Activity-based ridesharing: Increasing flexibility by time geography

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ABSTRACT

Ridesharing is an emerging travel mode that reduces the total amount of traffic on the road by combining people's travels together. While present ridesharing algorithms are trip-based, this paper aims to achieve significantly higher matching chances by a novel, activity-based algorithm. The algorithm expands the potential destination choice set by considering alternative destinations that are within given space-time budgets and would provide a similar activity function as the originals. In order to address the increased combinatorial complexity of trip chains, the paper introduces an efficient space-time filter on the foundations of time geography to search for accessible resources. Globally optimal matching is achieved by binary linear programming. The ridesharing algorithm is tested with a series of realistic scenarios of different population sizes. The encouraging results demonstrate that the matching rate by activity-based ridesharing is significantly increased from the baseline scenario of traditional trip-based ridesharing.

CCS Concepts

•**Applied computing** → **Transportation;**

Keywords

Ridesharing algorithm, Activity-based modelling, Time geography, Flexibility, Binary linear programming

1. INTRODUCTION

Ridesharing aims to be more economical and greener than private cars by reducing the total vehicle miles travelled. Since ridesharing requires coordination, any ridesharing algorithm should accommodate riders' flexibility. Current ridesharing algorithms are *trip-based*, i.e., they respect *a priori* defined origins and destinations, but leave the spatial flexibility of riders un-exploited. The spatial flexibility arises from the fact that some activities can be participated at one of various destinations that are functionally similar [14, 21, 20]. Accordingly *activity-based* travel planning broadly categorises activities as fixed, e.g., work-place related activities, and flexible activities, e.g., shopping. By incorporating an activity-based planning approach into a ridesharing algorithm, it is likely that the matching chances rise as a result of the expanded destination choices. This paper proposes *activity-based ridesharing* that employs time geography to build a choice set of alternative destinations and finds an optimal match fitting best into ridesharing partners' schedules. The research is significant in at least three ways:

- By expanding potential destination choice sets, the algorithm should significantly increase the matching rates of ridesharing;
- By designing an efficient filter based on time geography, it limits the combinatorial explosion for trip chains on feasible activities;
- By linear programming, it finds optimal solutions for riders.

The research hypothesis is that, compared with the trip-based method, an activity-based ridesharing algorithm ($ABRA$) can efficiently increase matching rates by considering alternative destinations for flexible activities, while keeping detour costs comparable within tolerance. The algorithm makes a significant contribution to ridesharing by introducing time geography that inherently is capable of increasing travel flexibility and thus matching rate, and meanwhile to time geography from a computational perspective.

$ABRA$ generally includes two steps: it initially builds up a pool of alternative destinations (and trips) for the targeted activities based on the trip's space-time budgets; and then finds feasible matchings considering these alternatives in addition to the original ones. Matching is conducted as static preplanning with everyone's daily schedules known. A daily schedule includes one or multiple trip chains, each of which includes multiple trips. Given its combinatorial computational complexity in deciding the destination choice set for a (especially long) chain of multiple flexible activities [9, 3], $ABRA$ proposes an efficient space-time filter for alternative destinations. The general principle is to impose a reasonable time window on these "floating" trips, while still allowing for detour tolerance for each trip. The assignment of time windows is generically dependent on the trip's space and time flexibilities. $ABRA$ has been set up to prove the hypothesis, which requires a non-heuristic solution to

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identify the theoretical potential of activity-based ridesharing. However, it is well recognized that in practical systems a dynamic, sub-optimal model is more applicable than the currently implemented static one.

The algorithm has been implemented and tested by a series of simulations in real-world context with synthetic populations for a shire of Greater Melbourne [13]. Points of interest (POIs) retrieved from the Yelp API (Copyright ©2016 Yelp Inc.) represent alternative destinations for flexible activities. Global optimization for maximum matching of rides is formulated by binary linear programming and implemented in MatLab. The experiment is run with different sample sizes, each twice, first applying trip-based planning using pre-defined destinations for all activities, and then applying activity-based planning, considering flexible activity destinations. The simulation results demonstrate a significant increase of successfully matched rides for the activity-based algorithm, strongly supporting the hypothesis in favor of activity-based ridesharing.

The rest of the paper is organised as: Section 2 reviews current ridesharing algorithms, activity-based travel analysis, and its connection with time geography; Section 3 is the conceptual framework, followed by its implementation in Section 4. Results are presented in Section 5, with discussions in Section 6. The paper is concluded in Section 7 with future directions.

2. LITERATURE REVIEW

The understanding of *locations* and *places* in information science and location-based services has a history from coordinated-based approaches to semantic-based approaches. *Place*, rather than being a synonym for a geographical location, is tightly linked with its service – i.e., its function, affordance and experience – while constraint by its spatial location [29, 23, 12]. In accordance with this observation, travel demand analysis underwent an evolution from trip-based to activity-based, the latter regarding travel as a secondary or derived demand to satisfy the necessity of activity participation at the destination [5, 22].

Ridesharing inherently is the bundle of activity-induced individual travels. However, rideshare planning is predominantly trip-based, matching travels from one unique location to another, rather than from activity to activity. Furuhata *et al.* [11] categorised current ridesharing systems into six classes: dynamic real-time ridesharing, carpooling, long-distance ride-match, one-shot match, bulletin-board, and flexible carpooling. Dynamic systems by short-term or even en-route matching (e.g., [1, 2, 10, 17]) have relatively higher flexibility only in the sense that last-minute requests can be handled; it is yet different from enlarging destination choices. Others have explored peer-to-peer solutions considering short-range radio communication between pedestrians' and car drivers' mobile phone apps [32]. A recent trend to involve social networks into ridesharing drives such algorithms as *Social-aware Ridesharing Group* query [16]. However, none of them allows the absence of unique destinations. This limitation (in choice) restricts the space-time budgets of individuals and thus the matching rates of ridesharing algorithms. But if the trips are treated as activity-based, the destination choice set is expanded effectively.

Activity-based travel demand analysis covers a wide range of steps, including trip-chain generation, activity scheduling, and choice set selection. Trip chaining, yet by an ambiguous definition, is "a trip sequencing of activities", as Thill and Thomas summarised based on their review of trip chaining studies [26]. This work, however, focuses on the generation of destination choice sets in ridesharing, rather than deal with trip-chain generation and activity scheduling itself, which is another research domain (e.g., [4, 7]). A full day schedule of activities, some fixed and some flexible, is assumed given.

Timmermans et al. [27] generalised four types of activity-travel modelling: constraints-based, utility-maximising, computational process, and microsimulation models. The first type, essentially time geography based, is the foundation of filtering potential alternative destinations in the proposed algorithm. It is, however, a restrictive modelling of the choice set that omits other criteria such as personal preferences [18]. A similar interest in time geography methods for ridesharing has been discussed by Rigby *et al.* [25], although they looked at another issue of selecting potential pick-up areas based on space-time accessibility. Kwan and Hong [15] initiated a network-based time geography method to formulate destination choice sets, which was expanded by Chen and Kwan [9] into a computational model for multiple fixed and flexible activities' choice set formation. Chen and Kwan's method builds a space-time prism by using fixed activities as control points, which cuts down the number of potential combinations with flexible activity destinations.

There are two aspects to be considered in such a constraint-based choice set formation: 1) the identification and separation of fixed and flexible activities, and 2) the set-up of the destination choice sets for flexible activities. The boundary between fixed and flexible is vague as it depends on the perception of the users [15, 24]. For example, some people only go to a certain restaurant for lunch, but others are more flexible. While Kwan and Hong [15] defined flexibility only in regard to location, Raubal *et al.* also accounted for time elasticity [24], which is adopted by the algorithm presented below as well.

The affordance (or function) a place exudes for certain activities [23, 12] can be collected from POI databases. However, the database might have an inconsistent classification system from the documented activity types used to retrieve flexible destinations. Such a problem can be fixed by the work of McKenzie *et al.* that mapped POI types into a present classification schema [19]. Another challenge is that people may carry out different activities at the same place, which makes the place semantically diverse to each person [6]. These problems are yet to be solved, but fall outside the focus of the current work.

3. METHODOLOGY

The contribution of this work is an activity-based ridesharing algorithm (*ABRA*) that effectively expands trip destinations to choice sets for higher ridesharing matching rates. To prove the significance of the algorithm, it is compared to trip-based ridesharing planning as a baseline. The activity-based ridesharing algorithm computes centrally the global optimum of all feasible matches. Cheaper (i.e., heuristic, or decentralized) solutions may exist, but the global optimum is adopted here to reveal the theoretical capability of the activity-based approach. There are four modules (stages) in this model (Figure 1): person initialiser (*M1*), trip chain builder (*M2*), candidate matching (*M3*), and solution optimization (*M4*). *M2* and *M3* are the essential parts of activity-based ridesharing that make up *ABRA*.

3.1 Model setting and assumptions

The scenario is set with a certain population, each person of which has a complete list of full-day activities with predefined running order (i.e., the activity sequence and planning is out of the study scope). Assume that no two consecutive activities can be done at the same location, and therefore must cause a *trip*, regardless of the activity's space and time flexibility. *M1* initializes the population by assigning them these activities with originally planned locations and travel time. The output of *M1* is a population with initially planned trips.

The basic unit to be matched is a trip rather than a series of trips, regardless of the duration of the stops. Once a person gets to an activity destination, the ride is completed. Such design is beneficial in a way that nobody is forced to wait for another person conducting his/her activity. If one trip fails to be matched, that trip will be travelled alone. Transfer at a non-activity location is not allowed to avoid additional waiting time. Maximum amount of shared capacity is set to 2 passengers. This model also assumes self-driving vehicles operating as taxis, which makes ridesharing in this case a flexible form of taxi sharing, so that persons do not need to distinguish their roles as a driver or a passenger. This assumption releases the bonds caused by vehicle ownership: the person who gets into the car first (traditionally the "driver") does not have to arrive at their destination at last. Consequently, there are no people ("drivers") who, in addition to contributing their own vehicle, also have to make the most detours; instead, the algorithm can flexibly optimize the sequence of pickups and drop-offs solely based on transport demand.

3.2 Trip chain construction

M2: Trip chain builder is one of the essential parts of *ABRA*. It mainly completes three tasks as shown by Figure 1: building trip chains, constructing space-time filters (*STF*), and retrieving feasible activity locations with these filters. The principle of *ABRA* is to expand a person's destination choice set for each location-flexible activity by finding places that are spatially diverse while functionally similar for that travel aim. For instance, if a person is looking for a supermarket, he/she can choose one from a few candidate locations depending on their time budget. There is a potential that different choices yield different chances to share a ride, which is to be proven by this work. Time-flexible but location-hard activities can also expand destination choice set, but indirectly. It allows for later arrival time, and thus is likely to provide more choices for its previous trip, if the previous destination is location-flexible. An example is when a person plans to shop for grocery on the way back home, he/she may stop at different grocery stores.

3.2.1 Building trip chains

Accommodating a person's space and time flexibility, *fixed* activities are defined here as activities that can be conducted only at a fixed time and at a certain place. Release of either rigidity induces to a *flexible* activity. Hence, the four types of activities are: hard-time-hard-location (HTHL), flexible-time-hard-location (FTHL), hard-time-flexible location (HTFL, which seldom happens and does not exist in the simulation), and flexible-time-flexible-location (FTFL).

Activities within a day are not independent; they are constrained by trips to other activities depending on the space and time flexibility of each activity. Say, a person has to start work at 9am in his/her office, before which he/she wants a coffee on the way from home. Then the activity of "grabbing a coffee" is limited by the next activity "working" in time, and thus in space. To determine where to buy the coffee, purely from a spatio-temporal perspective and omitting factors such as personal preference, an STF can be built. The construction of an STF requires two points with known location and time as *control points*: In this case, leaving home at a certain time and reaching work at 9am are the control points, and if this time window is sufficiently large to make stops or even small detours, the person has some flexibility to choose from a number of coffee places in between. Accordingly, a full day schedule must be split at control point activities, and be turned into a series of trip chains. Thus, the *strong* definition of a *trip chain* is a series of trips with two *fixed* activities at both ends and any number of flexible ones in between. Control point activities are hence named *splitters* (of trip chains) hereafter.

M2 is developed to find all splitters and to break a whole day schedule into trip chains at these splitters. In practice, a splitter is an activity isolating the trip chains on both sides (e.g., resistant to delay) and thus providing for space-time stability. In addition to HTHL activities (*fixed* activities), hard-location activities with a duration longer than a threshold (e.g., 1 hour) can also be used as splitters since they provide some capacity to absorb delays. Thus, a *weaker* version of a *trip chain* is that with at least a FTHL *splitter*.

Figure 2 shows the relations between activities, trip chains, and trips within a chain. A day contains at least one chain, and a chain must have at least one trip. Dash lines and dash-dot lines in the figure indicate some omitted details. The interior structure of a trip chain i is expanded. Let O_i be the origin of this chain, and D_i the last stop. Let $N(i) \in \mathbb{Z}_{>0}$ denotes the number of trips within chain i, where $\mathbb{Z}$ is the set of integers. Hence, there are totally $N(i)+1$ activities on this chain, including those at the origin and the final stop. Act_j^i denotes the j^{th} activity on chain i. The corresponding locations for Act_j^i form a set $S_j^i = \{s_{j,k}^i\}$, where $s_{j,k}^i$ is the k^{th} *candidate* location to conduct activity Act_j^i. The original location of an activity is indicated by $k = 0$. Thus, $O_i = s_{0,0}^i$ and $D_i = s_{N(i),0}^i$. The following part will use this chain to explain the construction of the STF.

3.2.2 Construction of space-time filters

The construction of a trip chain depend on the shape of an STF. STFs are derived from the concept of *space-time prisms* in time geography [20, 21]. A space-time prism is a 3-D geometry, 2-D in space plus one time axis, delineating the maximum range a moving object can reach given its start and end points' location and time. Hence, the prism functions as an STF on all accessible resources within this time window. A *potential path area* (PPA) [21] is the projection of such a prism on the x-y-plane; thus the PPA delimits the full range of accessible space within this time window. Only in isotropic space, the PPA is the ellipse with foci at the two given splitters that guarantees a location inside it can be traversed within time limit. In reality, the shape of the PPA is irregular considering network travel time. In Figure 3a, the black thick ellipse forms the PPA of the space-time prism spanned by the splitters O_i and D_i. For a flexible ac-

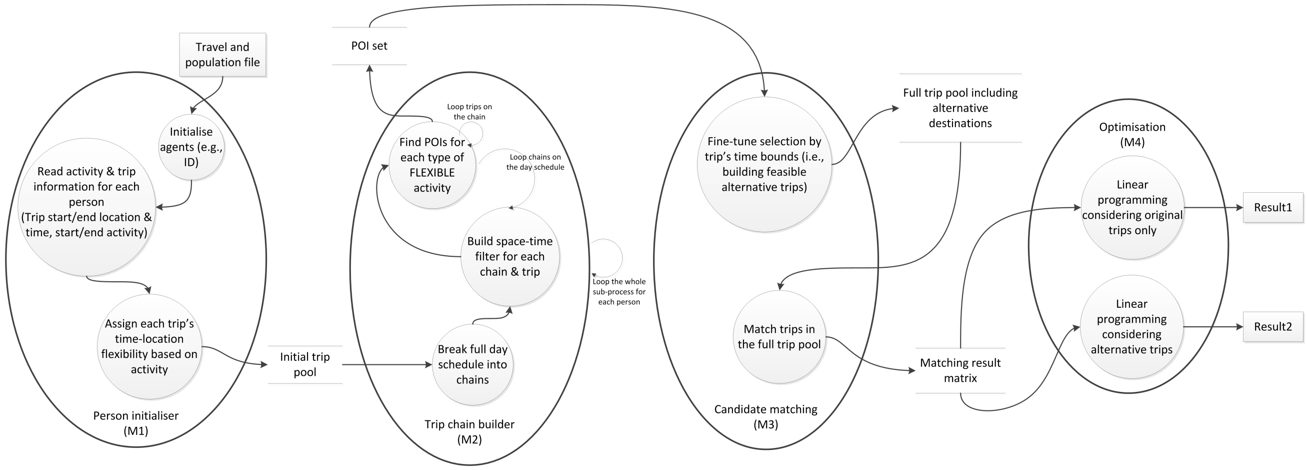


Figure 1: Workflow of the activity-based ridesharing model.

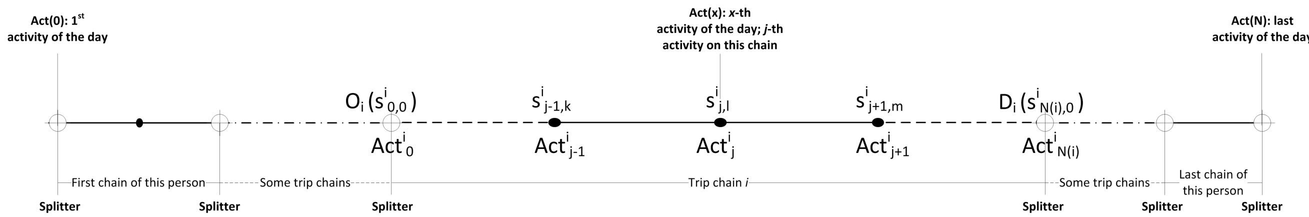


Figure 2: Activities of a day and trip chains.

tivity in between, the geographic space offers multiple POIs, but only the ones within the ellipse are feasible.

An STF is a derived concept, but handles more complicated cases. Think about a situation that the length of a trip chain is longer than 2, which means there are more than one flexible activities between two splitters. In Figure 3a, the current chain contains $N(i)$ trips, i.e., $N(i)-1$ *flexible* activities for which alternative locations should be searched. In Chen and Kwan's work [9], a theoretical space-time model for multiple flexible activities are given and tested with a simple programme with only two flexible activities between splitters. From computation's perspective, however, the combinatorial number of iterations will explode with the growth of trip chain length and the variety of location selections. The proposed STF solves this by imposing a hard time limit on each trip while still granting it flexibility. The solution is allowing for some detour for each trip, and fixing the time limits of earliest starting time and latest ending time of each trip. The advantage is that it reduces trips' interdependency and thus leads to less computational complexity. However, such design requires a revision on its solution, because it lacks the time bounding by its following trip. The revision will be discussed in Section 3.3.

Let $t_{k,l}^{i,j}$, where $i,j \in \mathbb{Z}_{>0}$ and $k,l \in \mathbb{Z}_{\geq 0}$, denotes the trip within chain i from $s_{j-1,k}^{i}$ to $s_{j,l}^{i}$. Thus, $t_{0,0}^{i,1}$ is the original 1^{st} trip of this chain and $t_{0,0}^{i,N(i)}$ is the original last trip to the last stop D_i. Also, define $EST(t_{k,l}^{i,j})$ and $LET(t_{k,l}^{i,j})$ as the earliest starting time and the latest ending time of $t_{k,l}^{i,j}$ respectively, which are used to delimit the the maximally tolerable time budget for that trip. Furthermore, the direct travel time of trip $t_{k,l}^{i,j}$ is denoted as $dTTime(t_{k,l}^{i,j})$. Moreover, start time ($StartTime$) and arrival time ($ArrTime$) are the actual travel timestamps of each person's trip by their initial planning. $ActDur(\cdot)$ denotes the activity duration at a stop.

Algorithm 1 outlines the process of calculating $EST(\cdot)$ and $LET(\cdot)$ of each trip. Note that the travel time for any alternative destination is always kept the same as its original's, that is $\forall(k,l)$, $EST(t_{0,0}^{i,j}) = EST(t_{k,l}^{i,j})$ and $LET(t_{0,0}^{i,j}) = LET(t_{k,l}^{i,j})$. The algorithm works as follows.

1. Any activity Act_j^i that is time-hard (TH) must be satisfied: The departure at a TH origin cannot be advanced, and arrival at a TH destination cannot be delayed.
2. Before finding the time bounds of each trip within a chain, the time bounds of the whole trip chain is first determined. If both splitters are TH, then the time bounds of the trip chain are simply the origin's $StartTime$ and the destination's $ArrTime$. Otherwise, the following formula is used to determine the maximum allowable duration (without activity duration) of a trip chain:

$$maxDur(i) = \min\{(1 + DetRate) * \sum_j dTTime(t_{0,0}^{i,j}), GlobalDet\}, \quad (1)$$

where $DetRate$ is the maximum detour time of a person in a trip (as a proportion to the direct travel time), and the resulting duration should never go over a global chain duration threshold $GlobalDet$. As shown by Algorithm 1, if only one of the splitters is TH, then the corresponding time bound is imposed (either the origin's $StartTime$ or the destination's $ArrTime$), while the other is adjusted according to the calculated maximum allowable duration in (1). If both splitters are time-flexible (TF), the destination splitter is assumed as TH and the destination's $ArrTime$ is used as a time bound, just to avoid advancing departure.

3. Next, the time bounds for each trip are determined. By using time bounds of the trip chain defined above, the maximum detour time of a trip chain (i.e. the time budget) can then be calculated as follows,

$$maxDet(i) = LET(t_{0,0}^{i,N(i)}) - EST(t_{0,0}^{i,1}) - \sum_{j\in\{1,\dots,N(i)-1\}} ActDur(Act_j^i), \qquad (2)$$

According to the definition of *splitter*, and given that no HTFL activities exist, it is easy to infer that any activity between the splitters on a trip chain are TF. Therefore, the maximum allowable duration of each trip is determined by distributing $maxDet(i)$ in proportion to the direct travel time of each trip relative to the total direct travel time of the original/actual trip chain. Note that the maximum detour time of a trip $DetRate$ is still imposed. Hence, the maximum detour time of a trip is calculated as follows:

$$maxDetTrip(t_{0,0}^{i,j}) = \min\{ maxDet(i) * \frac{dTTime(t_{0,0}^{i,j})}{\sum_j dTTime(t_{0,0}^{i,j})}, dTTime(t_{0,0}^{i,j}) * (1 + DetRate)\}. \qquad (3)$$

Only need to loop the trips and assign their time bounds accordingly (Algorithm 1). Finally, recall that $\forall(k,l)$, $EST(t_{0,0}^{i,j}) = EST(t_{k,l}^{i,j})$ and $LET(t_{0,0}^{i,j}) = LET(t_{k,l}^{i,j})$. Thus, the time bounds for all trips have been established.

3.2.3 Preliminary POI retrieval

A feasible POI set is built by a two-step retrieval: first by a rough screening with the time bounds of the whole trip chain, and then by fine-tuning with each trip's time constraints. The hierarchical design reduces duplicated retrieval time on infeasible regions. The fine-tuning process is implemented by M3 elaborated in the next section.

In Figure 3a, the outer black ellipse draws the rough STF set by the whole chain's time budget (Eq.2). As long as a POI corresponding to one of the activity types of this chain falls inside this region, it will be added to the POI pool for fine-tuning. All the displayed POIs in Figure 3a are in this pool. It therefore builds the *candidate* destination choice set S_j^i. The double-line circle and thick circle POIs represent S_j^i, while those in grey shades are POIs for other *flexible* activities.

3.3 Alternative trip construction and matchup

With the initially selected POI pool S_j^i, *M3* uses the time horizon of each trip $t_{k,l}^{i,j}$ to build up a finer STF that adjusts the choice set for Act_j^i. Given the current start point $s_{j-1,k}^i$ of the trip $t_{k,l}^{i,j}$, the finer STF (illustrated by the red ellipse in Figure 3a selects all the *feasible* POIs (thick circle POIs) from its *candidate* set S_j^i to construct a *feasible* destination

Algorithm 1 Setting time budget for synthetic trips

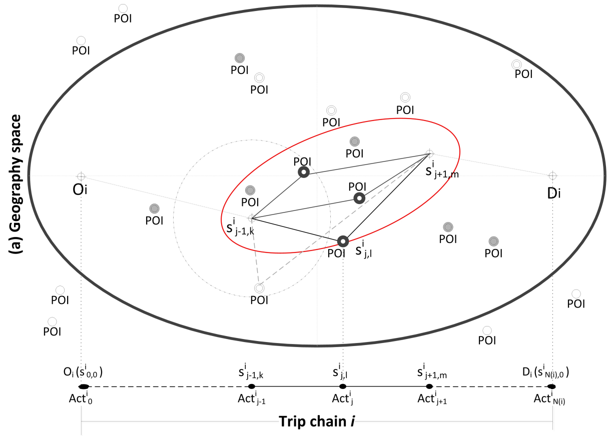
for each trip chain i **do** ▷ TIME BOUND FOR TRIP CHAIN
  if Origin splitter is TH **then**
    $EST(t_{0,0}^{i,1}) \leftarrow$ Origin's $StartTime$;
    if Destination splitter is TH **then**
      $LET(t_{0,0}^{i,N(i)}) \leftarrow$ Destination's $ArrTime$;
    else
      $LET(t_{0,0}^{i,N(i)}) \leftarrow EST(t_{0,0}^{i,1}) + maxDur(i) + \sum_{j\in\{1,\dots,N(i)-1\}} ActDur(Act_j^i)$;
    end if
  else
    $LET(t_{0,0}^{i,N(i)}) \leftarrow$ Destination's $ArrTime$;
    $EST(t_{0,0}^{i,1}) \leftarrow LET(t_{0,0}^{i,N(i)}) - maxDur(i) - \sum_{j\in\{1,\dots,N(i)-1\}} ActDur(Act_j^i)$;
  end if
  ▷ TIME BOUND FOR TRIPS
  calculate $maxDet(i)$ as in (2);
  for each trip $t_{0,0}^{i,j}$ of a chain i **do**
    calculate $maxDetTrip(t_{0,0}^{i,j})$ as in (3);
  end for
  for each trip $t_{0,0}^{i,j}$ (except last) of a i **do**
    $LET(t_{0,0}^{i,j}) \leftarrow EST(t_{0,0}^{i,j}) + maxDetTrip(t_{0,0}^{i,j})$;
    $EST(t_{0,0}^{i,j+1}) \leftarrow LET(t_{0,0}^{i,j}) + ActDur(Act_j^i)$;
  end for
end for

choice set $\mathscr{F}_{j,k}^i$:

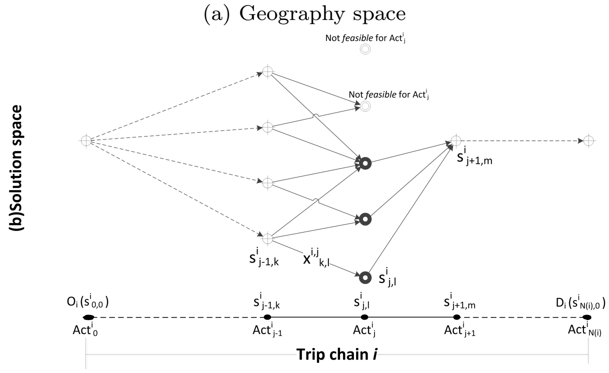
$$\mathscr{F}_{j,k}^i = \left\{ s_{j,l}^i \in S_j^i \,\middle|\, dTTime(t_{k,l}^{i,j}) \le LET(t_{k,l}^{i,j}) - EST(t_{k,l}^{i,j}) \right\} \qquad (4)$$

The meaning of this feasible set is illustrated by Figure 3b, labelled "solution space". Two points $s_{j-1,k}^i$ and $s_{j,l}^i$ are connected by a link if $s_{j,l}^i \in \mathscr{F}_{j,k}^i$. Correspondingly, the set of *feasible* POIs for Act_j^i is the union of POIs with in-degree (defined as the count of feasible trips travelling towards that POI) greater than 0 in this solution space.

However, geographically this is not true. As shown by the node with two arrows pointing inwards but nothing outwards, the time bounds of its previous and following stops are not satisfied. This is illustrated by the POI located outside the red ellipse and linked by the gray dash-line in "geography space". The problem is caused by the computation design lacking of the bounding by the following trip. Theoretically, the PPA delineated by two points is an ellipse, but delineated by one and the same point it degrades to a circle (see the dash-dot-dot circle on "geography space"). Let a node with *out-degree* (defined as the count of feasible trips starting from this node) equal to 0 be referred to as a *dead-end node*. Then there are two ways to handle dead-end nodes that are not final stops. After building this alternative trip network (i.e., the network in "solution space"), it is possible to either: 1) remove each dead-end node that are not a final node and all corresponding nodes that are linked to the removed nodes (by tracing back); and 2) use linear



(a) Geography space



(b) Solution space

Figure 3: Potential path area and alternative destinations of a trip chain and of the trips on the chain.

programming to remove such non-final dead-end nodes by imposing "flow conservation" constraints (explained in the next section). The latter is the approach taken in this work.

The next function of *M3* is to find all the potentially matched pairs of trips. The matching process attempts to match a pair of trips from two different trip chains, and builds a candidate set if the two trips satisfy the corresponding time budgets. Note that this implies that trips belonging to two trip chains of the same person will not be matched, since the time windows of these trip chains do not overlap. Thus, the feasibility of a match depends on the time budget of each person. A match is feasible if the travel time on the combined route between both person's pick-up and drop-off points is shorter than each person's total travel budget for that corresponding trip.

Figure 4 shows an example of the combined route of person P_1's trip from $Act^{i_1}_{j_1}$ to $Act^{i_1}_{j_1+1}$ and person P_2's trip from $Act^{i_2}_{j_2}$ to $Act^{i_2}_{j_2+1}$. The bold black arrows represent the feasible travel route and visiting sequence, among the four possible visiting sequences to the four locations. Note that a person's drop-off location cannot happen before the other's pick-up; otherwise, there will be no ridesharing. Judging the space-time feasibility of a visiting sequence with PPA, $P_1(j_1) \rightarrow P_2(j_2) \rightarrow P_1(j_1+1) \rightarrow P_2(j_2+1)$ is the only feasible sequence. An infeasible one, for example, $P_2(j_2) \rightarrow P_1(j_1) \rightarrow P_1(j_1+1) \rightarrow P_2(j_2+1)$, has its middle point $P_1(j_1)$ outside the ellipse with foci at $P_2(j_2)$ and $P_1(j_1+1)$.

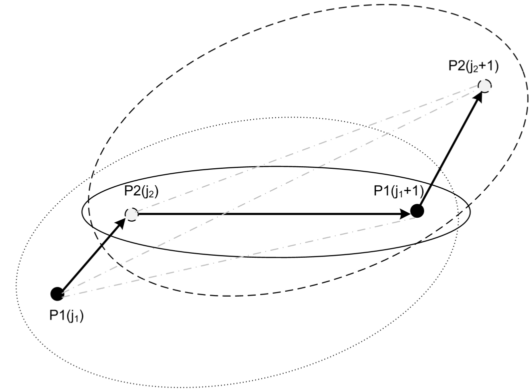


Figure 4: Combined route cost and visiting sequence.

3.4 Finding the optimal solution

The last module (*M4*), optimization, adopts binary linear programming (BIP) to calculate the maximum number of feasible trip matching that can be achieved.

In order to do this, each trip $t^{i,j}_{k,l}$ is assigned a binary variable $x^{i,j}_{k,l}$, where $x^{i,j}_{k,l} = 1$ indicates that trip $t^{i,j}_{k,l}$ is to be taken, and $x^{i,j}_{k,l} = 0$ indicates otherwise. Furthermore, each feasible matching of two trips is assigned a binary variable $u(t^{i,j}_{k,l}, t^{i',j'}_{k',l'})$, where 1 indicates that trips $t^{i,j}_{k,l}$ and $t^{i',j'}_{k',l'}$ are to be matched and 0 indicates otherwise. The trip binary variables $x^{i,j}_{k,l}$ and the matching binary variables $u(\cdot,\cdot)$ are grouped in the vector $\mathbf{X}$ and $\mathbf{U}$ respectively. The objective of the BIP is then to get the maximum sum of $u(\cdot,\cdot)$, which can be formulated as follows.

$$\max_{\mathbf{U}} \ \mathbf{1}^\top \mathbf{U}, \tag{5}$$

where $\mathbf{1}$ is a vector of ones, subject to:

$$\sum_{\left\{(k,l)\,\middle|\,t^{i,j}_{k,l} \in \mathscr{F}^i_{j,k}\right\}} x^{i,j}_{k,l} = 1, \tag{6a}$$

$$\sum_{\left\{k\,\middle|\,t^{i,j}_{k,\beta} \in \mathscr{F}^i_{j,k}\right\}} x^{i,j}_{k,\beta} = \sum_{\left\{l\,\middle|\,t^{i,j+1}_{\beta,l} \in \mathscr{F}^i_{j+1,\beta}\right\}} x^{i,j+1}_{\beta,l}, \tag{6b}$$

$$u(x^{i_1,j_1}_{k_1,l_1}, x^{i_2,j_2}_{k_2,l_2}) \leq x^{i_1,j_1}_{k_1,l_1}, \tag{6c}$$

$$u(x^{i_1,j_1}_{k_1,l_1}, x^{i_2,j_2}_{k_2,l_2}) \leq x^{i_2,j_2}_{k_2,l_2}, \tag{6d}$$

$$\sum_{\left\{(i',j',k',l')\,\middle|\,u(t^{i,j}_{k,l}, t^{i',j'}_{k',l'}) \in \mathbf{U}\right\}} u(t^{i,j}_{k,l}, t^{i',j'}_{k',l'}) \leq 1. \tag{6e}$$

Equation (6a) ensures that there is only one trip traversed between two consecutive activities within a chain. Equation (6b) implies that if a particular location is visited within a chain, the person also has to leave the location (the aforementioned "flow conservation" constraints). Similarly, (6c) and (6d) ensure that the matching only applies to trips that are actually carried out. Finally, (6e) implies that a trip can be matched to only one other trip.

4. SIMULATIONS OF ACTIVITY-BASED RIDESHARING IN YARRA RANGES

The algorithm is implemented and tested by simulating ridesharing behaviors with real world spatial and travel demand data. The study area is the Shire of Yarra Ranges, covering eastern and north-eastern suburbs of Greater Melbourne, Victoria, Australia. Assumedly, self-driving vehicles as taxis serve the population with ridesharing flexibility.

4.1 Simulated population and travel demand

The population in the simulation is based on the Victorian Integrated Survey of Travel and Activity (VISTA) 2009-2010 [30]. The spatial unit of VISTA is the finest spatial level of the Australian Bureau of Statistics. Trips in VISTA are recorded as origins and destinations at this zonal level. Table 1 shows the data structure of VISTA data with only fields relevant to this work.

Table 1: VISTA data structure

FieldName	**Meaning**	**Example**
ORIGSA1	Trip origin zone	2128101
DESTSA1	Trip destination zone	2128101
PERSID	ID of the trip owner	Y09H061326P02
TRIPID	ID of this trip	Y09H061326P02-T01
STARTIME	Start time of trip (min)	512
ARRTIME	End time of trip (min)	673
ORIGPLACE2	Origin activity code	201
DESTPLACE2	Destination activity code	301 (-2 is last trip of the day)
DURATION	Duration of the destination activity (mins)	131

Each entry in the table is a recorded trip of a surveyed person. It documents the starting and ending location, the corresponding starting and ending time of that trip, and the activities conducted or to be conducted at the origin and destination. It also records the activity duration at the destination. If a surveyed person has multiple trips on that day, there will be multiple entries associated to that person's ID.

VISTA surveys a representative sample of 1% of the households in Victoria. Despite the sample size being large enough, this simulation is run with a synthetic population generated from further census data on the socio-economical information of each household [13], which adjusts the survey sample proportional to the population. Each synthetic person has a travel agenda for a day.

4.2 Trip distribution and time horizon

Time and distance are two key factors in ridesharing. With the synthetic population and their travel demand as input, randomness is introduced to generate diverse trips so that no trips of two synthetic persons inherited from the same surveyed person will be exactly the same. Randomness is implemented in the following ways:

1) Each synthetic person's origin and destination (coordinates) are randomly generated, subject to the same SA1 zone as documented of its surveyed person. The direct shortest travel time ($dTTime$) between origin and destination is calculated in network travel time. Different time slots of travel are induced in such way.
2) The randomized assignment guarantees time integrity that a trip must be assigned enough time to be finished. Time assignment is shown by Algorithm 2. Randomness is introduced by δ, a shift from the documented variables (e.g., time, activity duration ($ActDur$)). When adding δ to the recorded ending time ($VS\_ArrTime$) for the randomized arrival time ($ArrTime_{rd}$), the result is ensured to be at least $ArrTime_{cal}$ since this is the physically minimal travel time, and move along the time of the following trips. After the assignment of trip time, the simulation follows Algorithm 1 to set time budgets. $DetRate$ is set as 30%.

Algorithm 2 Time integrity adjustment for synthetic trips

for each synthetic person p **do**
  for each trip t of person p **do**
    if t is the first trip of the day **then**
      $ArrTime \leftarrow VS\_StartTime + \delta + dTTime$;
    else
      $ArrTime_{rd} \leftarrow VS\_ArrTime + \delta$;
      $ArrTime_{cal} \leftarrow$ previous t's $ArrTime+$ previous t's $ActDur$ + this t's $dTTime$;
      $ArrTime \leftarrow max\{ArrTime_{rd}, ArrTime_{cal}\}$;
      if $ArrTime_{rd} < ArrTime_{cal}$ **then**
        Shift all the following trips' time by $(ArrTime_{cal} - ArrTime_{rd})$;
      end if
    end if
    $ActDur \leftarrow VS\_DUR + \delta$;
  end for
end for

4.3 Alternative destination choice set retrieval

The simulation adopts Yelp API to retrieve spatial locations of each type of activity. All the POIs within the study area's geographic boundary are drawn by querying with exactly the same words of the activity types documented in VISTA data, and saved in a local database. The simulation then simply searches this database, and uses the STF built from each trip's space-time budget to construct its destination choice set. Required information by the simulation includes: Retrieval keyword (activity type), latitude, and longitude of POI. Alternative trips are then built based on these POIs.

4.4 Optimization with linear programming

MatLab (R2016a) is used to solve the BIP problem and get the final solution for 1:1 matching. The objective function value ($fval$), which represents the number of matched pairs of trips, is of special interest to this work. A higher $fval$ means a higher matching rate. The computational burden on this part is heavy. Since the growth of population size leads to the increase of matching between trips in a superlinear manner, the matrix will expand drastically. This is the reason why a series of small samples are tested. The computaional complexity is discussed in section 6.

5. SYSTEMATICAL TESTS AND RESULTS

The experiment starts by initializing a large synthetic population and its trips, and is run with a series of subsampled populations to conquer the computational burden.

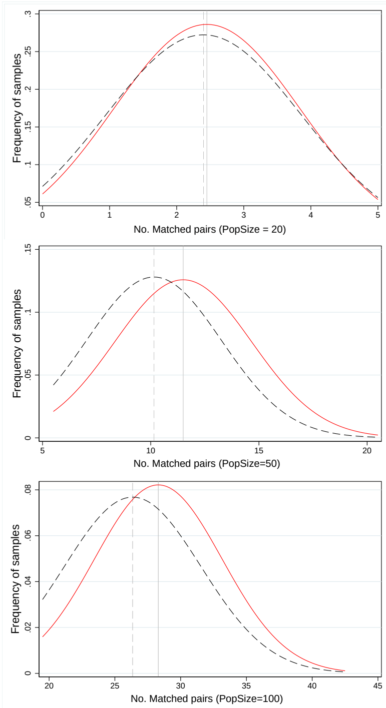


Figure 5: Distributions of number of matched pairs by population size. From top to bottom, the population sizes are 20, 50, and 100. Red solid curves are the results of considering alternative trips, while black dash ones are considering only original trips.

The initial population has 714 agents that make up of 1% of the synthetic population generated by Jain et al [13]. Despite losing the demographic composition, using subsampling rather than the full population relieves the computational burden in searching for a global optimum.

Table 2: Statistics of the tested samples

Population size		20	50	100
Avg. no. of original trips		58.9	150.8	287.2
Avg. no. of total trips		272.0	1223.9	1580.2
Mean. no. of matched pairs	Alts	2.45	11.5	28.3
	No Alts	2.4	10.15	26.35
	p-value	0.3299	**0.0001**	**0.0000**
Std.Dev. no. of matched pairs	Alts	1.39	3.17	4.86
	No Alts	1.47	3.12	5.19

Of the 52 simulated activity types, 28 are location-flexible activities that provide alternative trip chances. In total, 4,922 POIs are retrieved of all queried trips in the study area. The initial 714 population induces 2,185 original trips and 3,269 alternative trips, summing up to 5,454 trips. Regardless of location flexibility, *home* is the dominant destination. Considering only spatially flexible destinations, the population targets *supermarket* most, followed by *petrol station, fast food, shopping center, food store, newsagency and bookstore,* and *restaurant or café.*

Of the initial 714 people, the location-flexible activities only take a small percentage of the total activities. Each activity is associated with an original trip. The population yields 410 (18.8% of 5,454) original trips with flexible destinations. However, the less than one fifth original trips are dramatically enriched by the associated alternative trips that are about eight times their amount. Top-targeted activities after involving alternative trips become *petrol station, fast food, shopping center, restaurant or café, supermarket,* and *hardware.* These activities are of special interest of activity-based ridesharing.

With sizes of 20, 50, and 100, each population size is sampled randomly 20 times from the initial synthetic population pool of 714 agents. The matching runs twice on each random sample, one considering alternative trips and the other original trips only. The frequency distribution of the number of matched pairs for each population size is shown in Figure 5. From top to bottom, the population sizes are 20, 50, and 100 for each graph. Each curve is based on the randomly drawn 20 samples of that population size, with different approaches of matching: considering alternative trips (red solid curve) vs. not (black dash curve). Therefore, the statistical test aims to substantiate that, for each population size, the mean value of the red curve (marked by the vertical solid reference line) is significantly higher than its counterpart (dash reference line). Table 2 shows the statistics and statistical significance. "Alts" means the result by considering alternative trips, while "No Alts" refers to original trips only. Although Figure 5 does not demonstrate a visually apparent variation between the two curves, the test yields a significant result according to the dependent t-test. Choosing the dependent t-test allows for the interdependence that the results from the two runs are out of the same random sample.

It is encouraging to see the 50 and 100 population size cases yield a significant increase of matches by activity-based ridesharing. The bold p-values in Table 2 indicate high significance for population sizes 50 and 100. Though the smaller, 20 people cases do not pass the statistical significance test, no activity-based ridesharing test yields a lower amount of matches than its counterpart, which is a consistency expected by the model. In a majority of times, alternative destinations contribute to an increase of successful matches.

6. DISCUSSIONS

The experiment highlights some interesting but also challenging issues.

Representative sampling. The optimization part is not scalable to large population sizes. Therefore, smaller random samples are drawn. As seen in Table 2, the significance of the method depends on the population size. With larger population, more opportunities emerge due to a denser spatial distribution of and thus higher overlap of trips. Population size of 20 is generally too sparse in space (and time) to show an effect, in contrast to the samples of 50 and 100. Besides sample size, as shown in Table 3, the total number of feasible trips to be matched ($\|\mathbf{X}\|$) is not directly correlated to the extent to which *ABRA* can increase the ridesharing rate ("Gap"). "Gap" is calculated as the difference between the counts of matched pairs by considering alternative trips ("Alts") and not ("No Alts"). Nor correlated with "Gap" is the number of potential matches ($\|\mathbf{U}\|$, the number of feasible matches before BIP). The irregularity might be caused by the space and time sporadicity of trips with the lack of space and time overlap, which is partially induced by the small sample sizes. The heterogeneous distribution of alternative trips can be another reason: if only one person has many alternative trips, the overall matching rate is not necessarily increased. The sample size of 100 is relatively representative with trips dense enough and widely spread in space and time. "Gap" is foreseen to increase until trips get saturated.

Table 3: Statistics of trips and matching results: Samples of size 50 (**X** and **U** are explained in section 3.4)

#Matched pairs			$\|\mathbf{X}\|$		$\|\mathbf{U}\|$	
Gap	Alts	NoAlts	Alts	NoAlts	Alts	NoAlts
4	12	8	2008	169	3917	105
4	13	9	1076	161	2026	203
3	16	13	1172	179	1300	119
3	12	9	1022	155	2869	59
2	15	13	1619	144	11052	21
2	10	8	1921	139	441	17
1	8	7	1016	141	1845	123
1	14	13	227	137	42	41
1	20	19	1023	164	1170	138
1	11	10	1015	154	1929	194
1	7	6	1106	157	3111	33
1	7	6	1824	131	1190	45
1	11	10	999	140	1923	132
1	9	8	1130	165	999	46
1	8	7	1084	116	1033	34
0	12	12	1021	147	1891	136
0	11	11	155	149	146	146
0	12	12	1961	151	318	16
0	10	10	1058	140	166	12
0	12	12	1059	163	127	26

Scalability and efficiency. The current model is set as a static baseline model to investigate the benefit of activity-based ridesharing. It therefore searches for a global optimum to approximate the overall potential of activity-based ridesharing. However, questing for a global optimum makes it difficult to scale up. Let N, a, t, d be the population size, the average number of activities per person, and the average numbers of alternative trips and destinations per activity. Let β be a contingent constant such that the amount of potentially matched trips $\|\mathbf{U}\| = \beta t^a N$. The pre-computation complexity for matching candidates is $O(\|\mathbf{X}\|^2) = O((t^a N)^2)$. The optimization matrix has a size of $O(\beta t^a N) + O(daN)$, which takes too much time for an applicable system for BIP that strictly requires integer solutions solved by branch-and-bound. Consequently, only small samples could be drawn to address the computational burden. The constraint matrix for population sizes 50 and 100 can grow to tens of thousands rows by that many columns. With the initial full population size of 714, the constraint matrix jumps up to million by million.

Returning to the research question. Even with the limitations of scalability and sample sizes, the experiment substantiates the hypothesis that *ABRA* can significantly increase the successful matching rate compared with the traditional trip-based method. As aforesaid, the consistency is meaningful that *ABRA* is stably capable of increasing successful matches. With samples of population size 50 (Table 3), as many as four more pairs of trips can be matched. To the best case (the 1^{st} entry), the matching rate is increased by 50% with *ABRA*. It therefore highlights the effectiveness of the proposed algorithm.

7. CONCLUSIONS AND FUTURE WORK

This work proposes *activity-based ridesharing* as a novel method of ride-matching that aims to enlarge the chance of matching compared to trip-based methods. In activity-based ridesharing, people can lodge a request for a ride from an *activity* A to an *activity* B, rather than from location A to location B. The algorithm develops a space-time filter to construct the choice set of approachable destinations by extracting the POIs of the requested activity. This space-time filter is capable of handling multiple consecutive flexible activities, which is advantageous over simple space-time prisms. The experiments clearly prove the capability of activity-based ridesharing to increase successful matching rates. This outcome is trustworthy as the simulations are set in a real-world context. The implementation also demonstrates the correctness of the proposed (exact) solution of the global optimization problem.

However, it has also become clear that scalability is a serious challenge, for which a dynamic agent-based ridesharing model that employs real-time heuristics and accommodates human behavior heterogeneity is suggested as a future research direction: A **dynamic system** for ridesharing applications suits realistic scenarios better since people usually lodge a travel request on the fly. It can construct a space-time filter in a real-time manner, searching for nearby resources to quickly build a choice set. The candidate ride partner is consequently a local optimum approached by a decentralized decision process, which requires an agent-based model. Additionally, the agent-based model could accommodate **heterogeneous human behaviors** by developing heuristics, such as utilizing user ratings to filter out some POIs, or tailoring matches to the travel habits and visiting history of each person. Another interesting direction can involve the role of **social network** as heuristics in activity-based ridesharing. Social network not only implicitly bundles people's physical behaviors (e.g., [28, 31]), which affects the detour cost and chance of getting a ride, but also latently decides the preference to choose ride partners [8].

Another future work is the **semantic accuracy**. If the activity types of demand and supply data sets may not match exactly, the search of POIs by different activity types can actually be too narrow or too inclusive. In the experiment in this paper, activities documented in VISTA have not matched exactly with activities in the Yelp database. For example, *fast food, food store, restaurants* and *supermarket* are listed as different categories in VISTA, but are in one group in the Yelp database. Improving the matching quality will be an interesting topic for geographical semantics.

8. ACKNOWLEDGMENTS

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