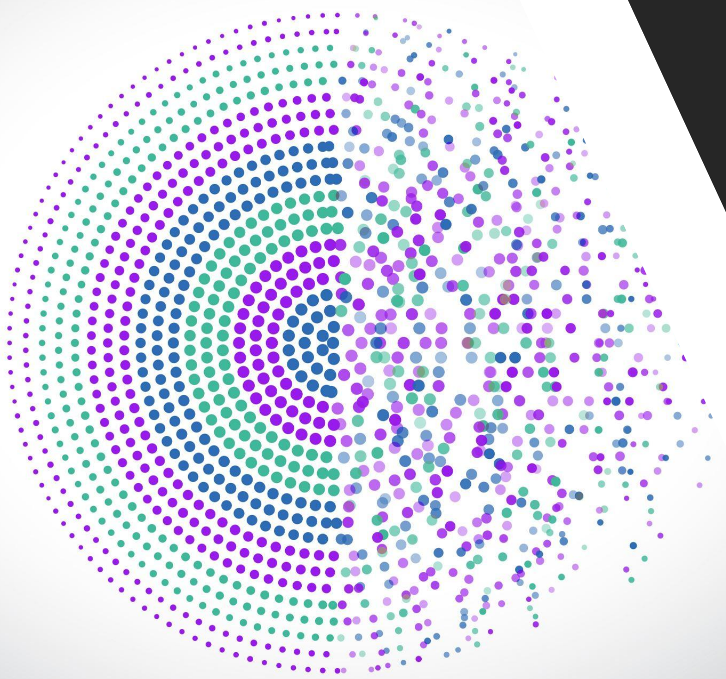

Reinforcement Learning

Applications and Future Research

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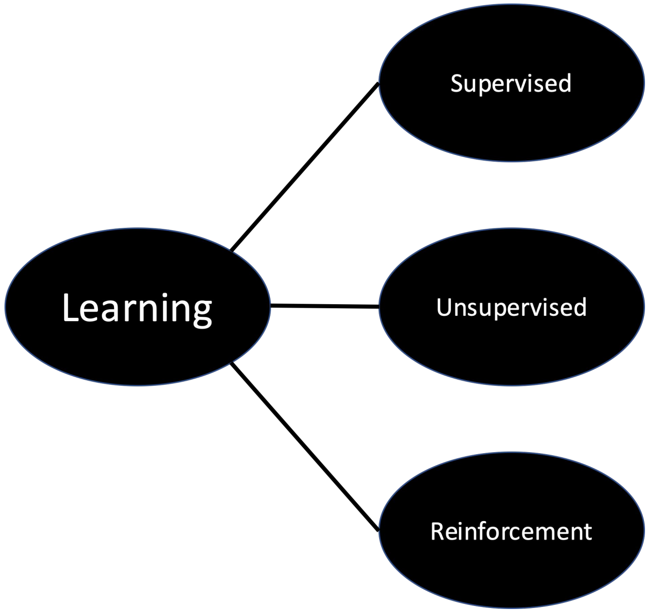
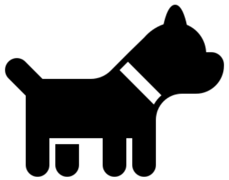
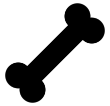
Reinforcement Learning

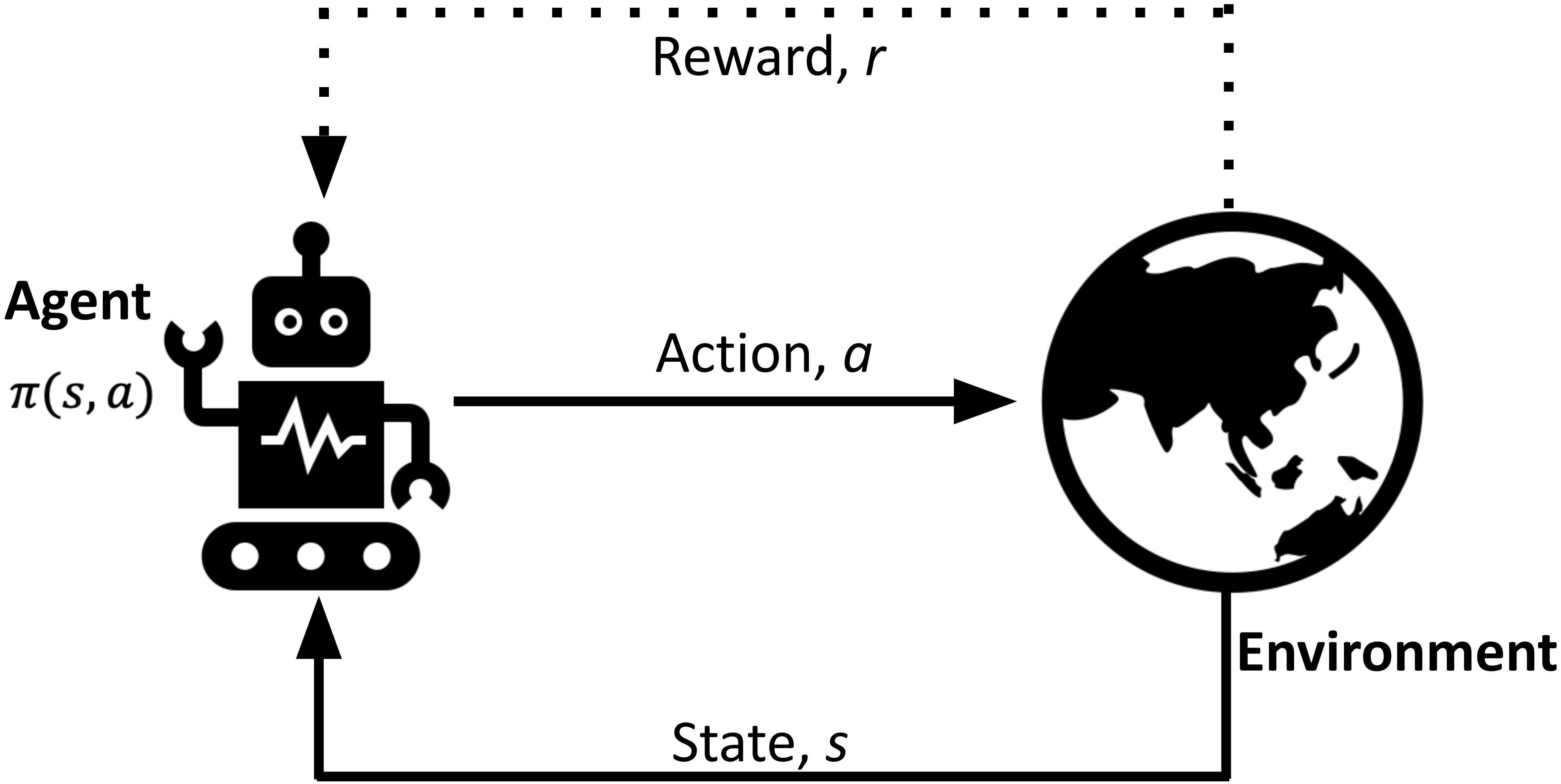


- A type of machine learning
- It is between supervised and unsupervised
- Inspired from how animals learn from experience.

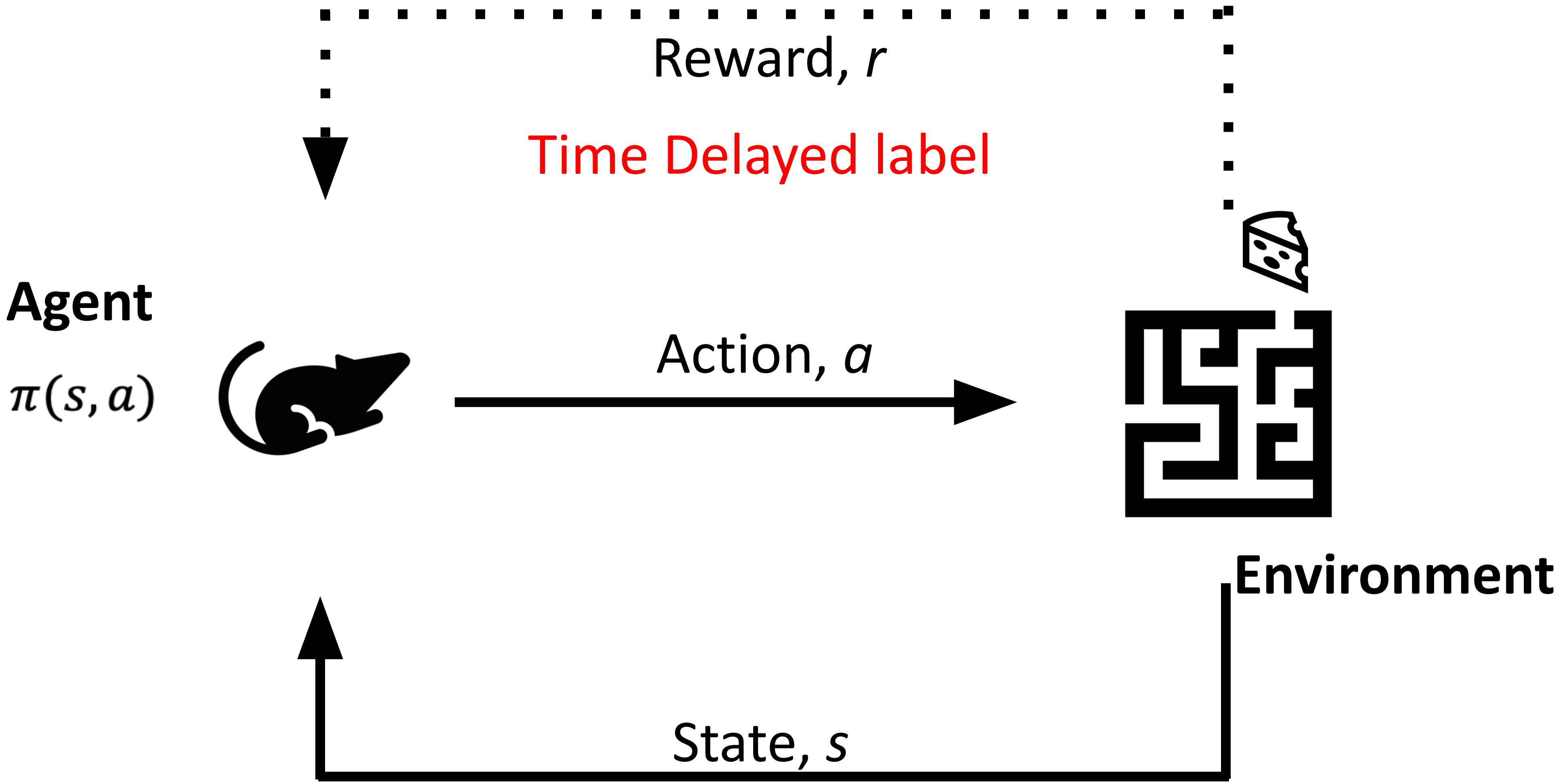




Reinforcement Learning



Reinforcement Learning

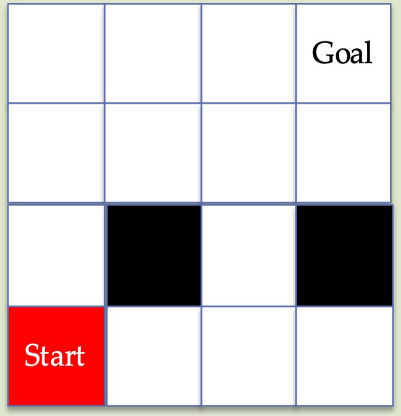


RL Components: State Space S

- Observation of environment.
- Set of all possible states the environment can be in.

$s \in S$

Agent finding path in the maze



s = [[0,0,0,0]
[0,0,0,0]
[0,X,0,X]
[1,0,0,0]]

Agent controlling steering wheel in self-driving car

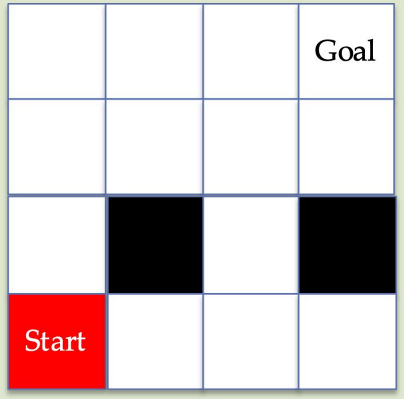
s = The image of the road in-front

Gulli, A., Kapoor, A., & Pal, S. (2019). *Deep learning with TensorFlow 2 and Keras: regression, ConvNets, GANs, RNNs, NLP, and more with TensorFlow 2 and the Keras API*. Packt Publishing Ltd.

RL Components: Action Space *A(s)*

Set of all possible things that the agent can do in a particular state *s*.

Agent finding path in the maze



s = [[0,0,0,0]
[0,0,0,0]
[0,X,0,X]
[1,0,0,0]]

a = [up, down, left, right, no change]

Agent controlling steering wheel in self-driving car

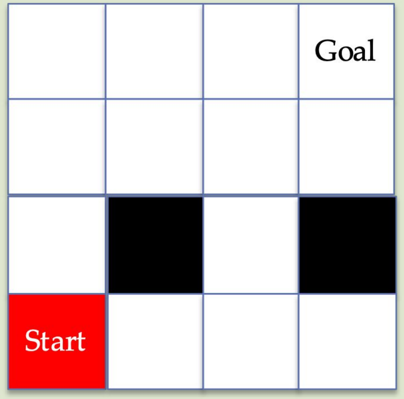
s = The image of the road in-front

a = The angle by which steering wheel is to be rotated

RL Components: Reward *r(s,a,s')*

A scalar value returned by the environment based on the agent's action/s

Agent finding path in the maze



$$s = \begin{bmatrix}[0,0,0,0]\\ [0,0,0,0]\\ [0,X,0,X]\\ [1,0,0,0]\end{bmatrix}$$

a = [up, down, left, right, no change]

Agent controlling steering wheel in self-driving car

s = The image of the road in-front

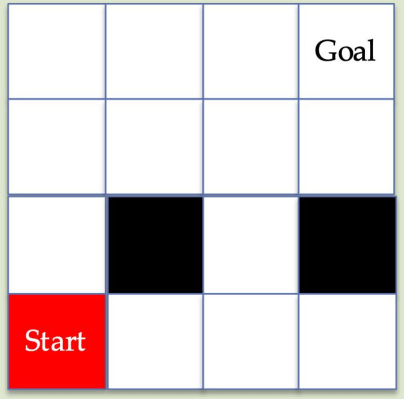
a = The angle by which steering wheel is to be rotated

RL Components: Policy $\pi(s)$

Mapping between each state and the action to take in that state

Optimal Policy $\pi^*(s)$

Agent finding path in the maze



s = [[0,0,0,0]
[0,0,0,0]
[0,X,0,X]
[1,0,0,0]]

a = [up, down, left, right, no change]

Agent controlling steering wheel in self-driving car

s = The image of the road in-front

a = The angle by which steering wheel is to be rotated

RL Components: Return G_t

Discounted sum of all future rewards starting from current time

$$G_t = \sum_{k=t}^{\infty} \gamma^k r_k = \gamma^t r_t + \gamma^{t+1} r_{t+1} + \ \dots + \gamma^{t+n} r_{t+n} + \ \dots$$

Discount factor $\qquad 0 < \gamma < 1$

Discounted total return

RL Components: Q function

Discounted sum of all future rewards starting from current time

$$G_t = \sum_{k=t}^{\infty} \gamma^k r_k = \gamma^t r_t + \gamma^{t+1} r_{t+1} + \ldots + \gamma^{t+n} r_{t+n} + \ldots$$

Discount factor $\quad 0 < \gamma < 1$

$$Q(s_t, a_t) = \mathbb{E}[G_t | s_t, a_t]$$

Expected total future reward an agent in state, *s*, can receive by performing action, *a*

RL Components: Q function

Discounted sum of all future rewards starting from current time

$$G_t = \sum_{k=t}^{\infty} \gamma^k r_k = \gamma^t r_t + \gamma^{t+1} r_{t+1} + \ \dots + \gamma^{t+n} r_{t+n} + \ \dots$$

Discount factor $\quad 0 < \gamma < 1$

$$Q(s_t, a_t) = \mathbb{E}[G_t | s_t, a_t]$$

$$\pi^*(s) = \arg\max_a Q(s, a)$$

RL Components: Value function

Discounted sum of all future rewards starting from current time

$$G_t = \sum_{k=t}^{\infty} \gamma^k r_k = \gamma^t r_t + \gamma^{t+1} r_{t+1} + \ \ldots + \gamma^{t+n} r_{t+n} + \ \ldots$$

Discount factor $\quad 0 < \gamma < 1$

$$V^{\pi}(s_t) = \mathbb{E}[G_t | s_t]$$

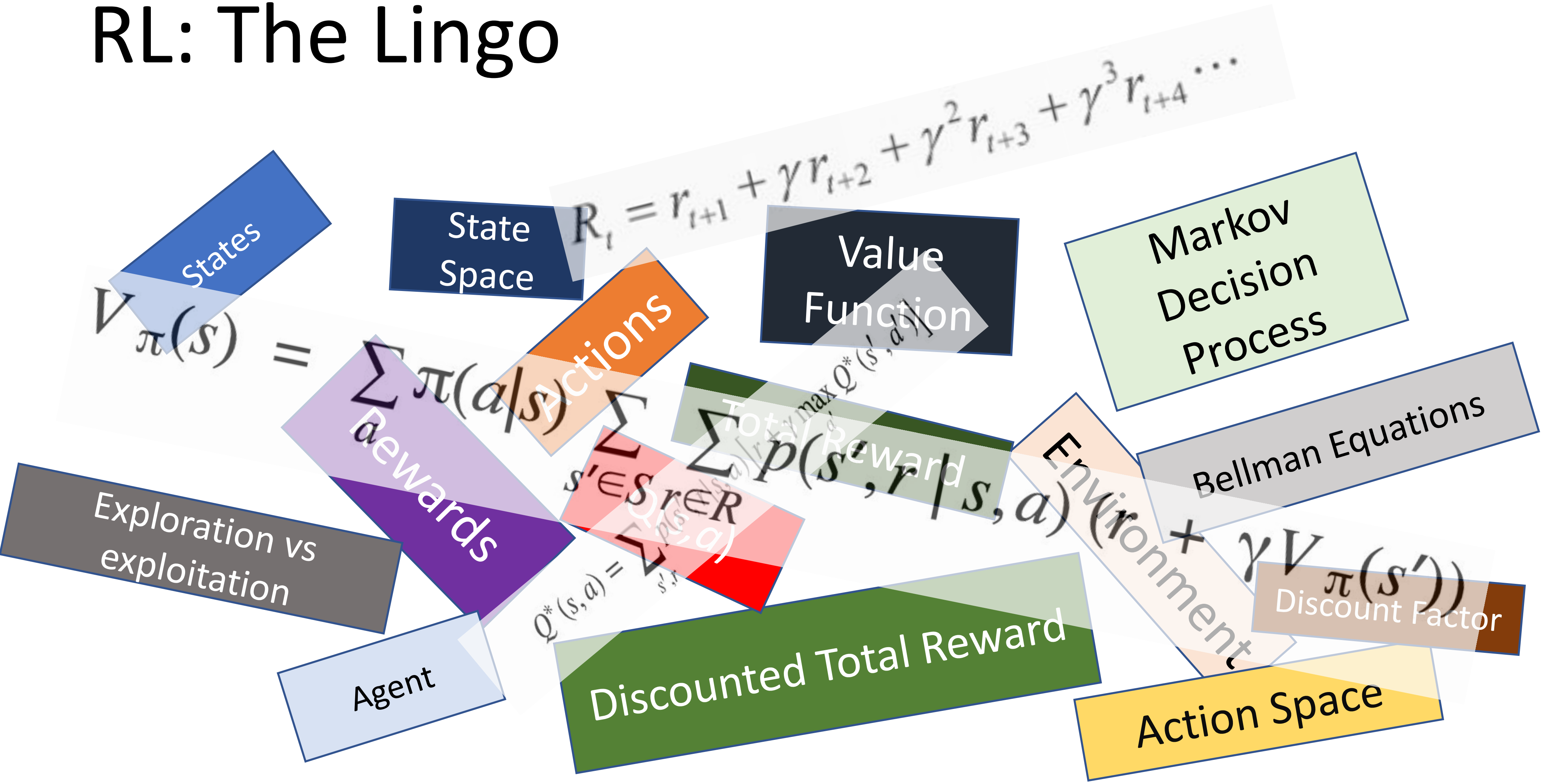
Reinforcement Learning Algorithms

- Value Based Learning
- Agent learns $Q(s,a)$

$$\pi^*(s) = \arg\max_a Q(s,a)$$

- Policy Based Learning
- Agent learn $\pi(s)$
- Samples an action from the policy.

RL: The Lingo



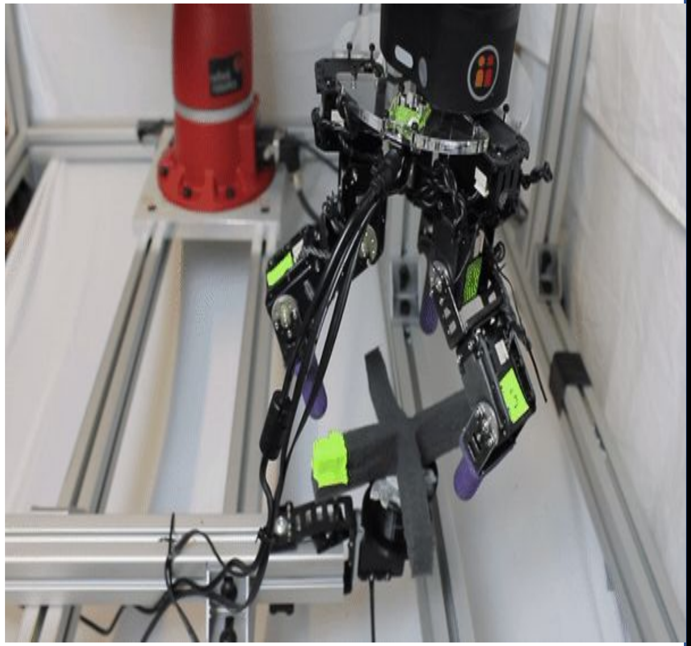
States
State Space
Value Function
Markov Decision Process
Actions
Rewards
Total Reward
Bellman Equations
Environment
Exploration vs exploitation
Q(s,a)
Discount Factor
Agent
Discounted Total Reward
Action Space
$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \gamma^3 r_{t+4} \cdots$
$V_\pi(s) = \sum_a \pi(a|s) \sum_{s' \in S, r \in R} p(s', r | s, a)(r + \gamma V_\pi(s'))$

Applications

Games

- Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., & Riedmiller, M. (2013). Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*.
- Mnih, V., Kavukcuoglu, K., Silver, D. *et al.* Human-level control through deep reinforcement learning. *Nature* **518,** 529–533 (2015). https://doi.org/10.1038/nature14236
- Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A., Chen, Y., Lillicrap, T., Hui, F., Sifre, L., van den Driessche, G[redacted] Graepel, T. and Hassabis, D. 2017. Mastering the game of Go without human knowledge. Nature, 550, 7676 (Oct. 2017), 354--359

Robotics



- Kumar, V., Todorov, E., & Levine, S. (2016, May). Optimal control with learned local models: Application to dexterous manipulation. In *2016 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 378-383). IEEE.
- Gupta, A., Eppner, C., Levine, S., & Abbeel, P. (2016, October). Learning dexterous manipulation for a soft robotic hand from human demonstrations. In *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 3786-3793). IEEE.
- Rajeswaran, A., Kumar, V., Gupta, A., Vezzani, G., Schulman, J., Todorov, E., & Levine, S. (2017). Learning complex dexterous manipulation with deep reinforcement learning and demonstrations. *arXiv preprint arXiv:1709.10087*.

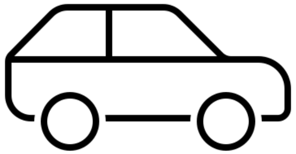
Finance

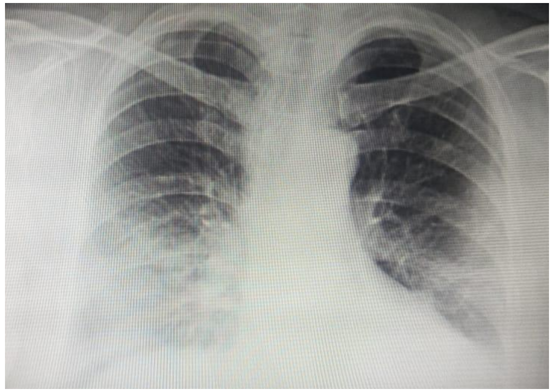
- Portfolio Optimization
- Optimal trade execution
- Pricing strategy in insurance agency

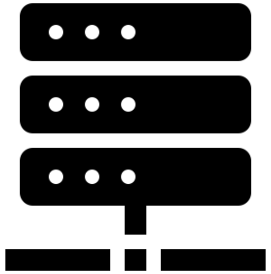
- Jiang, Z., Xu, D., & Liang, J. (2017). A deep reinforcement learning framework for the financial portfolio management problem. *arXiv preprint arXiv:1706.10059*.
- Zhang, Z., Zohren, S., & Roberts, S. (2020). Deep reinforcement learning for trading. *The Journal of Financial Data Science*, *2*(2), 25-40.
- Krasheninnikova, E., García, J., Maestre, R., & Fernández, F. (2019). Reinforcement learning for pricing strategy optimization in the insurance industry. *Engineering applications of artificial intelligence*, *80*, 8-19.

Applications Contd.

- Ridesharing order dispatching
- Medical Image report generation
- Data center cooling







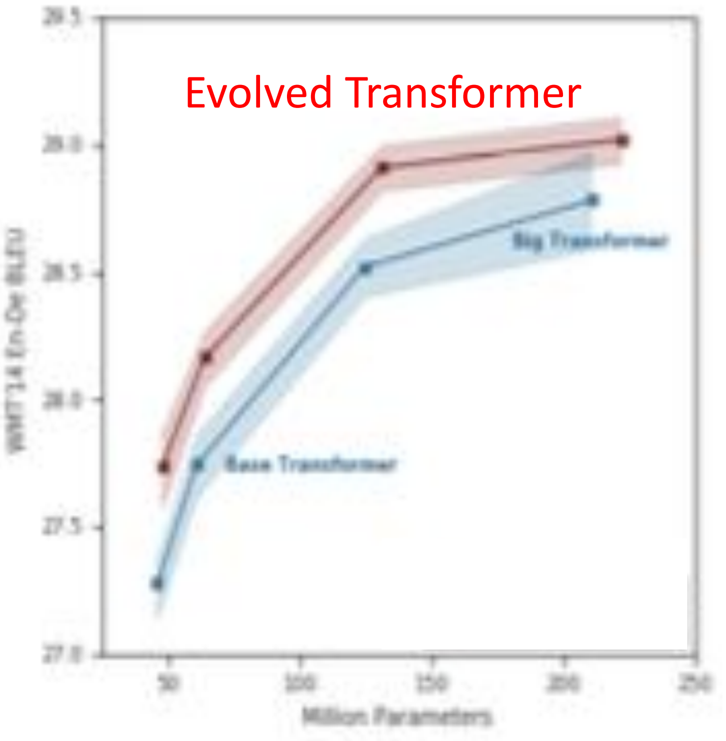
Future Research Directions

Automated Machine Learning

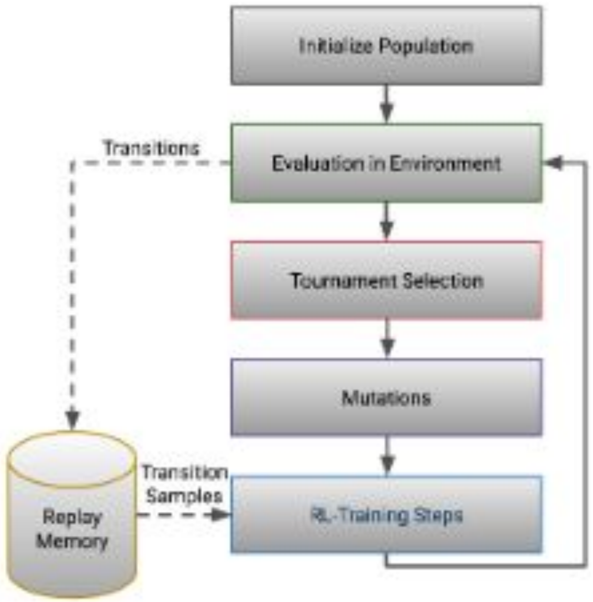
Data Preparation → Feature Selection → Automatic Model

- Model Search
- Hyperparameter Search

- Reinforcement Learning
- Evolutionary Algorithms



AutoRL

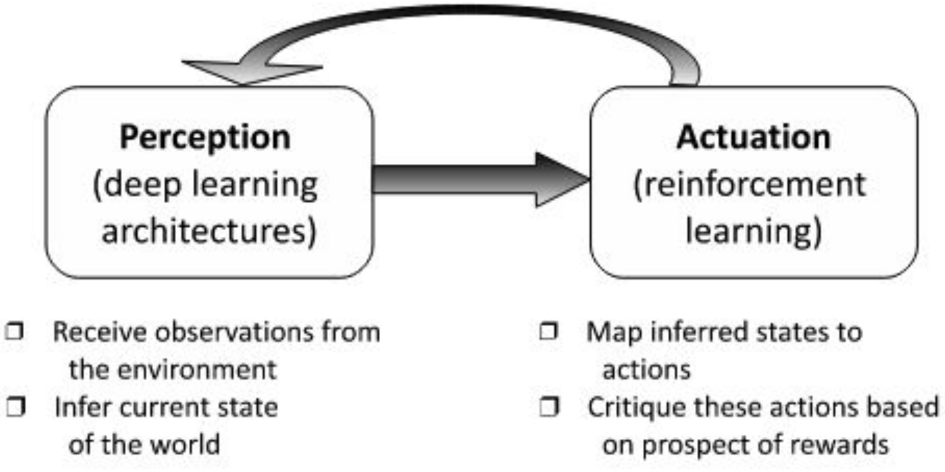


- RL is very sensitive to hyperparameters:
  - Epsilon- exploration/exploitation
  - Discount factor
  - Replay buffer
  - Learning rate
- Moving target problem
- SEARL – population based hyperparameter optimization
- Automated Reward- using Actor – Critic networks

- Franke, J. K., Köhler, G., Biedenkapp, A., & Hutter, F. (2020). Sample-Efficient Automated Deep Reinforcement Learning. *arXiv preprint arXiv:2009.01555*.
- Chiang, H. T. L., Faust, A., Fiser, M., & Francis, A. (2019). Learning navigation behaviors end-to-end with autorl. *IEEE Robotics and Automation Letters*, *4*(2), 2007-2014.

Artificial General Intelligence

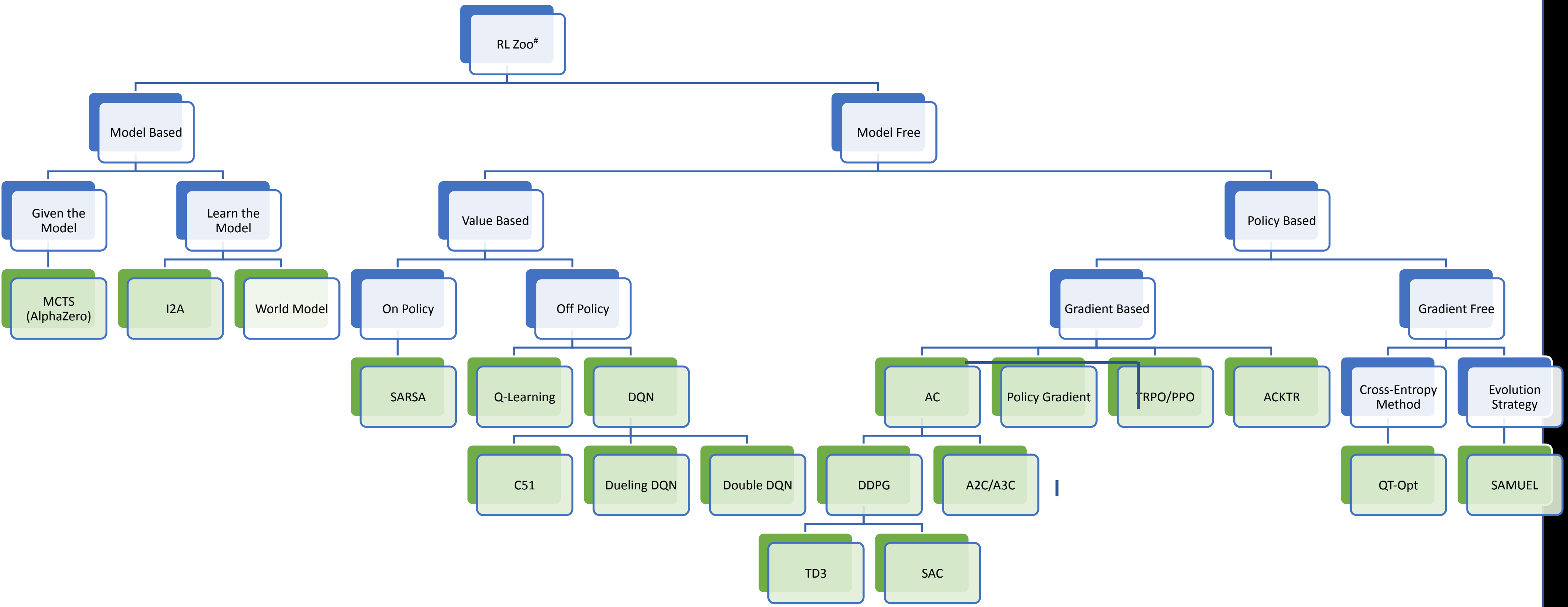
- Build AI systems with goals alignment – RL



- Cognitive Architectures – Clarion a model proposed by Sun

- Arel I. (2012) Deep Reinforcement Learning as Foundation for Artificial General Intelligence. In: Wang P., Goertzel B. (eds) Theoretical Foundations of Artificial General Intelligence. Atlantis Thinking Machines, vol 4. Atlantis Press, Paris.
- Sun, R. (2006). The CLARION cognitive architecture: Extending cognitive modeling to social simulation. *Cognition and multi-agent interaction*, 79-99.

RL Zoo



#Zhang H., Yu T. (2020) Taxonomy of Reinforcement Learning Algorithms. In: Dong H., Ding Z., Zhang S. (eds) Deep Reinforcement Learning. Spring[redacted]


Thank
You
köszönöm
Kiitos
Asante
Shukria
Vinaka
Maake
Dhanyavadagalu
감사합니다
Dankscheen
спасибо
Kam Sah Hammida
اركش
Manana
Dankon
Terima Kasih
Matondo
Dank Je
Mauruuru
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Taiku
Tack
Blagodaram
Ngiyabonga
Dziekuje
Chokrane
Grazie
Juspaxar
Arigato
Mochchakkeram
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Eskerrik Asko
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