Multiple scales of task and reward-based learning

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DeepMind

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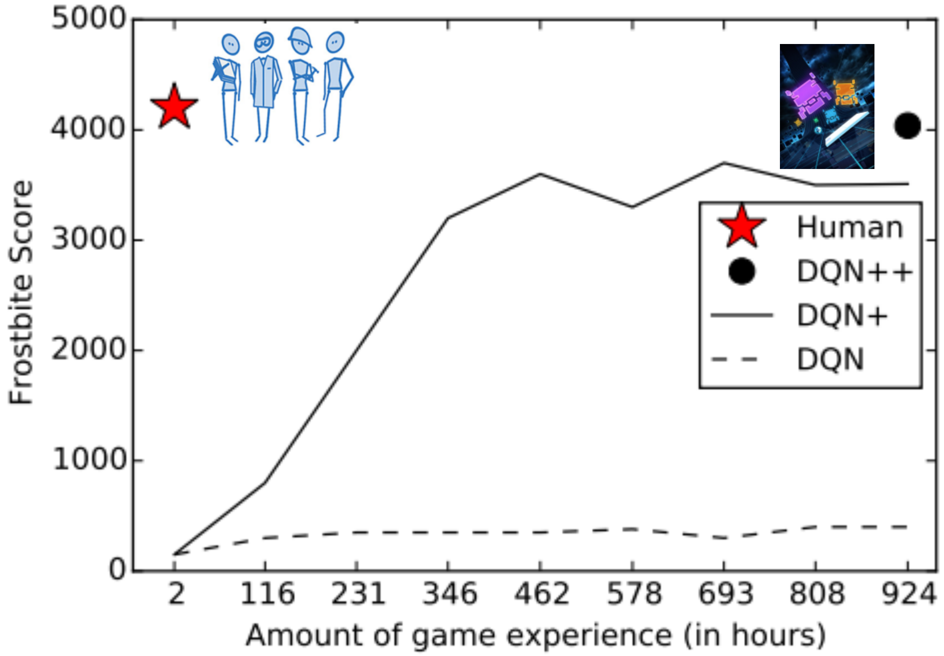
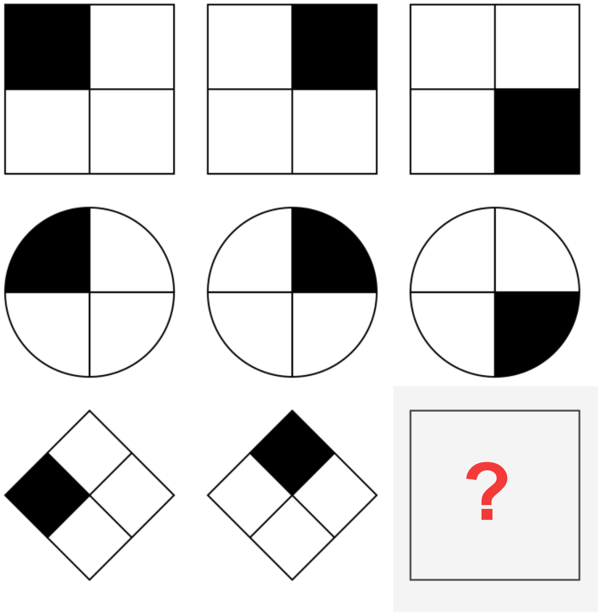


Building machines that learn and think like people, Lake et al, 2016

Raven's progressive matrices (J. C. Raven, 1936)



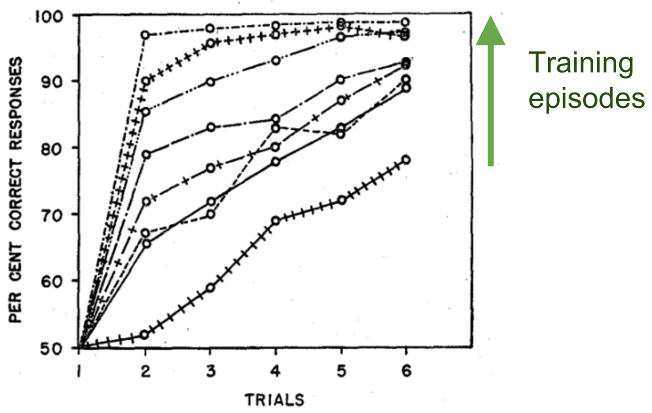
Meta-Learning: Learning inductive biases or priors

Learning faster with more tasks, benefiting from transfer across tasks and learning on related tasks

Evolutionary principles in self-referential learning (Schmidhuber, 1987)

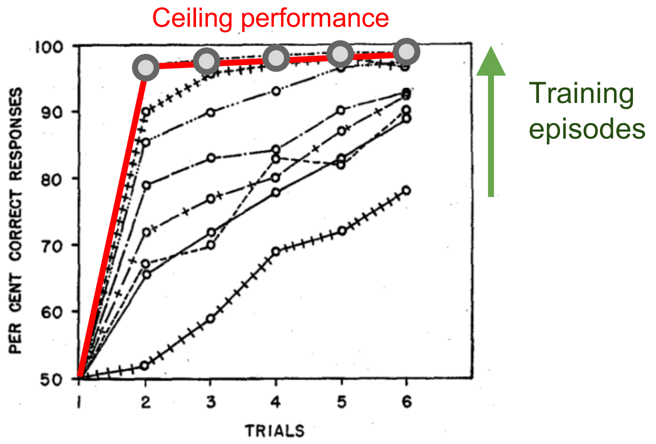
Learning to learn (Thrun & Pratt,1998)

Meta-RL: learning to learn from reward feedback



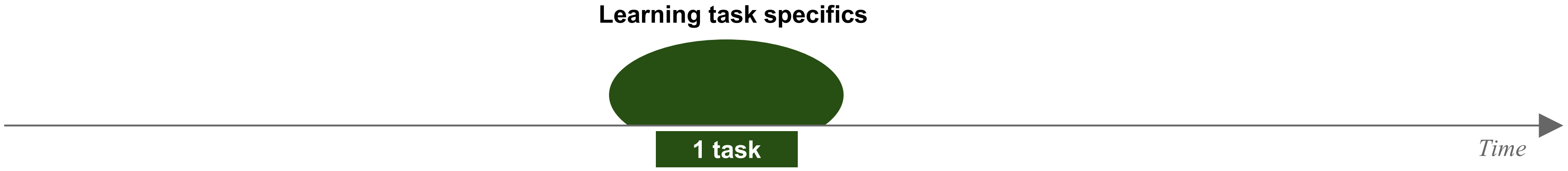
Harlow, Psychological Review, 1949

Meta-RL: learning to learn from reward feedback



Harlow, Psychological Review, 1949

Multiple scales of reward-based learning



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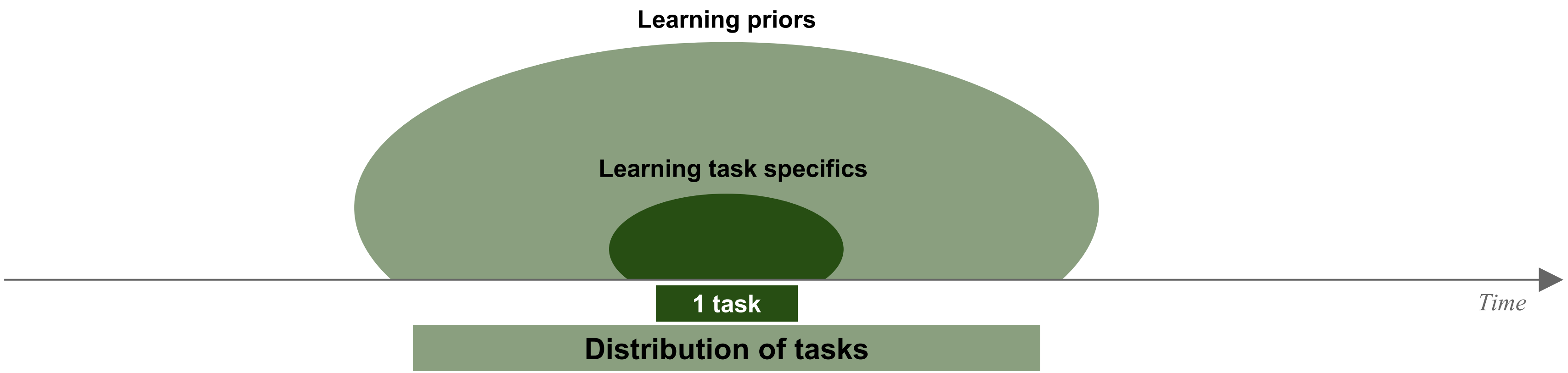
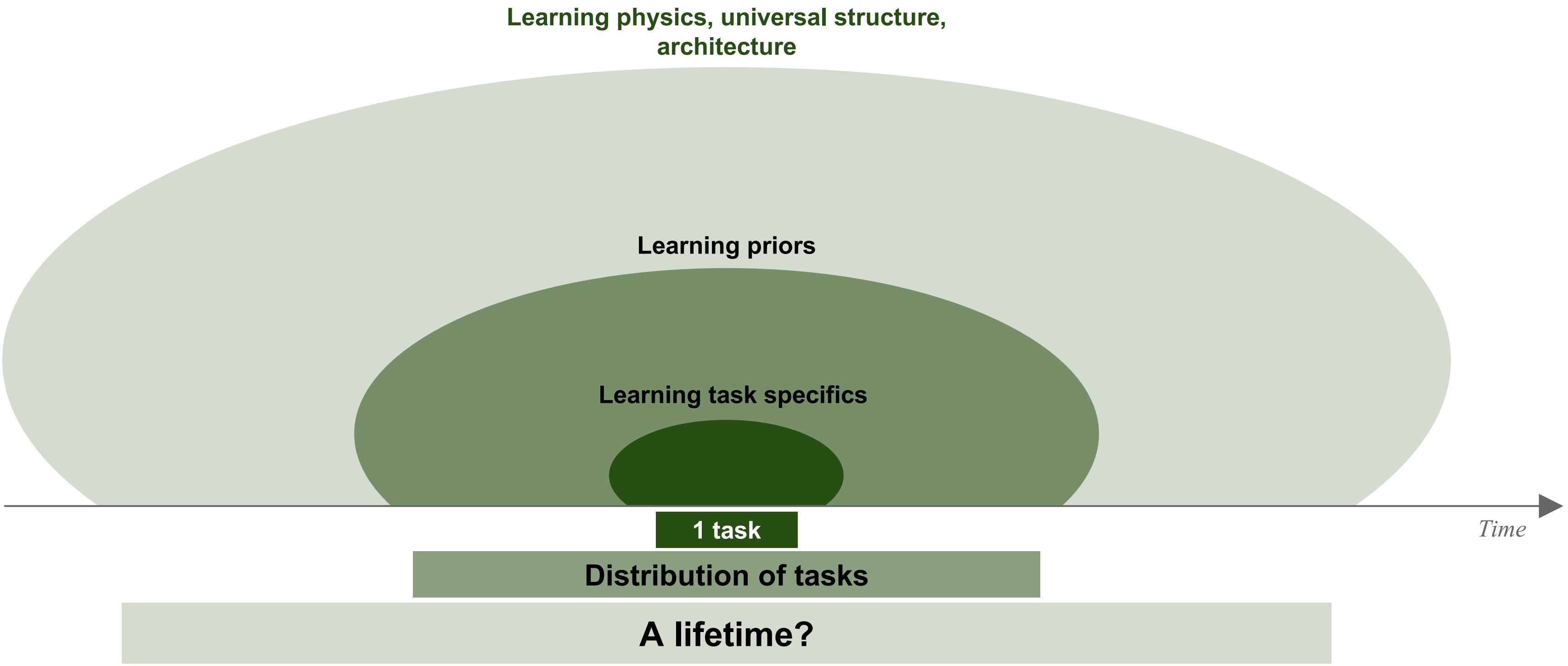
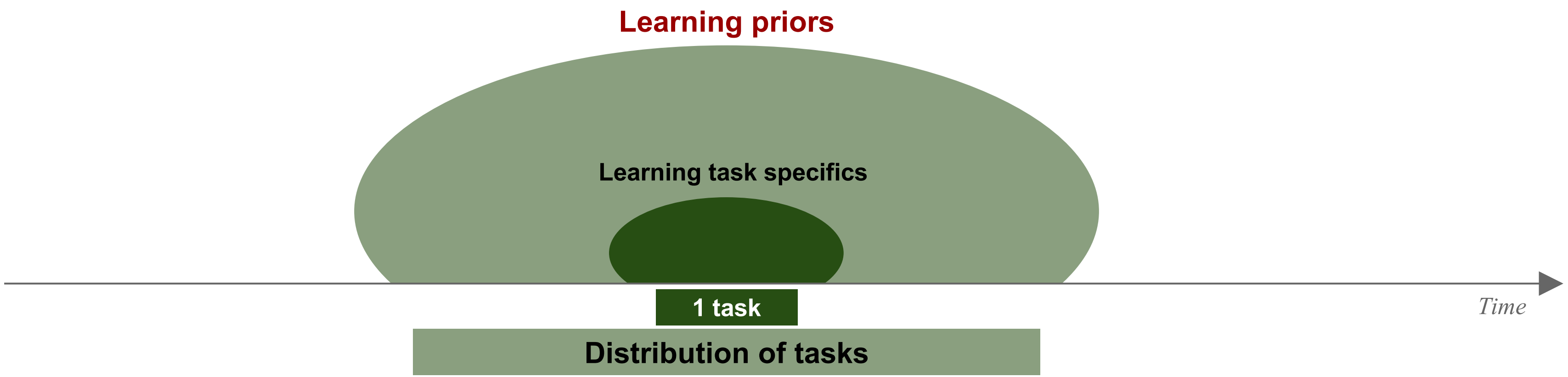


Nested learning algorithms happening in parallel, on different timescales

Multiple scales of reward-based learning



Multiple scales of reward-based learning



Different ways of building priors

Handcrafted features, expert knowledge, teaching signals

Learning good initialization
Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks (Finn et al, 2017 ICML)

Learning a meta-optimizer
Learning to learn by gradient descent by gradient descent (Andrychowicz et al, 2016)

Learning an embedding function
Matching networks for one shot learning (Vinyals et al, 2016)

Bayesian program learning
Human-level concept learning through probabilistic program induction (Lake et al, 2015)

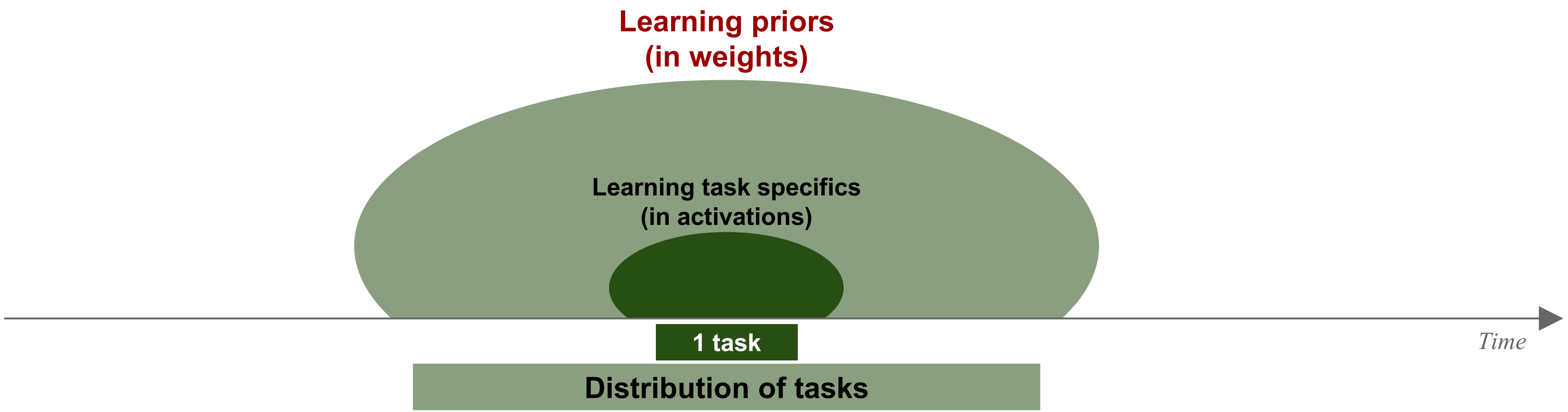
Implicitly learned via recurrent neural networks/external memory
Meta-learning with memory-augmented neural networks (Santoro et al, 2016)

…

What all these have in common is a way to build in assumptions that **constrain the space of hypotheses** to search over

RNNs + distribution of tasks to learn prior implicitly

Use activations of a recurrent neural network (RNN) to implement RL in dynamics, shaped by priors learned in the weights

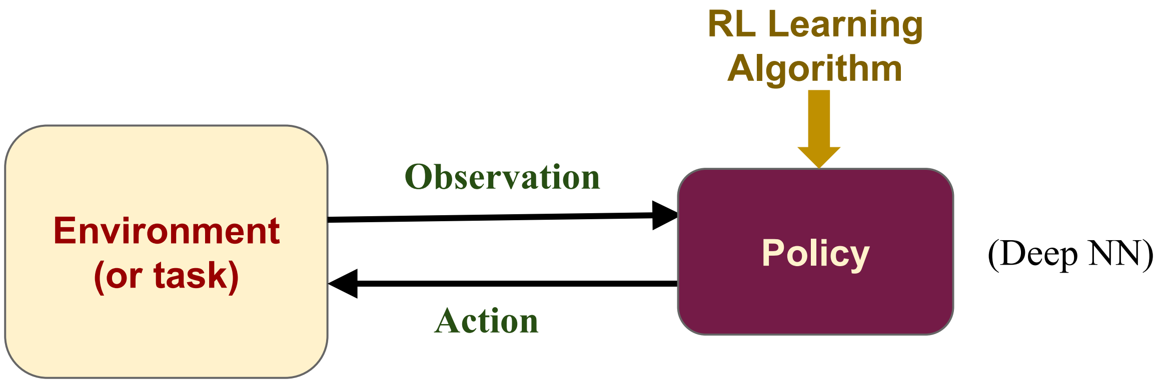


Constrain hypothesis space with task distribution, correlated in the prior we want to learn, but different in ways we want to abstract over (ie specific image, reward contingency)

Prefrontal cortex and flexible cognitive control: Rules without symbols (Rougier et al, 2005)

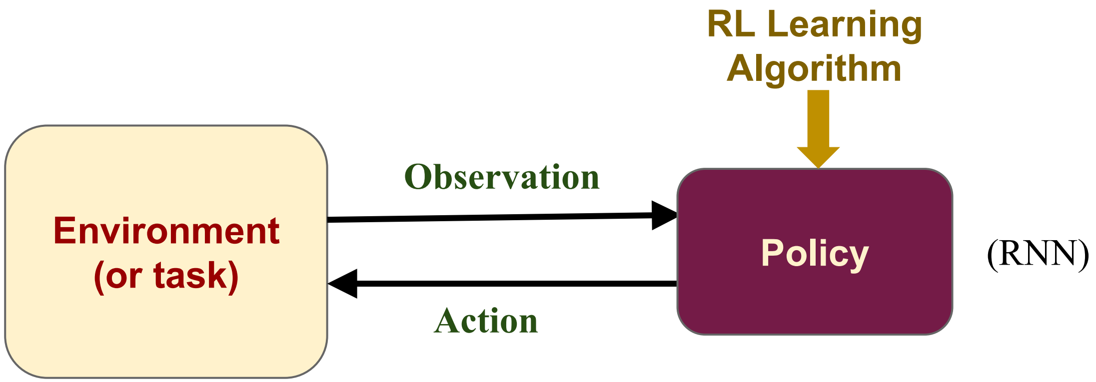
Domain randomization for transferring deep neural networks from simulation to the real world (Tobin et al, 2017)

Learning the correct policy



Map observations to actions in order to maximize reward for environment

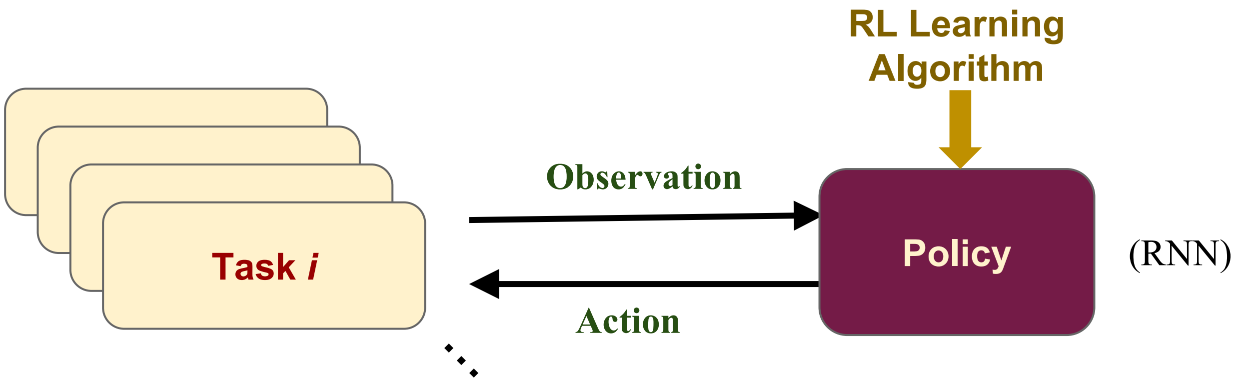
Learning the correct policy with an RNN



Map history of observations and states to future actions in order to maximize reward for a sequential task

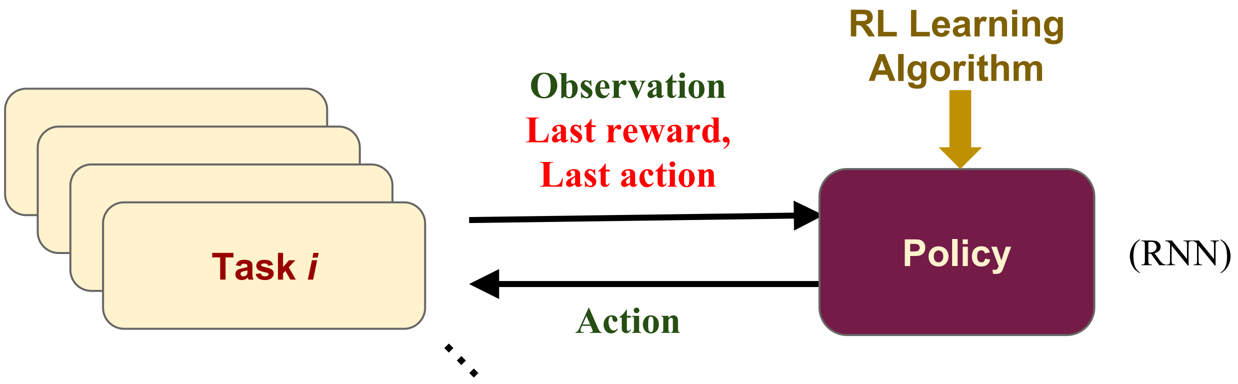
Song et al, 2017 eLife; Miconi et al, 2017 eLife; Barak, 2017 Curr Opin Neurobiol

Learning to learn the correct policy: meta-RL



Map history of observations and past rewards/actions to future actions in order to maximize reward for a distribution of tasks

Learning to learn the correct policy: meta-RL



Map history of observations and past rewards/actions to future actions in order to maximize reward for a distribution of tasks

Wang et al, 2016. Learning to reinforcement learn. arXiv:1611.05763
Duan et al, 2016. RL^2: Fast reinforcement learning via slow reinforcement learning. arXiv:1611.02779

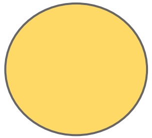
What is a “task distribution”?

What is “task structure”?

What is a task?

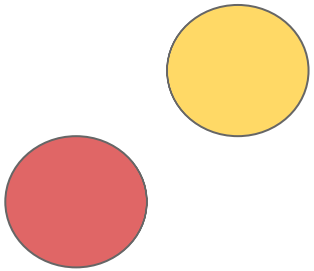
What is a task?

➢ Visuospatial/perceptual features



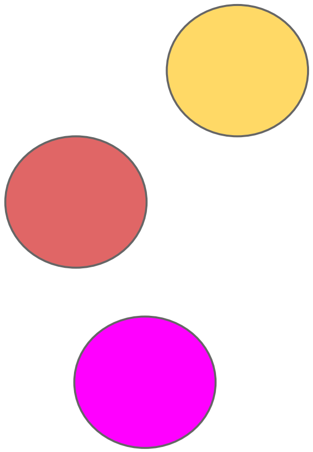
What is a task?

- Visuospatial/perceptual features
- Domain (language, images, robotics, etc.)



What is a task?

- Visuospatial/perceptual features
- Domain (language, images, robotics, etc.)
- Reward contingencies



What is a task?

- ➢ Visuospatial/perceptual features
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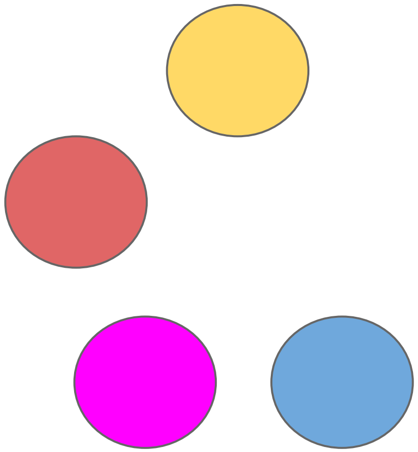
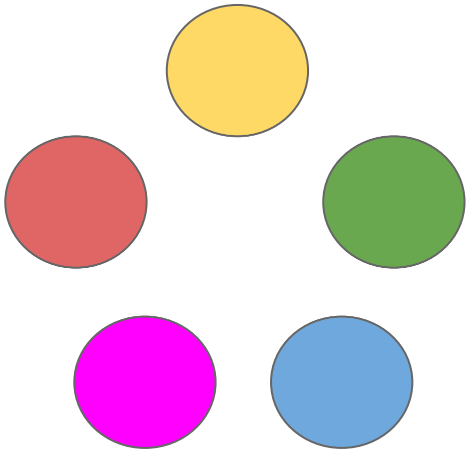
- ➢ Reward contingencies
- ➢ Temporal structure/dynamics



What is a task?

- ➢ Visuospatial/perceptual features
- ➢ Domain (language, images, robotics, etc.)
- ➢ Reward contingencies
- ➢ Temporal structure/dynamics
- ➢ Interactivity and actions



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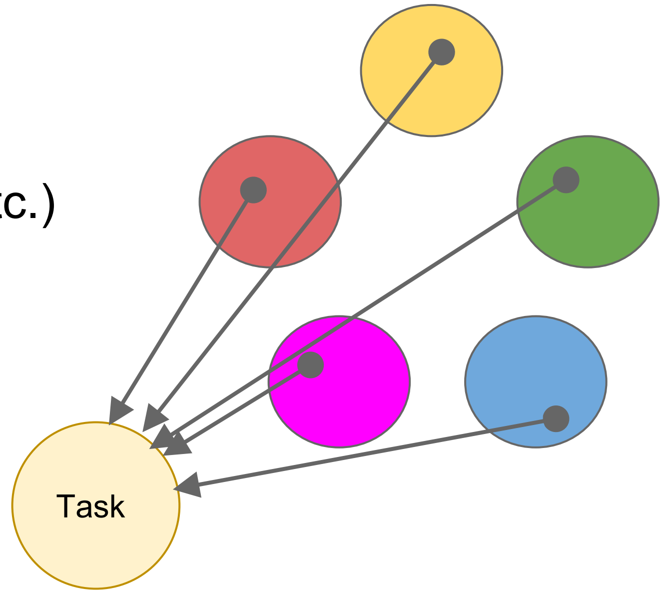

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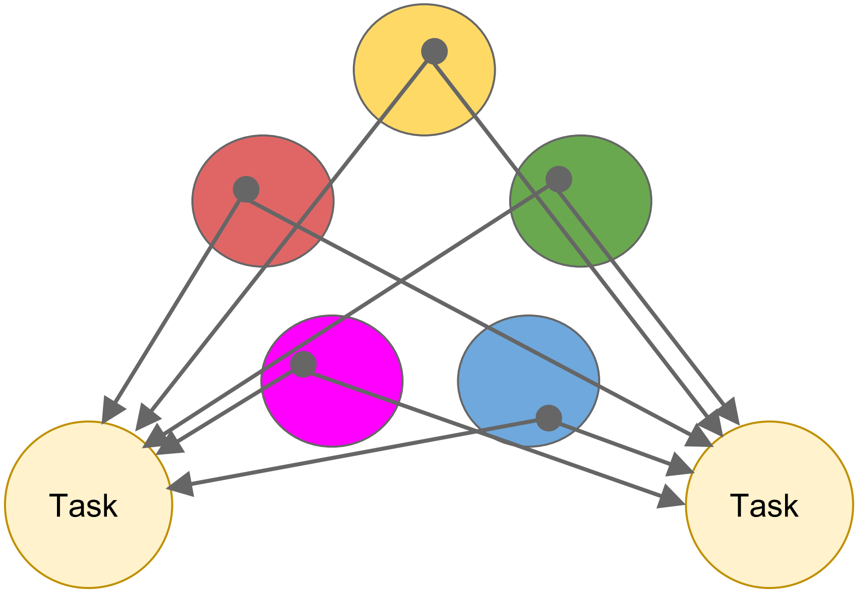
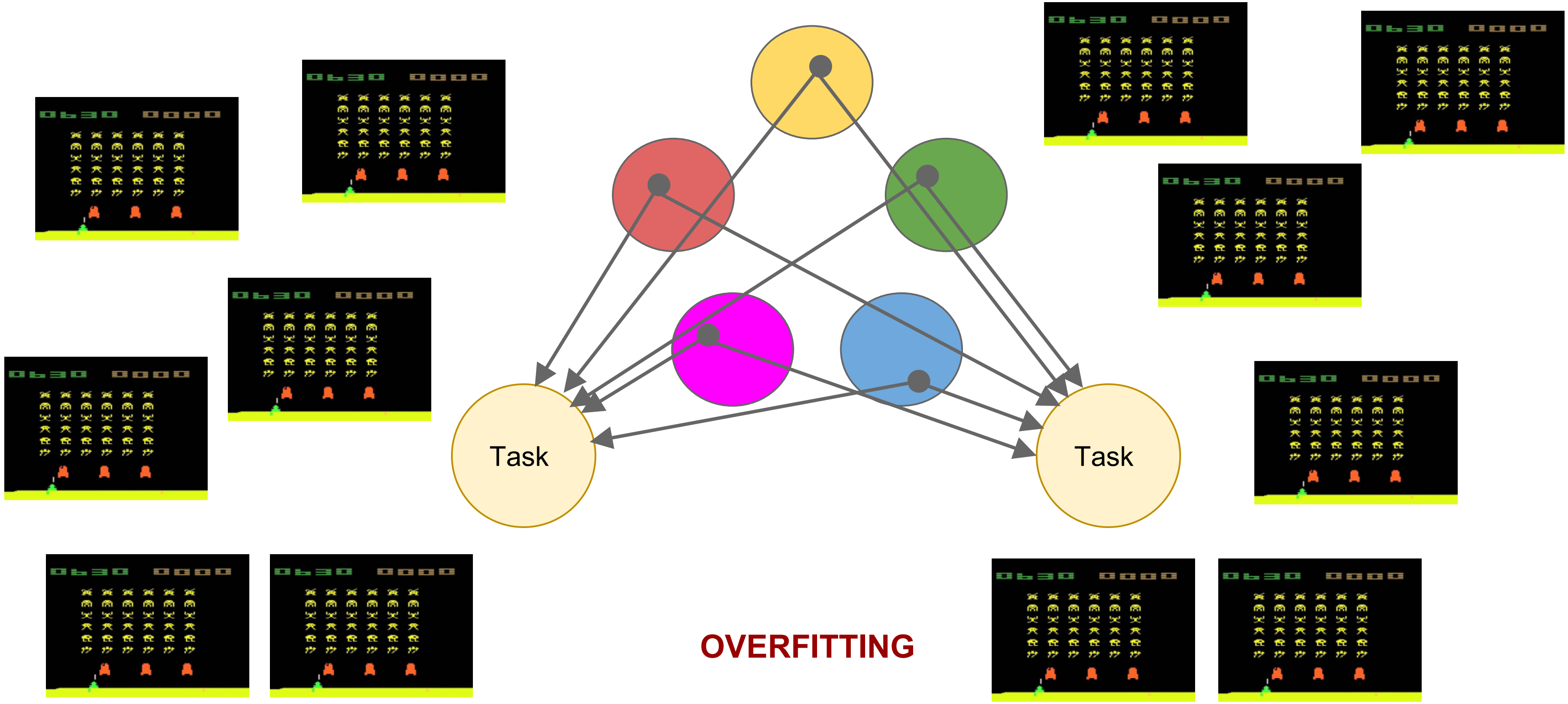
Training tasks

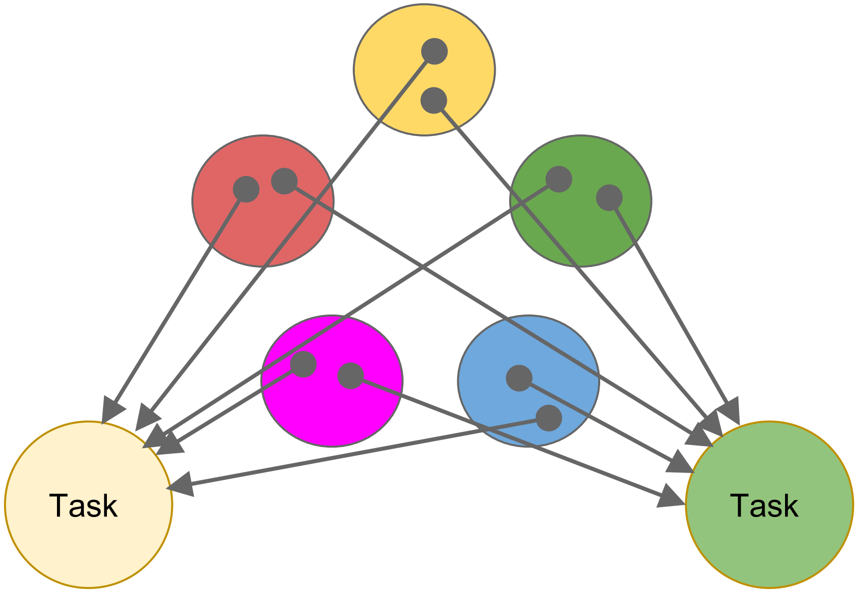


OVERFITTING

Training tasks

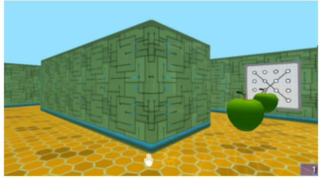


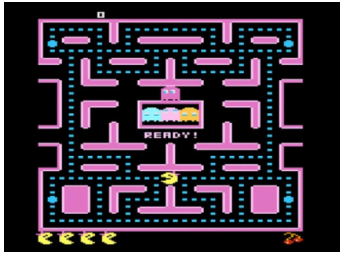
Training tasks

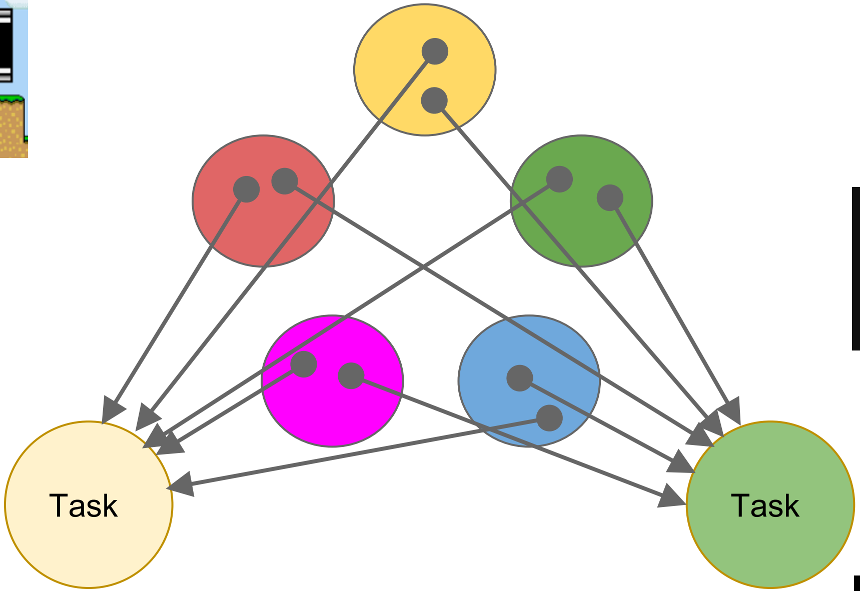


CATASTROPHIC FORGETTING
INTERFERENCE

Training tasks







CATASTROPHIC FORGETTING
INTERFERENCE

What is the sweet spot of task relatedness?

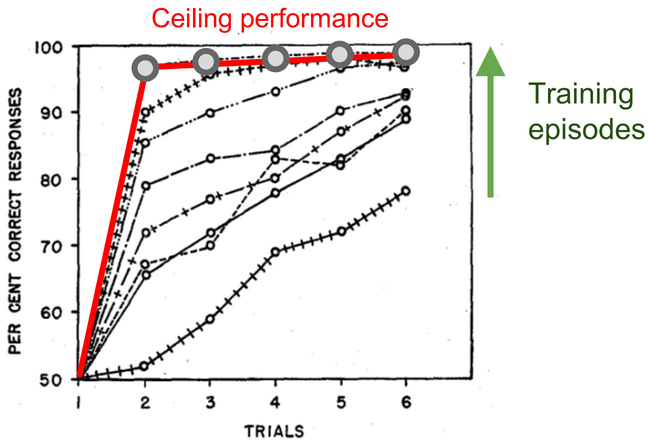
- ➢ Visuospatial/perceptual features
- ➢ Domain (language, images, robotics, etc.)
- ➢ Reward contingencies
- ➢ Temporal structure/dynamics
- ➢ Interactivity and actions

What is the sweet spot of task relatedness?

- ➢ Visuospatial/perceptual features
- ➢ **Domain (language, images, robotics, etc.)**
- ➢ Reward contingencies
- ➢ **Temporal structure/dynamics**
- ➢ **Interactivity and actions**

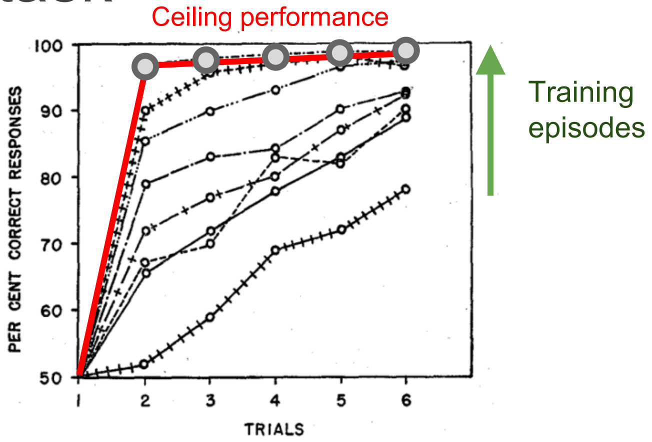
(but eventually vary over!)

Harlow task

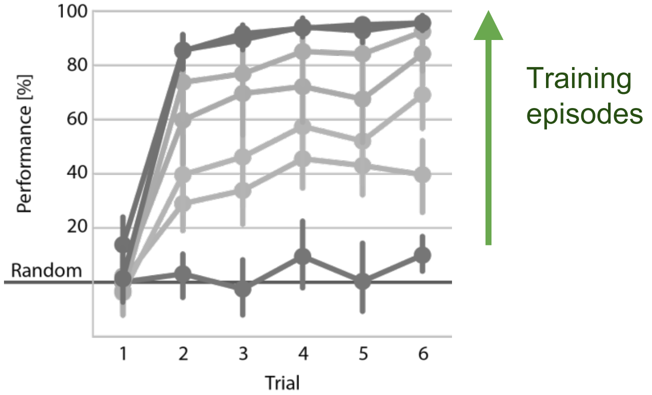


Harlow, Psychological Review, 1949

Meta-RL in the Harlow task

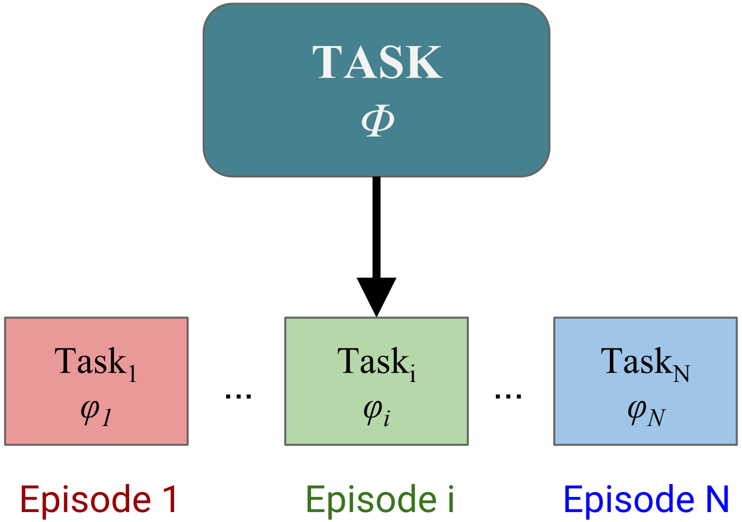


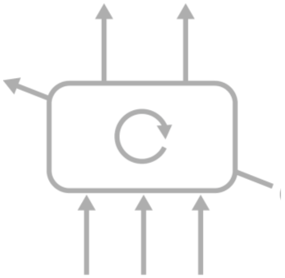
Meta-RL



Harlow, Psychological Review, 1949

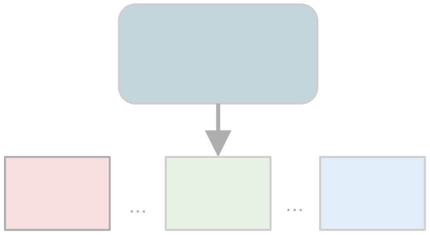
Ingredients: Environment

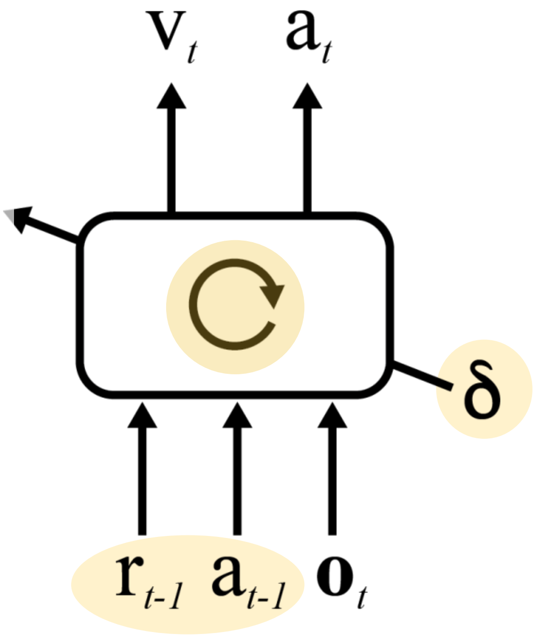




- **Distribution** of RL tasks with **structure**

Ingredients: Architecture



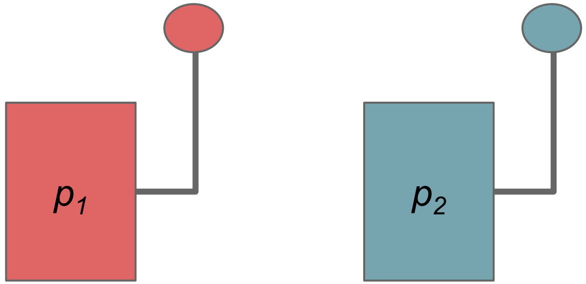


- **Primary** RL algorithm to train weights: Advantage actor-critic (*Mnih et al 2016*)
  - Turned off during test
- Auxiliary inputs in addition to observation: reward and action
- Recurrence (LSTM) to integrate history
- Emergence of **secondary** RL algorithm implemented in **recurrent activity dynamics**
  - Operates in absence of weight changes
  - **With potentially radically different properties**

Independent bandits

2-armed bandits
independently drawn from
uniform Bernoulli distribution

Held constant for 100 trials
=1 episode

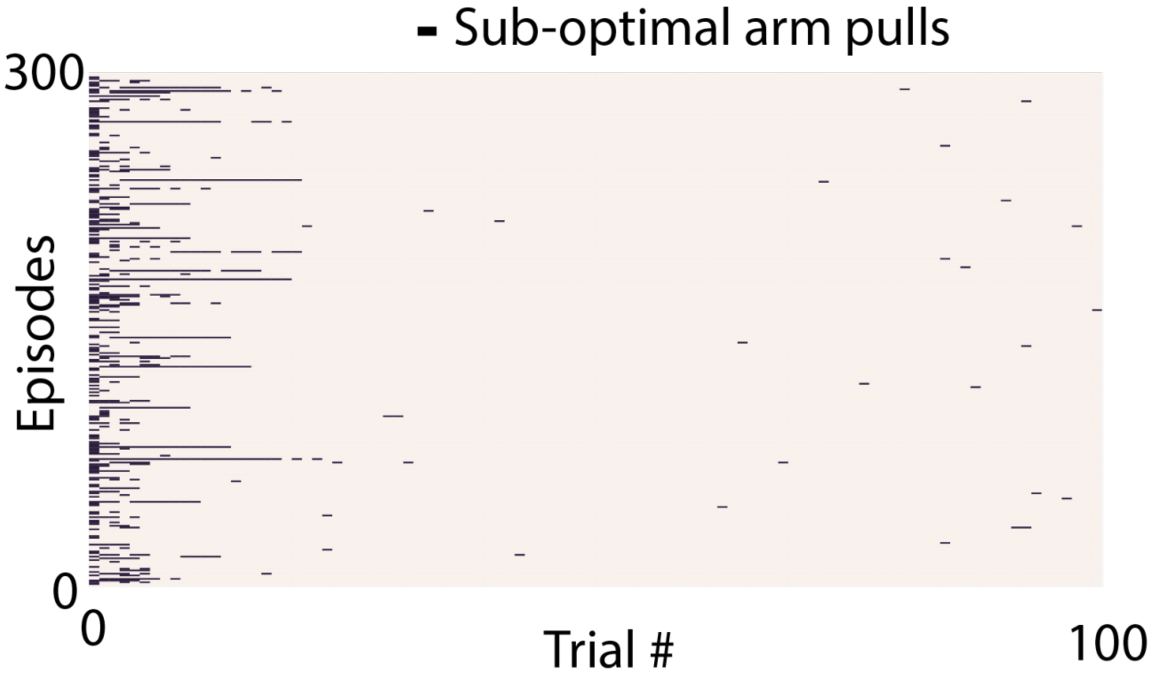


p_i = probability of payout,
drawn uniformly from [0,1],

Independent bandits

2-armed bandits independently drawn from uniform Bernoulli distribution

Tested with fixed weights



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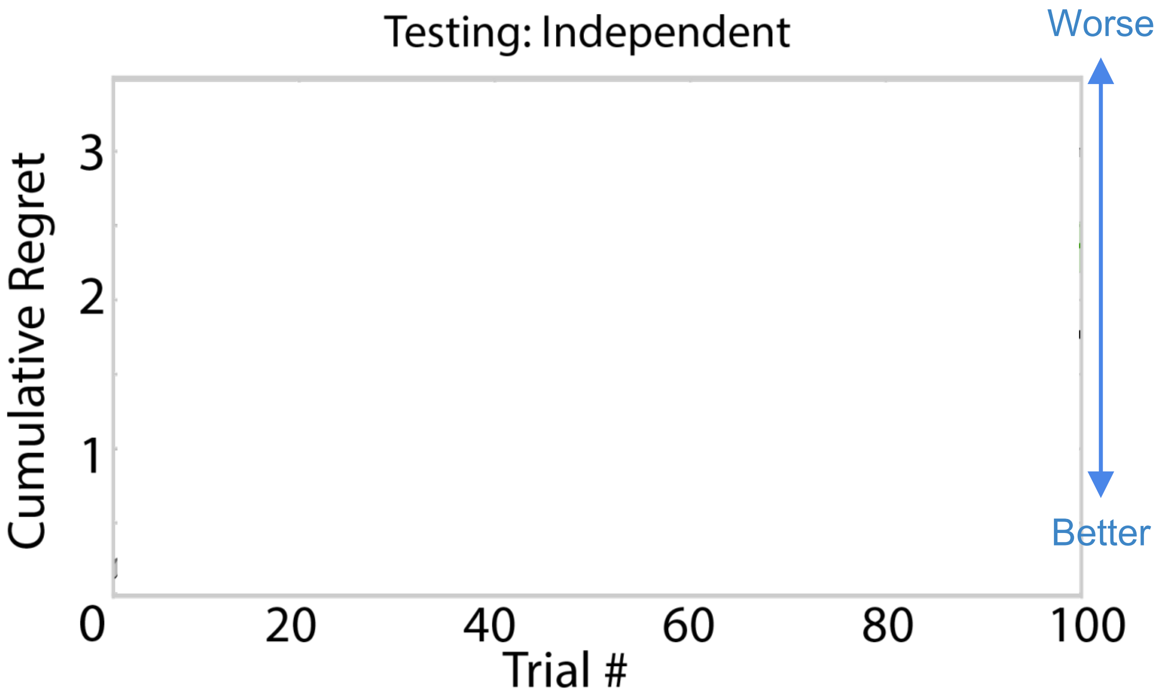
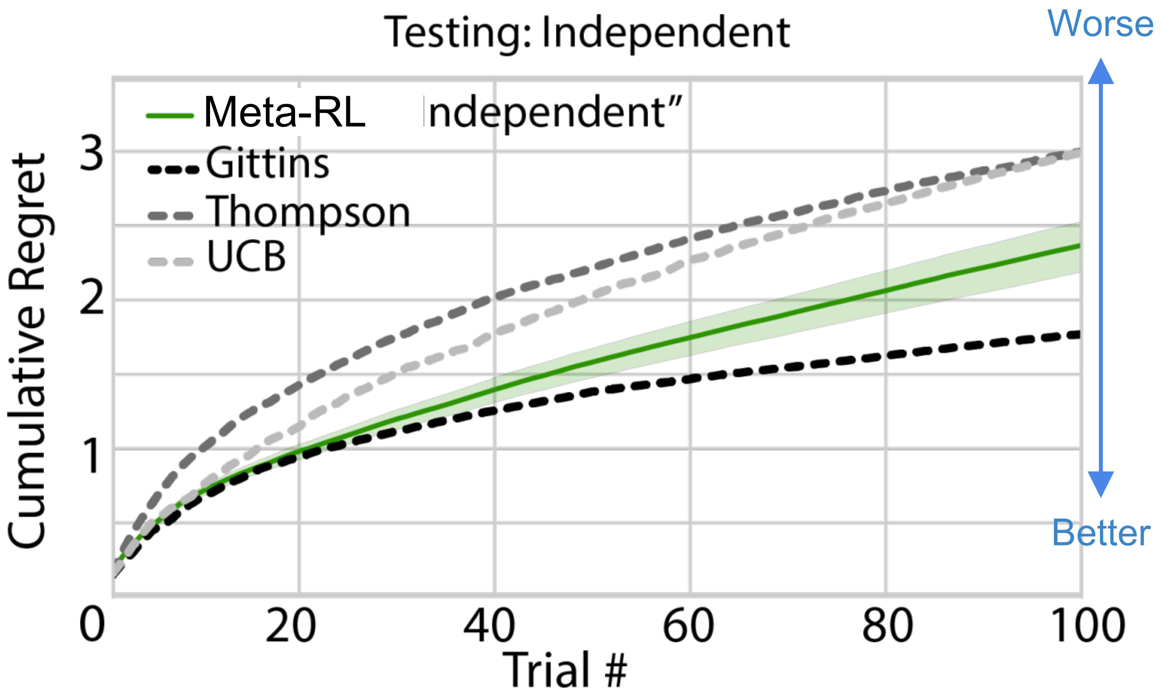


Independent bandits

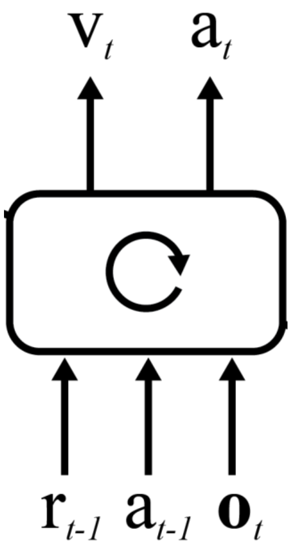
2-armed bandits independently drawn from uniform Bernoulli distribution

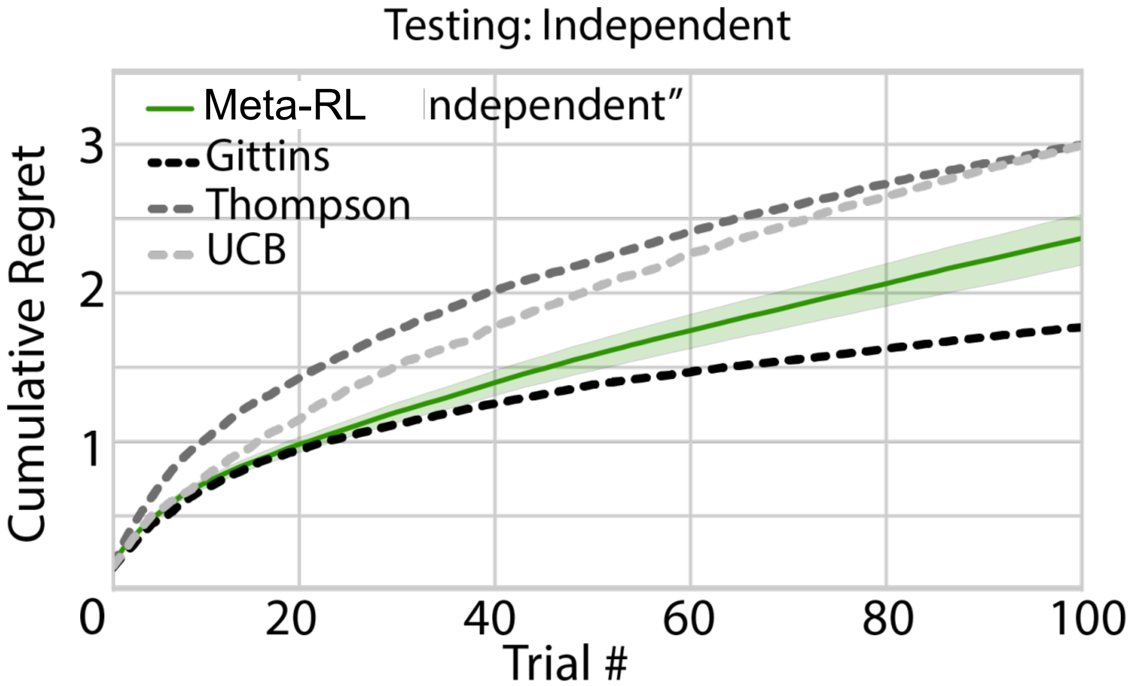
Tested with fixed weights

Performance comparable to standard bandit algorithms



Ablation Experiments





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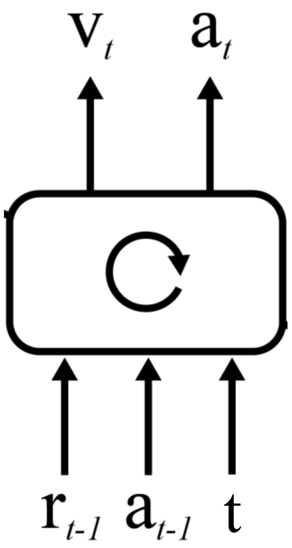

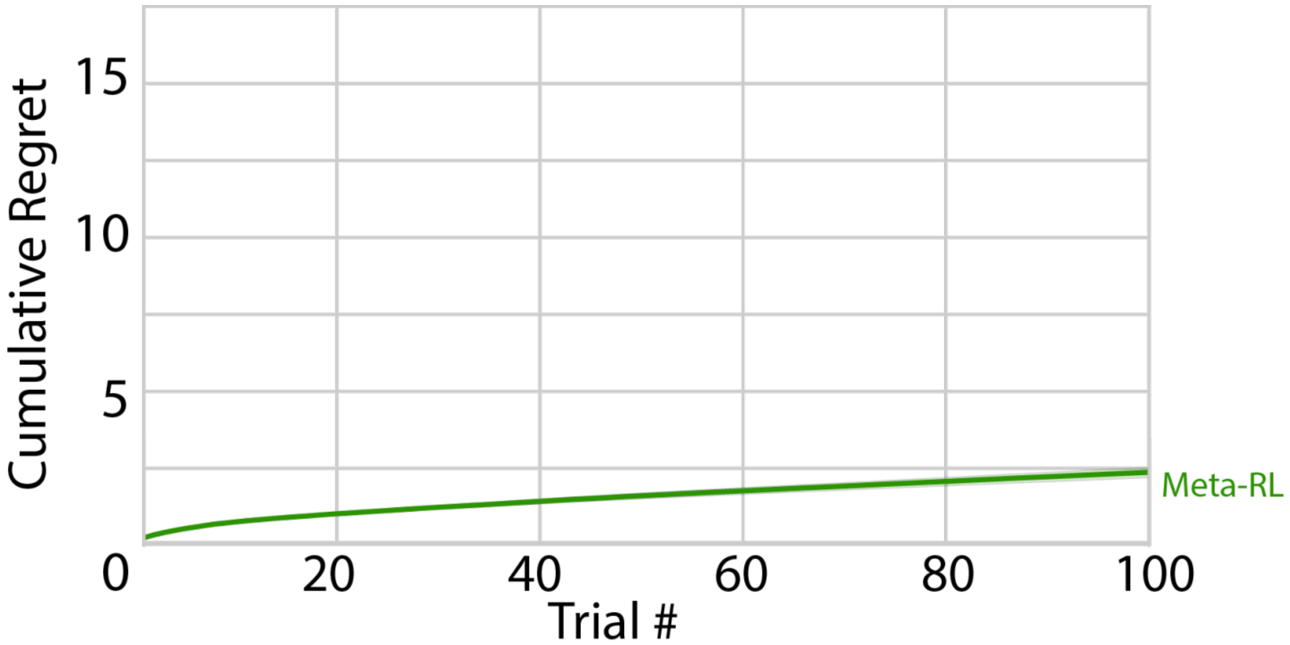

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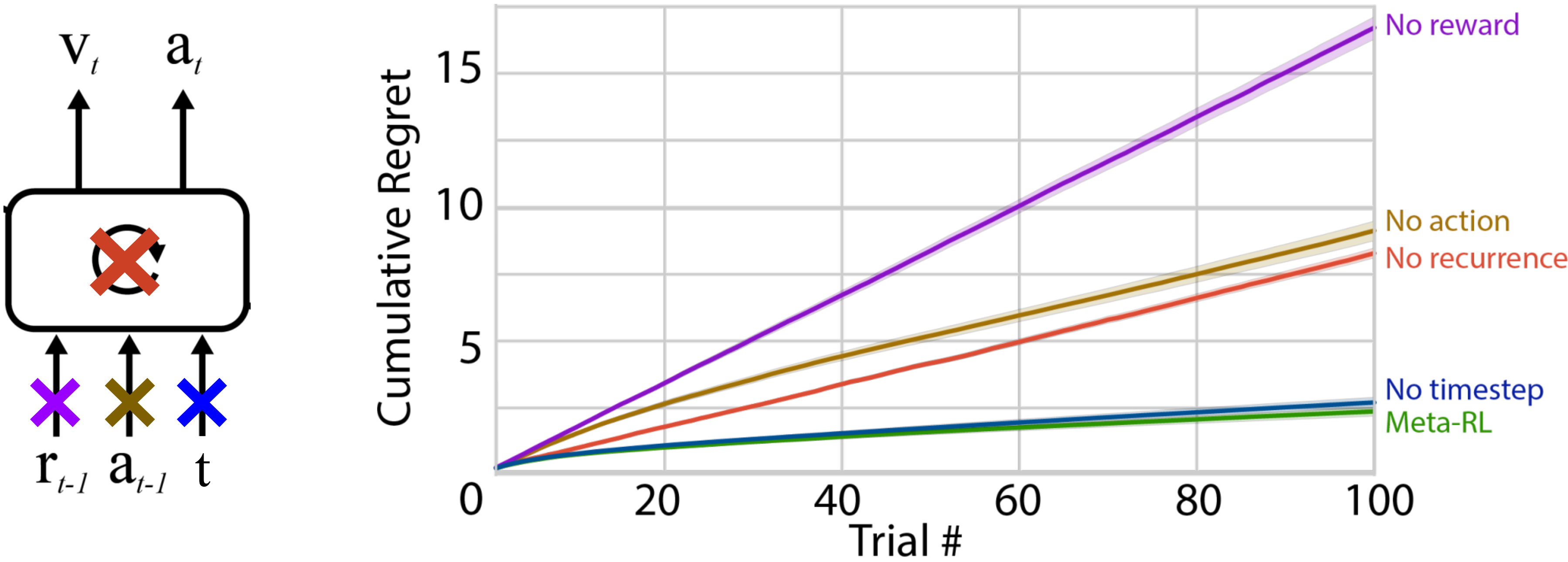
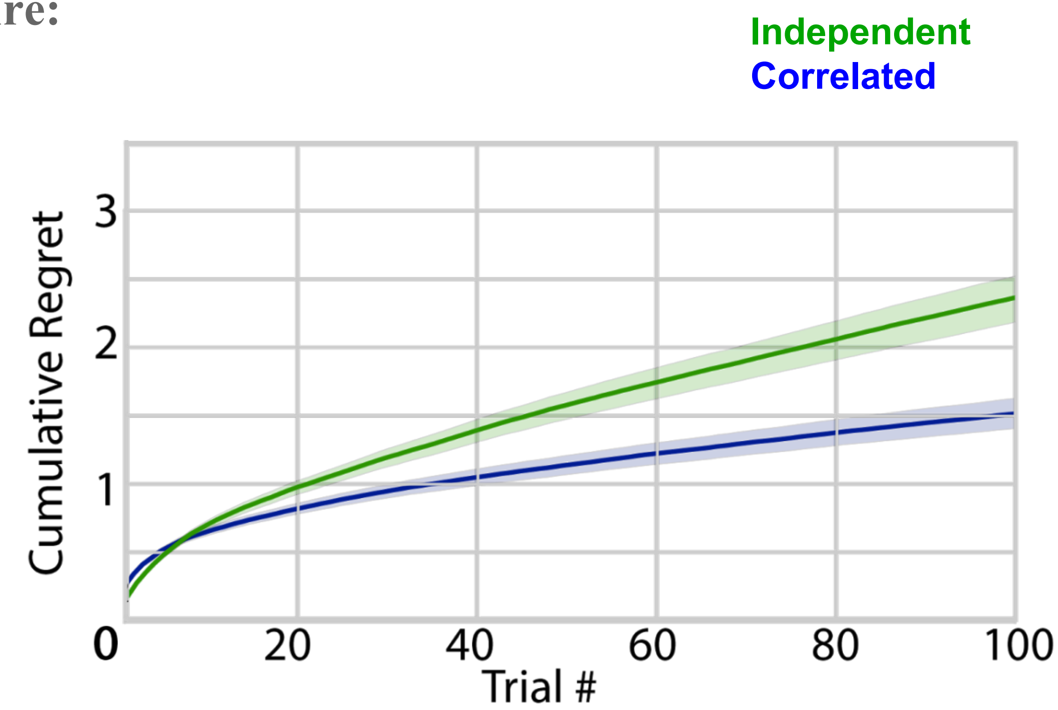


Structured bandits

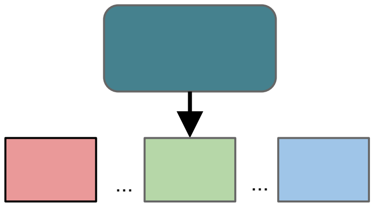
Bandits with **correlational structure:**

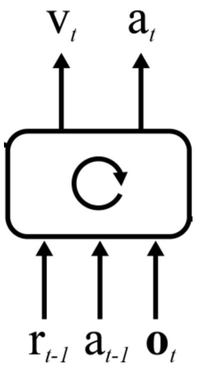
$$\{p_L, p_R\} = \{\boldsymbol{\mu}, 1\text{-}\boldsymbol{\mu}\}$$

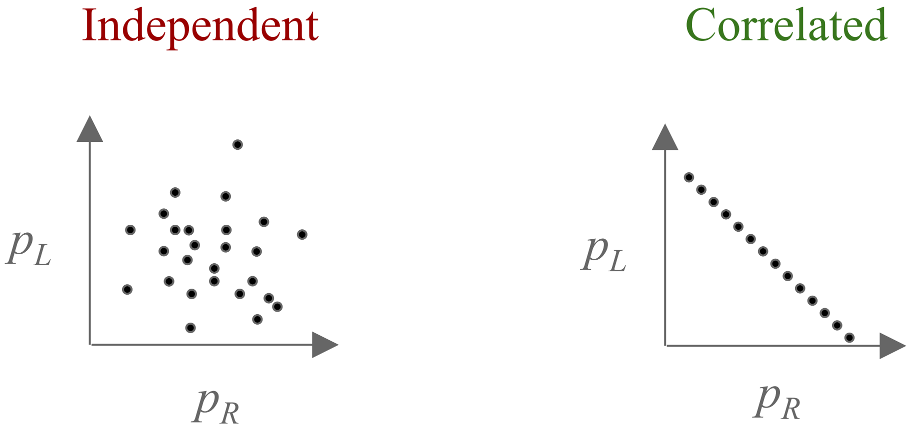
Meta-RL learns to exploit structure in the environment



LSTM hidden states internalize structure







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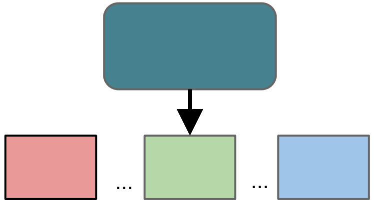

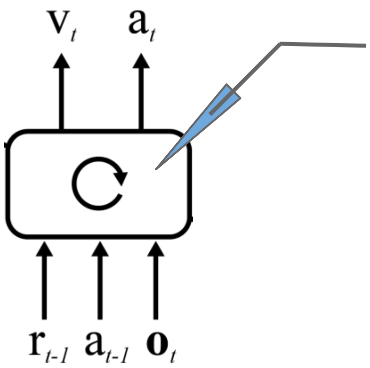

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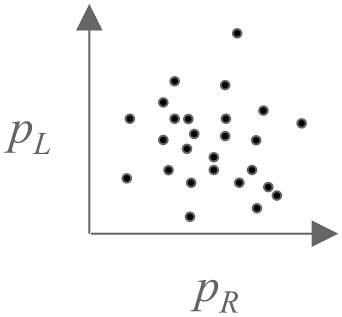
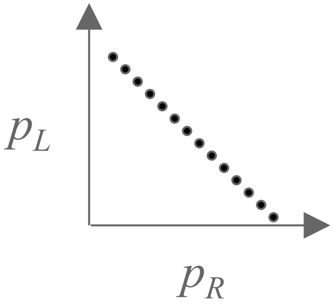


Correlated



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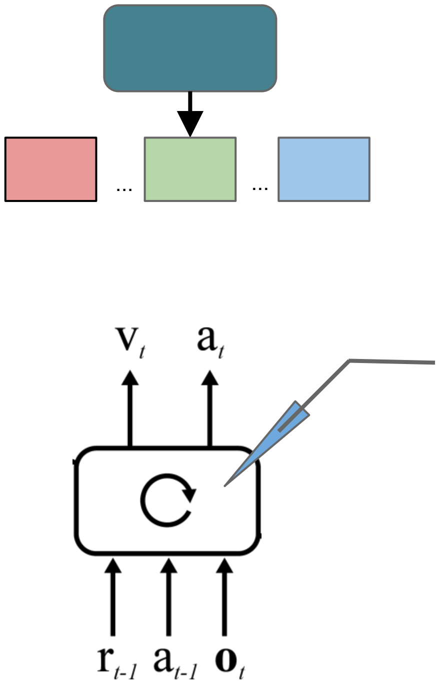

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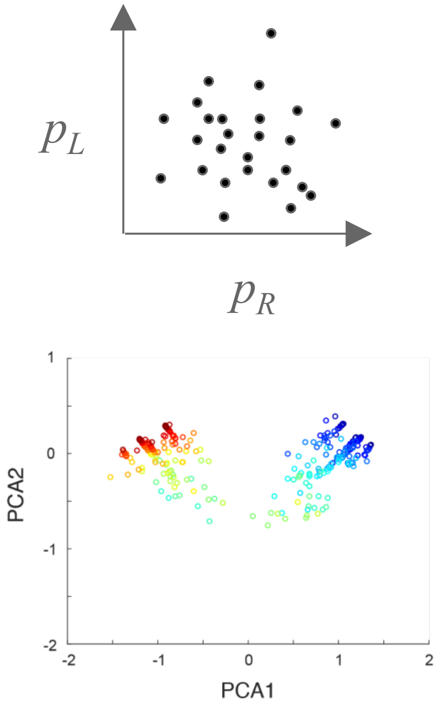

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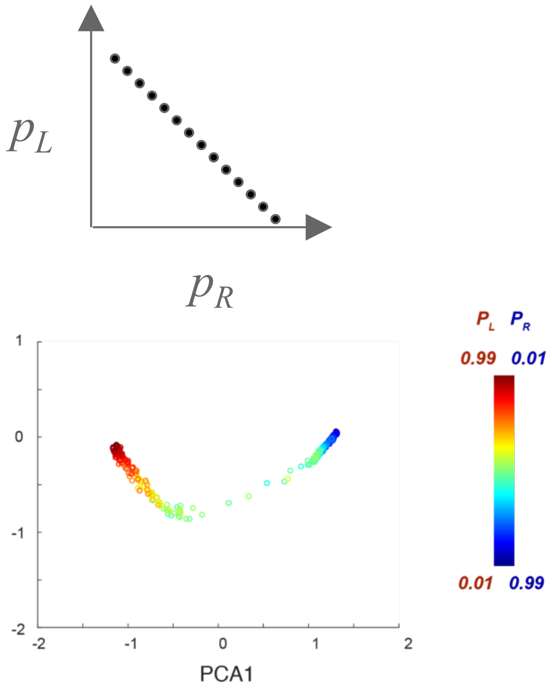

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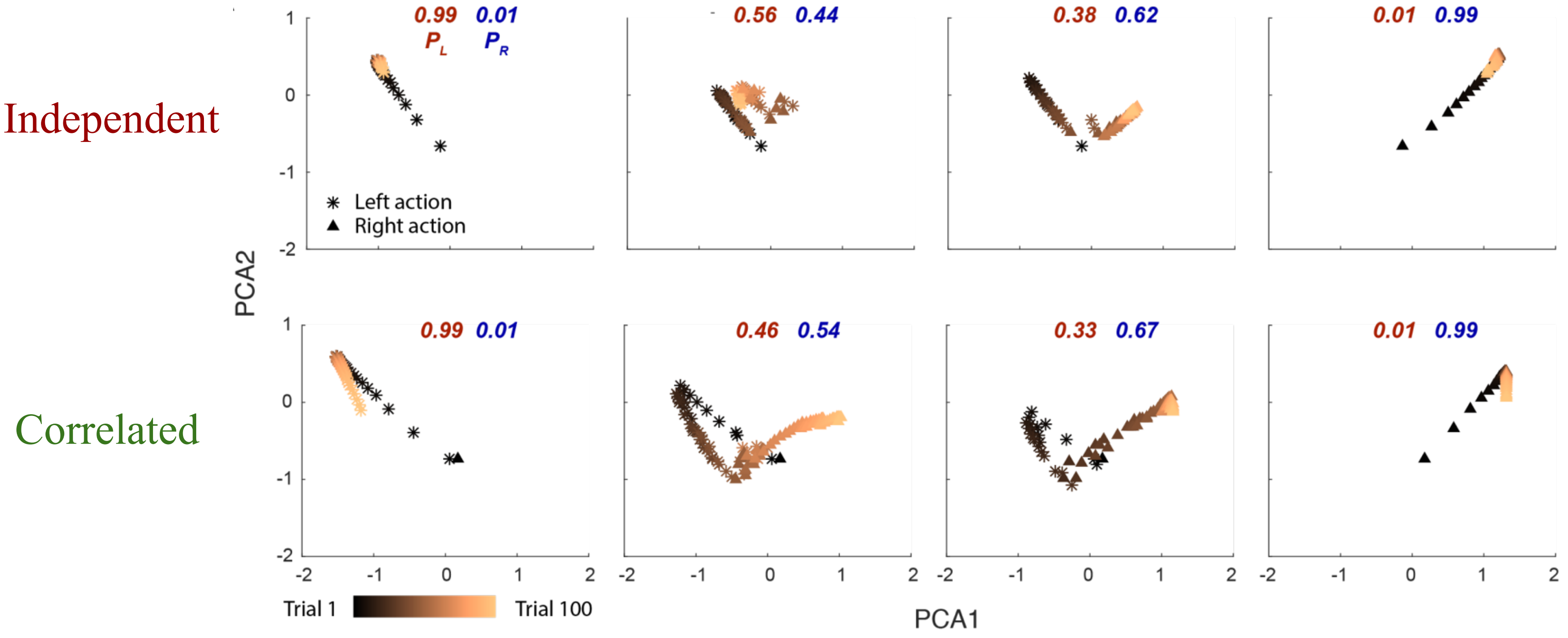
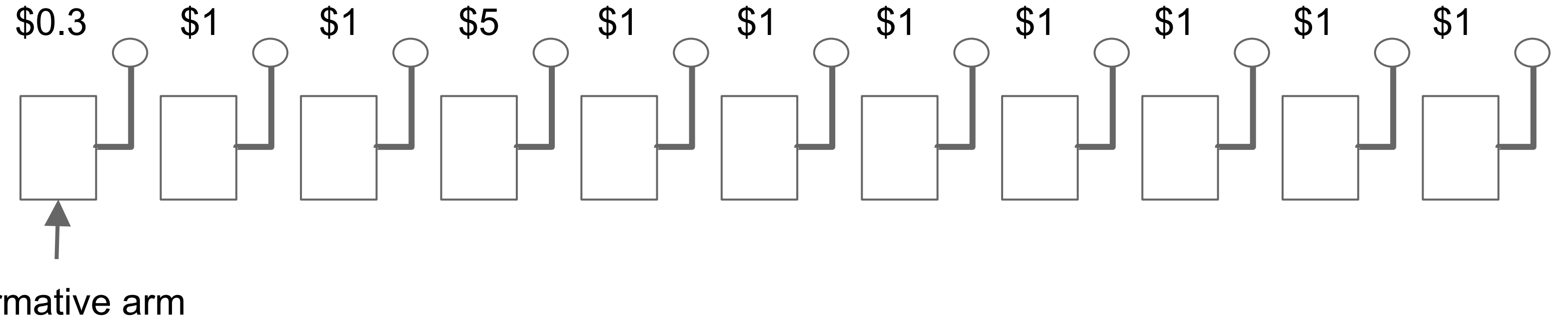


Structured bandits

11-arm bandits that require sampling lower-reward arm in order to **gain information** for maximal long-term gain



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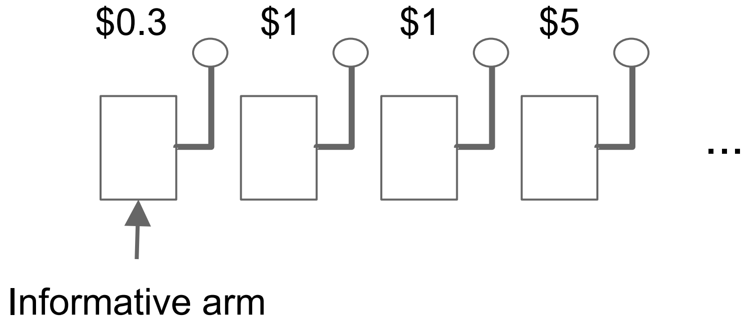
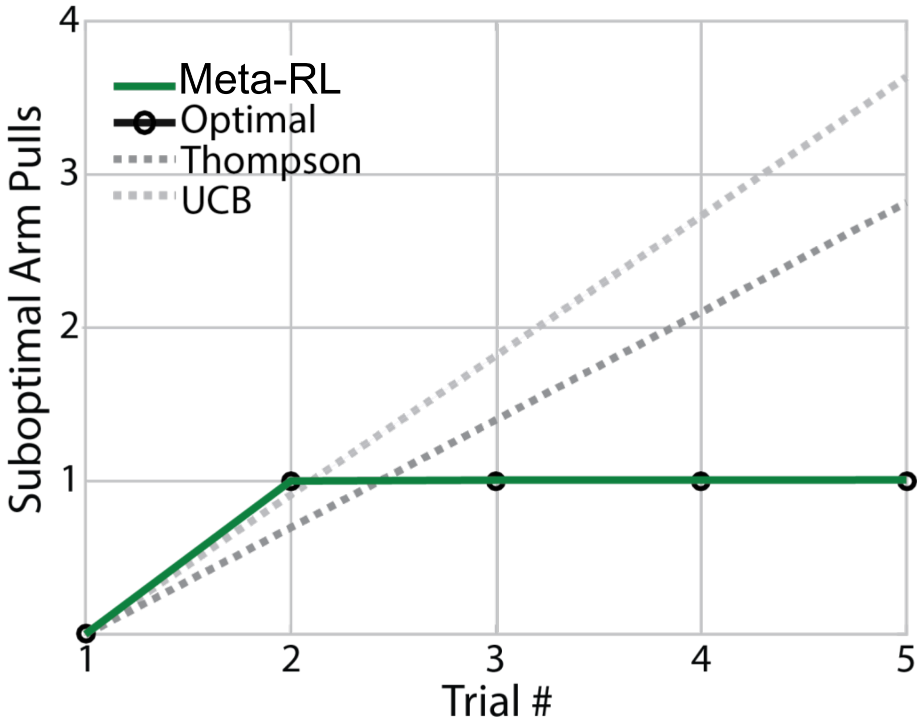
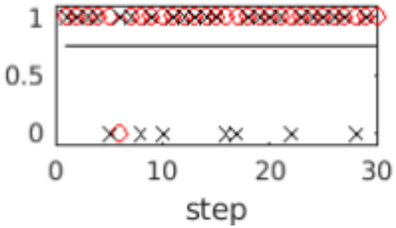




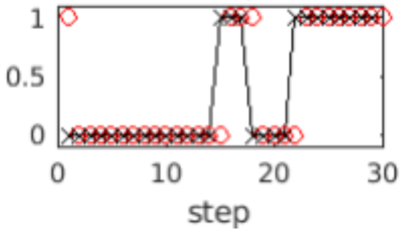
Volatile bandits

Each episode, a new parameter value for volatility is sampled

Low volatility episode



High volatility episode



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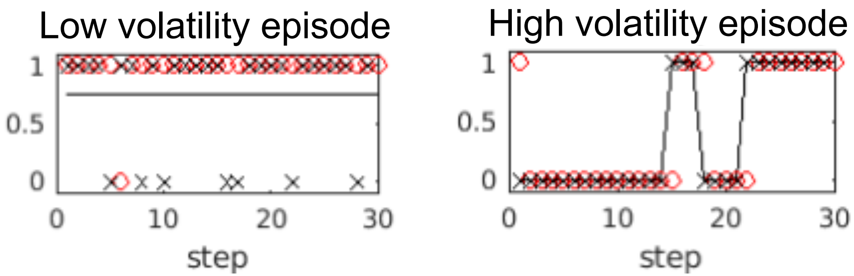
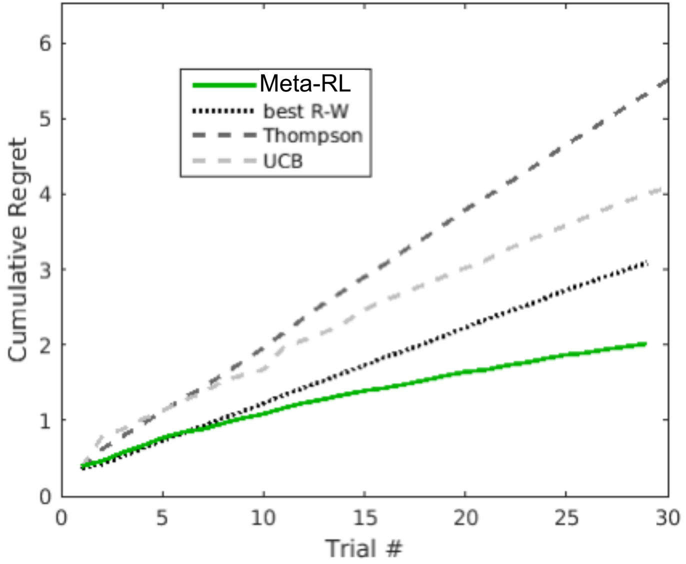
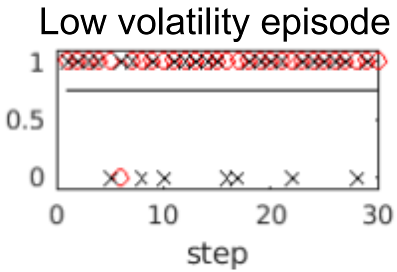


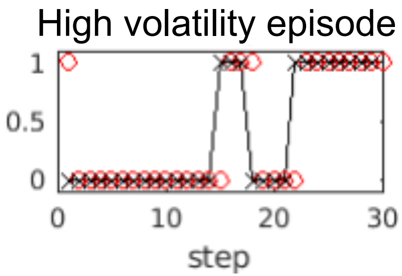
Meta-RL achieves lowest total regret over traditional methods



Volatile bandits

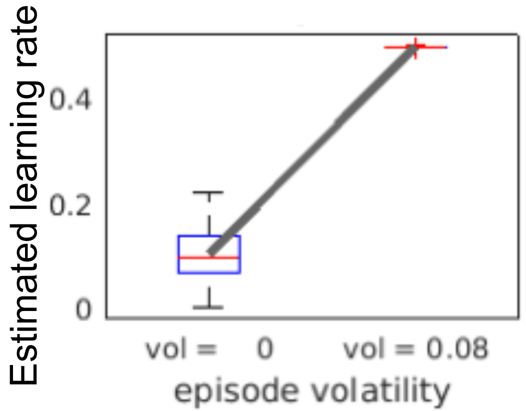
Each episode, a new parameter value for volatility is sampled



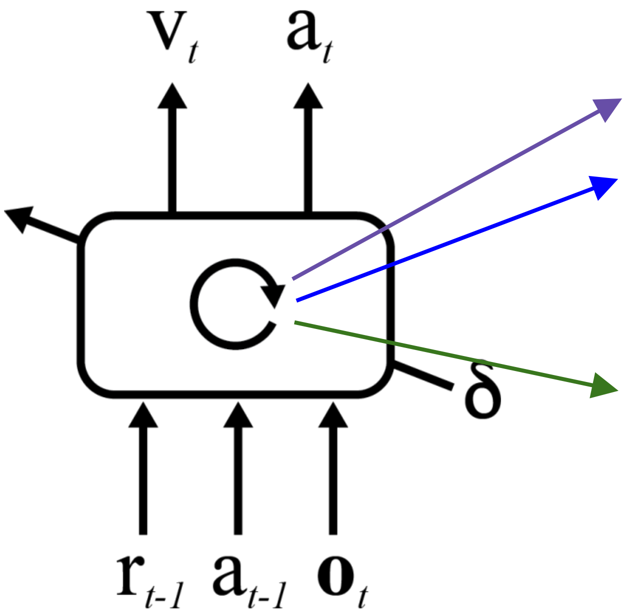


Meta-RL achieves lowest total regret over traditional methods

Also **adjusts effective learning rate** to volatility (despite frozen weights)

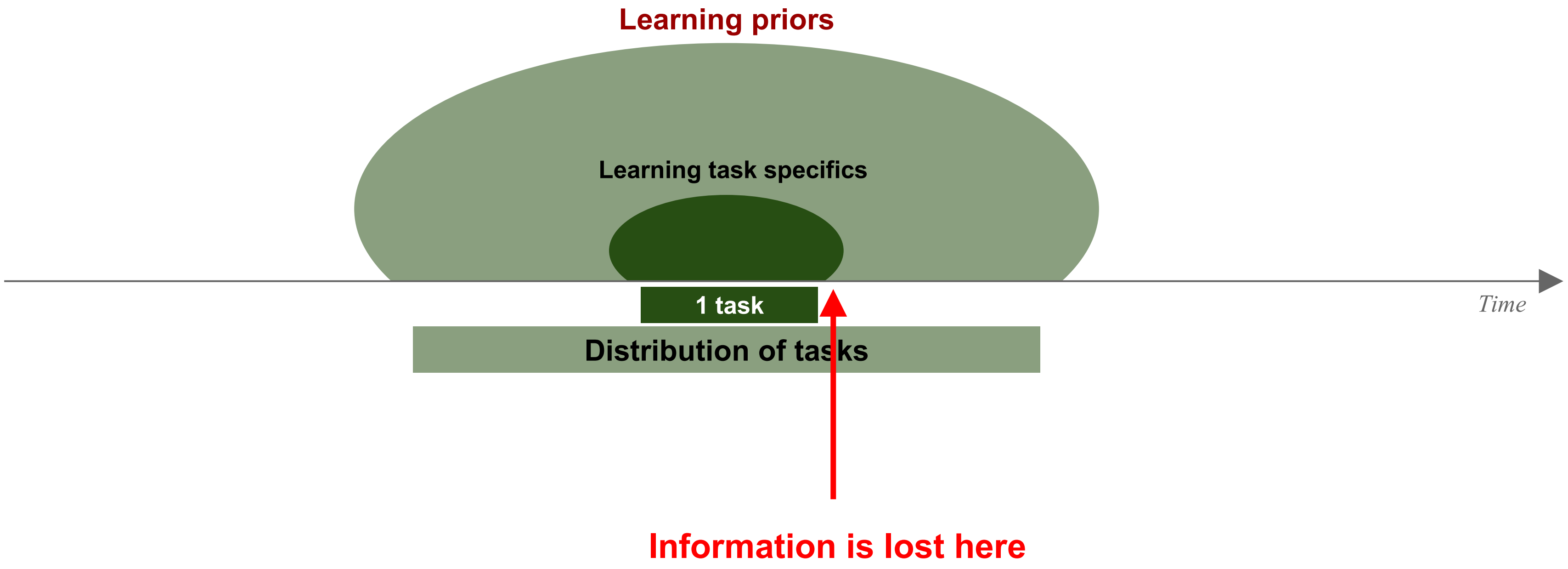


Emergent RL algorithm is capable of conforming to wide variety of task structure

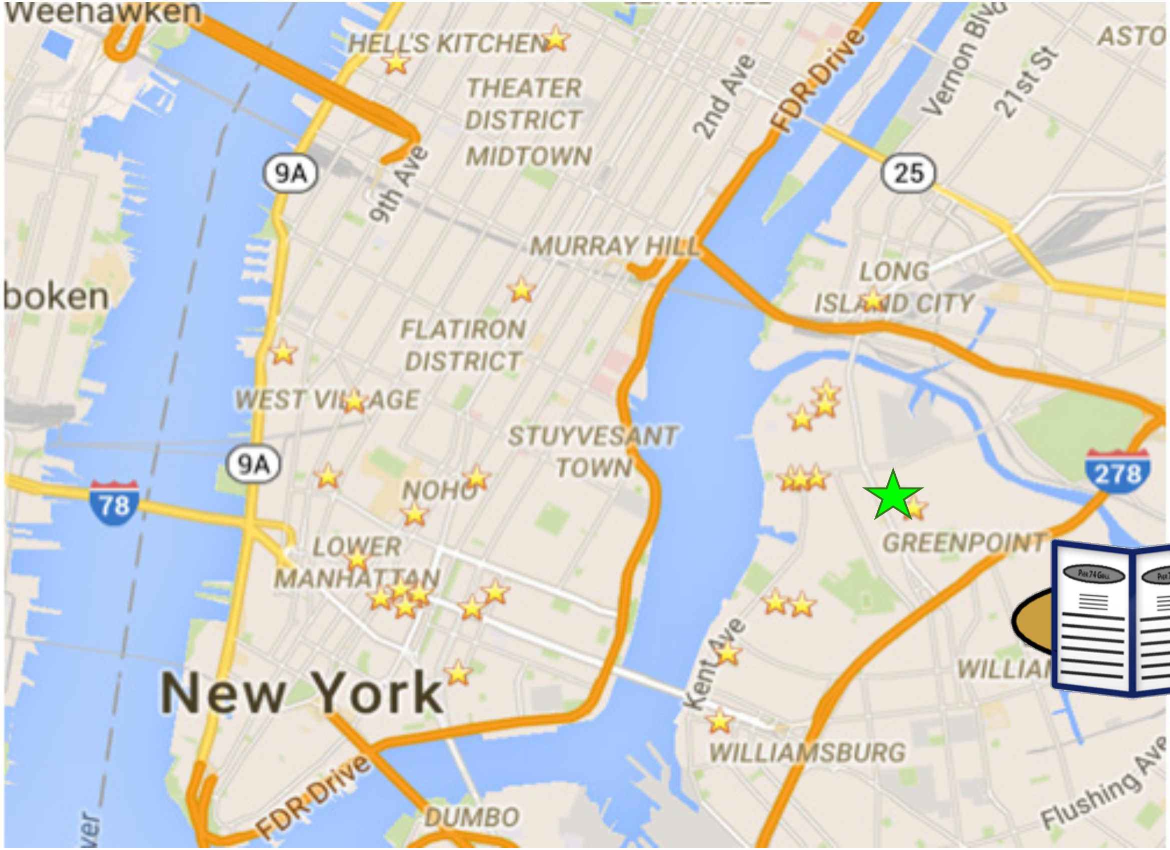


- Negotiate **exploration-exploitation** tradeoff
- **Leverage task structure** (correlations in environment, informative choices, abstractions, etc.)
- Display **different effective hyperparameters** (e.g., learning rate)
- ...

Drawbacks to using RNNs

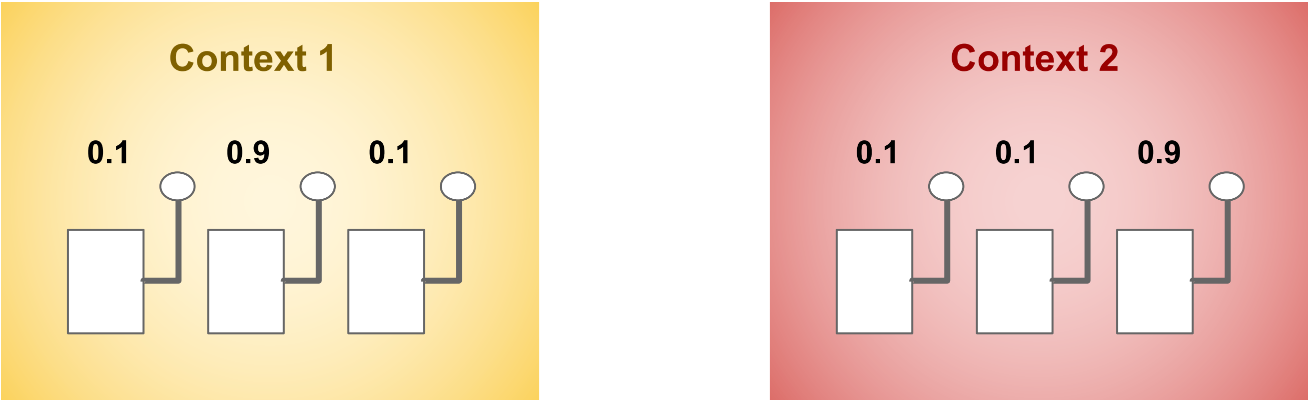


Using memory of specific past experiences to influence decision-making

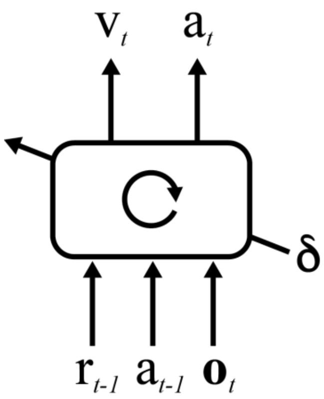


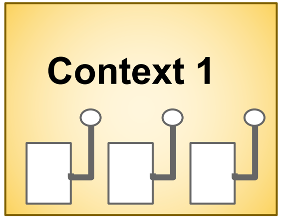
Contextual bandits

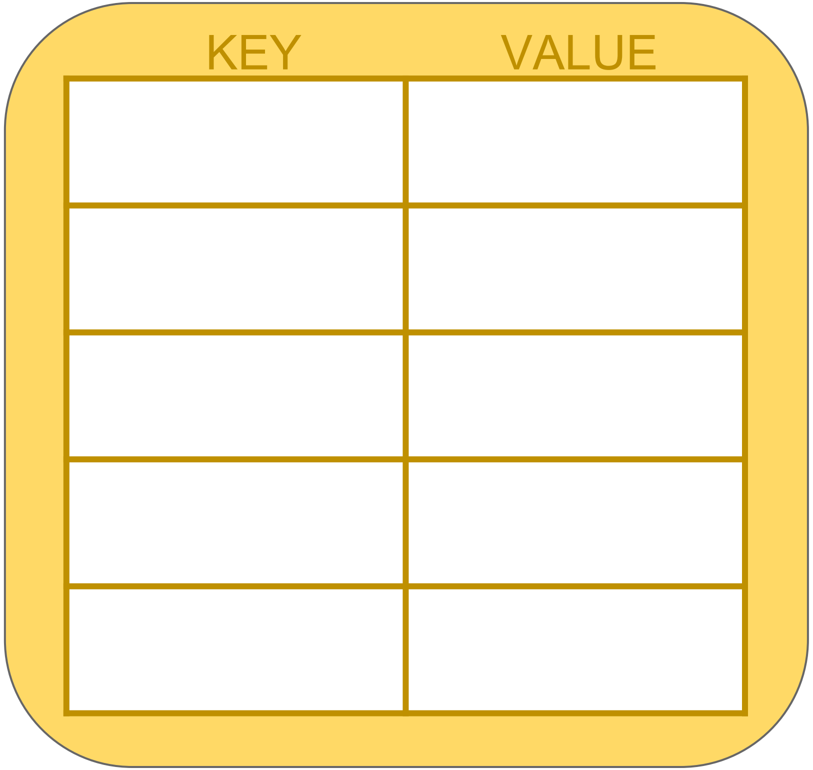
p_r =



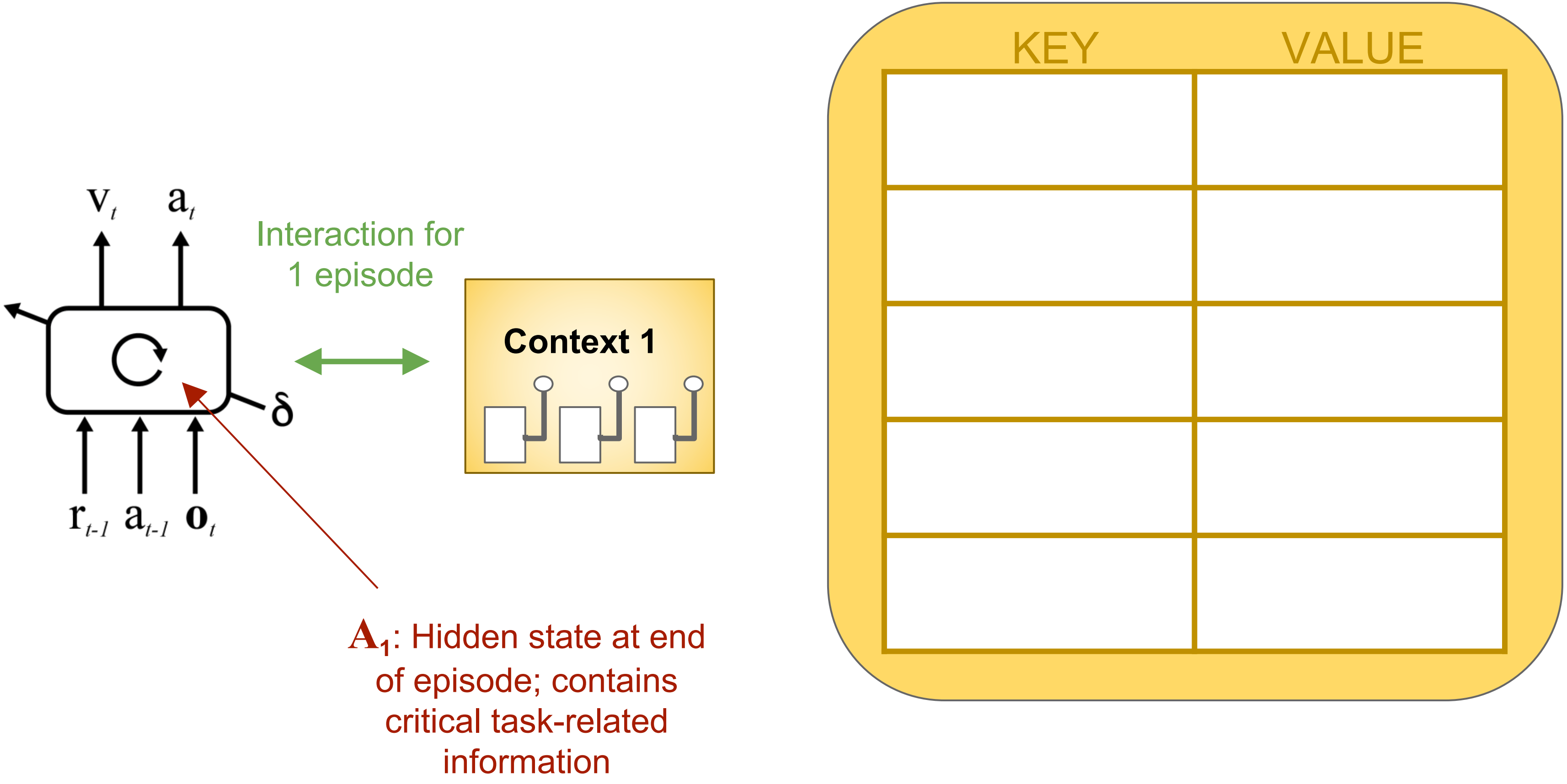
Using memory of past exploration



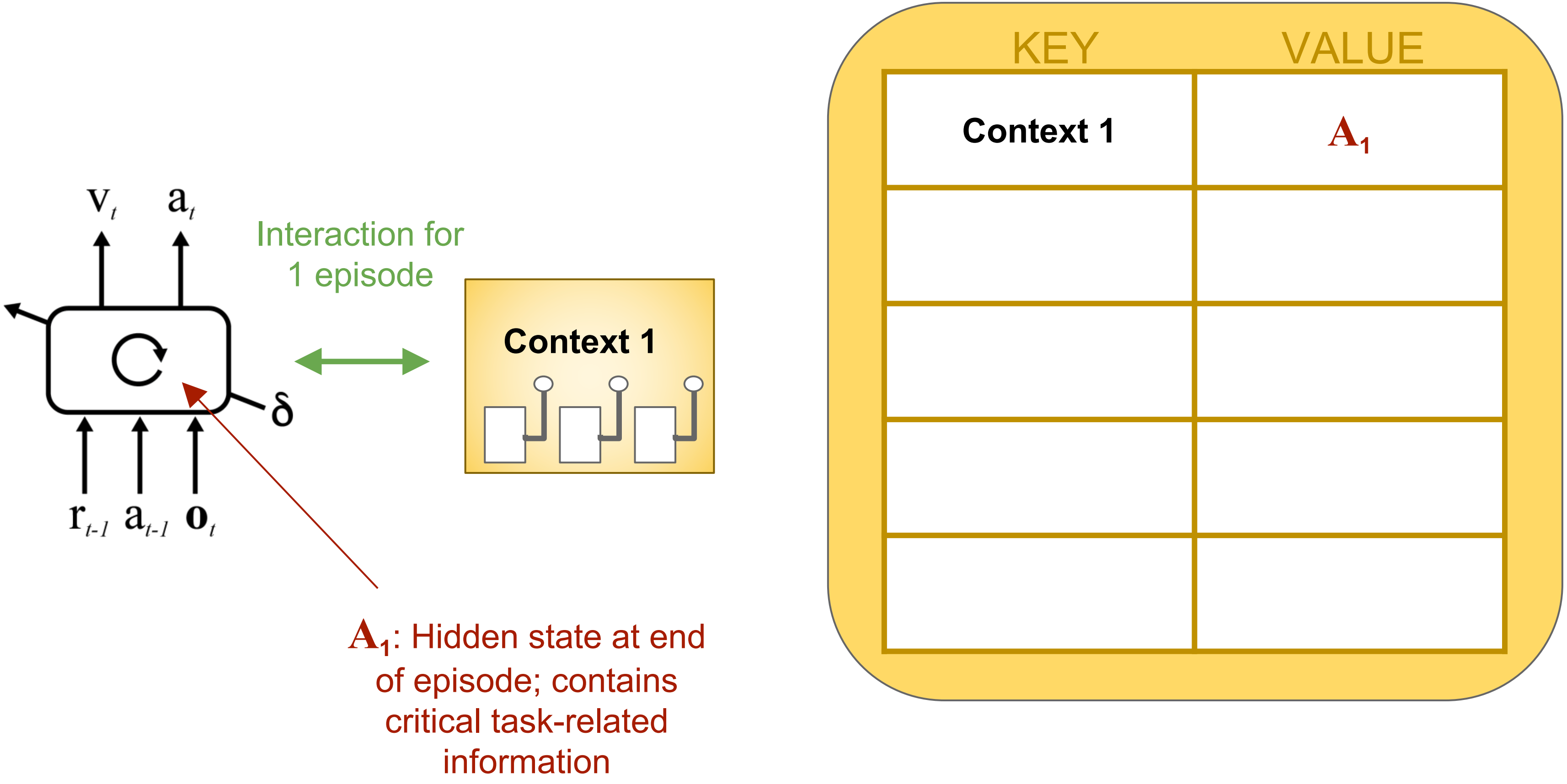




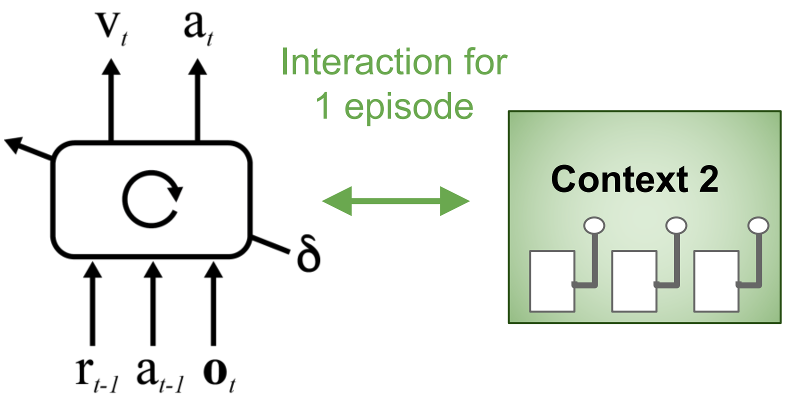
Using memory of past exploration



Using memory of past exploration

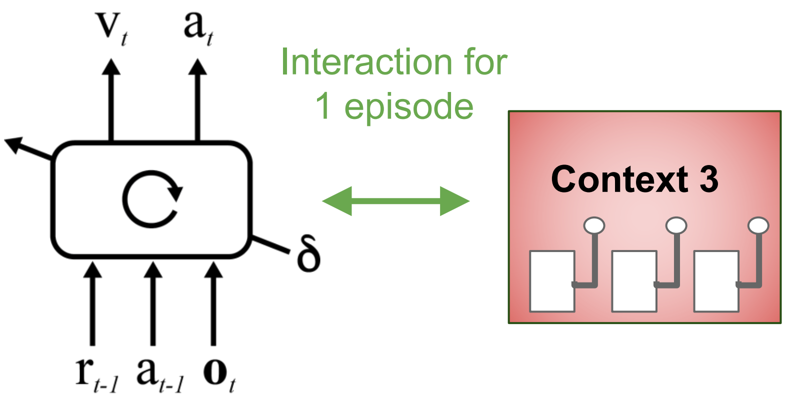


Using memory of past exploration



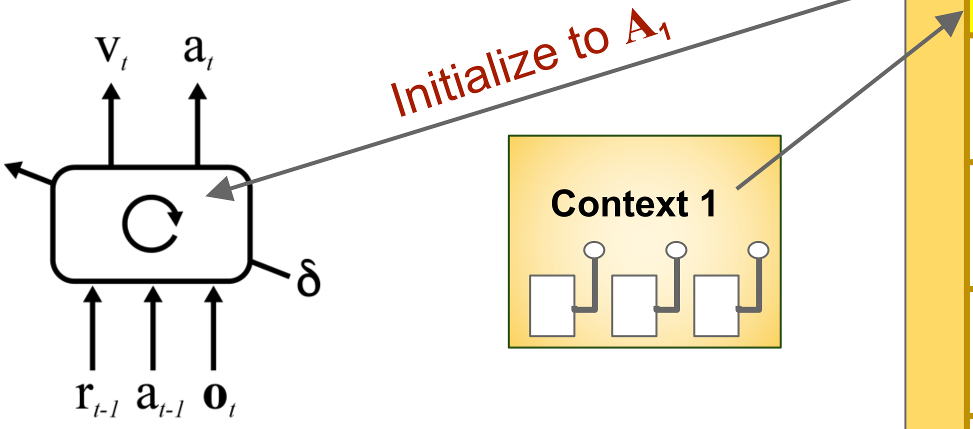
KEY	VALUE
Context 1	A_1
Context 2	A_2

Using memory of past exploration



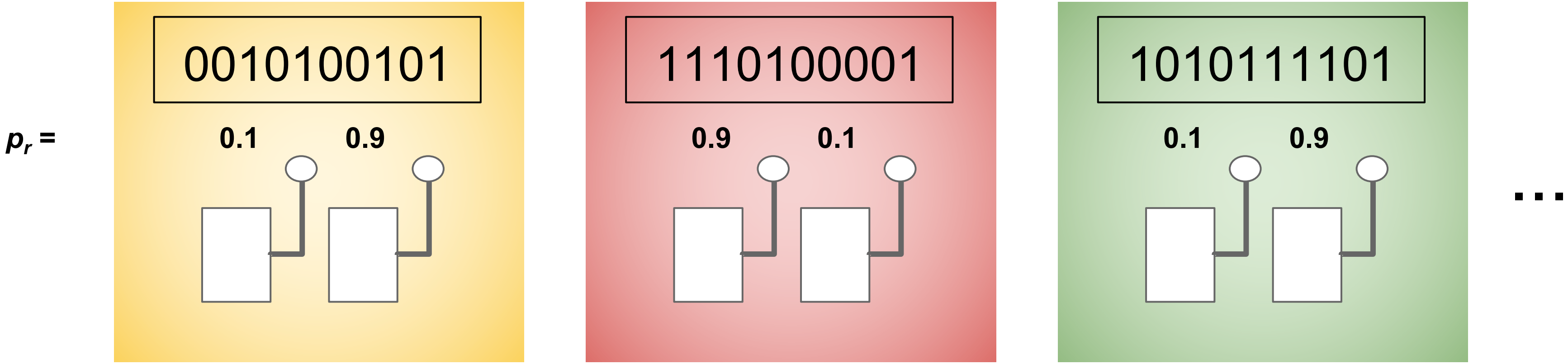
KEY	VALUE
Context 1	A_1
Context 2	A_2
Context 3	A_3

Using memory of past exploration



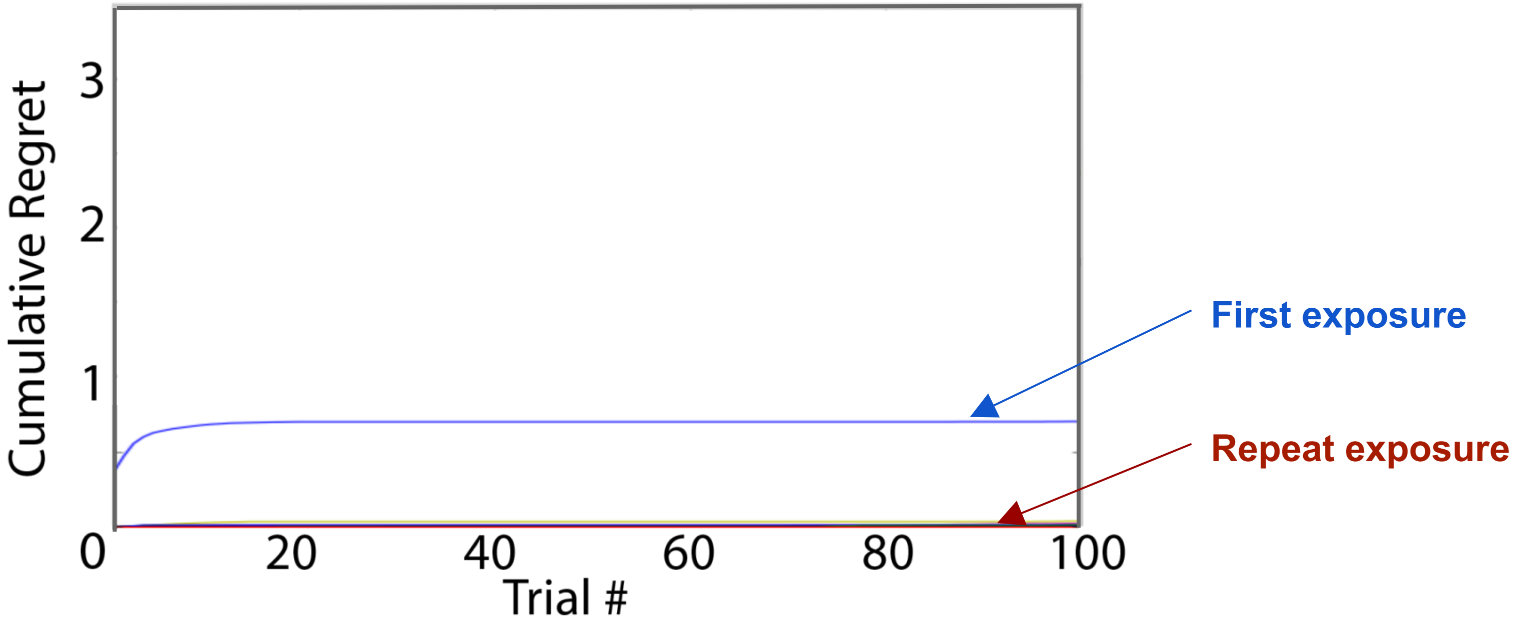
KEY	VALUE
Context 1	A_1
Context 2	A_2
Context 3	A_3

Contextual bandits: Barcodes



Ritter et al, in prep

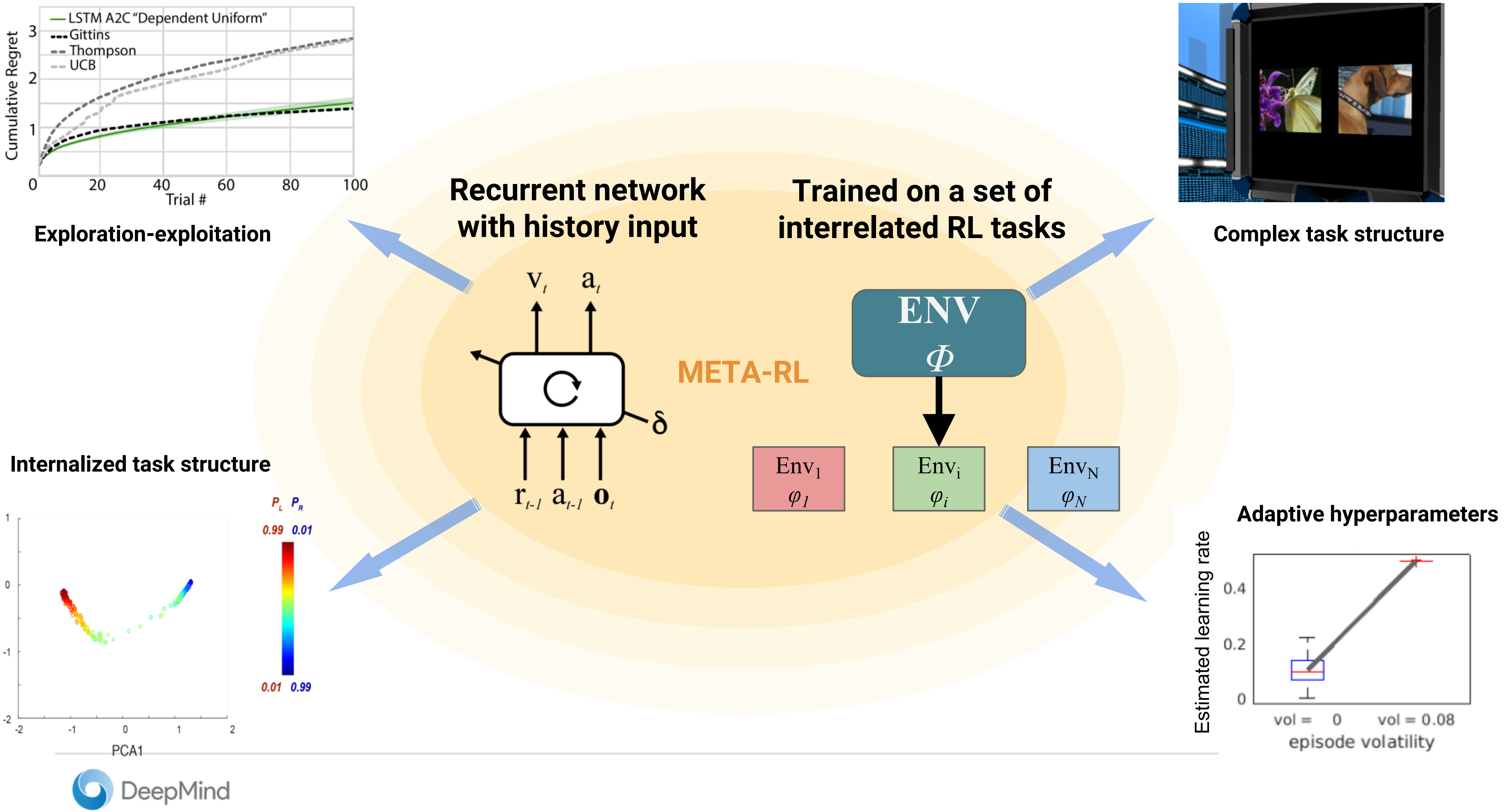
Contextual bandits: Barcodes



Ritter et al, in prep

Meta-reinforcement learning

- Key requirements:
  - Recurrent dynamics integrating past reward, history, and observations
  - Primary error-based RL algorithm that uses reward prediction error to adjust weights
  - Distribution of related tasks with shared structure
- Resultant effects
  - Structure of of tasks is absorbed into the weights as priors, leading to faster learning with more tasks
  - Learned RL algorithm is implemented in recurrent activation, not weights, with potential to be drastically different from base algorithm, matched to task structure



LSTM A2C "Dependent Uniform"
Gittins
Thompson
UCB
Cumulative Regret
Trial #
Exploration-exploitation
Recurrent network with history input
Trained on a set of interrelated RL tasks
Complex task structure
META-RL
ENV
Φ
Env₁ φ₁
Envᵢ φᵢ
Env_N φ_N
Internalized task structure
PCA1
Adaptive hyperparameters
Estimated learning rate
episode volatility
vol = 0
vol = 0.08
DeepMind

Thank you!

Matt Botvinick
Zeb Kurth-Nelson
Sam Ritter
Dharshan Kumaran
Chris Summerfield
Hubert Soyer
Joel Leibo
Dhruva Tirumala
Remi Munos
Charles Blundell
Demis Hassabis
...and many others at DeepMind

All of you

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joinus@deepmind.com