UT Austin Villa: Deep Learning for Passing Strategy

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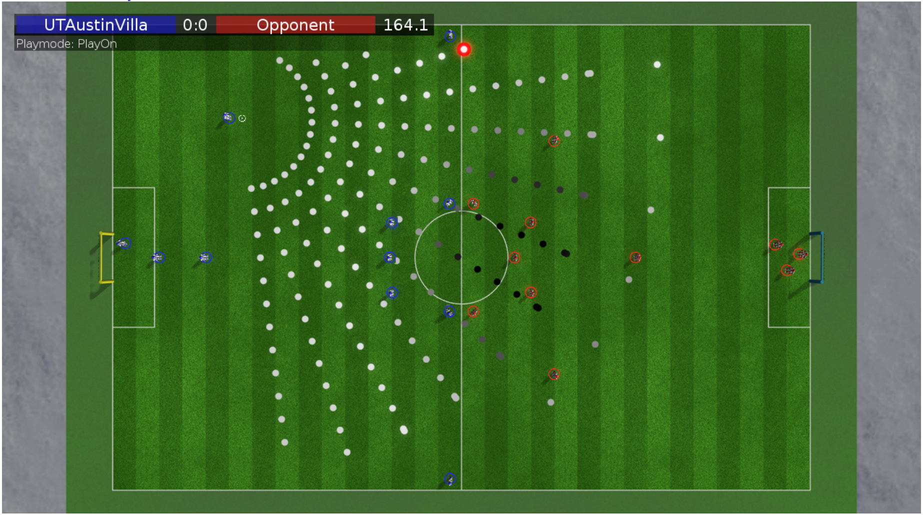
Where to pass the ball



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

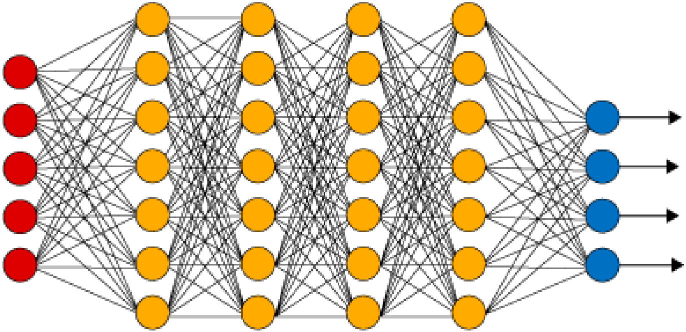
Hand-Coded Value Function

$$
\texttt{score}(\mathit{target}) = \begin{array}{l} -\|\mathit{opponentGoal} - \mathit{target}\| \\ \forall \mathit{opp} \in \mathit{Opponents}, -\max(25 - \|\mathit{opp} - \mathit{target}\|^2, 0) \\ +\max(10 - \|\mathit{closestTeammateToTarget} - \mathit{target}\|, 0) \end{array}
$$

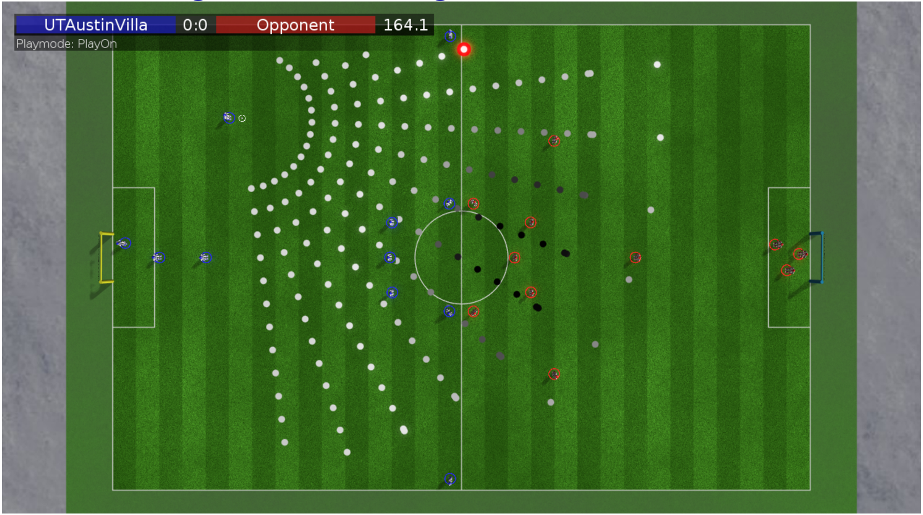
- \- farther distance from opponent's goal
- \- opponents close
- \+ teammates close

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



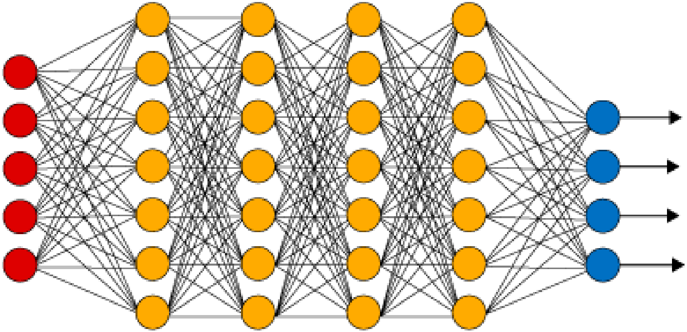
- Played 1000 games aginst magmaOffenburg (2nd place team 2017)
- For each passing scenario record all players and ball locations as well as potential locations to pass ball
- Recorded around 2300 scenarios with close to 150 kick location for each

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 interchangable
  - 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

Opponent	Hand-Coded Function	Neural Network
magmaOffenburg	3.722	3.925
FUT-K	4.807	4.961

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