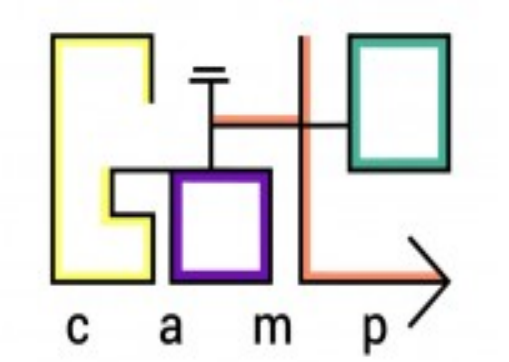
Reinforcement learning

What it does and why should you care?

LAMBDA



British Hedgehog Preservation Society

Terms

All questions are always welcome

Even if question feels stupid,

- Chances are, half of the group is just like you.

<a convenient slide for public survey>

Supervised learning

Given:

- objects and answers (x, y)
- algorithm family $a_\theta(x) \rightarrow y$
- loss function $L(y, a_\theta(x))$

Find:

$$\theta' \leftarrow argmin_\theta L(y, a_\theta(x))$$

Supervised learning

Given:

- objects and answers (x, y)

  [banner,page], ctr

- algorithm family $a_\theta(x) \rightarrow y$

  linear / tree / NN

- loss function $L(y, a_\theta(x))$

  MSE, crossentropy

Find:

$$\theta' \leftarrow argmin_\theta L(y, a_\theta(x))$$

Supervised learning

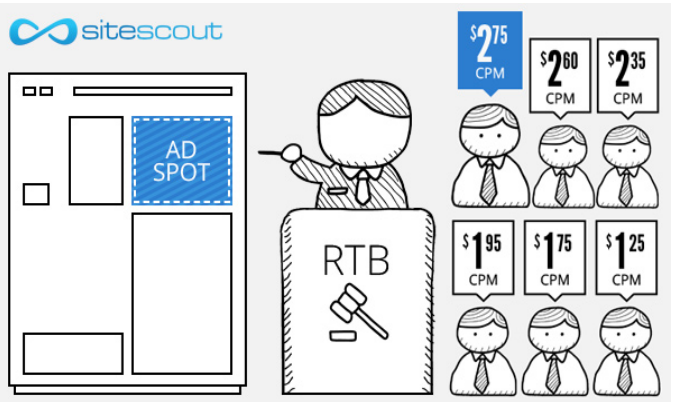
Great... except if we have no reference answers

Online Ads

Great... except if we have no reference answers

We have:

- YouTube at your disposal
- Live data stream
  (banner & video features, #clicked)
- (insert your favorite ML toolkit)



We want:

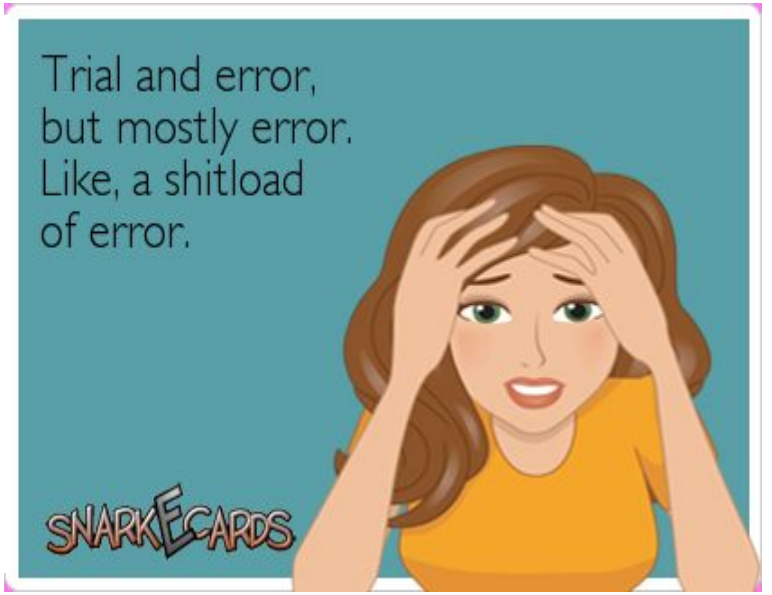
- Learn to pick relevant ads

Ideas?

Duct tape approach

Common idea:

- Initialize with naïve solution
- Get data by trial and error and error and error and error
- Learn (situation) → (optimal action)
- Repeat



Problems

Problem 1:

- What exactly does the “optimal action” mean?

Extract as much money as you can right now

VS

Make user happy so that he would visit you again

Problems

Problem 2:

- If you always follow the “current optimal” strategy, you may never discover something better.

- If you show the same banner to 100% users, you will never learn how other ads affect them.

Ideas?

Duct tape approach

Reinforcement learning

What-what learning?

Supervised learning

- Learning to approximate reference answers
- Needs correct answers
- Model does not affect the input data

Reinforcement learning

- Learning optimal strategy by trial and error
- Needs feedback on agent's own actions
- Agent can affect it's own observations

What-what learning?

Unsupervised learning

- Learning underlying data structure
- No feedback required
- Model does not affect the input data

Reinforcement learning

- Learning optimal strategy by trial and error
- Needs feedback on agent's own actions
- Agent can affect it's own observations

What is: bandit

Examples:

- banner ads (RTB)
- recommendations
- medical treatment

What is: bandit

observation

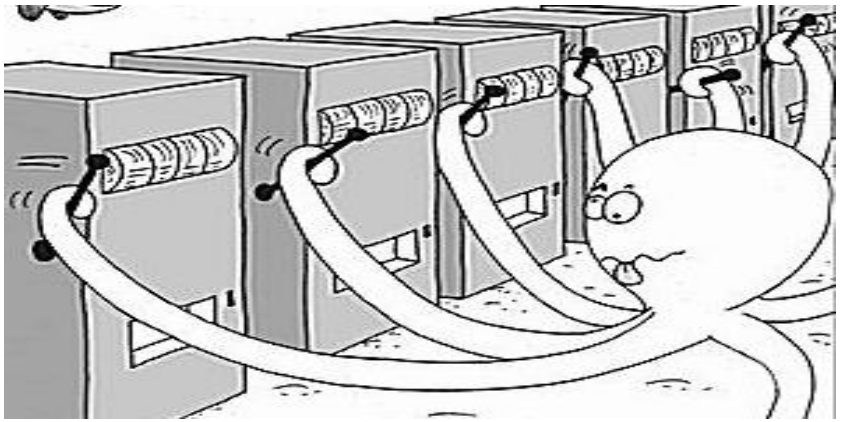
Agent

action

Feedback

Examples:

- banner ads (RTB)
- recommendations
- medical treatment



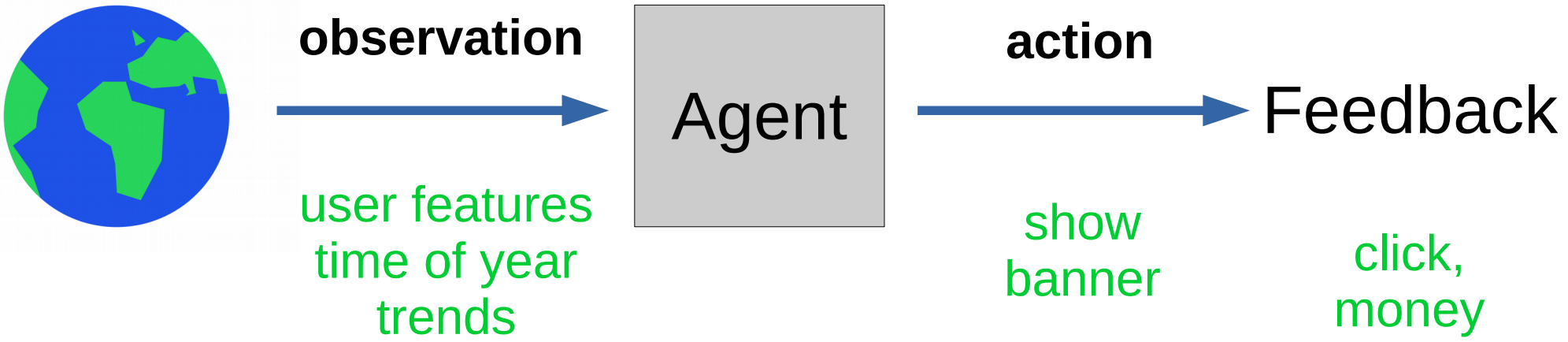
What is: bandit

Examples:

- banner ads (RTB)
- recommendations
- medical treatment

Q: what's observation, action and feedback in the banner ads problem?

What is: bandit



Examples:

- banner ads (RTB)
- recommendations
- medical treatment

What is: bandit

observation

user features
time of year
trends

Agent

action

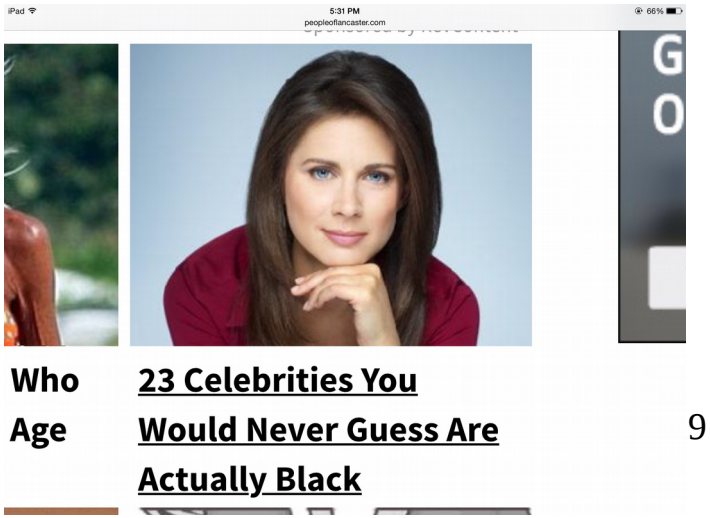
show
banner

Feedback

click,
money

Q: You're Yandex/Google/Youtube. There's a kind of banners that would have great click rates: the “clickbait”.

Is it a good idea to show clickbait?



What is: bandit

observation

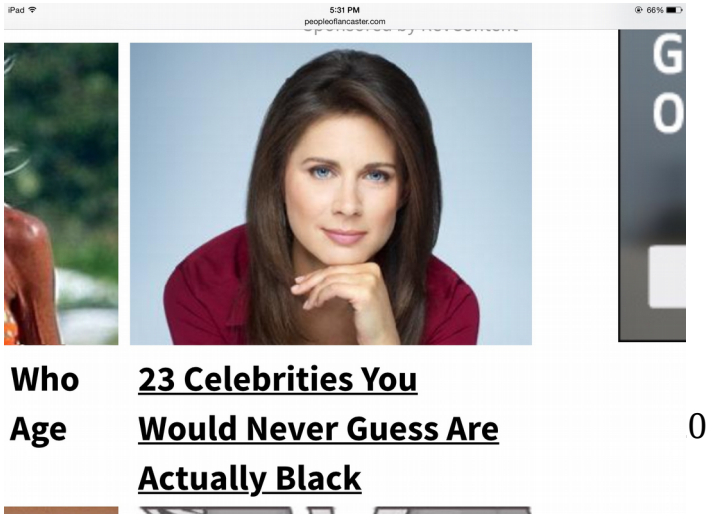
Agent

action

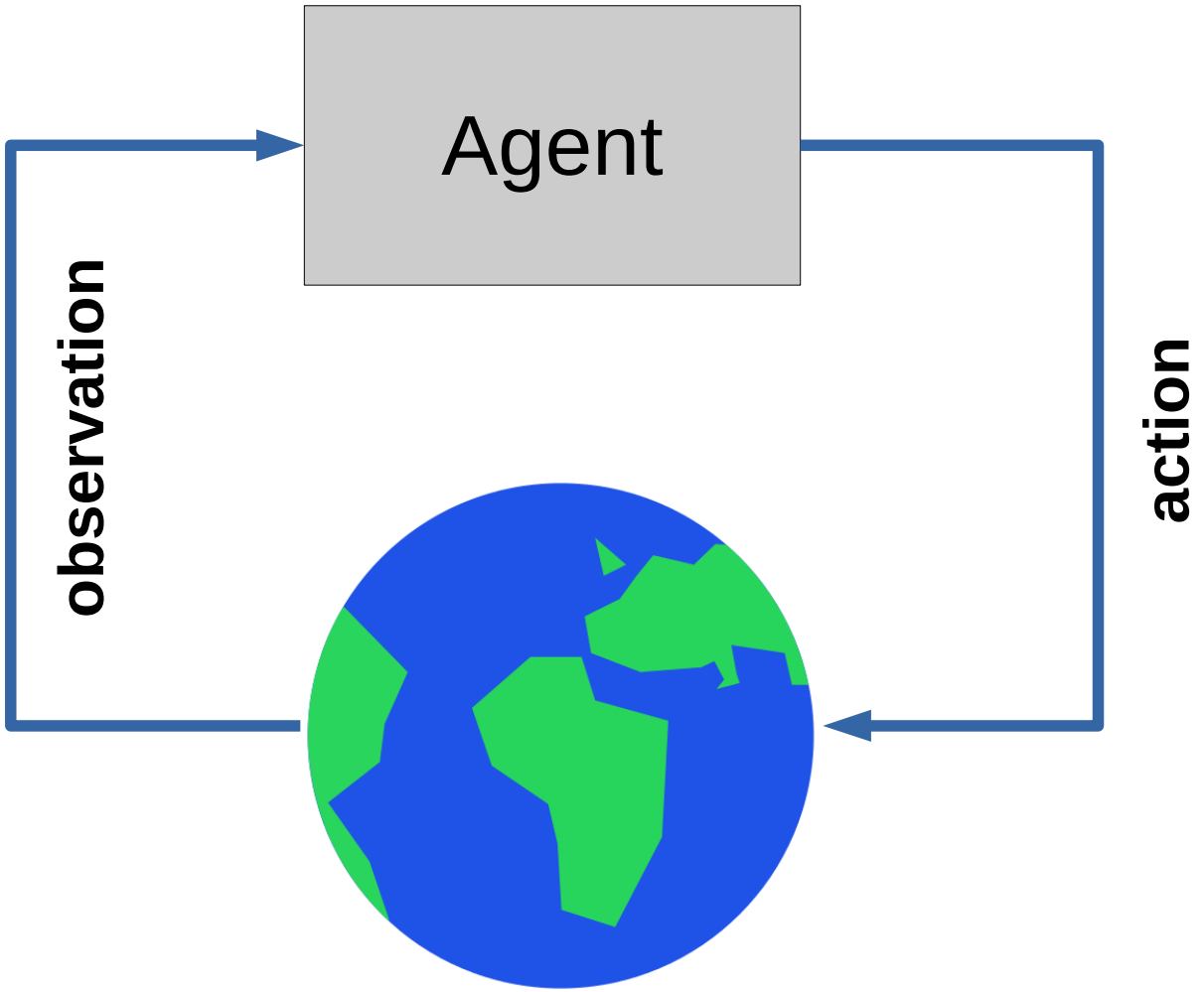
Feedback

Q: You're Google/Yandex/Youtube. There's a kind of banners that would have great click rates: the “clickbait”.

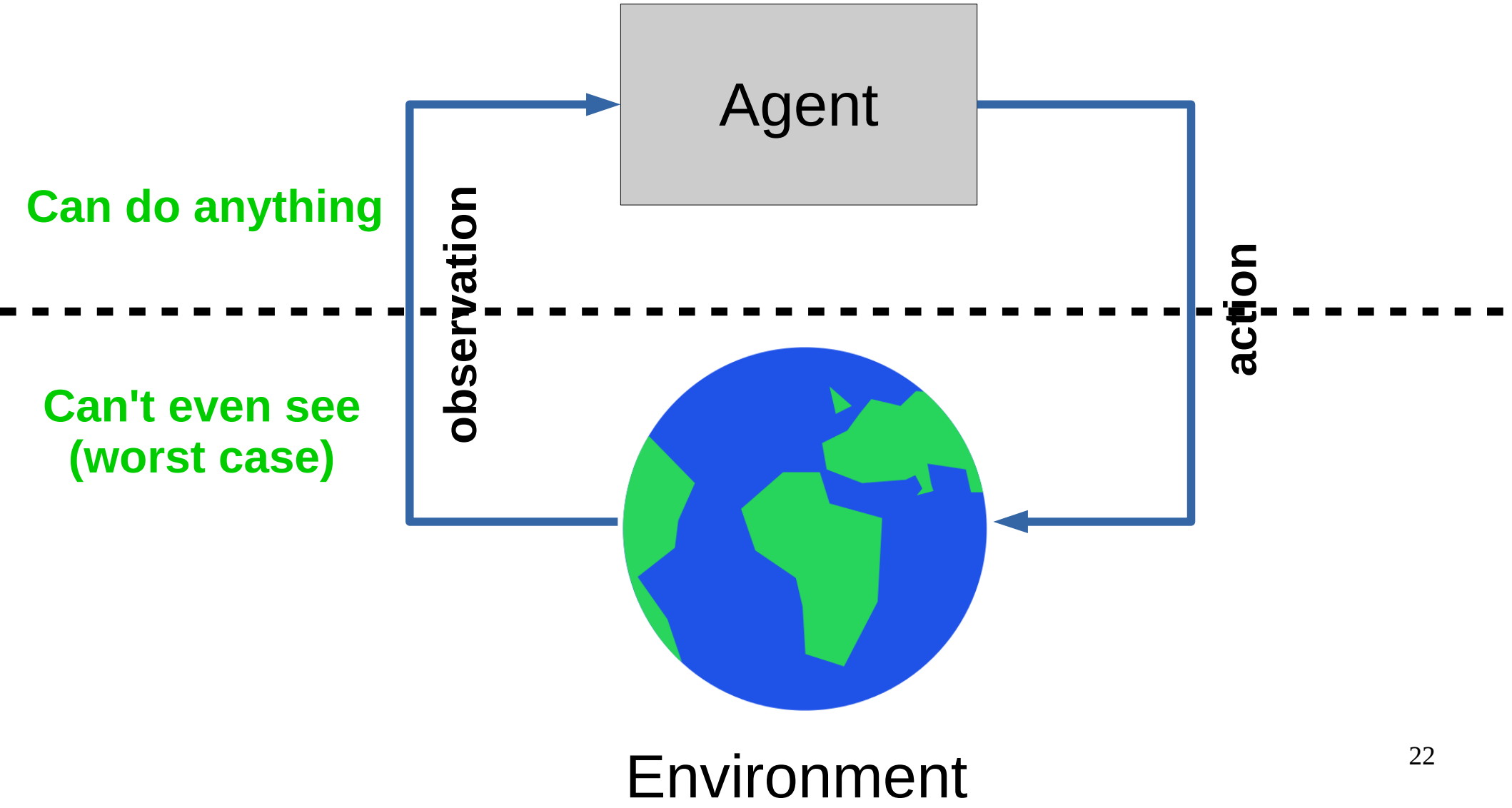
Is it a good idea to show clickbait?
No, no one will trust you after that!



What is: decision process



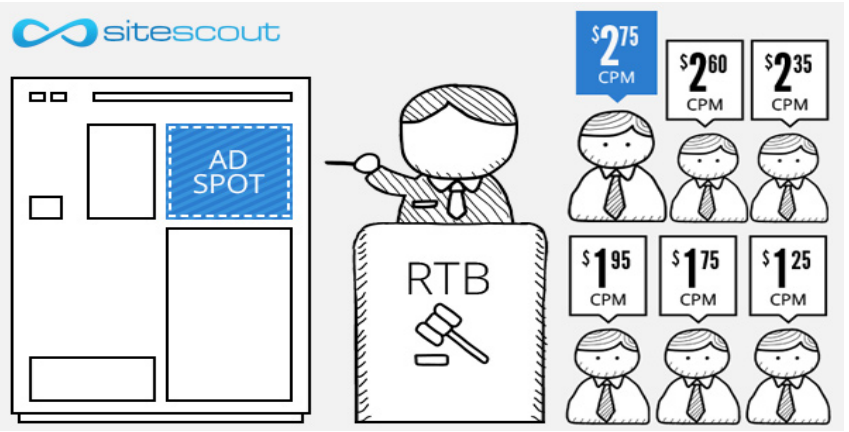
What is: decision process

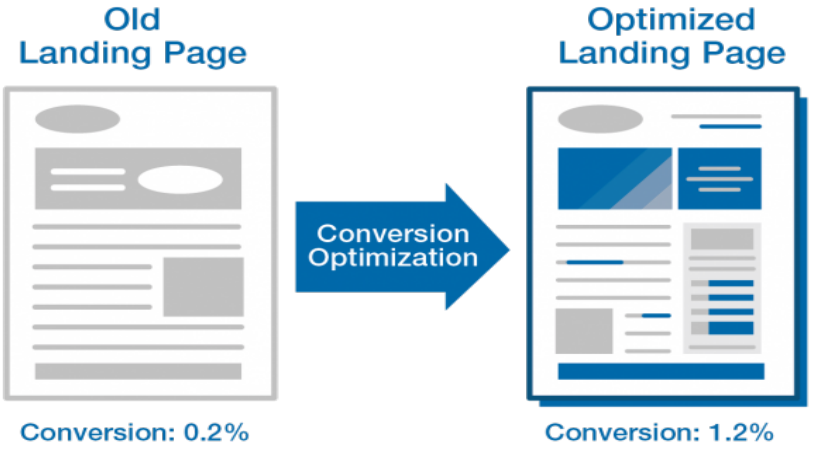


Applications: web

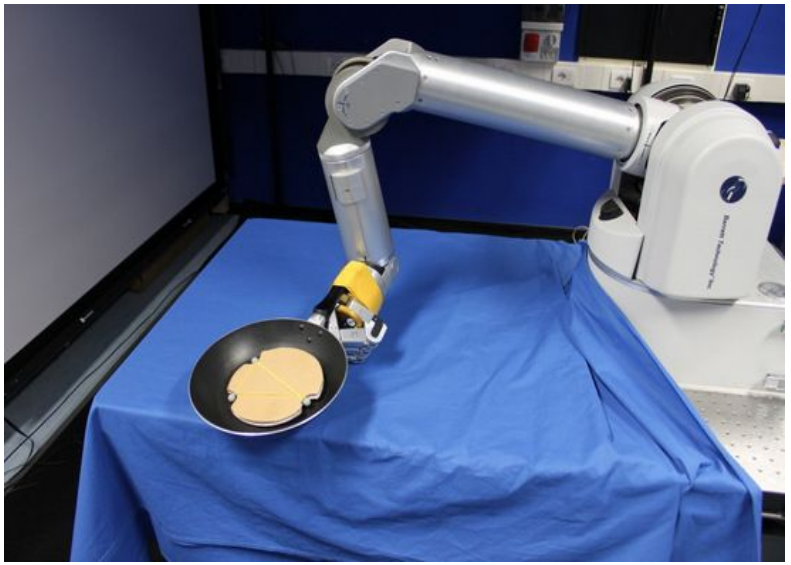
- **Cases:**
  - Pick ads to maximize profit
  - Design landing page to maximize user retention
  - Recommend movies to users
  - Find pages relevant to queries

- **Example**
  - Observation – user features
  - Action – show banner #i
  - Feedback – did user click?





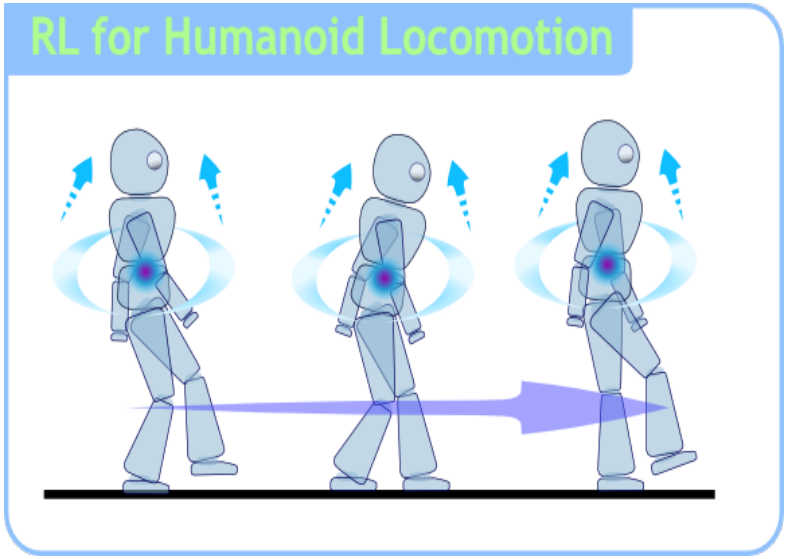
Applications: dynamic systems



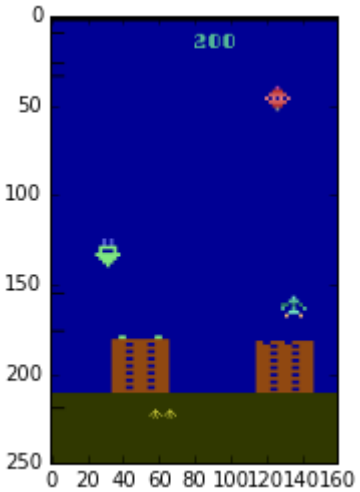
Applications: dynamic systems

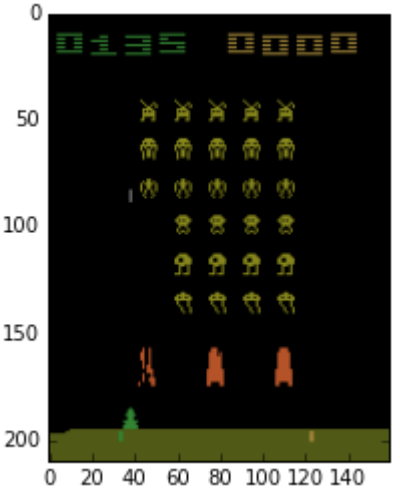
- **Cases:**
  - Robots
  - Self-driving vehicles
  - Pilot assistant
  - More robots!

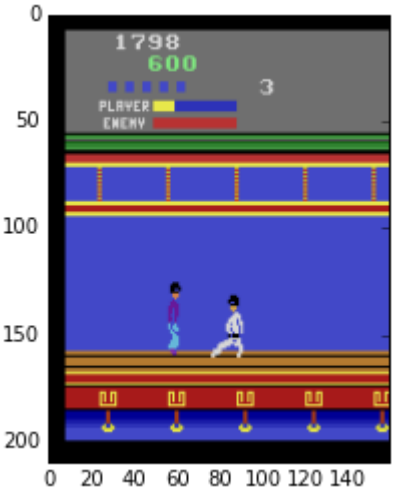
- **Example**
  - Observation: sensor feed
  - Action: voltage sent to motors
  - Feedback: how far did it move forward before falling



~~Applications~~: videogames

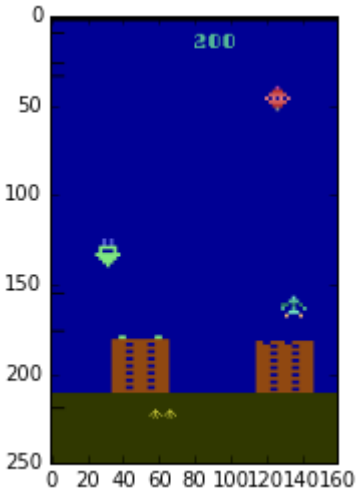


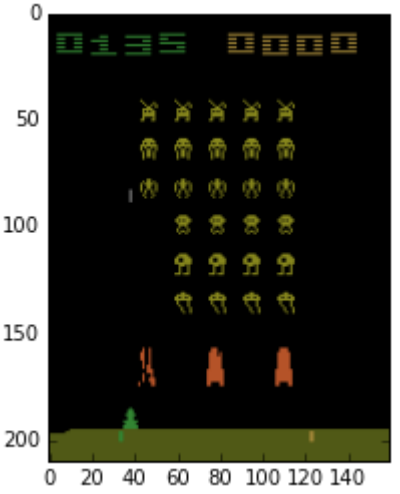


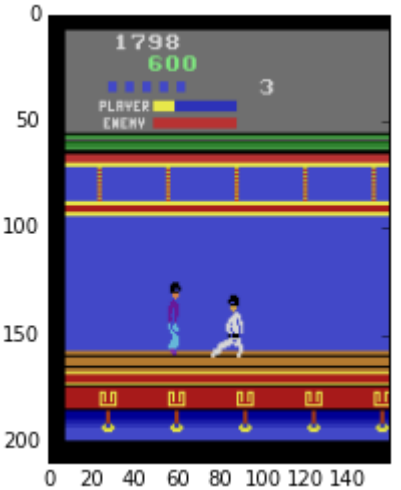


- **Q:** What are observations, actions and feedback?

~~Applications~~: videogames





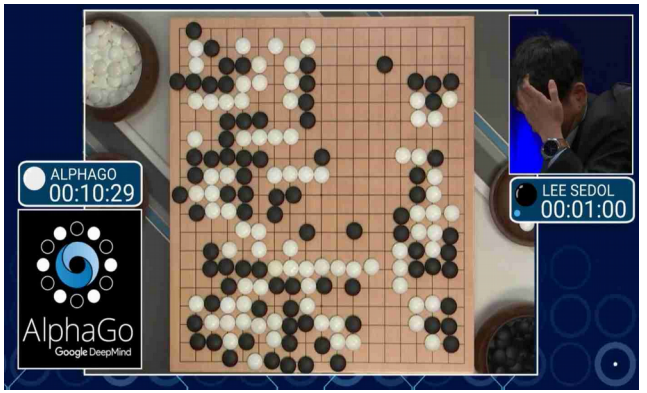


- **Q:** What are observations, actions and feedback?

More use cases

- Personalized medical treatment

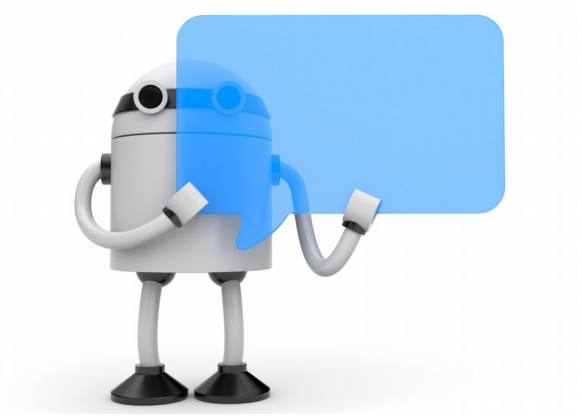
- Even more games (Go, chess, etc)

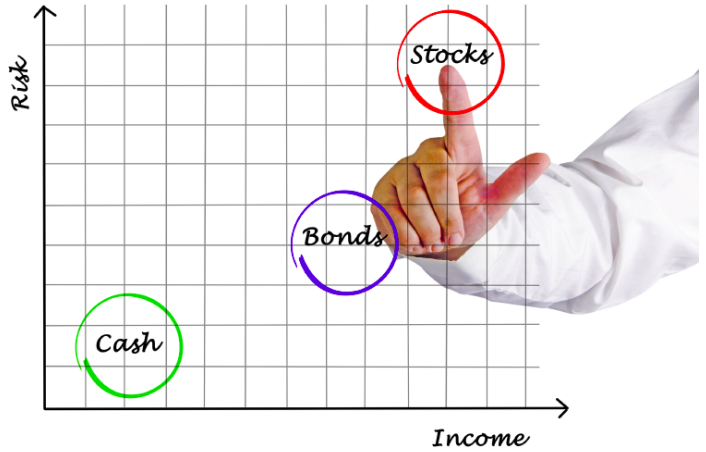


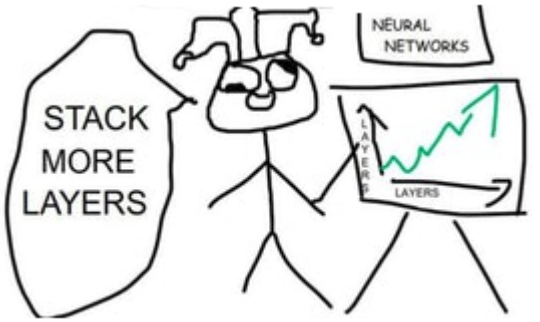
- **Q:** What are observations, actions and feedback?

Other use cases

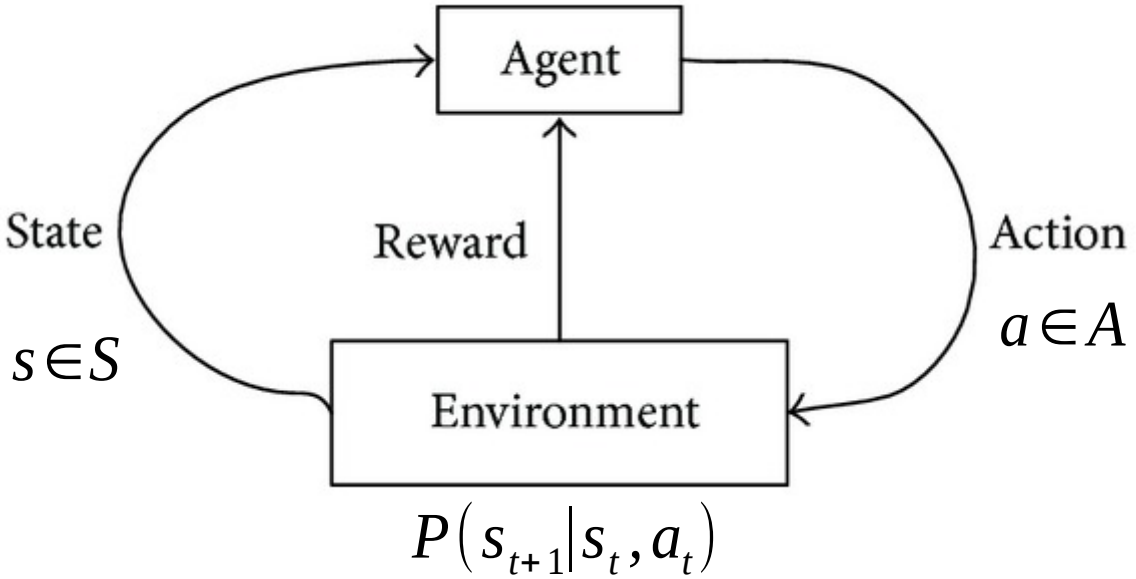
- Conversation systems
  - learning to make user happy
- Quantitative finance
  - portfolio management
- Deep learning
  - optimizing non-differentiable loss
  - finding optimal architecture







The MDP formalism

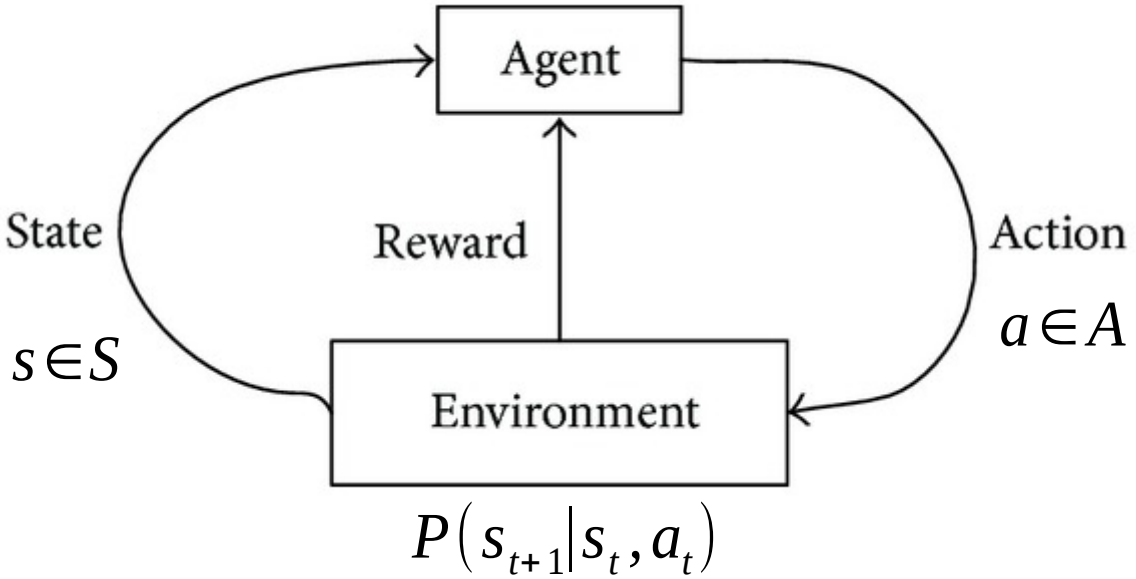


Markov Decision Process

- Environment states: $s \in S$
- Agent actions: $a \in A$
- Rewards $r \in \mathbb{R}$

- Dynamics: $P(s_{t+1}|s_t, a_t)$

The MDP formalism

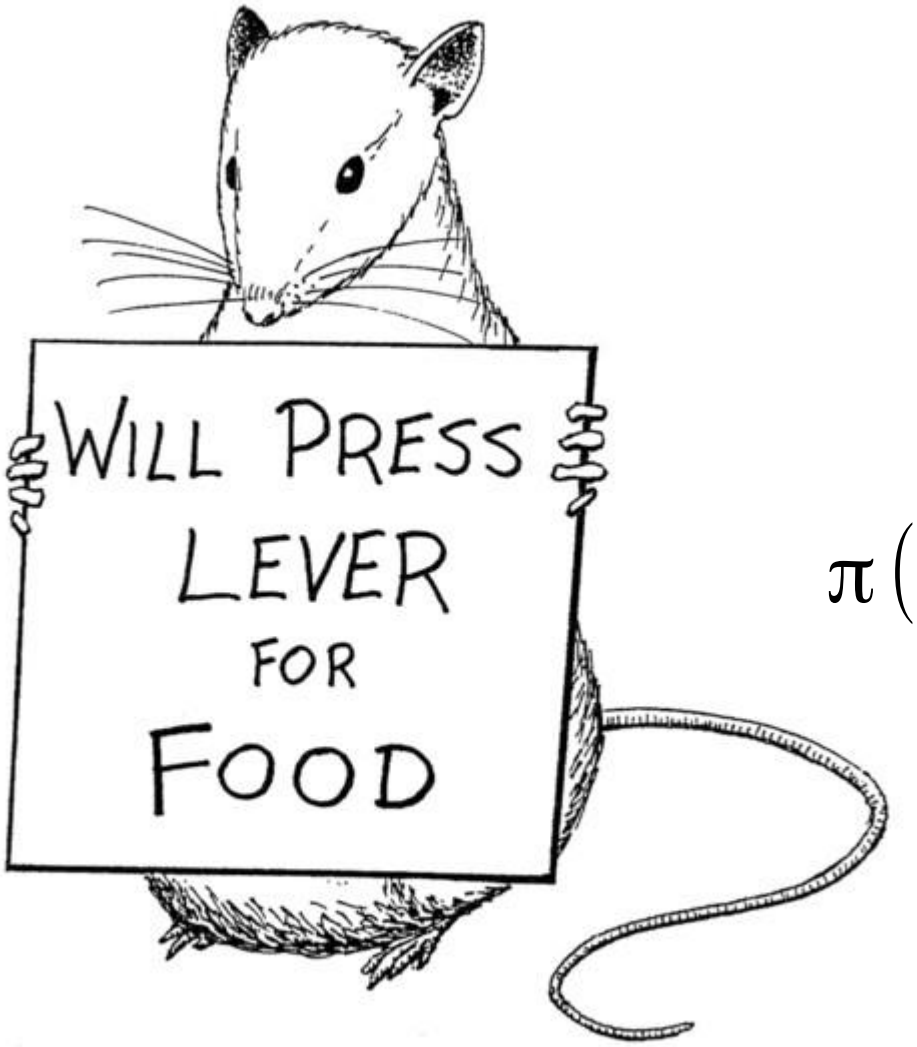


Markov Decision Process

Markov assumption

$$P(s_{t+1}|s_t, a_t, s_{t-1}, a_{t-1}) = P(s_{t+1}|s_t, a_t)$$

Total reward



Total reward for session:

$$R = \sum_t r_t$$

Agent's policy:

$$\pi(a|s) = P(\textit{take action } a | \text{in } \textit{state } s)$$

Problem: find policy with highest reward:

$$\pi(a|s) : E_\pi[R] \rightarrow max$$

Objective

The easy way:

$E_\pi R$ is an expected sum of rewards that agent with policy π earns per session

The hard way:

$$\underset{s_0 \sim p(s_0),\, a_0 \sim \pi(a|s_0),\, s_1, r_0 \sim P(s', r|s, a)}{E} \quad \underset{}{E} \quad \underset{}{E} \quad \ldots \quad \underset{s_n, r_n \sim \pi(a|s_{n-1})}{E} \left[r_0 + r_1 + r_2 + \ldots + r_n \right]$$

How do we solve it?

Value-based approach:

What is the expected reward I get if I take this action?

Value Iteration, Q-learning, SARSA, DQN

...

How do we solve it?

Value-based approach:

What is the expected reward I get if I take this action?

Value Iteration, Q-learning, SARSA, DQN

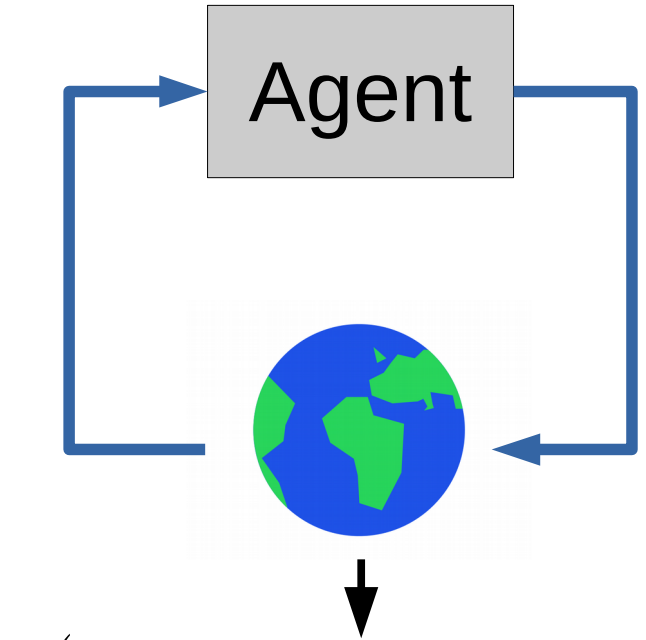
Policy-based:

Environment takes policy and computes expected reward.

Find such policy that produces best reward!

Crossentropy Method, Policy Gradient, TRPO, ES

Black box optimization setup



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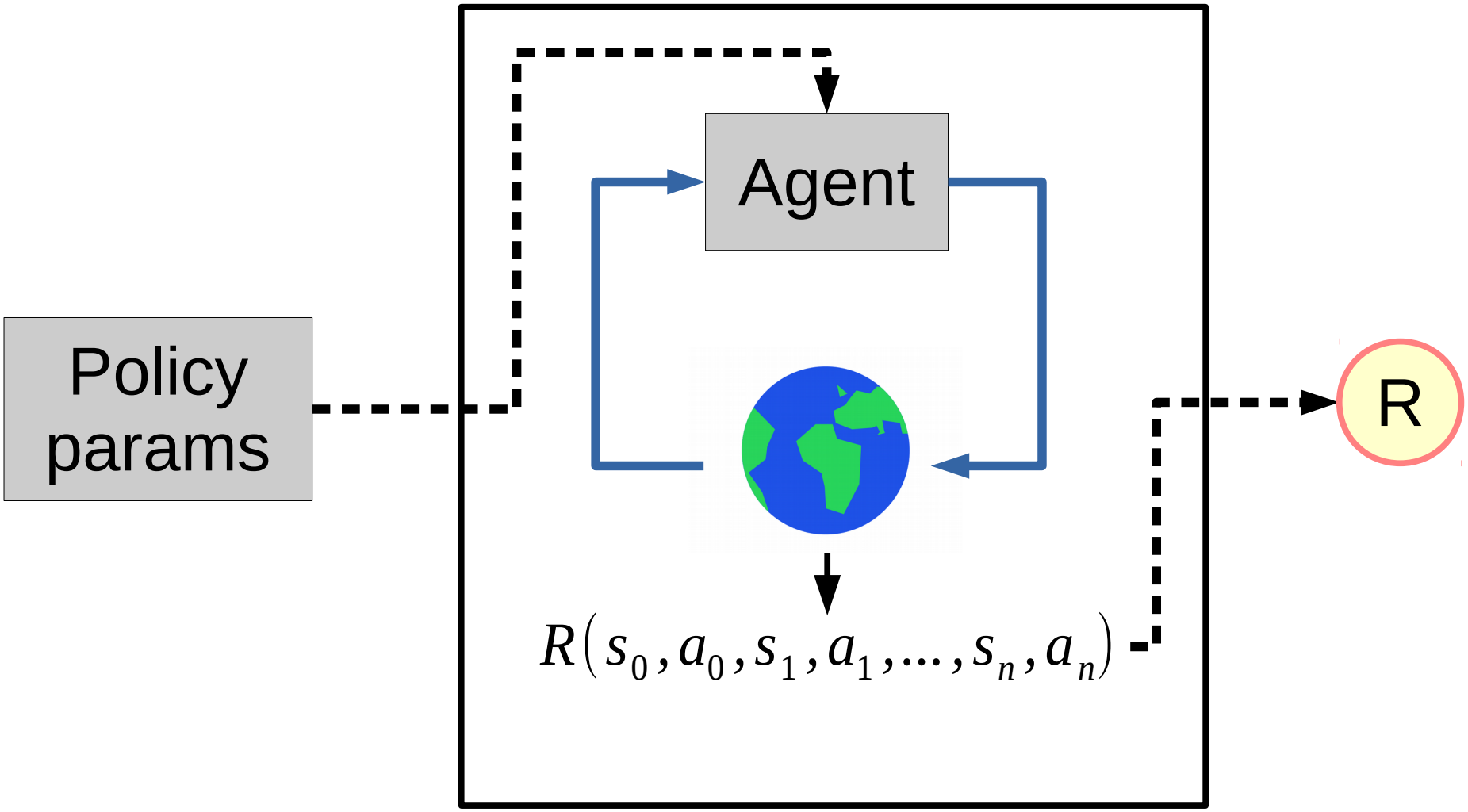

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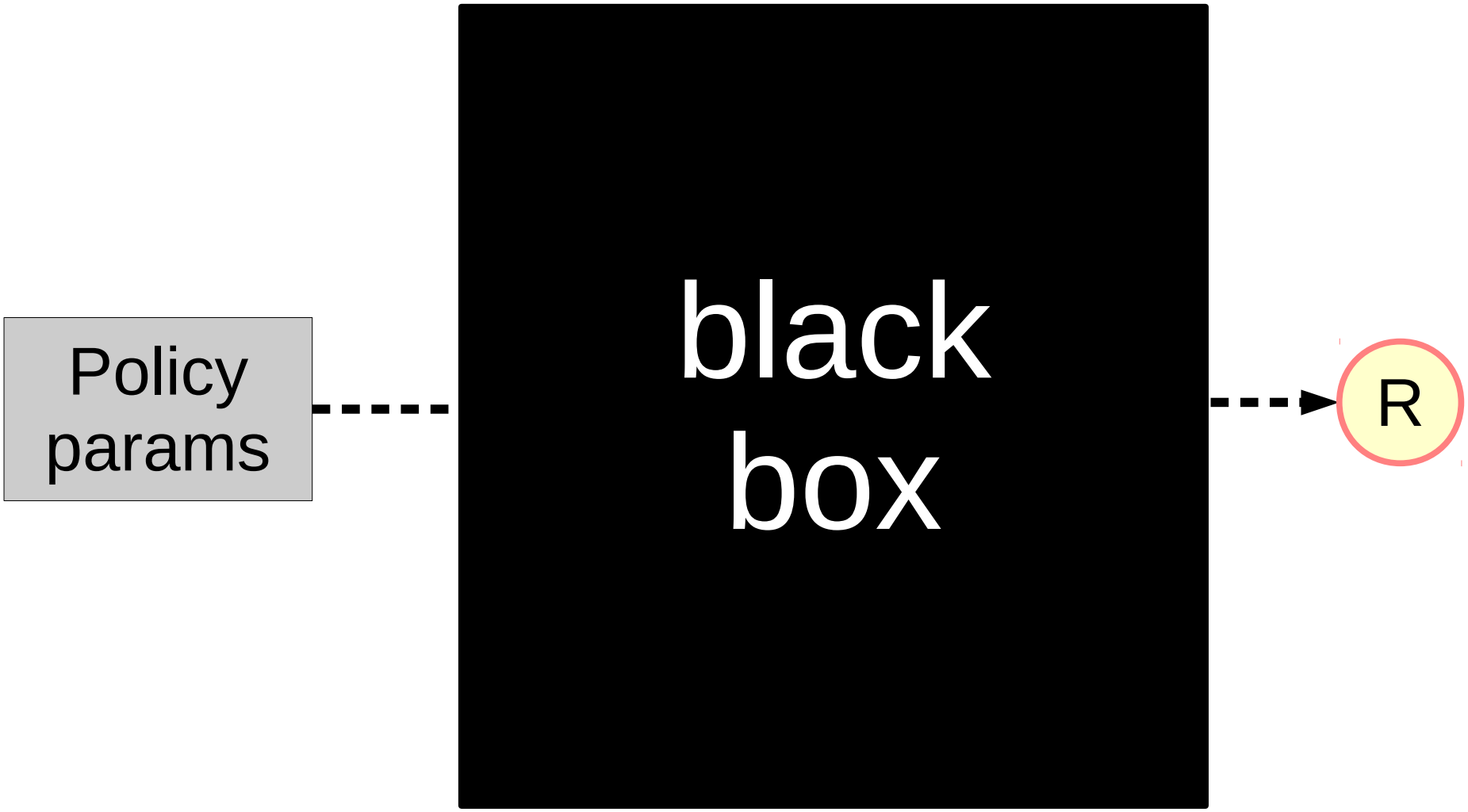

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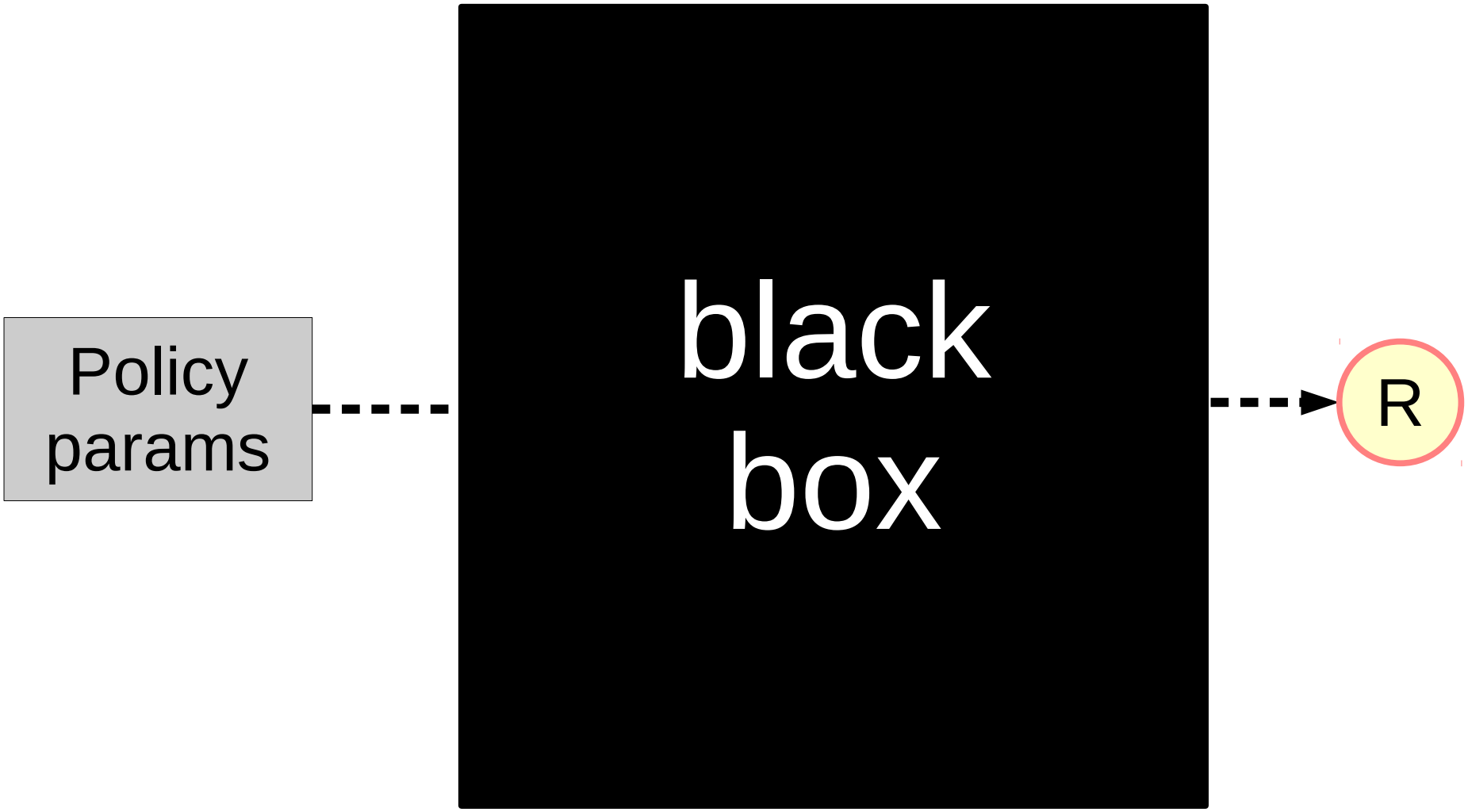


How to find argmax R?

How do we solve it?

General idea:

Play a few sessions

Update your policy

Repeat

Crossentropy method

Intialize policy

Repeat:

- Sample N[100] sessions
- Pick M[20] best sessions, called **elite** sessions
- Change policy so that it prioritizes actions from elite sessions

Tabular crossentropy method

- Policy is a matrix

$$\pi(a|s) = A_{s,a}$$

- Sample N games with that policy
- Get M best sessions (elites)

$$Elite = [(s_0, a_0), (s_1, a_1), (s_2, a_2), \ldots, (s_k, a_k)]$$

Tabular crossentropy method

- Policy is a matrix

$$\pi(a|s) = A_{s,a}$$

- Sample N games with that policy
- Take M best sessions (elites)
- Aggregate by states

$$\pi(a|s) = \frac{\sum_{s_t, a_t \in Elite} \#[s_t = s \,\&\, a_t = a]}{\sum_{s_t, a_t \in Elite} \#[s_t = s]}$$

Tabular crossentropy method

- Policy is a matrix

$$\pi(a|s) = A_{s,a}$$

- Sample N games with that policy
- Take M best sessions (elite)
- Aggregate by states

$$\pi(a|s) = \frac{took\ a\ at\ s}{was\ at\ s}$$

In M best games

Smoothing

- If you were in some state only once, you only take this action now.
- Apply smoothing

$$\pi(a|s) = \frac{[took\ a\ at\ s] + \lambda}{[was\ at\ s] + \lambda \cdot N_{actions}}$$

In M best games

Alternative idea: smooth updates

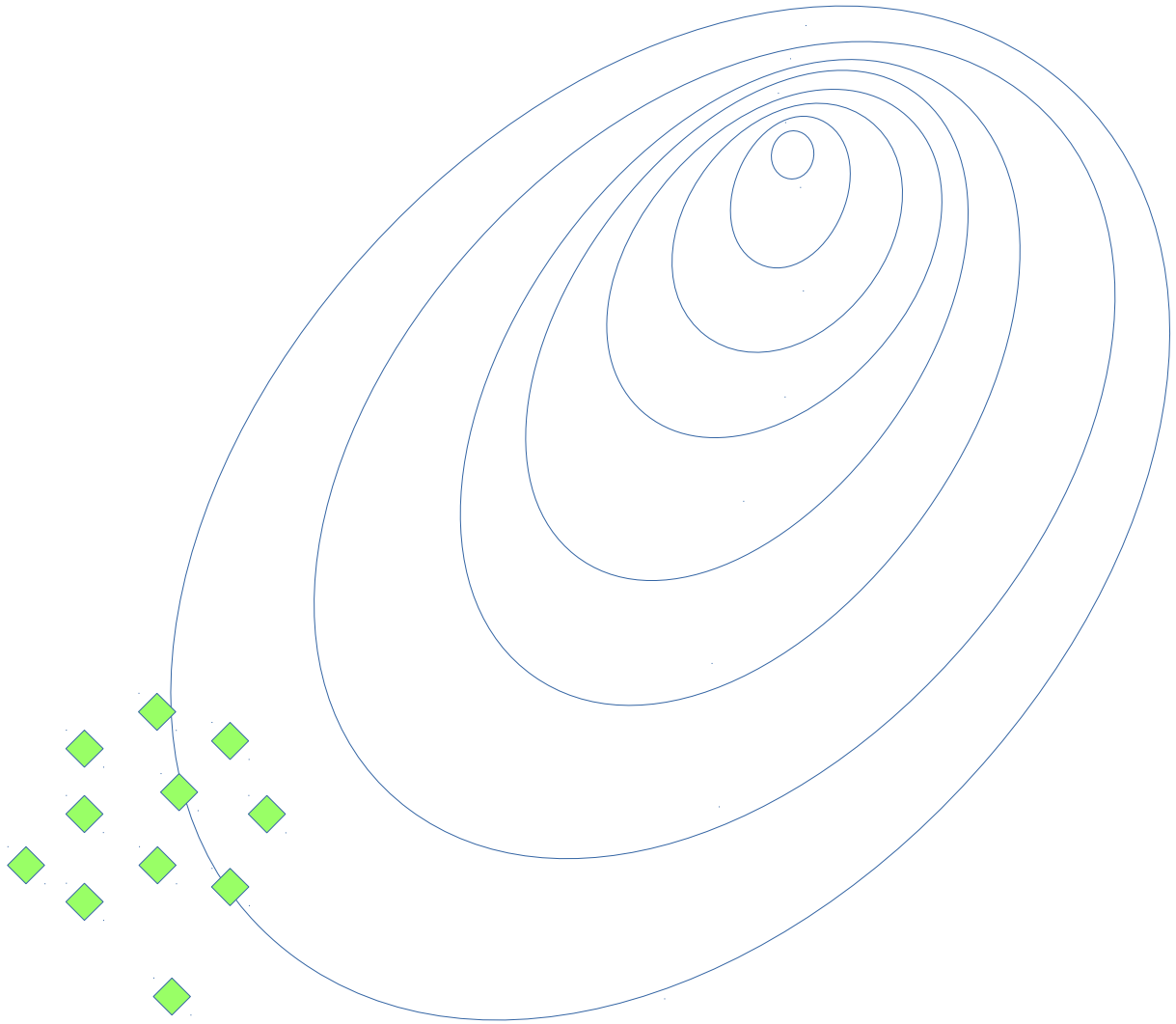
$$\pi_{i+1}(a|s) = \alpha \cdot \pi_{opt} + (1-\alpha)\pi_i(a|s)$$

Stochastic MDPs

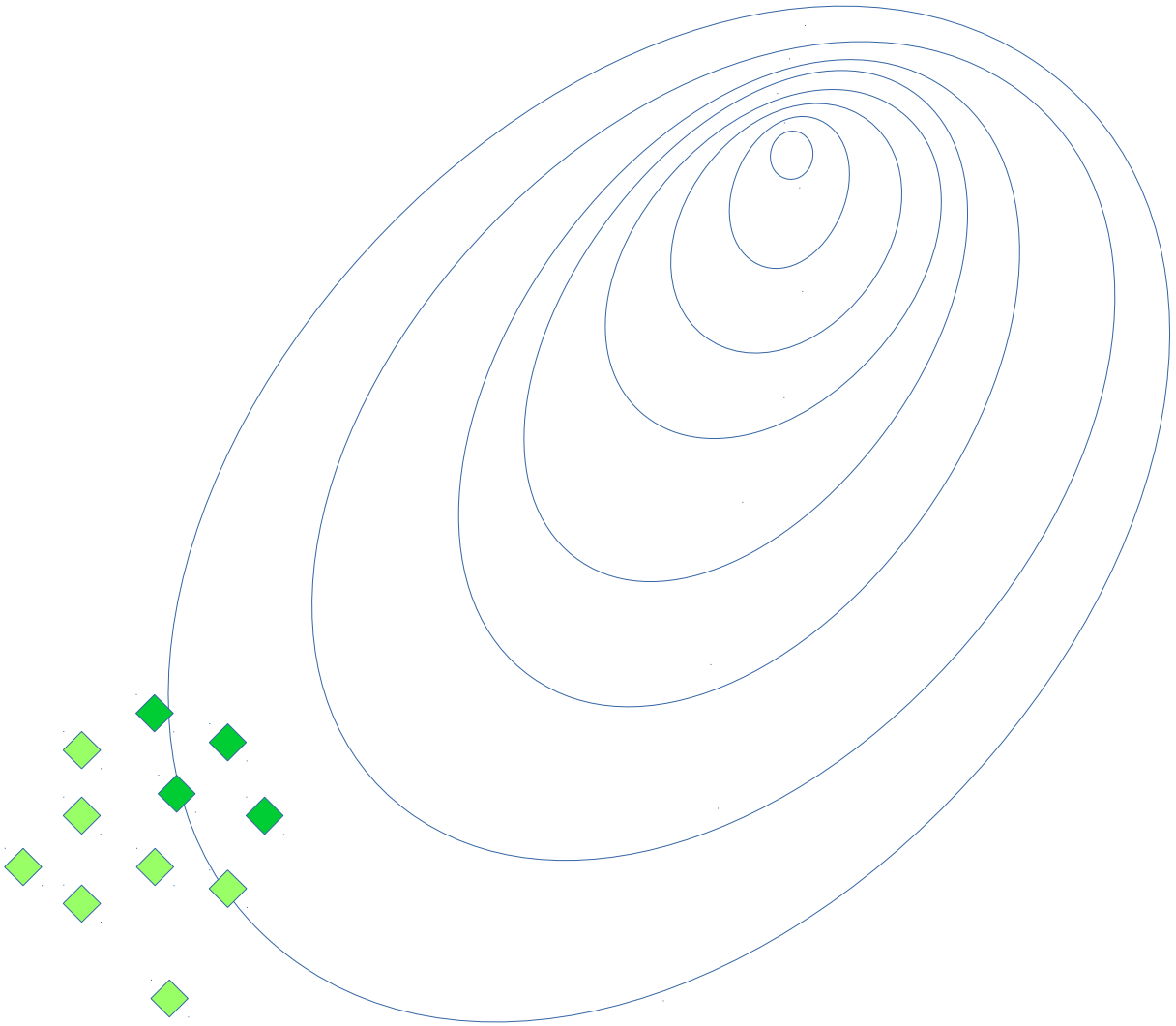
- If there's randomness in environment, algorithm will prefer “lucky” sessions.
- Training on lucky sessions is no good

- Solution: sample action for each state and run several simulations with these state-action pairs. Average the results.

Crossentropy Method



Crossentropy Method



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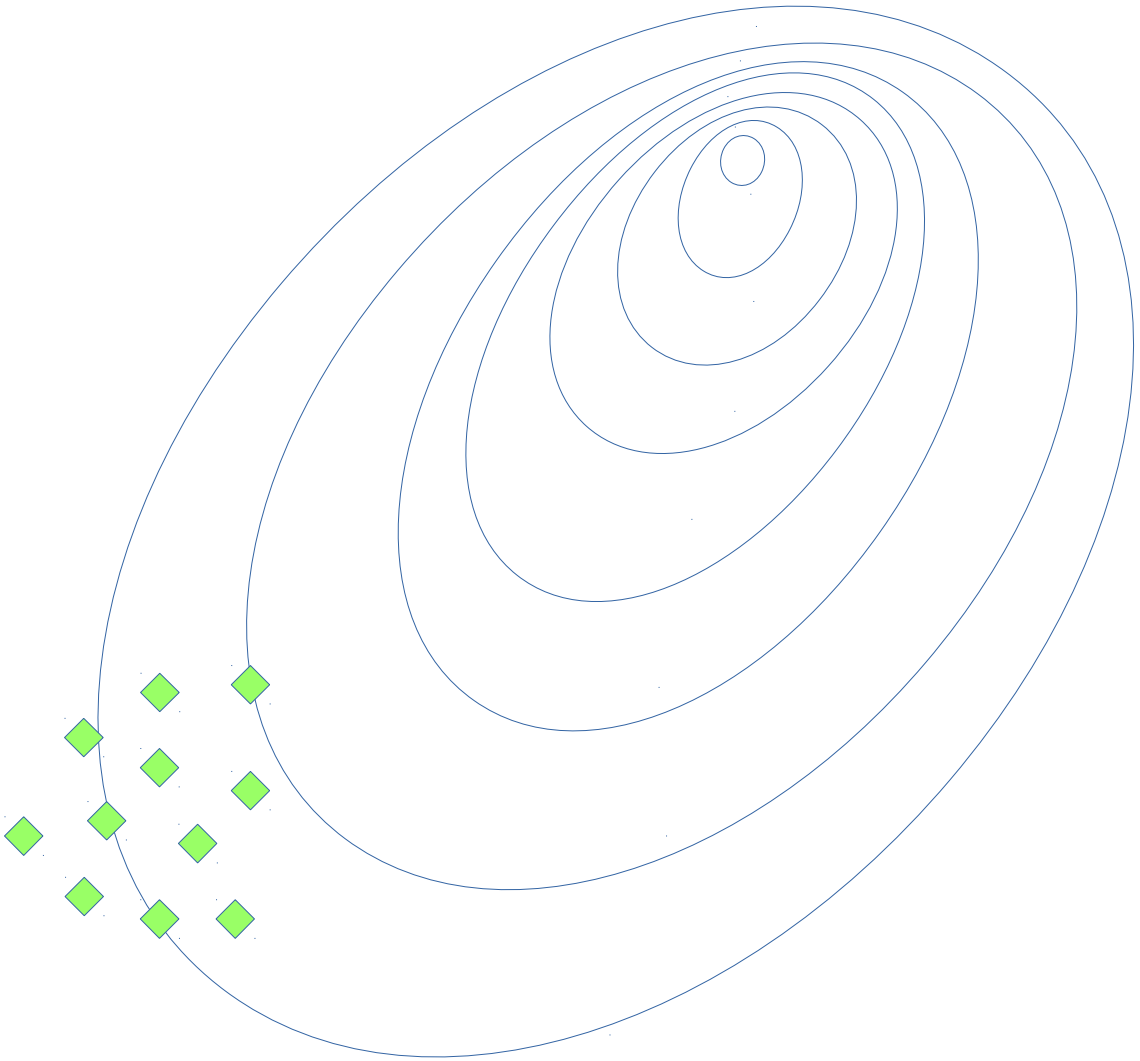

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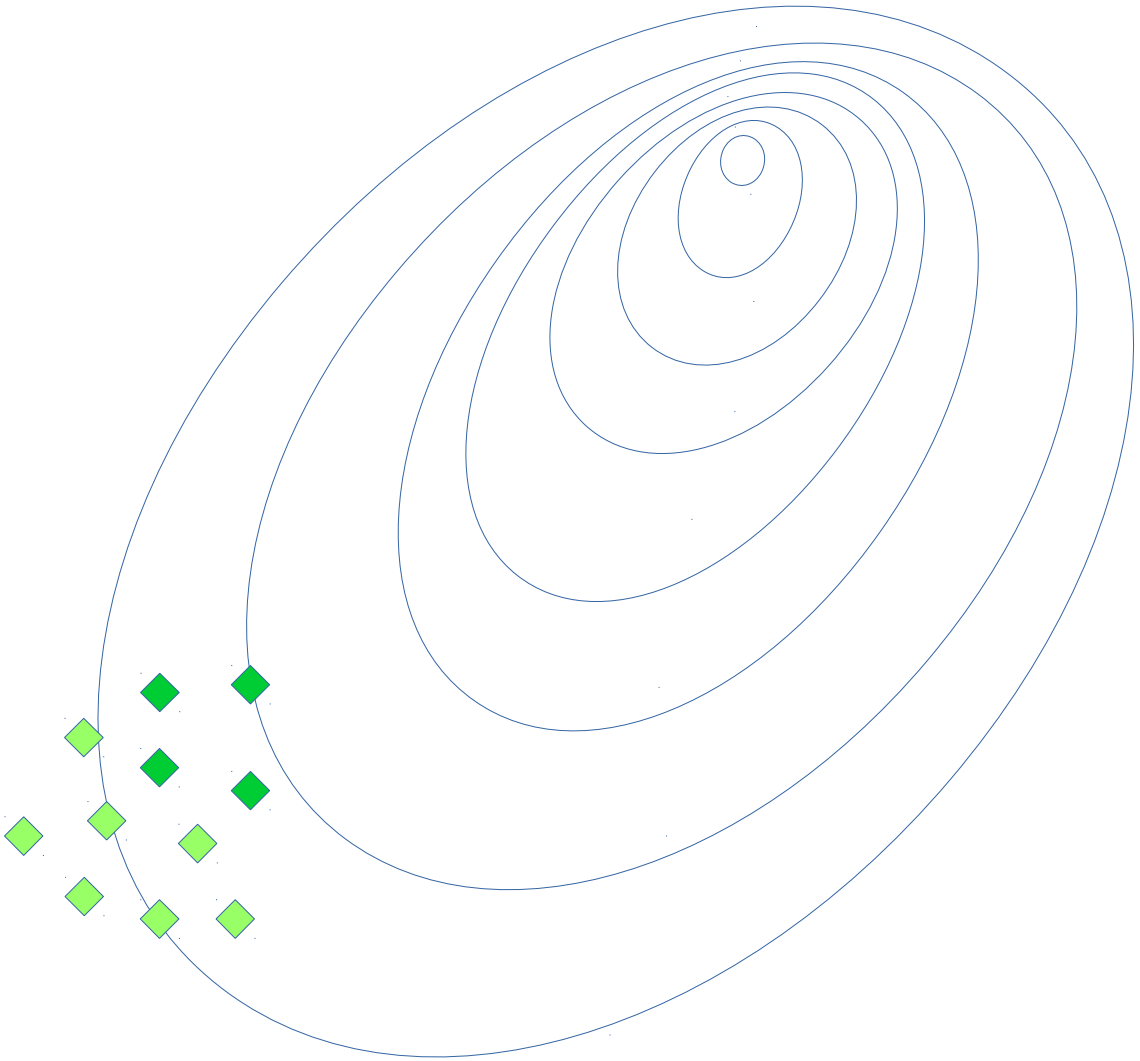

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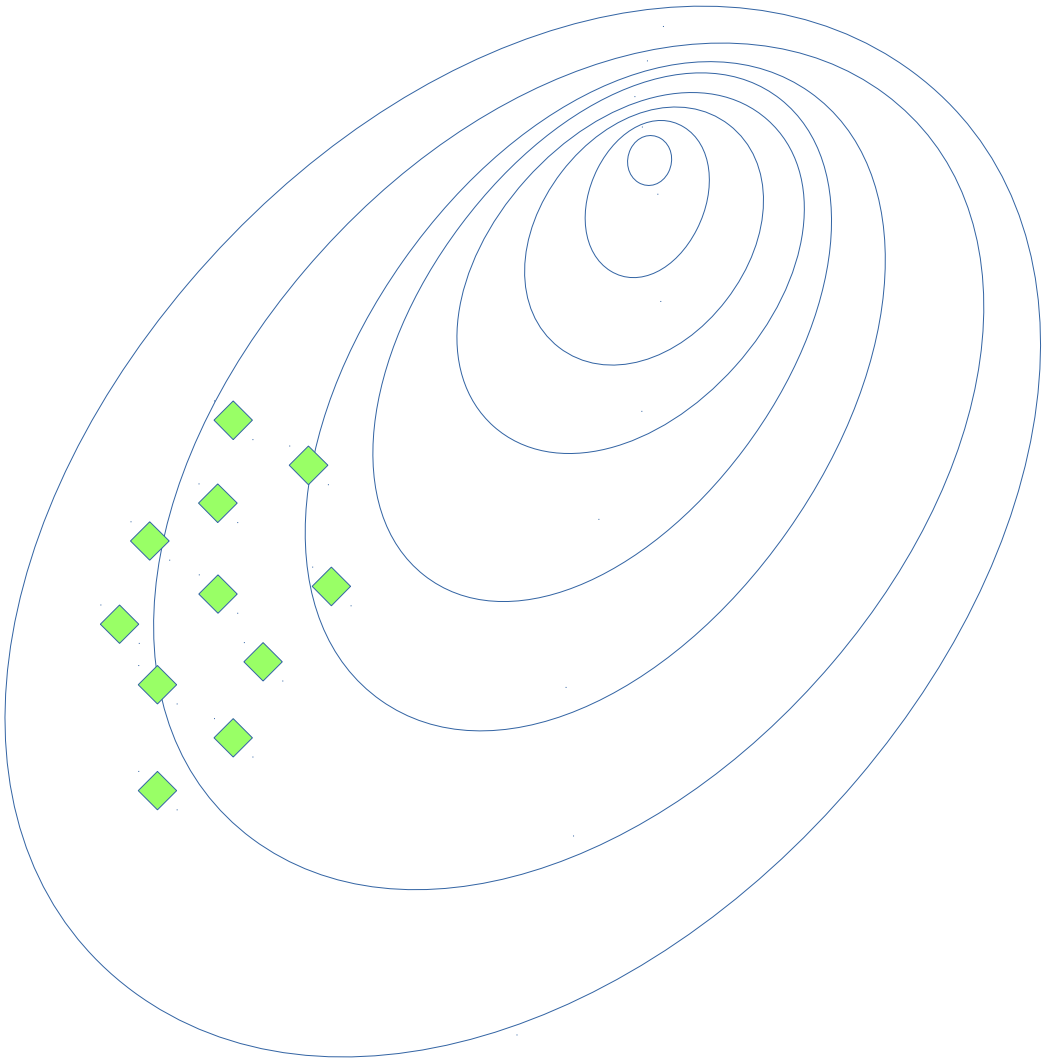

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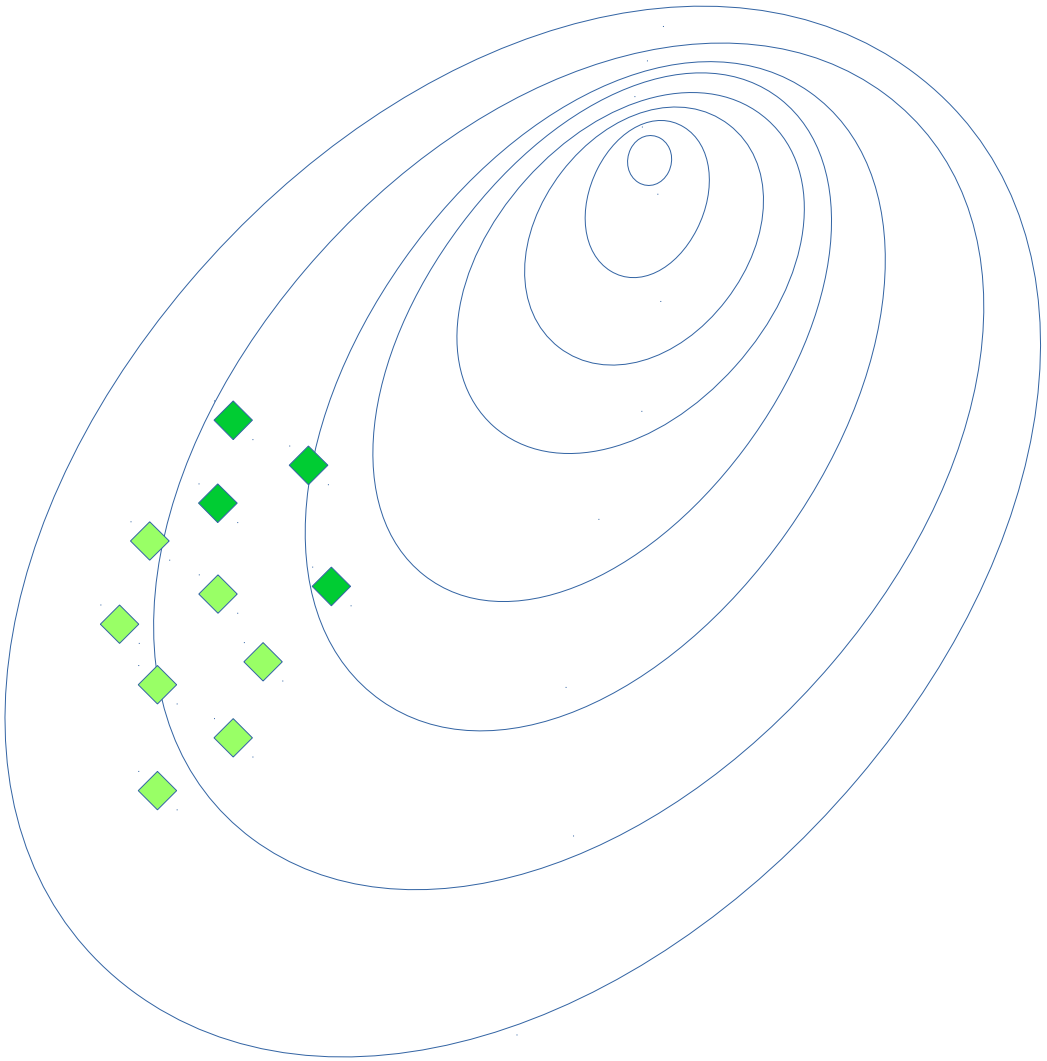

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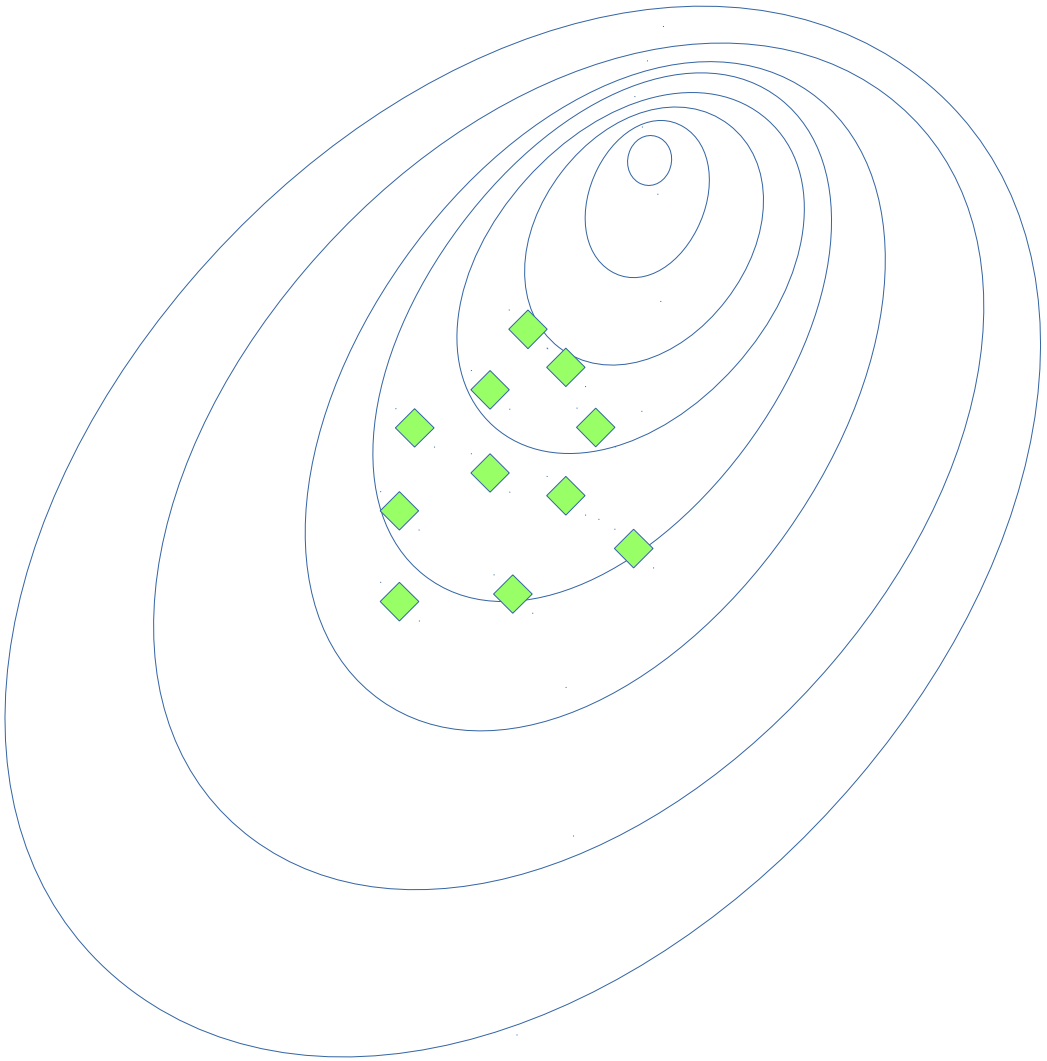
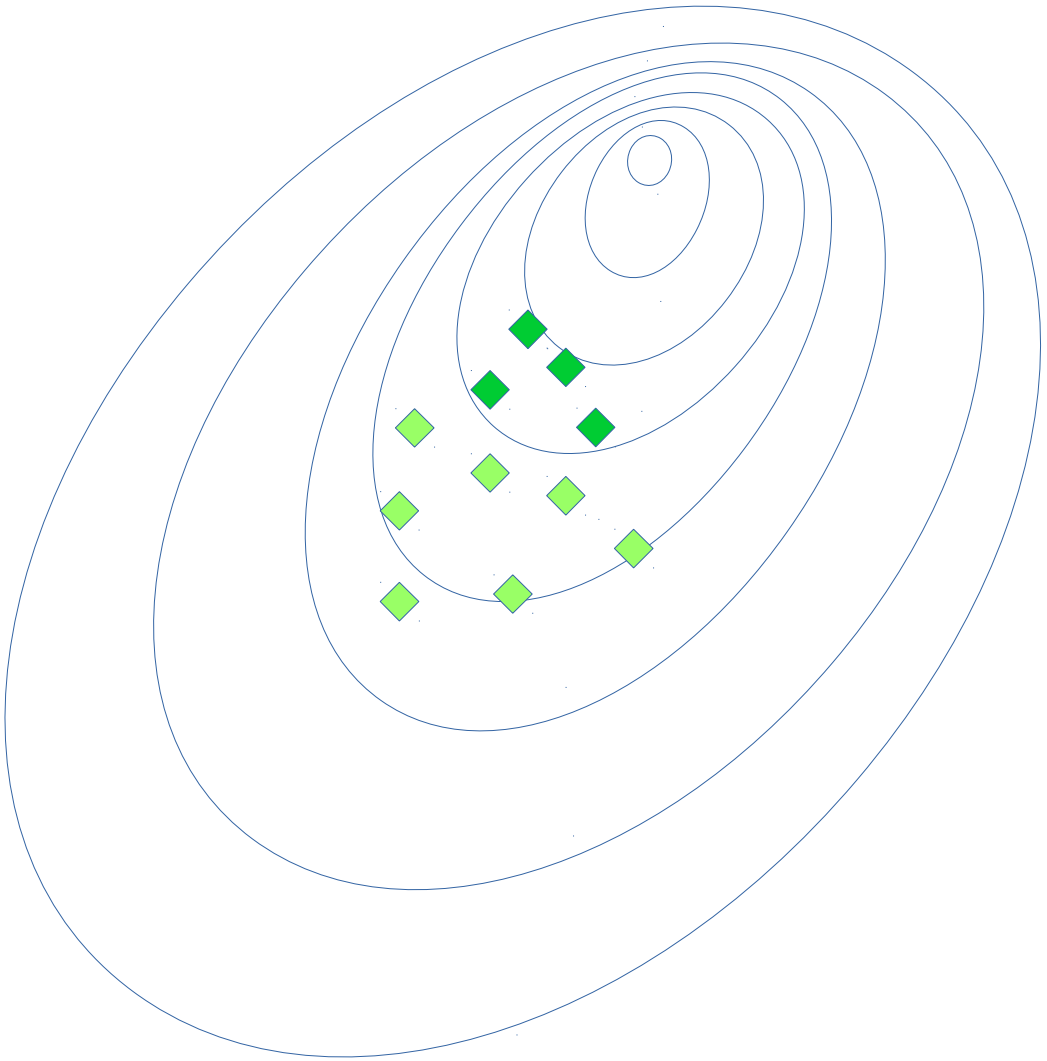
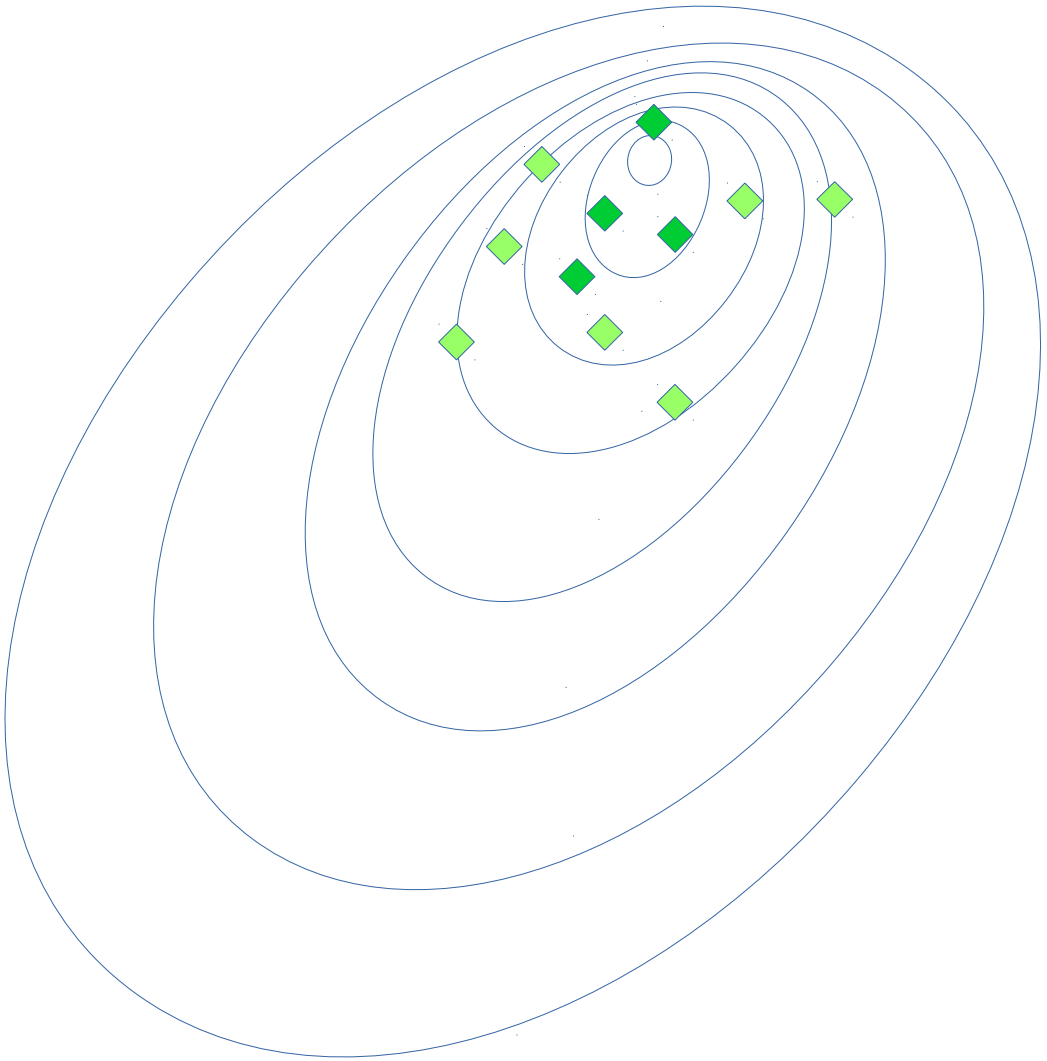


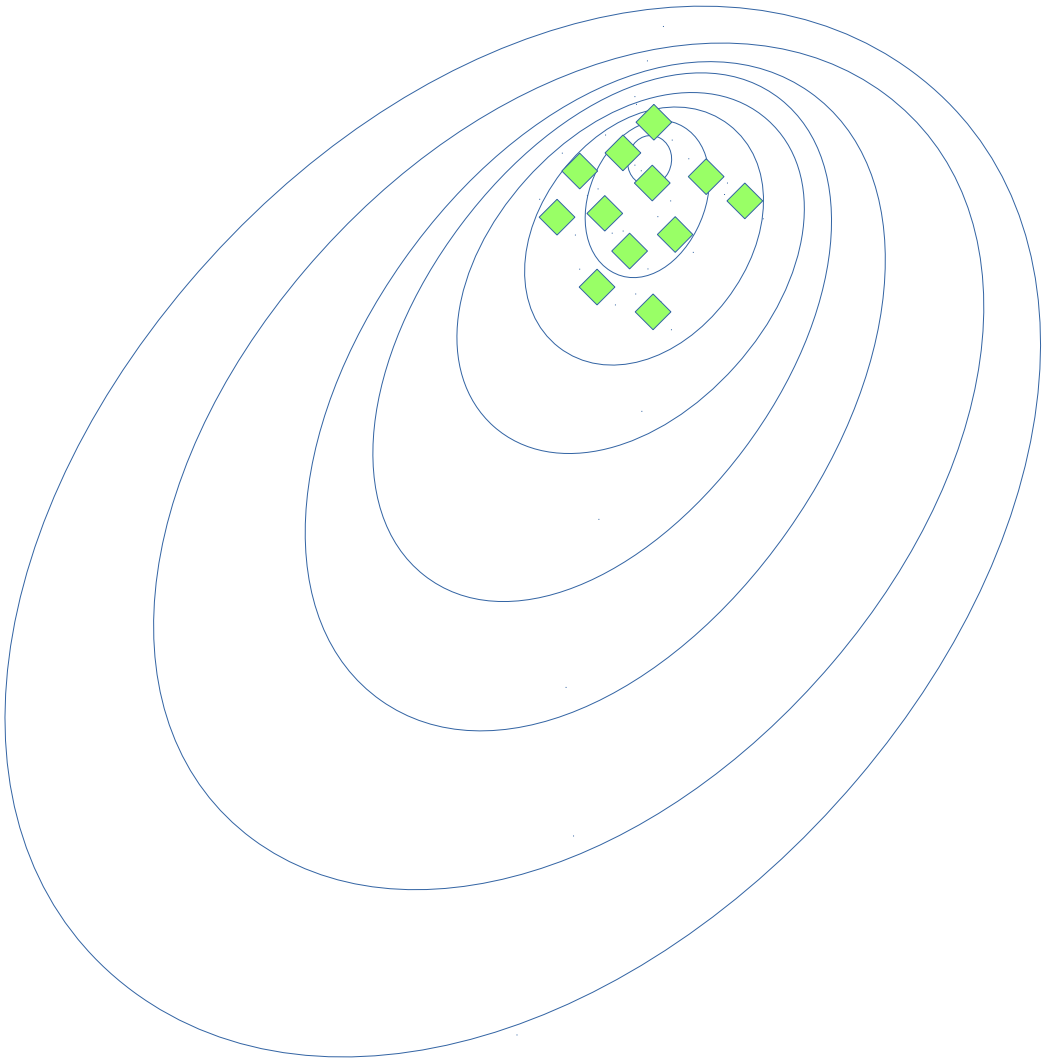
Crossentropy Method



Crossentropy Method



Crossentropy Method



Grim reality

If your environment has infinite/large state space

Approximate crossentropy method

- Policy is approximated
  - Neural network predicts $\pi_w(a|s)$ given s
  - Linear model / Random Forest / ...

Can't set $\pi(a|s)$ explicitly

All state-action pairs from M best sessions

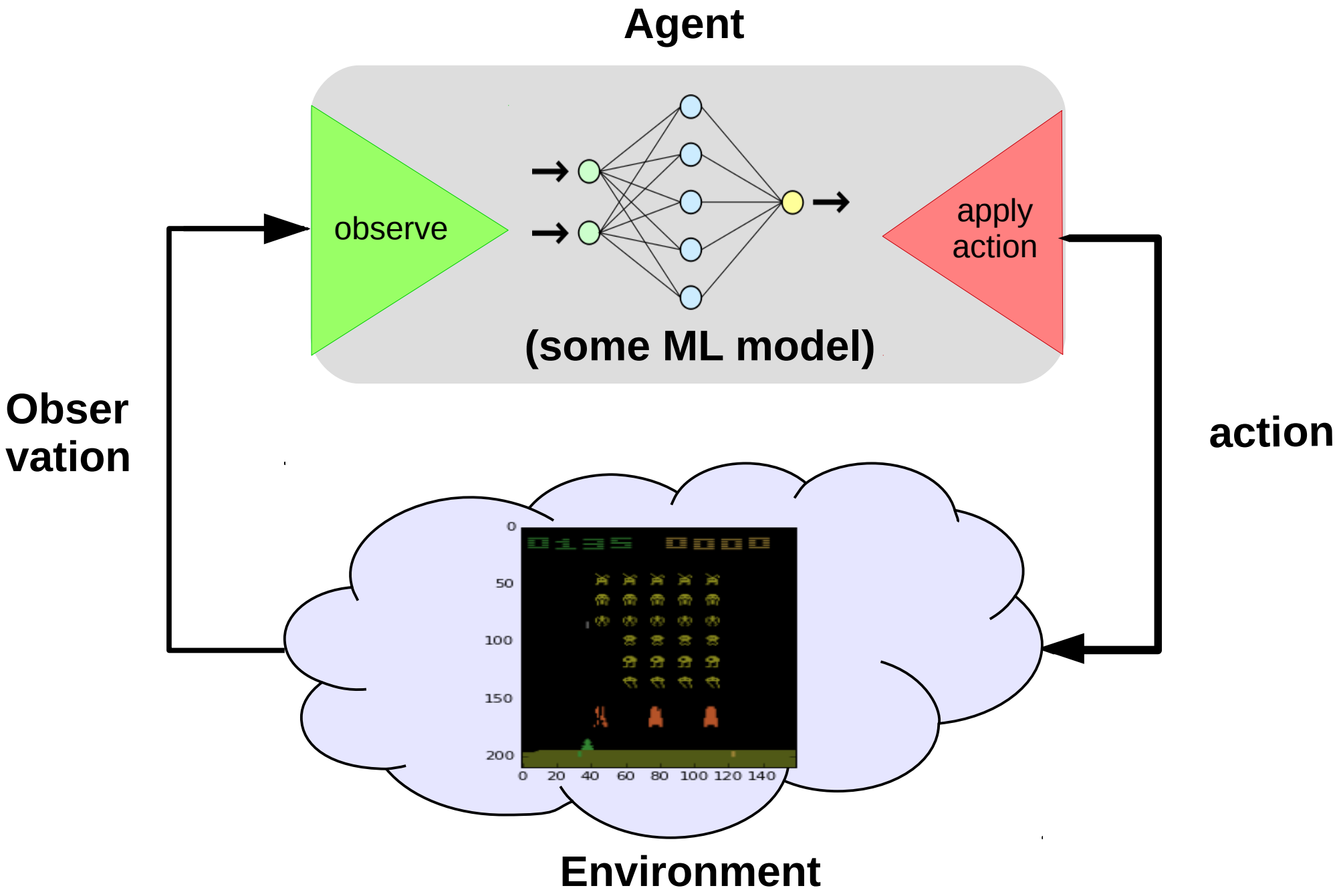
$$Elite = [(s_0, a_0), (s_1, a_1), (s_2, a_2), \ldots, (s_k, a_k)]$$

Approximate crossentropy method

- Policy is approximated
  - Neural network predicts $\pi_W(a|s)$ given s
  - Linear model / Random Forest / ...

Can't set $\pi(a|s)$ explicitly

Approximate RL



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Approximate crossentropy method

Neural network predicts $\pi_W(a|s)$ given s

All state-action pairs from M best sessions

$$Elite = [(s_0, a_0), (s_1, a_1), (s_2, a_2), \ldots, (s_k, a_k)]$$

Maximize likelihood of actions in “best” games

$$\pi = \underset{\pi}{argmax} \sum_{s_i, a_i \in Elite} \log \pi(a_i|s_i)$$

Approximate crossentropy method

Neural network predicts $\pi_W(a|s)$ given s

All state-action pairs from M best sessions

$$best = [(s_0, a_0), (s_1, a_1), (s_2, a_2), ..., (s_K, a_K)]$$

Maximize likelihood of actions in “best” games conveniently,

nn.fit(elite_states,elite_actions)

Approximate crossentropy method

- Initialize NN weights $W_0 \leftarrow random$

- Loop:
  - Sample N sessions
  - elite = take M best sessions and concatenate
  - $$W_{i+1} = W_i + \alpha \nabla [\sum_{s_i, a_i \in Elite} \log \pi_{W_i}(a_i|s_i)]$$

Approximate (deep) version

- Initialize NN weights $W_0 \leftarrow random$

model = MLPClassifier()

- Loop:
  - Sample N sessions
  - elite = take M best sessions and concatenate
  - $$W_{i+1} = W_i + \alpha \nabla [\sum_{s_i, a_i \in Elite} \log \pi_{W_i}(a_i|s_i)]$$

model.fit(elite_states,elite_actions)

Continuous action spaces

- Continuous state space
- Model $\pi_W(a|s) = N(\mu(s), \sigma^2)$
  - Mu(s) is neural network output
  - Sigma is a parameter or yet another network output
- Loop:
  - Sample N sessions
  - elite = take M best sessions and concatenate
  - $W_{i+1} = W_i + \alpha \nabla [\sum_{s_i, a_i \in Elite} \log \pi_{W_i}(a_i|s_i)]$

What changed?

Continuous action spaces

- Continuous state space **model = MLPRegressor()**
- Model $\pi_W(a|s) = N(\mu(s), \sigma^2)$
  - Mu(s) is neural network output
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- Loop:
  - Sample N sessions
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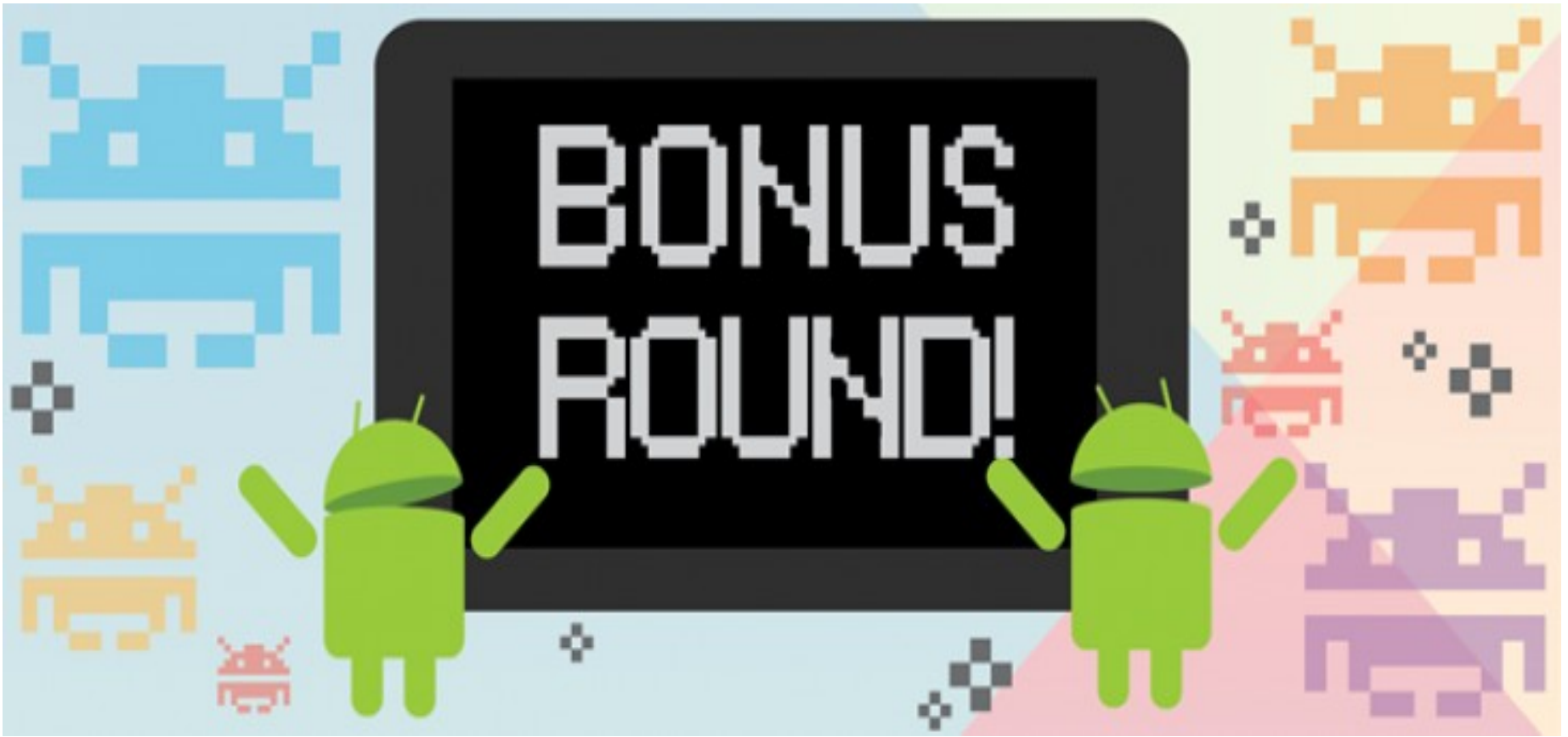
  - $W_{i+1} = W_i + \alpha \nabla [\sum_{s_i, a_i \in Elite} \log \pi_{W_i}(a_i|s_i)]$

model.fit(elite_states, elite_actions)

Nothing!

Tricks

- Remember sessions from 3-5 past iterations
  - Threshold and use all of them when training
  - May converge slower if env is easy to solve.
- Regularize with entropy
  - to prevent premature convergence.
- Parallelize sampling
- Use RNNs if partially-observable (later)


BONUS
ROUND!

Evolution Strategies

- Introduce distribution over weights

$$\theta \sim N\left(\theta | \mu, \sigma^2\right)$$

- Maximize expected reward

$$J = \underset{N\left(\theta|\mu,\sigma^2\right)}{E} R$$

Evolution Strategies

- Introduce distribution over weights

$$\theta \sim N\left(\theta | \mu, \sigma^2\right)$$

other P(θ) will work as well

- Maximize expected reward

$$J = \underset{N\left(\theta|\mu,\sigma^2\right)}{E} R$$

Evolution Strategies

- Introduce distribution over weights

$$\theta \sim N\left(\theta | \mu, \sigma^2\right)$$

- Maximize expected reward

$$J = \mathop{E}_{\theta \sim N\left(\theta|\mu,\sigma^2\right)} \mathop{E}_{\tau(\theta)=s,a,s',a',\ldots} R\left(\tau\right)$$

Evolution Strategies

- Expected reward (using math. Expectation)

$$J = \mathop{E}_{\theta \sim N(\theta|\mu,\sigma^2)} \; \mathop{E}_{\tau(\theta)=s,a,s',a',\ldots} R(\tau)$$

Q: How can we estimate J in practice?

for large/infinite state space

Evolution Strategies

- Expected reward (using math. Expectation)

$$J = \mathop{E}_{\theta \sim N(\theta|\mu,\sigma^2)} \; \mathop{E}_{\tau(\theta)=s,a,s',a',\ldots} R(\tau)$$

- Approximate with sampling

$$J \approx \frac{1}{N} \sum_{i=0}^{N} \sum_{\tau_i=s,a,s',a',\ldots} R(\tau_i)$$

Sample Θ from $\theta \sim N(\theta|\mu,\sigma^2)$

Evolution Strategies

- Expected reward (using math. Expectation)

$$J = \mathop{E}_{N(\theta|\mu,\sigma^2)} \; \mathop{E}_{s,a,s',a',\ldots} R(s,a,s',a',\ldots)$$

- Approximate with sampling

$$J \approx \frac{1}{N} \sum_{i=0}^{N} \sum_{\tau_i = s,a,s',a',\ldots} R(\tau_i)$$

sample full episodes

Sample Θ from $\theta \sim N(\theta|\mu,\sigma^2)$

Evolution Strategies

- Expected reward (using math. expectation)

$$J = \int N(\theta|\mu, \sigma^2) \cdot \int P(\tau|\theta) R(\tau) d\tau d\theta$$

- What we need

$$\nabla J = \frac{\partial J}{\partial ?}$$

Q: you compute ∇J w.r.t. what?

Evolution Strategies

- Expected reward (using math. expectation)

$$J = \int N(\theta|\mu, \sigma^2) \cdot \int P(\tau|\theta) R(\tau) d\tau d\theta$$

- What we need

$$\nabla J = \frac{\partial J}{\partial \mu, \partial \sigma^2}$$

Gradient w.r.t. distribution parameters

Evolution Strategies

- Expected reward (using math. expectation)

$$J = \int N(\theta|\mu, \sigma^2) \cdot \int P(\tau|\theta) R(\tau) d\tau d\theta$$

- What we need

$$\nabla J = \int \nabla [N(\theta|\mu, \sigma^2)] \cdot \int P(\tau|\theta) R(\tau) d\tau d\theta$$

Evolution Strategies

- Expected reward (using math. expectation)

$$J = \int N(\theta|\mu, \sigma^2) \cdot \int P(\tau|\theta) R(\tau) d\tau d\theta$$

- What we need

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Evolution Strategies

- Expected reward (using math. expectation)

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- What we need

$$\nabla J = \int \nabla [N(\theta|\mu, \sigma^2)] \cdot \int P(\tau|\theta) R(\tau) d\tau d\theta$$

Can't estimate by sampling!
∇ N (Θ|μ,σ) is not a distribution

Logderivative trick

Simple math

$$\nabla \log f(x) = ???$$

(try chain rule)

Logderivative trick

Simple math

$$\nabla \log f(x) = \frac{1}{f(x)} \cdot \nabla f(x)$$

$$f(x) \cdot \nabla \log f(z) = \nabla f(z)$$

Logderivative trick

Analytical inference

$$\nabla J = \int \nabla [N(\theta|\mu, \sigma^2)] \cdot \int P(\tau|\theta) R(\tau) d\tau d\theta$$

$$\nabla N(\theta|\mu, \sigma^2) = N(\theta|\mu, \sigma^2) \cdot \nabla \log N(\theta|\mu, \sigma^2)$$

Evolution Strategies

Analytical inference

$$\nabla J = \int [N(\theta|\mu, \sigma^2) \cdot \nabla \log N(\theta|\mu, \sigma^2)] \cdot \int P(\tau|\theta) R(\tau) d\tau d\theta$$

Q: How can we estimate ∇J in now?

Evolution Strategies

Analytical inference

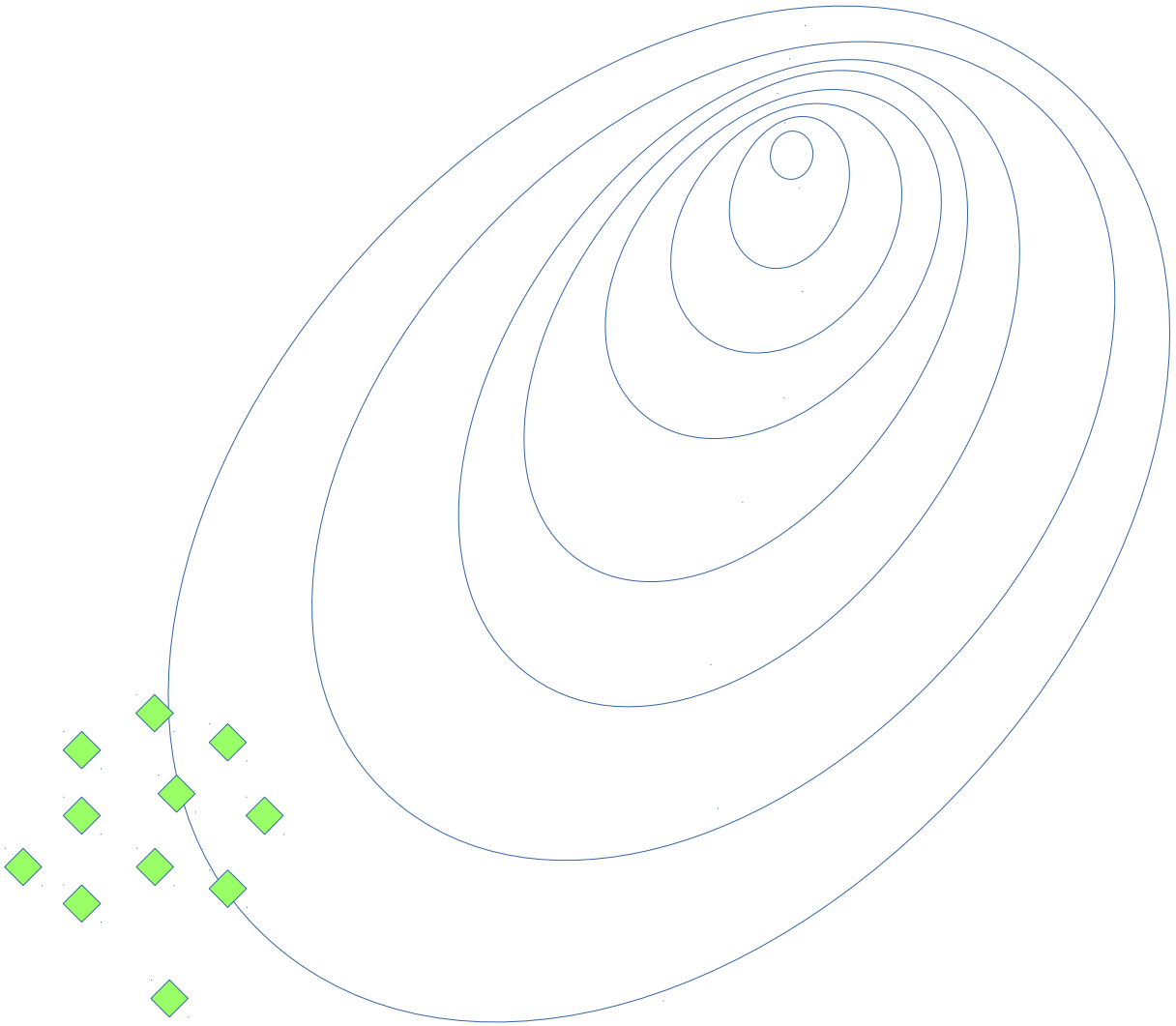
$$\nabla J = \mathop{E}_{\theta \sim N(\theta|\mu,\sigma^2)} \nabla \log N(\theta|\mu,\sigma^2) \cdot \mathop{E}_{\tau(\theta)=s,a,s',\ldots} R(\tau)$$

Sampled estimate

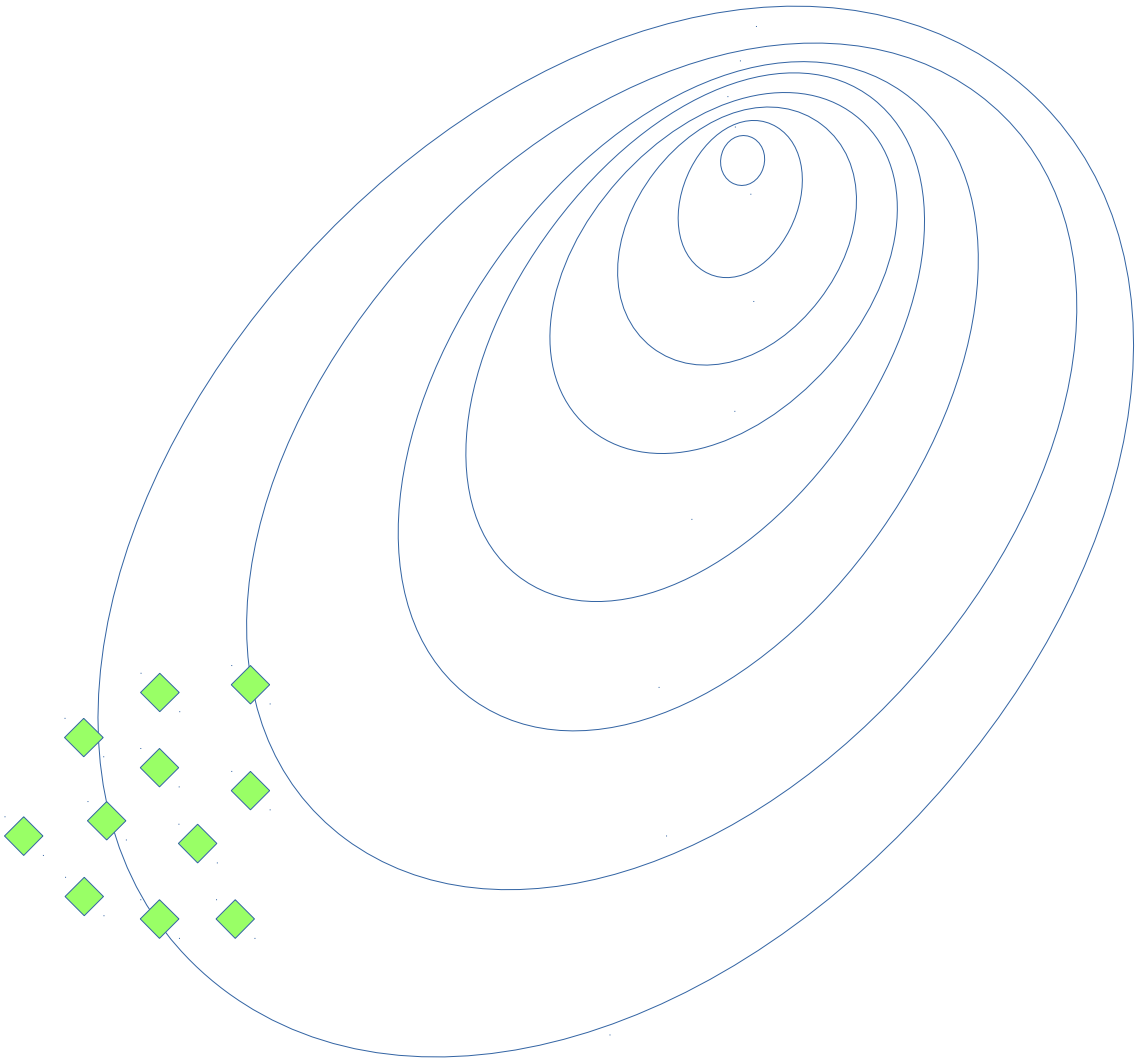
$$\nabla J \approx \frac{1}{N} \sum_{i=0}^{N} \nabla \log N(\theta|\mu,\sigma^2) \cdot \sum_{s,a \in z_i} R(s,a,\ldots)$$

Sample Θ from $\theta \sim N(\theta|\mu,\sigma^2)$

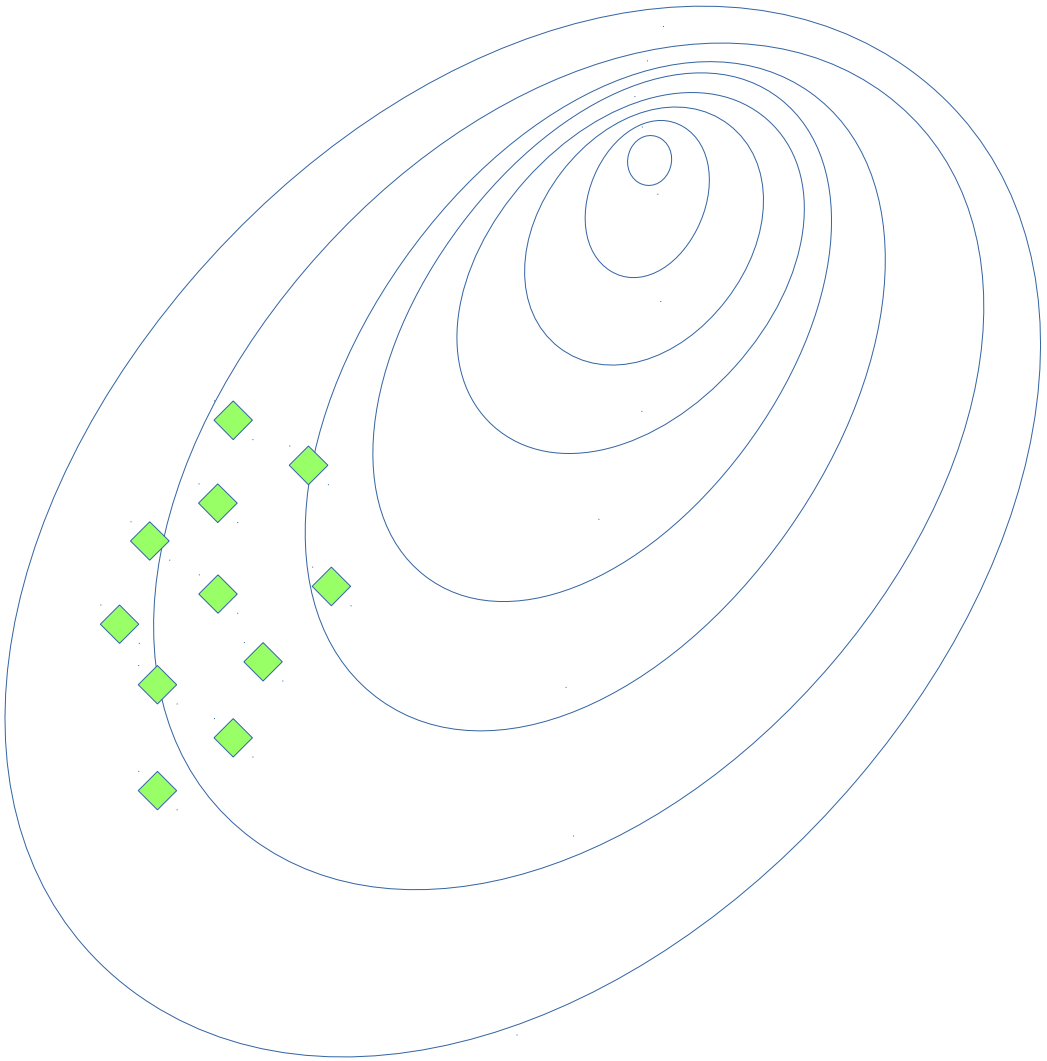
Evolution Strategies



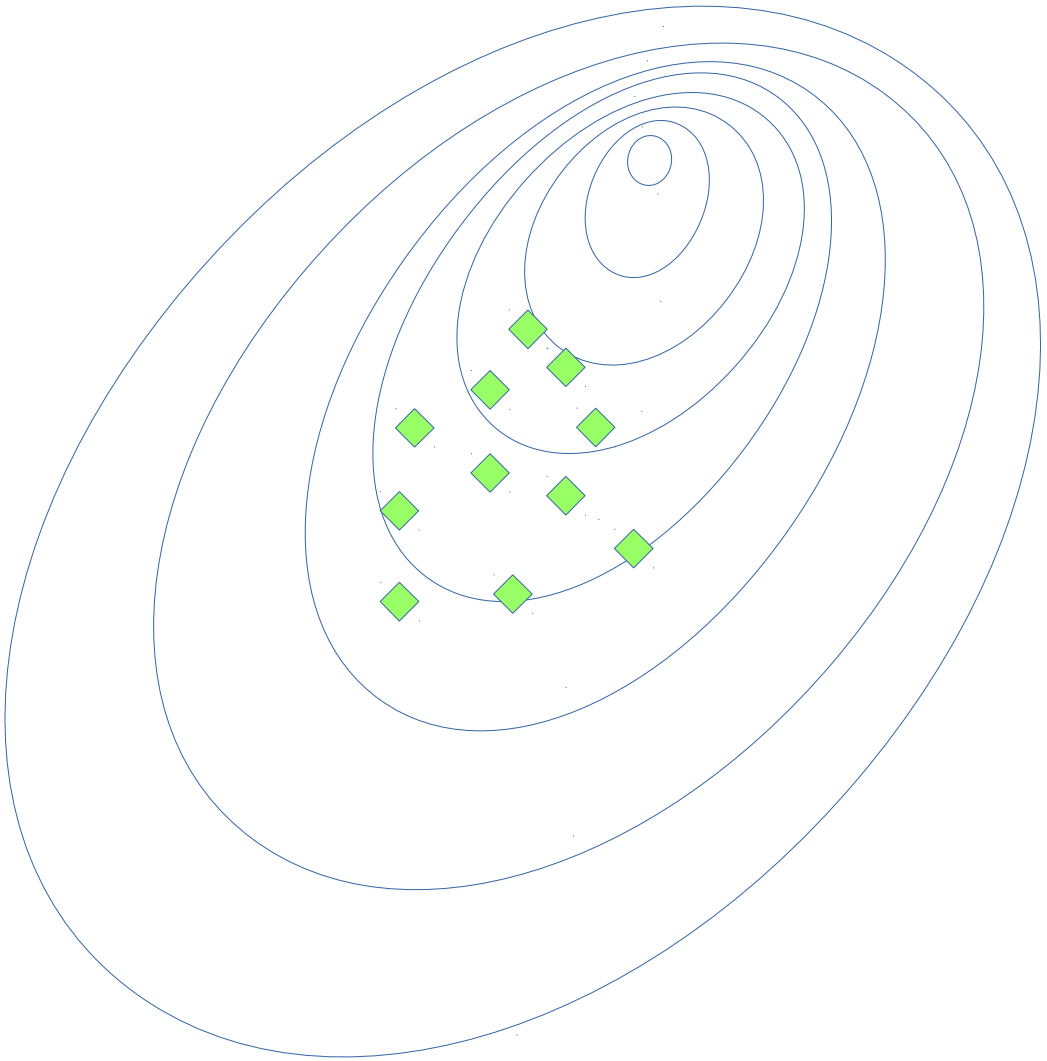
Evolution Strategies



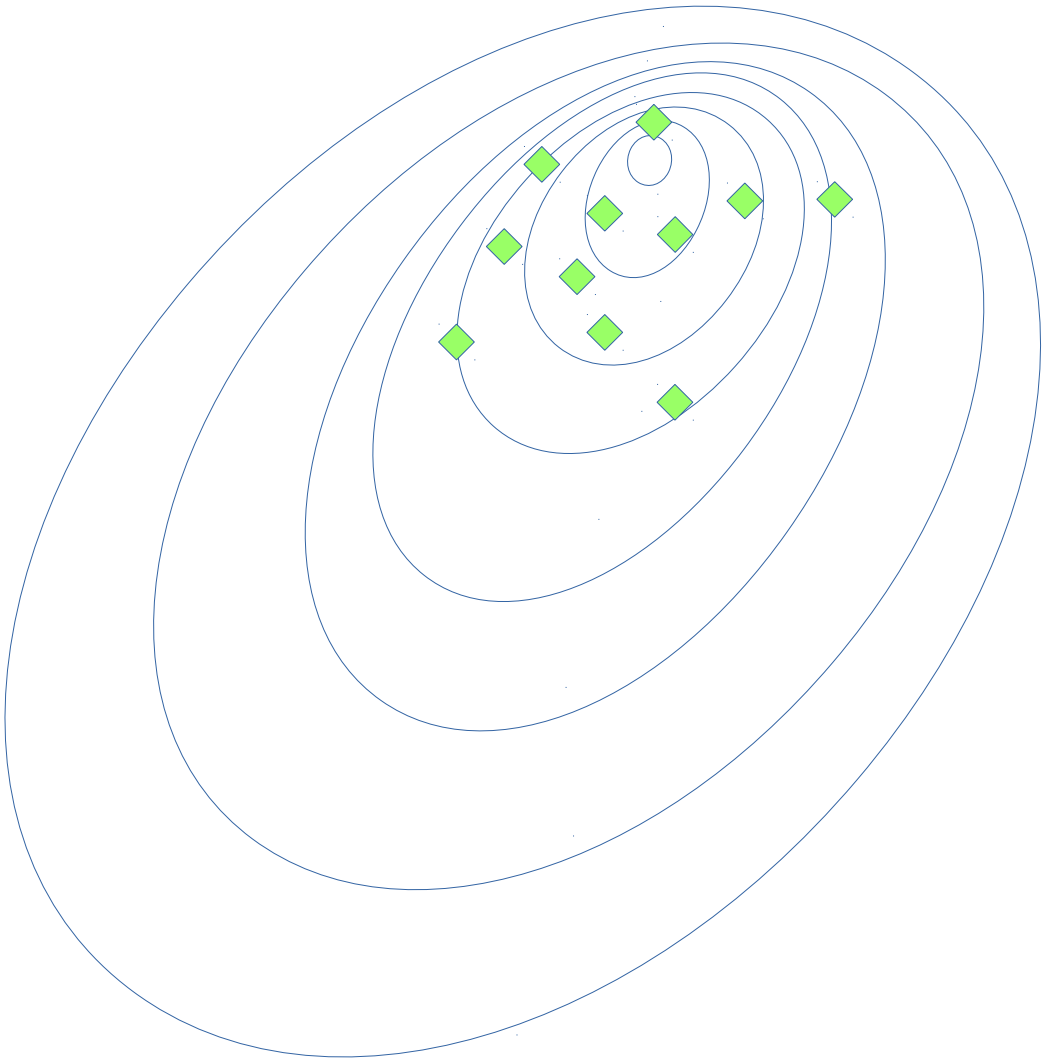
Evolution Strategies



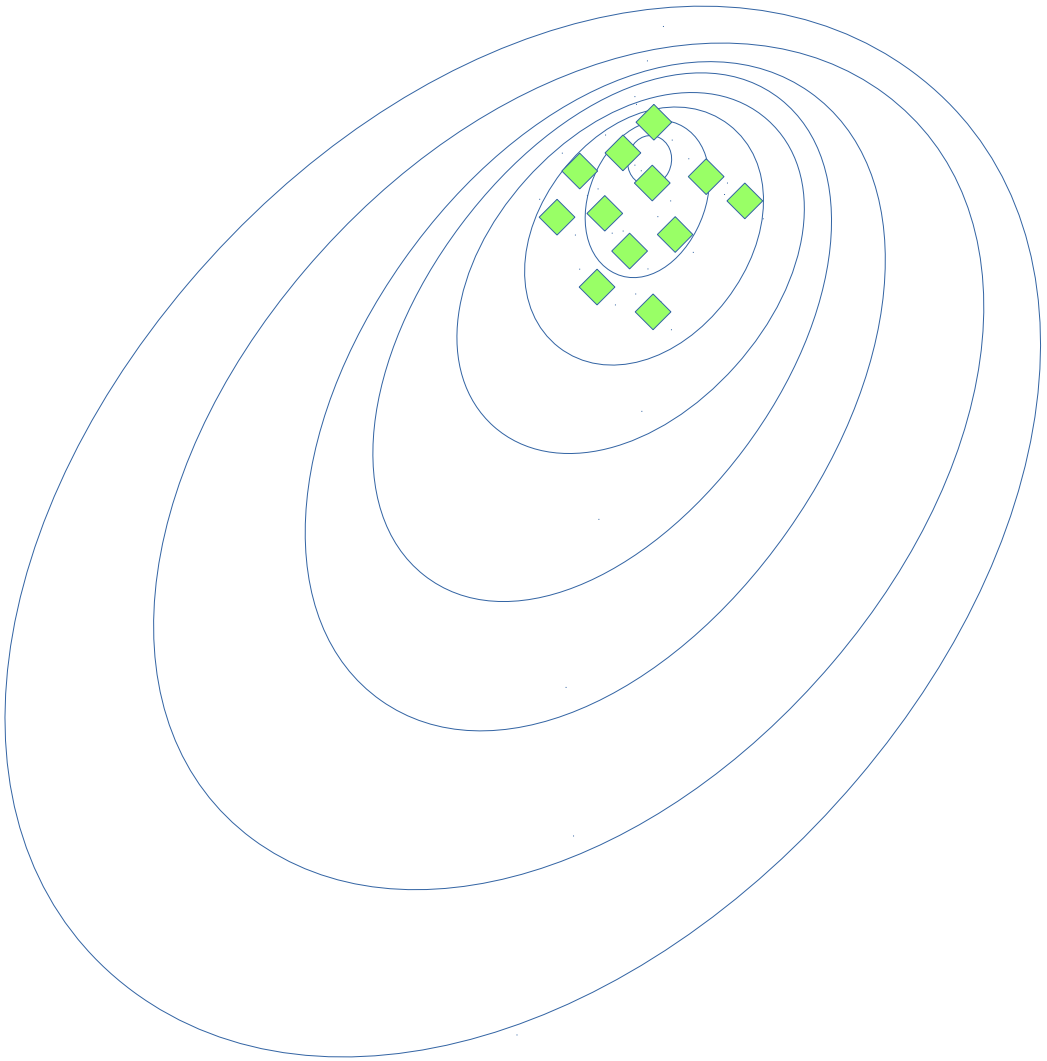
Evolution Strategies



Evolution Strategies



Evolution Strategies



Evolution strategies

Algorithm

1. Initialize μ_0, σ_0^2

2. Forever:

$$\nabla J \approx \frac{1}{N} \sum_{i=0}^{N} \nabla \log N\left(\theta | \mu, \sigma^2\right) \cdot \sum_{s,a,s',\ldots \in \tau_i} R\left(s,a,s',\ldots\right)$$

Evolution strategies

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$$\mu = \mu + \alpha \cdot \nabla_{\mu} J \qquad \sigma^2 = \sigma^2 + \alpha \cdot \nabla_{\sigma^2} J$$

Evolution strategies

Algorithm

1. Initialize μ_0, σ_0^2

2. Forever:

$$\theta = \mu + \sigma \cdot \xi \; : \; \xi \sim N(0,1)$$

sample $\theta_i, \tau_i, R_i : R_i = R(\tau_i) = R(\tau(\theta_i))$

$$\mu = \mu + \alpha \cdot \frac{1}{N \cdot \sigma} \cdot \sum_i \xi_i \cdot R_i \qquad \sigma^2 = \ldots$$

Reward baselines

TL;DR normalize reward

$$\underset{N(\theta|\mu,\sigma^2)}{argmax}\ E\ R = \underset{N(\theta|\mu,\sigma^2)}{argmax}\ E\ \frac{R-mean}{std}$$

$$A = \frac{R - E\,R}{Var\ R}$$

Evolution strategies

Features

- A general black box optimization
- **Easy to implement & scale**

Evolution strategies

Features

- A general black box optimization
- **Easy to implement & scale**

$$\nabla J \approx \frac{1}{N} \sum_{i=0}^{N} \nabla \log N\left(\theta | \mu, \sigma^2\right) \cdot \sum_{\tau_i = s, a, s', \ldots} R\left(\tau_i\right)$$

Q: You have 1000 CPUs.

Optimize this formula!

Evolution strategies

Features

- A general black box optimization
- **Easy to implement & scale**

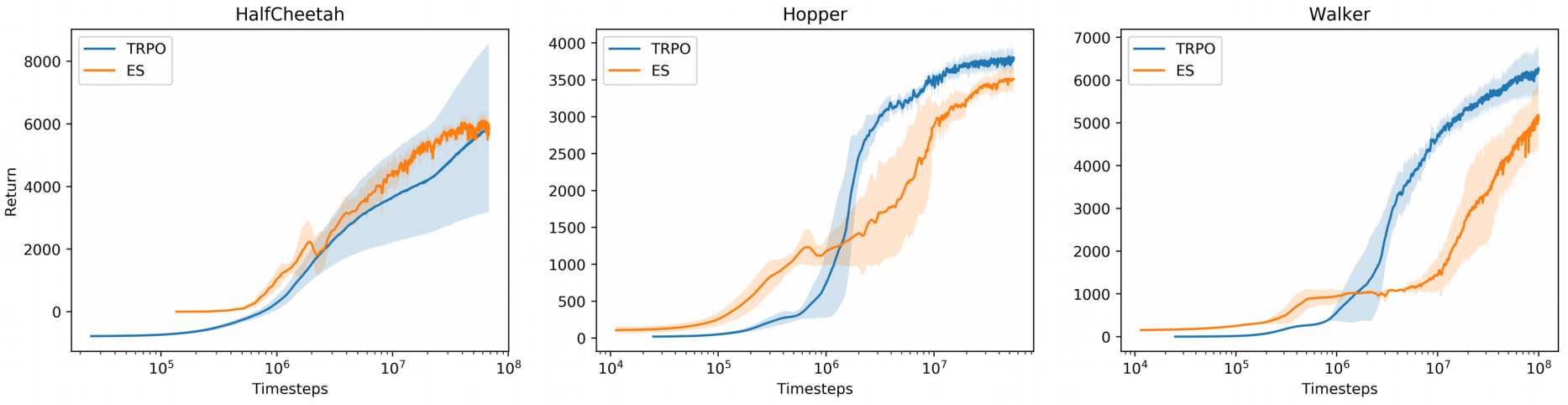
$$\nabla J \approx \frac{1}{N} \sum_{i=0}^{N} \nabla \log N\left(\theta | \mu, \sigma^2\right) \cdot \sum_{\tau_i = s, a, s', \ldots} R\left(\tau_i\right)$$

You can compute every session in parallel

Evolution strategies

Features

- A general black box optimization
- Some results on gym



https://blog.openai.com/evolution-strategies/

Common drawback

Both CEM, ES and all similar methods

- Train from full sessions only
- Require a lot of samples

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