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Extracting and Analyzing Semantic Relatedness between Cities Using News Articles

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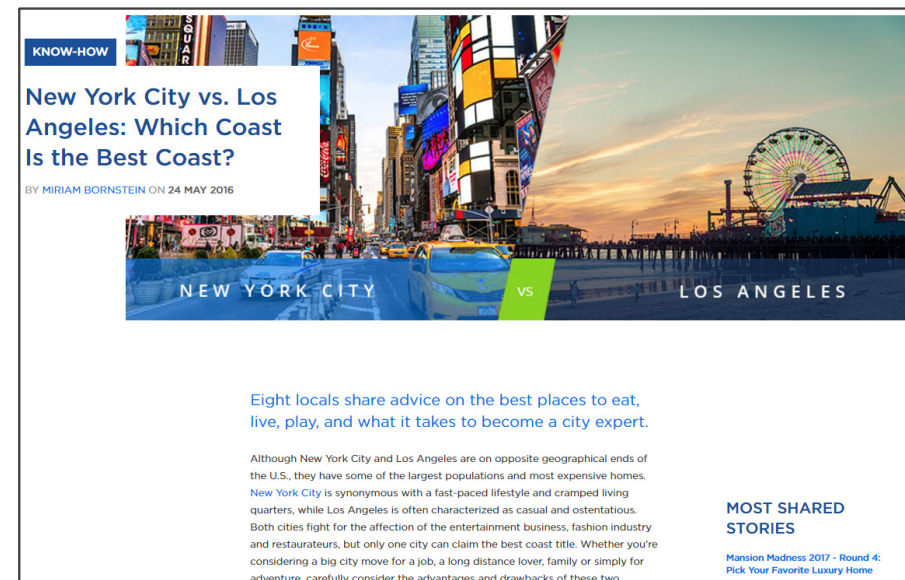
Introduction

- News articles are rich sources of information
- **Diverse topics**
 - Economy, politics, science, sports, ...
- **Various entities**
 - Persons, organizations, places, ...
- **Timely information**
 - Prompt report of latest events



Introduction

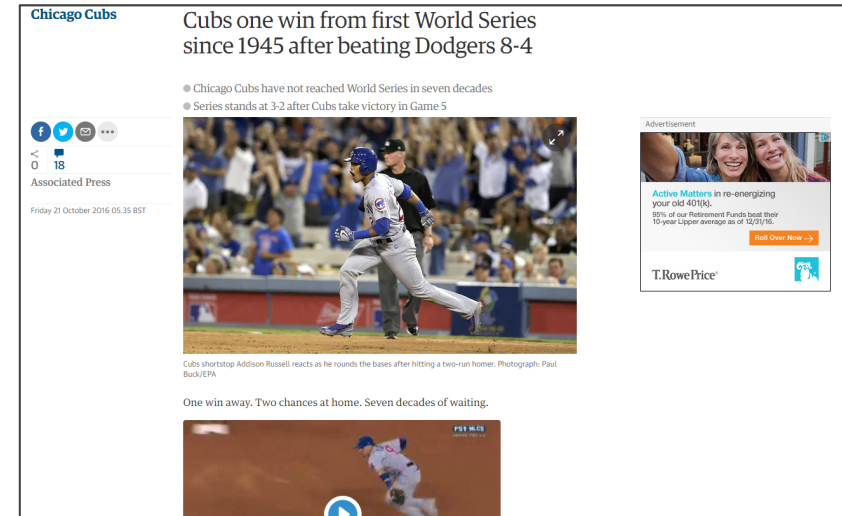
- **Cities**, as hubs of human activities, **are frequently mentioned in news articles**
- Two or more cities may **co-occur** in the same news article
- E.g., comparing the **lifestyles** of two cities



Los Angeles & New York City

Introduction

- E.g., **sports** may draw teams from two cities together



Los Angeles & Chicago

- E.g., cities may address **environmental** issues collaboratively



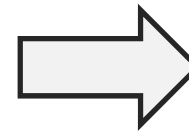
Los Angeles & New Orleans

Introduction

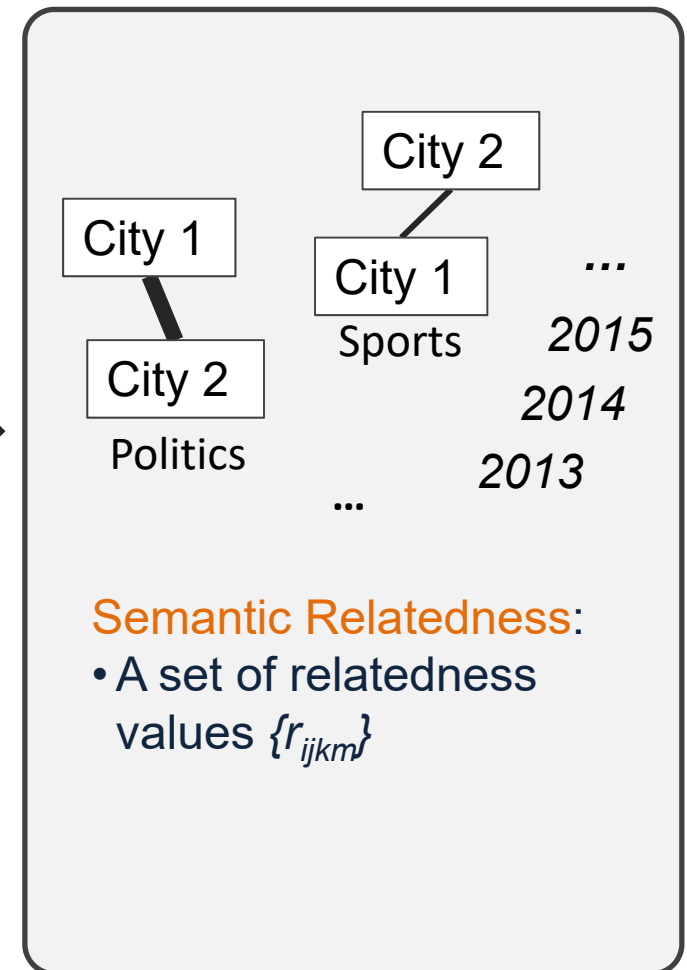
- Cities can be **related** under **a variety of topics** (**semantic relatedness**)
- Such **semantic relatedness** is partially **captured** in **news articles**
- **Objective:** to develop **a computational framework** that can automatically process a large number of news articles and extract semantic relatedness

Problem Formalization

Input

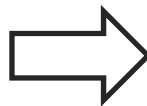
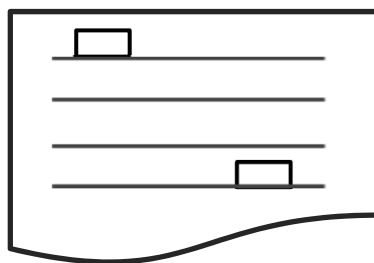


Output



Problem Formalization

- **Core idea:**
 - 1) Identify the topics of news articles
 - 2) Assign the topics to the cities
 - 3) Quantify the semantic relatedness
- **Key question:** given a news article, which topics is it talking about?



Culture?
Business?
Environment?
...

**Multi-label
classification
problem**

Framework

Model training



Human annotators

(1) Label

Topics



A set of news articles
with labeled topics

Topics:
Culture
Politics
Business
Sports
...

(2) Train

Model for text data
(Labeled LDA)

A multi-label
classification model

Topic extracting

(3) Finish
training

(4) Input



All news articles

Trained model
(Labeled LDA)

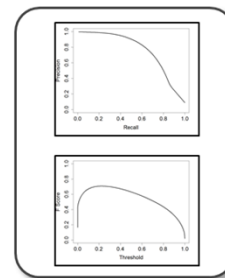
(5) Output



All news articles
with topic scores

Topic score:
Culture: 0.313
Politics: 0.001
Business: 0.245
Sports: 0.002
...

(6) Identify
threshold



Testing topic accuracies
at possible thresholds

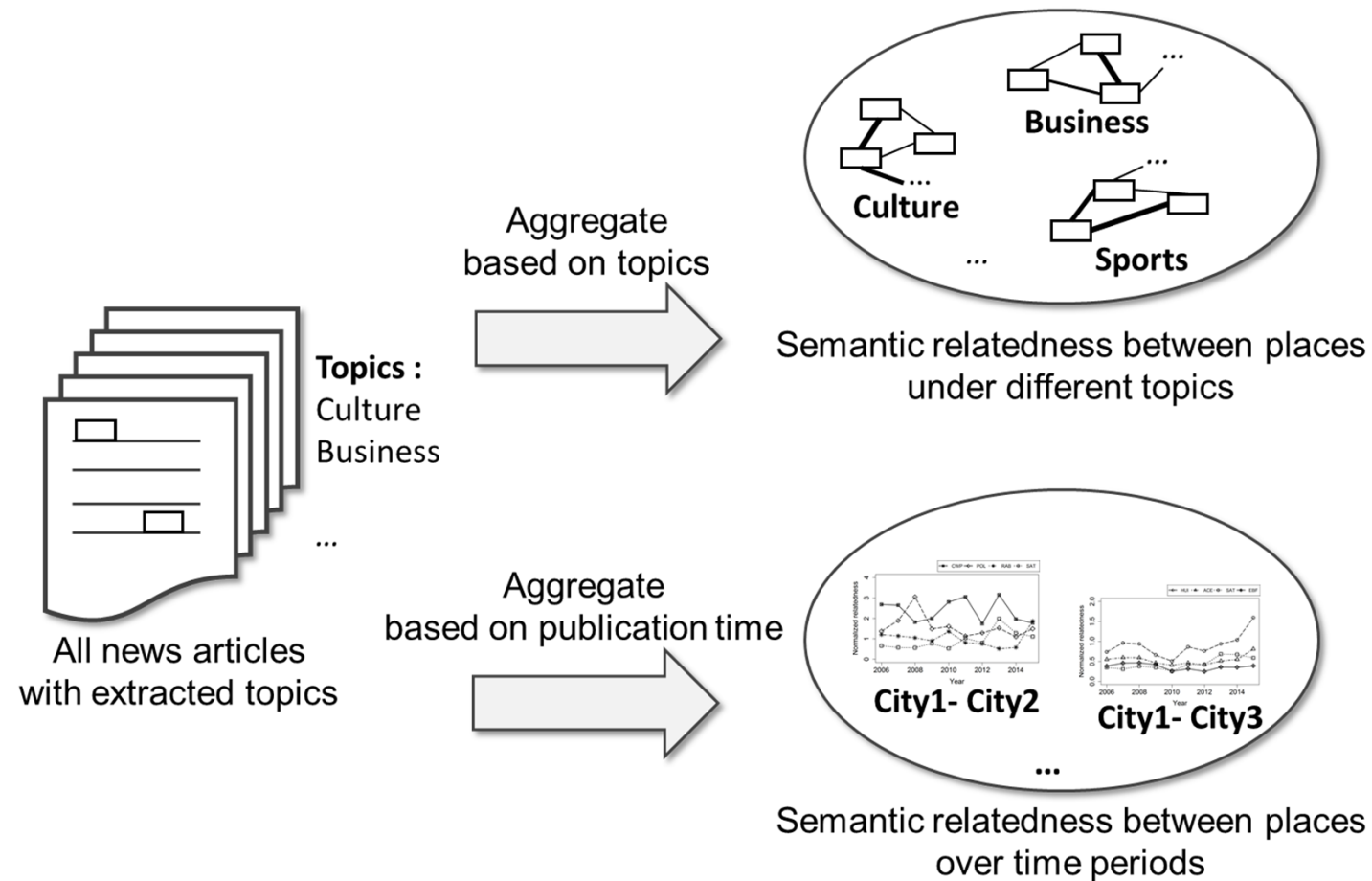
(7) Extract
topics



All news articles
with extracted topics

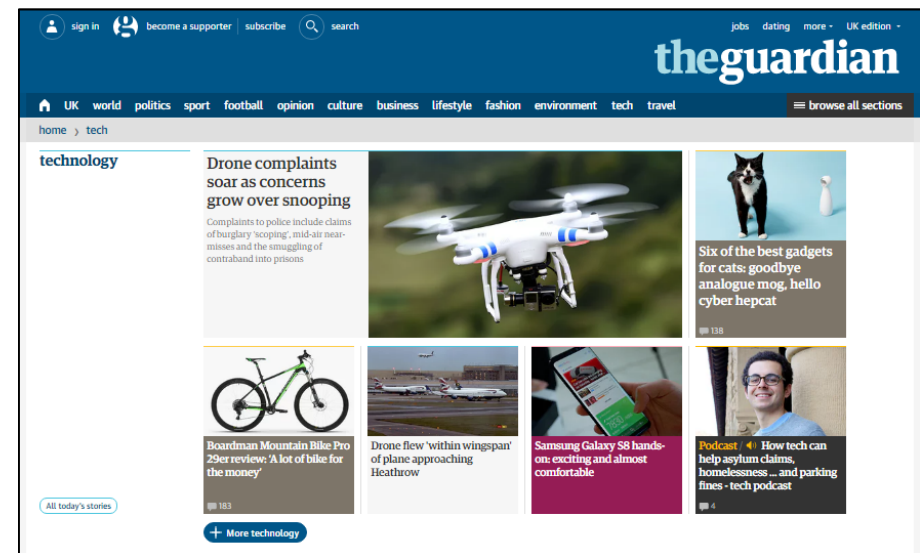
Topics :
Culture
Business
...

Framework



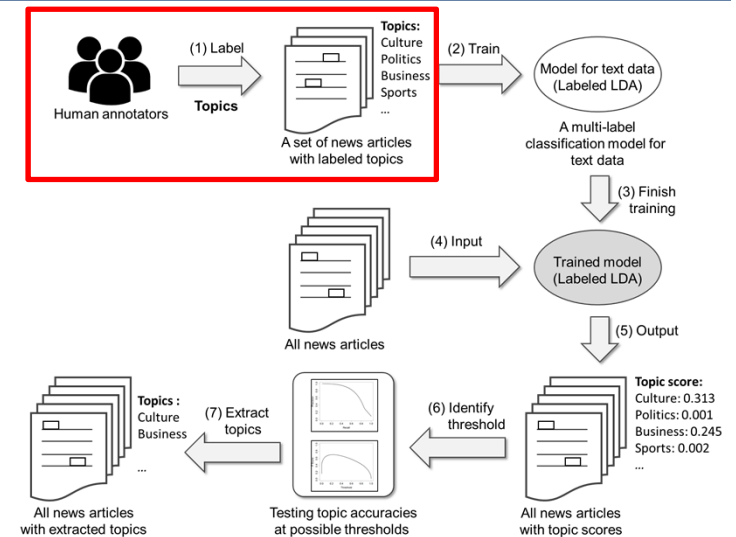
Experiments

- **Cities:** top 100 cities in the contiguous U.S.
- **Time:** 1/1/2006 and 12/31/2015
- News articles from The Guardian
 - **543,824 news articles**



Experiments

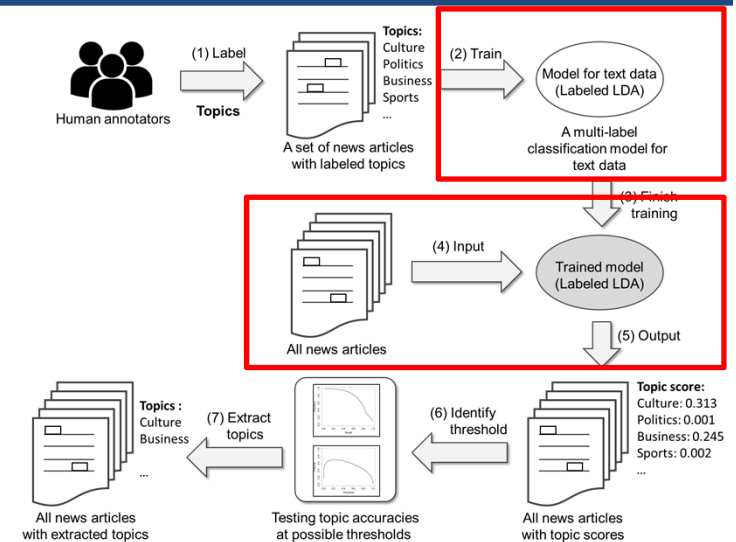
- **17 semantic topics** from IPTC
 - E.g., Culture, Politics, Sports, Disaster, Crime, ...
- **Obtaining training data**
 - Existing news tags
 - Mapping some tags to topics
 - **141,765** training data records



IPTC Topic	News Tags
Arts, Culture and Entertainment	culture, music, film, media, books, artanddesign, television, art, fashion, festivals, history, comedy, museums, opera, drama, poetry, documentary, painting, theatre, sculpture

Experiments

- **Training** the LLDA model



- **Topic extracting**

- Applying the trained LLDA model to all news articles

A training data record

IPTC labels	Processed text
Artscultureandentertainment Lifestyleandleisure	la hard city accept reality suffer personal setback illness sick gorgeous setting move santa monica beach...

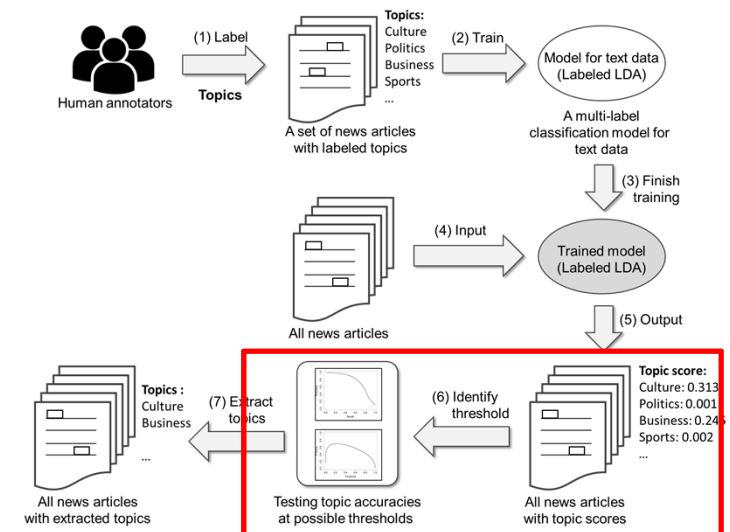
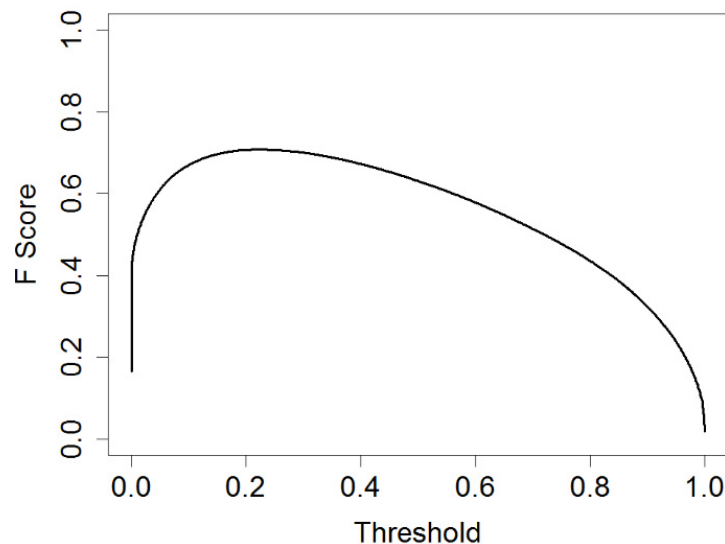
Experiments

- Identifying suitable **threshold**

$$\text{Precision} = \frac{|\text{Extracted Relevant Topics}|}{|\text{All Extracted Topics}|}$$

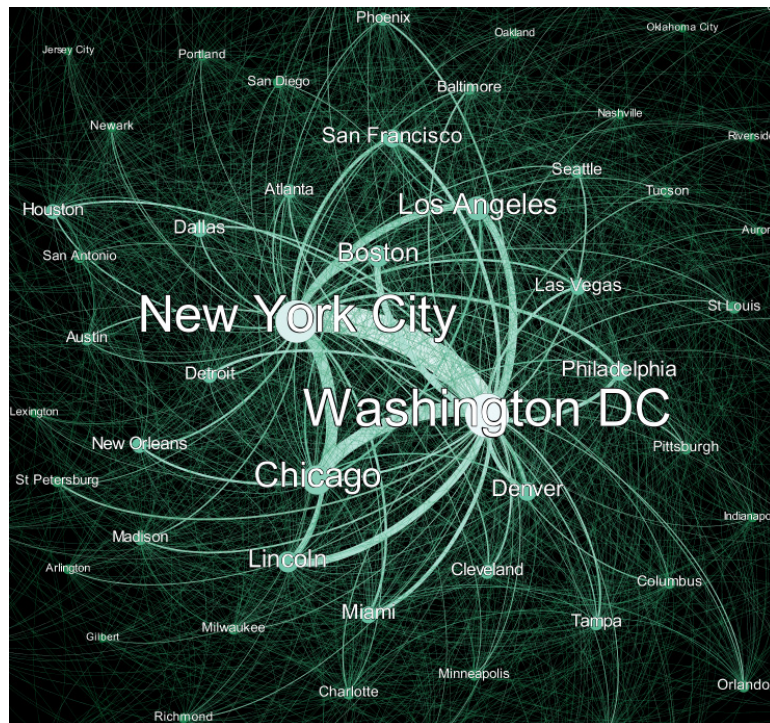
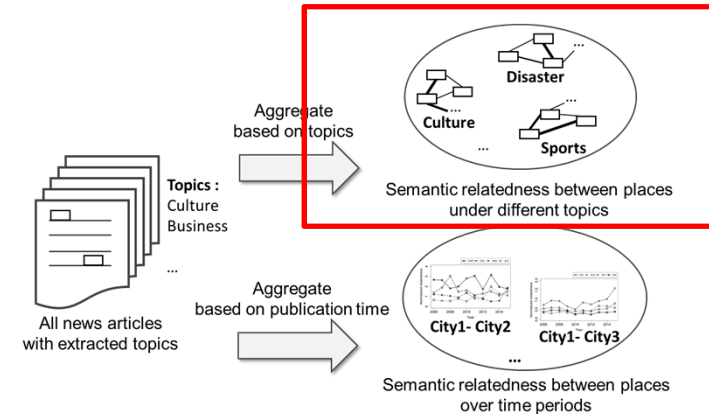
$$\text{Recall} = \frac{|\text{Extracted Relevant Topics}|}{|\text{All Relevant Topics}|}$$

$$F \text{ score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$



Experiments

- **Visualize** city relatedness
 - Based on **semantic topics**



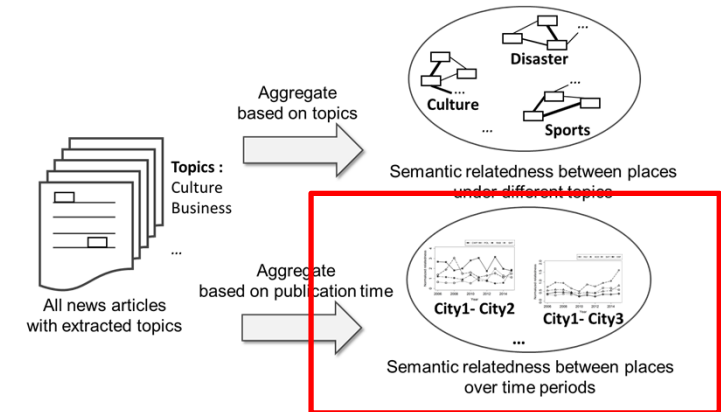
Politics



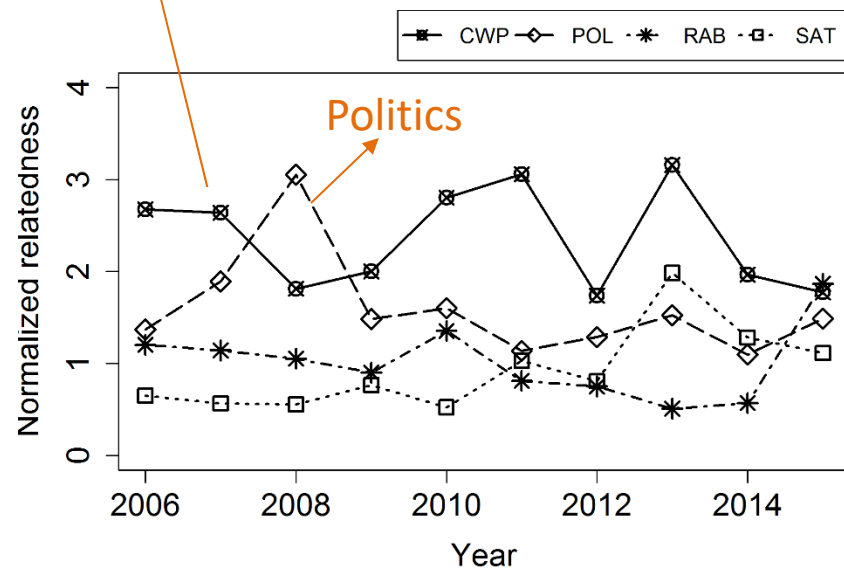
Science and Technology

Experiments

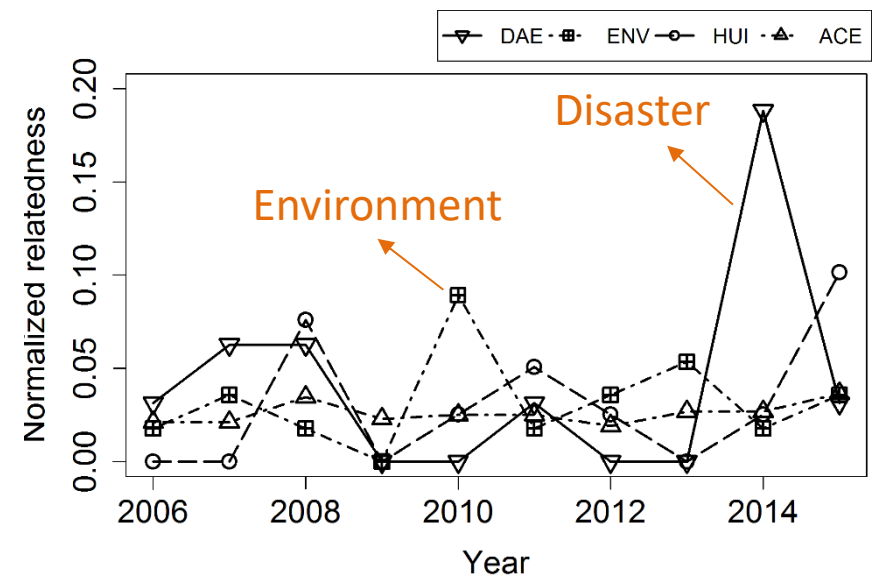
- Visualize city relatedness
 - Based on publication time



Conflicts, War and Protests



NYC and Washington DC



Los Angeles and New Orleans

Experiments

- Both **Los Angeles** and **New Orleans** were enrolled in the program in 2014



100 RESILIENT CITIES

ABOUT US NEWS OUR CITIES OUR PARTNERS

How Cities Recover from Natural Disasters

11.19.14 | BY [DAVID SCHREINER](#)

What can cities do to plan for and recover more effectively from disasters, especially when those disasters are continuing to increase in frequency and severity?

The [Financial Times](#) spoke with experts from the U.S. Department of Housing and Urban Development's (HUD) Rebuild by Design and 100 Resilient Cities, and suggests three broad steps, whether cities face too much water or too little, extreme heat or record cold:

We began working with our first group of 32 cities in **December of 2013**. In 2014, we received 330 applications from 94 countries for our second cohort, and [we announced the 35 cities of round 2 in December](#). The third 100 Resilient Cities Challenge closed in November of 2015 and we [announced our final group of cities in May 2016](#).

Distance Decay Analysis

- A weak distance decay effect was found in a previous research based on place co-occurrence in news articles (*Liu et al. 2014, Transactions in GIS*)

$$c_{ij} \propto \frac{c_i c_j}{d_{ij}^\beta}$$

- β is the friction coefficient; $\beta = 0.2$ in *Liu et al. 2014*
- City relatedness under different topics might have different distance decay effects

Distance Decay Analysis

All news: $\beta = 0.23$

Topic	β
Arts, Culture and Entertainment	0.21
Sport	0.08
Crime, Law and Justice	0.37
Science and Technology	0.19
Politics	0.32

Conclusions

- **News articles** partially capture the **semantic relatedness** between **cities**
- **A computational framework** is developed to “read” a large number of news articles and extract semantic relatedness
- An experiment based on more than 500,000 news articles shows **different network structures** and **temporal variations**
- **Varied distance decay effects** were observed for the different semantic relatedness

Thank You!

Questions?

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