UT Austin Villa: Deep Learning for Passing Strategy

Patrick MacAlpine, Brahma Pavse, Faraz Torabi, and Peter Stone

Department of Computer Science, The University of Texas at Austin

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Where to pass the ball

Kick locations with lighter circles having a higher score. Selected location shown in red.

- Evaluate possible kick locations and select highest value location
  - opponents close
  - teammates close
  - moves ball closer to opponent’s goal
Hand-Coded Value Function

\[
\text{score}(\text{target}) = \forall \text{opp} \in \text{Opponents}, - \max(25 - \|\text{opp} - \text{target}\|^2, 0) + \max(10 - \|\text{closestTeammateToTarget} - \text{target}\|, 0)
\]

- farther distance from opponent’s goal
- opponents close
+ teammates close
Train Deep Network from Game Data to Determine Kick Location Values

1. Play games and record scenarios where players kick the ball.
2. Determine the value for each potential kick location for each scenario.
3. Train a neural network to represent the value for each kick location using the data from the previous step.
Record kicking scenarios from games

- Played 1000 games against magmaOffenburg (2nd place team 2017)
- For each passing scenario record all players and ball locations as well as potential locations to pass ball
- Recorded around 2300 scenarios with close to 150 kick location for each
Kick Location Evaluation

- Kick ball to each location in scenario ten times
- Value is percentage of time that a goal is scored within 20 seconds of a kick
Train Deep Network from Collected Data

- Network trained with TensorFlow using backprop
- Input = player positions, ball, and kick location
  - Canonical representation where players are interchangeable
  - Y-axis (sideline-to-sideline) symmetry
- Output = estimated value of kick
Training Example Visualization

Visualization of the values of different kick locations according to a training example
Neural Network Visualization

Visualization of the values of different kick locations for the same state according to the neural network
Results

Average goal difference across 1000 games

<table>
<thead>
<tr>
<th>Opponent</th>
<th>Hand-Coded Function</th>
<th>Neural Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>magmaOffenburg</td>
<td>3.722</td>
<td>3.925</td>
</tr>
<tr>
<td>FUT-K</td>
<td>4.807</td>
<td>4.961</td>
</tr>
</tbody>
</table>

Score over 200 more goals against magmaOffenburg over 1000 games with deep neural network