Insights on Urban Mobility through Complexity Science

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1. About us
2. The Complex City
3. Land use allocation
4. Transport system
5. Land use – Transport coupling
6. Other aspects: Behavior, traffic, new technology
We are dealing with **COMPLEX SYSTEMS**

looking into the **SCIENCE of CITIES**, Socio-Technical Systems, Economic Complexity, and Complex Networks.
Bus Arrivals
Waiting time
½ x headway² = the area of each triangle

Ridership (Commuters/month)

Travel time

Voronoi partition

Comparison: empirical vs predicted

Biological Aging Expertise
Data Analysis expertise

Organizational Chart
Agent-Based Modeling of the Rapid Transit System

Reliability Analysis of Bus Arrivals

Lightless intersection control numerical simulations

Urban Morphology

Land-Use & Transport Modeling

Crowd Modeling and Simulations

Characterizing Public Transport Commuters

Resilience of Commuter Encounter Networks

Diffusion & Cascading Failures on Multiplex Networks

Aging, Biology & Computing: Healthspan

Identification of Regulators in a Human Gene Network

Dynamical Model of Twitter Activity Profiles
Recent Publications

Inferring Passenger Types from Commuter Eigentravel Matrices
*Transportmetrica B*, 2016.

Efficient Intersection Control for Minimally Guided Vehicles: A Self-Organised and Decentralized Approach
*Transportation Research C*, 2016.

Impacts of land use and amenities on public transport use, urban planning and design

Self-organized Traffic Flow at the Lightless Intersection: Algorithms, Policies and Simulations of the Environmental Impact
*Clean Technologies and Environmental Policy*, pp 1-13, 2016.

Dendritic growth model of multilevel marketing
*Communications in Nonlinear Science and Numerical Simulation* 43, pp. 100–110, 2016

Cluster Statistics and Quasisoliton Dynamics in Microscopic Optimal Velocity

Classification and unification of the microscopic deterministic traffic models
*Physical Review E* 92, 042802, 02 October 2015.

Entropy Based Modelling for Estimating Demographic Trends
*PLoS ONE* 10(9): e0137324, 18 September 2015.

Automated Identification of Core Regulatory Genes in Human Gene Regulatory Networks

A dynamical model of twitter activity profiles

The simplified self-consistent probabilities method for percolation and its application to interdependent networks

A Data-Driven Agent-Based Model of Congestion and Scaling Dynamics of RTD
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Why understand Cities?

2011: 3.6 billion people in urban areas (~50%)
2030: 4.3 billion people in urban areas (~60%)
2050: 6.3 billion people in urban areas (~70%)

http://intongueincheek.blogspot.sg/2011/02/world-population-living-in-urban-areas.html
Why understand urban mobility?

Movement/distribution of people impact transport efficiency, energy consumption, sustainability of a city

Manhattan - lattice
Sudan - random
Beijing - single blob
Greater Cairo - double blob

Dual-blob city type is most efficient but highly susceptible to targeted attack

Pang, Othman, Ng, Monterola, EFFICIENCY AND ROBUSTNESS OF DIFFERENT BUS NETWORK DESIGNS, Intl. J. of Mod. Phys. 2014
What is missing with conventional perspectives?

Mainly wrong statistical assumption.

Structure affects dynamics & responsiveness

The Architecture of Complexity: From Network Structure to Human Dynamics. ALBERT-LASZLO BARABASI
Challenges in understanding cities?

- Sum of parts ≠ System Behaviour
- Constant state of non-equilibrium
- People can learn and adapt - Self-organization
- People form networks - Social systems
“Make the best fake metropolis.”
Implementing policies based on intuition alone can be expensive, time consuming, and sometimes catastrophic.
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3. Land use allocation as a Complex System

- Many components/agents
  ~2.6M entities R,B,I

- Strongly coupled/interacting
  ~R, B, I interacts to complement each other

- Non-linear, non-reductionist
  People connect them, crowd dynamics

- Emergent phenomena/multiple phases
  Critical capacity, Growth, Economic activities

- Adaptive/evolving/non-equilibrium
  Allocation adapts to need, people behavior evolve

**Lesson 1:** Simple rules giving rise to complex patterns
Modeling the emergence of Land Use

Main elements to simulate emergence of land use

1. Diffusion - *jump to distance* $\lambda$ taken from $C(\lambda) = \lambda^{1.1/5}$ [Bettencourt, Science 2013]
2. Aggregation - *grow size to some* $R (R_B, R_R, R_l)$
3. Constraints - *define “non-developable” lands – forest, roads, etc*

Modeling the emergence of Land Use

- Consistently captures the general features of Singapore: segregated I that is mixed with $R$ and $B$
Modeling the emergence of Land Use

- Growth is based on a single growth seed assumed to be along the central business district
- Model is robust, captures the general features of other cities

Emergence of land use simulation

- Growth is based on a single growth seed assumed to be along the central business district
- Model is robust, captures the general features of other cities

## Table 1. Simulation results summary

<table>
<thead>
<tr>
<th>City</th>
<th>Simulated values</th>
<th>Actual values</th>
<th>Error</th>
<th>Base</th>
<th>Error</th>
<th>Base</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Simulated values</td>
<td>Actual values</td>
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<tr>
<td></td>
<td>$S$</td>
<td>$D$</td>
<td>Fitted parameters</td>
<td>$S$</td>
<td>$D$</td>
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<tr>
<td></td>
<td>$R$</td>
<td>$B$</td>
<td>$I$</td>
<td>$R</td>
<td>B$</td>
<td>$B</td>
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<tr>
<td>Toronto</td>
<td>0.409</td>
<td>0.33</td>
<td>0.17</td>
<td>0.797</td>
<td>0.932</td>
<td>0.968</td>
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<tr>
<td>Houston</td>
<td>0.617</td>
<td>0.264</td>
<td>0.156</td>
<td>0.685</td>
<td>0.946</td>
<td>0.934</td>
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<tr>
<td>San Francisco</td>
<td>0.533</td>
<td>0.313</td>
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<td>0.762</td>
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<td>0.948</td>
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<tr>
<td>Las Vegas</td>
<td>0.392</td>
<td>0.241</td>
<td>0.192</td>
<td>0.756</td>
<td>0.982</td>
<td>0.954</td>
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<td>Washington dc</td>
<td>0.515</td>
<td>0.297</td>
<td>0.197</td>
<td>0.609</td>
<td>0.98</td>
<td>0.947</td>
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<tr>
<td>Singapore</td>
<td>0.278</td>
<td>0.303</td>
<td>0.103</td>
<td>0.76</td>
<td>0.942</td>
<td>0.98</td>
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<tr>
<td>Vancouver</td>
<td>0.502</td>
<td>0.276</td>
<td>0.195</td>
<td>0.589</td>
<td>0.899</td>
<td>0.955</td>
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<tr>
<td>Seattle</td>
<td>0.492</td>
<td>0.286</td>
<td>0.174</td>
<td>0.721</td>
<td>0.944</td>
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<td>New york</td>
<td>0.524</td>
<td>0.334</td>
<td>0.274</td>
<td>0.634</td>
<td>0.9</td>
<td>0.803</td>
</tr>
</tbody>
</table>

Lesson 1: Simple rules giving rise to complex patterns


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4. Transport System as a Complex System

- Many components/agents
  ~ 1.2 M card id’s, 122 stations
- Strongly coupled/interacting
  ~2.17 M journeys/day, multiple routes
- Non-linear, non-reductionist
  correlated delays, crowd dynamics

- Emergent phenomena/multiple phases
  tipping points, critical loads
- Adaptive/evolving/non-equilibrium
  new lines are added, commuters’ behavior evolves

Lesson 2: agent based models are versatile tools in modeling complexity
Rapid Transit System (RTS) Singapore

- Among the busiest railways in the world
- 2.17M journeys per day (2012), 122 stations, 149 km
- Tap in tap out ticketing data / EZ link cards

Smart Fare Card

ANONYMISED DATASET
Rapid Transit System (RTS) Singapore

- Weekdays characterised by existence of AM and PM peak
- Week ends characteristically different from weekdays

Critical Origin-Destination pairs

- 1% of OD pairs account for 20% of journeys

Conservation of Flows within Zones

Commuters visit places, but eventually go back to their origin locations.

\[\text{sym}(A) = \frac{A + A^T}{2} = \sim 0.9995\]
Travel pattern symmetry

- 68.22% trips are symmetric in Singapore (formulated using Minkowski sum)
- 33.01% Asymmetric Flows - Suffolk County, Massachusetts

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>% Symmetric</th>
</tr>
</thead>
<tbody>
<tr>
<td>MONDAY</td>
<td>69.17%</td>
</tr>
<tr>
<td>TUESDAY</td>
<td>68.94%</td>
</tr>
<tr>
<td>WEDNESDAY</td>
<td>67.97%</td>
</tr>
<tr>
<td>THURSDAY</td>
<td>68.57%</td>
</tr>
<tr>
<td>FRIDAY</td>
<td>66.45%</td>
</tr>
</tbody>
</table>

Legara, Monterola, Lee, Hung 2015

*S. Phithakkitnukon and C. Ratti, Inferring Asymmetry of Inhabitant Flow Using Call Detail Records 2014
Route choice?
How do individuals choose their routes?

Single route

\[ p(\Delta t) = \frac{dP(\Delta t)}{d\Delta t} = \frac{1}{\beta} \exp(-\Delta t/\beta) \exp(-\exp(-\Delta t/\beta)) \]

Multiple routes \( p_G(t; \mu_i, \beta_i) = \sum_{i=1}^{N} p_i(\Delta t) = \sum_{i=1}^{N} \frac{a_i}{\beta_i} \exp(-t - \mu_i/\beta_i) \exp(-\exp(-t - \mu_i/\beta_i)) \)
How do individuals choose their routes?

**Time over “Convenience”**

- 70:30
  - 1 transfer (34 mins) vs 0 transfer (48 mins)

**“Convenience” over Time**

- 10:90
  - 2 transfers (38 mins) vs 0 transfer (45 mins)

**Three equally feasible routes**

- 35:31:34
  - 2 tr (37 mins) vs 1 tr (49 mins) vs 0 tr (50 mins)

**Multiple routes**

Weekdays characterised by existence of AM and PM peak

68.22% trips are symmetric in Singapore

Important constraints

Commuters visit places, but eventually go back to their origin locations.

OD pairing distribution is a power law

Route choice not necessarily shortest path
Full scale agent based model of RTS system

- Station passengers-land use design
- Spare capacity-route choice & OD pairs
Model validation

RTS - Model captures the travel time distribution of entire week

Bus - Model captures the travel time, passenger distribution of all service routes

197 onward

197 reverse
Transport – Full scale model of RTS-Bus dynamics Singapore

- RTS/Bus full-day simulation with more than 2 million commuters finishes in less than 4 minutes.
- Developed multi-touch visualization for the simulation.
- Achieved top prize in two top tiered international competition IEEE Scale challenge 2013, ICCS 2014
What accurate models can do? Scenario Modeling.

- Crowdedness and/or Disruption in one station impacts non-linearly the travel time of commuters.
- Ridership can be predicted after the system has been modified for expansion (+ network analysis).

Lesson 3: a good model allows prediction beyond mere data analytics.

- Total trips > 3M per day, average duration trips will start to increase proportionally.
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Datasets

OpenStreetMap
Datasets

Land Use Plan

Source: http://www.mnd.gov.sg/LandUsePlan/theme/default/image/hme_our_land_use_plan.jpg
Source: A High Quality Living Environment for All Singaporeans: Land Use Plan to Support Singapore’s Future Population, January 2013
Land Use and Amenities

Transport Points

OpenStreetMap
Transport Points & Amenities
Which land-use feature ultimately dictates the number of tap-ins and tap-outs within a station?

Sustenance
Education
Transit
Finance

Healthcare
Entertainment
Commercial
Other

Residential
Business
Industrial
Greenery

Water
Other
Prediction

Use the surrounding urban entities to estimate travel demand (# of tap-ins and # of tap-outs).

Hu Nan, Legara, Hung, Lee, Monterola, Land Use Policy 2016
Scenario Modeling

“Conceptual Plan” (2030)  Hypothetical Amenity Increase

Hu Nan, Legara, Hung, Lee, Monterola, Land Use Policy 2016
Scenario Modeling: Results

Amenity Increase

Summary: Commuter **demand** is strongly **amenity-driven**

- Evaluate the impact of land-use sector types and amenity densities and locations on public transit ridership
- Results indicate that amenities are highly predictive of transport demand
Commuter demand is non-monotonic with growth of amenities

- Quantify the relationship between land-use and transport systems
- Develop a decision-support tool to assess impacts of land-use configurations on ridership; evaluate “what-if” scenarios

**Lesson 4:** Interacting complex systems are possibly predictable

Station demands vary nonlinearly with amenity increase

URA planned Regional centers

Amenities are generally infrastructure-driven

Data from 73 cities

Figure 6. Standard deviation $\sigma(\Omega)$ vs. mean $\langle \Omega \rangle$ of distance from amenities to nearest transport points within each city. The reference line is $\sigma(\Omega) = \langle \Omega \rangle$.

Amenities decays exponentially from transport points consistently across different cities.
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Inferring Passenger Type from Commuter Travel Matrices

- Quantify commuter travel patterns
- Develop framework called *Eigentravel Travel Matrix* that serves as travel DNA of public transport commuters
- Accurately identify and categorize public transport commuters to about 80%

E. Legara, C. Monterola, Transportmetrika B, 2017
Traffic modeling and simulation

- Create a master model that explains the variations of hundreds of existing models
- Understand human driving behavior
- Construction of effective model for efficient large scale simulation

Lightless Urban Intersection Control for Minimally Guided Vehicles

- Highly efficient urban intersection control
- Use mature technologies to move beyond intersection control with traffic lights (minimal technological barrier /impact to conventional driving behaviours)
- Technology won’t be obsolete with the introduction of various levels of smart vehicles (unlike traffic light control).

A System of Systems Approach

Current Focus

- Pedestrians/Commuters
- Satisfaction level
- Health status
- Spending patterns
- Energy consumption

Rapid Transit System
Bus System
Taxi System
Private Cars
Insights on Urban Mobility through Complexity Science

1. About us
2. The Complex City – to use economy of scale requires complexity science perspective
3. Land use allocation – emergence can be modeled using simple rules
4. Transport system – criticality, efficiency, resilience can be probed using complexity science
5. Land use – Transport coupling – complex systems can be used for scenario planning
6. Other aspects: Behavior, traffic, new technology