Using Large Scale Taxicab Data to Estimate Link Travel Time, Predict Demand and Measure System Efficiency

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Introduction

• The era of big data
  • Advance in sensing technologies
  • Development of large scale pervasive computing infrastructure
• Big data and transportation engineering
  • Reconsider traditional research problems
  • Make infeasible problems feasible
• In this work
  • Using large scale taxi data from NYC
  • Taxi Ridership analysis
  • Link travel time estimation
  • Taxi system efficiency

Key Findings

• Urban form has significant impact on ridership
  • GWR explains up to 90% of the variance and achieves good prediction
  • Both coefficients and t-stats of determinants vary over space
• Failing to consider spatial variation will result in erroneous estimations of determinants

Link Travel Time Estimation

Motivation

• Accurate estimation of urban link travel time is essential for various applications in urban traffic operations and management
  • Traditional approaches using fixed sensors: expensive and limited coverage
  • Can we estimate link travel time using only partial information from taxi trips?

Methodology

• Finite mixture distribution
  \[ p(y_{ij}|x_{ij}, D) = \sum_{k=1}^{K} \pi_k p(y_{ij}|x_{ij}, k, D) \]
  \[ h(y_{ij}|x_{ij}, D) = \sum_{k=1}^{K} \pi_k p(y_{ij}|x_{ij}, k, D) \]
• Solution approach: EM algorithm
• Test network: A 1175x1780cm rectangle area in Midtown Manhattan, with 136 nodes and 254 directed links

Key Findings

• Algorithm converges rapidly and entire estimation takes less than 15 minutes
• Robust estimation results: MAPE controlled under 30%
• Can be extended easily as a Bayesian mixture model by making use of historical data

Taxi Data

• Source: NYCTLC
  • Information: geo-coordinate and timestamps for pick-up and drop-off locations, trip distance, trip fare and the number of passengers
  • Data extracted: October 5th to October 11th, 2009
  • Around 500,000 daily trips

Spatial Variation of Taxi Ridership

Motivation

• Statistical analysis of taxi ridership
  • Trips are varying spatially
  • The effects of determinants is nonhomogeneous

Methodology

• Geographically weighted regression
  \[ y_{ij} = \beta_0 + \beta_1 x_{ij} + \beta_2 x_{ij}^2 + \epsilon_{ij} + \delta_{ij} \]
  \[ \delta_{ij} = a \exp\left(-\frac{d_{ij}}{4} \right) \]
• Dependent variable: Taxi ridership
• Independent variables: commuting time, population, land use, median income, road density, subway accessibility

Key Findings

• Algorithm converges rapidly and entire estimation takes less than 15 minutes
• Robust estimation results: MAPE controlled under 30%
• Can be extended easily as a Bayesian mixture model by making use of historical data

Efficiency of Taxi Service System

Motivation

• Vacant taxi trips lead to unnecessary externalities
• How to quantify the efficiency of the system performance and how far is the current system from the theoretically optimal one?

Notions

• Optimal Matching: finding the optimal matching strategy between each pair of taxi driver and passenger
  • Unweighted trip integration: results in the minimum number of taxis required to satisfy all the trips.
  • Weighted trip integration: results in minimum total matching cost while achieving minimum number of taxis satisfying all the trips

Methodology

• Optimal matching: minimum weight perfect bipartite matching using Hungarian method
• Unweighted trip integration: maximum bipartite matching with max-flow algorithm
• Weighted trip integration: minimum weight bipartite matching using Hungarian method

Key Findings

• Optimal matching can reduce up to 90% of taxi idle time, 87% of vacant trip distance and 82% of revenue loss.
  • Using 2/3 of current taxis can serve all observed trips
  • Idle time, vacant trip distance and revenue loss can be reduce to half with fewer taxis
  • System level information is critical to improve the system efficiency

References