THE UNIVERSITY OF HONG KONG 香港大學
faculty of architecture 建築學院

iLab @HKURBANlab the urban big data lab

Computational Streetscapes
Big data, deep learning, and vector model

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Frank Xue
xuef@hku.hk
frankxue.com

Dept of REC
FoA, HKU

Outline

1. Background & motivation
2. Computational streetscapes
3. Discussion

Section 1

BACKGROUND & MOTIVATION

1.1 Background

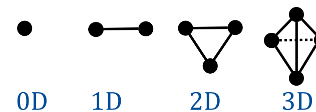
- Streetscape
  - Is a *narrow and linear urban space lined up by buildings, used for circulation and other activities* (Rapoport, 1987)
- Elements of streetscape
  - Road, sidewalk and amenities, landscaping, street furniture, connections, background buildings
  - Pedestrians, vehicles, animals, vegetation
- Computational streetscape
  - A topic under urban informatics/computing
  - Less laborious, more objective than manual audits
- For smart applications in many disciplines
  - Landscape, planning, architecture, psychology
  - Construction, conservation, logistics, robotics
  - Business planning, valuation and taxation, etc.

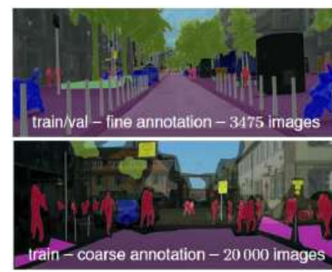
Typical Hong Kong street scenes, (a) *Hill Road* near HKU West Gate (b) *Hillier Street* at Sheung Wan (source: Diamfleoss; DDMLL @Wikipedia CC BY-SA)

1.2 Upstream urban data

- Accurate, (near) real time, big data of streets
- Through many devices
  - Underground: Optical fiber network
  - Ground: AR phone, Internet of things, mobile scanner
  - Low-altitude: Drone, helicopter, plane (camera, laser, radar)
  - High-altitude: Satellite (camera, radar)
- In multi-dimension data
  - 0D points: Crowd-sourced location, wind, traffic congestion
  - 1D linear features: Vibration, deformation
  - 2D images: Aerial photo, satellite photo, heat map
  - 3D point clouds: Geometry, deformation
  - *n*D over time
- Some data associated with meanings
  - Tagged / annotated dataset

Google street view car
(photo: Wikipedia)



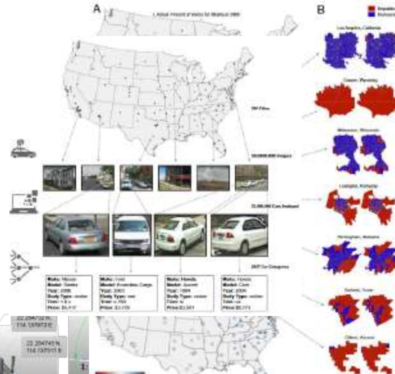


Tagged CityScapes dataset
(Cordts et al. 2017)

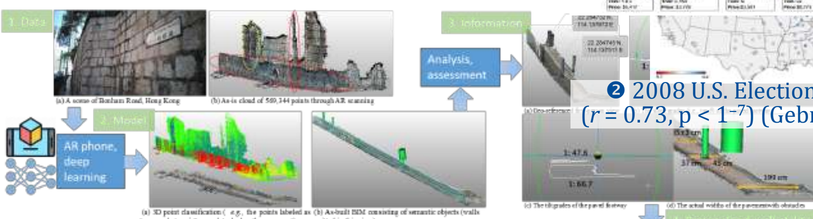
1.2 Downstream applications

- For
  - Urban objects: forestry, shade, density, …
  - Users: walk, cycling, safety, comfort, election
- On top of, e.g.,
  - ❶ Green view index
  - ❷ Street car models
  - ❸ As-build 3D modeling
  - ❹ “Black-box” DL models

❶ Green view indices for urban forestry & cycling (MIT 2017; Long & Liu 2017; Lu et al. 2019)



❷ 2008 U.S. Election prediction ($r = 0.73$, $p < 1^{-7}$) (Gebru et al. 2018)



Walking characteristic	Calculated value	Type of pedestrians				
		Wheelchair	Stroller	Luggage	Senior	Exercise
No. of steps	0	OK	OK	OK	OK	OK
Slope grade*	1:50.0~58.8	OK	OK	OK	OK	OK
Tilt grade†	1:47.6~66.7	OK	OK	OK	OK	OK
Footway width‡	45~199 cm	Failed	Limited	Limited	OK	OK
Clearance	Good	OK	OK	OK	OK	OK
Overall walkability (the worst)		Failed	Limited	Limited	OK	OK

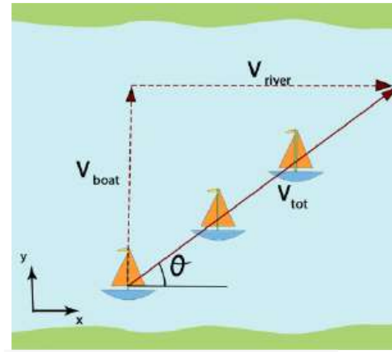
*: Reference maximum slope grade: 1:8~12 (wheelchairs); †: Reference maximum tilt grade of pavement: 1:15 (wheelchairs); ‡: Reference minimum width: 70~90 cm (wheelchairs), 40~70 cm (strollers), and 30~60 cm (luggage).

❸ Personalized walkability assessment (sidewalk) near HKU (Xue et al. 2018)

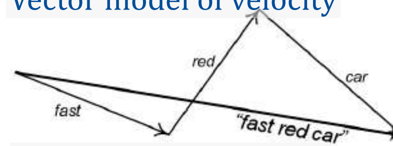
❹ Prediction (1-10 points) of safety & comfort street scenes in Shanghai (Liu et al. 2018)

1.2 Vector model & applications

- Vector algebra
  - $V_{\text{tot}} = V_{\text{boat}} + V_{\text{river}}$
  - $V_{\text{river}} = V_{\text{tot}} - V_{\text{boat}}$
  - **cos** θ : Closeness between V_{river} and V_{tot}
- Vector models (vector space models)
  - In math and physics
  - In natural language processing (Mikov et al. 2013)
    - "Einstein – scientist + painter" = Picasso
- Vector model about street elements …
  - *Hill Road* and *Hillier Street* sound very similar
    - But *how much* do they look alike?
  - Can we *compute* a street as a vector of elements?
    - Vector operators +, –, ×, **cos** θ, *corr*
  - What applications can be benefited?
    - How?



Vector model of velocity

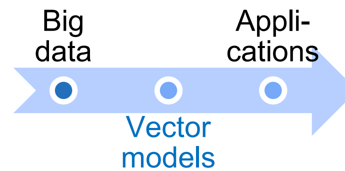


Vector model of words

Vector model of streetscape?

1.3 Opportunity

- Gaps
  - Hard-coded processing / method
  - Ad-hoc applications
  - No reusing of valuable urban information
- Opportunity for a midstream study on
  - A vector model of streetscape
  - General math-like operations
  - Multi-purpose usages / use cases
- Urban Big Data Platform (UBDP), HKU
  - Multi-source big data
    - Including streetscapes
  - Multi-scale urban information
    - Point, line, and area
  - Supported by HKU Platform Technology Fund ($915,870)
    - 2018—2020. PC: Prof. Webster



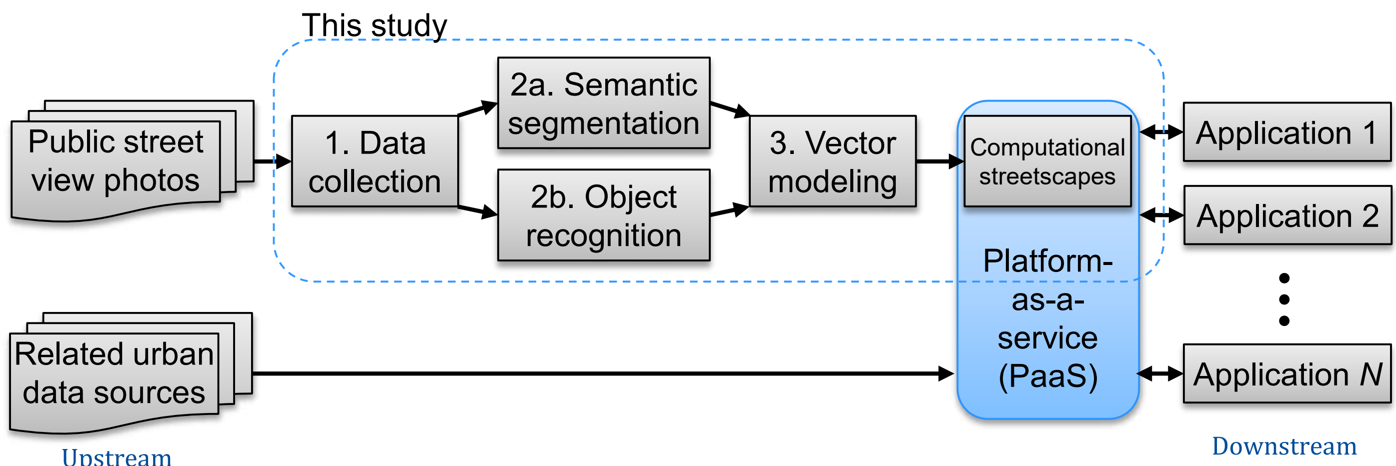
UBDP introduction page
http://fac.arch.hku.hk/ubdp

Section 2

COMPUTATIONAL STREETSCAPES

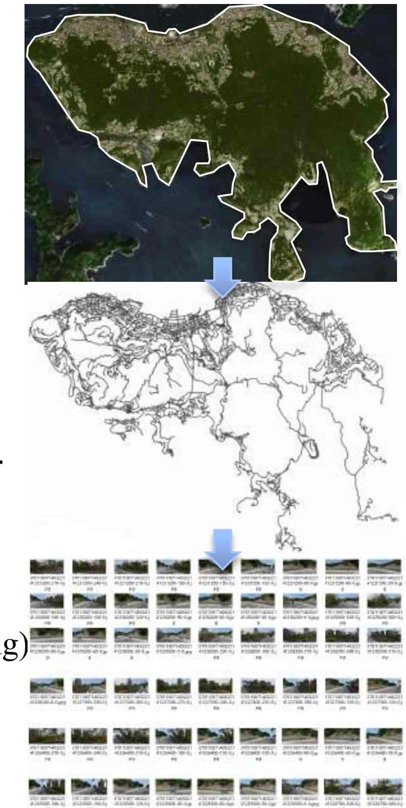
2 Method

- Theoretical stance
  - A midstream approach, distributed via Platform-as-a-Service (PaaS)
- 3 steps to channel upstream data to downstream
  - Step 1: Data collection
  - Step 2: Information extraction: (a) Semantic segmentation + (b) object recognition
  - Step 3: Vector modeling



2.1 Step 1: Street data collection

- Partner: Tecent Street View
  - 2D images; Source: *NavInfo*
  - Datum: GCJ-02, not WGC-84
- The Hong Kong Island
  - 78.6 km^2 Area
    - Both *high* and *low* density areas
  - 3,625 road segments (473.35 km) with street views
    - Extracted from *OpenStreetMap* database
    - No data of steps / corridors / foot bridge / private road …
  - 42,683 panorama coordinates
    - Resolution: 8.58m between two points
    - Some shared at segment connections
  - ~500,000 street photos (12 shots per point, every 30° heading)
    - 48 GB, Downloaded in ~10 days
    - Deep learning processing in 22 days
    - ~670,000 including connections, tunnels, …



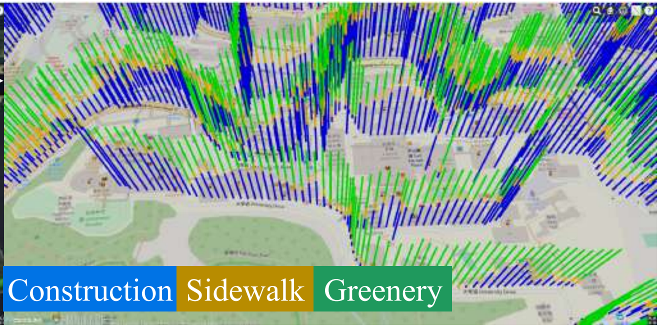
Data collection

2.2 Step 2a: Elements from semantic segmentation

- Semantic segmentation
  - DL model: *DeepLab* v3 CNN (trained on *cityscape*)
- Area by counting pixels
  - Construction: Building, infrastructure, wall
    - E.g., 45% + 0% + 2% = 47%
  - Sidewalk: Walking path, guardrail
  - Greenery: Vegetation
  - Other: Sky, street signs, etc.
- Lines by counting vertical image slices
  - Sidewalk, guardrail, unguarded sidewalk

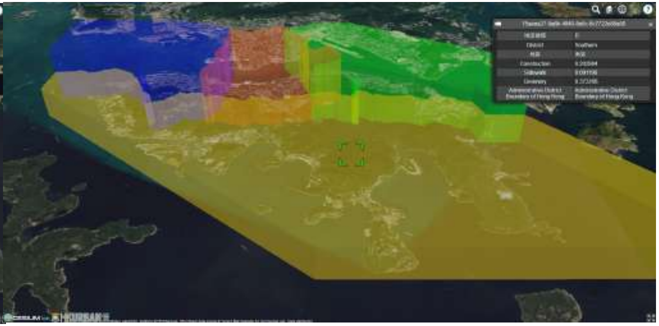
Example of semantic segmentation

2.2 Results of Step 2a



(a) Green view is high except for the high-density areas

(b) Visual fields around HKU Main Campus



(c) Level of sidewalk railing is satisfactory in general

(d) Average percentages of elements in the four districts

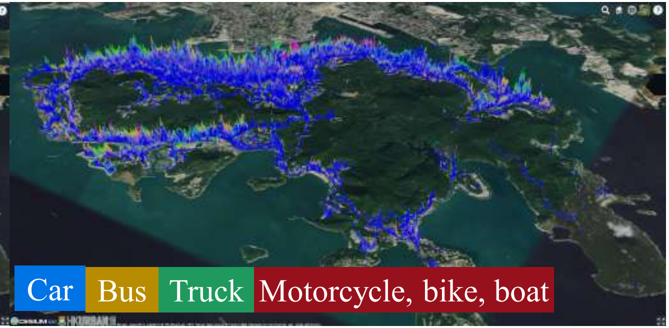
2.2 Step 2b: Elements from object recognition

- Object recognition
  - DL model: *Luminoth* v0.2.4 RNN (trained on COCO)
- Counting objects
  - Vehicles: Cars, buses, trucks, motorcycles, bicycles
  - Personal: Persons, backpacks, handbags
  - Street furniture: Traffic signs, traffic lights, bench, fire hydrants, …
  - City animals: Cats, dogs, birds
- Actions of people
  - Walking / standing: On a sidewalk, behind a guardrail (using segmentation results)
  - Road crossing: On a roadway, in front of a vehicle

Example of object recognition

2.2 Results of Step 2b

(a) More vehicles and persons in high-density areas; Street furniture and animals relatively even (except for *Shek O*)



(b) More buses in residential areas; trucks on major roads

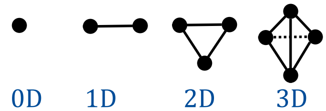
(c) More people walking in high-density (less greenery) areas

(d) Dogs/cats found in residential areas; more birds in low-density areas

>>DEMO_LINK<<

2.3 6D vector modeling

- Vectorization of 6 major street elements
  - Construction, sidewalk, greenery, vehicles, persons, street furniture
  - Balanced and normalized for each explicit dimension
- Hong Kong Island Datasets



  - 0D "point" data table (panorama coordinates) Better for elements/ behavior analyses
    - 42,683 vectors
  - 1D "street" data table (roads)
    - 784 vectors
  - 2D "District" data table (election district)
    - 4 vectors

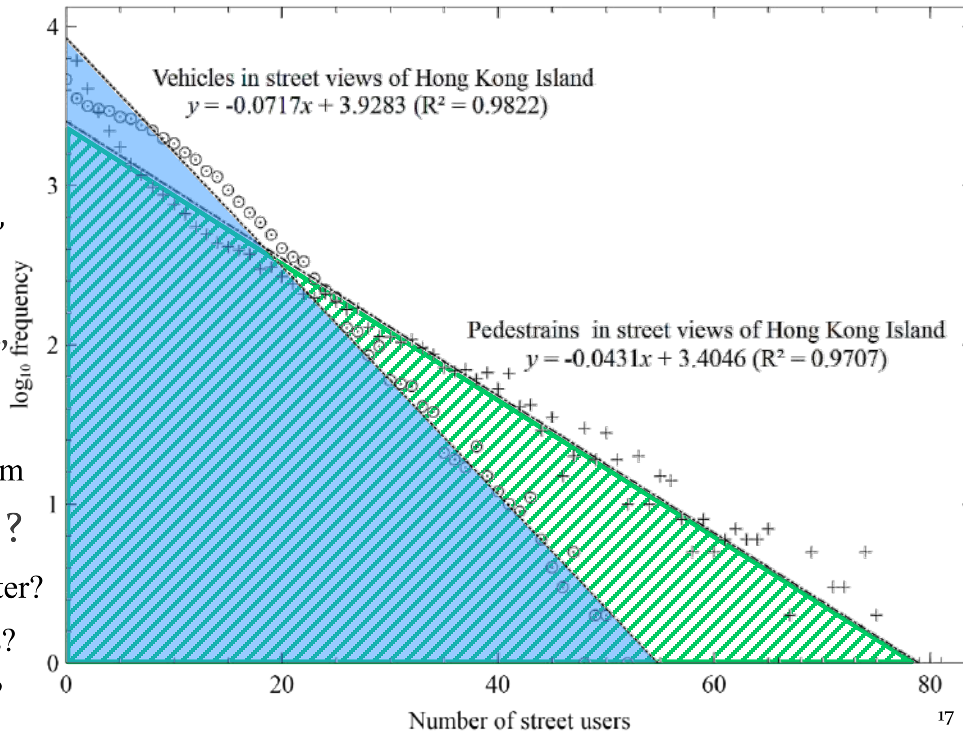
Better for calculus

- Vector calculus
  - Norm (| |), addition (+), subtraction (−)
  - Multiplication (×), division (/), dot product (·)
  - Cosine similarity (cos), correlation (ρ)
  - Gradient (∇), Laplacian (Δ)

2.4 Use case 1: Logarithmic usage of street

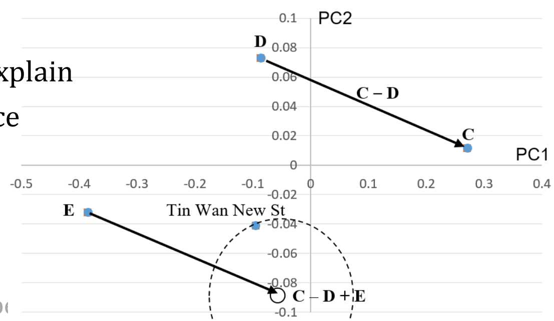
- Number of street users at a point obeys logarithmic distribution
  - Vehicles seen
    - Volume: Blue, ~322,000
    - Max: ~55
  - Pedestrians seen
    - Volume: Green, ~237,000
    - Max: ~80
- Average "density"
  - 237,000 / 473.35

    = 500.7 pedestrians/km
- Unique behavior ?
  - People always cluster?
  - Urban health issues?
  - Similar elsewhere ?



2.4 Use case 2: Streetscape algebra

- Similarity between *Hill Road* and *Hillier Street*
  - Cosine similarity: $\cos\theta = \mathbf{A}\cdot\mathbf{B} / |\mathbf{A}|\times|\mathbf{B}| = 0.7673$
  - 76.73%
- "*Queen's Road West – Central Western District + South District* = ____________?"
  - $\mathbf{C} - \mathbf{D} + \mathbf{E} = [-0.02706, -0.01939, 0.014958, -0.05959, 0.043838, 0.010644]^T$
  - The closest street in South District is
    - Tin Wan New Street (distance = 0.1209)
  - "*Queen's Road W* to *Central & Western District* is roughly equivalent to Tin Wan New Street to *South District*."
  - As illustrated
    - PC1 & 2 explain 65% variance



Vectors of Hill Rd (**A**) and Hillier St (**B**)

Dimension	Hill Rd (A)	Hillier St (B)
Construction	0.186837	0.305023
Sidewalk	0.011774	-0.148464
Greenery	-0.09866	-0.210708
Vehicles	-0.09689	0.049695
Persons	0.034738	0.157678
S. Furniture	0.052523	0.116280

Vectors of Queen's Rd W (C), Central Western (D), and South (E)

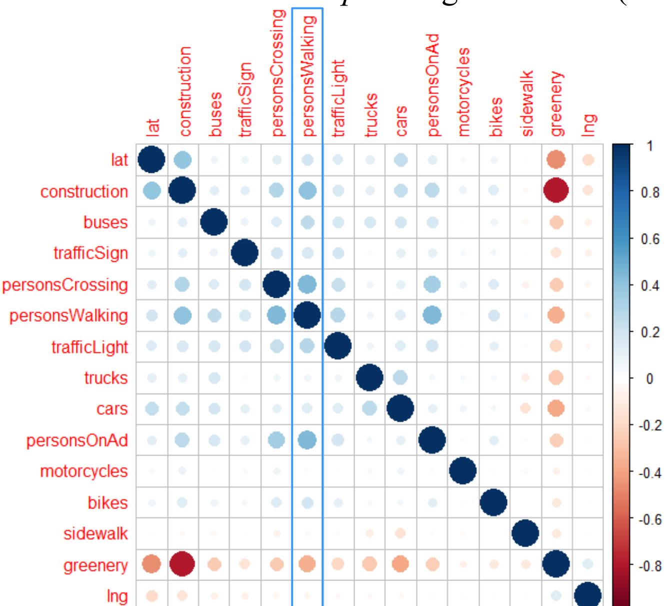
Dimension	Queen's Rd W (C)	Central & Western (D)	South (E)
Construction	0.195057	-0.07714	-0.29926
Sidewalk	-0.07509	-0.03884	0.016865
Greenery	-0.16886	0.070689	0.254503
Vehicles	0.011577	-0.02056	-0.09173
Persons	0.103898	-0.04118	-0.10124
S. Furniture	0.052947	-0.01499	-0.0573

Closest street vectors to C – D + E

Rank	Street name (South District)	dist
1	Tin Wan New Street	0.120894
2	South Horizon Drive	0.122902
3	Lee Hing Street	0.143904
4	Yi Nam Road	0.145450
5	Aberdeen Main Road	0.163997
6	Kwun Hoi Path	0.189905
7	Wah Fu Road	0.207953

2.4 Use case 3: Street element clustering

- Clusters based on Pearson’s correlation
  - “Nature” {longitude, greenery}, {sidewalk}, and “town” {others}
  - Walking in HK Island: Positive *r* to building, road-crossing, & ad.; Negative to green
  - Beware of *p* for big data: Most (>95%) bivariate correlations had $p < 0.00001$



		lng	lat	construction	sidewalk	green	car	bus	truck	motorcycle	bike	Person Walking	Person Crossing	Person On Ad	traffic Sign	traffic Light
Lng	r	1	-.180	-.146	-0.003	.137	-.033	-.076	-.036	-.013	-0.009	-.055	-.057	-.027	-.071	-.039
	sig		0.000	0.000	0.567	0.000	0.000	0.000	0.000	0.007	0.055	0.000	0.000	0.000	0.000	0.000
Lat	r	-.180	1	.397	.013	-.467	.244	.078	.118	.033	.063	.184	.126	.122	.078	.143
	sig	0.000		0.000	0.006	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
construction	r	-.146	.397	1	-.036	-.797	.246	.127	.114	.087	.131	.402	.295	.266	.127	.164
	sig	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sidewalk	r	-0.003	.013	-.036	1	-.113	-.152	-.049	-.097	-.029	0.000	.036	-.063	-.022	.017	.027
	sig	0.567	0.006	0.000		0.000	0.000	0.000	0.000	0.000	0.980	0.000	0.000	0.000	0.000	0.000
Green	r	.137	-.467	-.797	-.113	1	-.383	-.257	-.269	-.071	-.117	-.352	-.257	-.240	-.147	-.205
	sig	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Car	r	-.033	.244	.246	-.152	-.383	1	.186	.267	.069	.052	.132	.108	.104	.118	.137
	sig	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bus	r	-.076	.078	.127	-.049	-.257	.186	1	.176	0.003	.072	.255	.145	.177	.085	.173
	sig	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.532	0.000	0.000	0.000	0.000	0.000	0.000
Truck	r	-.036	.118	.114	-.097	-.269	.267	.176	1	.033	.039	.068	.062	.059	.030	.067
	sig	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000
motorcycle	r	-.013	.033	.087	-.029	-.071	.069	0.003	.033	1	.020	.028	.075	.028	.039	0.007
	sig	0.007	0.000	0.000	0.000	0.000	0.000	0.532	0.000		0.000	0.000	0.000	0.000	0.000	0.153
Bike	r	-0.009	.063	.131	0.000	-.117	.052	.072	.039	.020	1	.182	.149	.124	.058	.105
	sig	0.055	0.000	0.000	0.980	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000
Persons Walking	r	-.055	.184	.402	.036	-.352	.132	.255	.068	.028	.182	1	.445	.446	.161	.284
	sig	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000
Persons Crossing	r	-.057	.126	.295	-.063	-.257	.108	.145	.062	.075	.149	.445	1	.343	.186	.237
	sig	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000
Persons On Ad	r	-.027	.122	.266	-.022	-.240	.104	.177	.059	.028	.124	.446	.343	1	.105	.189
	sig	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000
Traffic Sign	r	-.071	.078	.127	.017	-.147	.118	.085	.030	.039	.058	.161	.186	.105	1	.185
	sig	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000
Traffic Light	r	-.039	.143	.164	.027	-.205	.137	.173	.067	0.007	.105	.284	.237	.189	.185	1
	sig	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.153	0.000	0.000	0.000	0.000	0.000	

Pearson’s correlations between some street elements (N = 42,566)

Section 3

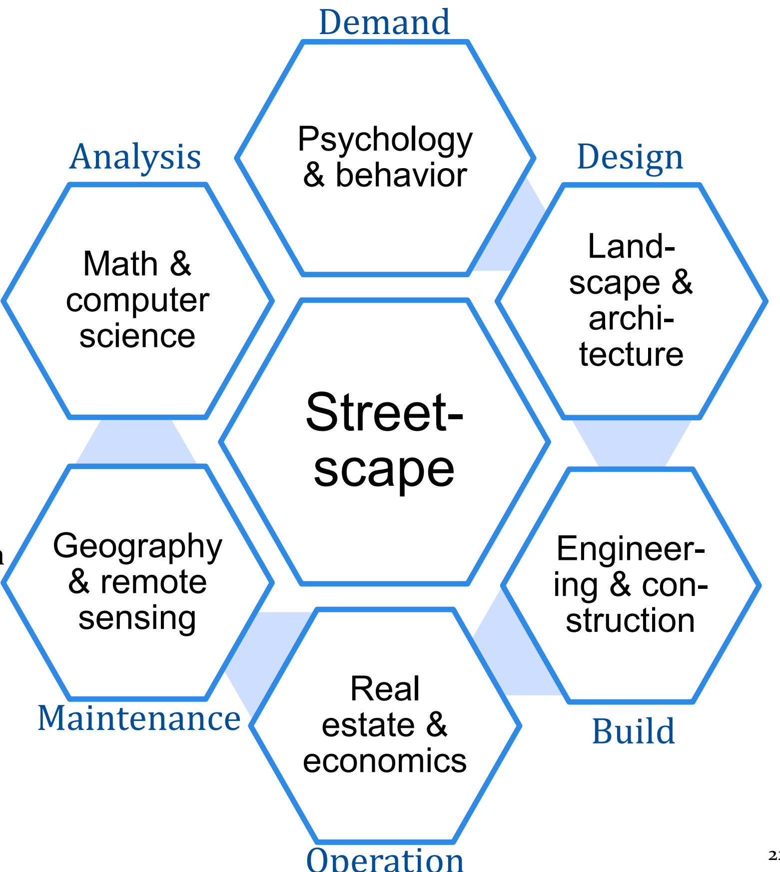
DISCUSSION

3.1 A wrap-up

- Work done
  - 3 steps for computational streetscapes
    - Big data collection, RNN and CNN processing, and vector modeling
  - 3 use cases of computational streetscapes
    - Logarithmic use behavior, street algebra, Street element clustering
- Pros
  - Big data, objective and low-cost
  - Automatic processing
  - Mathematical modeling and calculus
  - Multiple potential applications
- Cons
  - Limited by explicit, major street elements
    - Orthogonal decomposition
  - Some DL results are erroneous
    - Small elements, e.g., fire hydrants
  - GCJ-02 obstruction to WGS-84

3.2 In a life-cycle view

- Streetscape
  - Small but influential
  - Has a typical product life cycle
- Many disciplines needed
  - 10+
  - Each focuses certain phases
  - Calling for cross-disciplinary collaboration
    - E.g., explaining the log distribution, comparing the demand and supply of green on streets
- Linking related big data
  - 3D: Aerial LiDAR, …
  - Buildings: Ownership and price
  - Demography: Age distribution, education, income, …



3.3 Future work

- Future work
  - Minor elements
  - Implicit vector space
    - Fully independent dimensions
  - Integrating multi-source urban big data
  - Kowloon and New Territories

- Collaboration opportunities
  - ITF Midstream Research, RGC Research Impact Fund, RGC Collaborative Research Fund
  - Based on the “Urban Big Data Platform: Integrate to inspire” project
  - Contact: Prof. Chris Webster

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  - Street view data granted by partner Tencent (Guangzhou)

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THANK YOU !