How does AI play football? An analysis of RL and real-world football strategies

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INTRODUCTION

- A growing number of sports teams now adopt specialist roles for analytics.
- If we assume such trends are to continue, it is likely both compute power and the amount of available data will exponentially increase in forthcoming years.
- However, it will remain nearly impossible to collect real-world sport data in a scientific manner where variables can be controlled.
- This can not be helped since top level sports are highly competitive in nature and leave very little room for experimentation.
- **To solve this problem, agent-based simulation (ABS) can be used as a test-bed to simulate various scenarios in a scientific manner**

PRELIMINARIES

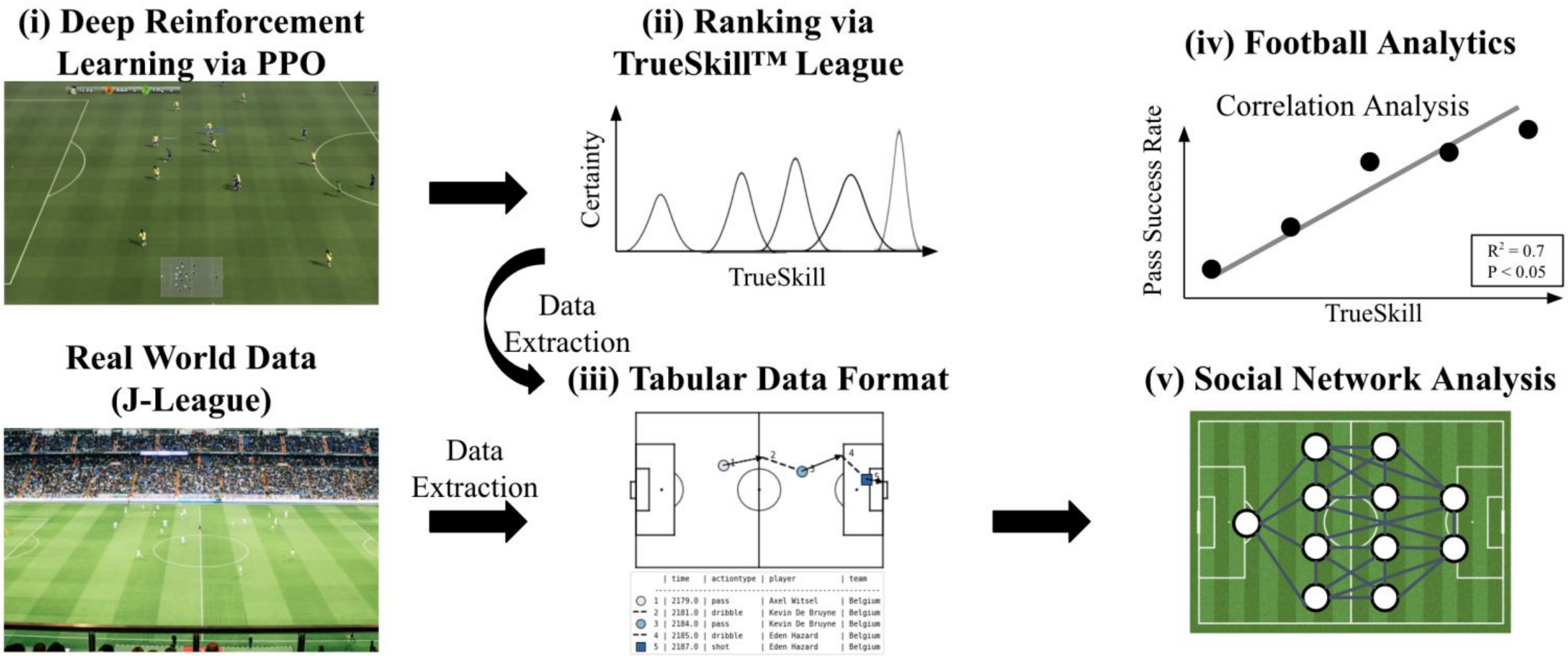
- **Proximal Policy Optimization**
  - To learn policies for agents to play Google Research Football, they follow the original paper and use Proximal Policy Optimisation (PPO) .
- **TrueSkill Ranking System**
  - It has been frequently used in many different multiplayer games and sports applications
  - Finally, a so-called conservative skill estimate can be calculated by

$$\boldsymbol{\mu - k * \sigma} \text{ (where k is usually set to 3)}$$

PRELIMINARIES

- **Social Network Analysis**
  - They focus on social network analysis (SNA) of passes
  - **Closeness Centrality**
    - This score indicates how easy it is for a player to be connected with teammates.
  - **Betweenness Centrality**
    - This score indicates how players acts as a bridge between passing plays, high deviation within a team may indicate well balanced passing strategy and less dependence on a single player.
  - **Pagerank Centrality**
    - A high pagerank score implies that the player is a popular choice for other players to pass too.

PROPOSED ANALYSIS FRAMEWORK



	time	actiontype	player	team
1	2179.0	pass	Axel Witsel	Belgium
2	2181.0	dribble	Kevin De Bruyne	Belgium
3	2184.0	pass	Kevin De Bruyne	Belgium
4	2185.0	dribble	Eden Hazard	Belgium
5	2187.0	shot	Eden Hazard	Belgium

PROPOSED ANALYSIS FRAMEWORK

Their framework consists of five parts.

1. Train agents using proximal policy optimisation in the Google Research Football simulation environment.
2. Rank the agents by the TrueSkill ranking system.
3. Extract event data concerning on-the-ball actions from the simulations and convert it into a tabular format. This format is similar to the Soccer Player Action Description Language (SPADL) but simplified to only include passes and shots. They also convert realworld football data into the same format as well.
4. Perform correlation analysis
5. Social network analysis on the obtained data.

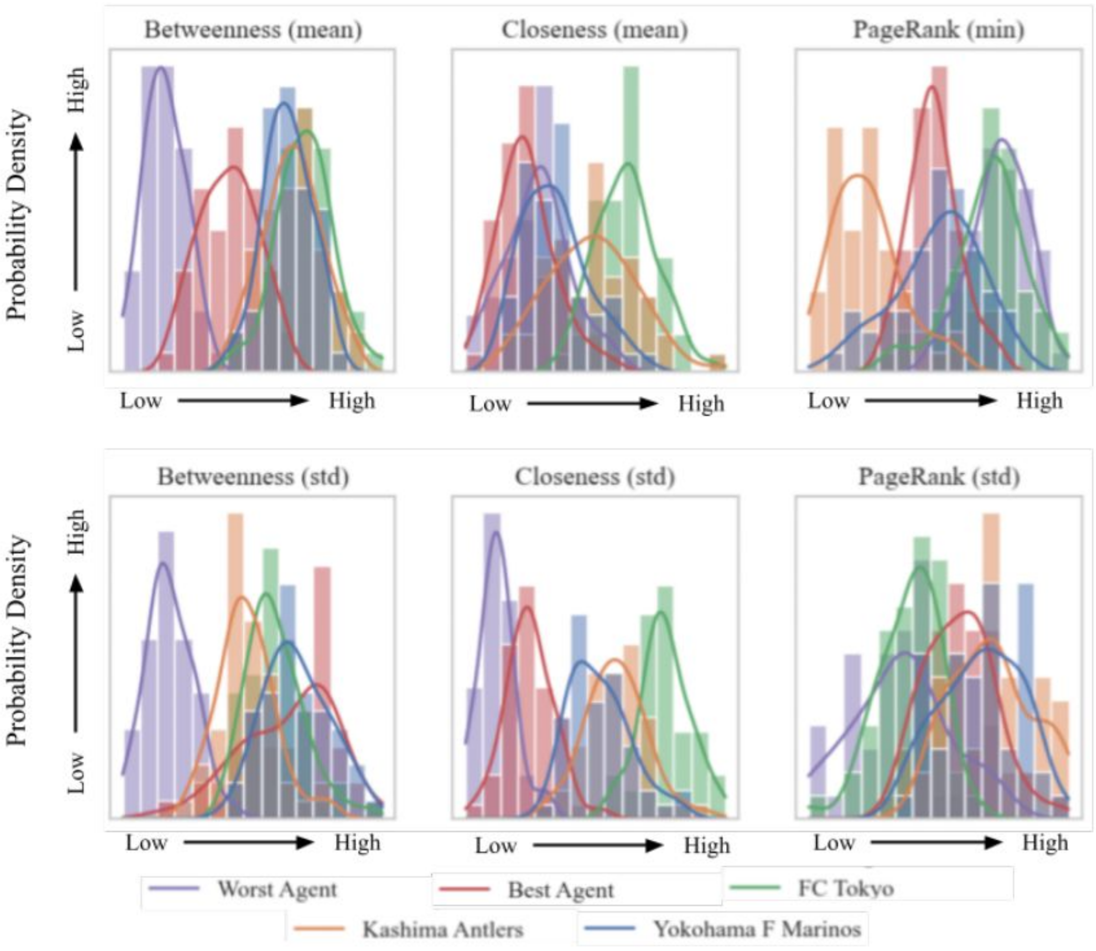
RESULTS AND DISCUSSION

- **Correlation Analysis with TrueSkill ranking**
  - ”Total Shots” and ”Betweenness (mean)” have a very strong positive correlation with TrueSkill rankings. On the other hand, ”PageRank (min)” has a nearly perfect negative correlation

Metric	Correlation Coefficient	*p*-value
Total Passes	-0.5	0.061
Total Shots	**0.77**	**0.001**
Successful Pass Pct	0.62	0.014
Successful Shot Pct	0.68	0.005
PageRank (std)	0.58	0.022
PageRank (mean)	-0.05	0.848
PageRank (max)	0.48	0.068
PageRank (min)	**-0.91**	**0.001**
Closeness (std)	-0.54	0.036
Closeness (mean)	-0.64	0.010
Closeness (max)	-0.61	0.015
Closeness (min)	-0.66	0.007
Betweenness (std)	0.65	0.009
Betweenness (mean)	**0.72**	**0.002**
Betweenness (max)	0.65	0.009
Betweenness (min)	0.0	0.0

RESULTS AND DISCUSSION

- **Comparative Analysis Between Simulated and Real-world Football**
  - ”Betweenness (mean)”, ”Betweenness (std)” and ”Closeness (std)” metrics for the worst agent is distant from the others
  - The fact that the best agent distribution of the same metric is much closer to that of J League teams implies that agent has learnt to play in a similar style through RL
  - However the same cannot be said for the other metrics, ”Closeness (mean)”, ”PageRank (std)” and ”PageRank (min)”.


Betweenness (mean)
Closeness (mean)
PageRank (min)
Betweenness (std)
Closeness (std)
PageRank (std)
Probability Density
Low
High
Worst Agent
Best Agent
FC Tokyo
Kashima Antlers
Yokohama F Marinos

CONCLUSIONS AND FUTURE WORK

- They compared the characteristics and play styles of RL agents of increasing competitiveness.
- They found many metrics that strongly correlate with the competitiveness (TrueSkill rating) of an agent.
- They suggest that an RL agent can learn to play football in similar style to that of real player without being explicitly programmed to do so.
- They plan to work on increasing the degree of freedom within the simulations to create a more realistic environment
    - This can be achieved by conducting multi-agent simulation where an RL agent controls a single active player in contrast to a whole team.