TACTICAL DIGITAL TWIN
RL FOR FOOTBALL STRATEGY

Tactical Digital Twin in Football

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Problem introduction

Modern football analysis fails to objectively evaluate the complex, real-time tactical contribution of players on the pitch.

Our project delivers a Tactical Digital Twin solution that uses advanced reinforcement learning and self-play to discover and optimize next-generation football strategies.
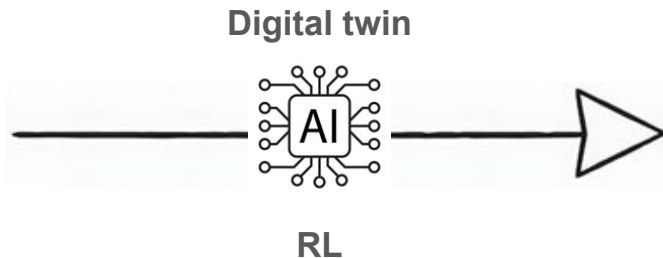
Problem introduction

'What happened'

Digital twin

AI

RL

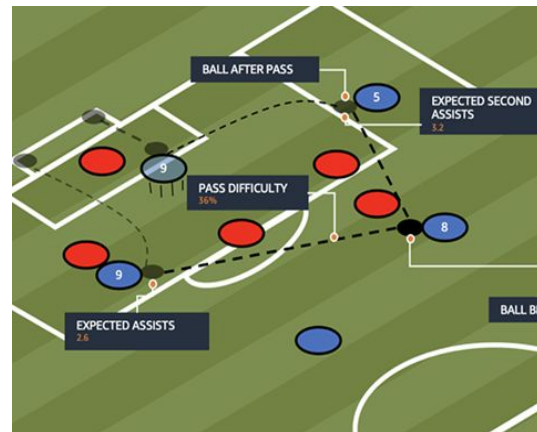*'What can happen'*

Descriptive analytics

Predictive & Prescriptive analytics

Value proposition

This project supports **Goal 9 (Industry, Innovation, and Infrastructure)** by promoting cutting-edge AI applications in the sports engineering sector, helping to improve infrastructure and innovation in performance optimization technologies.

Target 9.5: Enhance Research and Upgrade Industrial Technologies.

Target 9.4: Upgrade All Industries and Infrastructures for Sustainability.

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

Objectives

Develop a reproducible framework (digital twin) under realistic constraints, using real or synthetic data

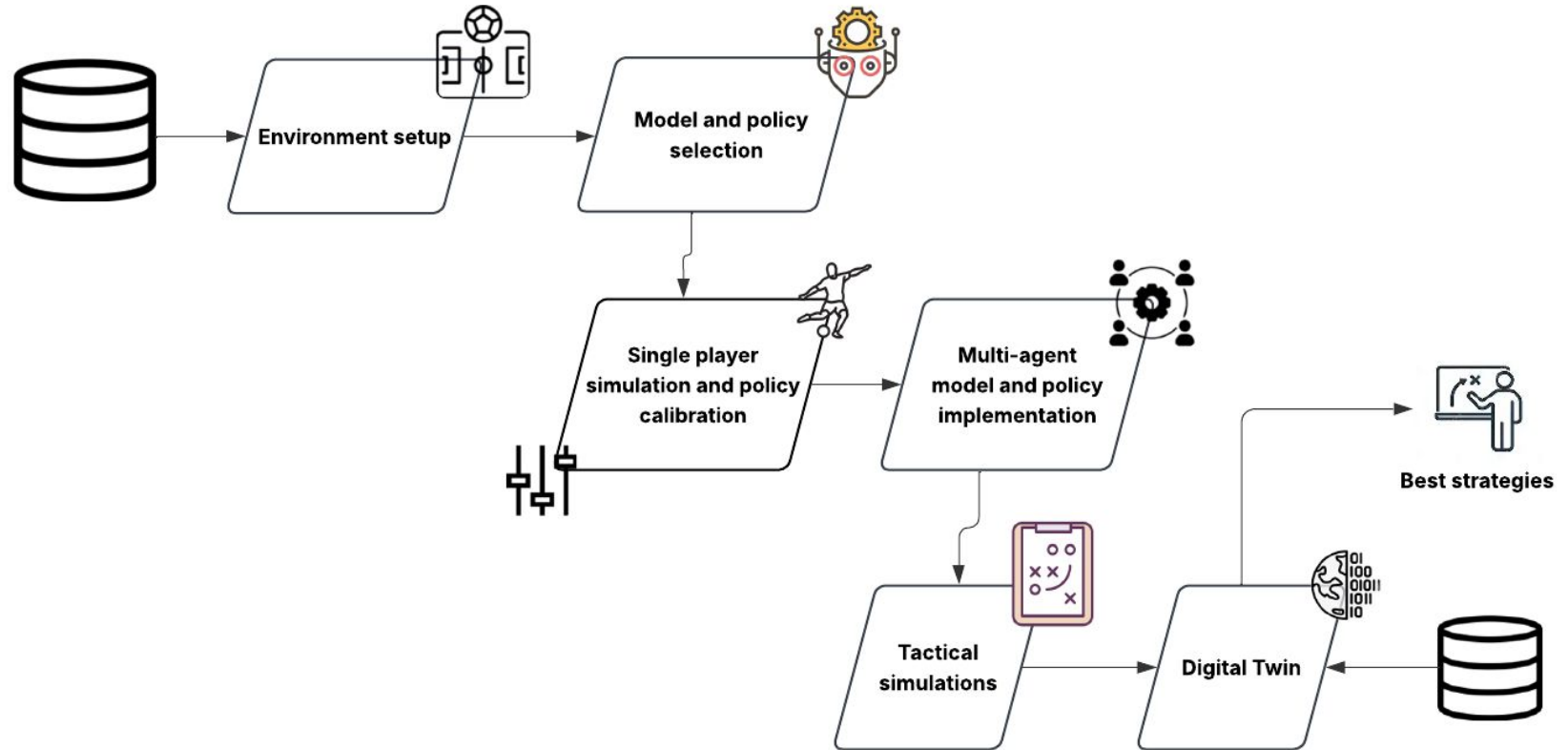Apply AI techniques to **simulate and optimize tactical behaviors**

Integrate real tracking or event data for **validation and calibration**

Design evaluation metrics to assess tactical effectiveness and realism

Functional Diagram

Environment - Objects

Pitch, **Ball**, and **Players** objects define the simulation world.

Dimensions:
Standard **120×80m** pitch

Coordinate System:
Normalized **[0,1]**

Position-Based Reward:
Elliptical reward grids
(Heatmaps)

Ball Radius:
Standard **0.11m** football

Dual Dynamics:
Between "**Free Physics**"
and "**Owned State**"

Tuned Friction:
Low-friction decay **0.15%**

Sensory Constraints:
Limited by Field of View

Probabilistic Execution:
Skills incorporate
parametric noise

Event-Based Reward:
goals, passes, tackles,
and saves

Environment - Single Agent

Setup: 1v1 on a half-pitch scale

- Attacker: the learning agent, initialized with the ball
- Defender: a programmed bot that follows/chases the attacker (non-learning)
- Objective: drive the ball towards the Goal while evading the defender

Observation Space: define the agent's sensory input

- All positions (player, ball) are scaled to [0,1] relative to the pitch size
- Internal States: Shooting Flag (is_shooting), Shot Power, and Direction.

Action Space: define the control output of the agent

- Movement: 2D vector for directional running
- Shooting: Binary Trigger (shoot or not), Power (intensity), and Direction vector.
- Realistic Constraints: must maintain possession while executing these actions

Environment - Multi Agent

Simultaneous Decision-Making

Multiple agents (attackers, defenders, goalkeeper) take decisions at the same timestep

Role-Specific Behaviors

Each player has a role (ATT, DEF, GK) that shapes how they move, reposition, defend or shoot

Individual Perspectives

Each agent observes the game from its own viewpoint: own state, ball state, nearby players, tactical context
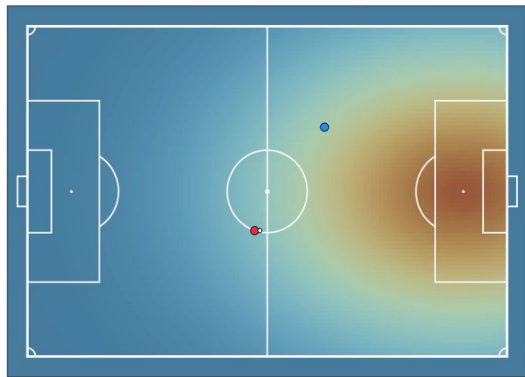
Emergent Team Dynamics

Agents can be rewarded both individually and as a team, leading to coordination patterns: pressing, covering, supporting, blocking

Environment - Tactical Scenarios
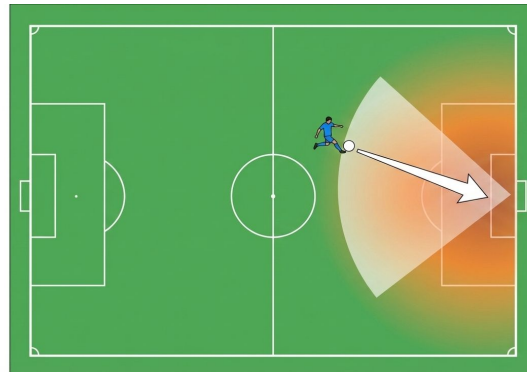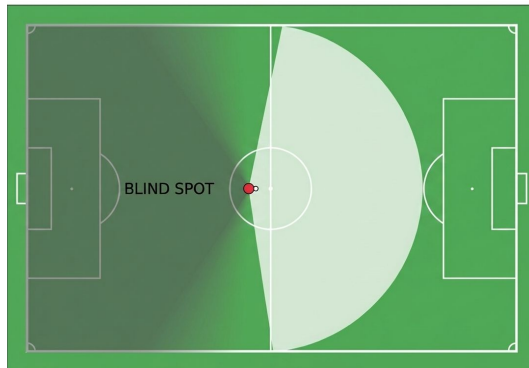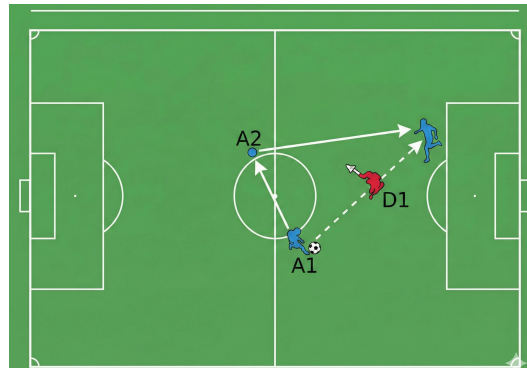
Move

Shot

View

Pass

PPO
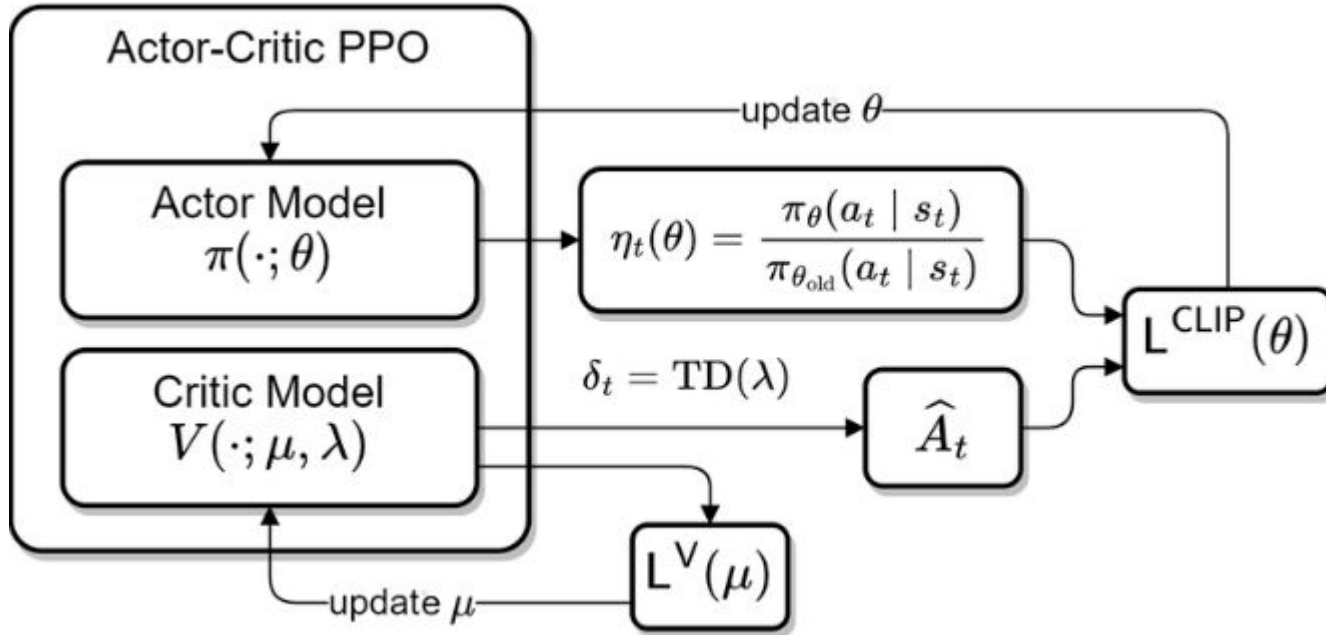
MARL
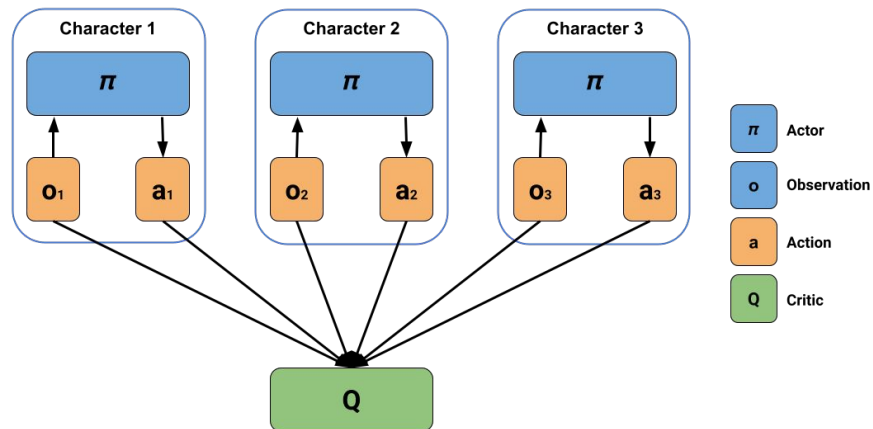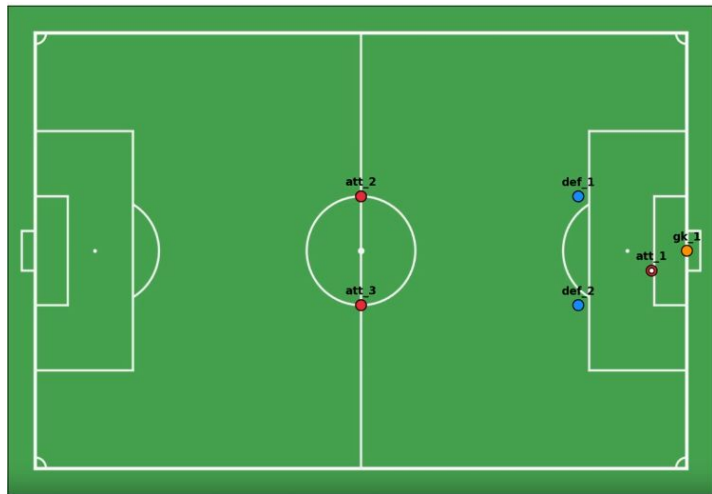
Centralized Training with Decentralized Execution

What we're doing next

Realistic players
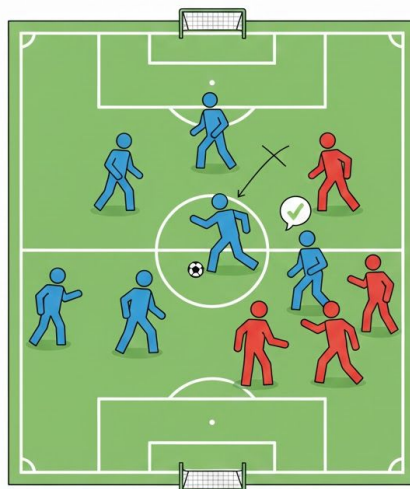
Adversarial learning

New reward function

Thank you !