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Large-scale nationwide ridesharing system: A case study of Chunyun

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ABSTRACT

In this paper, we propose a large-scale nationwide ridesharing system named CountryRoads, which is designed to resolve the surge of homeward-bound persons during holiday seasons. CountryRoads matches drivers who are willing to share their spare seats with passengers who are unable to obtain public transportation for long-distance trips. The system utilizes a variety of user interfaces, including text messages, mobile websites, and smart-phone applications to enable the participation of a variety of people. Further, it implements an online greedy-matching algorithm to solve the ridesharing problem in order to propose matches between drivers and passengers.

We deploy and evaluate CountryRoads during the Chinese Spring Festival travel season (Chunyun period), when all forms of transportation are stressed or near saturation, and when many lower-income individuals fail to reserve seats for rail or flight trips. We present our design choices, analytics, and lessons learned from our multi-year deployment in 2012, 2014, and 2015. The improvements over the years resulted in up to 17,272 users, 4777 ridesharing tuples, and an eventual success rate of 23.2% in 2015. This is a significant result considering that most of our participants use CountryRoads as a last resort in response to public transportation shortages.

1. Introduction

Ridesharing refers to the act of carpooling, and can result in many environmental and economic benefits, including relieving traffic congestion and reducing carbon emissions (Caulfield, 2009). With the aid of mobile devices that are equipped with global positioning system (GPS) navigation functions, on-demand ridesharing services have become a reality, and they have facilitated the growth of several transportation network companies, including Uber (2017) and Lyft (2017).

In this paper, we present a large-scale nationwide ridesharing system named CountryRoads, which is designed to resolve the surge of homeward-bound persons during holiday seasons. CountryRoads matches drivers who are willing to share their spare seats with passengers who are unable to obtain public transportation tickets. Unlike transportation network companies such as Uber and Lyft, which mainly provide short-distance ridesharing service within cities, CountryRoads focuses on

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long-distance ridesharing services between cities, which has not been considered to a great extent. To lower the bar for the participation of lower-income individuals, CountryRoads utilizes a variety of user interfaces, including text messages (Short Messaging Service, SMS), website, and smartphone applications (apps), and it combine them using a user-interface module to collect a user's route information. Based on this information, CountryRoads conducts an online greedy-matching algorithm to propose matches between drivers and passengers in the matching module. The matched users are notified via a notification module.

In this study, we deployed and evaluated CountryRoads during the yearly Spring Festival travel season in China (also known as the Chunyun period), when billions of people return to their hometowns to unite with their families. It is referred to as "the largest annual human migration in the world," and the 40-day period saw over 3.6 billion trips in 2014 (Xinhuanet.com, 2017). During this period, the demand for public transportation (railway, road, and air) far exceeds their regular capacities and there are significant increases in bus and air fares. For this reason, many people, especially lower-income individuals, are unable to reunite with their families. Because of the vast number of trips and the diversity of destinations during this short period of time, the simple addition of capacity or building of new transportation infrastructure is neither feasible (because of the prohibitively expensive investment required) nor desirable (because of the poor utilization of the infrastructure during non-peak periods).

On the other hand, the number of privately owned cars in China has significantly increased. At the end of 2014, the number of privately owned motor vehicles in China had exceeded 125 million (National Bureau of Statistics of China, 2014). This results in more travelers choosing to drive their own cars for the Chunyun trip as an alternative to public transit. However, these vehicles tend to have low occupancy during the Chunyun period because people often work far away from their hometowns. This inspired us to deploy and evaluate CountryRoads when the drivers who would otherwise drive home alone could share their empty seats with passengers who have been unable to obtain public transportation tickets.

To deploy a ridesharing system during the Chunyun period, we need to address three main challenges:

- First, home-going trips during the Chunyun period are a once per year occurrence, making it difficult for the proposed ridesharing system to incorporate a user credit system to promote trust between users.
- Second, users have low loyalty to the ridesharing system. Because they are anxious to go home, some may become impatient if a match is not proposed soon enough, and they may therefore purchase public transportation tickets, despite their cost, before they become unavailable.
- Finally, people who struggle the most to find other transportation means and who would therefore benefit most from ridesharing, are lower-income users. In many cases, the persons only possess basic phones that have very limited or no Internet connectivity. This greatly limits the possible types of interaction and information available to the system. We refer to this as low-information.

The main contributions of our work are as follows:

- We present a "one-shot" low-information ridesharing system named CountryRoads, which helps users to return home during the Chunyun period.
- We explore the user design space of a ridesharing system using the properties of CountryRoads. We mainly consider the design limitations in such a heterogeneous user space, in which it cannot be taken for granted that the target users have smartphones or Internet connectivity.
- We present a large-scale, multi-year deployment and evaluation of our one-shot, low-information ridesharing system, and present the lessons learned as well as the analysis of a real, large-scale user base.

We deployed CountryRoads during the Chunyun traffic surges in 2012, 2014 and 2015. Over the years, we improved the design by incorporating lessons learned each year. During the Spring Festival travel season from January 25 to February 18, 2015, CountryRoads collected 17,272 sets of traveler-route information (of which 7485 are driver itineraries and 9787 are passenger itineraries), and it proposed 4777 ridesharing tuples. Of these tuples, approximately 23.20% resulted in actual travel. This is a large increase of about 4677 tuples compared to 2012.

2. Related work

In this section, we discuss a literature review about the ridesharing problem. The main focus of the previous works has been on the implementation and deployment of a ridesharing system, as well as its sustainability from a socioeconomic perspective (Agatz et al., 2012; Chan and Shaheen, 2012; Furuhata et al., 2013).

2.1. Implementation and deployment

The main approach taken in ridesharing research is to formulate it as an optimization problem. Typical constraints are spatial factors such as user routes or origin–destination (OD) pairs, temporal factors such as departure/arrival time, and other application-related factors. Examples of common optimization objectives are: maximizing the number of served passengers, maximizing drivers' revenue, or maximizing the total mileage shared, although specific scenarios may require different optimization goals. Various methods, such as genetic algorithms (Guo et al., 2013), the Lagrangian relaxation-based algorithm (Yan et al., 2011), and the ant colony optimization paradigm (Maniezzo et al., 2004) have been proposed to enable the efficient solution of such optimization problems. These approaches are usually validated based on GPS trajectories (He et al., 2014; Ma et al., 2013), travel demand data (Agatz et al., 2011), and mobility data extracted from 3G call description records (Cici et al., 2014). Another research focus is the design of a real-time ridesharing service. With the emergence of mobile devices such as smartphones, a real-time ridesharing service becomes feasible, and this has been discussed in Stach and Brodt (2011). To improve the effectiveness of the service, it has been proposed to combine the ridesharing service with the taxicab network (Tian et al., 2013; Zhang et al., 2013a), recommender systems (Zhang et al., 2013b), and social networks (Mirisaee, 2010; Selker and Saphir, 2010). However, these works focus mainly on frequent users, where a reputation system can be built and a smartphone used to obtain detailed information.

While companies such as Uber (2017) and Lyft (2017) provide ridesharing services, there are few publicly available results about the real deployment of ridesharing systems or their design considerations. Even for the few available results, the deployment is limited to small, homogeneous groups of people such as university communities (Amey, 2011). Furthermore, many of these works focus on smartphone usage. Despite the fact that the advent of technology has brought increasing power to smartphones, many lower-income persons cannot afford smartphones, and still use basic phones. For these lower-income users, SMS is almost always the only option in a ridesharing system. In earlier work, authors have explored ways of using SMS for other systems such as the Web search systems (Chen et al., 2010) and information-retrieval systems (Biswas and Asif, 2013). In a previous study, the authors built a ridesharing service using Smart-M3 information sharing platform and developed an online questionnaire to better cognize whether prospective customers would accept ridesharing services as an alternate mode of transportation (Smirnov et al., 2013). Their service targets on the intra-city scenario, while our system is built for inter-city trips and we also provided access for people without smartphones.

2.2. Socioeconomic perspective

For a ridesharing system to be attractive and sustainable, we have to consider the provision of incentives as well as the pricing policy. Two main approaches have been proposed in the literature. One is market- and auction-based, such as the Vickrey payment scheme, which controls the deficit of the platform and provides the ridesharing service with the guarantee that users are incentivized to participate and behave truthfully (Kamar and Horvitz, 2009; Kleiner et al., 2011; Zhao et al., 2014). Other kinds of mechanisms, such as fair cost sharing, splits up travel costs between drivers and passengers (Bistaffa et al., 2015; Cheng et al., 2014). These works generally assume that the benefit of such rides are between users. In the Chunyun situation, social problems may arise if a significant number of users cannot afford the increased rates during these peak seasons. In addition, such rate structures have questionable legality in many locations.

A major concern for ridesharing users is trust. Because ridesharing often involves the process of riding with strangers, it is important to establish a way of setting up trust between participants in order to determine the success of a ridesharing experience. Alternatives to the creation of trust are the establishment of a reputation system (Jsang et al., 2007) or the integration of the ridesharing system with online social networks, which will enhance the connections between participants by taking advantage of their existing user profiles (Gidófalvi et al., 2008; Mirisaee, 2010; Selker and Saphir, 2010). However, in our study, this is not a feasible option as most lower-income people do not use these services regularly and Chunyun is only an annual occurrence.

Some prior work also attempts to deal with users' dynamic arrival patterns and impatience in a dynamic matching market framework by modeling drivers as the suppliers who have empty seats and passengers as demanders. While static matching markets have been extensively studied by economists (Roth and Sotomayor, 1992), there have been comparatively few studies of dynamic matching markets, in which the matching algorithm has to make allocations in the present while facing an uncertain future because users arrive at different times. In Akbarpour et al. (2014), the authors demonstrate that waiting to grow the market can be substantially more important than increasing the frequency of transactions. In Arnosti et al. (2014), the authors find that limiting the visibility of users can significantly improve the utility of users on both sides of the market in the mean field equilibrium. These works can improve the matching algorithms. Our work builds on these works and focuses on the design consideration of utilizing low-information, low-trust situations that arise by enabling lower-income individuals to access our system.

3. System overview

The system architecture of CountryRoads is shown in Fig. 1. The system consists of three main modules, namely, the user-interface module, the matching module, and the notification module. In the following three subsections, we discuss the design considerations and their impacts on the system.

The *User Interface Module* section introduces the three platforms through which users can input route and personal information into CountryRoads (*i.e.*, text messages, website, and smartphone apps). Then, the *Matching Module* section covers the online greedy-matching algorithm that is used by CountryRoads to pair up drivers and passengers based on their route

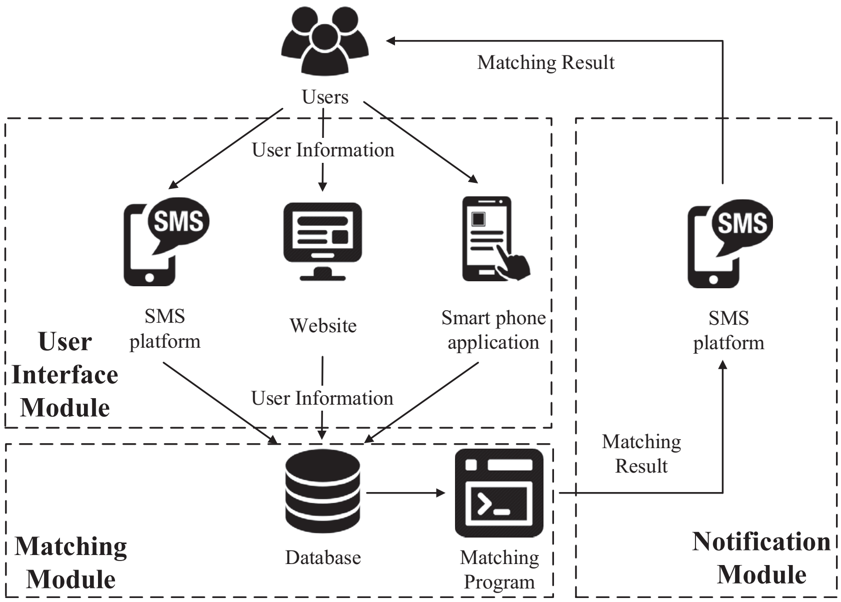

Fig. 1. CountryRoads system structure.

information. Finally, the *Notification Module* section describes how the users receive the matching result (*i.e.*, their ridesharing partner information).

3.1. Design considerations targeting lower-income individuals

One of the key considerations of CountryRoads is the design tradeoff that must be considered by a bipartite matching service (particular a ridesharing system) when their target user base is partially composed of lower-income individuals. The vast majority of applications in this – and many other – fields are designed with target users in the upper-middle income class public (Stach and Brodt, 2011). In this section, we present design decisions and tradeoffs considered in the CountryRoads system.

One key realization that was reinforced during our first trial in 2012 is the fact that persons who struggle the most to obtain public transportation tickets for the Spring Festival are from lower-income communities. Most of these individuals do not possess smartphones, while some have no mobile Internet access. Therefore, we need to design a flexible system that can incorporate users who may not possess smartphones or have Internet access.

Another challenge is that many of these low-income users do not regularly use ride-sharing services (*e.g.*, Uber and DiDi.) This means that our proposed system lacks an existing credit and user profile system that we can leverage (because the Chunyun travel season only takes place once a year).

We considered two main alternatives. First, we could provide all participants with a dedicated device or smartphone. However, in addition to the low scalability of this solution, a large group of users who do not own smartphones may not know how to use them either. However, basic phone penetration in China is almost universal. Therefore, our proposed system was designed to use a wide range of interaction methods including basic phones (using SMS text messages), smartphones, and websites.

While the inclusion of basic phones allows access for lower-income users, our system has to support an increased level of complexity, in that:

- Entering information through SMS can be complicated: the absence of field labels and text boxes increases the possibility of human error. As a result, we minimize the amount of mandatory information users provide when they sign up, and leave all other fields optional.
- Sending and/or visualizing media information is often not possible (lack of camera or MMS functionality), which limits the amount and type of information that these users can send and receive. This has an impact on user trust because, for example, pictures of the car status, car registration, or driver's license are not available. To deal with this constraint, we offer trip insurance to both drivers and passengers, which requires the driver's real name and driver's license number. Using this method, an intermediary (*i.e.*, CountryRoads) can verify the user identity and improve user trust. The offer of insurance provides a few advantages: (1) the drivers are incentivized to provide their information, (2) the verification can

be done, and (3) the drivers are incentivized to go through with the agreement when the agreement with the rider is fulfilled. In our implementation, the personal information provided for the insurance would not be made available to the rider, and only the verification information is displayed.
- There is a limited number of drivers relative to the number of riders. In this situation, one-to-multiple matching can potentially increase the matching delay and risk more matches than available seats. Therefore, to reduce this likelihood, CountryRoads only considers one-to-one matching, *i.e.*, one driver can only be matched to one passenger.

3.2. User interface module

Because of the design considerations stated above, CountryRoads allows users to interact with the system through an SMS platform, a website, and a smartphone app for both Android and iOS operating systems. By combining these three kinds of interfaces, CountryRoads is able to attract users from different classes and various socioeconomic walks of life. For example, lower-income users who possess no smartphones or Internet access may register for CountryRoads by simply sending an SMS message.

User accounts are uniquely identified by their mobile phone numbers, and are thus shared among these three interfaces so that users could switch from one interface to another smoothly. The difference between these three interfaces is that the SMS platform can only collect a user's route information, while using the other two interfaces, the users can also provide some personal information that may help to build trust between each other, and subsequently contribute to a successful shared trip. The route information is required, and includes the origin city, destination city and departure date. The personal information is optional, and may include name, gender, or the car's information (license plate number, car model, pictures, *etc.*), if the user registers as a driver.

The SMS platform utilizes natural language processing technology to extract the route information from the SMS text by comparing it with a dictionary of all the 361 city names in China. Because the SMS message formatting is limited and mistake-prone, other information is not mandatory.

As mentioned earlier, the smartphone app and the website allow users to provide their personal information besides their itineraries. Some users may not want to provide their personal information for privacy reasons. In CountryRoads, a user's personal information is only revealed to their partner once there is a match, which enables improved privacy protection when compared to the old-fashioned way of posting ridesharing requests on online bulletin boards, where everyone's information is made public.

3.3. Matching module

The main function of the matching module is to pair drivers with passengers by implementing the online greedy-matching algorithm described in the *Matching Algorithms* subsection under the *Ridesharing Matching Problem Formulation* section. All of the user information obtained from different user interfaces is stored in the same database. Each passenger would be added to a passenger queue, and wait to be matched; the same applies for each driver. Passengers and drivers only leave their queues once they are matched or their time expires, like reaching the departure date without being matched.

When implementing the online greedy-matching algorithm in the matching program, CountryRoads treats users from different user interfaces equally.

3.4. Notification module

The main function of the notification module is to inform users about proposed partners with whom they may share the trip. In the case of a proposed match, CountryRoads provides them with each other's contact information so that they can plan their trip as soon as possible. Because a large portion of users may not have Internet access, the contact information received by each user from their potential partner is their phone number. In this way, they can communicate through voice call or SMS, which are affordable basic features available from any cell phone.

Specifically, for each ridesharing tuple proposed by the matching module, CountryRoads sends two text messages: one is sent to the passenger with the driver's name and phone number, and the other message is sent to the driver with the passenger's name and phone number. In addition, users who access CountryRoads through the website or the smartphone app can view other optional personal information fields that may have been entered by their potential partner.

Because of the diversity of the user interface, it is difficult to track successful ride-sharing actions with our system. We then conducted a post-ride telephone survey to evaluate the successful rate, and the details are described in the *Evaluation and Results* section.

4. Ridesharing matching problem formulation

A key component of CountryRoads is the matching of users with limited information. In this section, we formalize the problem from a mathematical standpoint.

4.1. Mathematical formulation

In our system, we have two types of users: (1) drivers: those who drive their private vehicles home and have open seats, and (2) passengers: those who are seeking to find an empty seat. We formulate this problem as a bipartite matching problem. The basic structure of the problem is a bipartite graph, in which each node represents a driver or a passenger. Each edge of the bipartite graph represents a matching pair between the passenger and the driver to which the passenger is connected.

We denote the set of passengers as P and the set of drivers as D. Let $P \times D$ denote the set of all possible ordered pairs in the form of (p, d), where passenger $p \in P$ and driver $d \in D$. In this bipartite matching problem, we only allow one-to-one matches (*i.e.*, one driver can only be matched to one passenger), as described in the Design Considerations subsection. We define a matching as follows:

Definition 4.1 (*Matching*). A matching M is a set of ordered pairs, each from $P \times D$, with the property that each member of P and each member of D appear in at most one pair in M.

In our scenario, not every matching is *realistic* for two reasons. First, users join and leave the system dynamically, which means that not every driver is visible to every passenger within a particular matching time frame. Second, the user's preference is unknown, and many users can reject matches and may prefer to stay unmatched rather than accept an unsuitable pair based on their preferences.

Formally, for a passenger $p \in P$, we denote the arrival time of p as $t_a(p)$ and the expiration time as $t_e(p)$. The arrival time indicates the instant at which a user submits their route information, while the expiration time represents the instant at which the user is no longer available to be matched. In practice, $t_e(p)$ is the earliest of these instances: (a) a user's desired travel date has come; (b) a user unsubscribes from our service; (c) a user is matched. If a passenger is matched, we define the interval between $t_a(p)$ and the matching time as the passenger p's *waiting time*. We denote $t_a(d)$ and $t_e(d)$ similarly for a driver $d \in D$.

Then, we define the indicator function $I(p, d)$ for the pair (p, d) to indicate whether passenger p and driver d are visible to each other in the time domain as follows:

$$I(p,d) = \begin{cases} 1 & t_a(p) < t_e(d) \text{ or } t_a(d) < t_e(p) \\ 0 & \text{otherwise.} \end{cases}$$

where $t_a(p) < t_e(d)$ represents the situation where passenger p arrives before driver d's time expires, and conversely, $t_a(d) < t_e(p)$ represents the scenario where driver d arrives before passenger p's time expires. If neither of the two situations holds, we say that passenger p and driver d are not visible to each other in the time domain and they may not be matched together.

Then, we denote $U_p(d)$ as the utility function for a specific passenger p, which represents his benefit of being matched with driver d. We assume that remaining unmatched has no benefit and no harm, which corresponds to $U_p(\emptyset) = 0$. We define $U_d(p)$ similarly for driver d as his utility being matched with passenger p.

While these utilities are fundamental metrics for generating a matching, they are indeed user's private information, and it is unrealistic for a passenger (or driver) to report his utility of being matched with every *visible* driver (or passenger). In CountryRoads, we estimate a user's utility based on the route information and use a specific utility function with empirical parameters:

$$U_d(p) = U_p(d) = \frac{1}{1 + e^{(\alpha\Delta O + \beta\Delta D + \gamma Detour + \delta\Delta T)/\text{driver's mileage}}},$$

where $\alpha, \beta, \gamma, \delta$ are the weights of the four factors, origin deviation ΔO, destination deviation ΔD, detour distance *Detour*, and departure date deviation ΔT, and the *driver's mileage* is used to eliminate the variation between trips with different mileages. The details will be discussed in the Estimation of User's Utility subsection.

The system's goal is to choose a matching scheme that maximizes the benefits of the whole user group, which we define as *social utility*.

Definition 4.2 (*Efficiency & Social Utility*). For a matching M to be efficient, it should maximize the social utility, which is the sum of the utility that every user obtains from the matching.

In other words, the system's goal is to find an efficient matching. Let $E = P \times D$ represent the set of edges and $v_{pd} = U_d(p) + U_p(d)$ represent the weight associated with edge $(p, d) \in E$. We define binary variable $x_{pd} = 1$ if edge $(p, d) \in E$ is selected in the matching M, and 0 otherwise. Then, the bipartite matching problem can be formulated as the following optimization problem:

$$\begin{aligned} \text{maximize} \quad & \sum_{(p,d)\in E} v_{pd} x_{pd} \\ \text{subject to} \quad & \sum_{p\in P} x_{pd} \leqslant 1, \ \forall d \in D \end{aligned} \tag{1}$$

$$\sum_{d \in D} x_{pd} \leqslant 1, \ \forall p \in P \tag{2}$$

$$x_{pd} \in \{0, 1\}, \ \forall (p, d) \in E \tag{3}$$

$$x_{pd} = 0, \ \text{if } I(p, d) = 0. \tag{4}$$

where the objective function is the social utility of the matching M, Constraint (1) ensures that every driver can be matched at most once, Constraint (2) ensures that every passenger can be matched at most once, Constraint (3) ensures that x_{pd} is a binary variable, and Constraint (4) ensures that passenger p and driver d are visible in the time domain.

4.2. Matching algorithms

To solve the above bipartite matching problem, we utilize an online greedy algorithm that runs periodically. In each round, we use a greedy mechanism between the remaining users from previous rounds and new users in the current round, and use the edges with weights greater than or equal to a threshold τ. With a higher threshold, it would be harder for the matching algorithm to find an eligible matching pair, since extremely unsuitable pairs have been eliminated by the threshold. In practice, we use different thresholds for the years 2014 and 2015 to evaluate its impact on the matching results. Because the users may be impatient, our algorithm makes a tradeoff between myopic matching, which chooses the best pairs in each round, rather than waiting for a better choice.

Formally, our matching algorithm is stated as follows:

Online Greedy Matching: The matching is performed periodically every T minutes. In each round, the matching is achieved by a greedy mechanism using only edges with weights greater than or equal to a threshold τ. The greedy mechanism constructs a matching by adding the edges with the highest weight one after another, until there are no more unmatched pairs with edges between them.

Baseline Matching: We compare our matching algorithm with a baseline matching algorithm in the Choices of Parameters subsection. In this algorithm, we assume that it knows the entire future of the graph and that it calculates the maximum weight matching over all rounds simultaneously in an offline fashion after pruning the edges with weights below the threshold τ. The maximum weight matching can be efficiently calculated using the Hungarian method, which is an optimization algorithm that is commonly used in transportation problems (Kuhn, 1955).

5. Deployment and results

In order to fully understand the CountryRoads system and our assumptions, we deployed the system in the years 2012, 2014, and 2015. In this section, we discuss the deployment details for each iteration of CountryRoads and provide some lessons learned through each of them. We first discuss the 2012 deployment, which was designed as a small pilot experiment (only 100 matching tuples were proposed out of roughly 1000 users). Then, we describe the changes that we incorporated into the system to deal with scalability, leading to 4992 proposed matches in 2014 (of which we estimate that about 5% successfully traveled together). Finally, we detail the deployment for Chunyun 2015, and explain the changes we made based on some lessons learned from the previous year, achieving an estimated success ratio of over 23% with 4777 proposed tuples.

5.1. Annual deployment

The first deployment in 2012 was meant to be a small-scale proof-of-concept deployment. At this early stage, the interface of CountryRoads consisted of only the SMS platform, and the matching process was conducted by volunteers who manually matched the drivers with passengers. In addition, the notification process was manual, which made the overall system very inefficient. In the end, the system only formed about 100 ridesharing tuples. Take-away lessons were that this approach was not scalable and delays were long. This understandably resulted in the low success ratio. Furthermore, many potential users had concerns regarding legal issues, which may explain the low number of participants.

After identifying the main problem in the previous deployment (*i.e.*, scalability), in 2014, we used SMS text messages to implement our matching algorithm to automatically notify users when a match was proposed. In addition, we incorporated the three interface platforms described in the *User Interface Module* section, namely, SMS, website, and smartphone (Android and iOS) applications. We also took some steps to promote CountryRoads using advertisements on the Web and national television to attract more users and build trust with the system (*i.e.*, government approval). We describe this in more detail in the *Advertisement Strategy* section.

As a result of all these steps, CountryRoads attracted several orders of magnitude more users than in the previous deployment: 6470 driver routes and 15,207 passenger routes were collected in 2014. For the online greedy-matching algorithm, based on initial simulations, we chose a middle-level threshold τ of 0.6 (which was shown to be the optimal value in Fig. 2) and a small matching recomputation period T of 3 min. In theory, these values should yield good matches, while not being too restrictive on users having the exact same origin, destination and travel dates. In total, CountryRoads proposed 4992 ridesharing tuples.

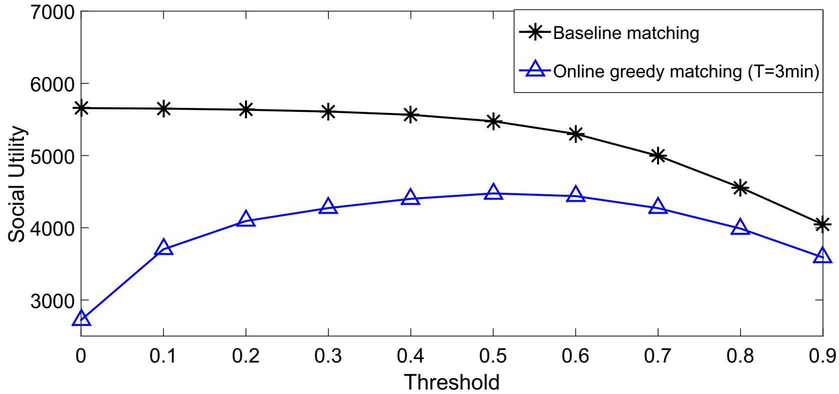

Fig. 2. The impact of the lack of knowledge of future information on the overall social utility maximization.

However, in practice this "optimal" threshold and strict time limit contributed to some poor matching suggestions. As a consequence, the estimated *success ratio* (number of tuples who actually traveled together over the total number of matches proposed by CountryRoads) was as low as 5.33% based on our survey of 244 passengers conducted after the 2014 Chunyun period. Basic deployment results from the 2014 Spring Festival travel season are summarized in Table 1. In addition, in the *Evaluation and Results* section, we further analyze the reasons for such a low success ratio, and the potential causes include the lack of user trust in their partners, and the phenomenon that most participants use our system as their last resort for Chunyun transportation.

In 2015, we made one major change to improve the success rate over the prior deployment. As indicated by the theoretical analysis, we increased the threshold τ to 0.9 in order to propose only matches with very similar route itineraries. This helped our system to better map the utility function of the risk-adverse users. During this third iteration of CountryRoads, we collected 9787 passenger routes and 7485 driver routes within the 25-day period from January 25 to February 18. In total, we proposed 4777 ridesharing tuples in 2015, and we interviewed 1013 passengers afterwards to determine whether they had successful travel with their drivers. Based on our finding of the 1013 tuples, 235 pairs ended up traveling together. The estimated success ratio is therefore 23.2%, which is an improvement of more than four times compared with the prior deployment. A summary of our main deployment results for the 2015 Spring Festival travel season is presented in Table 2.

5.2. User incentives

Advertisement played a major role of attracting new users in CountryRoads. Our major partner was the News Channel of China Central Television (CCTV), which is the predominant state-run television broadcaster in China. Since the project was introduced on CCTV News, an estimated 85 million viewers were notified. Subsequently, during the Spring Festival travel season, there were also many news reports about the Chunyun problem, which provided us good opportunities to promote our system and help those in need. We promoted CountryRoads both on our website and in television so that the lower-income people who had no access to Internet could hear about CountryRoads. We also cooperated with several big companies in Beijing (Tencent, Shanda, etc.) to promote CountryRoads among their employers.

While a small number of drivers are willing to share their seats and help others entirely out of good-will, while expecting no payback, for most drivers, monetary benefit would significantly increase their interest in ridesharing. In our survey, more than half of the drivers (56.82%, 50 out of 88) would split the gasoline cost and the highway toll with the passenger, and another 22.73% of the drivers (20 out of 88) would split the cost if the passenger is willing to pay. From the passenger's point of view, more than half of the passengers (57.14%, 32 out of 56) would split the cost with the driver and another 33.93% of the passengers (19 out of 56) are willing to pay if the driver requests. We further discuss the questionnaire in the *Evaluation and Results* section.

Table 1
Summary of the CountryRoads deployment for 2014 Spring Festival travel season.

Start date	January 3, 2014
End date	February 20, 2014
Duration	49 days
Number of drivers	6470
Number of passengers	15,207
Number of ridesharing tuples	4992
Success ratio (estimated)	5.33%

Table 2
Summary of the CountryRoads deployment for 2015 Spring Festival travel season.

Start date	January 25, 2015
End date	February 18, 2015
Duration	25 days
Number of drivers	7485
Number of passengers	9787
Number of ridesharing tuples	4777
Success ratio (estimated)	23.20%

Besides the fact that the drivers and passengers may reduce their travel expenses by sharing, we also provided subsidies for highway tolls to encourage user participation in 2015. We let the drivers decide whether they wanted to apply for the subsidy, and in 2015, about 20 drivers submitted applications.

For safety reasons, we required the users to complete a mobile phone number verification before using our system. In the event of traffic accidents and the accompanying liability, we cooperated with an insurance company and provided the users with free insurance. We also cooperated with a hospital to open a 24-h medical hot line so that the users could receive immediate medical instruction in case of emergency.

5.3. Estimation of user's utility

In a large-scale system such as CountryRoads, it is unrealistic for the users to report their utilities because of the large number of users. In practice, we therefore use the user's route information to estimate their utilities because the route information is the major factor employed to evaluate a ridesharing tuple. Specifically, we use the following four factors to estimate the utility:

(1) Origin deviation ΔO: the distance between the origin cities of the passenger and the driver;
(2) Destination deviation ΔD: the distance between the destination cities of the passenger and the driver;
(3) Detour distance *Detour*: the extra distance that must be travelled by the driver if he is to pick up and/or drop off the passenger before arriving at his own destination;
(4) Departure date deviation ΔT: the difference in departure dates of the passenger and the driver.

The origin deviation and destination deviation are not sufficient to evaluate the proximity of the passenger's and driver's routes because the different directions of the routes may cause different detour distances for the drivers, even in cases involving the same origin deviations and destination deviations. In practice, the distance between any two cities is calculated using free map services such as Google Map or Baidu Map. We adopt a utility estimation formula with the following form:

$$U_d(p) = U_p(d) = \frac{1}{1 + e^{(\alpha\Delta O + \beta\Delta D + \gamma Detour + \delta\Delta T)/\text{driver's mileage}}},$$

where $\alpha, \beta, \gamma, \delta$ are the weights of the four factors, and the *driver's mileage* is used to eliminate the variation between trips with different mileages. This formulation is similar to a Logistic function (Bod and Hay, 2003). The logistic function is widely used to convert the input factors into a probability. In our case, the logistic function is used to model the proximity of the passenger's and driver's routes, which may be affected by origin deviation, destination deviation, detour distance, and departure date deviation. The intuition behind it is that the more closely aligned is the passenger's route with the driver's route, it becomes easier for them to share a trip. In practice, we choose $\alpha = 1.5, \beta = 1, \gamma = 1, \delta = 1$ empirically to emphasize the origin deviation between the passenger and the driver, based on the fact that it would be more difficult for the driver to find and pick up the passenger than to drop off the passenger because the driver may not be familiar with the passenger's workplace, while the passenger can guide the driver to his/her destination. The choice of empirical values is based on this fact, which is derived from several users' suggestions. The drivers' mileage on the denominator is used for normalization as we found in practice that longer trips tends to have larger deviations between each other and we want to eliminate this influence. While α, β, and γ have no units, δ has a unit as km/day.

5.4. Choice of parameters

In this section, we discuss the parametric choices that are used in the online greedy-matching algorithm. Recall that in 2014, we adopted a middle-level threshold of 0.6, and increased it to 0.9. We evaluate how this change affects the efficiency, success ratio, and user's waiting time.

5.4.1. Impact on efficiency

To show the impact of different thresholds on the overall social utility, as discussed in the *Chunyun Ridesharing Matching Problem Formulation* section, we performed simulations using the 17,272 pieces of travelers' route information obtained in

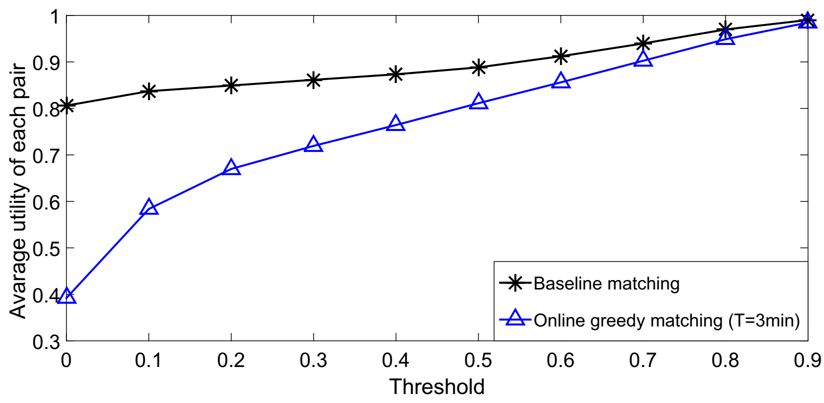

Fig. 3. The impact of different thresholds on the average utility of each matched pair.

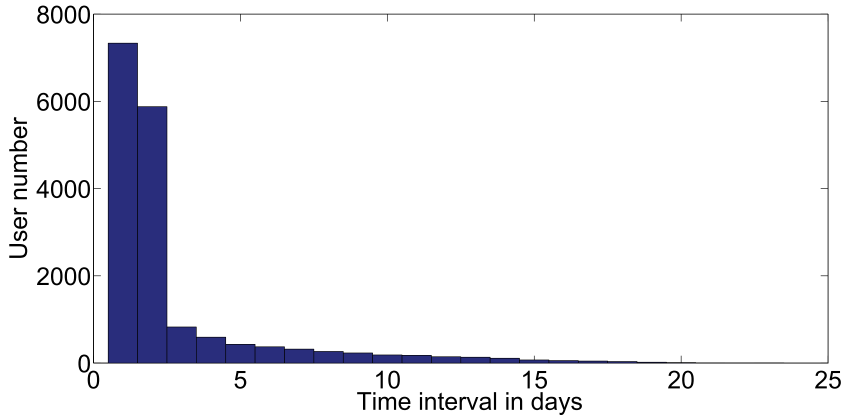

Fig. 4. The distribution of the time intervals between the registration time and the departure date of the users in the 2015 Chunyun period shows that participants use our ridesharing system as their last resort.

2015, and compared the efficiency of the online greedy-matching algorithm with that of the baseline matching algorithm in Fig. 2. From Fig. 2, we find that with a threshold of 0.6, the online greedy-matching algorithm generates the best outcome in terms of efficiency. With a lower threshold, the online greedy-matching algorithm may choose the matching pairs with low utilities and prevent the likelihood of choosing a better matching pair later. With a higher threshold, the matching algorithm may not be able to find an eligible matching pair. Furthermore, because the baseline matching algorithm knows the entire future, it always performs better than the online greedy-matching algorithm.

As the threshold increases, the average utility of each matched pair increases, as shown in Fig. 3. From our deployments, we found that the risk-adverse users during the Chunyun period adjusted their preferences to require a higher threshold.

5.4.2. Impact on success ratio

In the 2014 Chunyun period, we adopted a middle-level threshold of 0.6. Even though the threshold of 0.6 achieved the best overall social utility, the success ratio was about 5.33%. After changing to a high threshold of 0.9 in the 2015 Chunyun period, we managed to improve the success ratio to about 23.20%. This suggested that the users were more willing to deviate from their path by a small amount, and that the match was more likely to succeed when the utilities were much higher than previously expected.

We further evaluated the time intervals between the date on which the user signs up for CountryRoads and the departure date reported by the user. The distribution of the time intervals in days is shown in Fig. 4. We find that most of the users registered either one day or two days ahead of their departure dates. Because in China, train or flight tickets can be booked months ahead of the travel date, this result supports our assertion that most of the users may have been using CountryRoads as a backup plan in the last few days before they travel.

Table 3
Waiting time of the drivers and passengers in 2014 and 2015.

	2014 (days)	2015 (days)
Driver	0.74	2.99
Passenger	2.93	2.07

5.4.3. Impact on waiting time

The waiting time indicates the time interval between the time at which the users submit their route information and the time at which they receive the matching result. In Table 3, we show the average waiting time of matched drivers and passengers in 2014 and 2015.

Intuitively, a higher threshold would cause a longer waiting time because it would be harder to find an eligible matching pair. Therefore, the waiting time of the drivers and passengers should be longer in 2015 because of the increased threshold. In addition, in 2014 there is a higher passenger-driver ratio (15,207/6470) than 2015 (9,787/7485), and this results in a shorter waiting time for the drivers, at the expense of a longer waiting time for the passengers.

6. Lesson learnt and discussion

After the deployment of CountryRoads, we conducted a small anonymous questionnaire survey among some of our users to learn more about their preferences and additional needs. In 2015, we surveyed a total of 56 random passengers and 88 random drivers. This section details the feedback received from our participants (summarized in Table 4), which we compare with some observations extracted from our latest deployment's user database.

Table 4
Summary of the questionnaire survey results we obtained from 56 passengers and 88 drivers after the 2015 Chunyun period.

Question statement Choices*	Passenger (%)	Driver (%)
Q1: Would you share highway toll and fuel fees with the driver (or passenger)?		
A. Yes.	57.14	56.82
B. It depends on the driver's (or passenger's) request (or willingness).	33.93	22.73
C. No.	7.14	18.18
Q2: How flexible is your desired departure date?		
A. Must be the same day.	21.43	43.18
B. One day earlier or later is fine.	12.50	5.68
C. More than one day difference is fine.	66.07	48.86
Q3: If your destinations are about 100 km apart, would you travel with the driver (or passenger)?		
A. Yes, only if the driver could drop me off at home (I would send the passenger home first).	19.64	35.23
B. Yes, I would use other transportation means from the driver's destination (I would help the passenger transfer to another vehicle).	51.79	35.23
C. No, it is troublesome.	28.57	26.14
Q4: How fast do you want to get a matching suggestion after you submit your route information?		
A. As soon as possible.	12.50	22.73
B. Only tell me once there is a suitable driver (passenger).	71.43	65.91
C. One update per day.	16.07	9.09
Q5: What factors do you care about when sharing rides with others? (Multiple Choices)		
A. The driver's (passenger's) age and gender.	30.36	56.82
B. The driver's driving experience in years (whether the passenger can drive or not).	73.21	22.73
C. The car's condition (the amount of the passenger's luggage).	55.36	72.73
D. The driver's (passenger's) profession.	19.64	20.45
E. The driver's (passenger's) interests.	14.29	17.05
F. Other factors.	7.14**	4.55***
Q6: Would you provide the following information to the driver (passenger)? (Multiple Choices)		
A. Your name.	62.50	46.59
B. Your age.	46.43	50.00
C. Your gender.	57.14	63.64
D. Your job.	50.00	46.59
E. Your interests.	28.57	30.68
F. Can you drive or not (your driving experience in years).	67.86	56.82
G. The amount of luggage (the car's condition).	73.21	47.73

* When there were differences in the driver and passenger responses, the driver's statement is surrounded by parenthesis.

** Two passengers mentioned the driver's personality, one passenger mentioned the driver's attitude towards ridesharing, and another passenger was concerned about safety.

*** Two drivers were concerned about whether the passenger would smoke in the car, one driver was concerned about the passenger's criminal record, and another driver mentioned the passenger's personality.

In particular, we note the following findings from our survey.

- As discussed in the *User Incentives* subsection and from Q1, most of the users would be willing to share highway tolls and fuel expenses, which is the main reason for which participants desire to engage in a ridesharing service.
- From Q2, the desired departure date was flexible for most of the users, which differentiates CountryRoads from public transit modalities such as train or air, whose schedules are fixed and difficult to change. This could potentially improve future systems to reduce restrictions on time differences between pairs.
- From Q3, most of the users were willing to accept situations where there may be some deviations between each other's routes when sharing a ride.
- From Q4, most of the users would prefer one suitable match rather than multiple trials, which indicates that the focus should be on realizing improved matching as opposed to relying on user rejection of poor matches.
- From Q5 and Q6, the users are concerned about personal information besides the route information. As we show below, the availability of personal information and sex information would affect the success probability of a ridesharing tuple. The survey responses also indicates that the driving skill of the passenger would be an important factor.

Fig. 5 shows the impact of the amount of information provided by the driver in relationship to the success rate of the system. In particular, information pertaining to car registration, driver's license picture and an avatar significantly increase the success rate of the match leading to an actual shared trip. This suggests that the system can build up trust as more information is presented by the driver. We suspect that the users of this system may be more open to technology and comfortable with avatar as an online identity verification tools.

Similar results can be seen from the rider provided information vs. the success rate (Fig. 6). Most of the information provided increases the success rate. It is interesting to note that there is a slight decrease in the success rate when gender information is provided.

The effect of the gender on the success rate is shown in Fig. 7. The driver-rider pair is shown on the horizontal axis and the success and failure rates are shown on the vertical axis. The success rate increases significantly for male drivers and female riders. We suspect that the majority of the drivers are single male drivers, and may be motivated by matches with members of the opposite sex, thus explaining the high rate. However, while the initial survey suggested that female–female pairs would be considered safer for female riders, this appeared not to be the case. It is possible that this is due to the low number of female drivers (13 successful pairs with only 2 female–female pairs), when compared to 214 male drivers.

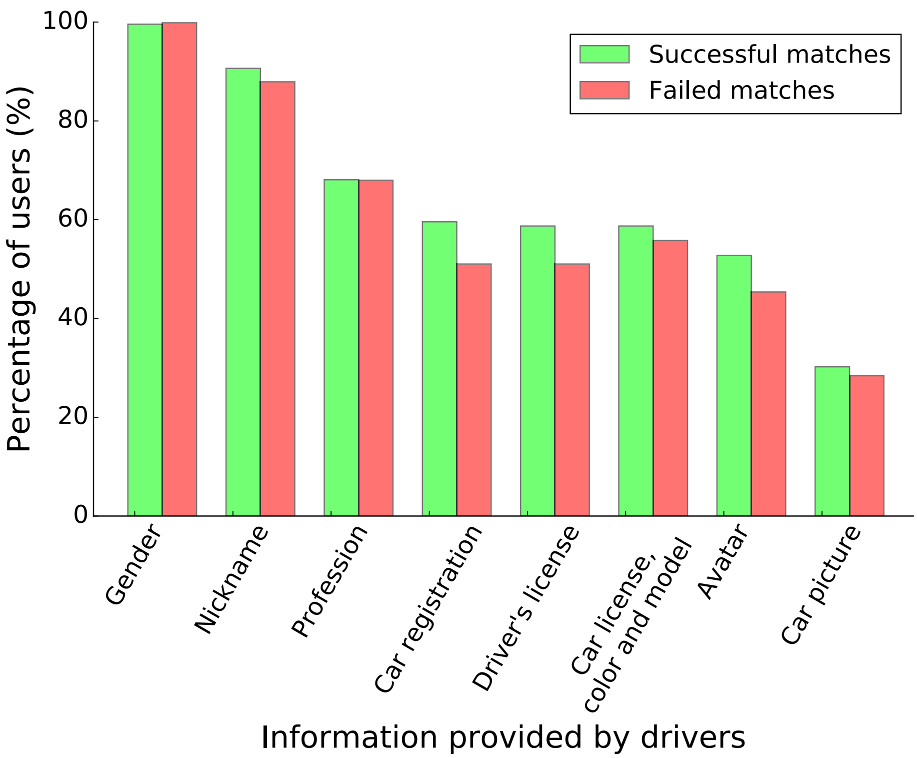

Fig. 5. The amount of personal information provided by the driver affects the success of the rideshare experience.

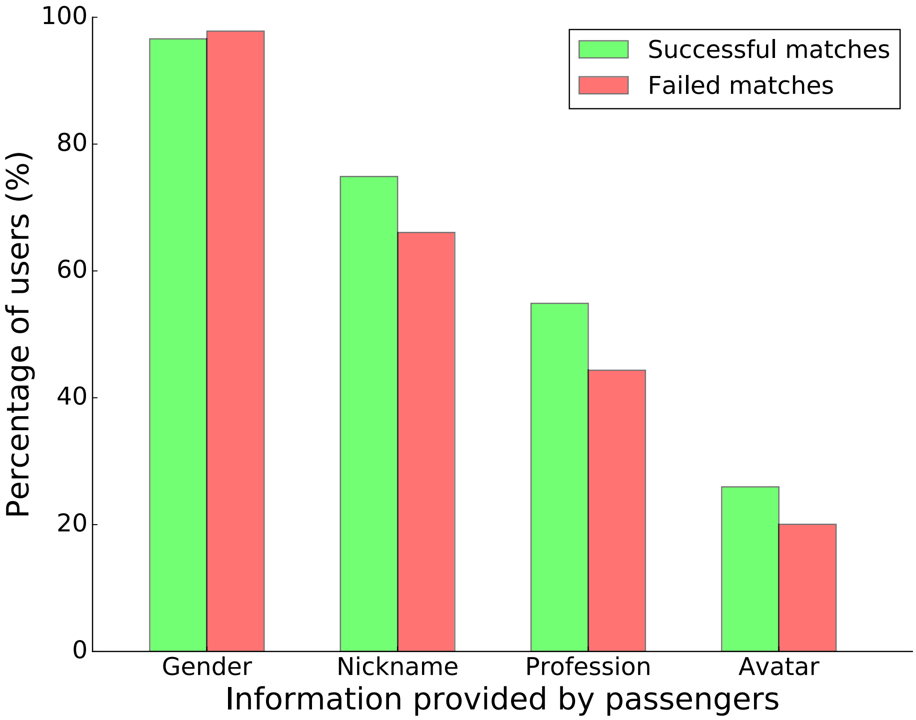

Fig. 6. The amount of personal information provided by the passenger affects the success of the rideshare experience.

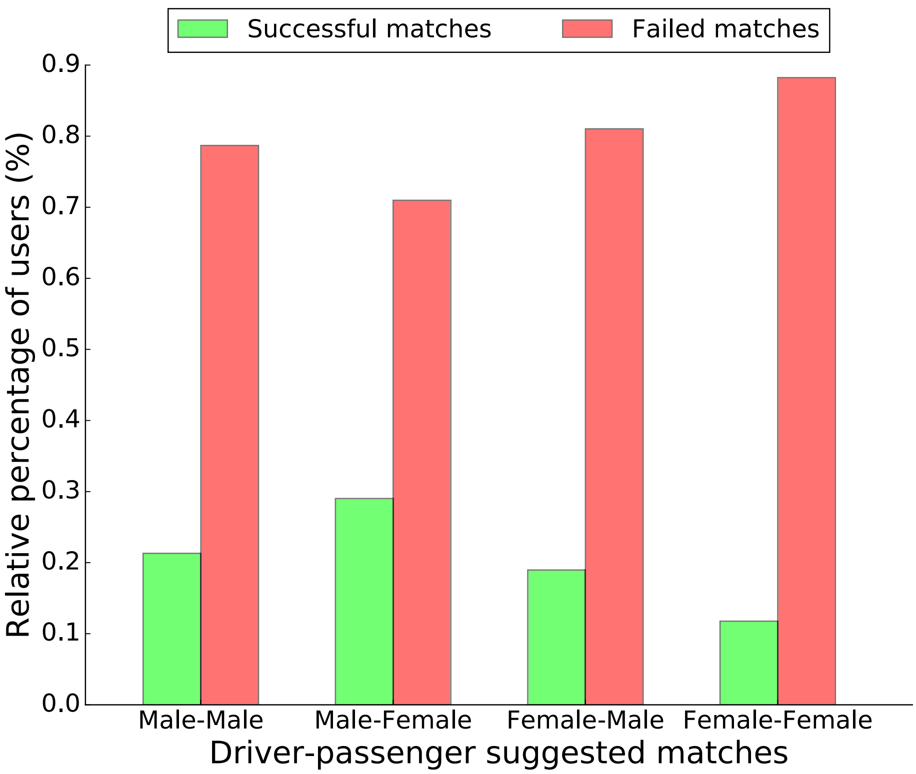

Fig. 7. Effect of gender in pairing success rate.

7. Conclusion

In this paper, we present CountryRoads, which is a one-shot low-information ridesharing system, to address the transportation shortage that exists during the Chinese Spring Festival travel season. We model the ridesharing problem as an online bipartite matching problem and implement an online greedy-matching algorithm in CountryRoads. In our paper, we present our design choices, analysis, and lessons learned. To evaluate our system, we deployed our system in 2012, 2014 and 2015, and we observed that the performance of the system improved each year. In 2015, CountryRoads was able to attract 17,272 users and resulted in 4777 ridesharing tuples, which was a significant improvement compared with about 100 tuples in 2012. We also managed to achieve a success ratio of 23.20%, which was a great improvement from 5.33% in 2014. We also present the lessons learned from the deployment experiences and discuss the factors that contribute to a successful ridesharing experience.

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