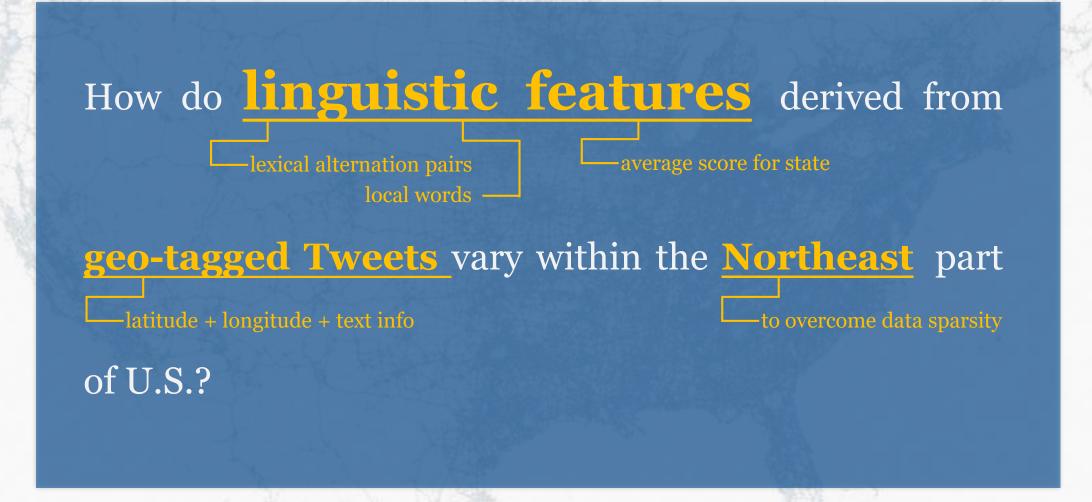


Andi Liao Advisor: Luc Anselin 2019/04/18







Boundary Clarification

Content

- No NLP!!!
- Spatial Linguistics

-Method: Spatial Data Science

Concept: Geo-Linguistics

Task

- Explore spatial linguistics variations at state level
- Predict geo-locations using text information



Mom-Mother

Relevant Literature: Geo-Linguistics Patterns

Spatial

- Spatial distribution of <u>lexical</u> alternation pairs
 - Multivariate mapping approach using 13 principal components
 - Regionalization methods for constrained hierarchical clustering and partitioning
- Spatial variations of AfricanAmerican Vernacular English
 - Mapping around 30 common nonstandard spellings on Twitter
 - Subregions align with movement patterns during the Great Migrations
- Huang, Guo, Kasakoff & Grieve (2016); Jones (2015)

Temporal

- Diffusion of lexical changes
 - An autoregressive model of word frequencies to demonstrate the linguistic influence between American cities
 - The network is helpful in identifying geographical and demographical factor that drives the spread of lexical innovation
- Linguistics evolvement in urban areas using frequently used terms
 - A logistics regression model consisting of geographical and demographical predictors
 - Absolute difference of the percentage of African Americans was the most powerful indicator of linguistics transmit
- Eisenstein, O'Connor, Smith, and Xing (2012, 2014)



Relevant Literature: Geo-Prediction Models

A probabilistic framework via Tweet contents

- Trained a local word classifier
- Constructed a lattice-based neighborhood smoothing model to balance cities and words of various distributions
- Both local word filtering and smoothing have positive impact on prediction accuracy, and with location estimators, 51% of
 Twitter users can be placed within 100 miles of their actual locations at the city level

Decomposing lexical variation as regional and topical variation

- Constructed a prediction model with the assumption that regions and topics interact to shape observed lexical frequencies
- The model can identify words with high regional affinity as well as geographically-coherent linguistic regions

A multi-elemental location inference method

- Combing text contents, profile location and place labelling
- The model can successfully predict 87% of Tweets locations at the average distance error of 12.2 km
- Cheng, Caverlee and Lee (2010); Eisenstein, O'Connor, Smith and Xing (2010); Laylavi, Rajabifard and Kalantari (2016)



Overcome Data Sparsity



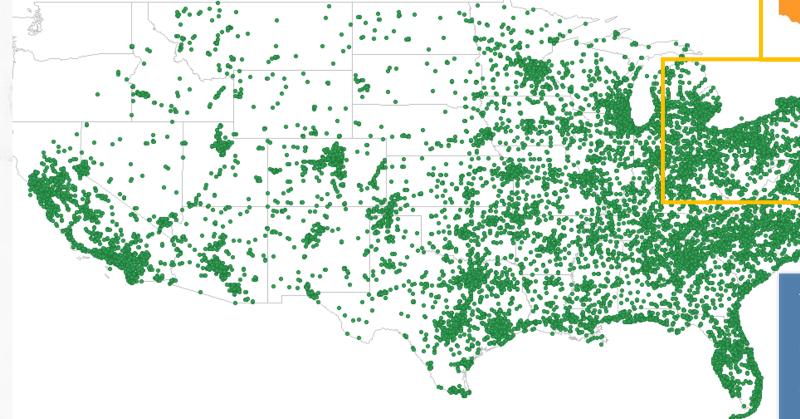
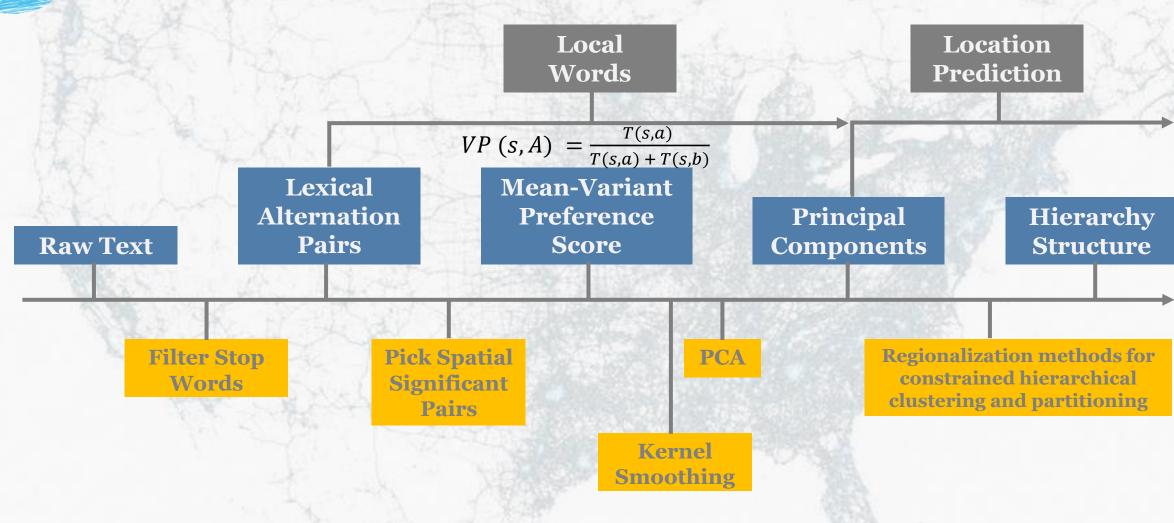


Figure 1: Spatial Distribution of Tweets Dataset

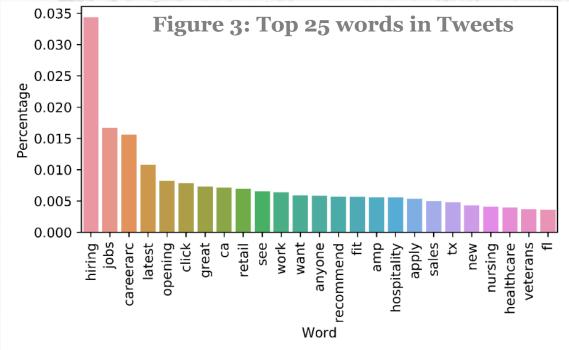
USA Geolocated Twitter Dataset

- **Records:** 204,820 observations
- Method: Twitter API
- <u>Time</u>: 2016/04/14-16
- Source: http://followthehashtag.com/

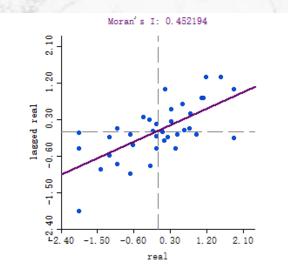


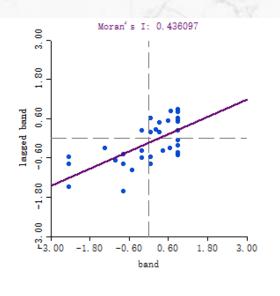


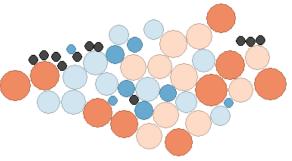
Results



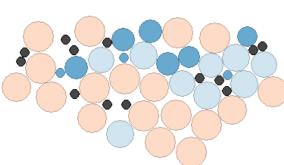
	Total Variances Explained	Singular Values
PC1	0.97181456	99.11797571
PC2	0.00711633	8.48181549
PC3	0.00201042	4.50821371
PC4	0.00178227	4.2447043
PC5	0.00168624	4.12876605











Band - Aid



Issue

- Data Sparsity
 - Not enough data for each user or county
 - Might overlook existing patterns
- What to include in local words
 - Too similar for each state
 - Prediction model failed
- We are where we tweet?
 - Geo-locations can cheat
 - Reply on self-report

Contribution

- Used spatial methods to study linguistics topics
- The Northeast region does have prefer words compared to the country

