Service aspect oriented Recommender Systems

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Preface

Selection of restaurants at lunch time, selection of attractions on theme park, selection of routes in traffic movement, selection of information on the web site and so on, the situations that receivers(people who want to use service) select services to use from multiple services occur on a daily basis. Recommender system is a technology to support receivers and to improve receivers' additional value by information technology.

However, there is no research considering "finiteness", "non-instantaneousness" and "fluidity". These are important properties of service to deal service in real world. "Finiteness" means the number of receivers using a same service at same time is limited, "non-instantaneousness" means there is a time difference between when receiver gets recommendation, when receiver selects service to use and when provider contributes service to receiver, "fluidity" means a set of service that scope of receivers' selection frequently rises and falls.

Additionally, most of past recommender system studies use accuracy, coverage and novelty as metric of algorithm, however these metrics mainly focus on receivers efficiency, It would appear that it is important to consider not only receivers efficiency but also service provider's purpose at the thought of lucrative and sustainability of service.

The main purpose of this doctoral dissertation is to describe the construction of design method for recommender system to realize service innovation for services involving "finiteness", "non-instantaneousness" and "fluidity". I established scheme of service improving receiver's efficiency and achieving provider's purpose at same time as service innovation.

I addressed the following three challenges to meet toward achieving this purpose: (1) validating possibility of service innovation realization in service models involving "finiteness", (2) verifying relation between situation of service, recommendation and strong of "non-instantaneousness" influence in service models involving "finiteness" and "non-instantaneousness", (3) constructing a concrete recommendation method to realize service innovation for service involving "fluidity".

This dissertation is organized as follows:

Chapter 1 explains the basic method and outlines the history of the process about recommender system and service engineering. I also explain several studies of game theory and combinatorial optimization as study area of similar perspective and clarify the main points “service innovation” of discussion in this research.

Chapter 2 proposes recommendation type service model as a general service model involving recommender system without specific services. The model is constructed to discuss essential conditions of service innovation, reasonableness, fairness and efficiency. Moreover I describe important properties of service to deal service in real world “finiteness”, “non-instantaneousness” and “fluidity”.

Chapter 3 constructs shared resource type TSP as a concrete model of recommendation type service model to consider feasibility of service innovation in service models involving “finiteness”, this chapter assumed service innovation as realization of Nash equilibrium Pareto optimal status in Game theory, and I make sure of how many service innovation solutions there are in small-scale problem by enumerate all solutions.

Chapter 4 focuses on service innovation in service models involving “finiteness” and ”non-instantaneousness”. In other word, this is the situations that can quantify receiver’s efficiency exactly however receiver’s efficiency depends on other receivers’ selections. These situations are another word for operation under the first-come-first-serve rule. Examples of this case are waiting time on theme park and traveling time on highway. I proposed a prediction method of congestion “the user-in-the-loop forecasting with the statement-based cost estimate” to realize service innovation by congestion mitigation. This method can predict approximate congestion by receivers’ preliminary declarations. I verify effect of this method by two simulations, theme park model and highway.

Chapter 5 focuses on service innovation for service involving “fluidity”. I implemented recommender system of event notices for real Web site, and verified how the system contributes to realize service innovation. I compared five methods, genre scoring, source scoring, popularity scoring, user-based collaborate filtering, item-based collaborate filtering and two new methods from combining the five methods above. Then, I apply a part of these methods to real Web site to validate effect of algorithm.

Chapter 6 is a general summary of the main points of this dissertation.

Chapter 1

Service engineering and recommender system

1.1. Introduction

It's not too much to say that our life gains its support from services. For example, if we will go to a central part of a city in a holiday, we will ride a train or a private car firstly. Railways and public roads are services. This study focuses on an operation of these services. In operating these services, an essential problem is a different between individual rationality and overall rationality.

A typical case is prisoner's dilemma [1] in game theories. This model indicates individual rationality don’t always result in overall rationality, and vice versa. It would appear that this phenomenon arise from incompatibility between a benefit anticipated and a benefit obtained actually.

In other cases, players can get more benefit action concentrated than different. This case is known as stag hunt game [2]. In this case, it is important to find players’ commonality.

This study attempts to correct some of these problems in nearer real society by information technology. In real world, this incompatibility is not simple like prisoner's dilemma in many cases, and sometimes even it is difficult to find your best action.

This chapter explains the basic method and outlines the history of the process about recommender system and service engineering. I also explain several studies of game theory and combinatorial optimization as study area of similar perspective and clarify the main points “service innovation” of discussion in this research.

1.2. Related works

1.2.1 Service engineering

The word of Service engineering was first mainly used by Tomiyama in area of study [3]. He defined service as an activity that changes the state of a service receiver in this paper (Figure 1.1). Most of service engineering studies refer to this definition of service. Shimomura proposed modeling technique for service engineering [4]. In this paper, he said service engineering aims at intensifying, improving, and automating this whole framework of service generation, delivery, and consumption. Motomura says service engineering is a study to control and optimize service by not so much feeling or experience but capturing as objective data [5]. He also says four-loop is important for productivity growth of service, observation, analysis, designing and application. There are a lot of service engineering studies; examples of observation are indoor positioning technology and vital sensor. Examples of analysis are text mining and large-scale data analysis. Examples of designing are modeling by Bayesian network and computer simulation. Examples of application are visualization and recommendation. We focus recommendation.

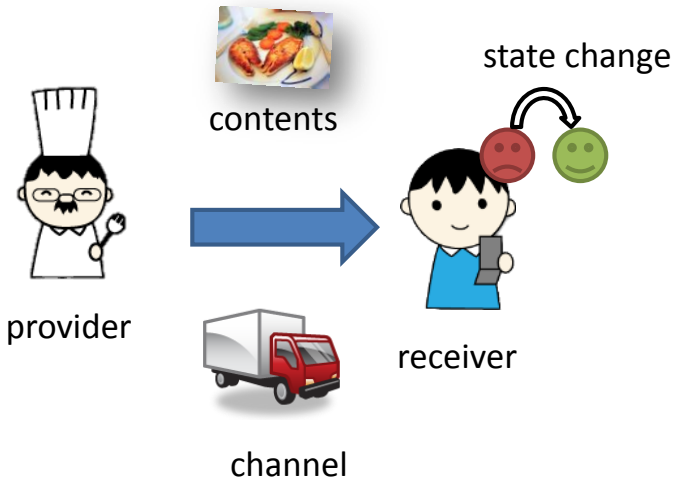


Figure 1.1: The definition of service

1.2.2 Theme park problem and car navigation problem

Congestion mitigation methods are suggested in research area of car navigation problem and theme park problem as a method avoiding synchronism and hunching phenomenon.

In theme park problem, theme park is translated as graphic structure which has nodes representing amusement attraction and roads, and each node has a passing cost (the amount of time for passing it). Also, each node has capacity; agents overflowed capacity can't enter amusement attraction and go into a queue.

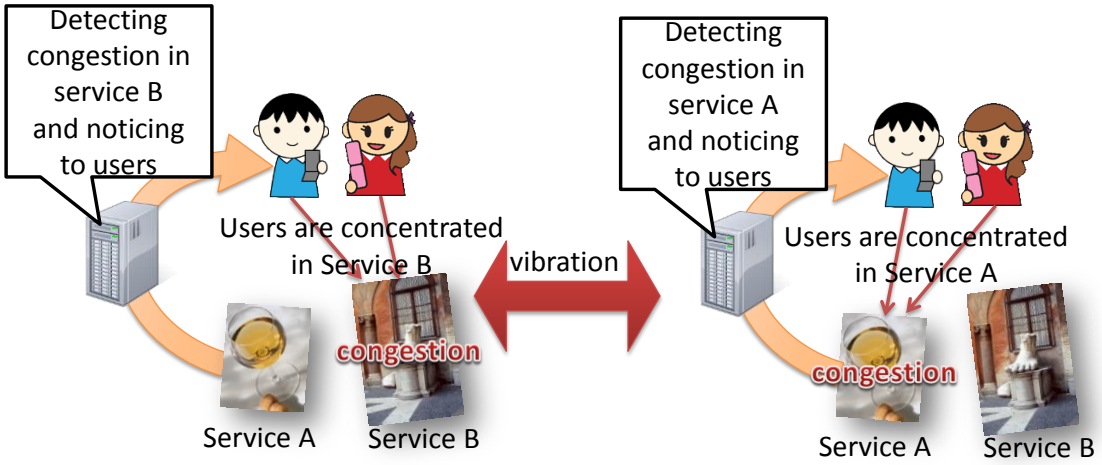


Figure 1.2 An example of hunching phenomenon

Agents visiting theme park has preference values for each amusement attraction; this problem is how to maximize sum of all agents' satisfactory degree (sum of visited amusement attraction's preference value).

There are suggested congestion mitigation methods in theme park problem are action presentation based on mathematical model [6], absorbing agents' next destination to congestion information [7], congestion mitigation with pre-boarding ticket [8] and predicting future congestion by collecting agents' schedule [9]. These studies verify effect of algorithm by computer simulation.

On the other hand, in car navigation problem, collaborative car navigation which

weights to routes weaken progressively with distance to calculate estimated rate of congestion is suggested [10]. There is a study which validates that only congestion information presentation may not expect that congestion mitigation like VICS by computer simulation [11].

These study have a commonality in a perspective of mass-user support, however it is difficult to compare these methods good in what point because of difference setting of problem and others. Additionally these studies stay supporting users' selection.

This study deals with service support in a broad sense and discusses what best selection is in the first place for users, and validates whole concept of information presentation to realize best selection.

1.2.3 Combinatorial optimization

A problem of choosing best combination when choosing combination meets given conditions is called combinatorial optimization. Combinatorial optimization is formulated following. **E** is a set, and **S** is a subset of feasible **E**.

Traveling salesperson problem (TSP) [12], knapsack problem and set covering problem are known as example problem of combinatorial optimization. Additionally, many combinational optimizations expect for minimum spanning tree problem and shortest path problem are known to belong class of NP-hard problem. It is said that there are no algorithms get exact solution in polynomial time for size of problem.

However, there are a large number of studies about combinational optimizations. Algorithms getting exact solution as soon as possible and algorithms getting precision approximate solution quickly are especially carefully-studied.

Combinatorial optimization is a matter after the application of correct information, thus this paper confine these studies to draw as a method. However, it is possible to consult broadly a problem which cost varies from hour to hour like dynamic TSP [13]. Also, given operation in real world, when it is difficult to handle overall users' information in a single central server, distributed constraint satisfaction algorithm [14] is needed to divide problem into sub problem for decentralized processing.

1.2.4 Game theory

As related studies in game theory, the tragedy of the commons [15] which is n-person non-cooperative game and has dilemma structure (social dilemma game) is closely connected to our study. One of our purposes is an avoidance of "tragedy".

Beyond that, congestion game is known as a class of game always has pure Nash equilibria, and efficiency algorithm for reaching Nash equilibria are suggested in symmetrical congestion game. [16] Additionally, there are studies about conditions and algorithms to reach Nash equilibria in which case incomplete information. [17]

1.3. Service

1.3.1 Definition of service

The word “service” became a household word in our life. However, what is a definition of services? As previously noted, we refer Shimomura’s definition of service that an activity that changes the state of a service receiver (Figure 1.1). Other definition, Looy et al [18] suggested services are goods which have for properties intangibility, perishability, simultaneity and heterogeneity. A property of intangibility means services can supply multiple people at once. A property of perishability means services aren’t material object nor visible. A property of simultaneity means services vanish at the same time as supplied, and services can’t demise to other people after supplied. A property of heterogeneity means services provide different profit depending on people. Because of these properties, it is necessary to quantify satisfaction level of peoples for modeling and simulation of services.

1.3.2 Needs of efficiency service

According to Japanese Cabinet Office’s “white paper on children and nurturing”, population of workers who assume services already began decreasing, the paper predict it will reach two thirds of current population of workers in 2050. Additionally, as compared to growth rate of labor productivity in industry is about five percent, growth

rate of labor productivity in service become diminished not exceeding one percent recently. Therefore, efficiency technology of service is needed.

One reason for stagnating growth rate of labor productivity in service is because of service has incorporeity and can't stock [19]. Therefore, it is necessary that supply adjustment by demand forecasting. However, it is difficult to adjust supply of service frequently because adjustment supplies of service involve physical change of facilities. It would appear that adjustment demand is useful for efficiency service. In other words, it may be possible that coordinating actions of service users can improve utilization efficiency of service.

Nowadays, cloud computing and big data analytics become an active area of research. It makes it possible to analyze users' action history and forecast users' schedule [20] in real time. This paper considers methods of information presentation to coordinate users' action and improve utilization efficiency of service.

1.4. Service innovation

Motomura [21] say it is necessary to realize service innovation in order to improve utilization efficiency of service. Service innovation means increasing receiver's additional value and provider's evaluation for purpose at one time. In this paper, we set service innovation as most important purpose and aim at the realization of service innovation. Especially, we deal situation that receiver select service to use and provider supports receiver to select service by recommender system. We define this situation as model of recommender type service, and explain more detail in next chapter.

Chapter 2

Flow model of recommendation type service

2.1. Introduction

In this chapter, we explain the model of recommender type service. This is a general model of service with recommender system in order to discuss a variety of service innovation's conditions and problems without concrete environments.

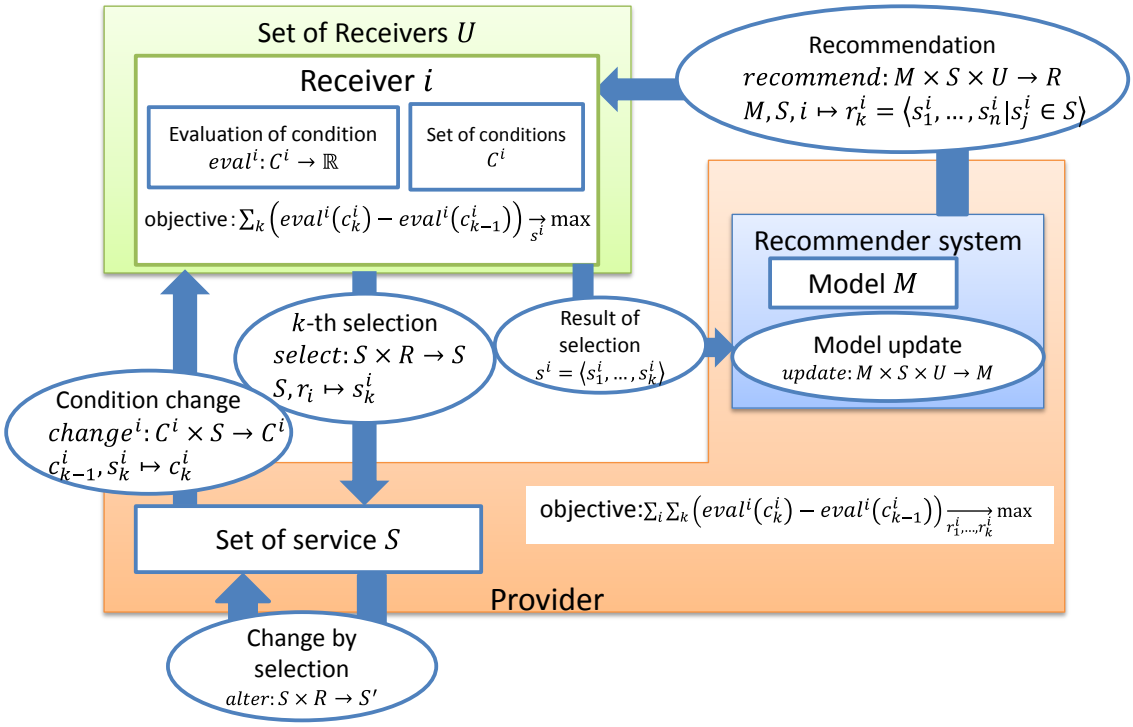


Figure 2.1: Flow model of recommender type service

2.2. Model

Figure 2.1 indicates model of recommender type service. This flow model mainly consists of receivers, services, provider, and recommender system. Receiver i determine k-th selection s_k^i by recommendation r_k^i. Selection means the services to use at that time. Selected service gives receiver condition change. Receiver evaluates selection s_k^i by difference between evaluations of conditions c_k^i and c_{k-1}^i.

Recommender system takes receivers' selection s_k^i and update model for recommendation. Then, next time, receivers can use recommendation by updated model. This is a general model of service and receiver with recommender system. Additionally, there is a provider to control service and recommender system. The provider has purpose, for example, maximizing selection of a certain service, or equalizing selection of all services. On the other hand, receivers want to select a best service for them.

2.3. Condition of service innovation

However, there is no need to use presented information for receivers. If users estimate better thinking by themselves than following presented information, they can think and act for themselves. Therefore, it's believed that presented information for coordination of receivers' action needs to inform two properties, reasonableness and fairness. Additionally, there is no point to do that overall utilization efficiency of service deteriorate than without presented information as a result. Thus, ideal presented information has three properties, reasonableness, fairness and efficiency.

2.3.1 Reasonableness

Receivers are assumed to be rational, they will refuse suggestions they make a loss. In some cases, it is not difficult to give them egocentric suggestions; however it may cause deterioration of overall efficiency. A situation of society satisfying all receivers' reasonableness is called Nash equilibrium; it is not always true that Nash equilibrium exists. Additionally, a problem to calculate Nash equilibrium belongs to class of PPAD-complete even in two receivers; it is not clear yet that polynomial time algorithm

to calculate Nash equilibrium exists. [22]

2.3.2 Fairness

A support system should be as fair as possible for receivers. In other words, it is undesirable that some receivers have advantage over others. Whether conscious or unconscious, if the system brings this unfair situation, receivers will avoid using the system eventually. Therefore, the system should show effort to resolve unfairness to receivers.

However, in the situation individual rationality different to overall rationality, just a fair information presentation will invoke overall inefficiency. Additionally, it is difficult to realize completely fair situation in a dynamic and unpredictable real world.

Though fairness is a hard problem to examine in computer simulations, it is necessary to consider for applying to a real world.

2.3.3 Efficiency

Efficiency is overall reasonableness in other words. It is called Pareto optimality in game Theory. An ideal situation is Pareto optimal Nash equilibrium and fair for all users. However, it may be extremely unusual. It means that a design of presented information that has unnoticeable unreasonableness and unfairness, even after improves overall efficiency is needed.

2.4. Property of service

Additionally I discuss three important properties of service to deal service, “finiteness”, “non-instantaneousness” and “fluidity”. Although these properties are involved a lot of services in real world, there are few studies focus on these.

2.4.1 Finiteness

“Finiteness” means the number of receivers using a same service at same time is

limited. The examples of services involving “finiteness” are highway, restaurant, attractions on theme park and so on. When service has “finiteness”, condition change of a receiver depends on other receivers’ selection. Thus, it would appear that it is important for realization of service innovation to share information of receivers’ selection.

2.4.2 Non-instantaneousness

“Non-instantaneousness” means there is a time difference between when receiver gets recommendation, when receiver selects service to use and when provider contributes service to receiver. Because receiver can’t generally select at the same time as get recommendation, most of services have this property in real world. If service involves “non-instantaneousness”, prediction of recommendations is not always corresponding with an actual condition change. In this case, it would appear that it is important for realization of service innovation to make recommendations considering time difference.

2.4.3 Fluidity

“Fluidity” means a set of service that scope of receivers’ selection frequently rises and falls. Examples of service are news, auctions and event information. When service has “fluidity”, it is difficult to collect data for recommendation because of services’ expiration and newly addition. Thus, it will be necessary for realization of service innovation to develop recommender system to react service’ age.

2.5. Service innovation in studies of recommender system

In studies of recommender system, the evaluations of recommender system are measured by accuracy of recommendation. Accuracy is a metric how close predicted value of recommendation to actual receiver’s evaluated value. On the other hand, several metrics are proposed other than accuracy, for example, coverage, learning rate,

novelty and so on. These metrics are mainly benchmarks for usability of receivers', it may be said that sum of these metrics is provider's efficiency, however sometime provider's efficiency can't be measured only in terms of these metrics. For example, provider wants to make a profitable customer, or provider wants receiver to buy expensive services.

Moreover, it is necessary for service innovation to consider both receiver's and provider's efficiency at the same time. Past studies of recommender system hardly made consideration relationship between receiver's efficiency and provider's efficiency. Motomura said it is important for realizing service innovation to go around the optimized design loop (Figure 2.2). Thus, actually, operating a real service and studying on the service is needed for true service innovation.

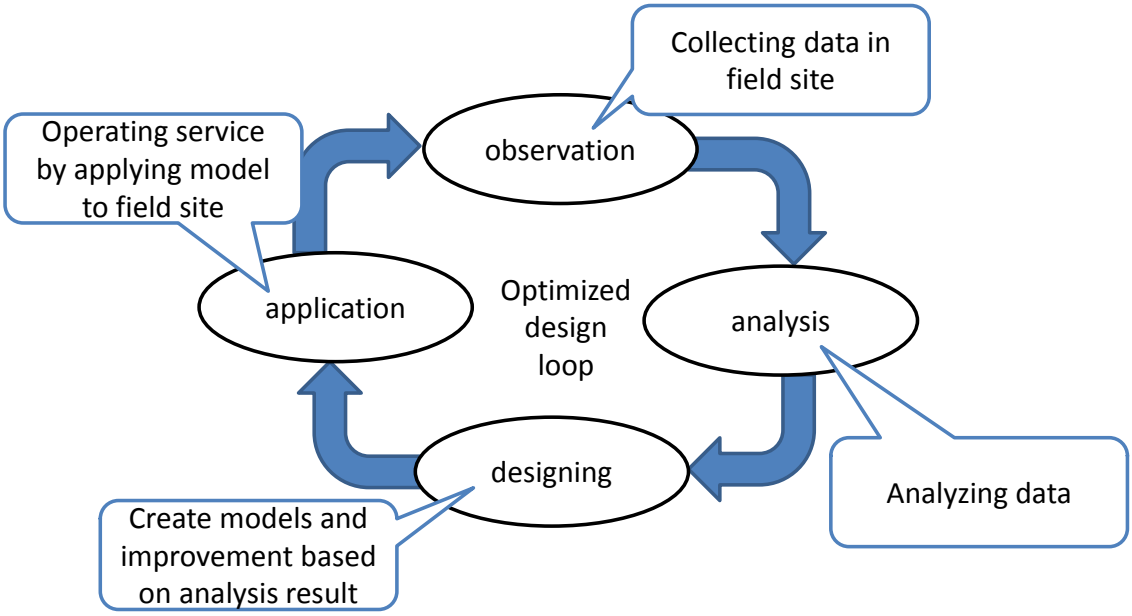


Figure 2.2: Optimized design loop for service innovation

Chapter 3

Shared Resources Type Traveling Salesperson Problem

3.1. Introduction

In this chapter, to realize service innovation in service models involving “finiteness”, we establish the presence or absence of status of service innovation in the first place by assuming service innovation as status of Pareto optimal and Nash equilibrium in Game Theory, and I make sure of how many service innovation solutions there are in small-scale problem by enumerate all solutions.

We deal with utilization method of goods by more than one person. A great deal of effort has been made on utilization method of goods by multi-agent simulation, for example, Theme Park Problem [23] and Car Navigation Problem [10]. These researches proposed efficient utilization method of goods in perspective of information technology. These new type of artificial intelligence called mass user support [24] [25] [26] are aiming not only to optimize individual utility but also to support a social system composed of a group of individuals. What seems to be lacking, however, is a discussion about its theoretical property and essence.

So this paper focus attention on shared resource, a kind of good, and analysis how it is used in perspective of Game Theory. This paper defines shared resource is good that has excludability and rivalry. For example, this can apply crowded roads, utility service windows, network traffic, amusement facilities, and so on.

To consider utilization method of shared resource, not only just one infrastructure but also many infrastructures, this paper proposes Shared resource TSP as an extended TSP model. Shared resource TSP can look at paradigm of not only Game Theory but also combinatorial optimization. To establish utilization methods are admissible at the social level, it is necessary to verify at paradigm of Game Theory.

3.2. Shared Resource Use Problem

3.2.1 Shared Resource

In this paper, shared resource is defined what people can get some profits by using. There are resources vanishing when used them (for example, oils, water, feed crop etc.) and resources decaying efficiency. This paper deals with latter as shared resources. When usage of shared resource is synchronized, its profit decays because of congestion. Examples in real world are roads, seats of restaurant, amusement attraction of theme park, bands of network and so on.

In this chapter, agents mean players who optimize their usage of shared resource. They correspond to mobile terminals of people, car navigation and themselves. Agents think about maximization of their profits, they don't meet each other halfway. They optimize based on their information, it is not always true to get a real optimized solution.

3.2.2 Model

First, to make shared resource using analyzable in perspective of Game Theory, the Shared resource Use Problem is formulated as follows:

- Set of agents: A = {a|a = 1, 2, ... , m}
- Set of shared resources: R = {r|r = 1, 2, ... , n}
- Set of strategies agent a can take: $\mathrm{S_a} = \{S_1, S_2, \dots\} \subseteq 2^E$
- Strategy of agent a: $\mathrm{X_a} \in S_a$
- Set of strategies all agents taking other than a: $\mathrm{X_{-a}}$
- Gain by using shared resources $g(B)$, B is a set of shared resources $\mathrm{B} \subseteq R$
- Cost by using shared resource r: $c(r)$

$$\mathrm{c(r)} = \mathrm{h}\big(\mathrm{n_r}(X_a, X_{-a})\big) \tag{3.1}$$

$h(n)$ is monotonically increasing function and $h(1) = 0$

- Number of agents using r: $\mathrm{n_r}(X_a, X_{-a})$

$$\mathrm{n_r}(\mathrm{X_a}, \mathrm{X_{-a}}) = \sum_{a=1}^{m} f(r, X_a) \tag{3.2}$$

$$\mathrm{f}(\mathrm{r}, \mathrm{X_a}) = \begin{cases} 1 & if\ r \in X_a \\ 0 & otherwise \end{cases} \tag{3.3}$$

・Payoff of agent a taking strategy $\mathrm{s_a}$: $\mathrm{p}(\mathrm{X_a})$

$$\mathrm{p}(\mathrm{X_a}) = g(X_a) - \sum_{r \in X_a} c(r) \tag{3.4}$$

・Social payoff that summation of all agent's payoff: u

$$\mathrm{u} = \sum_{\mathrm{a}=1}^{\mathrm{m}} p(X_a) \tag{3.5}$$

Agents select strategy to maximize their payoff. But, agents can't observe true payoff because of largeness of payoff matrix, so agents estimate payoff $\mathrm{p}'(\mathrm{X_a})$ and choose strategy according to this $\mathrm{p}'(\mathrm{X_a})$. That is to say, agents take $\mathrm{X_a^*}$ that satisfy following formula:

$$\mathrm{X_a^*} = \underset{X_a}{\operatorname{argmax}}\, p(X_a) \tag{3.6}$$

If every agent satisfies this formula, it's neither more nor less than Nash equilibrium solution in terms of Game Theory.

Added to these, this paper defines social utilization. Social utilization is a condition of society that implements both maximizing *u* with Nash equilibrium. If achieved social utilization, we may say all agents are satisfied in their own way and society is accordingly desirable condition. This paper examines the social utilization whether realizable or not, and if it's realizable, how difference in social utility of its solution between just maximizing u solutions.

3.3. Extended Traveling salesperson problem

To make sure above things, we will need to more concretize service infrastructure use problem. The condition required the specific model is

・it is possible to experiment by simulation

・it is possible to define Pareto optimal and Nash equilibrium

Set of strategy S is finite set

Payoff $\mathrm{p}(\mathrm{X_a})$ is defined real number

・it is arbitrarily to define number of agent and service infrastructure

As the model meets these requirements, this paper proposes Service Infrastructure TSP as an extended TSP model.

3.3.1 Outline of traveling salesperson problem

TSP is a combinatorial optimization to solve shortest cycle passing all cities only once. Define set of cities as follows:

$$\mathrm{V} = \{\mathrm{v_i} | i = 1,2,\dots,n\} \tag{3.7}$$

Set a cost to move between city i and j as c_{ij} and set generated circuit route x_{ij} as follows:

$$\mathrm{x_{ij}} = \begin{cases} 1 & : \text{When i to j is route} \\ 0 & : \text{otherwise} \end{cases} \tag{3.8}$$

Indicate objective function and constrained condition of TSP using aboves:

$$\min \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} c_{ij} x_{ij} \tag{3.9}$$

s.t. $$\sum_{\mathrm{j,j \neq i}} x_{ij} = 1 \; on \; i = 1,2,\dots,n \tag{3.10}$$

$$\sum_{i,i\neq j} x_{ij} = 1 \; on \; j = 1,2,\dots,n \tag{3.11}$$

$$x_{ij} \in (0,1) \; on \; i,j = 1,2,\dots,n \; and \; i \neq j \tag{3.12}$$

Additionally, solution should be circuit route in addition to these three constrained condition. Problems which costs are $c_{ij} = c_{ji}$ are called symmetric TSP, and problems which costs are $c_{ij} \neq c_{ji}$ are called asymmetric TSP. Problems which cities are allocated on a plane surface and c_{ij} is defined Euclidean distance between v_i and v_j are called Euclidean TSP. Euclidean TSP is always symmetric TSP.

Solution space of TSP depend on number of cities *n*, and total number of solutions becomes (*n*-1)!/2. Because total number of solutions explode with the increasing number of cities n, it is difficult to solve exact solution on a certain number of cities. Although TSP has been investigated as problem belongs to NP-hard for many years, polynomial time algorithm for exact solution remains undiscovered. However, efficient algorithm for exact solution and several heuristic methods have been found in history of TSP studies, and they have been applied to other problems.

In this paper, we modelization shared resources problem in the concrete based on TSP theories by assuming edges connecting between cities as shared resources. A motivation of using TSP theories is because there are several accumulate algorithms for exact solution and approximate solution, and it is possible to apply these algorithms to this study.

3.3.2 Extended TSP Model

There are two differences between TSP and the Service Infrastructure TSP is mainly two. First, TSP has only one agent (salesperson), but Service Infrastructure TSP has one or more agents. This property looks like n-TSP. but all agents travel all cities on Service Infrastructure TSP. Second, TSP's cost is constant; But Service Infrastructure TSP's cost is changing by route of other agents. To put it another way, Service Infrastructure TSP's has additional cost besides constant cost. Service Infrastructure TSP is formulated as follows:

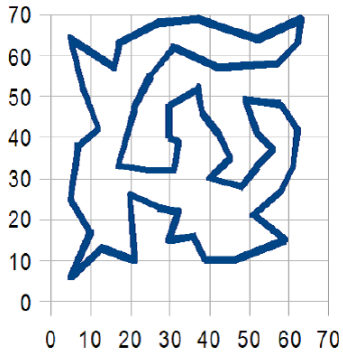


Figure 3.1: Example of TSP solution(eil51.tsp from TSPlib*)

・Set of agents:

$$A = \{a | a = 1,2, \dots, m\} \tag{3.13}$$

・Set of shared resources:

$$R = \{r | r = 1,2, \dots, n\} \tag{3.14}$$

・Set of edges:

$$E = \{e | e = 1,2, \dots, k\}, k = \frac{(n-1)!}{2} \tag{3.15}$$

・Matrix of cost to use edge e (constant cost):

$$C = \{c_e | e = 1,2, \dots, k\} \tag{3.16}$$

* TSPlib: http://elib.zib.de/pub/mp-testdata/tsp/tsplib/tsplib.html

・Time:

$$\mathrm{t} = 1,2,\dots,\mathrm{n} \tag{3.17}$$

・Agent a's matrix of route at t that is strategy:

$$\mathrm{X_a} = \{x_{aet} | a = 1,2,\dots,m\ t = 1,2,\dots,n\ e = 1,2,\dots,k\} \tag{3.18}$$

$$\mathrm{x_{aet}} = \begin{cases} 1 & \text{edge } e \text{ is agent } a'\text{s route at } t \\ 0 & otherwise \end{cases} \tag{3.19}$$

・Additional cost to use edge e at t:

$$\mathrm{d_{et}} = c_e \left(\sum_{a=1}^{m} x_{aet} - 1 \right) \tag{3.20}$$

Each $\mathrm{d_{et}}, \sum_{a=1}^{m} x_{aet}, \sum_{a=1}^{m} x_{aet} - 1$ is corresponding to $\mathrm{c(r)}, \mathrm{n_r}(X_a, X_{-a}), \mathrm{h}\big(\mathrm{n_r}(X_a, X_{-a})\big)$ in the Service Infrastructure Use Problem.

・real cost that sum of $\mathrm{c_e}$ and $\mathrm{d_{et}}$:

$$\mathrm{p_{et}} = c_e + d_{et} \tag{3.21}$$

In addition to this, objective function of service infrastructure TSP is

$$\min \sum_{\mathrm{a}=1}^{\mathrm{m}} \sum_{e=1}^{m} \sum_{t=1}^{n} p_{et} x_{aet} \tag{3.22}$$

$$\mathrm{s.t.} \quad \sum_{\mathrm{e}=1}^{\mathrm{k}} \sum_{t=1}^{n} x_{aet} = 1 \qquad a = 1,2,\dots,m \tag{3.23}$$

$$\mathrm{x_{aet}} \in (0,1) \qquad a = 1,2,\dots,m\ \mathrm{e} = 1,2,\dots,\mathrm{k}\ \mathrm{t} = 1,2,\dots,\mathrm{n} \tag{3.24}$$

all solutions make a route visiting all cities in a=1,2,...,m (3.25)

Now that service infrastructure TSP is defined as the specific model of service infrastructure use problem, the next step is to do experiment simulation.

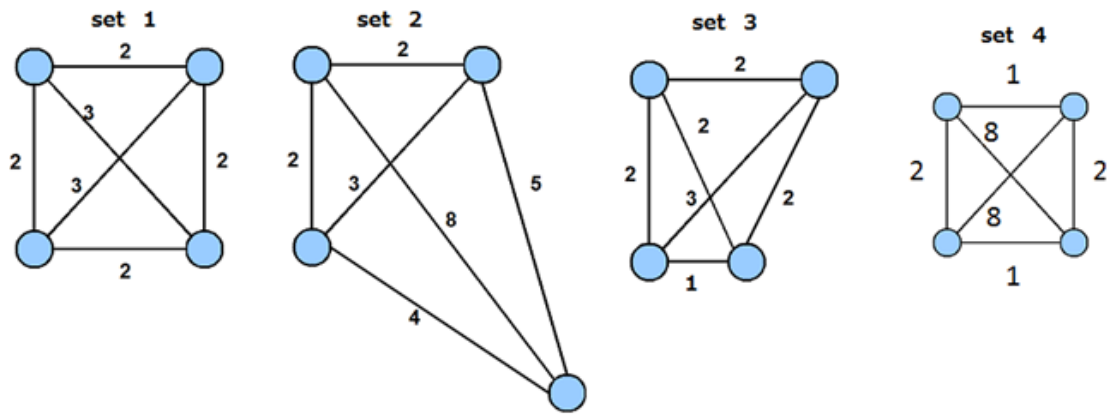


Figure 3.2: Sets of cities used to simulation

3.4. Experiment 1: Four cities

To make sure following two matters, the social utilization whether realizable or not, and if it's realizable, how difference in social utility of its solution between just minimizing total cost solutions, we need to enumerate all solutions and check them are minimizing total cost solutions, Nash equilibrium solutions, both, or neither. Therefore, this paper analyzes example problems that can be solved by exhaustive search. Settings of simulation on this paper are configured as follows:

- Number of agents: 5
- Number of cities: 4
- Sets of cities used are Figure 3.2
- How to give observable payoff $\mathrm{p}(\mathrm{X_a})$ is following two ways

Pattern 1: $\mathrm{p}'(\mathrm{X_a}) = \mathrm{p}(\mathrm{X_a})$ (Observable payoff is true payoff)

Pattern 2: $\mathrm{p}'(\mathrm{X_a}) = c_e$ (Ignore additional costs)

Number of cities is 4, so agents' strategies are classified two types as 2. "Direct" is a

strategy that select shortest route. ”Roundabout” is not selecting shortest route. (Figure 3.3)

This paper examine following three things:

・Show examples of typical solutions to discuss characteristic of this problem.

・Ratio of total cost is minimum in all solutions using each patterns.

・Average values of total cost of each patterns.

・Number of each solutions Nash equilibrium solutions, Pareto optimal solutions, both, minimal solutions.

The results of the experiment are shown in Figure 3.5 represents an example of Nash equilibrium solutions. Agents always use edges alone and avoid accruing additional costs. Figure 3.6 shows one of a greedy solution in city 1. No agents avoid other agents because agents don’t make consideration additional costs.

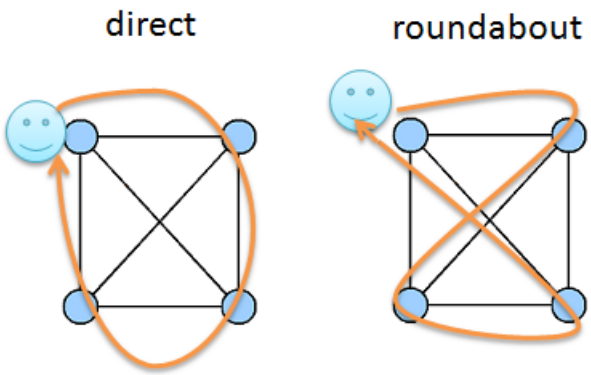


Figure 3.3: simplified strategies of agents

Figure 3.7 and Figure 3.8 are an example of Nash equilibrium solutions in city 2 and 3. These are same characteristics as Figure 3.5.

In the same way, Figure 3.9 is an example of Nash equilibrium solutions in city 4. But, in these solutions, agent 1 and agent 2 select just all the same root. This is because of cost of “roundabout” strategy more than sum of cost of “direct” strategy and additional cost.

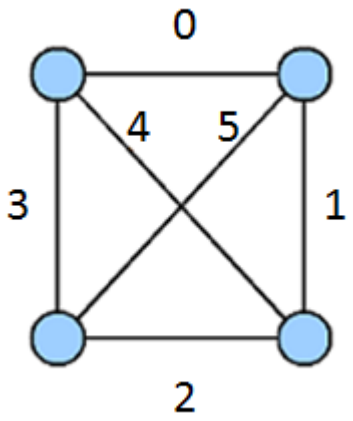


Figure 3.4: Edges number

Figure 3.10 is an example of Pareto optimal solutions in city 4. This solution is neither Nash equilibrium solution nor minimal solution. In this solution, agent 2 has high cost than any other agents, and other agents have low cost than any Nash equilibrium solution and minimal solution.

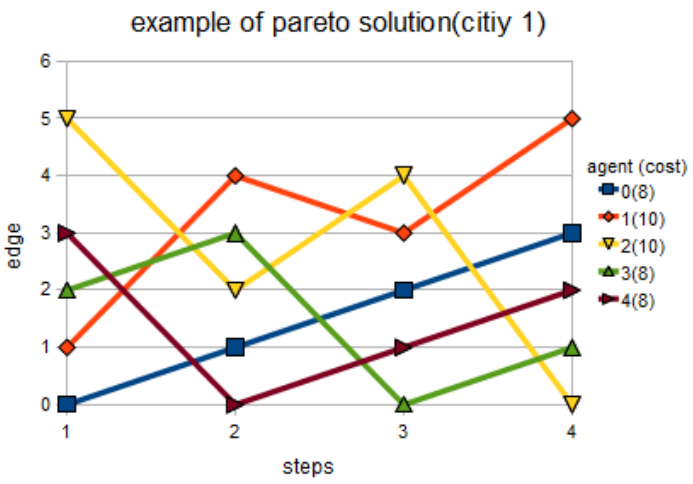


Figure 3.5: Example of solutions 1(city 1)

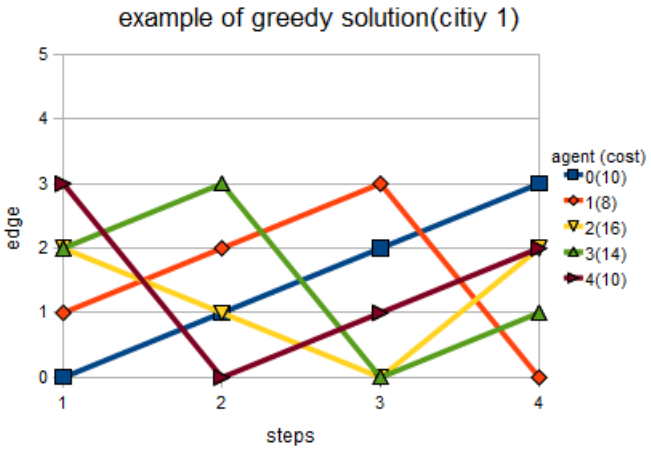


Figure 3.6: Example of solutions 2(city 1)

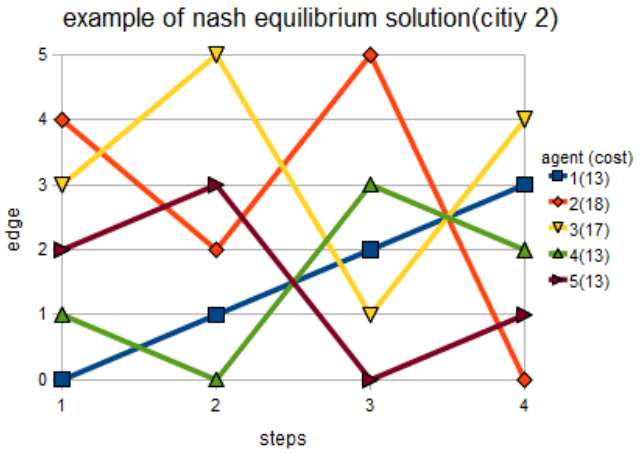


Figure 3.7: Example of solutions 3(city 2)

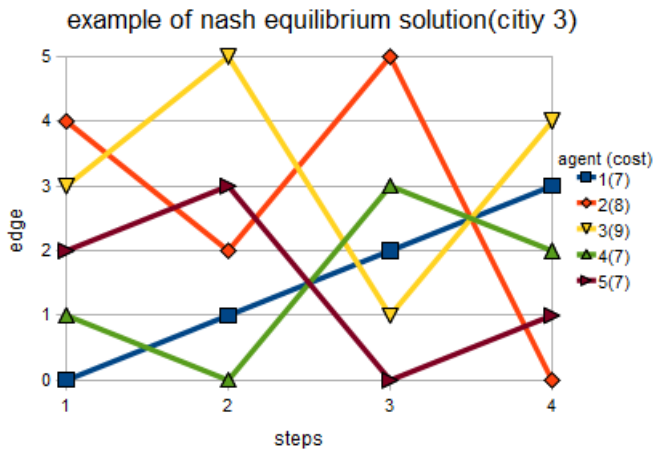


Figure 3.8: Example of solutions 4(city 3)

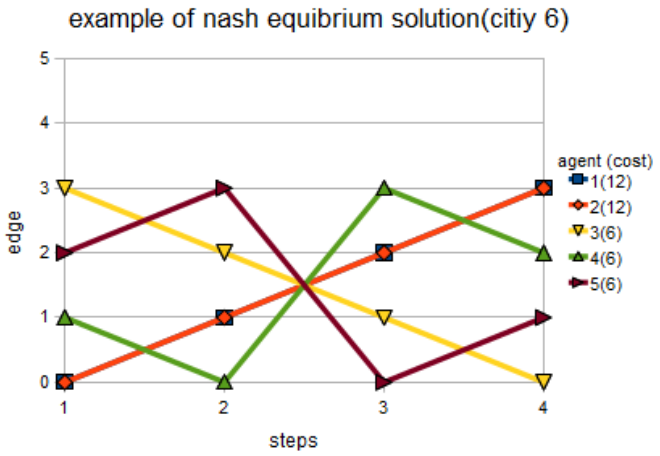


Figure 3.9: Example of solutions 5(city 6)

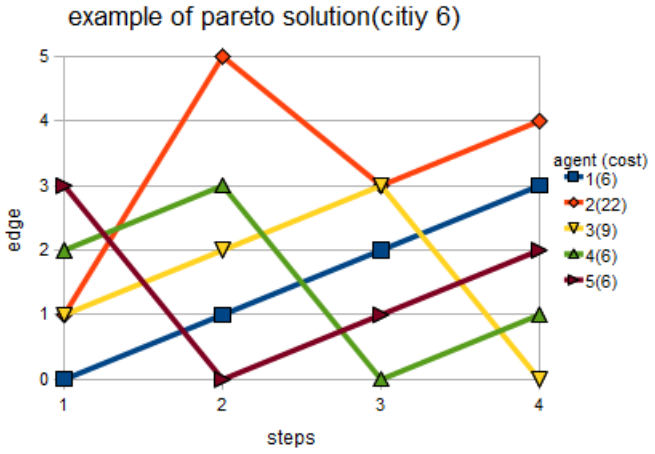
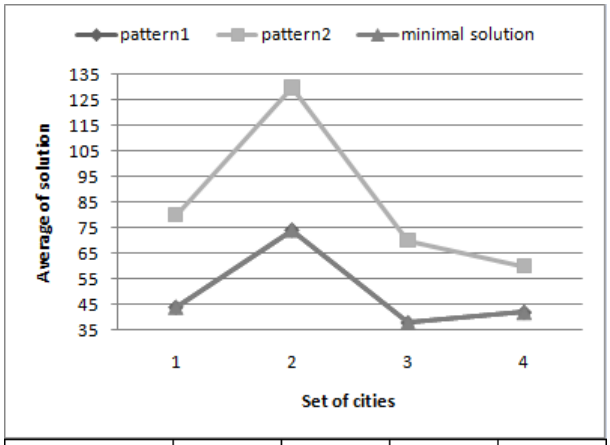


Figure 3.10: Example of solutions 5(city 6)

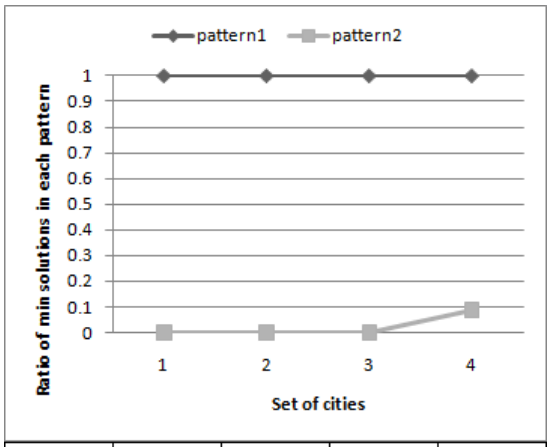
Next, as Figure 3.11 indicates, all Nash equilibrium solutions are also minimal solutions. This fact tells us that the Social Utilization can be actualized by individual optimizers. But if we want to always actualize the social utilization more agents or cities, it is difficult to know strategies of all other agents and get strictly all additional costs. So we need to embrace another strategy in those cases. Figure 3.12 shows that ratios of average values of total cost of each solution to minimal solution are up to 2 percent. It is debatable whether these ratios are significant.

Figure 3.13 and Figure 3.14 are a Venn diagrams indicate relations of solutions in this problem. They show existence rates of each solutions Nash equilibrium solutions, Pareto optimal solutions, minimal solutions, or several of them at the same time. Three examines produce the same results in cities 1, 2, 3. From this Figure, all minimal solutions are also Nash equilibrium solutions, and then all Nash equilibrium solutions are also Pareto optimal solutions. There is no solutions are not minimal solutions or Pareto optimal solutions and Nash equilibrium solutions. Only the result in city 4 is a little different from other results, Any Pareto optimal solutions are not Nash equilibrium solutions.



	1	2	3	4
pattern1	44	74	38	42
pattern2	80	130	70	60
minimal solution	44	74	38	42

Figure 3.11: Ratio of total cost is minimum in all solutions using each patterns



	1	2	3	4
pattern1	1	1	1	1
pattern2	0	0	0	0.087891

Figure 3.12: Average values of total cost of each patterns

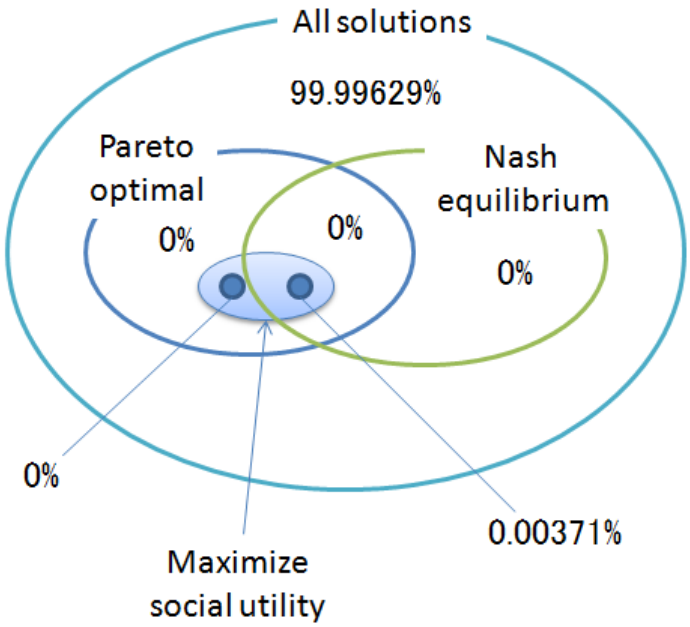


Figure 3.13: A Venn diagram of solutions in city 1-3

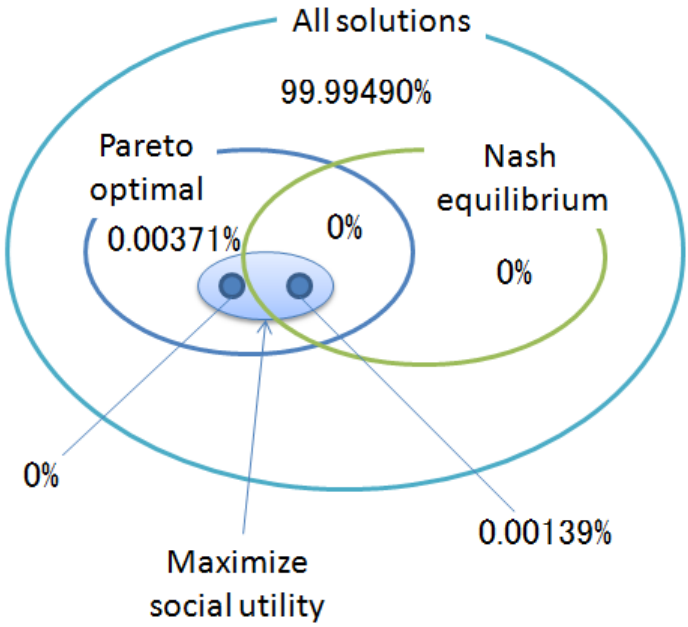


Figure 3.14: A Venn diagram of solutions in city 4

Results of shown Figure 3.13 and Figure 3.14 means social utilization can be sometimes actualized only agents optimizing for selfish ends in this time problems. But, only in service infrastructure TSP, it is unknown that problems are more number of agents or cities are the same as this time. Considering application in real world, for example, like start and goal in car navigation, like sequence in scheduling problem, there are more constrained conditions and more complexity in the problem. So we can't know relations of solutions until we confirm these problems. As this time, If all minimal solutions are also Nash equilibrium solutions, answer of this problem is sharing information of all agents, and all agents have to do is behaving selfish in accordance with information. If minimal solutions are not Nash equilibrium solutions, we should build a mechanism change structure of the game itself that agents playing. With a background like that, we should research this problem in the future.

3.5. Experiment 2: Two and Three Cities

Figure 3.15 indicates sets of cities that are used in this experiment. We focus two problem settings. First, number of cities is two, directed graph, number of agents is three. Second, number of cities is three, undirected graph, number of agents is three and four. In these settings, we enumerate all solution that can be Nash equilibrium by using generalized costs. Then, we branch these solutions in case which solution would be Nash equilibrium and calculate exist rate of following solutions in each case.

- Nash equilibrium solutions
- Pareto optimal solutions
- Maximize social payoff solutions (minimize sum of all agents' costs solutions)
- Solutions satisfying several or all these.
- Solutions conforming to none of these.

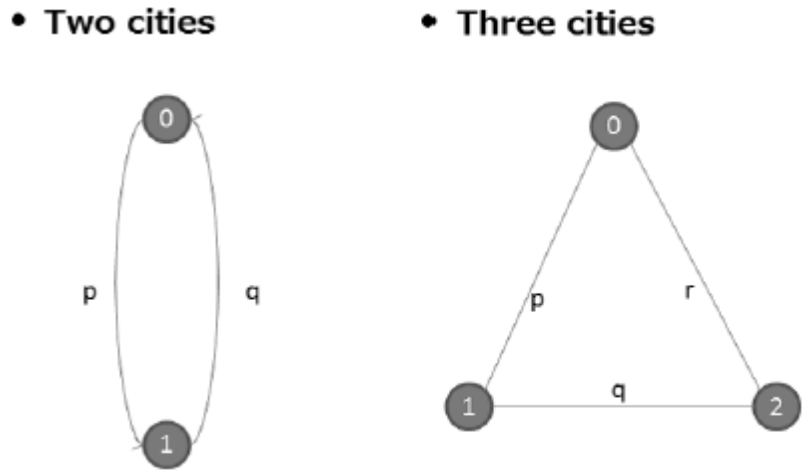


Figure 3.15: Sets of cities used in this experiment

First, to enumerate solutions that would be Nash equilibrium, this paper get cost matrix. Figure 2 shows cost matrix in 2 cities and 3 agents' problem. Solutions in shaded area are Nash equilibrium.

In each solution in cost matrix, coefficients of *p* and *q* equal each other. So we determine Nash equilibrium solutions regardless of value of *p* and *q* in two cities problem. In addition, exist rates of solutions are like figure 3 in this case.

If solutions are Nash equilibrium, they must be also Pareto optimal and maximize social payoff. In the other hand, all Nash equilibrium solutions have not fairness. Next, this paper considers 3 cities problem. It is difficult to list cost matrix because of space limitations, so this paper omit all of cost matrix.

Nash equilibrium solutions are classified follow two cases.

・p = q = r(equality to be true)

・p≧q = r(equality to be false)

Figure 4 7 shows exist rates of solutions in case equality to be true and false. In addition, parenthesized numerical values are exist rates of solutions that costs of agents are fair to each type solutions.

In this case, all Nash equilibrium solutions are also Pareto optimal and maximize social payoff too. That is to say, in these problems, if agents choose strategies reasonably, social payoff should be maximized. On the other hand, all Nash equilibrium solutions are not fair costs between agents; there are some fair solutions in Pareto

optimal solutions. A fact that costs are not fair means it is possible that some agents make a loss depends on their turns choose strategies. It's doubtable that this difference is acceptable.

payoff agent 0, agent 1, agent 2		strategy of agent 1			
		0→1	0→1	1→0	1→0
		strategy of agent 2			
		0→1	1→0	0→1	1→0
strategy of agent 0	0→1	3p+3q, 3p+3q, 3p+3q	2p+2q, 2p+2q, p+q	2p+2q, p+q, 2p+2q	p+q, 2p+2q, 2p+2q
	1→0	p+q, 2p+2q, 2p+2q	2p+2q, p+q, 2p+2q	2p+2q, 2p+2q, p+q	3p+3q, 3p+3q, 3p+3q

Figure 3.16: cost matrix in 2 cities and 3 agents problem

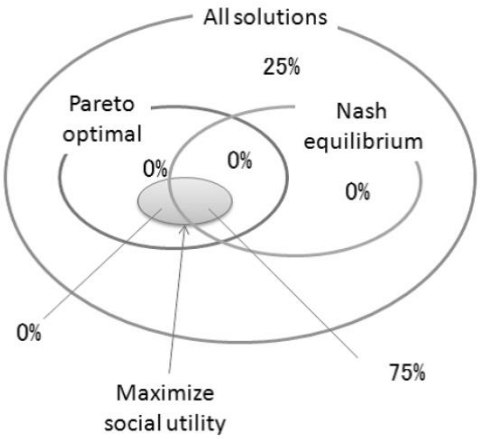


Figure 3.17: exist rates of solutions in 2 cities and 3 agents problem

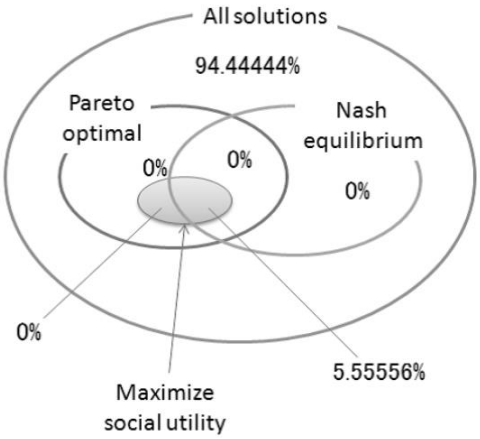


Figure 3.18: exist rates of solutions in 3 cities and 3 agents problem (equality to be true)

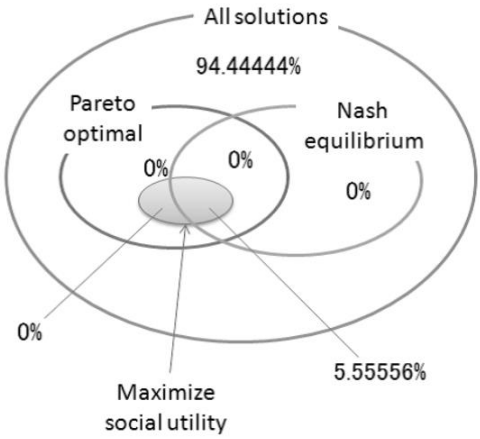


Figure 3.19: exist rates of solutions in 3 cities and 4 agents problem (equality to be true)

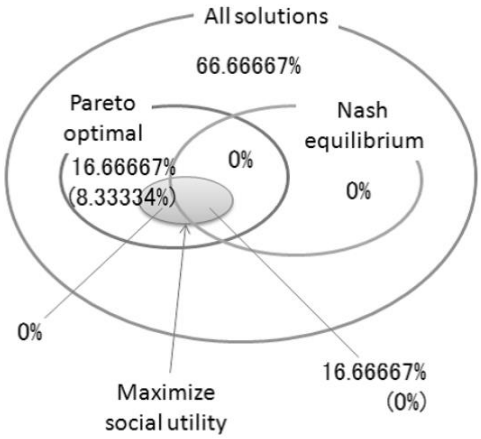


Figure 3.20: exist rates of solutions in 3 cities and 3 agents problem (equality to be false)

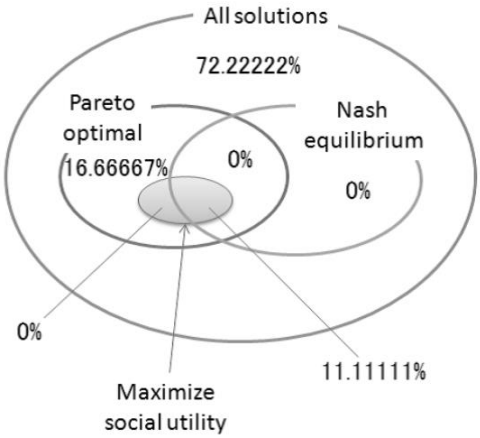


Figure 3.21: exist rates of solutions in 3 cities and 4 agents problem (equality to be false)

3.6. Conclusion

In this chapter, we defined and formulated service infrastructure use problem to discuss about utilization method of many agents for many service infrastructures, and analysis its theoretical property and essence. In service infrastructure use problem, this paper defined social utilization as a fine condition of social world. Next, I proposed service infrastructure TSP as a specific model of service infrastructure use problem to make sure social utilization whether realizable or not, and so on. Finally this paper do

experiment simulation and verified that the social utilization can be actualized by individual optimizers in this time problem.

In this chapter, I assumed service innovation as realization of Nash equilibrium Pareto optimal status in Game theory, and I made sure of how many solutions there are in small-scale problem by enumerate all solutions. As a result, there are 10 percent service innovation solutions in problems has two or three simple cities, and below 0.01 percent service innovation solutions in problems has four cities. Though only in small-scale problem, this result indicates that it isn't very likely to realize service innovation when receivers select randomly, and there are a few service innovation solutions, nonetheless, service innovation solutions exist.

Chapter 4

Co-utilization of Service Facilities

4.1. Introduction

This chapter focuses on service innovation in the situations service models involving “finiteness” and ”non-instantaneousness” that can quantify receiver’s efficiency exactly however receiver’s efficiency depends on other receivers’ selections. These situations are another word for operation under the first-come-first-serve rule. Examples of this case are waiting time on theme park and traveling time on highway. I proposed a prediction method of congestion “the user-in-the-loop forecasting with the statement-based cost estimate” to realize service innovation by congestion mitigation. This method can predict approximate congestion by receivers’ preliminary declarations. I verify effect of this method by two simulations, theme park model and highway.

Recent progress in information technology related to cellular phones and car navigation systems has enabled to develop new types of services on a communication network. As one of such service applications, we focus on the application for utilization of socially shared service facilities. The service facilities, in this paper, mean “first-come-first-served” facilities for any demands, and basically nobody can reserve these use in advance. The examples of these facilities include roads or highways in a traffic system, attractions in a theme park, public transportation and parking lots. Although we are aware that some of recent these facilities provide a kind of reservation service, we do not focus on reservation which possibly grows the idle time of facilities.

One of the important problems in service facility allocation is that over capacity users often make a long queue. The waiting time in a queue is really wasting of time, and it is especially serious in a traffic system. If they can adjust their schedules each other in advance, they may avoid over-concentrating to the facilities. However, the users often demand some facilities with individual constraints, and independent optimization is difficult. On behalf of the protection of the environment, the prevention

of over-concentration not only promotes effective use of existing facilities but enables new developing facilities down-sized. To promote effective use of facilities, we have tried to design a planning system to coordinate co-utilization of service facilities among users.

This problem is a kind of resource allocation problems, and Kurumatani has proposed the concept of "mass user support" to tackle this type of problem [24]. The goal of mass user support is not only to optimize individual utility but also to support a social system comprised of a group of individuals. Our application is one of mass user support systems.

One important issue to construct such a planning system is how to let users follow the system planning without reservation. The users should be treated fairly with the guarantee of individual free will, and it is not permitted to compel users to follow the system, even if the system tries to enhance not only social welfare but individual utility. This issue is a matter of game theory but it is not easy to analyze by usual game-theoretic approach. Thus, we have to analyze the problem by empirical game-theoretic approach [27].

Another issue is how to estimate uncertain future situation for individual planning. One of the simplest ideas is to utilize current congestion information and recommend users to avoid congested facilities. Some researchers have investigated the effectiveness of such current congestion information. Kawamura and Suzuki made multi-agent models to simulate visiting behavior of users in a theme park and event-hall, respectively [7], [28]. Mahmassani, Shiose, Yamashita, Yhoshii and Whale made traffic simulation models individually and they analyzed the effectiveness of current congestion information [29], [11], [30], [10], [31], [32]. Arnott also analyzed the effectiveness of such information with a theoretical traffic model [33]. Fischer investigated the behavior of selfish agents in a routing problem [34].

These researches basically reached the same conclusion that the simple utilization of current congestion information does not cause good effect. This is because that the current information depends on only current situation and it becomes unavailable when the user arrives at a facility in future. Such unavailability causes the temporal and spatial oscillation of facility demand, then, total performance is spoiled by these influence.

Another idea is to implement some kind of congestion forecasting. However, the forecasting from outside of the system may not be effective because the forecasted congestion information directly affects the user behavior and soon the forecast becomes a different one from a forecast. Thus, we have an assumption that the "user-in-the-loop" forecasting system is necessary, in which the user planning and congestion forecasting are connected each other to form the right feedback loop. Yamashita and Yoshii have introduced a primitive version of such idea to traffic models [10], [31], and we are developing a more general and practical theory for facility co-utilization.

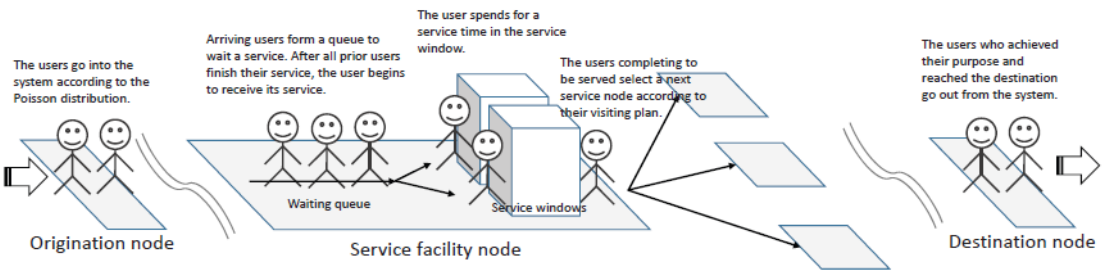


Figure 4.1: The outline of proposed simulation model

In this paper, we show the first idea of the user-in-the-loop forecasting and planning system for service facility allocation, and we propose the statement-based cost estimate for realizing the system. This paper is organized as follows. Section 2 describes a user-facility model and two experimental scenarios. In Section 3, we explain the user planning and cost estimate. Section 4 shows some experimental results, and we discuss in Section 5. Finally, we conclude our paper in Section 6.

4.2. Simulation Model

4.2.1 Environments

Service facilities and transiting users among these facilities constitute our simulation

model (see Figure 4.1). The simulation runs along simulation time t until t reaches the maximum time t_{max}. The users behave once in turn at each time t, and t is incremented by one after all the users behave.

A service facility, which provides users a kind of service under the first-come-first-served rule, is represented as a node. The nodes are connected by directed links, and these nodes and links constitute a graph network. The set of directed links regulate the users' possible transition paths between the nodes. Node i on the network has two given parameters, the number of service windows, w_i and the service time, s_i.

The service facility in node i can serve the number of w_i users simultaneously, and a user who begins to be served on node i has to spend for s_i time to pass to a next node. Usually, w_i is set to a finite number and the facility in node i is strictly operated for the number of w_i users under the first-come-first-served rule. Otherwise, w_i can be set as "infinity" and it defines that node i has unlimited service window, then it can serve all visiting users immediately and simultaneously. Over-capacity users have to wait in a queue, and the number of users queuing up on node i is denoted by $queue_i$.

The users appear at each time t according to the Poisson distribution until the total number of users reaches the maximum number N. The arrival rate of the Poisson distribution is denoted by λ. Each of the users departs an origination node and goes toward a destination node through some facility nodes on the network. In some experimental scenarios the users have to visit some given facilities as constraints. The users individually aim to minimize the travel time which is the difference between departing time from the origination and arrival time to the destination.

Each user has a plan which consists of a sequence of nodes the user intends to visit during its travel. It guides which node the user should go as a next. The plan of user j is denoted by $plan_j$, and how to decide $plan_j$ is the main interest of this paper. Our idea is described in the next section.

When arriving a new node, the user has to join a queue list to wait for its turn. After all prior users in the queue finish their service; the user begins to receive its service. If there is no prior user in the queue list, the user immediately enters into its service. The user who has just finished receiving its service chooses a next node from ones linked by the current node.

Because the waiting time in a queue depends on the number of prior queuing up users, the total travel time of the user depends on the other users' behavior. In other words, the travel time of users is interconnected through mutual travel plans and cannot be optimized individually. Total objective of this problem is to find a better coordinating way to minimize the average travel time of whole users.

For more algorithmic description of the user behavior, let user j be introduced the status parameter, $status_j$ and the current position, $position_j$. $status_j$ takes one value in status $\{inactive, waiting, served, terminated\}$. At the beginning of simulation, $status_j$ and $position_j$ are set to *inactive* and an origination node, respectively. At each time t, $status_j$ and $position_j$ are switched, according to the pseudo code in Figure 4.2. The travel time of user j is calculated when the user status reaches *inactive*.

4.2.2 Experimental scenarios

We introduce two experimental scenarios as a bench mark, i.e., the theme park scenario and the highway scenario. For choosing experimental scenarios, we focus on two constraint types of visiting service facilities. In the first constraint type, it is corresponding to the theme park scenario, the user is given the service facilities in advance that he/she has to visit, and decides the order of visit to reduce the travel time like Traveling Salesman Problem. In the second constraint type, it is corresponding to the highway scenario; the user is given the origination and the destination in advance, and has some alternative ways to reach the destination. The choice of the alternative affects travel time. The combination of such types of constraints can represent various condition of utilizing service facilities and we firstly investigate these scenarios as a bench mark.

```
switch (status_j)
 case "inactive":
  if user j appears at an origination node
   start_time_j ← t;
   position_j ← the next node indicated by plan_j;
   status_j ← waiting;
  break;

 case "waiting":
  if the current facility becomes ready to serve user j
   status_j ← served;
   remaining_time_j ← s_(position_j);
  break;

 case "served" :
  remaining_time_j ← remaining_time_j − 1;
  if remaining_time_j = 0
   position_j ← the next node indicated by plan_j;
   if position_j is a destination
    end_time_j ← t;
    travel_time_j ← end_time_j − start_time_j;
    status_j ← terminated;
   else
    status_j ← waiting;
  break;

 case "terminated":
  break;
```

Figure 4.2: Pseudo code of status transition

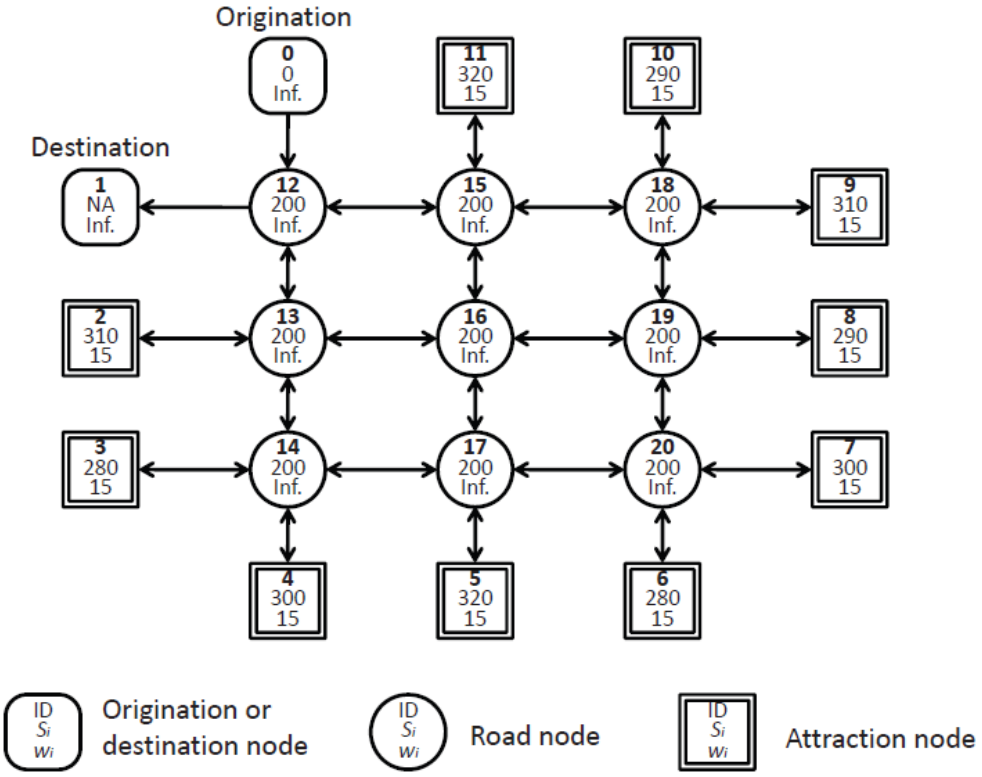


Figure 4.3: The network model of theme park scenario Each user arrives at the origination node 0, visits randomly given 4 attractions through road nodes, and finally goes to destination node 1.

Theme park scenario

This scenario consists of an origination node, a destination node, attraction nodes and road nodes (see Figure 4.3). Each visitor user coming to the theme park starts from the origination node and goes toward the destination node through randomly given four attraction nodes. “Randomly given” means that the users have the four attractions most to their taste and these are randomly defined. The user has to visit every given attraction just once in the travel. The road nodes bridge those nodes by enough throughputs with unlimited service window. Microscopically motivation of each user is toward optimizing a permutation of visited attractions, while we would tackle globally balancing the load of the attractions.

In this setting, the attractions have some different service time, which causes the difficulty in balancing the load of the attractions. The topological characteristic, i.e., the

distance from the origination or destination to each attraction, also causes the difficulty in consideration of estimating total moving time and avoiding congestion at the attractions.

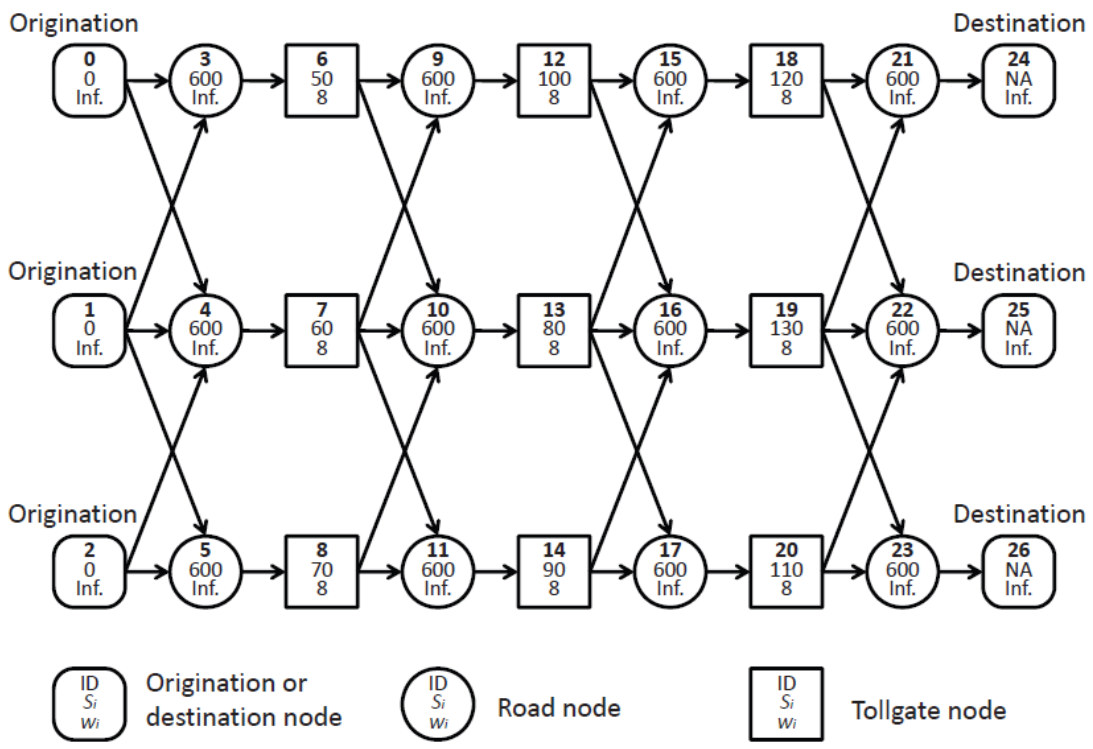


Figure 4.4: The network model of highway scenario Each user starts from a randomly selected origination node from three ones. The destination is also randomly given from three destination ones in advance. There are four user choosing points neighboring to tollgates.

We are concerned in this model with investigating the characteristic of dynamic service facility allocation rather than developing real application to an actual theme park or amusement park. This model can be positioned as one of typical service facility allocation problems in related works that have revealed to the relationship between user visiting behavior and information broadcasting in congested space [7], [6], [35], [36], [28]. This model can be extended to more complex simulation or combinatorial optimization problems by introducing complementarity, substitutability or order

constraints of facilities.

Highway scenario

In this scenario, there are three highway lanes connecting from three origination nodes and three destination nodes (see Figure 4.4). Highway commuter users depart off a randomly selected origination node and head for a destination node also randomly selected. Each lane, which is one-way, consists of several pairs of a road node and a tollgate node. The road node, which bridges tollgate nodes by one-way links, demands the users some time to pass through. The tollgate node is supposed as one of the abstract source of traffic jam and each of those nodes has different service time. The user can switch the lane through the connection links to avoid traffic jam. The global purpose in this scenario is to achieve user equilibrium situation [37], one of ideal situation in traffic systems, in which each user cannot find any better route than the current one they individually optimized.

Some related works in traffic researches theoretically or analytically investigate similar scenarios with several one-way lanes highway and commuters [38], [29], [30]. Although those researches structure more sophisticated traffic models, e.g., a Greenshield's V-K model or a cellular automata model, we have adopted this queuing model for the sake of simplification. We believe a method solving this simple model could be applied to other models by a little extension. In addition, some researches in resource allocation suppose that the users have perfect rationality or learnability in a repeatable situation [33], [39], [34], [38], [40], but our target is to construct more realistic way to achieve globally optimized situation without such assumption.

4.3. User Planning

4.3.1 Plan Search

For construction of user planning process, we suppose submissive users in the simulation. The indication by sufficiently optimized plans is enough to keep an incentive for users to follow the plans. In other words, if we can produce the system with very effective individual planning, there is no incentive of the user to refuse its plan and it is

unnecessary to compel the users to follow such plans.

In the simulation, planning of each user is carried out at the beginning of the user activity on the origination node and every planning interval, which is denoted by $interval_j$. The planning process of the user is independent with other users; therefore, whole planning is distributed and asynchronous process among all participating users.

The plan for user j, $plan_j$ consists of a sequence of nodes, and this sequence is constrained to start from the current position and complete at the destination node through some connecting nodes. Let $node_j^k$ denote the k-th node which user j intends to visit in $plan_j$. The scheduled time to visit the k-th node in $plan_j$ is denoted by $time_j^k$ and defined as follows.

$$\begin{aligned} \mathrm{time}_\mathrm{j}^\mathrm{k} &= \mathrm{t}, \mathrm{k} = 1. \\ \mathrm{time}_\mathrm{j}^\mathrm{k} &= time_j^{k-1} + cost_{\left(node_j^{k-1}\right)}\left(time_j^{k-1}\right), k \geq 2. \end{aligned} \tag{4.1}$$

Where, the notation $cost_i(t^*)$ represents the estimated required time to pass node i at current or future time t^*. We suppose the users inquire such cost to a central cost information server which is watching queue lists and provides cost information to demanding users. The estimated travel time, namely the evaluation of $plan_j$, is obtained as the last timekj to reach the destination. The objective of planning is to find $plan_j$ which minimizes the estimated travel time but it is not always correct estimation for the future situation. The cost estimate is described in the later.

This optimization problem in our model is the combination of two problems, a permutation problem and a shortest path problem. For example, in the highway scenario, the user does not have any stop point and expects to arrive at a destination node as soon as possible. This is actually the shortest path problem to find the shortest path from a current node to the destination node in the highway network. On the other hand, in the theme park scenario, the user has to go toward a destination through some given attraction nodes every once in a plan. It is considered as the combination problem to find an order of attractions and the shortest path connecting these attractions.

To make a plan, the combination of a simple local search and Dijkstra's algorithm [41] is implemented in each user. At the first step of planning, a random order of not-visited attractions is generated. Then, Dijkstra's algorithm makes a shortest path

connecting to the current position to the destination through these attractions following the order. If there are some same cost paths, one of these is randomly chosen. The shortest path corresponds with a sequence of nodes on the network. This sequence is kept as the initial candidate plan. If the user has no stop point like in the highway scenario, Dijkstra's algorithm simply connects the current position to the destination.

The travel time of the plan is estimated by equation 1. After estimating the candidate plan, a neighbor plan is generated by randomly exchanging an order of two stop-points in the candidate plan, and these are connected by the Dijkstra's algorithm again. If the neighbor plan excels the candidate one, it is replaced to the candidate plan; otherwise, the candidate plan is kept as it is. The generating and replacing process is repeated until replacement has not occurred for the pre-defined number of times. As default setting we chose 15 times as the pre-defined number because in the theme park scenario each user does not have many visited attractions and search space is enough small. The final candidate plan is accepted as a formal plan to indicate the user a next node to go.

The above process would cause good effect if accurate future cost estimate is possible, but it is not so easy. The actual behavior of a queue list in each facility is aggregate phenomenon by not only one user but all other users' activities. In other words, the actual, not estimated, travel time of each user is interconnected with other users, some of who is moving on the network, and others does not appear yet. Thus, how to estimate the cost in future situation is the most important key to resolve dynamic service facility allocation problem.

To construct the cost estimate, we can pick up some options, i.e., static or current information-based cost estimate and a kind of forecasting cost estimate. The static information-based cost estimate utilizes static characteristic of a system, e.g., a usual car navigation system calculates the shortest route based on a geographical road map. This estimate is not linked to other users' behavior and could work well in a not-congested system. In our simulation, the users based on such estimate always utilize service facilities by a usual way with disregarding congestion and their behavior merely spoils a part of facility capacity. Thus, we are not concerned with the current information-based cost estimate users. Some forecasting cost estimate from the outside of the system utilizes historical data in many trials, and such estimate also causes the similar effect of static information case. That estimate is possibly effective in the long

term load balancing but we are not concerned such long term effect because we suppose in this paper that the same situation does not repeat.

We focus on two ways, one is current cost estimate (CCE) as one of typical congestion information, and another is statement based cost estimate (SCE). The statement-based cost estimate is the main idea for the user-in-the-loop forecasting and we expect it to form right feedback to reduce undesirable unbalance and oscillation in the utilization of congested facilities.

4.3.2 Current Cost Estimate (CCE)

CCE is simply based on the current situation of each facility. The cost of facility i at future time $t^*(> t)$ is calculated with only the current number of queue list.

$$\mathrm{cost_i}(t^*) = \left(\frac{queue_i}{w_i} + 1\right) \cdot s_i + 1 \tag{4.2}$$

In the case w_i is set to be unlimited it is simply equivalent to $(s_i + 1)$. This cost is an approximated value rather than an exact one even if the user arrives at the facility *i* immediately. It is because that this cost does not take into account of timing when current served users go out. More exact current cost estimate could be built with including such timing but we do not concern with it here for simplification.

In the case $t^* = t$, the facility i equals to $\mathrm{position_j}$, and $\mathrm{cost_i}(t^*)$ means the estimated remaining time to finish the service in the current facility. It is estimated as follows.

$$\mathrm{cost_i}(t^*) = \begin{cases} remaining\_time_j & \text{if } j \text{ is in service,} \\ \left(\frac{pqueue_i}{w_i} + 1\right) \cdot s_i + 1 & \text{otherwise.} \end{cases} \tag{4.3}$$

Where, $pqueue_i$ represents the number of prior queuing users against user *j* in the queue lists of facility *i*.

4.3.3 Statement-based Cost Estimate (SCE)

The following description starts from just after a user decides a plan because the

SCE runs on cyclic process between planning and cost estimation. Focus on $plan_k$ which contains the sequence of pairs of $node_j^k$ and $time_j^k$. When the plan is fixed, it is also fixed when user j intends to arrive at each node included in the plan. Based on this schedule, the set of "statements", each of which represents the potential timing of user arrival, is generated.

$$statement_j(i, t^*) = \begin{cases} 1 & if\ \exists k, t^* = time_j^k, \\ 0 & otherwise. \end{cases} \tag{4.4}$$

In other words, $statement_j(i, t^*)$ takes 1 if user j intends to arrive node j at the future time t^*; otherwise, it takes 0. These statements are uncertainly tentative and the user can change the plan anytime but the aggregation of these statements becomes effective information to harness whole load balance. After deciding a plan, these statements are sent to the central cost information server.

Next, the number of potential users which are scheduled to join the queue at node i in the time range $[t, t^*]$ is defined.

$$num_i(t^*) = queue_i + \sum_{T=t}^{t^*} \sum_j statement_j(i, T)\,. \tag{4.5}$$

We suppose that there are the number of $num_i(t^*)$ prior users against the user who intends to arrive at time t^* and the user can start being served after their service. Node i is statistically expected to deal with the number of $(t^* - t) \cdot w_i / s_i$ users for time $(t^* - t)$, and the expected queue number at time t^* is defined as follows.

$$queue_i^*(t^*) = \max\left[0, num_i(t^*) - (t^* - t) \cdot \frac{w_i}{s_i}\right] \tag{4.6}$$

The SCE at time $t^*(> t)$ can be defined by replacing the current queue length to the expected length in equation (4.2).

$$cost_i(t^*) = \left(\frac{queue^*(t^*)}{w_i} + 1\right) \cdot s_i + 1 \tag{4.7}$$

This is also equivalent to $(s_i + 1)$ if $\mathrm{w_i}$ is set to unlimited. In the case $\mathrm{t}^* = t$ it takes the same manner in Equation (4.3).

The SCE synchronizes with the aggregation of user plans and it can harness the users to avoid congestion each other. Each user can optimize and change own plan individually, and that change is rightly reflected to the cost estimate in the central server. We call this process the user-in-the-loop forecasting with the SCE.

4.4. Computer Experiments

4.4.1 Setting

For computer experiments, we prepared the combination of the two scenarios (see Figures 3 and 4 again) and the two cost estimate ways. We denote the theme park scenario and the highway scenario by the symbols “T” and “H”, and the CCE and the SCE by the symbols “C” and “S”, respectively. There are four experimental settings, i.e., “TC”, “TS”, “HC” and “HS”. In addition, we introduced five types of user appearance density, (N, λ) = (1,000, 0.1),(2,000, 0.2),(3,000, 0.3),(4,000, 0.4),(5,000, 0.5), to each setting, since the density of users is the key factor to cause congestion on the facility network. In these settings, all the users have appeared until about t = 10,000. The capacity of facilities is enough large to deal with all the users for the case N = 1,000 and congestion could not occur in such a case. On the other hand, congestion could emerge on every facility in the case N = 5,000. The combination of setting and density is denoted like TC-1000, TC-2000,..., HS-5000. The planning interval $\mathrm{interval}_j$ is set to 300 in each case, according to preliminary experiments. The maximum time t_{max} is set to 40,000 and all the users have sufficiently finished their activity until this time.

4.4.2 Experiment 1

In experiment 1, the simulation was run 50 times per a setting. Table 4.1 and Table 4.2 show the average travel time and its standard deviation in the simulation results. In addition, the instance transitions of queue lengths in the settings TC, TS, HS and HC-3000 are depicted in Figure 4.5.

Table 4.1: The performance comparison with two cost estimate ways in the theme park scenario In each TC or TS cell, the upper amount is the average travel time, and the lower is standard deviation. Each ratio cell shows the ratio of the average travel time in TC and TS cases.

	1000	2000	3000	4000	5000
TC-	4065.8	8043.3	14001.1	20270.2	26691.2
	(20.5)	(159.3)	(151.2)	(160.4)	(177.0)
TS-	4063.2	7862.5	13308.5	18816.6	24210.2
	(11.3)	(204.0)	(232.7)	(263.8)	(348.0)
Ratio (TS/TC)	99.94%	97.75%	95.05%	92.83%	90.70%

Table 4.2: The performance comparison with two cost estimate ways in the highway scenario In each HC or HS cell, the upper amount is the average travel time, and the lower is standard deviation. Each ratio cell shows the ratio of the average travel time in HC and HS cases.

	1000	2000	3000	4000	5000
HC-	2694.5	3542.7	5712.1	8145.5	10671.2
	(9.3)	(69.0)	(147.2)	(104.4)	(118.8)
HS-	2681.4	2848.0	5277.8	7738.6	10236.2
	(3.4)	(94.8)	(99.6)	(74.5)	(70.8)
Ratio (HS/HC)	99.51%	80.39%	92.40%	95.01%	95.92%

First, we focus on the results of the theme park scenario. The averaged travel time takes a similar value in the both cases of TC-1000 and TS-1000. The facilities in these cases have enough capacity to deal with all the users and there is no much accumulative queue list. The both of cost estimate do not make a difference in the travel time. On the other hand, the increase of N makes TS results better than TC. For example, in the case of N = 5,000, the planning with the SCE can save about 9.3% of the travel time against the CCE.

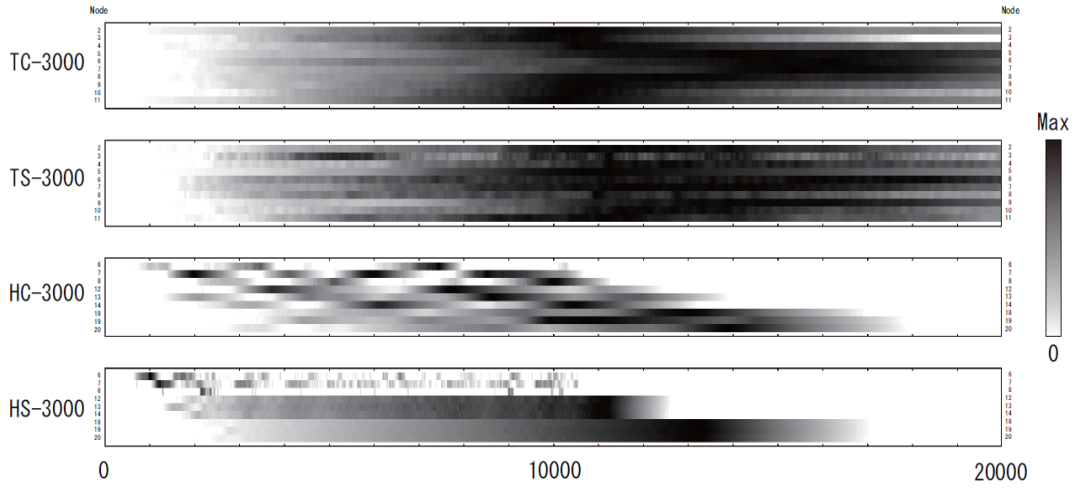


Figure 4.5: The example transition of queue length in each facility. The horizontal indicates the simulation time [0, 20000]. Each line corresponds to the indicated facility node. The light and shade represent the normalized length of queue, which is divided by the observed maximum queue length in each queue.

The difference of queuing behavior is shown in Figure 4.5. Any simulations exhibited similar characteristics of queue length fluctuation in each setting, and the figure is drawn with a set of single simulations in each setting. In the theme park scenario, it might be heard curious, the user with the CCE does not take into account of current congestion. It is because that the remaining attractions of the user at an instant are fixed and the total waiting time of remaining attractions takes the same value in any plan under the CCE. Thus, the user of TC tries to optimize a plan ignoring current congestion, and prefers to visit the attractions close to the origination node, gradually further ones, and the ones close to the destination in turn.

See Figure 4.5, and the transition of queue lengths in TC-3000 indicates that the queue lengths of the attraction close to the origination or destination nodes, i.e., nodes 2, 3, 10 and 11, take larger density in early stage of simulation, while the queue lengths of further attractions, i.e., nodes 5, 6, 7 and 8, take a peak in little later time. The temporal difference of taking a peak causes temporal unbalance of facility demand. On the other hand, the user of TS-3000 can temporally optimize a plan with consideration of future congestion, and the load of each attraction depends on the service time setting rather

than the topological setting. This is the reason that the user of TS-3000 takes better performance thanTC-3000.

Next, we focus on the results of the highway scenario. The result in the case of N = 1,000 is similar with the theme park scenario, but in the case of N = 2,000 the user of HS shows the highest performance against HC. In this case, the SCE can save about 19.4% of the travel time against the CCE. The user flow around the density of N = 2,000 could be the critical point of congestion in which little difference of flow control makes a large difference of the travel time. The SCE in N = 5,000 saves only about 4.0% of the travel time against the CCE, however, it saves the largest total travel time of all the users than other cases.

See Figure 4.5 again, and we can confirm the large difference between queuing behavior of HC-3000 and HS-3000. The user in HC-3000 tries to avoid congestion and selects a tollgate which is estimated to have less waiting time than others. The selecting user has to spend a while on a road node to reach the tollgate. For some time, successive users refer to the almost same cost as the former, and they cluster to go to the same tollgate. The effect of this clustering emerges later, and this time delay causes oscillation of queue lengths as shown in Figure 4.5. It spoils the performance of the CCE. On the other hand, the SCE can successively harness users flow based on forecasted future situation, and the users flow smoothly adapts to the traffic load. In HS-3000 case, each tollgate is equally congested at any time, and that is the most effective way to use this type of structure.

4.4.3 Experiment 2

We cannot compel users to follow an indicated plan even if the plan contributes to reduce not only the individual travel time but the total one. Keeping the incentive to behave along the plan is one of the most important matters to manage this type of system. It is desirable that the indicated plan is the best one than any other potential plans like a best response in game theory. However, it is not easy to find the best plan because the user cannot observe an entire payoff matrix in advance and merely they can know the consequence of their behavior. The SCE tries to draw a part of payoff matrix in progress for the users who believe the SCE.

Table 4.3: The travel time of the normally decided plan and the random one. These plans are of the same user and the other users' plans are not changed. The upper and the lower values in each cell are the average travel time and the standard deviation.

	Normal Plan	Random Plan	Ratio (Ran./Nor.)
TC-3000	13589.7 (3847.9)	14088.1 (4037.5)	104.70%
TS-3000	12758.9 (4516.0)	12978.4 (4625.0)	103.27%
HC-3000	5584.2 (1787.7)	5680.5 (1927.8)	104.80%
HS-3000	5091.8 (1424.6)	5099.4 (1444.1)	100.06%

To investigate the optimality of an individual plan by the SCE, we carried out another simulation with TC, TS, HC, and HS-3000, in which simulation the plan of a randomly selected user is replaced to a random one without changing all other situation. In TC/TS-3000 case, a random plan means a plan which consists of a random sequence of given attractions and shortest paths connecting these attractions by Dijkstra's algorithm. There are 4! = 24 possible patterns of attraction orders for each user, and one pattern is randomly picked up as a random plan. In HS/HC-3000 case, a random plan is constrained to start from a given origination node and reach to a given destination node. We run 200 trials of the simulation for each setting and these results can empirically show the optimality of the cost estimate. In this experiment, if we find the improvement of the travel time by replacement of the selected alternative to random one, it means that some users did not select the best choice. On the other hand, if we do not find the improvement by random replacement, it means that almost users could probably find the best choice in their plan.

The graphs in Figure 4.6 show the ratio distribution of the travel time of a replaced random plan and a normal one in each case. In these graphs, a band indicator less than 1.0 corresponds to the case that the travel time of the random plan outperforms that of

the normally decided one, and a band more than 1.0 indicates that the normally decided plan is better than the random one. Table 4.3 shows the averaged travel time and the ratio in those two plans, which are calculated from the same simulation results.

In the results of the theme park scenario, we can see that there are many better plans than the normally decided one in both cases of TC-3000 and TS-3000. The percentage of better plans in TC-3000 is about 36%, and about 43% in TS-3000. This is not good news but the reason is simple. In the theme park scenario, the former users and the latter users share the facilities in the same network. The former users optimize their plans before the latter users appear, and their plans interfere each other in the later part of the former user plans. The estimated cost by the former users is changed by the latter users, and the former users consequently failure to optimize their plans.

In the results of the highway scenario, in the case of HC-3000, the 49% percentages of random plans show better performance than the normally decided one. In the case of HS-3000, the random plans show almost same performance as the normal one. The users in the highway scenario flow one-way from an origination side to a destination side in the network, and the former users are temporally and spatially separated from the later users. Thus, the planning with the SCE works very well. The fact that the random plans and the normal plan show same performance in HS-3000 means that the users cannot find other better plan than the current one and the whole behavior achieves near user-equilibrium situation. It is Nash-equilibrium situation of traffic systems and it is important that the users with the SCE can achieve such situation without preliminary knowledge, perfect rationality or learnability in a repeatable situation.

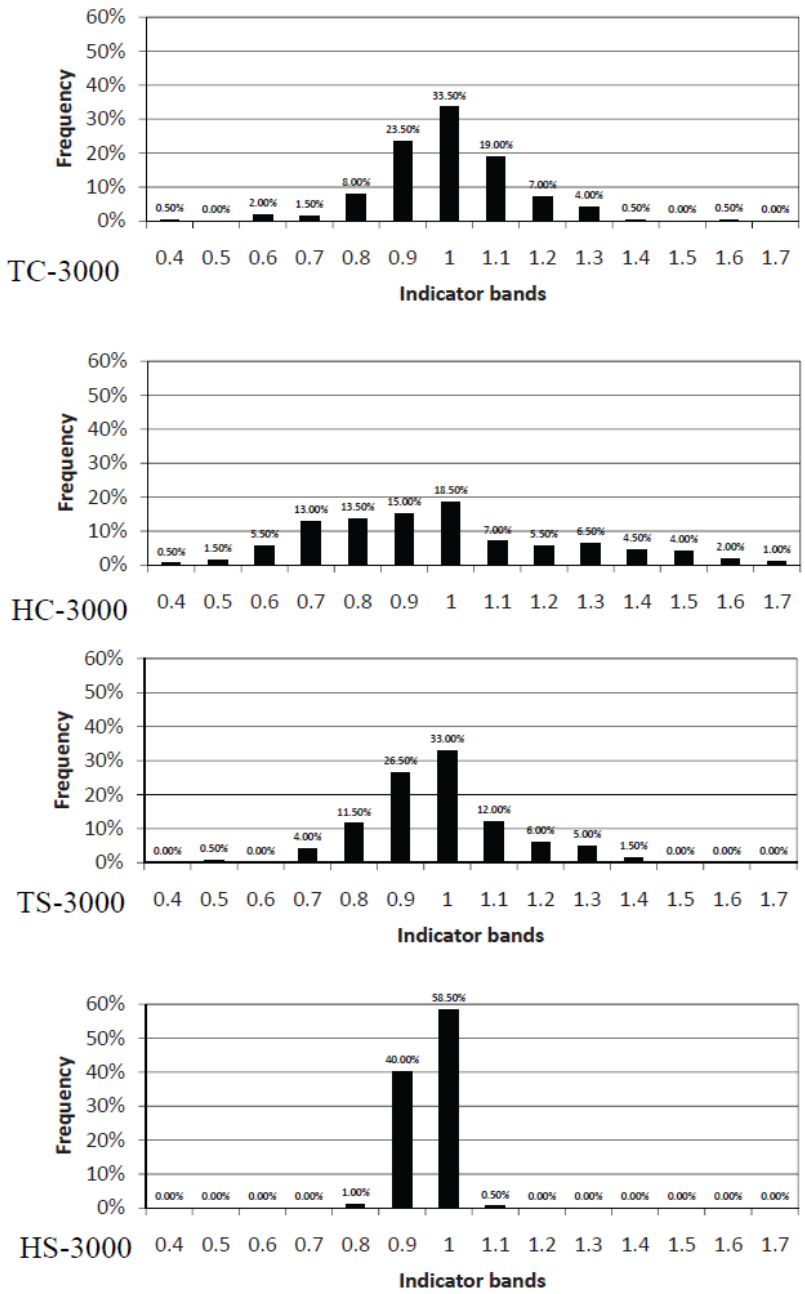


Figure 4.6: Ratio distribution of (the travel time by randomlly replaced plan)/(the travel time by normally decided plan). The graphs are shown along indicator bands on X axis with the percentage on Y axis. Each indicator band on X axis means corresponding the range of ratio, e.g., the indicator “0.9” means the range between [0.9, 1.0).

4.5. Discussion

The experimental results show that the SCE has better performance than the CCE. The SCE is a kind of advance queue simulation and indirect negotiations among the users. Although simultaneous participation of whole users takes good effect in principle, the SCE is spoiled its performance by the situation that the latter user behavior interferes the later part of the former user plan. It is particularly conspicuous in the theme park scenario. To improve the performance of the SCE, a supplementary term which counts up potential users is necessary to add to Equation 5. Such a supplementary term does not have to include the detail of individual user plans, and a kind of stochastic prediction could be applied.

In the experiments, we have picked up only the CCE as a contrast. Although we could build other planning with ad-hoc heuristics and it may be better than the proposal, we do not concern with such a heuristic method. The heuristic method for this type of problem would utilize explicit or implicit features of problem setting, and the change of setting, e.g., topology of a network, easily affects the performance of it. It could not be a fundamental solution of the problem.

In addition, the experimental results with some density patterns of users showed that the performance difference between the SCE and the CCE is not simple. In the theme park scenario, the SCE consistently exhibited better performance than the CCE, and the performance difference became linearly larger according to the density of users. In the highway scenario, although the SCE exhibited better performance than the CCE, the advantage of the SCE seems unstable and not linearly. It indicates that the effectiveness of coordination between the users is not simple and the relationship between the congestion behavior of the system and the coordination should be carefully investigated.

If this user-in-the-loop forecasting is applied to a real application, e.g., car navigation systems, we have to carefully investigate the diffusion process of the system in advance. The system must give the users sufficient incentive to follow a plan during a transitional period of diffusion. Otherwise, nobody could use the system even if everybody knows it contributes to improve total performance of facility allocation. The supplementary term of the users who does not use the proposed system could be

necessary.

Our first aim of this research is to lead users' behavior to Nash-equilibrium or user-equilibrium by sophisticated information technology. Of course we know that game theory clarifies such equilibrium does not always become the best result in any situation, but the total time slot of a facility is fixed and individual efficient use of facilities could lead to improve the total system performance. The complexity in more realistic problems makes a system difficult to be analyzed in game theoretical fashion but we can know a part of the full picture by empirical analysis and it is important to tackle such complicated problems [42].

Further our interest is, if it exists, to bridge the gap between Nash-equilibrium and Pareto optimum in facility allocation problems. In this paper we modeled like that the cost of users is based on only time cost and any facility is free to use. However, many actual facilities, e.g., highways, require not only time but money cost which is one of outside parameters of the system. We cannot easily control the time cost under the facility capacity constraint but it is possible to intervene the money cost control, actually such control is studied in road pricing researches. If we can control the money cost of each facility in real time by the statements of users, it could change game structure and contribute to bridge the gap between Nash-equilibrium and Pareto optimum in the system. Market-oriented way related with the statements, time cost and money cost would be available for such control [27].

Our proposal is effective to improve the global load of systems, and it would be more effective to combine more local excellent contrivance. For example, Dresner proposes the reservation system in which car drivers adjust entering timing to an intersection with each other and they can pass through the intersection without stop signals [43]. The idea, like seamless connection of our proposal and such systems, is effective to drastically reduce traffic jam.

In the experiment, we do not confirm the optimality of social welfare with the proposed method. To investigate the optimality of social welfare, we have to find the optimum solution to maximize the social welfare, however, the solution space of this problem is very huge and finding the optimum solution is difficult. For example in TC-3000 and TS-3000 with 3000 user agents, each user has 24 possible visiting patterns and the whole solution space of these settings is 24^{3000}. In HC-3000 and HS

cases, each user has 11 alternatives on average from the origination to the destination, and the total solution space is 11^{3000}. In addition, the social optimum may force some users to receive individually worse plan unfairly and it cannot be acceptable for all users. According to the above reason, it is not easy to discuss about the head room to optimal solutions here and it will try as a further step.

4.6. Conclusions

In this chapter, I proposed the user-in-the-loop forecasting with the statement-based cost estimate, and applied to two types of facility allocation models, i.e., the theme park scenario and the highway scenario. The computer experiments showed that the proposed estimate caused better result in the both scenarios than the current cost estimate. In the highway scenario, the users with the statement-based cost could achieve user-equilibrium without preliminary knowledge, perfect rationality or learnability. However, the users in the theme park scenario could not select the best response because the latter users unexpectedly affected the later part of the former user's plan. As a next step, I will focus on supplementation of potential or not-participating users' effect, modeling of time and money cost, and introducing of market mechanisms.

Chapter 5

Event Notice Recommendation

5.1. Introduction

This chapter focuses on service innovation for service involving “fluidity”. I implemented recommender system of event notices for real Web site, and verified how the system contributes to realize service innovation. I compared five methods, genre scoring, source scoring, popularity scoring, user-based collaborate filtering, item-based collaborate filtering and two new methods from combining the five methods above. Then, I apply a part of these methods to real Web site to validate effect of algorithm.

There are many various sized events such as concerts and festivals held especially with a focus in the city area. Many individuals consult an event notice (hereinafter referred to as event information) when participating an event that has the information of the place, date and content of the event. Though there may be differences if the individual recognized the event information actively or passively. Now, if it is possible to maximize the matching opportunity of an individual and an event considering the likes and dislikes of the individual, it will be very meaningful for both the promoter and participant of the event.

In recent years, services which first collect information from multiple information sources then deliver and offer information selectively depending on the individuals likes and dislikes from the users browsing history are spreading [44], [45]. These services use information recommendation technology [46] [47] such as collaborate filtering [48], [49], [50]. By applying this technology, it is possible to provide information that most suit the individuals likes and dislikes among the much information and has a possibility of maximizing the matching opportunity. However, since many of the previous studies target information with a value which does not change over time such as books and movies, recommendation that consider time course were not needed.

Considering that event information is recommended to individuals using information

recommendation technology, not only likes and dislikes but the time until the event is held becomes an important factor to consider. On one hand, it is desirable for event information to be offered at the timing when the individual is considering their plans, but on the other hand it is necessary to collect many browsing history of event information's at an early stage considering to effectively conducting information recommendation, meaning not always both requests will be matched. Since the value of event information is lost after its exhibit date, there is a need to suitably manage them before the exhibit date. However there are no researches among the information recommendation technology which consider these qualities.

In this paper, we present a mechanism to effectively recommend information, considering the likes and dislikes of a participant and the state of the event information taking account the time change of the event information. Then, we will show that by suitably changing the recommendation algorithm depending on the state of the event information, recommending event information can be done effectively. The authors have been examining the basic performance of recommendation algorithms such as cooperative filtering [51] and observing a hybrid method of cooperative filtering [52]. In this paper, we will discuss a method to apply to event information using the results of these researches. Furthermore, we will verify the efficacy by using a data from a actual service that offers event information at Sapporo as a test data.

5.2. Outline of Event Notice Recommendation

In this chapter, we will show the outline of the event information recommendation we assume in this paper. First, we call the individual who receives the recommendation of event information a user. We assume that this user wish to find event information that suit their likes and dislikes. Event information includes such information as exhibit date, genre, information source and many more information. For this reason, we assume a web system which list up a certain number of event information according to information recommendation technology and offer the user a list of headline of the event information. We assume that when the user fined a information that is of interest from the list, the user will click the headline and obtain details of the event information. In other words, the information that is clicked by a user implies that the user is

interested in the information.

From the above presupposition, the aim of information recommendation is to conjecture which information is likely to be clicked among the non-clicked information using the click history and present them to the user.

In order to achieve this, we score against the pair of a user and event information. Then we sort this pair in descending order of score and preferentially present event information that are likely to be clicked. Therefore, the goal here is to develop a scoring method to highly score event information that is likely to be clicked.

As a relevant study of scoring, there is MovieLens [48] that target rental video. In the scoring of rental video, seeing that old video is a sufficient recommendation subject, rental record and user item value that are once acquired are available for long terms. Since over time large number of rental video becomes available to score, scoring with the assumption that reaction of users are available in some extent has been thought of as the main point [53], [54], [55], [56].

On one side, regarding the event information that is a target of scoring, such as new things offered depending on time course or event that has finished being removed from subject are always repeated. Also the exhibit date of each event differs. Therefore, it can be expected to be difficult to gain an effective recommendation result by using the same scoring against all information since there is variation in the number of clicks by the event information. On the other hand, when many clicks are accumulated and is at a state where scoring is usable, there may be a situation where the event is just about to be held and the value of the information is on the verge of being lost.

Furthermore given that the user's action is eventually connected to the participation of an event, there is a need to consider not only the accordance of the likes and dislikes of the event content but also the circumstances of the even exhibit place, time and date.

However to isolate the problem, we focus on the likes and dislikes in this paper. In order to score event information concordant of its property, as a starting point we implemented some simple scoring referring methods that are researched in research such as MovieLens and we applied actual data and conducted a comparative experiment. Furthermore, by combining these methods depending on individuals and the state of event information, we propose a scoring expected with higher accuracy.

5.3. Model

In this chapter some scoring are assumed and in order to conduct comparative evaluation user, event information and click were defined.

Firstly, let **U** be the set of users using the system and **E** be the set of event information possible to recommend, **U** and **E** are defined as below.

$$\mathbf{U} = \{u_1, u_2, \dots, u_n | n \in \mathbb{N}\} \tag{5.1}$$

$$\mathbf{E} = \{e_1, e_2, \dots, e_m | m \in \mathbb{N}\} \tag{5.2}$$

Event information is assumed to have information source and genre as their attribute. Genre represents event such as “festival” and “performance” as content classification, information source represents classification such as event organizer.

$$e_j = \langle genre_j, source_j \rangle \tag{5.3}$$

$$genre_j \in \mathbf{G}, source_j \in \mathbf{S} \tag{5.4}$$

Here $genre_j$ denotes the genre of event information e_j, $source_j$ denotes the information source of e_j. **G** denotes the set of genre and **S** denotes the set of information source.

Click condition $r(u_i, e_j)$ of event information e_j of user u_i is defined as below.

$$r(u_i, e_j) = \begin{cases} 1 & : \text{When } u_i \text{ clicks } e_j \\ 0 & : \text{otherwise} \end{cases} \tag{5.5}$$

Here $\sum_{e_j \in \mathbf{E}} r(u_i, e_j)$ is called number of users clicks by user u_i, $\sum_{u_i \in \mathbf{U}} r(u_i, e_j)$ is called number of event information clicked of even information e_j.

5.4. Scoring

In this chapter scoring of user u_i against event information e_j using $r(u_i, e_j)$ is performed. Since there are event information of events that are already finished included in **E**, event information that haven't finished that belong to **E** are scored with a real number. Value of the score is assumed to be a higher value if the event information is likely to be clicked by a user. In the situation where countable event information are presented to users in descending order of score, not the value of the score but the order depending on the magnitude relation is important. When assuming the combination of various scoring, the distribution of scores being close in each scoring is desirable.

When aiming to achieve such scoring, it can be assumed that the situations when scoring work effectively may differ, 5 scoring: i) Genre Scoring, ii) Information Source Scoring, iii) Popular Scoring, iv) User CF Scoring, v) Item CF Scoring and 2 scoring which combine these: vi) Weighted Sum Scoring, vii) Individual Weighted Sum Scoring are implemented. In order to realize a method to optimally convert these scoring based on the accumulation state of click condition, comparison and examination of scoring is conducted.

Firstly the score calculation method and the basis of adopting this 7 scoring is stated.

5.4.1 Genre Scoring

Using genre $genre_j$ of event information e_j, scoring against user u_i is denoted as below.

$$score^G(u_i, e_j) = \frac{\sum_{e_k \in \mathbf{E}} \{r(u_i, e_k) g(e_j, e_k)\}}{\sum_{e_k \in \mathbf{E}} g(e_j, e_k)} \tag{5.6}$$

$$g(e_j, e_k) = \begin{cases} 1 & : genre_j = genre_k \\ 0 & : otherwise \end{cases} \tag{5.7}$$

Genre Scoring is a scoring to give high score to suitable genre event information against user's that click event information with a bias. Moreover, this scoring does not

need other users click condition and only uses click condition of the recommend target. Therefore, it is expected to be effective against event information with low number of event information clicked.

Conversely, if the recommended target has small number of user's click, it will be hard to estimate which genre was clicked a lot and it can be considered that an effective scoring cannot be conducted.

5.4.2 Source scoring

Using source source_j of event information e_j, scoring against user u_i is denoted as below.

$$\mathrm{score}^{s}(u_i, e_j) = \frac{\sum_{e_k \in \mathbf{E}} \{ r(u_i, e_k) s(e_j, e_k) \}}{\sum_{e_k \in \mathbf{E}} s(e_j, e_k)} \tag{5.8}$$

$$s(e_j, e_k) = \begin{cases} 1 & : \mathrm{source}_j = \mathrm{source}_k \\ 0 & : \mathrm{otherwise} \end{cases} \tag{5.9}$$

Information Scoring is a scoring to give high score to even information with suitable information source against user's that click event information with a bias. Similar to Genre Scoring Therefore, it is expected to be effective against event information with low number of event information clicked.

Similar to Genre Scoring, Information Scoring, if the recommended target has small number of user's click, it will be hard to estimate which genre was clicked a lot and it can be expected that an effective scoring cannot be conducted.

5.4.3 Popularity scoring

On the basis of number of event information clicked of target event information e_j, scoring is calculated as below.

$$\mathrm{score}^{\mathrm{P}}(\mathrm{e_j}) = \sum_{\mathrm{u_i} \in \mathbf{U}} \mathrm{r}(\mathrm{u_i}, \mathrm{e_j}) \tag{5.10}$$

In contrast to the above-mentioned 2 scoring, Popularity Scoring calculate score on the basis of number of event information clicked instead of the recommend target user's click. Therefore, score can be calculated against such as new users with little number of user's clicks. There can be efficacy expected against user's which prefer popular event information on the whole.

On the other hand, this scoring is not effective on user's who click event information regardless of the popularity on the whole.

5.4.4 User-based CF scoring

The score of this scoring is calculated with the definitional equation of User base Corporative Filtering shown as below.

$$\mathrm{score}^{\mathrm{U}}(\mathrm{u_i}, \mathrm{e_j}) = \overline{\mathrm{r_i}} + \frac{\sum_{\mathrm{u_k} \in \mathrm{T}} \{\mathrm{sim}^{\mathrm{U}}(\mathrm{u_i}, \mathrm{u_k})(\mathrm{r}(\mathrm{u_k}, \mathrm{e_j}) - \overline{\mathrm{r_k}})\}}{\sum_{\mathrm{u_k} \in \mathrm{T}} \mathrm{sim}^{\mathrm{U}}(\mathrm{u_i}, \mathrm{u_k})}, \tag{5.11}$$

$$\overline{\mathrm{r_i}} = \frac{\sum_{\mathrm{e_j} \in \mathbf{E}} \mathrm{r}(\mathrm{u_i}, \mathrm{e_j})}{|\mathbf{E}|} \tag{5.12}$$

$\overline{\mathrm{r_i}}$ is the number of user's clicks rate of user $\mathrm{u_i}$. T is set of user $\mathrm{u_k}$ with degree of similarity $\mathrm{sim}^{\mathrm{U}}(\mathrm{u_i}, \mathrm{u_k})$ against user $\mathrm{u_i}$, which is $\mathrm{T} \subseteq \mathrm{U}$.

There have been many methods proposed to calculate the degree of similarity $\mathrm{sim}^{\mathrm{U}}(\mathrm{u_i}, \mathrm{u_k})$ of user $\mathrm{u_i}$ and user $\mathrm{u_k}$ [46], [47], [54], [57], [58], [59]. Since the value of $\mathrm{r}(\mathrm{u_i}, \mathrm{e_j})$ is 0 or 1, Tanimoto coefficient which is the degree of similarity index between sets is used in this paper.

$$\mathrm{sim}^{\mathrm{U}}(\mathrm{u_i}, \mathrm{u_k}) = \frac{\sum_{\mathrm{e_j} \in \mathbf{E}} \{\mathrm{r}(\mathrm{u_i}, \mathrm{e_j})\mathrm{r}(\mathrm{u_k}, \mathrm{e_j})\}}{\sum_{\mathrm{e_j} \in \mathbf{E}} \{\mathrm{r}(\mathrm{u_i}, \mathrm{e_j}) + \mathrm{r}(\mathrm{u_k}, \mathrm{e_j}) - \mathrm{r}(\mathrm{u_i}, \mathrm{e_j})\mathrm{r}(\mathrm{u_k}, \mathrm{e_j})\}} \tag{5.13}$$

The computational complexity of User CF Scoring is proportional to the number of

event information and user. However, since the effect on score calculation against user with small number of user's clicks is little, the computational complexity can be cut down by suitably setting the size of T.

To incarnate an effective scoring with User CF Scoring, there is a need of enough clicks accumulated in the system and it is possible to incarnate a scoring which flexibly match users likes.

5.4.5 Item-based CF scoring

Using the definitional equation of Item Based Cooperative Filtering [58] with a switch of user and event information against User CF Scoring, the score is calculated as shown blew.

$$\mathrm{score}^{\mathrm{I}}(u_i, e_j) = \overline{s_j} + \frac{\sum_{e_l \in \mathbf{L}} \{\mathrm{sim}^{\mathrm{I}}(e_j, e_l)(r(u_i, e_l) - \overline{s_l})\}}{\sum_{e_l \in \mathbf{L}} \mathrm{sim}^{\mathrm{I}}(e_j, e_l)}, \tag{5.14}$$

$$\overline{s_j} = \frac{\sum_{u_i \in \mathbf{U}} r(u_i, e_j)}{|\mathbf{U}|} \tag{5.15}$$

$\overline{s_j}$ is the number of event information clicked rate of event information e_j. L is set of event information e_g with high degree of similarity $\mathrm{sim}^{\mathrm{I}}(e_j, e_g)$ against event information e_j which is $L \subseteq E$.

$\mathrm{sim}^{\mathrm{I}}(e_j, e_k)$ is degree of similarity of event information e_j and event information e_k, and uses the same Tanimoto coefficient as User CF.

$$\mathrm{sim}^{\mathrm{I}}(e_j, e_k) = \frac{\sum_{u_i \in \mathbf{U}} \{r(u_i, e_j) r(u_i, e_k)\}}{\sum_{u \in \mathbf{U}} \{r(u_i, e_j) + r(u_i, e_k) - r(u_i, e_j) r(u_i, e_j)\}} \tag{5.16}$$

The calculation method is basically the same as User CF Scoring but Item CF Scoring calculate score on the basis of similarity between the recommend target user's click and event information. Therefore, this scoring is effective when the similarity of events is correctly computable.

5.4.6 Weighted sum scoring

The sum of a linear weight appended to each score obtained by the above-mentioned 5 scoring and combination of scoring is conducted as below.

$$\begin{aligned} \mathrm{score}^{\mathrm{ALL}}(\mathrm{u_i}, \mathrm{e_j}) = {} & \mathrm{w^G score'^G}(\mathrm{u_i}, \mathrm{e_j}) + \mathrm{w^A score'^S}(\mathrm{u_i}, \mathrm{e_j}) \\ & + \mathrm{w^M score'^P}(\mathrm{e_j}) + \mathrm{w^U score'^U}(\mathrm{u_i}, \mathrm{e_j}) \\ & + \mathrm{w^I score'^I}(\mathrm{u_i}, \mathrm{e_j}) \end{aligned} \tag{5.17}$$

s.t. $$0 \leq \mathrm{w^G}, \mathrm{w^A}, \mathrm{w^M}, \mathrm{w^U}, \mathrm{w^I} \leq 1 \tag{5.18}$$

$$\mathrm{w^G} + \mathrm{w^A} + \mathrm{w^M} + \mathrm{w^U} + \mathrm{w^I} = 1 \tag{5.19}$$

The weight parameter is all the same with all user. To reduce the impact of small and large score, the average of E is normalized to 0, and the standard deviation is normalized to 1 $\mathrm{score'^G}(\mathrm{u_I}, \mathrm{e_j}), \mathrm{score'^A}(\mathrm{u_I}, \mathrm{e_j}), \mathrm{score'^M}(\mathrm{e_j}), \mathrm{score'^P}(\mathrm{u_I}, \mathrm{e_j}), \mathrm{score'^I}(\mathrm{u_i}, \mathrm{e_j})$ by the 5 score $\mathrm{score^G}(\mathrm{u_I}, \mathrm{e_j}), \mathrm{score^A}(\mathrm{u_I}, \mathrm{e_j}), \mathrm{score^M}(\mathrm{e_j}), \mathrm{score^P}(\mathrm{u_i}, \mathrm{e_j}), \mathrm{score^I}(\mathrm{u_i}, \mathrm{e_j})$.

When a weight against a certain score is 1 and all other score has a weight of 0, it will be the same when a simple substance scoring with weight of 1 is conducted. Therefore if a weight is set suitably, at least an equal or better result as the best simple substance result can be expected.

5.4.7 Individual Weighted Sum Scoring

This is a scoring where weight of Weighted Sum Scoring stated in 5.4.6 is configurable with each user. Compared with using the same weigh with all users, equal or greater results can be expected. Moreover if effective scoring differs depending on user, efficacy of this scoring can be considered to be high where individual weight is adjustable.

The above 7 scoring is used for experiment and comparison of evaluation value and correlation of score is discussed throughout the experiment.

5.5. Evaluation method

In actual operation, E is denoted as the whole set of event information that is used in scoring. Event information that is non-clicked and not finished that belong to E are used for scoring. However since this evaluation experiment uses past data, E is divided as the set of event information for scoring E' and event information for evaluation P and score of P is calculated using E'.

Next, the evaluation value of scoring against a user is discussed. Since the situation where user u_i did not intentionally click event information e_j and the situation where event information e_j had not been presented is not distinguished in this model, the evaluation method by relevance ratio cannot be used。

So, the evaluation value of the result of scoring against user u_i is defined as below.

$$\mathrm{eval}(a, \mathbf{P}, u_i) = \frac{\sum_{e_j \in \mathbf{P}} \left(r(u_i, e_j) \times \frac{\mathrm{rank}(a, e_j, u_i) - 1}{|\mathbf{P}| - 1} \right)}{\sum_{e_j \in \mathbf{P}} r(u_i, e_j)} \tag{5.20}$$

a denotes the scoring of the evaluation target. $\mathrm{rank}(a, e_j, u_i)$ is the rank of event information sorted in descended order of the calculated score by scoring a against user u_i about each event information in set P. Furthermore, by dividing $\mathrm{rank}(a, e_j, u_i) - 1$ by the number of elements -1 of set P, the rank is normalized as the highest rank 0 and the lowest rank 1. The average of the normalization rank of all event information e_j which is an element of set P and also $r(u_i, e_j) = 1$ is the evaluation value of $\mathrm{eval}(a, P, u_i)$ as above equation.

During the calculation of the evaluation value, since the higher the rank of the information that is clicked is the evaluation value access 0, the smaller the value of $\mathrm{eval}(a, P, u_i)$ is, the more the scoring is suitable. Moreover, although the above equation shows the evaluation value of a scoring against user u_i, the average of all the user of this is the evaluation value of the scoring.

5.6. Experiment

5.6.1 Settings

In this paper, instead of using an imaginary evaluation sample, data that are obtained from an actual operated service is used for evaluation experiment. Specifically, actual data（from April,2010 to Janurary,2014） from an event information delivery service called “Bemall Sapporo -your information magazine-*” which is managed by “CHOWA GIKEN,Corp.” were used in the experiment. Bemall is a user registered event information delivery service and the Website has over 300thousand PV per month at current June, 2014. The data and option of the experiment is shown in Table 5.1. Figure 5.1, Figure 5.2, Figure 5.3 and Figure 5.4 are screen-shot of the website “Bemall Sapporo”. User search event notices want to see in top page, and user can see detail of event notice by clicking event title. Figure 5.5 is number of event notices by genre in “Bemall Sapporo”. We can find that there is great variability among genre from this figure. Figure 5.6 is users’ profile of “Bemall Sapporo”. This figure indicates that number of females larger than number of male, and the largest age-group is 20’, after that 40’ in the second place, and the third place is 30’.

90% of the event information that are clicked and not-clicked are offhandedly divided into E’ and the rest of 10% is offhandedly divided into P, then the evaluation value is calculated. This operation is repeated 10 times per one user and the average of this is used as the average evaluation value.

User set U is used for Popularity Scoring and Item CF Scoring and 4952 user that is using the service is used. User set T is used for the evaluation target for the subset of users used for User CF Scoring. 50 of the number of event information clicked in high order of E’ is used for the subset of event information used for Item CF Scoring.

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* Bemall Sapporo: http://bemall.jp/sapporo

Table 5.1: Data and settings in this experiment

Set of users for evaluation **T**	61 users clicks over 100 event notices without overlaps of 4,952 users service using.
Set of event information **E**	6,892 event notices associated sources of 9,957 event notices appeared past.
Set of genre **G**	{festival, spectate, music, movie, performance, art, lecture, commerce event, match, offering, travel, learning, eating, amusement, cosmetic, etc., column ,information, news, advertisement, present } a total of 20 genres.
Set of source **S**	{Hokkaido Shimbun press, JR Tower, United Cinemas, etc.} a total of 244 sources.

Figure 5.1: Screen-shot of the “Bemall Sapporo” PC version top page

Figure 5.2: Screen-shot of the “Bemall Sapporo” PC version event detail page

Figure 5.3: Screen-shot of the “Bemall Sapporo” mobile version top page

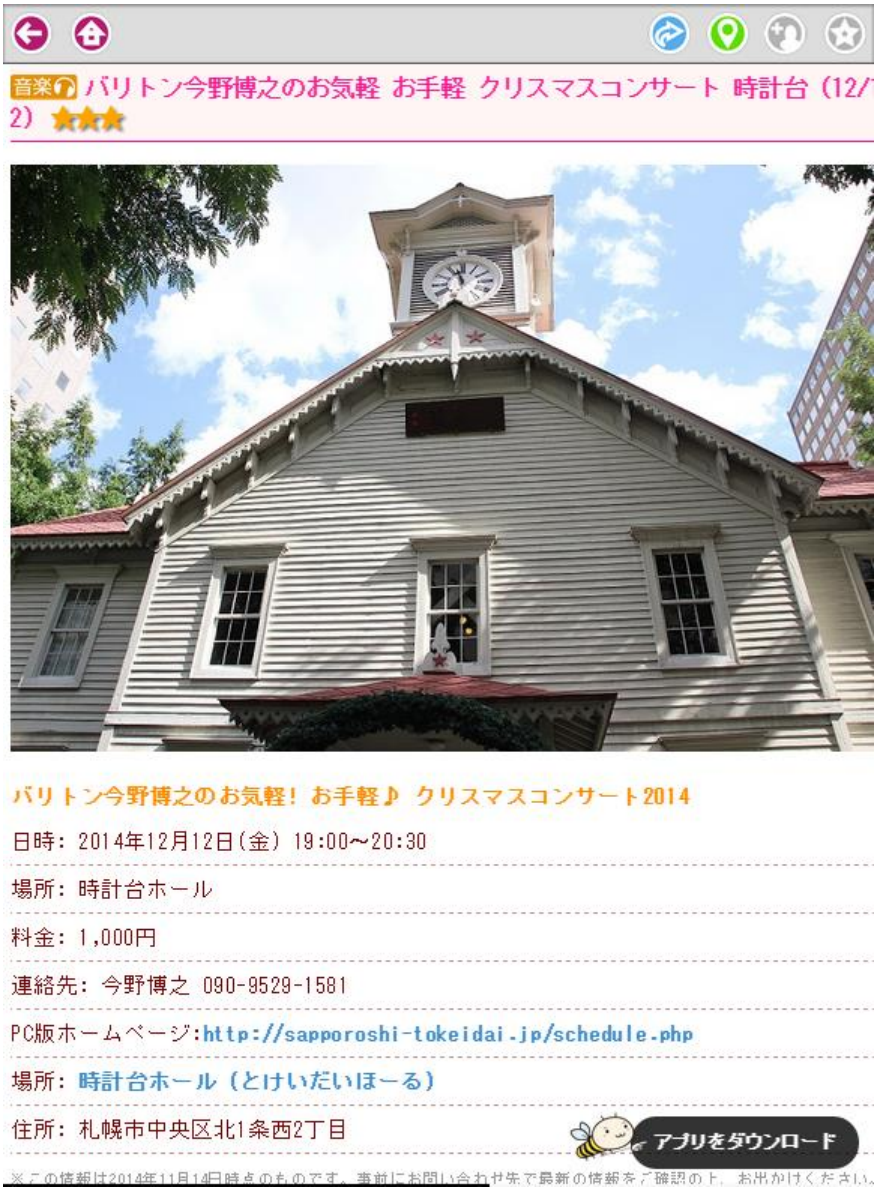

Figure 5.4: Screen-shot of the “Bemall Sapporo” mobile version event datail page

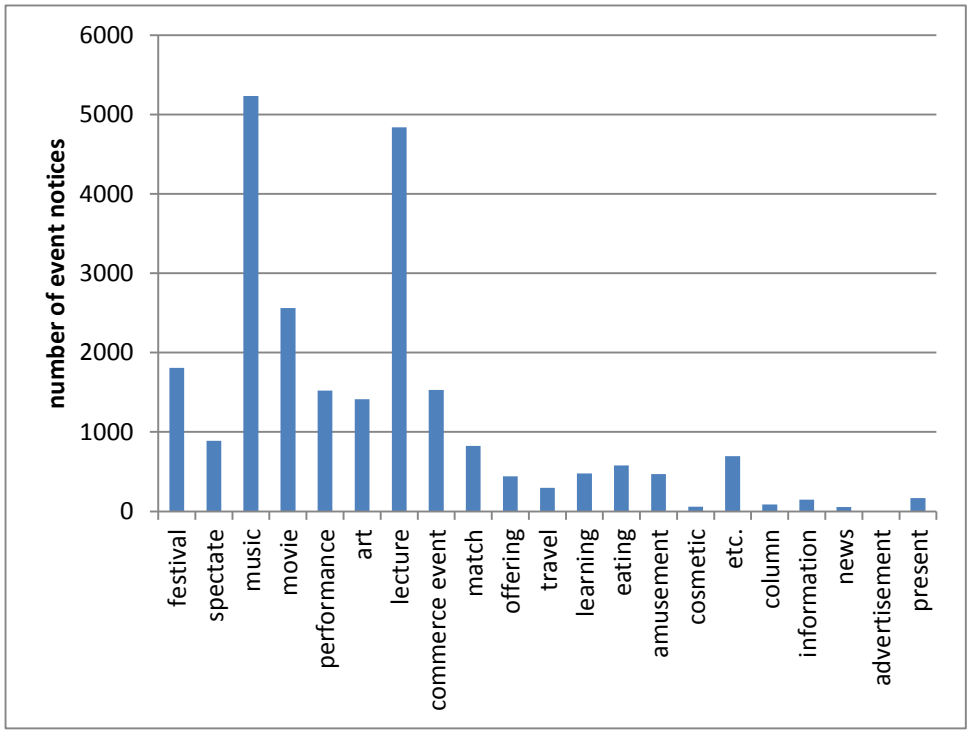

Figure 5.5: Number of event notices by genre in “Bemall Sapporo”

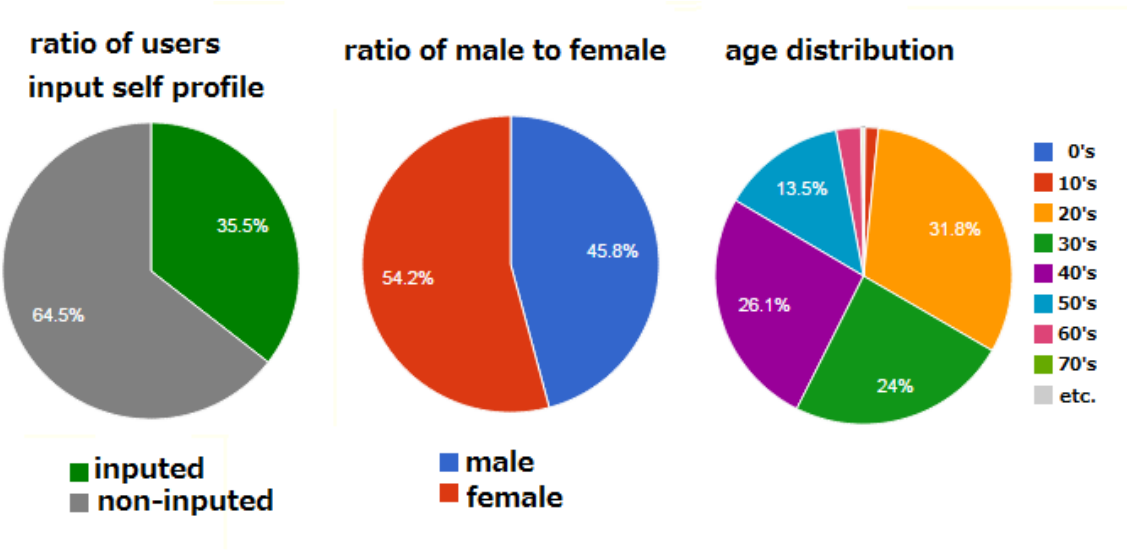

Figure 5.6: users’ profile of “Bemall Sapporo”

5.6.2 Experiment 1

First, the decision procedure of the weight of Weighted Sum Scoring and Individual Weighted Sum Scoring will be stated. As stated in chapter 4, all the user use the same weight with Weighted Sum Scoring and user-specific weight is used with Individual weighted Sum Scoring. With a restriction of sum of all weights being 1, the weight of each scoring are changed from 0 to 1 incremented by 0.1 and a combination of weight which minimize the average evaluation value was obtained. Figure 5.7 shows the combination of the obtained weight with Weighted Sum Scoring. Figure 5.8 shows average value and standard deviation of the combination of the weight of each user with Individual Weighted Sum Scoring.

On one hand Item CF Scoring had the largest weight in both Weighted Sum Scoring and Individual Weighted Sum Scoring, Popularity Scoring had a value near 0. This is because both scoring use the similar data and scoring policy and it can be assumed that the score obtained from the relatively high performance Item CF Scoring were prioritized.

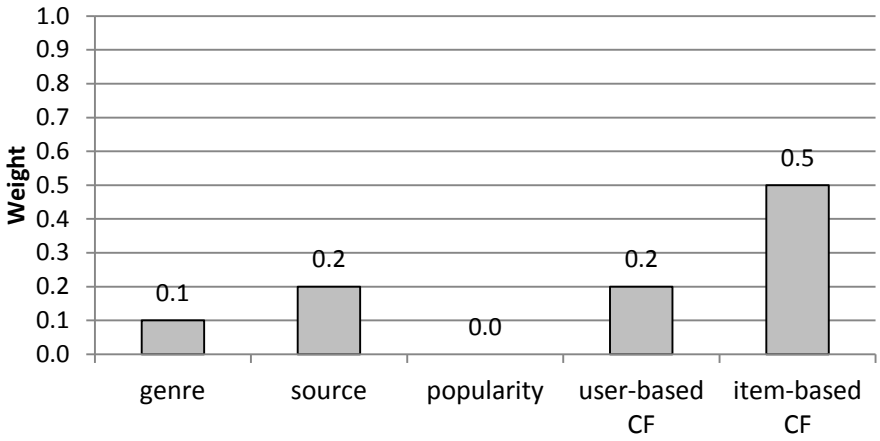

Figure 5.7: the combination of the obtained weight with Weighted Sum Scoring

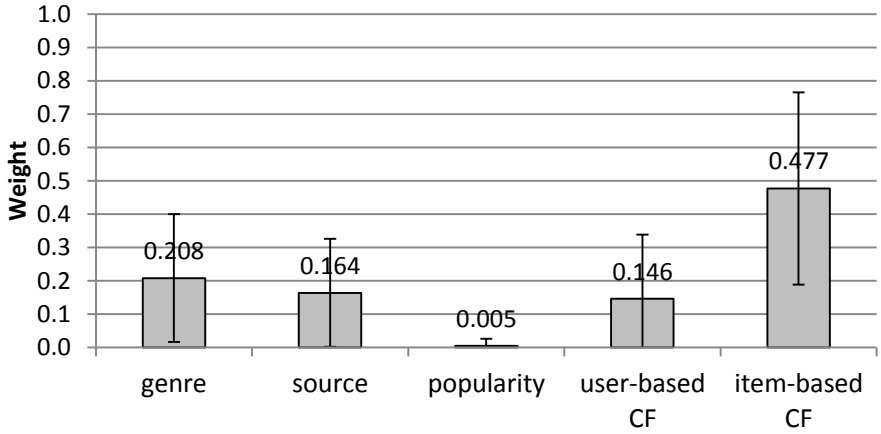

Figure 5.8: average value and standard deviation of the combination of the weight of each user with Individual Weighted Sum Scoring

5.6.3 Experiment 2

Next, the evaluation value $\mathrm{eval}(a, P, u_i)$ of each user with each scoring were calculated in order to compare the performance of each scoring. Figure 5.9 shows the average value and standard deviation of each user's evaluation value.

In the independent 5 scoring, the average evaluation value using Item CF Scoring had the smallest value of about 0.16. Averages of the other independent scoring were in between about 0.20 to 0.25. On one hand, the standard deviation of using all independent scoring were about 0.18, not much difference were observed using different scoring. The average of Weighted Sum Scoring was 0.15 and the average of Individual Weighted Sum Scoring was 0.14 which show better results than any other independent scoring. While the standard deviation of both Weighted Sum Scoring and Individual Weighted Sum Scoring showed lower value compared to independent scoring.

It is said that CF has a difficulty to perform well against sparse data. However, in the condition of obtaining the amount of experiment data as used in this experiment, it was revealed that CF can be effectively available against e vent information. Moreover, since Popularity Scoring show the second highest performance and it can be said that by simply recommending information that other users click frequently, performance to some extent can be demonstrated.

Since difference in feature and effect were showed in the results of each scoring against event information throughout this experiment, development and devise of a new recommendation method considering these features can be expected.

Although the weight of each user needs to be tuned with Individual Weighted Sum Scoring need, the evaluation value was about 0.09 smaller than Weighted Sum Scoring. As seen from the standard deviation of weight from Figure 5.8 of Experiment1, the weights of Individual Weighted Sum Scoring vary greatly depending on users, and the individual adjustment worked effectively on scoring. In the feature, there is a need to consider not only the click state but also consider using geographical information and time element in scoring. From this, improvement in performance can be expected when incorporating scoring where individual difference is noticeable.

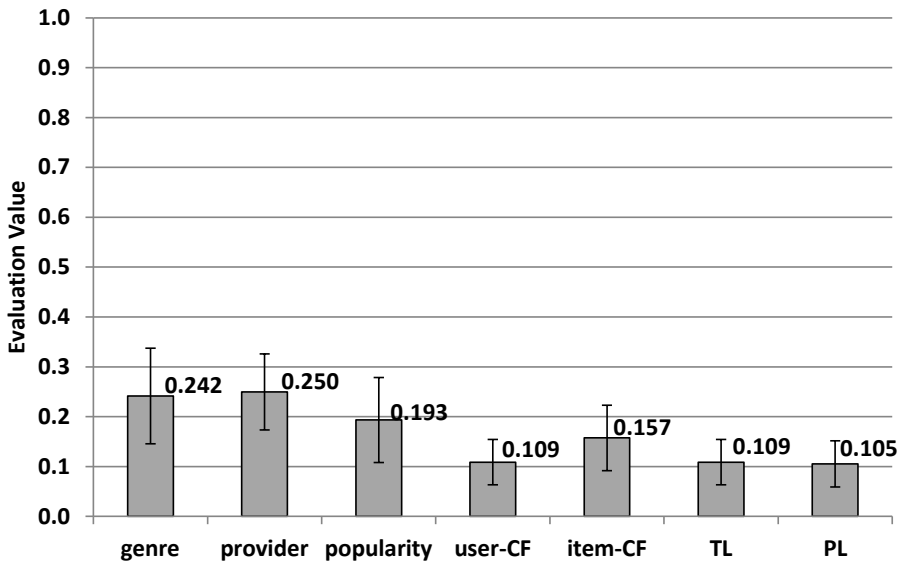

Figure 5.9: the average value and standard deviation of each user's evaluation value

5.6.4 Experiment 3

The evaluation value in Experiment2 uses the rank of order when sorted by score. This meaning when the rank of information that is already clicked is high, the scoring is effectively performed. On the other hand, when considering operating a real service,

an implementation where the service presents countable event information with a high score can be considered. In this situation, recall ratio which is the ratio that covers the presented countable event information within the information the user find interest in, become one of the key evaluation index.

Then, in addition to the evaluation index in Experiment2, the recall ratio of 5%, 10%, 20% of the high ranked event information within event information which apply r(u,e)=1 of event information set **P** for evaluation were examined. Results are shown in Figure 5.9, Figure 5.10, Figure 5.11.

Individual Weighted Sum Scoring which obtained a high evaluation in Experiment2, had a result of recall ratio of 49% with 5% of high ranked information, recall ratio of 61% with 10% of high ranked information, and recall ratio of 75% with 20% of high ranked information

This result indicates that half of the event information which users find interest in is included in the 5% of high ranked information. This means that if 50 out of 1000 event information were recommended, half of the event information which users find interest in is included in this. Furthermore, Individual Weighted Sum Scoring which had the best evaluation value in Experiment2 also had the best results in Experiment3. The service which this paper uses as experiment data, continuously handle about 300 distribution candidate event information which has a near exhibition date. Therefore, if 15 event information which is 5% of this is presented, half of the event information which is considered that the user is interested in has been presented.

In turn, since User CF Scoring has 47% recall ratio from the 5% high score result, using only User CF Scoring as operation can be considered for increase in speed.

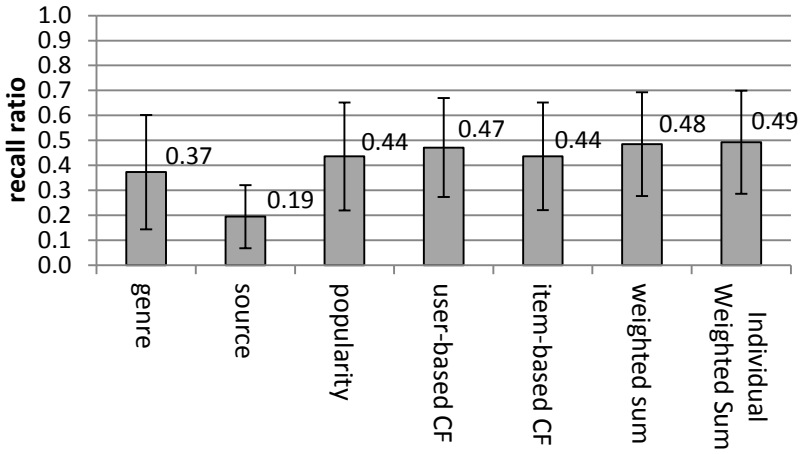

Figure 5.10: the recall ratio of 5% of the high ranked event information

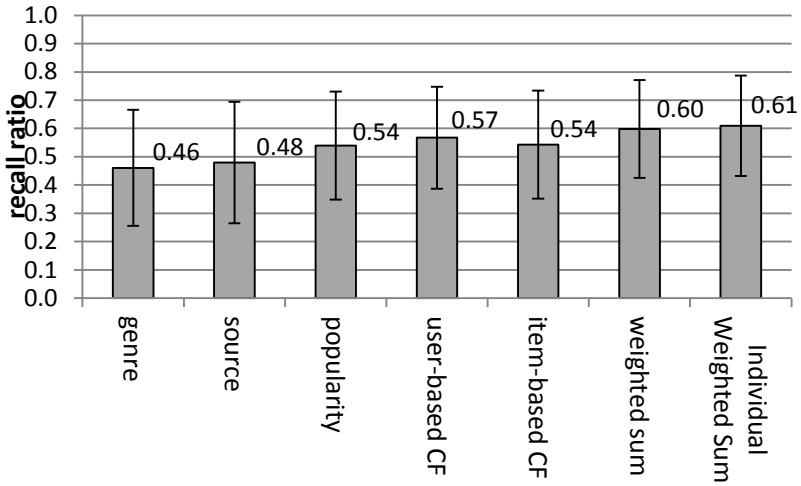

Figure 5.11: the recall ratio of 10% of the high ranked event information

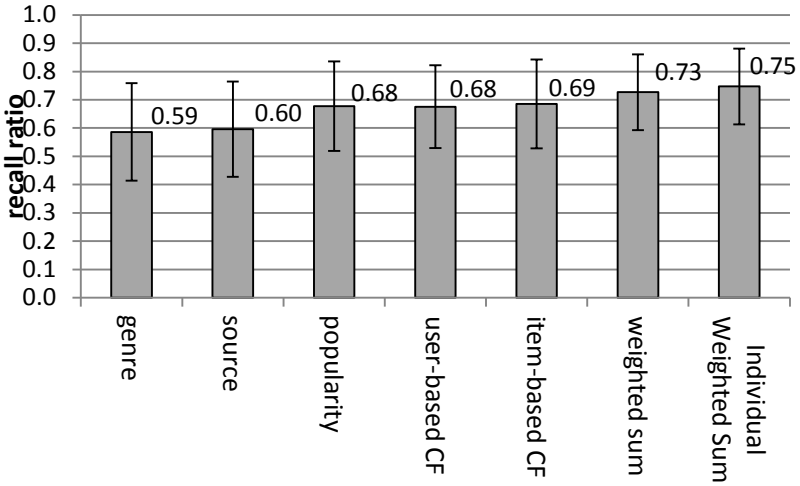

Figure 5.12: the recall ratio of 15% of the high ranked event information

5.6.5 Experiment 4

In Experiment2 and 3, the average performance of each scoring was examined but the number of event information clicked was not considered.

It is considered that if there aren't a constant number of user's clicks and number of event information clicked in scoring using CF, valid score is not calculated. Therefore, if the number of event information clicked is small, it is considered that mainly using Genre Scoring and Information Source Scoring which only employ click history of other event information is effective.

To investigate the actual trend, the difference of evaluation value with each scoring was examined after dividing the number of event information clicked using the setup of Experiment2. The result if showed in Figure 5.12.

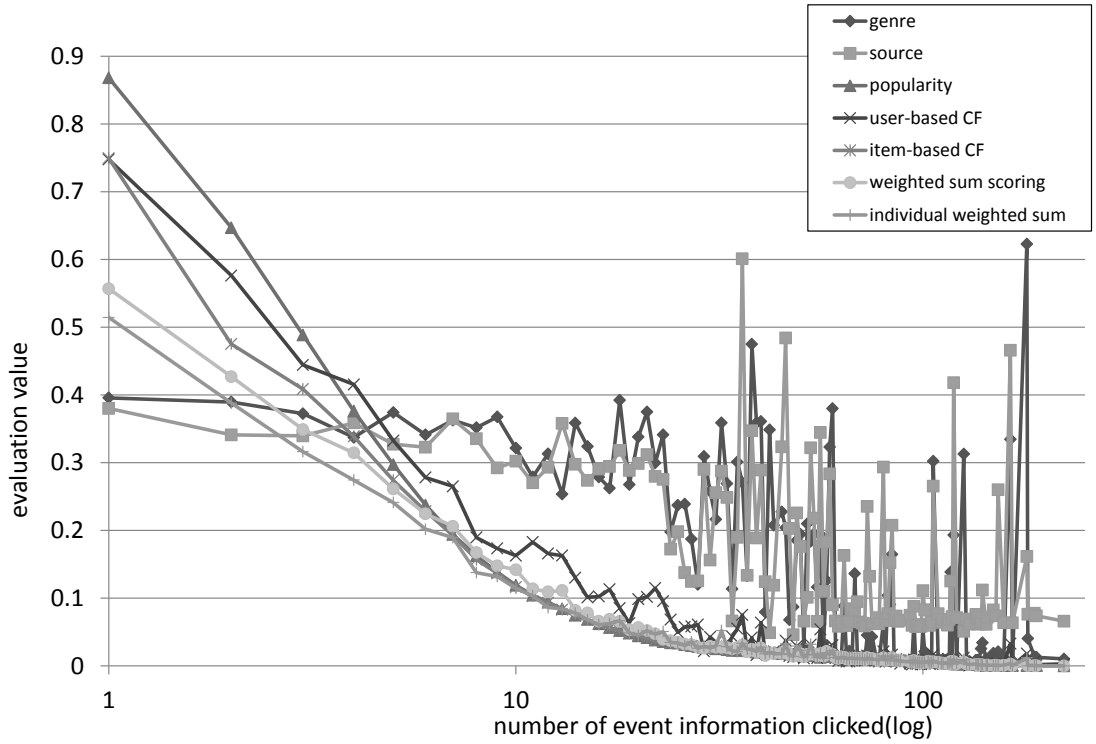

Figure 5.13: average of evaluation value with each scoring divided by the number of event information clicked

As expected, Genre Scoring and Information Source Scoring showed better evaluation value compared to other scoring against the event information with small number of event information clicked. Popularity Scoring and various CF had better evaluation value after the number of event information clicked surpassed 4 to 5. Even though Popularity Scoring showed bad evaluation value against event information with small number of event information clicked, it showed the same level of evaluation value as the best performed Item CF Scoring when the number of event information clicked is high

From this Experiment, it was revealed that Genre Scoring and Information Source Scoring was more effective compared to Individual Weighted Sum Scoring against event information with small number of event information clicked. In this research, weight is changed depending with user in the implementation of Individual weighted

Sum Scoring. However, there is a possibility of improving performance by changing the weight depending on the number of event information clicked

Moreover, Popularity Scoring has the same evaluation value as Item CF Scoring against event information with large number of event information clicked. Therefore from the view point of computation time, even though speed improvement is done by using Popularity Scoring instead of Item CF Scoring, not much performance will change with the presumption of combination use.

Understandably, event information with small number of event information clicked has bad evaluation value on the whole. Out of all the event information that are evaluation subjects, 75% of event information have 10 or less number of event information clicked in the data used in this experiment. In this way, real data are often sparse data. Therefore, the key point of scoring is how well the evaluation value of event information with small number of event information clicked can be improved.

On the other hand, event information with 20 to 30 number of event information clicked have an evaluation value of near 0 which is the best value depending on scoring. In other words, in terms of this event information, enough number of event information clicked has been collected already and the accuracy of the recommendation can be investigated by increasing the number of the present time of event information with small number of event information clicked. However, since this will present event information that may not be an interest for the user, it is important to collect and use the click condition with good balance. It is considered an important factor to optimize the obtaining of the number of user's clicks and the collection method of data that increase accuracy of scoring in the whole system.

In this research, improvement in convenience of service is focused by applying scoring to real service. Considering operating in real life, even though past data with click condition were used in this experiment, there is a need to consider how to conduct scoring whit both the user and event information having small number of event information clicked and small number of use's clicks which is difficult to calculate as implemented in this paper.

The approach considered for this is to calculate the degree of similarity between users with not the click condition but with user profile information such as age, sex,

residence.

5.7. Conclusions

In this paper, in order to realize the scoring necessary for event information recommendation system, performance comparison was conducted using users past lick data of event information delivery system “Bemall Sapporo -your information magazine-”.

To investigate the effective scoring towards recommending event information 5 scoring genre, information source, popularity, user based cooperative filtering, item based cooperation filtering, item based cooperative filtering were implemented and experimented. As a result, it was revealed that popularity and item based cooperate filtering show good results. Furthermore, it was revealed that by using weighted sum calculated from appropriately adding weight to the score obtained from using the 5 kind of scoring, the evaluation value can further be improved.

Moreover, after investigating the influence that the number of clicks the event information obtained has to the evaluation value of each scoring, it was found that when using Genre Scoring or Information Source Scoring against event information with small number of clicks, better evaluation value was obtained compared to using other scoring.

In other words it can be assumed that by examining to apply method to adequately convert scoring depending on click number of event information or separately applying an effective scoring against event information with small number of clicks, further performance improvement can be expected.

Chapter 6

Summary

Recommender system is a technology to support receivers and to improve receivers' additional value by information technology. On the other hand, most of past recommender system studies focus on only receivers efficiency, It would appear that it is important to consider not only receivers efficiency but also service provider's purpose .

In this doctoral dissertation, service innovation is focused on as scheme of service improving receiver's efficiency and achieving provider's purpose at same time. The main purpose of this study is to construct design and method for recommender system to realize service innovation. For this purpose, several discussions and considerations were described as following chapter.

In chapter 1, the conventional works for recommender system and service engineering were summarized. I also described similar studies in game theory and combinatorial optimization. Then I explain definition of service innovation in this study.

In chapter 2, I proposed a general service model named "recommendation type service model" involving recommender system without specific services. Then I discussed essential conditions of service innovation, reasonableness, fairness and efficiency.

In chapter 3, I constructed a concrete model of recommendation type service model named "shared resource type TSP" to consider feasibility of service innovation. I assumed service innovation as realization of Nash equilibrium Pareto optimal status in Game theory, and I made sure of how many solutions there are in small-scale problem by enumerate all solutions. As a result, there are 10 percent service innovation solutions in problems has two or three simple cities, and below 0.01 percent service innovation solutions in problems has four cities. Though only in small-scale problem, this result indicates that it isn't very likely to realize service innovation when receivers select randomly, and there are a few service innovation solutions, nonetheless, service innovation solutions exist.

In chapter 4, service innovation in the situations that can quantify receiver's efficiency exactly however receiver's efficiency depends on other receivers' selections was focused. I proposed a prediction method of congestion "the user-in-the-loop forecasting with the statement-based cost estimate" to realize service innovation by congestion mitigation. This method can predict approximate congestion by receivers' preliminary declarations. I verified effect of this method by two simulations, theme park model and highway. I also describe the results obtained with the method conducted to resolve congestion better than method just notifying congestion to receivers in the both scenarios.

In chapter 5, service innovation in the situations that receivers and services increase and decrease was focused. I implemented recommender system of event notices for real Web site, and verified how the system contributes to realize service innovation. I compared five methods, genre scoring, source scoring, popularity scoring, user-based collaborate filtering, item-based collaborate filtering and two new methods from combining the five methods above. As a result, even in event notice which user-item relation matrix is sparse, item-based collaborate filtering demonstrates superior performance in five methods, and it is made clear that two new methods show a higher performance than the results from all five methods. Then, I applied a part of two new methods to real Web site. Although it is difficult to conclude that this result is an objective fact because the experiments used online data in real service, there are indications that the reinforcement of algorithm partially conducted to service innovation.

In this paper, several approaches were proposed to analyze and evaluate service innovation in recommendation type service. Furthermore, the results of evaluation experiment illustrate the effectiveness or the efficiency of the proposal method.

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Bibliography

[1] A. Rapoport, Prisoner's dilemma: A study in conflict and cooperation, University of Michigan Press, 1965.

[2] B. Skyrms, The stag hunt and the evolution of social structure, Cambridge University Press, 2004.

[3] T. Tomiyama, "Service engineering to intensify service contents in product life cycles," Environmentally Conscious Design and Inverse Manufacturing, 2001. Proceedings EcoDesign 2001: Second International Symposium on. IEEE, pp. 613-618, 2001.

[4] Y. Shimomura and T. Tomiyama, "Service modeling for service engineering," Knowledge and Skill Chains in Engineering and Manufacturing. Springer US, pp. 31-38, 2005.

[5] Y. Motomura, "User Modeling in Service Engineering," The Journal of the Institute of Electronics, Information and Communication Engineers, 94(9), pp. 783-787, 2011(in Japanese).

[6] H. Kawamura, K. Kurumatani and A. Ohuchi, "Modeling of theme park problem with multiagent for mass user support," Springer Berlin Heidelberg,, pp.48-69, 2006.

[7] H. Kawamura, T. Kataoka and K. Kurumatani, "Investigation of global performance affected by congestion avoiding behavior in theme park problem.," IEEJ Transactions on Electronics, Information and Systems, Vol. 10, No. 124,, pp.1922-1929, 2004.

[8] T. Tone and K. Kohara, "A study of the effects of congestion information and a priority boarding pass in a theme park with multi-agents," IEEJ transactions on electronics, information and systems C, 127(3), pp. 407-415 (in Japanese), 2007.

[9] T. Imagawa, H. Kawamura, K. Kurumatani and A. Ohuchi, "Schedule-sharing System for Congestion Reduction in Theme Park Problem," IEICE Technical Report, Artificial Intelligence and Knowledge-Based Processing, 106(585), pp. 1-6, 2007 (in Japanese).

[10] T. Yamashita, K. Izumi, K. Kurumatani and H. Nakashima, "Smooth traffic flow with a cooperative car navigation system," AAMAS '05 Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems, USA, pp. 478-485, 2005.

[11] T. Shiose, T. Onitsuka and T. Taura, "Effective Information Provision for Relieving Traffic Congestion," Computational Intelligence and Multimedia Applications, 2001. ICCIMA 2001. Proceedings. Fourth International Conference on. IEEE, pp.138-142, 2001.

[12] J. K. Lenstra, A. R. Kan and D. B. Shmoys, "The traveling salesman problem: a guided tour of combinatorial optimization," Vol. 3. New York: Wiley, 1985.

[13] A. Larsen, O. B. Madsen and M. M. Solomon, "The a priori dynamic traveling salesman problem with time windows," Transportation Science 38.4 , pp. 459-472, 2004.

[14] M. Yokoo, E. H. Durfee, T. Ishida and K. Kuwabara, "The distributed constraint satisfaction problem: Formalization and algorithms," Knowledge and Data Engineering, IEEE Transactions on 10.5, pp 673-685, 1998.

[15] G. Hardin, "The tragedy of the commons," science 162.3859, pp. 1243-1248, 1968.

[16] A. Fabrikant, C. Papadimitriou and K. Talwar, "The complexity of pure Nash equilibria," Proceedings of the thirty-sixth annual ACM symposium on Theory of computing. ACM, pp. 604-612, 2004.

[17] R. Beier, A. Czumaj, P. Krysta and B. Vöcking, "Computing equilibria for congestion games with (im) perfect information," Proceedings of the fifteenth annual ACM-SIAM symposium on Discrete algorithms. Society for Industrial and Applied Mathematics, pp. 746-755, 2004.

[18] L. B. Van, P. Gemmel and R. Diedonck, Services management: An integrated approach, Pearson Education, 2003.

[19] T. Naitou, Introduction to service enginnering, University of Tokyo Press, 2009 (in Japanese).

[20] Y. Motomura and T. Kanade, "Probabilistic human modeling based on personal construct theory," J Rob Mechatron , 17(6)., pp. 689-696, 2005.

[21] Y. Motomura, Y. Nishida, M. Mochimaru, K. Hashida, M. Akamatsu and K. Naito, "Service Innovation Spiral of Data-based Analysis, Modeling, and Service Design," The 22nd Annual Conference of the Japanese Society for Artificial Intelligence,, 3B3-1 (in Japanese), 2008.

[22] C. Daskalakis, P. W. Goldberg and C. H. Papadimitriou, "The complexity of computing a Nash equilibrium," SIAM Journal on Computing 39.1, pp. 195-259, 2009.

[23] H. Kawamura, K. Kurumatani and K. Suzuki, "Modeling of Theme Park Problem with Multiagent for Mass User Support," Working Note of The IJCAI-03 Workshop on Multiagent for Mass User Support, Acapulco,Mexico, pp. 1-7, 2003.

[24] K. Kurumatani, "Mass user support by social coordination among citizens in a real environment," Multi-Agent for Mass User Support. Springer Berlin Heidelberg, Springer Berlin Heidelberg ,pp. 1-17, 2004.

[25] K. Kurumatani, "Social coordination with architecture for ubiquitous agents: Consorts," Proceedings of International Conference on Intelligent Agents, Web Technologies and Internet Commerce. Vol. 2003, p. 87, 2003.

[26] K. Kurumatani, "User intention market for multi-agent navigation-an artificial intelligent problem in engineering and economic context," AAAI2002 Workshop on Multiagent Modelling and Simulation of Economic Systems, pp. 1-4, 2002.

[27] M. P. Wellman, ""A market-oriented programming environment and its application to distributed multicommodity flow problems," Artificial Intelligence Research, Vol.1,, pp.1-22, 1993.

[28] R. Suzuki and T. Arita, "Effects of Information Sharing on Collective Behaviors in Competitive Populations," Proceedings of the Eight International Symposium on Artificial Life and Robotics, pp.36-39, 2003.

[29] H. S. Mahmassani and R. Jayakrishnan, "System performance and user response under real-time information in a congested traffic corridor," Transportation Research Part A: General 25.5 , pp.293-307, 1991.

[30] J. Wahle, A. L. Bazzan, F. Klügl and M. Schreckenberg, "Decision dynamics in a traffic scenario," Physica A: Statistical Mechanics and its Applications 287.3, pp.669-681, 2000.

[31] T. Yoshii, H. Akahane and M. Kuwahara, "An evaluation of effects of dynamic route guidance on an urban expressway network," Proceedings of the 2nd World Congress on Intelligent Transport Systems,, pp1995-2000, 1995.

[32] T. Yoshii, H. Akahane and M. Kuwahara, "Impacts of the accuracy of traffic information in dynamic route guidance systems," Proceedings of The 3rd Annual World Congress on Intelligent Transport Systems, (CD-ROM), 1996.

[33] R. Arnott, A. D. Palma and R. Lindsey, "Does providing information to drivers reduce traffic congestion?," Transportation Research Part A: General 25.5, pp.309-318, 1911.

[34] S. Fischer and B. Vöcking, "Adaptive routing with stale information," Proceedings of the twenty-fourth annual ACM symposium on Principles of distributed computing. ACM, pp.276-283, 2005.

[35] N. Muguda, P. R. Wurman and M. R. Young, "Experiments with planning and markets in multiagent systems," ACM SIGecom Exchanges 5.1 , pp.34-47, 2004.

[36] J. E. Prado and P. R. Wurman, "Non-cooperative planning in multi-agent, resource-constrained environments with markets for reservations," AAAI 2002 Workshop on Planning with and for Multiagent Systems., pp.60-66, 2002.

[37] J. G. Wardrop, "Some theoretical aspects of road traffic research," Proc.of the Institute of Civil Engineers, 2,, pp.325-378, 1952.

[38] F. Klügl and A. L. Bazzan, "Simulation Studies on Adaptive Route Decision and the Influence of Information on Commuter Scenarios," Intelligent Transportation Systems. Vol. 8. No. 4. Taylor & Francis Group,, pp.223-232, 2004.

[39] B. W. Arthur, "Inductive reasoning and bounded rationality," The American economic review, pp.406-411, 1994.

[40] F. Klügl, A. L. Bazzan and J. Wahle, "Selection of information types based on personal utility: a testbed for traffic information markets," Proceedings of the second international joint conference on Autonomous agents and multiagent systems. ACM, pp.377-384, 2003.

[41] E. W. Dijkstra, "A note on two problems in connexion with graphs.," Numerische mathematik 1.1, pp.269-271, 1959.

[42] M. P. Wellman, "Methods for empirical game-theoretic analysis," Proc.of Twenty-First National Conference on Artificial Intelligence, pp1152-1155, 2006.

[43] K. Dresner and P. Stone, "Multiagent traffic management: A reservation-based intersection control mechanism," Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 2. IEEE Computer Society, pp.530-537, 2004.

[44] G. Linden, B. Smith and J. York, "Amazon. com recommendations: Item-to-item collaborative filtering," Internet Computing, IEEE 7.1, pp. 76-80, 2003.

[45] A. S. Das, M. Datar, A. Greg and S. Rajaram, "Google news personalization: scalable online collaborative filtering," Proceedings of the 16th international conference on World Wide Web. ACM, pp. 271-280, 2007.

[46] T. Kamishima, "Algorithms forRecommender Systems (1)," Transactions of JSAI, 22.6, pp. 826-837, 2007 (in Japanese).

[47] F. Ricci, L. Rokach and B. Shapira, "Introduction to recommender systems handbook," Springer US., 2011.

[48] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom and J. Riedl, "GroupLens: an open architecture for collaborative filtering of netnews," Proceedings of the 1994 ACM conference on Computer supported cooperative work. ACM, pp. 175-186, 1994.

[49] J. L. Herlocker, J. A. Konstan, L. G. Terveen and J. T. Riedl, "Evaluating collaborative filtering recommender systems," ACM Transactions on Information Systems (TOIS) 22.1, pp. 5-53, 2004.

[50] D. Goldberg, D. Nichols, B. M. Oki and D. Terry, "Using collaborative filtering to weave an information tapestry," Communications of the ACM 35.12, pp. 61-70, 1992.

[51] A. Yamashita, H. Kawamura, H. Iizuka and A. Ohuchi, "Performance Evaluation of Recommendation Algorithms Based on Rating-recommendation Interaction," IPSJ TOM23, 2, 2, pp. 47-57 (in Japanese), 2009.

[52] A. Yamashita, H. Kawamura and K. Suzuki, "Adaptive fusion method for user-based and item-based collaborative filtering," Advances in Complex Systems 14.02, pp. 133-149, 2011.

[53] M. Balabanovic' and Y. Shoham, "Fab: Content-Based, Collaborative Recommendation," Communications of The ACM, Vol. 40, No. 3, pp. 66-72, 1997.

[54] J. S. Breese, D. Heckerman and C. Kadie, "Empirical Analysis of Predictive Algorithms for Collaborative Filtering," in Uncertainty in Artificial Intelligence 14, pp. 43-52, 1998.

[55] T. Hofmann, "Probabilistic Latent Semantic Analysis," in Uncertainty in Artificial Intelligence 15, pp. 289-296, 1999.

[56] B. J. Schafer, J. A. Konstan and J. Riedl, "E-Commerce Recommendation Applications," Data Mining and Knowledge Discovery, Vol. 5, pp. 115-153, 2001.

[57] J. L. Herlocker, J. A. Konstan, A. Borchers and J. Riedl, "An Algorithmic Framework for Performing Collaborative Filtering," in Proc. of the 22nd Annual ACM SIGIR Conf. on Research and Development in Information Retrieval, pp. 230-237, 1999.

[58] B. Sarwar, G. Karypis, J. Konstan and J. Riedl, "Item-Based Collaborative Filtering Recommendation Algorithms," in Proc. of the 10th Int'l Conf. on World Wide Web, pp. 285-295, 2001.

[59] U. Shardanand and P. Maes, "Social information filtering: algorithms for automating "word of mouth"," In: Proceedings of the SIGCHI conference on Human factors in computing systems. ACM Press/Addison-Wesley Publishing Co., pp. 210-217., 1995.