Deep Decision Trees for Discriminative Dictionary Learning with Adversarial Multi-Agent Trajectories: Supplementary Material

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The complete figures for the Fig. 4, 5, 8 and 9 of the paper are shown in Fig. 1, 2, 3 and 4 respectively.

1. Decision tree algorithm

Let the set of plays be $\mathcal{X}$ and the desired number of epochs be $\mathrm{nEpochs}$. The process of learning feature weights α in decision nodes and the classifier weight π in prediction nodes using back-propergation can be summarised as follows.

Algorithm 1: Decision Tree Building Procedure

function BuildDecisionTree($\mathcal{X}$,nEpochs)
Input: Set of plays $\mathcal{X}$
Desired number of epochs $\mathrm{nEpochs}$
Align the plays in $\mathcal{X}$ using the algorithm proposed in [1]
for $i \in [1, ..\mathrm{nEpochs}]$ **do**
  Compute classification error by iterating Eq. 7
  Break $\mathcal{X}$ into a set of random mini-batches
  for $j \in \mathrm{mini-batches\ from}\ \mathcal{X}$ **do**
    Update α and π using stochastic gradient decent (SGD)
  end
end

2. Relative Strategy Plots

The frequency of a dictionary element depends whether the team is playing home or away; or winning, losing or drawing (See Fig. 5). The Bhattacharyya distance between histograms for home and away teams is 0.126, for winning and drawing team histograms the distance is 0.269, between winning and losing histograms the distance is 0.253 and the distance between losing and drawing histograms is 0.244.

3. Effect of game context

Figure 6 shows how the shooting rate of two teams varies with the current score and current time. For example in Fig. 6 (a), towards the end of the match home team pushes hard which results in an increase in their shooting rate and enables them to secure a draw. In Fig. 6 (b) as they already have a lead, the home team focuses more on defending, hence their shooting rate decreases towards the end of the match.

References

[1] A. Bialkowski, P. Lucey, P. Carr, Y. Yue, and I. Matthews. Large-scale analysis of soccer matches using spatiotemporal tracking data. In *ICDM*, pages 725 – 730, 2014. 1

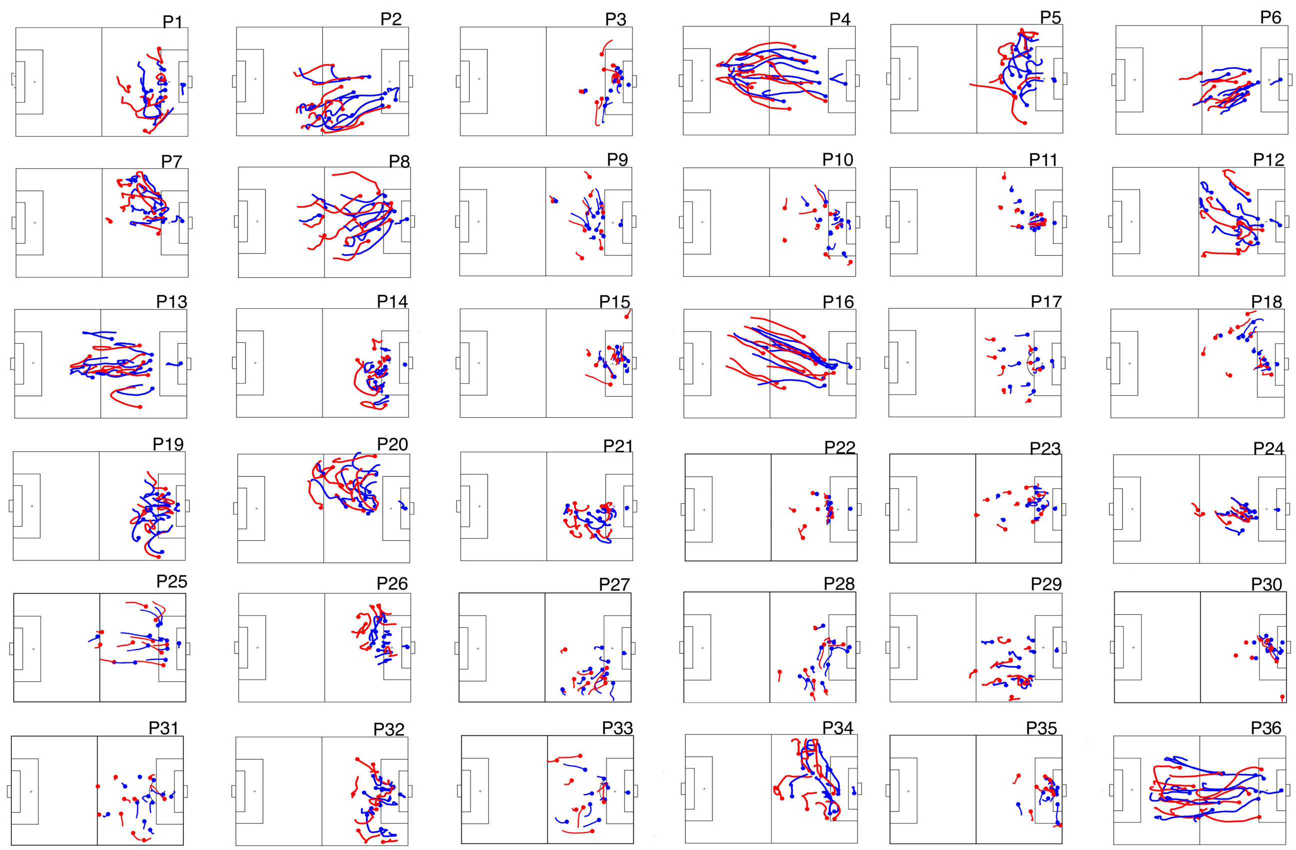

Figure 1: Play book of scoring methods.(Red is attacking team running left-to-right. Blue is defensive team defending running right-to-left)

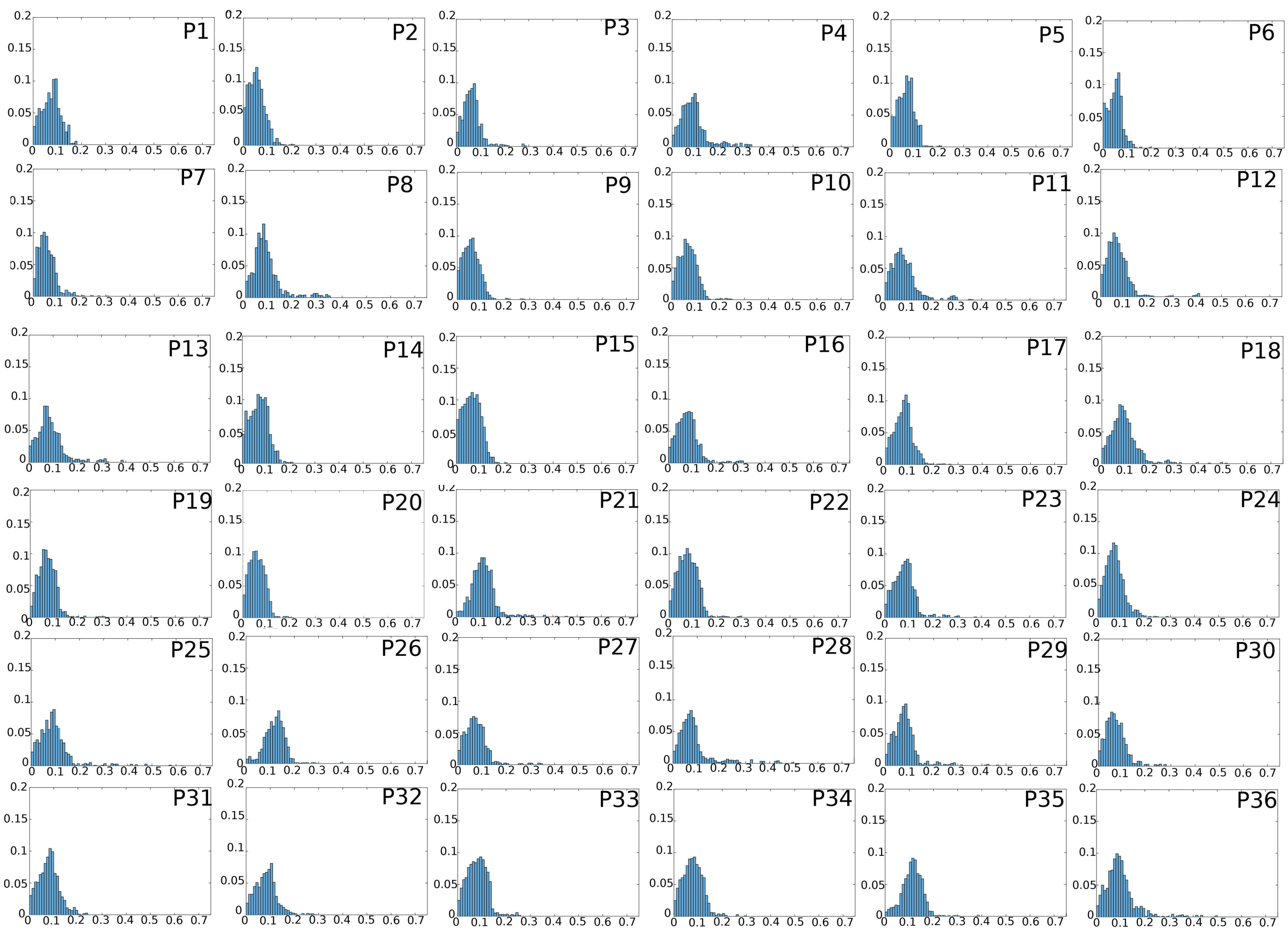

Figure 2: Histogram of the expected goal values for each scoring method. In all plots the x-axis show the expected goal value and the y-axis shows the frequency.

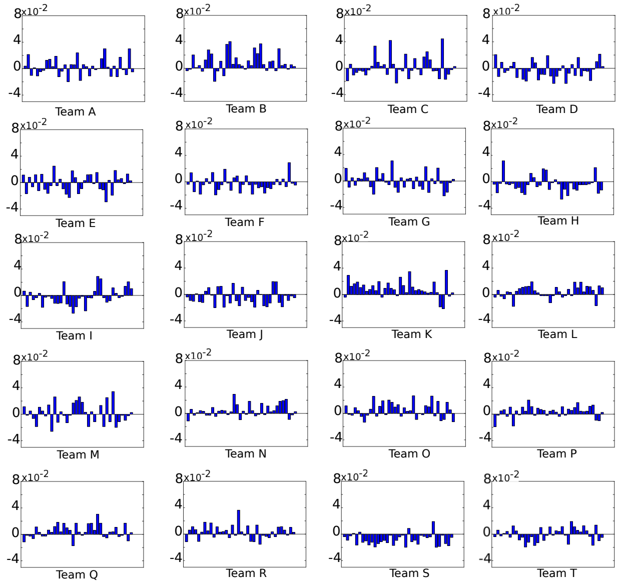

Figure 3: Relative Offensive Strategy Plot. League wide offensive strategy is subtracted at a team level. In all plots the x-axis shows the shot type and y-axis shows the f^{RSO}.

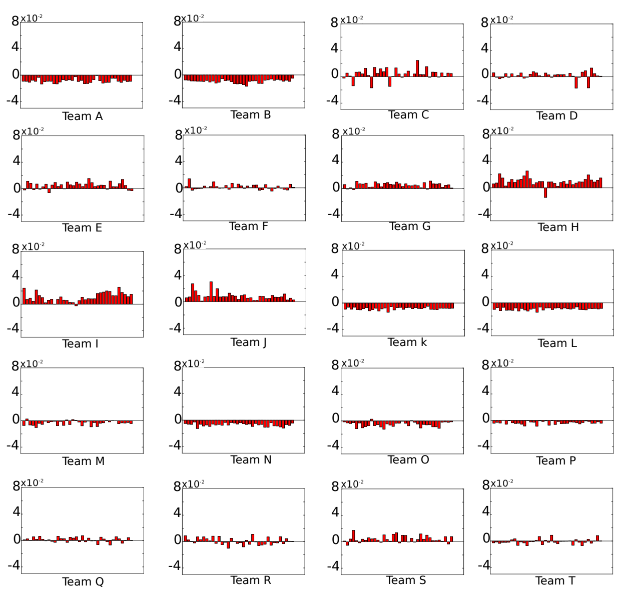

Figure 4: Relative Defensive Strategy Plot. League wide average defensive strategy is subtracted at a team level. In all plots the x-axis shows the shot type and y-axis shows the f^{RSD}.

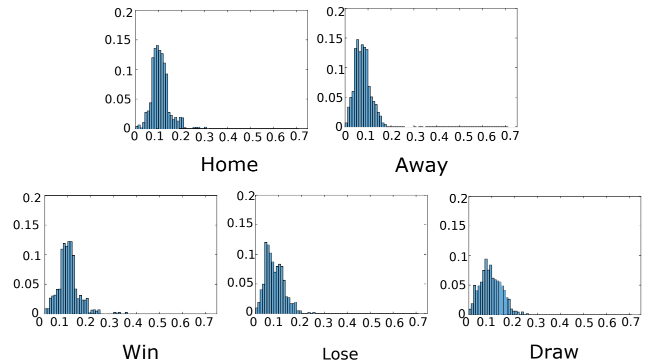

Figure 5: Distribution of shot quality of a team with (a) home (b) away, (c) winning, (d) losing and (e) drawing contexts. In all plots the x-axis show the expected goal value and the y-axis shows the frequency.

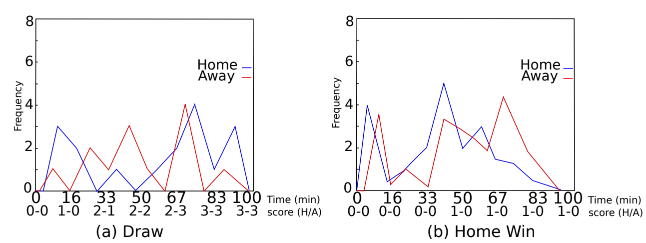

Figure 6: Distribution of shot frequency with time and score. The plots show that a team's shooting behaviour greatly varies with the time remain and current score. For example in (a) the home team decides to attack more towards the end of the game where as in (b) they decide to defend more.