ML @ ICL

Reinforcement learning

In a nutshell

Supervised learning

Given:

- objects and answers (x, y)
- algorithm family $a_\theta(x) \to y$
- 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

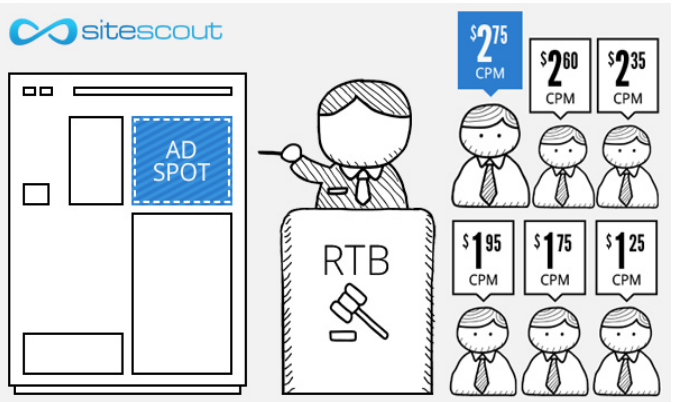
Great... except if we have no reference answers

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:

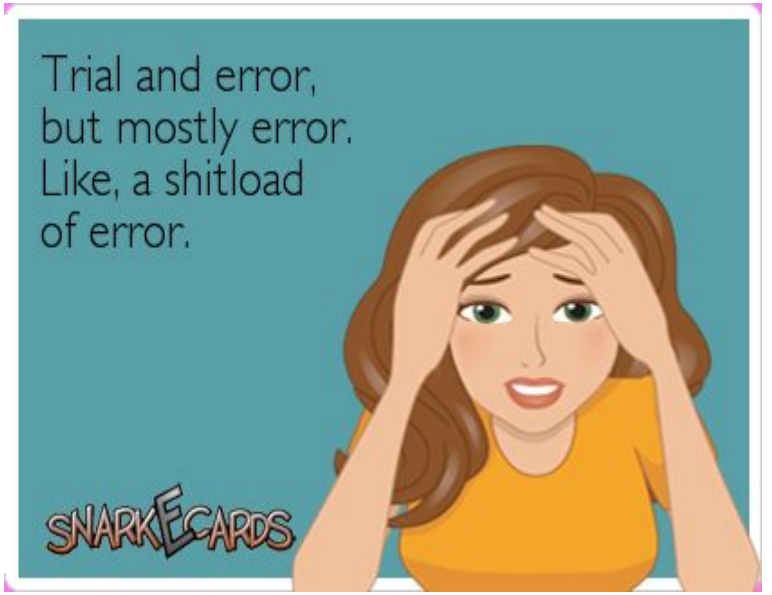
- Learn to pick relevant ads

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

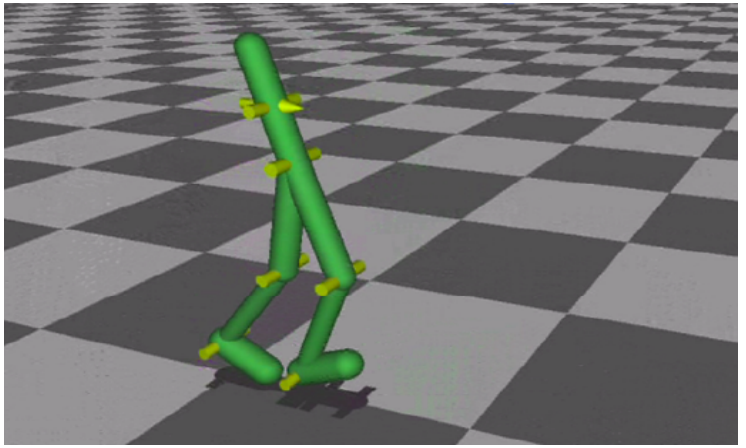


Giant Death Robot (GDR)

Great... except if we have no reference answers

We have:

- Evil humanoid robot
- A lot of spare parts
  to repair it :)



We want:

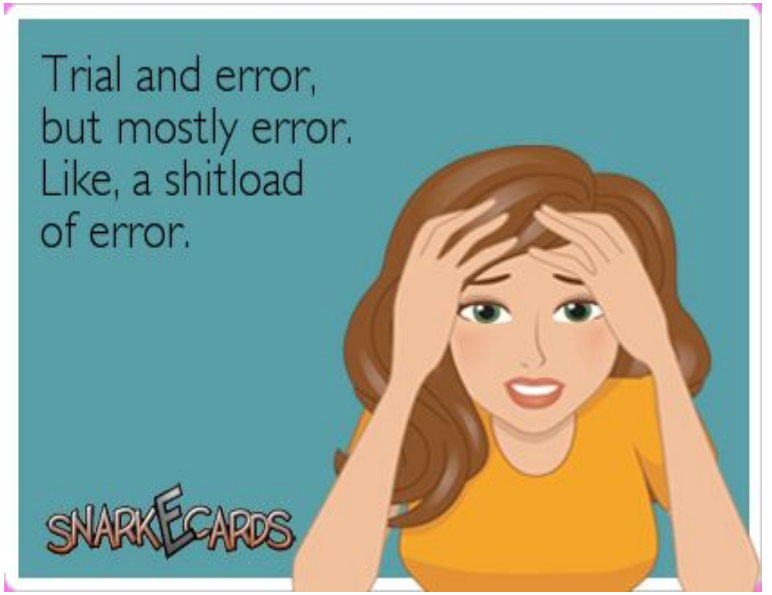
- ~~Enslave humanity~~
- Learn to walk forward

Ideas?

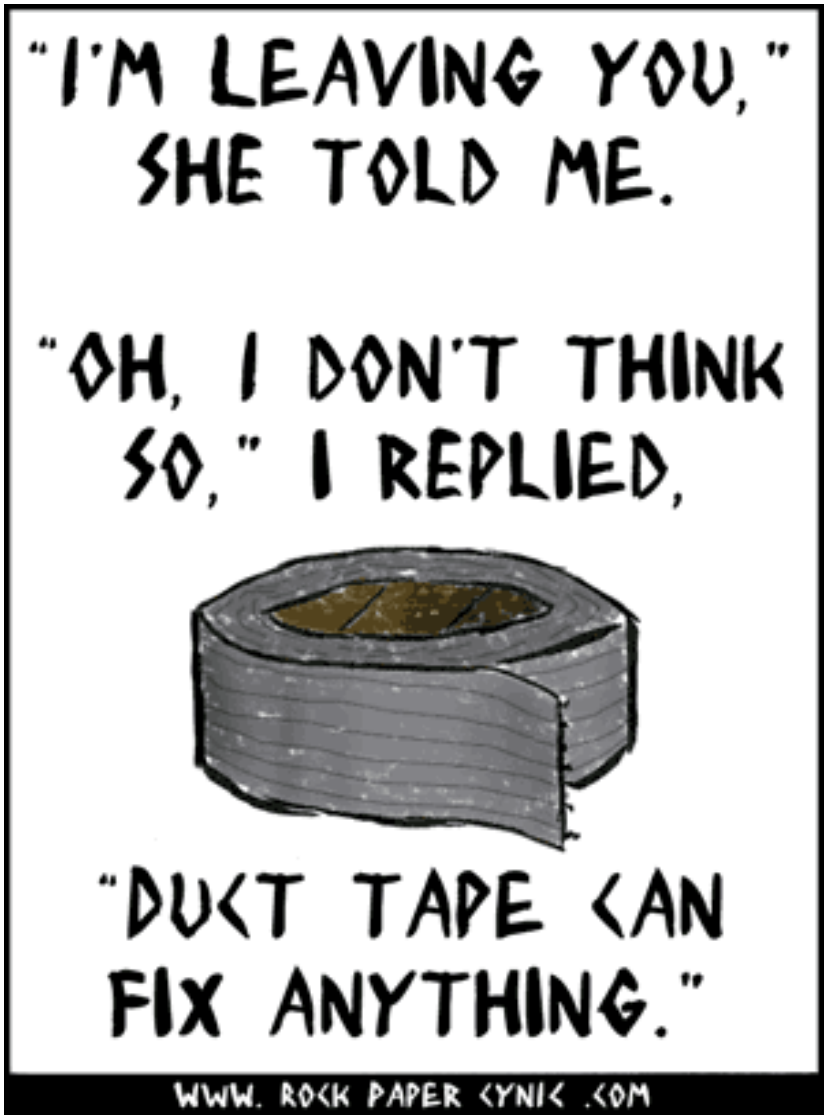
Duct tape approach (again)

Common idea:

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



Duct tape approach



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

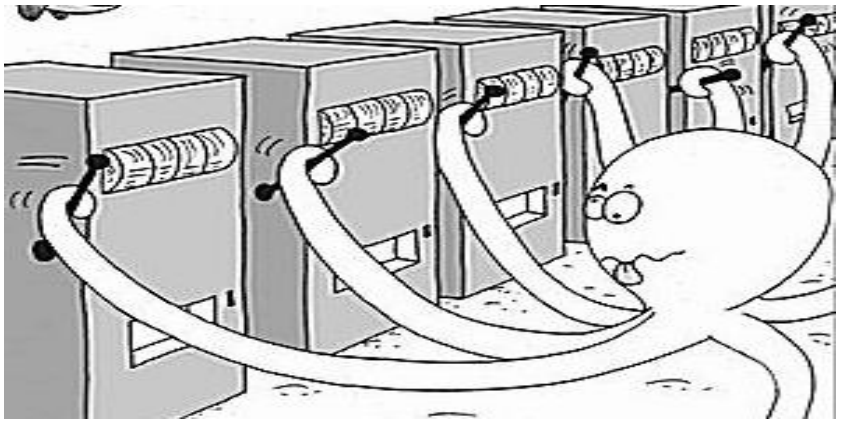
Agent

action

Feedback

Examples:

- banner ads (RTB)
- recommendations
- medical treatment



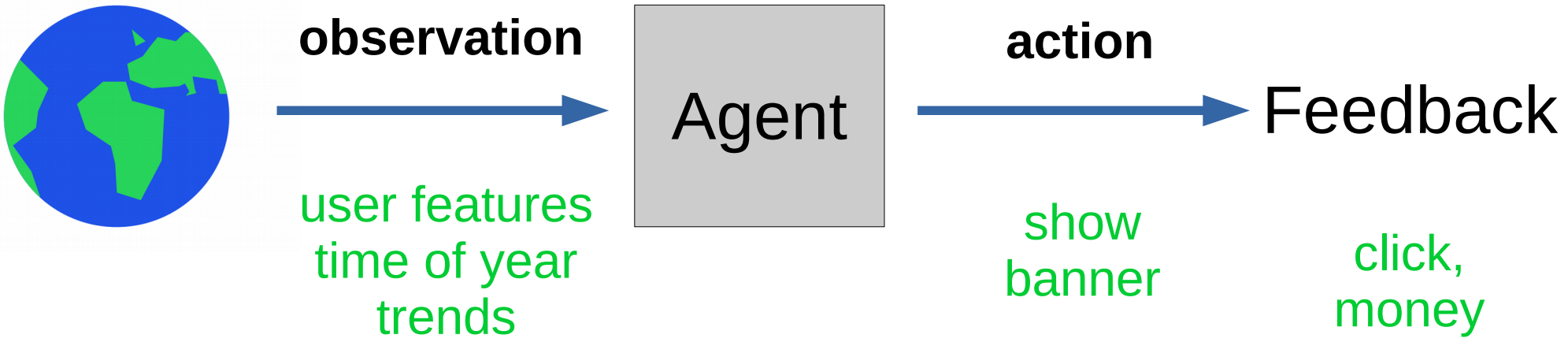
What is: bandit

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

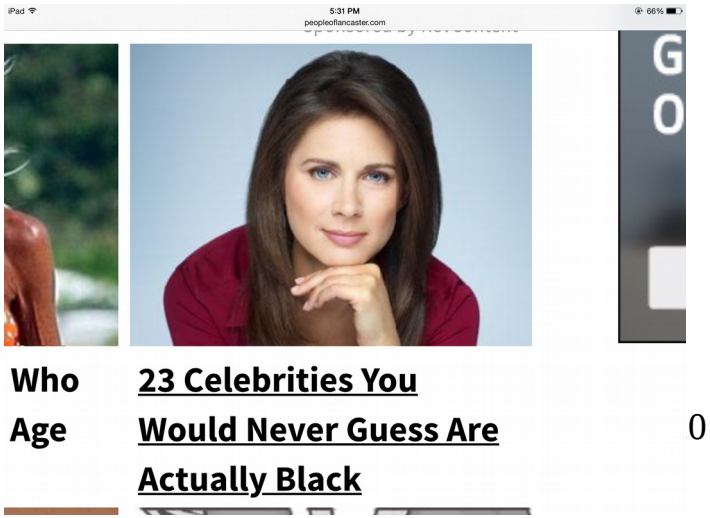
show
banner

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

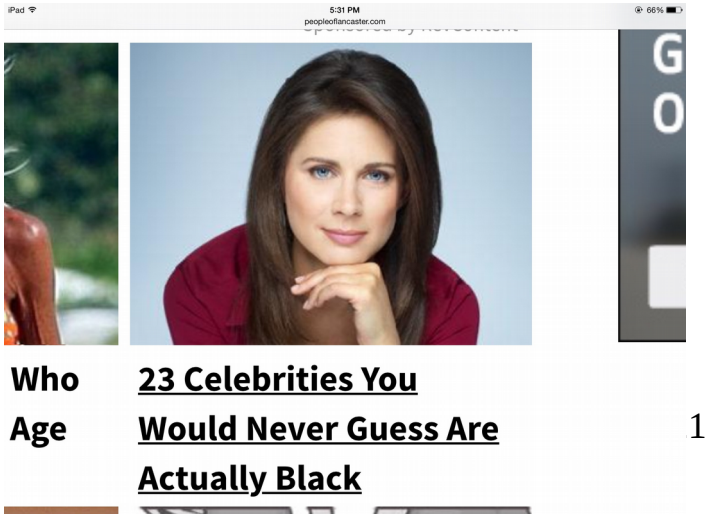
Agent

action

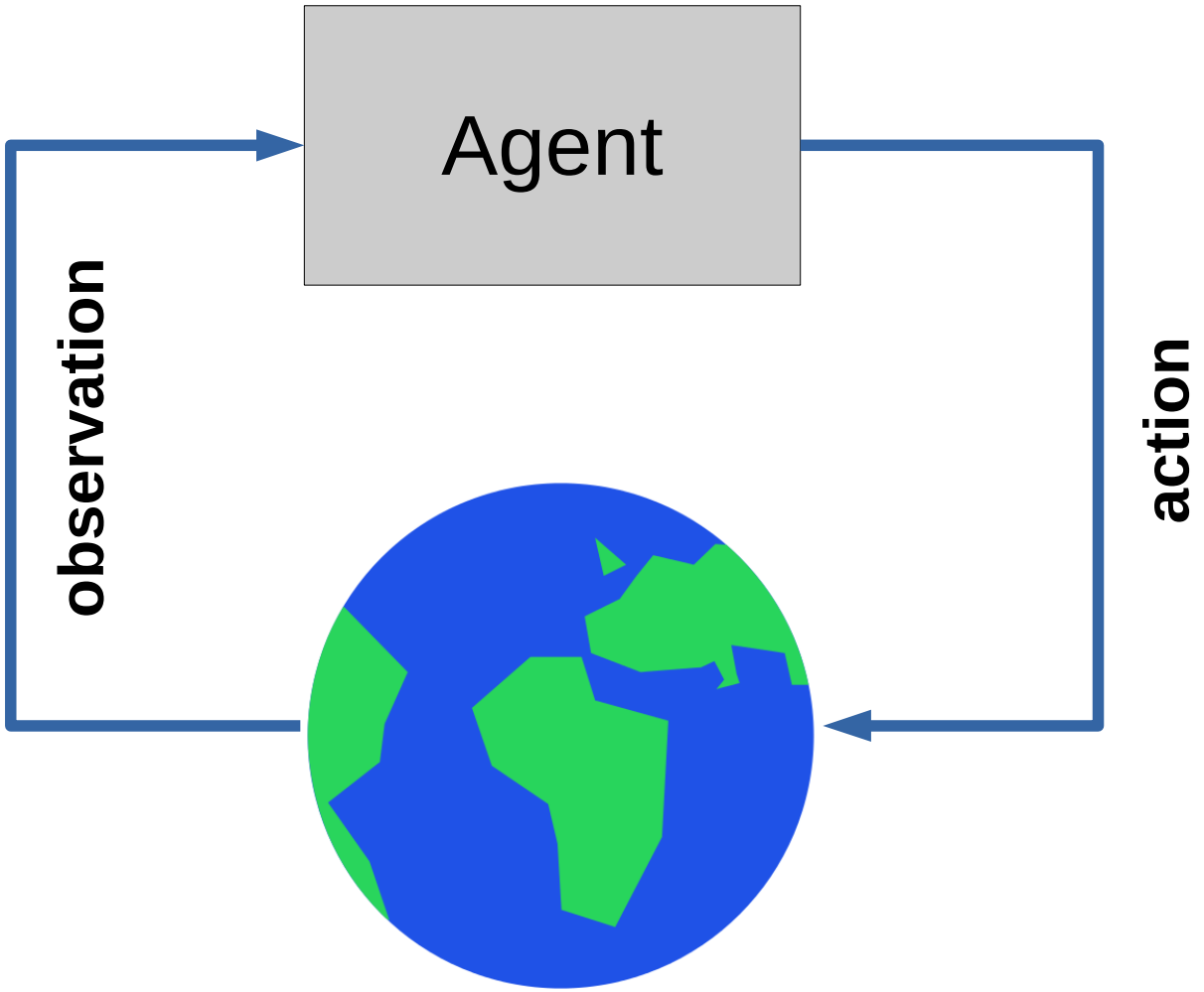
Feedback

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

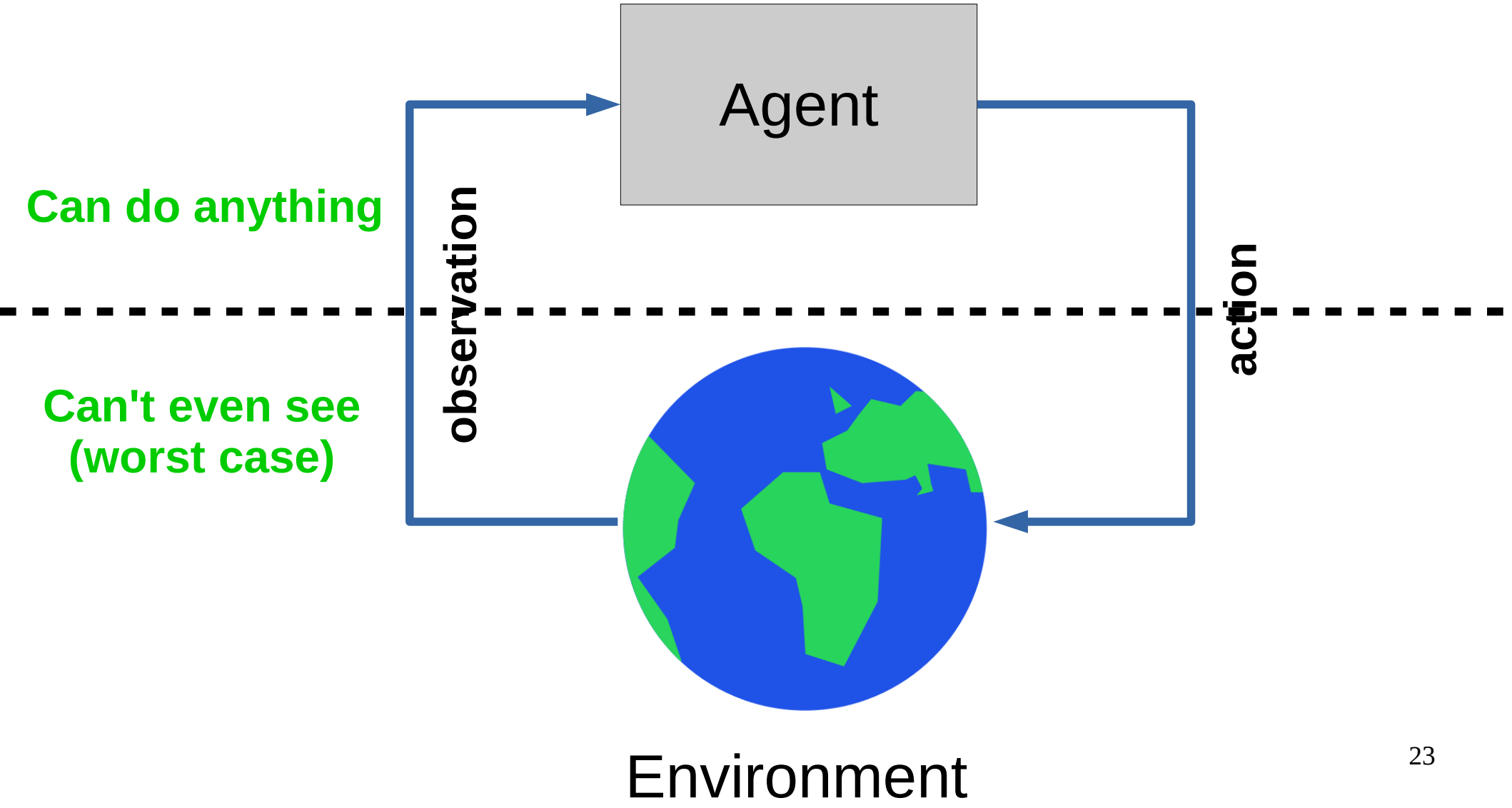
Is it a good idea to show clickbait?
No, no one will trust you after that!



What is: decision process

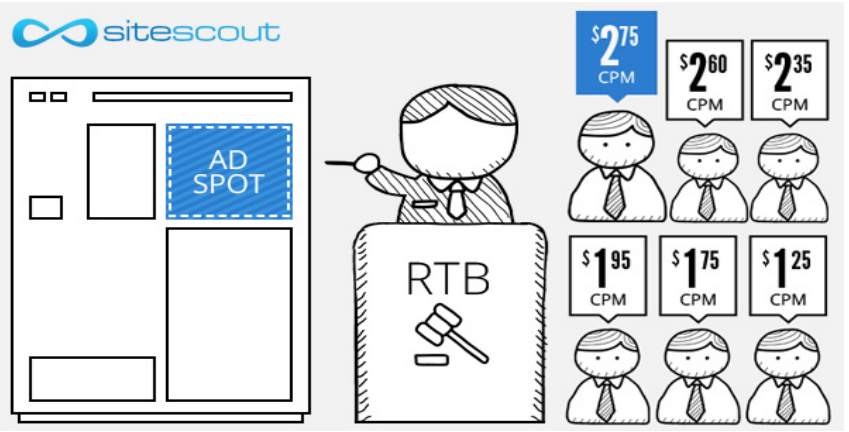


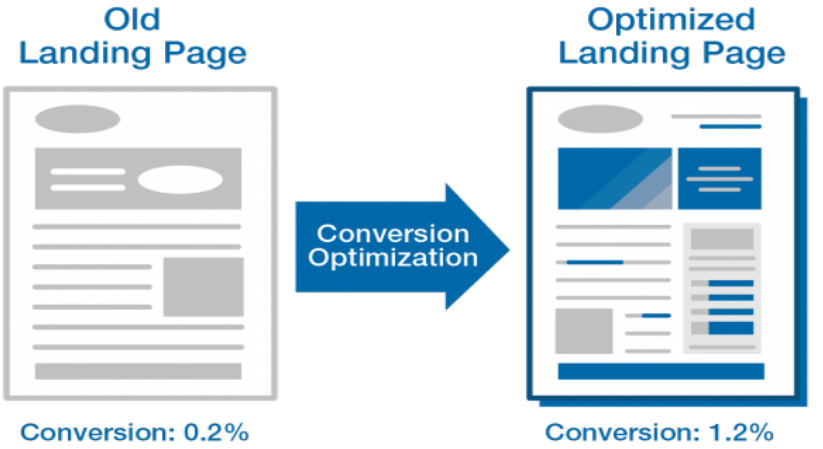
What is: decision process



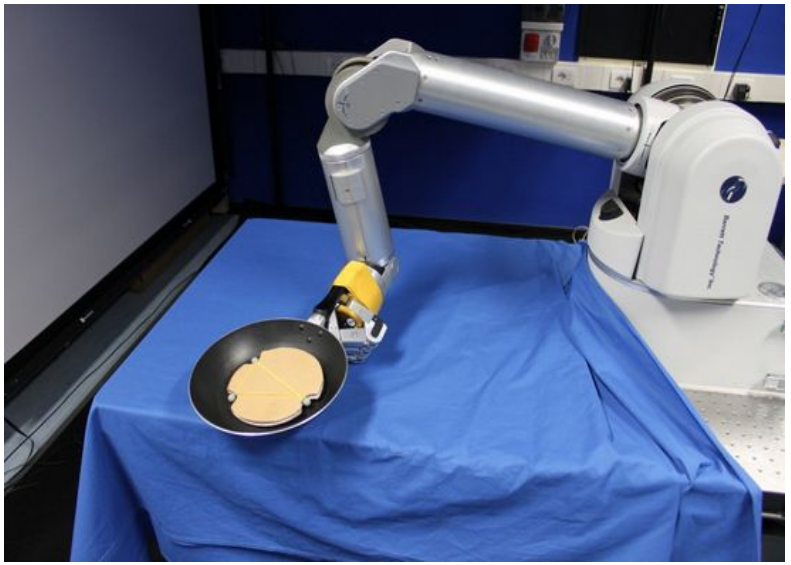
Reality check: web

- **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?





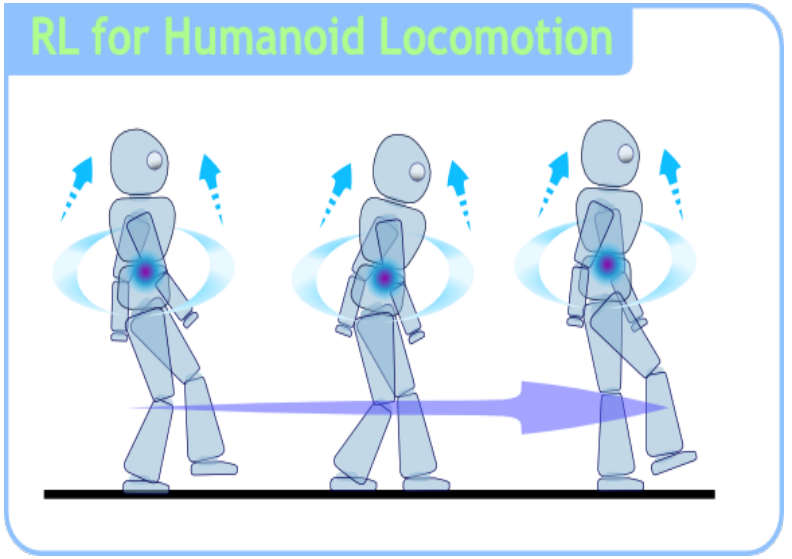
Reality check: dynamic systems



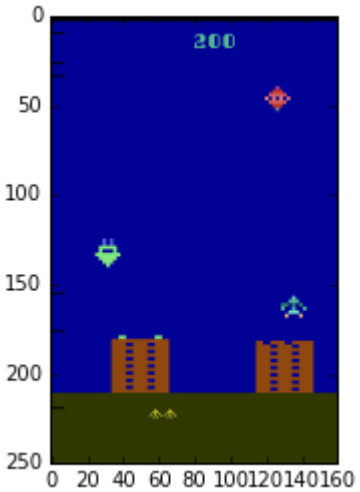
Reality check: dynamic systems

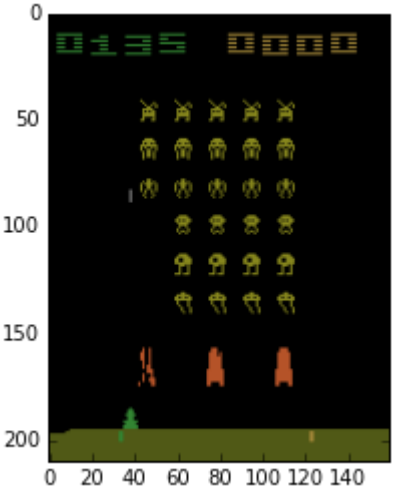
- **Cases:**
  - Robots
  - Self-driving vehicles
  - Pilot assistant
  - More robots!

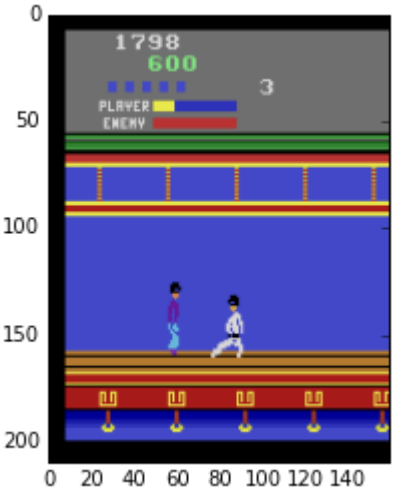
- **Example**
  - Observation: sensor feed
  - Action: voltage sent to motors
  - Feedback: how far did it move forward before falling



~~Reality~~ check: videogames

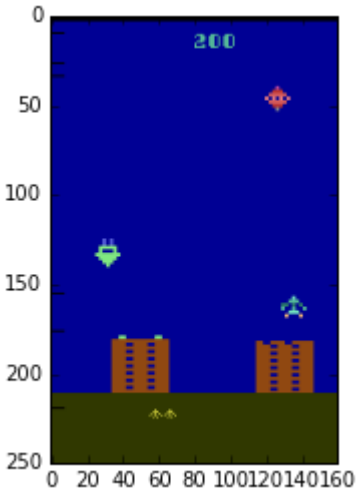


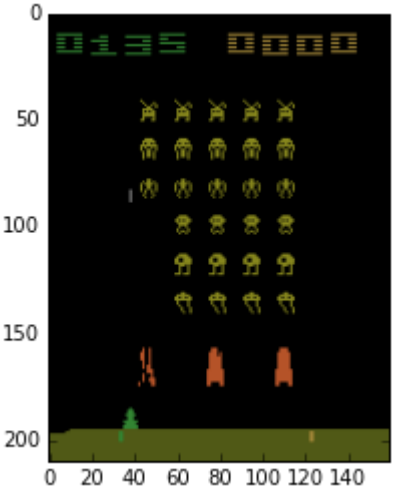


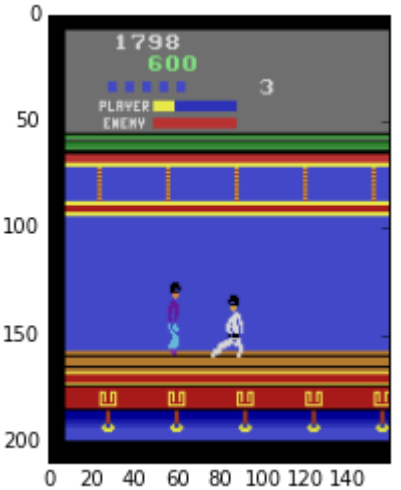


- **Q:** What are observations, actions and feedback?

~~Reality~~ check: videogames





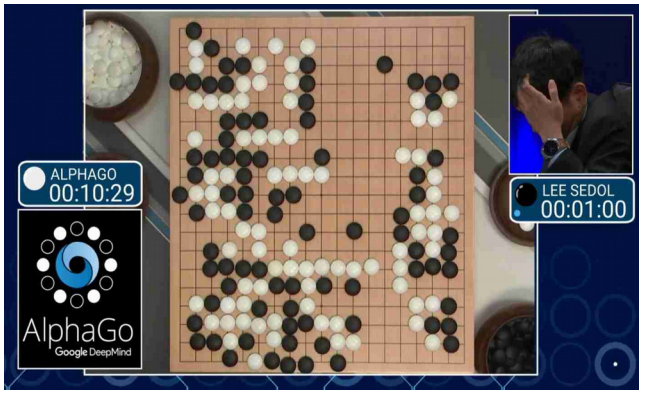


- **Q:** What are observations, actions and feedback?

Other use cases

- Personalized medical treatment

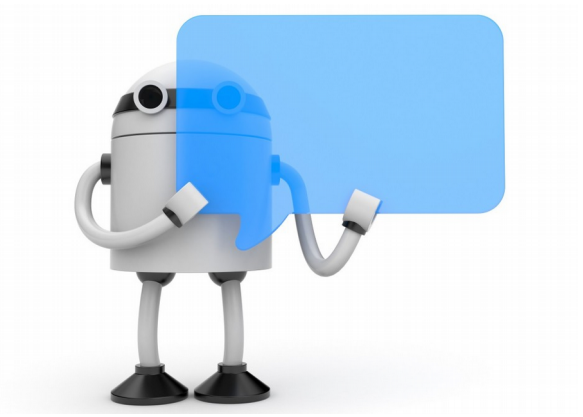
- Even more games (Go, chess, etc)

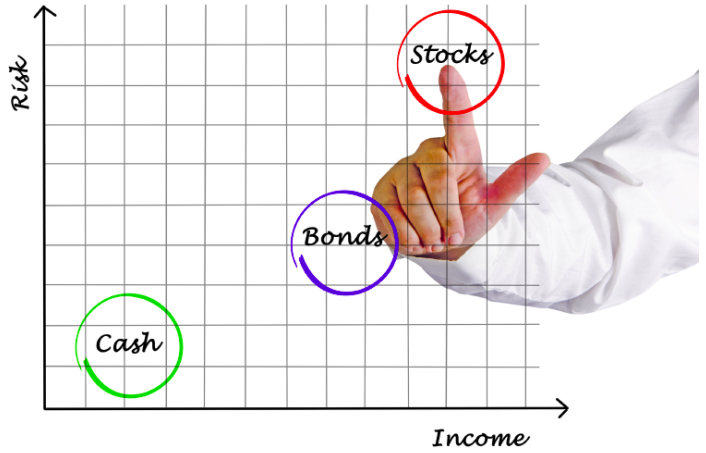


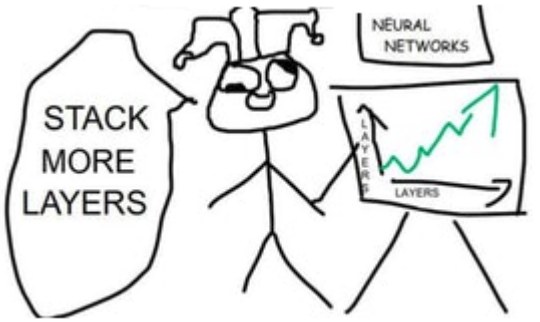
- **Q:** What are observations, actions and feedback?

Other use cases

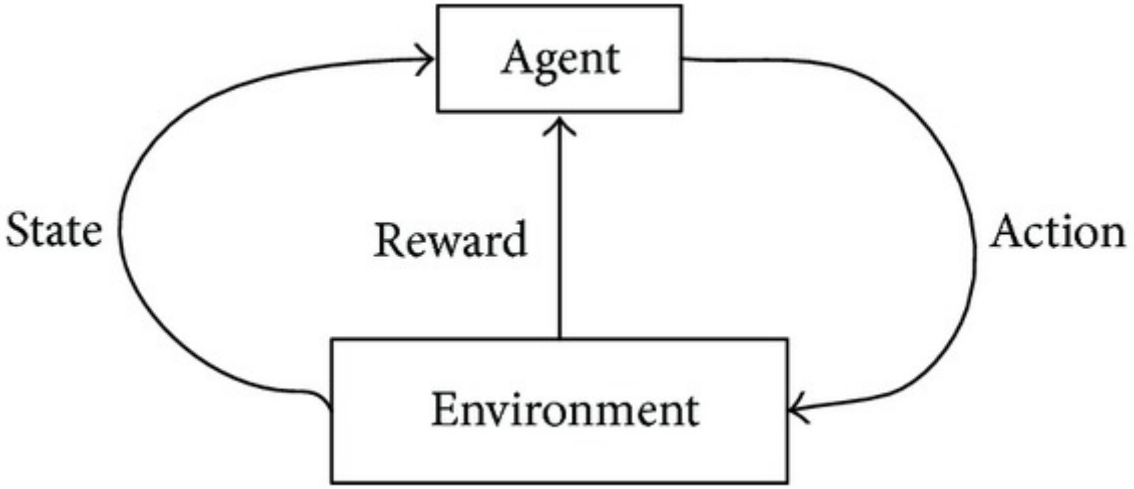
- Conversation systems
  - learning to make user happy
- Quantitative finance
  - portfolio management
- Deep learning
  - optimizing non-differentiable loss
  - finding optimal architecture







The MDP formalism

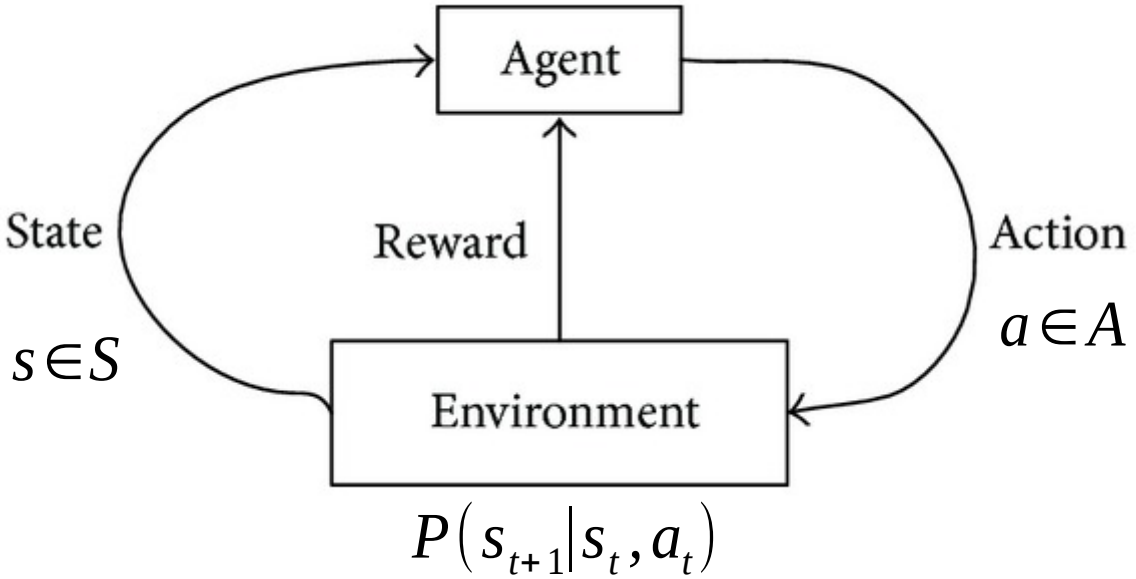


Markov Decision Process

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

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

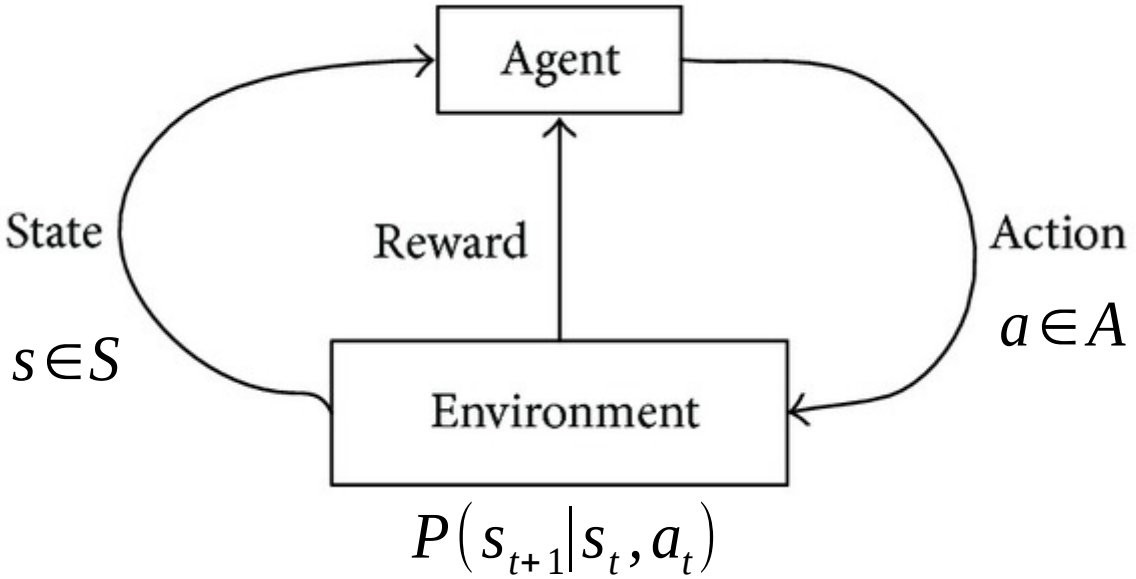
The MDP formalism



Markov Decision Process
Markov assumption

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

The MDP formalism



Markov Decision Process

Markov assumption

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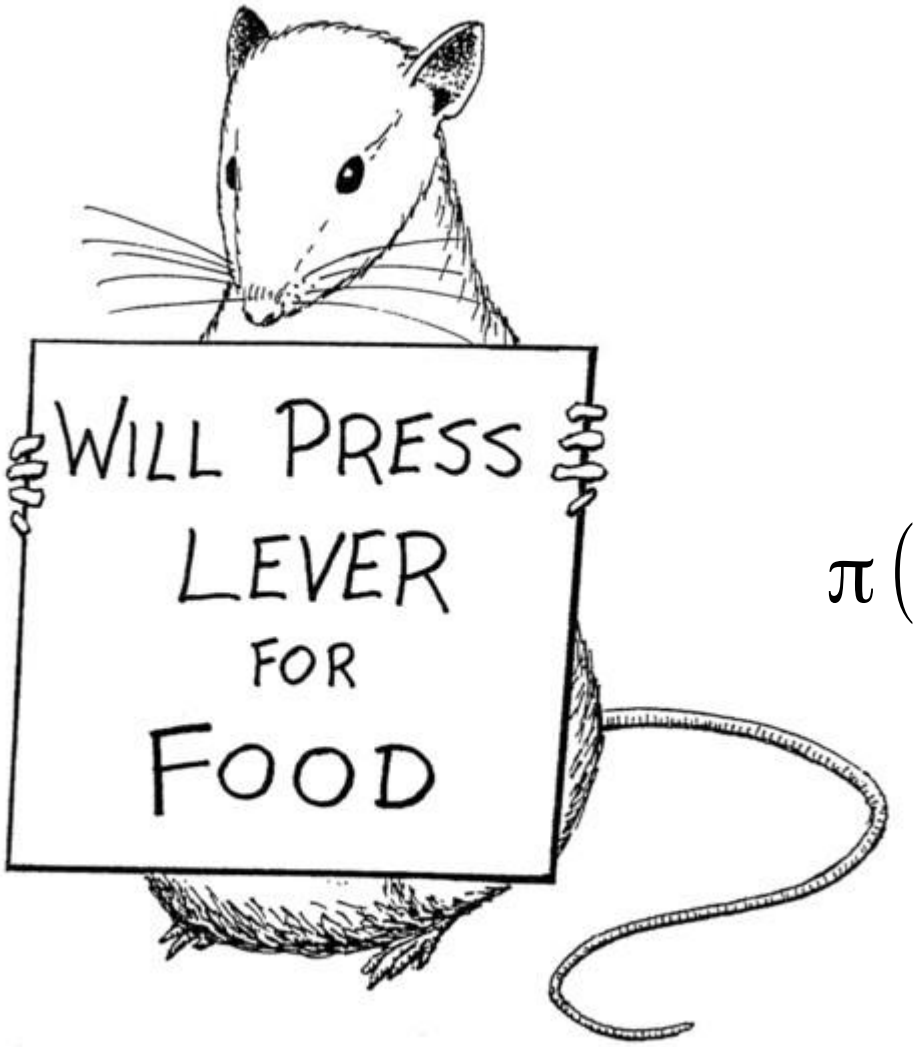
Total reward



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:

$$\underset{s_0 \sim p(s_0),\, a_0 \sim \pi(a|s_0),\, s_1, r_0 \sim P(s', r|s, a)}{E} \quad \underset{}{E} \quad \underset{}{E} \quad \dots \quad \underset{s_T, r_T \sim P(s', r|s_{T-1}, a_{t-1})}{E} \left[r_0 + r_1 + r_2 + \dots + r_T \right]$$

Objective

The easy way:

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

The hard way:

$$\underset{s_0 \sim p(s_0),\, a_0 \sim \pi(a|s_0),\, s_1, r_0 \sim P(s', r|s, a)}{E} \quad \underset{}{E} \quad \underset{}{E} \quad \ldots \quad \underset{s_T, r_T \sim P(s', r|s_{T-1}, a_{t-1})}{E} \left[r_0 + r_1 + r_2 + \ldots + r_T \right]$$

How do we solve it?

General idea:

Play a few sessions

Update your policy

Repeat

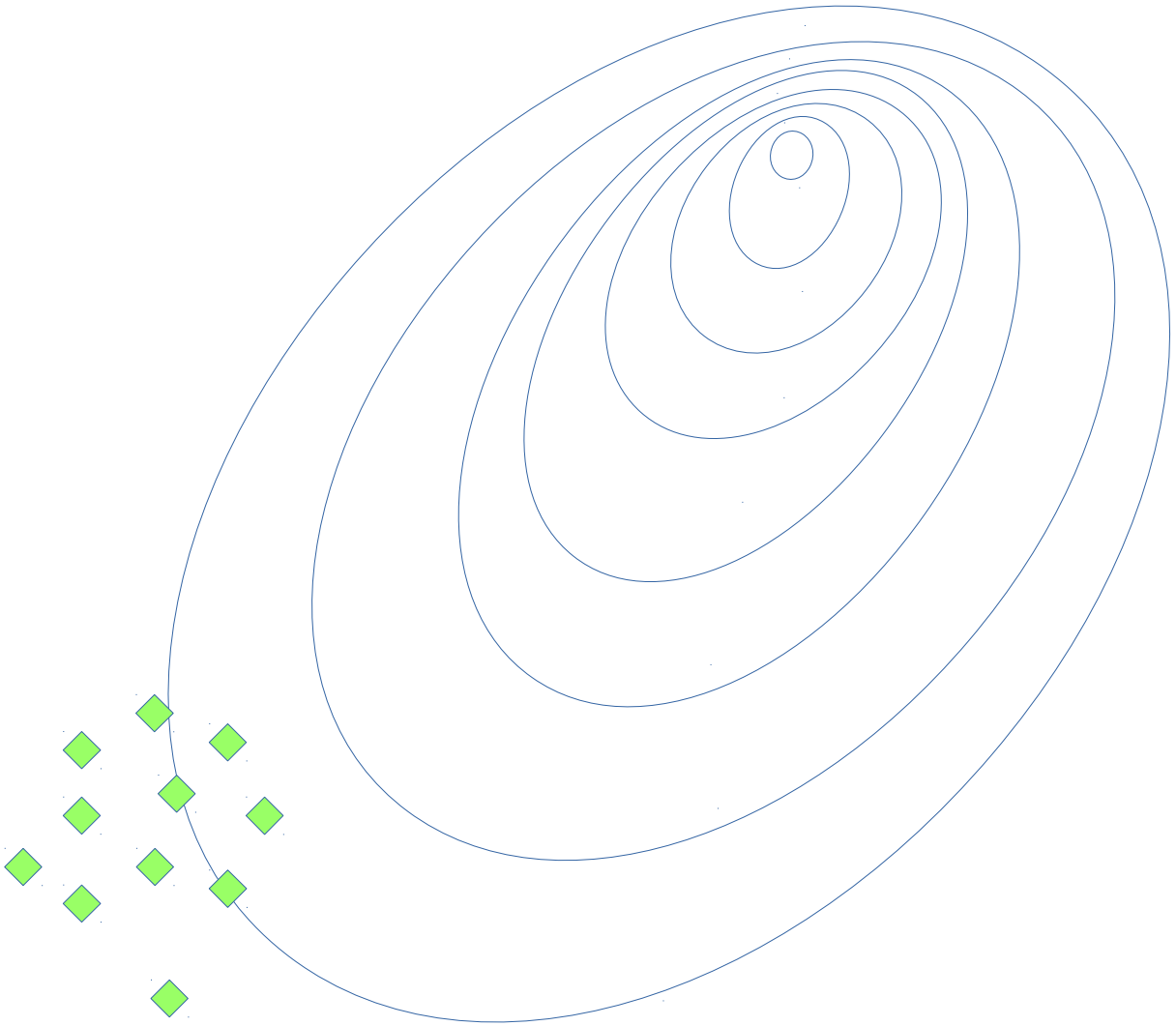
Crossentropy method

Intialize policy

Repeat:

- Sample N[100] sessions
- Pick M[25] best sessions, called **elite** sessions
- Change policy so that it prioritizes actions from elite sessions

Step-by-step view



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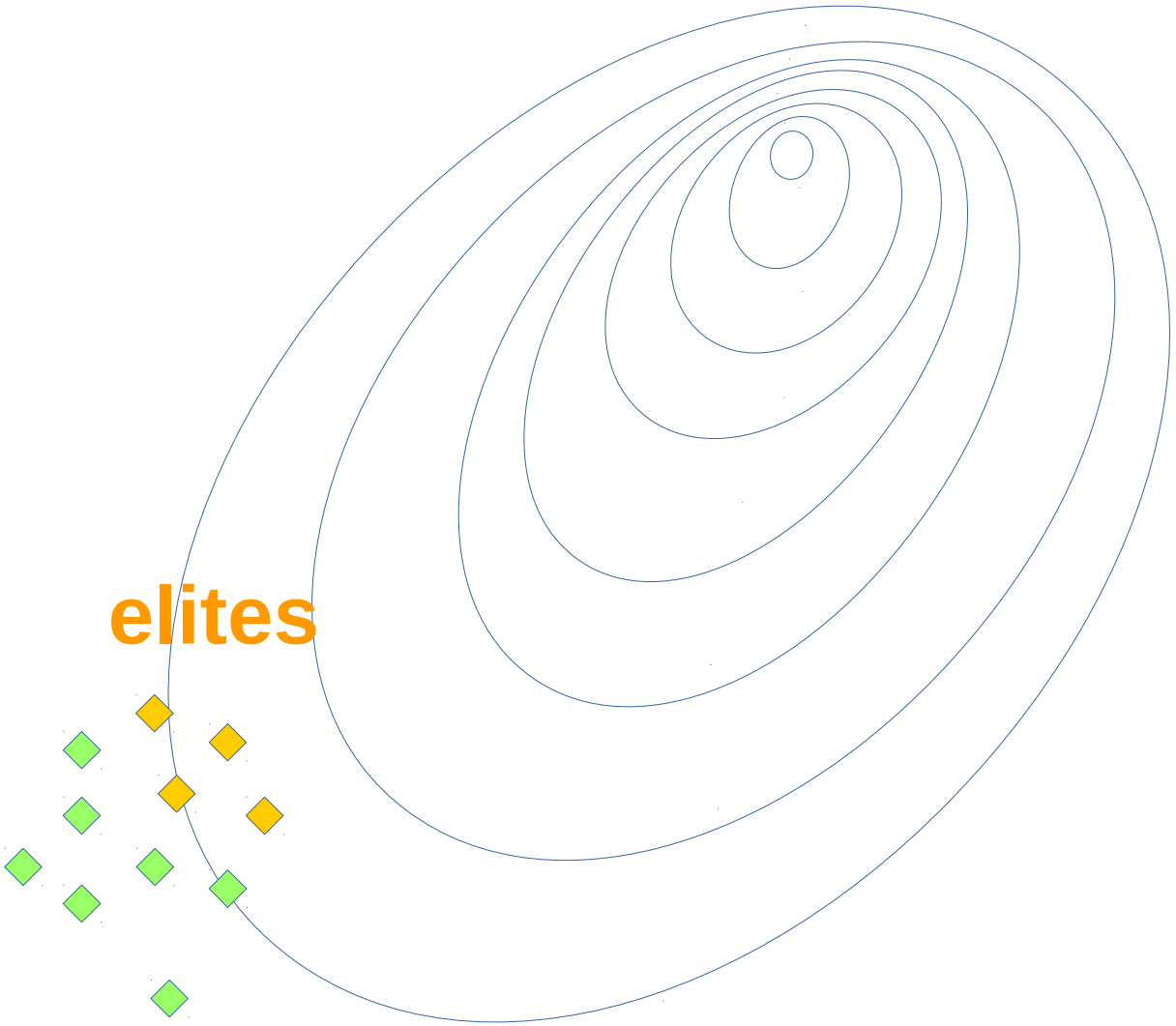

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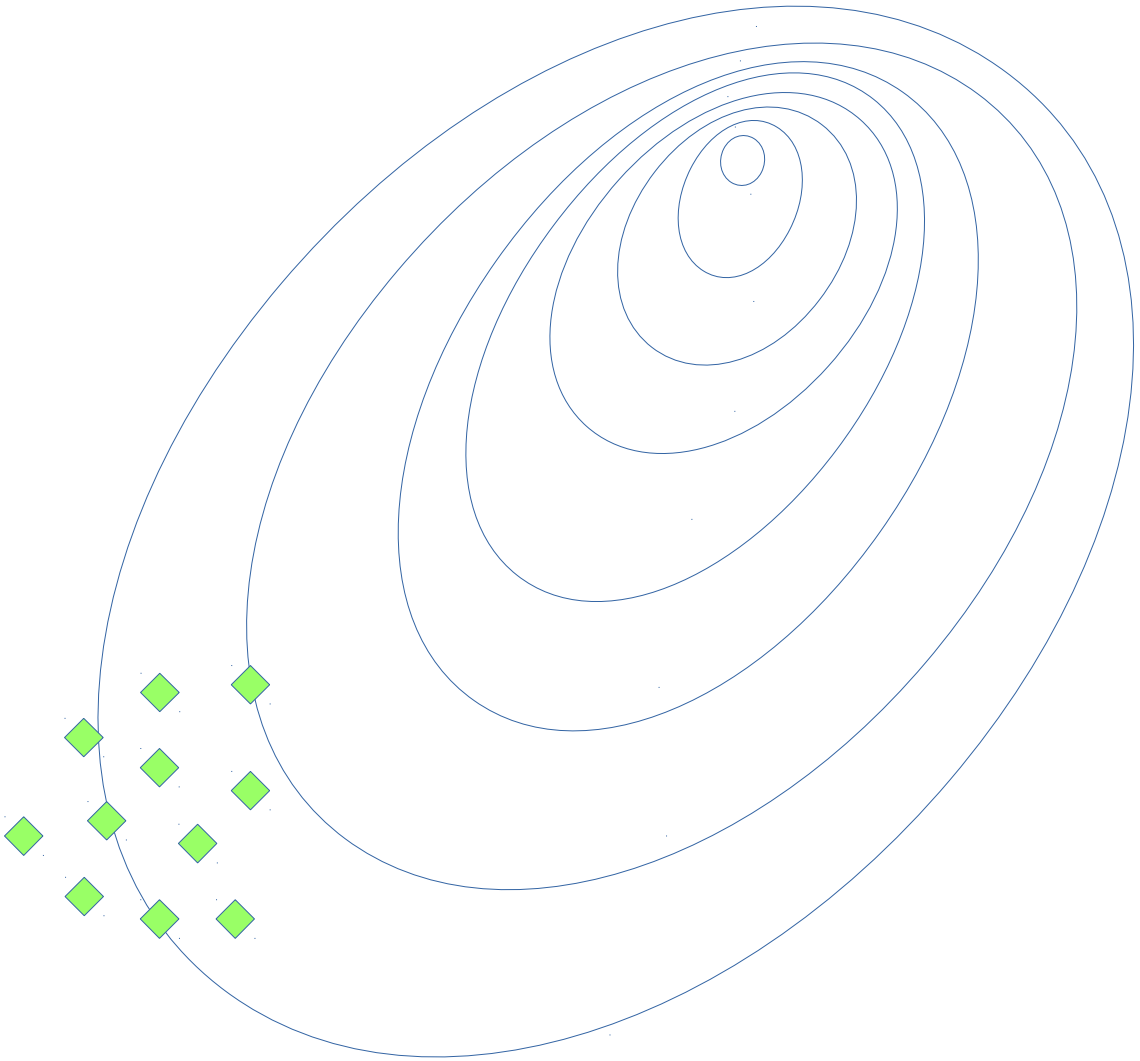

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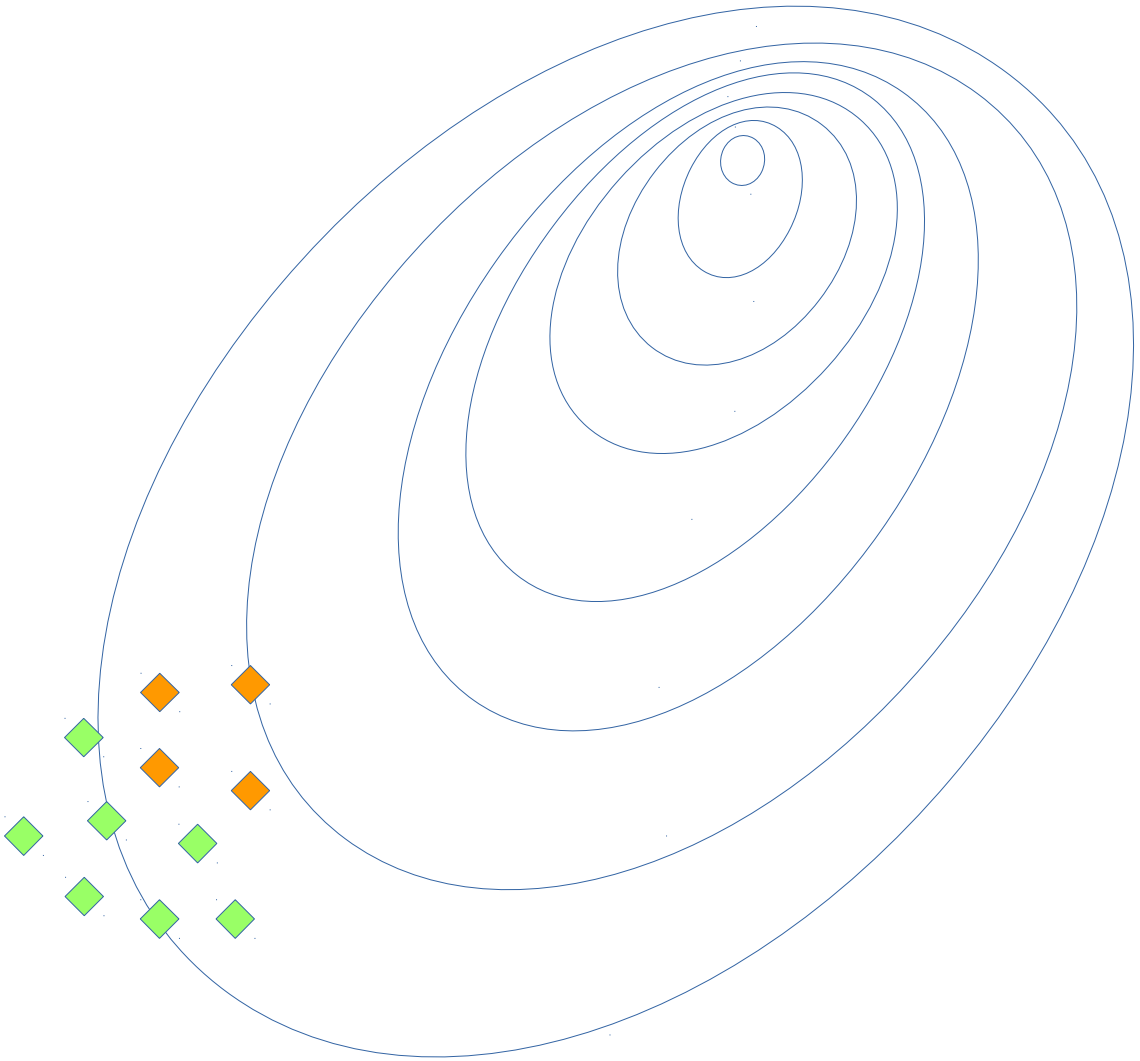

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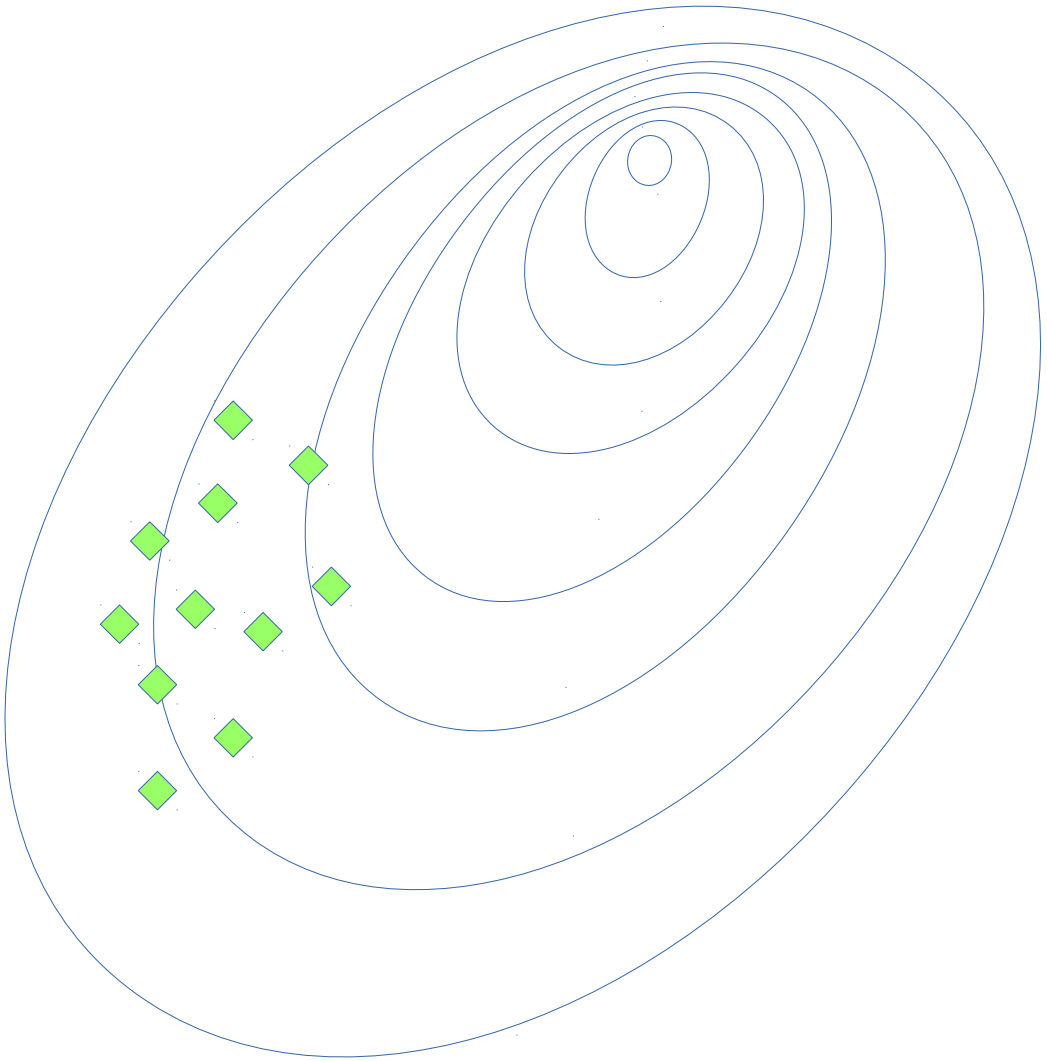

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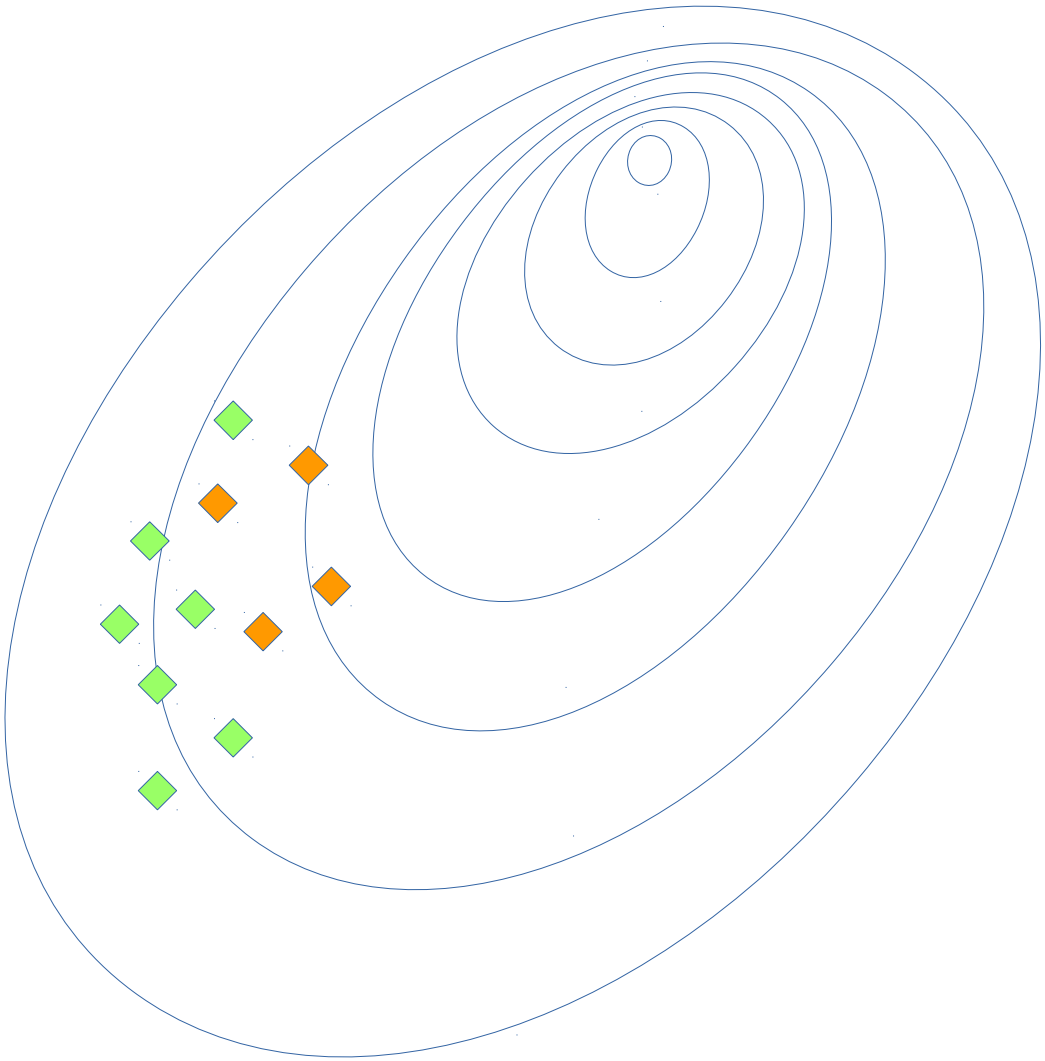

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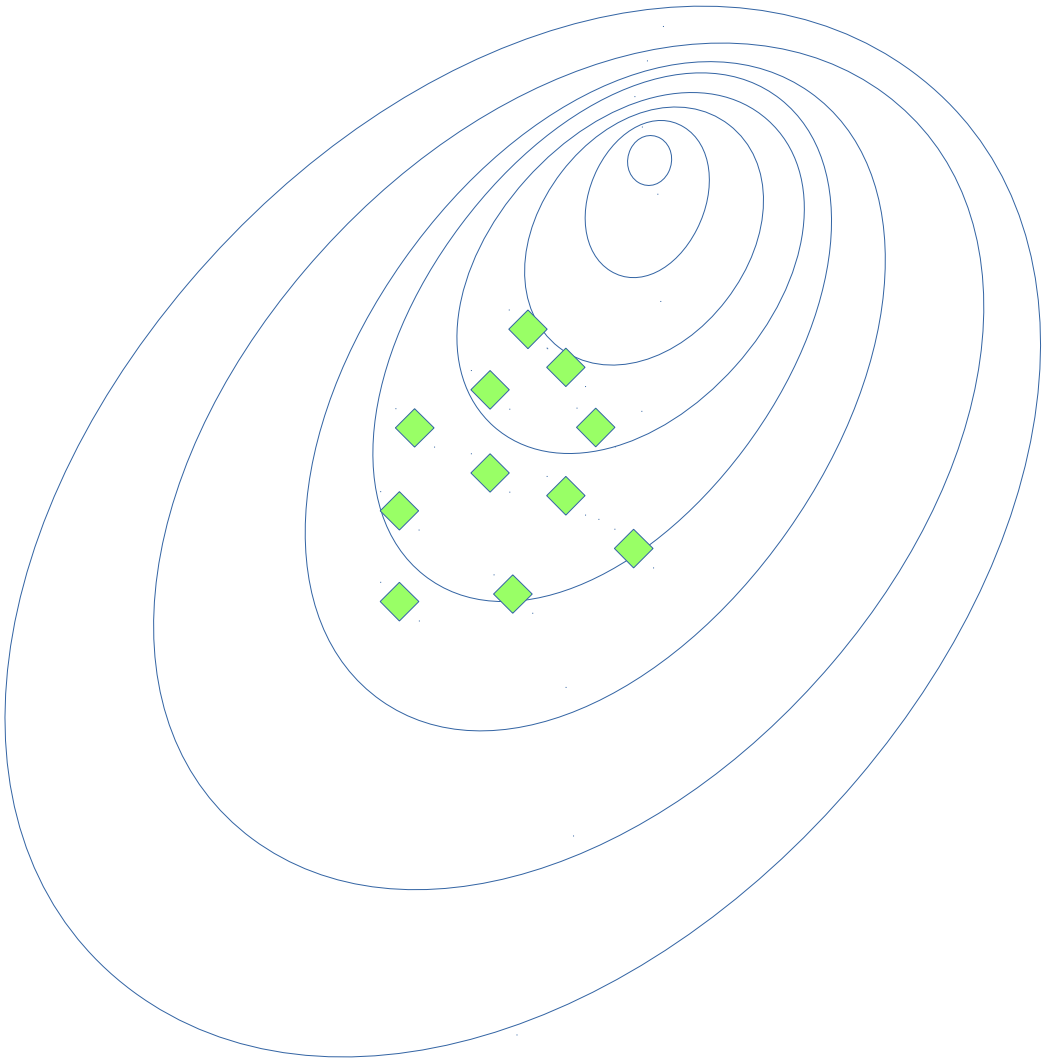

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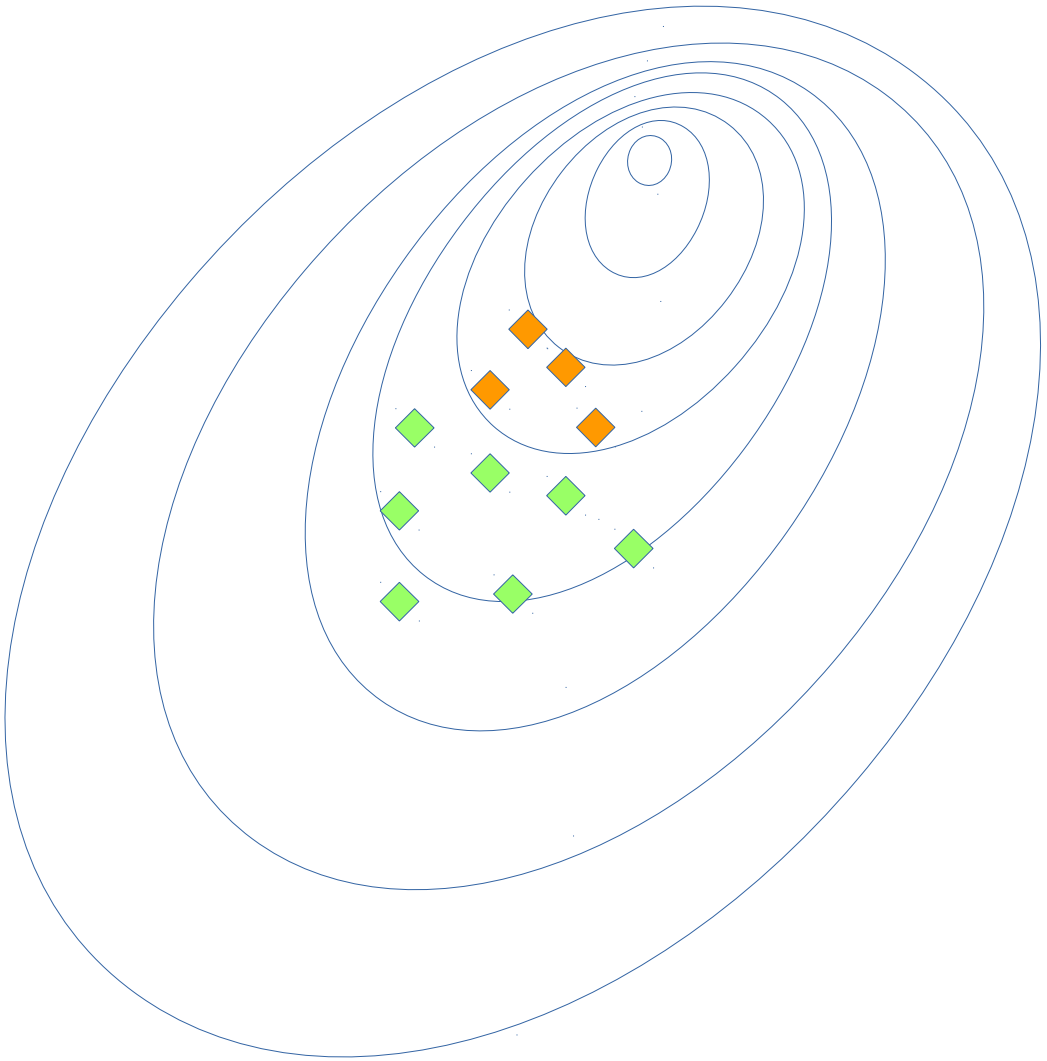

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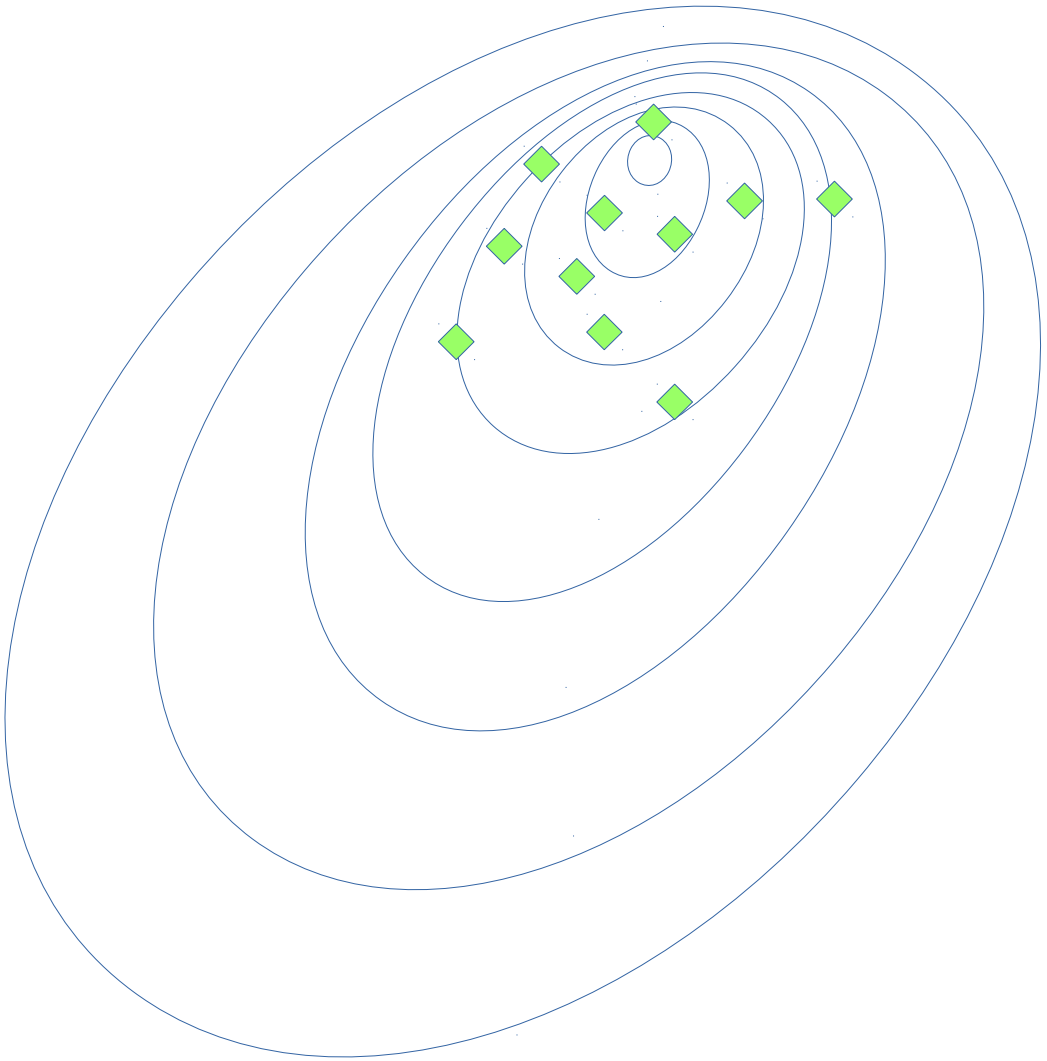

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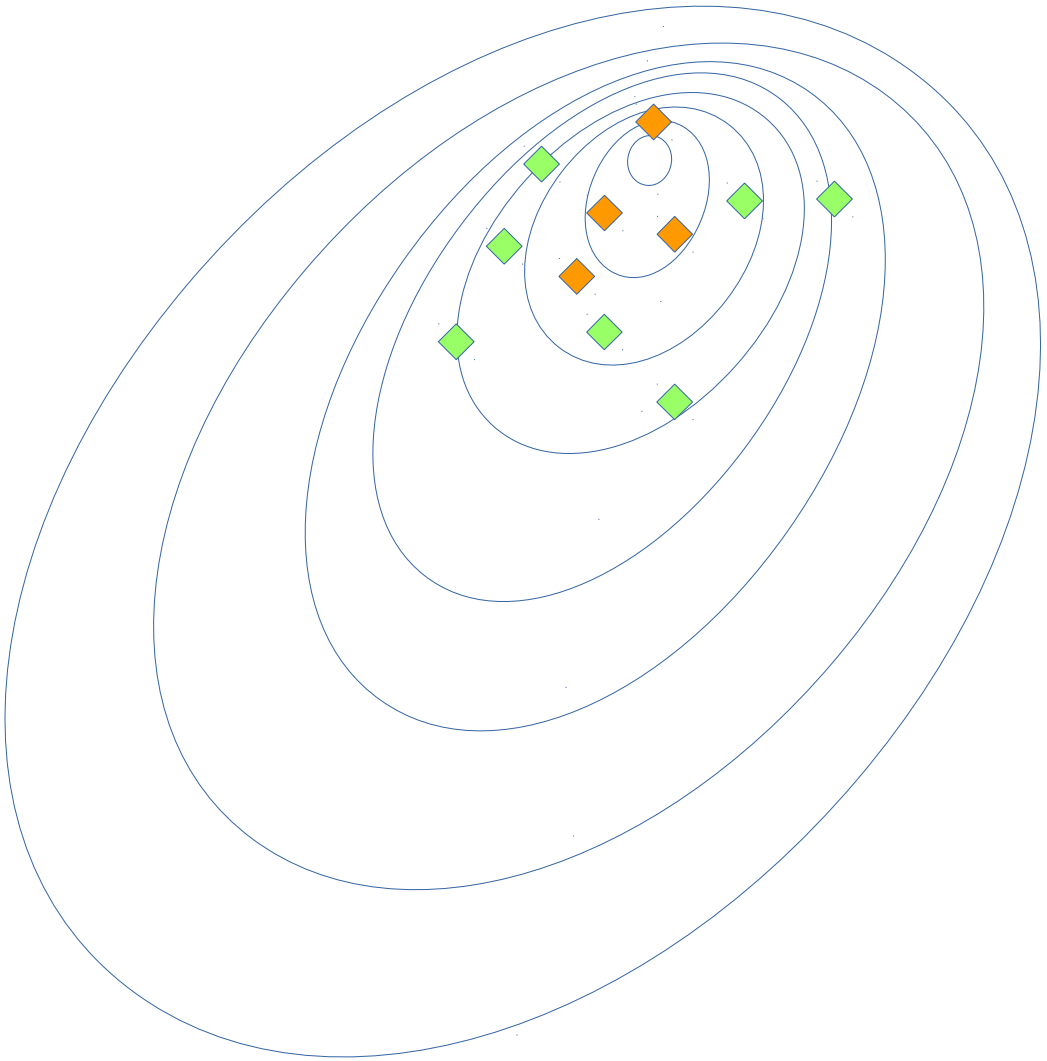
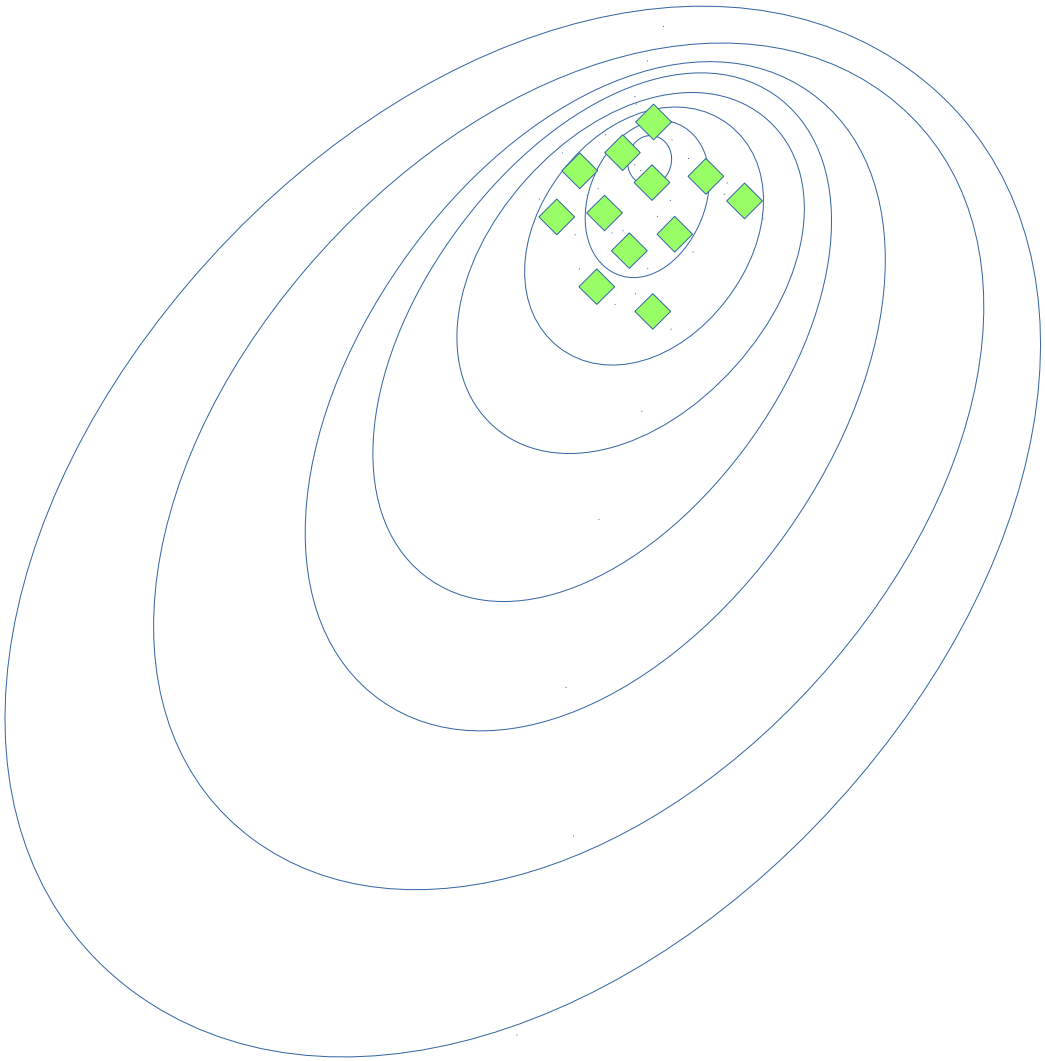


Step-by-step view



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

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

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

- Initialize NN weights $W_0 \leftarrow random$

- Loop:
  - Sample N sessions
  - $Elite = [(s_0, a_0), (s_1, a_1), (s_2, a_2), \ldots, (s_k, a_k)]$
  - $W_{i+1} = W_i + \alpha \nabla [\sum_{s_i, a_i \in Elite} \log \pi_{W_i}(a_i | s_i)]$

Approximate crossentropy method

- Initialize NN weights **nn = MLPClassifier(...)**

- Loop:
  - Sample N sessions
  - $Elite = [(s_0, a_0), (s_1, a_1), (s_2, a_2), \ldots, (s_k, a_k)]$
  - ***nn.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?

Approximate crossentropy method

- Initialize NN weights **nn = MLPRegressor(...)**

- Loop:
  - Sample N sessions
  - $Elite = [(s_0, a_0), (s_1, a_1), (s_2, a_2), \ldots, (s_k, a_k)]$
  - ***nn.fit(elite_states,elite_actions)***

Almost 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)