PPO×Family

第五讲：探索时序建模

主办 中国计算机学会 CCF

承办 上海人工智能实验室 Shanghai Artificial Intelligence Laboratory

协办 GAIAA 北京大学人工智能研究院 浙江大学 上海高等研究院 SHANGHAI INSTITUTE FOR ADVANCED STUDY ZHEJIANG UNIVERSITY 商汤 sensetime

支持 知乎 机器之心 智源 新一代人工智能研究平台 paperweekly

向真实的决策问题前进（时序建模）

长期记忆

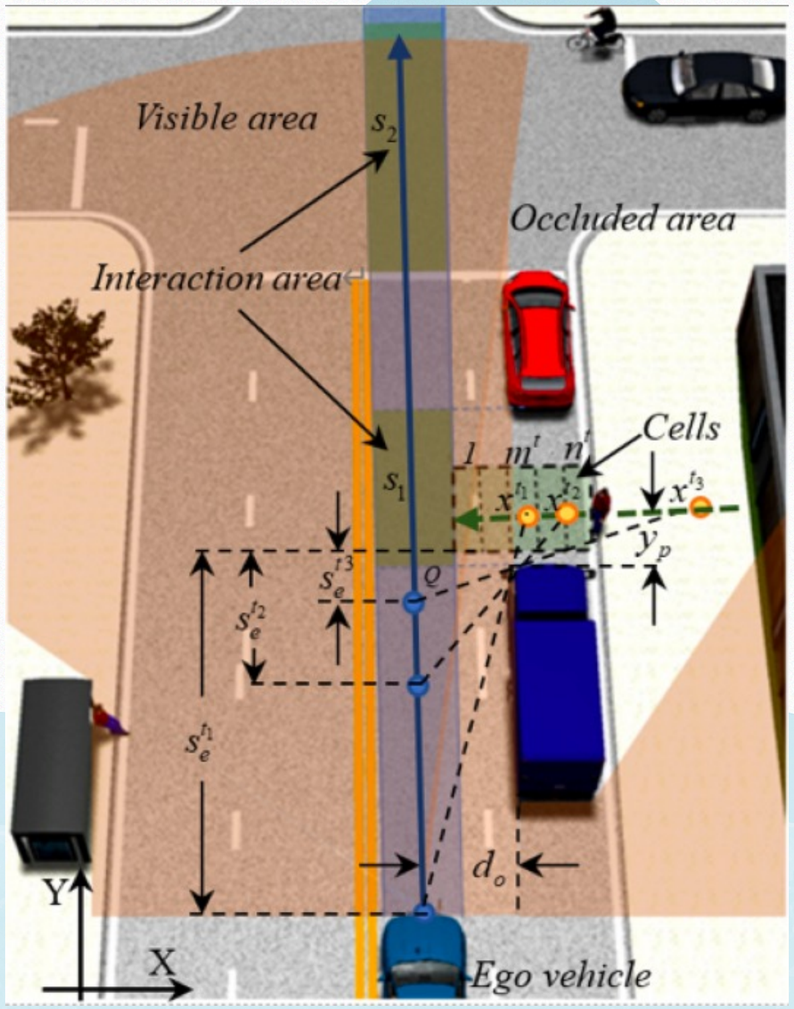
（资源收集，科技发展）

短期记忆

（战场侦查，技能衔接）

多智能体协作

（部队阵型，兵种配合）

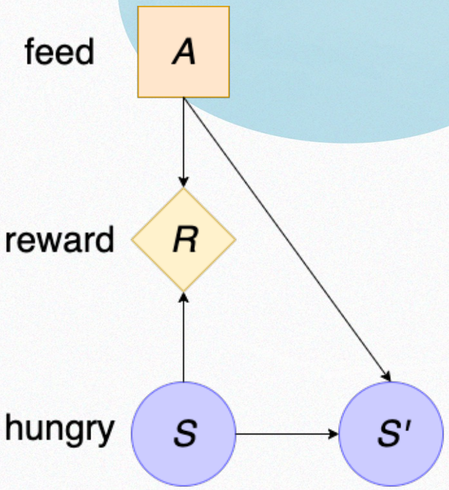


POMDP Overview

部分可观测马尔可夫决策概述

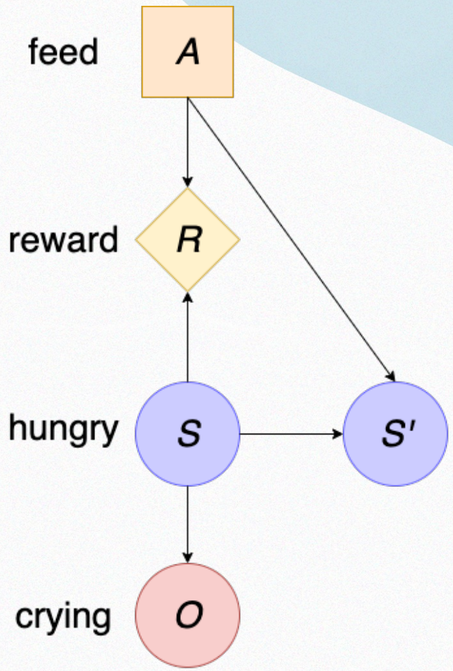
Ref: https://www.nature.com/articles/s41598-022-08810-z

标准 MDP 的缺陷



time *t* time *t+1*

标准 MDP

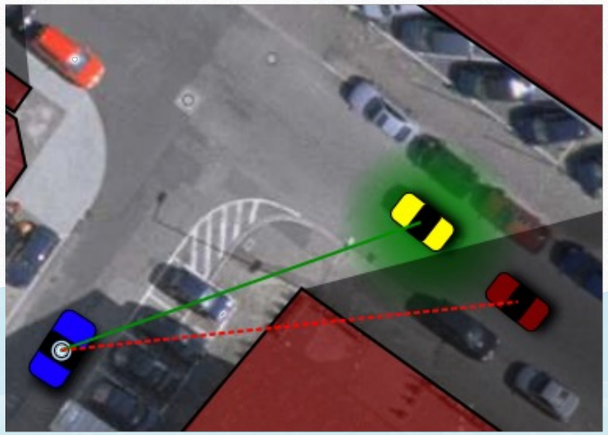


time *t* time *t+1*

部分可观测 MDP

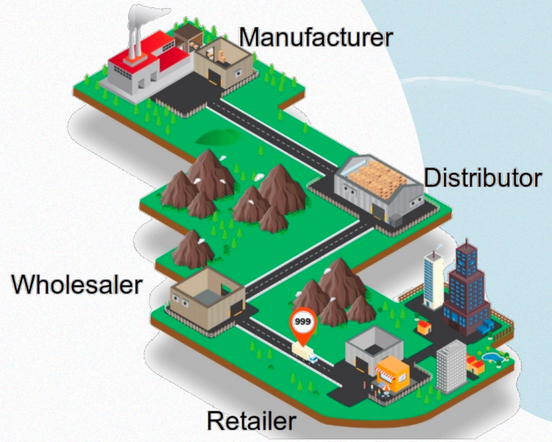
POMDP 无处不在

自动驾驶



机器人控制

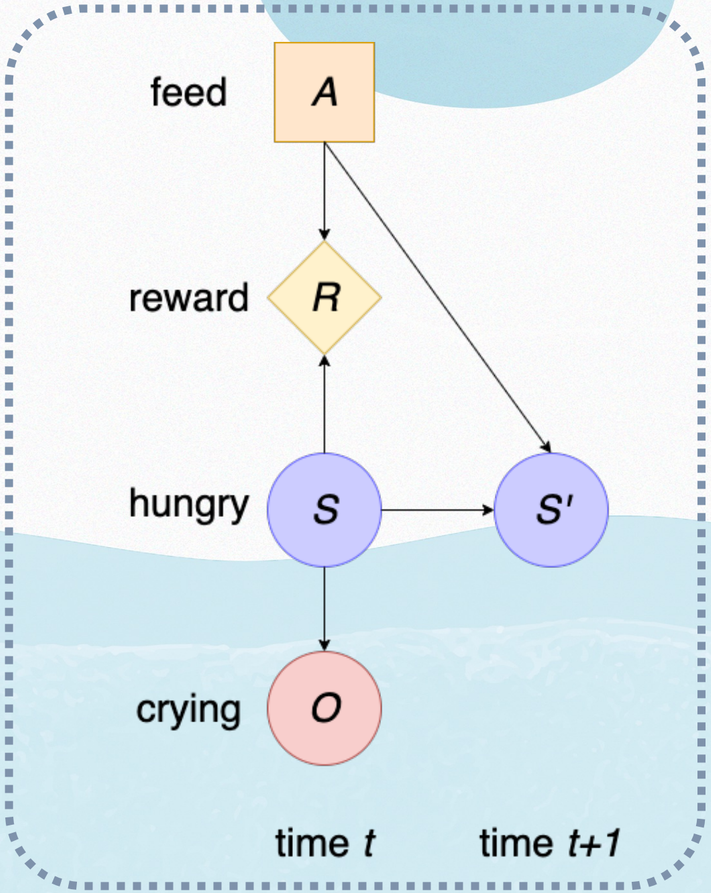
供应链优化

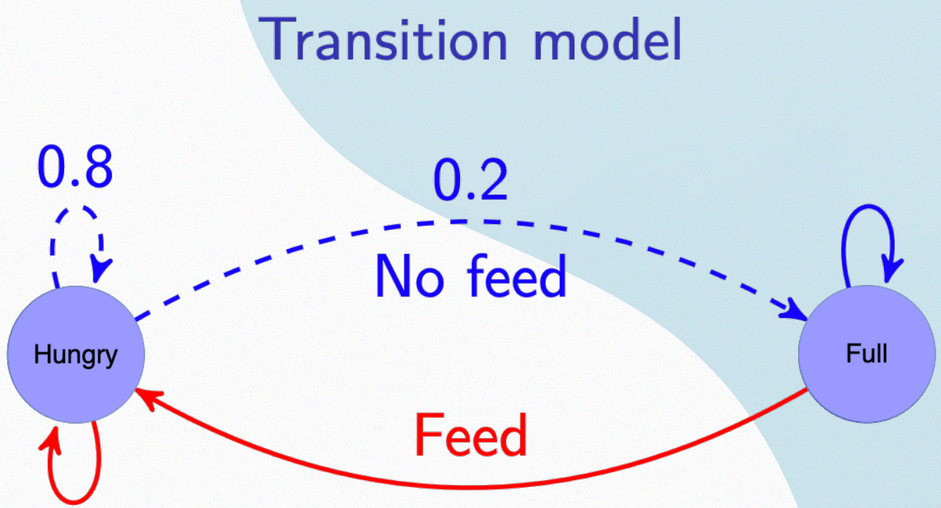


Ref: https://arxiv.org/pdf/2209.10342.pdf

Definition

POMDP的定义



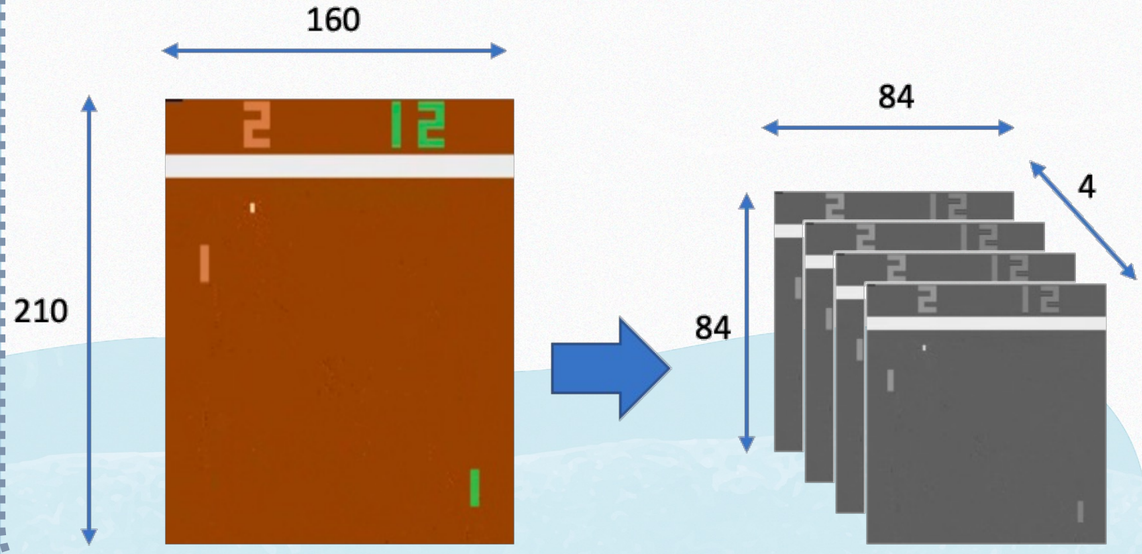


- POMDP = MDP + 观察模型
- 观察模型：O(o|s) 或 O(o|s,a)
- 决策行为只能根据观察信息 O 作出，因为无法得到准确的状态 S

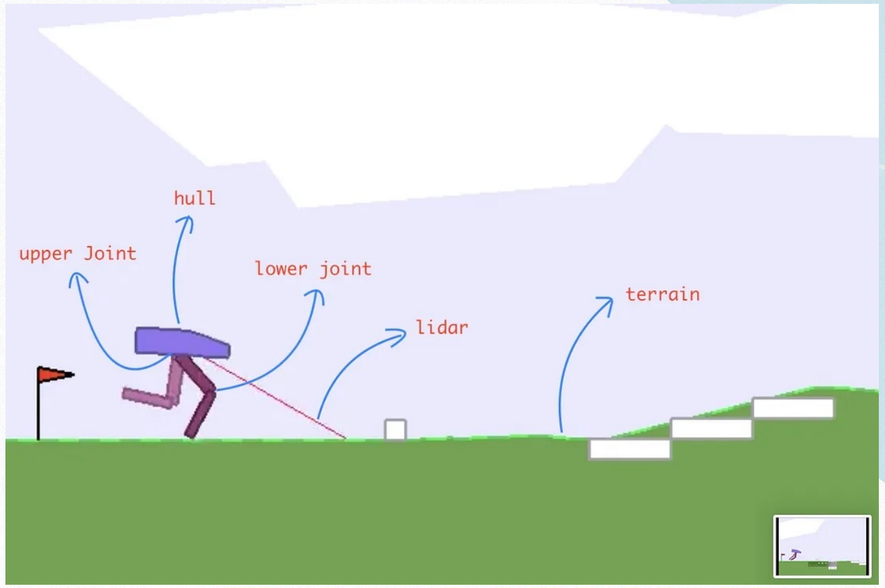
wiki: https://en.wikipedia.org/wiki/Partially_observable_Markov_decision_process

POMDP的解法（数据篇）

叠帧：补足运动信息



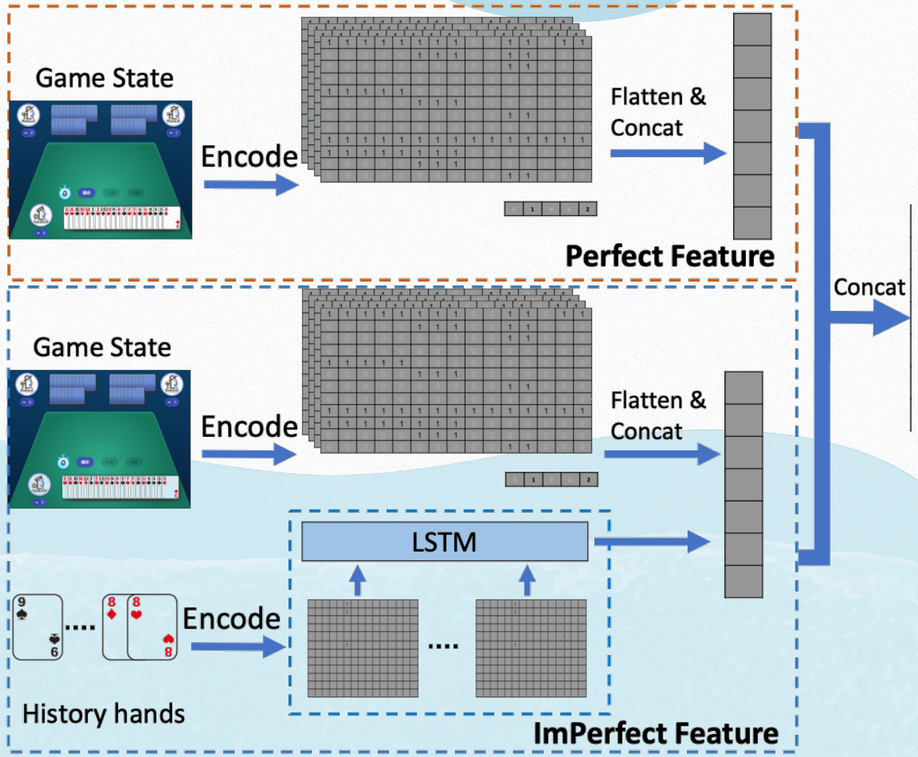
添加参数：补足物理特质信息（力学系数）



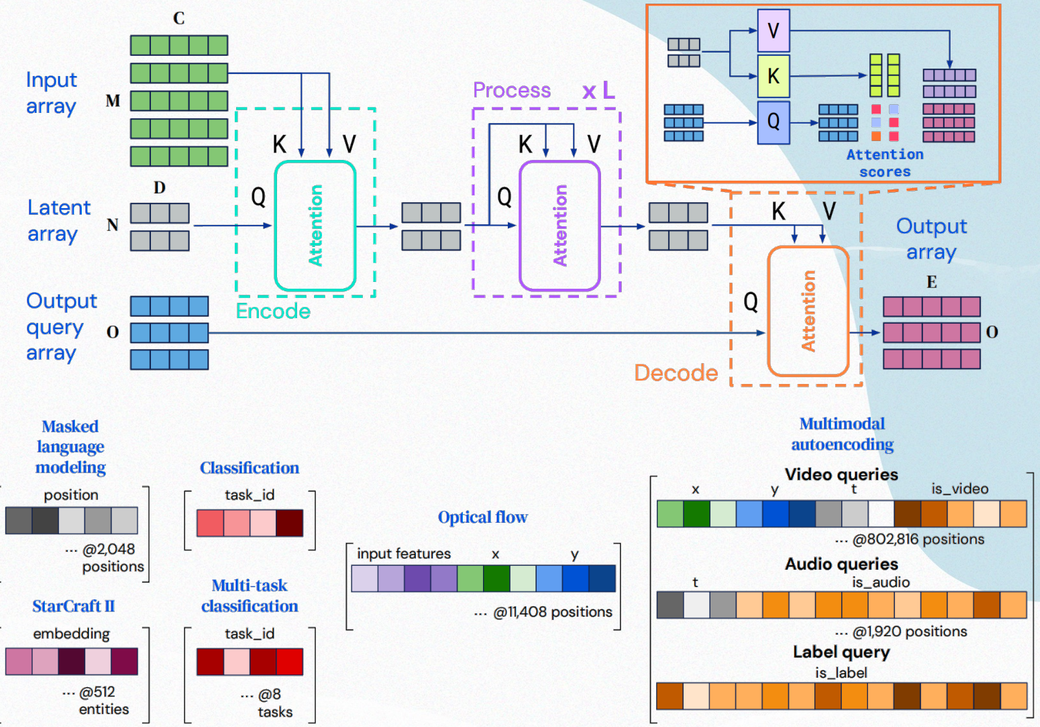
Nature DQN: https://storage.googleapis.com/deepmind-media/dqn/DQNNaturePaper.pdf
BipedalWalker + DI-engine: https://di-engine-docs.readthedocs.io/zh_CN/latest/13_envs/bipedalwalker_zh.html

POMDP的解法（网络篇）

完美的价值网络：补足博弈信息



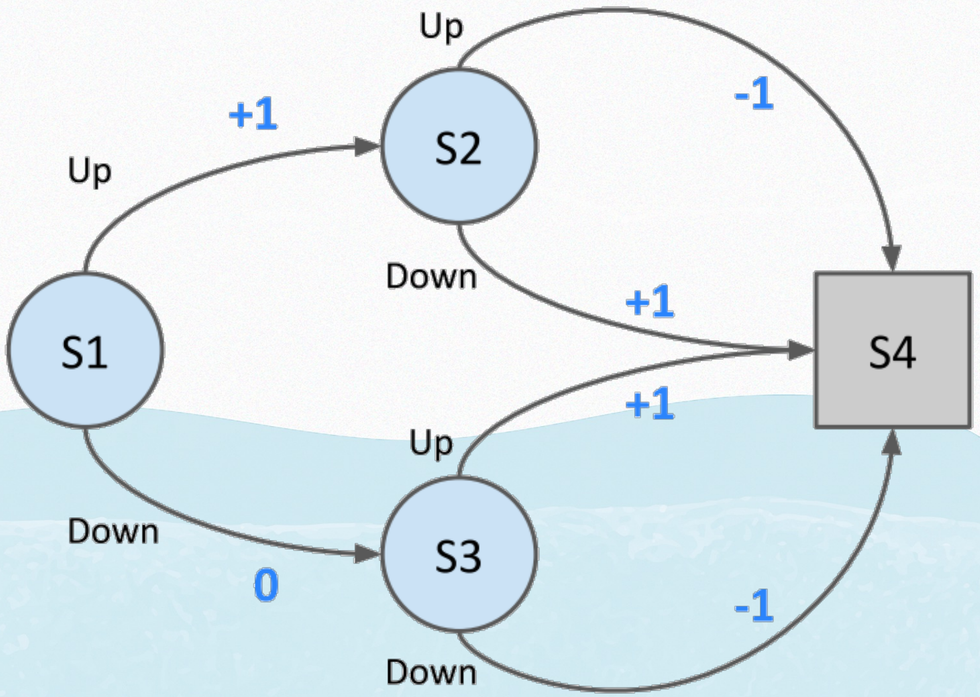
更强大的神经网络：减小预测误差



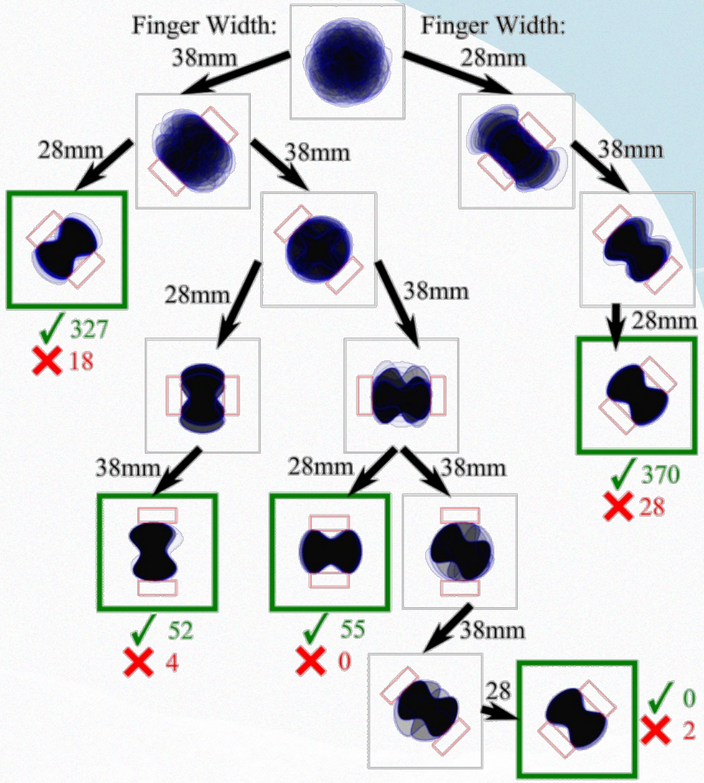
PerfectDou: https://arxiv.org/pdf/2203.16406.pdf
PERCEIVER IO: https://arxiv.org/pdf/2107.14795.pdf

POMDP的解法（优化篇）

多用 N-step

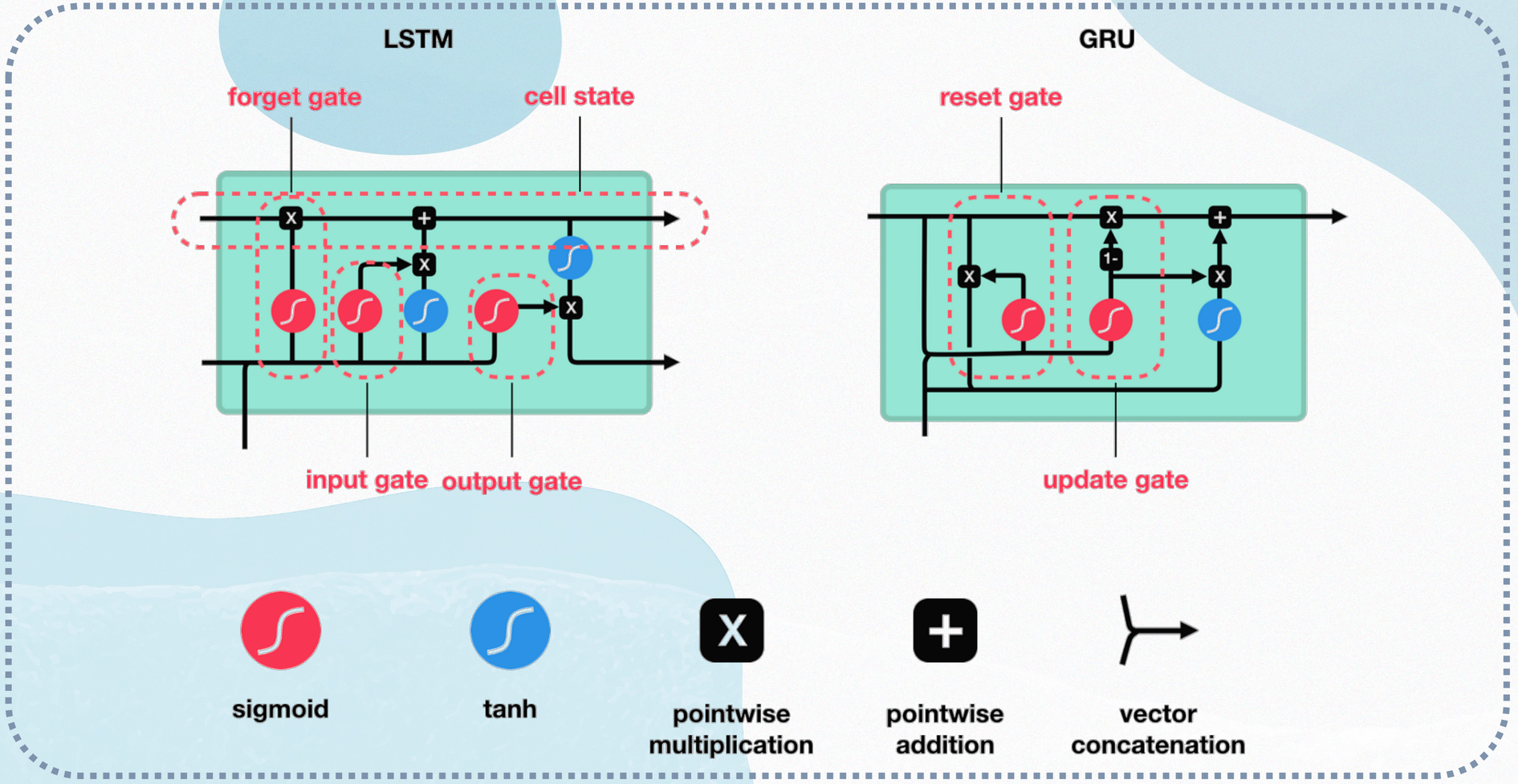


善用 MCTS



课程作业一题解: https://github.com/opendilab/PPOxFamily/blob/main/chapter1_overview/chapter1_homework_solution.pdf
POMCP: https://papers.nips.cc/paper/2010/file/edfbe1afcf9246bb0d40eb4d8027d90f-Paper.pdf
Belief MDP 补充材料: https://github.com/opendilab/PPOxFamily/tree/main/chapter5_time/chapter5_supp_belief.pdf

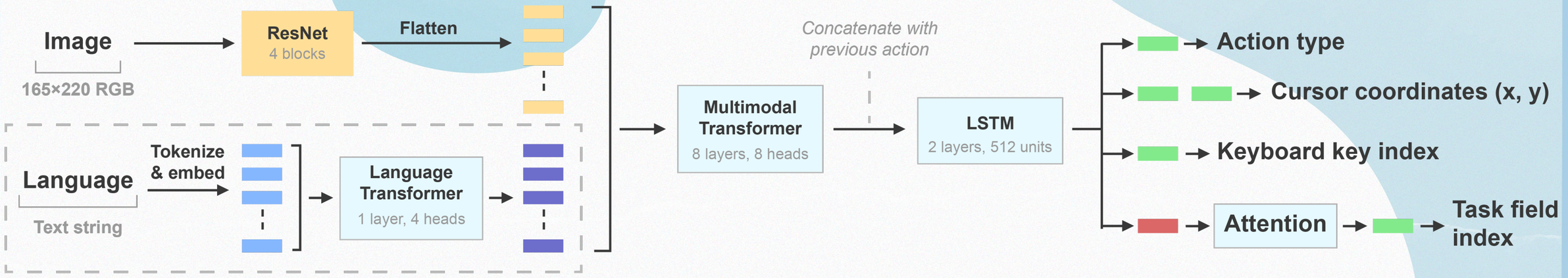
有记忆的PPO：LSTM篇



Ref: https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21

理论：PPO+LSTM

架构

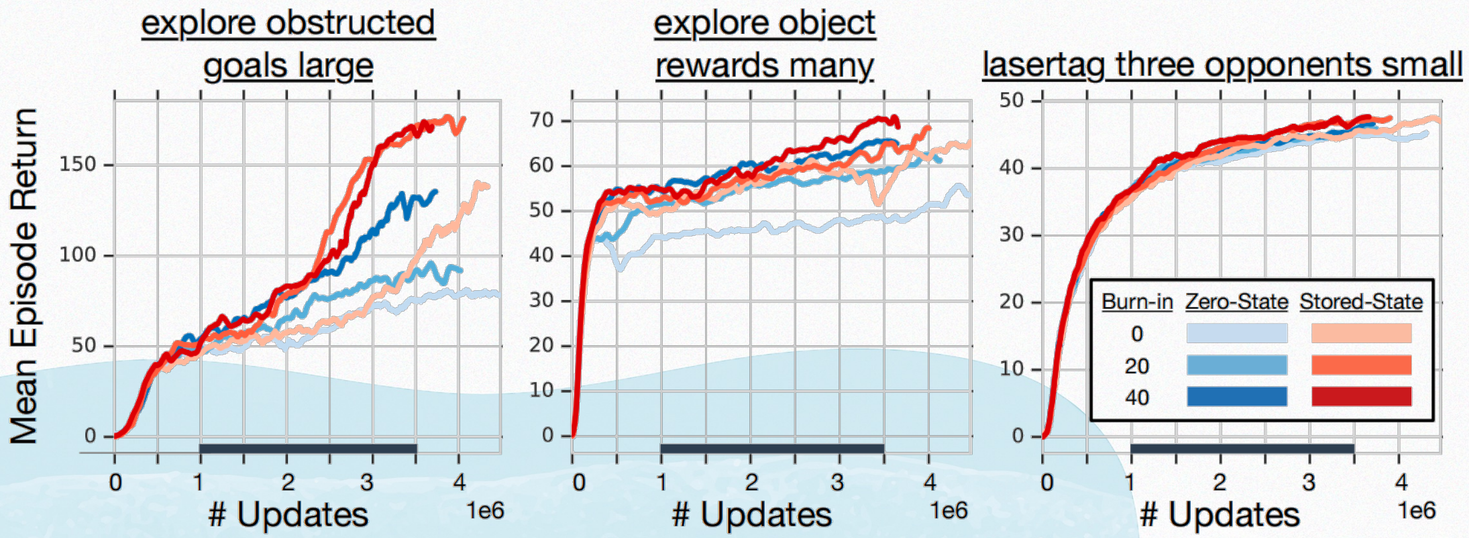


编码器（encoder）+ 时序模块（LSTM）+ 预测器（head）

- 编码器和预测器将观察（输入）和动作（输出）空间的复杂性内聚起来，

  LSTM 只在特征向量空间进行时序信息的记忆和建模

理论：PPO+LSTM



技巧

隐状态的传递 + Burn In 机制

- 数据收集时需额外存储隐状态
- 训练开始加载隐状态并 Burn In
- Burn In 即取序列最开头的一部分数据，用训练端最新的网络沿着时间步向前展开，产生更加新的隐状态，但不参与梯度计算

R2D2: https://openreview.net/pdf?id=r1lyTjAqYX

理论：PPO+LSTM

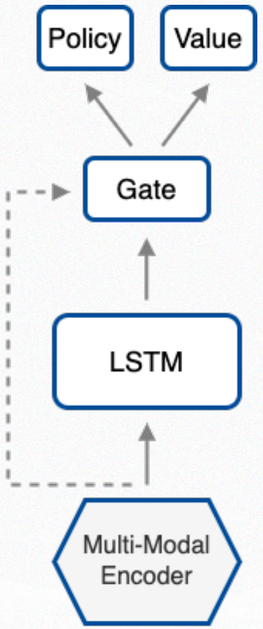
技巧

反应型环境（answer quantitative question）

记忆型环境（obstructed goals large）

Residual Link：

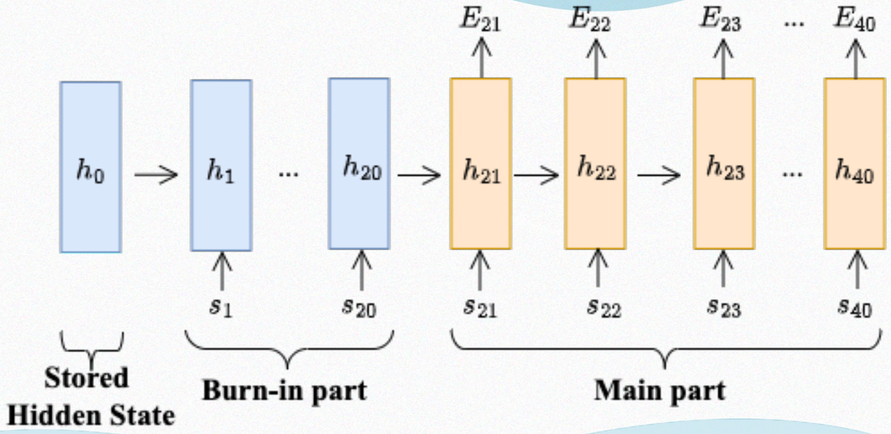
兼顾反应型与记忆型环境



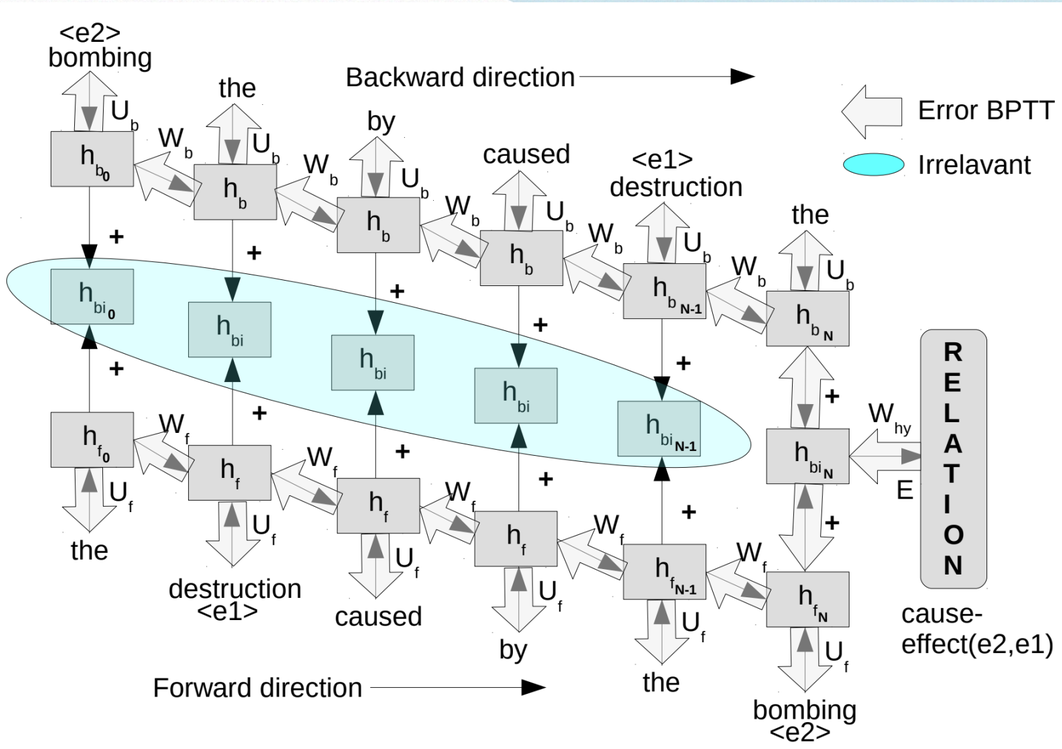
DeepMind Lab: https://github.com/deepmind/lab

理论：PPO+LSTM

优化



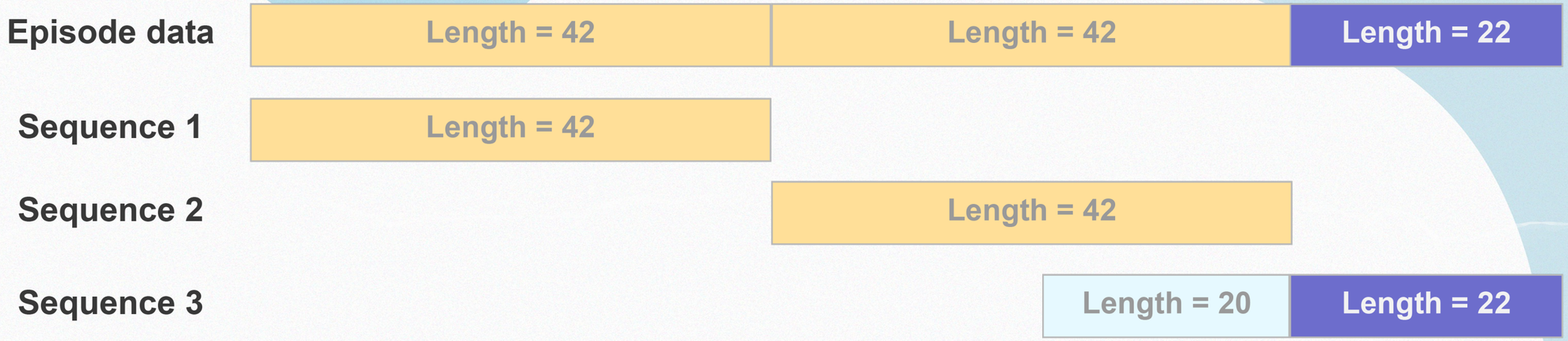
- 预加载和 Burn In 的隐状态都不参与梯度计算
- 使用隐状态和观测信息编码获得当前帧的 Embedding 和传递给下一帧的隐状态



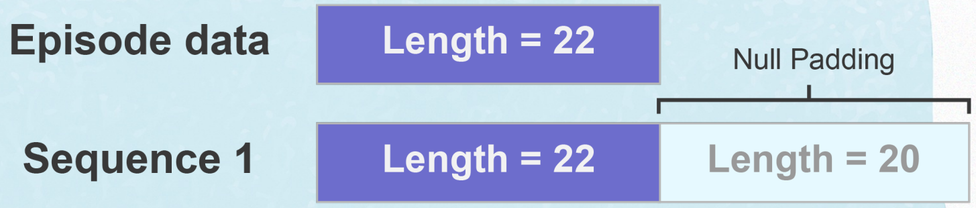
BPTT: https://en.wikipedia.org/wiki/Backpropagation_through_time
Ref: https://www.researchgate.net/figure/Backpropagation-Through-Time-BPTT-in-standard-BRNNs_fig5_316684826

代码：如何准备统一的轨迹数据

Case 1: Episode length > Sequence length



Case 2: Episode length ⩽ Sequence length

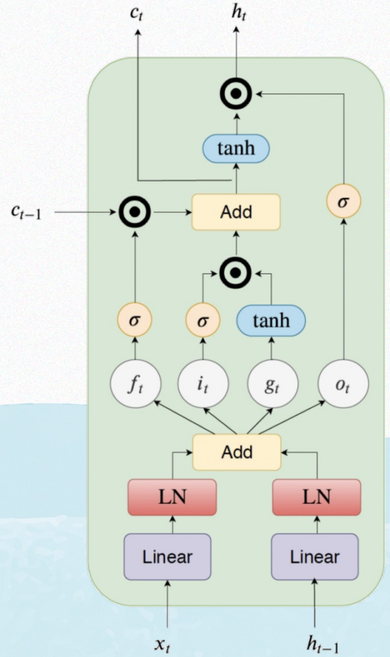


Note: For null padding,
Observation = zeros_like (obs), Reward = 0
Done = True, Hidden State = None

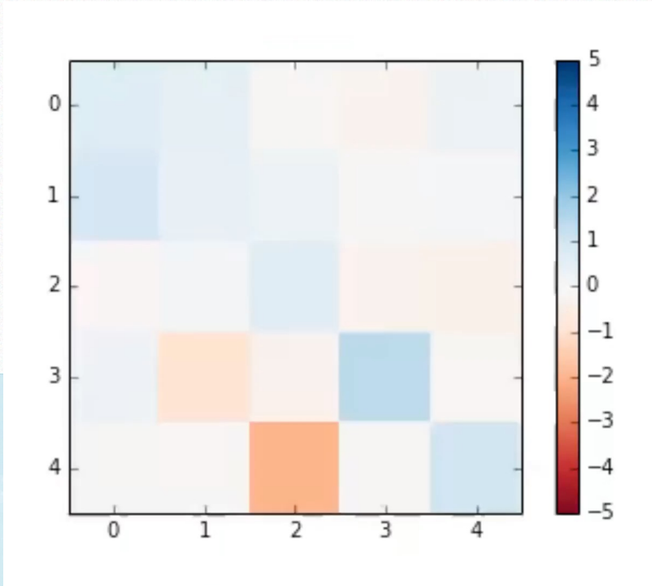
完整示例：https://opendilab.github.io/PPOxFamily/

代码：RL中应用LSTM的三重境界

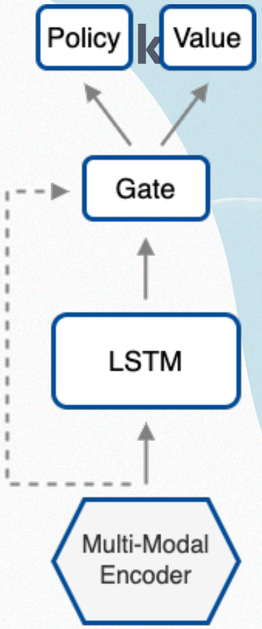
LSTM + LayerNorm



LSTM +

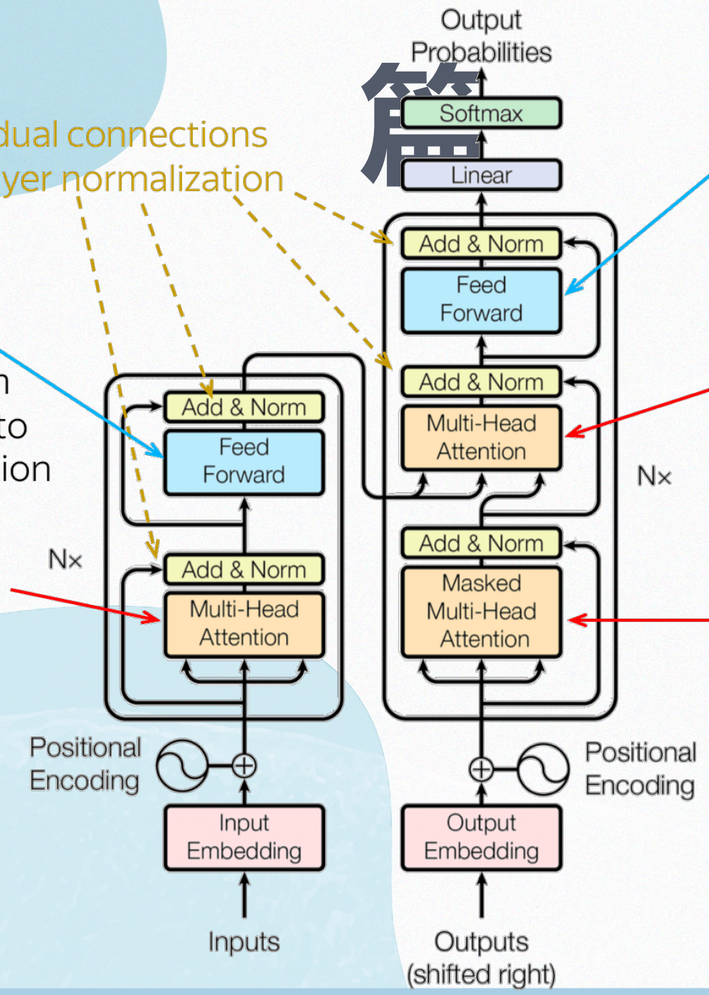


LSTM + Residual



完整示例：https://opendilab.github.io/PPOxFamily/
Ref: https://smerity.com/articles/2016/orthogonal_init.html

有记忆的PPO：Transformer



Residual connections and layer normalization

Feed-forward network:
after taking information from other tokens, take a moment to think and process this information

Encoder self-attention:
tokens look at each other

queries, keys, values are computed from encoder states

Feed-forward network:
after taking information from other tokens, take a moment to think and process this information

Decoder-encoder attention:
target token looks at the source

queries – from decoder states; keys and values from encoder states

Decoder self-attention (masked):
tokens look at the previous tokens

queries, keys, values are computed from decoder states

Ref: https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html#transformer_intro

理论：Transformer + RL 的劣势

Transformer 的训练

需要一系列复杂的技巧来优化其性能

- 复杂的学习率调整策略（如余弦衰减）
- 复杂的梯度裁剪技巧
- dropout 的各种变体
- 特定的权重初始化方案
- 特殊的 normalization 网络层和使用位置
- 位置编码的各种技巧

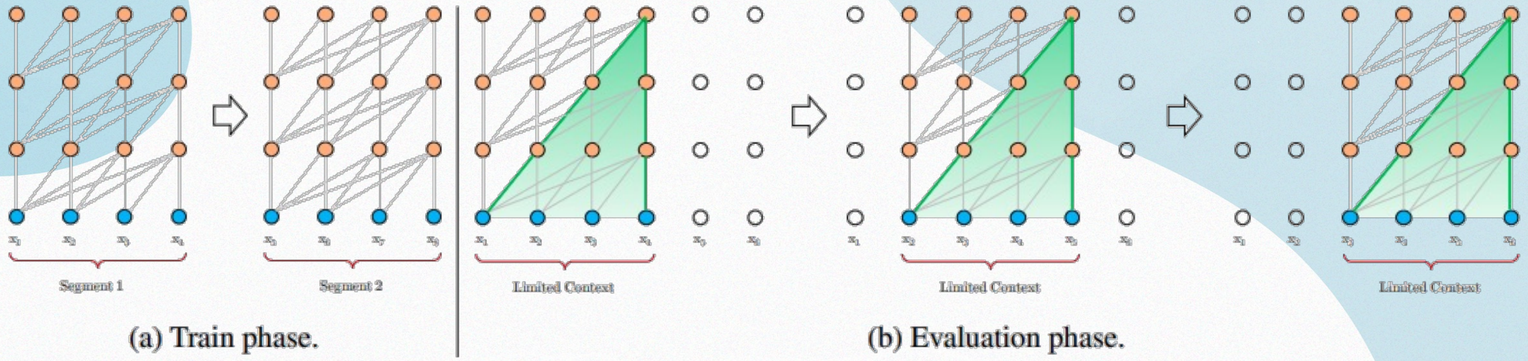
强化学习应用 Transformer

还具有监督学习所没有的一些挑战，其中包括

- 长期的时间依赖性
- 环境奖励的稀疏性
- 平衡强化学习的探索和利用

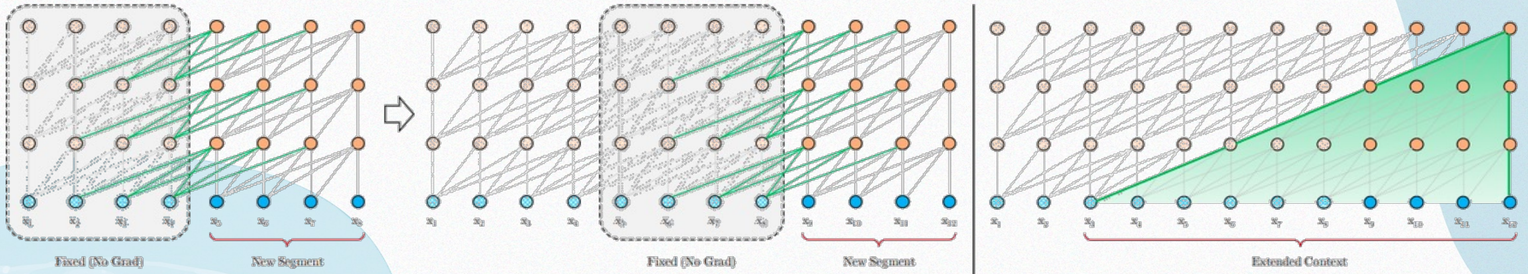
理论：Transformer + RL 的优势

标准 Transformer



(a) Train phase. (b) Evaluation phase.

Transformer-XL



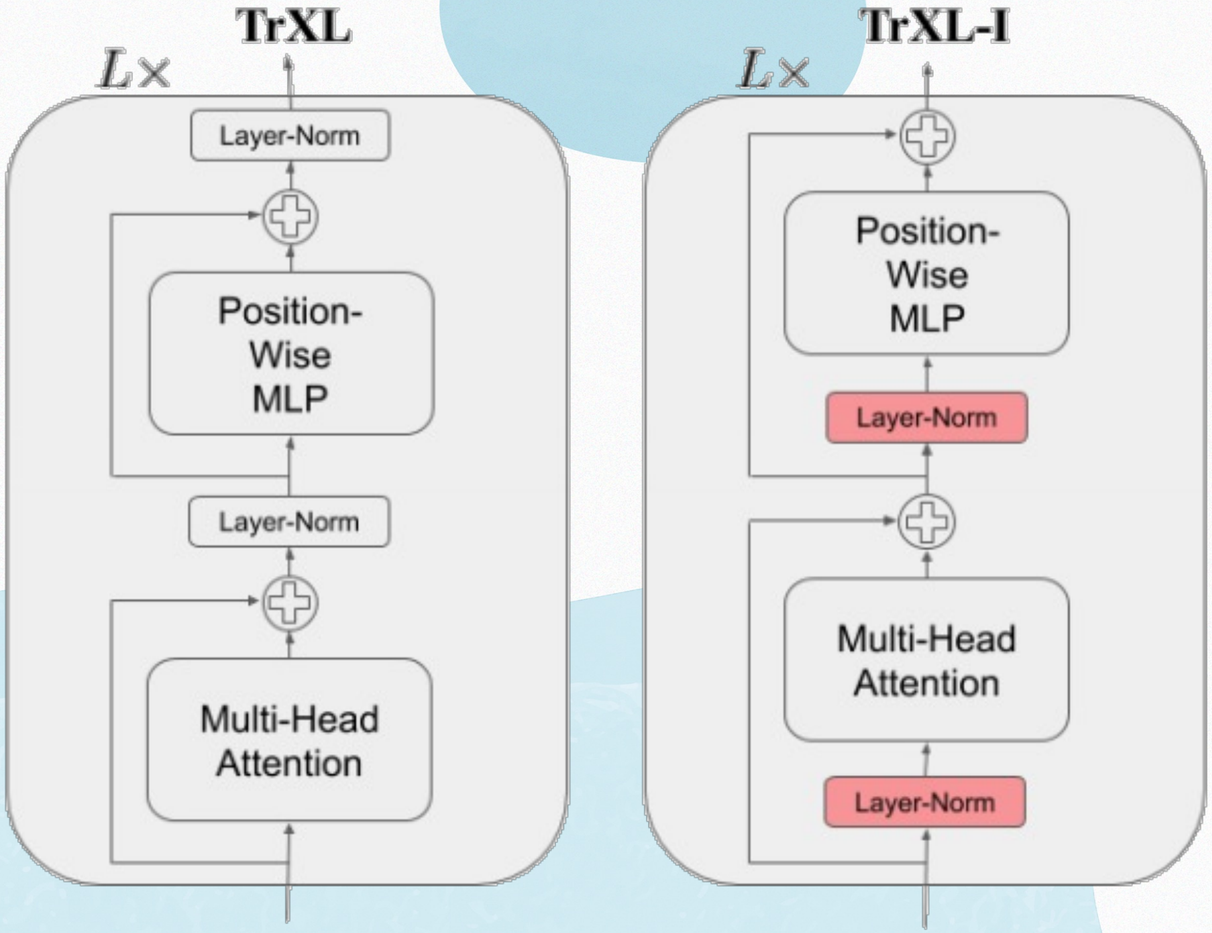
(a) Training phase. (b) Evaluation phase.

- Transformer 相比 LSTM 可以处理更长期的时序依赖，这对一些长期记忆型决策尤为重要
- Transformer 相比 LSTM 更适应 RL 这种在线学习，高方差的优化过程

Transformer-XL: https://arxiv.org/pdf/1901.02860.pdf

理论：PPO+GTrXL

LN

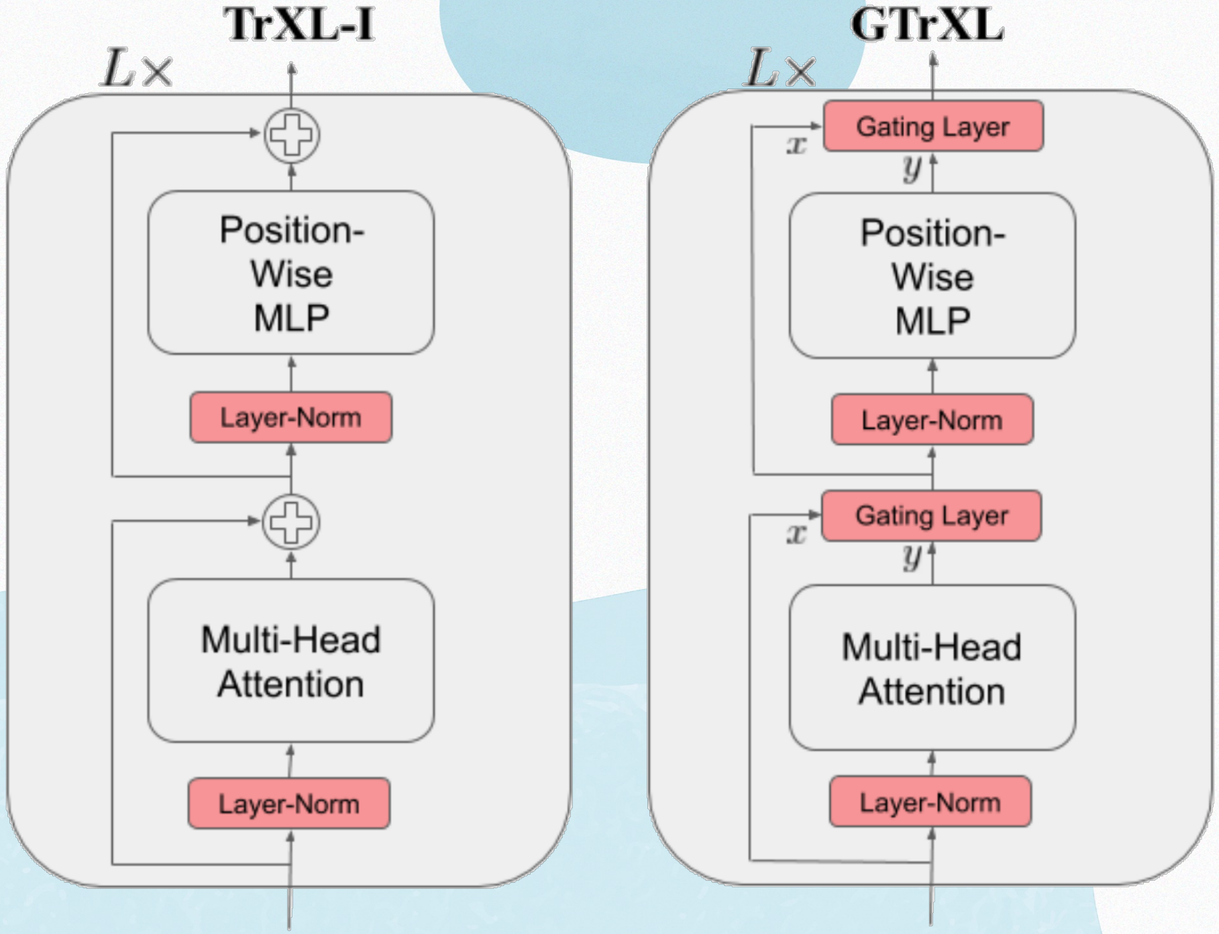


- 思路：让网络初始时更接近马尔可夫假设，即仅用当前状态进行决策，忽略其他时间步的信息
- 原理：让智能体先学习一个符合马尔可夫假设的、较为简单的策略，再学习更复杂的能处理时序信息的策略
- 例子：一个人应当先学会如何走路，再记住走过的路径，更好地规划路径

GTrXL: https://arxiv.org/pdf/1910.06764.pdf

理论：PPO+GTrXL

Gate



$$r = \sigma(W_r^{(l)} y + U_r^{(l)} x)$$

$$z = \sigma(W_z^{(l)} y + U_z^{(l)} x - b_g^{(l)})$$

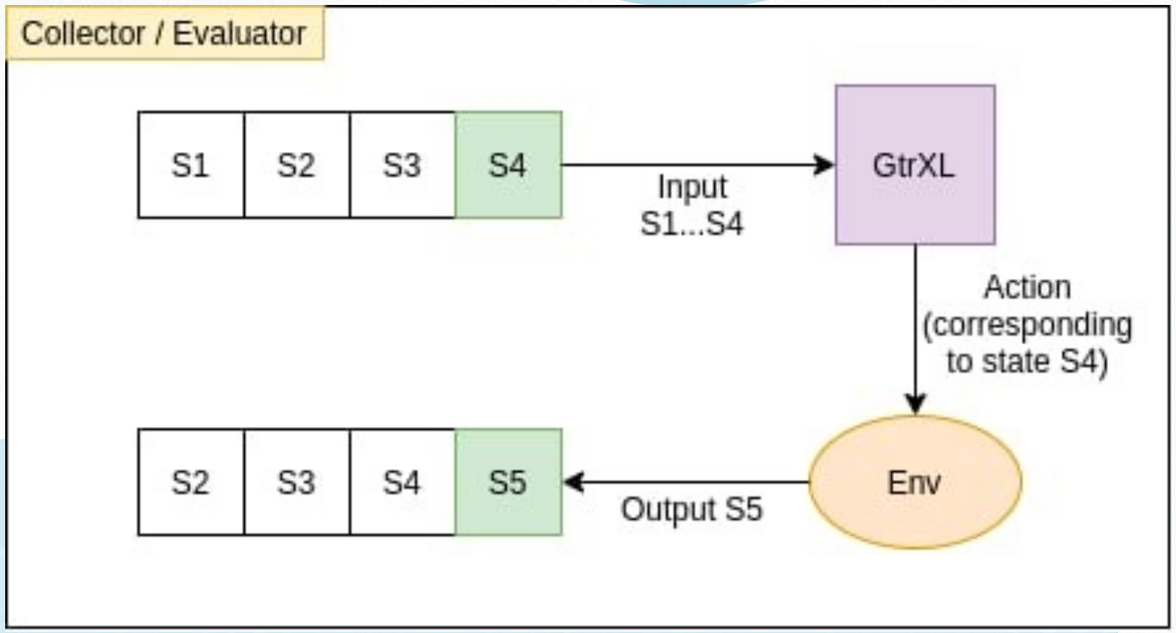
$$\hat{h} = \tanh(W_g^{(l)} y + U_g^{(l)} (r \odot x))$$

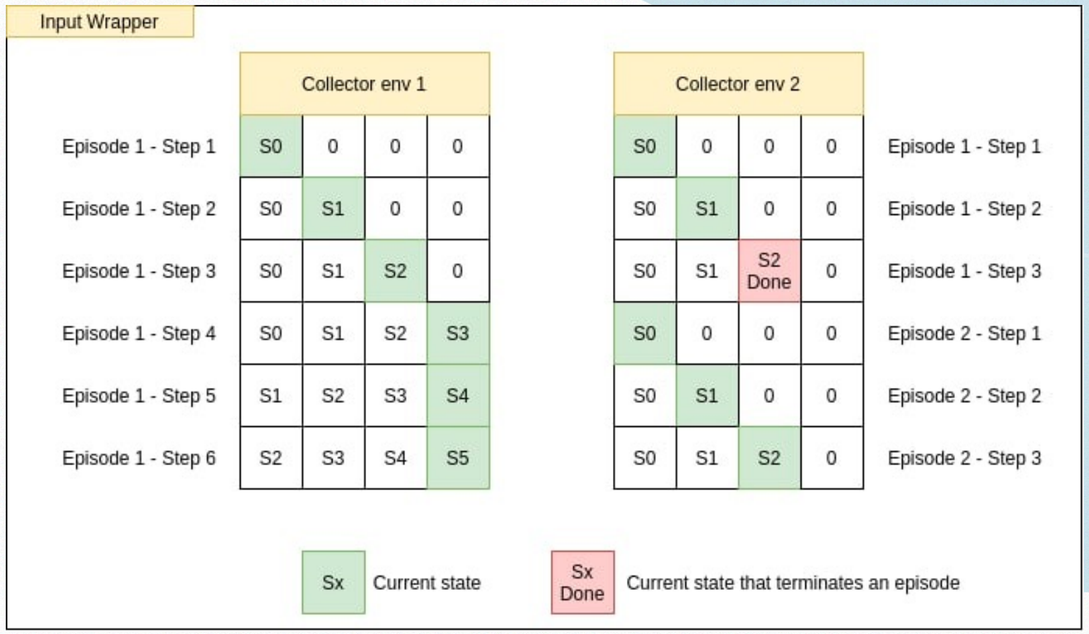
$$g^{(l)}(x, y) = (1 - z) \odot x + z \odot \hat{h}$$

- 思路：通过门控机制更灵活地组合反应型策略和记忆型策略
- 技巧：通过对 bias 的特殊初始化，让 Gate 初始化为恒等映射，即在原版设计的基础上学习

GTrXL: https://arxiv.org/pdf/1910.06764.pdf

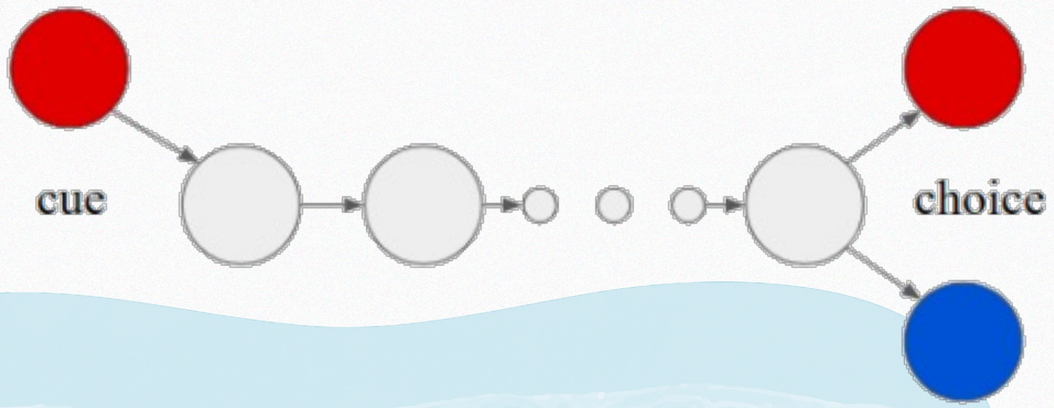
代码：GTrXL + PPO 应用小妙招





完整示例：https://opendilab.github.io/PPOxFamily/

实践：PPO+memory len



任务目标

- 测试智能体的长期记忆能力，跨越多步记住一个比特的信息（cue）

MDP元素

- 观察：时间步和当前信息（随机）
- 动作：2维离散动作，选择+1 or -1
- 奖励：稀疏奖励，即智能体是否最终选择正确的cue

DI-engine + memory len: https://di-engine-docs.readthedocs.io/zh_CN/latest/13_envs/bsuite_zh.html

实践：PPO+memory len

Policy	Memory len (N)	收敛性	收敛所用环境交互步数（Env Steps）
PPO+LSTM	12	Yes	5.8k
PPO+LSTM	30	Yes	78k
PPO+LSTM	50	Yes	383.5k
PPO+LSTM	100	No	>90M未收敛
PPO+GTrXL	12	Yes	2.1k
PPO+GTrXL	30	Yes	7k
PPO+GTrXL	50	Yes	11.4k
PPO+GTrXL	100	Yes	32.3k

视频样例：https://github.com/opendilab/PPOxFamily/issues/48

Summary

总结：PPO + 时序建模

小节	算法要点	代码和实践要点
POMDP 概述	• POMDP 的定义和特点 • 从数据编码角度应对（叠帧） • 从网络设计角度应对（完美价值网络） • 从优化方法角度应对（N-step）	/
PPO + LSTM	• 整体网络架构设计 • 隐状态维护更新问题 • 反应型和记忆型决策 • 时序展开如何优化	准备统一的轨迹数据 RL 中应用 LSTM 的三重境界
PPO + Transformer	• Transformer + RL 的优劣势 • LayerNorm 的位置之争 • 门控（Gate）调节机制	Transformer 的记忆模块实现 memory len 环境对比测试

RWKV-LM 补充材料: https://github.com/opendilab/PPOxFamily/tree/main/chapter5_time/chapter5_supp_rwkv.pdf

下节预告

（六）群体之趣：统筹多智能体

- Dec-POMDP：多智能体协作的特殊之处
- MAPPO：套用 PPO —— 建立基石
- HAPPO：化用 PPO —— 追寻本源