TACTICAL DIGITAL TWIN
RL FOR FOOTBALL STRATEGY

# Tactical Digital Twin in Football

Michele Curci - s337117
Lorenzo Ferrandi - s349309
Xueyufei Zhang - s336472

# Problem introduction

Modern football analytics mainly focuses on **descriptive, post-match metrics.**

However, tactical decisions depend on **contextual, multi-player interactions** that are poorly represented by traditional, player-centric metrics.


Our challenge is to study these interactions through **controlled simulations**, enabling the evaluation of **alternative tactical decisions** in simplified football scenarios.

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# 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.

# Objectives

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**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

# Research questions

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**Counterfactual Reproducibility**: To what extent can agents trained via Proximal Policy Optimization (PPO) successfully resolve high-leverage tactical scenarios extracted from real-world historical event data?

**Robustness through Adversarial Play**: How does the introduction of an asynchronous adversarial evolution mechanism impact the stability and emergent coordination of offensive passing policies compared to static defensive baselines?

**Impact of Agent Heterogeneity**: How do variations in physical and technical player attributes—specifically locomotion speed and shooting precision—alter the feasibility and selection of optimal tactical trajectories within the simulation?

**Reward Shaping and Convergence**: Can the combination of dense spatial potential fields (Elliptical Reward Grids) and sparse event-based rewards sufficiently mitigate the credit assignment problem in complex multi-agent football scenarios?

# User Persona

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**Thomas Lindberg**

Technical Performance Analyst

MSc Sports Data Analytics
UEFA B License
Expert in Python/R & Tracking Data

## GOALS

Automate tactical feature extraction from raw tracking data
Run *what-if* match simulations
Use data models to validate tactical decisions objectively

## FRUSTRATIONS

Manual data cleaning and tagging take too much time
Raw coordinates are difficult to translate into tactical insights
Current tools are too rigid to match our specific scenarios

## NEEDS

Export raw simulation data for internal team dashboards
Quickly test tactical changes like pressing or tackling
Automatically identify opponent habits and defensive gaps

# Thomas's Journey

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## 1. Stuck in Raw Data

Thomas spends hours manually cleaning tracking data after a match. The process is slow, and the raw numbers lack tactical context for the coaches.

## 2. Searching for Context

He searches for a tool to automate feature extraction from raw data. He needs a platform that can quickly test tactical scenarios ("what-if" analysis).

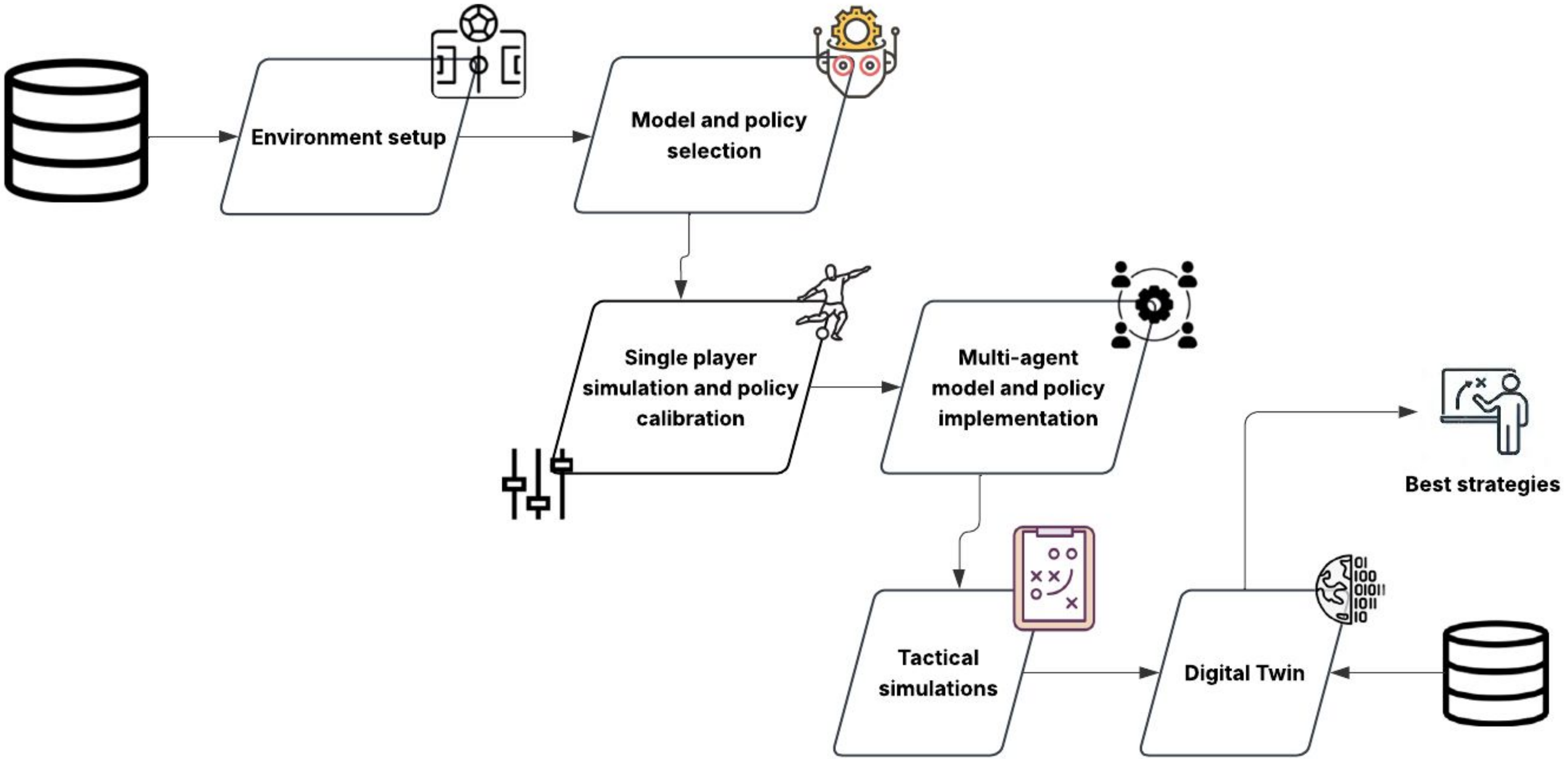
## 3. Simulating the Pitch

Thomas adopts the new digital twin system to run automated match simulations. This allows him to objectively validate different tactical adjustments.

## 4. Empowering the Staff

He provides the coaching staff with model-validated insights. The clear, evidence-based reports save time and make his tactical briefings more effective.

# Functional Diagram



# Environment - Objects

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**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

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## **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

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### 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

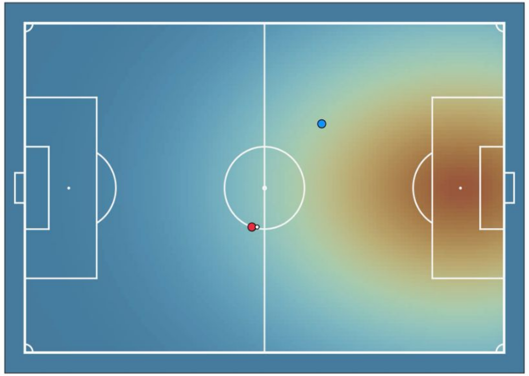
Each agent observes the game from its own viewpoint: own state, ball state, nearby players, tactical context

### Emergent Team Dynamics

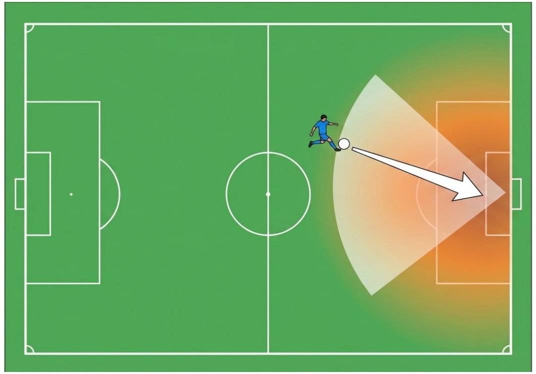
Agents can be rewarded both individually and as a team, leading to coordination patterns: pressing, covering, supporting, blocking

# Environment - Tactical Scenarios

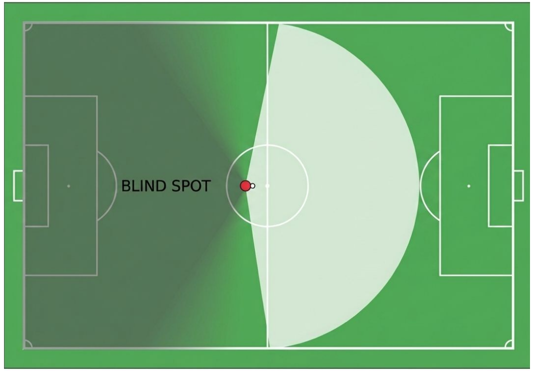
Move



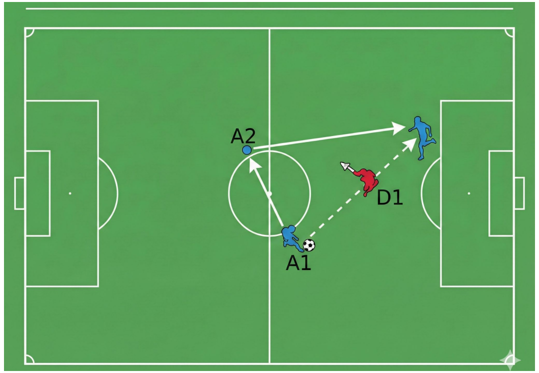
Shot



View




Pass



# PPO

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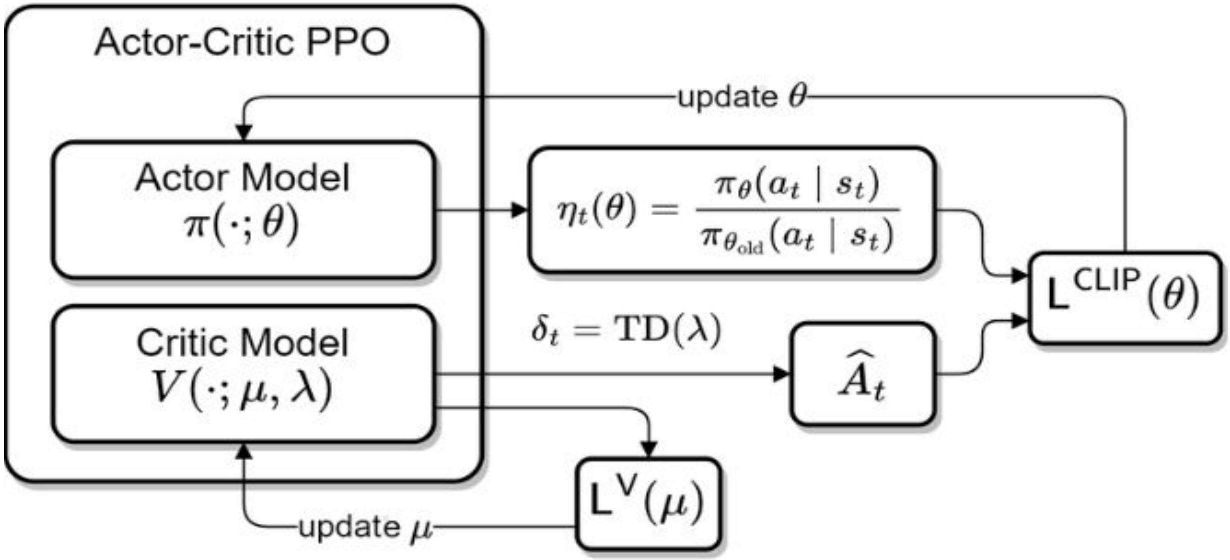


https://huggingface.co/learn/deep-rl-course/unit8/intuition-behind-ppo

# MARL

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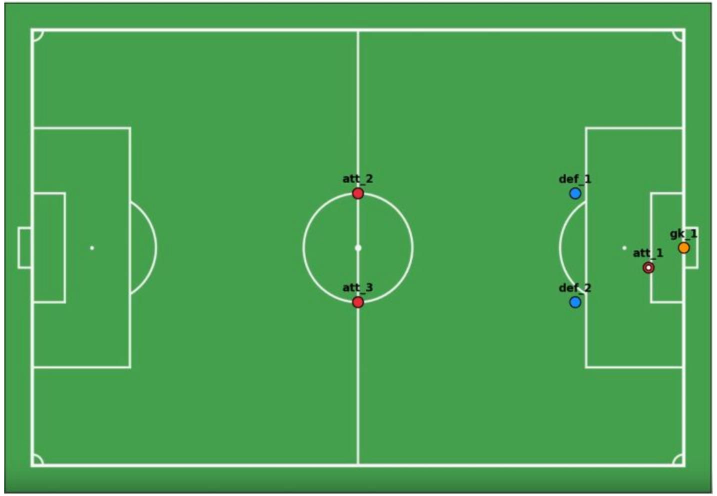
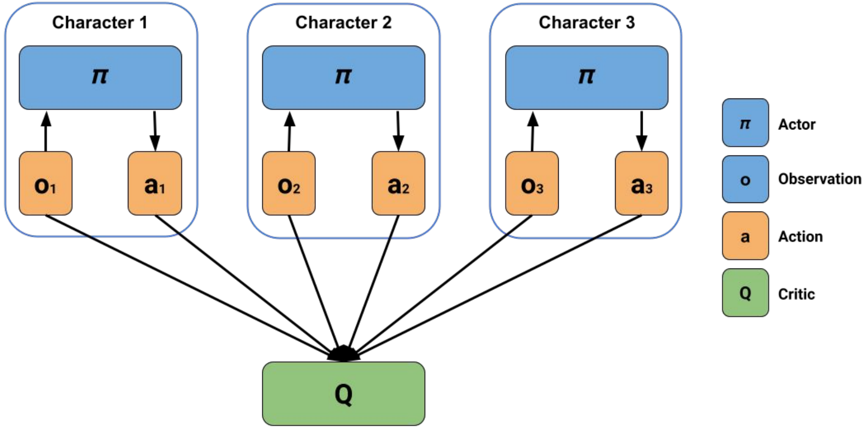



Centralized Training with Decentralized Execution

# Adversarial Learning

## Asynchronous Evolution Mechanism

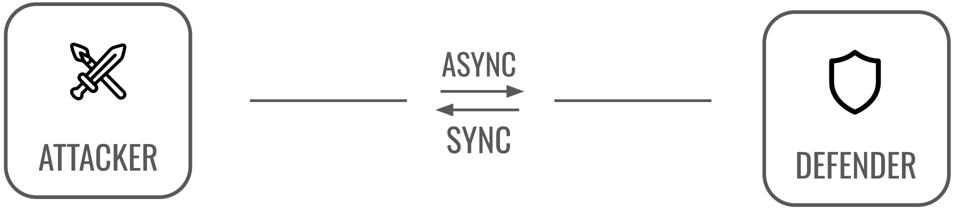
This method replace the traditional synchronous approach, updates with **alternating freezing training**. In 3000 episodes, the training focus switches every 500 episodes. This simulates a cycle where a “coach gives specific tactical instructions”.

## Opponent Pool

By training against a diverse historical opponent pool, agents will build a tactical memory that ensures they remain robust against any playstyle, not just the latest one.

## Independent Policy Mapping

Each agent has its **own policy network** instead of using a shared central logic. This makes it possible to add *Realistic Attributes* such as different speed multipliers, different base shot power, etc.



# Realistic Player Profiling

**Player heterogeneity** is introduced by parameterizing agents with different **physical and technical attributes**, enabling the representation of multiple player profiles within the same environment.

The learning algorithm and policy architecture remain **unchanged**.

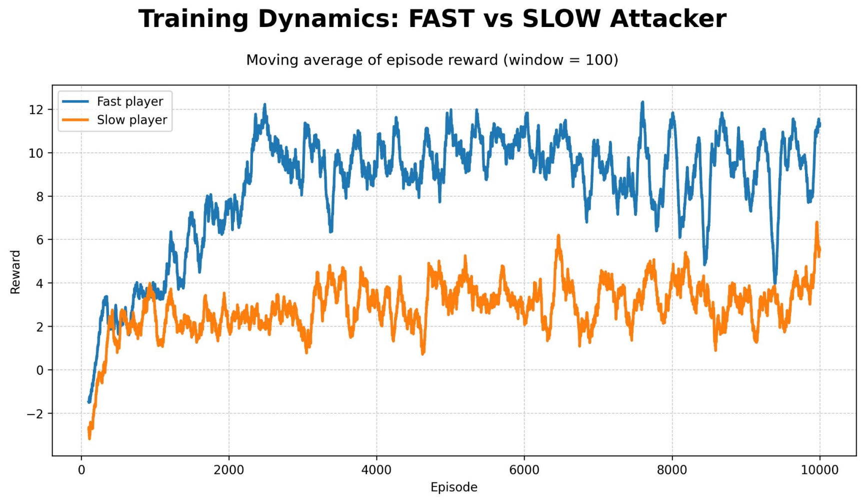
The following characteristics can be independently modified while keeping the learning algorithm unchanged:

- **Movement speed** (affects displacement per step)
- **Shooting power** (affects ball velocity after shot)
- **Shot precision** (affects angular noise in shot direction)

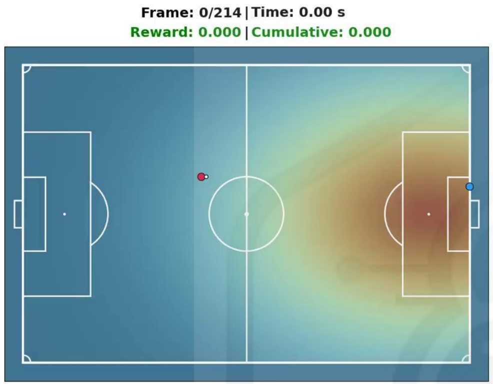
This enables controlled analyses of how individual player skills influence learned behaviors and interaction dynamics.

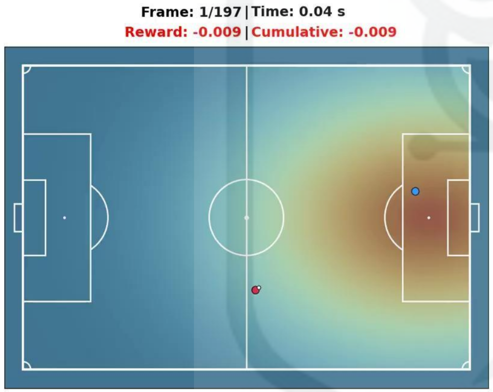
# Speed-Based Player Categorization

Two agents are trained under **identical conditions**, differing only in **attacker speed**, in a *MOVE* scenario.




**Mean reward (last 10%):**
**FAST:** 9.33 **SLOW:** 3.45

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With identical training settings, the fast attacker achieves higher average rewards, which corresponds to **longer possession** and **more effective defender bypassing** in the videos.

# What-if

Dataset: STATSBOMB

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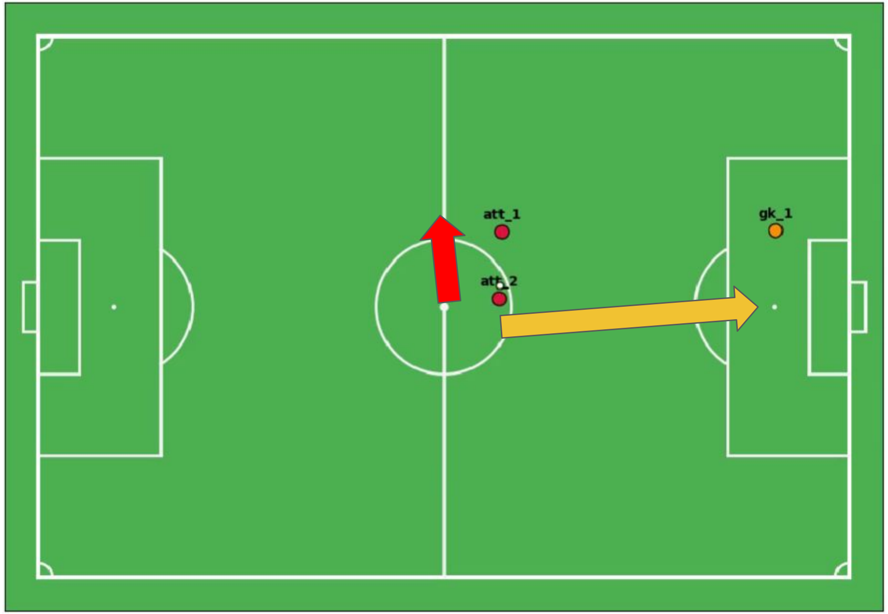
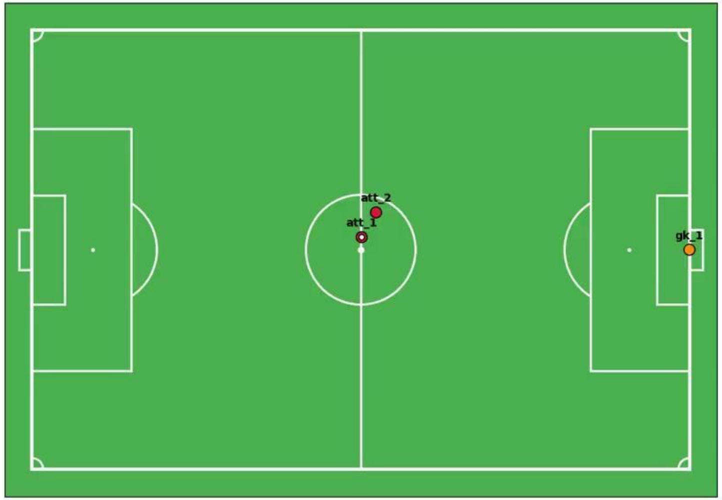
Assists with failed shot




Frame: 0/240



# What-if

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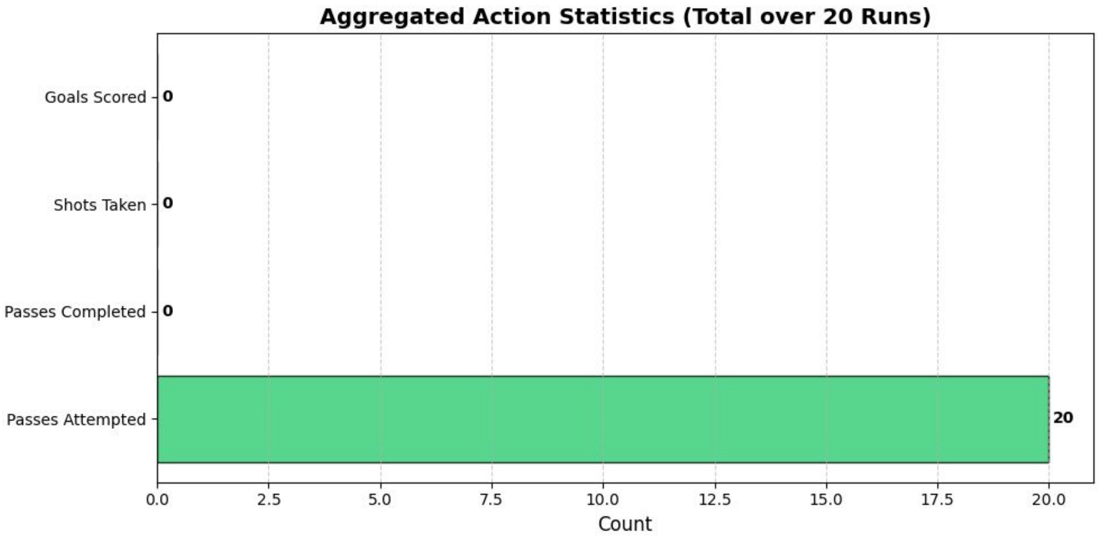
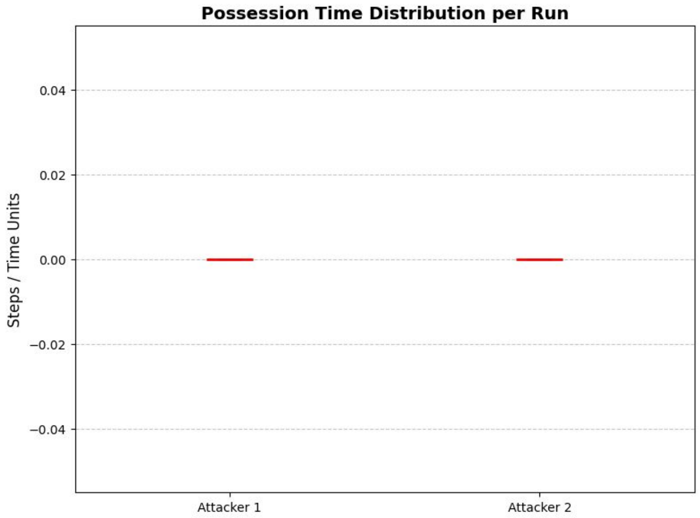
Results show poor performance of the model. The model learns only to pass and often very badly.



# Thank you !

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