A Markov Framework for Learning and Reasoning About Strategies in Professional Soccer

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Increased demand in data-driven decision-making support

Optimizing strategies = fundamental element in team sports & coaches are confronted with many questions:

WHAT is the right decision to make?

"When outside the penalty box, should you shoot immediately or move before shooting?"

"Which locations on the pitch are most effective to score goals?"

WHAT IF a different tactic had been followed?

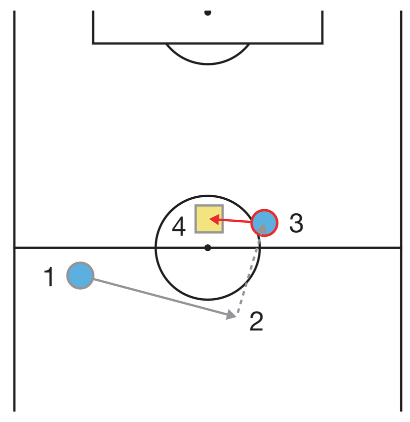
"How would shooting more often from outside the penalty box affect our expected number of goals?"

To aid coaches with tactical planning, we propose

A **framework** to:

1. **LEARN** an accurate model that captures a team's offensive behavior
2. **REASON**, also in counterfactual way, about strategies

Given:
Event stream data collected during games, which describes all on-the-ball actions

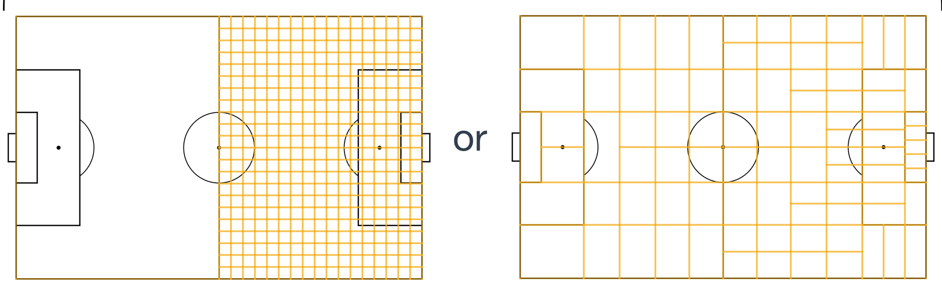


	Time	Action	Start	End	Result	Player	Team
1	37:16	pass	(57, 11)	(64, 38)	success	L. Sané	Man City
2	37:19	dribble	(64, 38)	(48, 43)	success	J. Stones	Man City
3	37:22	pass	(48, 43)	(48, 33)	fail	J. Stones	Man City
4	37:24	interception	(48, 33)	(48, 33)	success	R. Firmino	Liverpool

Component 1: LEARNING

Model offensive behavior of team as MDP

States: Transient field states ∪ Absorbing states



- Lost possession
- No goal
- Goal

Better for analyzing: shot behavior / movement strategies

Actions: Move to → (0,0) | (0,1) | (0,2) | … all zones; Shoot

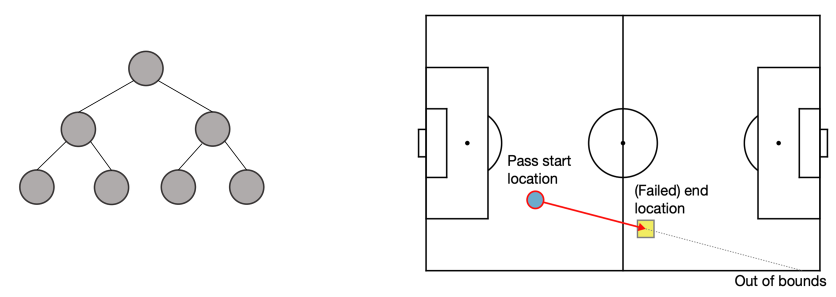
	(0,0)	(0,1)	(0,2)	… all zones	Shoot
Policy	0.4	0.06	0.007	…	0.03
Transition function	0.8	0.6	0.4	…	0.01
Reward	0	0	0	…	1

These probabilities are learned from data

Estimate transition model from event stream data

1 **Challenge 1**: the intended end location of actions is unknown

Use predictive modeling + domain knowledge



→ Predict intended end location

2 **Challenge 2**: sparse data to estimate transition model

Use hierarchical Bayesian model: estimate prior model of "typical team"
+ specialize to each team based on their observed data

Transition probability model

$$o_{t,s,a} \sim Bernoulli(p_{t,s,a})$$
$$p_{t,s,a} = invlogit(\gamma_{t,s,a})$$
$$\gamma_{t,s,a} \sim \mathcal{N}(\mu_{s,a}, \sigma^2_{t,s,a})$$
$$\sigma^2_{t,s,a} \sim Half-Normal(5.0)$$

Policy model

$$A_{t,s} \sim Categorical(\vec{p}_{t,s})$$
$$\vec{p}_{t,s} = softmax(\vec{\lambda}_{t,s})$$
$$\lambda_{t,s,a} \sim \mathcal{N}(\alpha_{s,a}, v^2_{t,s,a})$$
$$v^2_{t,s,a} \sim Half-Normal(5.0)$$

team t, state s, action a, $\mu_{s,a}$ and $\alpha_{s,a}$ based on data of other teams

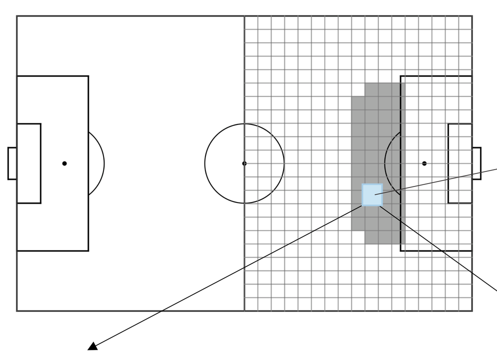
Component 2: REASONING

1 Reason about learned policies (WHAT)

Use probabilistic verification on MDP with fixed policy to compare different strategies:

- **Offensive** strategies (performing certain actions)
- **Defensive** strategies (not allowed to perform certain actions)

General idea



For a specific state

P=? [X "goal"] ← → P=? [X "flank" & F "goal"]

Compare to find best option

2 Reason about alternative policies (WHAT IF)

Step 1: Change MDP's policy to reflect alternative one

We look at ↑ or ↓ performing certain actions

- 2 options for movement: (1) proportional or (2) keep aggressiveness
- 2 options for shots: (1) uniform or (2) targeted; redistribution over movement + adapted efficiency of shots

Step 2: Estimate effect of new policy

2 options

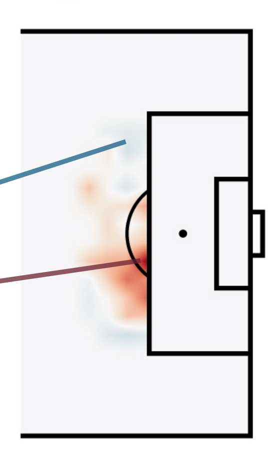
- Compare value function before and after
- Estimate expected number of goals using the fundamental matrix

Use cases

1 Reasoning about shot policies

Q1: Which action is more likely to lead to a goal?

Everton



Here, moving once prior to shooting is better

Here, directly shooting is better

Q2: What if teams shoot more from outside the penalty box?

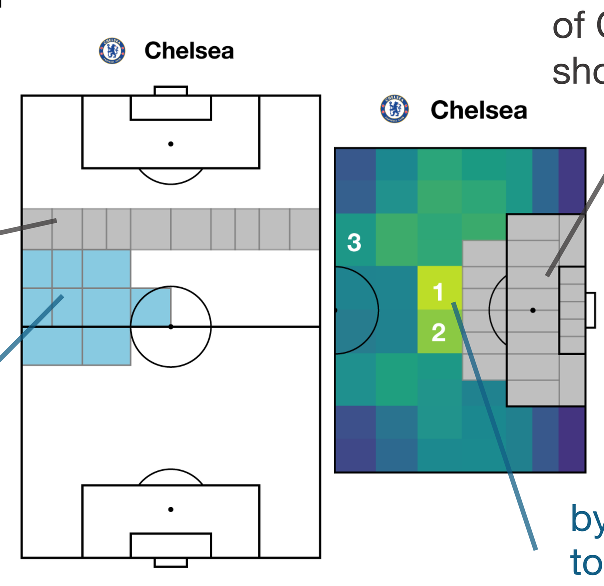
0.6 goals ~ 0.6 points

More long distance shots →

ENG - Premier League	+5%	+10%	+20%
Man Utd	0.1	0.3	0.6
Chelsea	0.1	0.3	0.5
Liverpool	0.1	0.2	0.4

2 Reasoning about defensive strategies

Q1: How to decrease opponent's chances of
(1) creating danger during build-up?
(2) shooting?



Decrease chance of Chelsea creating danger from here

by forcing them to avoid this region

Decrease chance of Chelsea shooting from here

by forcing them to avoid these states

Q2: What is the remaining effect once opponent adapts?

Percent decrease in Chelsea's chances of scoring before vs. after they adapt their movement policy: ± 12 vs. ± 4 (proportional) and ± 3 (keep aggressiveness)

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