Resource Allocation in Organizations: Behavioral Extensions

Abstract

We apply a formal model to understand the effects of the relative learning rates of embedded agents and the institutional field on organizational outcomes.

Keywords:
Embedded Agency

Title: Sub-title

Our understanding of institutional phenomena has come a long way since Selznick (1957) made the observation that organizations adopted new goals suited to existing structures instead of changing the structures that may have outlived their utility.

The rest of this article is organized as follows.

BACKGROUND

Scott (1995) visualized institutional fields as a community of organizations that partakes of a common meaning system and whose participants interact more frequently and fatefully with one another than with actors outside the field.

MODEL

We develop a simple model consisting of two players who participate in a repeated game of matching [1]. The payoffs are captured by the matrix in Table 1

Insert TABLE 1 about here.

To help improve the intuition in the analysis, we define a few categories.

Field Start Position

The Field Start Position is a characterization of the choice preference of the institutional field at the start of the interaction.

The third level section We do so since the scale is symmetric across the Center (C), any initial mapping of Left (L) and Left of Center (LC) can be mapped onto an equivalent Right (R) or Right of Center (RC) configuration.

Insert FIGURE 1 about here.

DISCUSSION

Having laid out the formal model and having described the assumptions and classifications made in the previous section, we now consider if the model described above is a reasonable abstraction of the phenomenon that we wish to theorize upon.

[1] I am grateful to Phanish Puranam for having introduced me to this model of reinforcement learning during a workshop at the Indian Institute of Science on 16th December, 2016. His definitions and code have been extensively reused in this work.

INTERPRETATION OF MODEL RESULTS

On the topic of the general hypotheses

Figure 1 lays out the average score charts for four agent-field combinations while enforcing the field to start in Right of Center (this is the same as saying $p^0_{0,F} = 0.75$).

Leading into H1a We do so since the scale is symmetric across the Center (C), any initial mapping

Hypothesis 1a: When the institutional field is open to influence, slow learning adversarial agents will raise overall performance higher than slow learning agents with a neutral orientation

Leading into H2a This trend is confirmed further in Figure 1 where the learning rates of agents are increased even further to 'Fast'.

Hypothesis 2a: For the same initial outcome preferences, the overall performance score varies curvilinearly with difference in the rates of learning of the agent and the institutional field

LIMITATIONS AND FUTURE WORK

The formal computational modeling approach to theorizing organizational phenomena comes across as being both valuable and challenging simultaneously.

CONCLUSION

We started out attempting to improve our understanding of the mechanisms behind the embedded agent - institutional field engagement.

References

Scott, W. R. 1995. ***Institutions and organizations. foundations for organizational science***. Thousand Oaks, CA: Sage Publications.

Selznick, P. 1957. ***Leadership in administration: A sociological interpretation***. Berkeley and Los Angeles: University of California Press.

APPENDIX A: SIMULATION CODE

```
# Using reinforcement learning to a game of repeated matching
# Modified from a version obtained from Phanish Puranam

import random
import numpy as np
import csv

def position(p):
    if (p < 0 or p > 1):
        return "PositionUndef"
    if p <= 0.10:
        return "L"
    if p <= 0.35:
        return "LC"
    if p <= 0.65:
        return "C"
    if p < 0.9:
        return "RC"
    return "R"

num_periods=100 #number of periods to simulate the model
num_pairs=1000 #number of pairs of agents

pAs=[0.5, 0.75, 0.95]
pBs=[0.05, 0.5, 0.95]
phiAs=[0.05, 0.3]
phiBs=[0.05, 0.3, 0.7]
models = []
for pB in pBs:
    for phiB in phiBs:
        for pA in pAs:
            for phiA in phiAs:
                modelName="F["+position(pA)+"-"+learning(phiA)+"] U["+
                    position(pB)+"-"+learning(phiB)+"]"
                models.append([modelName, pA, phiA, pB, phiB])
```

FIGURE 1

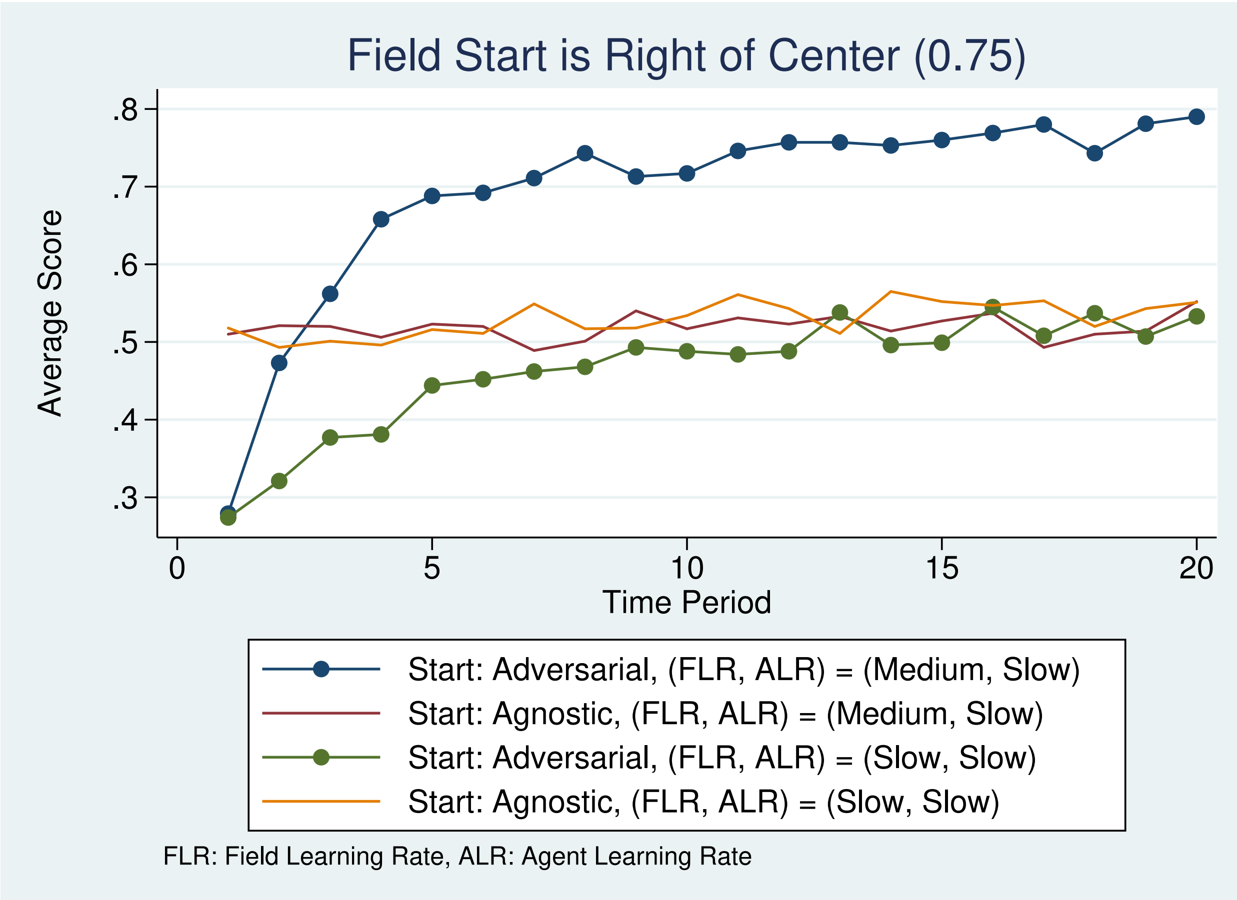
Field Start is Right of Center (0.75)
Average Score
.8
.7
.6
.5
.4
.3
0
5
10
15
20
Time Period
Start: Adversarial, (FLR, ALR) = (Medium, Slow)
Start: Agnostic, (FLR, ALR) = (Medium, Slow)
Start: Adversarial, (FLR, ALR) = (Slow, Slow)
Start: Agnostic, (FLR, ALR) = (Slow, Slow)
FLR: Field Learning Rate, ALR: Agent Learning Rate

TABLE 1: Payoff Matrix

	$choice_F(t) = 0$	$choice_F(t) = 1$
$choice_A(t) = 0$	$[payoff_F(t), payoff_A(t)] = [1,1]$	$[payoff_F(t), payoff_A(t)] = [0,0]$
$choice_A(t) = 1$	$[payoff_F(t), payoff_A(t)] = [0,0]$	$[payoff_F(t), payoff_A(t)] = [1,1]$