Predicting Player Trajectories in Shot Situations in Soccer

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Outline

- **Motivation**
- Method
- Results
- Conclusion

Motivation

- How would player X behave in a particular situation?
- What happens if we replace player Y?
- Find a player that behaves similarly to player Z

Motivation

- Is player behaviour latent information in their movement data?
- Given a tracking data set, is it possible to learn individual player movement patterns?

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Data

- Swedish top-tier league (Allsvenskan)
- First half of the 2019 season, which spans March-November
- 79 games
- 276 players
- 1 668 shots (193 goals, 1 475 non-goals)
- Tracking data for all players and the ball
- Data provided by Signality

Data

- Extracted 20 second sequences around shots
- 150 players with most played games
- 21 284 training sequences
- 5 188 validation sequences

Model

- Policy π
- State $x \equiv (s, c)$
- Action a
- Expert $\pi*$

Model

- **Behavioural Cloning**

$$\pi : s, c \rightarrow a$$

- **General Imitation learning**

$$\pi : s_o, c \rightarrow \tau = \{a_0, s_1, \ldots, a_{T-s}, s_T\}$$

Model

- **Behavioural Cloning**

  Distribution of states given by $\pi^* : P^* = P(x \,|\, \pi^*)$

  $\hat{\pi}_\theta = \text{argmin}_\theta \, \mathbb{E}_{x \sim P^*} \ell(\pi^*(x), \pi_\theta(x))$

- **General Imitation learning**

  Distribution of states given by $\pi_\theta : P(x \,|\, \theta)$

  $\hat{\pi}_\theta = \text{argmin}_\theta \, \mathbb{E}_{x \sim P(s|\theta)} \ell(\pi^*(x), \pi_\theta(x))$

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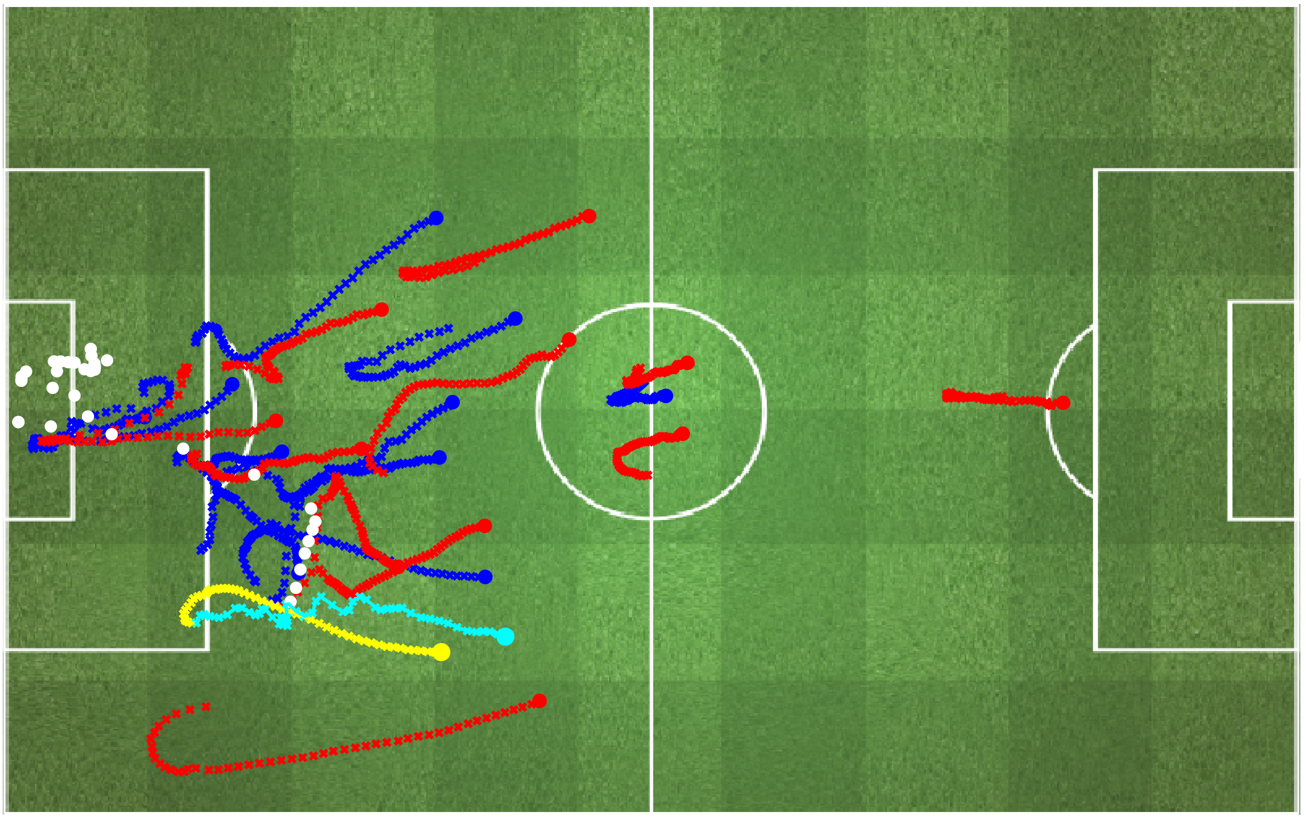
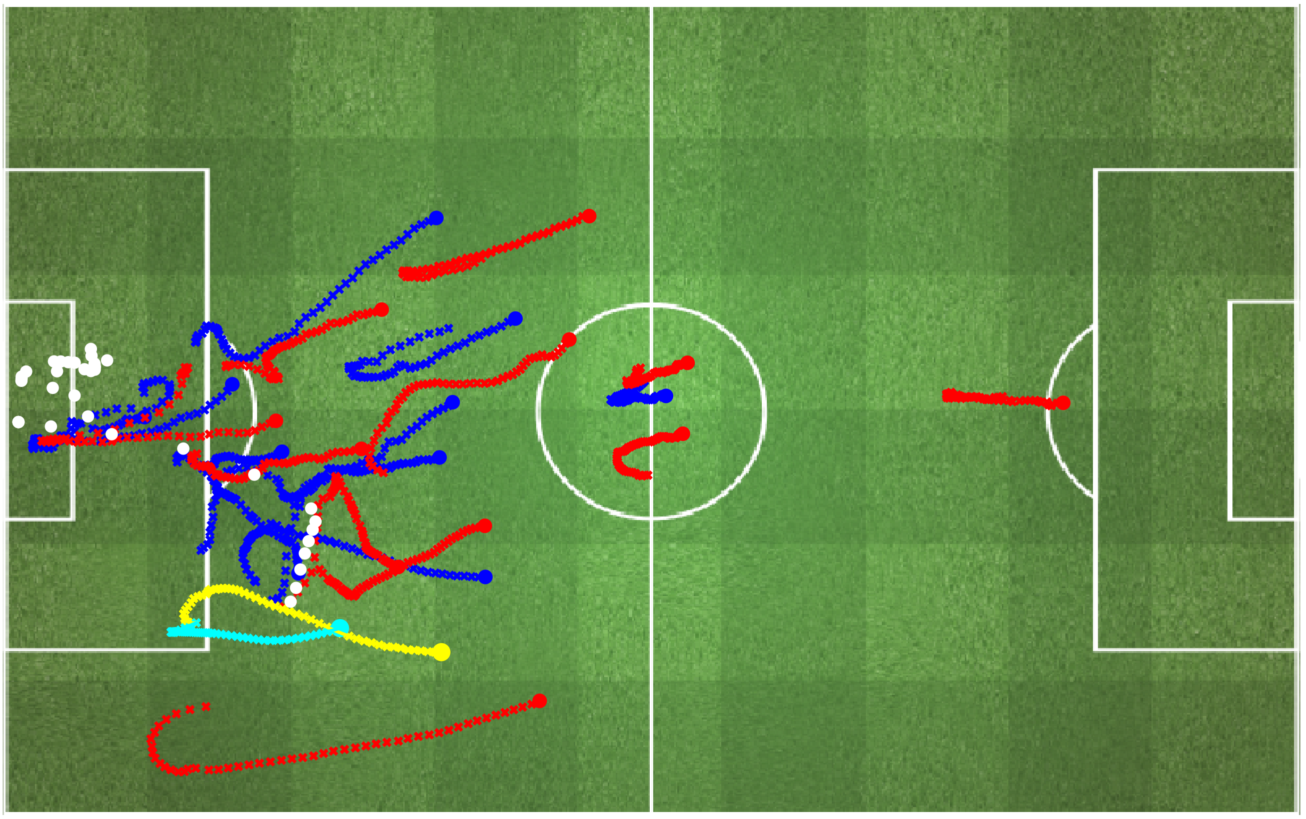
Action comparison



Absolute actions

Error=9.01, σ=7.22m



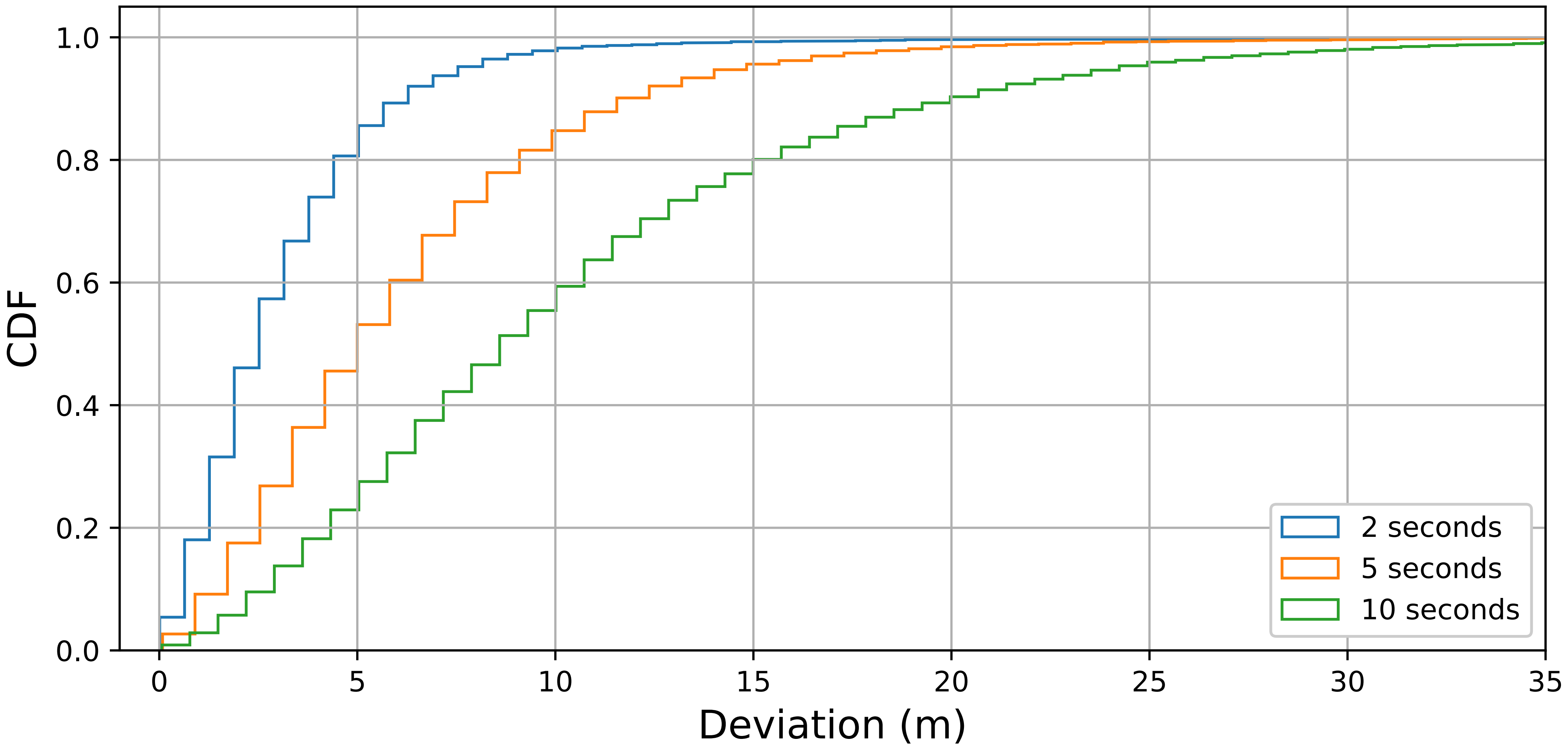
Relative actions

Error=6.89, σ=5.84m

Window size

Window	Mean	Stdev	Conf interval
10	7.60	6.23	[7.47, 7.73]
20	7.14	5.70	[7.02, 7.26]
30	7.42	6.05	[7.30, 7.55]
40	7.72	6.04	[7.60, 7.85]
50	7.23	6.30	[7.10, 7.36]

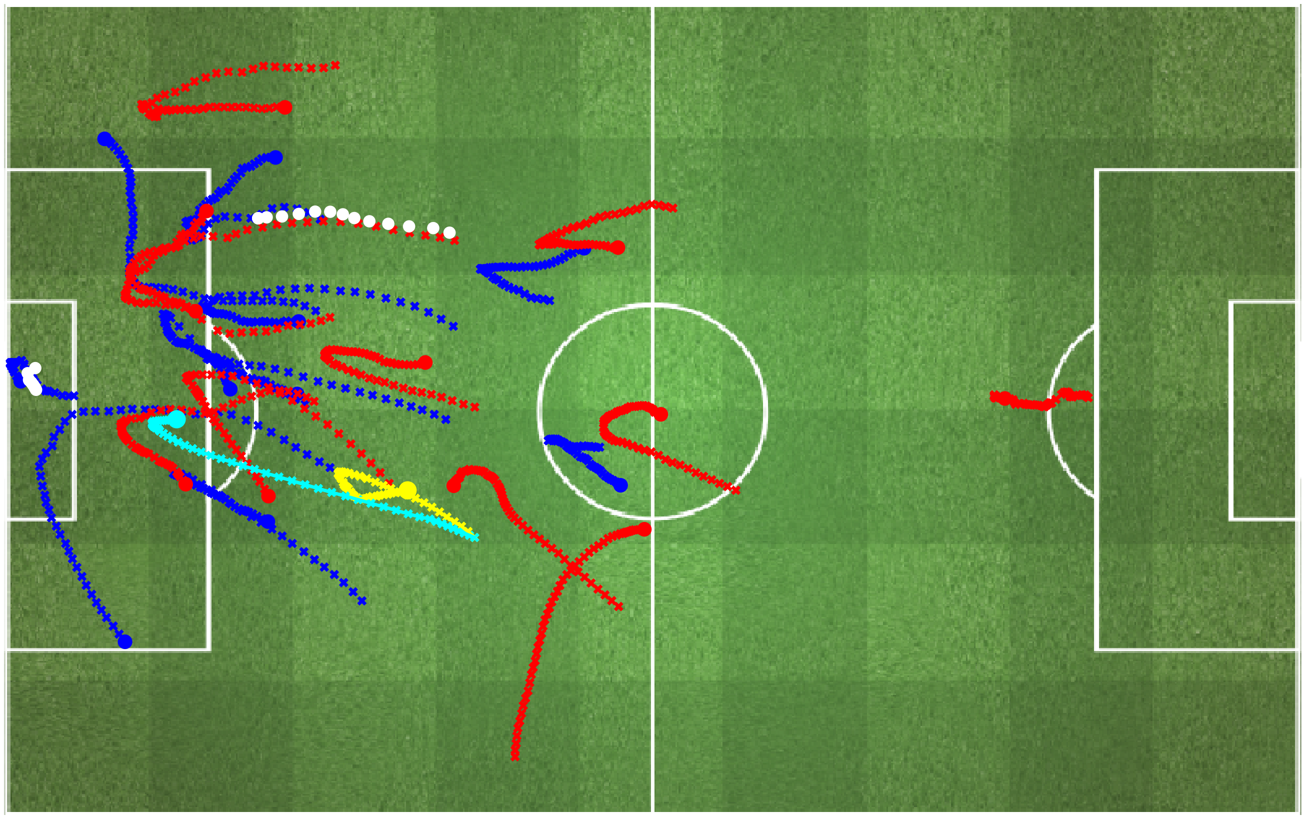
CDF over time



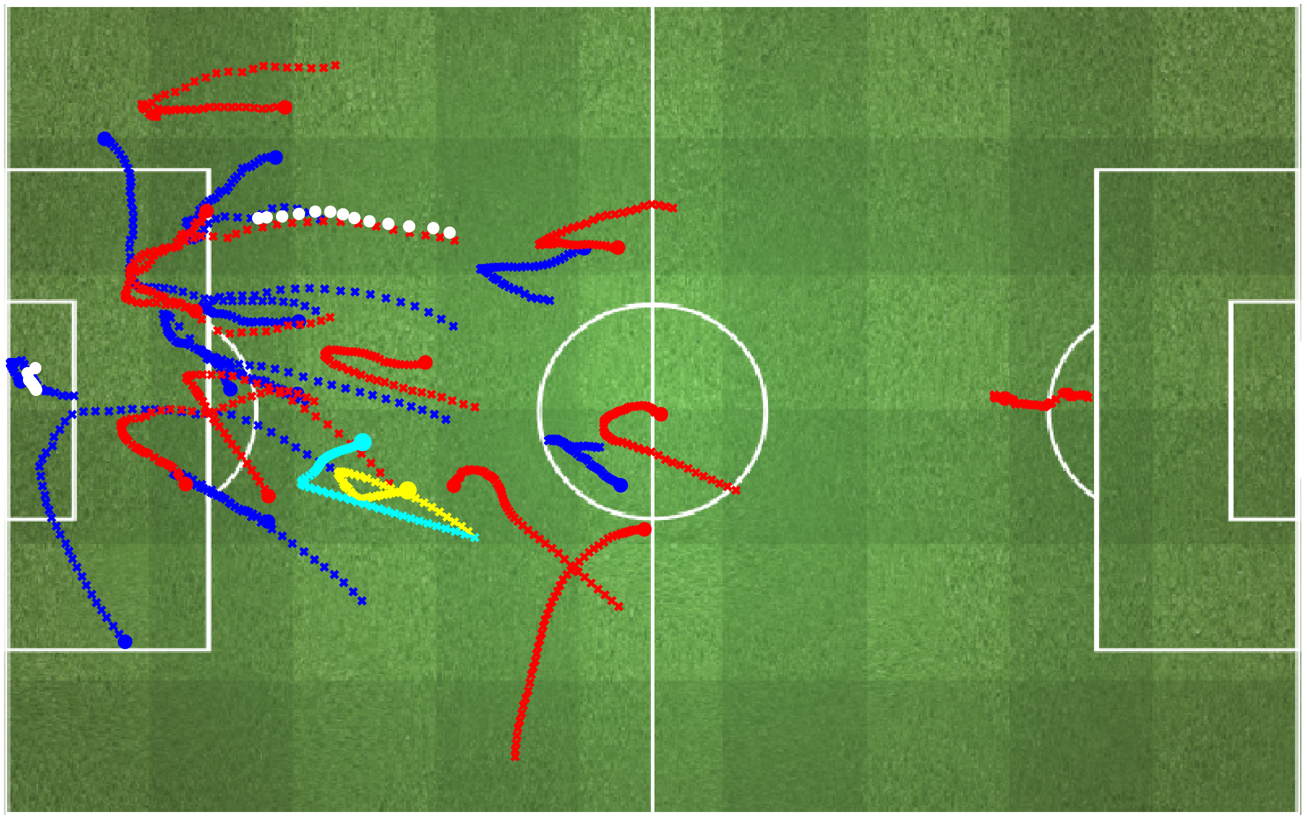
Cross-evaluation

		Observed expert player									
		G1	D1	D2	D3	D4	M1	M2	M3	O1	O2
Model player (Policy)	G1	**3.56**	8.33	7.82	10.22	10.96	8.83	11.54	10.01	10.02	7.75
	D1	7.1	**6.86**	6.46	7.96	7.63	7.35	9.51	7.28	7.82	7.22
	D2	6.71	8.05	**5**	7.25	7.77	8.03	10.04	8.01	8.19	8.75
	D3	4.63	7.85	5.63	7.19	7.74	8.13	8.69	7.34	7.24	6.8
	D4	14.17	16.05	10.98	13.82	**6.81**	12.15	13.18	12.74	12.08	10.84
	M1	4.24	8.04	5.94	7.08	7.67	**5.75**	8.48	6.4	7.07	5.82
	M2	5.61	8.69	6.75	7.4	7.26	7.14	**8.17**	6.16	7.46	7.27
	M3	4.98	7.54	5.79	**7.02**	7.22	6.27	**8.17**	**5.56**	6.58	**5.08**
	O1	5.73	8.69	7.23	8.14	7.65	6.76	8.31	6.39	**6.31**	6.33
	O2	4.63	8.22	7.92	8.99	8.62	8.75	9.9	8.06	8.74	5.6

Rollout example



Defensive policy



Offensive policy

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Conclusion

- It is possible to learn the behaviour of individual players given their movement data
- Future research
    - Extend to more types of situations
    - Multi-agent modelling
    - Extrinsic measurement such as expected goals

Thank you

Questions?

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