



TACTICAL DIGITAL TWIN  
RL FOR FOOTBALL STRATEGY

# Tactical Digital Twin in Football

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# 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.

**9** INDUSTRY, INNOVATION  
AND INFRASTRUCTURE





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# 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



## Thomas Lindberg

Technical Performance Analyst

MSc Sports Data Analytics

UEFA B License

Expert in Python/R & Tracking Data

# User Persona



## 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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## 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).

## 4. Empowering the Staff

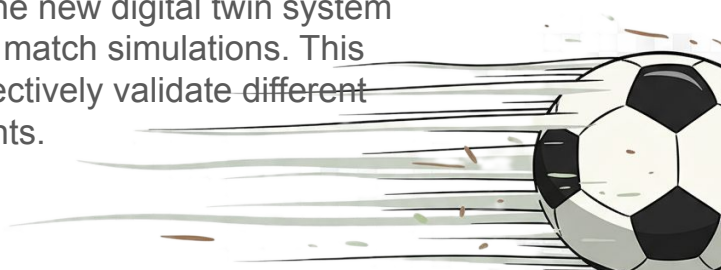
He provides the coaching staff with model-validated insights. The clear, evidence-based reports save time and make his tactical briefings more effective.

## 1. Stuck in Raw Data

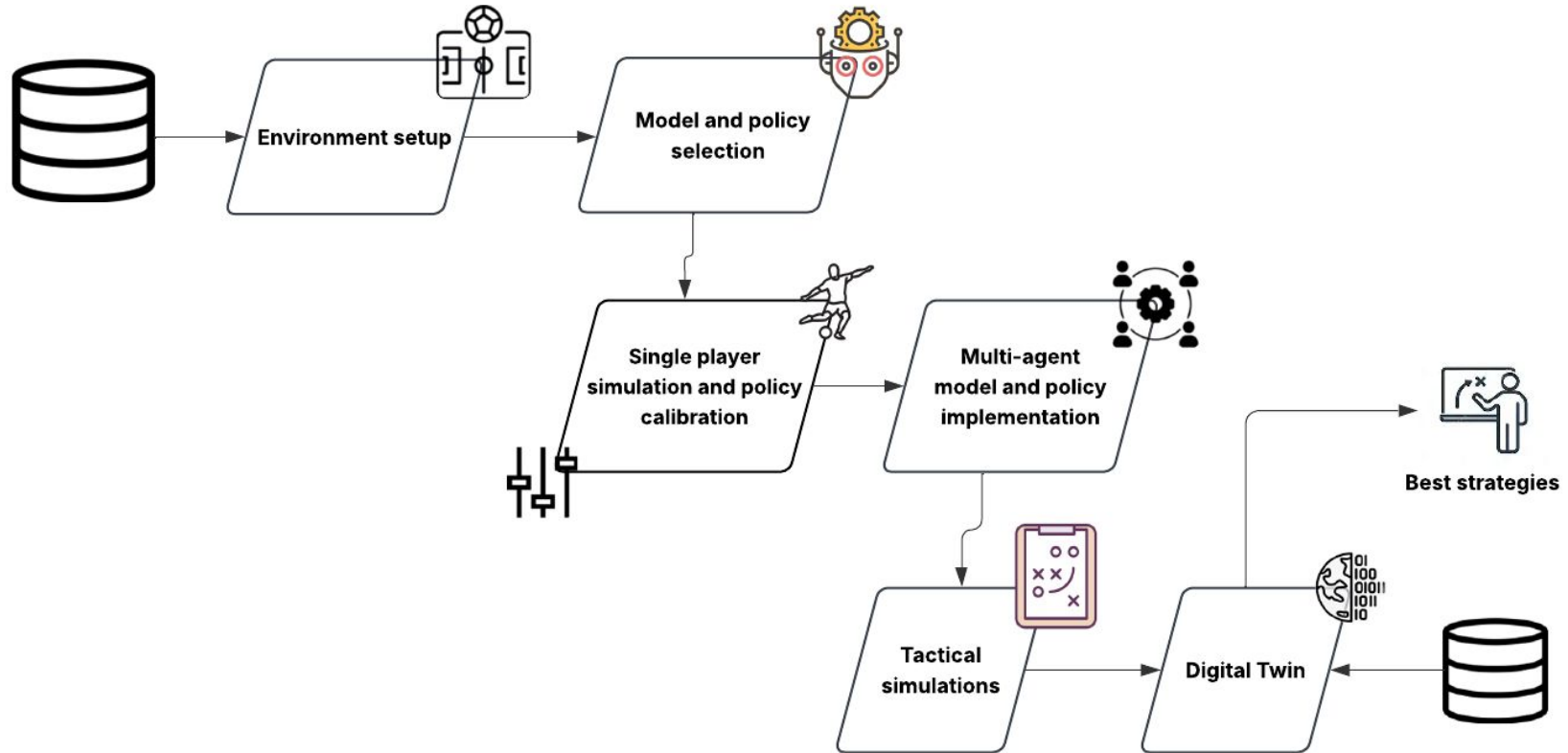
Thomas spends hours manually cleaning tracking data after a match. The process is slow, and the raw numbers lack tactical context for the coaches.

## 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.



# 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



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# 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



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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

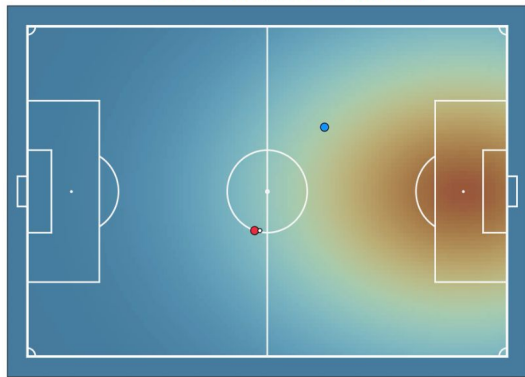
Agents can be rewarded both individually and as a team, leading to coordination patterns: pressing, covering, supporting, blocking

# Environment - Tactical Scenarios

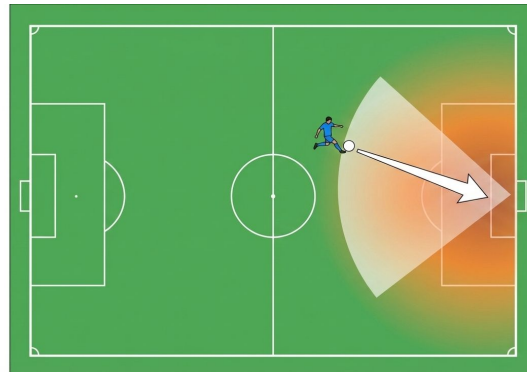


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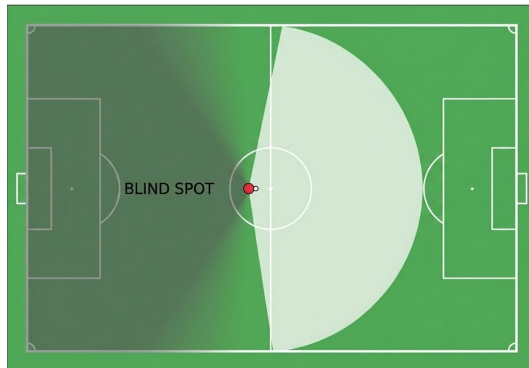
Move



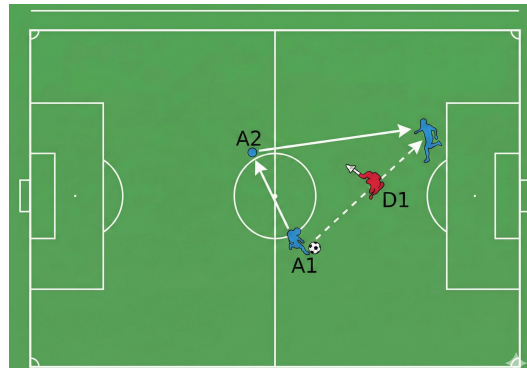
Shot



View



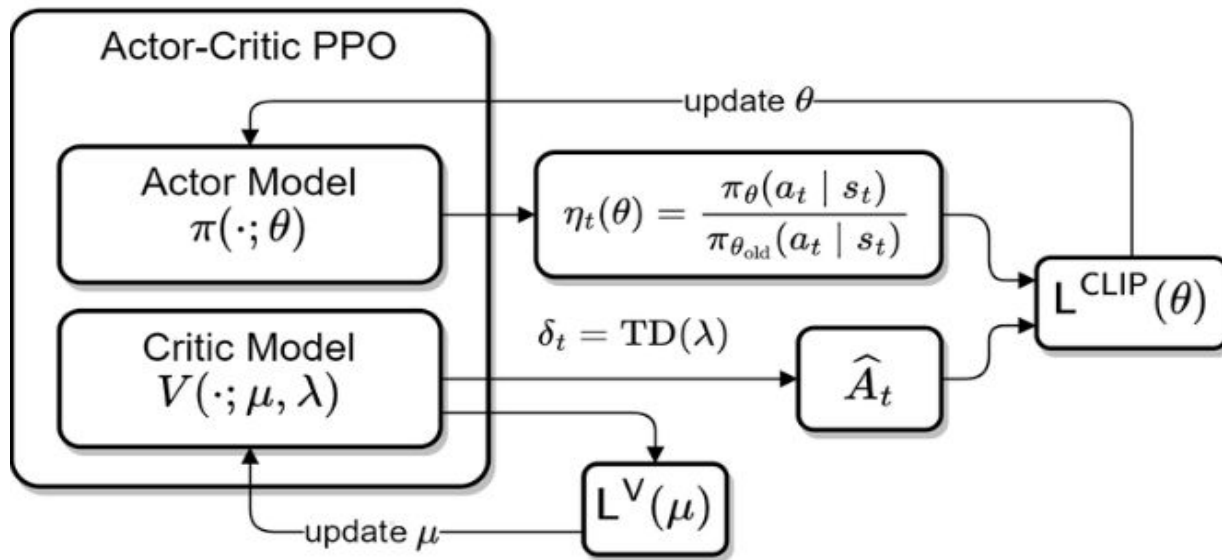
Pass



# PPO



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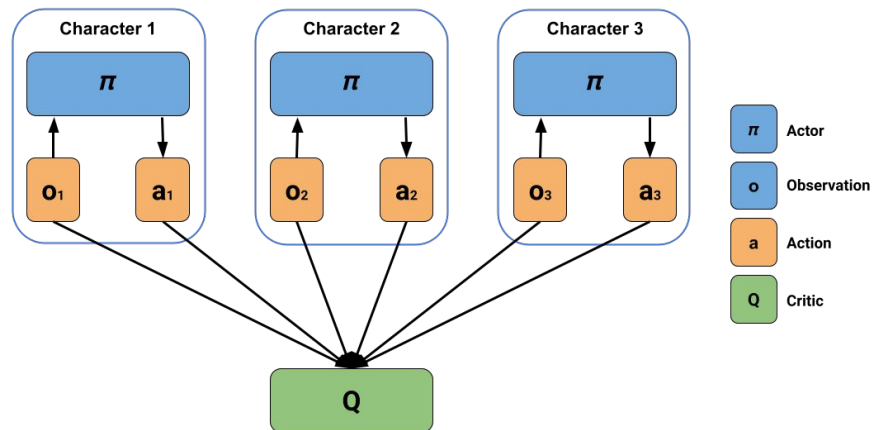
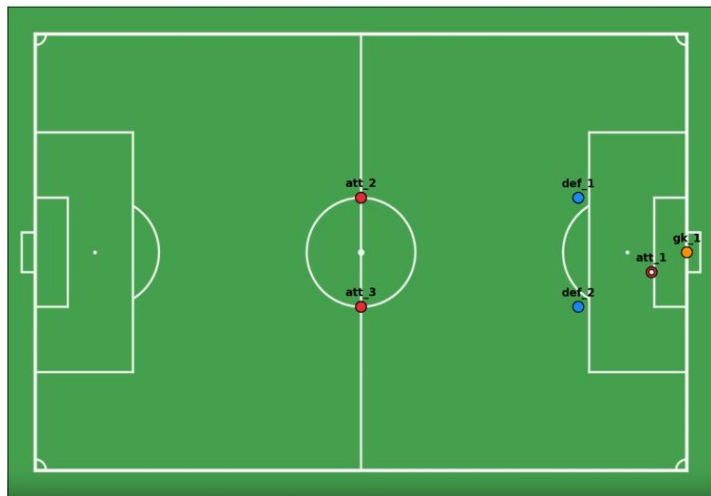


<https://huggingface.co/learn/deep-rl-course/unit8/intuition-behind-ppo>

# MARL



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Centralized Training with Decentralized Execution

# Adversarial Learning

## Asynchronous Evolution Mechanism

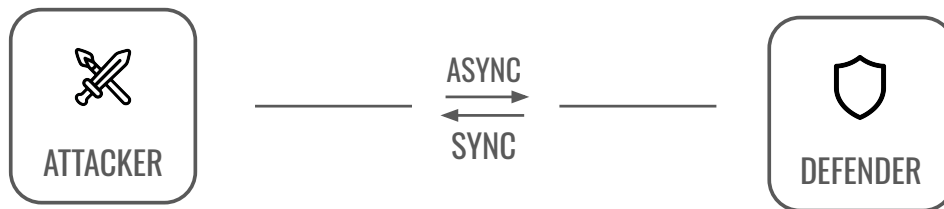
This method replace the traditional synchronous approach, updates with **alternating freezing training**. In 3000 episodes, the training focus switches every 500 episodes. This simulates a cycle where a “coach gives specific tactical instructions”.

## 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.





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# 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)

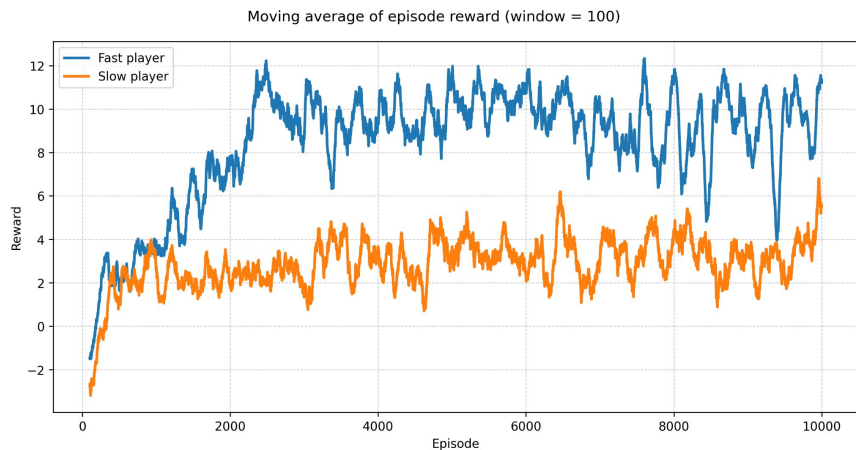
This enables controlled analyses of how individual player skills influence learned behaviors and interaction dynamics.



# Speed-Based Player Categorization

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

## Training Dynamics: FAST vs SLOW Attacker

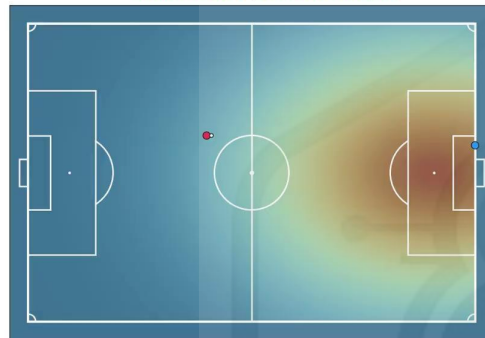


Mean reward (last 10%):

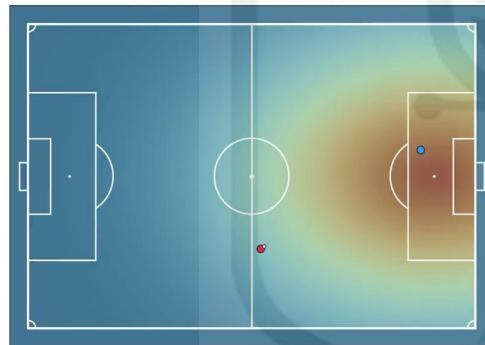
**FAST: 9.33**     **SLOW: 3.45**

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

Frame: 0/214 | Time: 0.00 s  
Reward: 0.000 | Cumulative: 0.000



Frame: 1/197 | Time: 0.04 s  
Reward: -0.009 | Cumulative: -0.009



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# What-if

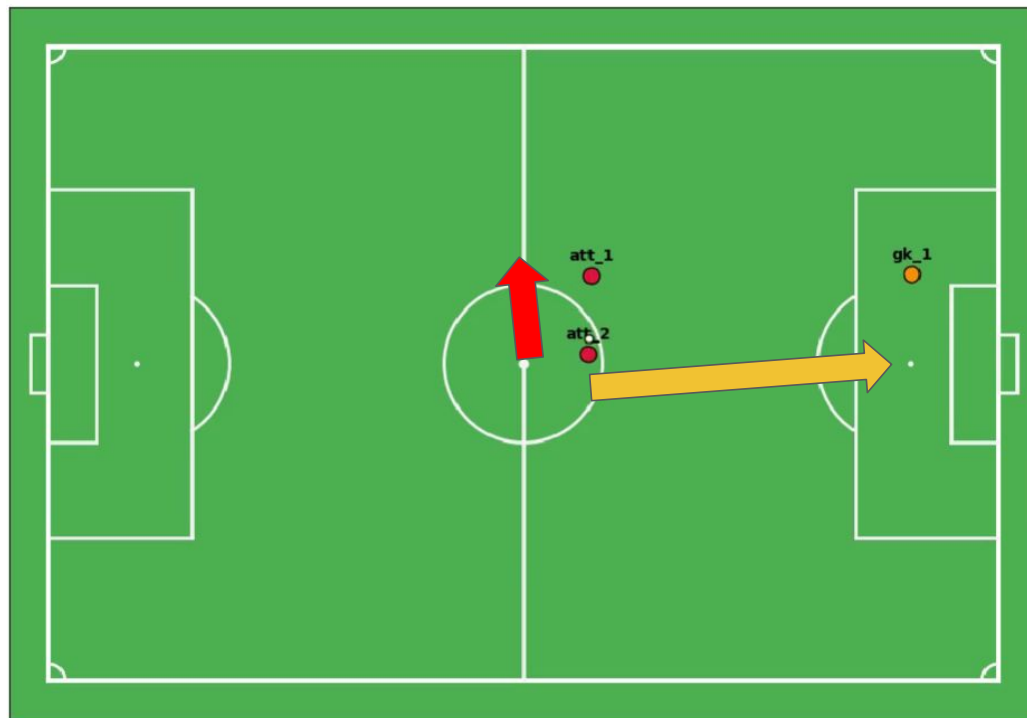


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## Assists with failed shot

Dataset

**STATSBOMB**

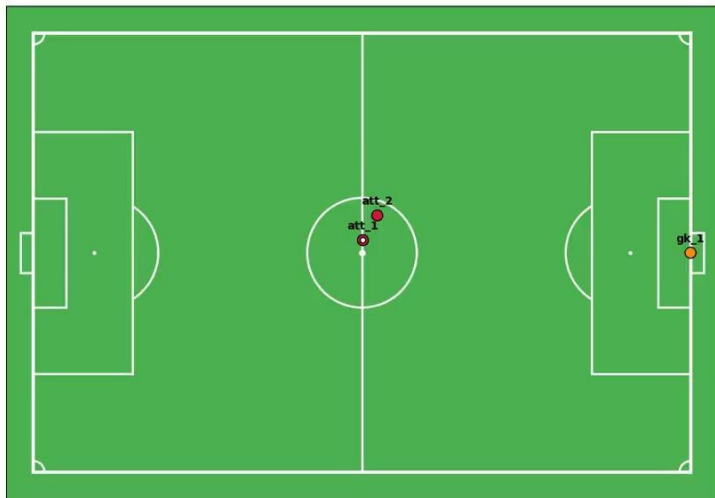


# What-if

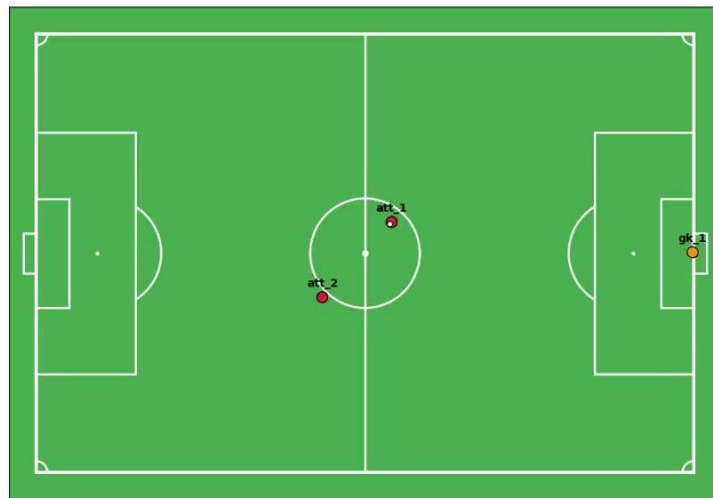


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Frame: 0/240



Frame: 1/240



# Thank you !



**Politecnico  
di Torino**



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