Co-Evolving Business Models: A Case Study with the Internet Service Provider (ISP) Industry

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Abstract

In this paper, co-evolution is used to examine the long-term evolution of business models in an industry. Two types of co-evolution are used: synchronous, whereby the entire population of business models is replaced with a new population at each generation, and asynchronous, whereby only one individual is replaced..

Keywords: agent-based modeling, co-evolution.

1. Introduction

It may be useful, for strategic planning purposes [19], to be able to generate possible future trajectories for an industry. Industrial Organization (IO) and Game Theory (GT) [7] are often used to predict the outcome of rather simple economic situations. One problem is that exact results are out of reach as soon as the modeled situation becomes realistic. Oligopolistic behavior continues to be a challenge to economic theorists, even in cases restricted to competition in price alone. Another problem is the difficulty of integrating innovation into such calculations, as the space of possibles has to be predefined. We have used simulated co-evolutionary dynamics to examine the long-term dynamics of business models in the Internet Service Provider (ISP) industry. Evolutionary ideas have been present in economics for some time in connection with game theory [2,20]. More recently, following the pioneering work of Holland [10], numerous researchers have applied evolutionary algorithms [10, 9,18] directly to the adaptive behavior of economic agents [1,5,6,11,13,14,15,16].

The work of Marks and colleagues [13,14,15,16] is particularly relevant to this paper as it describes how genetic algorithms can be used to breed brand strategies (for example, store strategies such as frequency and duration of promotions) for brands of coffee in a US regional market; using a simple market-response model, they co-evolved strategies. Some of their work uses a multi-population GA where each population corresponds to a particular firm that has a specific cost structure, brand recognition, etc. In this article, we are concerned with the long-term trajectory of an industry, not necessarily with optimizing a specific strategy for a particular firm; as a result all the components of a business model are variable, including the cost structure (although the cost structure may impact, say, quality of service) and a single population is used. One remarkable feature of the work of Marks and colleagues is the use of an empirically-grounded fitness function calculated using econometric techniques; in other words, how the market is going to respond to a particular change in strategy is quantitatively plausible. The work presented here has a similar grounding in market research data on the ISP industry (1995-2001). The major advance of this paper is our extensive analysis of the results of the co-evolutionary dynamics. Other co-evolutionary work in economics include the works of Curzon Price [4] and Miller [17].

2. Agent-Based Model

2.1. Customer agents

The order book matches orders in a continuous. A customer is in one of 6 categories (Small Budget: SB, Email Addict: EA, Family User: FU, Night User: NU, Always Connected: AC, Timid User: TU). While in reality the makeup of a marketplace changes in time it is static in our simulation. The makeup of the agent population could be described as mature. A large fraction of the consumers, 35%, have broadband while most of the remaining, also 35%, are limited only by their small budgets. New users of the internet represent only 7% of the total population. Smaller specialty clusters make up the remaining 23% consists of specialty classes. In simulations we use 100 agents, with 50 SB agents, 10 EA agents, 10 FU agents, 10 NU agents, 50 AC agents and 10 TU agents. Customer agents are described by 9 parameters that describe how an agent chooses an offering and/or switches offerings.

There are 4 variables describing the relative importance of (a) modem speed, (b) monthly price, (c) service level, (d) being subjected to advertising; and 4 variables describing desired (a) price per month, (b) modem speed, (c) service level, (d) hours of internet usage during each of three 8 hour blocks of the day. Desired internet usage is the same for each of the 28 days of the month. The desired service level is a measure of what fraction of login attempts the user hopes will be successful. In the early days of ISPs all of the access lines would sometimes be busy. The desired service level parameter range is 0 to 100%. Once created, none of the above properties may change during the course of the simulation. Each customer category is characterized by a mean value for each of the parameters; the population of customer agents is created by generating agents that have parameters values drawn from a uniform distribution in the interval mean value +/- 20%. Each customer agent evaluates each ISP offering option and then either chooses the one with the highest rating or makes a stochastic roulette-wheel style choice. When evaluating the offerings each agent examines every offering by computing a score which takes into account the characteristics of the offering. Once an agent chooses an offering it cannot cancel for any reason until their contract expires. An agent cannot be subscribed to more than one offering at a time.

2.2. ISP agents

ISP agents provide the offerings that customer agents choose. Each ISP has number of ports (modems) each of which can provide a single user internet access. ISPs collect money from customer agents, gather and provide some statistics, update the number of ports they desire, adjust the actual number of ports they have, and make some payments to sustain their business. They do not kick agents out for non-payment, fine tune their offerings dynamically, or adjust the shape of their response function. Each ISP has a desired maximum level of usage as a fraction of possible usage. That is, if an ISP can accommodate 100 users with 56KB/s ports they may aim to have, at most, 75 users online during peak times. The reasoning for this is that on a week to week basis an ISP may get a sudden influx of customers. If at any point there are less ports available than requested by customers then customers *service level* perception will decrease. As *service level* is typically one of the important characteristics customers use to make their internet provider choices ISPs are interested in maintaining a positive image. On the other hand, ports cost money to purchase and upkeep, due to *depreciation*. To remain competitive in a *net revenue* sense, ISPs also have the ability to adjust down the number of ports. By *usage* we mean the number of hours ports are accessed by agents. A single port can support 24 hours/day of usage. As the day is broken into three blocks, (*early; middle; evening*), each port has a maximum usage of 8 hours in this period. If an ISP has a single port and four users each want two hours of access during the *evening*, they will all succeed. The ISP will note a *desired utilization* for this port type and time of day of 8 hours and an *actual utilization rate* of 100%. If suddenly an additional user joins the party each subscriber will be said to have accessed the port with an *actual utilization rate* of 80%. The ISP will then note a *desired utilization* for this port and time of day of 10 hours. At the end of each week, each ISP is given information on the *desired usage* experienced by their customers broken down by service type and time of day.

2.3. Simulation specifications

One simulation runs for 100 weeks. Initially, no agents are signed up for an offering. All agents begin their interaction with ISPs from the first week. ISPs all begin with 5 ports of each type. Our experiment included a market of 10 ISPs each with a single offering.

3. Co-Evolution

3.1. Synchronous co-evolution

In synchronous co-evolution, the entire population is replaced with a new generation at the end of the simulation, following traditional GA mechanisms. ISPs are assigned a fitness value which is net income at the end of the simulation. Each individual is mutated and mates with a partner drawn from biased roulette wheel sampling based on fitness. This is repeated for 1000 generations.

3.2. Asynchronous co-evolution

In asynchronous co-evolution, a randomly selected individual in the population is replaced at the end of one simulation. It is replaced by mutating it and crossing over with an individual selected by biased roulette-wheel sampling in a manner similar to the one described in 3.1. The new individual is then tested against its competitors; if its fitness is lower than the fitness of the individual it replaced, the new individual is discarded and the population remains unchanged.

This process is iterated for 10,000 generations. Clearly in the asynchronous case many generations may pass with little to no change in the population makeup. New individuals may not be competitive and therefore not lead to a change in the population.

3.3. Encoding and operators

The chromosome is formally made up of a mixture of real, integer, and Boolean variables. Table 1 shows the fields included in chromosome used.

Variable	*Type*	*Minimum*	*Maximum*
Cost per minute	Real	\$0.00	\$1.00
Cost per month	Real	\$0.00	\$100.00
Free Hours per month	Real	0	24 (hours/day) * 28(days/month)
Sign up Fee	Real	\$0.00	\$100.00
Contract Length	Integer	0	12 months
Service Type	Integer	0	Number of Service Types
Use Advertisement	Boolean	True	False
Activate Offering	Boolean	True	False

Table 1: Parameters modified in the course of evolution.

For mutation, Gaussian noise is added to each real and integer valued gene with a zero mean and a variance equal to 3% of the permissible gene value range. For example, if a gene can take a value from 0 to 100, our variance for this gene is 3. Furthermore, we require the new gene value to be within the permissible range.

The crossover operator used in this study is a simple, uniform random one-point crossover.

4. Experiment and Results

In order to analyze the results of the synchronous and asynchronous co-evolutionary runs, a k-means clustering algorithm was used and tested with various values of k for each co-evolutionary run [12]. In both the synchronous and asynchronous co-evolutionary experiments, we found that the ISPs could be best described by six clusters.

Tables 2 and 3 show the values of the various co-evolved parameters typical of each of the six clusters. Table 2 is for synchronous runs, while Table 3 is for asynchronous runs.

	Offering Parameters						Performance	
	\$/min	\$/mo.	FHPM (hr)	SUF (\$)	CL (mo)	ST	Sub.	% of Pop
1	0.69	24.61	559.91	64.39	8.07	1.81	462	15.35
2	0.28	34.09	554.64	28.85	8.31	1.86	452	15.02
3	0.64	18.69	223.13	71.21	8.89	1.58	537	17.84
4	0.27	27.94	217.38	35.16	9.12	1.62	436	14.49
5	0.24	25.36	457.78	74.64	8.49	1.85	481	15.98
6	0.72	29.12	396.75	20.28	8.52	1.62	642	21.33

Table 2: Clusters obtained with synchronous co-evolution.

	Offering Parameters						Performance	
	\$/min	\$/mo.	FHPM (hr)	SUF (\$)	CL (mo)	ST	Sub.	% of Pop
1	0.19	25.82	566.33	29.89	10.16	1.98	509	16.91
2	0.65	25.77	613.36	34.05	10	1.99	743	24.68
3	0.62	23.97	522.93	47.72	10.41	2.98	534	17.74
4	0.11	20.12	524.83	66.95	10.79	1.94	248	8.24
5	0.59	21.16	575.47	64.06	10.52	2.01	656	21.79
6	0.10	23.22	463.87	48.47	10.68	2.98	320	10.63

Table 3: Clusters obtained with asynchronous co-evolution.

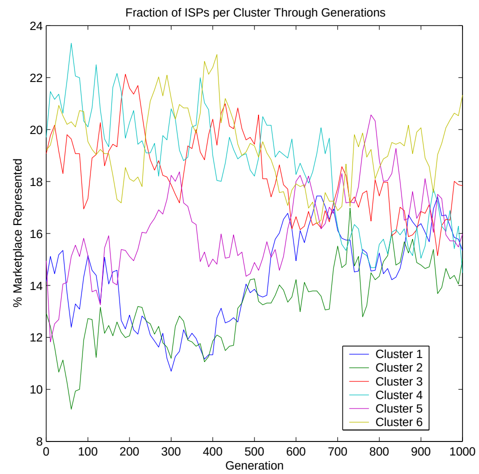

Fig. 1: Market shares of clusters obtained with synchronous co-evolution.

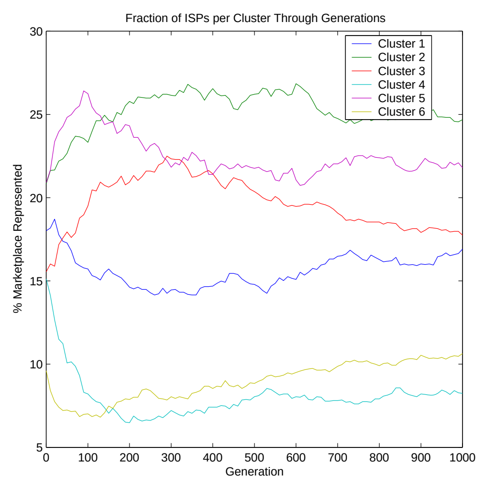

Fig. 2: Market shares of clusters obtained with asynchronous co-evolution.

Figures 1 and 2 show the respective market shares of the various identified clusters. It is apparent from those graphs that the synchronous is much more irregular than the asynchronous one, as one would expect. In addition, market shares are more evenly distributed among clusters with the synchronous co-evolutionary dynamics than with the asynchronous one where there is some degree of market concentration. One of the interesting results of the experiments is the existence of a dominant cluster across all marketplace asynchronous co-evolutionary runs. In other words, as shown on Figure 3, certain clusters have a 40% probability of being present in the ISP ecosystem, suggesting that such clusters represent structurally dominant offerings or business models. There is no such emergence of dominant clusters in the synchronous case.

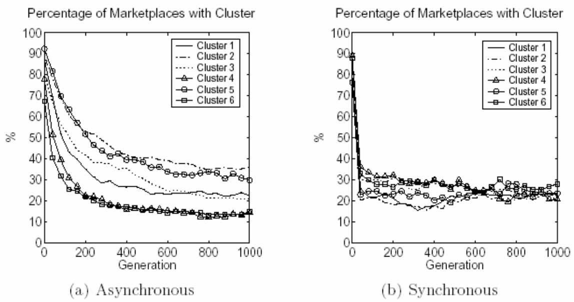

Fig. 3: Percentage of co-evolutionary runs where each cluster is present.

5. Conclusion

This article introduces a simple co-evolutionary model for describing the potential future trajectories of the ISP industry. Synchronous and asynchronous forms of co-evolution are used. The asynchronous dynamics, which arguably more closely reflects the actual dynamics of the industry, reproduces stylized features of the real marketplace, such as some degree of market concentration, and generates dominant offerings that seem to be present in a large fraction of future scenarios.

6. References

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