Vulture Combat

Potential Fields, Reinforcement Learning and Bayesian Networks Applied to Starcraft Broodwar

Analysis of the Game

Elements for Winning a Match

Build Orders

Information Gathering

Macro

Micro

Terran Tactics

Timing Attack

Pushing

Harassment

Unit Analysis

Marines

Vultures

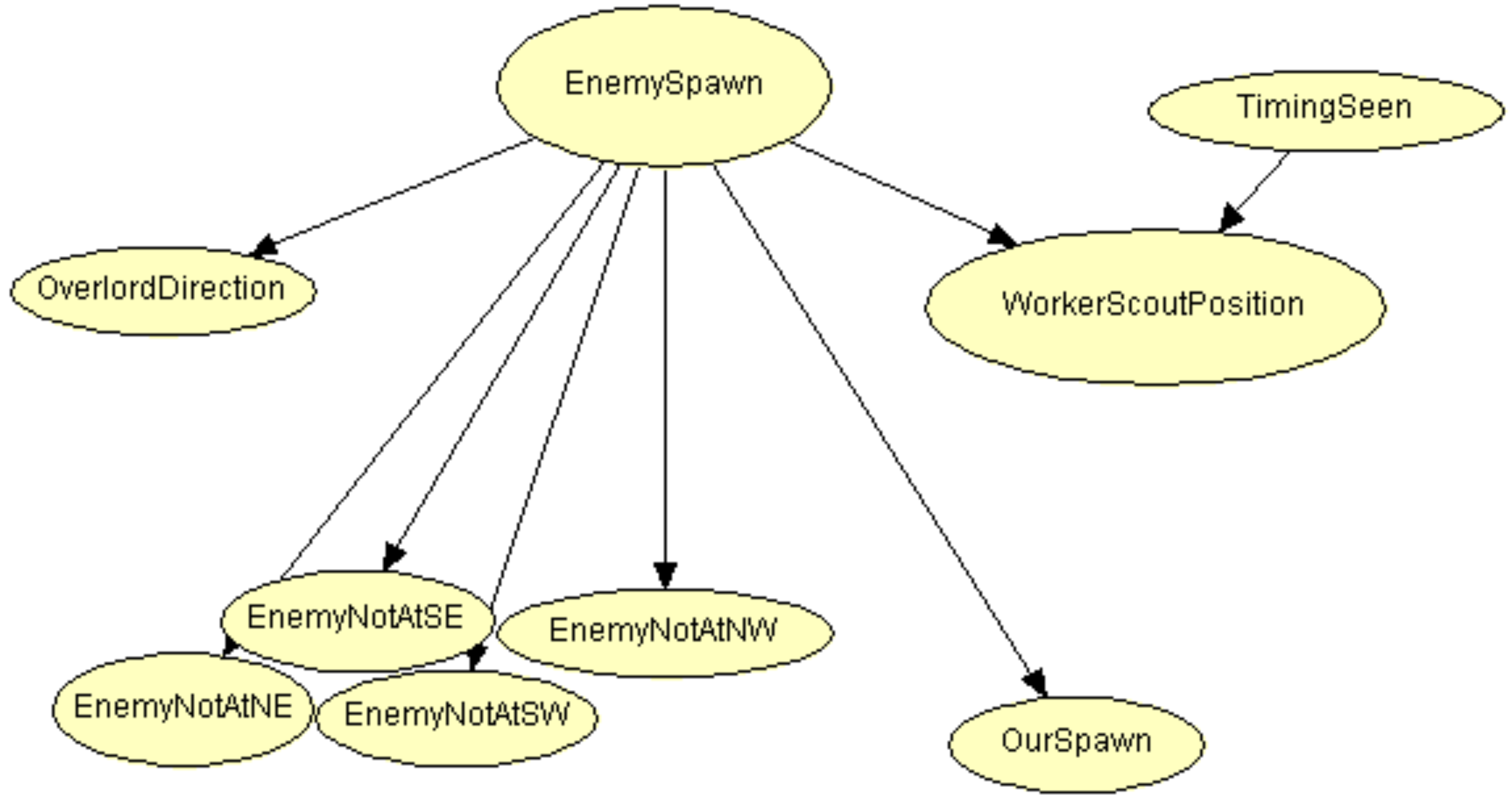
Wraiths

Bayesian Networks

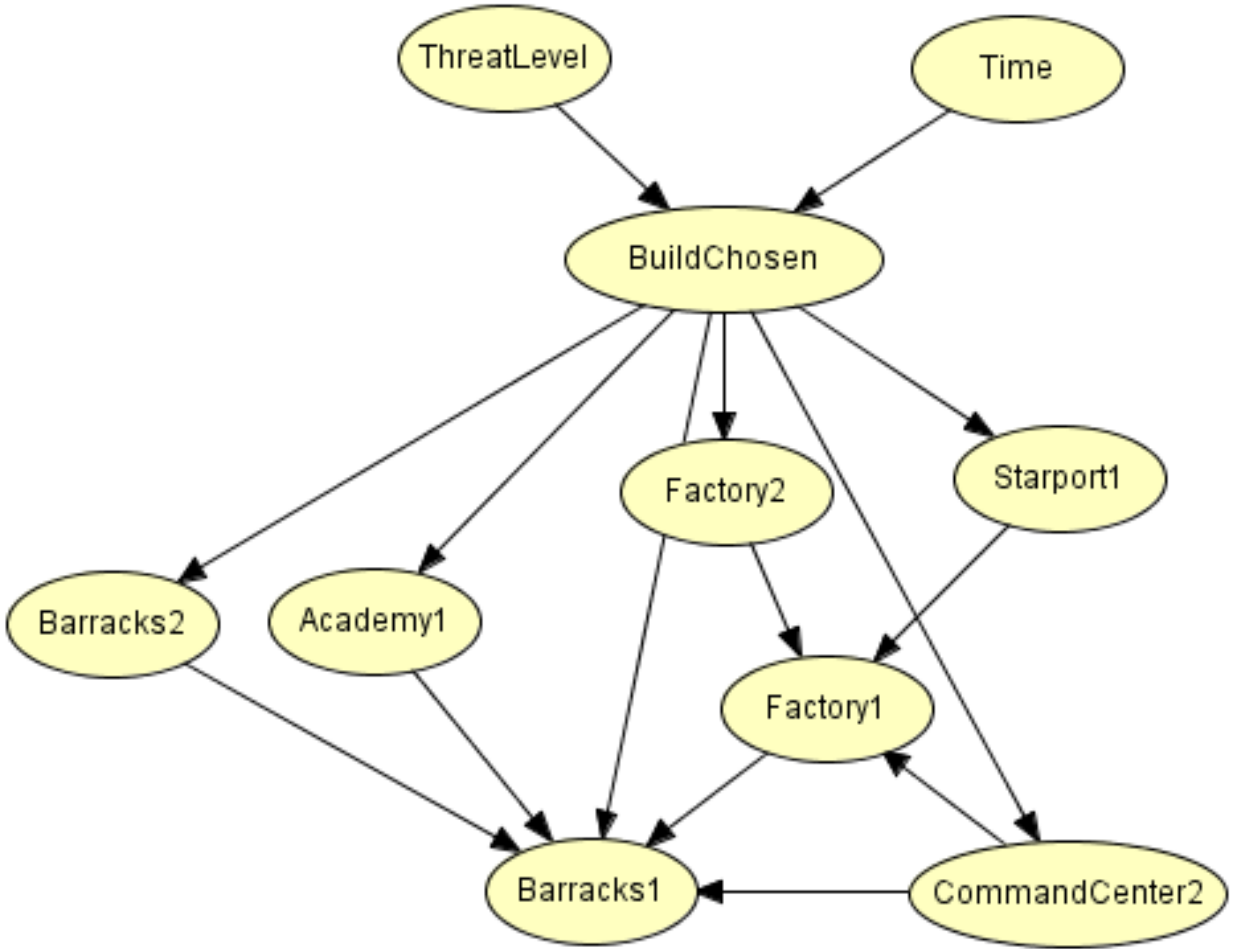
Choice of Decision Model

Bayesian Networks

Decision Trees



Spawn Prediction



Threat Level Prediction

Potential Fields

General Behavior

$$Attractive = \begin{cases} f * c & \text{if } d > s \\ 0 & \text{else} \end{cases}$$

$$Repulsive = \begin{cases} -f * c & \text{if } d > s \\ 0 & \text{else} \end{cases}$$

Using the numerical representation of a vector.

Example of a Potential Field Function

Behavior determined by sign (+ or -)

Difference between *due* and *de*

Using *(2de - due)*

$$MDP = \begin{cases} f_{MDP} \times (2de - due) & \text{if } de < sr \\ 0 & \text{if } de > sr \end{cases}$$

List of Potential Fields

Maximum Distance Positioning

Edges and Cliffs

Squad Center

Ally Units

Weapon Cooldown

Changes Made During Implementation

All weights or forces are positive.

The magnitude of the forces is learned.

Reinforcement Learning

Generalization of Q-Learning

Environment Variables

A State is defined as the combination of all the following characteristics:

- Distance to Ally
- Distance from Current Tile to Ally
- Distance to Center of Squad
- Distance from Current Tile to Center of Squad
- Distance to Enemy
- Distance from Current Tile to Enemy
- Distance to Cliff or Edge
- Distance from Current Tile to Cliff or Edge

- Number of units
- Health Lost
- Damage Dealt
- Number of Units
- Time
- Weapon’s Cool Down
- Shooting Range

Formulas

Q-Approximation

$$\hat{Q}_f = f_{MDP}(2de-due)+f_{AU}(2da-dua)+f_{EAC}(2dc-duc) \\ +f_S(2ds-dsv)+f_{CD}(2de-due)$$

Reward

$$R(s) = C_1 numberOfUnits - C_2 healthLost + C_3 damageDealt \\ + C_4 numberOfKills - C_5 time$$

Updating Rules

General Rule

$$f_i \leftarrow f_i + \alpha[R(s) + \gamma(max\hat{Q}_f(a', s')) - \hat{Q}_f(a, s)]\frac{\partial \hat{Q}_f(a, s)}{\partial f_i}$$

Application to the Ally Unit Coefficient

$$f_{AU} \leftarrow f_{AU} + \alpha[R(s) + \gamma(max(\hat{Q}_f(a', s'))) - \hat{Q}_f(a, s)](2da - dua)$$

Learning Algorithm

In Every Frame

1. Form the current unit position select the highest *Q(a,s)* value (where *a* represents the action of moving to the 8 surrounding tiles).
2. Select the highest value for *Q'(a',s')* form this state *s'* = δ*(a,s)* (where *a'* represents the action of moving to the 8 surrounding tiles).
3. Calculate the reward R(s,a).
4. Save all the values.
5. Move to the new position.

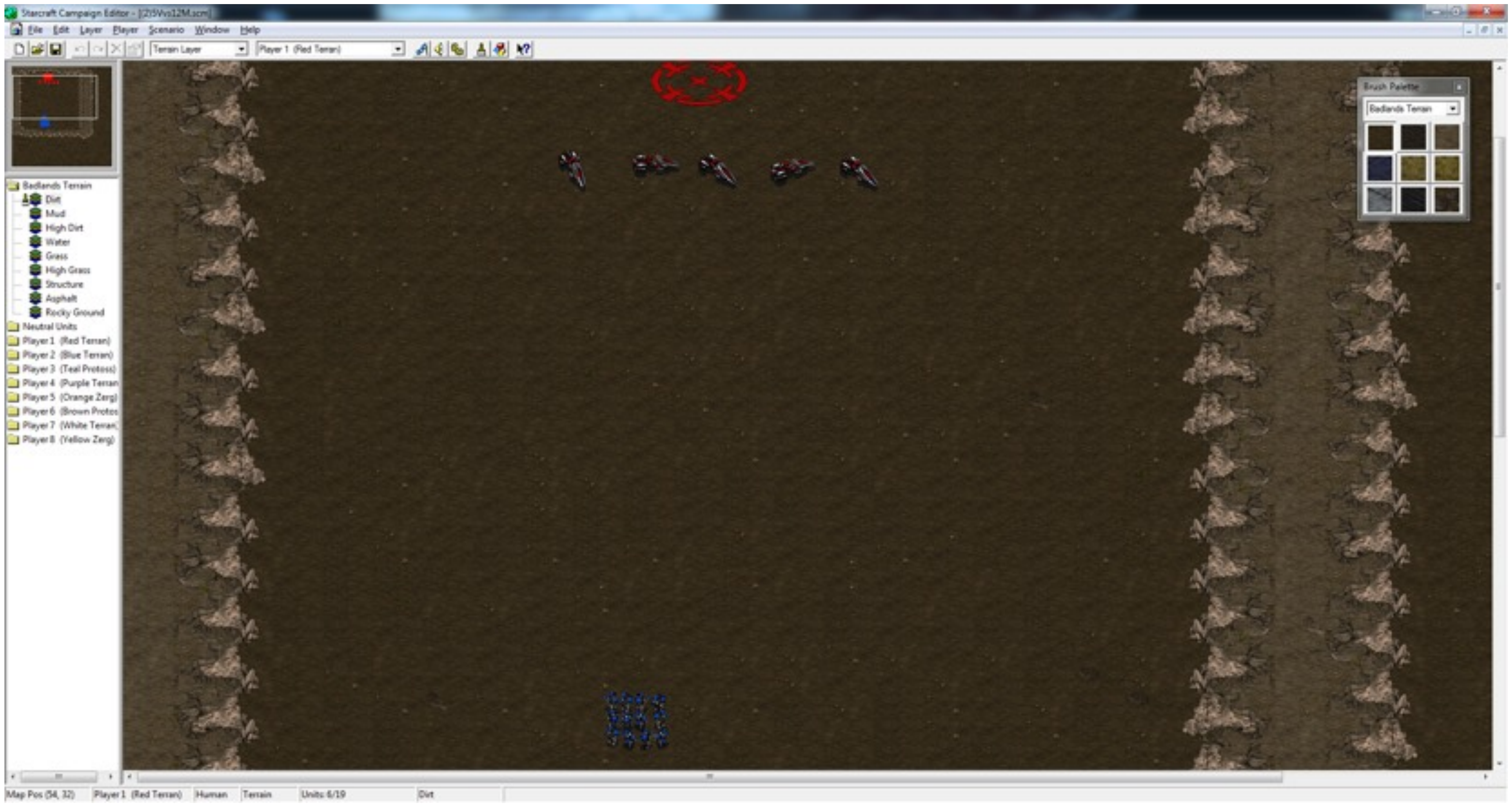
Every 25 frames

1. For every set of values saved in the buffer:

   Calculate the new weights with their corresponding update rule.

2. Save the new accumulated weights to the weights/coefficients used to calculate the next move (*Q* and *Q’* values).

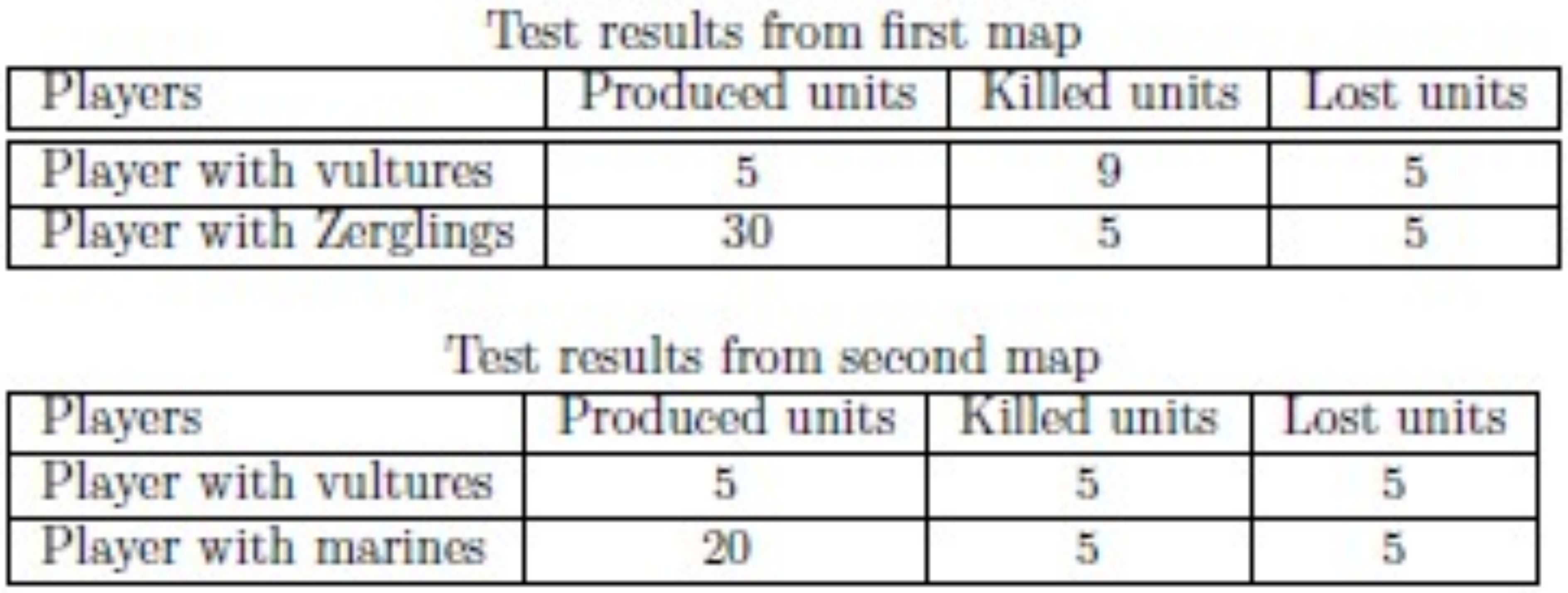
Tests



Building a Test Map

Base Case

Testing without reinforcement learning or potential fields:



Test results from first map

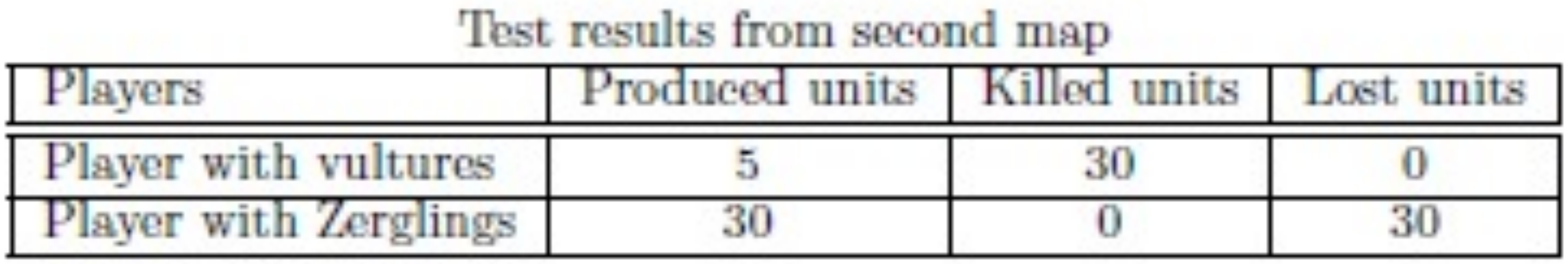
Players	Produced units	Killed units	Lost units
Player with vultures	5	9	5
Player with Zerglings	30	5	5

Test results from second map

Players	Produced units	Killed units	Lost units
Player with vultures	5	5	5
Player with marines	20	5	5

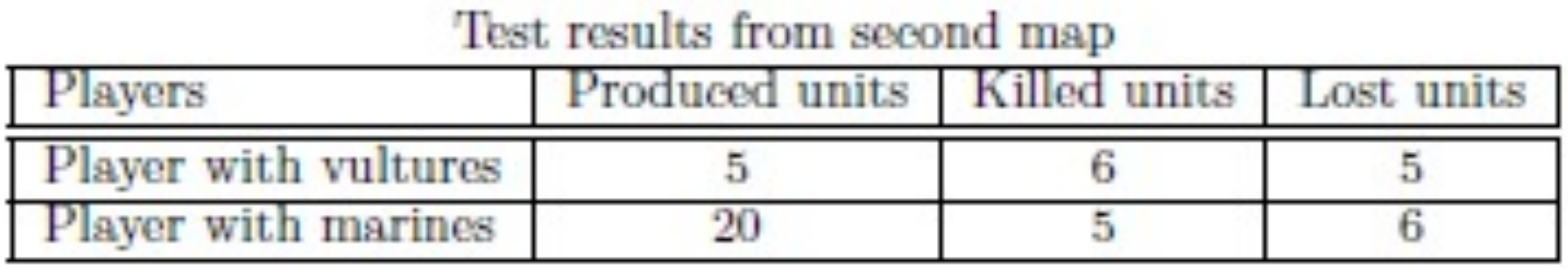
Base Case

Testing with potential fields, but not reinforcement learning:



Test results from second map

Players	Produced units	Killed units	Lost units
Player with vultures	5	30	0
Player with Zerglings	30	0	30



Test results from second map

Players	Produced units	Killed units	Lost units
Player with vultures	5	6	5
Player with marines	20	5	6

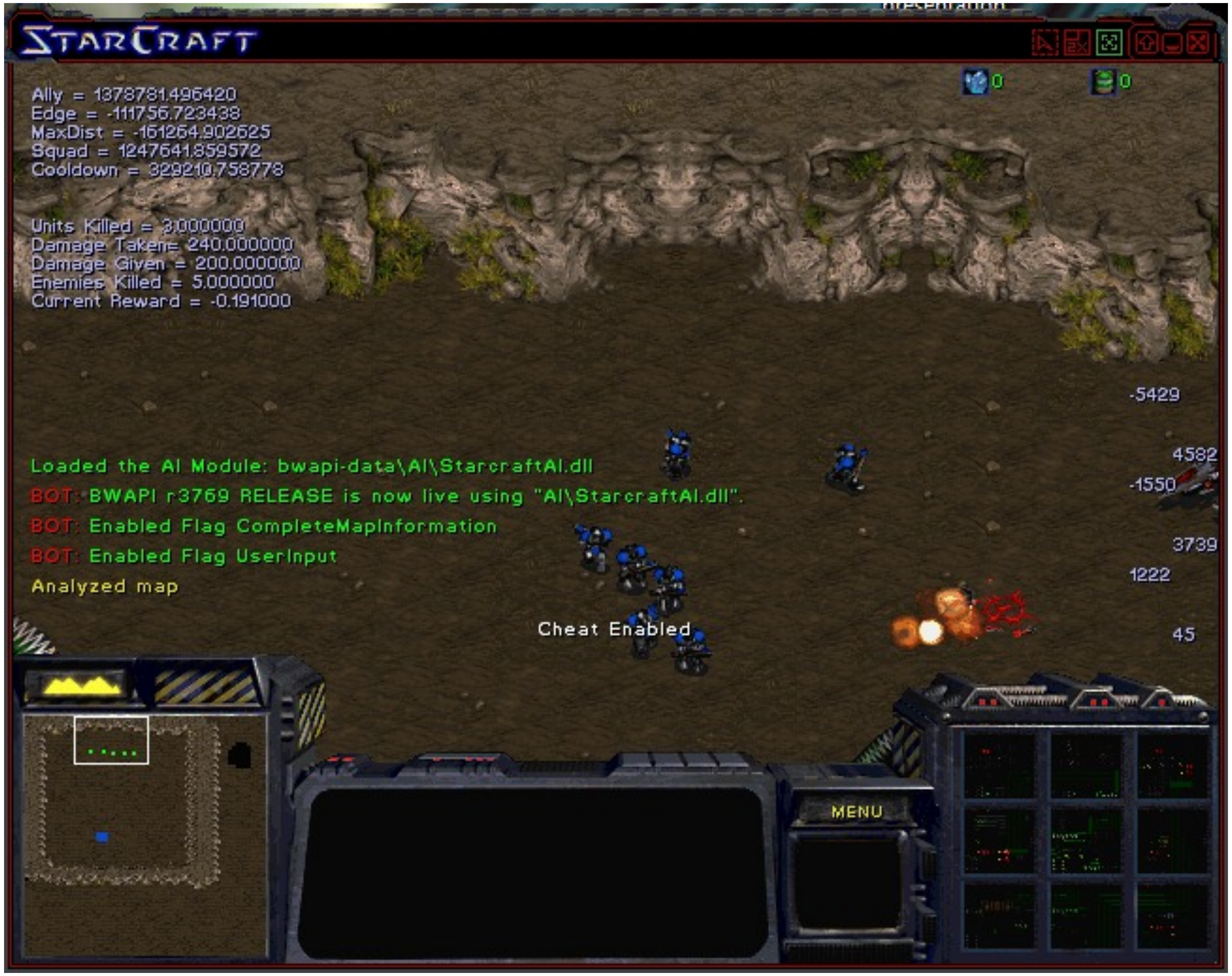
Will it converge?

Which Alpha and Gamma values?

How many iterations are needed?

Convergence

Running tests with different values



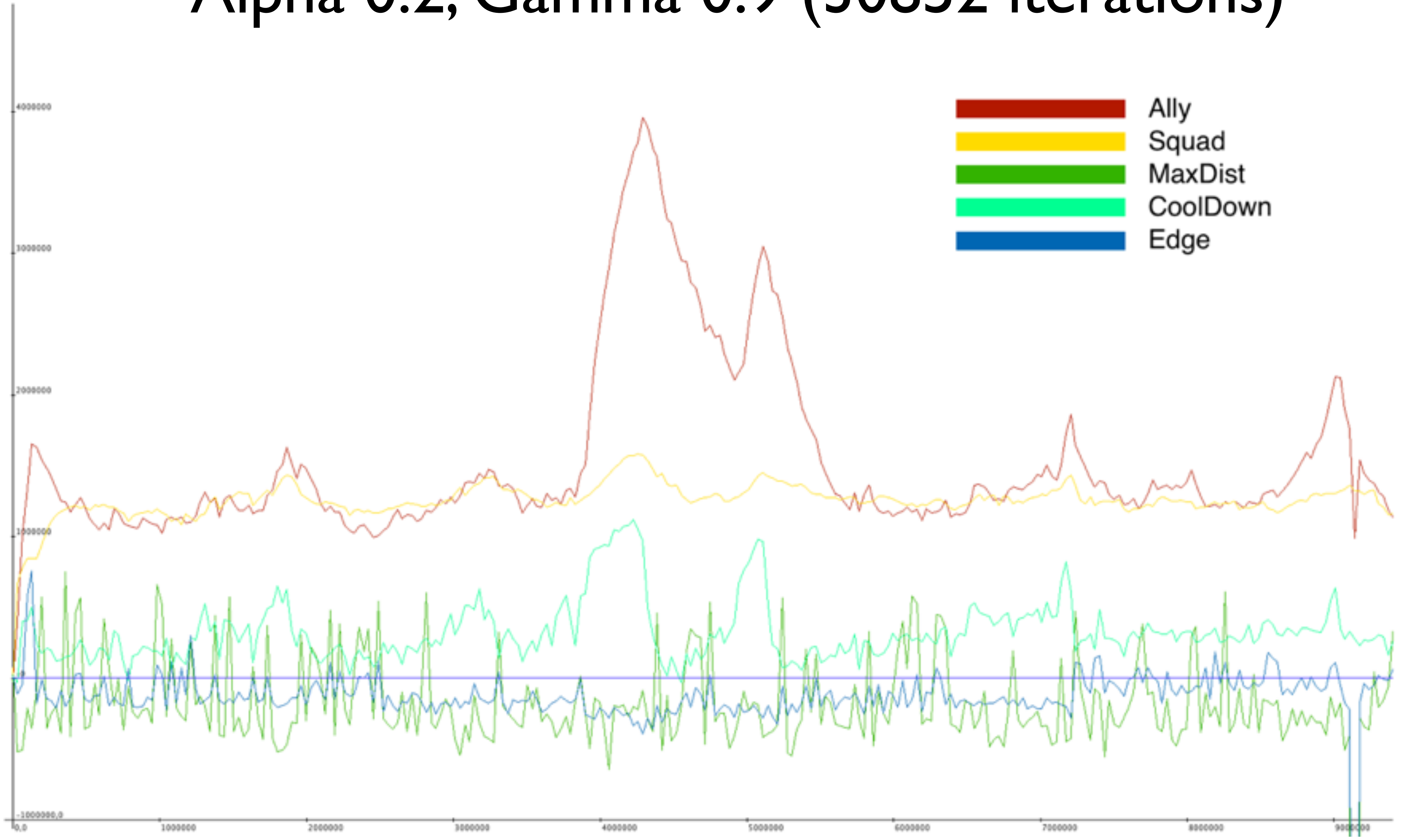
```
Ally = 1378781.496420
Edge = -111756.723438
MaxDist = -161264.902625
Squad = 1247641.859572
Cooldown = 329210.758778

Units Killed = 3.000000
Damage Taken= 240.000000
Damage Given = 200.000000
Enemies Killed = 5.000000
Current Reward = -0.191000
```

```
Loaded the AI Module: bwapi-data\AI\StarcraftAI.dll
BOT: BWAPI r3769 RELEASE is now live using "AI\StarcraftAI.dll".
BOT: Enabled Flag CompleteMapInformation
BOT: Enabled Flag UserInput
Analyzed map
```

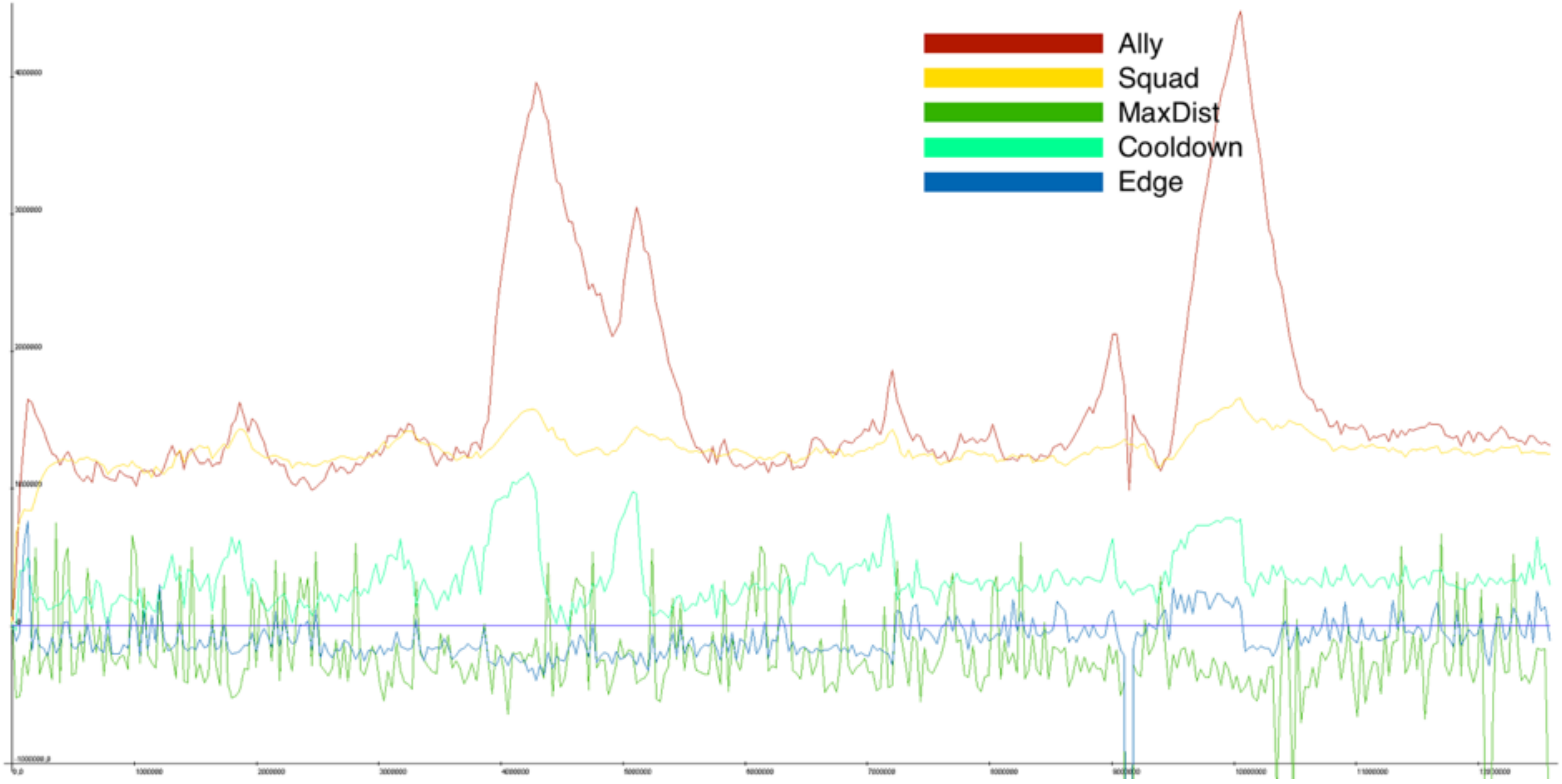
Convergence

Alpha 0.2, Gamma 0.9 (30852 iterations)

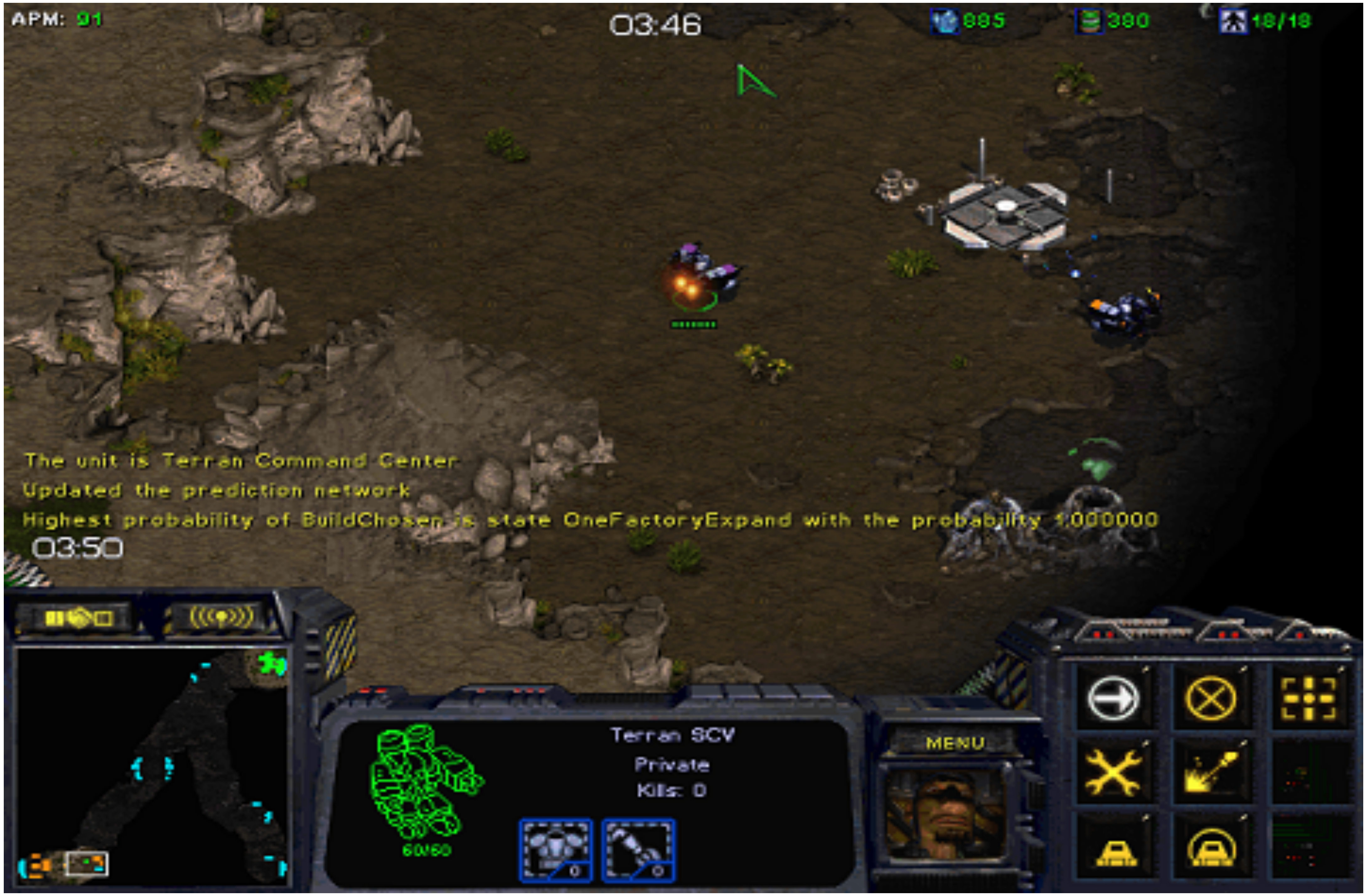


Convergence

Alpha 0.4, Gamma 0.6 (135936 iterations)



Predict spawn and build order



The unit is Terran Command Center
Updated the prediction network
Highest probability of BuildChosen is state OneFactoryExpand with the probability 1.000000
03:50

Future Works

Potential Fields

Does not work well on full games.

Add more variables.

Repair vultures.

Add cases for aggressive/defensive scenarios.

Apply movement speed upgrade.

Reinforcement Learning

Compare different reward functions.

Check enemy race/ unit types.

Keep bot running until all of the values converged.

Bayesian Networks

Use data mining

Add more build orders

Create extra networks

Conclusion

Identify parts of the games were machine intelligence was applicable.

Apply several concepts of machine intelligence for different circumstances.

Potential Fields + Reinforcement Learning.

Bayesian Networks.

Show improvement through testing.