



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.





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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**



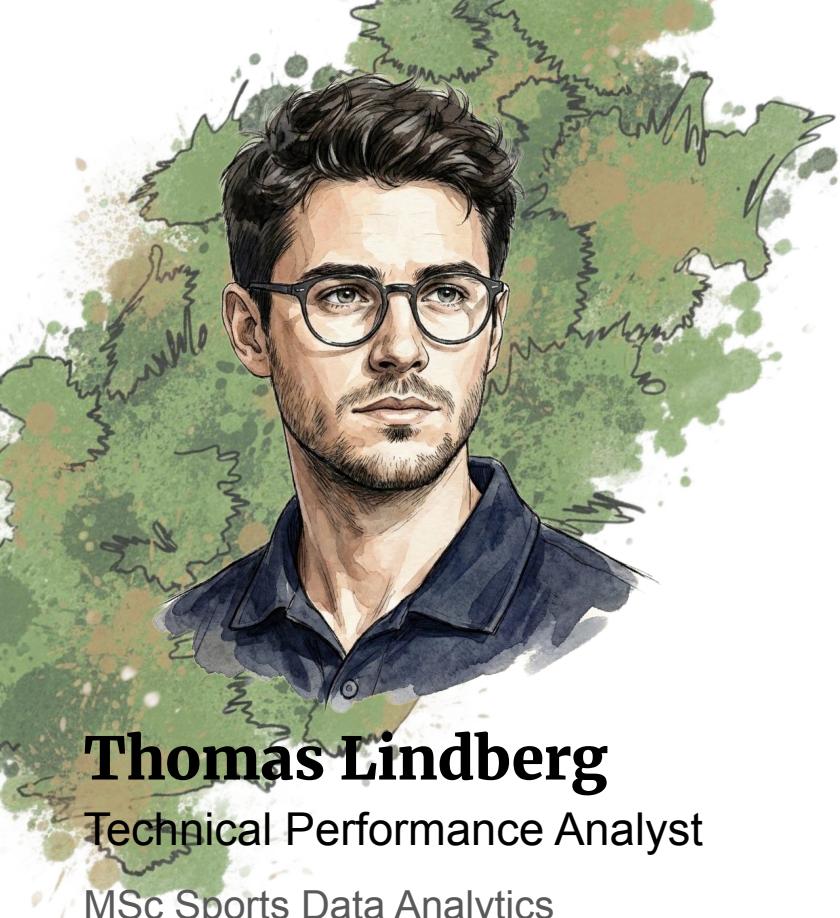
Integrate real tracking or event data for **validation and calibration**



Design evaluation metrics to assess tactical effectiveness and realism



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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

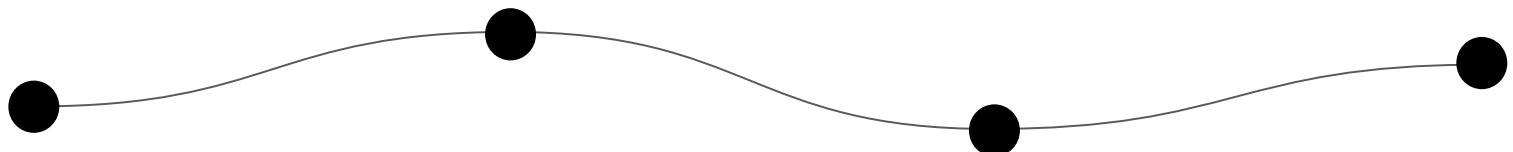


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Thomas's Journey

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.

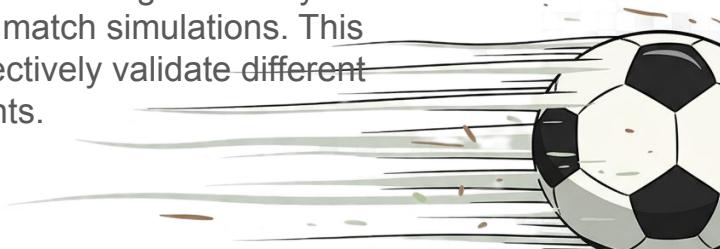


2. Searching for Context

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

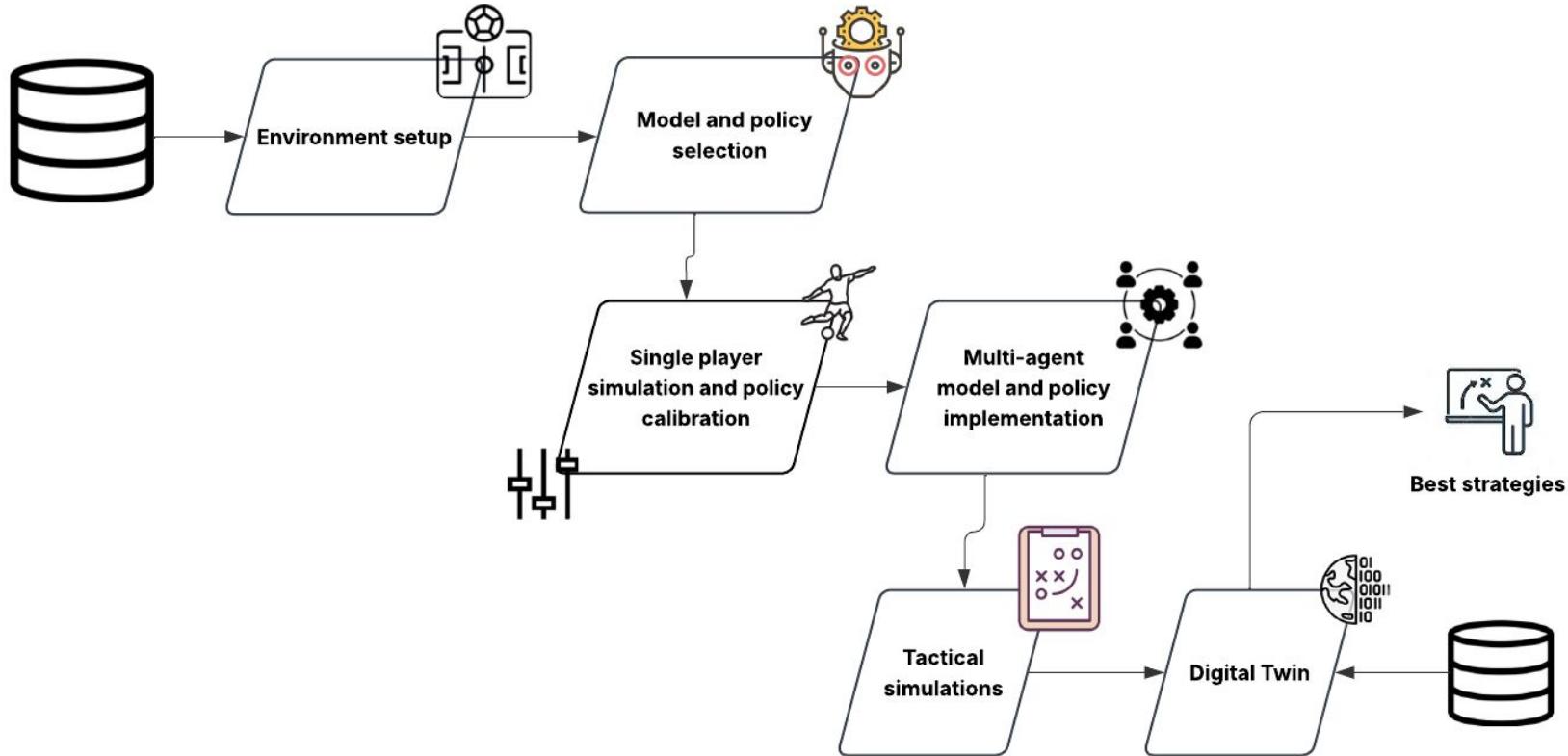
Thomas adopts the new digital twin system to run automated match simulations. This allows him to objectively validate different tactical adjustments.



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





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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



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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

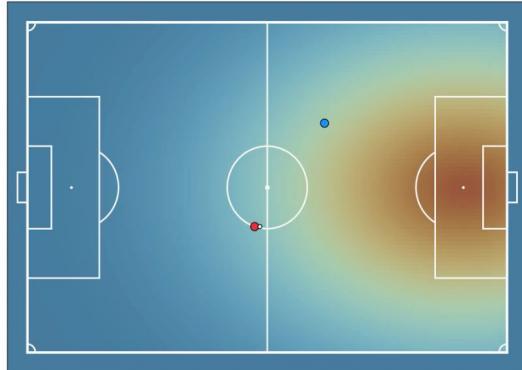
Agents can be rewarded both individually and as a team, leading to coordination patterns: pressing, covering, supporting, blocking



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Environment - Tactical Scenarios

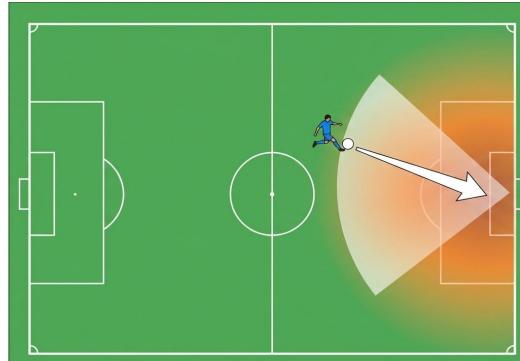
Move



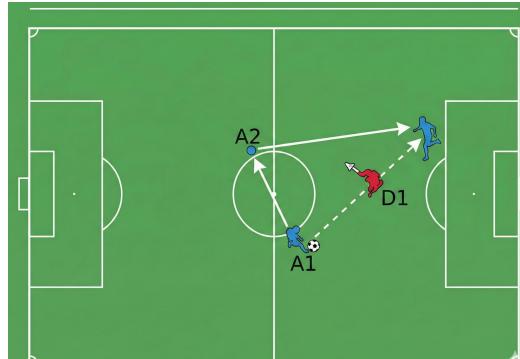
View



Shot



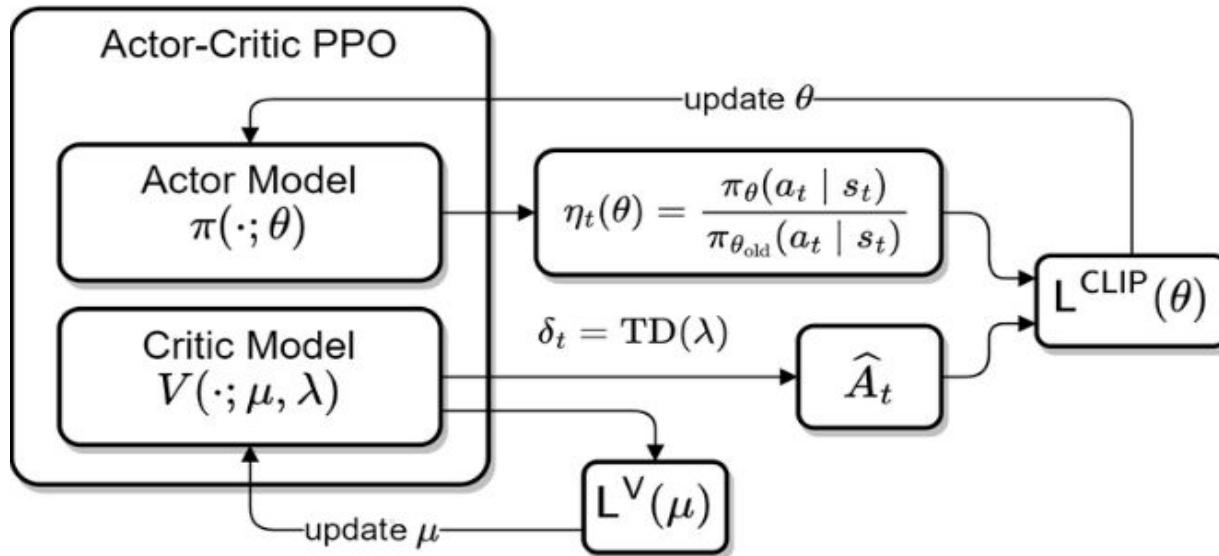
Pass





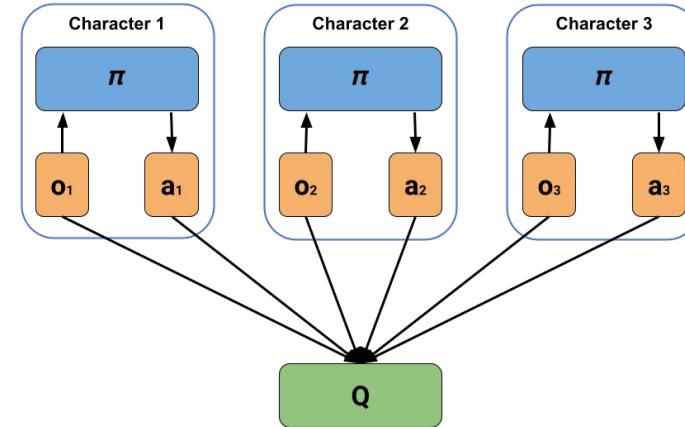
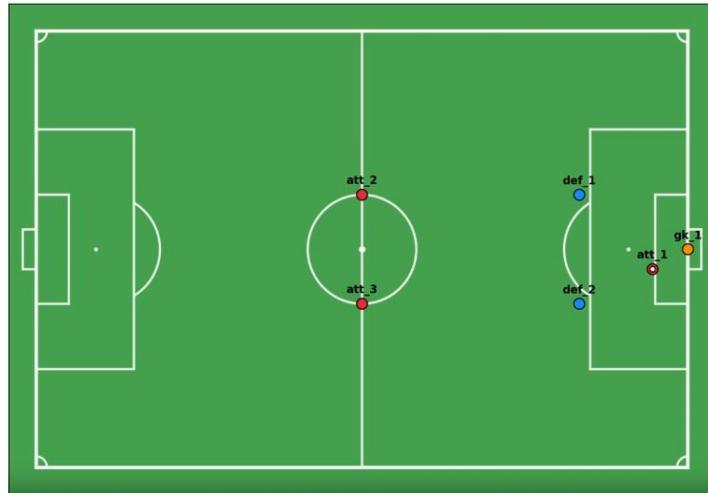
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PPO



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

MARL



Centralized Training with Decentralized Execution



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Adversarial Learning

Asynchronous Evolution Mechanism

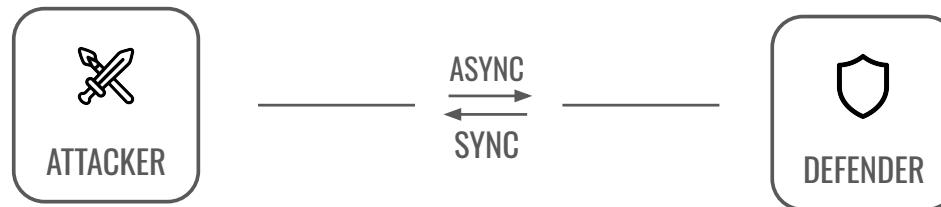
This method replaces the traditional synchronous approach, updating with **alternating freezing training**. In 3000 episodes, the training focus switches every 500 episodes. This simulates a cycle where a “coach gives specific tactical instructions”.

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)

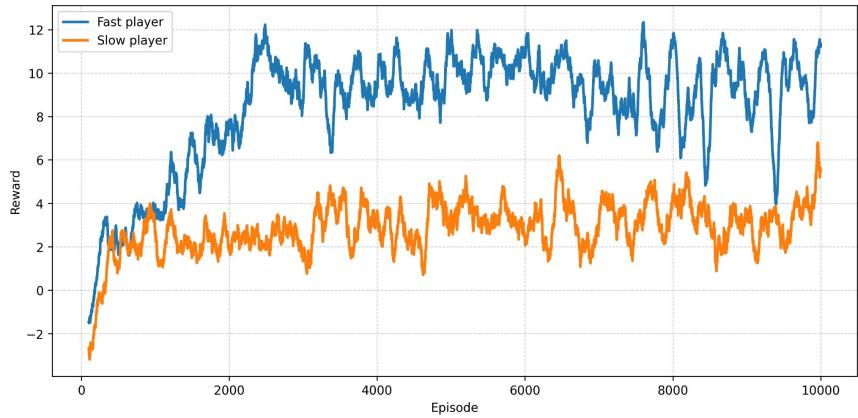
This enables controlled analyses of how individual player skills influence learned behaviors and interaction dynamics.

Speed-Based Player Categorization

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

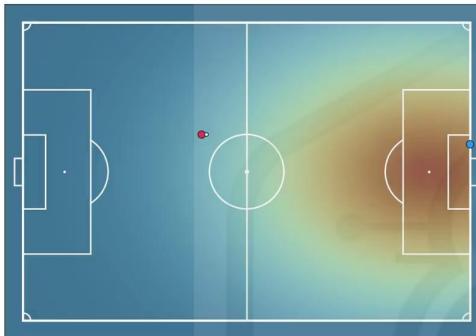
Training Dynamics: FAST vs SLOW Attacker

Moving average of episode reward (window = 100)



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

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



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



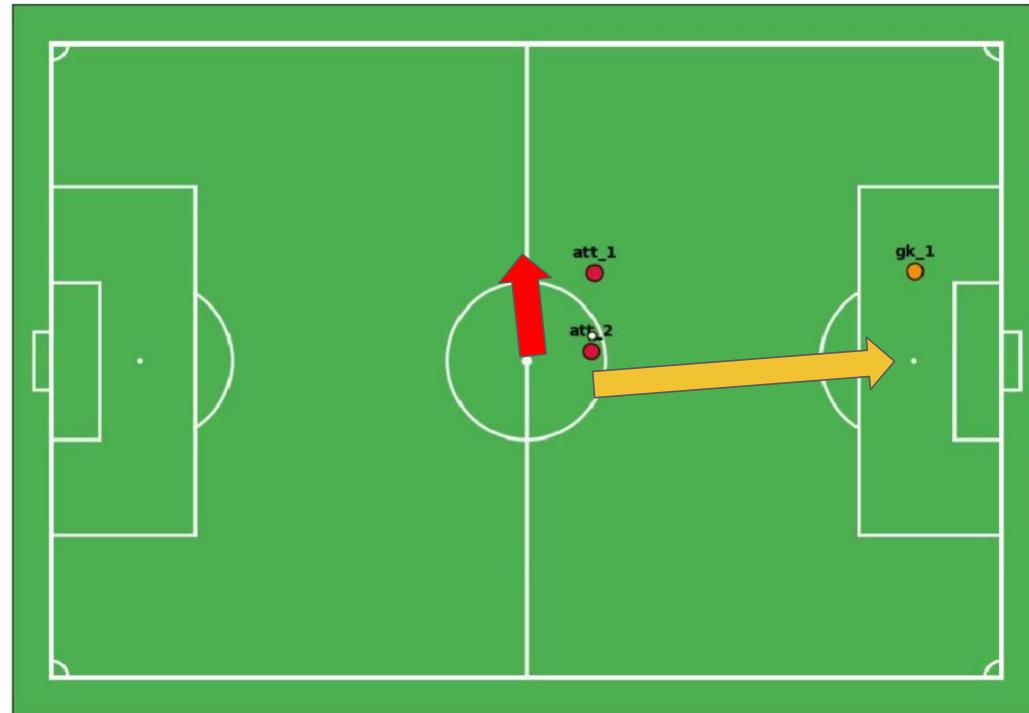
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What-if

Assists with failed shot

Dataset

STATSBOMB

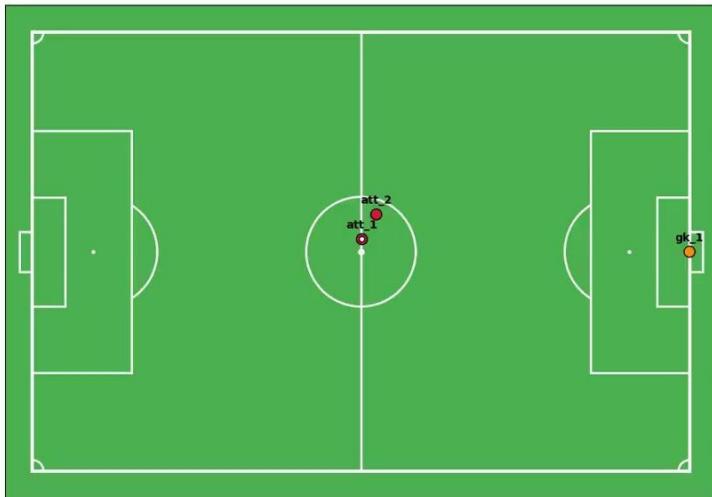




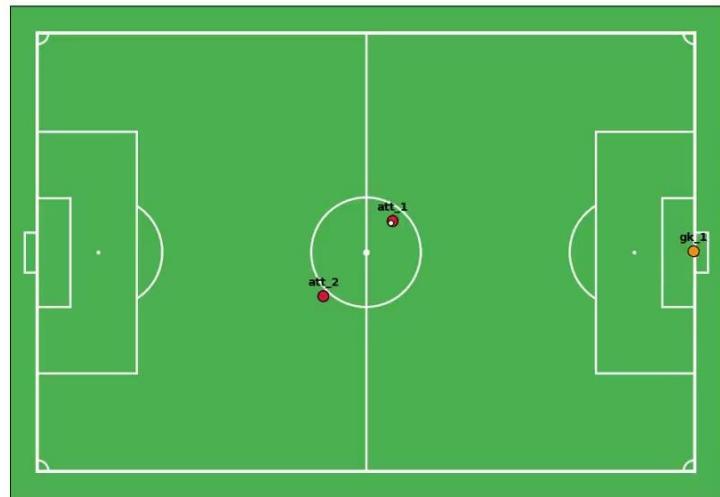
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What-if

Frame: 0/240



Frame: 1/240



Thank you !



Politecnico
di Torino



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DB
MG