

When Do Transformers Shine in RL? Decoupling Memory from Credit Assignment



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Paper is available at [arXiv](#) and code is open-sourced

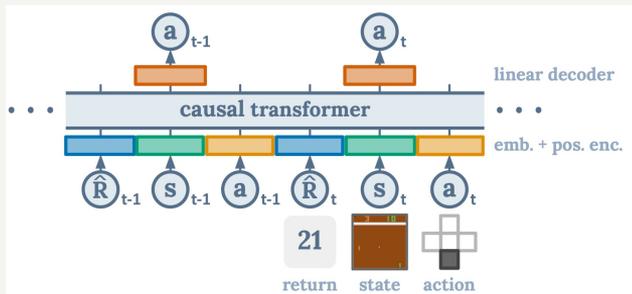


Mystery

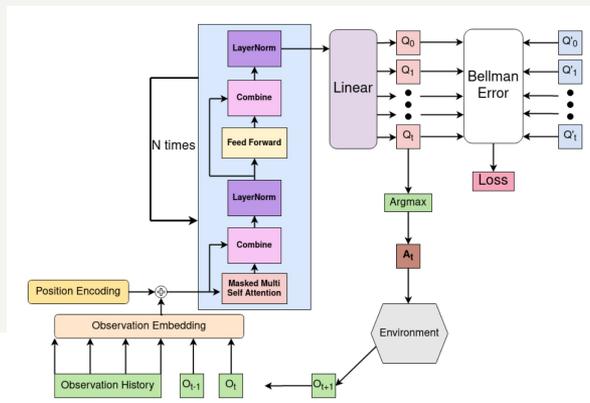
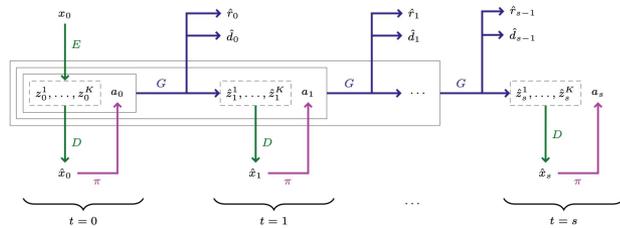


Transformers have been successful in **RL**

- **Offline RL:** Decision transformer (Chen et al., 2021)
- **Model-Based RL:** IRIS (Micheli et al., 2022)
- **Model-Free RL:** Deep Transformer DQN (Eslinger et al., 2022)



Why?



Why do Transformers shine in **SL**?

Excel at long-term dependencies

Attention mechanisms have become an integral part of compelling sequence modeling and transduction models in various tasks, allowing modeling of dependencies without regard to their distance in the input or output sequences [2, 19]. In all but a few cases [27], however, such attention mechanisms are used in conjunction with a recurrent network.

In this work we propose the Transformer, a model architecture eschewing recurrence and instead relying entirely on an attention mechanism to draw global dependencies between input and output. The Transformer allows for significantly more parallelization and can reach a new state of the art in translation quality after being trained for as little as twelve hours on eight P100 GPUs.

From Attention Is All You Need

Temporal dependency: *memory*?

Long-range dependence

🗨️ 1 language ▾

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From Wikipedia, the free encyclopedia

Long-range dependence (LRD), also called **long memory** or **long-range persistence**, is a phenomenon that may arise in the analysis of [spatial](#) or [time series](#) data. It relates to the rate of decay of [statistical dependence](#) of two points with increasing time interval or spatial distance between the points. A

The Problem of Learning Long-Term Dependencies in Recurrent Networks

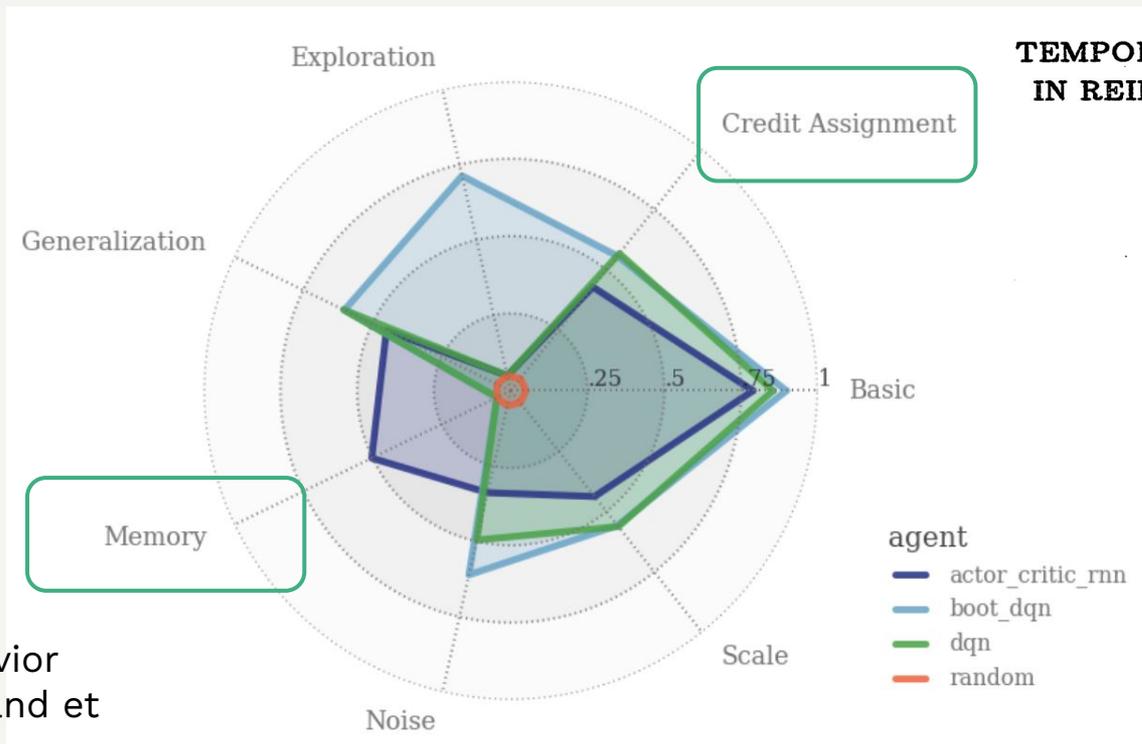
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***Supervised learning
perspective***

Capabilities in RL: memory and credit assignment



**TEMPORAL CREDIT ASSIGNMENT
IN REINFORCEMENT LEARNING**

**A Dissertation Presented
By
Richard S. Sutton**

From behavior
suite (Osband et
al., 2019)

Memory and Credit Assignment: they are distinct!

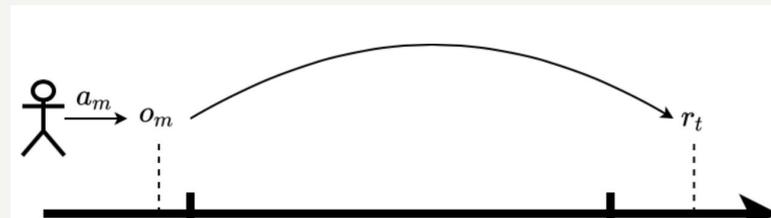
Memory

The ability to recall distant past events



Temporal credit assignment

The ability to determine *when* the actions that deserved credit occurred (Sutton, 1984)



We have intuition!

Scenario 1: Alice *remembers her passcode* set a month earlier, and opens a safe full of money.

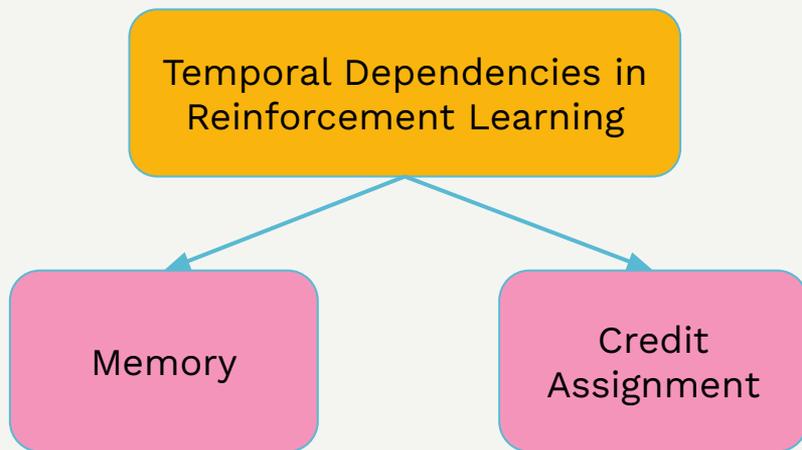
Memory



Scenario 2: Bob *picks up a key* (then he can always see the key), and a month later he opens a safe full of money.

Credit Assignment

Why do Transformers shine in RL? Memory or Credit Assignment? Or Both?



Although we have intuition, we don't have clear mathematical definitions.

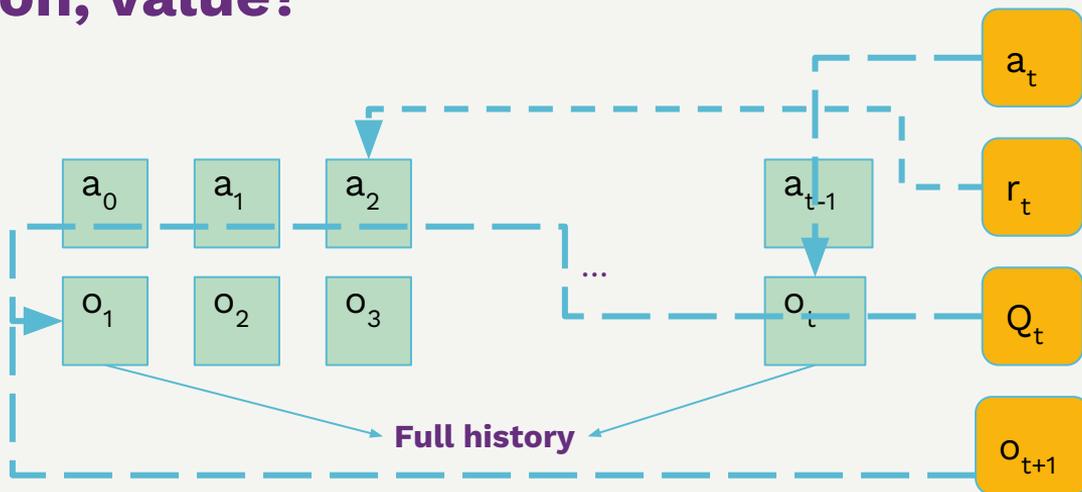
This prevents us from understanding RL.

Measuring Temporal Dependencies



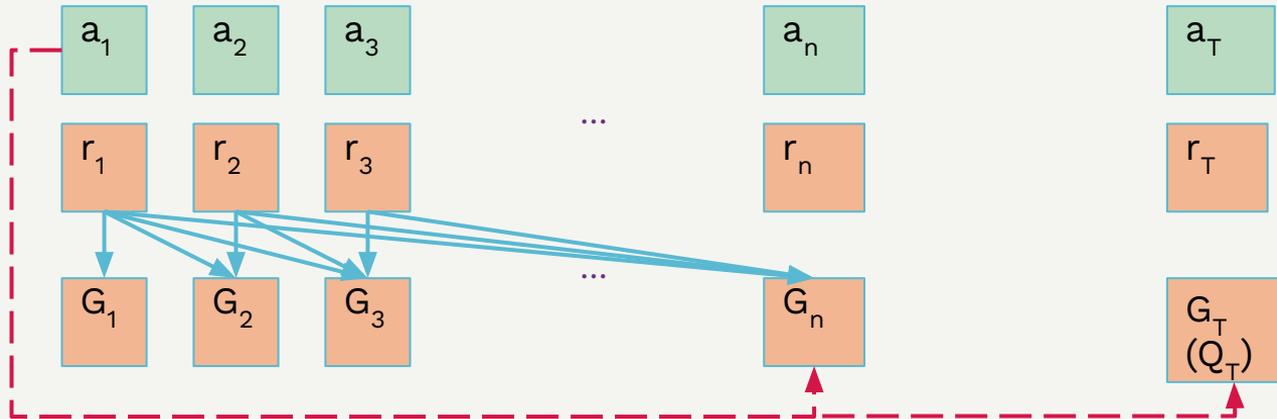
Memory lengths (intuition)

- History: all previous observations and actions
- **How long is the minimal history required to predict / generate current reward, observation, action, value?**



Credit assignment length (Intuition)

How long does it take for a greedy action to see its benefits regarding its n -step rewards (G_n)?



Examples: decoupling memory and credit assignment

Scenario 1: Alice remembers her passcode set a month earlier, and opens a safe full of money.

- Credit assignment length = 1 day
- Memory length = 1 month

Scenario 2: Bob picks up a key (then he can always see the key), and a month later he opens a safe full of money.

- Credit assignment length = 1 month
- Memory length = 1 day



Proposing configurable toy tasks: Passive and Active T-Mazes

Passive T-Maze



Corridor Length T

Mem len: T
CA len: 1

O: Oracle (to get the info of G,
randomized in each episode)
S: Start; J: Junction
G1, G2: Goal candidates (to get bonus)

Active T-Maze



Corridor Length T

Mem len: T
CA len: T

*Going to O is only
credited when the
agent reaches G*

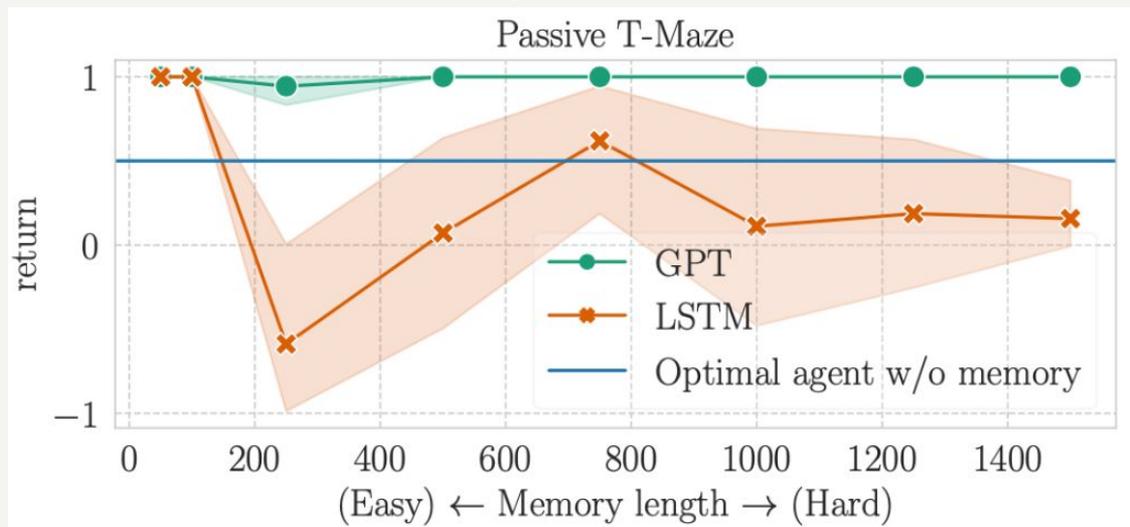
Evaluating Transformer-based RL



Transformer-based RL excel at long-term memory

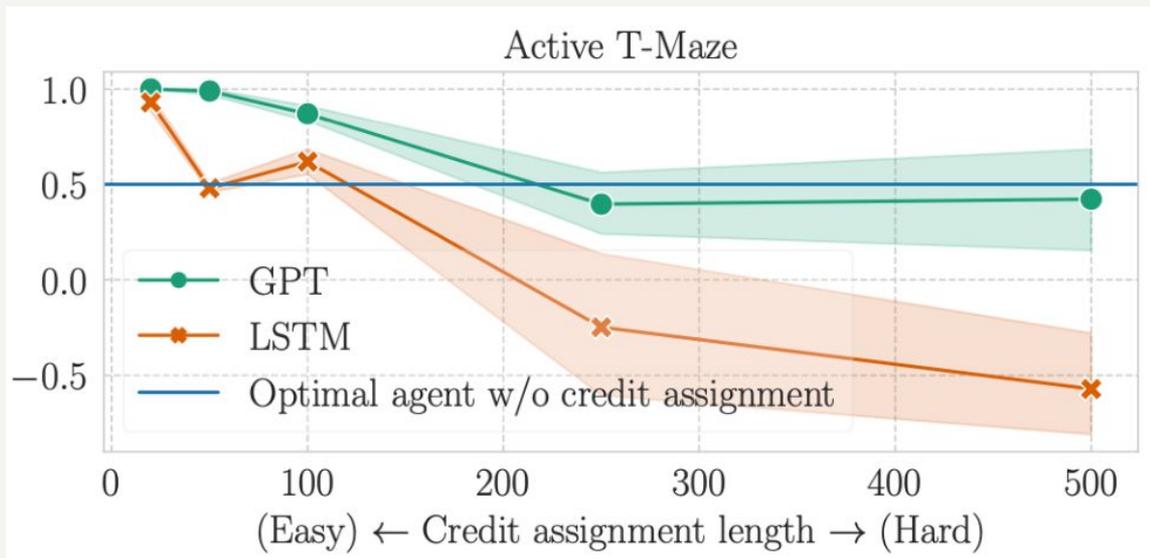
RL algorithm: DDQN w/ eps greedy

Sequence model: LSTM or Decoder-only Transformer (GPT-2)



Perfectly solved by GPT-2

Transformers cannot help long-term credit assignment in RL



In Active T-Maze, Transformers can reach the Junction.
Transformers helps, but degrades severely when the CA length ≥ 250

Future work

- Developing scalable RL systems for high-dim long-term memory tasks
- Searching sequence architectures or RL algorithms for long-term credit assignment

Thank you for watching!

