How far is traffic from user equilibrium?

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Understanding the complex interaction between road infrastructure, traffic conditions and travel choices (e.g. route choice, departure time) has been a long-standing challenge to understand mobility patterns in cities. The path travellers follow in the complex traffic networks has been arguably the most influential decision that dynamically redefines the relation between the supply provided by road infrastructure and the demand generated by travel plans of drivers. Nearly all techniques that aim for congestion alleviation build on accurate estimations of travel demand and thus on underlying route choices. The mainstream understanding on this complex interplay builds on the definition of user equilibrium (UE) state, namely Wardrop's first principle: "the journey times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route" (1).

While UE assumes that travellers have the perfect knowledge of travel costs along the network, and choose the routes that minimize their travel costs, stochastic user equilibrium (SUE) states that travellers might not be fully informed about network conditions, and therefore choose the routes that minimize their perceived travel costs. Shortest path algorithm is the straightforward way to establish UE conditions; however, there is a vast literature of discrete choice models that could be exploited to reach SUE conditions (2).

While congestion seems an unavoidable sign of a vibrant city with economic growth and social interactions, drivers increasingly take advantage of real-time information through GPS devices and smart phones. With everyone being easily monitored by the new sensors, researchers can start testing the assumptions behind the equilibrium state on network traffic patterns. There are few studies that test the empirical existence of Wardrop's first principle. (3) evaluate the habitual routes reported by 188 respondents. Assuming 90% overlapping is required to define two routes as the same, 37% of respondents follow a shortest time path (travel times are estimated using a traffic assignment model), and 22% follow a shortest distance path. Similarly, (4) design a Web-based survey and evaluate 236 routes between 182 OD pairs. Again, assuming 90% threshold for two routes to be considered the same, 26.7% of respondents choose the shortest distance path, while 17.8% choose the shortest time path. (5) collect GPS records from 143 participants and evaluate their route choice decisions in a period of 13 weeks where there is a disruptive event of bridge reopening. Their analysis concludes that about 40% of trips follow the shortest time path using a 10% overlapping threshold. Note that all studies are conducted with limited amount of data and test the equilibrium assumptions with respect to similarity between actual and shortest paths at the individual level. In this work, we explore the relationship between observed and shortest paths from two perspectives: (i) user perspective that compares individual path similarities and (ii) network perspective that is focused on traffic loads at the nodes.

First, we compare the actual routes and the shortest paths in terms of overlap percentages. In order to determine the shortest path, we use two types of travel cost; free flow travel time that results from speed limits in road classes and estimated travel time computed with GPS observations. Figure 1 presents route overlaps between the actual paths and the shortest paths based on two travel costs defined above. If two routes completely overlap, the difference should be 0. If they do not overlap at all, the difference should be 100%. Using the most strict overlap definition, we observe that around 29% of paths are in full compliance with shortest paths that rely on either one of the travel costs. Considering 5% threshold to consider two paths the same, this value goes up to 33% and 35% for free flow and estimated travel time, respectively. More importantly, even though estimated travel time consistently produces more paths with less than 30% difference, the overall distribution of values does not seem to be largely affected by the travel cost definition.

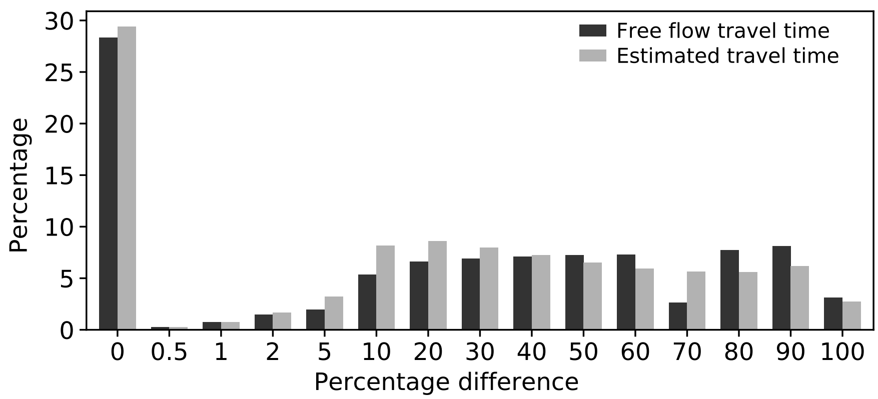

FIGURE 1: Difference between actual routes and shortest paths

Second, we calculate the node loads that depict the number of paths that go through a particular node in the network. Figure 2(a) presents the loads that result from actual routes (denoted by l_{act}) as revealed by GPS tracks and map-matching implementation (6) and the ones that are associated with shortest paths based on free flow travel time (denoted by l_{ff}). There is a strong proportionality between two node load types; Pearson's linear correlation coefficient is 0.86. This is a very high score; however, we notice that scatter in the plot becomes more evident with increasing l_{act}, which indicates lower estimation quality for high load carrying components. Additionally, we fit a linear function of the form $l_{act} = a * l_{ff} + b$, where a and b are calculated as 0.75 and 88, respectively. Despite high correlation, linear regression results (a being far from 1) point out consistent overestimation of l_{act} and indicate strong bias in the estimation of traffic loads with free flow travel times.

Similarly, Figure 2(b) depicts the node loads from actual routes (i.e. l_{act}) and shortest paths based on estimated travel time (denoted by l_{est}). Pearson's linear correlation coefficient is significantly higher than the previous case; it is 0.95. More importantly, scatter seems to be homogeneous over the range of actual node loads. Lastly, we fit a linear function of the form $l_{act} = a * l_{est} + b$, where a and b are calculated as 1.05 and 31, respectively. This indicates a considerable improvement over the free flow travel time, as the value of a is much closer to 1.

To have a better understanding of estimation quality, we calculate mean absolute error

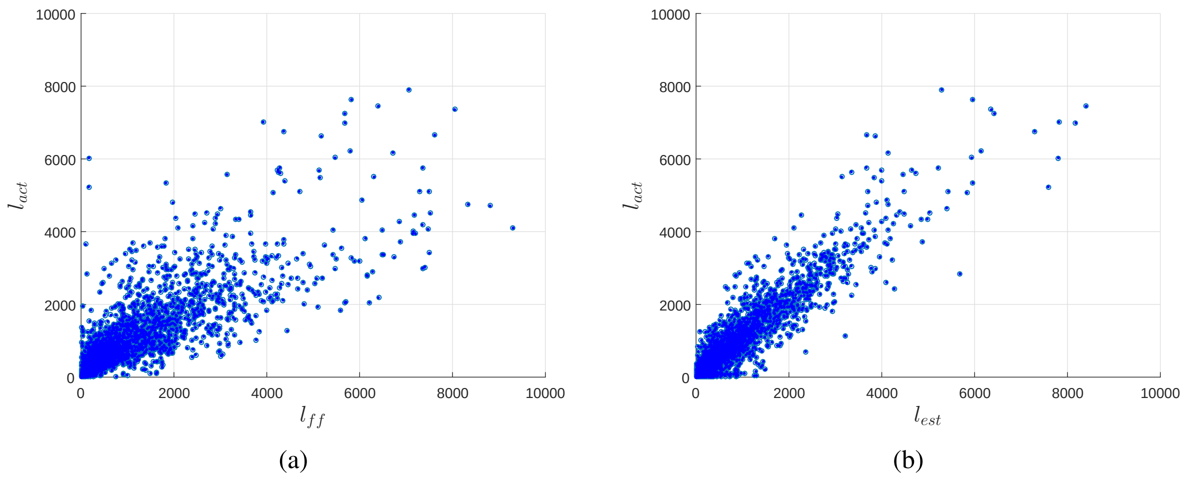

FIGURE 2: Node loads (a) with free flow travel time, (b) with estimated travel time.

(MAE) and root mean squared error (RMSE) with the following formulas.

$$\text{MAE}_x = \left[\sum_V (l_{act}(v) - l_x(v))\right] /|V| \tag{1}$$

$$\text{RMSE}_x = \left[\left(\sum_V (l_{act}(v) - l_x(v))^2\right) /|V|\right]^{1/2} \tag{2}$$

where $l_x(v)$ is the estimated load at node or vertice v with either free flow or estimated travel time. With free flow travel times, MAE and RMSE are 149 and 405, respectively. Estimated travel times lead to much smaller error values; 99 and 232 for MAE and RMSE, respectively. This represents a 34% decrease in MAE and 43% reduction in RMSE. The findings of this analysis imply that drivers anticipate traffic conditions across the alternative routes to a certain extent, they do not make decisions based on free flow travel times, and equilibrium state provides a proper estimator of network-wide traffic patterns.

This study empirically tests equilibrium assumptions from user and network perspective and using two travel cost definitions; free flow and estimated travel time. Free flow travel time is calculated using the distance of links and associated speed limit, while estimated travel time is computed with GPS observations and map-matching results. User perspective analysis does not indicate a significant difference between two travel cost definitions, and in both cases, it strongly rejects the assumption regarding widespread use of shortest paths. However, network perspective examination focuses on node loads and reveals significant differences between the two types of shortest path. Although free flow travel time does produce a strong correlation between actual and estimated node loads, results are strongly scattered. On the other hand, estimated travel time produces node loads that are very much in line with actual patterns.

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