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Research Article

A Study on P2P Lending Mode using Generalized Stochastic Petri Nets

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ABSTRACT: This paper leverages Generalized Stochastic Petri Nets to construct a peer-to-peer lending model and analyze the time efficiency and the performance of it. The optimization of process is of much importance since it relates not only to user experience but also to trust on platforms, which influences the behavior of users and the lending outcomes. By calculating the efficiency of four processes respectively, we find that the loan searching process by lenders is relatively inefficient. The reason may be that lenders are hard to choose plenty of listings and prudent to make decisions due to information asymmetry. Thus we suggest that platforms bring out recommendation systems and specifically incorporate soft information to fit the particular context. This paper supplements research about the process of peer-to-peer lending and has practical significance for platforms.

KEY WORDS: peer-to-peer lending, process, GSPN, time efficiency, recommendation

1.Introduction

Small and medium enterprises (SMEs) account for a large proportion of total economy. But financing SMEs, which is a crucial process for SMEs, is a challenging task for traditional banking systems. SMEs are more informationally opaque, risky, financially constrained, and bank-dependent than large firms (Wehinger 2014), while banks face inadequate financial information and record, deficient business management knowledge, and lack of confidence when lending to SMEs (Mawocha et al. 2015). Due to development of IT, SMEs may tend to Internet and use another innovative method of financing, peer-to-peer lending (hereinafter to be referred as P2P lending).

P2P lending refers to loans between lenders and borrowers directly on the Internet rather than through intermediation (Lin et al. 2009). The first P2P lending platform in the world is Zopa, founded on March 2005 in UK. The transaction volume of P2P lending is considerable last few years. In 2014 the transaction volume of P2P lending in US is nearly $5.5 billion, which is a supplement for traditional banking. P2P lending both attracts borrowers and lenders. For borrowers, the process is simple for borrowers and they can apply the listing without complex documents. Lenders can directly choose borrowers and finance them and the rate of return is high.

However, there exists the problem of information asymmetry, which impairs the reliability of P2P lending. Previous researches mainly study the risk of information asymmetry, e.g., the factors of default or factors of lending (Puro L et al. 2010; Li S et al. 2011; Emekter R 2015). But we believe that information asymmetry can also destroy the efficiency of P2P lending. P2P lending is more efficient than traditional banking because borrowers don’t have to provide complex documents and lenders can directly finance borrowers without scrutiny towards them. However, information asymmetry impair such benefit because when lenders make decisions they can’t judge the credit status of borrowers accurately and postpone decision-making, causing inefficient of P2P lending.

This study focuses on the performance of the process of P2P lending, of which the research is few. Although the process of P2P lending in different platforms is similar and almost fixed, yet there is still room for improvement. With information asymmetry the process may not be efficient. To cut down unnecessary process and optimize time-consuming process, the efficiency can be increased and thus both participants and platforms can be benefited.

2. Literature review

2.1.P2P lending

2.1.1 Information Asymmetry

Information asymmetry in P2P lending refers to that lenders don't know borrowers' credit status as borrowers do (Emekter R et al. 2015). As is known to all, information asymmetry can result in adverse selection (Akerlof 1970) and moral hazard (Stiglitz and Weiss 1981) and is a key problem in financial transaction. In traditional banking systems, financial intermediaries, e.g., banks, can mitigate the risk due to information asymmetry between borrowers and lenders (Leland and Pyle 1977). That is because banks maintain much information of potential borrowers and have experience to distinguish risky borrowers, use many ways, e.g., collateral, scrutinization to enhance the trust in the borrowers (Emekter R et al. 2015).

However, the problem of information asymmetry in P2P lending is even worse. First, the key feature of online P2P lending is disintermediation. Though lenders act as intermediaries as they screen borrowers and make investment decisions, they are usually not professional investors and lack of experience, which does no good for the problem. Second, collateral and other mechanisms are hard to be implemented in P2P lending platforms due to transaction cost. Third, nearly all transactions in P2P lending are conducted online, i.e., lenders and borrowers don't meet face-to-face but make decisions totally through Internet and scrutinization is scarce. The anonymity of P2P lending in such online context causes borrowers to exhibit greater uncertainty, which worsens the problem and reduces lenders the willingness of investing.

2.1.2 Trust

Due to information asymmetry, trust is a prime determinant of transaction for lenders(Gefen D et al. 2003). In the literature, trust is analyzed by the framework of ‘‘antecedents–trust–outcomes’’(JB Rotter 1971), i.e., trust is conceptualized as specific trust beliefs and general trust beliefs(Mayer RC et al. 1995). Specific trust beliefs are antecedents of general trust beliefs and behavioral intention is the outcome of general trust beliefs. Dongyu Chen et al. (2014) delineated specific trust beliefs as knowledge-based, institution-based, and cognition-based, which is modified from the model of Gefen D et al. (2003) to suit P2P lending while general trust beliefs are described as trust in intermediary[1] and trust in borrower.

Many literatures investigate trust towards borrower and they find that lenders use both hard information and soft information about borrowers to create trust and thus make investing decisions (Iyer et al. 2009; Freedman and Jin 2014; Lin et al. 2013). Hard information refers to quantitative information that can be accurately expressed, e.g., demographic information, debt to income ratio(Collier B C, Hampshire R 2010), FICO score, credit grade(Duarte et al. 2012; Emekter R et al. 2015). Hard information is often difficult to obtain, insufficient, or unreliable, so lenders may tend to soft information, which is available in P2P lending platforms and can be diagnostic(Michels 2011). Soft information refers to non-standard qualitative information(Iyer et al. 2009), e.g., narrative, appearance, social networking(e.g., virtual community and friendship).

However, few studies focus on trust towards intermediary. Trust in intermediary can be defined as the subjective belief with which a lender believes that the intermediary conducts fair rules and procedures, provides high-quality service and is safe and reliable for transactions (Mayer RC et al. 1995).Some literatures use questionnaires to investigate trust in intermediary and find that trust in intermediary is important for lenders' investing decisions. However, the questions they set are usually simple and due to the mthod they use, they can only derive an overall result and does not do in-depth analysis. In this paper, we further investigate trust in intermediary and focus on the process in P2P lending, which is a vital part of high-quality service provided by them and affects trust in intermediary. In addition, we believe that information asymmetry in P2P lending not only causes risk of default but also causes inefficiency of process in P2P lending because lenders can't fetch accurate and comprehensive information of borrowers and they may spend a lot of time screening and choosing borrowers and listings.

[1] Intermediary hereinafter refers to P2P lending platforms rather than banks.

2.2. GSPN

The Generalized Stochastic Petri Net (hereinafter to be referred as GSPN) is a powerful tool to analyze system performance. It integrates the essential features of concurrency, synchronization and a sequenced presentation of complex systems (Vinayak R et al. 2014). The GSPN model is well displayed in figures.

A GSPN is a six-tuple GSPN=(P,T,I,O,M_0,λ)(Xie et al. 2004) where $P=\{P_1,P_2,\ldots,P_m\}$ is the set of places while T is the set of transitions. M_0 denotes the initial mark and λ is the speed of the transition.

In addition to traditional applications, e.g., web services (Deivamani M et al. 2015) , networking protocol (Vinayak R et al., 2013), supply chain (Tan X, Tayi G K 2015),GSPN has been used in many contexts in Internet finance and e-commerce. For example, WMPVD Aalst(1999) uses Petri Net to make workflow management for e-commerce, which is interorganizational rather than traditionally centralized. Katsaros P et al. (2005) use Colored Petri Net to check three atomicity properties for the NetBill electronic cash system, i.e., money atomicity, goods atomicity and certified delivery. D Sanchezcharles et al.(2015) define a graphical modeling tool CrowdWON for crowdsourcing using Petri Net extensions.

In short, though there are some applications of Petri Net in Internet finance about process, the literature about the process of P2P lending is limited. But the efficiency of process of P2P lending is of much importance while GSPN is a powerful tool to analyze it. The efficiency is related not only to user experience but also to trust on platforms, which is essential for behaviors of lenders and outcomes.

3.Modeling

Some scholars analyze the mode of P2P lending. For example, Wang Z Y et al. (2015) divide the modes of platforms into two kinds: intermediary platforms and mixed platforms. Dong L et al. (2016) believes there are four modes of platforms: pure intermediary mode, guarantee mode, mode of credit asset securitization and mode of assignment of debt.

Basically there are three modes in P2P lending: pure intermediary mode in which platforms only act as intermediaries and provide connection among borrowers and lenders, e.g., Prosper, PPDai, the mixed mode in which platforms guarantee, retrieve payment or set interest rates , e.g., Lending Club, Zopa, non-profit mode in which interest rate is zero, e.g., Kiva. In terms of process, the difference among them is little for that only interest rates or guarantors are different, which does not affect the process. Without loss of generality, we discuss pure intermediary mode in this paper, which is the most general.

A typical pure intermediary mode is as follows. Borrowers upload their information (e.g., income, education background) and platforms review the information. Then borrowers create loan requests, which are called listings, including information about loan amount, interest rate, term and purpose. They may also use BBS to communicate with lenders, i.e., narratives (Prystav F 2016, Dorfleitner G et al. 2016). After that, platforms review listings.

Once the listing becomes active, lenders search listings and choose to invest. In some platforms, the listing is closed once it receives enough bids. Others provide an auction mode in which borrowers can choose to close the listing immediately if money is urgent need or choose to continue the listing. Additional bids can lower interest rates, which benefit borrowers. If the listing does not receive full amount of bid in certain days, the listing will be closed and money already raised will usually be invalid and returned to lenders[2],i.e., “take-it-or-leave-it” basis (Barasinska N, Schäfer D 2014). In this paper we incorporate the additional auction process into bidding process. The process is shown in Figure1.

[2] In some P2P lending platforms, the listing that does not receive enough money in certain days will be closed and the bid is still valid, e.g., Smava.

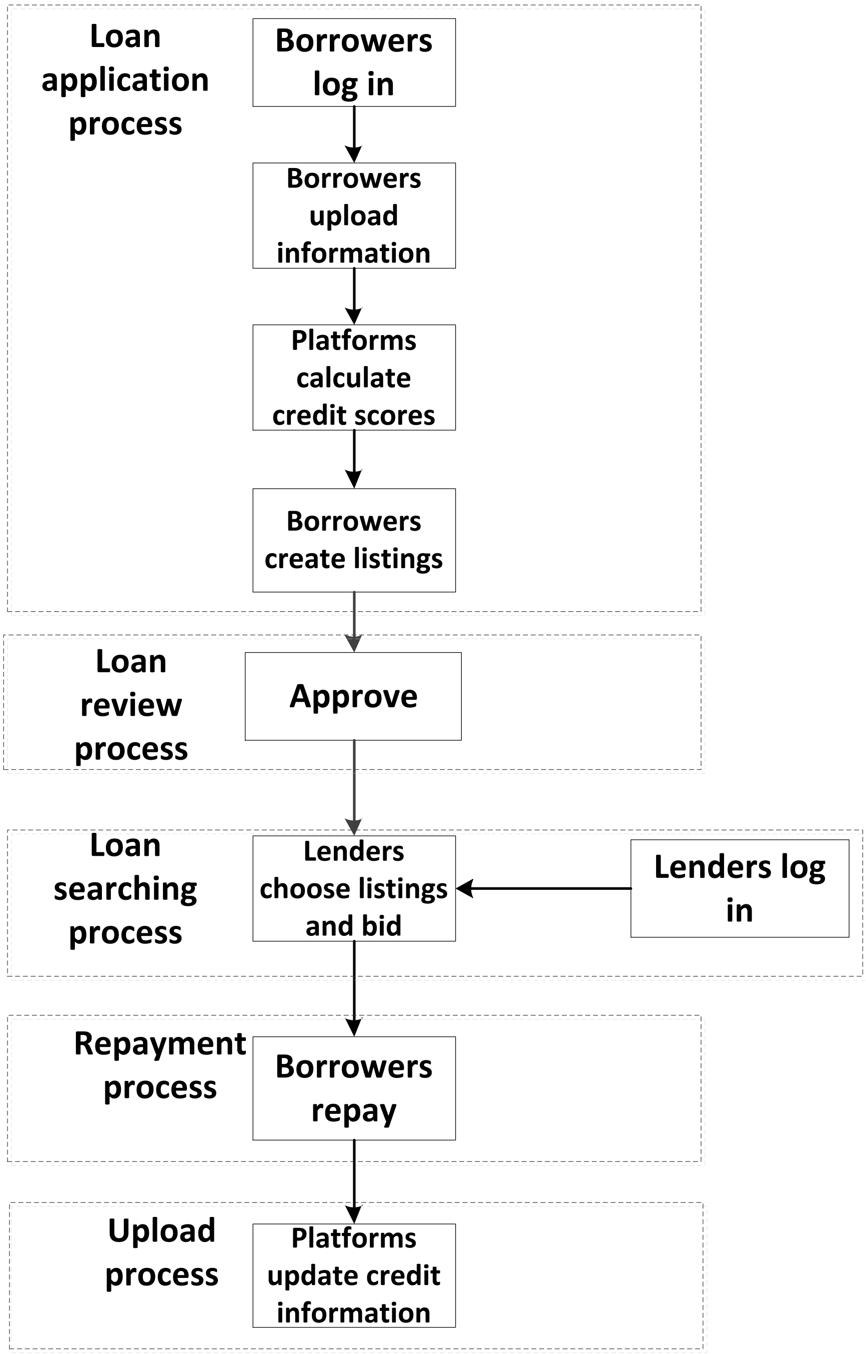

Figure 1. The business process of P2P lending

Information asymmetry is the main risk in P2P lending, which causes default. We believe that harm of information asymmetry is far more than that. Due to information asymmetry, lenders spend a lot of time screening and choosing borrowers and listings, which impair the efficiency of P2P lending. In figure1, when lenders choose listings they have little information about borrowers and listings and may postpone their decision time. Thus we have hypothesis 1:

H1: Loan searching process is efficient.

In this paper, we use GSPN model to analyze the efficiency and performance of P2P lending process (See Figure 2). The meaning of places and transitions is shown in Table 1 and Table 2. To determine the fire speed, according to websites of P2P lending platforms and experience, we assume λ={10,8,8,7,5,10,2,1,10}[3].

Table1 Meaning of transitions	
Transition	Meaning
t1	Borrowers log in
t2	Borrowers upload information
t3	Platforms review
t4	Borrowers create listings
t5	Platforms review listings
t6	Lenders log in
t7	Lenders choose listing and pay for it
t8	Borrowers repay
t9	Platforms update credit information

Table2 Meaning of places	
Marking	Meaning
P1	Borrowers' accounts are available
P2	Borrowers need money
P3	Borrowers log in
P4	Before the review of borrowers
P5	After the review of borrowers
P6	Before the review of listings
P7	After the review of listings
P8	Lenders' accounts are available
P9	Lenders need investment
P10	Lenders log in
P11	Listing receive enough money
P12	After payment

[3] It needs to be noticed that repayment process is the longest one, which is inherently determined by features of P2P lending. There are some differences about loan review process among different platforms, e.g., the loan review process is conducted before bidding in PPDai and after bidding in Prosper. We adopt the first one. According to websites of P2P lending platforms, it takes about five business days in PPDai and no longer than seven days in Prosper for platforms to review. According to Liu D et al.(2015), there are some anecdotal evidence that in PPDai there are rapid review after bidding, but we don't adopt that because it is not credible. Besides it won't take much time.

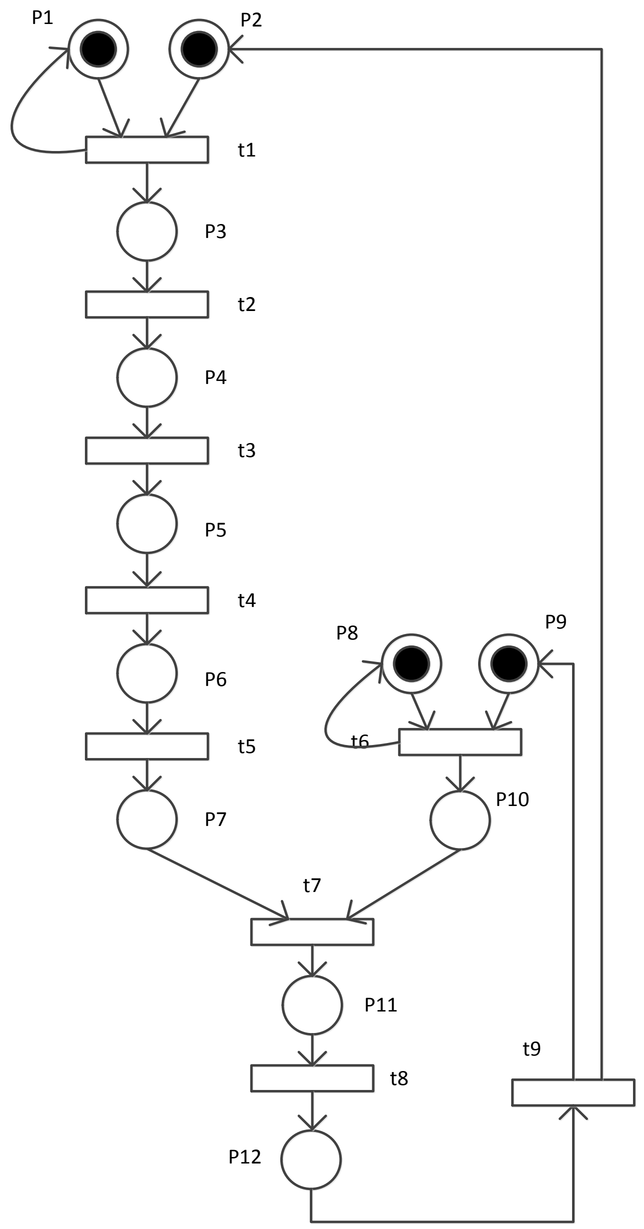

Figure 2. GSPN model for P2P lending

4.Result

4.1.Simplication

In order to facilitate the analysis, we simplify the GSPN model according to Long and Luo's performance equivalent simplification methods (Long S, Luo W 2006). The result is shown in Figure 3. Accordingly, the fire speed should be modified and the result is shown in Table 3. The reachability graph and transition matrix is shown in Figure 4 and Figure 5 respectively.

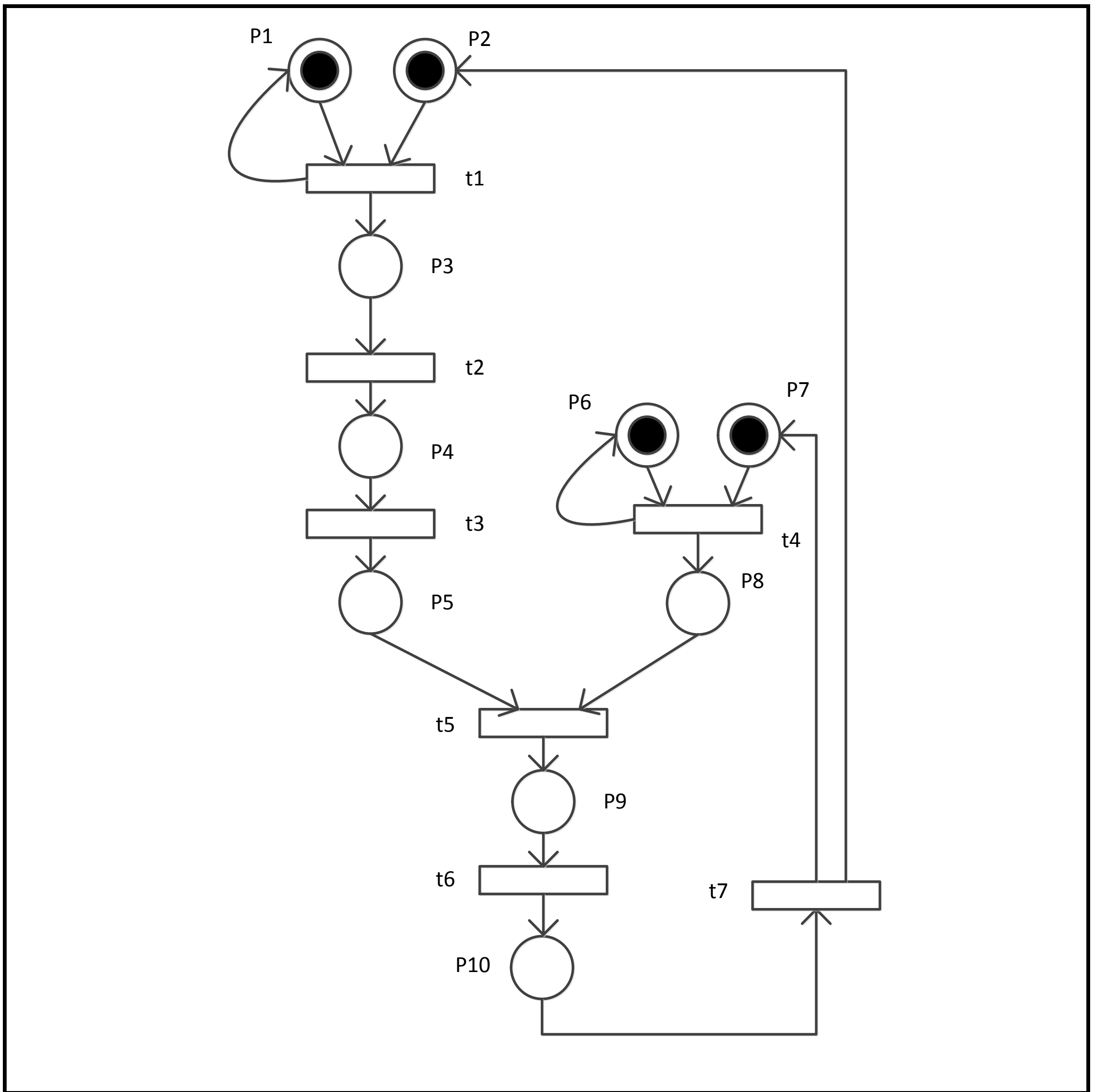

Figure 3. GSPN after simplication

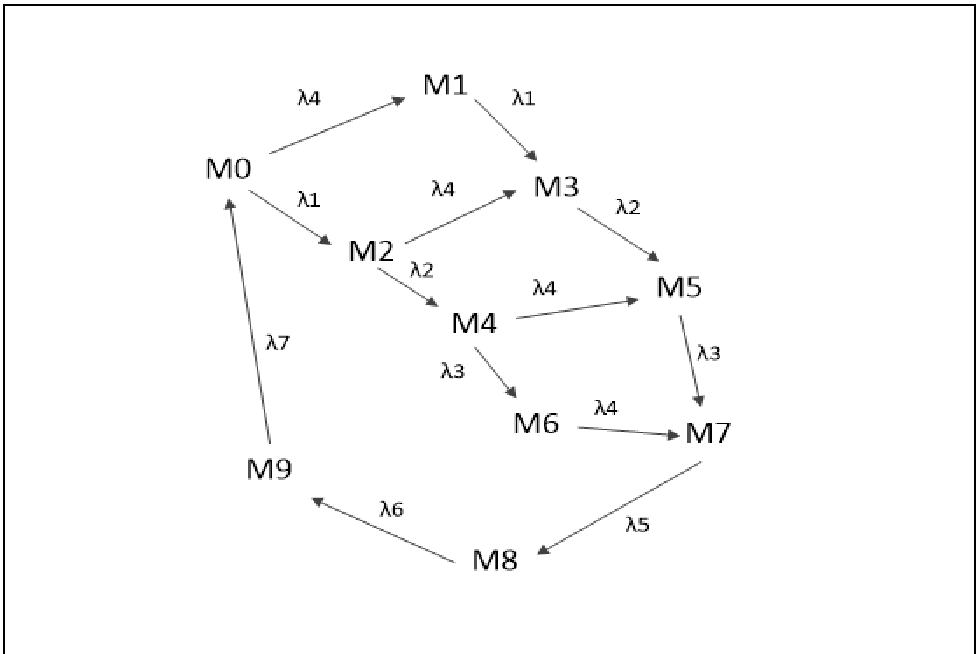

Figure 4. Reachability graph

$$Q=\begin{bmatrix} -20 & 10 & 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -10 & 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -13 & 10 & 2.55 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -3 & 0 & 2.55 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -15 & 10 & 5 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -5 & 0 & 5 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -10 & 10 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -2 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 1 \\ 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -10 \end{bmatrix}$$

Figure 5. Transition matrix

Table 3. Speed λ' after simplication

Transition	Speed λ	New transition	New speed λ'
t1	10	t1	10
t2	8	t2	2.55
t3	8		
t4	7		
t5	5	t3	5
t6	10	t4	10
t7	2	t5	2
t8	1	t6	1
t9	10	t7	10

4.2The Steady State Distribution of Tangible States

According to XQ=0, $\sum X_i=1$, the PIPE software gives us the result of the steady state distribution of tangible states(See Table 4) , which is verified manually by us. The result is shown in Table 5.

Table 4. Set of Tangible States

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
M0	1	1	0	0	0	1	1	0	0	0
M1	1	1	0	0	0	1	0	1	0	0
M2	1	0	1	0	0	1	1	0	0	0
M3	1	0	1	0	0	1	0	1	0	0
M4	1	0	0	1	0	1	1	0	0	0
M5	1	0	0	1	0	1	0	1	0	0
M6	1	0	0	0	1	1	1	0	0	0
M7	1	0	0	0	1	1	0	1	0	0
M8	1	0	0	0	0	1	0	0	1	0
M9	1	0	0	0	0	1	0	0	0	1

Table 5. Steady state distribution of tangible sates	
Marking	Value
M0	0.02178
M1	0.02178
M2	0.01736
M3	0.15348
M4	0.00295
M5	0.08417
M6	0.00148
M7	0.21781
M8	0.43563
M9	0.04356

4.3.Time efficiency analysis

Based on Little's law and the equilibrium theory, we define a subsystem of GSPN:PN'=(P',T',F',M0,λ'), where P'=P-{P1, P2, P6, P7}, F' is a subset of F where arcs directly connecting P1, P2, P6, P7 are removed. T' and λ' are the same as T and λ in original GSPN. Within the same period, the number of token entered the subsystem equals to that left places {P1, P2, P6, P7}. Because the subsystem contains all the transitions, the average execution time of this subsystem is equal to that of the original system.

For subsystem:

4.4.Tokens in PN'

The tokens in places in PN' are as follows.

P(M(P3=1))= P(M2)+P(M3)= 0.17084

P(M(P4=1))= P(M4)+P(M5)= 0.08712

P(M(P5=1))= P(M6)+P(M7)= 0.21929

P(M(P8=1))= P(M1)+P(M3)+P(M5)+P(M7)= 0.47724

P(M(P9=1))=P(M8)= 0.43563

P(M(P10=1))=P(M9)= 0.04356

The number of tokens entered in subsystem PN' is N=P(M(P3=1))+ P(M(P4=1))+ P(M(P5=1))+ P(M(P8=1))+ P(M(P9=1))+ P(M(P10=1))= 1.43368

In the subsystem PN', the number of tokens left through transition t1 and t4 equals the number of tokens entered the system per unit time, i.e., λ=λ1*P(M(P2=1))+λ6*P(M(P9=1))=10*0.04356+10*0.04357=0.8713

4.5.Average execution time

The average execution time is : T=N/λ=1.645449

4.6.Operational performance analysis

Define A1 as the efficiency of borrowers applying listings, A2 as the efficiency of platforms reviewing listings, A3 as the efficiency of lenders choosing listings, A4 as the efficiency of repayment.

A1= P(M2)+P(M3)= 0.17084

A2= P(M4)+P(M5)= 0.08712

A3= P(M7)= 0.21781

A4= P(M8)= 0.43563

5.Discussion and conclusion

The result shows that the loan application process is efficient. One reason is that the P2P lending platforms provide easy-to-use and elaborate functions. They not only show borrowers a concise interface in which borrowers input loan amount, interest rate and life of loan and they will get monthly payments needed immediately for reference but also use fine service distinguishing different types of borrowers, e.g., students, owners of online shops, as different requirements are needed for different types of borrowers.

The loan review process is efficient. Many platforms ask borrowers to upload their certificates about income and house and thus quickly be certain about borrowers' credit. Repayment process usually takes months even years depending on the profile of loan listing. We don't specify the two processes above-mentioned because they are more related to risk control and context setting rather than process optimization.

The loan searching process by lenders is relatively inefficient, which is the same as H1. There may be 2 reasons. First, though P2P lending platforms provide plenty of information about borrowers, which is beneficial for lenders to discern the risk and help them to make decisions, the searching cost is very high due to cognitive overload (Zacharakis and Meyer 2000). P2P lending markets grow fast and plenty of listings exist, with which lenders are hard to make decisions. Second, lenders make decisions prudently due to information asymmetry(Yoo B J et al. 2010). Although some platforms provide investment-auxiliary functions (Emekter R et al. 2015), e.g., matchmaking systems in Lending Club and "fast investment" in PPDai, they basically choose listings according to life of loan, credit rate and interest rate to generate portfolio recommendations and minimize lending risks. These recommendations simply use hard information and may be inaccurate as some other soft factors may be considered when lenders make decisions(Michels 2011). For example, the narratives(Dorfleitner G et al. 2016) about purpose, social networks(Freedman and Jin 2008, Lin et al. 2011, Liu D et al. 2015) may count. Taking soft information into account, recommendations may fit in exactly with borrowers' wishes and the loan searching process may be optimized.

There are plenty of literatures about P2P lending, but few of them consider the process of P2P lending. We believe that information asymmetry not only causes default risk but also causes inefficiency of P2P lending. Empirical results prove our hypothesis.. Petri net is a powerful tool to model the process of system and analyze the performance. We divide P2P lending into 4 processes: the loan application process, the loan review process, the loan searching process and the payment process. We find that loan searching process is inefficient. By incorporating soft information into recommendation systems we can shorten the loan searching process and optimize the overall process. Results show that when we increase the speed of the loan searching process, the efficiency of overall process will increase .Our study is beneficial to recognize the online transaction process and the operation of P2P lending market. Our study extend some literature about trust(Chen D et al. 2014) as efficiency not only relates to volume of transaction but also influences trust for platforms. Our study has some empirical implications. First, P2P lending platforms may provide recommendation functions to help lenders make decisions. Second, they may improve recommendation results by incorporating soft information.

However there are some limitations. First, the mode of P2P lending in this paper is a typical one and cannot incorporate other modes. There are different processes in different modes and the result may be different. Even in one mode, the process may be slightly different and the specific data may be different. Future study may consider more modes and processes, analyzing different ways of optimizing in different modes. Second, our data about fire rates are empirical rather than statistic. Future study may consider using real transaction data and the results may be more accurate.

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