Multi-modal Activity-based Mobility Generation Applied to Microscopic Traffic Simulations

Lara CODECÁ[1,*] **and Jérôme HÄRRI**[1]

[1]EURECOM, Communication Systems Department, 06904 Sophia-Antipolis, France
[*]Lara.Codeca@eurecom.fr, corresponding author.

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Extended Abstract

Introduction

In recent years, we collectively decided that to achieve sustainable growth in our cities, we are going in the direction of smart-city and smart-mobility studies. With the increasing amount of data available and the presence of extensive communication infrastructure for vehicles and people to connect, many efforts are made towards mobility optimizations. Applications such as personal trip planners and similar are in widespread use at the moment, and they have an impact on mobility patterns in and around a city. Using a mobility simulator framework it is possible to study their impact on the overall traffic congestion, and possibly develop an intelligent and coordinated trip planner that keeps into account different modes of transportation and parking availability that would satisfy the user without impairing the system.

To achieve a deployable solution, we need to base our optimizations on realistic topology representations and realistic mobility models of our modern cities. Although significant progress has been made on the realism of mobility simulators, substantial work needs to be done to achieve realistic mobility patterns. We aim to build a comprehensive framework that allows the creation of a realistic topology and infrastructure for a city and to generate realistic mobility for it.

We selected SUMO[1] microscopic mobility simulator because it is open-source, flexible and performant, with the advanced multi-modal featured that we require, and most importantly, the user and developer community is very active and always ready to help. The first part of this framework is already available on GitHub under GPLv2 license, and it comprises of (i) the toolchain used to generate a scenario starting from OpenStreetMap[2] data, (ii) the toolchain used to generate reasonable mobility based on a representation of origin-destination time-dependent matrices[3], and (iii) our case study of the Principality of Monaco and its surroundings[4]. The Monaco SUMO Traffic Scenario is available at `https://github.com/lcodeca/MoSTScenario`.

Despite that the mobility generator already implemented provides reasonable mobility features, it is not detailed enough when it comes to personal trip planning, activity-based mobility, and parking patterns and behaviors. The new tool we are implementing now is meant to tackle these challenges.

Research Objectives

In the vast field of research that is smart-city optimizations towards sustainable mobility, this new toolchain focuses on personal trip planning based on (i) activity chains, (ii) various modes of transports, and (iii) parking areas.

Research question. How can we achieve a mode shift that keeps into account realistic activity chains with multi-modal capabilities and possible parking optimization? What is going to be the impact on the individual and the overall mobility and traffic congestion? Is it possible to develop a personal trip planner that maximize the gains for both the user and the system?

Methodological Approach

Chains of Activities To build realistic personal trip plans, we implement the activity-based mobility model. With the use of user-defined activity chains composed by a home location, at least a primary activity, and a variable number of secondary activities, it is possible to achieve elaborate trip plans. The location of these activities is based on their order in the chain and the given origin-destination matrix. Plenty of work has been done to estimate activity chains and origin-destination matrices from real data[5,6], in the framework we intend to implement the state-of-the-art models available to obtain microscopic simulator-friendly personal plans.

Parking Optimization To achieve sustainable mobility, lowering the levels of traffic congestion seems an obvious target. Among its component, we can find the overhead in traffic and pollution that is brought by vehicles that are cruising looking for a parking place[7]. One of the solutions we intend to investigate is based on data collected from intelligent parking systems and a benchmark of multiple optimizations ranging from user-optimum to system-optimum. The Python Parking Monitoring Library[8] is a component of the framework that has already been implemented, and it is available at `https://github.com/lcodeca/PyPML`. During the optimization studies, we realized that the origin-destination time-dependent matrices previously used to build the mobility were not providing a realistic behavior concerning parking areas usage. Hence, the need for the more complex activity-based mobility generation.

Machine Learning The increasing quantity of data that are available in the last years opened the road for unsupervised machine learning techniques applied to traffic optimizations. Parking areas optimization and personal trip planning optimizations are not two stand-alone problems, and they require to be considered together. Multi-agent reinforcement learning techniques are already used in transportation planning[9], so the framework that we are building needs to be compatible with the reinforcement learning libraries already available to the research community. Implementations such as RLLIB[10] are compatible with SUMO simulator and our tools.

Preliminary Implementation

The preliminary version of the Activity-based Mobility Generation for SUMO Simulator is already available on GitHub at `https://github.com/lcodeca/SUMOActivityGen` under EPL 2.0 license. This tool requires the latest features for multi-modal person trip definition provided by SUMO only in the development version. We have an ongoing collaboration with the SUMO developers, and the required features will be in the next official release.

Features

- User-defined activity chains are composed by origin (home), at least one primary activity, and secondary activities.
- Primary activities have a start time and duration defined as mu and sigma of a normal distribution.
- Secondary activities have only a duration defined as mu and sigma of a normal distribution.
- Origin-destination traffic assignment zones are used to select the home location and primary activity location.
- The secondary activity locations are selected based on their position in the chain: (i) in a circular area around the home location, (ii) in an elliptical area where home and primary activity are the foci, (iii) in a circular area around the primary activity location.
- The modes already implemented are (i) public transportation, (ii) private vehicle with and without parking requirements, and (iii) on-demand (taxi and similar).

Expected Impact

Realistic Optimizations With the use of this mobility modeling framework, is going to be possible to develop more realistic optimizations in the context of sustainable mobility for smart cities.

Interdisciplinary Studies Additionally, the framework is generic and can be used to model multiple cities in order to compare optimizations, and it can be used for unforeseen studies. From previous experiences, providing an open-source framework to the research community enable the exchange of knowledge and facilitate interdisciplinary studies.

Release The framework is meant to be modular by design, enabling the straightforward implementation of additional mobility generation models. The the Activity-based Mobility Generation for SUMO Simulator is available on GitHub at `https://github.com/lcodeca/SUMOActivityGen` under EPL 2.0 license.

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