Towards Collaborative and Adversarial Learning:

A Case Study in Robotic Soccer

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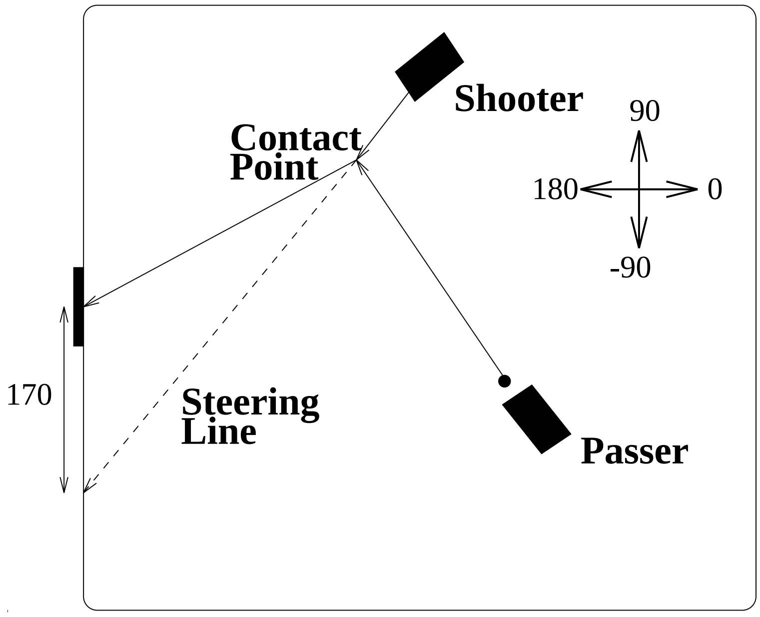
Outline

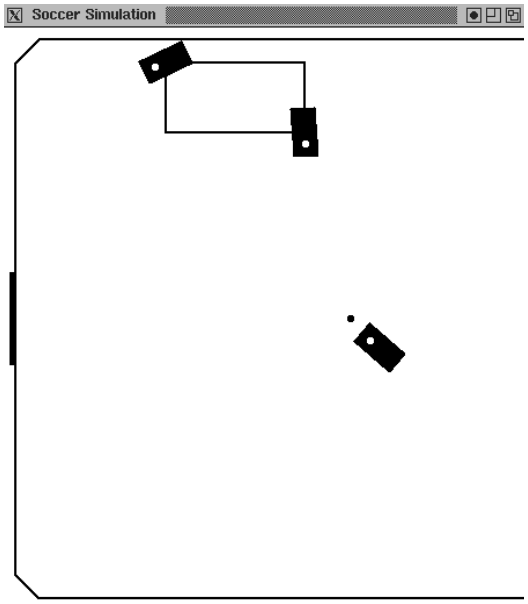
A taste of in-progress works

- Learning to shoot (**finished**)
- Applying the learned behavior to Multi-Agent scenarios

  (**Simulator Switch**)
- Learning to defend
- Learning to pass

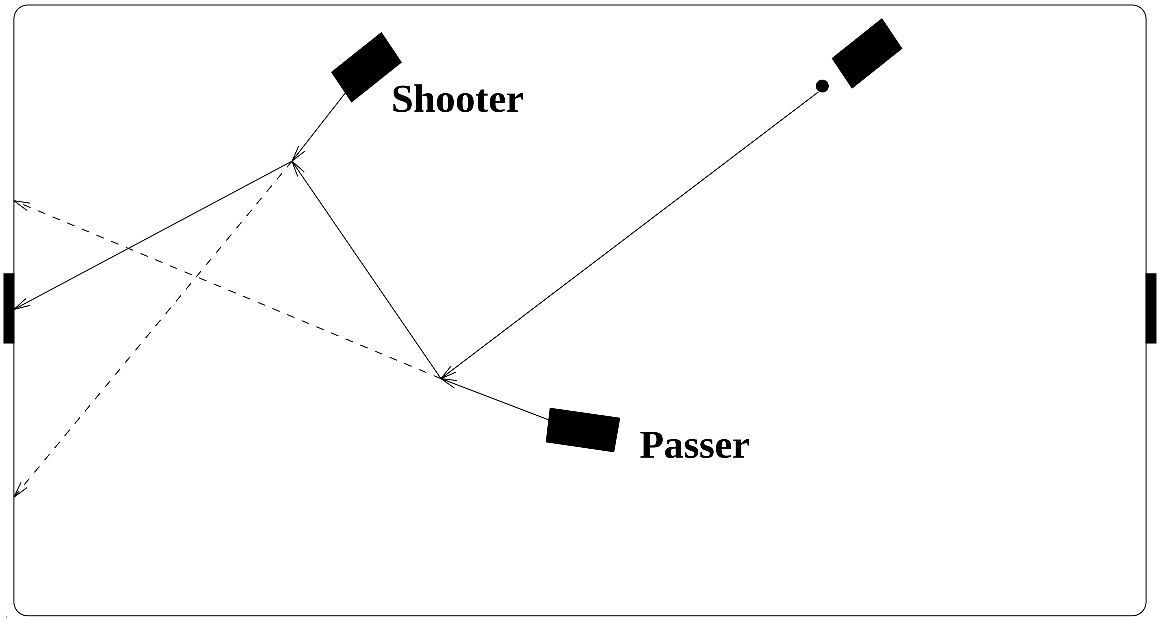
Learning to Shoot a Moving Ball





- Simulates real robots
- Learning is done using a Neural Network
- Generalizes to different situations
- Learned with 95% success
- video

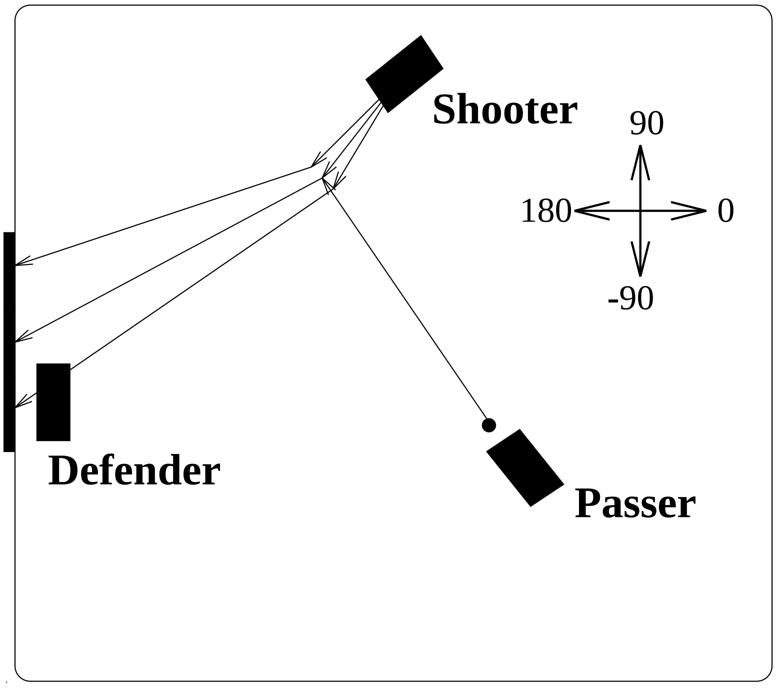
Chaining Shots as Passes



Collaborative

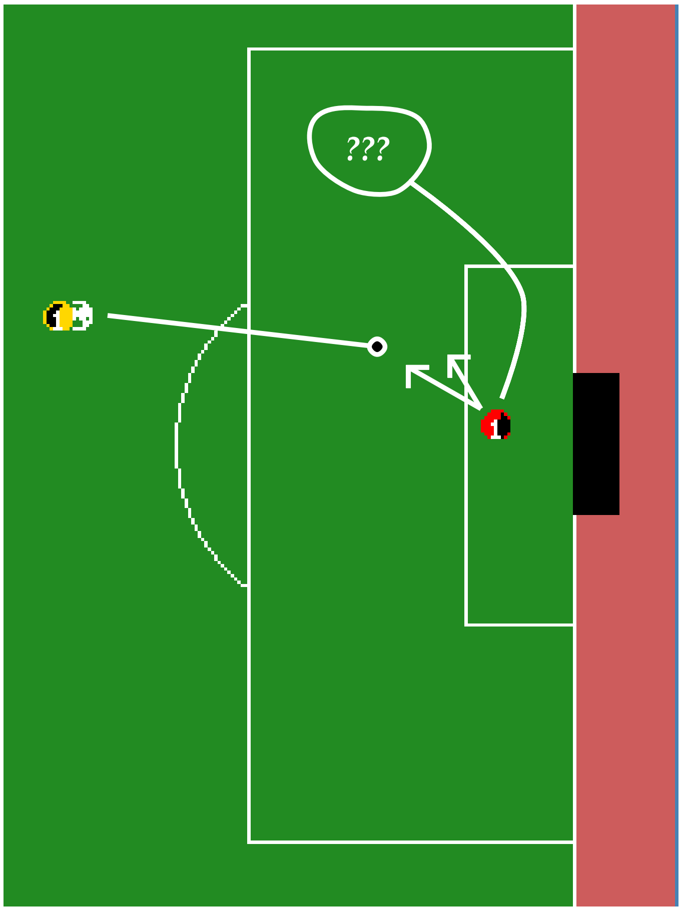
Passing to a point is the same as shooting at a point

Defending Against Aimed Shots



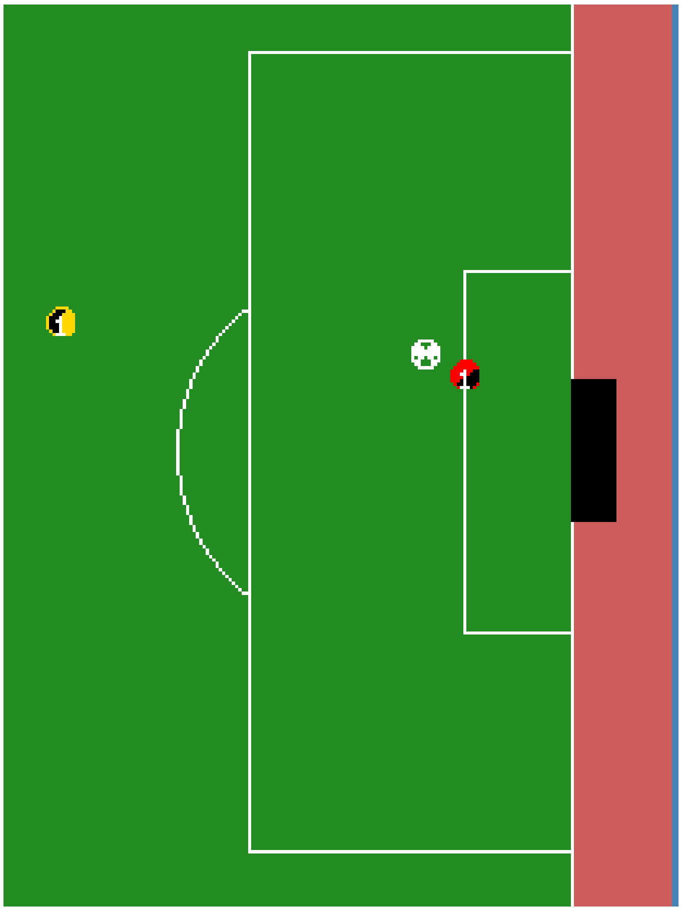
- **Adversarial**
- Learn to block shots that are aimed at different parts of the goal

Learning to defend in Noda's Simulator



- If the Defender moves straight to the ball, it misses
- It learns to intercept the ball's path
- It uses a Neural Network with inputs for:
  - Ball distance
  - Ball angle
  - Ball velocity (speed and direction)

Re-using the learned behavior



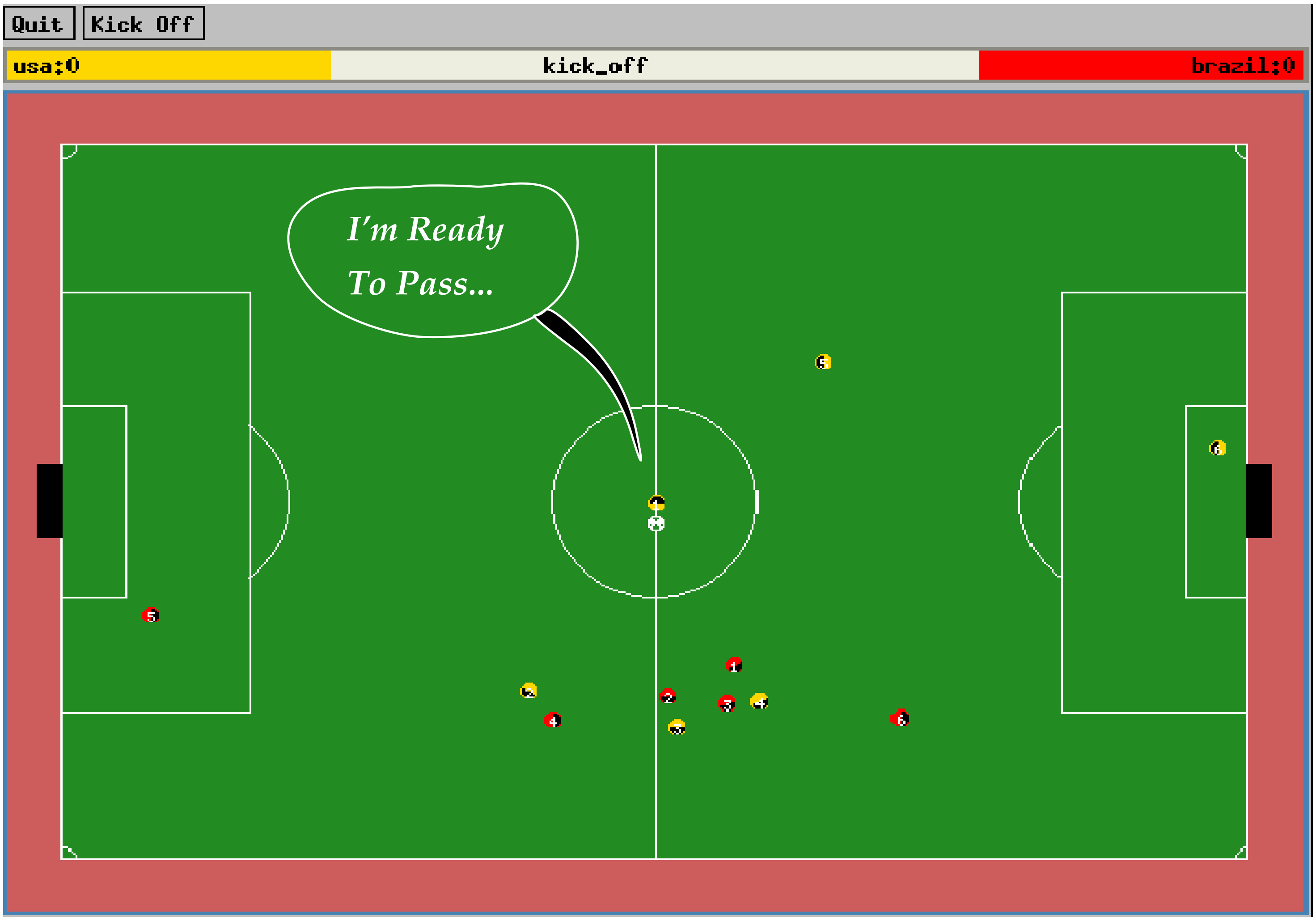
- In general, the Defender can intercept any ball moving towards it
- It can use the learned behavior to receive passes from teammates or to intercept passes from opponents

A Higher Level Multiagent Behavior

- Shooting and Defending are low-level behaviors used in a multi-agent scenario.
- Soccer also requires higher-level multi-agent learning.
- Passing explicitly requires collaboration.
  - Passer decides to pass.
  - Receiver prepares to receive.
- Communication is necessary.
- Communication can be the result of Planning.

Consider the case in which a single passer can pass to one of several teammates among defenders.

When the Passer has the ball, it announces its intention



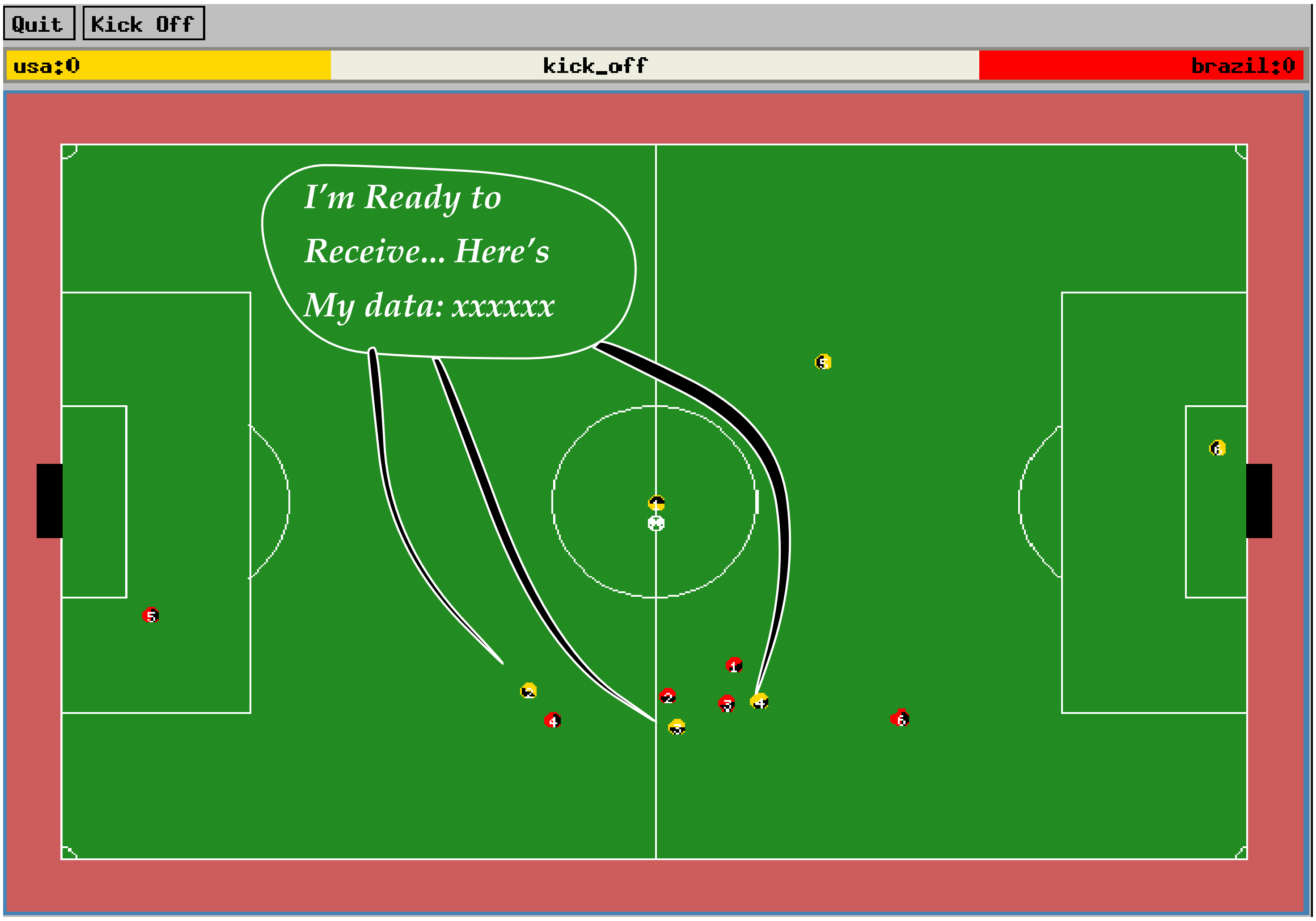
1 Passer:

3 Receivers:

4 Defenders:

+2 other players per team

When the Receivers are facing the ball, they tell the Passer what the world looks like to them



The Data includes:

- **Distance and Angle to the Passer**
- **Distance and Angle to teammates (sorted by distance)**
- **Distance and Angle to opponents (sorted by distance)**
- **Counts of teammates and opponents within given distances and angles when facing the Passer**

Decision Tree Learning

Learn the chances of a given pass succeeding

1. Choose a receiver.
2. Record the input data for that receiver.
3. Pass the ball.
4. Record the result.

Decision Tree inputs include data from the passer's and the receiver's perspectives.

- 174 continuous attributes.
- many values may be missing.
- trained on random receiver choices.

In this case, the first split is on the number of opponents within 6 degrees of the receiver from the passer's perspective.

- Pass will fail if > 0
- else keep branching

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C4.5 [release 8] decision tree interpreter      Tue Mar 19 13:49:09 1996
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Decision Tree:

passer opponents ang6 > 0 : F (420.0/131.1)
passer opponents ang6 <= 0 :
|   passer receiver distance <= 18.5 :
|   |   passer teammates dist4 ang8 <= 1 :
|   |   |   passer teammates dist12 ang8 <= 1 : S (320.0/73.7)
|   |   |   passer teammates dist12 ang8 > 1 :
|   |   |   |   passer opponent3 distance <= 17.6 : F (5.0/2.3)
|   |   |   |   passer opponent3 distance > 17.6 : S (14.0/1.3)
|   |   passer teammates dist4 ang8 > 1 :
|   |   |   passer opponents dist4 ang4 <= 0 : S (12.0/2.5)
|   |   |   passer opponents dist4 ang4 > 0 :
|   |   |   |   passer opponent1 distance <= 19.1 : F (2.0/1.0)
|   |   |   |   passer opponent1 distance > 19.1 : M (2.0/1.0)
|   passer receiver distance > 18.5 :
|   |   passer opponent1 angle <= 14 :
|   |   |   passer opponents dist12 ang4 <= 0 :
|   |   |   |   receiver players dist12 ang8 > 1 : F (16.7/7.6)
|   |   |   |   receiver players dist12 ang8 <= 1 :
|   |   |   |   |   passer opponent2 angle <= 22 : F (258.3/106.9)
|   |   |   |   |   passer opponent2 angle > 22 : S (65.1/32.8)
|   |   |   passer opponents dist12 ang4 > 0 :
|   |   |   |   receiver opponent3 distance <= 6.9 : F (25.6/13.8)
|   |   |   |   receiver opponent3 distance > 6.9 : S (69.4/32.0)
|   |   passer opponent1 angle > 14 :
|   |   |   receiver teammate1 distance <= 19.7 :
|   |   |   |   passer opponent1 angle <= 22 : S (85.0/28.9)
|   |   |   |   passer opponent1 angle > 22 :
|   |   |   |   |   receiver players dist8 ang12 > 1 : M (2.0/1.0)
|   |   |   |   |   receiver players dist8 ang12 <= 1 :
|   |   |   |   |   |   passer opponent2 distance <= 23.1 : S (46.6/11.8)
|   |   |   |   |   |   passer opponent2 distance > 23.1 : M (9.1/4.6)
|   |   |   receiver teammate1 distance > 19.7 :
|   |   |   |   receiver opponent2 distance <= 15.6 : S (36.7/23.0)
|   |   |   |   receiver opponent2 distance > 15.6 : F (36.7/21.2)
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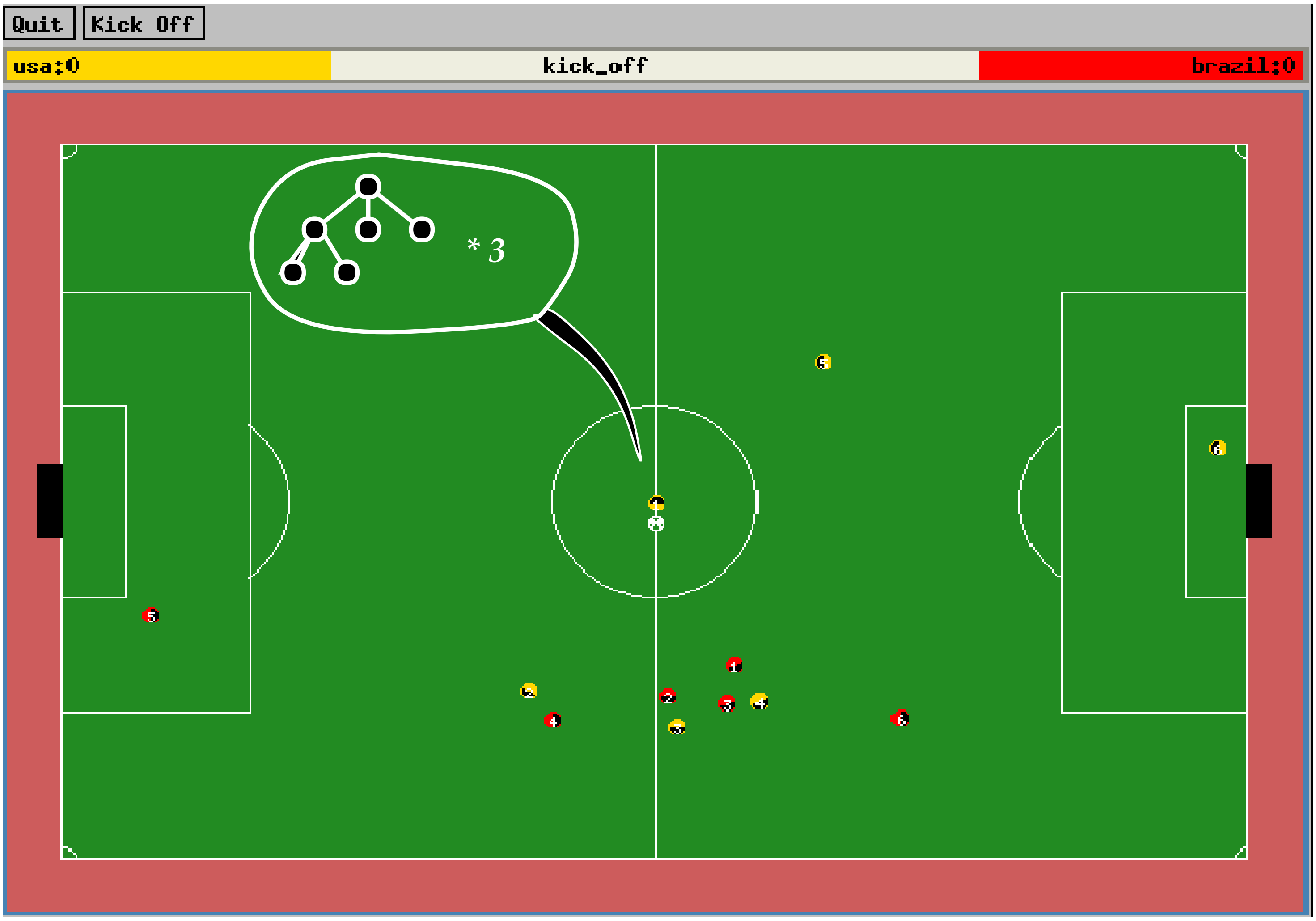
For each **Receiver**, the **Passer** uses the trained

DECISION TREE

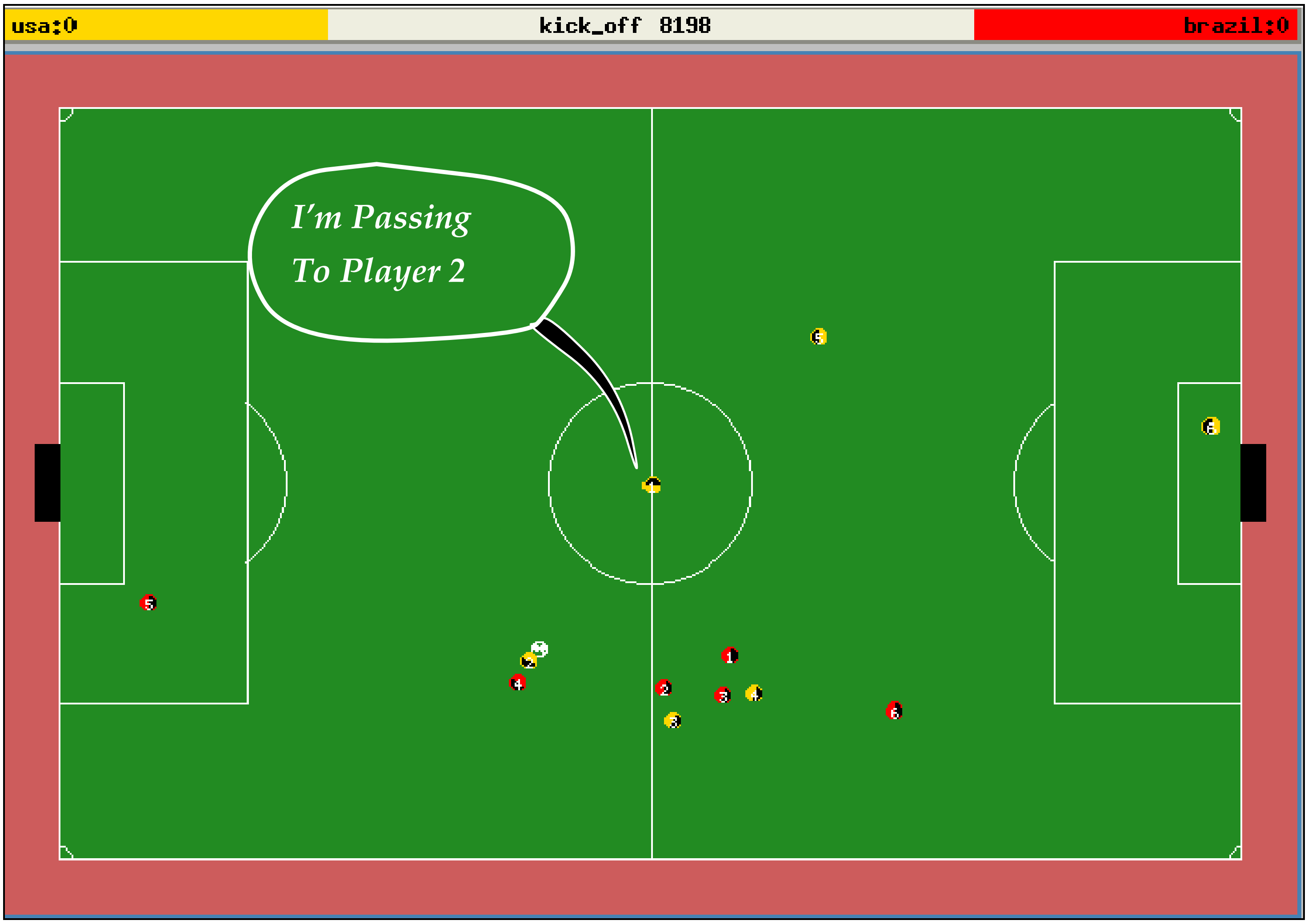
for deciding to whom to pass



Sample Decision Tree Output

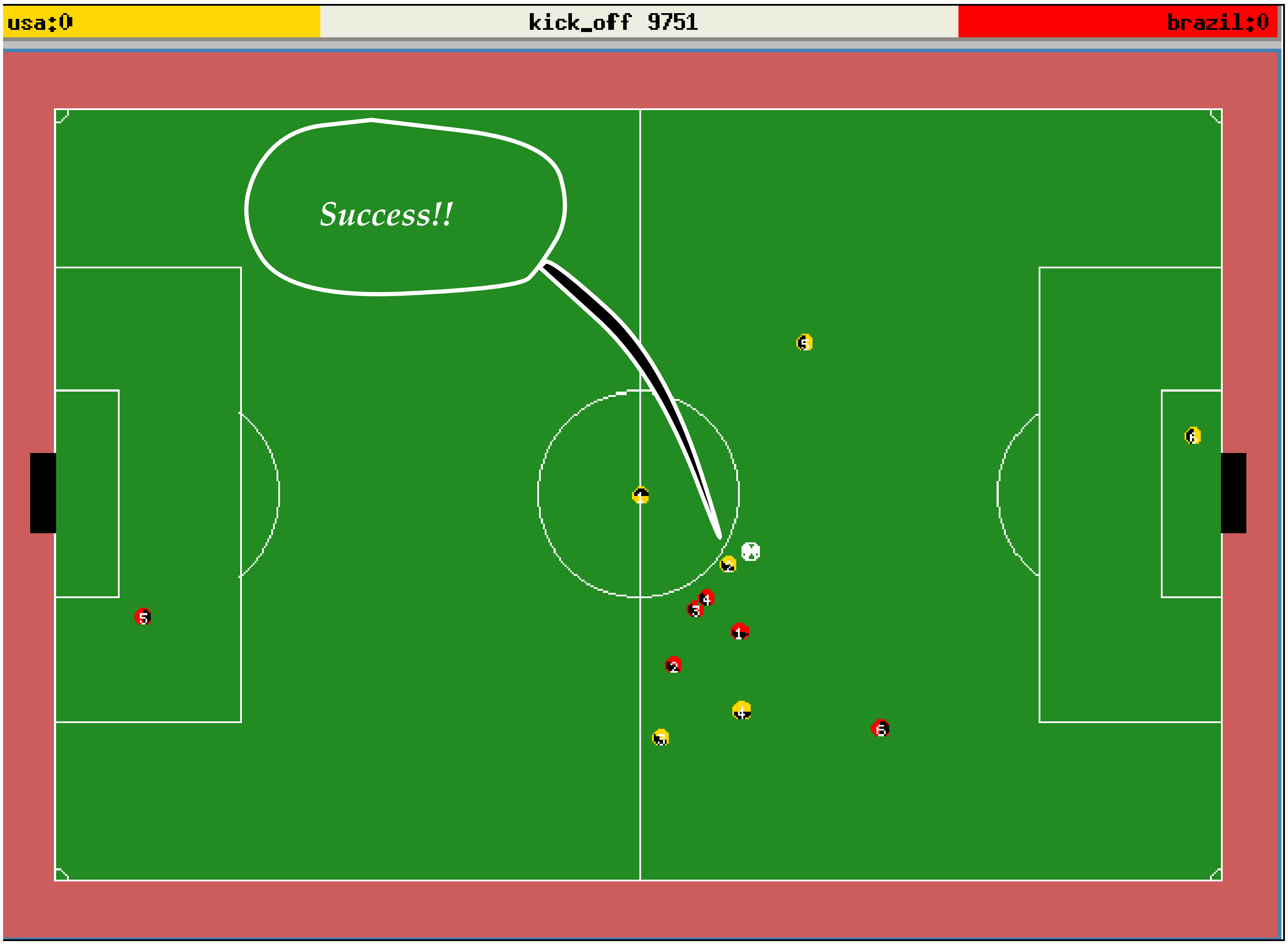
→ **Receiver 2 : Success with confidence 0.8**
Receiver 3 : Failure with confidence 0.6
Receiver 4 : Success with confidence 0.3

Then the Passer announces where the pass is going



- The designated Receiver moves to meet the ball.
- All other teammates know not to expect the ball.
- The opponents may attempt to intercept the pass.

Finally, the Receiver announces the result of the pass



Preliminary Results:

Passing to random teammate: ~ 40% success
Using the decision tree: ~ 60% success

Summary

- Soccer is a great domain for multiagent learning.
- We learn both Collaborative and Adversarial behaviors.
- Learning is appropriate for both single-agent behaviors (shooting and defending) and multiagent ones (passing).

Levels of Learning

1. Shooting and Defending
2. Passing
3. Planning

   ⋮

4. Full Games

As we keep building upon behaviors to achieve higher-level reasoning, the multiagent aspects become both more challenging and more exciting.