Collaborative activity-based ridesharing

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Abstract

A new ridesharing model called *collaborative activity-based ridesharing* is proposed to enhance not only overall matching rates but also the matches between preferred ride partners. By coalescing the merits of two recently suggested innovative ridesharing models – the *social network-based ridesharing* and the *activity-based ridesharing* – the new model leverages people's preference to their social networks and the space-time flexibility of daily activities to improve the matching outcome. The capabilities and advantages of the proposed model are justified by a group of agent-based simulations in a realistic study area. The influence of geography on the match outcome is discussed in particular.

Keywords: Ridesharing algorithm, Collaborative travel, Social networks, Time geography, Spatio-temporal index

1. Introduction

Ridesharing, defined in the scope of this paper, is a transport mode that harnesses both private cars and taxis to combine two (groups) of travellers

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into the same vehicle in an ad-hoc manner, if all or part of the two groups' travels are overlapped in space and time. The ad-hoc manner means rides are matched on variable demands from day to day, or strictly speaking, on real-time demands instead of by pre-arrangement. With its potentials of reducing traffic volume, energy consumption, and travel cost compared to private cars, ridesharing arguably is promising to become popular among the public (Ferreira and D'Orey, 2015). Despite being an attractive concept, ridesharing does not guarantee to encourage uptake.

The challenges of switching to ridesharing are many folds (Amey, 2010), including economic, behavioural, institutional, and technological aspects. Ferguson (1997) analysed the reasons why carpool suddenly declined in the US in the 1980's. He summarised physical (urban form), sociodemographic (auto availability, real marginal cost of motor fuel, age and education, and gender and lifestyle) and economic (fuel cost) factors. While some of the factors still play a role, the story for the internet age seems more complicated when technology can make social changes. Population growth, urbanisation, the wealth increase, and the indicated lifestyle and social status beyond rational economic decisions continue retaining auto ownership and making congestion worse[1]. Meanwhile, the internet and shared economy offer the potential to reduce car ownership[2]. While the old factors retaining car owners may still exist, this paper focus on reducing the barriers switching to ridesharing by proposing a refined *technological* solution.

People are reluctant to share with strangers for safety reasons or to sacrifice time for detour (Amey, 2010; Koebler, 2016; Chaube et al., 2010; Wessels, 2009). Consequently, the uptake potential of ridesharing (Santi et al., 2014; Bischoff and Maciejewski, 2016) might be exaggerated. The two issues of concern are trust and spatio-temporal flexibility. Social ties have an impact on peoples ridesharing decisions: higher willingness of ridesharing and higher de-

[1]https://www.forbes.com/sites/quora/2017/06/22/what-will-car-ownership-look-like-in-the-future
[2]http://www.businessinsider.com/no-one-will-own-a-car-in-the-future-2017-5

tour tolerance are granted to closer social acquaintances (Chaube et al., 2010; Wessels, 2009). Relying on real-life social networks for ridesharing, on the other hand, might threaten the match rate by refusing offers from *nearby* strangers. The outcome is contingent on the spatial distributions of travel demands and of social networks (Wang et al., 2017). However, there is a potential to enlarge the candidate choice set. Given that many daily activities (e.g., grocery shopping) are flexible in terms of space and/or time, travel destinations can be chosen flexibly to fit into ridesharing schedules (Bhat and Koppelman, 1999; Miller, 2005). Opening the choices of alternative destinations hence offers a potential way to enhance the rides between friends: if a shared ride with a friend was originally not feasible, an alternative destination can reverse the situation. Even if there is still no feasible ride from a friend, alternative destinations can still potentially increase the overall ridesharing rates by matching more strangers within shorter distance.

The main contribution of this paper is to propose a new solution for ridesharing to tackle trust and detour flexibility at the same time. In particular, the paper addresses the influence of spatial densities and distributions of social network links and of travel demands, as the basis to reduce detour while pairing people with some social ties. The proposed approach, *Collaborative Activity-based Ridesharing* (CAR), is a combination of two previously suggested innovative ridesharing models: *social network-based ridesharing* (Wang et al., 2017) and *activity-based ridesharing* (Wang et al., 2016). CAR inherits the **trust-based** strategy of social network-based ridesharing with heterogeneous detour tolerances and willingness to share a ride with friends versus non-friends. Social network contacts are referred to as *friends* hereafter, defined in the sense of ridesharing collaboration rather than the meaning of "friends" in daily life. In terms of **flexibility**, CAR expands ridesharing opportunities by considering alternative travel destinations for similar travel aims based on given space-time budget in the same manner as activity-based ridesharing. The combination of the two enables a spatio-social dual index to speed up the search for ride matches.

The hypothesis is that CAR can significantly increase the overall matching rate compared with social network-based ridesharing, and significantly increase the number of matches with friends compared with activity-based ridesharing.

Based on realistic travel demand data, an agent-based simulation for ridesharing pre-planning of a day is built to implement the CAR model. The simulation is run with the pre-generated social networks of small world topology embedded into space. Two spatial structures are investigated in the simulation: random distributions and distance-decays. The simulation is run with multiple methods: trip-based ridesharing, social network-based ridesharing, activity-based ridesharing, and CAR. With different geographic configurations of the underlying social network, results from each simulation are compared to investigate which algorithm comes out as the best in terms of detour cost, the numbers of overall matches and of matched friends. A special focus of the discussion is on the geographic characteristics of the study area, of the population distribution, and of the social network distribution. The findings yield implications on how geography affects the performance of CAR.

The paper is structured as follows: Section 2 is a review of the existing ridesharing models and how geography inspires new ridesharing models. Sections 3 and 4 are the model specification and implementation, followed by the results in Section 5 and discussions in Section 6. Major conclusions and future indications are given in Section 7.

2. A review of ridesharing and its potential

According to the review by Furuhata et al. (2013), ridesharing has its origin since last century and has been quickly developed recently. Though acknowledging the ambiguity of the definition, the authors defined *ridesharing* as "*a mode of transportation in which individual travellers share a vehicle for a trip and split travel costs ... with others that have similar itineraries and time schedules*" (p2, (Furuhata et al., 2013)). They foresaw ridesharing to increase its usability by *on-demand* ridesharing, which emphasises the importance of trust and flexibility due to the lack of pre-arrangement of rides. Despite multiple algorithmic improvements for ridesharing, including real-time en-route planning (e.g., Agatz et al. (2011); Ma et al. (2013); Bischoff and Maciejewski (2016)) and multi-hop ridesharing (Drews and Luxen, 2013), the mainstream ridesharing solutions still fall short in two ways: 1) they ignore the riders' socio-psychological preferences and motivation for ridesharing (Chaube et al., 2010; Koebler, 2016; Wessels, 2009), which results in a low rate of ridesharing compared with its full potential (Amey, 2010; Santi et al., 2014; Bischoff and Maciejewski, 2016); and 2) almost all of the applications are trip-based, with specified fixed origin/destination pairs and thus low flexibility for destination choices.

Trust measures in ridesharing nowadays are mainly captured by peer-rating systems widely applied by such platforms as Uber and Airbnb. Such peer economy, however, is confronted with cognitive challenges due to the lack of legitimacy regularity (i.e., formal rules to regulate the business as traditional corporations), which deteriorates as the platforms grow (Witt et al., 2015). While a peer-rating system provides more information for customers decision-making, it does not solve the problem, for example, that people feel unreliable and unpredictable in their ridesharing schedules. Such bad feeling as lack of reliability is exacerbated when people have bad temper with a stranger (Koebler, 2016).

As a technical solution to the issue, several algorithms have incorporated social networks as a constraint in ridesharing matching. For example, Li et al. (2015) proposed a social network-based group query that matches rides *only* among social network connections. Bistaffa et al. (2015) provided a similar solution. However, these applications are exclusive to friends while missing any offer from a stranger. A possible consequence is a lower matching rate due to less opportunities, compared to non-social ridesharing, which was not further investigated by those authors. Since people accept detour costs only to an acceptable limit (Milakis et al., 2015; He et al., 2016), pursuing a ride *only* with friends can be prohibitive. In contrast, the recently proposed *social network-based ridesharing* (Wang et al., 2017) assigns heterogeneous detour tolerances and ridesharing willingness to different ridesharing partners, including not only friends, but also strangers. In this way, matches between strangers remain possible but matches between direct or indirect friends are prioritized even at higher detour costs. Notwithstanding, the chance to increase ridesharing rates still depends on the spatial distribution and the density of these social networks (Wang et al., 2017).

The *activity-based ridesharing* (Wang et al., 2016) based on time geography might be a solution to the low matching rate of ridesharing by offering alternative destinations for the same travel purpose (namely, the activity at the destination (Bhat and Koppelman, 1999)). Time geography is a set of theories to model accessible resources and feasible human travel behaviours subject to given space-time budgets. The concept can be traced back to the 1970's (Hägerstrand, 1970), and has later been formalised by computational implementation models (e.g., Miller (2005); Song and Miller (2015)). Time geography induces activity-based approaches (Ellegård and Svedin, 2012) by which multiple locations are selected as candidates to perform an activity (Justen et al., 2013; Fang et al., 2011). Many previous studies have concentrated on adopting time geography for joint activities (Arentze, 2015; Miller, 2013). The space-time constraints in finding accessible locations (for activities), however, are only part of the space-time constraints for a bundled travel containing flexible activities between spatially or temporally non-flexible activities. The latter apparently has stronger constraints requiring matches for the whole movement.

Besides the temporal constraints, the spatial distribution of travel demands and social networks affect matching rates. Tachet et al. (2017) found, regardless of specific geographical contexts across multiple cities, a universal mathematical law between the *shareability* (the maximum number of trips to be possibly shared) of rides and a dimensionless quantity composed of detour tolerance and the density of trips. However, their argument falls short in a few aspects: 1) They do not represent the heterogeneity in travel demand distribution in reality, assuming evenly distributed trips in their simulation and investigating only the urban centres of multiple cities (where population spreads evenly and densely). 2) They estimated an optimistic potential of ridesharing but overlooked people's willingness to share rides that varies with social parameters (degrees of friendship, perceived costs of detours). Vanoutrive et al. (2012) investigated the influential factors for carpooling, a pre-organised ridesharing. They found that different travel purposes (e.g., to home versus to workplace) bounded with their corresponding travel direction yield different carpool rates. With social networks weighing in, ridesharing chances are implicitly shaped by the spatial distribution of social networks. For a monocentric urban form, social networks contribute to higher overlap of trips at outskirts than random pairs, while random encounters in city centre might introduce more shared rides with strangers (Wang et al., 2015). The spatial embedment of social networks is also associated with the underlying function of places and thus travel purposes (Xu and Belyi, 2017). The suggested CAR model, therefore, behaves according to the geography of social networks and travel demands.

3. The *Collaborative Activity-based Ridesharing* (CAR) model

The *Collaborative Activity-based Ridesharing* (CAR) model is based on the integration of social network-based and activity-based ridesharings: utilising social networks to cut down unnecessary searches and leveraging alternative destinations to increase preferred matches. The workflow of CAR is elaborated in Section 3.1, of which the core part is a spatio-social index based on time geography theory (Section 3.2). The influence of spatial distributions of social networks and travel demands is discussed in Section 3.3.

3.1. The workflow of CAR

The workflow of CAR is presented in Figure 1, developed from Figure 1 in Wang et al. (2016). The major modification is the introduction of the *social network file* and the *spatio-social index* that affects the matching procedure in module 3 (*M3*, see the bullet point below). This workflow is applicable to a full day pre-planning model for ridesharing rather than a real-time one. A full day starts at 4am (when the travel density is the lowest of a day) and runs

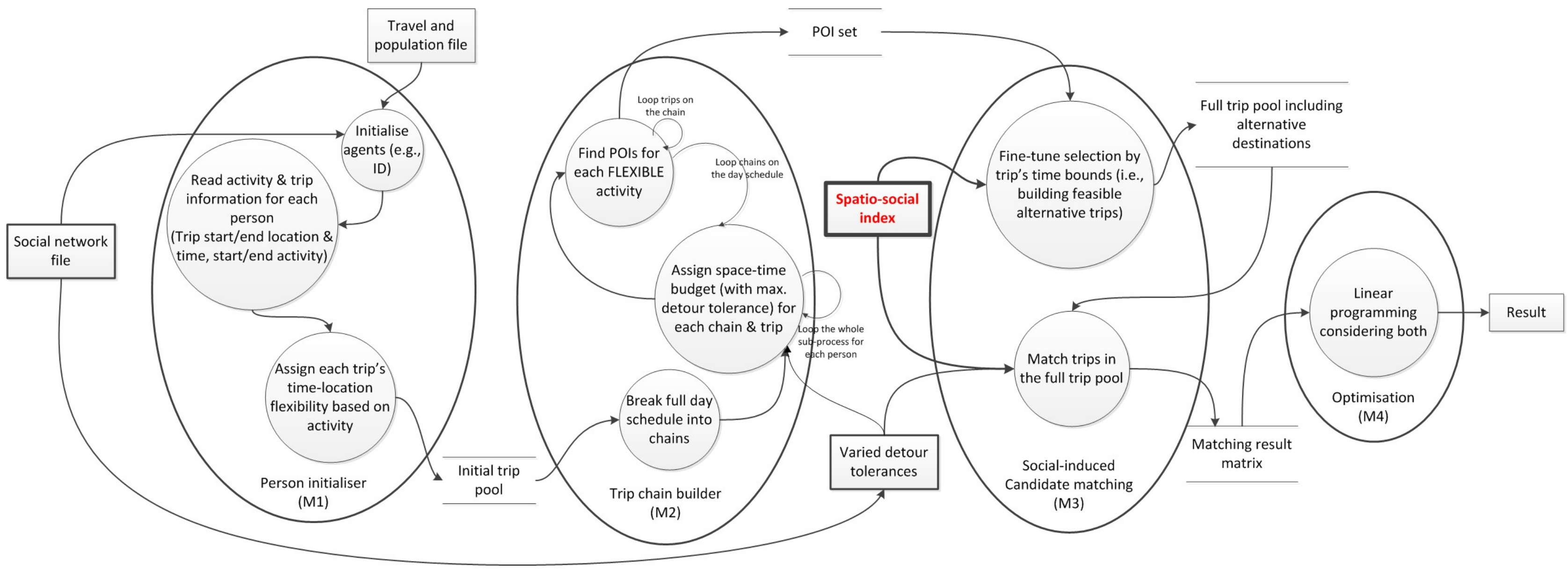

Figure 1: Workflow of the CAR model.

24 hours. The model is incorporating activity-based ridesharing (Wang et al., 2016) and social network-based ridesharing (Wang et al., 2017). The activity-based ridesharing model searches for alternative destinations of a similar travel purpose (activity at the destination) satisfying a person's budget on each travel to enlarge trip choices. Alternative destinations are represented by Points of Interest (POIs) in the study area for each type of travel purpose. For instance, rather than simply going to **a specific** *supermarket A*, this algorithm might find feasible travels to **any** supermarket within 10 minutes' drive from a current location and 20 minutes from the next fixed destination after the grocery shopping. It hence expands ridesharing choices. The activity-based approach is encoded in CAR with social network-based ridesharing, which renders higher detour tolerance to closer social contacts (e.g., a direct friend) while lower detour tolerance to a less familiar person (say, a stranger). CAR proceeds in the steps shown below:

- Module 1 (M1): At the beginning of each day, the model collects the whole population's full day travel activity intentions and the social network structure permuted for the population.

- Module 2 (M2): The model divides each person's full day schedule into trip chains, i.e., series of trips with short stop time at the destinations (Wang et al., 2016; Thill and Thomas, 1987). A maximum time budget is assigned to each trip, which is used to retrieve the POIs within that budget.

- Module 3 (M3): CAR fine-tunes the alternative destinations from a certain category of POIs, builds alternative trips between activities, and matches trips subject to the space-time budgets to every partner in the same car. Different from the activity-based ridesharing that equivalently matches any pair, CAR renders priority to closer friends as the social network-based ridesharing does. The *spatio-social index* (Section 3.2) is introduced as a filter to efficiently decide 1) the set of accessible POIs given a type of activity and a type of social network degree; 2) the feasible trips to be matched given the spatial and social constraints.

- Module 4 (M4): Input the potential matching pre-computation matrix into binary integer programming to decide the final matching. The optimisation maximises the number of matches subject to space-time budget and detour tolerance depending on the social network.

3.2. Time geography and the Spatio-Social Index

CAR introduces a *spatio-social index* (SSI) inspired by the computational entities in time geography. A *space-time prism* is a geometric entity delineating the boundary of an approachable area given the space-time budget (e.g., Miller (2005)). A *potential path area* (PPA) is the projection of the prism onto a 2-dimensional plane (Miller, 2005). The prism itself encoding time is called *potential path space* (PPS). SSI can be regarded as a PPA at a coarser spatial resolution for fast retrieval. Taking advantage of the heuristic from social networks, SSI speeds up the search for: 1) feasible POIs to build alternative travels, and 2) potential trips to be matched satisfying social-network-dependent time budgets.

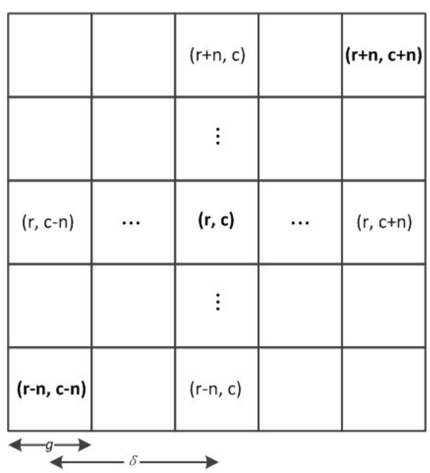

Figure 2: The SSI and the 8-connected n-neighbourhood.

SSI is a gridlock index that partitions the whole area into grid cells (Figure 2), where each cell is a square with edge length g. The geographic location $(x,\, y)$ of a point p is projected to its corresponding grid gi at row r and column c, as long as p falls inside that cell. The operation to find the index of a point is denoted as Eq. 1. A POI has a unique gi, while a trip has one each for its origin and destination. When querying a feasible potential trip, at least one of the origin or the destination should fall inside the approachable grids. Note that the SSI is just a coarse filter.

$$I(p) = gi \tag{1}$$

Single-constraint query. Given a time budget (δ in geographic space and n in the gridlock space, where $\lceil \delta \rceil = n * g$) as the total time for shortest travel and detour, SSI retrieves all the 8-connected n-neighbourhood cells of the centroid query point (Figure 2), if there is only *one* constraint (e.g., time and location constraints at the origin *or* the destination). These cells are utilised to query points fall within them. The operation of searching 8-connected δ-neighbourhood is defined by Eq. 2.

$$I_\delta(p) = I(p) \bigoplus n \tag{2}$$

Double-constraint query. SSI works in a derived way from the single-constraint query, searching the accessible range between *two fixed* points p_1 and p_2 (with fixed space-time constraints), for instance, leaving workplace no earlier than 5pm and getting back home no later than 6:30pm. SSI generates a δ-neighbourhood for both constraint points, and returns the cells in the overlapped area $I_\delta(p_1) \cap I_\delta(p_2)$, ignoring the time dimension. In the case of the constraints by *one* trip's origin and destination, the δ is the same for both ends given a particular trip. In Figure 3, the prisms $\triangle \mathrm{OO_1O_2}$ and $\triangle \mathrm{DD_1D_2}$ are two identical PPS's by the single constraints from the origin and the destination, respectively. The PPA is the intersection of the projections of prisms $\triangle \mathrm{OO_1O_2}$ and $\triangle \mathrm{DD_1D_2}$, i.e., $\mathrm{PPA} = \mathrm{O_1O_2} \cap \mathrm{D_1D_2} = I_\delta(O) \cap I_\delta(D)$. The red rectangle, which is PPA times the time duration, is the bounding box of the accurate double-constraint PPS

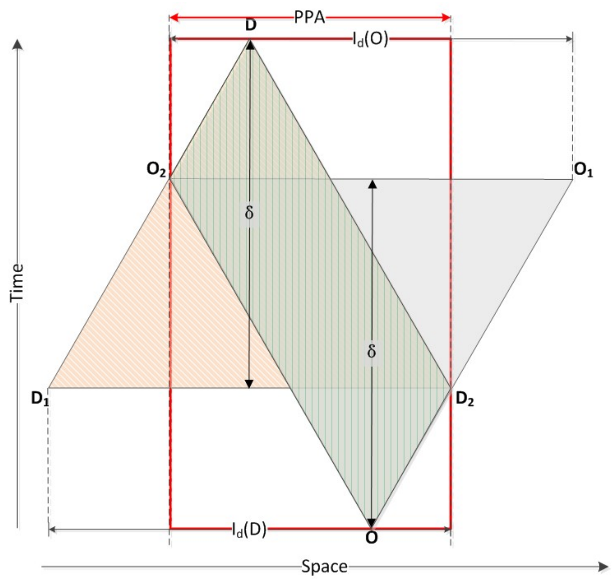

Figure 3: The SSI overlapped area and PPA in time geography
(space is simplified as one dimension; $\mathrm{I_d(O)}$ is $I_\delta(O)$, $\mathrm{I_d(D)}$ is $I_\delta(D)$).

(the green prism $\mathrm{OO_2DD_2}$).

Deciding the time budget δ. SSI decides δ depending on the degree of separation e in a social network so that a higher detour tolerance $d = T(e)$ (in percentage of the shortest travel cost) is granted to topologically closer friends. $T(e)$ is inversely correlated to e, which is specified later in Eq 4. Particularly, direct friends ($e = 1$) get the highest detour tolerance, followed by indirect friends ($e = 2$) and finally strangers ($e = \infty$). The time budget is determined by the detour tolerance and the shortest travel time (t_s):

$$\delta = (d + 1) \cdot t_s = (T(e) + 1) \cdot t_s,\ e \in \{1,\ 2,\ \infty\}. \tag{3}$$

Because δ is the maximum accessible range from the current point, both single-constraint and double-constraint queries must return the grids covering the upper bound of travels. Such design guarantees that the grid index is unlikely to cut off possible selections. The returned grids do not compose an accurate PPA since the ridesharing matching will continue to refine the selections (POIs or trips) within those cells, but is sufficient to cut down the computational burden.

3.3. The influence of spatial distribution

Wang et al. (2017) discussed the varying results in social network-based ridesharing from different spatial settings of the social networks. The parameters describing social networks are the topological factor (the average degree of connections, denoted by $\bar{n}$) and the spatial factor (spatially aggregated or random distributions of nodes). In their observation, the likelihood to share rides is not monotonic with the density of rides, which means increasing the spatial density of rides may even result in a lower matching rate due to competition within a certain distance range. On the opposite, low density of friendships might put the efforts searching for friends in vain. The spatial density of friendships therefore is correlated with the success of ridesharing with social contacts.

The spatial configuration of social networks obviously affects the density of friends in space. Ridesharing social networks emerge from historical travel experience, which in reality may not yet be known. Thus, ridesharing social network has to be set for investigating the behaviour of these models. In this work, the classical small world network is applied as the topological structure of each social network. The spatial configuration is set on top of the small world structure in two ways, a randomly distributed network and a spatially aggregated network (following the distance decay function Eq.6). The clustering of any generated social network is likely to be in favour of matching friends. In addition, the topological structure contributes to spatial density of friends as well. Higher node degrees (more friends) on average lead to higher density of friendships in space, given the same study area. To compare the difference in ridesharing outcomes from varied spatial distributions of social networks, this model runs four combinations of friendship degrees and spatial configuration (Section 4).

4. The comparison of different models and empirical studies

To testify the advantage of CAR over alternatives, a group of control experiments with different ridesharing models are run based on a realistic travel survey dataset in Yarra Ranges, Victoria. Composed of several suburbans located east and northeast to Melbourne, Yarra Ranges has a heterogeneous landscape with hills and rivers, and thus highly clustered spatial distribution of population. The area is selected due to its lack of convenient public transportation, especially for the last-mile problem.

The travel demand and activities are adopted from the processed datasets by Jain et al. (2017) based on the Victorian Integrated Survey of Travel and Activity (VISTA) 2009-2010 (Victorian Department of Transport, 2011). VISTA dataset includes *travel person ID, origin/destination locations, origin/destination timestamps, origin/destination activities,* and *duration of the activity*. The SSI grid is set with a unit of 1 minute's drive for the simplicity of calculation.

There are four ridesharing models investigated and compared. All the models are implemented by Repast Simphony (`https://repast.github.io/repast_simphony.html`). Table 1 lists the characteristics each model considers. Social network-based ridesharing (Wang et al., 2017) and activity-based ridesharing (Wang et al., 2016) are abbreviated by SNeRs and ABRA, respectively. Trip-based and ABRA models are run with the lowest and the highest detour tolerances ($d = 10\%, 30\%$) each time as baselines. SNeRs and CAR, in contrast, adopt varied detour tolerances and ridesharing willingness as a function of the degree of separation e in a social network (Eq.4). Previous studies (Wessels, 2009; Chaube et al., 2010) suggest significantly varied detour tolerances and travel willingness with different social contacts. In accordance with SNeRs, the detour tolerance is set per Eq 4 and willingness per Eq 5.

$$T(e) = \begin{cases} 30\%, & e = 1 \\ 25\%, & e = 2 \\ 7\%, & e = \infty \end{cases} \tag{4}$$

Table 1: Catalogue of models and parameter settings

Notation	**Model**	$\bar{n}$	**Spa**	**Detour tolerance & willingness**
t10	Trip-based	–	–	10%, 100%
t30	Trip-based	–	–	30%, 100%
ab10	ABRA	–	–	10%, 100%
ab30	ABRA	–	–	30%, 100%
sw6	SNeRs	6	random	$T(e)$, $W(e)$ per Eq.4 & Eq.5
sw6d	SNeRs	6	decay	
sw12	SNeRs	12	random	
sw12d	SNeRs	12	decay	
car6	CAR	6	random	
car6d	CAR	6	decay	
car12	CAR	12	random	
car12d	CAR	12	decay	

$$W(e) = \begin{cases} 100\%, & e = 1 \\ 80\%, & e = 2 \\ 10\%, & e = \infty \end{cases} \tag{5}$$

These parameter values are representative of the social heterogeneity in ridesharing, but are not unique values and can vary from region to region.

Two parameters are considered in a social network: the average degree of friends $\bar{n}$ (note that this should be distinguished from the degree of separation e) and the spatial distribution (Spa) of the social network. The topological structures of the social networks in this study obey small world structures. The average degree $\bar{n}$ in a social network is set to be 6 and 12, which values are not universal but varying from case to case (e.g., Wang et al. (2015); Shi et al. (2016); Schläpfer et al. (2014)). Whatever the particular value of $\bar{n}$, a social network generally yields a low density network (Faust, 2006). These networks are then embedded in space with random spatial distribution or with distance decay in space. Let the home distance between each two persons be l_{ij}. The distance decay function, particular to the study area, is formulated by Eq. 6. This is a piecewise function such that 1) the social ties of the middle-range distances between 500 metres and 10,000 metres follow a power law distribution $f(l_{ij}) = \alpha l_{ij}^{-\beta}$ (where $\beta = 2.0$ precisely for this case, and α obeys the normalisation specified later); while 2) the probabilities of very short (<500 metres) and very long (>10,000 metres) distance social ties are moderated. The whole range is divided into bins with an interval of 500 metres. The probability of a social tie of a distance is the cumulative probability of the corresponding bin. In Eq. 6, $F(l_{ij})$ is the cumulative probability of $f(l_{ij})$ at each bin $[\lfloor \frac{l_{ij}}{500} \rfloor \cdot 500, (\lfloor \frac{l_{ij}}{500} \rfloor + 1) \cdot 500)$, where α satisfies that $\int_{500}^{10000} f(l_{ij}) dl_{ij} = 60\%$. The breakpoints 500 and 10,000 are decided due to the characteristics of the population distribution. Especially, the average distance between residential spatial clusters caused by natural barriers is about 10km.

$$p(l_{ij}) = \begin{cases} 20\%, & 0 \leq l_{ij} < 500 \\ F(l_{ij}) = \int_{\lfloor \frac{l_{ij}}{500} \rfloor \cdot 500}^{(\lfloor \frac{l_{ij}}{500} \rfloor + 1) \cdot 500} f(l_{ij}) dl_{ij}, & 500 \leq l_{ij} < 10000 \\ 20\%, & l_{ij} \geq 10000 \end{cases} \tag{6}$$

The comparison between spatial and non-spatial networks contribute to understanding the interwoven spatio-social influence on ridesharing. Higher degree indicates higher social network density in both topological and spatial senses. Each CAR or SNeRs model for *each* different social network structure is randomly run 5 times with a randomly permuted social network of that structure, while trip-based and ABRA models with each detour tolerance are run only once since social networks are not considered in matching. However, the statistics in Table 4 for trip-based and ABRA models pertaining to social network structures (e.g., number of matched friends) are still calculated as the mean of 5 permutations for each social network structure.

Output variables to be investigated are shown in Table 2. The number of matches and the detour cost can be contradictory at times. However, given the detour tolerance, it matters more to investigate the number of matches.

Table 2: Output variables to be compared

Variable	Meaning
$\|\mathbf{U}\|$	Size of the pre-computation matrix before optimisation
n	Number of matches after optimisation
n_f	Number of matches between direct or indirect friends
n_{f_1}	Number of matches between direct friends
s	Detour cost, overall
s_{f_1}	Detour cost, direct friends
s_{f_2}	Detour cost, indirect friends
s_{f_∞}	Detour cost, strangers

5. Results

As shown in Table 1, there are four social network structures under study, each being permuted five times. Table 3 displays the link statistics of the four social networks (average of five permutations): SN6 is the small world social network with the average degree of 6 and random distribution in space, and SN6d is its counterpart with distance decay in space (i.e., links are spatially clustered). The same holds for SN12 and SN12d of an average degree of 12. The link length is calculated as the Euclidean distance in metres between the home locations (the origins of each person's first trips) of a pair. Given a certain population, higher friendship density reduces the average home distance between friends, denoting a higher potential of ridesharing. Distance decay by design is associated with shorter friendship distance than random distribution. The link density is higher in SN12 and SN12d, and links are shorter in cases with distance decay.

The calculation results are demonstrated in Table 4, where each value is the mean of simulation outputs from five permutations of each social network structure. The significance is tested with t-test on a 0.05 significance level. $\|\mathbf{U}\|$ is the size of the pre-computation matrix before optimisation, i.e., the number

Table 3: Statistics of the direct friendship links in each social network (Link length in metres)

	SN6	SN6d	SN12	SN12d
Count	2142	2212	4284	4271
Min. len.	46.31	28.43	30.12	23.68
Max. len.	41842.63	35160.04	37156.79	36243.97
Mean len.	15690.15	12018.69	15409.15	13270.13

of all possible matches. n, n_f, and n_{f_1} are the final number of matches, the number of matches between first and second degree friends, and that between direct friends only. The last four columns are the detour costs (as in percentage of each rider's direct shortest travel time) of the matched rides, respectively, between anyone, direct friends, indirect friends, and strangers. Results from the same social network structure are highlighted in the same colour for comparison between different models.

For the number of matches, these are the major findings:

- Considering *alternative destinations* consistently yield higher number of matches (n), no matter whether social networks are taken into account or not (n in Table 2 ABRA vs. trip-based: e.g., $ab10\_6 : t10\_6 = 141 : 119, ab30\_6 : t30\_6 = 409 : 385$, and CAR vs. SNeRs: e.g., $car6 : sw6 = 198 : 135.4, car12d : sw12d = 239.4 : 165.4$).

- Prioritising *social networks* in an algorithm (CAR vs. ABRA, and SNeRs vs. trip-based) can significantly increase the matches between friends (n_f and n_{f_1}), given the same social network. As a baseline, the trip-based model and activity-based model yield no matches between friends by random chance. (e.g., n_f in Table 2, $car12d : sw12d : ab30\_12d : t30\_12d = 122.2 : 84.8 : 0 : 0$)

- Considering *alternative destinations* further contributes to a significant surge of matches between *friends* compared with social network-based

Table 4: Simulation outputs by each model

(Bold numbers: significantly higher than its counterpart with random social network.)

Model	$\|\mathbf{U}\|$	n	n_f	n_{f_1}	s	s_{f_1}	s_{f_2}	s_{f_∞}
t10_6	227	119	0	0	0.0653	0	0	0.0653
t10_6d			0	0		0	0	0.0653
t10_12			0	0		0	0	0.0653
t10_12d			0	0		0	0	0.0653
t30_6	1854	385	0	0	0.2089	0	0	0.2089
t30_6d			0	0		0	0	0.2089
t30_12			0	0		0	0	0.2089
t30_12d			0	0		0	0	0.2089
ab10_6	1854	141	0	0	0.0666	0	0	0.0666
ab10_6d			0	0		0	0	0.0666
ab10_12			0	0		0	0	0.0666
ab10_12d			0	0		0	0	0.0666
ab30_6	49452	409	0	0	0.2120	0	0	0.2120
ab30_6d			0	0		0	0	0.2120
ab30_12			0	0		0	0	0.2120
ab30_12d			0	0		0	0	0.2120
sw6	491.6	135.4	24.6	5.6	0.0946	0.1851	0.1943	0.0721
sw6d	506.0	135.8	27.4	**11.0**	0.1000	0.2309	0.1946	0.0730
sw12	634.2	164.0	75.2	10.0	0.1272	0.1702	0.1897	0.0761
sw12d	656.2	165.4	**84.8**	**18.0**	0.1411	0.2347	0.1988	0.0721
car6	14293.2	198.0	36.8	9.2	0.0974	0.1984	0.2051	0.0730
car6d	13721.8	202.8	**47.4**	**18.0**	0.1051	0.2373	0.1926	0.0727
car12	19471.0	233.6	108.6	12.4	0.1292	0.1869	0.1993	0.0690
car12d	19003.4	239.4	**122.2**	**22.4**	0.1362	0.2154	0.1947	0.0721

model (CAR vs. SNeRs, e.g., n_f in Table 2, $car12d : sw12d = 122.2 : 84.8$).

- The number of matches between friends generally rises with the decrease of home distance between friends (from SN6 to SN12d). The bold numbers in Table 4 display the significant difference in the number of matched friends between corresponding spatially aggregated and random social networks, even though the difference in overall matching rate is not significant.

Regarding detour cost, the findings are mainly:

- Given the same social network structure, there is no significant difference in detour cost between the corresponding results of CAR and of SNeRs (rows in the same colour), since a detour is capped by its tolerance limit.
- Comparing the costs of direct and indirect friends (s_{f_1} vs. s_{f_2}), social networks with spatial aggregation constantly yield higher detour cost between direct friends while random social networks result in higher cost between indirect friends.
- The overall detour cost increases as social networks get denser from SN6 to SN12d, but all within detour tolerances.

The regularity of the pre-computation size $\|\mathbf{U}\|$ causes the high computational burden in the models considering alternative destinations (ABRA and CAR) compared with their counterparts (trip-based and SNeRs). In sacrifice of computation efficiency, however, the models encompassing alternative destinations lead to higher numbers not only of overall matched rides but also of rides between friends.

6. Discussions

Based on the observations shown in Section 5, the proposed *collaborative activity-based ridesharing* demonstrates the following advantages and disadvantages that give hints on the feasibility of the model and its future improvements.

The hypothesis that CAR can significantly increase the overall matching rate compared with social network-based ridesharing is proved by the simulation results. Since the capability of activity-based ridesharing to increase matching rates (n) has been justified (Wang et al., 2016), alternative destinations extend the destination choice set and thus the matching rate.

The most important advantage of CAR is its reinforcement of *favoured* matches, even compared with social network-based ridesharing (SNeRs). Despite a higher overall matching rate, it is unsure to what extent activity-based ridesharing can match *friends* by random chance. In fact, the simulation results (ab10 and ab30) show no stochastic match between friends in any social network structure. What makes CAR remarkable is that it facilitates a significant increase in *certain* matches – the matches between friends – over random chances. The matching rate between friends by CAR is shown significantly higher than not only activity-based ridesharing, but also social network-based ridesharing, which is a stronger statement than the hypothesis. CAR therefore utilises alternative choices to match *friends'* rides that would not be matched if the original routes were not substituted by the alternative ones.

Since detour cost is controlled by detour tolerance, there is no significant difference in detour cost between the outputs from CAR and social network-based ridesharing. The positive indication is that CAR effectively reinforces the increase of favoured matches at no cost of extra detour.

A characteristic of the study area is its heterogeneity in landscape (hills and rivers) and thus the population distribution. The highly clustered and uneven population, in contrast to the urban areas under study by Tachet et al. (2017) who assumed travel demands are evenly distributed, might lead to a significantly different result even with trip-based ridesharing. Embracing social network can lead to a more distinguishable difference in matching rate. With social network-based ridesharing, trials to share rides with a friend residing in another cluster might fail due to the infeasibility of space-time budgets. Despite CAR searches for alternative destinations subject to space-time budgets, the simulation results manifest the influence of spatially aggregated friendships, contributing to significantly more matches between friends (bold numbers in Table 4), though the overall matching rate is not significantly higher. At least the spatial aggregation of friendships denotes a higher satisfaction rate measured by the likelihood of ridesharing with friends. The regularity between spatial distributions of population and friendship and ridesharing outcome is still debatable, which calls for more empirical studies in diverse areas in terms of such factors as landscapes, population densities, friendship distributions, and urban configurations.

In spite of an increased matching rate, the downside of activity-based ridesharing is its heavy computational burden, as reported by Wang et al. (2016). The significantly expanded matrix size $\|\mathbf{U}\|$ has already indicated the heavier computational burden in the searching and matching stage (M3 in Figure 1). SSI leverages the heuristic of social networks to effectively cut down the searching space of *unfavoured* potential matches from strangers. The sacrifice of the total number of matches by the design of the spatio-social index (SSI) is disputable, depending on the spatial distribution of social networks and trip density: When trips are dense in space, SSI is capable of narrowing down unnecessary searches by limiting the search range for strangers to a small area. But if trips are spatially sparse, especially when social networks are scarce as well, SSI may deteriorate ridesharing opportunities. For this reason, further investigation in the influence of space is needed with empirical data from diverse study areas. The design of a dynamic SSI is worthwhile for a real-time ridesharing application.

7. Conclusions and future work

Coalescing two previously suggested innovative ridesharing algorithms – social network-based ridesharing and activity-based ridesharing – this study proposes a new ridesharing algorithm called *collaborative activity-based ridesharing* (CAR) to address the barriers of trust and flexibility in ridesharing. Agent-based simulation results based on empirical dataset substantiate the capacity of CAR to increase favourable rides without sacrificing more detour time, which potentially encourages public acceptance of ridesharing.

Since geographic studies are contingent, future work should involve more study areas to generalise the regularity between spatial configuration and ridesharing outcomes. Alternatively, the algorithms can be encapsulated into a tool to be applied in any locality. Harvesting coupled information of social networks and travel behaviours is necessary but difficult due to confidentiality. If possible to collect such coupled information, the feasibility of CAR could be measured more accurately and practically. Another direction of future work is the design of more efficient search indices for rides-matching considering spatial contexts. The upgrade of indices may also contribute to the dynamic modification of CAR. A dynamic CAR model would be more applicable in reality but is confronted with issues of computational efficiency and swift response. A possible solution based on search indices is a space-time partitioning of the problem for parallel computing.

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