UTILIZING THE POSITIVE IMPACTS OF SOFTWARE PIRACY IN MONOPOLY INDUSTRIES

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ABSTRACT

Succeeding under rampant software piracy is a critical task for software publishers today. Instead of treating software piracy as a destructive force, a few scholars have realized the positive influence of software piracy, that is, it may accelerate the diffusion of innovations. Furthermore, fewer scholars have tried to develop strategies to control and manipulate software piracy to utilize its positive influence. In this paper, a model is introduced that simulates a computer software market as a complex adaptive system. The model develops dynamic and self-learning marketing strategies that help software publishers utilize software piracy to speed up a new product diffusion process, maximize profits, and minimize costs in a monopoly marketing environment. Also, the model demonstrates that the profits and the diffusion speed are also influenced by the topologies of social networks and the locations of pirates.

Keywords: software piracy, complex adaptive system, diffusion of innovations.

1 INTRODUCTION

"Software piracy is the copying and/or distribution of software for personal and/or business use without the authorization of the copyright holder" (Symantec 2016).

Software piracy has become a major concern in information technology (IT) industries. A global survey conducted by Business Software Alliance reveals that 39% of all software products installed on PCs worldwide during the year 2015 were pirated copies. The loss to the IT industries was $52.2 billion (Business Software Alliance 2015).

Major research on software piracy today focuses either on developing anti-piracy technologies or adjusting the marketing strategies of software publishers to reduce the damage caused by software piracy. However, software piracy could also bring benefits to software publishers, that is, it may accelerate the diffusion of innovations. So far, only a few scholars have realized the positive influence of software piracy, and even fewer scholars have tried to develop strategies to control and manipulate software piracy to utilize its

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positive impacts. In addition, a gap exists between the research on software piracy and the research on diffusion of innovations. Scholars who have conducted research on software piracy barely paid any attention to the impacts of social network topologies, while scholars who have conducted research on diffusion of innovations failed to expand their horizon to cover the subject of software piracy. There are only very few scholars who utilized the classical Bass model (Bass 1963) to control the software piracy.

In this paper, we introduce a model to simulate a computer software market as a complex adaptive system. The model develops dynamic and self-learning marketing strategies that help a software publisher utilize the positive impacts of software piracy to speed up a new product diffusion process, maximize profits, and minimize costs in a monopoly marketing environment. Besides these strategies, the model demonstrates that profits and the diffusion speed also rely on the topologies of social networks and the locations of pirates.

The rest of the paper is organized as follows: Section 2 provides reviews of existing research on the positive impacts of software piracy and the influences of network topologies on the diffusion of innovations. Section 3 discusses the design of the model and the modeling methodologies. Section 4 presents and discusses the experimental results with respect to both homogeneous and heterogeneous consumers. Section 5 provides the final conclusions.

2 LITERATURE REVIEW

2.1 Reviews of Positive Impacts of Software Piracy

Some scholars recognized the positive influences of piracy, such as benefiting a new product's diffusion, increasing market shares, and finally, helping software publishers establish a dominating market share and maximize profits. Conner and Rumelt (1991) pointed out that piracy is a more efficient "gift-giving" method than mailing free software to consumers because the costs of gifts are carried by consumers, not software publishers. Givon, Mahajan, and Muller (1995) analyzed the positive impacts of piracy by building an extended Bass diffusion model. The model tracks down both piracy and legal diffusions. Results indicate that six out of seven consumers use pirated software, but these pirates are responsible for generating 80% of new software buyers. On the other hand, Givon et al. (1995) only addressed how piracy affects the size of a consumer base, not other marketing factors, such as prices and costs. An increasing market share does not necessarily result in increasing profits. Givon, Mahajan, and Muller (1997) extended the Bass diffusion model by incorporating two competing software products, Lotus 1-2-3 and Microsoft Excel, in the presence of piracy and the possibility of brand switching by the consumers. The model implies that the success of Microsoft Excel over Lotus 1-2-3 may have been due to its higher tolerance towards piracy.

Scholars have not only realized the positive impacts of piracy, but also considered how to properly control the amount of piracy in order to maximize benefits. Prasad and Mahajan (2003) developed another extended Bass diffusion model. They examined the relationship between the speed of a diffusion process and other marketing factors, including prices, degrees of tolerance of piracy, protection costs, and market entrance time of each version of multiple-generation software. The model demonstrated that proper controls of piracy at the different stages of a product life cycle are able to maximize both market share and profits of a software publisher. The model analyzes three cases: monopoly, multiple generations under a monopoly, and a competitive condition. From this analysis, Prasad and Mahajan drew the following conclusions. First of all, under the monopoly scenario, a software publisher should start with minimum protection. After the diffusion reaches its peak, the software publisher should impose a maximum protection for the rest of the diffusion cycle. Secondly, under the multiple generation scenarios, the tolerance level of the previous generation is closely related to the expected profit margins of the following generation. Thirdly, under the competitive scenario with results briefly analyzed, Prasad and Mahajan only suggested that the software publishers should set the protection level lower versus the protection level in the monopoly environment.

Haruvy, Mahajan, and Prasad (2004) examined how piracy affects the diffusion process of subscription software. In this model, the subscription software still functions with certain disabled features after an expiration date. Consumers could choose to pay to renew the subscription, pirate, or not renew at the end of each time period. The model indicates that an optimal combination of protection levels and prices facilitates faster adoptions and higher prices for the subscription software. It also points out that tolerance of piracy will be less profitable when piracy control is costly, information is precise, penetration is quick, externalities are low, future profits are greatly discounted, customer inertia is low, or its product life is short.

The existing research utilizes the Bass model to study the impacts of software piracy on the diffusion of a new product. However, the Bass model relies on several unrealistic assumptions. The first assumption is that the coefficients of internal and external influences are constant through the entire adoption process. These two coefficients are calculated from the data in past sales periods. Applying such coefficients assumes that a market is static and will never change in the future. The second assumption is that every consumer could influence all other consumers. Therefore, the topology of a social network is not included in the Bass model. The third assumption is that marketing strategies, including the adjustment of prices and costs, are not considered during the innovation process (The Bass model 2007).

2.2 Reviews of Impacts of Network Topologies on Diffusion of Innovations

The diffusion of innovations is a theory established by Everett Rogers in 1962. It explains how a new idea or technology is dispersed and adopted through a social network. The spread of diffusions relies heavily on the topologies of social networks. Delre, Jager, and Janssen (2006) explained how the network structure, together with consumer heterogeneity affect the diffusion speed. In their agent-based model, a consumer's adoption depends on both the consumer's own preference and neighbors' influences. Results suggest that the speed of diffusion is affected by the randomness of the network; for example, the diffusion speed is low in a regular network (lattice), increases in a small-world network, and is very slow in a random network. Also, the results show that the more heterogeneous the consumers are, the faster the speed of diffusion.

Choi, Kim, and Lee (2010) investigated why some diffusion fails, while others succeed, by varying the network cliquishness (close and extensive connections) and bridges (random connections). The findings indicate that a new product is more likely to succeed in a cliquish network than a random network. However, once the diffusion goes beyond a certain critical mass, the diffusion speed accelerates in a network that has more random bridges.

Bohlmann, Calantone, and Zhao (2010) analyzed the influence of locations of initial innovators, network topologies, and acceptance thresholds on the diffusion of innovations. Their model is experimented using various locations of innovators and acceptance thresholds on a cellular automaton, a small-world network, a scale-free network, and a random network. Bohlmann et al. (2010) concluded that the location of initial innovators, the network topology, and the acceptance threshold affect diffusion patterns differently among various network structures. Increasing acceptance threshold delays the peak adoption time and reduces the number of new adopters. A more clustered network is more likely to diffuse under high adoption thresholds (conservative consumers). The location of initial innovators, the network topology, and the acceptance threshold have less impact on the diffusion patterns in a random network due to the relative absence of clustering.

3 MODEL DESCRIPTION

In my model, there is one software publisher and a large number of consumers. A consumer is modeled as an agent in an agent-based model. The agent-based model functions as a fitness evaluation function for the marketing strategies. The modeled social network is a small-world network in which each node represents one consumer in the agent-based model.

3.1 Design of a Consumer

Consumers have homogeneous/heterogeneous reservation prices, promotion acceptance thresholds, and piracy detection thresholds. Only one innovator possesses the product initially and the rest of the consumers are either pirates or legal buyers. A consumer is allowed to possess at most one product. If a legal buyer finds out at least one of his neighbors possesses the product, he makes his purchase decision by evaluating the influences of the promotion campaign and the price of the software publisher. If a pirate sees his neighbors possessing the product and knows that he would not be caught, then he, through piracy, gets the product, regardless of the promotion cost and the price of the software publisher.

3.2 Design of a Software Publisher

The software publisher is modeled as a population of marketing strategies. The design employs the Pittsburgh classifier (Smith 1983). The Pittsburgh classifier is a rule-based machine-learning algorithm in which each individual in the population consists of a rule set. In my model, each rule contains conditions and corresponding actions. The conditions of each rule are the amount of market share, current status of the sales, and the current profit of the software publisher. The corresponding actions are various adjustments of prices, promotion costs, and piracy detection costs. Those marketing strategies are able to dynamically adjust prices, promotion costs, and piracy detection costs based on the current market situation through an entire product life cycle.

3.3 Workflow

In this model, every marketing strategy is injected into the agent-based model, and the agent-based model functions as a fitness evaluation for the strategy. Strategies are selected sequentially from the population. The selected strategy guides the agent-based model to go through an entire diffusion process until each consumer possesses the product or specified time steps reached. The profit and diffusion speed are the fitness values of the strategy, with the profit having a higher priority than the diffusion speed. The diffusion speed is defined as the number of time steps taken to finish the diffusion process.

When every strategy of the population has executed the same task and acquired its fitness, the offspring population is produced through a reproduction process. Every strategy in the offspring population repeats the same task as their parents to acquire its fitness values. Finally, a new population is selected from both the parents and the offspring population. The new strategy population repeats the same operation above until a specified number of generations is reached.

4 EXPERIMENTS AND RESULTS

Several experiments under different conditions are presented. The base case has no pirates. The experiments range from adaptive marketing strategies, to the experiments concerning the impacts of opinion leaders and the position of pirates within the market.

Each experiment consisted of 50 runs. The profit and diffusion speed of the best-so-far strategy of each run was recorded. The profits and the diffusion speed of the 50 runs were compared among the different scenarios statistically at 95% confidence interval using the Kolmogorov-Smirnov test.

4.1 Dynamic and Self-Learning Marketing Strategy

Figure 1 demonstrates the best of best-so-far marketing strategies under one scenario: there is only one pirate among the homogeneous consumers and the pirate is a direct neighbor of the innovator.

The software publisher starts with a high price and a low cost. The reservation prices and promotion cost thresholds of the consumers are invisible to the software publisher, so a self-learning marketing strategy helps the software publisher adjust his price, promotion cost, and piracy detection cost gradually, and move towards the reservation prices, promotion cost thresholds, and detection cost thresholds of the consumers ($15 in this case). After reaching these thresholds, the promotion cost and price fluctuate slightly, but they stay close to the thresholds.

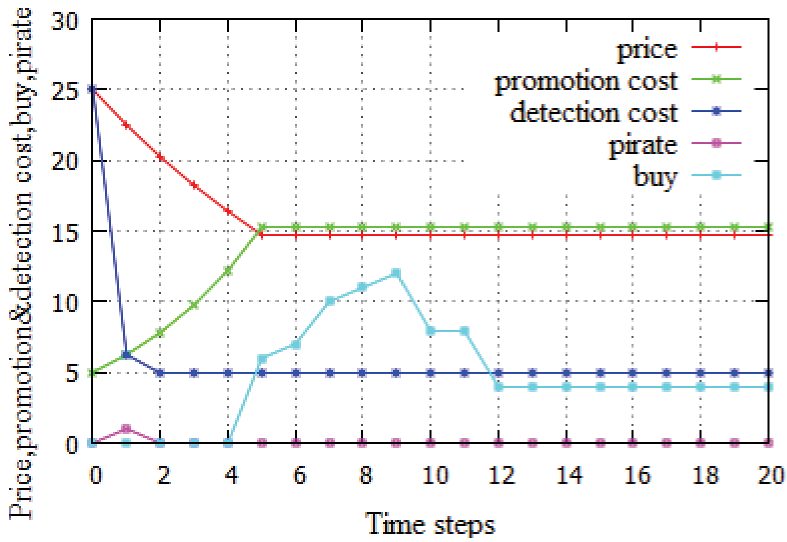
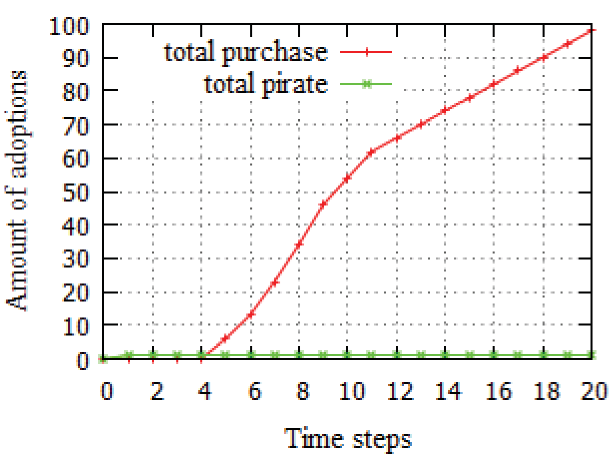


Figure 1: Impacts of the best of best-so-far strategies on the price, promotion cost, and detection cost, amount of purchase, and amount of piracy.

Figure 2 illustrates the total purchase and total piracy produced by the same strategy in the same network. The total purchase is a typical S-shaped diffusion curve (Rogers 2003). Figure 3 indicates that the total profit starts to increase when the purchase starts at time step 5.



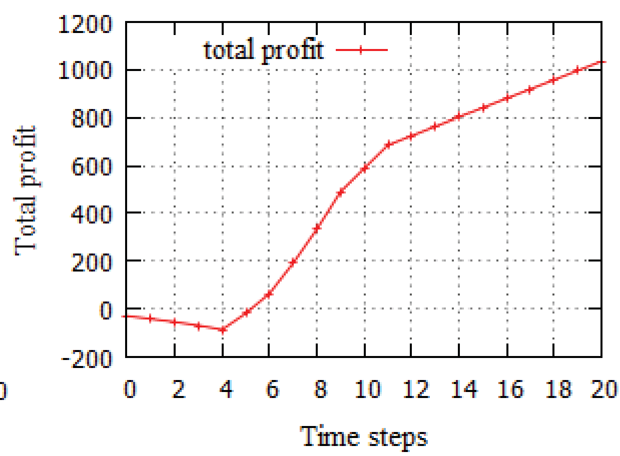


Figure 2: Impacts of best of best-so-far strategies on total purchase and piracy.

Figure 3: Impacts of the best of best-so-far strategies on total profit.

4.2 Impacts of Opinion Leaders

An opinion leader is a consumer who has most directly connected neighbors. The following experiments show whether a pirate opinion leader is influential among either homogeneous or heterogeneous consumers. We start with a hypothesis.

Hypothesis 1. *The consumer who has the most connections (opinion leader) is an ideal candidate for being a pirate.*

4.2.1 Homogeneous Consumers

An opinion leader is able to influence more consumers than the other consumers. Therefore, an opinion leader seems like an ideal candidate for being a pirate. We tested that expectation.

Experiments were conducted on a small-world network of 100 consumers, in which two consumers, (#11 and #83), were opinion leaders. In the first experiment, consumer 11 was a pirate (P_11). The profits were compared with the profits in the non-piracy scenario (NP). The results revealed that the *p_value* was zero, the mean of NP was $932.56, and the mean of P_11 was $905.62. Therefore, NP was significantly higher than P_11 on profits. The diffusion speed was also compared with the diffusion speed in the non-piracy scenario (NP). The results revealed that the *p_value* was 0.954. Therefore, there was no significant difference between NP and P_11 when it came to the diffusion speed.

In the second experiment, consumer 83 was the pirate (P_83). The profits were compared with the profits in the non-piracy scenario (NP). The results revealed that the *p_value* was 0.009, the mean of NP was $932.56, and the mean of P_83 was $902.17. Therefore, NP was significantly higher than P_83 on profits. The diffusion speed was also compared with the diffusion speed in the non-piracy scenario (NP). The results revealed that the *p_value* was 0.155. Therefore, there was no significant difference between NP and P_83 when it came to the diffusion speed.

The results of these experiments indicate that the opinion leader is not necessarily a good candidate for being a pirate. Therefore, hypothesis 1 is not true for this condition. Why is the opinion leader not necessarily a good candidate for being a pirate? Let's compare the diffusion patterns of the best-so-far strategy among NP, P_83, and P_11 from one single run.

Figures 4 and 5 show adoptions and whether they were through purchases or piracy. In Figure 4, NP, P_11, and P_83 have the same adoption patterns. As shown in Figure 5, P_83, the pirate adopts the product at time step 8. Also, at time step 8, there are eight purchases and one piracy, so the total adoption amount is nine, which is same as the adoption amount of NP at time step eight. For P_11, the piracy happens at time step 4. At time step 4, there are three purchases and one piracy for a total adoption amount of four, which is the same as the adoption amount of NP at time step 4**.**

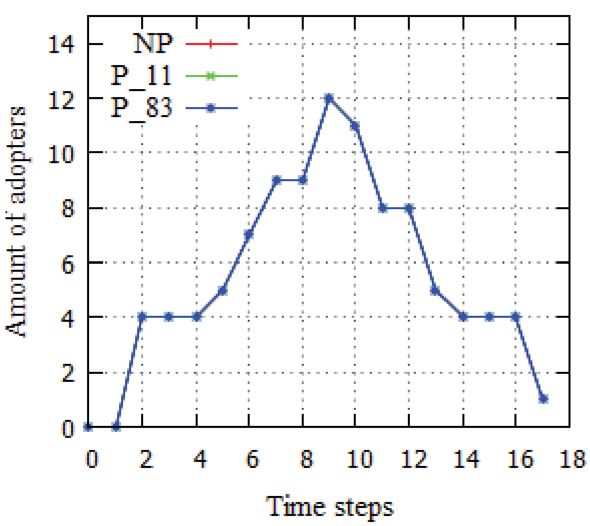


Figure 4: Comparison of the amount of adoptions among NP, P_11, and P_83.

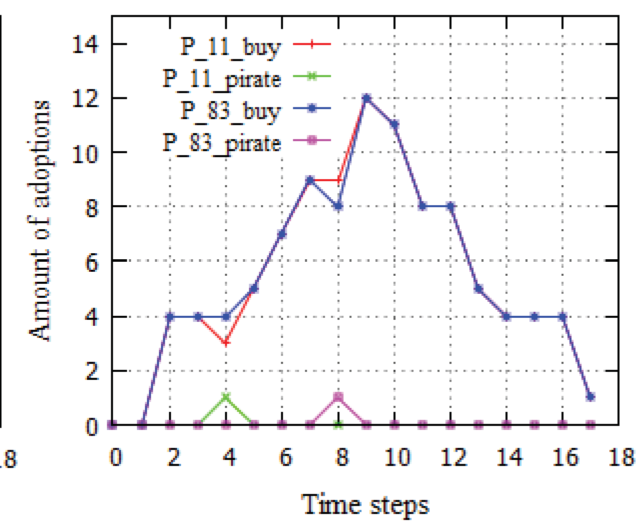


Figure 5: Comparison of the amount of purchases and piracy between P_83 and P_11.

The adoption starts at time step 2. P_11 pirated the product at time step 4, and P_83 pirated the product at time step 8. This indicates that other legal buyers have already adopted the products before the pirates P_11 and P_83 did so. A pirate only makes a difference on the diffusion patterns when he is able to influence other consumers while legal buyers did not adopt due to the restrictions in price and promotion costs. After the legal buyers started the adoption, the software publisher's price and promotion cost were adjusted to the acceptable levels of legal buyers and detection cost were adjusted to the acceptable level of a pirate. Under such condition, a pirate could not make a difference in the diffusion pattern and the diffusion speed anymore, and the only difference he made was reducing the profit of the software publisher.

Regarding profits, with P_11, the publisher lost $17.89 at time step 4 due to piracy, and with P_83 lost $26.33 at time step 8 due to piracy. Therefore, with P_11, the publisher's total profit was $939.31. With P_83, the publisher's total profit was $896.45. With no pirates (NP), the publisher's total profit was $1015.2. As a result, with either pirate, the publisher had less profit when compared to the scenario with no pirates.

4.2.2 Heterogeneous Consumers

Heterogeneous consumer experiments were conducted on the same network in which consumer 11 and 83 were the opinion leaders. In the first experiment, consumer 11 was again a pirate. The profits were compared with the profits in the non-piracy scenario (NP). The results revealed that the *p_value* was 0.017, the mean of NP was $429.06, and the mean of P_11 was $412.12 Therefore, NP was significantly higher than P_11 on profits. The diffusion speed was also compared with the diffusion speed in the non-piracy scenario (NP). The results revealed that the *p_value* was 0.358. Therefore, there was no significant difference between NP and P_11 when it came to the diffusion speed.

In the second experiment, consumer 83 was again the pirate (P_83). The profits were compared with the profits in the non-piracy scenario (NP). The results revealed that the *p_value* was 0.032, the mean of NP was $429.06, and the mean of P_83 was $412.18. Therefore, NP was significantly higher than P_83 with regards to the profits. The diffusion speed was also compared with the diffusion speed in the non-piracy scenario (NP). The results revealed that the *p_value* was 0.508. Therefore, there was no significant difference between NP and P_83 with respect to the diffusion speed.

Figure 6 illustrates the adoptions of NP, P_11, and P_83. From this Figure, we observed that NP, P_11, and P_83 did not have the same adoption patterns anymore, due to the heterogeneity of the consumers.

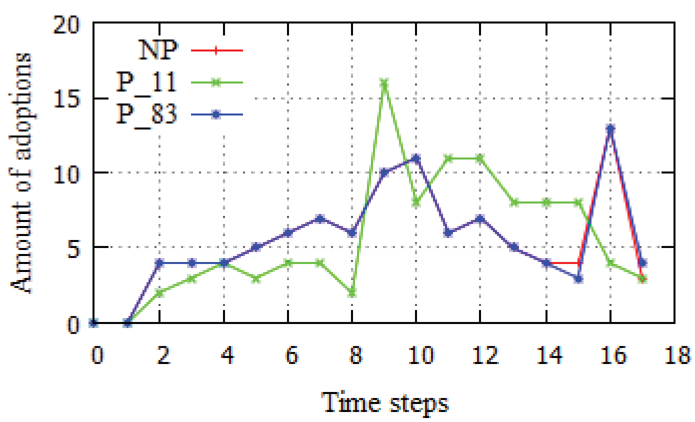


Figure 6: Comparison of the amount of adoptions among NP, P_11, and P_83 with respect to heterogeneous consumers.

For homogeneous consumers, a good strategy adjusts its price, promotion cost, and detection cost gradually gravitates towards the thresholds ($15) of a consumer, after the adoption starts, it keeps the price and promotion cost close to the thresholds and keep the piracy detection cost as low as possible. As long as the strategy follows such rules, the amount of adoptions at each time step is determined by the network topology.

In the case of heterogeneous consumers, the consumer adopts the product and the number of consumers who adopt the product at each time step become uncertain due to the heterogeneity of the consumers. A strategy could only propose one price and one promotion cost at each time step. So, what is the optimal price and promotion cost to set at each time step? The strategy makes the decision based on one rule, that is, maximizing its fitness values, which, in this model, are the profits and the diffusion speed. The importance of the self-learning strategy is more obvious in the case of heterogeneous consumers.

Conclusions Concerning Opinion Leader/Piracy:

- A pirate only makes a difference on the diffusion patterns when he is able to influence other consumers while legal buyers failed to adopt due to the restrictions in prices and promotion cost.
- Assigning an opinion leader as a pirate does not necessarily increase profits and accelerate diffusion speed. As a result, an opinion leader is not necessarily a good candidate for being a pirate.
- Dynamic self-learning marketing strategies alone are not enough to increase profits and accelerate diffusion speed. The network topology is another important factor which contributes to the performance of profits and diffusion speed.

4.3 Impacts of the Positions of Pirates

From the above experiments, we conclude that in order for pirates to make a difference in profits and diffusion speed, they have to adopt the product before the adoption of legal buyers start. When does that happen?

The answer lies in the positions of pirates in the network. If a pirate is among the direct neighbors of the innovator, then he has a higher probability of being in contact with the new product before legal buyers do. Due to the fact that a pirate is only restricted by the piracy detection cost, he adopts the product much quicker than legal buyers who are restricted by both the price and the promotion cost. It is likely that the moment a pirate adopts the product, a software publisher is still adjusting his price and promotion cost to meet the reservation prices and promotion cost thresholds of consumers. Does such design guarantee that the publisher achieve higher profits and faster diffusion speed with pirates present? This was tested with homogenous and heterogeneous consumers in small-world networks, with pirates at different distances from the innovator.

Hypothesis 2. *Positioning pirates among direct neighbors of the innovator guarantees a higher profit and faster diffusion.*

A total of 15 small-world networks were created by using three random seeds, and each random seed was coupled with five rewiring probabilities. The direct neighborhood of the innovator was defined as L1, and the director neighborhood of L1 was defined as L2, and so on. Consumer 5 was defined as the innovator in every network. Starting from the first level (L1), second (L2) and third level (L3) neighbors of the innovator, each consumer was made a pirate sequentially, and the experiment was conducted on each scenario. The profits and the diffusion speed of each scenario were compared with the profits and the diffusion speed of the non-piracy scenario (NP).

4.3.1 Homogeneous Consumers

The results in Table 1 show that the pirates in L1 are able to increase the profits and accelerate the diffusion speed. Condition L1:7 indicates that if consumer 7 in layer 1 was a pirate, he caused higher profits or accelerated diffusion speed significantly. “None” indicates that no pirate made a difference. All results were statistically significant. In Table 1, the results indicated that a pirate in L1 either increased the profits or diffusion speed, or did not make any difference at all.

Table 1: Comparison of the profits and the diffusion speed of homogeneous consumers on networks of seed 1, seed 2, and seed 3.

Rewiring probability	**Network of seed 1**		**Network of seed 2**		**Network of seed 3**	
	Profit	Diffusion speed	Profit	Diffusion speed	Profit	Diffusion speed
0.01	L1: 7	L1: 7	None	L1: 7	L1: 6, 7	L1: 6, 7
0.03	L1: 6	L1: 6, 7	L1: 7	L1: 7	L1; 7	L1: 7
0.05	None	None	L1: 34	L1: 34	L1: 7	L1: 7
0.07	L1: 4, 64	L1: 4, 64	None	None	L1: 7, 96	L1: 7, 96
0.1	L1: 4, 64	L1: 4, 64	None	None	None	None

The results in Table 1 partially confirmed the hypothesis 2, that is, it is possible to increase profits and accelerate diffusion speed by having a pirate among the direct neighbors of the innovator. However, from the above results, not every pirate in L1 was able to make a difference. Therefore, hypothesis 2 is only partially true, that is, positioning a pirate among direct neighbors of the innovator has the possibility to increase both profits or diffusion speed, but there is no guarantee that every pirate in the direct neighbors can make a difference. This leads to an obvious question: *Why do only certain pirates in L1 make a difference on profits and diffusion speed?*

For the network in Figure 7, consumer 7 was set as a pirate (P_7). Then the adoption pattern and the profits of the best-so-far strategy of P_7 is compared with the adoption pattern and the profits of the best-so-far strategy of the non-piracy scenario (NP).

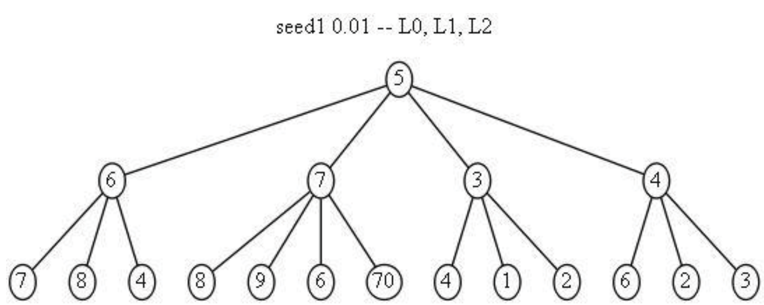


Figure 7: L0, L1, and L2 of the network seed 1, rewiring probability 0.01.

Figure 8 compares the amount of new purchase and piracy at each time step between NP and P_7. Figure 9 compares the accumulated adoptions (purchases and piracy) between NP and P_7. From Figures 8 and 9, we found the answer to the question:

- Pirates at L1 do not follow the same adoption patterns as consumers in the NP.
- P_7 pirated the product at time step 1, which was before the adoptions of all other legal buyers.
- Besides self-learning marketing strategies, the amount of adoption of P_7 at each time step also depends on the topology of the network.

Figure 10 compares the profits earned at each time step for conditions NP and P_7. Figure 11 compares the accumulated profit between NP and P_7. From Figures 10 and 11, we see that although the profit of P_7 dropped at time step 10 and 12 due to fewer adoptions vs. NP, it did not affect the total profit. The final profit of P_7 was still higher than the profit of NP.

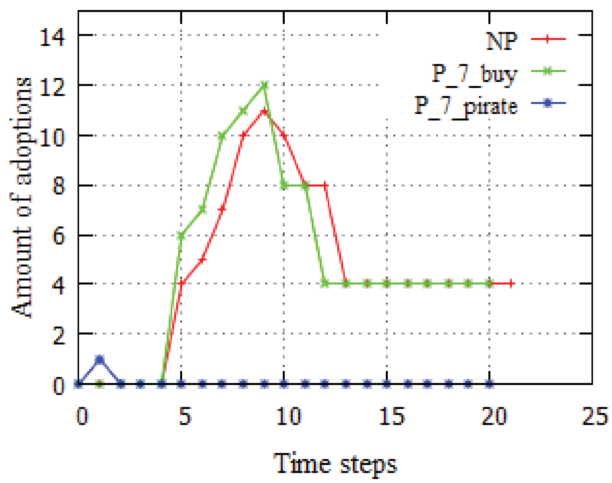


Figure 8: Comparison of the amount of purchases and piracy at each time step between NP and P_7.

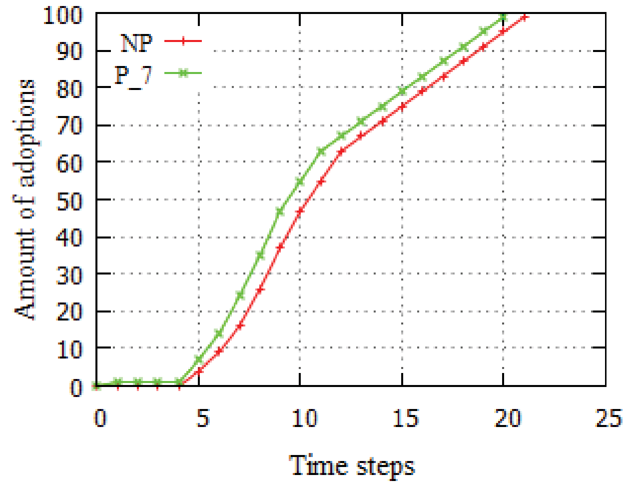


Figure 9: Comparison of the amount of total adoption between NP and P_7.

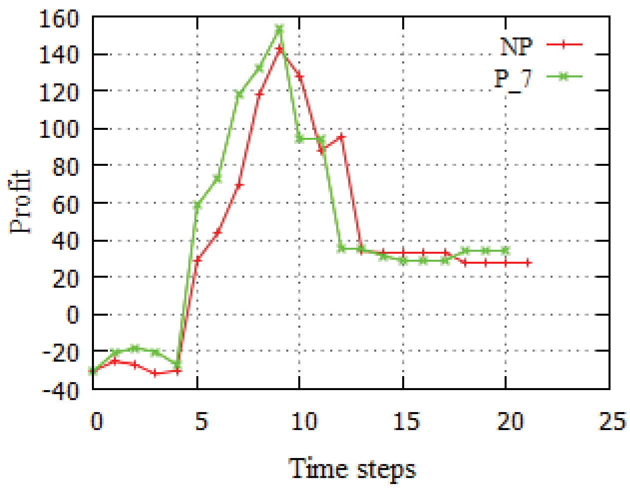


Figure 10: Comparison of profits at each time step between NP and P_7.

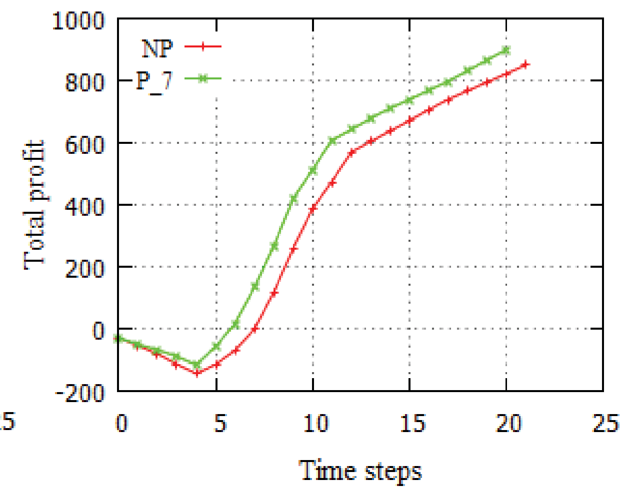


Figure 11: Comparison of total profits between NP at each time step between NP and P_7.

4.3.2 Heterogeneous consumers

Experiments with heterogeneous consumers were repeated on the same 15 networks. In Table 2, the results indicate that pirates in L1 either increased profits or diffusion speed, or do not make differences at all. Due to the heterogeneity of the consumers, in the networks of seed 2 (rewiring probability 0.01 and 0.03), pirate 84 in L2 increased profits significantly. Also, due to the heterogeneity of the consumers, there are several occasions, besides pirates in L1, a few pirates in L2 or L3 also increased the profits or diffusion speed significantly.

Table 2: Comparison of the profits and the diffusion speed of heterogeneous consumers on the networks of seed 1, seed 2, and seed 3.

Rewiring probability	**Network of seed 1**		**Network of seed 2**		**Network of seed 3**	
	Profit	Diffusion speed	Profit	Diffusion speed	Profit	Diffusion speed
0.01	None	L1: 7	L2: 84	None	L1: 7	L1: 7
0.03	L1: 7, 6	L1: 7	L2: 84	None	L1: 7 L2: 9	L1: 7
0.05	L1: 7 L3: 1	L1: 7 L3: 1	L1: 34 L3: 58, 93	L1: 3 L3: 81, 93	L1: 7 L2: 9	L1: 7
0.07	L1: 7, 64	L1: 64	L1: 34 L2: 84	None	L1: 96	L1: 7
0.1	L1: 7, 64	L1: 4, 7, 64	L1: 34	L1:34, 6, 3, 4	L1: 96	L1: 7

Conclusions Concerning the Location of Pirates:

- Pirates in LI guarantees that pirates adopt the product before other legal buyers do.
- Pirates in L1 have the possibility to result in higher profits and faster diffusion speed. However, not every pirate in L1 is able to achieve that. An important factor is the network topology.
- Dynamic self-learning marketing strategies need to cope with network topologies and positions of pirates in order to increase profits and accelerate diffusion speed.

5 CONCLUSIONS

In this paper, we presented a model which simulates a software market as a complex adaptive system. This model develops dynamic and self-learning marketing strategies that help a software publisher utilize the positive impacts of software piracy. Expriments were conducted on 15 small-world networks and numerous positions of pirates, for both homogeneous and heterogenous consumers.

Through the comparisons between different scenarios and analysis of the experimental results, we drew several conclusions. First of all, in order to increase profits and accelerate diffusion speed, an opinion leader is not necessarily an ideal candidate for being a pirate. Secondly, positioning a pirate among the direct neighbors of an innovator has a better chance of making a difference in profits and diffusion speed. Thirdly, dynamic and self-learning marketing strategies are not enough to increase profits and accelerate diffusion speed, as network topologies and positions of pirates also play important roles.

REFERENCES

Bass, F. M. 1963. "A Dynamic Model of Market Share and sales Behavior." *Winter Conference American Marketing Association*, Chicago, IL, pp 269

Bohlmann, J. D., R. J. Calantone, and M. Zhao. 2010. "The Effects of Market Network Heterogeneity on Innovation Diffusion: An Agent-Based Modeling Approach." *Journal of Product Innovation Management* 27(5): 741–760

Business Software Alliance. 2016. "Seizing Opportunity Through License Compliance". http://globalstudy.bsa.org/2016/downloads/studies/BSA_GSS_US.pdf. Accessed Dec. 14, 2016

Conner, K. R., and R. P. Rumelt. 1991. "Software piracy: an analysis of protection strategies." *Management Science* 37(2): 125–139.

Choi, H., S. Kim, and J. Lee. 2010. "Role of Network Structure and Network Effects in Diffusion of Innovations." *Industrial Marketing Management* 39(1): 170–77.

Delre, S. A., W. Jager, and M. A. Janssen. 2006. "Diffusion Dynamics in Small-World Networks with Heterogeneous Consumers." *Computational and Mathematical Organization Theory* 13 (2): 185–202.

Givon, M., V. Mahajan, and E. Muller. 1997. "Assessing the Relationship between the User-Based Market Share and Unit Sales-Based Market Share for Pirated Software Brands in Competitive Markets." *Technological Forecasting and Social Change* 55(2): 131–144.

Givon, M., V. Mahajan, and E. Muller. 1995. "Software Piracy: Estimation of Lost Sales and the Impact on Software Diffusion." *Journal of Marketing* Vol. 59 (January 1995): 29-37.

Haruvy, E., V. Mahajan, and A. Prasad. 2004. "The Effect of Piracy on the Market Penetration of Subscription Software." *The Journal of Business* 77 (S2): S81–107.

Lilien. L, Gary, A. Rangaswamy, and A. De Bruyn. 2007. "Bass Model: Marketing Engineering Technical Note". Technical note, a supplement to the materials in Chapters 1, 2, and 7 of *Principles of Marketing Engineerin*g. Pennsylvania, DecisionPro, Inc.

Prasad, A., and V. Mahajan. 2003. "How many pirates should a software firm tolerate?" *International Journal of Research in Marketing*, 20(4): 337–353.

Rogers, E. M. 2003. *Diffusion of Innovations*. 5th edition, pp. 112. New York: Simon & Schuster, Inc.

Smith, S. F. 1983. "Flexible learning of problem solving heuristics through adaptive search". In *Proceeding of the Eighth International Joint Conference on Artificial Intelligence* pp. 421-425.

Symantec Enterprise 2016. "Types of Piracy". https://www.symantec.com/about/legal/anti-piracy. Accessed Dec. 14, 2016.

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