MULTI-AGENT REINFORCEMENT LEARNING

Lesson 3: Learning Dynamics – The Evolutionary Game

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It is not the strongest of the species that survives, nor the most intelligent that survives. It is the one that is the most adaptable to change.

THE DANCE OF AGENTS: A STORY OF CONSTANT MOTION

Single-Agent Learning is a Solo Performance

- The world is a static stage.
- The agent learns steps to a fixed rhythm.
- Goal: Perfect one routine.

Multi-Agent Learning is a Group Dance

- Every dancer's move changes the dance.
- The rhythm changes with every step.
- Goal: Learn to adapt and coordinate.

Today, we learn the choreography of this dance: the dynamics of multi-agent learning.

RECAP & AGENDA

Previously On MARL...

- We explored fundamental architectures:
  - CTCE: The God Controller
  - CTDE: Unified Command
  - DTDE: Total Anarchy
- These are the "blueprints" of our agents.

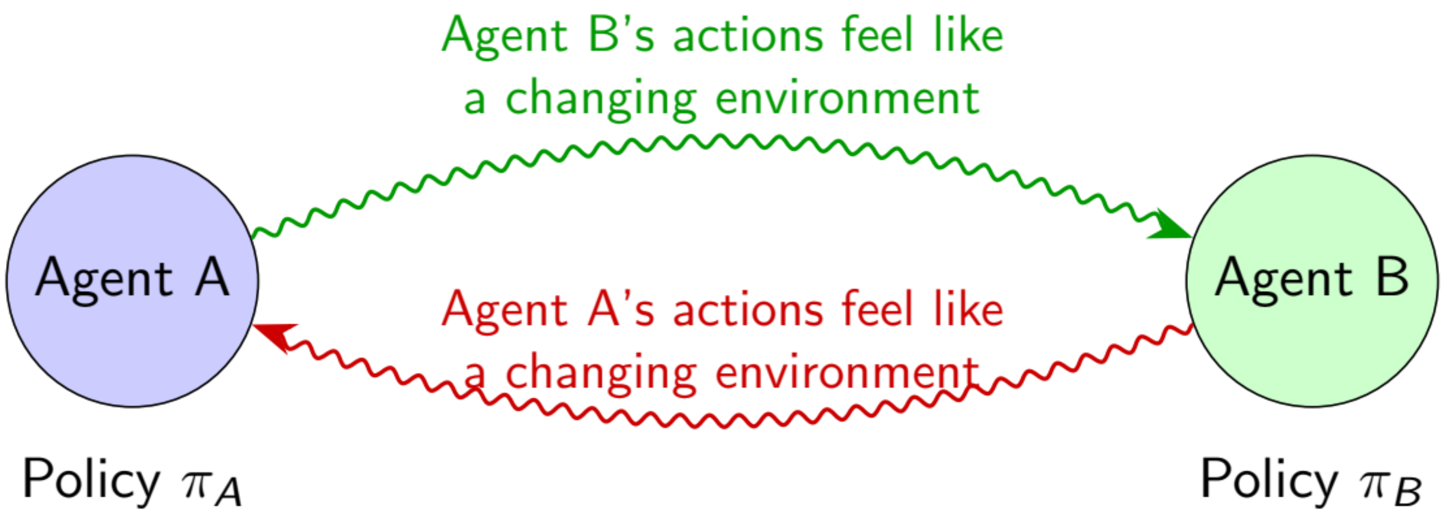
Today's Mission

- Now we see how these agents *evolve*.
  1. **Self-Play**: Creating a perfect sparring partner.
  2. **Policy Gradients**: The math of social influence.
  3. **Mean Field Theory**: Taming the chaos of the crowd.
- **Live Demo!**

THE CORE CHALLENGE: LEARNING ON SHIFTING SANDS

The Central Problem in MARL

From any single agent's perspective, the environment is a **moving target**. As other agents learn and change their policies, the optimal policy for our agent also changes.



The Billion-Dollar Question

How do we achieve stable learning when the "correct" answer is always changing?

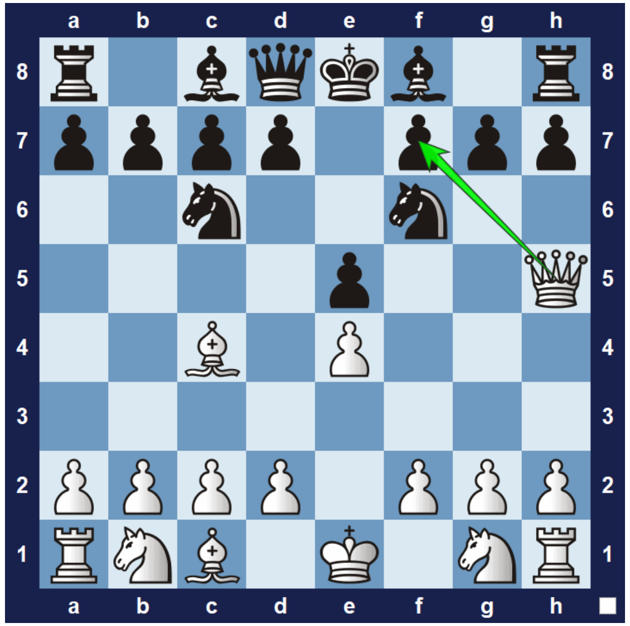
SECTION 1: SELF-PLAY

Fighting Your Own Shadow

THE PROBLEM: OVERFITTING TO A PREDICTABLE FOE

Imagine training a chess AI against a fixed opponent that *only* uses a beginner's 4-move checkmate strategy.

- The AI will quickly learn to counter this one specific attack.
- It becomes the world champion of defending the 4-move checkmate.
- **But it's strategically brittle!** It fails against any other strategy. It has *overfit* to its opponent.



This is the **Red Queen's Fallacy**: you can run faster and faster (get a higher reward), but you're not actually getting smarter if your opponent is standing still.

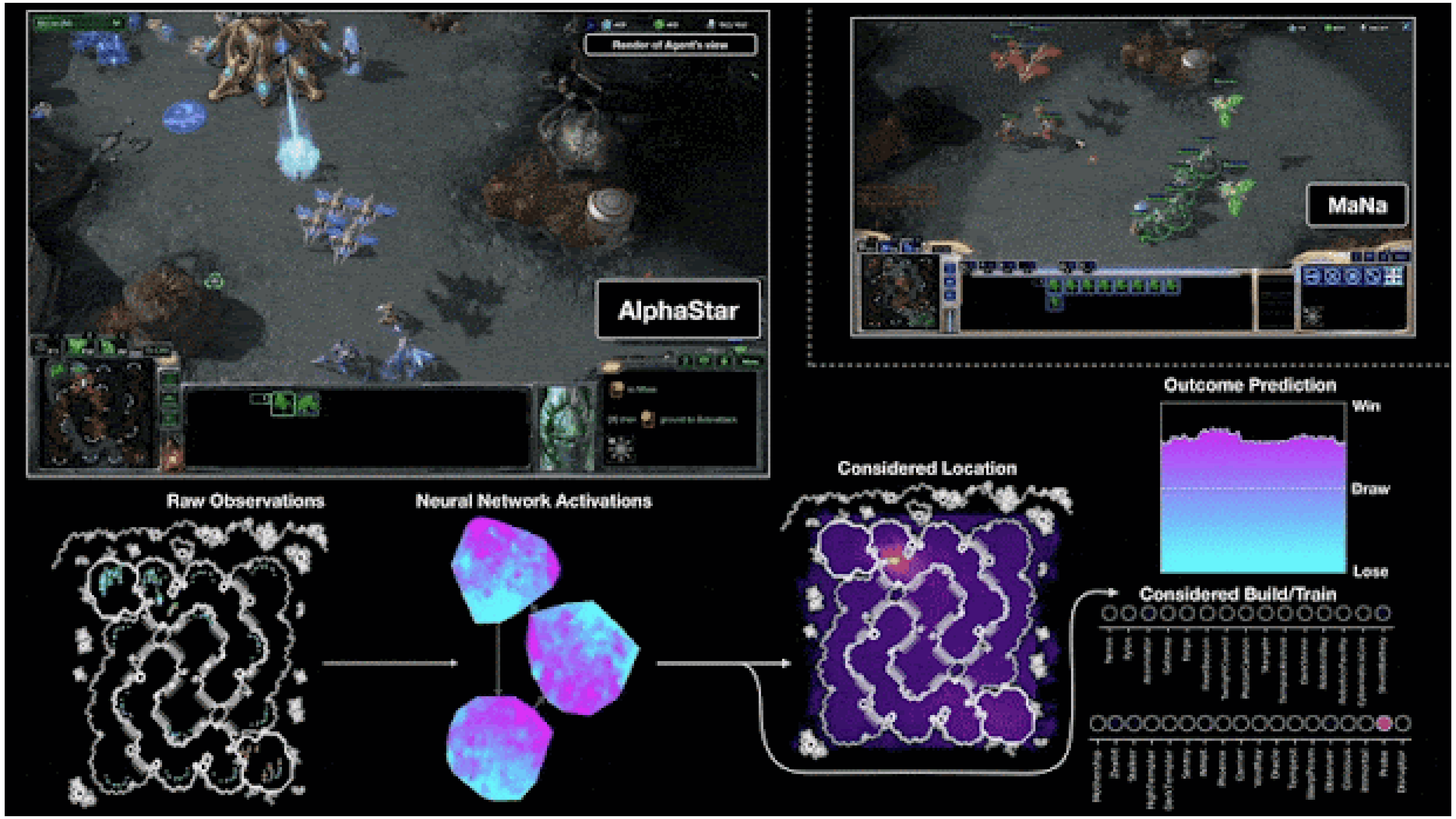
THE SELF-PLAY SOLUTION: A DYNAMIC CURRICULUM

What if your opponent was always a slightly better version of you?

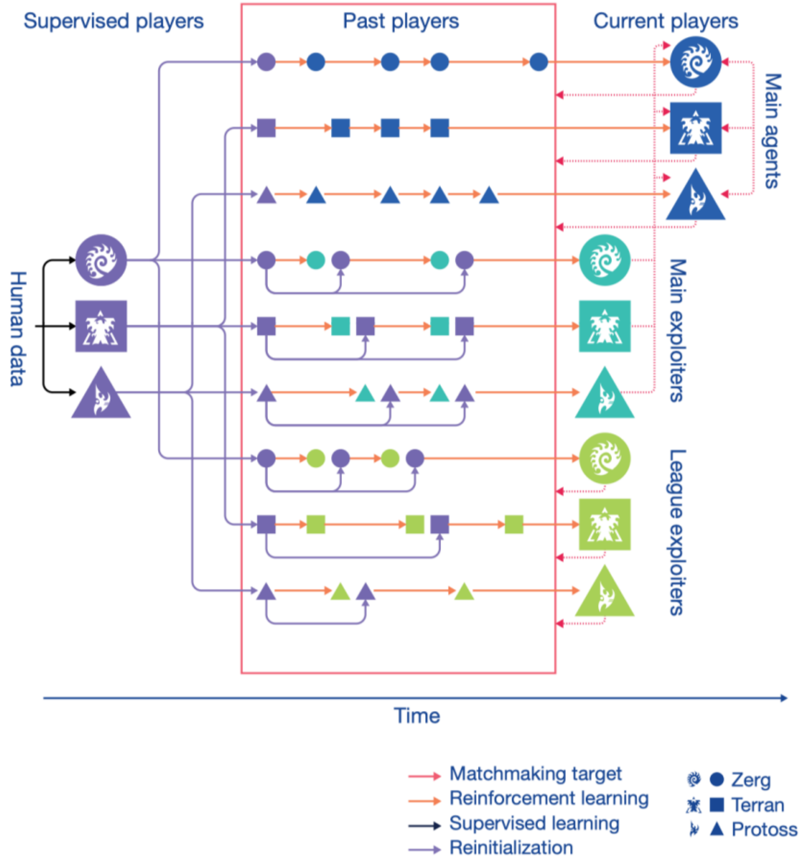
Self-play provides an **autocurriculum**—an automatically generated sequence of increasingly difficult training tasks.

- **Continuous Improvement**: You must constantly adapt to beat your past self.
- **Robustness**: By playing against a diverse pool of your own past strategies, you build a policy that is not easily exploited.
- **Emergent Complexity**: Complex, human-like strategies can emerge from this simple process.

CASE STUDY: ALPHA STAR'S LEAGUE TRAINING



https://deepmind.google/discover/blog/alphastar-mastering-the-real-time-strategy-game-starcraft-ii/



https://xlnwel.github.io/blog/reinforcement%20learning/AlphaStar/

DEEPER DIVE: POLICY-SPACE RESPONSE ORACLES

Self-play isn't just a hack; it's an approximation of a powerful game-theoretic algorithm.

The PSRO Loop:

1. **Start** with a set of initial policies (the meta-strategy or "league").
2. **Compute Best Response**: For each agent, train a new policy that is an optimal "best response" to the current mix of opponent policies in the league.
3. **Add to League**: Add this newly trained best-response policy to the league.
4. **Repeat**: Go back to step 2.

What does this achieve?

This process iteratively builds a strategy set that converges towards a **Nash Equilibrium** of the game. AlphaStar's league is a practical, large-scale implementation of this core idea.

SECTION 2: POLICY GRADIENTS

The Subtle Art of Social Influence

THE CHALLENGE OF INTERDEPENDENT GRADIENTS

In single-agent RL, the policy gradient is straightforward: "If an action led to a good outcome, do it more."

$$\nabla_{\theta_i} J(\theta_i) = \mathbb{E}_{\tau \sim \pi_i} \left[\sum_{t=0}^{T} \nabla_{\theta_i} \log \pi_i(a_t|s_t) \quad \underbrace{A_i(s_t, a_t)}_{\text{How good was this action?}} \right]$$

In multi-agent RL, the outcome for agent i depends on everyone's policy (θ_i and θ_{-i}).

The gradient $\nabla_{\theta_i} J_i(\theta_i, \theta_{-i})$ is contaminated by the choices of others! How can we assign credit or blame correctly?

APPROACH 1: INDEPENDENT LEARNING (THE OPTIMIST)

Analogy: Ignorant Dancers

Each dancer tries to perfect their moves in isolation, hoping everyone else does the same.

Method: (IQL, IPPO)

- Each agent treats all other agents as part of the static environment.
- It calculates its gradient $\nabla_{\theta_i} J(\theta_i)$ completely ignoring the fact that θ_{-i} are also changing.
- **Pro**: Incredibly simple and scalable. It's just single-agent RL replicated N times.
- **Con**: Severely violates the stationarity assumption. Often fails to converge, leading to chaotic, unstable policies.

APPROACH 2: CENTRALIZED CRITIC (THE COORDINATOR)

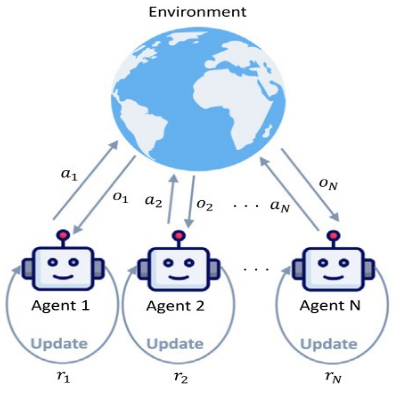
Analogy: The Dance Instructor

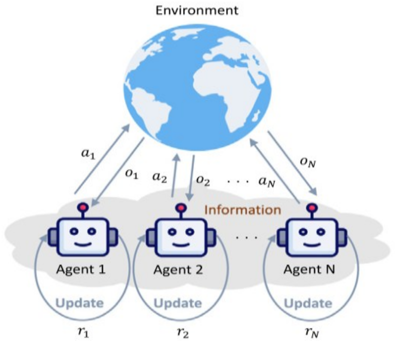
A central instructor watches everyone and gives personalized feedback, but the dancers must perform on their own during the final show.

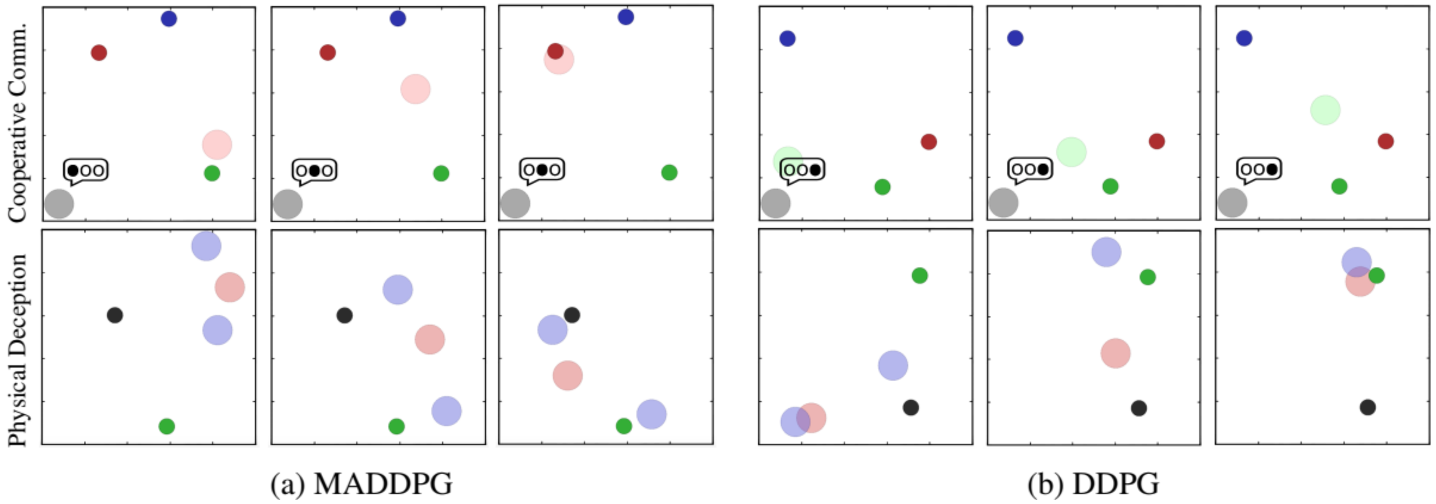
Method: (MADDPG, COMA, MAPPO)

- Follows the Centralized Training, Decentralized Execution (CTDE) paradigm.
- **During training**: A centralized critic sees everyone's observations and actions $(s, a_1, ..., a_N)$.
- This allows the critic to learn an accurate value function $Q_i(s, a_1, ..., a_N)$ and provide a stable, informed gradient to each agent.
- **During execution**: The critic is thrown away. Each agent acts using only its local policy.

CASE STUDY: INDEPENDENT & CENTRALIZED







https://www.sciencedirect.com/science/article/pii/S2949855424000042

https://arxiv.org/pdf/1706.02275

SECTION 3: MEAN FIELD THEORY

From Individuals to Population Trends

THE CURSE OF MANY AGENTS

Problem: The joint action space grows *exponentially* with the number of agents.

- 2 agents, 4 actions each: $4^2 = 16$ joint actions. (Easy)
- 5 agents, 4 actions each: $4^5 = 1,024$ joint actions. (Manageable)
- 10 agents, 4 actions each: $4^{10} > 1,000,000$ joint actions. (Intractable)
- 100 agents... 😵

We need a way to simplify!

Can we approximate the effect of the crowd without modeling every single individual?

MEAN FIELD THEORY: THE ”STATISTICAL AVERAGE” APPROACH

Instead of tracking every agent, track the behavior of the *average* agent.

The core assumption of MFT is that the influence of any single agent on another becomes negligible as $N \to \infty$. What matters is the **collective, average effect** of the population.

- An N-player game is simplified into N parallel 2-player games.
- Each game is played between an agent i and the "mean field" (the average policy of all other agents, $\bar{\pi}$).

HOW MEAN FIELD RL WORKS: THE MATH

The standard Q-function depends on all individual agent actions and states:

$$Q_i(s_i, a_i, s_{-i}, a_{-i})$$

This is approximated in Mean Field Q-learning by taking the expectation over the *average action* $\bar{a}$ from the mean policy $\bar{\pi}$:

$$Q_i(s_i, a_i) \approx \mathbb{E}_{\bar{a}_{-i} \sim \bar{\pi}}[Q_i(s_i, a_i, \bar{a}_{-i})]$$

The Payoff

The Q-function for agent i now only depends on its own state-action and the *mean policy* of its neighbors, drastically reducing complexity.

APPLICATION: SWARM ROBOTICS

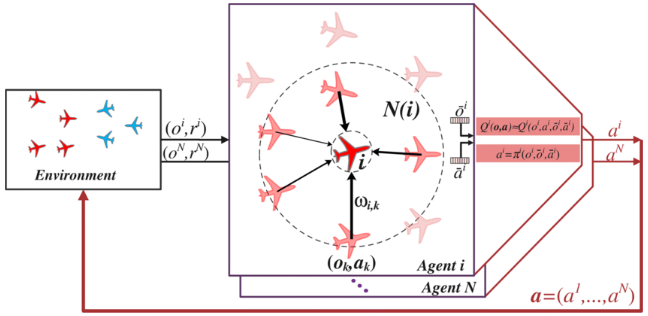
Challenge

- Coordinate thousands of simple drones or robots.
- It's intractable to model every drone-to-drone interaction.

Mean Field Solution

- Each drone doesn't need to know what every other specific drone is doing.
- It only needs to react to the average movement, density, and direction of the swarm in its vicinity.

https://www.azorobotics.com/Article.aspx?ArticleID=4



https://link.springer.com/article/10.1007/s10489-022-03840-6

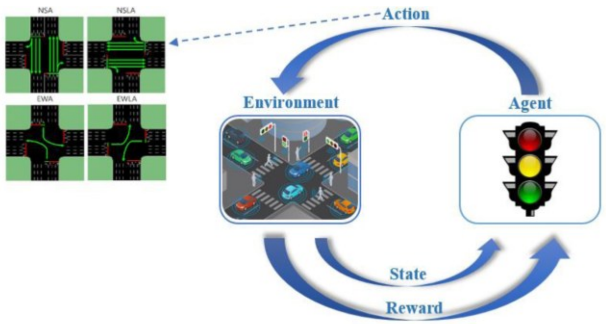
APPLICATION: ECONOMICS & TRAFFIC

Challenge

- Simulate city-wide traffic flow or financial markets with millions of participants.
- The behavior of any one driver or trader is statistically insignificant.

Mean Field Solution

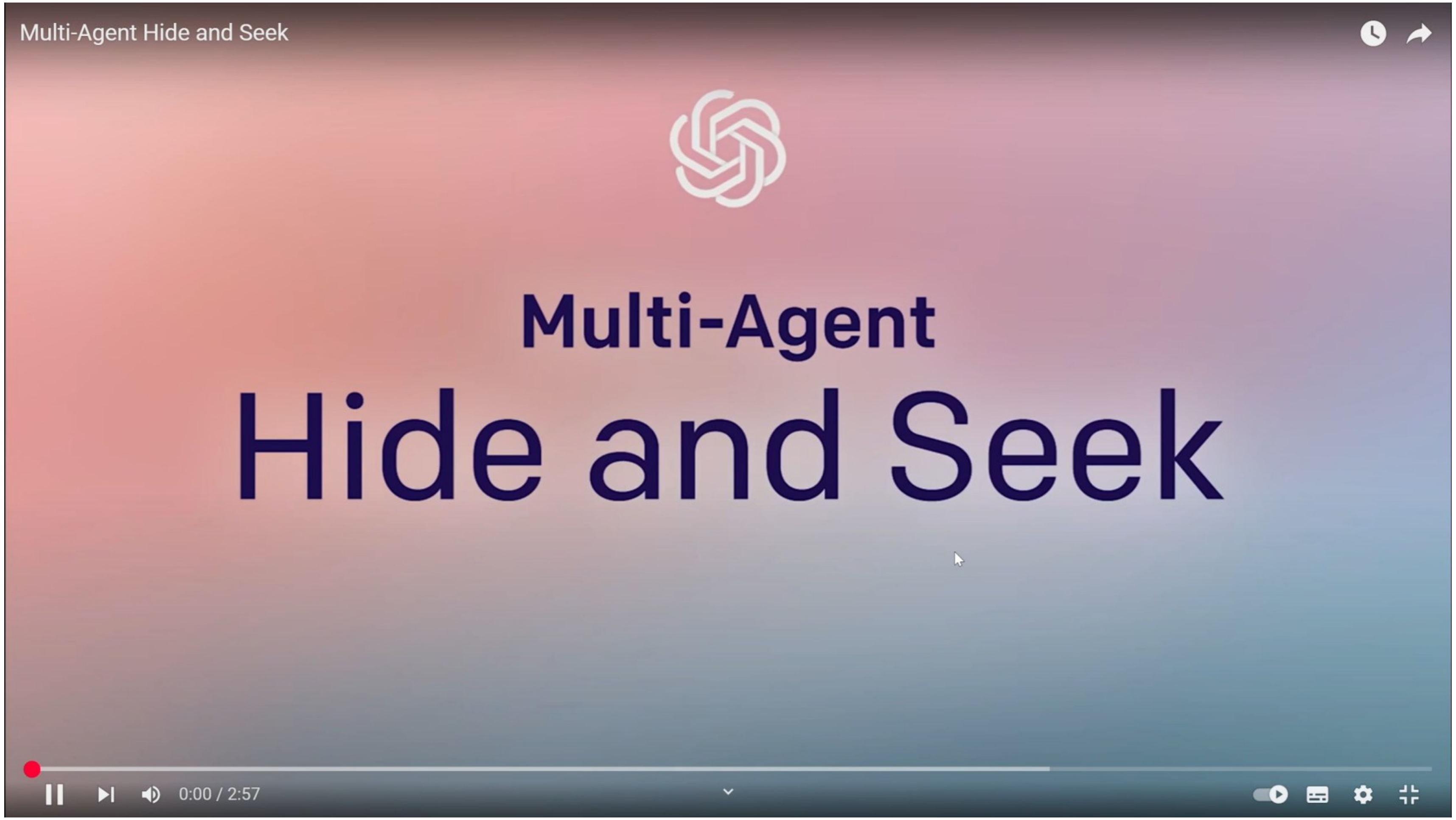
- Model how an individual driver reacts to average congestion levels.
- Model how a trader reacts to average market sentiment (e.g., bull vs. bear market).



https://www.sciencedirect.com/science/article/pii/S1084804522001394

https://www.frontiersin.org/journals/artificial-intelligence/articles/10.3389/frai.2021.749878/full

LIVE DEMONSTRATION



https://www.youtube.com/watch?v=kopoLzvh5jY

Let's watch these learning dynamics in action...

SUMMARY KEY TAKEAWAYS

1. **Learning dynamics are the core of MARL**: Non-stationarity is not a bug, it's a feature of this "evolutionary game."
2. **Self-Play creates a robust learning curriculum**: It forces agents to become robust and general by creating a never-ending arms race (AlphaStar).
3. **Policy gradients require careful coordination**:
   - *Independent Gradients* (The Optimist): Simple, but often unstable.
   - *Centralized Critics* (The Coordinator): Stable and effective, the cornerstone of modern CTDE methods.
4. **Mean Field Theory is the key to massive scale**: It tames the curse of dimensionality by replacing individual interactions with a population average.

HOMEWORK: INDEPENDENT VS. CENTRALIZED PPO

Theoretical Questions

1. Read Lowe, R. et al. (2017). *Multi-Agent Actor-Critic for Mixed Cooperative-Competitive Environments.*
2. In 3-4 sentences, explain how MADDPG's centralized critic provides a stable learning signal, and why this is not possible for an independent learner.

Practical Challenge

- **Goal**: Complete a MAPPO (Multi-Agent PPO) implementation and compare its performance against a provided IPPO baseline.
- **Environment**: PettingZoo's 'simple_spread', where agents must learn to cover target landmarks.
- **Task**: A Python script with the IPPO baseline and a MAPPO skeleton is provided. Your job is to fill in the missing sections in the `MAPPOAgent`'s `update` method.

NEXT TIME ON MARL…

Lesson 4: Real-World Complexities – From Theory to Practice

We leave the ideal world behind and tackle the messy, practical challenges of real-world MARL.

- **Challenge 1: The Fog of War (Partial Observability)**
  - How do agents make decisions with incomplete information?
  - Using Memory and Attention to see through the mist.
- **Challenge 2: The Art and Science of Communication**
  - From learned "secret handshakes" to efficient, compressed messages.
  - Hierarchical Coordination: The "Manager-Worker" paradigm.
- **Challenge 3: Robustness and Safety**
  - How to build agents resilient to adversarial attacks and noise.
  - Balancing performance with critical safety constraints.

Questions?