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Panayotis Papoutsis, Safa Fennia, Constant Bridon, Tarn Duong. Relaxing door-to-door matching reduces passenger waiting times: a workflow for the analysis of driver GPS traces in a stochastic carpooling service. 2020. hal-02525906v2

**HAL Id: hal-02525906**

**<https://hal.science/hal-02525906v2>**

Preprint submitted on 10 Aug 2020 (v2), last revised 11 Feb 2021 (v3)

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# Relaxing door-to-door matching reduces passenger waiting times: a workflow for the analysis of driver GPS traces in a stochastic carpooling service

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## Abstract

Carpooling has the potential to be a key component of the transport mix in post-carbon, ecologically sustainable societies. In a world first, Ecov provides innovative carpooling services where carpooling is transformed from an individualistic, private mode of transport to a hybrid private-public mode. Passengers make carpooling requests at pre-selected meeting points without a priori matched drivers, and these requests are stochastically matched in real-time to the passing driver flow. Since drivers and passengers are constrained to converge at meeting points along these trajectory segments, highly convenient door-to-door travel is not feasible for the majority of users. The trade-off is that these meeting points act as aggregators to reach a critical mass of closely matched passenger demand and driver supply more quickly and more sustainably. Due to the innovative nature of stochastic carpooling, off-the-shelf data science workflows are unable to provide pertinent analysis to guide the service operator. We introduce a workflow, comprising of a combination of data science and GIS (Geographic Information Systems), which processes driver GPS traces in order to provide important indicators to guide the operational decision-making. We illustrate it on a currently operational carpooling service in the outskirts of the city of Lyon, France. This workflow provides evidence that relaxing deterministic door-to-door matching, and hence expanding the potential pool of participating drivers, in a real-time stochastic carpooling service, is a key factor to reduce passenger waiting times. Waiting times and other performance indicators, comparable with high performance bus services in peri-urban areas, can be achieved at a significantly lower cost.

Keywords: data science-GIS, driver flow, driver participation rate, carpooling, passenger waiting time

## 1 Introduction

The business model of current market leaders in carpooling, such as Uber, Lyft, Kapten and others, involve constructing large fleets of professional drivers who respond to the passenger requests. This model provides door-to-door carpooling services, where a passenger makes a request at a given time to travel from a given origin to a given destination. This request is

then matched deterministically from the database of available drivers. Whilst these door-to-door services possess a high level of convenience as they respond closely to individual travel requirements in both time and space. The fact that it satisfies these requirements makes the door-to-door carpooling services incompatible with a large scale utilisation and is not ecological. Thus these market leading carpooling service providers now recognise that large scale utilisation of carpooling depends crucially on relaxing this door-to-door requirement by incentivising both passengers and drivers towards pre-selected meeting points (Stiglic et al. 2015). For example, "Suggested Pickup Points" are proposed by Uber (2019) to passengers so that the drivers avoid taking inefficient and/or infrequent routes. This incentivisation is well-established for public transport services where these predefined meeting points correspond to bus stops or train stations. Thus large-scale utilisation of carpooling requires a paradigm shift from considering carpooling as an exclusively individual means of transport to a closer alignment to mass public transport models, as presaged in Cooper (2007).

In a world first, a range of hybrid public-private carpooling services are proposed by the carpooling provider Ecov (Ecov.fr). Further following the public transport model, within Ecov's services, these meeting points and road segments are not defined informally between passengers and drivers, but their placement are decided in consultation with local government authorities so that they respond to the mobility requirements in the local area, which take into account various factors such as aggregated traffic flow, socioeconomic characteristics, pedestrian accessibility, local government regulations, etc. Since they are fixed, physical meeting points, we do not require those matching algorithms which are concerned with the identification of dynamic meeting hotspots between passengers and drivers (Schrieck et al. 2016). These meeting points are marked with fixed, physical structures which are easily visible by drivers on the road, analogous to bus or coach shelters. These meeting points are connected to each other to define route segments, which have a large massification potential, like traditional bus lines. Unlike many of its competitors, the Ecov carpooling services do not cater to densely populated, highly urbanised areas, but rather to peri-urban or rural areas which are often marginalised by transport providers. The lack of transport options in these areas is a key contributing factor in many social issues, like chronic unemployment (Fransen et al. 2019). For these sparsely populated and less well digitally connected areas, the physical meeting points provide local residents access to an economically and ecologically sound transport service.

The other world leading innovation that Ecov carpooling services bring to the market is the shift away from the deterministic matching between passengers and drivers to a stochastic matching. Carpooling usually operates with the individual passenger request being matched deterministically to a particular driver with an agreed departure, destination, and time frame. This deterministic matching requires considerable planning and is well-adapted to infrequent, long distance journeys and/or densely populated areas, e.g. as demonstrated by the market penetration in France of the long-distance carpooling provider BlaBlaCar (www.blablacar.fr). On the other hand, for frequent, short distance journeys (from 10 to 40 km roughly) in more sparsely populated areas, which comprises the bulk of home-work commutes, this type of planned carpooling is not adapted. Ecov's carpooling approach removes these pre-planning requirements, as it allows a passenger to make an immediate carpooling request without reservation at a meeting point, since the service subsequently displays the desired destination on an electronic sign on the side of a main road in order to alert the passing drivers of this request in real-time. Since the actual driver who will collect the passenger is not known in advance, but is only known to be drawn from the population of drivers, this is a *stochastic matching*. The innovations proposed by

Ecov are only sparsely covered by the recent comprehensive review of the evolution of carpooling services in the past two decades (Wang & Yang 2019).

The physical meeting points provided by Ecov require an integrated infrastructure to facilitate this real-time stochastic matching, as illustrated in Figure 1. Our example is the “Lane” carpooling service ([lanemove.com](http://lanemove.com)) operated by Ecov, in conjunction with Instant System ([instant-system.com](http://instant-system.com)), since May 2018 in the south-eastern peri-urban regions around Lyon, France. The orange structure on the right functions like a bus shelter to provide (a) protection from inclement weather whilst the passenger waits, and (b) a prominent visual point of reference for drivers on the road. The passenger makes a carpooling request on the console (the green device with a horizontal yellow stripe) close to the shelter. This request is displayed on the electronic sign on the roadside. In this configuration, the electronic sign is located close to the meeting point, but this can vary considerably according to the local geographical characteristics. A driver who wishes to embark the passenger in response to their request is able to do so safely in the reserved parking place.



Figure 1: Configuration of a physical meeting point for the “Lane” real-time carpooling service. The orange structure functions like a bus shelter. A passenger notifies potential drivers of their carpooling request using the console, which is then displayed on the roadside electronic sign. A driver can safely embark the passenger in the reserved parking place. Reproduced with permission from Ecov.

These meeting points are unable singly to provide a sufficiently high level of service for passengers and drivers for stochastic matched carpooling. To assure this, they are organised into carpooling lines where each line is made of at least two meeting points. The schematic of the carpooling lines in the Lane network is shown in Figure 2. The visual similarities of the schematic of this carpooling service with those associated with bus or train services is designed to induce the perception of Ecov carpooling as a form of public transport. There are 5 physical meeting points, denoted by the circles with the stylised  $\mathcal{L}$ , which function analogously to bus stops. According to mobility studies in this territory, the coloured lines connect the meeting points that have a sufficient driver flow between them to maintain a carpooling service with stochastic matching. These connected meeting points form a carpooling line, again analogous to a bus line, where carpooling is only available between these pre-selected meeting points.

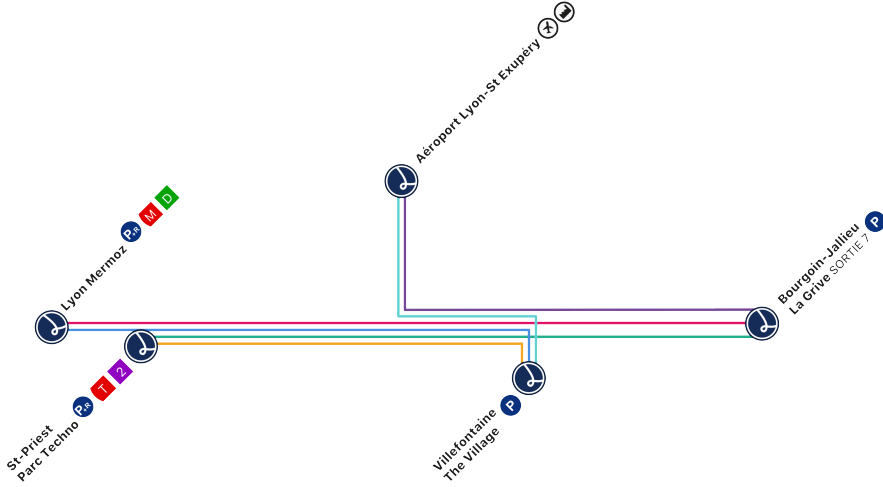


Figure 2: Schematic diagram of the Lane carpooling service, which resembles the geographically restrained trajectories of a public transport service. Reproduced with permission from Ecov.

In this carpooling service, minimal restrictions are placed on the passengers’ participation, which consist mostly of arriving at a meeting point during the service operating hours, and being prepared to *not* have a fixed departure time. On the other hand, the onus is placed on the population of drivers since they collectively must be ready to respond to a passenger carpooling request in a timely manner. Due to this asymmetry of the involvement of passengers and drivers, according to several empirical studies, the constitution and the retention of a sufficiently sizeable population of participating drivers who can respond to passenger carpool requests in a timely manner is the key element of this stochastic carpooling service (Zhu 2017, 2018).

In this paper, firstly we present the theoretical reasons of why door-to-door matching is insufficient to ensure a regular carpooling service. Secondly we present a data science-GIS workflow which we utilise to verify, based on observed data collected from an operational stochastic carpooling service, that meeting point matching leads to reduced passenger waiting times.

## 2 Door-to-door matching as an obstacle to mass carpooling utilisation

Carpooling has seen an explosion of utilisation in recent years. There are many underlying reasons, with concerns ranging from greenhouse gas emissions to road congestion, air pollution, land use, as well as economic costs. It is also attracting intense interest since carpooling is crucial element of almost all developments plans for smart cities (Ghoseiri et al. 2010, Ghoseiri 2012). As alluded in the introduction, door-to-door matching of complete trajectories from the origin to the destination is a structural obstacle to the transformation of carpooling as a mass transit service.

To illustrate the difficulties of spatio-temporal matching for door-to-door trajectories (i.e. passenger-driver matching in space and in time), we can represent it with partition of a 3D cube divided into smaller sub-cubes, where the  $x$ -axis is the longitude, the  $y$ -axis the latitude and the  $z$ -axis the time, as shown in Figure 3. On the left, there are 9 sub-cubes, where each sub-cube represents the origin/destination of a door-to-door trajectory. The blue sub-cube in

the lower left represents all the trajectories whose origins are, say, within a 5 km radius around a residential neighbourhood between 07:00 and 09:00 on Tuesday, and the green sub-cube the trajectories whose destination are within a 5 km radius of the workplace between 08:00 and 10:00 on Tuesday. So for two trajectories to match spatio-temporally in a door-to-door sense, they must share the same sub-cube for the origin, and similarly for the destination: this condition is met only by the 1 pair of green and blue sub-cubes among all possible 27 pairs of sub-cubes. On the right, the conditions for a door-to-door matching are stricter, say the origin is 1 km within the residential neighbourhood during 07:00 to 07:30, and the destination is 1 km within the workplace during 08:30 to 09:00. This represents 1 pair out of 125 pairs of sub-cubes. Recall that Ecov’s carpooling services comprise non-professional drivers who do not create a trajectory upon a passenger request, but rather mutualise their existing trajectories, so door-to-door matching leads to a combinatorial dilution of spatio-temporal matches. Thus for Ecov, it is crucial to avoid exact door-to-door matching and to move towards matching highly frequented partial road segments of door-to-door trajectories.

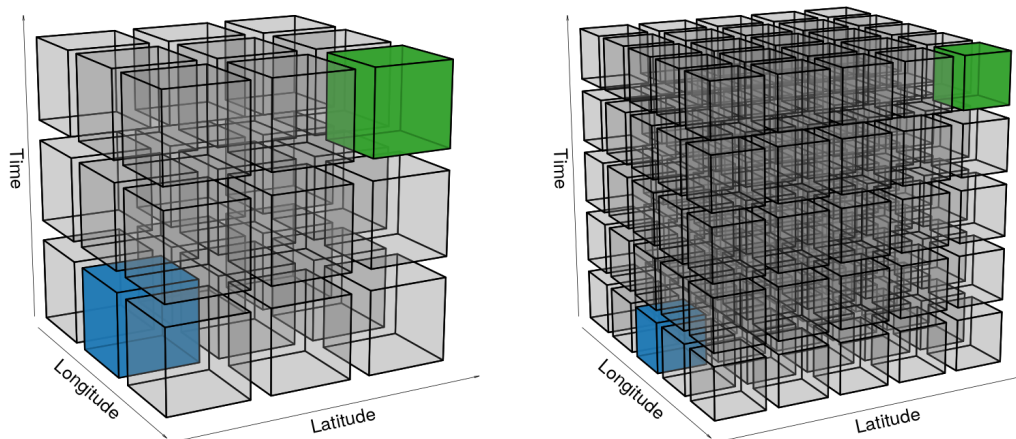


Figure 3: Spatio-temporal door-to-door matching fragments the population of mutualisable trajectories. (Left) Relaxed matching conditions. (Right) Restricted matching conditions. Blue sub-cube represents the origin (residential neighbourhood), green the destination (workplace), and trajectories which share the same origin and destination sub-cubes are considered to be door-to-door matches.

To supplement the heuristic observations for door-to-door matching in Figure 3, we demonstrate that the probability that two users (i.e. a driver and a passenger) share the same origin and destination at the same time decreases rapidly as the spatio-temporal matching conditions become more stringent. For the sake of simplicity, we suppose that the origin and destination for a driver and a passenger are both represented by independent random variables which are uniform over all sub-cubes in Figure 3. If we draw a random sample of 1000 each of drivers and passengers, then the probability of any door-to-door match between these drivers and passengers, as a function of the number of sub-cubes, is given in Figure 4. If there is only 1 sub-cube (i.e. no spatio-temporal constraints) the probability of a match is 1. This probabilistic certainty decreases rapidly as the spatio-temporal constraints are added: for 27 sub-cubes, this probability

is 0.7, and for 125 sub-cubes, it falls to 0.26. Thus it is almost impossible for a carpooling service, if it is based on complete door-to-door spatio-temporal matching, to evolve into a mass transit service. [Stiglic et al. \(2015\)](#), [Li et al. \(2018\)](#) provide more complex synthetic models to affirm that meeting points are essential to the feasibility of the mass carpooling services.

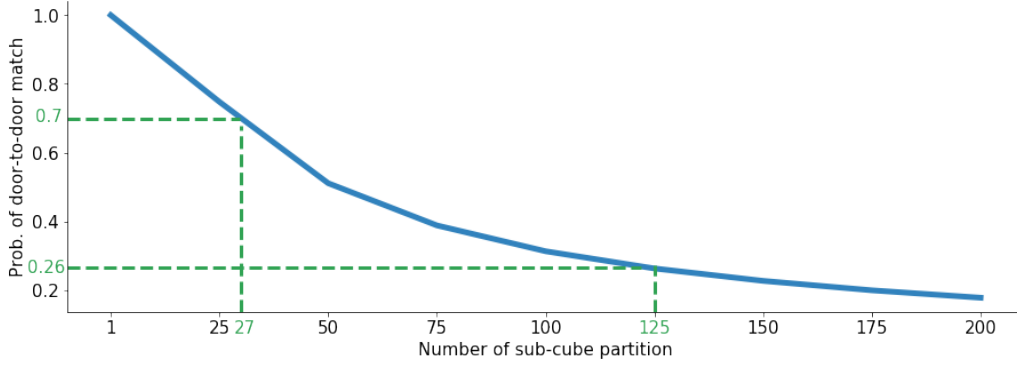


Figure 4: Probability of door-to-door matches for uniformly distributed drivers and passengers, as a function of the number of sub-cube partition classes. Higher number of sub-cubes represent more stringent spatio-temporal matching conditions.

Given that the probability of door-to-door matches diminishes rapidly, apart from increasing the number of available drivers we propose also to enlarge the pool of potential matching by relaxing the spatial conditions. In Figure 5, this is represented by extending the origin and destination to cover 12 sub-cubes each in a horizontal layer, rather than as single sub-cubes. This increases the probability of a match from 0.26 to 0.39.

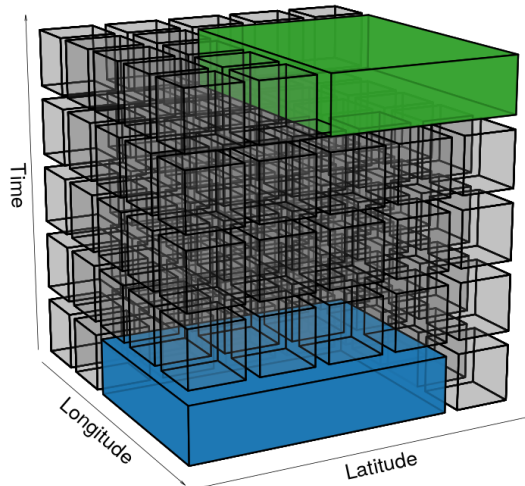


Figure 5: Meeting points aggregate the spatio-temporal matching of mutualisable trajectories. The green sub-cube represents the coverage area of the origin meeting point (residential neighbourhood), the blue the destination meeting point (workplace).

The previous analysis was based on the uniformly distributed origin and destinations. To offer a more realistic example, we analyse some data generated by an operational Ecov carpooling service. Our main data source is the GPS traces of drivers who are registered with Ecov’s services, which can be considered to be a form of crowd-sourced data collection (Lee & Liang 2011). Passenger GPS traces are more difficult to obtain, and as we are not able to replicate exactly the synthetic example of passenger-driver matching above, we use door-to-door matching of driver GPS traces to illustrate the diminishing probabilities. This supplements the results for synthetic data experiments in Stiglic et al. (2015), Li et al. (2018) with empirical results.

Since these GPS traces provide highly detailed spatio-temporal information, we are able to determine the number of empirical door-to-door matches, as well as the effect on the number of matches when matching is carried out between two fixed, physical carpooling meeting points. For an illustrative example in Figure 6, we analyse the  $n = 121$  GPS traces of drivers who travelled from the Bourgoin La Grive meeting point (solid black circle labelled B) to the Saint-Priest Parc Technologique meeting point (solid black circle labelled S) in the Lane carpooling service during the morning operating hours (06:30 to 09:00) during the work week 2019-11-25 to 2019-12-01. We temporarily ignore the location of the carpooling meeting points, and focus on the GPS traces and their origin and destinations. A hierarchical clustering with complete linkage was carried out on the spatial locations of these origins and destinations. The dissimilarity matrix used for this hierarchical clustering is composed of the Euclidean distance between the 4-vector comprising the (origin longitude, origin latitude, destination longitude, destination latitude) of each trajectory. This dissimilarity takes into account both the origin and the destination. On the other hand, it does not take into account the intermediate GPS points as these actual route taken is not critical for our purposes. We cut the dendrogram at  $h = 6000$  to yield 9 spatial clusters. These clusters are represented with the different colours: the origin and destinations are the diamonds, and the GPS traces are the points. So GPS traces with the same colour can be considered as door-to-door spatio-temporal matches. This fragmentation of the driver traces in Figure 6 into different door-to-door clusters is the empirical equivalent to the theoretical division of the unit cube into many sub-cubes in Figure 3.

The number of GPS traces per cluster is given in Table 1: whilst cluster 1 contains 75% of the mutualisable traces, so this leaves the other 25% spread sparsely over the other 8 clusters, fragmenting the supply of the carpooling trajectories.

Door-to-door cluster	1	2	3	4	5	6	7	8	9	Total
Number of GPS traces	76	15	7	9	4	1	7	1	1	121

Table 1: Spatio-temporal door-to-door matching fragments the number of mutualisable trajectories in the Bourgoin > St-Priest carpooling line, during its morning operating hours 06:30–09:00, from 2018-11-25 to 2018-12-01. Door-to-door matches induced by hierarchical clustering of GPS traces. The first line of the table contains the number of the clusters and the second line the number of traces for each cluster.

To quantify the augmentation of the carpooling potential by relaxing door-to-door matching for a given pair of carpooling meeting points, we compare the cluster with the largest cardinality, since it contains the most number of trajectories that can be considered to be close door-to-door spatio-temporal matches and whose trajectories coincide (mostly) with the Bourgoin > St-Priest carpooling line, to the number of the trajectories which pass by both meeting points, regardless of their true origin and destination. In the case for Table 1, there are 76 traces in the



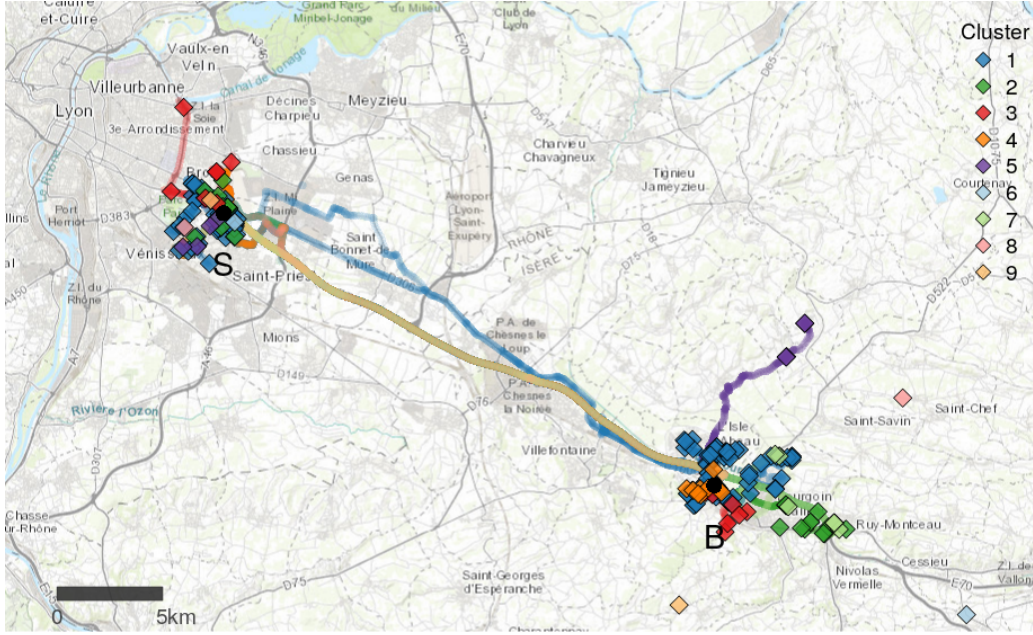


Figure 6: Spatio-temporal door-to-door matching fragments the number of mutualisable trajectories in the Bourgoin > St-Priest carpooling line, during its morning operating hours 06:30–09:00, from 2018-11-25 to 2018-12-01. The clusters of GPS traces of door-to-door matches are colour coded, with the GPS points as the solid circles, and the origins/destinations as the solid diamonds. The meeting points are the solid black circles: B = Bourgoin, S = St-Priest.

largest door-to-door cluster in blue, whereas there are a total of  $n = 121$  traces which pass from Bourgoin to St-Priest (i.e. aggregating all clusters). Thus meeting point matching represents an increase 45 traces or 59% of the carpooling driver potential over door-to-door matching. This increased number of observed meeting point matches to 121 (an increase of more than 50%) is the empirical equivalent of the aggregation of the theoretical fragmented carpooling potential by merging several sub-cubes in the unit cube in Figure 5.

This hints at the potential of meeting point matching over door-to-door matching for a small-scale data set of driver GPS traces. In the next section we introduce a workflow which allows us to confirm this increased potentiality through the automated analysis of a large number of GPS traces. Since a direct comparison of passenger waiting times is not possible since a door-to-door carpooling service (which serves the same population as the Lane carpooling service) is not operational, we propose an indirect comparison in three stages: (i) extract all driver GPS traces on the Bourgoin > St-Priest line in the morning operating hours 06:30–09:00 to serve as the meeting point matches, (ii) extract the largest hierarchical cluster of these GPS traces to serve as the door-to-door matches, and (iii) compute the driver flows, for both sets of matches, and then convert them using our model to passenger waiting time predictions. To be confident that the predicted passenger waiting times are reasonable, we demonstrate the predicted waiting times track closely the observed ones in the Lane service, and so we suppose that the predicted waiting times for the door-to-door matches will have similar comparability to the observed waiting times in a putative door-to-door carpooling service.

### 3 Data science-GIS workflow for a stochastic carpooling service

The Data Science-GIS department of Ecov has developed many workflows in response to the multiple challenges posed by the collection, storage and analysis of numerous, heterogeneous data sources stochastic carpooling services: for brevity we focus on the GPS traces workflow, as illustrated in Figure 7. The left part of the Figure 7 contains the main data sources: the GPS traces, the meeting point locations, the origin-destination matrices, the route finder API and the base maps. The first two are stored as PostGIS SQL databases on a secure server owned by Ecov, the origin-destination matrices are provided by the French national statistical agency (INSEE 2018), the route finder API is provided by the GPS navigation operator (TomTom 2019), and the base maps are accessed from the cartography provider OpenStreetMaps (OpenStreetMap contributors 2019). There are specialised data wrangling techniques specific to spatial databases, known collectively as *geoprocessing*, and these are carried out, in conjunction with traditional data wrangling, in the central lozenge. The critical geoprocessing concerns the topological simplification of the GPS traces onto its network map of carpooling meeting points and lines. Whilst GPS traces are a rich source of information of driver behaviour, they are voluminous and complex, and whose complexity can be highly variable depending on the GPS technology deployed. Our approach is based on network analysis tools (Guidotti et al. 2017) and complexity reduction/harmonisation algorithms (Douglas & Peucker 2011). This topological simplification is essential to be able to mutualise GPS traces which share common arrival times at the carpooling meeting points. Once these GPS traces are in a suitable format, we are able to produce the required outputs, such as maps of the the geographical extent of the GPS traces, the driver flow per route segment in the carpooling lines and/or per time interval, and subsequently the corresponding waiting times and travel times, as outlined in the right lozenge.

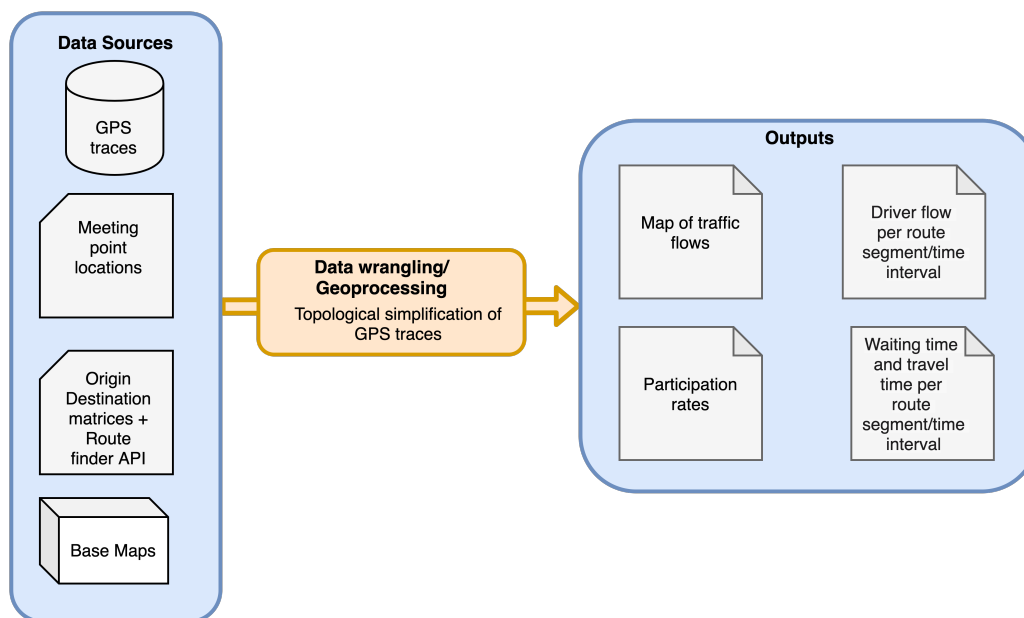


Figure 7: Data science-GIS workflow for the analysis of driver GPS traces in stochastic carpooling service. Left. Spatio-temporal input data sources. Centre. Data wrangling and geoprocessing. Right. Generated outputs.

### 3.1 Topological simplification of GPS traces on a carpooling line

The basis for the topological simplification of the GPS traces is the network of the Lane carpooling network from Figure 2. This network is represented as a directed graph, where each node is a meeting point and the edge connects two nodes if they form segment of a carpooling line, as shown in Figure 8. For brevity, the node labels have been abbreviated to the first letter of the name of the meeting point, i.e. L = Lyon Mermoz, S = St-Priest Parc Technologique, A = Aéroport Lyon-St Exupéry, V = Villefontaine The Village, and B = Bourgoin La Grive Sortie 7. Since the primary objective is to match passenger and driver trajectories on the arrival times at the meeting points, then the actual route taken between these two meeting points is of secondary interest so we can represent all routes connecting from one meeting point to the other as a single directed edge. The identification of all GPS traces which share arrival times at the two meeting points, by ignoring the intermediary routes taken, to a single directed edge in the graph, is the mathematical abstraction which facilitates the massification of the driver trajectories which are able to fulfil a passenger carpooling request which respects the latter’s spatio-temporal conditions.

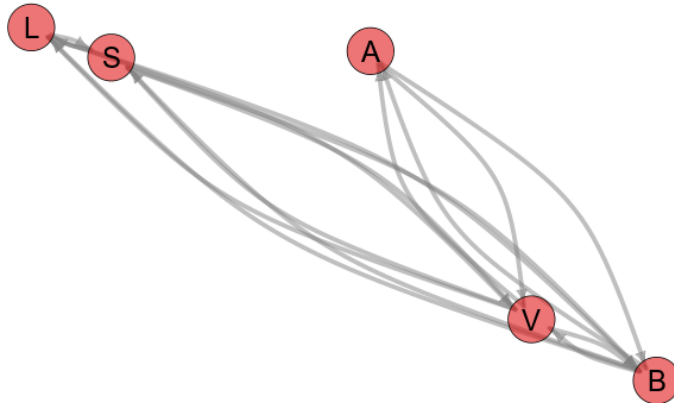


Figure 8: Network of carpooling lines represented as a directed graph. Nodes are the meeting points, edges connect meeting points whenever a carpooling service between them is assured.

A GPS trace is displayed as the sequence of blue circles in Figure 9. It has a complex topology since it is represented by 530 GPS points which follow (more or less) the road network. This complex topology is simplified by retaining a small number of key indicators derived from the complete GPS trace, following [Lee & Liang \(2011\)](#). In addition to the nodes associated with the origin (first GPS point) and destination (last GPS point), we retain only those meeting place nodes if the GPS trace contains a point within a 1 km radius of the nodes. The GPS trace in Figure 9 passes within 1 km of the B, V and S meeting place nodes, so the resulting simplified topology consists of the 5-node sequence: {origin > B > V > S > destination}. These simplified topologies represent a considerable reduction in data complexity, whilst the crucial characteristics with respect to the carpooling service are retained. The individual GPS locations are a secondary detail since it is vastly more important to know if a driver (a) passes by a carpooling meeting point and (b) travels in which direction to which other meeting point(s) in the network. This approach contrasts with [Tiakas et al. \(2009\)](#) who attempt to match driver trajectories along the entire length of the traces.

For the GPS trace in Figure 9, the complete trace contains 530 GPS points whereas the trace

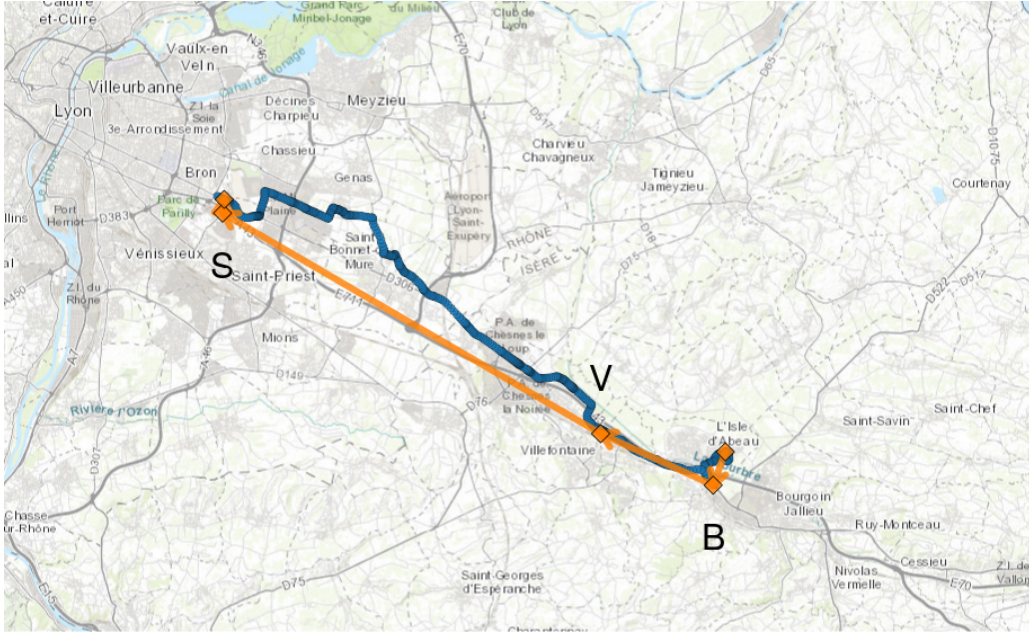


Figure 9: Topological simplification of a GPS trace in the Bourgoin > Bourgoin carpooling line, during its morning operating hours 06:30–09:00, on 2019-11-28. The complete GPS trace are the 530 blue circles; the sequence of five nodes, as its simplified topology, are the orange arrows, and the orange diamonds are the origin, carpooling meeting points, destination nodes. The meeting points are S = St-Priest, V = Villefontaine, and B = Bourgoin.

for the simplified topology contains only 5 points (the origin, the Bourgoin meeting point, the Villefontaine meeting point, the St-Priest meeting point and the destination). This represents a data compression rate of over 99% yet the latter retains the important information to decide the matching potential of this GPS driver trace with a passenger carpooling request on the Bourgoin > St-Priest carpooling line. In Table 2 are the data compression performance for all the GPS traces on the Bourgoin > St-Priest line from 2019-07-25 to 2020-02-17. The first column is the average number of GPS points in the complete driver traces, the second is the average number of GPS points of the simplified topologies of the complete GPS traces, and the last column is the average data compression rate ( $1 - \# \text{ points in simplified trace} / \# \text{ points in complete trace}$ ).

Line	# points in complete GPS traces	# points in simplified GPS traces	% compression
B > S	313	5	98.3

Table 2: Data compression rate on the Bourgoin > St-Priest carpooling line, during the morning operating hours 06:30 am to 09:00 am, for all driver GPS traces from 2019-07-25 to 2020-02-17. The first column is the average number of GPS points in the complete driver traces, the second is the average number of points of the simplified GPS traces, and the third column is the average data compression rate.

### 3.2 Driver flow estimation

Recall that a carpooling service is assured between Bourgoin and St-Priest since edge connects the two nodes in Figure 8. So if the directed graph of the simplified topology of a GPS trace contains  $\{B > V > S\}$  or  $\{B > S\}$  as a subgraph, then this driver's GPS trace is able to participate in this carpooling line. This is the case for all 121 GPS traces under consideration. Furthermore,  $n = 31$  GPS traces have an arrival time at Bourgoin within 08:00 am to 08:30 am, i.e., a close spatio-temporal match for a passenger request for departure at the Bourgoin meeting point (in a residential neighbourhood) between 08:00 and 08:30 am, with a destination at the St-Priest meeting point (in a neighbourhood with a high employment density). Of these 31 GPS traces, only 17 of them are door-to-door matches (as defined as belonging to the largest door-to-door cluster of GPS traces in Table 1) share a departure time from their origins in the same interval of 08:00 am to 08:30 am. These are both door-to-door and meeting point matches and their simplified traces are displayed in Figure 10 as the orange diamonds/arrows. The simplified traces of the remaining 14 meeting point only matches are the blue diamonds/arrows. The latter represent an 82% increase in the number of drivers who can potentially respond to a passenger carpooling request for the Bourgoin > St-Priest line.

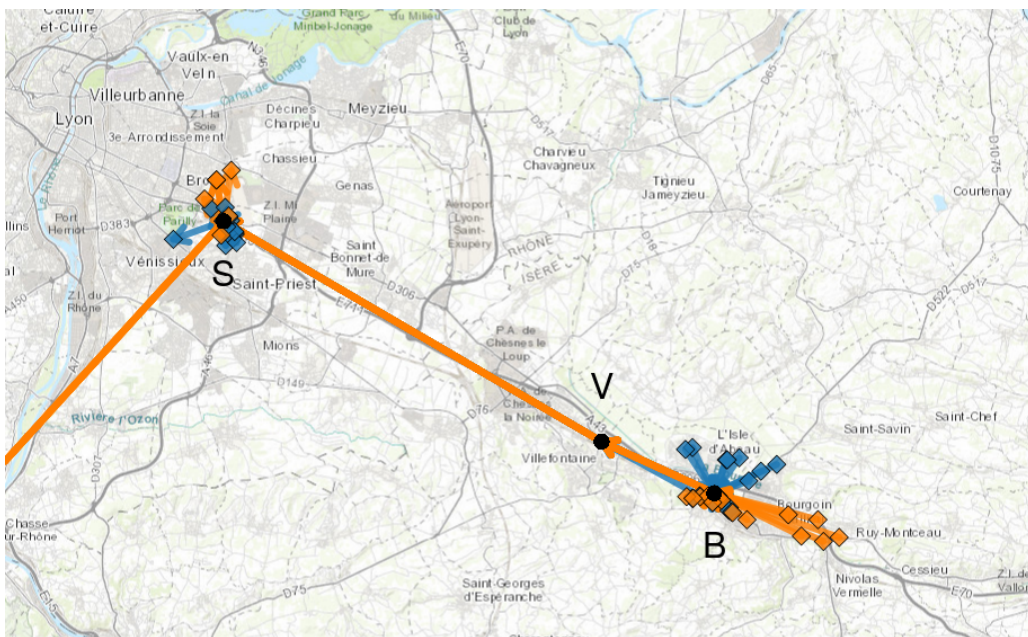


Figure 10: Matching on meeting points increases the number of driver spatio-temporal matches in comparison to door-to-door matching, during a single 30 minute period (08:00-08:30), on 2019-11-28. The orange arrows are the GPS traces which are both meeting point and door-to-door ( $n = 14$ ), and the blue arrows are the GPS traces which are meeting point matches but not door-to-door match matches ( $n = 17$ ). The diamonds are the origin/destination points. The solid black circles are the meeting points: S = St-Priest, V = Villefontaine, and B = Bourgoin.

Table 3 summarises the impact of meeting point matching over door-to-door matching. The first three columns focus on the entire period of the morning operating hours of the Lane carpooling service (06:30–09:00) whereas the second set of three columns on the single 30 minutes period (08:00–08:30) as this latter, restricted period is a more realistic time frame that potential

passengers are willing to wait for a driver to arrive. The first column contains the number of door-to-door matches, the second the number of meeting point matches, and the third is the percentage increase, i.e.  $(\# \text{ meeting point matches} - \# \text{ door-to-door matches}) / \# \text{ door-to-door matches}$ . These percentage increases in the carpooling driver potential can be considered to be empirical verification of the expected theoretical increase in carpooling potential when incorporating meeting point matches in Figure 5 in comparison to a carpooling potential based solely on door-to-door matches in Figure 4.

Week n°	06:30–09:00			08:00–08:30		
	# Door-to-door	# Meeting point	% increase	# Door-to-door	# Meeting point	% increase
2019W36	54	100	85	18	24	33
2019W37	67	99	48	20	21	5
2019W38	81	122	51	20	27	35
2019W39	72	119	65	20	28	40
2019W40	43	94	119	9	19	111
2019W41	48	106	120	12	29	141
2019W42	50	103	106	18	33	83
2019W43	30	85	183	11	27	145
2019W44	43	63	47	9	14	56
2019W45	48	102	113	14	28	100
2019W46	41	71	73	12	22	83
2019W47	60	110	83	15	30	100
2019W48	76	121	59	17	31	82
2019W49	58	94	62	19	32	68
2019W50	47	99	111	5	22	340
2019W51	82	103	26	21	27	29
2020W01	12	23	92	4	6	50
2020W02	53	96	81	14	23	64
2020W03	63	100	59	14	27	93
2020W04	74	105	42	16	23	44
2020W05	55	104	89	16	23	44
2020W06	44	110	150	14	27	93
2020W07	57	96	68	13	23	77

Table 3: Weekly driver flow increase of meeting point matching compared to door-to-door matching in the Bourgoin > St-Priest carpooling line, during the morning operating hours 06:30–09:00, from 2019-09-02 to 2020-02-17. The first column contains the number of door-to-door matches, the second the number of meeting point matches, and the third is the percentage increase from the door-to-door matches.

These simplified GPS traces with timestamps, in addition to being direct means of aggregating driver GPS traces to augment the number of possible spatio-temporal matches to a passenger carpooling request, they also greatly facilitate the calculation of detailed temporal profiles of the driver flows on each of the segments in the carpooling service. Table 4 displays the average driver flow for 15 minute intervals during 06:30 to 09:00 (morning operating hours). Intervals of 15 minutes correspond roughly to the maximum time that passengers are willing to wait

in a real-time stochastic matching carpooling service. Moreover, [Smith & Demetsky \(1997\)](#), [McShane & Roess \(1990\)](#) indicated that these 15 minutes intervals are an optimal choice because the variation in driver flows for shorter intervals is less stable.

		Driver flow				
	Line	06:30- 06:45	06:45- 07:00	07:00- 07:15	07:15- 07:30	07:30- 07:45
B > S		1	1.5	2.5	1.5	3
	Line	07:45- 08:00	08:00- 08:15	08:15- 08:30	08:30- 08:45	08:45- 09:00
B > S		1.5	2	2	2	1

Table 4: Driver flow on the Bourgoin > St-Priest carpooling line, per 15 minute intervals, during the morning operating hours 06:30–09:00 for a typical week.

### 3.3 Waiting time prediction

From the passenger point-of-view, a key quality measure of a carpooling service is the driver arrival in a suitable time frame. The estimation of the time of arrival (ETA) is a vast subject of active research in itself, see [Wang & Yang \(2019\)](#) for a recent review of these methods within the larger context of the characterisation of carpooling services. For deterministic matching carpooling, the problem of waiting time prediction is the estimation of the travel time of the matched driver to reach the given passenger. For stochastic matching, since a specific driver is not matched to the given passenger, the problem is different since it is the estimation of the arrival time of the first driver from the population of available drivers. Given that we have already established a highly detailed spatio-temporal profile of the average driver flow on the segments between meeting points (in Table 4), with the added hypothesis of driver arrivals as a Poisson point process, then it is straightforward to convert these driver flows into an estimation of the waiting time. It is a reasonable assumption that the first geolocated driver will pick up the passenger: according to unpublished figures supplied by Ecov, the majority of regular carpooling journeys are assured by motivated drivers who are willing to share their geolocation, and only a minority by unregistered and/or non-geolocated drivers.

Suppose that a passenger makes a carpool request at 08:10 am at the Bourgoin meeting point to travel to St-Priest. Then the expected waiting time is the length of the interval divided by the average driver flow in the interval 08:00 – 08:15, i.e. 7.5 minutes from Table 5.

Since these GPS traces are drawn from an operational carpooling service, we also have access to observed waiting times for roughly 1 500 carpooling requests with a recorded waiting time on the Bourgoin > St-Priest carpooling line from 2019-07-25 to 2020-02-17. So we are able to evaluate the accuracy of these predicted waiting times with respect to these observed ones, as illustrated in Figure 11. Each box plot covers a 15 minute interval during the opening hours with at least one observed waiting time. The blue box plots represent the observed waiting times and the predicted waiting times are the horizontal red lines. During the morning opening hours, the direction of travel is from Bourgoin to St-Priest, whilst in the evening it is the reverse from St-Priest to Bourgoin. The predicted waiting time as the reciprocal of the average driver flow is fairly reliable, especially in the morning operating hours. In Figure 12 are the box plots of the RMSE error for the morning opening hours from Bourgoin to St-Priest for each interval.

		Predicted waiting time (min)				
		06:30-	06:45-	07:00-	07:15-	07:30-
Line		06:45	07:00	07:15	07:30	07:45
B > S		15.0	10.0	6.0	10	6.0
		07:45-	08:00-	08:15-	08:30-	08:45-
Line		08:00	08:15	08:30	08:45	09:00
B > S		5.0	7.5	7.5	7.5	15

Table 5: Waiting time predictions for a carpool request on the Bourgoin > St-Priest carpooling line, per 15 minute intervals, during the morning operating hours 06:30–09:00 for a typical week.

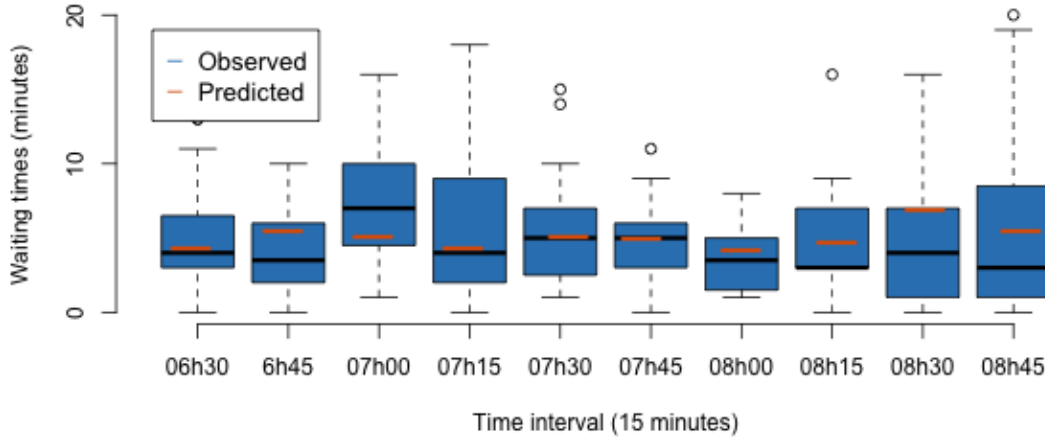


Figure 11: Comparison of predicted and observed waiting times for the Bourgoin <-> St-Priest carpooling line for a typical day. The blue box plots are the observed waiting times, and the predicted waiting times are the horizontal red line, for each 15 minute interval.

More formally let  $W(i, t)$  be the waiting time until the first driver arrival for a carpool request made at time  $t$  made for carpooling line segment  $i$ ,  $i \in 1, \dots, n_S$ . Assuming a Poissonian driver arrival process, the waiting time and the driver flow are inversely proportional to each other, i.e.  $W(i, t)f(i, j) \propto \text{const}$ , where  $f(i, j)$  is the driver flow for segment  $i$  and time interval  $\tau_j$ . Then  $W(i, t) \propto \text{len}(\tau_j)/f(i, j)$  where  $j = \{k : t \in \tau_k, k \in 1, \dots, n_T\}$  implies that  $t$  is contained in the time interval  $\tau_j$ ,  $\text{len}(\cdot)$  returns the length of a time interval,  $n_S$  is the number of carpooling line segments and  $n_T$  is the number of time intervals. For simplicity, we set the constant of proportionality to one as this corresponds to the assumption that all geolocated drivers are willing to respond to a carpooling request, then the predicted waiting time until the first driver arrival for a carpool request made at time  $t$  made for carpooling line segment  $i$ ,  $i = 1, \dots, n_S$  is thus calculated as

$$\hat{W}(i, t) = \text{len}(\tau_j)/\hat{f}(i, j)$$

where  $j = \{k : t \in \tau_k, k \in 1, \dots, n_T\}$  and  $\hat{f}(i, j)$  is an estimate of the driver flow using the sliding



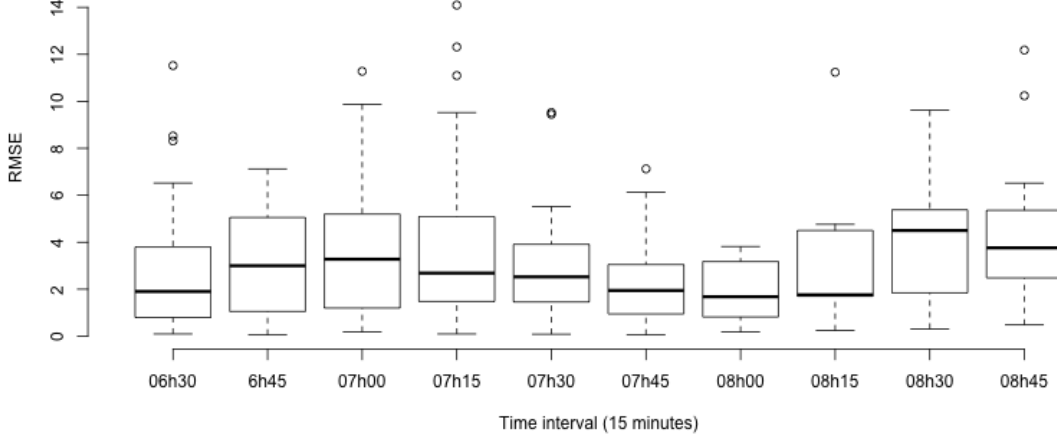


Figure 12: The RMSE error between the observed and predicted waiting times for the Bourgoin <> St-Priest carpooling line for a typical day.

window sample mean as outlined in Table 4.

In Table 6 are the predicted waiting times based on the driver flows from Table 3. Since our predicted passenger waiting times, especially in the morning operating hours, resemble the observed waiting times, then we can be confident that the decreases in the predicted waiting times with meeting-point matches in Table 6 in comparison to those for door-to-door matches will be indeed perceived by passengers.

From a passenger point of view, whilst the magnitude of waiting time is important as a perception of the service quality, it is equally important that these predicted waiting times be as close to the observed ones, whatever their magnitude. In this case, a prediction of 15 minutes is better than 5 minutes since the former is closer to, but longer than, the observed waiting time than the latter. Therefore we propose the following metric to measure these discrepancies for a given threshold  $\delta$ :

$$\text{PE}(W(i, t), \hat{W}(i, t); \delta) = \frac{1}{N_{\tau_j}} \sum_{k=1}^{N_{\tau_j}} \mathbf{1}\{|W(i, t) - w_{i,t}^{(k)}| < \delta\} \quad (1)$$

where  $w_{i,t}^{(k)}$  is the  $k^{\text{th}}$  observed waiting time for the time interval  $\tau_j$  and  $N_{\tau_j}$  is the number of observed waiting times for this interval. This metric, as a function of  $\delta$ , illustrated in Figure 13 for the 15 minutes interval for 06:30–09:00 for the same day of Figure 11.

### 3.4 Driver participation rate estimation

We have focused mostly on the impact of meeting point matches over the door-to-matches as a means to in decreasing the passenger waiting times, and now we turn to a brief examination of the role of the driver participation rate. For any carpooling service, the availability of drivers who are able to respond in a timely manner to the passenger requests is crucial. For deterministic matching, this involves dispatching the closest available driver to the passenger’s location: since

Week n°	Predicted waiting time 06:30–09:00			Predicted waiting time 08:00–08:30		
	Door-to-door (min)	Meeting point (min)	% decrease	Door-to-door (min)	Meeting point (min)	% decrease
2019W36	13.9	7.5	-46	8.3	6.2	-25
2019W37	11.2	7.6	-32	7.5	7.1	-5
2019W38	9.3	6.1	-34	7.5	5.6	-26
2019W39	10.4	6.3	-39	7.5	5.4	-29
2019W40	17.4	8.0	-54	16.7	7.9	-53
2019W41	15.6	7.1	-55	12.5	5.2	-59
2019W42	15.0	7.3	-51	8.3	4.5	-45
2019W43	25.0	8.8	-65	13.6	5.6	-59
2019W44	17.4	11.9	-32	16.7	10.7	-36
2019W45	15.6	7.4	-53	10.7	5.4	-50
2019W46	18.3	10.6	-42	12.5	6.8	-45
2019W47	12.5	6.8	-45	10	5.0	-50
2019W48	9.9	6.2	-37	8.8	4.8	-45
2019W49	12.9	8.0	-38	7.9	4.7	-41
2019W50	16	7.6	-53	30.0	6.8	-77
2019W51	9.1	7.3	-20	7.1	5.6	-22
2020W01	14.2	7.8	-45	10.7	6.5	-39
2020W02	11.9	7.5	-37	10.7	5.6	-48
2020W03	10.1	7.1	-30	9.4	6.5	-30
2020W04	13.6	7.2	-47	9.4	6.5	-30
2020W05	17.0	6.8	-60	10.7	5.6	-48
2020W06	13.2	7.8	-41	11.5	6.5	-43
2020W07	53.6	41.7	-22	30	30	0

Table 6: Passenger waiting time decrease for meeting point matching compared to door-to-door matching in the Bourgoin > St-Priest carpooling line, during the morning operating hours 06:30–09:00 and for 8:00–08:30, from 2019-09-02 to 2020-02-17.

these locations can be anywhere, this usually involves a large fleet of drivers to provide a rapid response. For stochastic matching to a fixed passenger location, the total number of drivers required for a similar response time can be much lower since the closest available driver is drawn from the existing driver flow. A key question for Ecov is what driver participation rate leads to passenger waiting times around 5 to 10 minutes, as observed in the Lane carpooling line in Figure 11?

The driver participation rate is  $P = N/N_0$  where  $N$  is the total number of the drivers who are motivated to carpool in response to a passenger request, and  $N_0$  is the total numbers of drivers who undertake journeys in the same geographical region as the carpooling service. Both  $N$  and  $N_0$  are difficult to define and to estimate precisely. We propose that the number of drivers who share their geolocation with Ecov be our proxy for  $N$ , even though Ecov’s carpooling service allows for passengers to carpool with unregistered and/or non-geolocated drivers. From anecdotal evidence, the majority of regular carpooling journeys are assured by motivated drivers who are willing to share their geolocation, and only a minority by unregistered and/or non-geolocated drivers. It is also difficult to enumerate those drivers in the same geographical region as the carpooling meeting

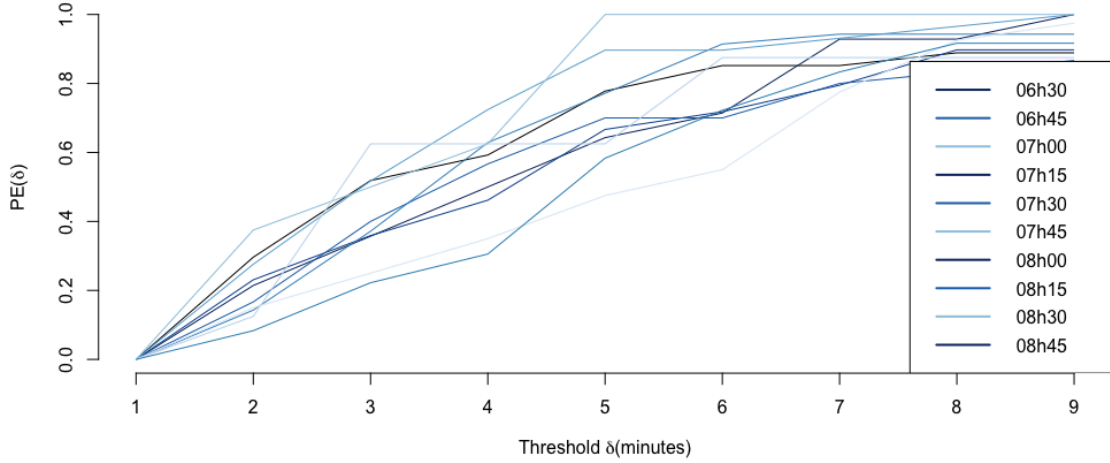


Figure 13: Evolution of the PE metric of the observed and predicted waiting times per interval of 15 minutes for 6:30–09:00 for a typical day, as a function of the threshold  $\delta$ .

points, since the GPS traces for all drivers in general are not available. Our proxy is derived from inferring likely trajectories from the reference origin-destination matrix available for home-work journeys. In our case, a county-level origin-destination matrix is provided by the French official statistical agency (INSEE 2018). Since the county level data are insufficiently detailed to decide if the drivers with these origins-destinations travel on the same pre-selected road segments of the carpooling service, we infer likely trajectories. These inferred likely trajectories are determined by the TomTom route finder API (TomTom 2019) as the fastest route starting on Tuesday 8am from the origins (county centroids) to the destinations (county centroids), as shown in Figure 14. We employ a route finder API rather than an explicit model-based methodology, e.g. Tang et al. (2016), to infer these most likely routes. Thus  $N_0$  is the sum of the driver flow from the origin-destination pairs whose likely trajectories includes road segments in the carpooling service. There are  $N_0 = 3821$  drivers whose likely trajectories for the Bourgoin > St-Priest carpooling line. From Table 4, there are  $N = 20$  between 06:30 and 09:30. This yields a driver participation rate of  $P = N/N_0 = 0.52\%$ . Even with this low driver participation rate, average waiting times for passengers of 5–10 minutes are observed for these time intervals in Table 5. This demonstrates that a small number of regular drivers assure the punctuality of the carpooling service, and the potential for stochastic carpooling to rival the waiting times proposed by traditional mass transit services does not require infeasible elevated driver participation rates.

Whilst as first glance, the current driver participation rate of 0.52% appears to be too low, it is already able to ensure a reasonable regularity for passenger requests on the Bourgoin > St-Priest line during its morning operating hours. If we were able to increase this driver participation rate modestly, then predicted passenger waiting times would fall substantially, as illustrated in Figure 15, approaching those of a high frequency metro/subway train systems, and exceeding those of traditional bus lines. The methods for increasing driver participation, as they lie largely outside of data science, are out of scope of this paper. Nonetheless they are of intense interest to Ecov and it has already carried out some behavioural economics experiments to understand

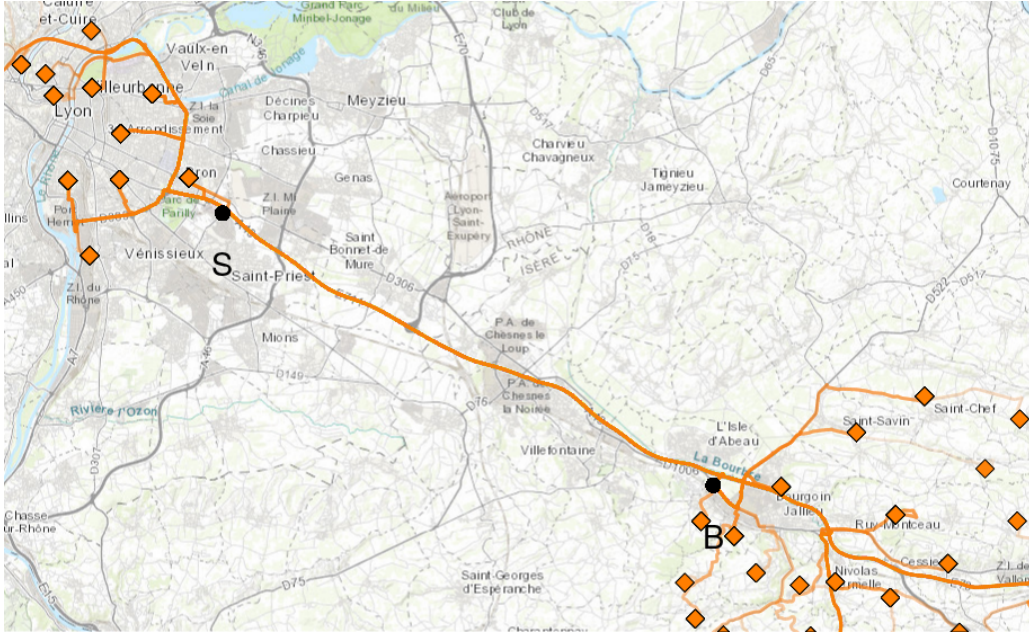


Figure 14: Likely driver itineraries from the TomTom route finder API in the same geographical region as the Bourgoin > St-Priest carpooling line. The origins and destinations (county centroids) are the orange diamonds. The solid black circles are the meeting points: S = St-Priest, B = Bourgoin.

driver motivations to participate in a non-profit carpooling service (Zhu 2017, 2018).

### 3.5 Software

The workflow, since it proposes a novel combination of data science and GIS, draws on software from both of these domains. The GPS traces are stored in the time-aware polyline format (Attam 2016) in a PostGreSQL database. Whilst this format allows for efficient storage of the GPS coordinates and the timestamps, it is not compliant with any standard format for spatial databases. Thus it is transformed into a PostGIS encoding (PostGIS Project Steering Committee 2019) which is one of the standard formats and is fully compatible with PostGreSQL database clients. For the data processing and analysis, e.g. to create the simplified topology of a GPS trace, a combination of R and Python packages are employed. We cite only the main ones which are focused on processing and analysing spatial databases, such as the `sf` package (Pebesma 2018) in R, and the `GeoPandas` (GeoPandas Developers 2019) and `PyGeos` (van der Wel 2019) packages in Python. Whilst these packages are able to handle most geoprocessing tasks, they are not complete, interactive GIS platforms in the strict sense like ArcGIS (ESRI 2019) or QGIS (QGIS Development Team 2019). The data science-GIS platform hosted at Ecov thus is a savvy combination of all of these tools in order to provide the computing infrastructure which is capable of agile responses to the analysis requirements for real-time stochastic matching carpooling services.

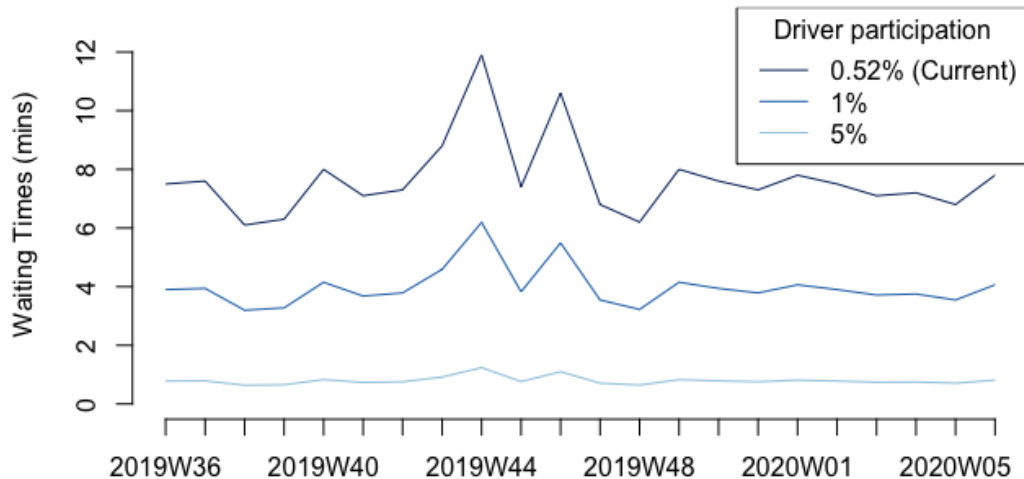


Figure 15: The decrease of the predicted passenger waiting time as a function of the driver participation rate in the Bourgoin > St-Priest carpooling line, during the morning operating hours 06:30 am to 09:00 am from 2019-07-25 to 2020-02-17.

## 4 Conclusions and future work

In this paper we introduced a data science-GIS workflow to facilitate the stochastic matching between drivers and passengers on pre-selected road segments in the real-time carpooling services proposed by Ecov. These differ from competing services which offer door-to-door matching for complete trajectories. Whilst the latter offer a high level of personal convenience in highly urbanised regions, door-to-door matching structurally inhibits a large-scale adoption of carpooling. The mutualisation of high throughput road segments via meeting point matching resolves this obstacle, especially in peri-urban and rural regions. The crucial mathematical abstraction in this workflow is to reduce the complexity of driver GPS traces to a graph-based topology which represents the pre-selected road segments of the carpooling service. We illustrated this workflow on a carpooling service currently operated by Ecov in a peri-urban region in south-eastern France. The physical meeting points, by facilitating the convergence of a critical mass of drivers and passengers drawn from a much larger geographical area, forms the foundation of the high level of user satisfaction of a real time carpooling service. This high customer satisfaction depends crucially on the passenger waiting times which can be comparable to or be even lower than those with traditional bus services in these peri-urban regions. These reduced waiting times are achieved at a modest financial cost by abandoning the door-to-door matching of their competitors, and employing instead their innovative stochastic meeting point matching. The presented workflow represents only a small fraction of the envisaged, complete data platform. Nonetheless, it already details a functioning prototype for the combination of two closely related, but historically separate, disciplines of data science and GIS into a single workflow which responds to the

complex questions arising from addressing mobility requirements in the neglected peri-urban and rural regions. This workflow lays solid foundations of an agile data platform which is able to accompany Ecov’s anticipated expansion of the scope and quality of its carpooling services into the future.

## 5 Acknowledgements

The authors thank Ecov for providing the data sets of driver GPS traces and passenger waiting times. The authors also thank Bertrand Michel from Central Engineering School of Nantes and Gérard Biau from Sorbonne University for their feedback.

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