Towards Space and Time Coupled Social Media Analysis

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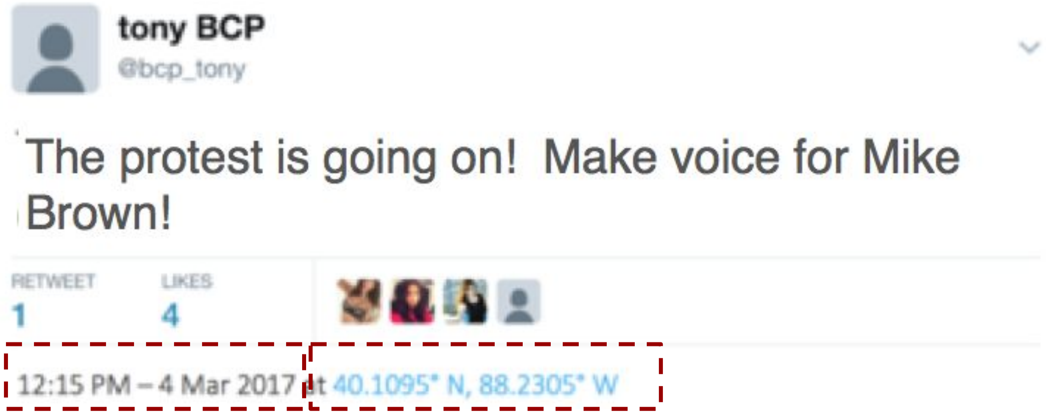
Explicit Space and Time Information in Social Media



Time **Location**

Daily Stats:

10 M+ geo-tagged tweets

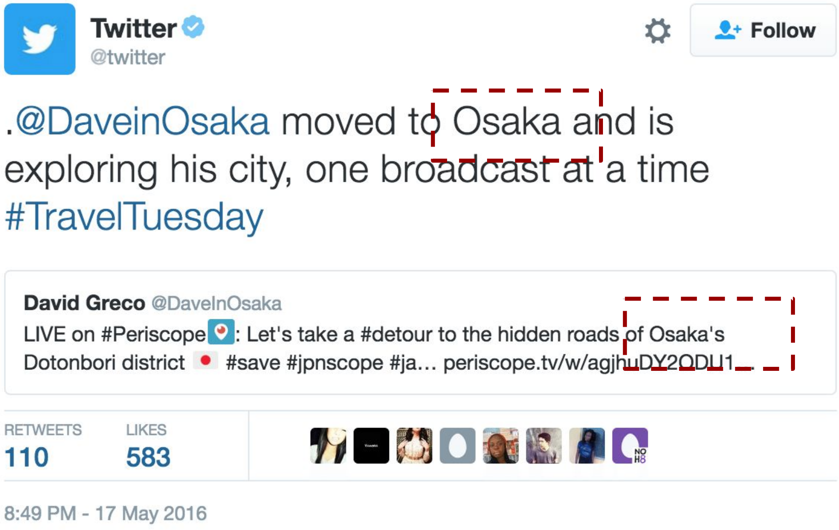
20 M+ geo-tagged Instagram posts

8 M+ Foursquare checkins

Implicit Space and Time Information in Social Media

Location Entity

Time Expression



The Rise of Social Sensing

The confluence of **people**, **devices**, and **environments**

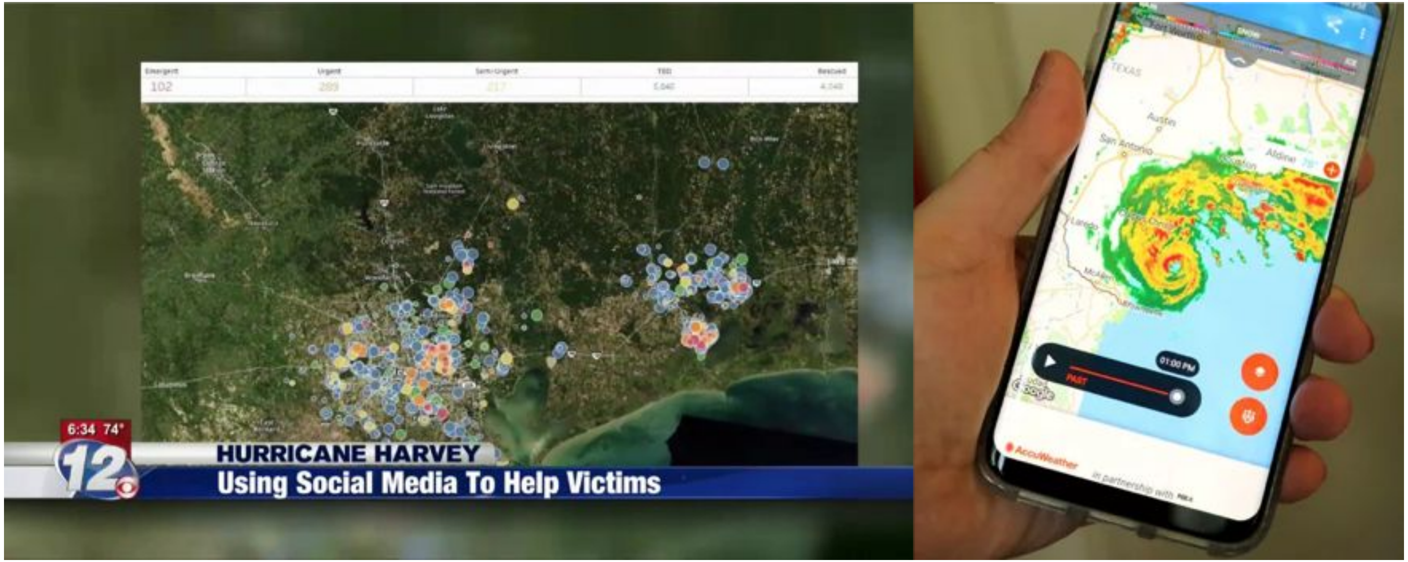
Offline Activities

Online Activities

Example 1: Hurricane Harvey

“Social media becomes a savior in hurricane Harvey relief.”

— NBC News



21.2 Million tweets in a five-day span

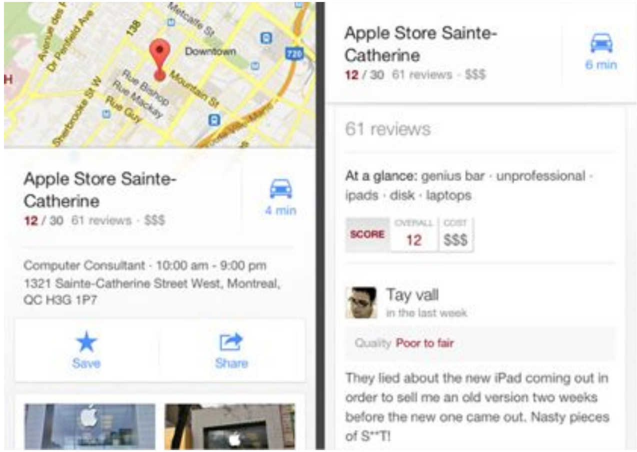
Example 2: Urban Exploration

Data Producer

People leave behind them billions of traces of their visited places.

Data Consumer

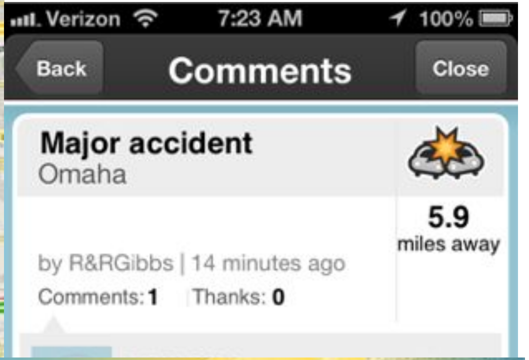
Travelers see and understand their destinations before they arrive.



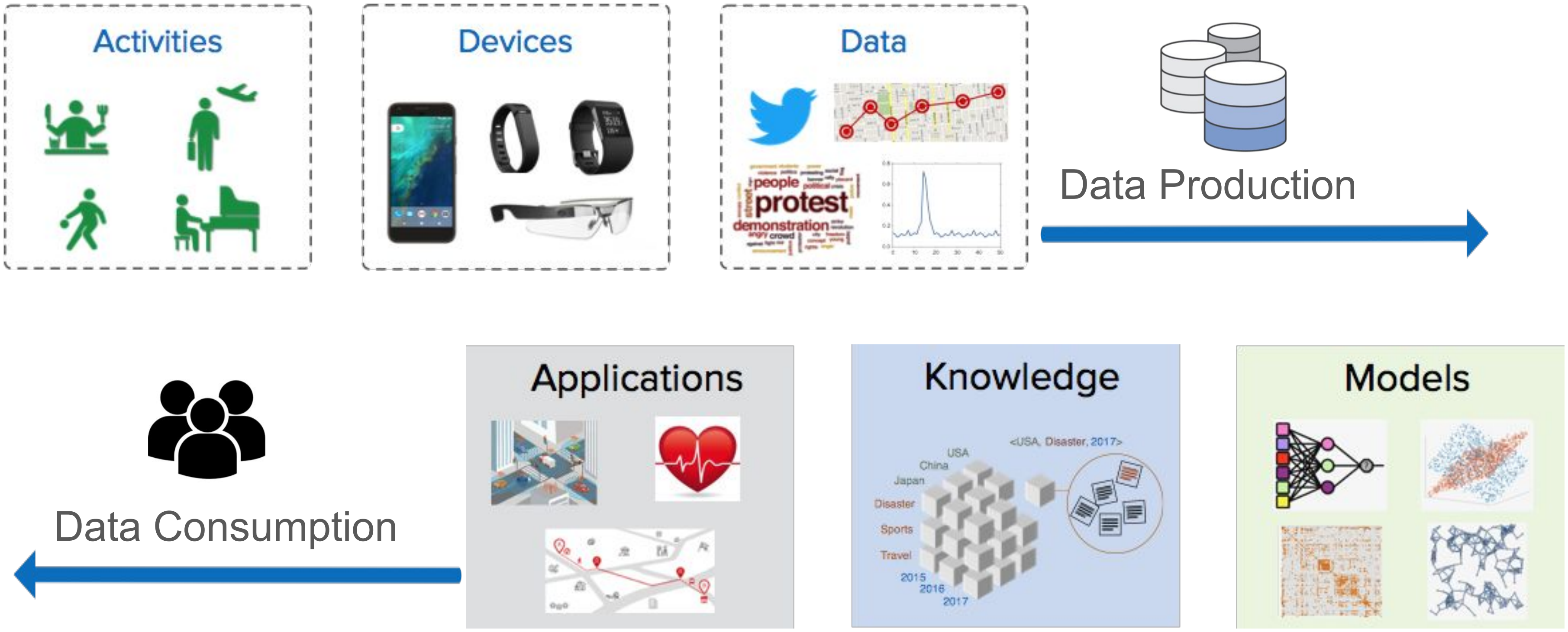
Example 3: Smart Transportation

People as traffic sensors:

- Accidents
- Jams
- Hazards
- Construction



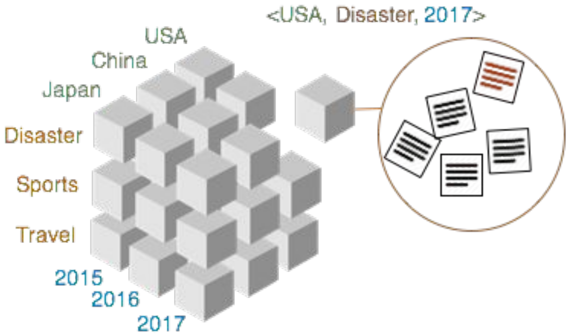
An Ecosystem of People and Data



General Challenges

How to combine multiple factors for joint analysis?

How to address data sparsity in the multi-dimensional space?



How to design online and scalable methods?

What Will Be Covered in This Tutorial?

1. Spatiotemporal activity modeling
   - How to find the typical activities in different regions and periods?
2. Spatiotemporal event detection and forecasting
   - How to detect and forecast unusual spatiotemporal events?
3. Spatiotemporal mobility modeling
   - How to model human movement regularities from semantic trajectories?
4. Location recommendation and prediction
   - How to improve location recommendation and prediction systems?

Outline

Introduction

Part 1: Spatiotemporal Activity Modeling

Part 2: Spatiotemporal Event Detection

Part 3: Spatiotemporal Mobility Modeling

Part 4: Location Recommendation and Prediction

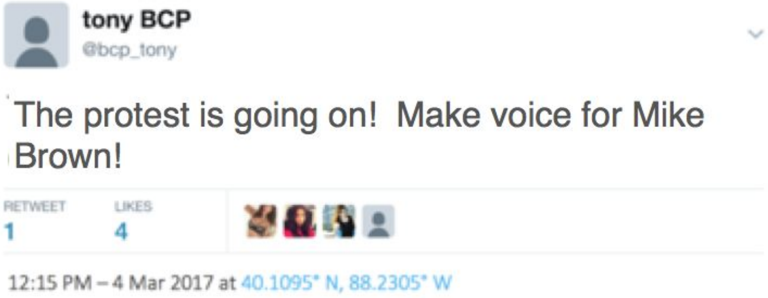
Summary & Research Frontiers

Part I: Spatiotemporal Activity Modeling

Problem Definition

Input: a collection of geo-tagged social media records

- Each record has: a location, a timestamp, a text message



Task: predict people's typical activities in different regions and periods

- Multiple schemas, e.g.
  - Region + time -> keywords
  - Region + keywords -> time
  - Time + keyword -> region

"What are the fun things to do around the Hilton Hotel?"

"Where should I go to hang out with my friends at 9pm?"

Representative Approaches

Similarity-Based Methods

- Li et. al. WWW 2015

Probabilistic Graphical Modeling Methods

- Sizov et. al. WSDM 2010

Representation Learning Methods

- Zhang et. al. WWW 2017

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Semantic Annotation of Mobility Data Using Social Media [Wu et. al. WWW 2015]

Input: GPS location history, a collection of spatiotemporal social media

Goal: annotate GPS location history with social media keywords to reflect user activities

Why using social media?

- "Static annotation" vs "dynamic annotation"
- Including up-to-date event information.

Input: Location history of a mobile user

Record ID	Time	Longitude	Latitude
r_1	2013-1-20	40.75051	-73.99349
r_2	2013-2-10	40.68312	-73.97597
r_3	2013-2-19	40.75051	-73.993499

Input: Geo-tagged tweets from the crowd

Time	Longitude	Latitude	Tweets
2013-1-20	40.75051	-73.99349	LETS GO RANGERS
2013-1-20	40.61219	-74.15814	I'm at Buffalo Wild Wings
2013-1-20	40.75050	-73.99350	I'm @ Madison Square Garden for Pittsburgh Penguins vs New York Rangers

Annotation

Record ID	Annotations
r_1	madison, garden, rangers, penguins
r_2	nets, barclays, center, nba
r_3	rangers, madison, square, montreal, canadiens

Three Annotation Strategies

Frequency-Based Methods

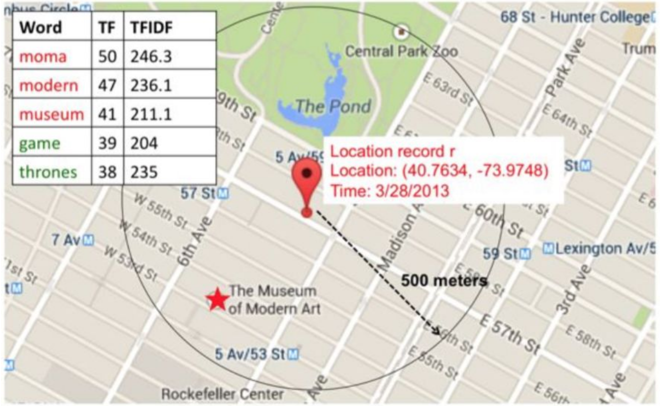
- Use TF-IDF weighting to select representative keywords

Gaussian Model

- Model the distribution of a keyword as a mixture of Gaussians

Kernel Density Estimation

- Estimate the kernel densities of keywords based on observed samples



Kernel Density Estimation: More Details

Assumption: the semantics of a location record *ri* can be inferred from the documents posted at nearby locations within a short time
Time sensitivity: define a time window and collect documents *Di* that fall into it.
Relevance: Rank words based on the scores estimated by Kernel Density Estimation (KDE)

$$s_w^{KDE}(r_i; L_i(w), H) = \frac{1}{|L_i(w)|} \sum_{loc_j^D \in L_i(w)} K_H(loc_i^U - loc_j^D)$$

$$K_H(x) = |H|^{-1/2} K(H^{-1/2}(x))$$

Locations of all the occurrences of word w

Kernel function

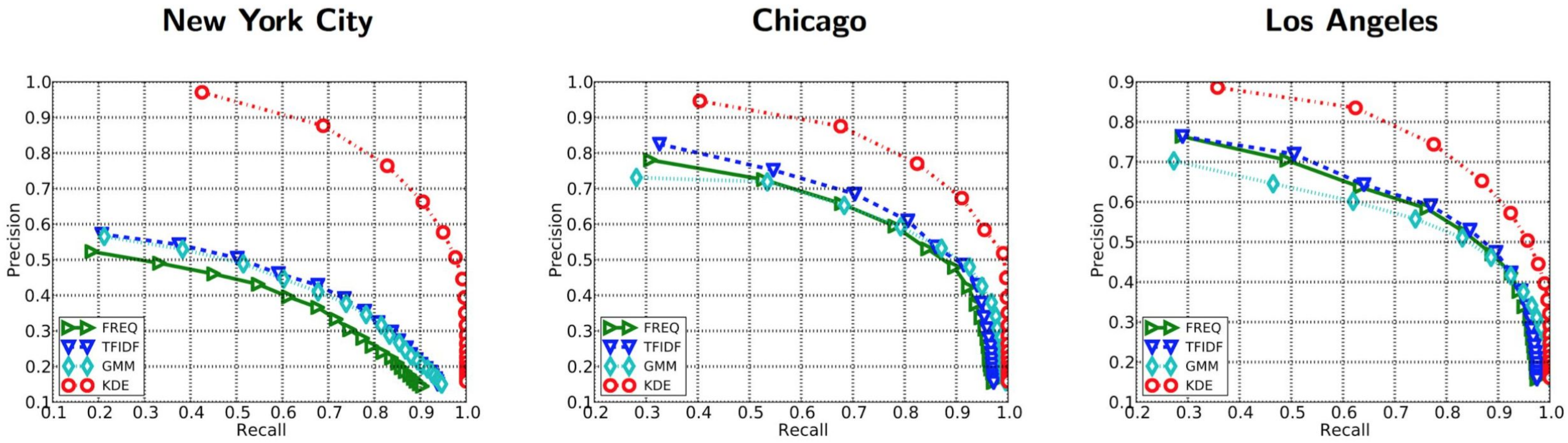
Geo-coordinates of record *ri*

Bandwidth

Experiments

Datasets:

- **Context documents**: geo-tagged tweets from NYC, Chicago and LA
- **Users' location histories**: GPS coordinates and timestamps of tweets
- **Groundtruth**: manually judge whether the extracted keywords reflect user intention



Representative Approaches

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- Sizov et. al. WSDM 2010

Representation Learning Methods

- Zhang et. al. WWW 2017

GeoFolk: Latent Spatial Semantics in Web 2.0 Social Media [Sizov et. al. WSDM 2010, TIST 2012]

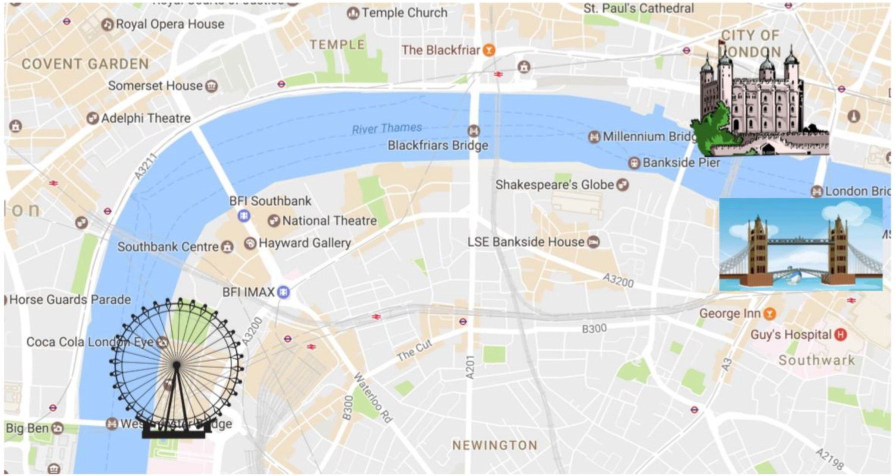
Goal: use topic modeling to uncover the latent activities from social media.

Each latent topic is **multidimensional** (location, time, text):

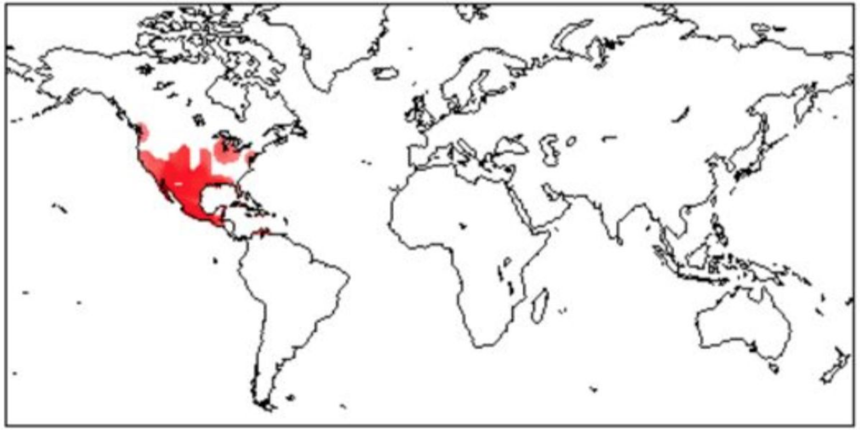
- Single dimension: insufficient for reliable content disambiguation
- Combination: better content characterization

Applications

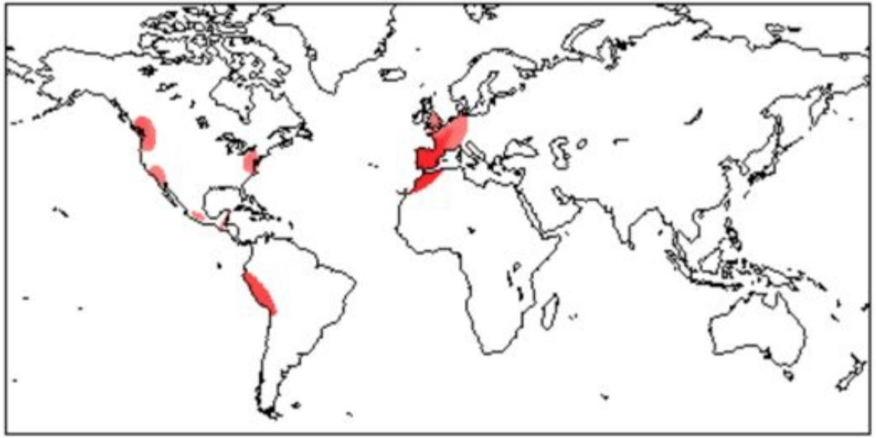
- Topic discovery for regions
- Recommender system
- Content categorization



Examples



Mexican Food

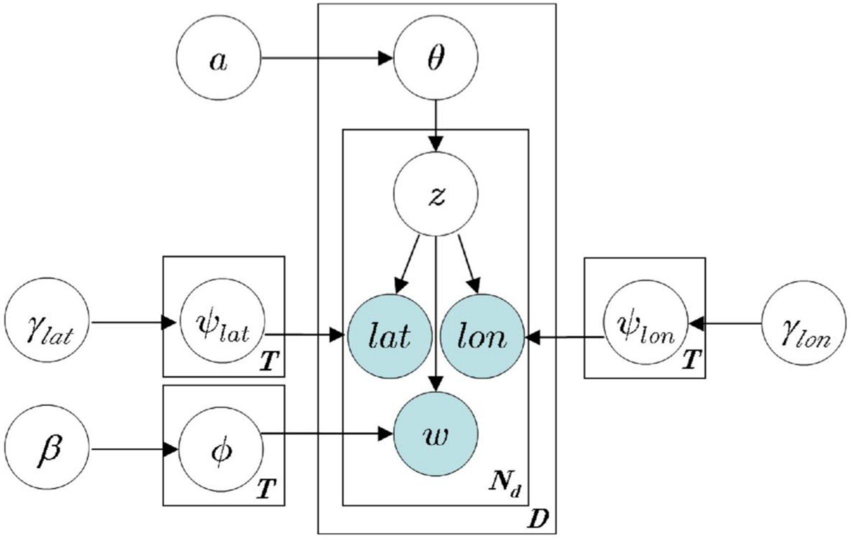


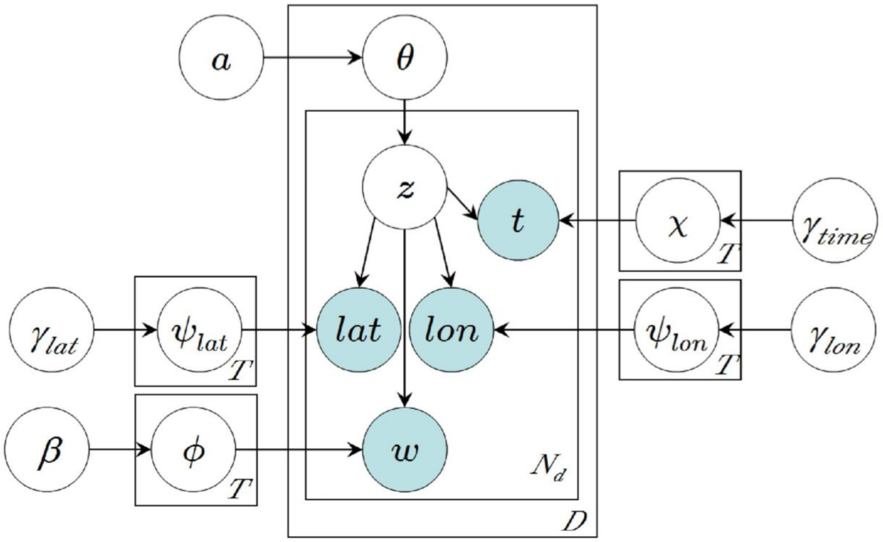
Spanish Food

Geographical Topic Discovery and Comparison, Yin et al, WWW 2011

GeoFolk: Geographical Topic Modeling

Input: each document is associated with tags, GPS coordinates (and time).





Experiments

Dataset: 28, 770 Flickr images with tags and coordinates

Task 1: Classification and clustering

Model	avg(accuracy)
GeoFolk	0.421
LDA	0.374
Tags	0.282
Coordinates	0.187

classification

Model	avg(accuracy)
GeoFolk	0.328
LDA	0.255
Tags	0.117
Coordinates	0.102

clustering

Task 2: Tag recommendation

Model	MRR
GeoFolk	0.212
LDA	0.119
Tags	0.073
Coordinates	0.027

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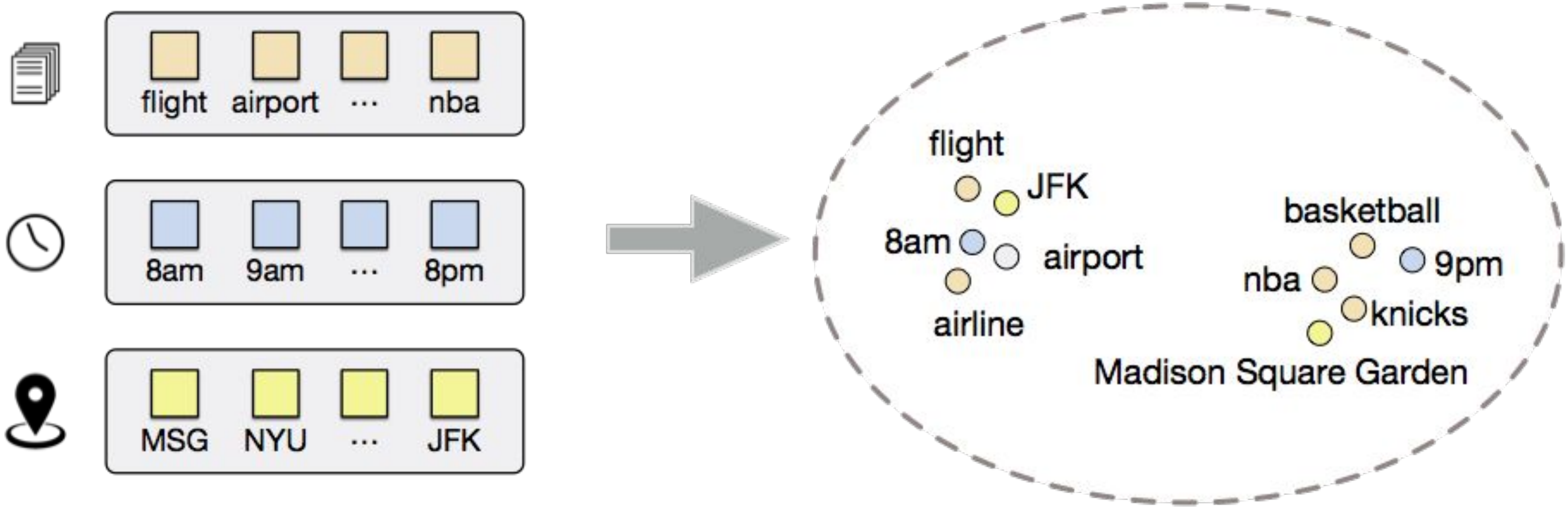
Representation Learning Methods

- Zhang et. al. WWW 2017

Regions, Periods, Activities: Uncovering Urban Dynamics via Cross-Modal Representation Learning [Zhang et. al. WWW 2017]

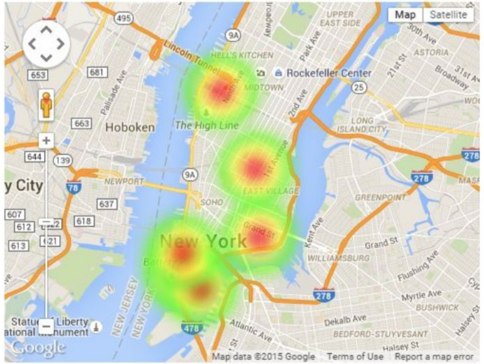
Idea: map geographical regions, temporal periods, and textual keywords into a latent semantic space to preserve their correlations.



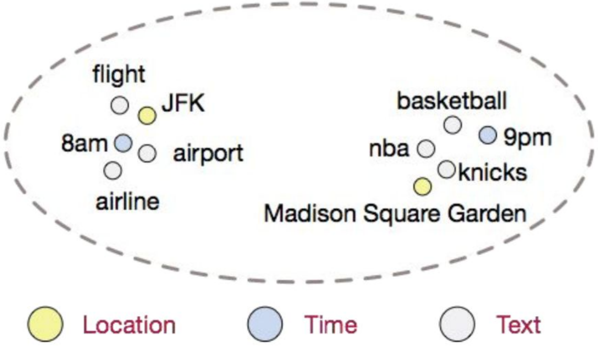
Regions, Periods, Activities: Uncovering Urban Dynamics via Cross-Modal Representation Learning [Zhang et. al. WWW 2017]

Hotspot Detection → Joint Embedding

Detect regions and periods where people's activities burst



Map regions, periods, and keywords into the same space



Hotspot Detection: A Mode-Seeking Procedure

A spatial (temporal) hotspot is a density maxima in the 2D (1D) space.

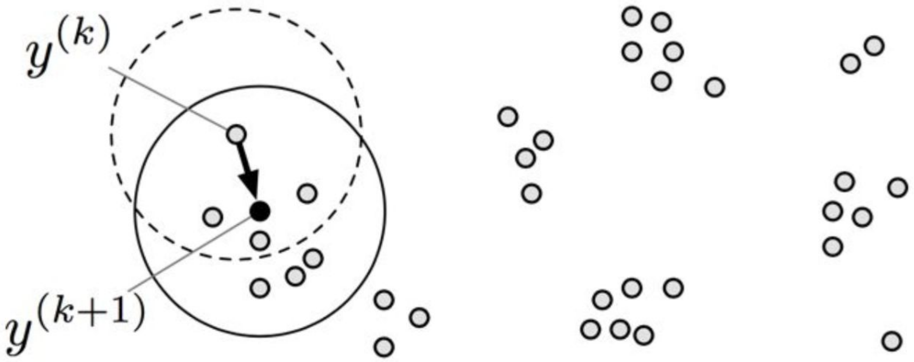
We design a fast mode seeking procedure to find the hotspots.

Benefits:

- Fast
- No distribution assumptions

Kernel density estimation:

$$f(\mathbf{x}) = \frac{1}{nh^d}\sum_{i=1}^{n} K(\frac{\mathbf{x}-\mathbf{x}_i}{h})$$



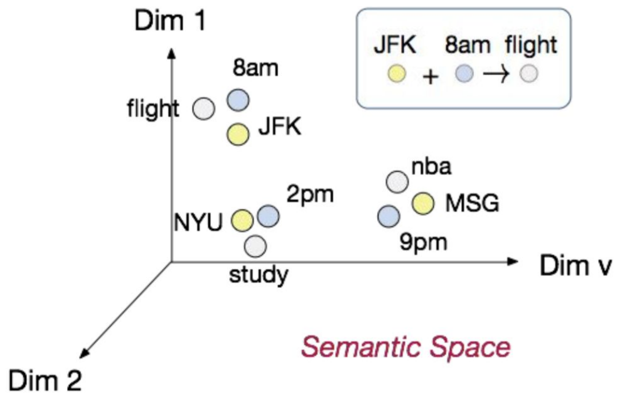
Cross-Modal Embedding: Designing Philosophy

Map regions, periods, and keywords into the same space:

- **Region**: a spatial hotspot
- **Period**: a temporal hotspot

Aim to preserve two types of correlations:

1. **Co-occurrence**: two units are correlated if there co-occur frequently
2. **Neighborhood**: two regions (periods) are correlated if they are adjacent



Cross-Modal Embedding: Two Strategies

Reconstruction-based embedding

1. Consider each record as a relation
2. Mark off one unit i and try to predict it from the observed units

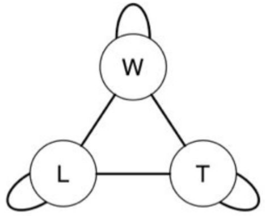
$$p(i|r_{-i}) = \exp(s(i, r_{-i})) / \sum_{j \in X} \exp(s(j, r_{-i}))$$

Overall objective:

$$O = -\sum_{r \in \mathcal{C}} \sum_{i \in r} \log p(i|r_{-i})$$

Graph-based embedding

1. Use a graph to encode the correlations between regions, periods, and activities
2. Learn graph node embeddings to preserve the graph structure



$$O = O_{WW} + O_{LL} + O_{TT} + O_{WL} + O_{WT} + O_{LT}$$

$$O_{XY} = \sum_{i \in X} d_i \mathrm{KL}(p'(\cdot|i)||p(\cdot|i)) + \sum_{j \in Y} d_j \mathrm{KL}(p'(\cdot|j)||p(\cdot|j))$$

Embedding Visualization

(a) LGTA (b) CrossMap

Visualizing the feature vectors generated by LGTA and CrossMap for three activity categories: “Food” (cyan), “Travel & Transport” (blue), and “Residence” (orange).

Quantitative Evaluation: Attribute Recovery

Mark off one attribute (location, time, or text) and predict it based on the observed ones.

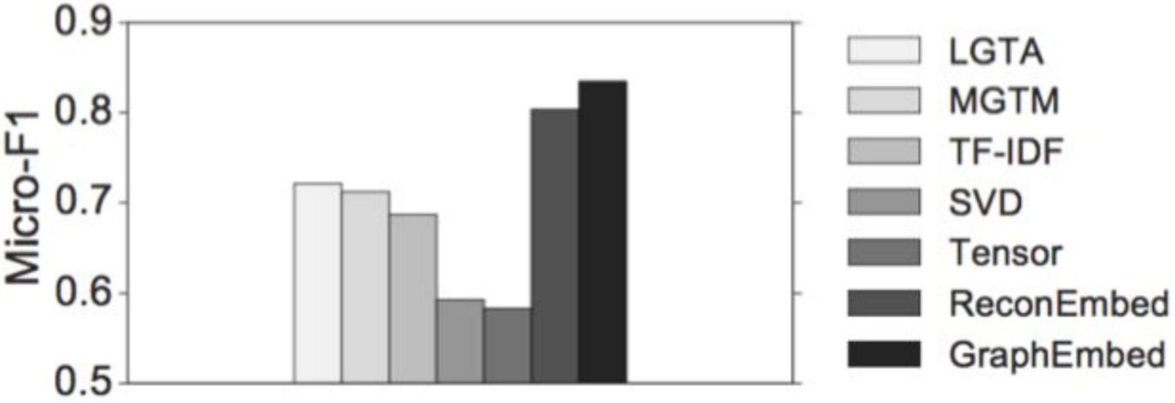
Mean reciprocal ranks:

	Text		Location		Time	
Method	Tweet	4SQ	Tweet	4SQ	Tweet	4SQ
LGTA	0.376	0.6107	0.3792	0.6083	-	-
MGTM	0.3874	0.5974	0.4474	0.5753	-	-
TF-IDF	0.62	0.8505	0.4298	0.7097	0.3197	0.3431
SVD	0.4475	0.7137	0.3953	0.646	0.3256	0.3187
Tensor	0.4382	0.6826	0.3871	0.6251	0.3179	0.2983
RECON	0.6877	0.9219	0.6526	0.9044	0.3582	0.3612
GRAPH	**0.7011**	**0.9449**	**0.6758**	**0.9168**	**0.3895**	**0.3716**

Application: Activity Classification

The embeddings can be used as feature vectors for downstream applications.

Example: Foursquare checkins belong to nine categories. We predict the category based on the embeddings.



Classification F1 Score.

Reference

Annotate POIs with categories

- On the semantic annotation of places in location-based social networks. Ye et al. KDD 2011
- Placer: semantic place labels from diary data. Krumm et al. UbiComp 2013

Annotate Regions with functions

- Inferring urban land use using large-scale social media check-in data. Zhang et al. Networks and Spatial Economics 2014
- Geographical topic discovery and comparison, Yin et al. WWW 2011
- Discovering regions of different functions in a city using human mobility and pois. Yuan et al. KDD 2012
- Latent geospatial semantics of social media, Sizov et al. TIST 2012

Annotate Visits with Semantics

- A conceptual view on trajectories. Spaccapietra et al. DKE 2008
- Semantic trajectories: Mobility data computation and annotation. Yan et al. TIST 2013
- Semantic annotation of mobility data using social media. Wu et al. WWW 2015

Multimodal Representation Learning

- Regions, Periods, Activities: Uncovering Urban Dynamics via Cross-Modal Representation Learning. Zhang et al. WWW 2017

Part II: Spatiotemporal Event Detection

What is a Spatiotemporal Event?

An unusual activity bursted in a local area and a specific duration while impacting a considerable number of people.

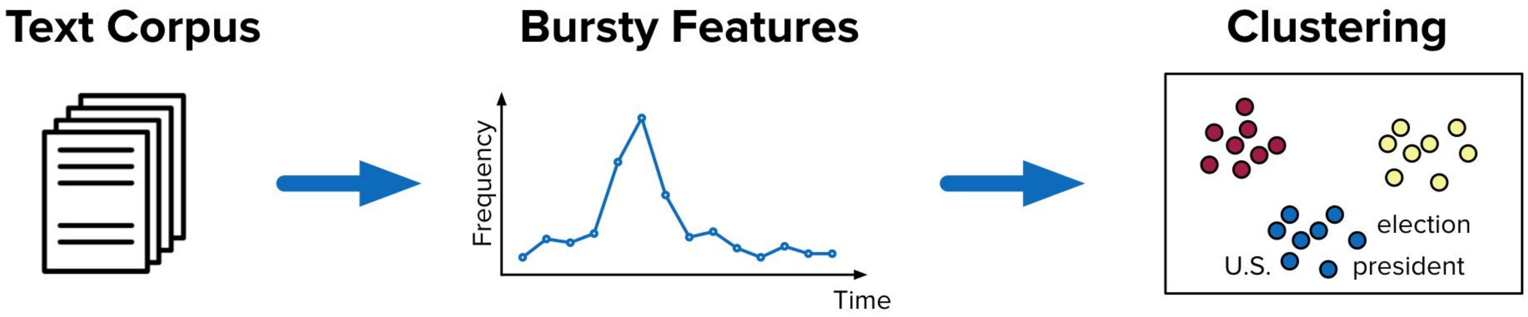
Festival

Concert

Protest

Prior Art: Global Event Detection

Feature-based methods:



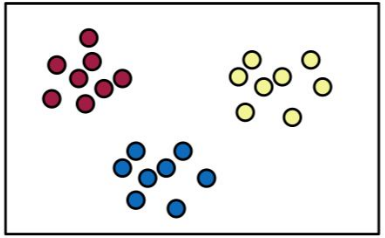
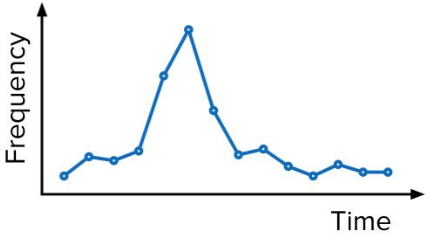
News
[Fung 2005]
Social Media
[He 2007, Weng 2011, Li 2012]

Wavelet Transform
[Weng 2011]
Gaussian Mixture
[He 2007]
Binomial Distribution
[Fung 2005, Li 2012]

Co-occurrence
[Fung 2005, He 2007]
Temporal Distribution
[Weng 2012]
Mixed Similarity
[Li 2012]

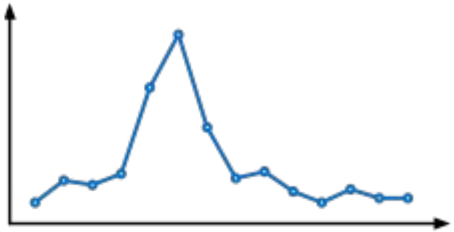
Prior Art: Global Event Detection

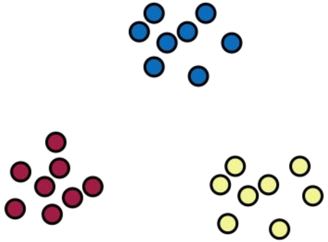
Document-based methods:

Text Corpus	Document Cluster	Filtering
		
News [Allan 1998] **Social Media** [Aggarwal 2012] **Diplomatic Record** [Chaney 2016]	**Topic Modeling** [Chaney 2016] **TF-IDF Similarity** [Allan 1998] **Content & Structure** [Aggarwal 2012]	**Bustiness Score** [Chaney 2016] **Novelty Discovery** [Allan 1998, Aggarwal 2012]

How About Using Them to Detect Spatiotemporal Events?

Existing global detection tools





Detect global burstiness

Cluster similar text

Batch Detection

Spatiotemporal Events

Locally Bursty

Text is Short & Messy

Online Data

Representative Approaches

Feature-Based Detection: First detect bursty keywords/phrases from the input, then group relevant features into events.

- E.g., Chen et. al. CIKM 2009, Abdelhaq et. al. PVLDB 2013

Document-Based Detection: Consider each document (e.g., tweet, check-in) as a basic unit and detect bursty document clusters as events.

- E.g., Zhang et. al. SIGIR 2016, Zhang et. al. KDD 2017

Spatiotemporal Event Forecasting: Predict whether a specific type of spatiotemporal event will occur in the future

- E.g., Zhao et. al. KDD 2016

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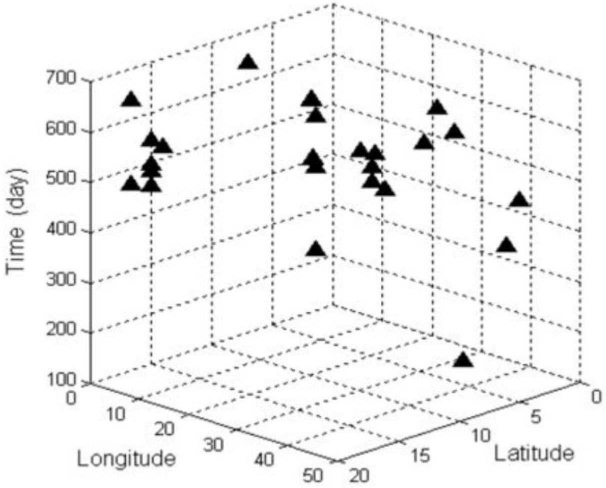
Event Detection from Flickr Data through Wavelet-based Spatial Analysis [Chen et. al. CIKM 2009]

A feature-based approach:

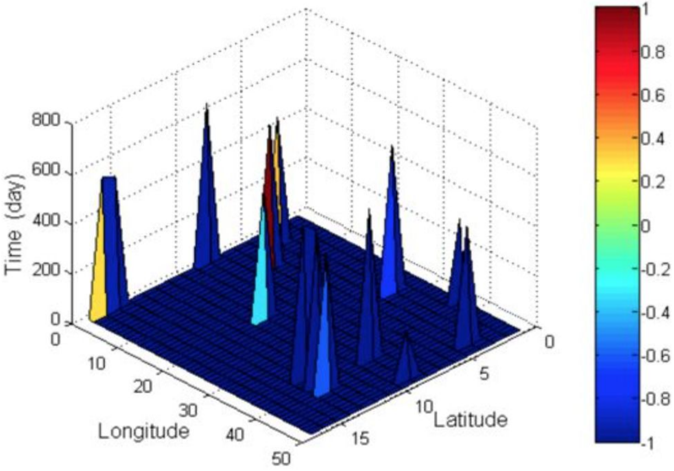
1. Use Wavelet analysis to find spatiotemporally localized Flickr tags
2. Cluster event-related tags into events based on both semantic and spatiotemporal similarities.

Detecting Event-related Tags

- For each tag, map every occurrence into a point in the 3D (lat, lng, time) space
- User Wavelet analysis handle 3D signals and find event-related (bursty) tags



(a) usage occurrences in the original 3D space



(b) surface plot in the original 3D space

Event Generation

Cluster bursty tags into spatiotemporal events:

Tag similarity

$$\boxed{S(q_i, q_j)} = \frac{\boxed{SemSim(q_i, q_j)}}{1 + \boxed{SpaDist(q_i, q_j)}}$$

Semantic similarity

Spatiotemporal similarity

$$SemSim(q_i, q_j) = \frac{|P(q_i) \cap P(q_j)|}{\min\{|P(q_i)|, |P(q_j)|\}}$$

$$KL^N(m_i, sd_i; m_j, sd_j) = \frac{1}{2}(\log(\frac{sd_j^2}{sd_i^2}) + \frac{sd_i^2}{sd_j^2} + \frac{(m_i - m_j)^2}{sd_j^2} - 1)$$

Example Bursty Tags and Events

No.	Event Tags	Time	Location (la, lo)	Event Description
E_1	partnershipwalk akf agakhanfoundation	10/29/2006, 11/10/2007	(29.719322, -95.37212)	Partnership Walk is an initiative of Aga Khan Foundation USA to raise funds and awareness to help communities in Africa and Asia. It is held annually at Atlanta, Chicago, Dallas, Houston, Los Angeles.
E_2	southoaklandcountysoccer socs storm95	09/15/2007, 09/22/2007, 09/29/2007, 10/07/2007	(42.49387, -83.20573)	Weekly games of team SOCS Storm95 in south oakland country soccer club in 2007.
E_3	crosswalkamerica crosswalk scottgriessel creatista griessel	07/02/2006, 08/01/2006, 08/20/2006, 09/01/2006, 07/02/2007, 08/06/2007, 08/23/2007, 09/01/2007	(33.99294, -110.07808)	Crosswalk is a journey made by a couple of progressive Christians who trekked across the country from April to September. Griessel is the photographer of this walk.
E_4	f1 formulaone unitedstatesgrandprix	07/02/2006, 06/17/2007	(39.693844, -86.23974)	The United States Grand Prix was a Formula One race held on July 2, 2006, and June 15-17, 2007, at the Indianapolis Motor Speedway.
E_5	asl northpark deaf gpccd	04/22/2006, 04/14/2007	(34.239143, -116.894745)	The annual ASL fundraising picnic party at Pittsburgh North Park hosted by GPCCD in April.
E_6	beachjam amusementrides moreyspiers wildwoodbeachjam amusements beachcamping	05/20/2006, 05/20/2007	(38.987007, -74.81043)	The Beach Jam is an annual camping event on the Wildwood, NJ, beach at Morey's Piers that includ amusement rides. There is a 3-day Spring Beach Jam before Memorial Day.

EvenTweet: Online Localized Event Detection from Twitter [Abdelhaq et. al. PVLDB 2013]

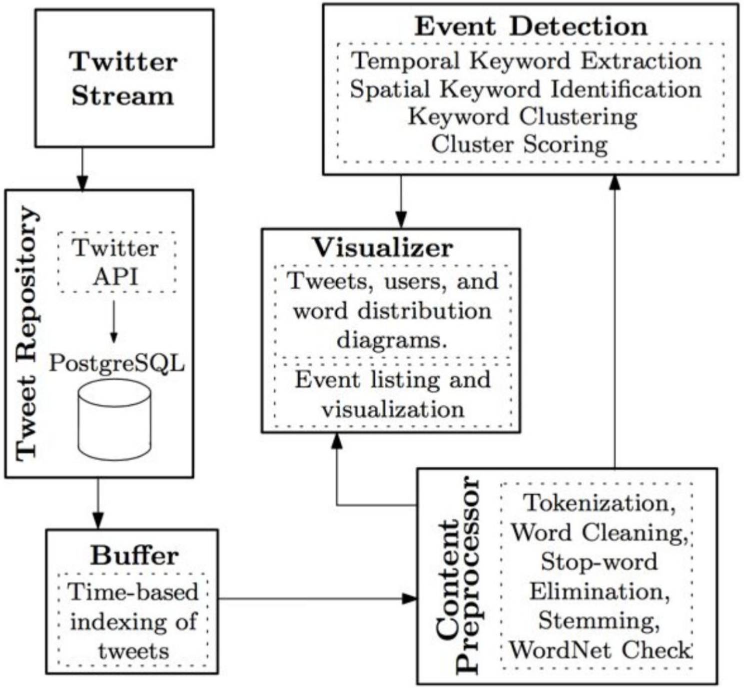


Figure 1: System overview of EvenTweet

Online detection:

- Partition time into intervals
- Trigger the detector when the current bin is saturated

Feature-based detection:

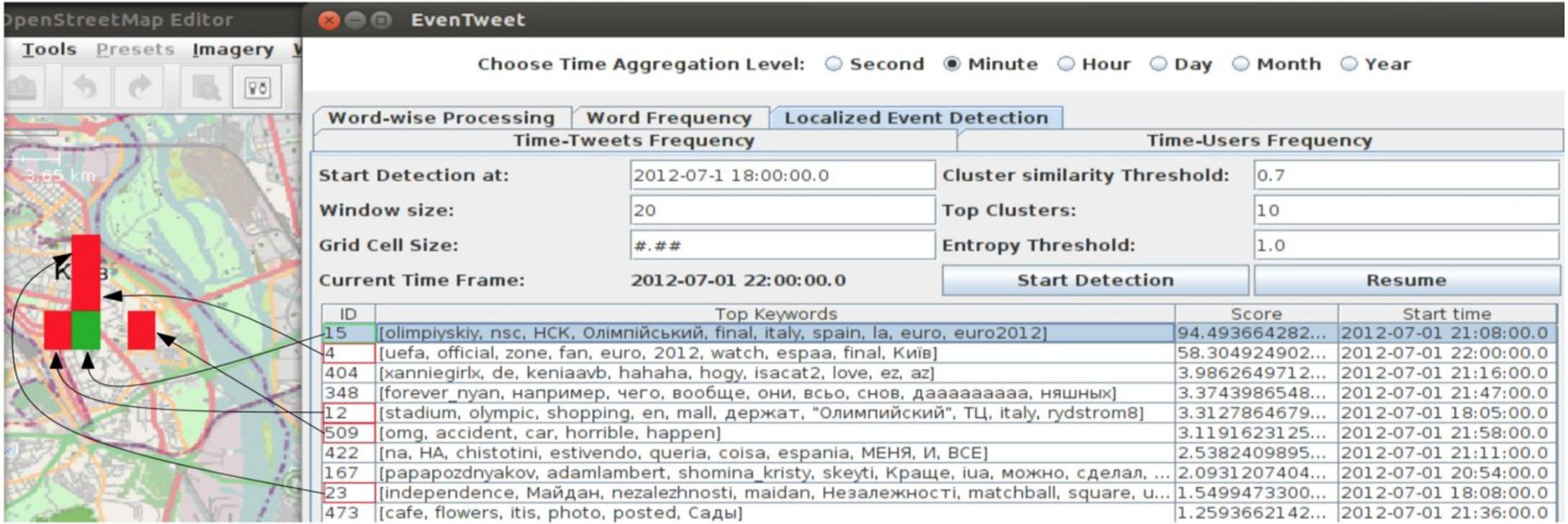
- Each keyword is a feature
- Detect bursty features and cluster them into local events

The Online Detection Process

1. Select temporally bursty keywords from the current query bin by comparing against previous bins.
2. Select spatially localized keywords by computing keyword entropies.
3. Cluster the localized keywords into events based on spatial distributions.
4. Compute the burstiness score of the clusters and rank them.

Examples [Abdelhaq et. al. PVLDB 2013]

A local event is represented as a collection of bursty and localized keywords



Representative Approaches

Feature-Based Detection: First detect bursty keywords/phrases from the input, then group relevant features into events.

- E.g., Chen et. al. CIKM 2009, Abdelhaq et. al. PVLDB 2013

Document-Based Detection: Consider each document (e.g., tweet, check-in) as a basic unit and detect bursty document clusters as events.

- E.g., Zhang et. al. SIGIR 2016, Zhang et. al. KDD 2017

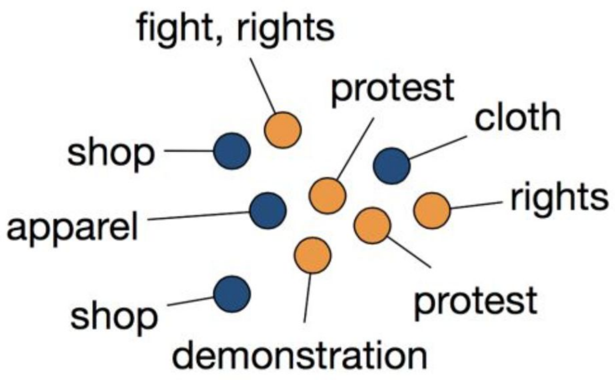
Spatiotemporal Event Forecasting: Predict whether a specific type of spatiotemporal event will occur in the future

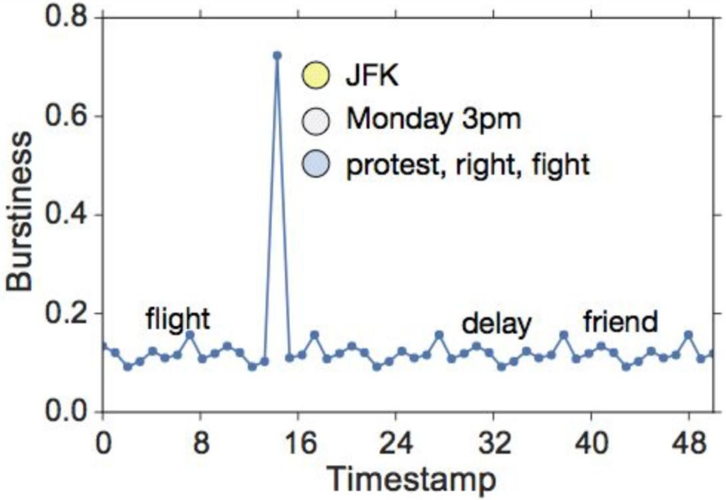
- E.g., Zhao et. al. KDD 2016

GeoBurst: Real-Time Local Event Detection in Geo-Tagged Tweet Streams [Zhang et. al. SIGIR 2016]

A document-based approach:

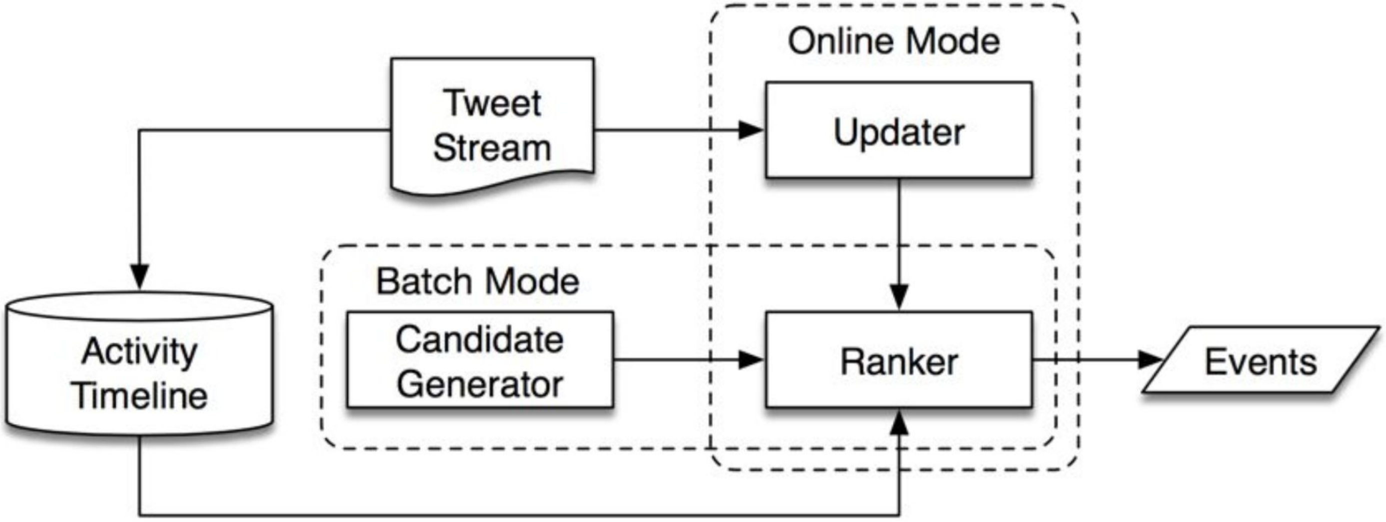
A local event is a geo-topic cluster that is spatiotemporally bursty.





GeoBurst: A Two-Step Detector

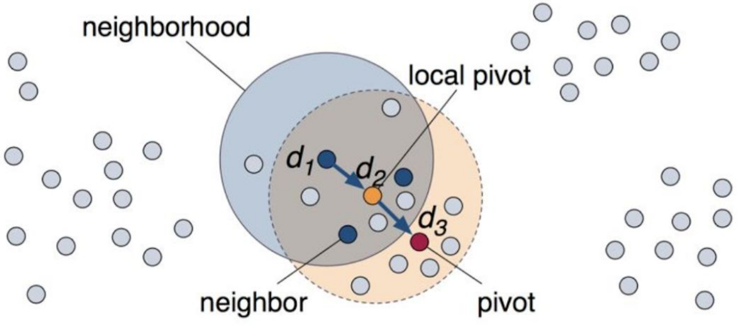
1. Candidate generation: detect all the geo-topic clusters in the query window
2. Candidate ranking: select top-K candidates by spatiotemporal burstiness



Candidate Generation & Ranking

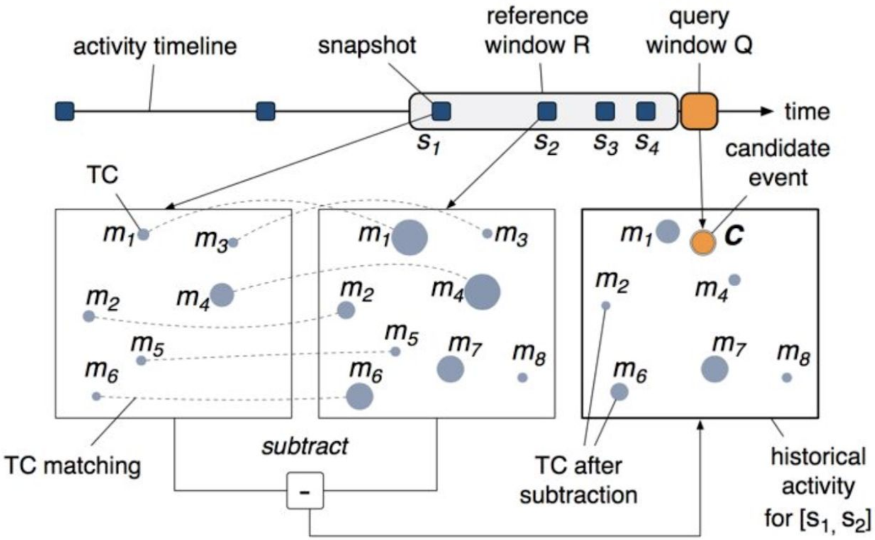
Candidate generation

- The event occurring spot acts as a ***pivot*** that produces relevant tweets around it.
- Define geo-topic authorities and perform authority ascent to find pivot tweets.



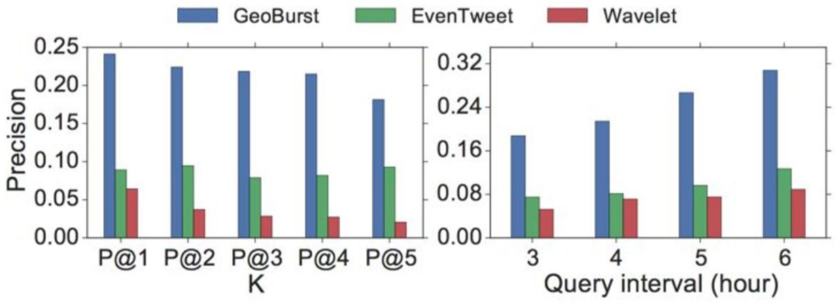
Candidate filtering

Summarize typical activities in different regions to rank the candidates.

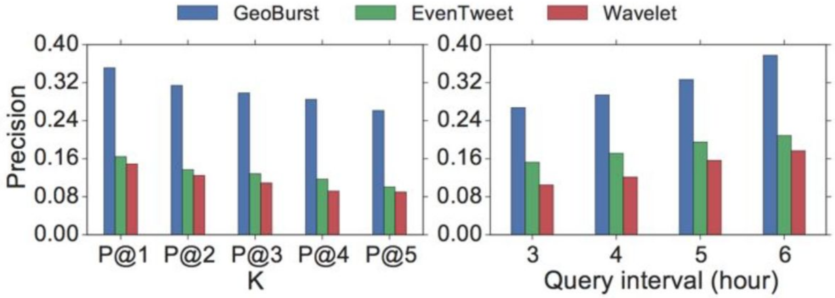


Empirical Performance

Effectiveness comparison:

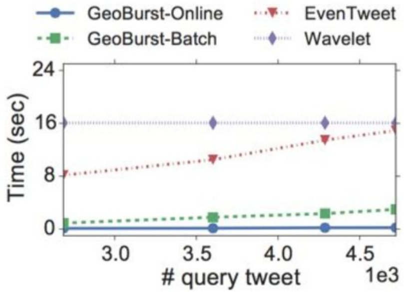


(a) Precision comparison (NY).

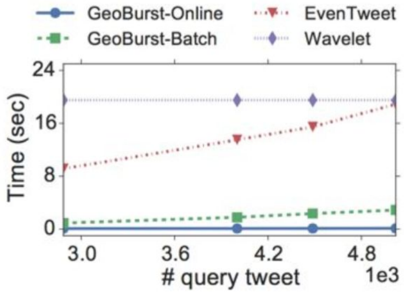


(b) Precision comparison (LA).

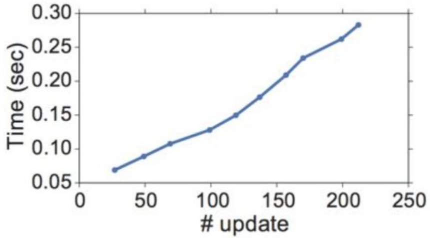
Efficiency:



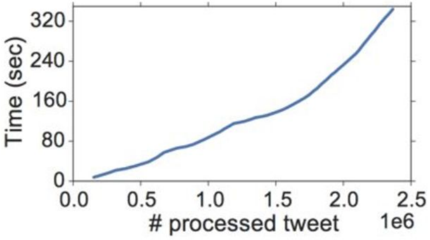
(a) Running time (NY).



(b) Running time (LA).



(a) Time v.s. # update (NY).



(a) Time v.s. # tweet (NY).

TrioVecEvent: Embedding-Based Online Local Event Detection in Geo-Tagged Tweet Streams [Zhang et. al. KDD 2017]

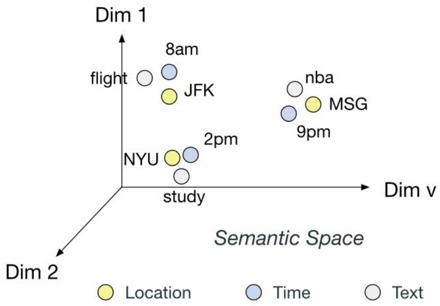
Motivation:

1. How can we better capture the semantics of short text during candidate generation?
   - Previous methods are mostly based on bag-of-words representations
2. How to better identify true events from the candidate pool?
   - Previous methods manually design burstiness scoring functions and select top-k bursty clusters

An Overview of TrioVecEvent

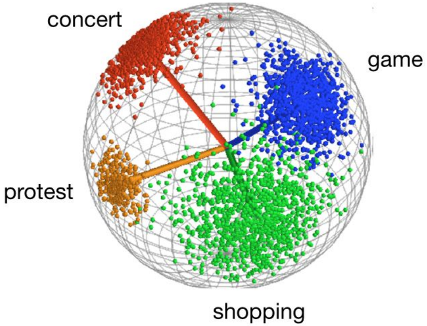
Cross-Modal Embedding

Embed location, time, and text into the same low-dimensional space.



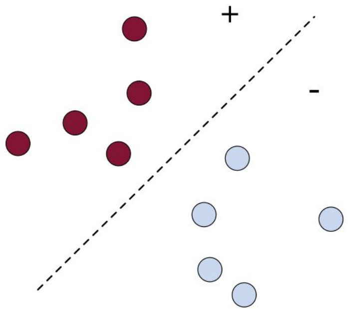
Candidate Generation

Cluster the tweets into geo-topic clusters as candidate events.

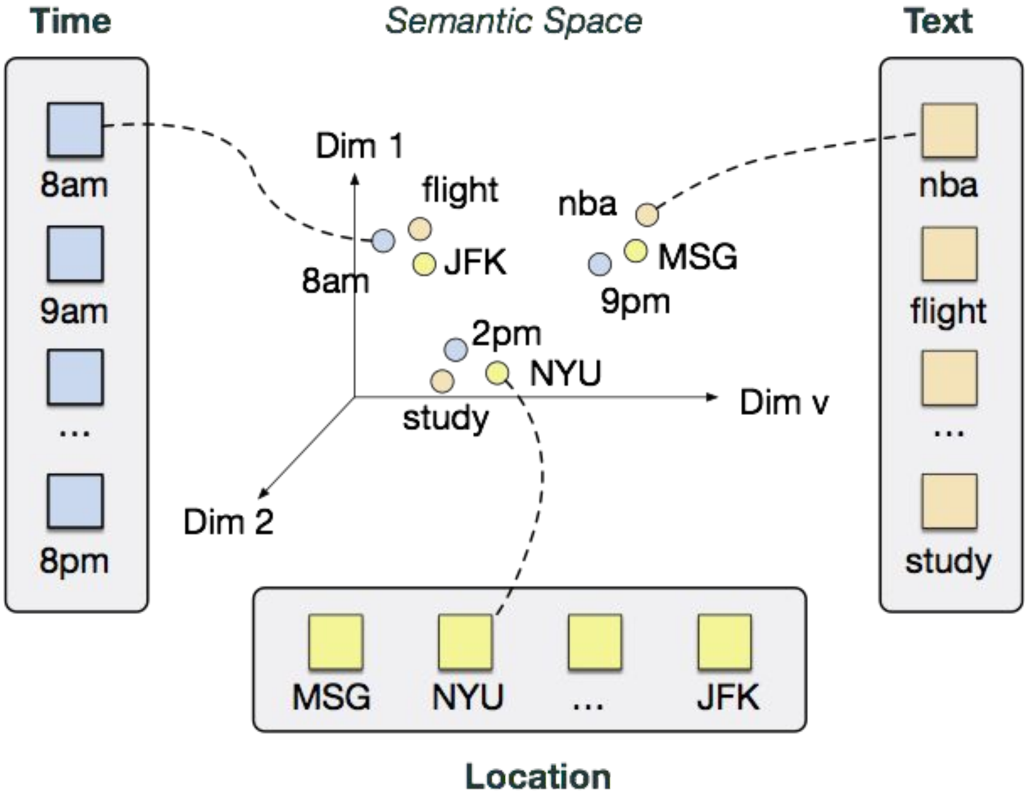


Classification

Extract features for the candidates and identify true events.



Cross-Modal Embedding



Correlated units tend to be close in the embedding space.

Preserve:

1. Intra-type similarity
2. Inter-type similarity

Learning Cross-Modal Embeddings

Objective of preserving the information of corpus C

$$\boxed{J_C} = -\sum_{d \in C} \sum_{i \in d} \log \boxed{p(i|d_{-i})}$$

Probability of observing unit i given the others in document d

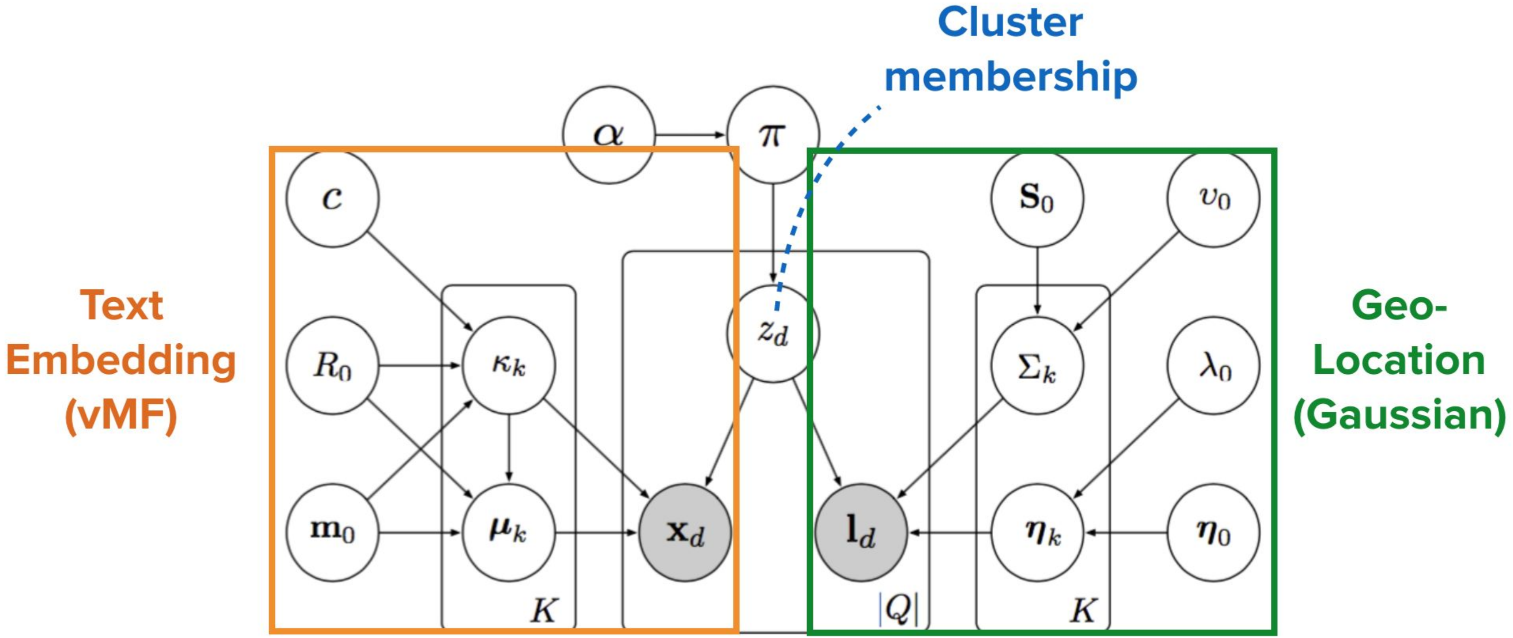
$$\boxed{p(i|d_{-i}) = \frac{\exp(\boxed{s(i, d_{-i})})}{\sum_{j \in X} \exp(s(j, d_{-i}))}}$$

Similarity between unit i and the others.

$$\boxed{s(i, d_{-i}) = \mathbf{v}_i^{\mathrm{T}} \sum_{j \in d_{-i}} \mathbf{v}_j / |d_{-i}|}$$

Find Geo-Topic Clusters: A Bayesian Mixture Model

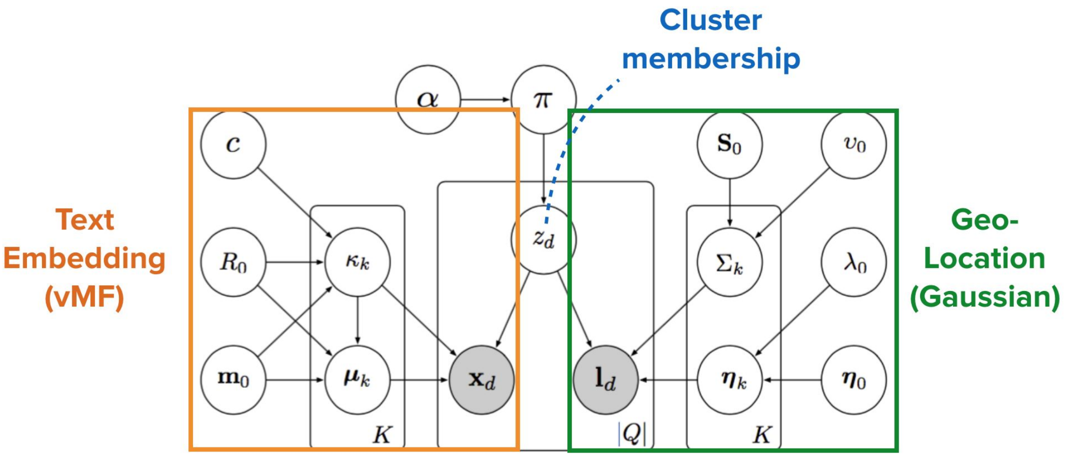
Each tweet consists of: 1) a location; and 2) a text embedding.

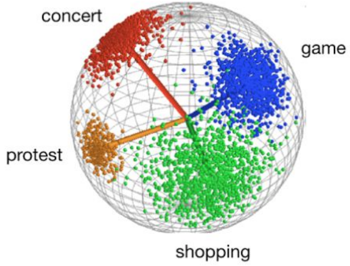


Find Geo-Topic Clusters: A Bayesian Mixture Model

Each tweet consists of: 1) a location; and 2) a text embedding.

$$\pi \sim \textbf{Dirichlet}(.|\alpha)$$
$$\{\boldsymbol{\eta}_k, \sigma_k\} \sim \textbf{NIW}(.|\eta_0, \lambda_0, \mathbf{S}_0, \upsilon_0)$$
$$\{\mu_k, \kappa_k\} \sim \Phi(.|\mathbf{m}_0, R_0, c)$$
$$z_d \sim \textbf{Categorical}(.|\pi)$$
$$\mathbf{l}_d \sim N(.|\eta_{z_d}, \sigma_{z_d})$$
$$\mathbf{x}_d \sim \textbf{vMF}(.|\mu_{z_d}, \kappa_{z_d})$$





Inferring Cluster Membership

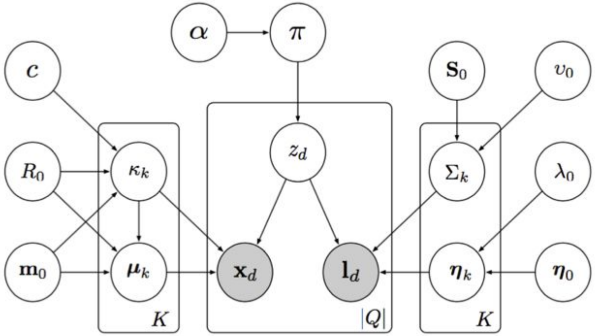
MCMC Inference:

$$p(z_d = k|\mathbf{x}_d, \mathbf{l}_d, \Theta)$$

$$\propto \boxed{p(z_d = k|\mathcal{Z}^{\neg d}, \Theta)} \cdot \boxed{p(\mathbf{x}_d|z_d = k, \Theta)} \cdot \boxed{p(\mathbf{l}_d|z_d = k, \Theta)}$$

$(n^{k,\neg d} + \alpha)$ ***"Rich-Get-Richer"***

Semantic Coherence $$\frac{C_D(\kappa_k)C_D(\|\kappa_k(R_0\mathbf{m}_0 + \mathbf{x}^{k,\neg d})\|_2)}{C_D(\|\kappa_k(R_0\mathbf{m}_0 + \mathbf{x}^{k,\neg d} + \mathbf{x}_d)\|_2)}$$

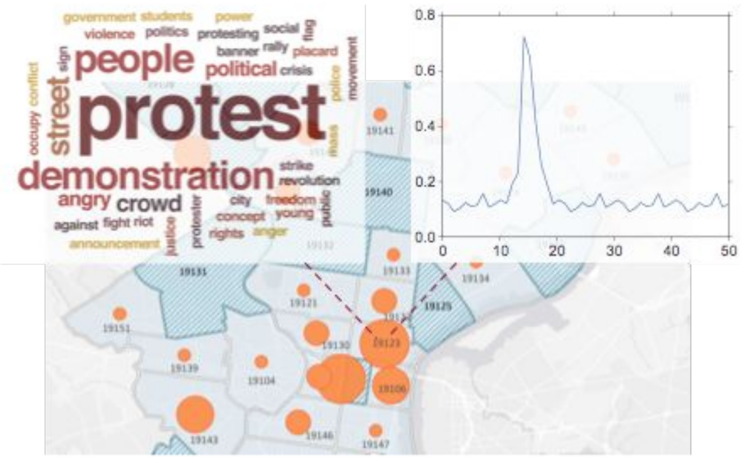


Geographical Proximity $$\frac{\lambda^{k,\neg d}(\upsilon^{k,\neg d} - 1)|\mathbf{S}^{\mathcal{L}^k \cap \mathcal{L}^{\neg d}}|^{\upsilon^{k,\neg d}/2}}{2(\lambda^{k,\neg d} + 1)|\mathbf{S}^{\mathcal{L}^k \cup \{\mathbf{l}_d\}}|^{(\upsilon^{k,\neg d}+1)/2}}$$

Candidate Filtering: Classification

What geo-topic clusters are true events?

Should be coherent, bursty, and locally unusual.

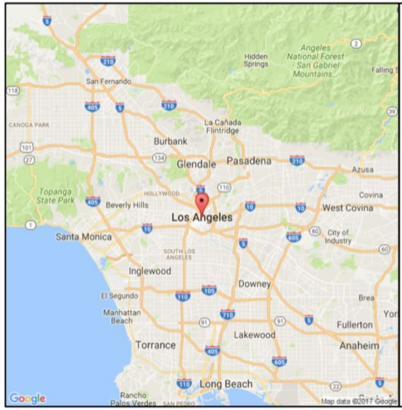


Coherency Features:
spatial, temporal, and semantic concentrations

Unusual Features:
spatial and temporal unusualness

Burstiness Feature:
number of tweets

Illustrative Events



- Standing for **justice**! @ LAPD Headquarters http://t.co/YxNUAloQcE
- At the LAPD **protest** downtown **#EzellFord #MikeBrown** http://t.co/kWphv6dXOr
- Hands Up. Don't **Shoot**. @ Los Angeles City Hall
- Black, Brown, poor white, ALL **oppressed** people **unite**. #ftp #lapd **#ferguson** #lapd **#mikebrown #ezellford** http://t.co/szf3mJRJwV
- Finished **marching** now **gathered** back at LAPD police as organizers speak some truth **#EzellFord #MikeBrown #ferguson** http://t.co/M33n9IMOzC

Event in LA: a protest rally at the LAPD headquarter

- **Hoboken Fall Arts & Music Festival** with bae @alli_holmes93 @ Washington St. Hoboken
- On Washington Street. (at **Hoboken Music And Arts Festival**) https://t.co/YbLSdZhLZV
- Sweeeeet. Bonavita **Guitars**, at the **Hoboken festival**. http://t.co/2Cw1Qz4UGo
- I'm at **Hoboken Music And Arts Festival** in Hoboken, NJ https://t.co/i4bSM3mrjb
- It's a **festy music** day.

Event in NYC: Hoboken Fall Arts & Music Festival

Quantitative Evaluation

P: Precision, R: Pseudo Recall, F1: Pseudo F1 Score

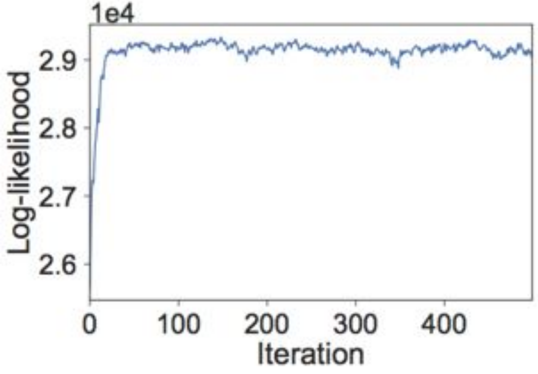
Method	LA			NY		
	P	R	F1	P	R	F1
EvenTweet	0.132	0.212	0.163	0.108	0.196	0.139
GeoBurst	0.282	0.451	0.347	0.212	0.384	0.273
GeoBurst+	0.368	0.483	0.418	0.351	0.465	0.401
TrioVecEvent	**0.804**	**0.612**	**0.695**	**0.765**	**0.602**	**0.674**

EvenTweet [PVLDB'13]: bursty feature selection, top-k selection

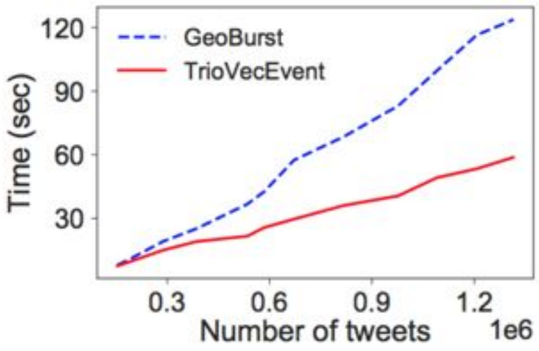
GeoBurst [SIGIR'16]: document-based detection, top-k selection

GeoBurst+ [TIST'17]: supervised detection

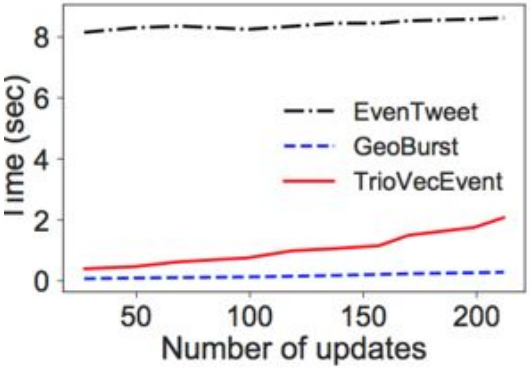
Efficiency of TrioVecEvent



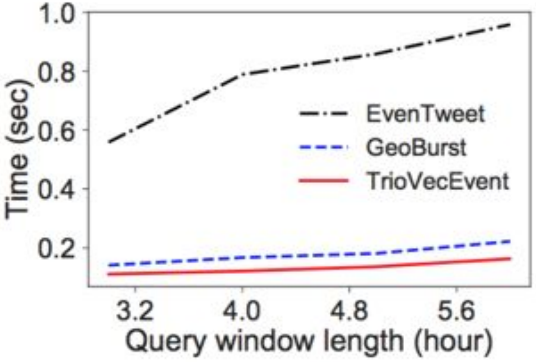
(a) Geo-topic clustering convergence.



(b) Summarization throughput.



(c) Online clustering time.



(d) Candidate filtering time.

An Overview of Representative Approaches

Feature-Based Detection: First detect bursty keywords/phrases from the input, then group relevant features into events.

- E.g., Chen et. al. CIKM 2009, Abdelhaq et. al. PVLDB 2013

Document-Based Detection: Consider each document (e.g., tweet, check-in) as a basic unit and detect bursty document clusters as events.

- E.g., Zhang et. al. SIGIR 2016, Zhang et. al. KDD 2017

Spatiotemporal Event Forecasting: Predict whether a specific type of spatiotemporal event will occur in the future

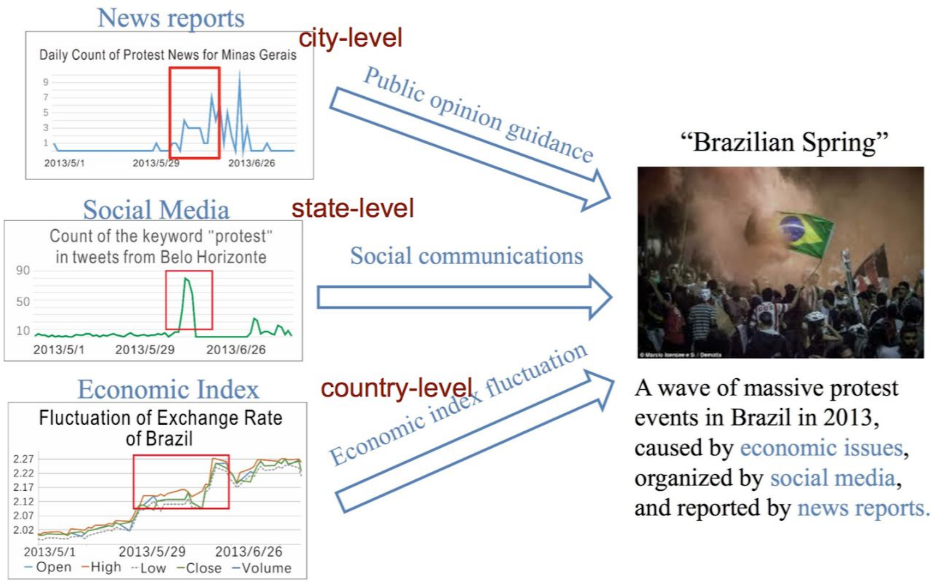
- E.g., Zhao et. al. KDD 2016

Hierarchical Incomplete Multi-Source Feature Learning for Spatiotemporal Event Forecasting [Zhao et. al. KDD 2016]

Task: use multiple data sources to predict whether certain event types will occur in the future.

Why multiple data sources?

- Spatiotemporal events are often influenced by different aspects of the society.
- Different data sources complement each other.
- One single source cannot cover all aspects of an event.



Slide from Liang Zhao:
http://people.cs.vt.edu/liangz8/materials/papers/HIML_slides.pdf

Challenges for Event Forecasting

Hierarchical topology

- E.g., country-level, state-level, city-level
- Higher-level features can influence lower-level ones

Interactive missing values

- Different data sources, different spans
- Need to consider the interactions among different sources.

Feature sparsity

- Only a small set of features are useful
- Need to use geo-hierarchy to select useful features

Hierarchical Incomplete Multi-Source Feature Learning

Given the multi-source data for a location l at time t, predict whether the event will happen at time τ

$$f : \{\underbrace{X_{t,l_1}}_{\text{city}}, \cdots, \underbrace{X_{t,l_N}}_{\text{state,... ,country}}\} \rightarrow Y_{\tau,l}$$

- Each location has features at multiple levels *l=(l1, l2, ...lN)* E.g., (San Francisco, CA, USA)

Variables are dependent on the variables in their parent level

$$(level-1)\ \ Y_{\tau,l} = \alpha_0 + \sum_{i=1}^{|\mathcal{F}_1|} \alpha_i^T \cdot [X_{t,l_1}]_i + \varepsilon$$ city-level

$$(level-2)\ \ \alpha_i = \beta_{i,0} + \sum_{j=1}^{|\mathcal{F}_2|} \beta_{i,j}^T \cdot [X_{t,l_2}]_j + \varepsilon_i$$ state-level

$$(level-3)\ \ \beta_{i,j} = W_{i,j,0} + \sum_{k=1}^{|\mathcal{F}_3|} W_{i,j,k}^T \cdot [X_{t,l_3}]_k + \varepsilon_{i,j}$$ country-level

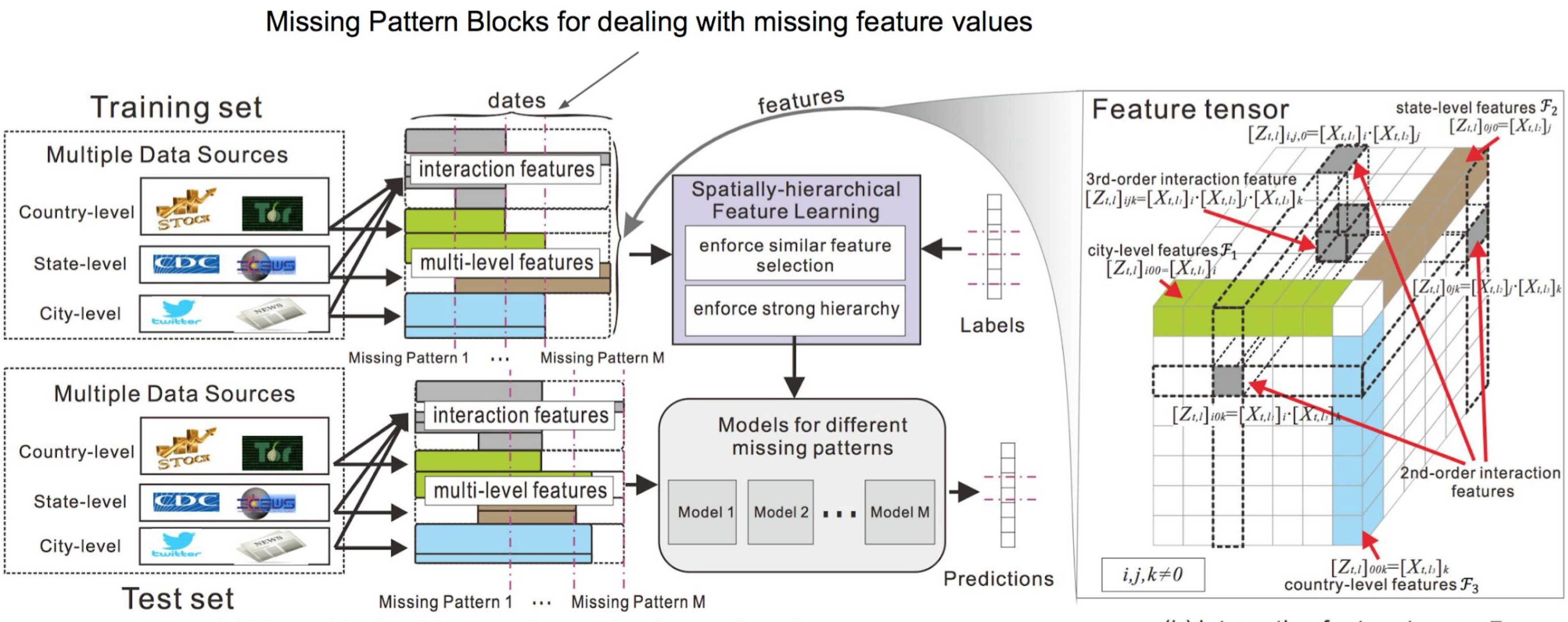
Encode hierarchical feature correlation by nth-order strong hierarchy

$$\Rightarrow\ Y_{\tau,l} = \sum_{i=0}^{|\mathcal{F}_1|} \sum_{j=0}^{|\mathcal{F}_2|} \sum_{k=0}^{|\mathcal{F}_3|} W_{i,j,k} \cdot [X_{t,l_1}]_i \cdot [X_{t,l_2}]_j \cdot [X_{t,l_3}]_k + \varepsilon$$

Tensor form:

$$\Rightarrow\ Y_{\tau,l} = W \odot Z_{t,l} + \varepsilon$$

Hierarchical Incomplete Multi-Source Feature Learning



(a) hierarchical multi-source interaction feature learning

(b) interaction feature tensor $Z_{t,l}$

Experiments

Datasets: 10 datasets for civil unrest (CU) and influenza (FLU)

Missing data ratio (3%)

Method	Argentina	Brazil	Chile	Colombia	El Salvador	Mexico	Paraguay	Uruguay	Venezuela
LASSO	0.5267	0.7476	0.5624	0.8032	0.3148	0.7823	0.5572	0.4693	0.8073
LASSO-INT	0.5268	0.7191	0.5935	0.7861	0.5269	0.777	0.4887	0.5069	0.7543
iMSF	0.4795	0.4611	0.5033	0.7213	0.5	0.5569	0.4486	0.4904	0.5
MTL	0.3885	0.5017	0.5011	0.4334	0.3452	0.4674	0.4313	0.3507	0.5501
Baseline	0.5065	0.7317	**0.6148**	0.8084	**0.777**	**0.8037**	0.7339	0.7264	**0.7846**
HIML	**0.5873**	**0.8353**	0.5705	**0.8169**	0.7191	0.7973	**0.7478**	**0.8537**	0.7488

CU forecasting performance AUC

	Missing data ratio				runtime
Method	21%	30%	50%	70%	(second)
LASSO	0.9180	0.9056	0.9036	0.8753	493.92
LASSO-INT	0.9142	0.9027	0.9073	0.8403	508.49
iMSF	0.8949	0.8899	0.8930	0.8628	88.90
MTL	0.6129	0.5303	0.6253	0.5568	223.78
Baseline	0.9044	0.9045	0.8562	0.4359	**31.97**
HIML	**0.9372**	**0.9368**	**0.9364**	**0.9357**	851.83

FLI forecasting performance AUC

Reference

Spatiotemporal Event Detection

- Event detection from flickr data through wavelet-based spatial analysis. Chen et al. CIKM 2009
- A probabilistic model for spatio-temporal signal extraction from social media. GIS 2013
- Identifying local events via space-time signals in twitter feeds. Krumm et al. GIS 2015
- Eventweet: Online localized event detection from twitter. Adbelhaq et al. PVLDB 2013
- GeoBurst: Real-time local event detection in geo-tagged tweet streams. Zhang et al. 2016
- TrioVecEvent: Embedding-Based Online Local Event Detection in Geo-Tagged Tweet Streams. Zhang et al. 2017
- Earthquake shakes twitter users: real-time event detection by social sensors. Sakaki et al. WWW 2010
- Crowd sensing of traffic anomalies based on human mobility and social media. Pan et al. GIS 2013
- Extracting city traffic events from social streams. Anantharam et al. TIST 2015

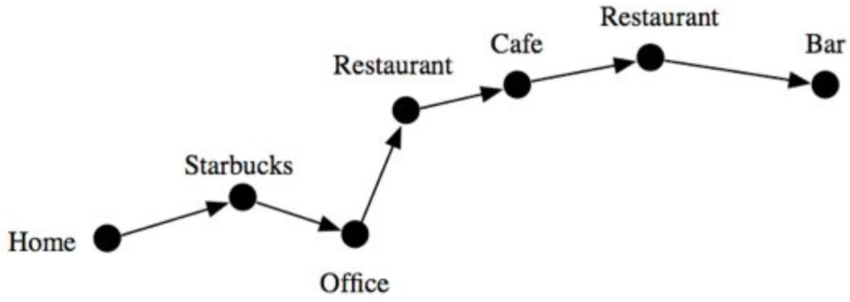
Spatiotemporal Event Forecasting

- “beating the news” with embers: forecasting civil unrest using open source indicators. Ramakrishnan et al. KDD 2014
- Spatiotemporal event forecasting in social media. Zhao et al. SDM 2015
- Combining heterogeneous data sources for civil unrest forecasting. Korkmaz et al. ASONAM 2015
- Hierarchical Incomplete Multisource Feature Learning for Spatiotemporal Event Forecasting. Zhao et al. KDD 2016
- Spatiotemporal model fusion: multiscale modelling of civil unrest. Hoegh et al. J. the Royal Statistical

Part III: Spatiotemporal Mobility Modeling

Problem Description

Semantic trajectory: each GPS record also has semantic information (e.g., place category, text message)



Task: given a collection of semantic trajectories, how to model the movement regularities of the populace?

- Mobility modeling can occur at either **user level** or **crowd level**.

Representative Approaches

Pattern-based approaches: mining pre-defined mobility patterns from semantic trajectories

- Sequential pattern mining (e.g., Zhang et al. PVLDB 2014)

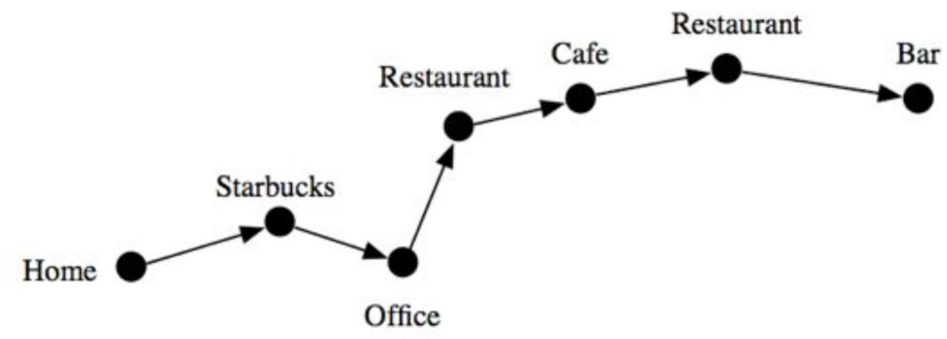
Model-based approaches: build statistical model to describe human movements

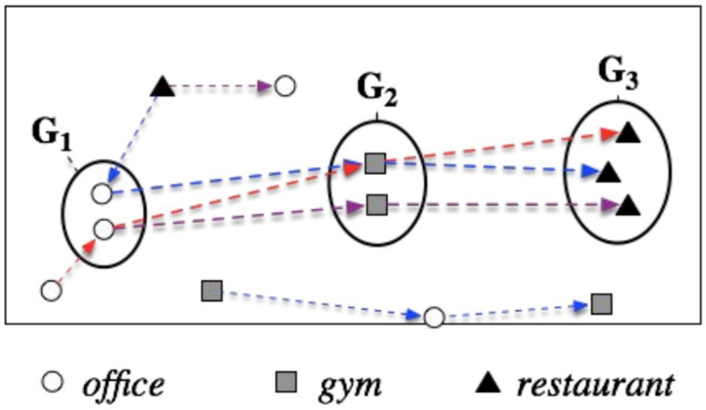
- User-level mobility models (e.g., Yuan et al. KDD 2013)
- Hidden markov models (e.g., Zhang et al. KDD 2016)
- Recurrent neural network models (e.g., AAAI 2016, Yao et al. CIKM 2017)

Splitter: Mining Frequent Sequential Patterns from Semantic Trajectories [Zhang et al. PVLDB 2014]

Each record in the trajectory has category information (e.g., office, hotel, gym)

Frequent sequential movement pattern: a movement sequence that frequently appear in the input trajectories





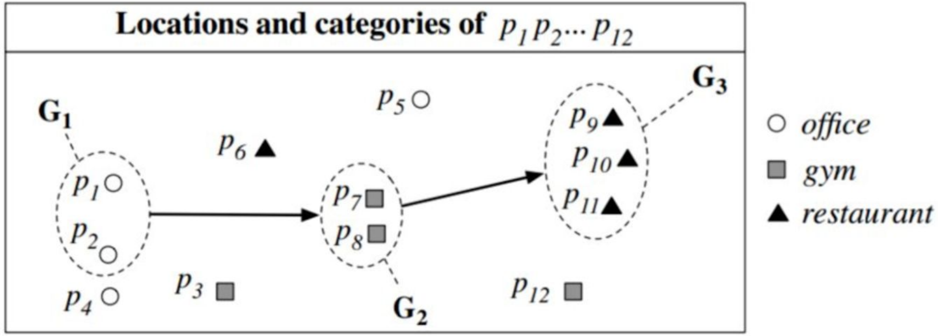
How to Define Sequential Movement Patterns?

We cannot consider each location as an independent item because of spatial continuity!

Similar places should be grouped while respecting:

- Semantic consistency
- Spatial compactness
- Temporal continuity

Example pattern: G1 -> G2 -> G3:



Problem Description

Input: a collection of N semantic trajectories, a support threshold K

Output: the sequential movement patterns that appear in no less than K trajectories

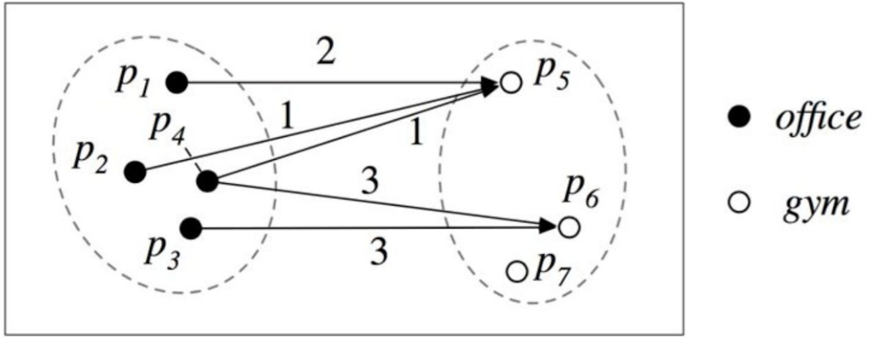
Splitter: A Top-down Mining Approach

How do we group similar places to form sequential movement patterns?

- There is an exponential number of possibilities, impossible to enumerate every option!

Key idea of Splitter:

- First mine category-level frequent transitions (coarse pattern)
- Then break each coase pattern into spatially compact ones (fine-grained pattern)



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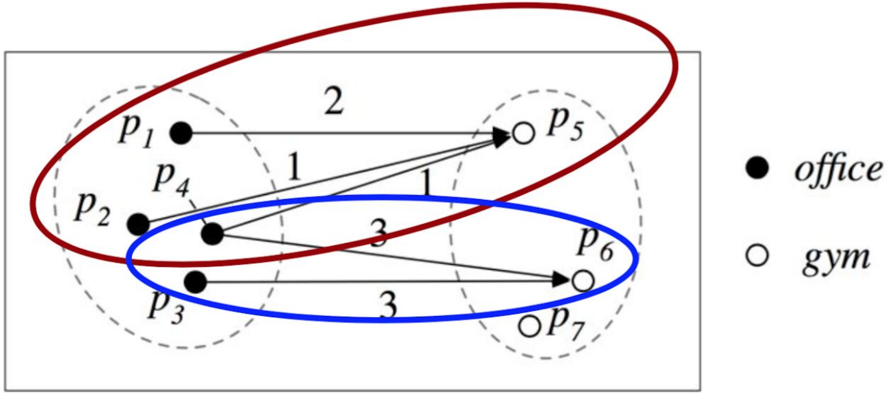
- First mine semantics-level frequent transitions (coarse pattern)
- Then break each coase pattern into spatially compact ones (fine-grained pattern)



Splitter: A Top-down Mining Approach

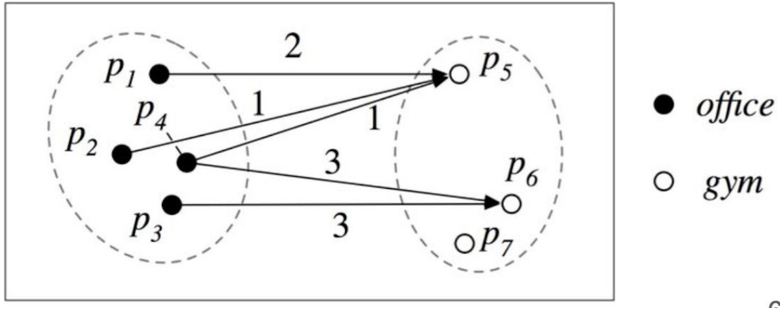
Coarse Pattern Mining: (1) Group the places with the same category; (2) Apply time-constrained sequential pattern mining

Object	Semantic Trajectory
o_1	<(p_3, 0), ($\boldsymbol{p_1}$, 10), ($\boldsymbol{p_7}$, 30), ($\boldsymbol{p_9}$, 40)>
o_2	<(p_5, 0), (p_7, 30), ($\boldsymbol{p_2}$, 360), ($\boldsymbol{p_7}$, 400), ($\boldsymbol{p_{10}}$, 420)>
o_3	<(p_3, 0), (p_6, 30)>
o_4	<(p_2, 0), ($\boldsymbol{p_1}$, 120), (p_6, 140), ($\boldsymbol{p_8}$, 150), ($\boldsymbol{p_{11}}$, 180)>
o_5	<(p_{12}, 50), (p_8, 80), (p_{11}, 120), (p_4, 210)>

Object	Timestamped item sequence
o_1	$\langle(G_2, 0), (G_1, 10), (G_2, 30), (G_3, 40)\rangle$
o_2	$\langle(G_1, 0), (G_2, 30), (G_1, 360), (G_2, 400), (G_3, 420)\rangle$
o_3	$\langle(G_2, 0), (G_3, 30)\rangle$
o_4	$\langle(G_1, 0), (G_1, 120), (G_3, 140), (G_2, 150), (G_3, 180)\rangle$
o_5	$\langle(G_2, 50), (G_2, 80), (G_3, 120), (G_1, 210)\rangle$

Fine-Grained Pattern Mining: (1) regard each transition as a high-D point; (2) perform iterative clustering in the high-D space to find patterns.

E.g., regard every length-2 transition as a 4D point: p1 -> p5, p2 -> p5, p4 -> p5, p4 -> p6, p3 -> p6.

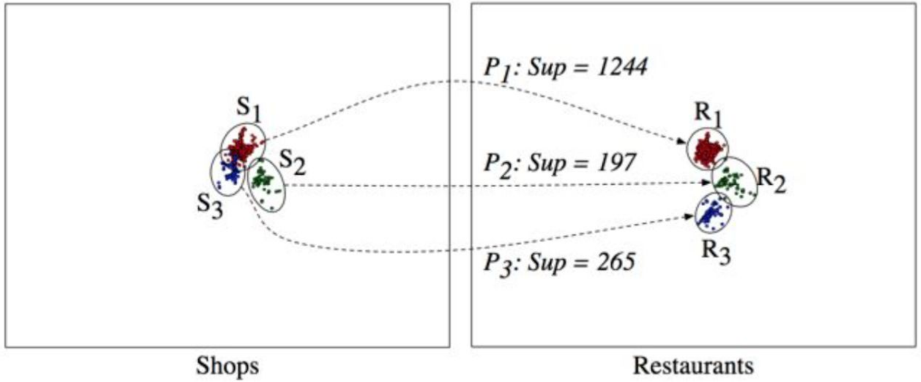


Example Patterns

Coarse Patterns

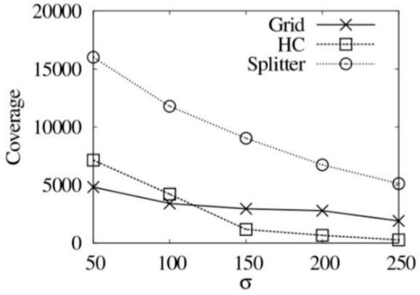
	Pattern	Sup
length=2	Shop → Food	1819
	Food → Shop	1464
	Professional → Nightlife Spot	1121
	Outdoor → Food	947
	Residence → College & University	647
length=3	Shop → Food → Shop	262
	Professional → Food → Nightlife Spot	240
	Entertainment → Food → Shop	178
	Transportation → Shop → Shop	174
	Residence → Outdoor → Food	163

Fine-grained Patterns

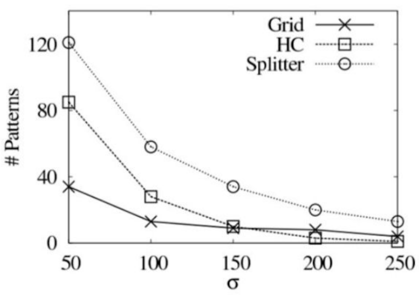


Experiments

Pattern Coverage

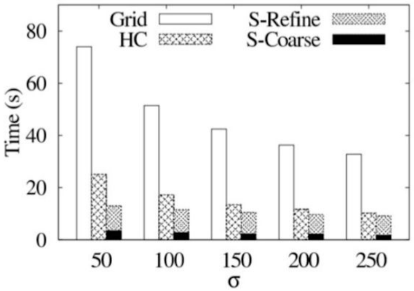


(a) Coverage *w.r.t.* σ.

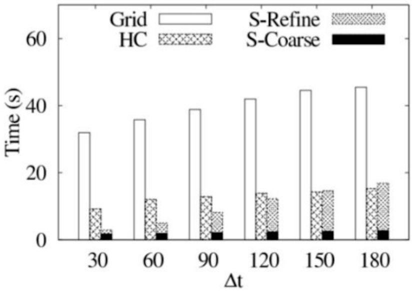


(b) Pattern number *w.r.t.* σ.

Efficiency



(a) Running time *w.r.t.* σ.



(b) Running time *w.r.t.* Δt.

Who, Where, When, What: User-Level Mobility Modeling [Yuan et. al. KDD 2013, TOIS 2015]

Input: a collection of checkins of different users

- Each post contains a user ID, a timestamp, a venue and a text message
- Each venue is associated with a venue ID and geo-coordinates

Output: multi-dimensional user-level mobility models

- who visits which place at what time for what activity

Previous studies: consider at most three factors out of the four

- Where What: geographical topic modeling
- Where When What: geographical event detection
- Who Where When: spatiotemporal mobility behavior modeling for users
- Who Where What: user-level geographical topic profiling

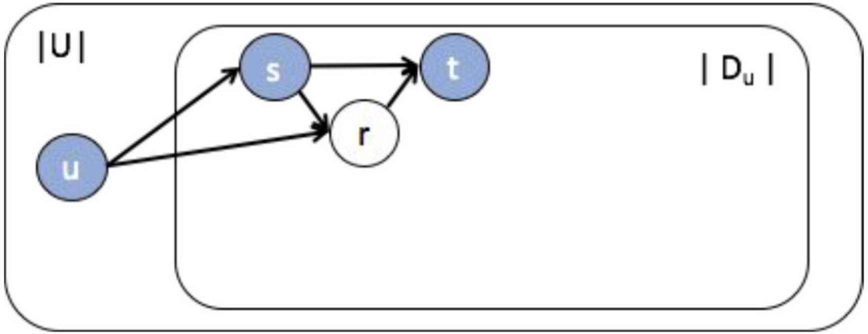
Overview

User u’s mobility centers at several personal geographical regions r (home, work, …)
The region r where a user u stays is influenced by day s

- E.g., weekday: work region; weekend: shopping region

Visiting time is determined by region r and day s

- E.g., visiting shopping region at weekday evening & weekend afternoon



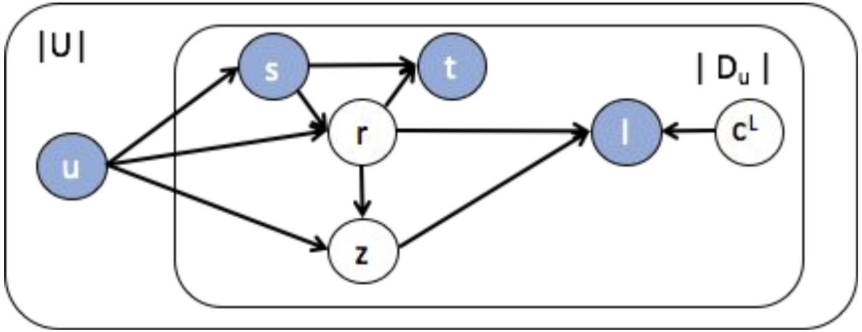
Overview

User u's topic interests is influenced by u's topic preference and region r

- E.g., u: "reading" and "shopping". u@Times Square: "shopping"

User u chooses a POI l based on either topic z or region r

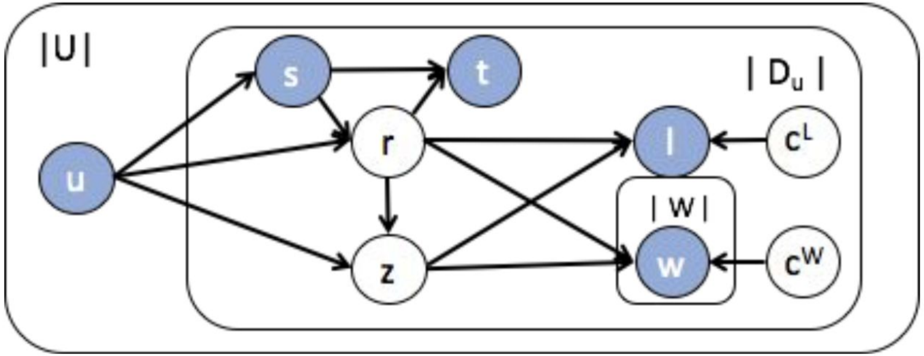
- Nearby POI within r that meets the topic requirement z (e.g., meal)
- Different users make different trade-offs between z and r



Overview

User u chooses a set of words w based on either topic z or region r

- Different user makes different trade-offs between z and r
- E.g., user u is shopping at home region: “grocery”, “family”



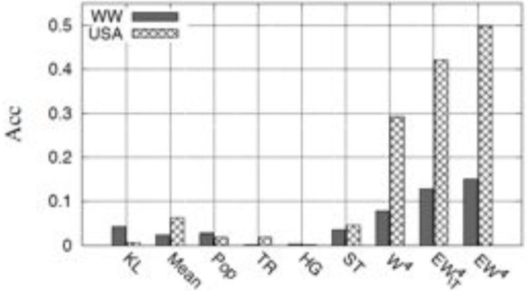
Experiments

Datasets
- 89,007 world-wide tweets (WW)
- 171,768 microblogs in USA (USA)

Venue prediction for tweet
- Rank venues by P(l|u,s,t,w)

Visitor prediction
- Rank users by P(u|s,t,l)

Venue prediction for user.
- Rank venues by P(l|u,s,t)



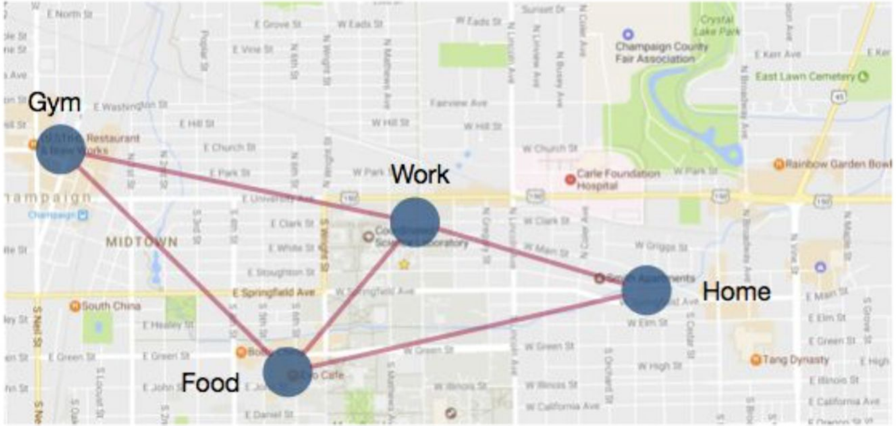
Acc	WW	USA
PMM	0.4163	0.4021
W^4	0.5063	0.5863
EW^4	0.5351	0.7679

Acc	WW	USA
PMM	0.0423	0.1102
W4	0.0776	0.2953
EW^4	0.1423	0.5054

GMove: Group-Level Mobility Modeling Using Geo-Tagged Social Media [Zhang et. al. KDD 2016]

Input: the semantic trajectories for a collection of users

Goal: (1) What are the intrinsic states underlying people's movements? (2) How do people move sequentially between those latent states?



Dilemma in Learning Mobility Models

Individual-level modeling: learn a model for each individual user

Each user has a limited number of records, we suffer from **data scarcity**!

Global-level modeling:

Different users have different moving behaviors, we suffer from **data inconsistency**!

Gmove: Group-Level Mobility Modeling

Idea: divide the users into coherent groups, and learn one model for each group.

- Reduce data sparsity by aggregating the movements of multiple users.
- Ensure data consistency as the users in the same group have similar movement regularity.

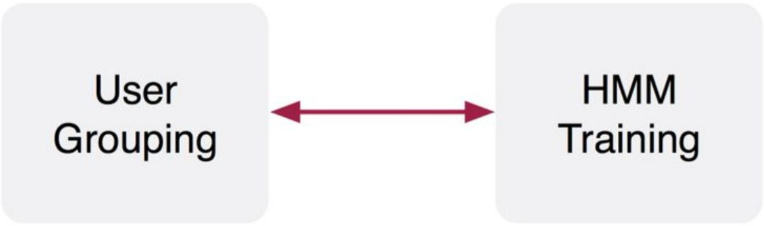
	Data Sparsity	Data Consistency
Individual-level	X	O
Global-level	O	X
Group-level	O	O

HMM Ensemble Learner

User grouping and mobility modeling mutually enhance each other:

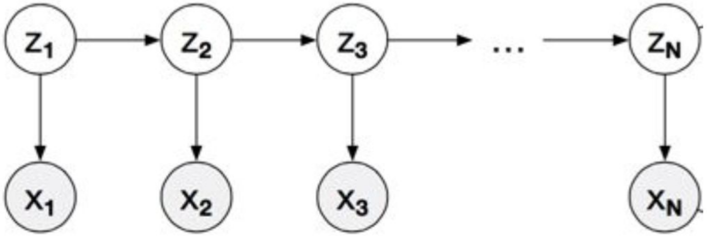
- Better user grouping leads to more consistent training data
- Better mobility modeling helps infer the user membership more accurately

An Iterative Process:

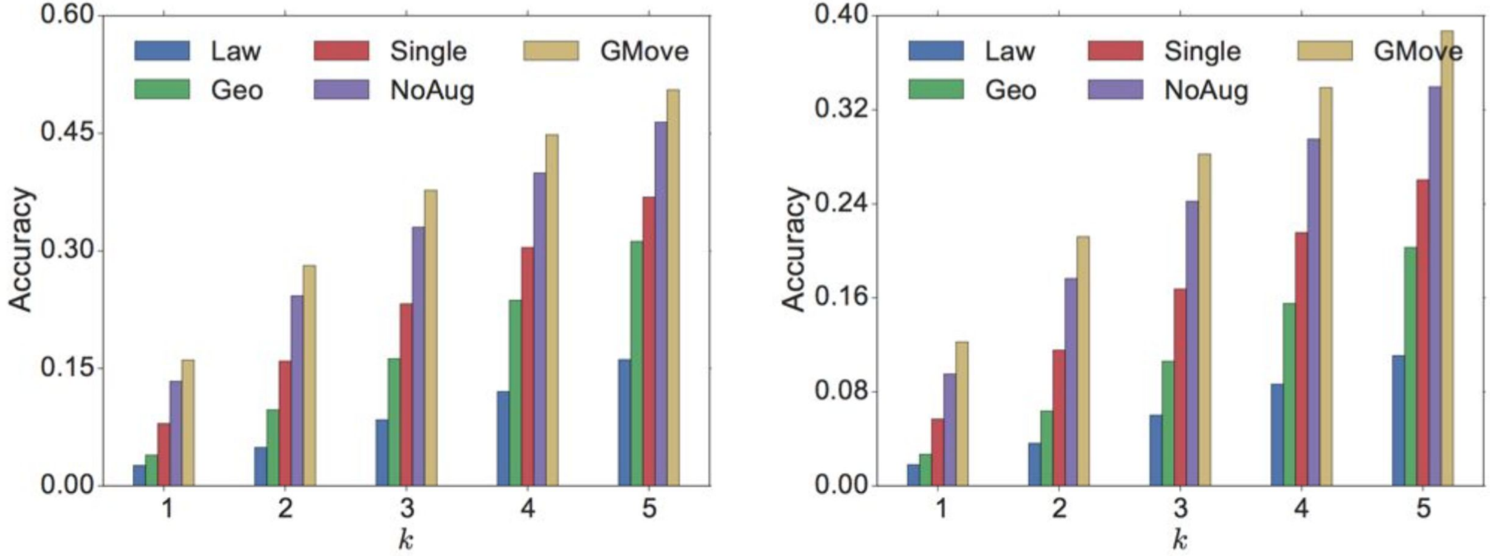


For each user u, compute the posterior probability that u belongs to group g:

$$p(g|u;\mathcal{H}^{\text{new}}) \propto p(g)p(u|g;\mathcal{H}^{\text{new}})$$



Quantitative Evaluation: Next Location Prediction



(a) LA (b) NY

Predicting the Next Location: A Recurrent Model with Spatial and Temporal Contexts [Liu et al. AAAI 2016]

Model the sequential aspect of user mobility

- Recent visits are more influential

Some mobility behaviors are periodic

Users tend to visit nearby places

How to model the spatial, periodic and sequential data?

Spatial Temporal Recurrent Neural Networks

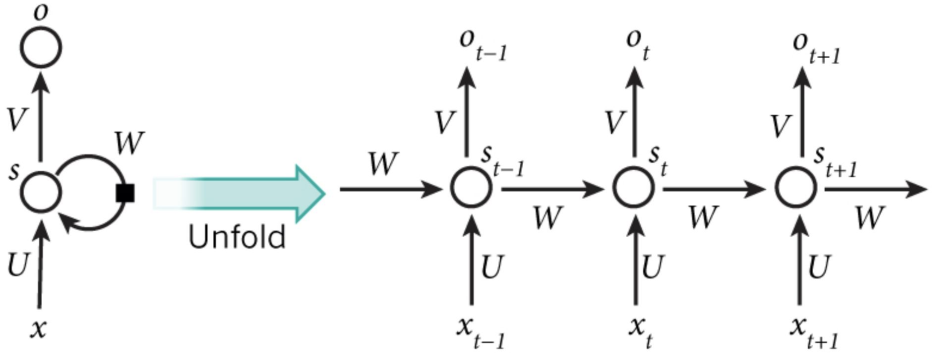
2pm Oct 24, Tue | 11am Oct 29, Sun | 11am Nov 05, Sun | 3pm Nov 26, Mon | 6pm Nov 26, Mon

Recurrent Neural Networks

Perform the same task for every element of a sequence-->unfold

RNNs have a “memory” which captures information about what has been calculated so far

Variants: Long Short Term Memory (LSTM), Gated Recurrent Units (GRU)



Recurrent Neural Networks Tutorial, Part 1 – Introduction to RNNs. https://goo.gl/1BvJ7J

Spatial Temporal Recurrent Neural Networks

Basic RNN: User's status at t is influenced by

$$\mathbf{h}^u_{t_k} = f\left(\mathbf{M}\mathbf{q}^u_{t_k} + \mathbf{C}\mathbf{h}^u_{t_{k-1}}\right)$$

- The characteristics of the visited location
- The status at t-1

RNN With Temporal Context: the status at t is further influenced by

$$\mathbf{h}^u_t = f\left(\sum_{q^u_{t_i} \in Q^u, t-w<t_i<t} \mathbf{T}_{t-t_i}\mathbf{q}^u_{t_i} + \mathbf{C}\mathbf{h}^u_{t-w}\right)$$

- The the locations visited within a period in the past
- The gap time t-t_i of these visits to t

Spatial Temporal Recurrent Neural Networks

RNN With Spatial Temporal Context: the importance of a previous visit is also dependent on the distance to current location

$$\mathbf{h}^u_{t,q^u_t} = f\left(\sum_{q^u_{t_i} \in Q^u, t-\hat{w}<t_i<t} \mathbf{S}_{q^u_t - q^u_{t_i}} \mathbf{T}_{t-t_i} \mathbf{q}^u_{t_i} + \mathbf{C}\mathbf{h}^u_{t-\hat{w}, q^u_{t-\hat{w}}}\right)$$

Prediction: how likely user u visits location v?

$$o_{u,t,v} = (\mathbf{h}^u_{t,q_v} + \mathbf{p}_u)^T \mathbf{q}_v$$

- u's current status
- u's static preference
- v's characteristics

Location prediction on Gowalla dataset

		recall@1	recall@5	recall@10	F1-score@1	F1-score@5	F1-score@10	MAP	AUC
Gowalla	TOP	0.0052	0.0292	0.0585	0.0052	0.0097	0.0106	0.0372	0.6685
	MF	0.0100	0.0538	0.1146	0.0100	0.0179	0.0208	0.0527	0.7056
	MC	0.0091	0.0543	0.1015	0.0091	0.0181	0.0184	0.0510	0.7029
	TF	0.0116	0.0588	0.1120	0.0116	0.0196	0.0204	0.0551	0.7097
	PFMC	0.0159	0.0792	0.1535	0.0159	0.0264	0.0279	0.0671	0.7363
	PFMC-LR	0.0186	0.0940	0.1823	0.0186	0.0313	0.0331	0.0763	0.7580
	PRME	0.0203	0.0990	0.1896	0.0203	0.0330	0.0344	0.0847	0.7695
	RNN	0.0257	0.1349	0.2286	0.0257	0.0450	0.0416	0.0921	0.7875
	ST-RNN	**0.0304**	**0.1524**	**0.2714**	**0.0304**	**0.0508**	**0.0493**	**0.1038**	**0.8115**

SERM: A Recurrent Model for Next Location Prediction in Semantic Trajectories

Modeling users' interests.

- Input data: semantic enriched trajectories
- A record has: user, time, coordinates and text

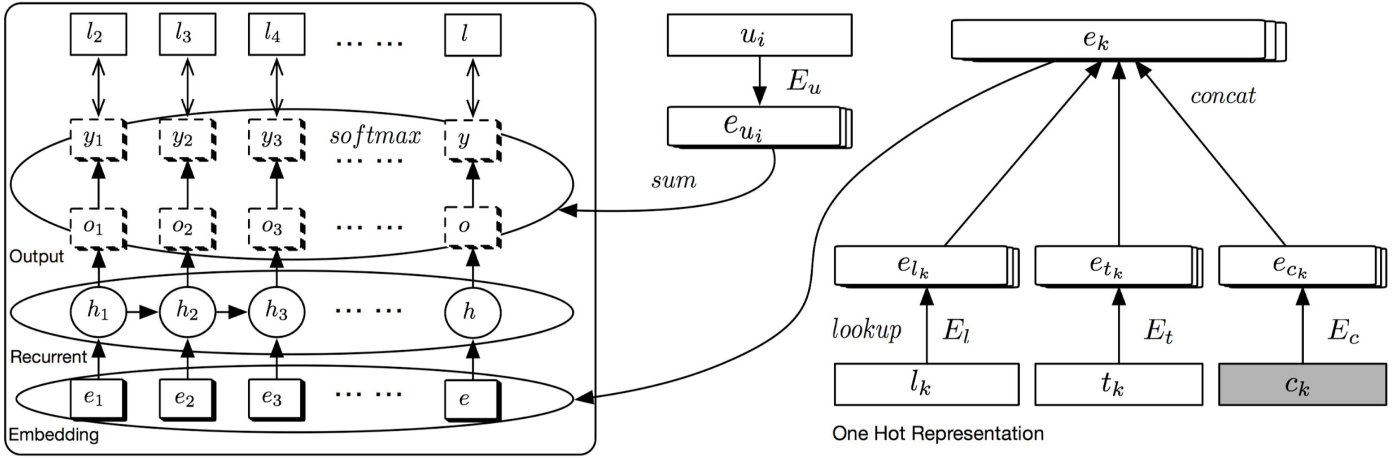
To model a user's next step mobility, we need to consider

- Current location and time. *Location and time embeddings*
- What is the user doing? Activity semantics. *Content embeddings*
- The user's static preference over locations. *User embedding*

SERM: A Recurrent Model for Next Location Prediction in Semantic Trajectories

Factors to consider

- Current location and time. *Location and time embeddings:* e_{lk}, e_{tk}
- What is the user doing? Activity semantics. *Content embeddings:* e_{ck}
- The user's static preference over locations. *User embedding:* e_{uk}

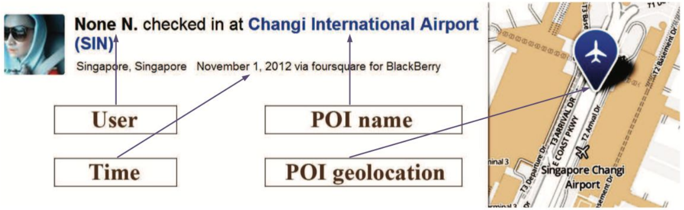


Part IV: Location Recommendation & Prediction

Location Recommendation

Input: a collection of users' check-in records

- Each record has: user, a visiting timestamp, a visited point-of-interest (POI) and its geolocation



Task: recommending unvisited POIs to users

- Help user explore new places
- Help business owners attract more customers

Time is an important context information

- Recommend brunch restaurants in the morning
- Recommend theaters in the evening

Representative Approaches

User-Based Collaborative Filtering

- Yuan et. al. SIGIR 2013

Matrix Factorization Model

- Gao et. al. RecSys 2013

Probabilistic Models

- Yin et. al. CIKM 2015

Time-aware Point-of-interest Recommendation

[Yuan et. al. SIGIR 2013]

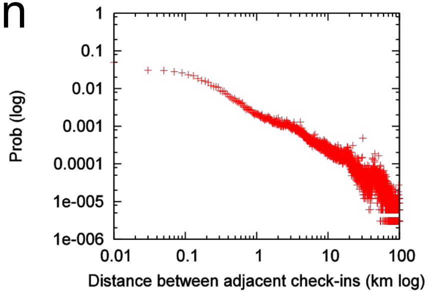
Goal: to recommend POIs for a target user to visit at a specific timeslot in a day:

- Split a day into 24 slots based on hour

Observations: user mobility is influenced by

- Geographical factor: users tend to visit their nearby places
- Temporal factor: users tend to visit different places at different time (morning: libraries; night: pubs)

1. Modeling geographical factor: power-law willingness function



- The willingness of a user to visit *dis* km far away POI:

$$wi(dis) = a \cdot dis^k$$

- The probability a user *u* visit a POI *l* at time *t* is proportional to
  - The product of the willingness of visiting *l* from each visited POI of *u*
  - The visiting popularity of *l* at time *t*

Geographical and Temporal Factors

2. Modeling temporal factor: time-aware collaborative filtering

- Consider time dimension when estimating similarity between two users *u* and *v* at time *t*

$$w_{u,v} = \frac{\sum_l c_{u,l} c_{v,l}}{\sqrt{\sum_l c_{u,l}^2}\sqrt{\sum_l c_{v,l}^2}} \Rightarrow w_{u,v}^{(t)} = \frac{\sum_{t=1}^{T}\sum_l c_{u,t,l} c_{v,t,l}}{\sqrt{\sum_{t=1}^{T}\sum_l c_{u,t,l}^2}\sqrt{\sum_{t=1}^{T}\sum_l c_{v,t,l}^2}}$$

$c_{u,l}$: # check-ins made by user *u* at POI *l*

$c_{u,t,l}$: #check-ins made by user *u* at POI *l* at time *t*

Data Sparsity!!!

check-in records of u

$c_{u,l}$	l_1	l_2
t_1	1	0
t_2	0	1

check-in records of v

$c_{v,l}$	l_1	l_2
t_1	0	1
t_2	1	0

Similarity: 0?

- Users' check-in behaviors at different timeslots are correlated
  - Users tend to visit the same POIs at 12pm and 6pm (for meals)
  - Estimate the cosine similarity $\rho_{t,t'}$ between each pair of timeslots t and t', and use it to smooth check-in records
  - Estimate the temporal similarities using the smoothed records, and then rank POIs based on collaborative filtering

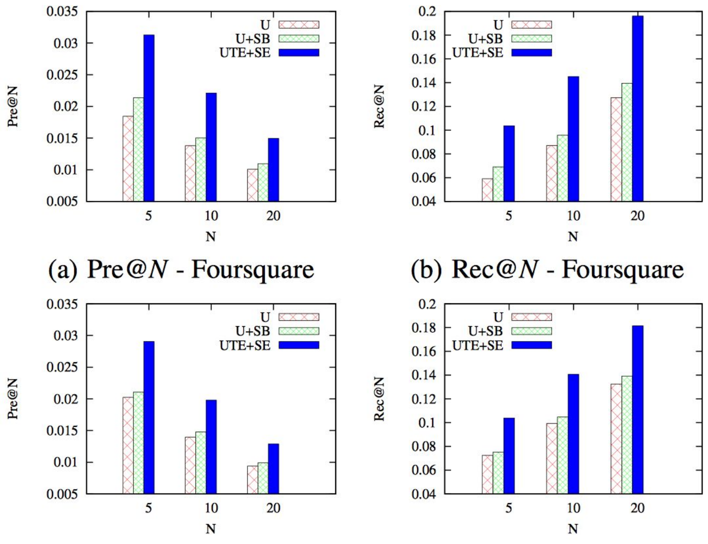
Performance

Linearly combine the geographical and temporal recommendation scores of each POI as its final score

Experiments

- Datasets: Foursquare and Gowalla check-ins
- Metrics: Precision@N and Recall@N
- Methods: user-based CF(U), U + time-unaware spatial model (U+SB), our time-aware CF and spatial model (UTE+SE)

Exploiting time information can significantly
Improve the recommendation accuracy



(a) Pre@N - Foursquare (b) Rec@N - Foursquare

(c) Pre@N - Gowalla (d) Rec@N - Gowalla

Exploring Temporal Effects for Location Recommendation on Location-Based Social Networks [Gao et. al. RecSys 2013]

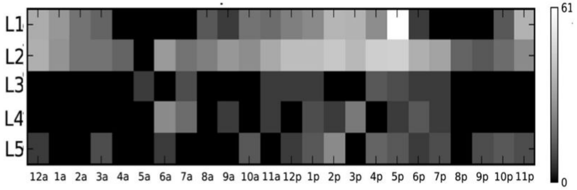
Goal: to recommend POIs for a target user to visit:

- Split a day into 24 slots based on hour

Observations:

- Human movement exhibits significant daily pattern
  - A user regularly arrives to office at 9am, and goes to a restaurant at 12pm
- Temporal properties of a user's daily check-in preferences
  - Non-uniformness: visiting distinct POIs at different hours of a day
  - Consecutiveness: visiting similar POIs in consecutive hours

Daily Check-in Activities



Modeling Temporal Properties

Basic matrix factorization: $$\min_{\mathbf{U}_i \geq 0, \mathbf{L}_j \geq 0} \sum_{i}^{m} \sum_{j}^{n} \mathbf{Y}_{ij} (\mathbf{C}_{ij} - \mathbf{U}_i \mathbf{L}_j^\top)^2$$

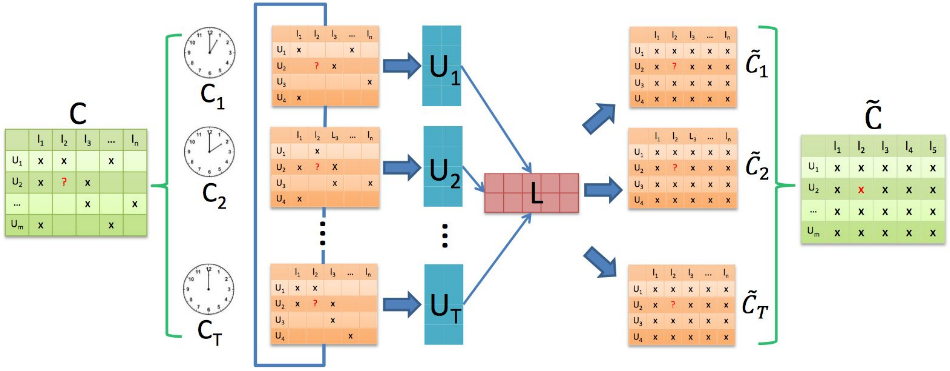
m users, *n* POIs. user-location check-in count matrix $C \in R^{m \times n}$, user preference matrix $U \in R^{m \times d}$, POI characteristic matrix $L \in R^{n \times d}$, indicator matrix $Y \in R^{m \times n}$

- Non-uniformness: visiting distinct POIs at different hours of a day
  - Learn time dependent user preference matrices U_t at each time $_t$
- Consecutiveness: a user’s characteristics at consecutive hours are similar.
  - Use cosine coefficient $\psi_i(t, t-1)$ of user u_i’s check-in preference at time *t* and *t-1* to regularize the U_t and U_{t-1}
- Jointly optimize and learn U_t and L w.r.t. non-uniformness and consecutiveness

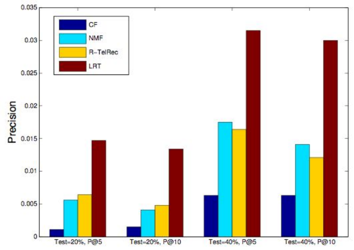
Recommendation and Performance

Recommendation: given a target user u_i and a candidate POI l_j

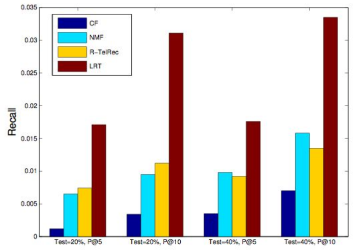
1. Compute the time dependent recommendation scores for all timeslots
2. Aggregate these scores by some strategies (sum, mean, etc.) as the final score



Performance on Foursquare check-ins



(a) Recommendation Performance (Precision)



(b) Recommendation Performance (Recall)

Time effects are helpful for POI recommendation

Joint Modeling of User Check-in Behaviors for Point-of-Interest Recommendation [Yin et. al. CIKM 2015]

Goal: to suggest home-town or out-of-town POIs to users

Factors to be exploited

- Content effect: POI description, e.g., “vegetarian restaurant”
- Temporal effect: user activity exhibits temporal cyclic patterns w.r.t. hour and day
- Geographical influence: people tend to check in around several centers, e.g., “office”
- Word-of-mouth effect: people tend to visit region-level popular POIs

Generative model

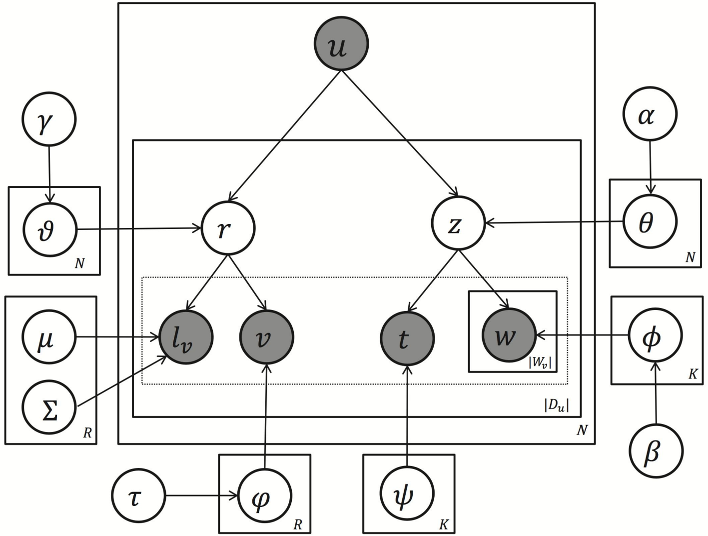
Each user has a distribution over topics (e.g., “dinning”)

We learn temporal topics based on the descriptions (w) of POIs and visiting time (t)

- POIs visited at the same time with similar descriptions tend to belong to the same topic

Each region *r* has a distribution over POIs (*v*) and their geo coordinates (l_v)

Parameters are estimated by Gibbs Sampling



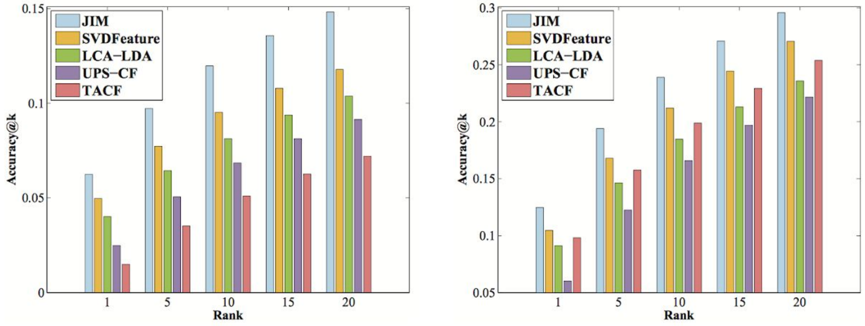
Recommendation and Performance

Given a target user, sort candidate POIs v according to its generative probability

$$P(v, l_v, W_v | u_q, t_q, l_q, \hat{\mathbf{\Psi}})$$

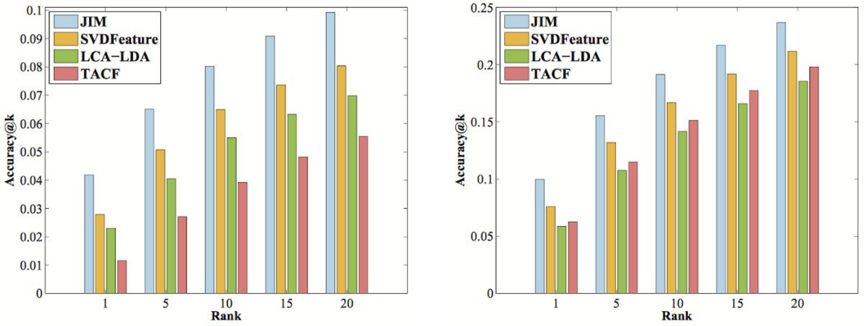
Performance

- In-town/out-of-town recommendation: distance(user’s current loc, user’s home) > 100km



(a) Out-of-town Recommendation (b) Home-town Recommendation

Top-k Performance on Foursquare



(a) Out-of-town Recommendation (b) Home-town Recommendation

Top-k Performance on Twitter

Location Prediction

Input: a collection of users' trajectories

- Each visit has: user, a visiting timestamp, the geo-coordinates of the visited place

User	Time	Coordinates
7909162	2015 06 03 15:44:24	58.34985748, 11.93956238
7909162	2015 06 03 17:56:07	58.36145307, 11.91453369
3818771	2015 06 03 18:11:49	43.17244007, -79.03869084
7111652	2015 06 03 20:16:33	35.96498954, -83.91925795
...	...	...

Task: to predict the location that a target user is going to visit **next** or visit **at a target time**

Applications:

- Logistic planning
- Advertisement targeting
- Pick-up location prediction for carpool

Representative Approaches

Frequent Pattern-based Models

- Monreale et. al. KDD 2009

Hidden Markov Models

- Ye et. al. SDM 2013

Probabilistic Models

- Yuan et. al. WSDM 2017

Supervised Ranking Models

- Noulas et. al. ICDM 2012

WhereNext: a Location Predictor on Trajectory Pattern Mining [Monreale et. al. KDD 2009]

Goal: given the trajectories of users, and the prefix of the trajectory of a target user, predict the next location the user is going to visit.

Basic assumption: people often follow the crowd (common paths)

- Model typical behaviors → predict future movement

Typical behaviors: T-patterns

- A sequence of regions and commuting time

$$RailwayStation \xrightarrow{15min} CastleSquare \xrightarrow{50min} Museum$$

Prediction Pipeline

Extract T-patterns from trajectories

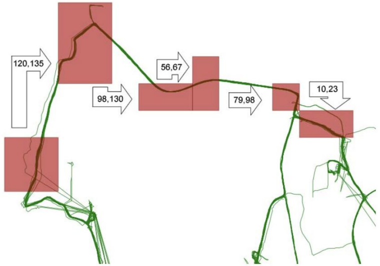
Build T-pattern Tree

- decision tree

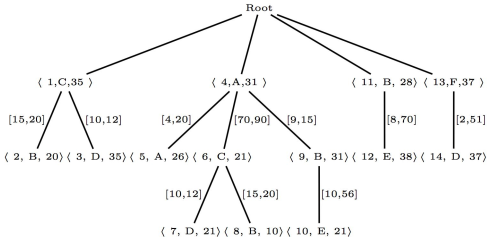
Given a target trajectory, find the best path on the tree that matches the trajectory

- Calculate the matching score for each path

Select the children of the best node that produces the prediction as the next possible locations



Extract T-patterns



Build T-pattern tree

What’s Your Next Move: User Activity Prediction in Location-based Social Networks [Ye et. al. SDM 2013]

Goal: to predict the next venue on LSBNs data

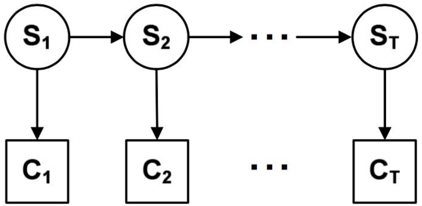
- Each record is labeled with semantic information (name and category of the venue)

The prediction space is huge: millions of venues

2-step method

- Predict the category of user activity at the next step (e.g., entertainment:cinema)
- Predicting a venue given the estimated category distributions

Mixed HMM

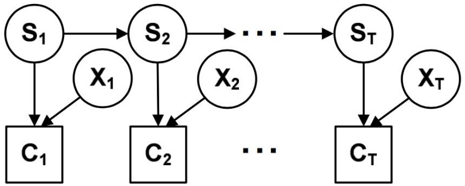


Basic HMM

- Observations: check-in categories

Mixed HMM with Temporal and Spatial Covariates

- Checkin behaviors are influenced by time and location
  - Outdoor → food; @midnight: Outdoor → nightlife
  - Current pos: a shopping mall → next activity: shopping
- Checkin categories are determined by states and time
  - Time: day of a week + hour of a day

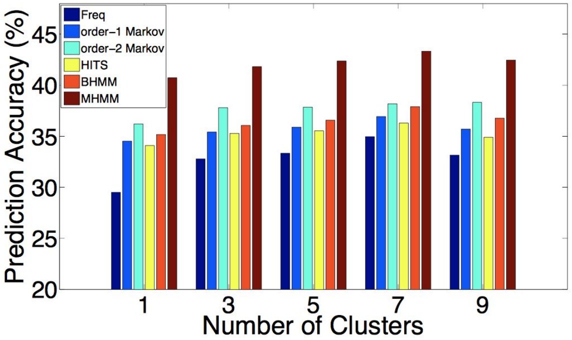


Given the most likely category, rank locations of the category by some ranking schemes (e.g., check-in count, user count, etc.)

Performance

Dataset: 13 million Gowalla check-ins, each check-in has user_id, lat, lng, time, name and category of the location

Category prediction



Location prediction

	Top-1	Top-2	Top-3
PMM [5] with two states	16.82	26.91	34.31
Max check-in by user	**45.63**	**58.80**	**62.81**

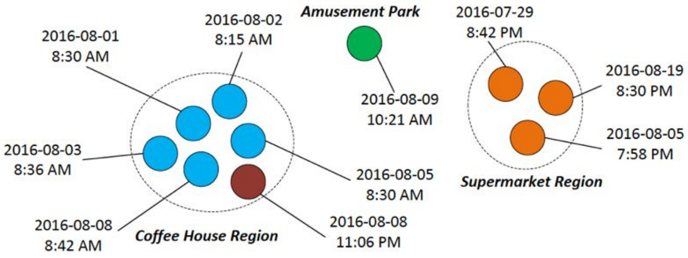
PRED: Periodic Region Detection for Mobility Modeling of Social Media Users [Yuan et al. WSDM 2017]

Goal: predict the geo-coordinates of a user at a specified time

Input: GPS trajectories, each record consists of <user, lat/lng, time>

Basic assumption: a user tend to periodically visit a set of regions

- Visiting a coffeehouse every morning
- Visiting a supermarket every Friday evening



Predict locations using the user’s periodic regions

- The regions in which a user shows periodic visiting behavior
- Consists of geo-regions and visiting periods
- Neither is known

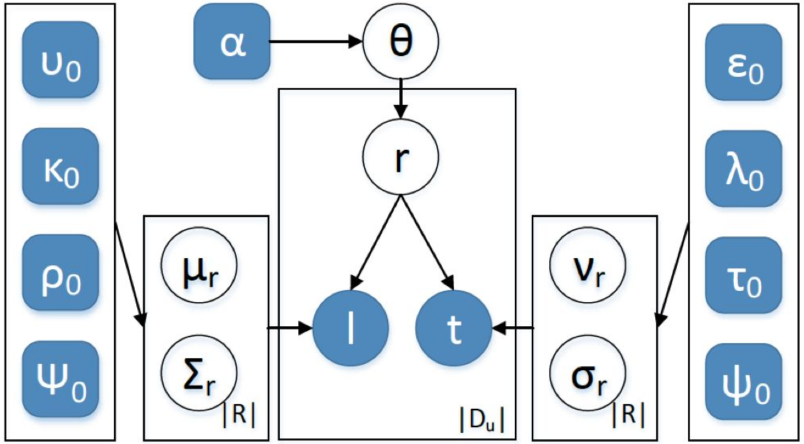
Basic Idea

Clustering records by exploiting spatial and temporal information jointly

- Close in distance
- The gap time between two consecutive records should approximately be a multiple of the period

Generative model: for each record

- Sample a region r
- Sample geo coordinates from the spatial Gaussian distribution of r
- Sample a gap visiting time from the temporal Gaussian distribution of r



Prediction and Performance

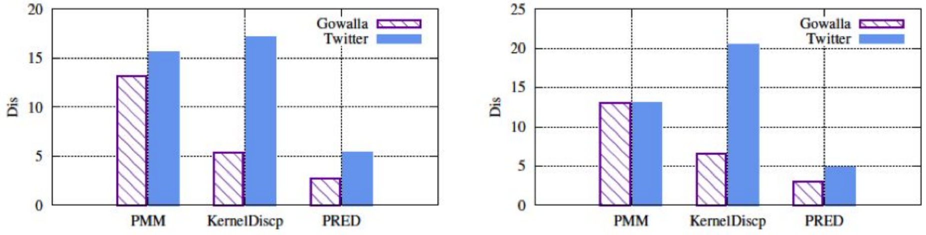
Given a target user u and target time t, we find the region with the greatest visiting probability, and return its center as the predicted location.

Datasets: Gowalla check-ins (Gowalla) of 550 users and Tweets (Twitter) of 550 users

Evaluation metric

- Error distance: Euclidean distance

  between the true and predicted locations



(a) Macro Error Distance (b) Micro Error Distance

- Macro (averaged by users); Micro (averaged by test instances)

Mining User Mobility Features for Next Place Prediction in Location-based Services [Noulas et. al. ICDM 2012]

Goal: given a collection of check-ins, a target user u and his/her current check in <*l’*, *t’*>, predict the venue that u is going to visit next.

- Check-in: <venue, time>

Model the prediction problem as a ranking task: compute score for each venue

Features

- User Mobility Features
  - Historical Visits: the count of visits of u at a venue
  - Categorical Preferences: the count of visits of u at venues of a category
  - Social Filtering: how many times u’s friends visit a venue

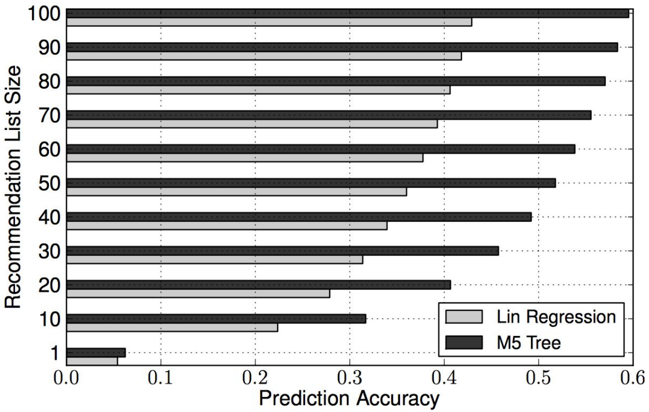
Mining User Mobility Features for Next Place Prediction in Location-based Services [Noulas et. al. ICDM 2012]

Features

- User Mobility Features
- Global Mobility Features
  - Popularity: count of check-ins at a venue
  - Geographic Distance: how far a venue is to u's all visited venues
  - Activity Transitions: sequence of category transition between consecutive check-ins
- Temporal Features
  - The numbers of check-ins made at a venue (category) within a hour / day

Supervised classifiers:

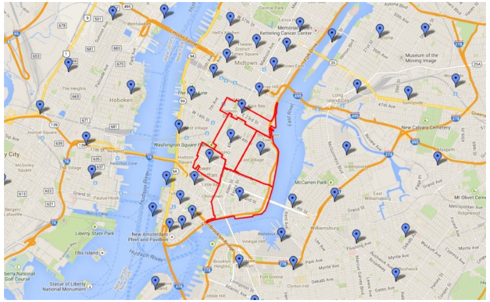
- linear regression
- M5 model trees

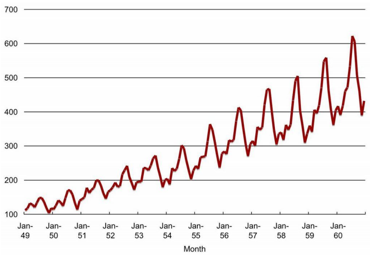


Part V: Research Frontiers and Summary

Integrating Heterogeneous Modalities and Sources

A trend in the confluence of multiple modalities (text, image, space, time, user) and different sources (surveillance camera, traffic sensor, social media, etc)

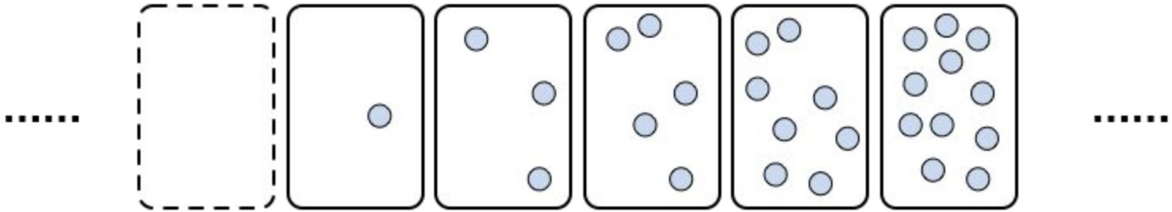




How to combine different modalities and sources for **ambient intelligence**?

Online and Efficient Learning

In many scenarios, the data continuously arrive in large volumes.



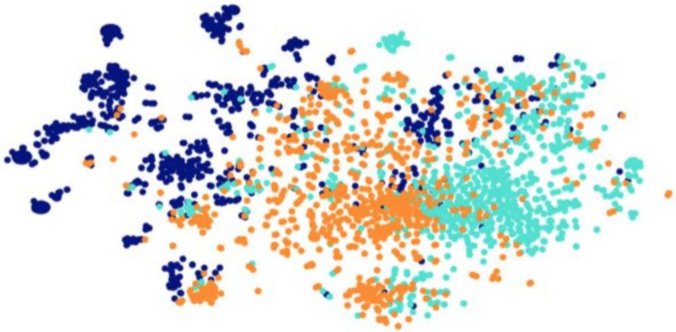
How do we design online and efficient learning algorithms?

- Semantic drift, high throughput

Representation Learning for Social Sensing Data

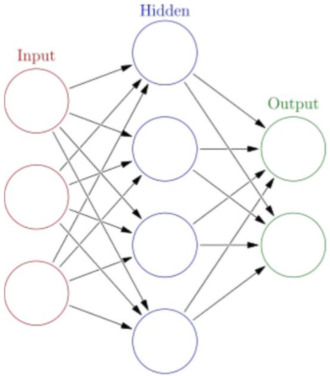
Unsupervised representation learning

- How to capture the correlations among different factors
- The learned representations are useful for downstream applications



Supervised representation learning

- Optimize representations for the task at hand
- Often need sufficient data



Learning with Data and Label Sparsity

Data sparsity:

- How to model human activities from small data?
- Can we incorporate external knowledge effectively?

Label sparsity:

- How to build models if the labels are scarce?
- Unsupervised learning, semi-supervised learning, transfer learning

Summary

Space and time coupled social media analysis can be a game changer for many applications.

- Smart city, traffic scheduling, disaster control, mobile healthcare

Many different methodologies have been proposed:

- Topic models, cross-modal embedding, sequential models

Important research challenges remain to be solved:

- Online learning, modality fusion, data scarcity

Thanks!