Introduction to Reinforcement Learning

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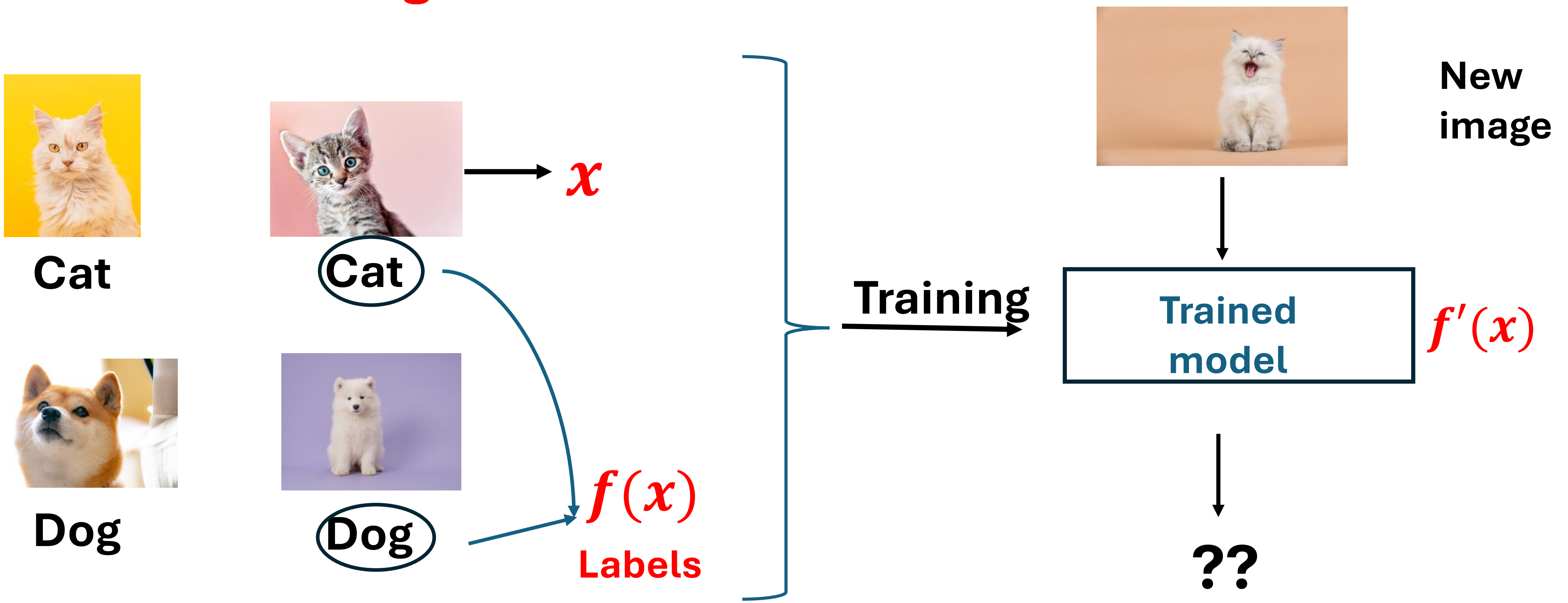
Paradigms of Machine Learning

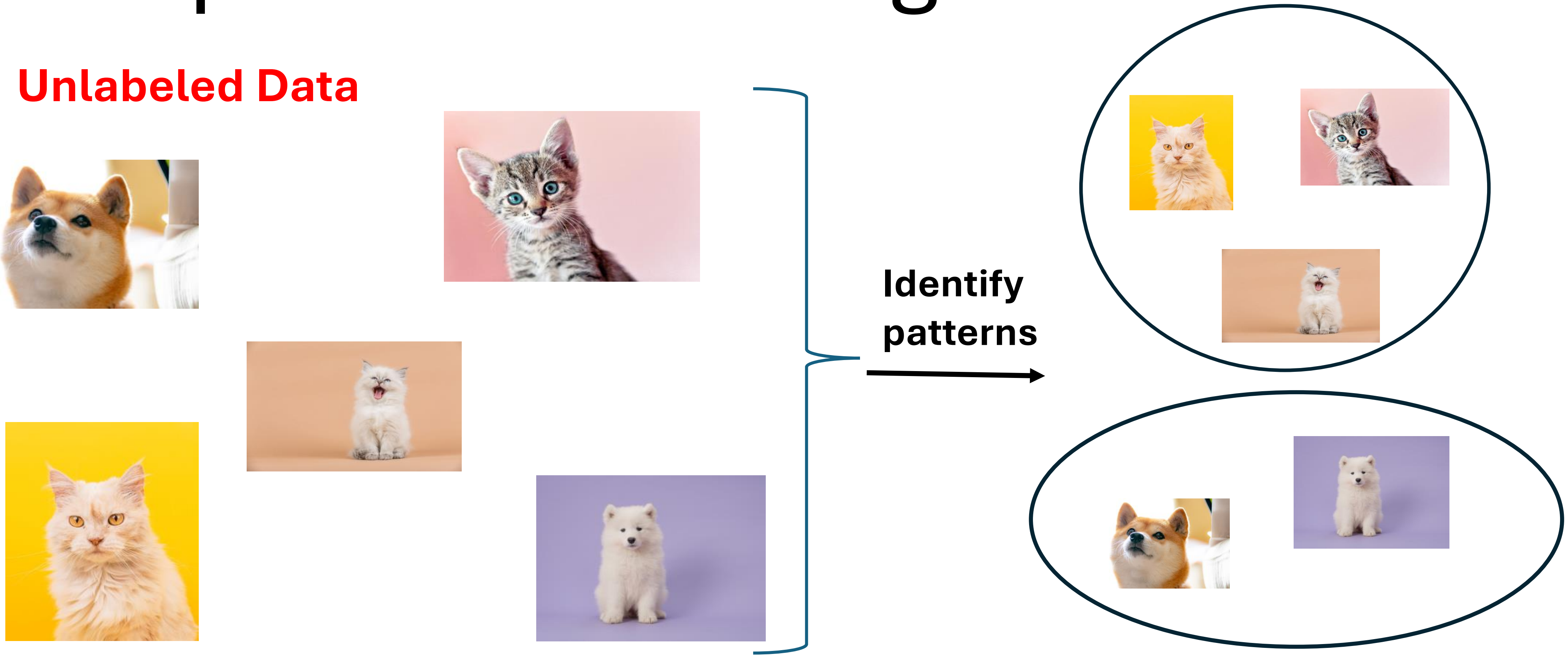
- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

Supervised Learning

Labeled Training Data



Unsupervised Learning



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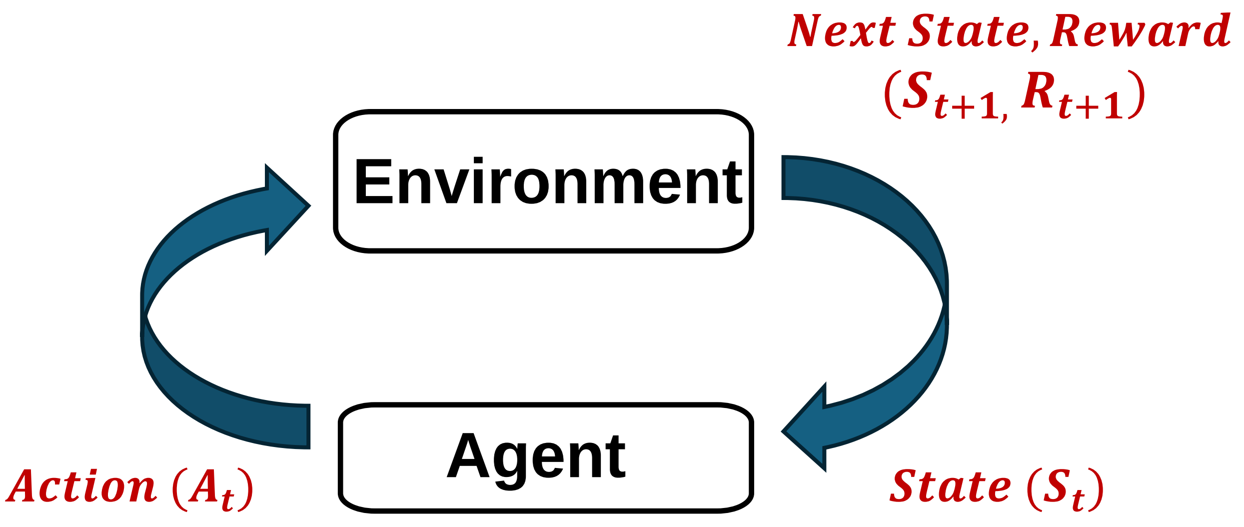
Reinforcement Learning

Feedback:
Score,
new display

State:
Display

Actions:
UP / Left /
Right / Down

Learn by Trial and Error



1. Agent observes the state and takes action
2. Environment puts the agent in a new state &
3. Gives a reward based on the action taken

GOAL: Learn policy to maximize the cumulative reward $\sum_t R\_t$

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  - Fitting a function for the given labeled data (x, y)
  - $y \approx f(x)$

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  - Identifying patterns in unlabeled data
  - E.g. Clustering
- Reinforcement Learning

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  - Identifying patterns in unlabeled data
  - E.g. Clustering
- Reinforcement Learning
  - Learning sequential tasks through trial and error
  - Feedback through reward/penalty

RL Demonstrations

Autonomous Helicopter

Pong game

AlphaGo by DeepMind

Photos provided by Pexels

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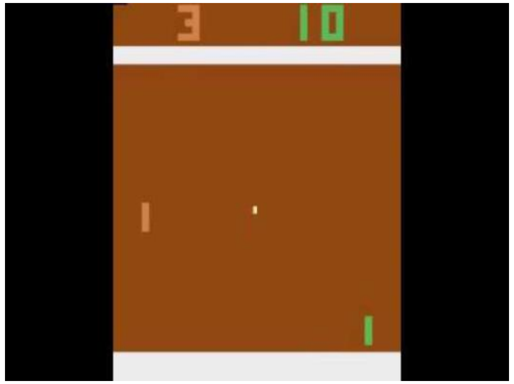

AlphaGo by DeepMind

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One State RL: Multi-arm Bandits

- Simplified version of RL problem: "Multi-arm Bandit" problem.
  - Only one state
  - Multiple actions (a.k.a. arms)
    - $\mathcal{A}$ – Action set

- A reward distribution corresponding to each arm
  - $\mathcal{R}_a$ – Reward distrution for action a
  - $\mu_a = \mathbb{E}[\mathcal{R}_a]$ – Expected reward for action a

- Applications: Recommendation systems, Ad placement, ...

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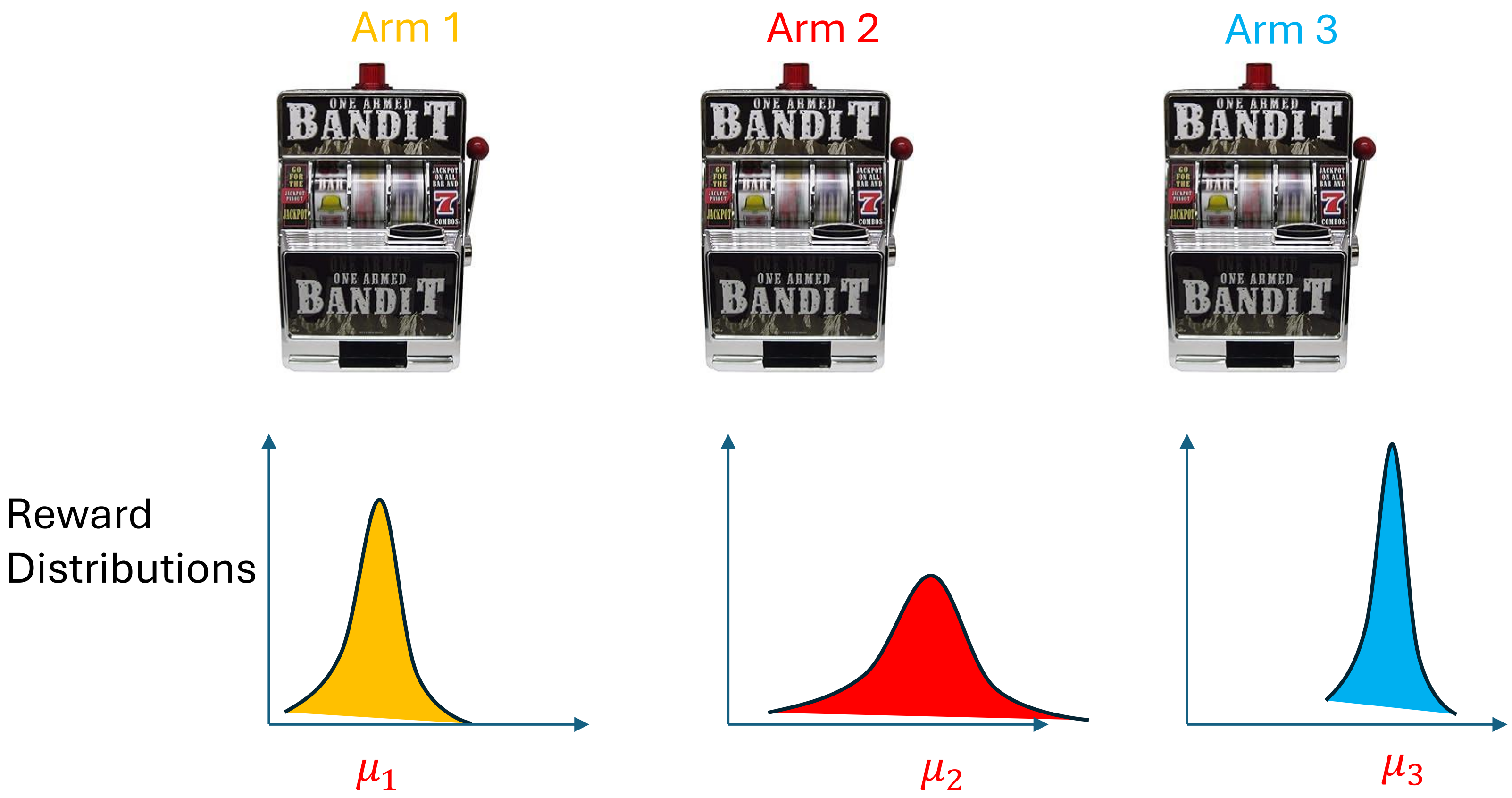
Multi-arm Bandits



Problem:

- Reward distributions are **unknown**
- Given **T chances** to pull the arms
- Which arms should be pulled to **maximize the total reward** in those T rounds

Exploration
Vs
Exploitation dilemma

ETC (Explore-Then-Commit)

1. **Explore:** Play each arm N times

2. Compute the sample average rewards $\bar{\mu}(a) = \frac{1}{N}\sum_{t=1}^{KN} R_t \, 1\{a_t = a\}$ for each arm $a \in \mathcal{A}$

3. **Commit:** Play the arm with the highest sample average for the remaining $T - KN$ rounds

μ^* - Optimal arm's expected reward

a_t - Arm played in round t

K - Number of arms

R_t - Sample reward obtained in round t

T - Total number of rounds

Performance (ETC Vs Best possible reward) : $T\mu^* - \sum_{t=1}^{T} \mathbb{E}[R_t]$

How much to Explore? $N \approx (\frac{T}{K})^{\frac{2}{3}}$

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ϵ-Greedy (Explore uniformly)

1. Play each arm once

2. In each round t:
    - Toss a coin with bias ϵ.
    - If it lands in head: Explore - Play any arm randomly
    - Else: Exploit - Play the arm with the highest sample average so far

What ϵ to choose? $\epsilon \approx (\frac{K}{T})^{\frac{1}{3}}$

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UCB (Upper Confidence Bound)

Optimism under UnCertainty

1. Play each arm once in the first K rounds

2. For $t > K$:
   - Play the arm with the highest $UCB_t(a) = \underbrace{\overline{\mu_{t-1}}(a)}_{\text{Exploit}} + \underbrace{\sqrt{\frac{2\log T}{n_{t-1}(a)}}}_{\text{Explore}}$
   - Based on the observed sample reward R_t, update $n_t(a_t)$ and $\overline{\mu_t}(a_t)$
     - $n_t(a_t) = n_{t-1}(a_t) + 1$
     - $\overline{\mu_t}(a_t) = \frac{1}{n_t(a_t)}[(n_t(a_t) - 1)\, \overline{\mu_{t-1}}(a_t) + R_t]$

Exploit: High sample reward arms are favoured
Explore: Least played arms are favoured

Contextual Bandits – Multiple states

- News article Recommendation systems

- Articles – arms
- Like / Dislike – Reward
- User – State

Different users have different preferences to articles

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