Lecture 9:
Introduction to Reinforcement Learning

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References

These slides are almost the exact copy of Practical RL course week 1 slides.
Special thanks to YSDA team for making them publicly available.

Original slides link: week01_intro

Outline

- From Supervised Learning to Reinforcement Learning
- Multi-armed bandits
- The Markov Decision Process
- Crossentropy method
  - Tabular crossentropy method
  - Approximate crossentropy method
- Practice

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

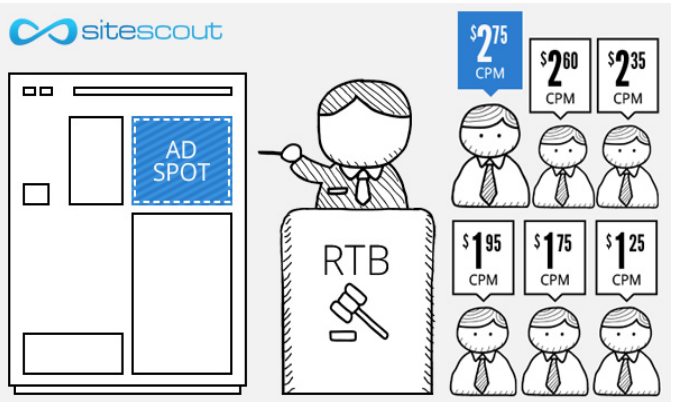
Great... except if we have no reference answers

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:

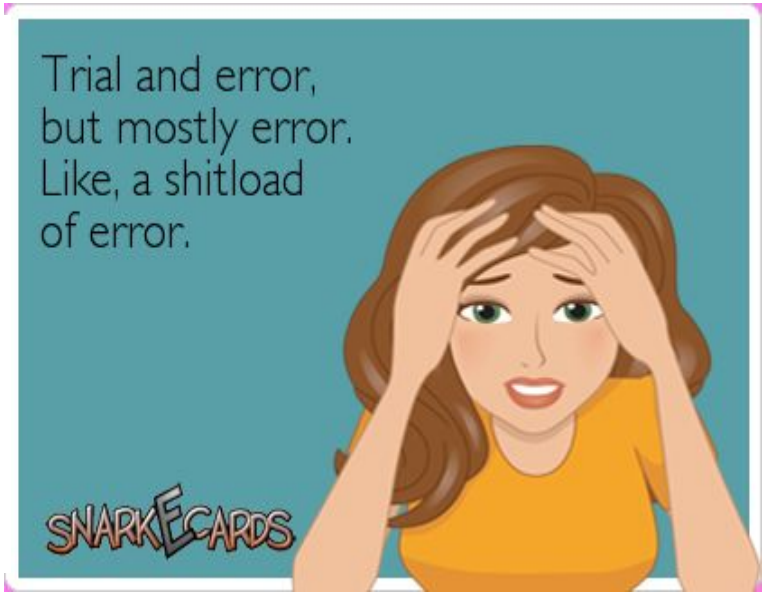
- Learn to pick relevant ads

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

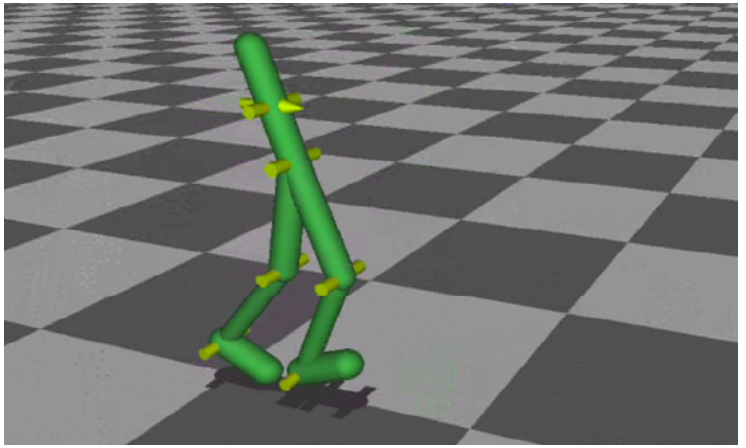


Giant Death Robot (GDR)

Great... except if we have no reference answers

We have:

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



We want:

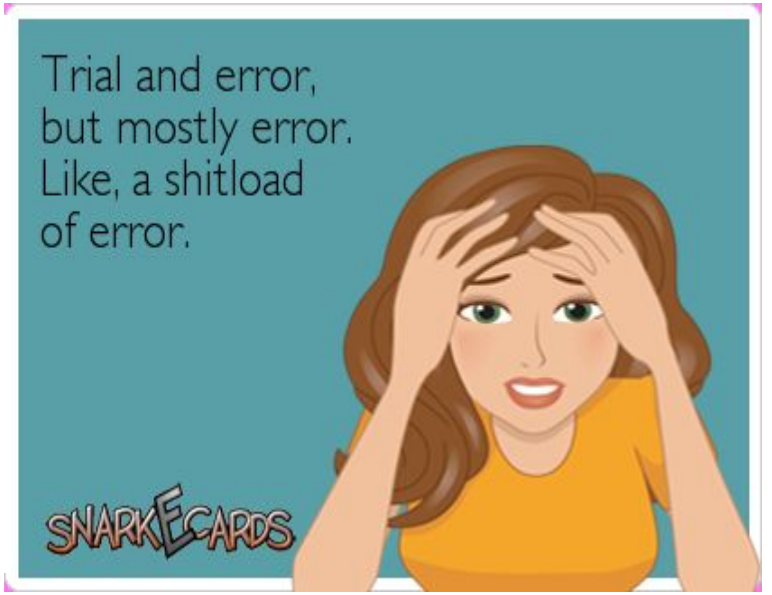
- ~~Enslave humanity~~
- Learn to walk forward

Ideas?

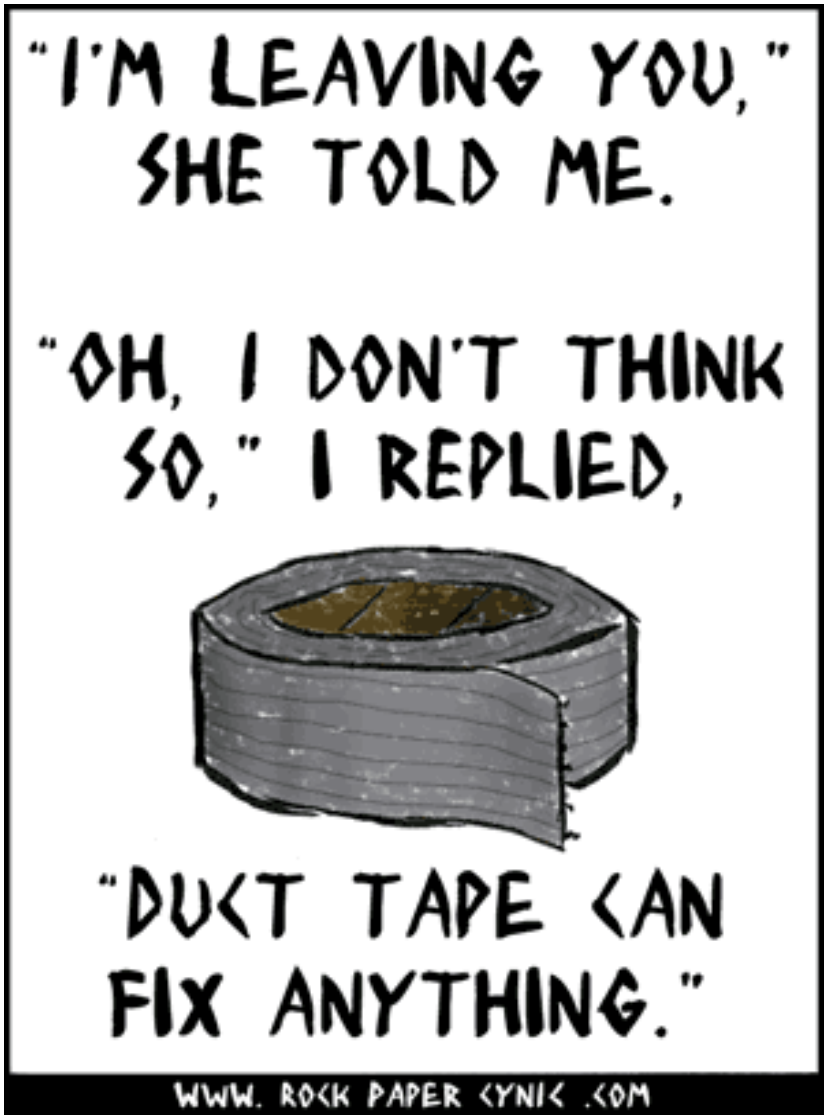
Duct tape approach (again)

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 is: bandit

Examples:

- banner ads (RTB)
- recommendations
- medical treatment

What is: bandit

Examples:

- banner ads (RTB)
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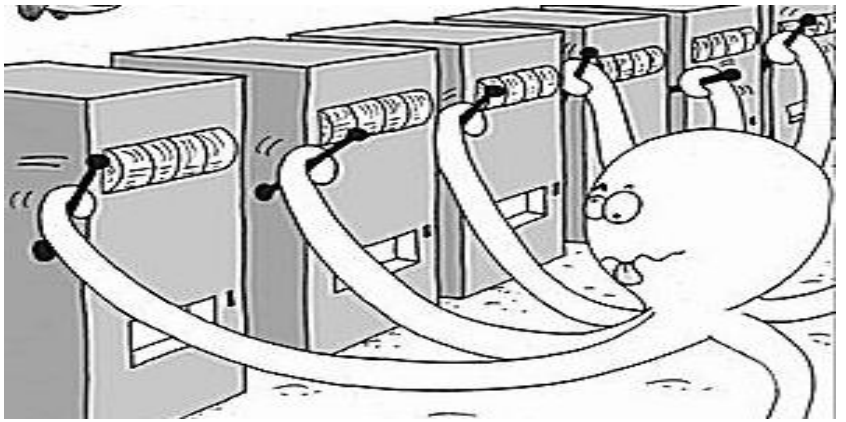


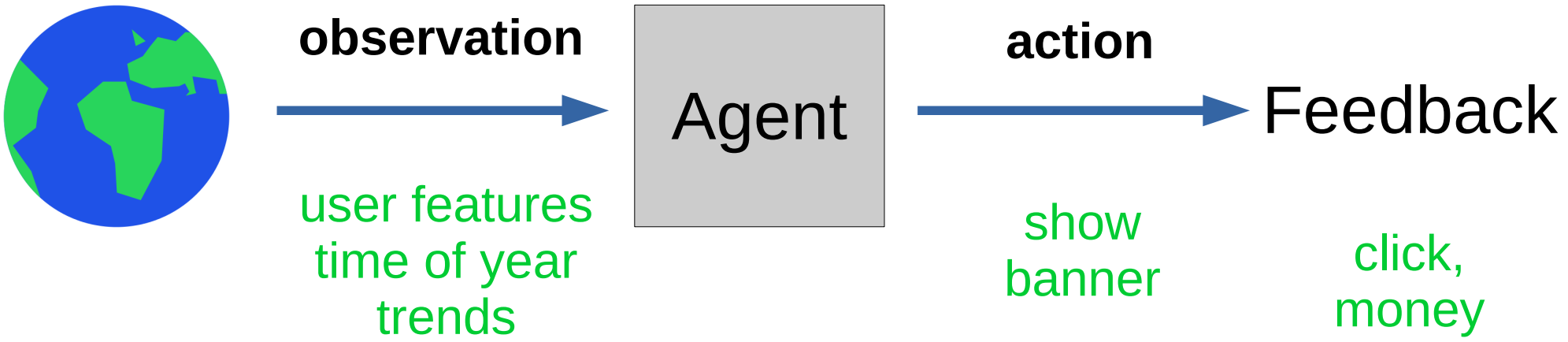
What is: bandit

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

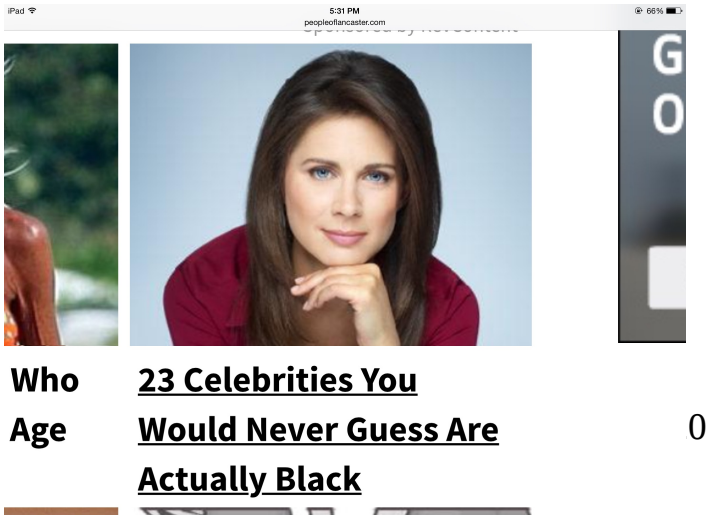
show
banner

Feedback

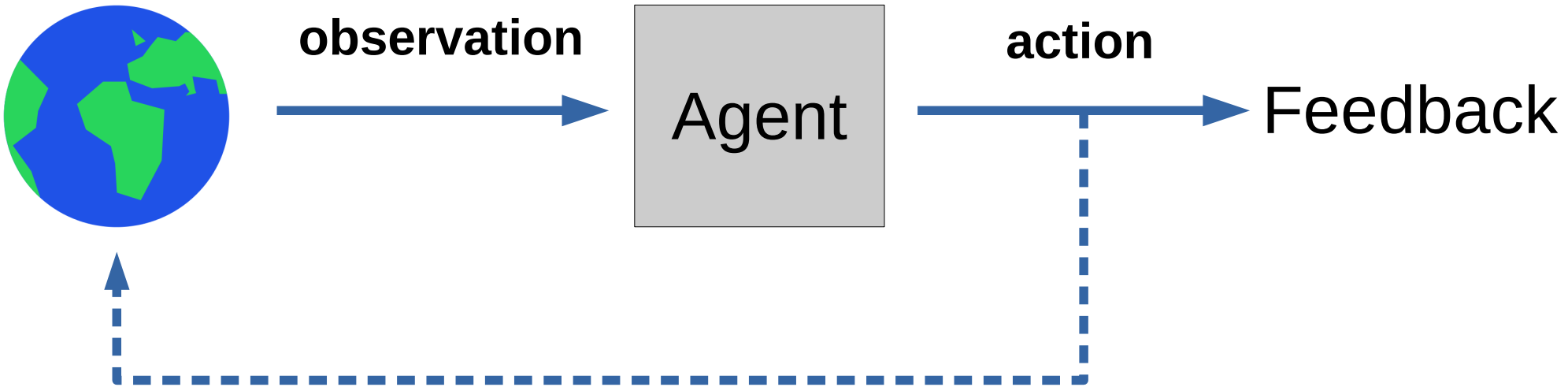
click,
money

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?

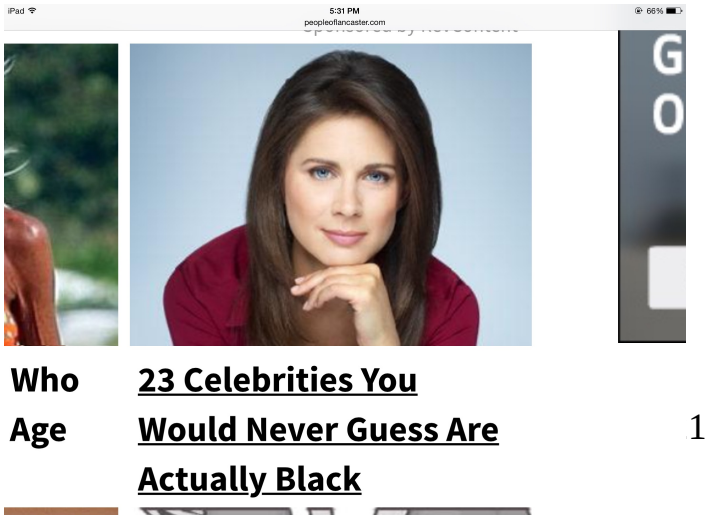


What is: bandit

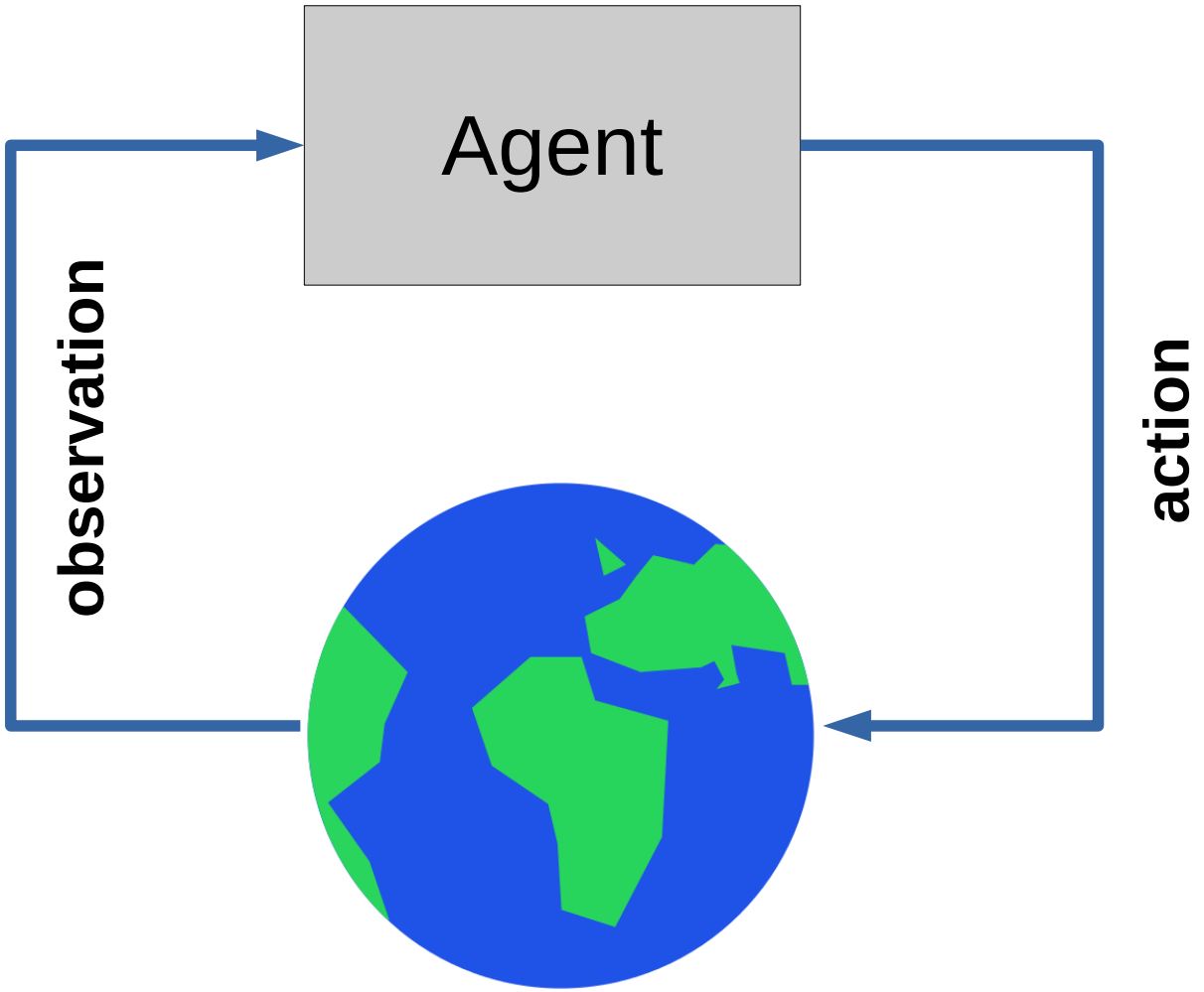


Q: You're Yandex/Google/Youtube. There's a kind of banners that would have great click rates: the “clickbait”.

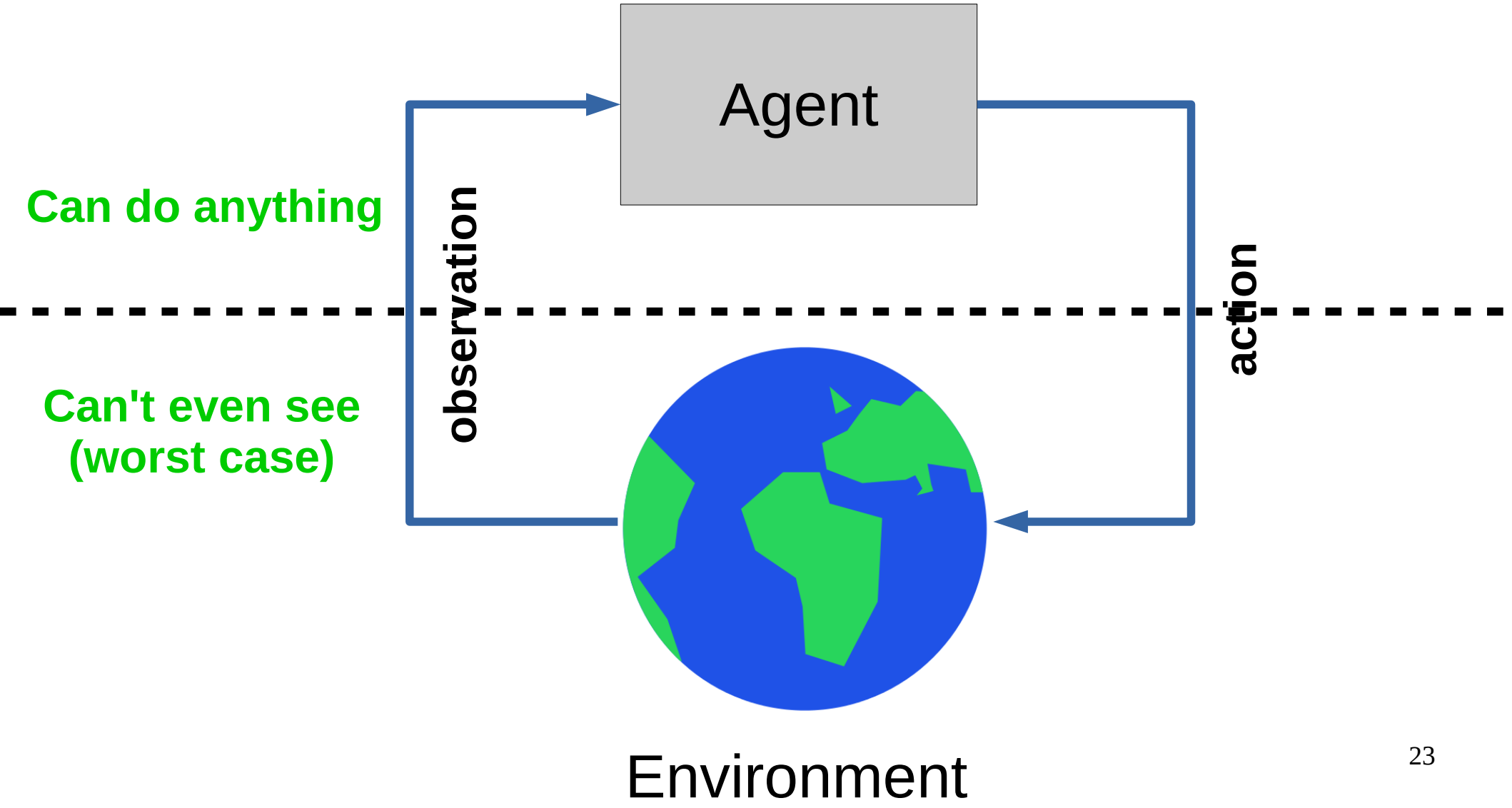
Is it a good idea to show clickbait?
No, no one will trust you after that!



What is: decision process

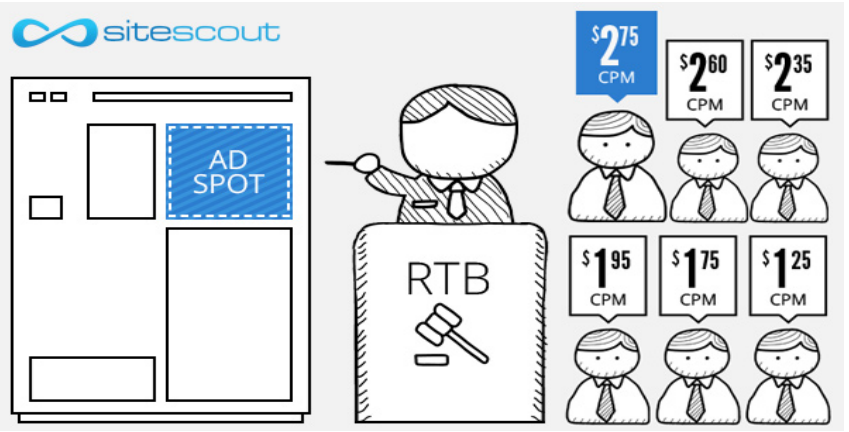


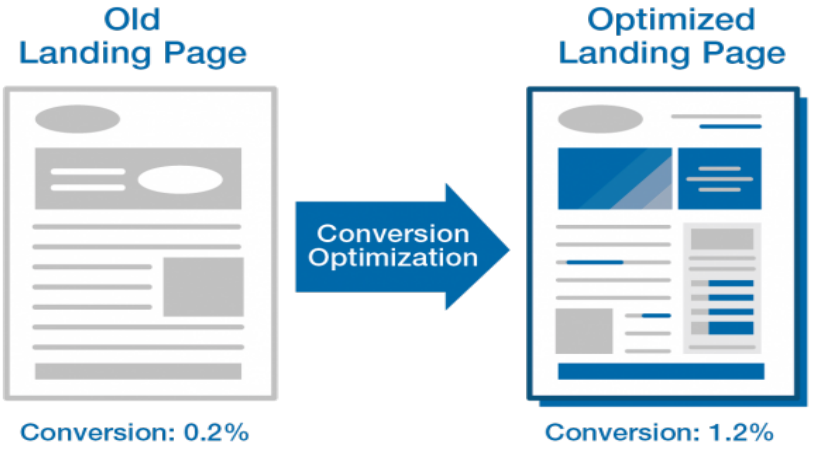
What is: decision process



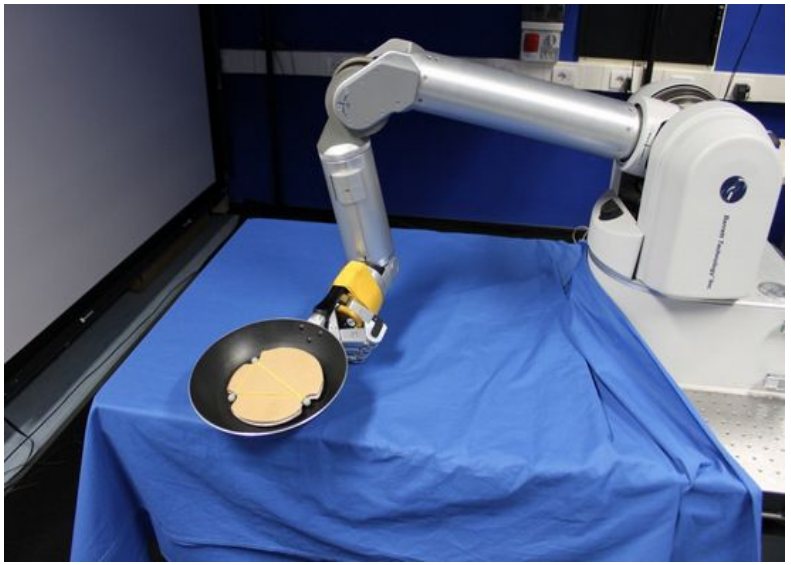
Reality check: web

- **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?





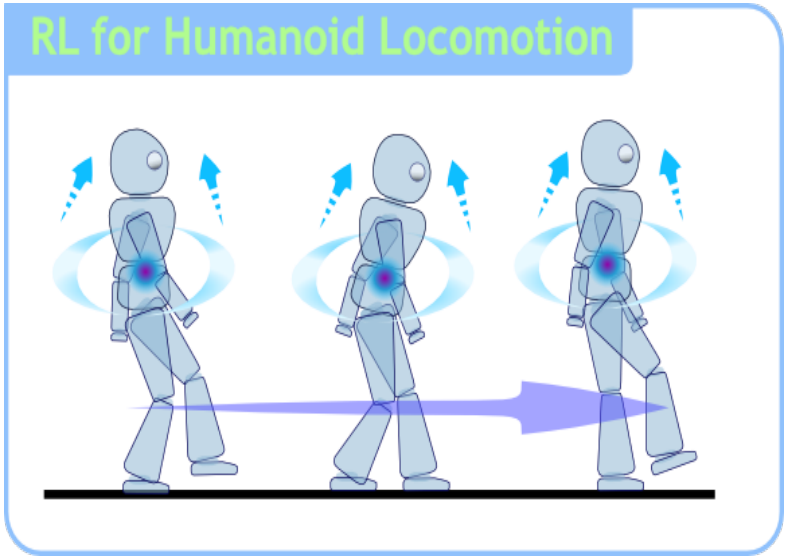
Reality check: dynamic systems



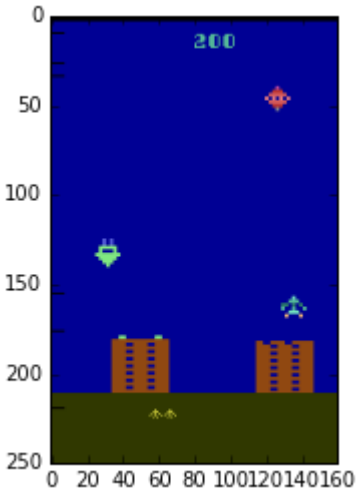
Reality check: dynamic systems

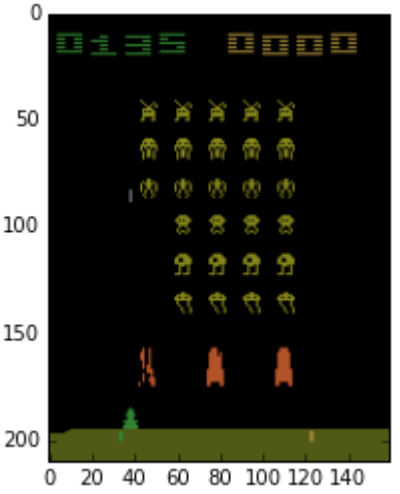
- **Cases:**
  - Robots
  - Self-driving vehicles
  - Pilot assistant
  - More robots!

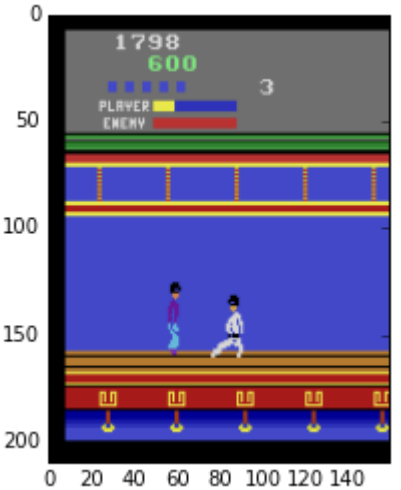
- **Example**
  - Observation: sensor feed
  - Action: voltage sent to motors
  - Feedback: how far did it move forward before falling



~~Reality~~ check: videogames

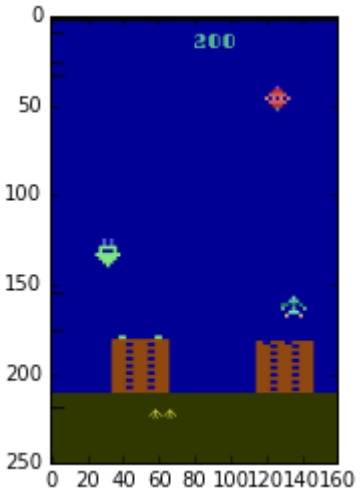


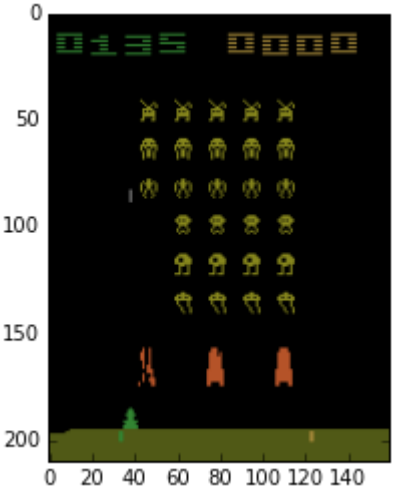


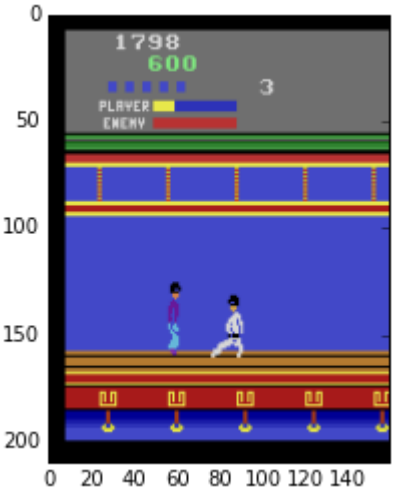


- **Q:** What are observations, actions and feedback?

~~Reality~~ check: videogames





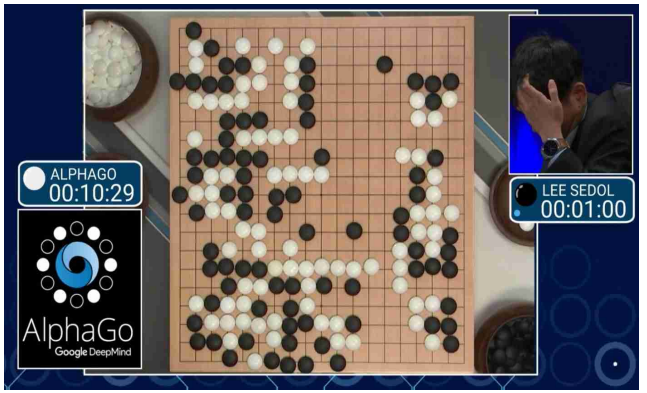


- **Q:** What are observations, actions and feedback?

Other use cases

- Personalized medical treatment

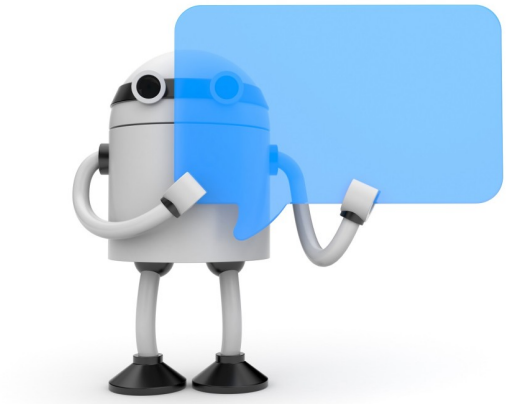
- Even more games (Go, chess, etc)

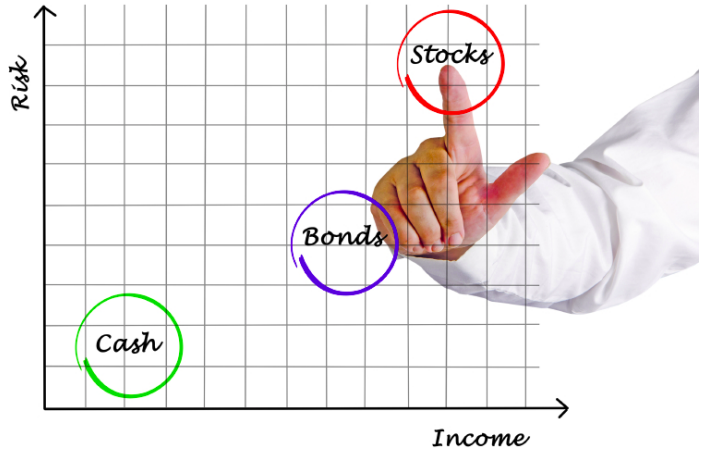


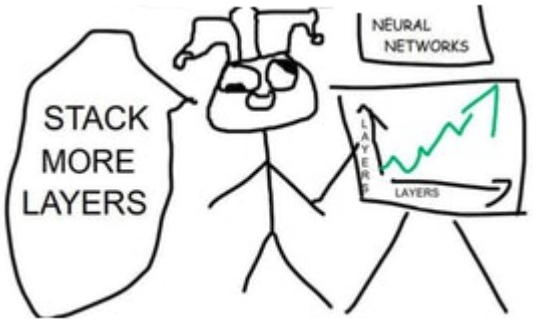
- **Q:** What are observations, actions and feedback?

Other use cases

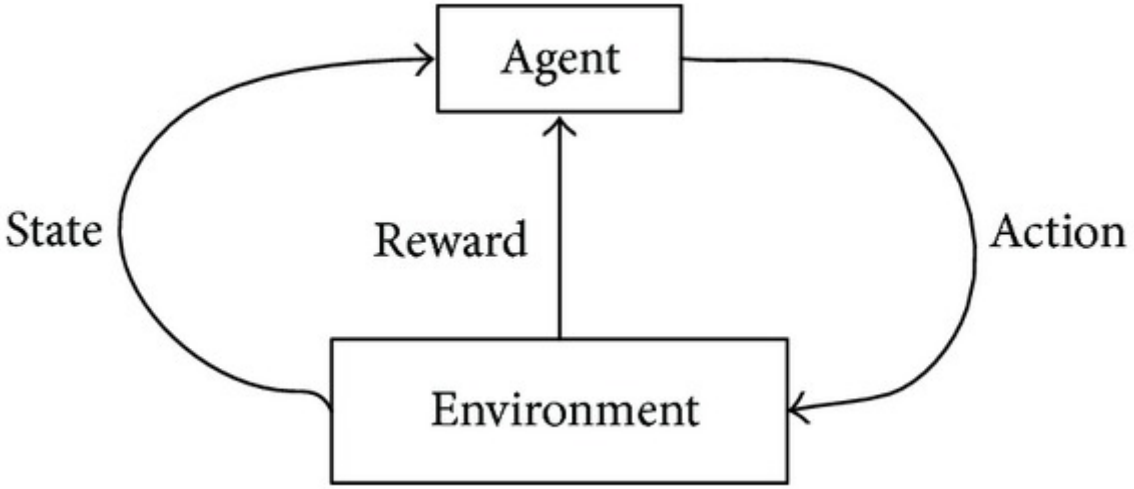
- Conversation systems
  - learning to make user happy
- Quantitative finance
  - portfolio management
- Deep learning
  - optimizing non-differentiable loss
  - finding optimal architecture







The MDP formalism

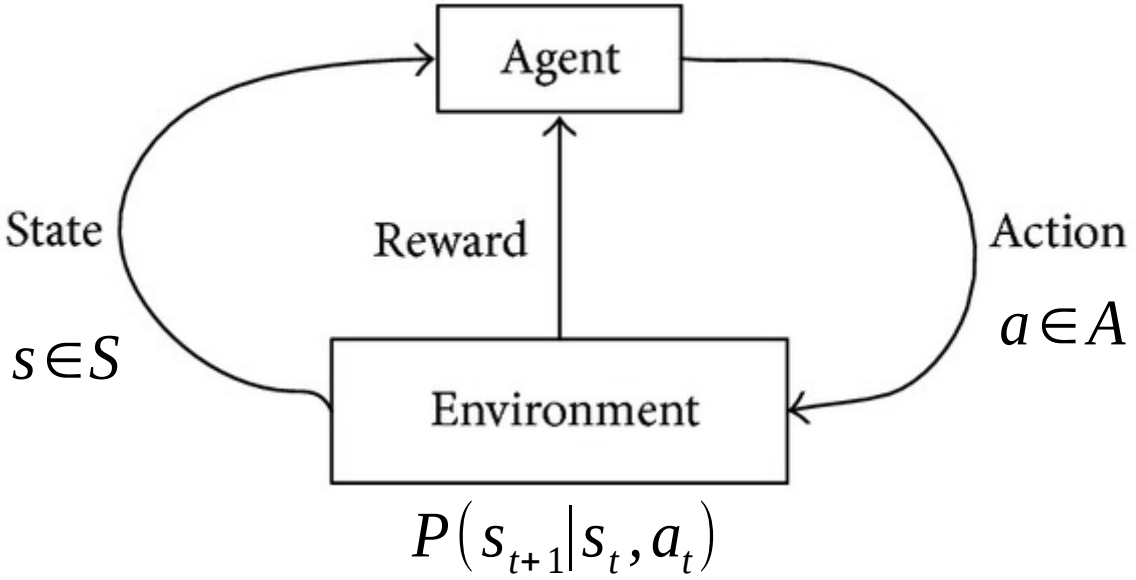


Markov Decision Process

- 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

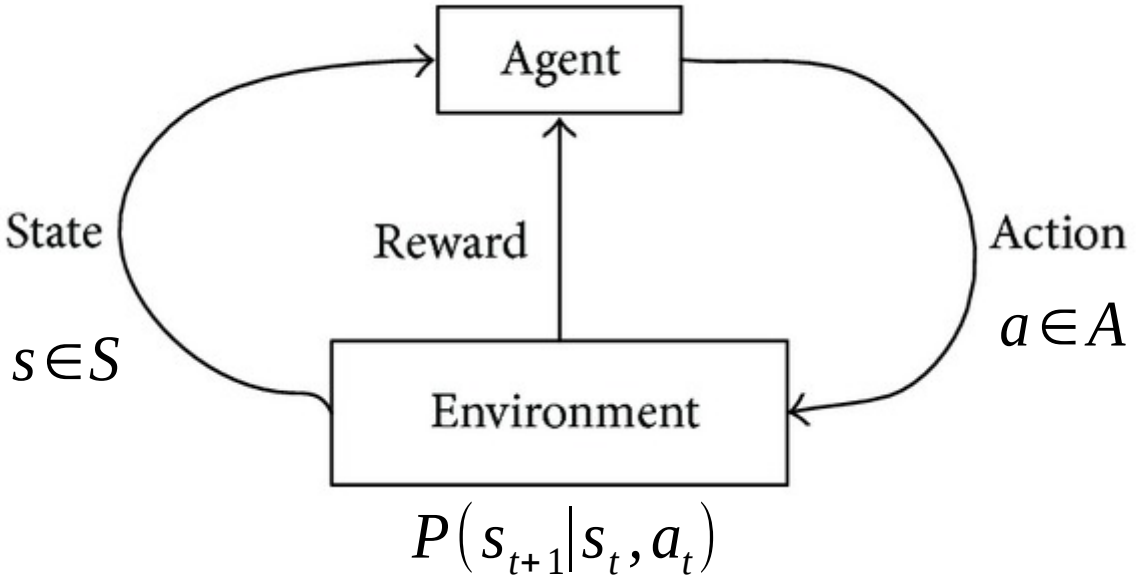


Markov Decision Process

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

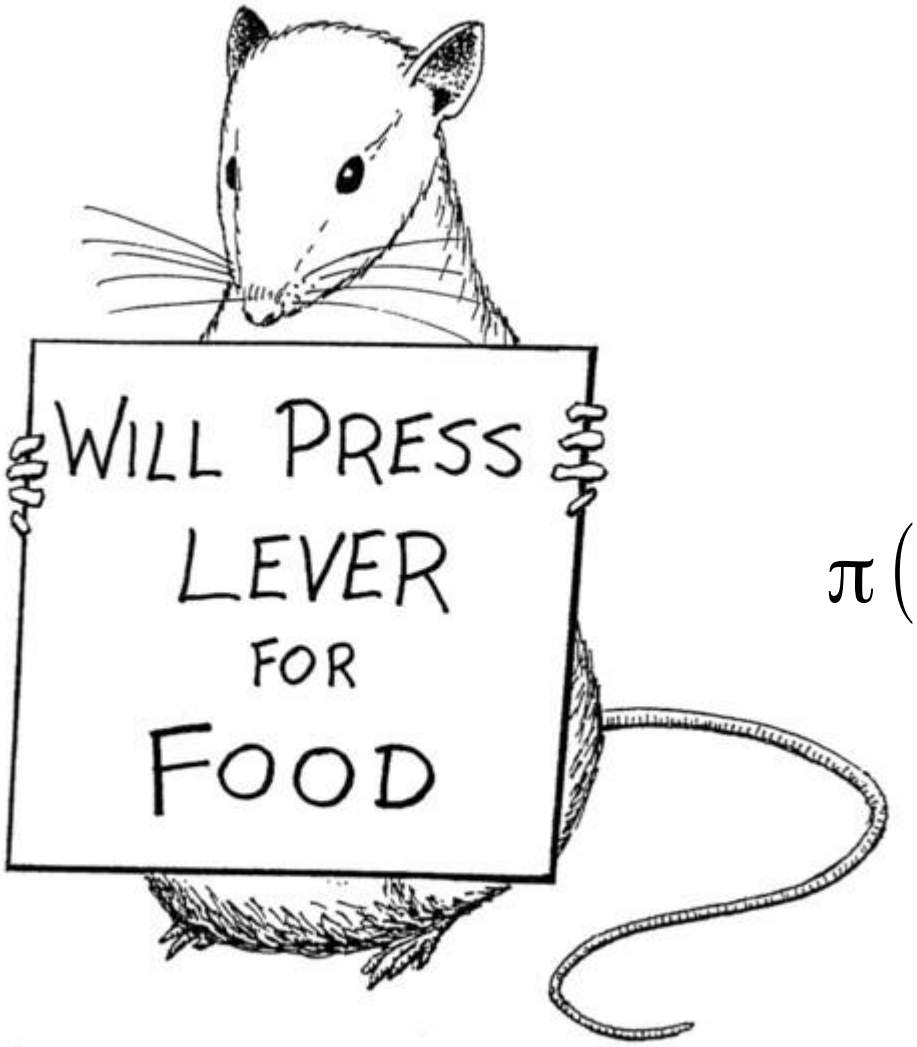


Markov Decision Process

Markov assumption

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

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

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

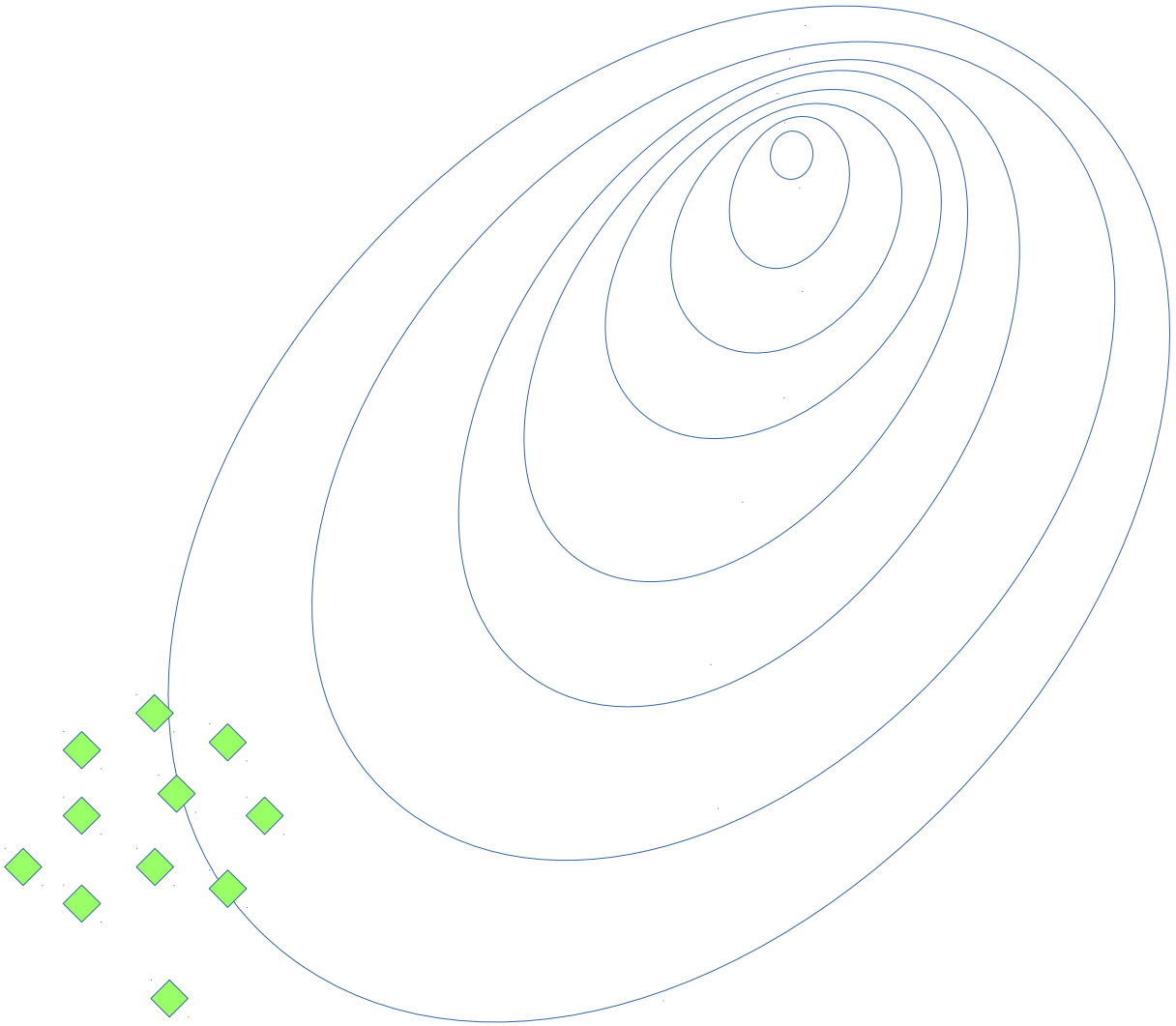
Crossentropy method

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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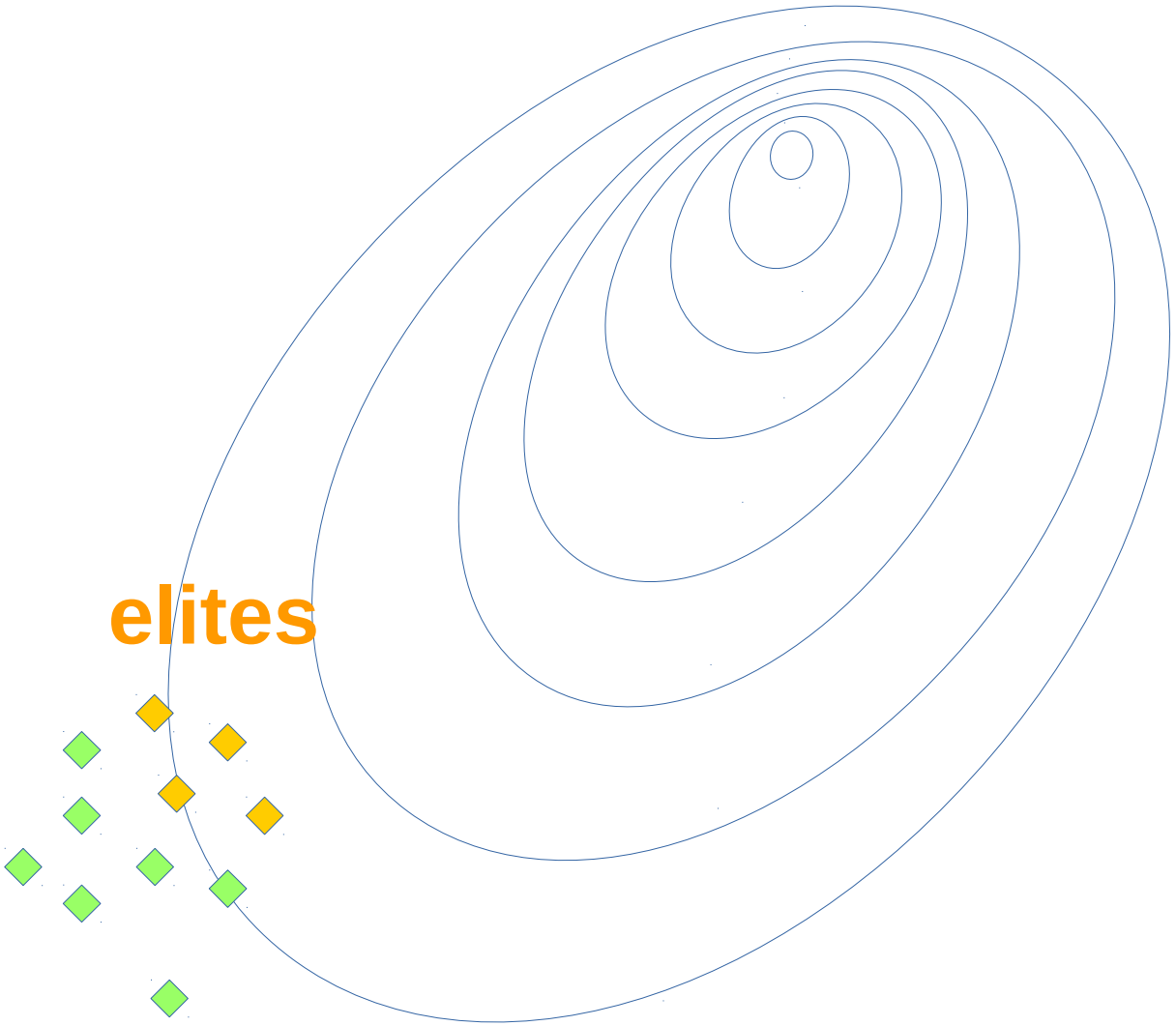

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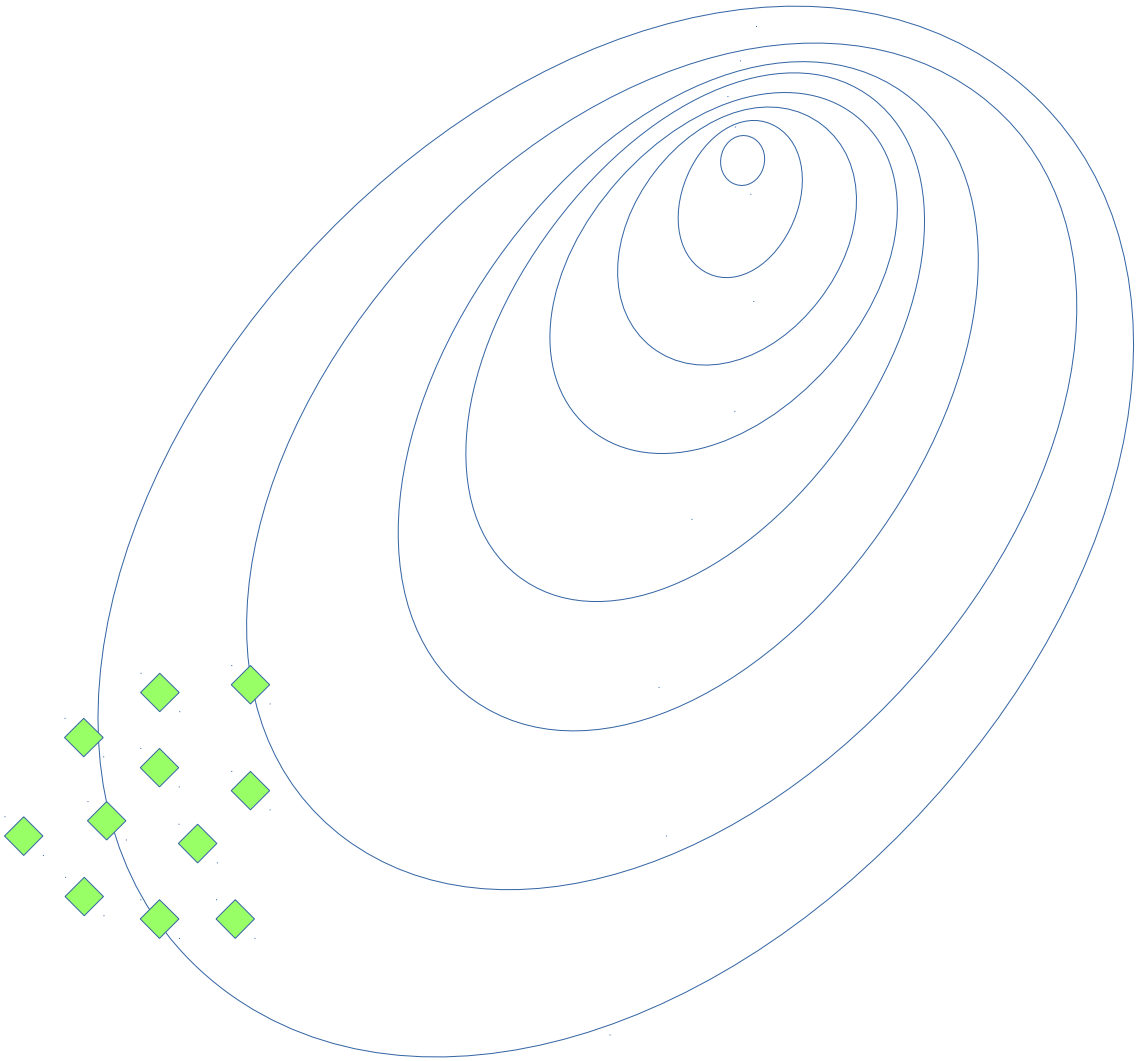

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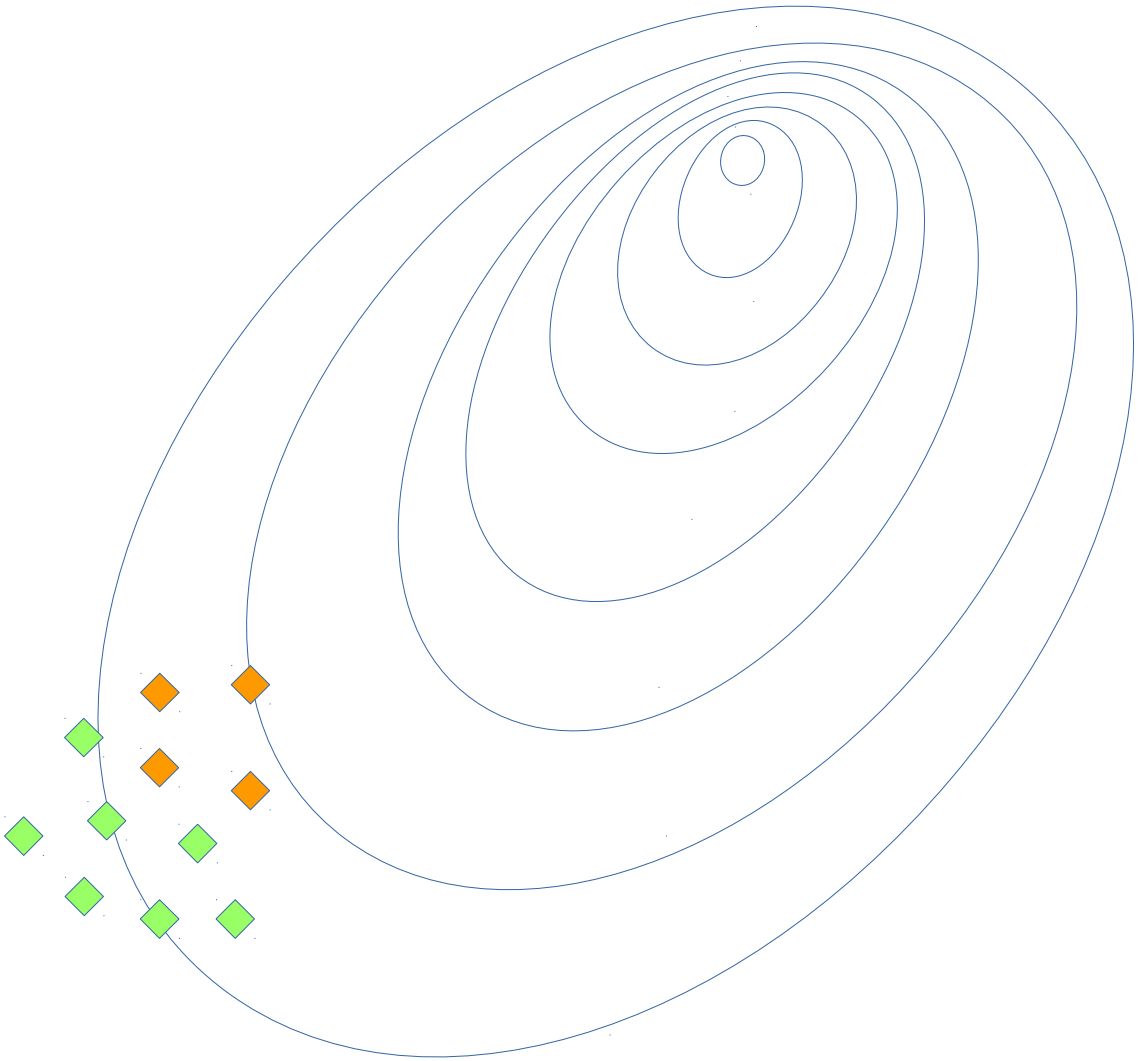

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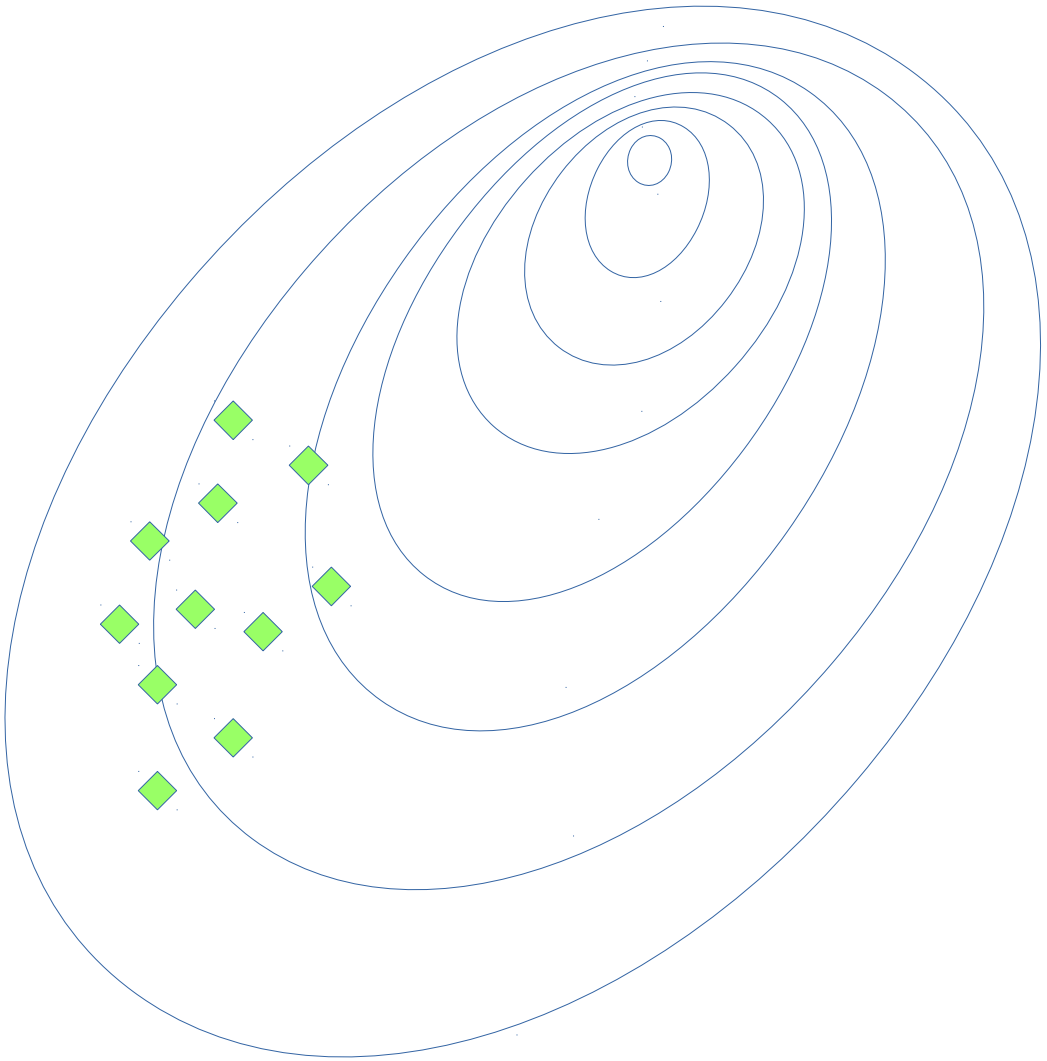

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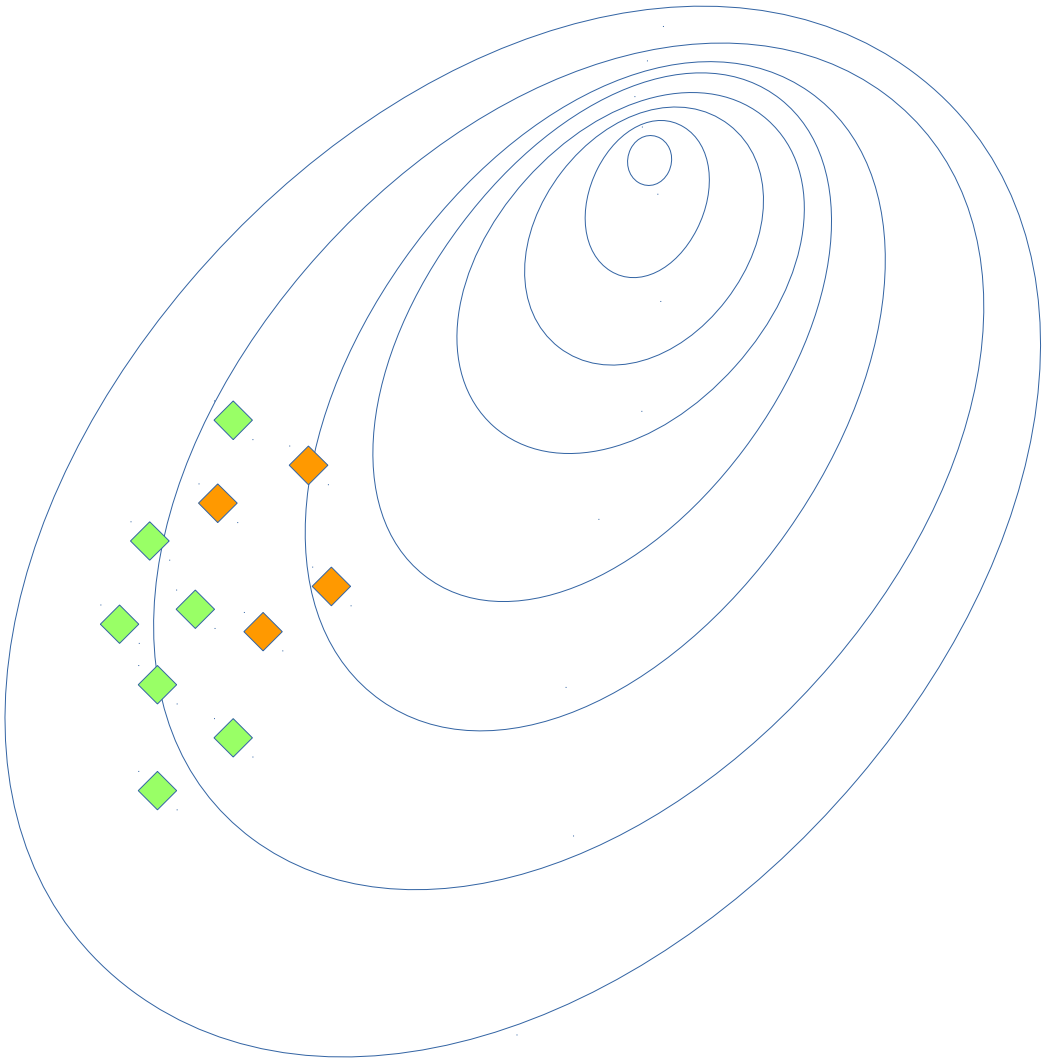

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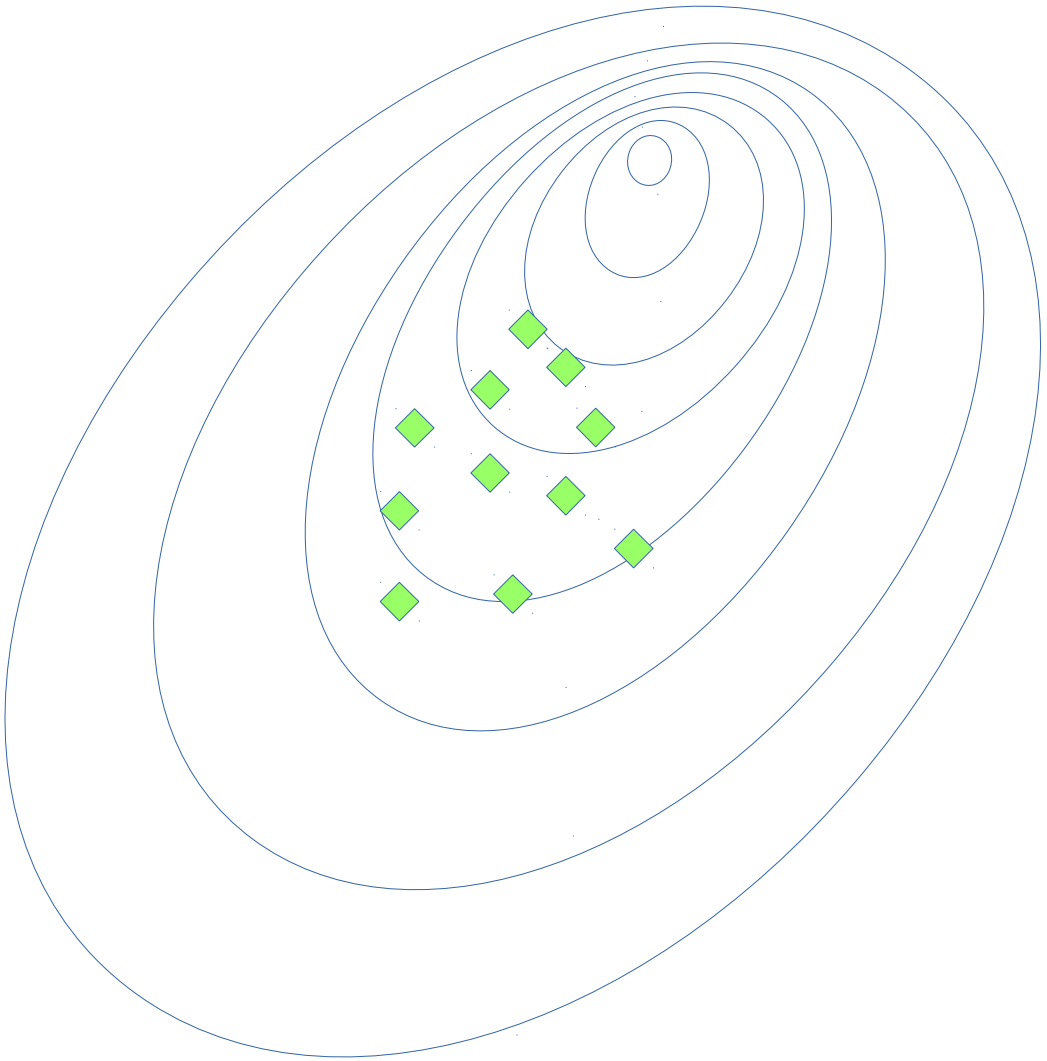

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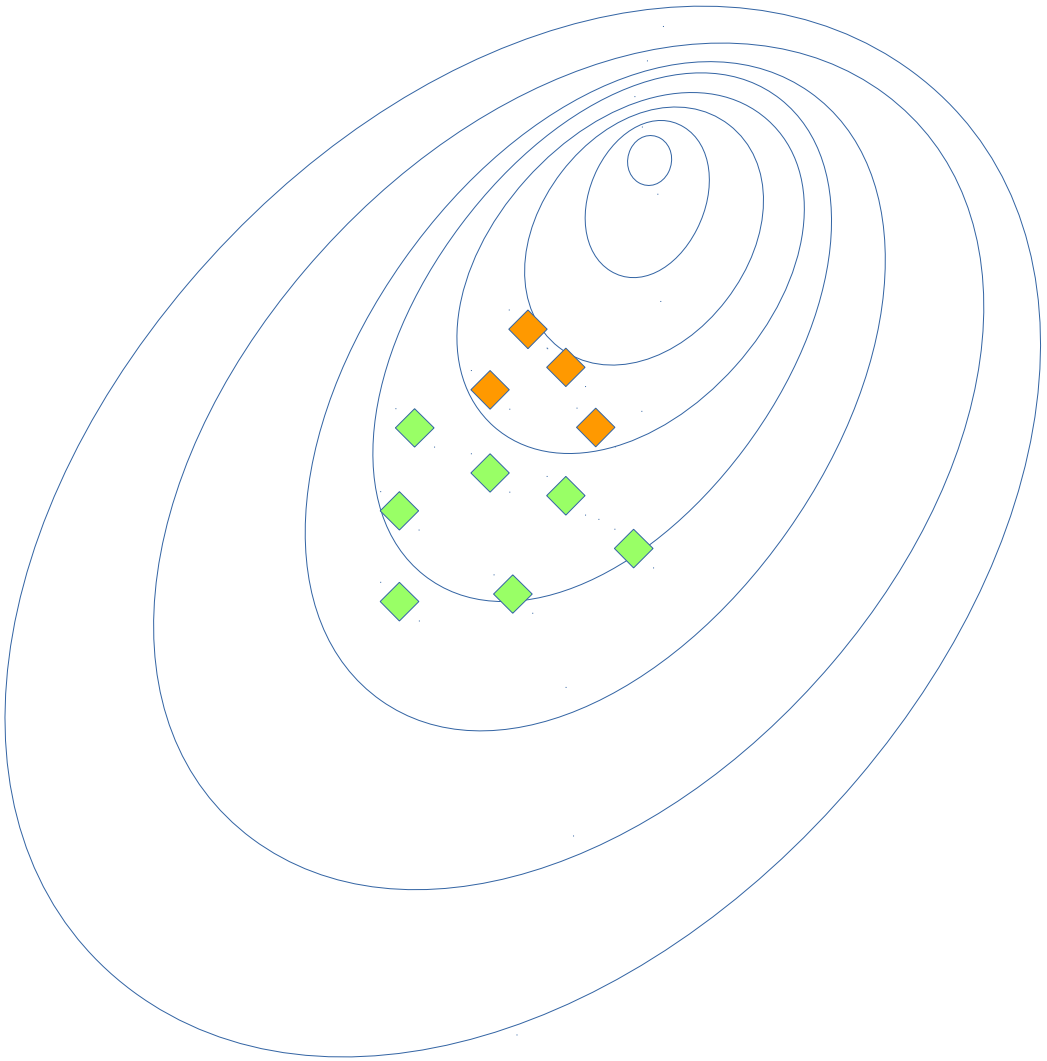

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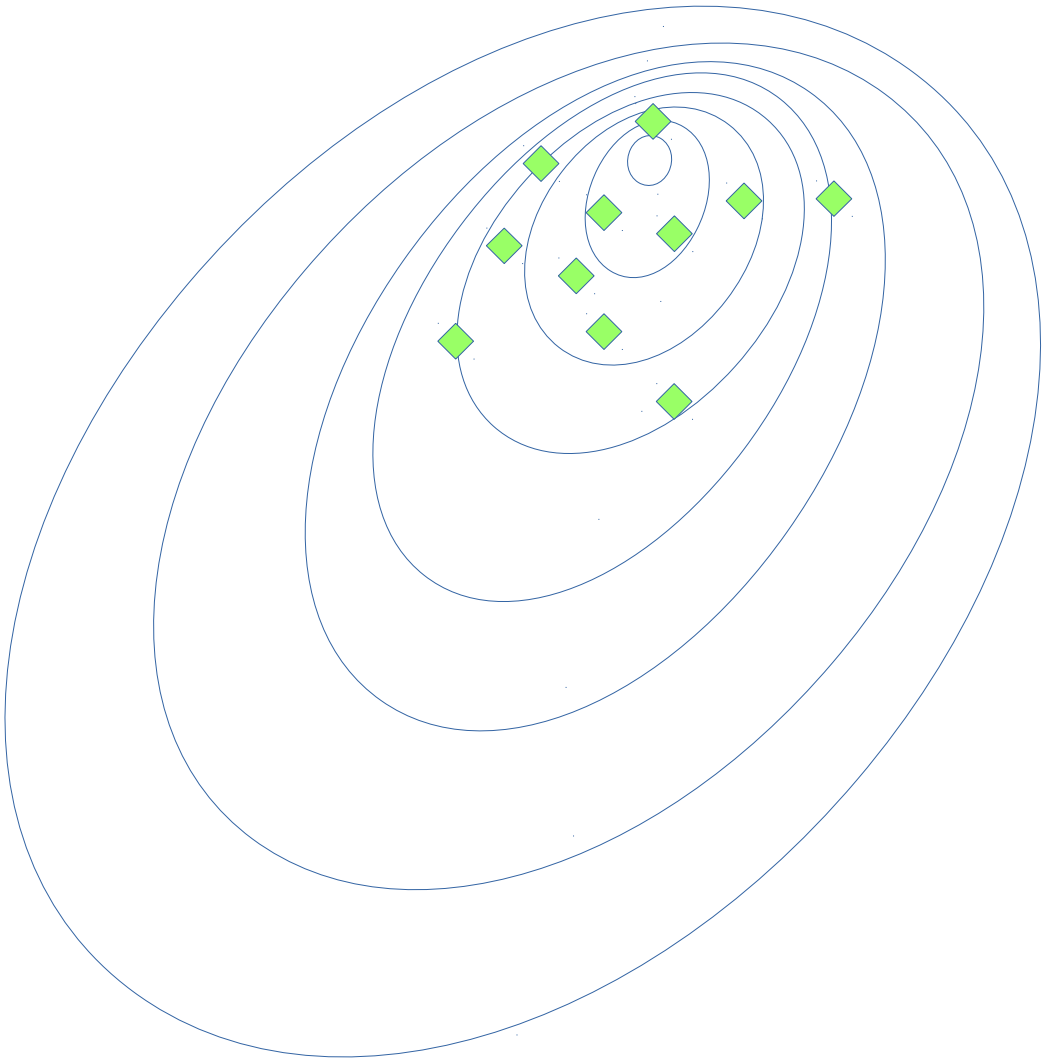

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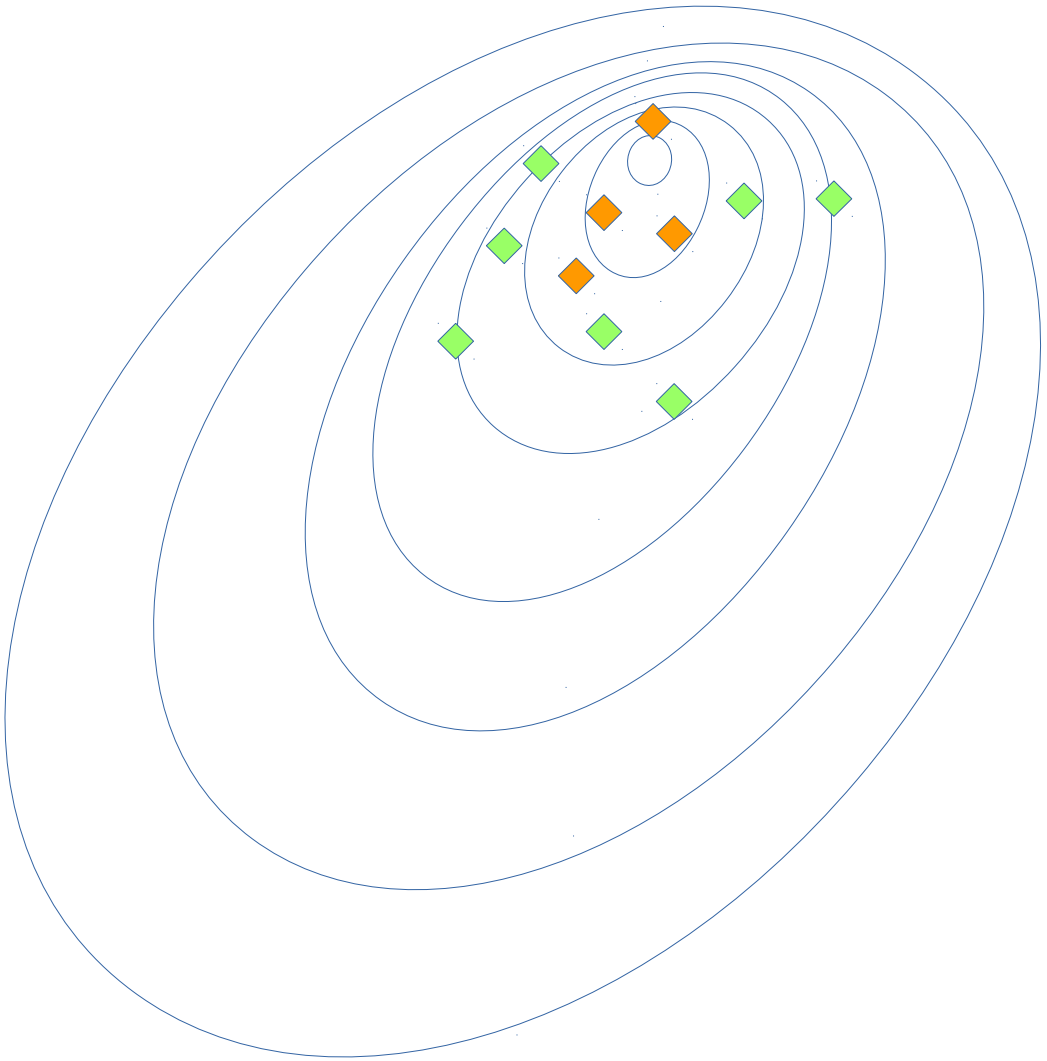

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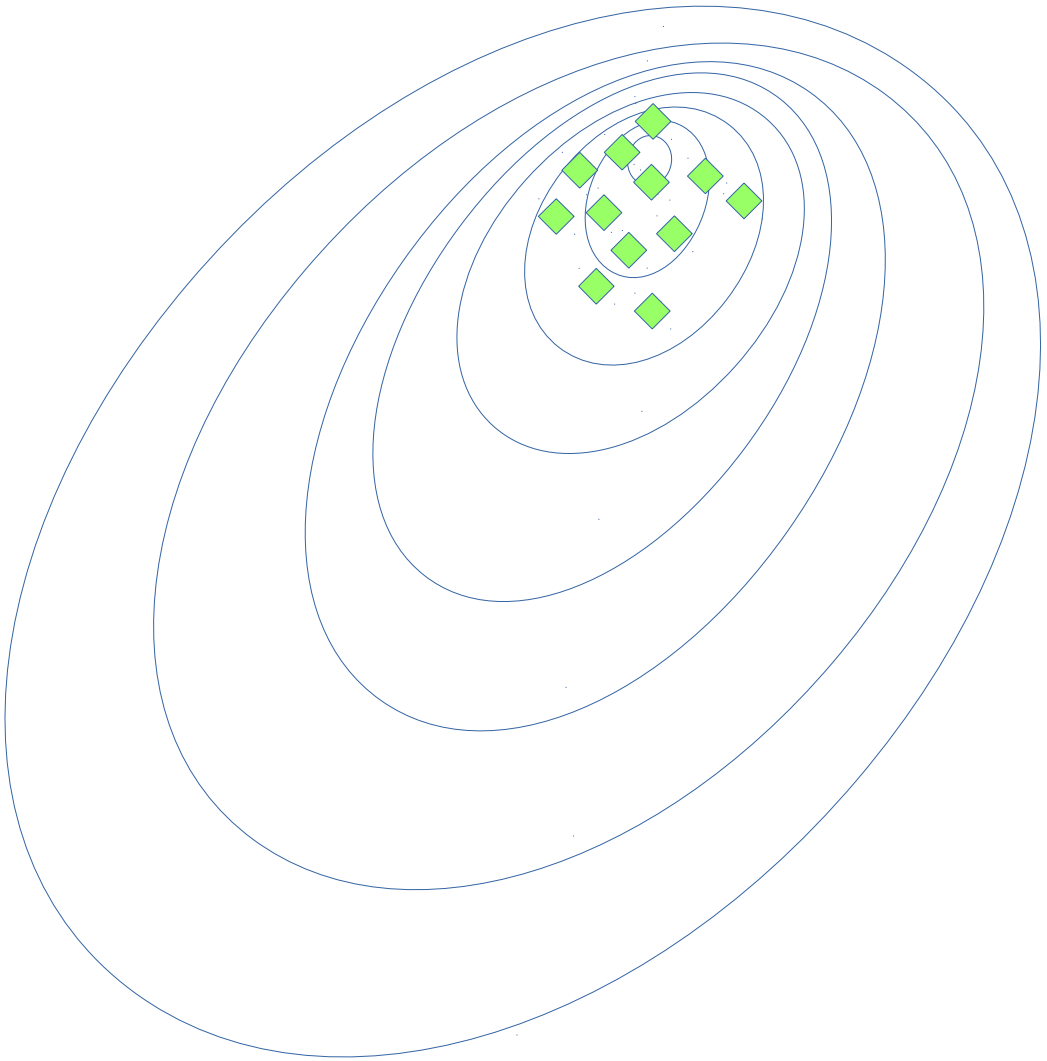


Tabular crossentropy method

- 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)

Q: How is RL different from **supervised 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

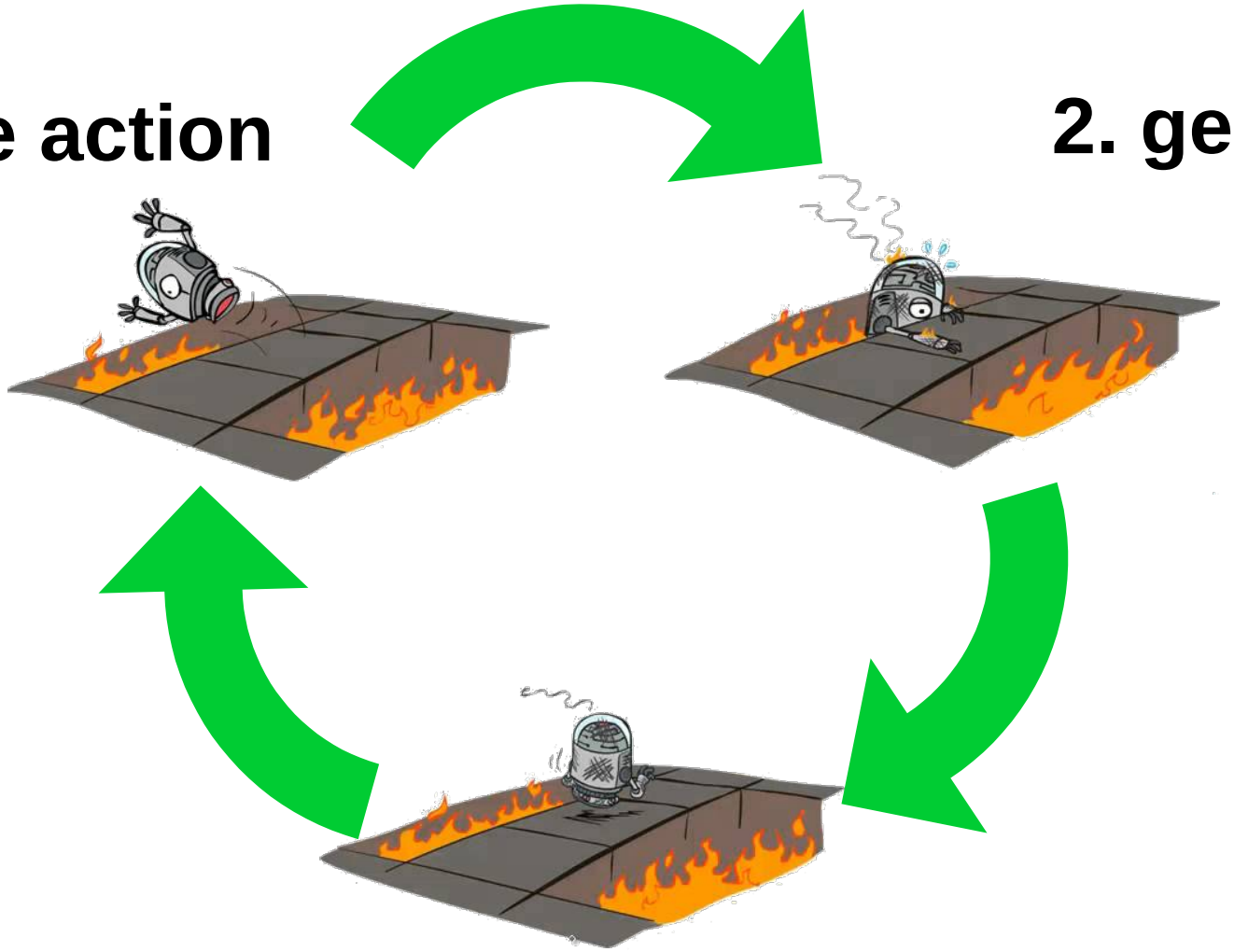
Reinforcement learning

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

Reinforcement learning is easy!

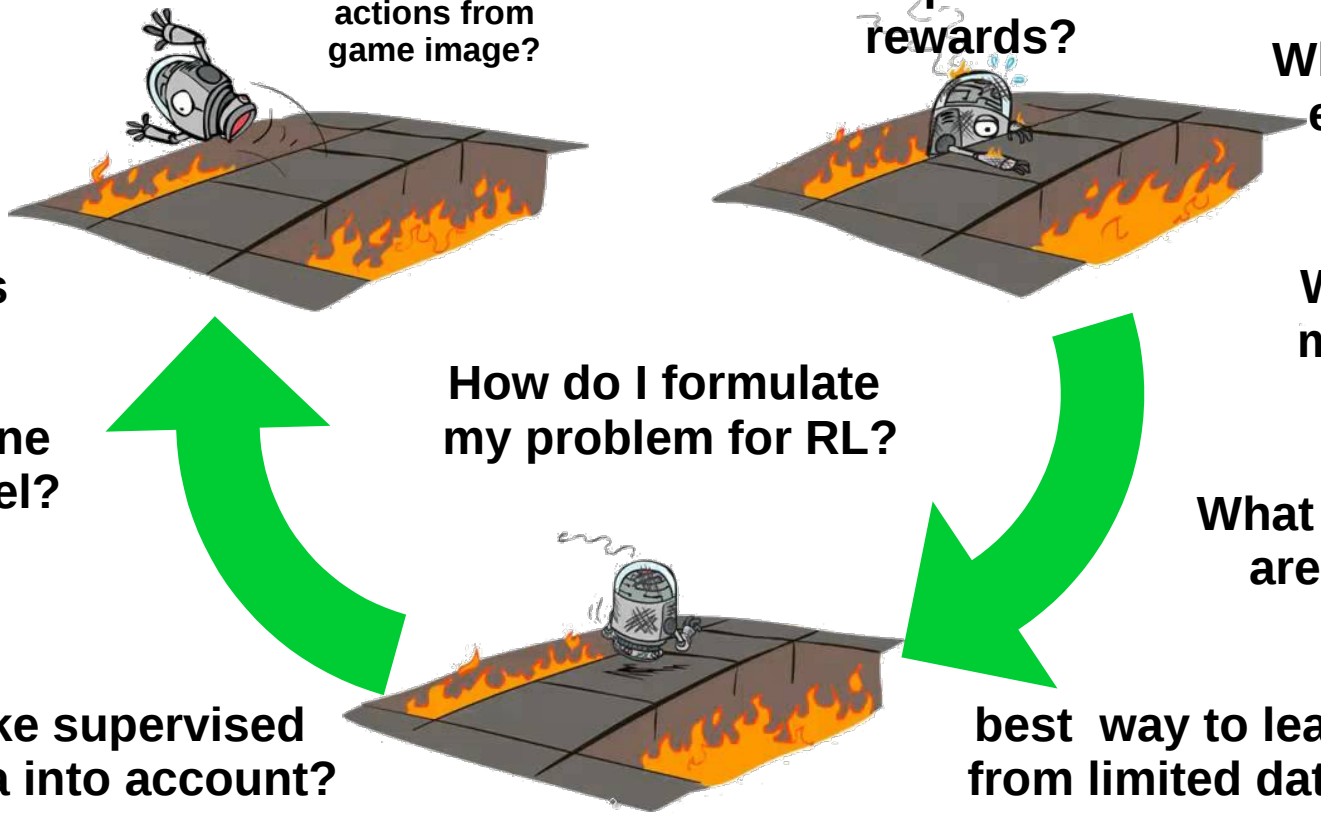
1. take action

2. get reward



3. improve policy

Reinforcement learning is challenging!



How to explore?

What if there's many actions?

1. take action

How to infer actions from game image?

How not to break anyting when acting?

Continuous actions?

How to define policy model?

When not to use RL?

take supervised data into account?

did my algorithm overfit to simulation?

3. improve policy

How do I know if it converged or not?

best way to learn from limited data?

What if observations are incomplete?

What if there are multiple agents?

How do I formulate my problem for RL?

Which rewards are easier to learn?

Sparse rewards?

2. get reward

Which actions caused reward?

Can agent cheat reward?

Outro and Q & A

- RL is different both from Supervised and Unsupervised learning
- Remember the Markov assumptions
- Try to think in terms of distributions
- The crossentropy method is simple and still very powerful approach