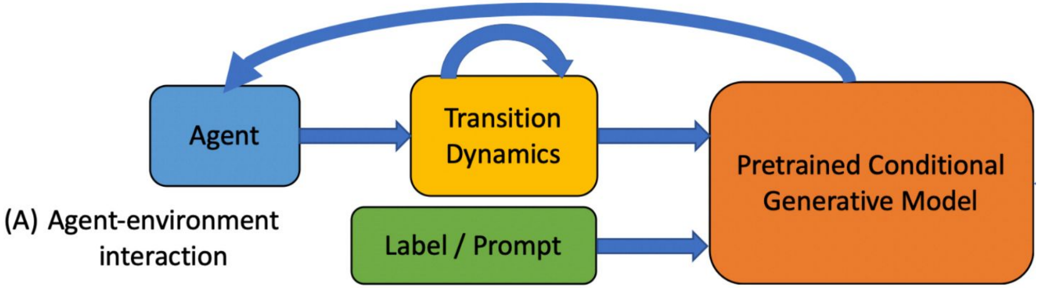
Policy goal: to maximize state entropy of the state
Policy prior: -
Value prior: -
Reward prior: -

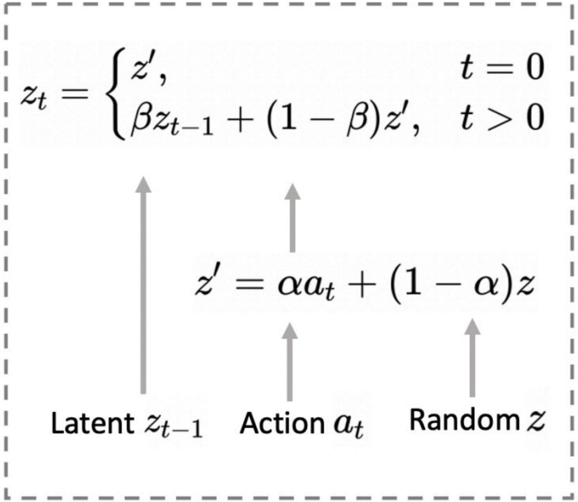




Palm up: Playing in the Latent Manifold for Unsupervised Pretraining [28]

Image world: learn good perception





Building image world

- First, learn the smooth latent for the dataset by generative modelling (StyleGAN)
- Define the action as delta direction on the latent space
- Transition dynamics is the interpolation between action and current latent

Palm up: Playing in the Latent Manifold for Unsupervised Pretraining [28]

Real world: achieve the instructed task

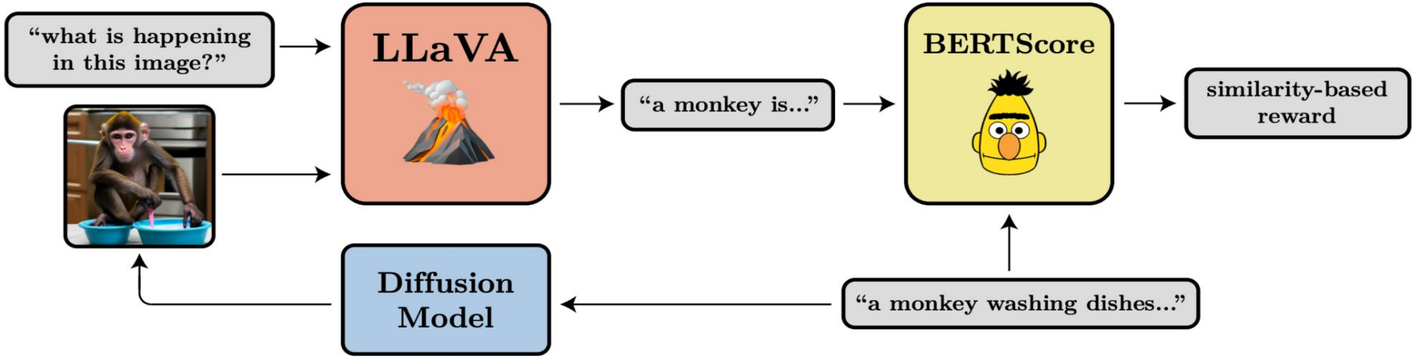
- Apply offline RL in robotic trajectories
  a. autonomously collected data including failures
  b. expert demos
- RL on mixed quality dataset is better than BC on expert data only

Task category	Q-T	DT	IQL	RT-1
drawer pick and place	64%	49%	11 %	17%
open and close drawer	33%	11%	11%	0%
move object near target	71%	40%	60%	58%
Average success rate	**56%**	33%	27%	25%

Policy goal: to complete the instructed task
Policy prior: static dataset
Value prior: -
Reward prior: -

Q-transformer: Scalable offline reinforcement learning via autoregressive q-functions [29]

Pixel world: generate instructed image

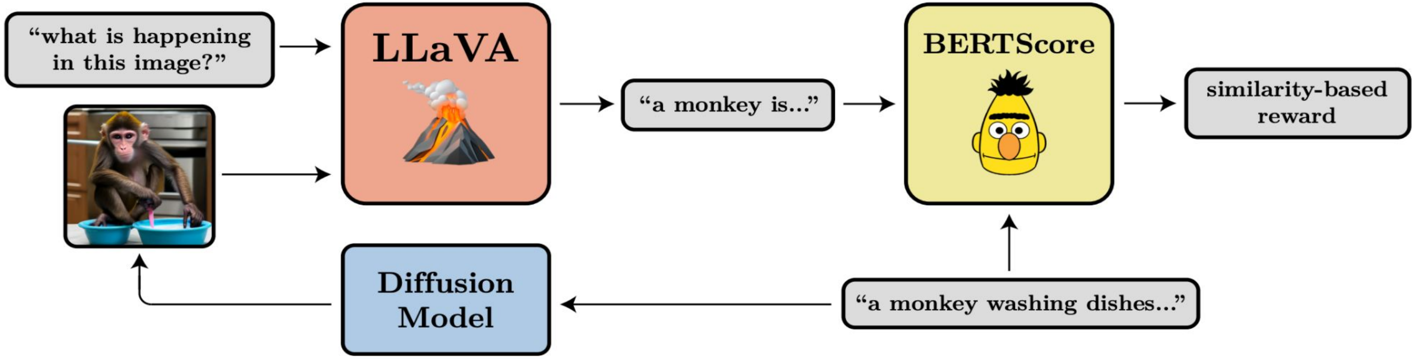


Policy goal: to output image satisfying the conditions
Policy prior: diffusion model
Value prior: -
Reward prior: vlm

- Models the diffusion step as decision making in MDP
- Use the off-the-shelf reward model
- Objective: compressibility, aesthetic quality, prompt alignment

Training diffusion models with reinforcement learning [30]

Pixel world: generate instructed image



$$R(\mathbf{s}_t, \mathbf{a}_t) \triangleq \begin{cases} r(\mathbf{x}_0, \mathbf{c}) & \text{if } t = 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\pi(\mathbf{a}_t \mid \mathbf{s}_t) \triangleq p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t, \mathbf{c})$$

$$\rho_0(\mathbf{s}_0) \triangleq \left(p(\mathbf{c}), \delta_T, \mathcal{N}(\mathbf{0}, \mathbf{I})\right)$$

- Policy is modelled by one-step denoising
- Initial state is normal dist w/ sampled condition
- Trained by REINFORCE or PPO

Training diffusion models with reinforcement learning [30]

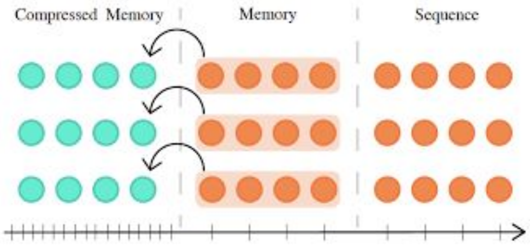
Things to do

Things left to be done

Many important capabilities are lacking in current methods

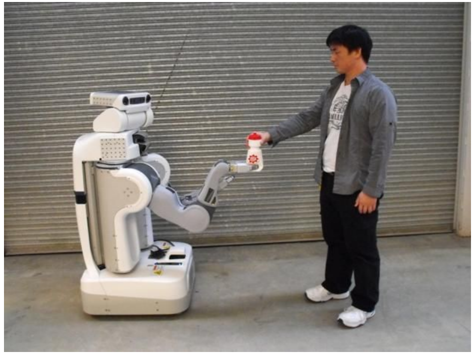
Memory

- Memory is necessary in many worlds due to **partial observability**
- Still, most methods use memoryless policies



Long-horizon

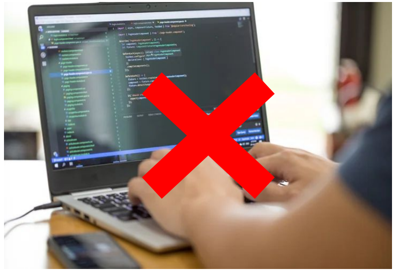
- Discount factor might limit the horizon of policy by multiplication
- Bellman **bootstrapping** might be unstable at very long-horizon



Things left to be done

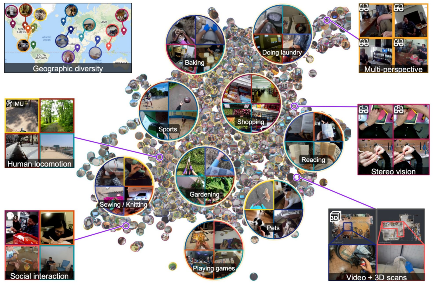
Autonomous training & deployment

- Many works assume **episodic resets** during training and deployment



Inductive bias

- Lots of works employ human inductive bias such as **reward engineering**
- This could limit the generalizability and capacity of the models



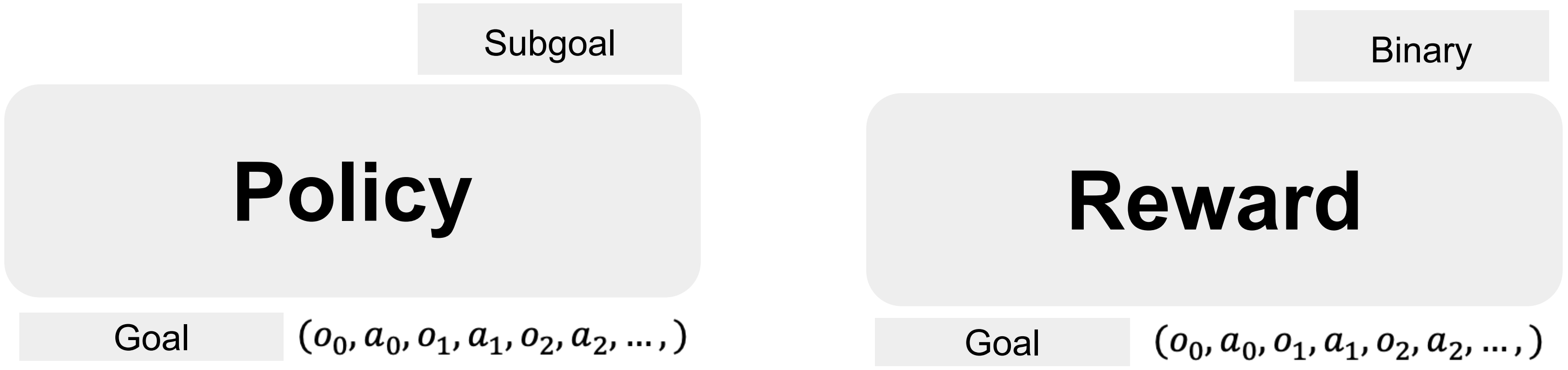
Use of all the prior knowledge

- Most works use limited amount of prior knowledge

Proposed structure

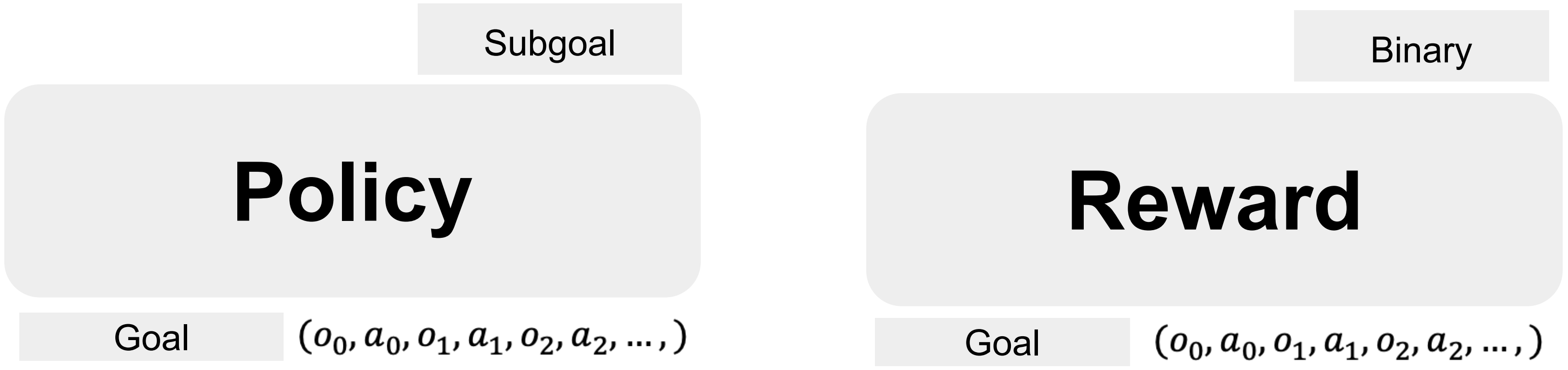
Abstraction helps

- We can abstract low-level actions into higher-level subgoals
- This helps to plan in long-horizon by turning multiple actions into the single subgoal
- Similarly, abstracted states can help efficient memorizing in long-term



Proposed structure

- Policy: given goal and **historical** input, outputs subgoal
- Reward: given goal, outputs the probability that the goal is **achieved**
- Policy can form hierarchy by recursively querying subgoals
- Using recursive memory architectures (e.g., RMT, MAMBA[31, 32]) practically enables infinite context



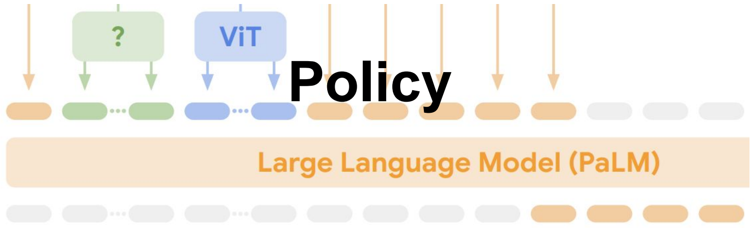
Using pretrained models for policy & reward

Policy

- Use common sense model.
- Use models trained by dataset modelling (e.g., goal-conditioned BC)
- Action: subgoals in different abstraction levels

Reward

- Common sense model
- Alignment model (e.g., CLIP) between goal and trajectory



Policy: Given (state), what is the subgoal for AI do to achieve (goal)?

Reward: Given (goal), does (trajectory) achieve it?

Common sense model prompting

Training policy from static data

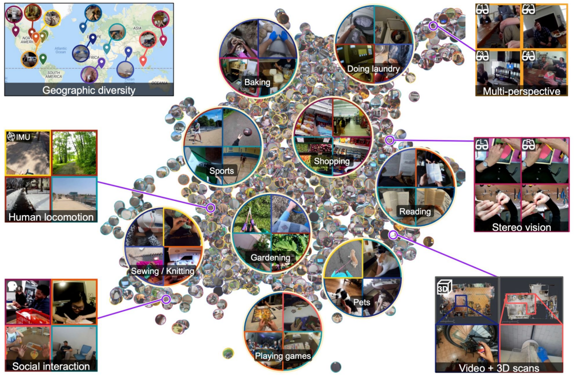
Use offline goal-conditioned RL to the trajectory dataset (k-steps long subgoal)

$$Q^*(s_t, g, goal) \leftarrow R(s_t, g, goal) + \gamma \max_{\hat{g}(g)} Q^*(s_{t+k}, \hat{g}, goal)$$

$$\mathbb{E}_{\tilde{a}_t \sim p_{\tilde{A}}} \left[P^\pi(s_T \neq g | s_t, \tilde{a}_t) \right] = 1$$

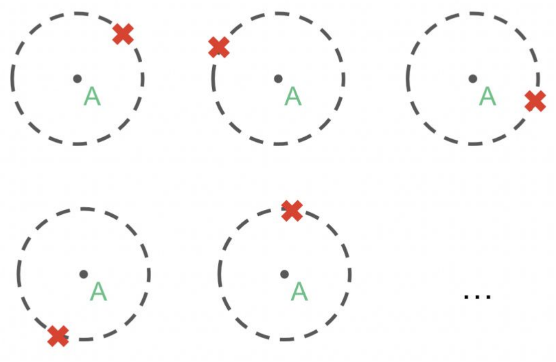
Apply conservatism for unseen actions and goals[33]

- Policy and reward function can be initialized by pre-trained models
- Goals and subgoals are randomly sampled from trajectory
- In addition, trajectory can be labelled by the reward function



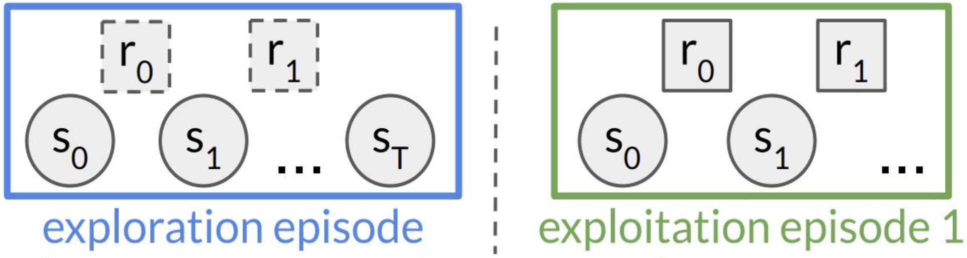
Meta reinforcement learning of policy

- Policy can **meta-learned** by training from diverse environments
- This is equivalent to learning **bayes adaptive optimal policy** from the distribution of environments
- It will provide the optimal exploration and exploitation strategy [34]



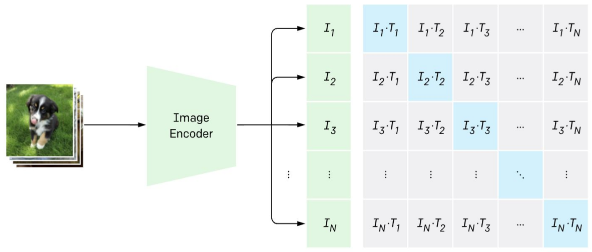
Training in many worlds (different way of opening doors)

E.g., open the door by pulling (fails) → memorize such information → try pushing



Training reward

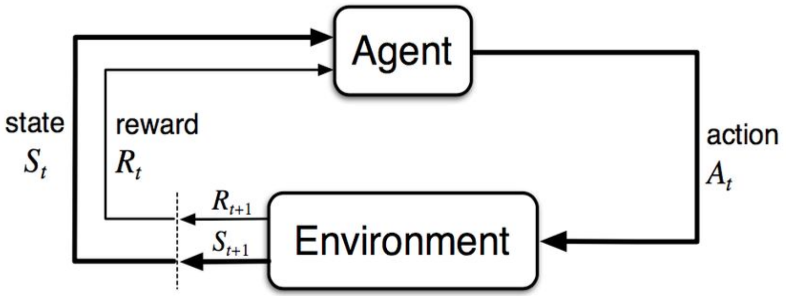
- **Fine-tune** pretrained models by contrastive learning (CLIP) or instruction-tuning method using (trajectory, goal) paired datasets
- Reward function can also be trained from the **online** data, which is challenging since it is unlabeled
- One could use label bootstrapping[35] technique, similar to SSL

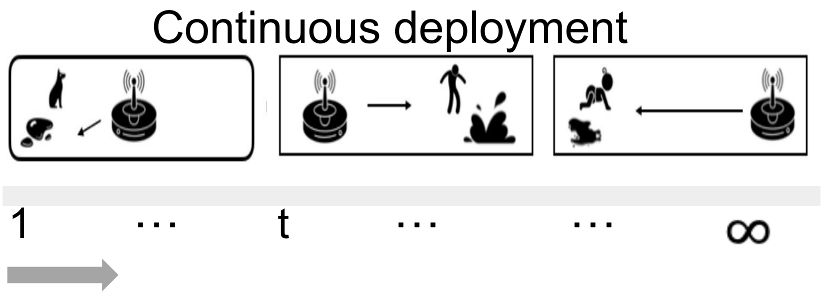


Similarity between (goal) and (trajectory)

Online bootstrapping

Online reinforcement learning

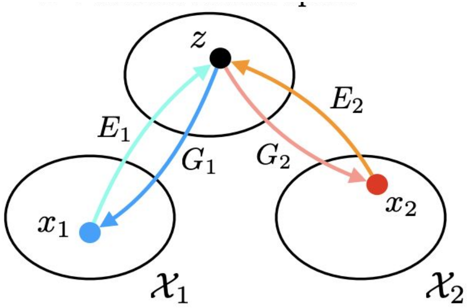




- We run online RL to the target environment with policy and reward initialized by priors
- Reward can be given by the reward function for the goals pursued by the policy + hindsight re-labelling
- Efficient exploration is enabled by priors and meta-learning by memory
- **Human instruction** can be included in the state and followed by agent

Use all the prior knowledge

- How to leverage text data to help robotic learning?
- Information transfer between different data is needed



Assume two trajectories (A) and (B) and policy learned there as <A>, <B>

Hierarchical transfer: subgoals from <B> can be followed by <A> or vice-versa

Policy transfer: (B) / <B> can be a policy prior for <A>

Perception transfer: training in (B) can provide a perception prior for <A>

Semantic transfer: training generalizes between data that has the same semantics

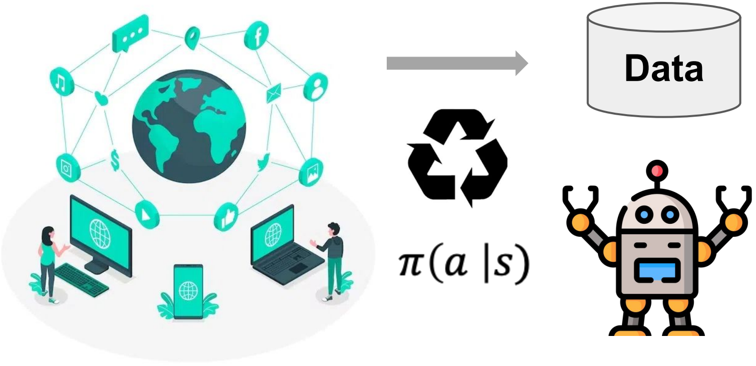
Ex) information transfer to learn robotic policy

Training / Type	**Perception**	**Policy**	**Hierarchical**
RL	ICVF(v), VIP(v)	Cal-QL(a)[36]	-
SL / USL	MAE(i), R3M(v)	Demo-guided RL (a)[37]	SayCan(t)[38]

(i), (v), (a), and (t) denotes image, video, low-level action, and text dataset, the origin of information.

- Semantic transfer can be employed in addition (e.g., two trajectories are policy transferable after changing modality by semantic transfer)
- E.g., pixel goal generalizes to the text goal[39]

Automatic data collection

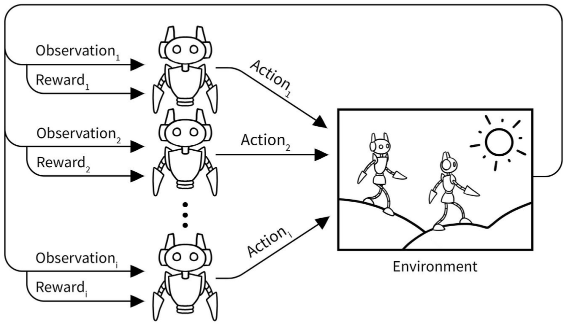


Shortcomings of using static data

- Limited amount and diversity
- Not adaptive to the **changing** world
- Not **consider** to model's performance

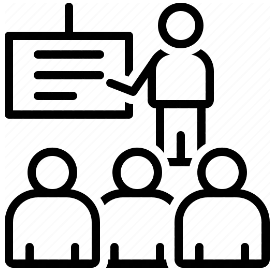
- Quality data is important to train reward function
- We propose to use **dataset collection policy** in arbitrary world (e.g., Internet)
- This can be trained by RL to maximize **information gain**
- Heuristic objective such as model uncertainty about data could be employed (cf. similar RL exploration objective[40, 41])

Social: multi-agent RL

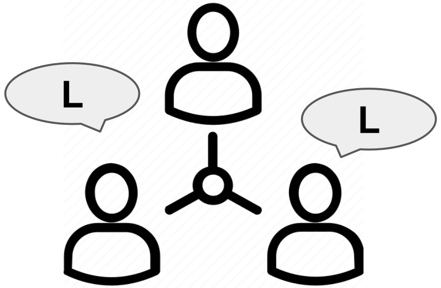


Multi-agent RL

emerges



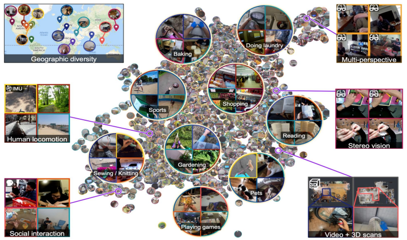
imitation: to mimic others' better performance



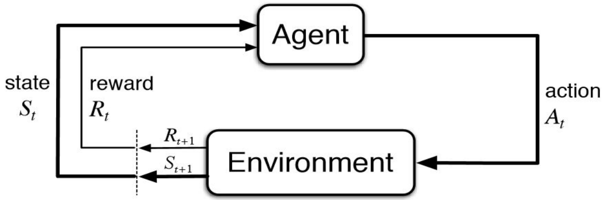
language: to cooperate to achieve the goal

- Multiple intelligences can interact to each other in deployment,
- This makes the world more complicated, promoting the emergence of more complex intelligence
- Language and imitation behavior is expected to emerge[5, 42]

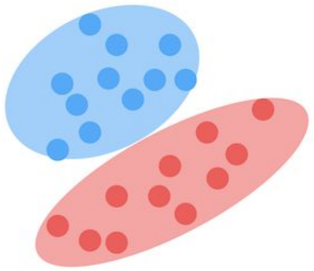
Summary



Static data



Offline goal-conditioned RL

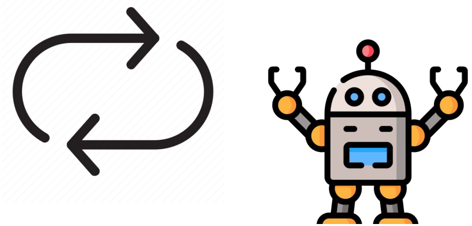


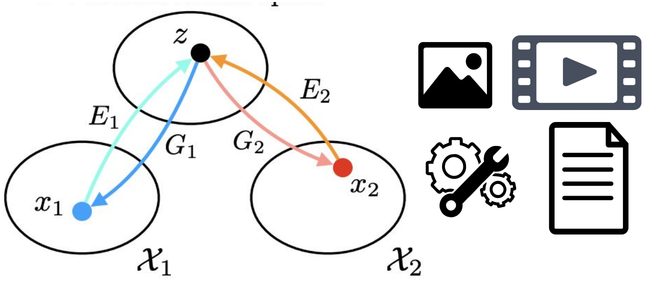
Dataset modelling

+

World

(S, A, T, Ω, O)



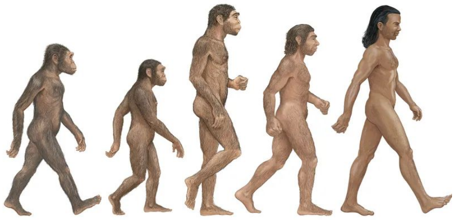


Dataset world

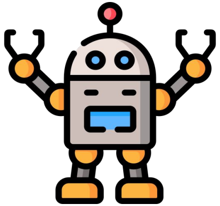
Online reinforcement learning

information transfer
to leverage different datasets

Toward 'helpful' intelligence



VS



What should be the highest level of goal for AI?

To survive

?

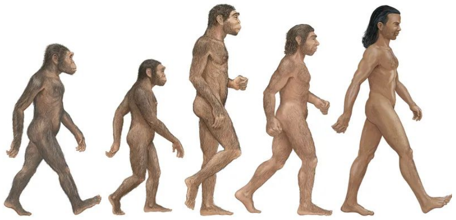
The intelligence should be helpful for human

Many capabilities of AI are **subset** of "being helpful"

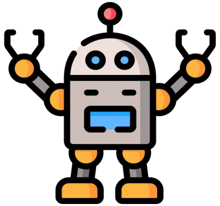
- AI plays the game well to entertain human
- answers the questions to assist human
- explores the world to gain knowledge for doing future tasks

Just like many capabilities of human is for survival

My target: AGI in real world



vs



To survive

To be helpful for human

(AGI def.) “An intelligence that **maximizes** its **helpfulness** objective in a world which has an **infinite** number of **tasks** that are sufficiently **different** and identified as **productive** by humans. ”

- We can use our **framework** to maximize “helpfulness”
- My **ultimate goal** is creating such AGI, especially in the real world.

Projects

My roadmap

Improving goal-conditioned RL

- Hierarchical policy
- Long-horizon
- Stitching
- Conservatism

Offline goal-driven reinforcement learning in video, text

- Reward function bootstrapping
- Efficient memory by RL
- Information transfer
- Adapting different memory architectures

Real world robotics

- Active training by RL (data collection)
- Autonomous practice & adaptation
- Multi-modality (sensor)
- Explainability

Multi-agent RL

- Language & imitation emergence

AGI in real world

- Apply all the methods

Improving algorithm: learning hierarchical policy

Q function can be interpreted as probability of achieving (goal) by (action)

$$P(s_T = g | s_t, a_t) = Q^*(s_t, a_t, g)$$

(prob to achieve goal) = (prob to achieve subgoal) x (prob to achieve goal by subgoal)

$$Q^*(s_t, g^1, goal) \leftarrow (\max_g Q^*(s_t, g, g^1)) \{R(s_t, g^1, goal) + \gamma \max_{\hat{g}(g^1)} Q^*(s_{t+k}, \hat{g}, goal)\}$$

- This end-to-end learns the Q function with hierarchy where the high-level subgoals are grounded to the low-level
- g(g') denotes the set of subgoals that has the horizon length of g'

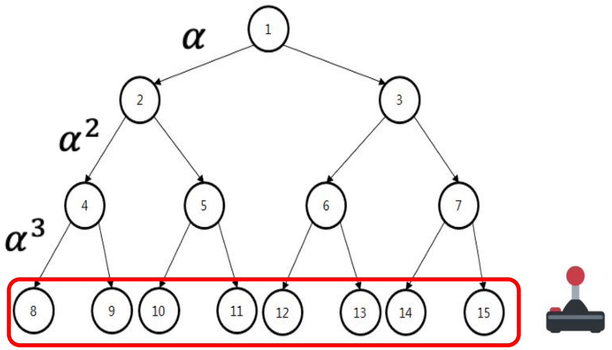
Improving algorithm: learning hierarchical policy

- Policy should output the low-level action at the end
- To prevent excessive number of querying subgoals, we discount each query by multiplying alpha

$$Q^*(s_t, g^1, goal) \leftarrow \alpha(\max_{g} Q^*(s_t, g, g^1)) \{R(s_t, g^1, goal) + \gamma \max_{\hat{g}(g^1)} Q^*(s_{t+k}, \hat{g}, goal)\}$$

$$\begin{cases} \max_{g} Q_H^*(s_t, g, g^1) = 1 \\ \alpha = 1 \end{cases} \quad if\ g^1 = \text{lowest level}$$

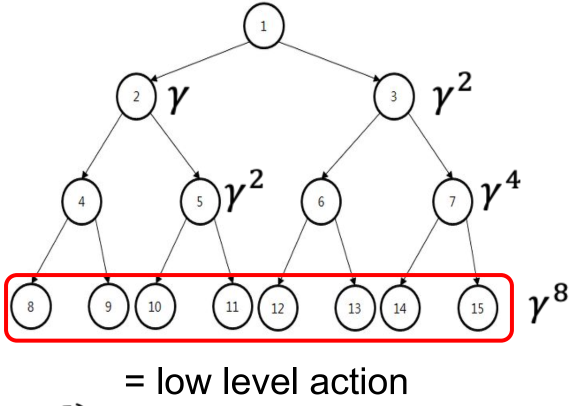
Best possible refinement steps may also be limited to n



= low level action

Improving algorithm: dealing with long-horizon

- Discounting factor limits the possible horizon of policy. Ex) (0.99)^500 = 0.007
- To address this, we can multiply a single gamma after the subgoal completion



$$Q^*(s_t, g, goal) \leftarrow R(s_t, g, goal) + \gamma \max_{\hat{g}(g)} Q^*(s_{t+k}, \hat{g}, goal)$$

- Grounding is done by (prob to achieve goal) = (prob to achieve subgoal) x (prob to achieve goal by subgoal)

I.e. $$Q_H^*(s_t, g^1, goal) \leftarrow \alpha \max_{g} Q_H^*(s_t, g, g^1)\, Q^*(s_t, g^1, goal)$$

Offline RL in video

- Learning in video data is promising
  - since large amount of data can be leveraged this way
- Downstream policy(e.g., robot) can utilize the video policy by information transfers
  - **H**: follow the next frame as a subgoal
  - **S**: From consequent frames, extract action by inverse dynamics
  - **P**: Use video policy representation

YouTube

State: frame

Action: next frame

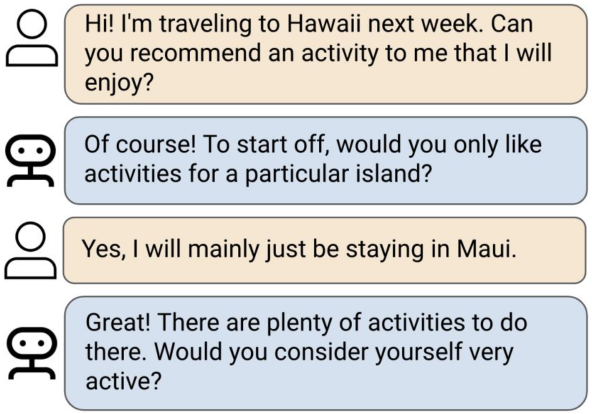
Next State: next frame

$$a = I(s, s')$$

Policy prior: video prediction model

Offline RL in text

- offline RL can be employed in the text domain
  → in contrast to data modelling approach (LLM)
- Goal and actions might be randomly sampled from the bunch of text
- Semantic transfer is crucial for good abstraction



LLM can aid the training by the role of
(1) Dynamics (e.g., to generate dialogue)
(2) Reward
(3) Policy prior

$$\tau_1 = (\underbrace{\boxed{o_0, a_0, o_1, a_1}}_{\text{State}}, o_2, a_2, \underbrace{\boxed{o_3, a_3, o_4, a_4}}_{\text{Action}}, o_5, a_5, o_6, a_6, \underbrace{\boxed{o_7, a_7, o_8, a_8}}_{\text{Goal}}, \ldots,)$$

The list of papers that were referenced in the slide:

https://docs.google.com/document/d/1H72ztZhrEOff1NOJICSPO1T3S_PyVVCbvBCeH_g9Qxg/edit?usp=sharing