SENSEABLE CITIES
MOBILITY & URBAN PLANNING

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HubCab is an interactive visualization that invites you to explore the ways in which over 150 million taxi trips connect the City of New York in a given year. Show me how it works.
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**Taxi Pickup**
- West 15th Street
- Total Pickups: 1069
- Average duration: 12.4 min
- Average distance: 3 mi

**Taxi Dropoff**
- E 54th Street
- Total Dropoffs: 1033
- Average duration: 10.2 min
- Average distance: 2.3 mi
Quantifying the benefits of vehicle pooling with shareability networks

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Taxi services are a vital part of urban transportation, and a considerable contributor to traffic congestion and air pollution causing substantial adverse effects on human health. Sharing taxi trips is a possible way of reducing the negative impact of taxi services on cities, but this comes at the expense of passenger discomfort quantifiable in terms of a longer travel time. Due to computational challenges, taxi sharing has traditionally been approached on small scales, such as within airport perimeters, or with dynamical ad hoc heuristics. However, a mathematical framework for the systematic understanding of the tradeoff between collective benefits of sharing and individual passenger discomfort is lacking. Here we introduce the notion of shareability network, which allows us to model the collective benefits of sharing as a function of passenger inconvenience, and to efficiently compute optimal sharing strategies on massive datasets. We apply this framework.

At the basis of a shared taxi service is the concept of ride sharing or carpooling, a long-standing proposition for decreasing road traffic, which originated during the oil crisis in the 1970s (6). During that time, economic incentives outbalanced the psychological barriers on which successful carpooling programs depend: giving up personalized transportation and accepting strangers in the same vehicle. Surveys indicate that the two most important deterrents to potential carpoolers are the extra time requirements and the loss of privacy (7, 8). However, the lack of correlations between socio-demographic variables and carpooling propensity (8), the design of appropriate economic incentives (9), and recent practical implementations of taxi-sharing systems in New York City (http://bandwagon.io) give ample hope that many social obstacles might be overcome in newly emerging “sharing economies” (10, 11).
Figure 1: Shareability networks. (A) Trip sharing model and taxi capacity. Each of the three cases involves three trips $T_1$, $T_2$, and $T_3$ to be shared, but ordered differently in time $t$. The top case corresponds to a feasible sharing according to our model with $k = 2$, and the trips can be accommodated in a taxi with capacity $\geq 2$. The middle case corresponds to a model with $k = 3$ since three trips are combined; notice that the three trips can be combined in a taxi with capacity two since two of the combined trips are non-overlapping. The bottom case corresponds to $k = 3$, but here a taxi capacity $\geq 3$ is needed to accommodate the combined trips. (B) Example of maximum matching (d) in a simple shareability network. The links belonging to the maximum matching are displayed in bold. (C) Example of maximum weighted matching (d). (D) Exemplary subset of the shareability network corresponding to 100 consecutive trips for values of $\Delta = 30\text{ sec}$ and (E) $\Delta = 60\text{ sec}$, showing network densification effects and thus an increase of sharing opportunities with longer time-aggregation. Open links point to trips outside the considered set of trips. Isolated nodes are represented as self-loops. Node positions are not preserved across the networks.
Working hour optimization

TYPES OF CAR MODES
Cumulated time with and without passenger in a typical working day

- With passenger
- Without passenger

TRIPS SERVED BY HOUR AND CAR (CUMULATIVE FOR 1 HOUR)
- Current situation
- Model
- Avg. number of trips for the current system
- Avg. number of trips for the model

The displayed cars represent the median number of trips for both the system and model.
We developed a new intersection control paradigm called AIM.
“In Milan, traffic lights are instructions.  
In Rome, they are suggestions.  
In Naples, they are Christmas decorations.”

Antonio Martino  
Former Minister of Foreign Affairs (1994) and Minister of Defense (2001-2006)
Access to intersection based on Incompatibility Network and vehicle trajectories.
Access to intersection based on Incompatibility Network and safety constraints

Safety constraint

- based on tailgate distance (a.k.a. two seconds rule) for vehicles with compatible trajectories
- based on vehicle stopping distance for vehicles with incompatible trajectories

Typically, $d_{\text{tail}} < d_{\text{stop}}$
City Drive
Expo 2015 Site, Lendlease, Milano  (CRA – Carlo Ratti Associati)