A Quantitative Comparison of Solo and Shared Ride

SACHIN K SALIM under the guidance of SWAPRAVA NATH

Department of Computer Science and Engineering IIT Kanpur

February 2, 2020



- 3 Ridesharing problem (RSP)
- In NP-hardness
- 5 Optimal Solution Algorithm
- 6 Approximate algorithms
 - 7 Simulation

- In urban India, it's observed that people prefer travelling alone rather than pooling their ride for day-to-day activities even though the latter offers cheaper fare.
- This could be attributed to a variety of reasons including comfort, waiting time and security.

- In urban India, it's observed that people prefer travelling alone rather than pooling their ride for day-to-day activities even though the latter offers cheaper fare.
- This could be attributed to a variety of reasons including comfort, waiting time and security.
- But if more people prefer to pool their rides in a locality, the total distance travelled by all the cars reduces, thereby saving fuel and making a lesser impact on environment.
- We make an attempt to quantify this improvement by modelling the locations in a city on a graph comparing the expected lengths of shortest routes when all passengers travel solo to that of shared ride.



- 3 Ridesharing problem (RSP)
- In NP-hardness
- 5 Optimal Solution Algorithm
- 6 Approximate algorithms
 - 7 Simulation

- In a paper by M. Furuhuta et. al, the authors discuss about the history of ridesharing and classify it based on the target market, service type, matching activity, pricing policy, etc.
- D. C. Parkes et. al, proposed a new pricing mechanism called *Spatio-Temporal Pricing* that is smooth in space and time. This ensures that drivers will not reject the trip dispatched to them and keeps them from flocking in a particular area for higher prices.

- In a paper by M. Furuhuta et. al, the authors discuss about the history of ridesharing and classify it based on the target market, service type, matching activity, pricing policy, etc.
- D. C. Parkes et. al, proposed a new pricing mechanism called *Spatio-Temporal Pricing* that is smooth in space and time. This ensures that drivers will not reject the trip dispatched to them and keeps them from flocking in a particular area for higher prices.
- Almost the entire literature in ridesharing is focused on optimizing the ride for passengers and drivers. Here, our focus is on matching the passengers to a driver such that there is least impact on the environment.



3 Ridesharing problem (RSP)

- 4 NP-hardness
- 5 Optimal Solution Algorithm
- 6 Approximate algorithms
 - 7 Simulation

Problem Statement

Given a city with a list of passengers having a pickup point and a drop-off point, what is the shortest route of a driver to pick up all passengers and drop them off given the driver's current location?

- $\mathcal{P} = 1, 2, \dots, k$: Set of passengers in ridesharing.
- $\mathcal{L} \subset \mathbb{N} \times \mathbb{N}$, Set of locations.
- $p_i, d_i \in \mathcal{L}$: pickup and drop-off locations of passenger i
- δ : L × L → N where δ(a, b) gives the distance between locations a and b. For simplicity we take δ to be the manhattan distance.

- $\mathcal{P} = 1, 2, \dots, k$: Set of passengers in ridesharing.
- $\mathcal{L} \subset \mathbb{N} \times \mathbb{N}$, Set of locations.
- $p_i, d_i \in \mathcal{L}$: pickup and drop-off locations of passenger *i*
- δ : L × L → N where δ(a, b) gives the distance between locations a and b. For simplicity we take δ to be the manhattan distance.
- \mathcal{D} : the driver.
- $o_{\mathcal{D}} \in \mathcal{L}$: origin of the driver \mathcal{D} , i.e., the initial location.
- \mathcal{C} : Capacity of \mathcal{D} 's vehicle.

- $\mathcal{P} = 1, 2, \dots, k$: Set of passengers in ridesharing.
- $\mathcal{L} \subset \mathbb{N} \times \mathbb{N}$, Set of locations.
- $p_i, d_i \in \mathcal{L}$: pickup and drop-off locations of passenger i
- δ : L × L → N where δ(a, b) gives the distance between locations a and b. For simplicity we take δ to be the manhattan distance.
- \mathcal{D} : the driver.
- $o_{\mathcal{D}} \in \mathcal{L}$: origin of the driver \mathcal{D} , i.e., the initial location.
- \mathcal{C} : Capacity of \mathcal{D} 's vehicle.
- \mathcal{R} : Set of feasible routes of \mathcal{D} .
- $r \in \mathcal{R}$: A sequence of locations in \mathcal{L}

A route r is feasible iff it satisfies the following three conditions:

• The route r covers all the passengers' pickup and drop-off point. Thus $|r| = 2|\mathcal{P}|$.

A route r is feasible iff it satisfies the following three conditions:

- The route r covers all the passengers' pickup and drop-off point. Thus $|r| = 2|\mathcal{P}|$.
- ② The pickup point of a passenger *i* comes before the drop-off point for all *i* ∈ *P*.

A route r is feasible iff it satisfies the following three conditions:

- The route r covers all the passengers' pickup and drop-off point. Thus $|r| = 2|\mathcal{P}|$.
- ② The pickup point of a passenger *i* comes before the drop-off point for all *i* ∈ *P*.
- Solution a ∈ r, number of pickups until a must not be more than the sum of number of drop-offs until a and the capacity C.

Our objective is to find the shortest length route $r^* \in \mathcal{R}$ such that

$$r^* = \operatorname*{argmin}_{r \in \mathcal{R}} \sum_{i=1}^{|r|-1} \delta(r_i, r_{i+1})$$

where r_i is the i^{th} location in the route r.

Solo riding problem

- An order (π_1, \ldots, π_k) is decided over the k passengers.
- The driver \mathcal{D} picks up each of these passengers and then drops them off before picking another passenger in the order given by π .
- The algorithm would have to figure out the order of the passengers to be followed so that the total length of the travel route is minimized.

Shared riding problem

- All permutations of $(p_1, d_1, \ldots, p_k, d_k)$ are considered such that:
 - p_i comes before d_i for all $i \in \mathcal{P}$
 - the occupied passengers do not cross the capacity of cab

when the passengers are served in the given order.

• The problem is to find out the order that minimizes the cost of the total travel.

Sample routes

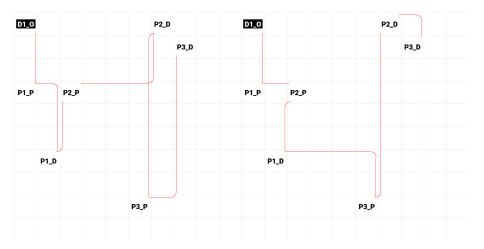


Figure: Left: A sample solo-ride route (Distance = 36) Right: A sample shared-ride route (Distance = 26)

Our objective

The problem in hand is to compare the following two values:

- minimum cost path in solo-riding
- minimum cost path in shared-riding



- 3 Ridesharing problem (RSP)
- 4 NP-hardness
- 5 Optimal Solution Algorithm
- 6 Approximate algorithms
 - 7 Simulation

Open Travelling Salesman Problem

OTSP is a variation of TSP in which the salesman does not return to the starting point. The problem is to find out the shortest Hamiltonian path in a graph G starting from a given vertex.

Formal definition of OTSP

Given a complete graph G = (V, E) with positive weighted edges and a starting vertex $s \in V$, determine if there exists a Hamiltonian path whose sum of weights of edges in the path is not more than a given number k.

Input: graph G; an instance of Hamiltonian path problem. Output: graph G'; by the reduction of HP to OTSP. Input: graph G; an instance of Hamiltonian path problem. Output: graph G'; by the reduction of HP to OTSP.

- Create a complete graph G'(V', E') with V' = V, s' = s and $E' = \{(i,j) : i, j \in V, i \neq j\}$.
- **2** Define the weight function $w : E \to \mathbb{N}$ as:

$$w(e) = egin{cases} 0 & ext{if } e \in E \ 1 & ext{if } e \notin E \end{cases}$$

Solution Pass the instance (G', 0) as input to the OTSP problem.

A Hamiltonian path exists in G starting from s

- \implies the cost of each corresponding edge in G' would be 0.
- \implies the total cost of that HP in G' would be 0.

A Hamiltonian path exists in G starting from s

- \implies the cost of each corresponding edge in G' would be 0.
- \implies the total cost of that HP in G' would be 0.

No HP exists in G

 \implies The cost of any HP in G' must be more than 0.

A Hamiltonian path exists in G starting from s

- \implies the cost of each corresponding edge in G' would be 0.
- \implies the total cost of that HP in G' would be 0.

No HP exists in G

 \implies The cost of any HP in G' must be more than 0.

G has a Hamiltonian path starting at $s \iff G'$ has a Hamiltonian path of cost at most 0 starting at s'. Hence, OTSP is NP-hard.

We are given a graph G(V, E), an instance of OTSP problem and we show here how to convert this to an instance of solo-RSP.

We are given a graph G(V, E), an instance of OTSP problem and we show here how to convert this to an instance of solo-RSP.

- Define a bijective map $\psi: V \to \mathcal{L}$, from vertex set V to locations L.
- Construct a driver \mathcal{D} with origin as $o_{\mathcal{D}} := \psi(s)$.

We are given a graph G(V, E), an instance of OTSP problem and we show here how to convert this to an instance of solo-RSP.

- Define a bijective map $\psi: V \to \mathcal{L}$, from vertex set V to locations L.
- Construct a driver \mathcal{D} with origin as $o_{\mathcal{D}} := \psi(s)$.
- Construct |V| − 1 passengers with each passenger's pickup and drop-off location, p_i = d_i = ψ(v_i), v_i ∈ V/s.

• Define
$$\delta(a,b) := w(\psi^{-1}(a),\psi^{-1}(b))$$

We are given a graph G(V, E), an instance of OTSP problem and we show here how to convert this to an instance of solo-RSP.

- Define a bijective map $\psi: V \to \mathcal{L}$, from vertex set V to locations L.
- Construct a driver \mathcal{D} with origin as $o_{\mathcal{D}} := \psi(s)$.
- Construct |V| − 1 passengers with each passenger's pickup and drop-off location, p_i = d_i = ψ(v_i), v_i ∈ V/s.

• Define
$$\delta(a,b):=w(\psi^{-1}(a),\psi^{-1}(b))$$

It is evident from the above definition that an HP with length \leq k starting at *s* exists in OTSP instance iff a route exists in the translated solo-RSP instance with length \leq k and driver's origin at o_D . Hence, solo-RSP is NP-hard.

shared-RSP

- Shared RSP is a superclass of solo-RSP problem as it deals with capacity of cab with any finite natural number.
- Since the instances over which the minimum is to be found out in shared-RSP is a superset of that of solo-RSP, it's intuitive that shared-RSP is also NP-hard.



- 2 Literature Review
- 3 Ridesharing problem (RSP)
- In NP-hardness
- 5 Optimal Solution Algorithm
- 6 Approximate algorithms
 - 7 Simulation
 - 8 Future directions

Let's discuss the DP approach [5] to solve OTSP problem. This algorithm runs in $O(k^2 * 2^k)$ time where k is the number of passengers.

Algorithm

 $\begin{array}{l} \mathcal{V} = \text{set of vertices;} \\ s = \text{starting vertex;} \\ w(a,b) = \text{weight of the edge } (a,b); \\ \text{for } \mathcal{S} \subseteq \mathcal{V} \text{ with } |\mathcal{S}| = 2 \text{ and } s \in S \text{ do} \\ & \mid C(\mathcal{S},i) = w(s,i); \\ \text{end} \end{array}$

Dynamic Programming Approach

Algorithm contd.

for
$$k \leftarrow 2$$
 to $n - 1$ do
for $S \subseteq V$ with $|S| = k$ and $s \in S$ do
for $i \in S \setminus \{s\}$ do
 $| C(S, i) = \min\{C(S \setminus \{i\}, j) + w(j, i)\} \quad \forall j \in S \setminus \{i, s\};$
end
end
end

Dynamic Programming Approach

Algorithm contd.

for
$$k \leftarrow 2$$
 to $n - 1$ do
for $S \subseteq V$ with $|S| = k$ and $s \in S$ do
for $i \in S \setminus \{s\}$ do
 $| C(S, i) = \min\{C(S \setminus \{i\}, j) + w(j, i)\} \quad \forall j \in S \setminus \{i, s\};$
end
end

end

$$C(\mathcal{V}) = \infty;$$

for $i \in V \setminus \{s\}$ do
$$\begin{vmatrix} C(\mathcal{V}, i) = \min\{C(\mathcal{V} \setminus \{i\}, j) + w(j, i)\} & \forall j \in \mathcal{V} \setminus \{i, s\};\\ C(\mathcal{V}) = \min(C(\mathcal{V}), C(\mathcal{V}, i)); \end{vmatrix}$$

end

Result: $C(\mathcal{V})$

The fare of passenger $i \in \mathcal{P}$ is given by Shapley value [1] defined as follows:

$$Sh_i(\mathcal{P}, \mathbf{v}) = rac{lpha}{n!} \sum_{S \subseteq \mathcal{P} \setminus \{i\}} |S|! \; (|\mathcal{P}| - |S| - 1)! \; (\mathbf{v}(S \cup \{i\}) - \mathbf{v}(S))$$

where α is the fare per unit distance and v(S) for any $S \subseteq \mathcal{P}$ is the length of the shortest route to serve all the passengers in S and none of the passengers not in S.

The fare of passenger $i \in \mathcal{P}$ is given by Shapley value [1] defined as follows:

$$Sh_i(\mathcal{P}, \mathbf{v}) = \frac{lpha}{n!} \sum_{S \subseteq \mathcal{P} \setminus \{i\}} |S|! \; (|\mathcal{P}| - |S| - 1)! \; (\mathbf{v}(S \cup \{i\}) - \mathbf{v}(S))$$

where α is the fare per unit distance and v(S) for any $S \subseteq \mathcal{P}$ is the length of the shortest route to serve all the passengers in S and none of the passengers not in S.

The Shapley value fare ensures individual rationality by distributing the total fare among the passengers in such a way that no passenger pays more for solo ride than shared ride.



- 2 Literature Review
- 3 Ridesharing problem (RSP)
- In NP-hardness
- 5 Optimal Solution Algorithm
- 6 Approximate algorithms
 - 7 Simulation

8 Future directions

We describe a method [4] to get a 2-approximate solution to solo-ride ridesharing problem.

We describe a method [4] to get a 2-approximate solution to solo-ride ridesharing problem.

Algorithm

• Construct Minimum Spanning Tree T of G with o_S as root using Prim's Algorithm.

We describe a method [4] to get a 2-approximate solution to solo-ride ridesharing problem.

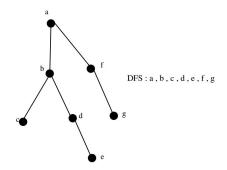
Algorithm

- Construct Minimum Spanning Tree T of G with o_S as root using Prim's Algorithm.
- Let W be the pre-order walk in T. A pre-order walk is a sequence of vertices visited in the order of DFS of T along with its return. See fig: 2 for an example.

We describe a method [4] to get a 2-approximate solution to solo-ride ridesharing problem.

Algorithm

- Construct Minimum Spanning Tree T of G with o_S as root using Prim's Algorithm.
- Let W be the pre-order walk in T. A pre-order walk is a sequence of vertices visited in the order of DFS of T along with its return. See fig: 2 for an example.
- Return the Hamiltonian tour R_{apx} visited in the order of the above pre-order walk.



Pre-order walk : a, b, c, b, d, e, d, b, a, f, g, f, a

Figure: Example: Pre-order walk (credits: [4])

Proof

The above algorithm runs in polynomial time since Prim's Algorithm has a polynomial complexity.

Let \mathcal{R}_{opt} be the shortest Hamiltonian tour in G. Let $C(S_e)$ is the sum of the weights of the edges in S_e .

Proof

The above algorithm runs in polynomial time since Prim's Algorithm has a polynomial complexity.

Let \mathcal{R}_{opt} be the shortest Hamiltonian tour in G. Let $C(S_e)$ is the sum of the weights of the edges in S_e .

Since \mathcal{W} is the MST,

$$C(T) \leq C(\mathcal{R}_{opt})$$

since \mathcal{R}_{opt} is also a spanning tree.

Proof

The above algorithm runs in polynomial time since Prim's Algorithm has a polynomial complexity.

Let \mathcal{R}_{opt} be the shortest Hamiltonian tour in G. Let $C(S_e)$ is the sum of the weights of the edges in S_e .

Since \mathcal{W} is the MST,

$$C(T) \leq C(\mathcal{R}_{opt})$$

since \mathcal{R}_{opt} is also a spanning tree.

Since in the pre-order walk $\mathcal W,$ every edge is visited twice except the final few edges since it doesn't come back to the starting point,

$$c(\mathcal{W}) \leq 2 * C(T)$$

. Combining both the inequalities above, we get,

$$c(\mathcal{W}) \leq 2 * C(\mathcal{R}_{opt})$$

Now, observe that $\mathcal R$ is effectively a 'short-cut' of $\mathcal W$ since no vertices are visited are visited twice in $\mathcal R$ unlike $\mathcal W$ because the vertices are visited directly without tracing the route back. Under the assumption of triangle inequality, this would give

 $c(\mathcal{R}_{apx}) \leq C(\mathcal{W})$

Now, observe that \mathcal{R} is effectively a 'short-cut' of \mathcal{W} since no vertices are visited are visited twice in \mathcal{R} unlike \mathcal{W} because the vertices are visited directly without tracing the route back. Under the assumption of triangle inequality, this would give

 $c(\mathcal{R}_{apx}) \leq C(\mathcal{W})$

and thus we have proved that

$$c(\mathcal{R}_{\textit{apx}}) \leq C(\mathcal{R}_{\textit{opt}})$$

Note: If the triangle inequality doesn't hold in G, we can return \mathcal{W} instead of \mathcal{R}_{apx} since our original problem doesn't prevent us from visiting the same vertex twice.



2 Literature Review

- 3 Ridesharing problem (RSP)
- 4 NP-hardness
- 5 Optimal Solution Algorithm
- 6 Approximate algorithms

7 Simulation

8 Future directions

Simulation results

The minimum total distance was calculated for a 1000X1000 grid for 1 driver and passengers varying from 1 to 5. The locations of driver and passengers were generated at random and the average of shortest distances over 1 lakh iterations were calculated. The following plots show these results.

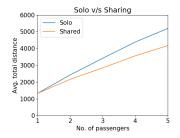


Figure: Avg. total distance for solo and shared ride

Simulation results

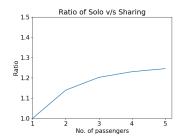


Figure: Ratio of avg. total distance for solo and shared ride

As we could see from the ratio plot, the ratio

$$r = \frac{\text{length of shortest solo-ride route}}{\text{length of shortest shared-ride route}} \simeq 1.25$$

for one driver and 5 passengers. We can see from the plot that this value is converging to a ratio $\simeq 1.25$



2 Literature Review

- 3 Ridesharing problem (RSP)
- 4 NP-hardness
- 5 Optimal Solution Algorithm
- 6 Approximate algorithms
 - 7 Simulation

8 Future directions

• The exponential time complexity of the optimal solution algorithm is a hindrance in implementing this algorithm in real case scenario.

- The exponential time complexity of the optimal solution algorithm is a hindrance in implementing this algorithm in real case scenario.
- The NP-hardness of shared-riding is to be proven formally.

- The exponential time complexity of the optimal solution algorithm is a hindrance in implementing this algorithm in real case scenario.
- The NP-hardness of shared-riding is to be proven formally.
- An approximation algorithm for shared riding is to be found out such that the deviation from this approximate solution from optimal solution is correlated with that of solo-ride. This will enable us to give a ratio of them for larger number of passengers.

References



LLOYD S SHAPLEY

"The Shapley value", Cambridge University Press, 1988

- HONGYAO MA, DAVID C. PARKES and FEI FANG "Spatio-Temporal Pricing for Ridesharing Platforms"
- 📔 M Furuhata, M Dessouky, F Ordonez, ME Brunet, X WANG, S KOENIG

"Ridesharing: the State-of-the-art and Future Directions"

ARASH RAFIE

"Approximation Algorithms (Travelling Salesman Problem)" (URL: http://www.sfu.ca/~A14/lecture25.pdf)

UMESH VAZIRANI

"Dvnamic Programming" (URL: https://people.eecs.berkeley.edu/~vazirani/ algorithms/chap6.pdf)