INDUSTRIAL & SYSTEMS ENGINEERING
UNIVERSITY of WASHINGTON

Uncovering physics-regularized data generation processes for individual human mobility: A multi-task Gaussian process approach based on multiple kernel learning

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Date: Jan 11, 2024
Time: 1:30 pm - 2:20pm
Location: MEB 106

Biography

Ekin Uğurel is a third-year PhD student in the THINK lab at the University of Washington-Seattle, where he is co-advised by Professor Cynthia Chen and Professor Shuai Huang. His work at the UW is currently supported by the College of Engineering Dean's Fellowship. Prior to pursuing graduate study, Ekin graduated with a bachelor's degree in Civil Engineering from the University of Texas at Austin, where he conducted research with Professor Christian Claudel. Ekin's current research aims to innovate novel methods to model mobile data (i.e. GPS traces from mobile devices) for human mobility analysis. He is particularly interested in kernel-based techniques to uncover non-linear spatiotemporal relationships in high dimensions. Ekin finds mobile data a particularly powerful tool for the future, as it can give an approximation of human movements at various geographical scales. He is also interested in applications of mobile data for inference in social science (i.e., in disaster detection, innovation studies, and travel behavior). In his free time, Ekin enjoys playing soccer, shooting hoops, and enjoying all that the state of Washington has to offer.

Abstract

Passively-generated mobile data has grown increasingly popular in the travel behavior (or human mobility) literature. In the past five years, two issues have significantly impacted academic communities interested in this type of data: (1) Recent progress on consumer privacy protection norms and the public's increasing awareness of exploitative data collection practices have resulted in a greater share of individuals opting out of location-based data sharing agreements with third-party apps. This means that for most individuals, data is observed at a lower frequency than before (while for some, they are not observed at all). (2) On the flip side, due to privacy-preserving research agreements with data aggregators, researchers can rarely share the raw data they use with journals or the general public, effectively ruling out the possibility of validating findings or disputing claims. To address both issues simultaneously, we propose a hybrid conditional-generative Gaussian process framework to create synthetic individual mobile data that provably replicates observed travel patterns without compromising privacy. Our approach integrates physical knowledge to regularize the framework such that the generated data obeys the laws of physics as well as constraints imposed by the built and natural environments. Furthermore, to capture travel behavior heterogeneity at the individual level, we further propose a data-driven multiple kernel learning approach to determine the optimal composite kernel for every user-period pair. Our experiments demonstrate that: (1) The optimal composite kernel for user-period pairs can be significantly different, while not utilizing this discovered kernel results in sub-par model performance; (2) physics-regularization not only reduces model bias but also improves uncertainty estimates associated with the predicted locations.