Are Streets Indicative of Place Types?

Rui Zhu[1], Grant McKenzie[2], Krzysztof Janowicz[1]

[1]STKO Lab
Department of Geographt
UC Santa Barbara

[2]Platial Lab
Department of Geography
McGill University

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Place-based GIS

- Beyond metric information about **locations or geometries**
- **Interaction with human**:
  - capacity, atmosphere, accessibility, reviews, opening hours, prices of services, and products they offer,
  - moods, opinions, and experiences

Place Types

Place types are best understood as **proxies** for a wide range of **latent characteristics** that we do not typically model explicitly in an information system. Examples:

- *Fire stations* are located to maximize the coverage
- *Book stores* are found in quiet communities
- *Bars* are usually closed during daytime
- People are more likely to discuss about arts, history, and culture in a *museum*

Semantic Signatures

- The set of **thematic**, **temporal**, and **spatial** bands that uniquely characterize place types
- Spatial signatures: to use **spatial structures and interactions** to characterize the semantics of place types

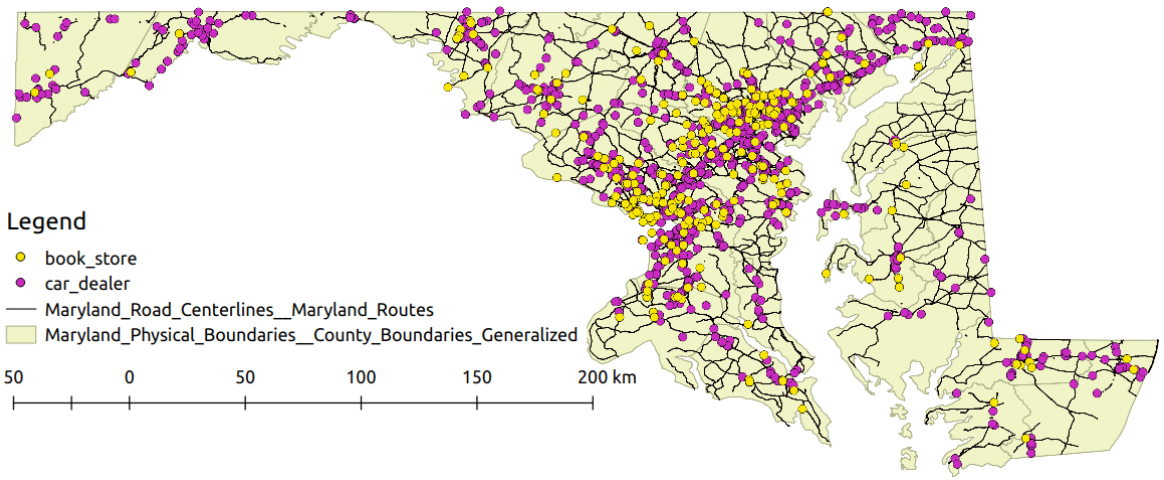
Spatial Signatures

Zhu et. al (2016) proposed a set of statistics to characterize the spatial structures and interactions of geographic information (e.g., point of interests) from different perspectives.

Spatial Point Pattern		**Spatial Autocorrelations**	**Spatial Interaction with Other Geographic Features**		**Place-based statistics**	
Local	*Intensity*	*Global Moran's I*	Population	*min*	*Number of distinct states (or counties)*	
	Mean distance to nearest neighbor			*max*		
	std. of distance to nearest neighbor			*mean*	*Entropy of states (or counties)*	
	Kernel density (range)			*std.*	*Number of adjacent states (or counties) that have the same feature type*	
	Kernel density (bandwidth)		Road Network	*min of shortest distance*		
	Ripley's K (range)			*max of shortest distance*		
	Ripley's K (mean deviation)			*mean of shortest distance*	*Number of distinct feature types for nearest neighbor*	
	std. ellipse (rotation)	*Semivariogram (first distance lag)*		*std. of shortest distance*		
	std. ellipse (std. along x-axis)			*entropy of nearest road types*	*Entropy of feature types for nearest neighbor*	
	std. ellipse (std. along y-axis)		Climate	*mean precipitation*		
Global	*Intensity*	*Semivariogram (median distance lag)*		*std. precipitation*	LDA-based approach	*Mean KL Divergence of the topic distribtion*
				mean temperature max		
	Kernel density (range)			*std. temperature max*		
				mean temperature min		
		Semivariogram (last distance lag)		*std. temperature min*		*Entropy of the topic distribution*
	Kernel density (bandwidth)			*mean water vapor pressure*		
				std. water vapor pressure		

Spatial Interaction with Streets

- **Research question**: are streets indicative of places? (Note: places refer to POIs in our work)
- **Hypothesis**: the type of a place is implicitly embedded in its interaction with a street network given that the relationship between places and streets differs based on the **properties** and **affordances** of the place type



Road networks, book stores and car dealers in Maryland, USA

Google Places vs Foursquare Venues

- Study region: the State of Maryland, USA
- Road network: Maryland Road Centerlines dataset[1], which contains about **4816 street centerlines** for all public roadways in Maryland
- **Point of Interest (POI)** datasets

Dataset	Number of POIs	Number of place types
Google Places[2]	38354	99
Foursquare Venues[3]	132429	403

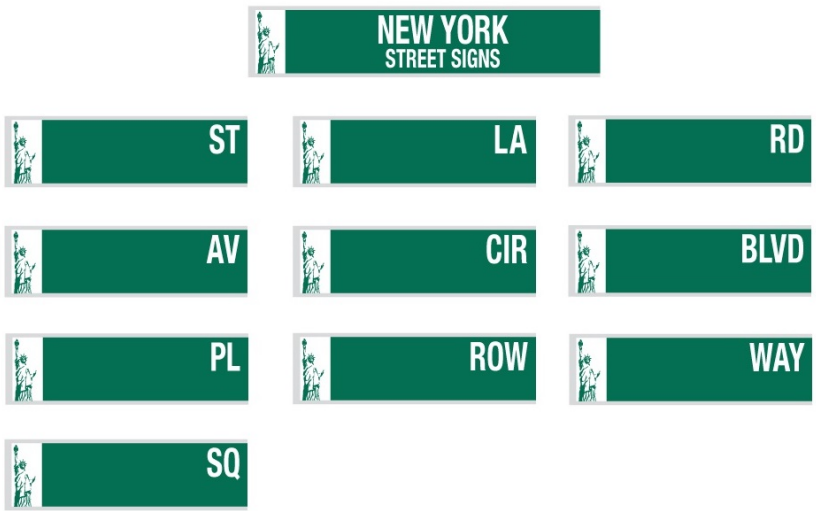
[1] http://data.imap.maryland.gov/datasets/
[2] https://cloud.google.com/maps-platform/places/
[3] https://developer.foursquare.com/

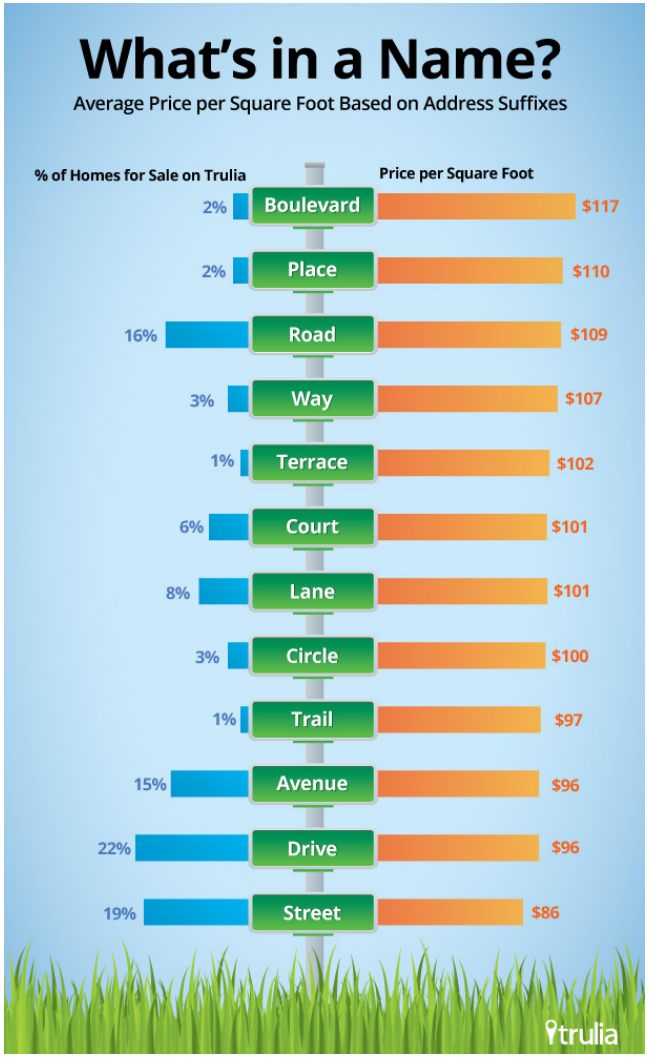
Street-based Spatial Signatures

Two types of spatial signatures are introduced:

- **Proximity** to closest street
  - Example: natural reserves vs restaurants
  - Statistics: min, max, mean, std
- **Suffix** to closest street
  - Example: bakery vs car dealer
  - statistics: entropy, Jensen Shannon Divergence (JSD)

Street Suffix





Proximity to Closest Street

For each place of a place type, we compute the **shortest distance to the road network**. Then we have a distribution of shortest distance for each place type.

- Example statistics: **mean** shortest distance of a place type

$$s^{proximity} = \frac{\sum_{j=1}^{N} d_j}{N}$$

where N is the number of places of a specific place type

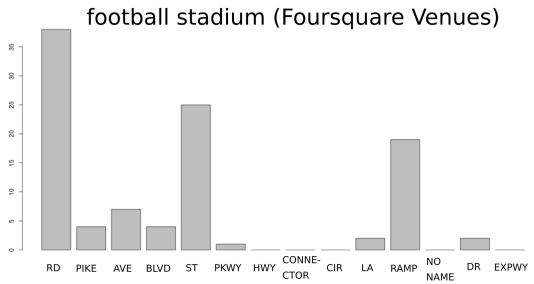
- Examples:

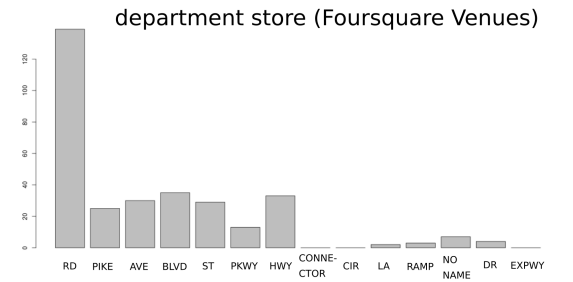
Place Types	Distance to Closest Street (in meters)			
	Min	Max	Mean	Std
`restaurant`	0.01	15084.88	503.29	785.35
`natural feature`	8.90	14881.89	1423.70	2172.93
`stadium`	15.20	1870.40	468.42	387.72

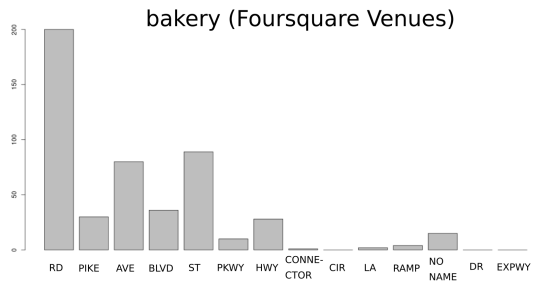
Suffix of Closest Street

Thanks to its **cultural implication**, street suffix embeds **latent characteristics**, such as the width, the importance, and the neighborhood of streets.

- **14 suffix types** in the data: e.g., roads (RD), turnpikes (PIKE), avenues (AVE), boulevards (BLVD), streets (ST), parkways (PKWY), connectors (CONNECTOR), circles (CIR), and lanes (LA)
- Suffix type distribution:







- **Entropy** and **Jensen Shannon divergence (JSD)** are used to quantify and compare the distributions

Overview of Experiments

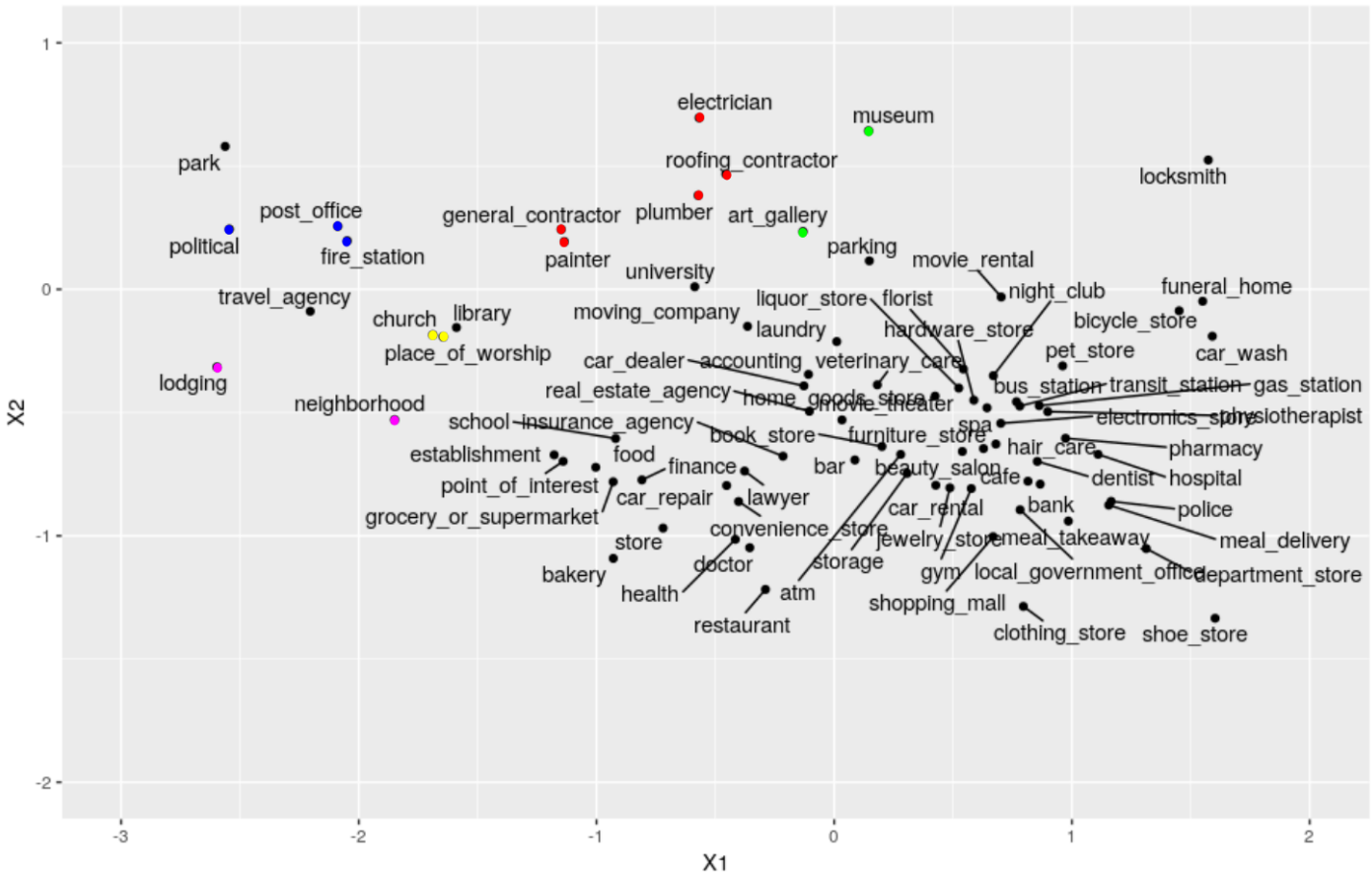
We test the proposed signatures by:

- Exploring the relation of place types **within one dataset**, i.e., Google Places
- Aligning place types **across datasets**, i.e., Google Places and Foursquare Venues

Exploration in Google Places

- 5 statitsics: **min, max, mean** and **std** of distances to the closest street, and the **entropy** of street suffix
- **Multidimensional scaling (MDS)** to transfer the 5-dimension space into a 2-dimension map
- The **relation/relatedness** of place types is reflected by their **pairwise distance** in the 2-dimension map

Exploration in Google Places



- House modeling and construction
- Religion
- Public services
- Arts

Place Type Alignment

- We use the **suffix distribution of the closest street** to align place types between Google Places and Foursquare Venues
- **Jensen Shannon divergence (JSD)** is used to compare the suffix distribution pairwise

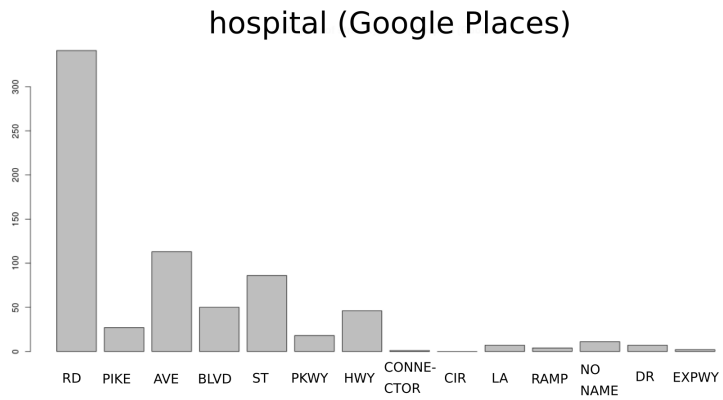
Place Type Alignment

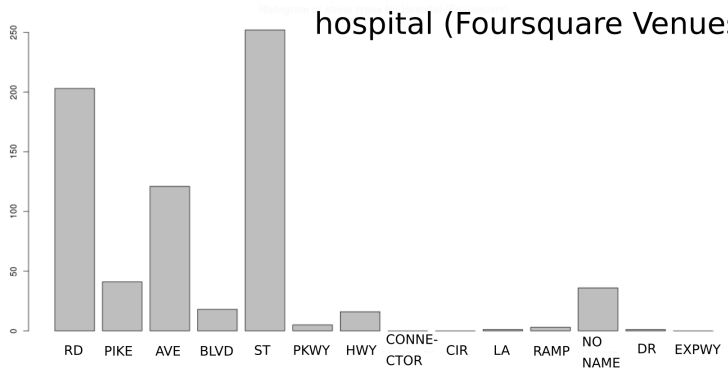
- Examples: pairwise JSD is ranked for each place type

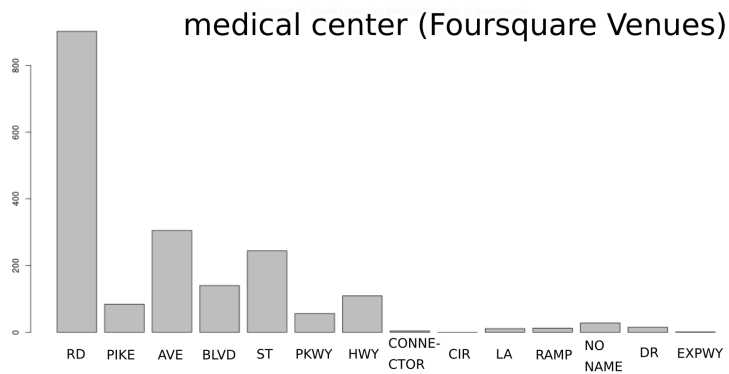
Place Type in Google Places	*Top 5 Match in Foursquare Venues*				
	1	*2*	*3*	*4*	*5*
amusement park	**theme park**	bike rental bike share	motel	lounge	market
hospital	**medical center**	salon barbershop	miscellaneous	drugstore pharmacy	laundry service
post office	fire station	city	bridge	flower shop	brewery

Place Type Alignment

- Comparison of hospital from Google Places with hospital and medical center from Foursquare Venues







Conclusions

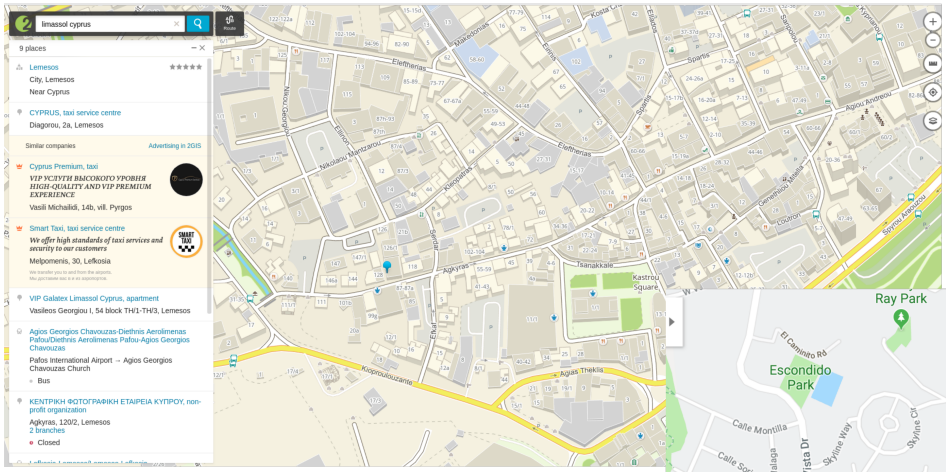
- **Street-based spatial signatures** were introduced to quantify the semantics of place types
- Two types of interactions, **proximity to** and **suffix of the closest street**, were explored
- Experiments, both **within one dataset** and **across different datasets**, showed the potential of characterizing place types using the interaction with streets

Discussion and Future Work

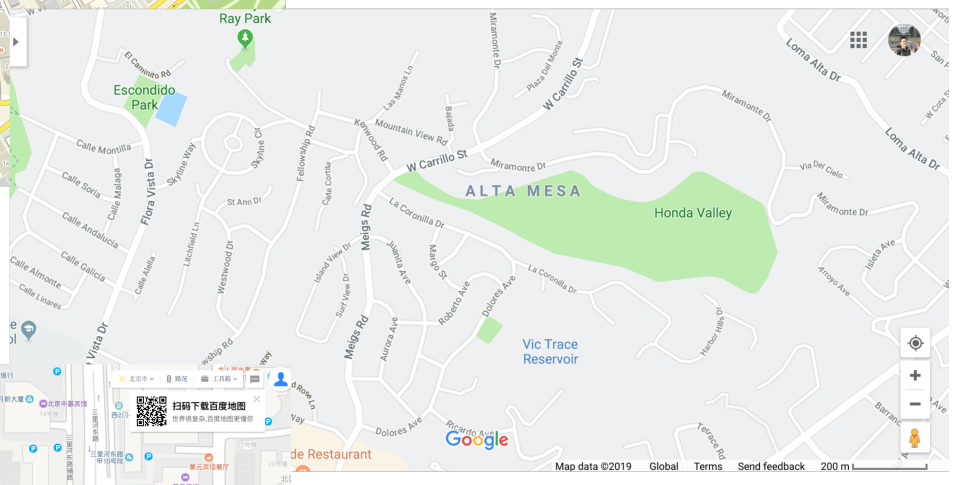
- **More sophisticated models** will be applied to understand the interaction between places and streets
- Street-based signatures will be **combined with other semantic signatures** to address **geospatial challenges** such as coreference resolution, open geospatial data cleaning, and place disambiguation
- We plan to apply the approach **across different cities and countries** as a new means to compare and understand the culture implication of places

Street Suffix across Cultures

Limassol, 2GIS



Santa Barbara, Google Maps



Beijing, Baidu Maps