

Play Selection in American Football

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 - Exact solution is feasible under some assumptions
 - For more general cases, approximations of the expected reward-to-go function are provided (API and OPI)

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- Rewards:
 - Touchdown: 6.8
 - Field goal: 3
 - Safety: -2
 - Opposition score $= -\frac{6.8x}{100}$

DP Equation

$$\mu^k(i) = \arg \max_{u \in U} \left[\sum_{j \in S} p_{ij}(u) (g(i, u, j) + J^{\mu^{k-1}}(j)) \right] \quad \forall i \in S$$

- $p_{ij}(u)$: transition probabilities
- $g(i, u, j)$: reward function
- $J^{\mu^{k-1}}(j)$: reward-to-go function

J is computed exactly using the 15250 possible states of the system.

Simulations

- We create a reasonable class of policies and implement it.
- Policies are compared by calculating the points from one drive.
- Simulations for an optimal heuristic policy are run from the starting state of $(x_i, y_i, d) = (80, 10, 1)$.
- Example of a simulation:

$$\begin{bmatrix} 25 \\ 10 \\ 1 \end{bmatrix} \xrightarrow{P_0} \begin{bmatrix} 17 \\ 2 \\ 2 \end{bmatrix} \xrightarrow{R_0} \begin{bmatrix} 14 \\ 10 \\ 1 \end{bmatrix} \xrightarrow{P_0} \begin{bmatrix} 10 \\ 6 \\ 2 \end{bmatrix} \xrightarrow{P_0} \begin{bmatrix} 10 \\ 6 \\ 3 \end{bmatrix} \xrightarrow{R_0} \begin{bmatrix} 8 \\ 4 \\ 4 \end{bmatrix} \xrightarrow{K_3} T$$

Approximated DP algorithm

$$\mu^k(i) = \arg \max_{u \in U} \left[\sum_{j \in S} p_{ij}(u) (g(i, u, j) + \tilde{J}^{\mu^{k-1}}(j)) \right]$$

API and OPI Algorithm

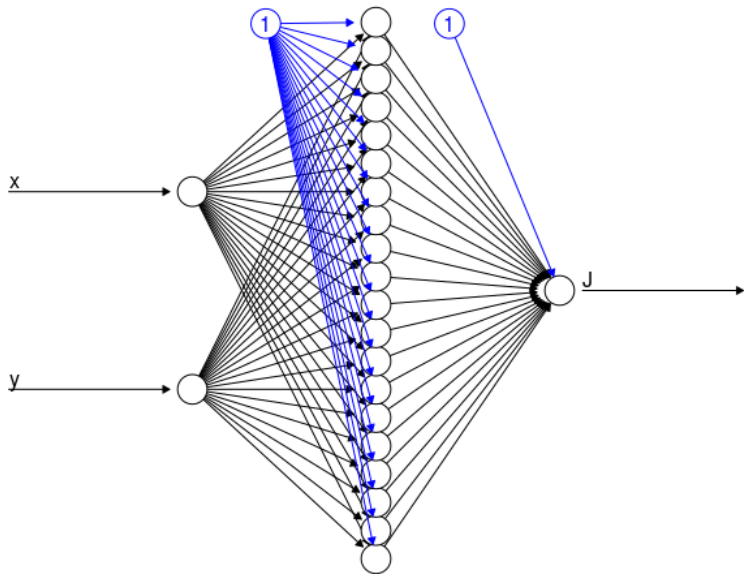
- Algorithm:

- 1 Start an initial policy μ_0
- 2 For each $k \in \{1, \dots, K\}$:
 - 1 Given μ_{k-1} , simulate N_s sample trajectories
 - 2 Fit the neural network using the sample data to estimate the $J^{\mu_{k-1}}$
 - 3 Update policy to get μ^k

- Two different ways to make the approximations

- API: Many training sample points, few iterations
- OPI: Few training sample points, many iterations

Neural Network



Seahawks should have run!