

Geo-Multimedia Analysis and Applications

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Outline

- Introduction
- Two cases
 - Landmark Analysis
 - Cross-Region Food Analysis
- Conclusions



Outline

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Introduction

The fast development of various networks leads to rich multimedia data



Internet



sensor network



mobile network



Internet of things



social network



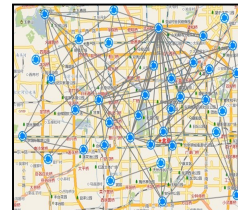
news



weblog



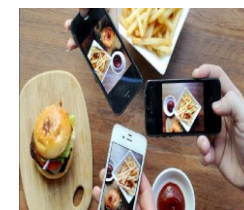
TV news



user behavior data



surveillance video



images



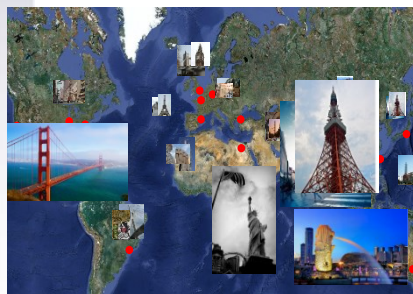
Introduction

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Geo-multimedia data



flickr



YouTube



foursquare

我在#Singapore#，在NUS的斜坡路 <http://t.cn/zjnc9L> (来自 @图钉)



Singapore
新加坡共和国是位于马来半岛南端的一个岛国。其北面隔柔佛海峡与马

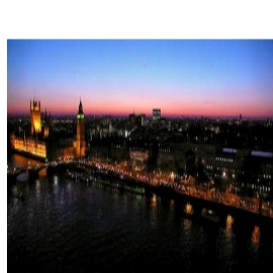
话题详情 49

新加坡 新加坡 Pasir Panjang - 显示地图

新浪微博

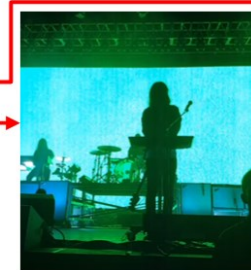
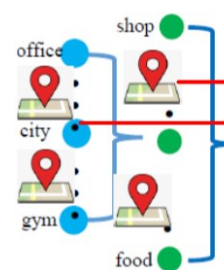
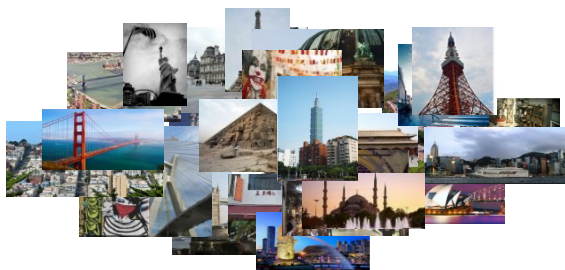
Three characteristics

Location with different granularities



(51.6174,0.1246)

landmarks: Big Ben



Liujiang Jazz Club



Shopping Mall

check-in: venues



scene category



Cuisine American

Course Main Dishes

Ingredients chili-powder
garlic cinnamon ground-
cumin onion-powder
pepper flank-steak



Cuisine French

Course Desserts Breakfast
and Brunch

Ingredients bread brown-
sugar melted-butter egg milk
maple-syrup vanilla-extract
sugar ground-cinnamon



Cuisine Chinese

Course Appetizers; Main
Dishes

Ingredients medium-
shrimp ground-pork bamboo-
shoot canola-oil sesame-oil
ground-white-pepper wonton-
wrapper corn-starch soy-sauce
chile-sauce

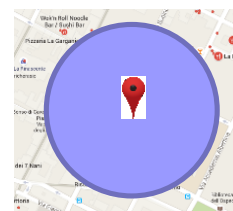
region-level

Three characteristics

■ multi-modality and heterogeneity



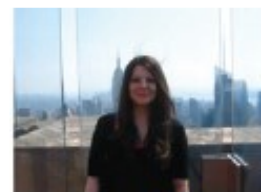
multi-modality



Location



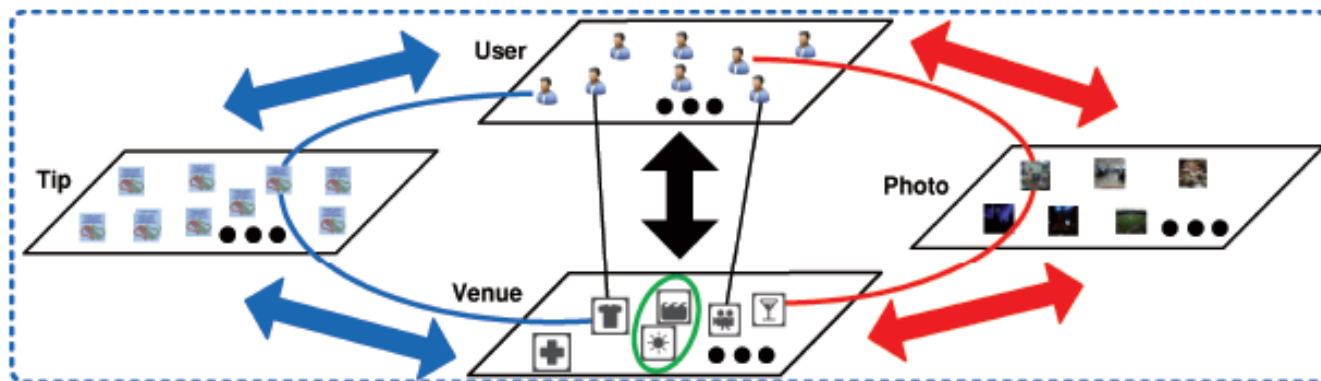
Time



{Female, Middle-Aged, Caucasian}



multi-context



multi-interaction

Three characteristics

■ Big Geo-Multimedia Data

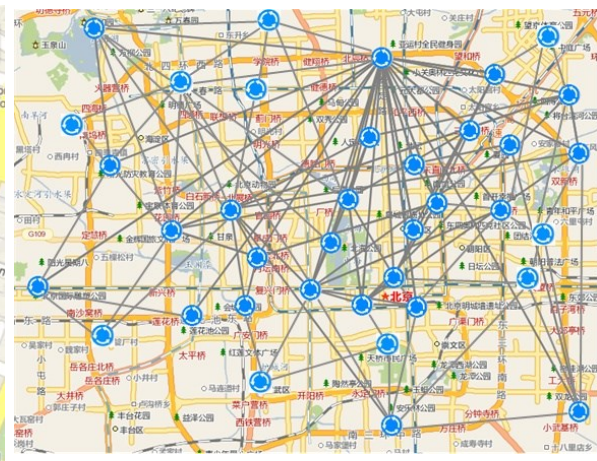
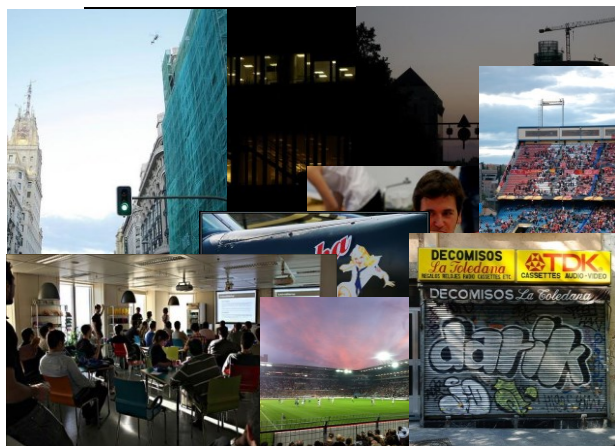




**Such rich Geo-Multimedia Big data
holds great potentials but also
encompass challenges**

Opportunities

- **Big** geo-multimedia data treasure
 - Travel data, including landmarks, GPS trajectories
 - Check-in data, different venues
 - Event data, hot event data



Opportunities

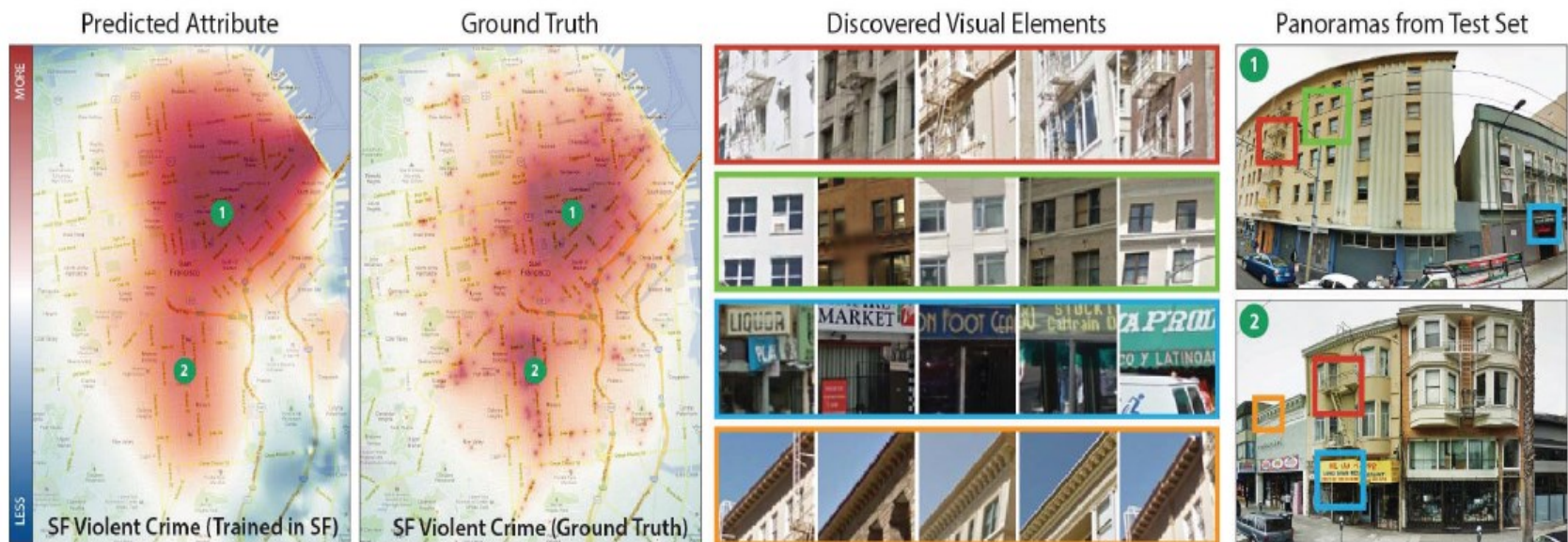
- geo-multimedia computer vision
- Geo-Multimedia high-level attribute learning



Abhimanyu Dubey, Nikhil Naik, Devi Parikh, Ramesh Raskar, and Csar A. Hidalgo. Deep Learning the City: Quantifying Urban Perception at a Global Scale. **ECCV 2016**.

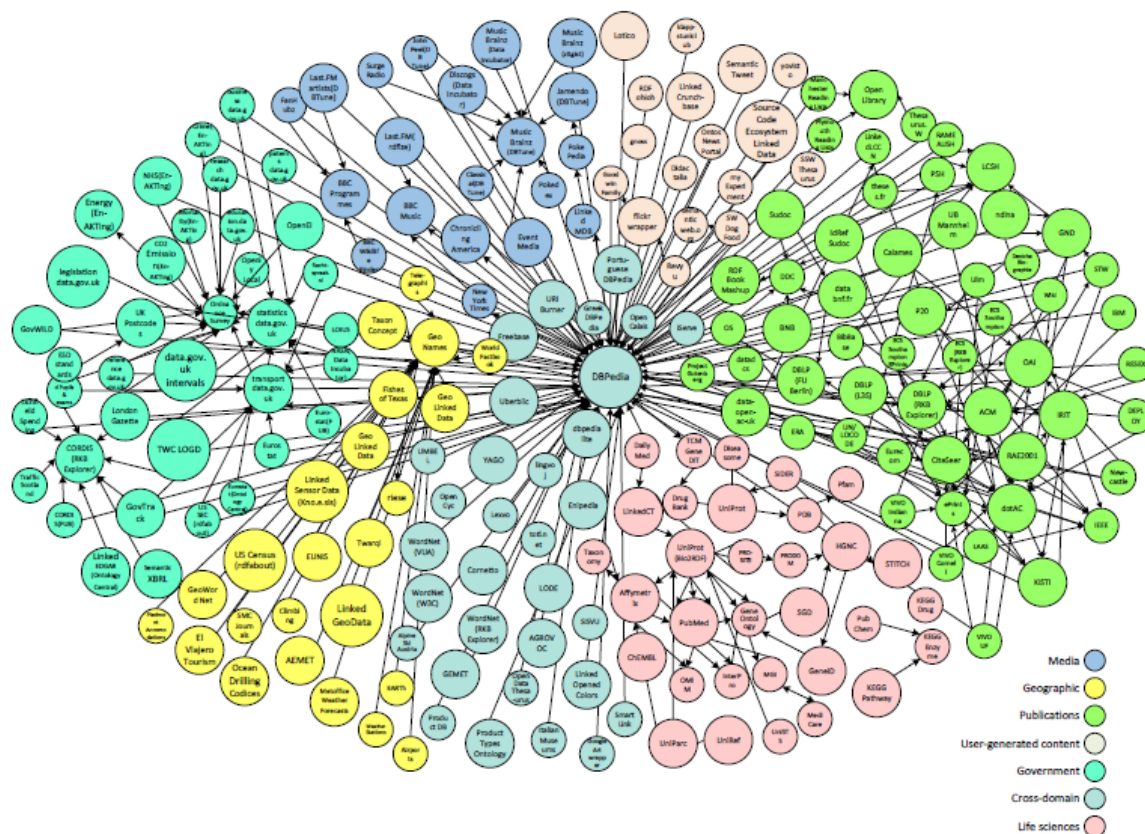
Opportunities

- geo-multimedia computer vision
relationship prediction between visual elements and a
number of city attributes e.g. violent crime rates



S. M Arietta, A. A Efros, R Ramamoorthi, and M Agrawala. City forensics: Using visual elements to predict non-visual city attributes. Visualization and Computer Graphics IEEE Transactions on, 20(12):2624–2633, 2014.

■ geo-multimedia knowledge graph construction and learning



Yu-xin Peng et al. Cross-media analysis and reasoning: advances and directions. Front Inform Technol Electron Eng. 2017



Opportunities

- Various applications in different fields
 - ☐ Region oriented food culture analysis
 - ☐ Region oriented user behavior analysis
 - ☐ Location based retrieval and recommendation
 - ☐ User profile
 - ☐ Other location based services
 - ☐



Challenges

- Effectively manage geo-multimedia big data, from access, store to retrieval
- Overcome the noisy content and location ambiguity
- Overcome the semantic gap
- Learn geographical hierarchy visual features
- Large scale geo-multimedia data feature learning (Web Vision)
-



Research Problems

- Organizing, summarizing and browsing the geo-multimedia data
- Mining and extracting the knowledge from the geo-multimedia data
- Predicting geographic location and other high-level attributes from photos/videos
- Exploring various applications, especially in vertical fields



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Two cases

■ Landmark Analysis



■ Cross-Region Food Analysis



Two Cases

■ Landmark Analysis



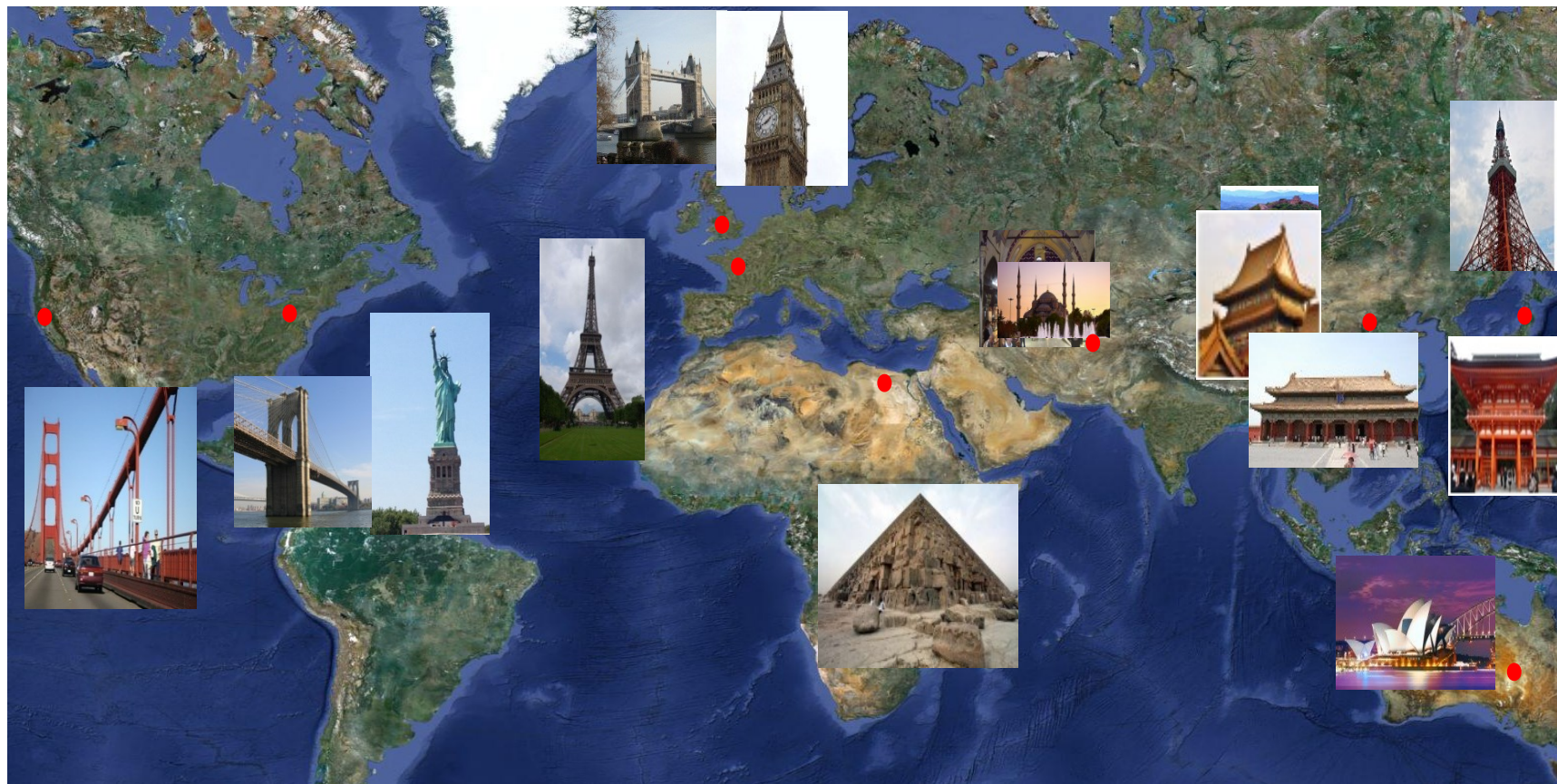
■ Cross-Region Food Analysis





Motivation

Landmark: A recognizable place that might be of interest to tourists due to notable physical features or historical significance - Wikipedia



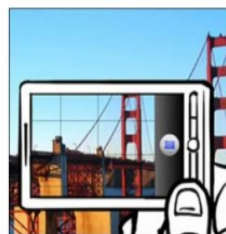


Motivation

flickr



Tour recommendation



Location recognition



Virtual 3D street



Motivation



Relevant Tags:
Japan, gate, Kiyomizu-dera
temple, Kyoto Torii, architecture,

Temple



Relevant Tags:
Kiyomizu-der, cherry blossoms,
sakura, April

April Sakura



Relevant Tags:
color, autumn leaf, maple,
kiyomizu-dera temple, red,

Autumn Maple



Our idea

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pictures			
time	2006年8月29日	2008年4月8日	2012年11月21日
tags	Japan August 2006 Kiyomizu-dera Kyoto tour	Japan geotagged Kyoto Higashiyama Kiyomizu-dera Gate Sakura Blossoms	autumn color autumn leaf kiyomizu-dera temple kyoto japan maple
title	Kyoto Orange, version 672	Entrance Gate to Kiyomizu-dera	Autumn Color at Kiyomizu-dera tour Panorama of the city center of Kyoto from Kiyomizu-dera (the right hand).
Desc.	They have this amazing red-orange all over the shrines temples in Kyoto.	Kiyomizu-dera, Southern Higashiyama architecture	
	Global theme	Location theme	Time theme



Mining three kinds of themes for landmark analysis



Spatio-Temporal Theme Modeling

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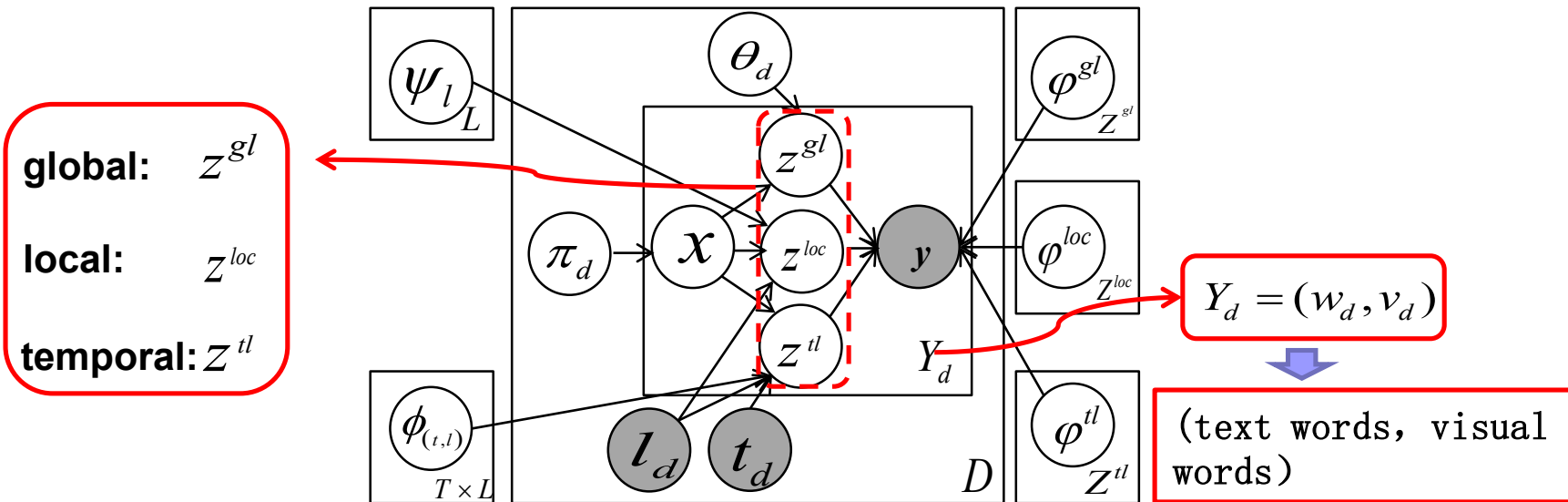
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Three kinds of themes

- Global theme z^{gl} : shared by all landmarks
- Local theme z^{loc} : landmark specific unique physical and historical characteristics
- Temporal theme z^{tl} : time-specific theme from one landmark

Spatio-Temporal Theme Modeling

■ The graphical representation





Spatio-Temporal Theme Modeling

■ Log-likelihood of the dataset

$$\begin{aligned}
 L(D) = & \sum_{d \in D} \sum_{y \in Y} n(d, n) \\
 & \times \log[p(x = gl|d) \sum_{z \in Z^{gl}} \theta_{d,z} \varphi_{z,y}^{gl}] \\
 & \times p(x = loc|d) \sum_{z \in Z^{loc}} \psi_{l_d,z} \varphi_{z,y}^{loc} \\
 & \times p(x = tl|d) \sum_{z \in Z^{tl}} \phi_{(t_d,l_d),z} \varphi_{z,y}^{tl}
 \end{aligned}$$

■ Mutual-Information-Based Regularization

$$\max(L(D) + \lambda_1 I_l(L; Z^{loc}) + \lambda_2 I_{(l,t)}((L, T); Z^{lt}))$$



$$I_l(L; Z^{loc}) \triangleq \sum_{l \in L} \sum_{z \in Z^{loc}} p(l, z) \log \frac{p(l, z)}{p(l)p(z)}$$

$$I_{(l,t)}((L, T); Z^{lt}) \triangleq \sum_{(l,t) \in (L, T)} \sum_{z \in Z^{lt}} p((l, t), z) \log \frac{p((l, t), z)}{p((l, t))p(z)}$$

■ Parameter Estimation EM



Spatio-Temporal Theme Modeling

- Time distribution of theme for one landmark

$$p(t|z, l) = \frac{\phi(l, t)p(t, l)}{\sum_{t' \in T} \phi(l, t')p(t', l)}$$

- Location distribution of theme for a time interval

$$p(l|z, t) = \frac{\phi(l, t)p(t, l)}{\sum_{l' \in L} \phi(t, l')p(t, l')}$$



Experiment

■ Dataset

- 20 landmarks from 6 countries
- 435,810 images, 22,703 words
- Jan 01, 2010 to Dec 31, 2012

Landmark	Landmark
Arc De Triomphe	Big Ben
Brooklyn Bridge	Buckingham Palace
Eiffel Tower	Washington Monument
Forbidden City	Golden Gate Bridge
Great Wall	Kiyomizu-dera
London Eye	Lincoln Memorial
Statue of Liberty	Notre Dame
Summer Palace	Sydney Opera House
Tokyo Tower	Tower Bridge
Trafalgar Square	White House



Theme visualization

$$\text{sim}(Z_i, d_j) = \frac{(w_{z_i}, v_{z_i})(w_{d_j}, v_{d_j})}{|(w_{z_i}, v_{z_i})| |(w_{d_j}, v_{d_j})|}$$

Local #5



0.157004



0.152931



0.152222



0.150788



0.150391

Local #26



0.135706



0.135705



0.131267



0.130258



0.126970

Theme visualization

$$\text{sim}(Z_i, d_j) = \frac{(\mathbf{w}_{z_i}, \mathbf{v}_{z_i})(\mathbf{w}_{d_j}, \mathbf{v}_{d_j})}{\|(\mathbf{w}_{z_i}, \mathbf{v}_{z_i})\| \|(\mathbf{w}_{d_j}, \mathbf{v}_{d_j})\|}$$

Temporal #67



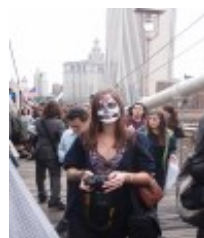
0.101686



0.101680



0.101607



0.101482



0.101471

Temporal #70



0.203266



0.203159



0.202948



0.185978



0.183135



Quantitative evaluation

Metric: number of discovered local themes and temporal themes

# Methods	# local themes	# temporal themes
PLSA	17	22
TM	20	25
mmSTTM_Text	27	39
mmSTTM	30	45

Metric: MAP for number of discovered themes

# Methods	MAP@10 For Words	MAP@10 For Photos
PLSA	0.6188	0.5887
TM	0.6867	0.6368
mmSTTM_Text	0.7837	0.7411
mmSTTM	0.8399	0.8025



Location distribution of themes

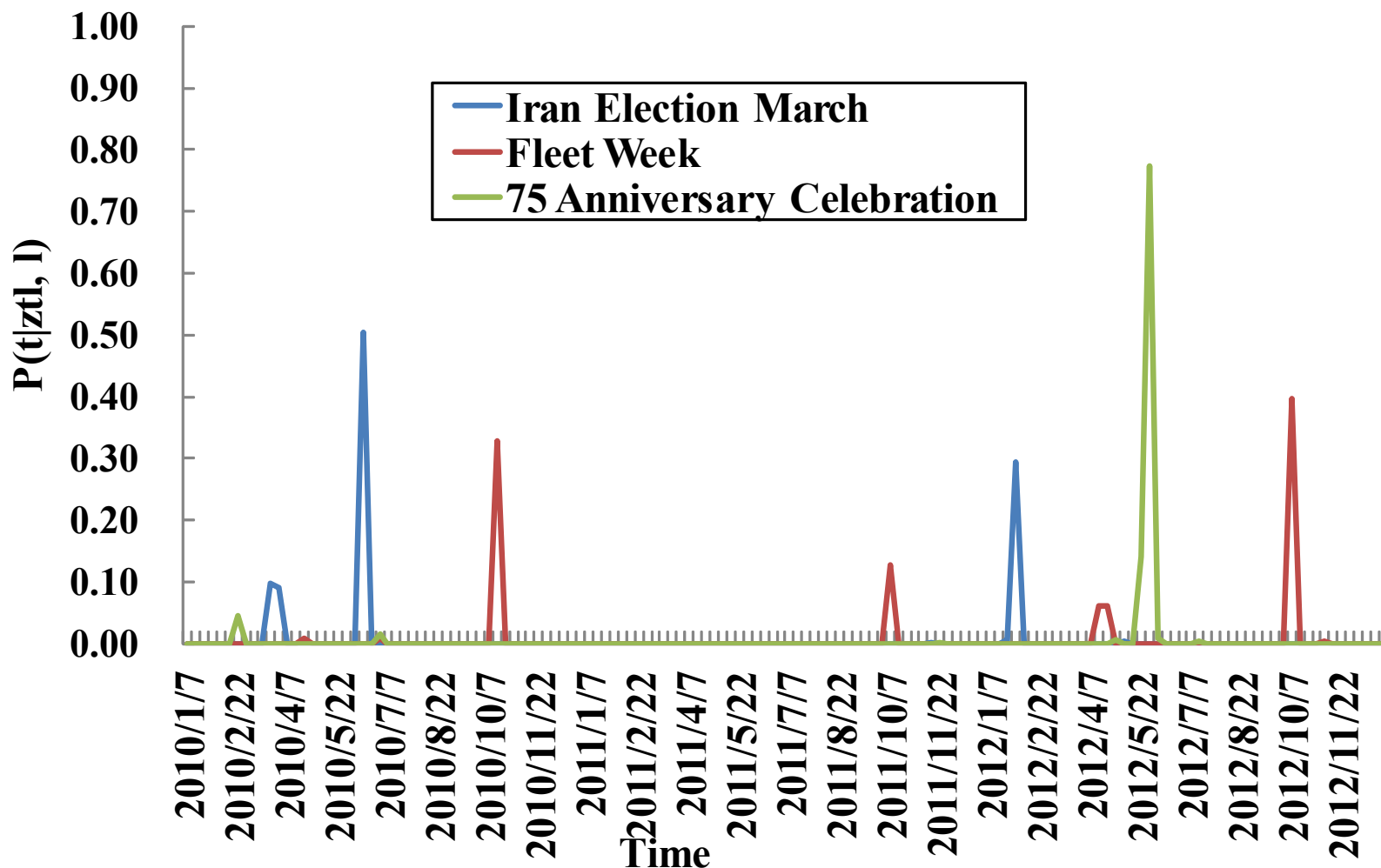
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Landmarks		07/22/2012-07/31/2012	
		$P(l z_{tl},t)$	Relevant photos
Tower Bridge		0.64	
Big Ben		0.30	
London Eye		0.05	
Buckingham Palace		0.003	
Trafalgar Square		0.0001	



Temporal distribution of themes



Two Applications

■ Landmark Analysis



■ Cross-Region Food Analysis



Motivation

- Each region/country/city has formed a distinct identity, distinguishing itself from other regions
- Different aspects jointly determine the identity



Architecture

Athletic activity

Social activity



Vegetation

Food

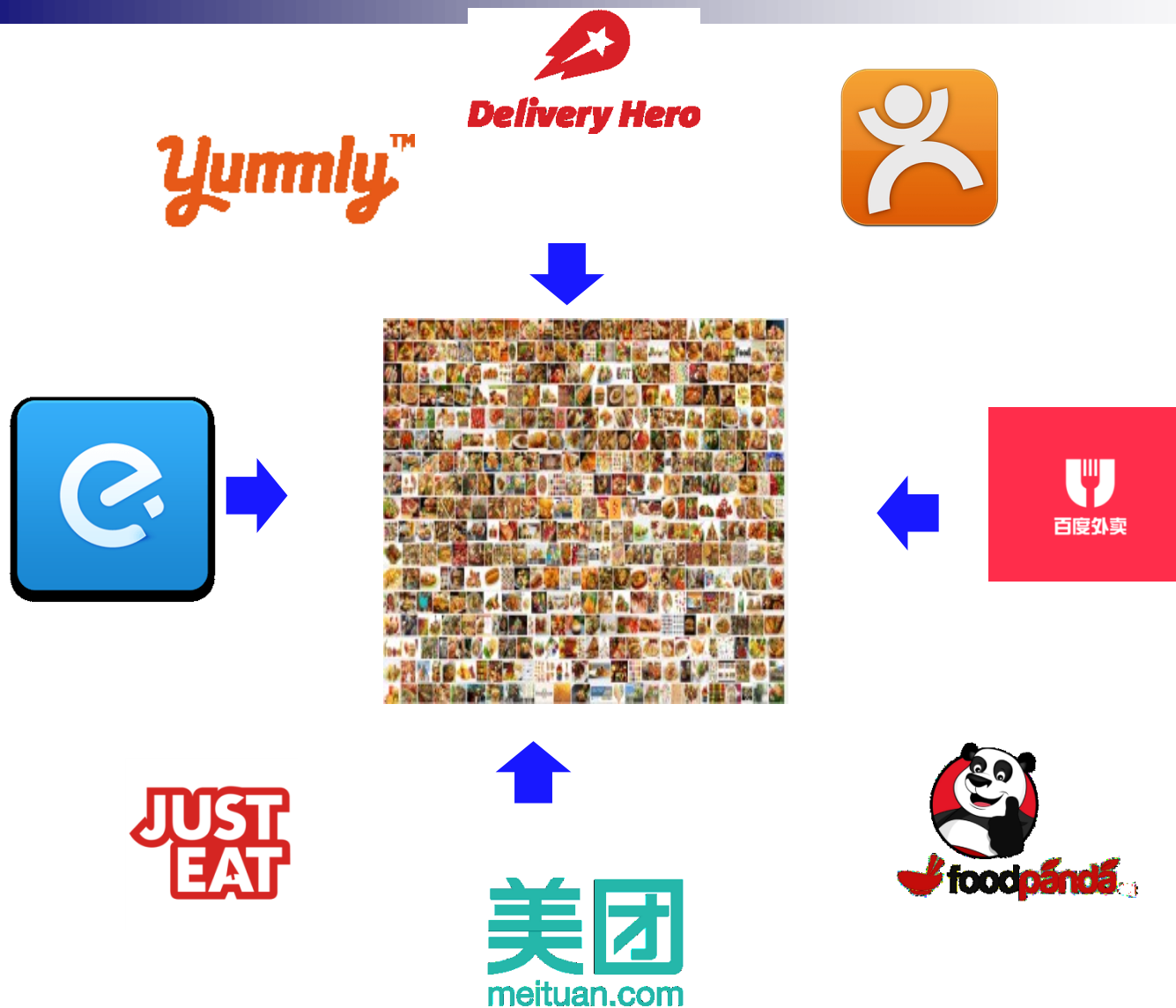
Transportation



Motivation

- Food has always been a significant aspect of region identity.
- The Food recipes from different regions are strong signals of the culinary habits of individuals from various parts of the world
 - Food ingredients: East Asian: “soy sauce ” and “sesame oil”
 - Food flavor: The flavor of Asian is more similar than Europe
 - Food visual appearance
 -
- Cross-region food analysis
 - can facilitate deep understanding of food from the health, marketing and cultural perspectives
 - Enable various applications: food preference learning and recommendation, cuisine classification and health diet analysis

Motivation-Data Collection

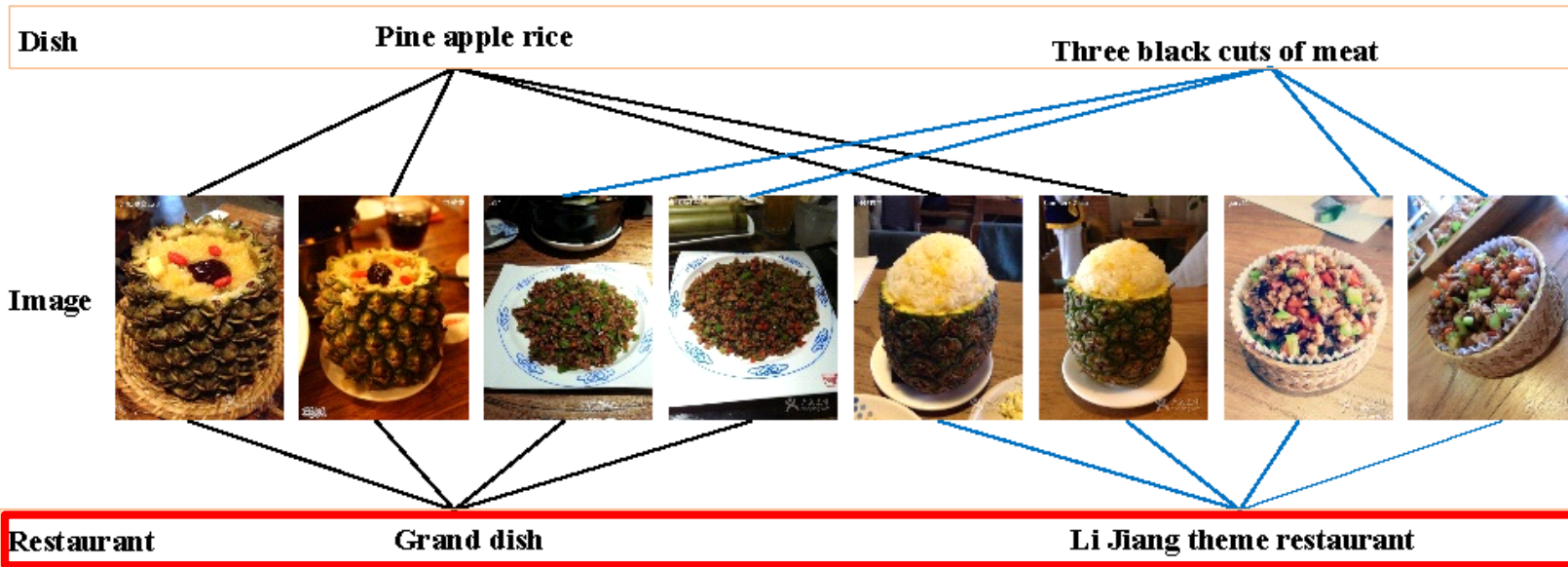


Recipe-Sharing Website: Yummly



Photos			
Ingredients	"1 medium onion, chopped fine", "1 teaspoon canola oil", "3 teaspoons sugar", "1 15-oz can tomato sauce", "1 pound boneless, skinless chicken breasts 	"6 bone-in chicken thighs", "1/2 cup maseca masa flour plus 1/2 cup water", "2 dried ancho chiles, stems removed", "2 medium tomatoes, cut in half", "3 cloves garlic, peeled", "2 chayote squash, or 2 large potatoes",	"1 pound mild Italian chicken sausage", "3 carrots", "1 stalk celery", "1 tablespoon extra virgin olive oil", "8 cups chicken broth "1 tablespoon dried Italian seasoning",
Text/Name	Chicken Enchiladas	Ancho Chicken Soup with Masa Dumplings	Hearty Italian Basil Sausage Soup
Cuisine	Mexican	Mexican	Italian
Course	Main Dishes	Soups	Soups

Venue Review Website: Dianping





Our Data Collection: Yummly-66K

■ Data Collection

- 66,615 recipes
- Each recipe: food image, ingredients, course, cuisine(region)

#items	#Cuisine	#Course	#ingredients
66,615	10	13	2,416

Cuisine	#items	Cuisine	#items
American	13,262	Italian	9,401
Greek	4,998	Japanese	4,804
Mexican	7,960	Indian	5,470
French	6,173	Spanish	4,014
Thai	5,282	Chinese	5,251

<http://isia.ict.ac.cn/dataset>

Our Data Collection: Yummly-66K

■ Data Collection



Cuisine American
Course Main Dishes

Ingredients chili-powder
garlic cinnamon ground-
cumin onion-powder
pepper flank-steak



Cuisine French
Course Desserts Breakfast
and Brunch
Ingredients bread brown-
sugar melted-butter egg milk
maple-syrup vanilla-extract
sugar ground-cinnamon



Cuisine Chinese
Course Appetizers; Main
Dishes
Ingredients medium-
shrimp ground-pork bamboo-
shoot canola-oil sesame-oil
ground-white-pepper wonton-
wrapper corn-starch soy-sauce
chile-sauce

Data Input

Yummly



Cuisine: American

Course: Main Dishes

Ingredients:

chili-powder onion-powder
garlic pepper
cinnamon flank-steak
ground-cumin



Cuisine: French

Course: Desserts; Breakfast
and Brunch

Ingredients:

milk sugar bread egg
maple-syrup brown-sugar
vanilla-extract melted-butter
ground-cinnamon



Cuisine: Chinese

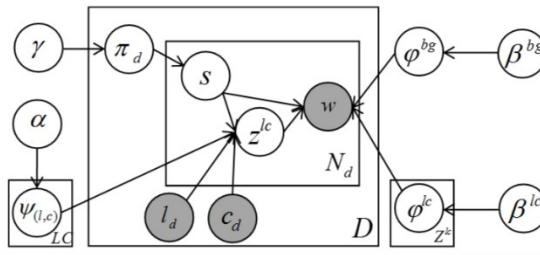
Course: Appetizers; Main dishes

Ingredients:

wonton-wrapper soy-sauce
ground-pork chile-sauce
medium-shrimp corn-starch
bamboo-shoot canola-oil
sesame-oil

Cuisine-Course Theme Modeling and Visualization

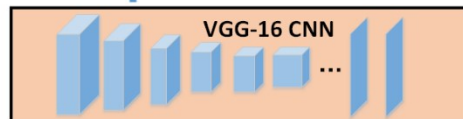
Bayesian Cuisine-Course Theme Model



Manifold Ranking for Theme Visualization

$$J(F) = \frac{1}{2} \left(\sum_{i,j=1}^N S_{ij} \left\| \frac{f_i}{\sqrt{D_{ii}}} - \frac{f_j}{\sqrt{D_{jj}}} \right\|^2 + \lambda \sum_{i=1}^N \|f_i - y_i\|^2 \right)$$

$$= \text{Tr}(F^T L F) + \lambda \|F - Y\|^2$$

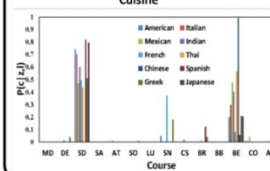
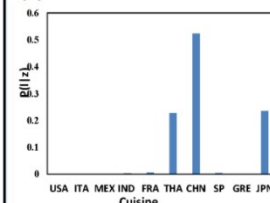


Applications

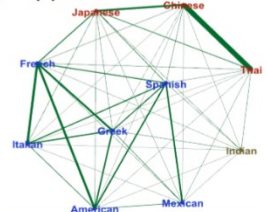
(1) Multi-modal Cuisine Summarization



(2) Cuisine-Course Pattern Analysis



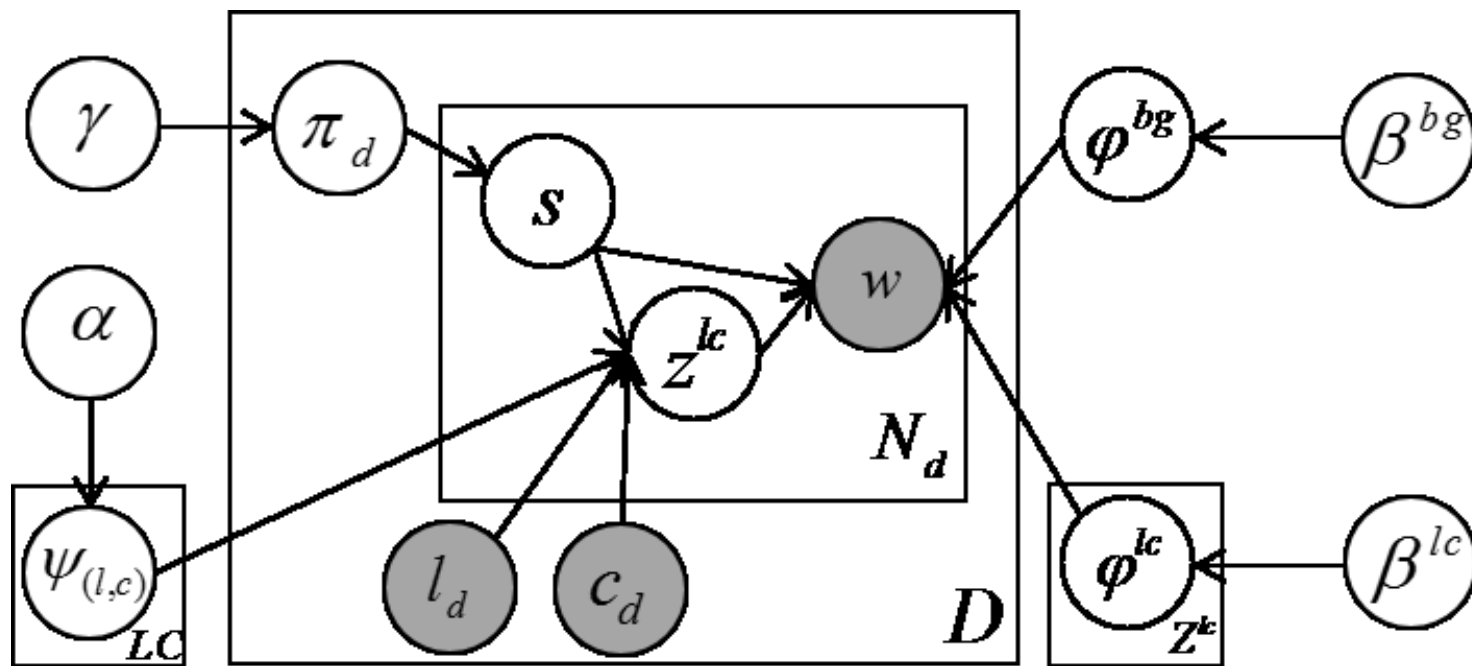
(3) Cuisine Recommendation



Ingredients:
ground-beef
soy-sauce
corn-starch
spice-powder
garlic
minced-ginger

Cuisine: Chinese
Course: Main Dish

Bayesian Cuisine-Course Theme Model



- w : the ingredients
- l_d : the cuisine label
- c_d : the course label

■ Generative Process

- 1) Draw a distribution over ingredients $\varphi^{bg} \sim Dir(\beta^{bg})$ for the background theme
- 2) For each cuisine-course theme $z \in \{1, \dots, Z^{lc}\}$, draw a multinomial distribution $\varphi_z^{lc} \sim Dir(\beta^{lc})$ over ingredients
- 3) For each cuisine-course pair $(l, c) \in \{1, \dots, LC\}$, draw a multinomial distribution $\psi_{(l,c)} \sim Dir(\alpha)$ over cuisine-course themes.
- 4) For each recipe $d \in \{1, \dots, D\}$
 - a) draw $\pi_d \sim Beta(\gamma)$,
 - b) for each ingredient $w_{d,n} \in \mathbf{w}_d$
 - i) Draw a switch variable $s_{d,n} \sim Binomial(\pi_d)$
 - ii) if $s_{d,n} = bg$
draw an ingredient $w_{d,n} \sim Multi(\varphi^{bg})$
 - iii) if $s_{d,n} = lc$
draw a theme $z_{d,n} \sim Multi(\psi_{(l_d, c_d)})$
draw an ingredient $w_{d,n} \sim Multi(\varphi_{z_{d,n}}^{lc})$

■ Model Inference

(i) sample s given the current estimate of z

$$p(s_i = bg | w = w_i, \mathbf{s}_{\neg i}, \mathbf{z}_{\neg i}, \mathbf{W}_{\neg i})$$

$$\propto \frac{n_{w_i, \neg i}^{bg} + \beta^{bg}}{\sum_{w'} n_{w', \neg i}^{bg} + W \beta^{bg}} \frac{n_{d, s_i, \neg i} + \lambda}{n_{d, bg, \neg i} + n_{d, lc, \neg i} + 2\lambda}$$

$$p(s_i = lc | z_i, w = w_i, \mathbf{s}_{\neg i}, \mathbf{z}_{\neg i}, \mathbf{W}_{\neg i})$$

$$\propto \frac{n_{(l_d, c_d), z_i, \neg i}^{lc} + \alpha}{\sum_z n_{(l_d, c_d), z, \neg i}^{lc} + Z \alpha} \frac{n_{d, s_i, \neg i} + \lambda}{n_{d, bg, \neg i} + n_{d, lc, \neg i} + 2\lambda}$$

(ii) sample z given the current estimate of s

$$p(z_i | s_i = lc, w = w_i, \mathbf{z}_{\neg i}, \mathbf{s}_{\neg i}, \mathbf{W}_{\neg i})$$

$$\propto \frac{n_{z_i, w_i, \neg i}^{lc} + \beta^{lc}}{\sum_{w'} n_{z_i, w', \neg i}^{lc} + W \beta^{lc}} \frac{n_{(l_d, c_d), z_i, \neg i}^{lc} + \alpha}{\sum_{z'} n_{(l_d, c_d), z', \neg i}^{lc} + Z \alpha}$$

Bayesian Cuisine-Course Theme Model

- Parameter estimation

$$\hat{\pi}_{d,s} = \frac{n_{d,s} + \gamma}{n_{d,bg} + n_{d,lc} + 2\gamma} \quad s \in \{bg, lc\}$$

$$\hat{\psi}_{(l,c),z} = \frac{n_{(l,c),z}^{lc} + \alpha}{\sum_{z'} n_{(l,c),z'}^{lc} + Z\alpha}$$

$$\hat{\varphi}_w^{bg} = \frac{n_w^{bg} + \beta^{bg}}{\sum_{w'} n_{w'}^{bg} + W\beta^{bg}}$$

$$\hat{\varphi}_{z,w}^{lc} = \frac{n_{z,w}^{lc} + \beta^{lc}}{\sum_{w'} n_{z,w'}^{lc} + W\beta^{lc}}$$

Theme Visualization-Manifold ranking

$$J(F) = \frac{1}{2} \left(\sum_{i,j=1}^N S_{ij} \left\| \frac{f_i}{\sqrt{D_{ii}}} - \frac{f_j}{\sqrt{D_{jj}}} \right\|^2 + \lambda \sum_{i=1}^N \|f_i - y_i\|^2 \right) \quad (5)$$

$$= Tr(F^T L F) + \lambda \|F - Y\|^2 \quad (6)$$

$$\min_F \{Tr(F^T U F) + \lambda \|F - Y\|^2\}$$

VGG-16 deep features

$$y_{(l,c),i} = \begin{cases} \frac{\hat{\varphi}_z^{lc} \mathbf{w}_{d_i}^T}{|\hat{\varphi}_z^{lc}| |\mathbf{w}_{d_i}|} & (l, c) \in o \\ 0 & otherwise \end{cases}$$

A background image showing a person's hand holding a glass of red wine. In the foreground, there is a dining table with a dark, textured placemat. On the table, there is a white plate with a piece of food, a small white bowl containing a dark liquid, and a white knife and fork. The person's arm and hand are visible, wearing a light-colored sleeve.

Applications

1. Multi-modal cuisine summarization

2. Cuisine-course pattern analysis

3. Cuisine recommendation

- Multi-modal cuisine summarization

$$p(z|l_q) = \frac{p(z, l_q)}{p(l_q)} = \frac{\sum_{c \in C} p(z, l_q, c)}{\sum_{c \in C} p(l_q, c)} = \frac{\sum_{c \in C} \psi_{(l_q, c), z} p(l_q, c)}{\sum_{c \in C} p(l_q, c)} \quad (11)$$

- Cuisine-Course Pattern Analysis

$$\begin{aligned} p(l|z) &= \frac{p(l, z)}{p(z)} = \frac{\sum_{c' \in C} p(l, z, c')}{\sum_{c' \in C} \sum_{l' \in L} p(z|c', l') p(c', l')} \\ &= \frac{\sum_{c' \in C} \hat{\psi}_{(l, c'), z} p(c', l)}{\sum_{c' \in C} \sum_{l' \in L} \hat{\psi}_{(c', l'), z} p(c', l')} \end{aligned}$$

$$p(c|z, l) = \frac{\hat{\psi}_{(l, c), z} p(c, l)}{\sum_{c' \in C} \hat{\psi}_{(l, c'), z} p(c', l)}$$

■ Cuisine Recommendation

- Being similar to a given cuisine. “I quite enjoyed the Chinese food. Are there any other cuisines with similar style?”
- Being relevant to a given cooking. “I have some ingredients at hand, what kind of cuisine and course do I can cook?”

(1)

$$CuiSim(l_i, l_j) = \exp\left\{-\frac{D_{js}(\psi_{l_i} || \psi_{l_j})}{2\sigma^2}\right\}$$

$$\psi_l = \{p(z|l)\}_{z \in Z}$$

(2)

$$p((l, c)|d_q) = \sum_z p((l, c)|z)p(z|d_q)$$



Experiment

- Evaluation of Theme Model
- Evaluation of Theme Visualization
- Evaluation of Multi-modal Cuisine Summarization
- Evaluation of Cuisine-Course Pattern Analysis
- Evaluation of Cuisine Recommendation

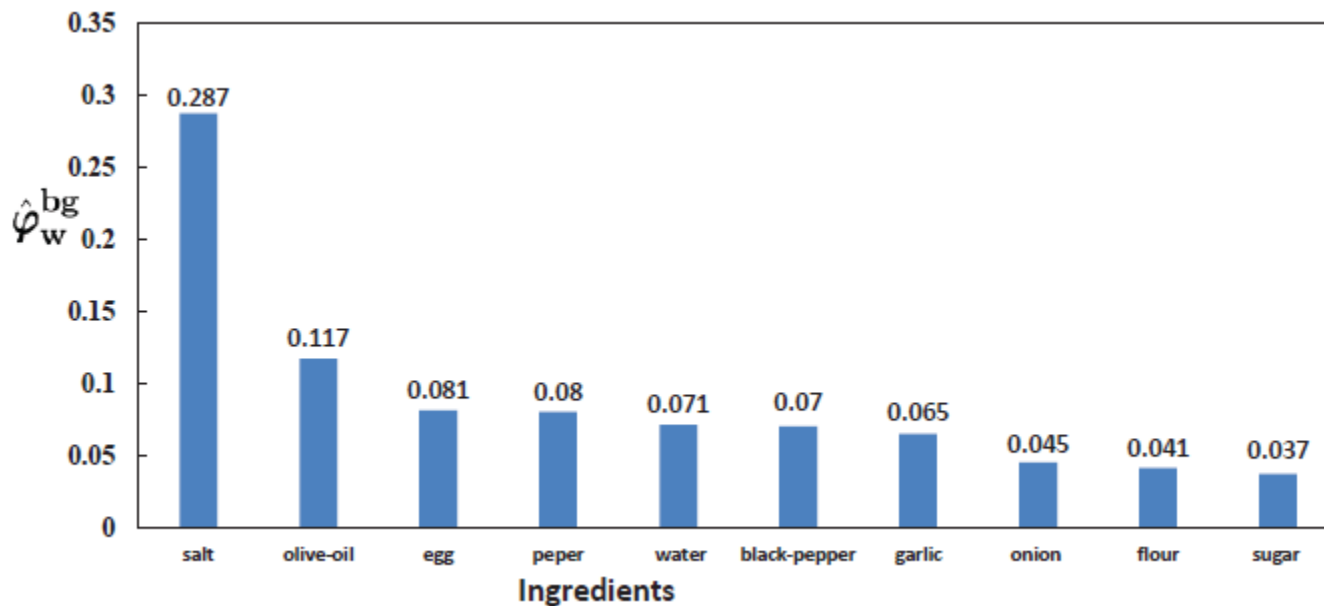
Evaluation of the theme model

- Some examples of discovered themes

Topic #68	Topic #88	Topic #91
soy-sauce 0.195 sesame-oil 0.079 green-onion 0.066 scallion 0.060 ginger 0.054 fresh-ginger 0.049 sugar 0.049 rice-vinegar 0.039 vegetable-oil 0.037 water 0.036	noodle 0.059 mushroom 0.046 cabbage 0.035 sprout 0.034 ground-pork 0.030 star-anise 0.030 baby-bok-choy 0.029 bok-choy 0.028 chicken 0.026 firm-tofu 0.025	boneless-skinless-chicken 0.236 chicken 0.102 chicken-breast 0.089 bell-pepper 0.040 onion 0.035 chicken-thigh 0.035 boneless-chicken-breast 0.029 shrimp 0.028 ground-pepper 0.027 beef 0.018
Topic #89	Topic #12	Topic #91
mango 0.093 coconut-milk 0.085 milk 0.080 ice-cube 0.0691 water 0.064 tea 0.0377 coconut 0.034 thai-basil 0.023 sticky-rice 0.022 banana 0.021	butter 0.074 flour 0.062 ground-cinnamon 0.056 vanilla-extract 0.042 salted-butter 0.039 milk 0.037 sugar 0.037 chopped-pecan 0.033 sour-cream 0.029 vegetable-oil 0.029	boneless-skinless-chicken 0.236 chicken 0.102 chicken-breast 0.089 bell-pepper 0.040 onion 0.035 chicken-thigh 0.035 boneless-chicken-breast 0.029 shrimp 0.028 ground-pepper 0.027 beef 0.018

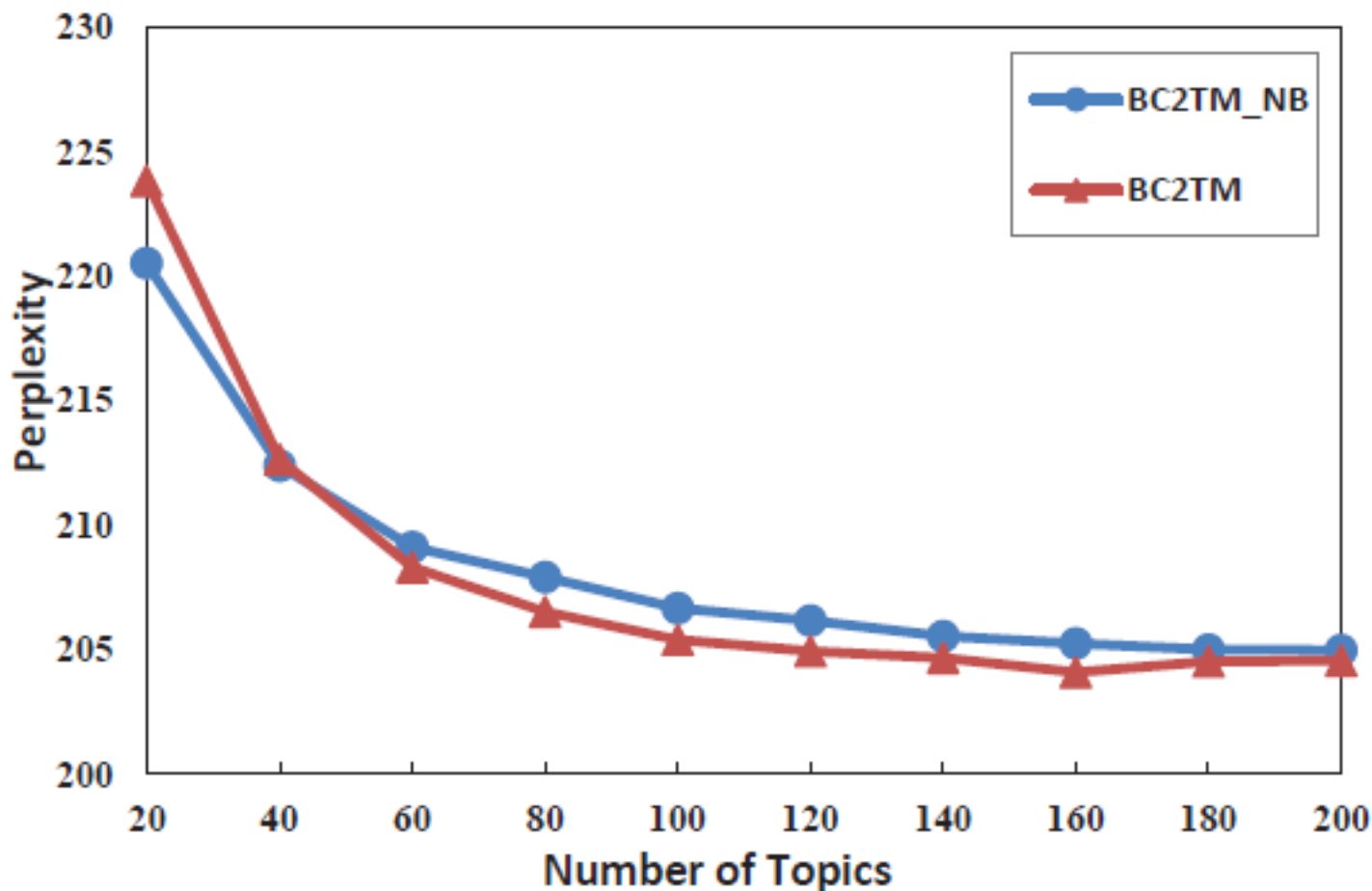
Evaluation of the theme model

- Background themes



Evaluation of the theme model

■ Perplexity



Evaluation of Theme Visualization

Theme #68

soy-sauce 0.195
 sesame-oil 0.079
 green-onion 0.066
 scallion 0.060
 ginger 0.054
 fresh-ginger 0.049
 sugar 0.049
 rice-vinegar 0.039
 vegetable-oil 0.037

Images					
	0.416	0.383	0.366	0.352	0.349
recipe	Sesame Oil Chicken	Beef Soboro	Japanese-Noodle-Sauce-Base	Chinese-Braised-Potatoes	Chinese-Pan-Fried-Red-Rockfish-Fillets
cuisine	Chinese	Japanese	Japanese	Chinese	Chinese

Evaluation of Theme Visualization

Theme #91

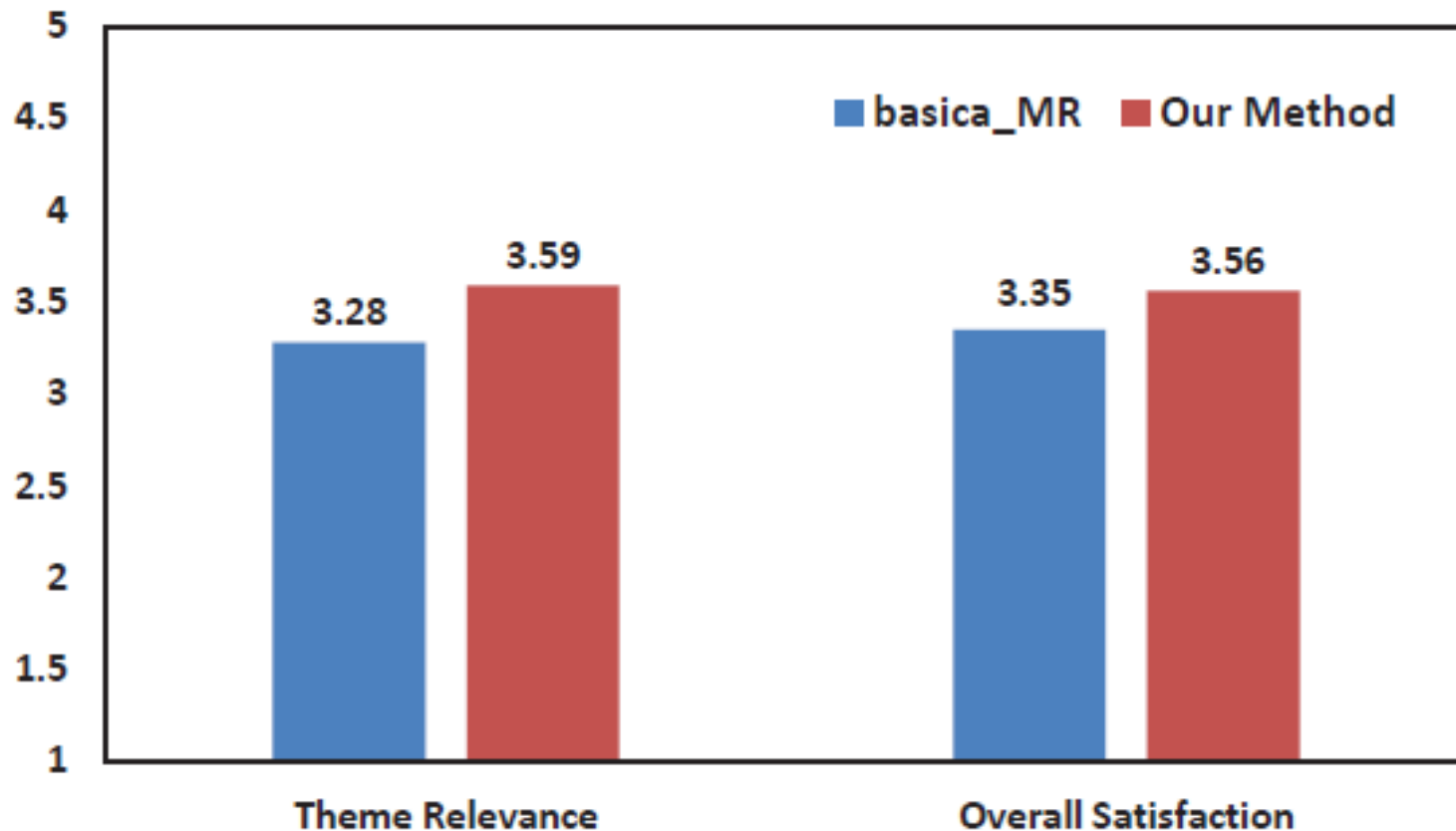
boneless-skinless-chicken 0.236
 chicken 0.102
 chicken-breast 0.089
 bell-pepper 0.040
 onion 0.035
 chicken-thigh 0.035
 boneless-chicken-breast 0.029
 shrimp 0.028
 ground-pepper 0.027
 beef 0.018

Theme #91

Images					
	0.306	0.281	0.277	0.271	0.264
recipe	Chicken Parmigiana-Martina Stewart	Italian Chicken With Basil	Homemade Baked Chicken-Nuggets	Allfoodrecipes	Middle Eastern Crispy Chicken
cuisine	Italian	Italian	Japanese	Thai	Japanese



Evaluation of Theme Visualization



Multi-modal cuisine summarization

Chinese Cuisine



(a) Summary for Chinese Cuisine

Multi-modal cuisine summarization

■ Italian Cuisine



Topic36

Topic44

Topic51



Topic83

Topic95

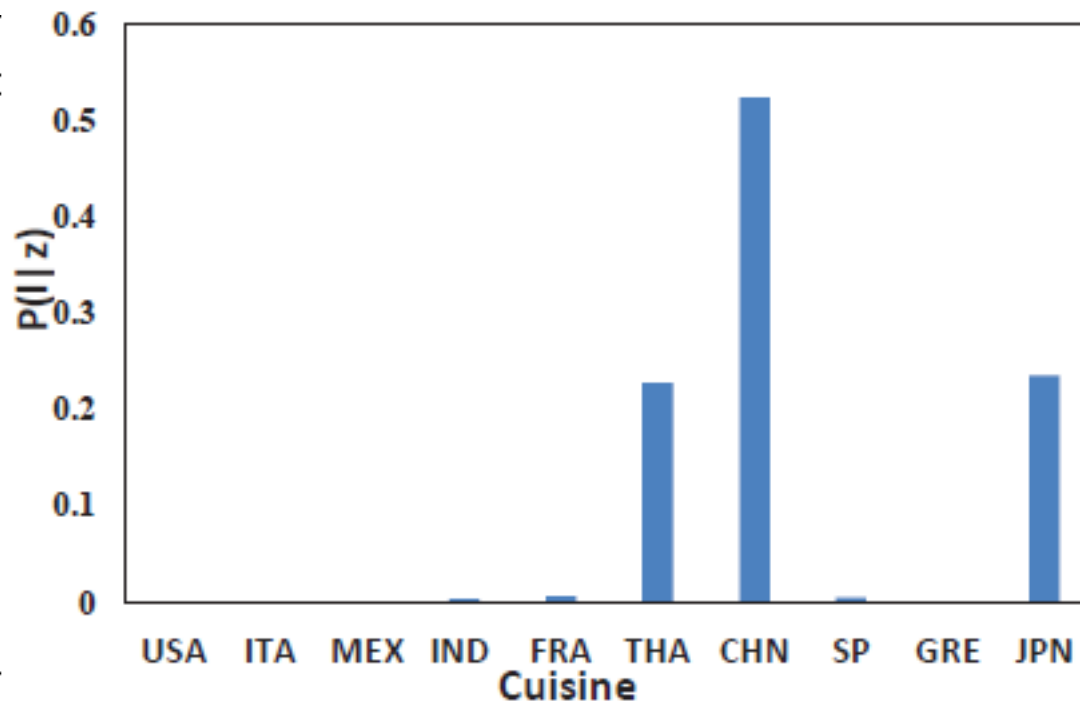


Cuisine-Course Pattern Analysis

- Cuisine distribution conditioned on certain theme

Theme #68

soy-sauce	0.195
sesame-oil	0.079
green-onion	0.066
scallion	0.060
ginger	0.054
fresh-ginger	0.049
sugar	0.049
rice-vinegar	0.039
vegetable-oil	0.037
water	0.036



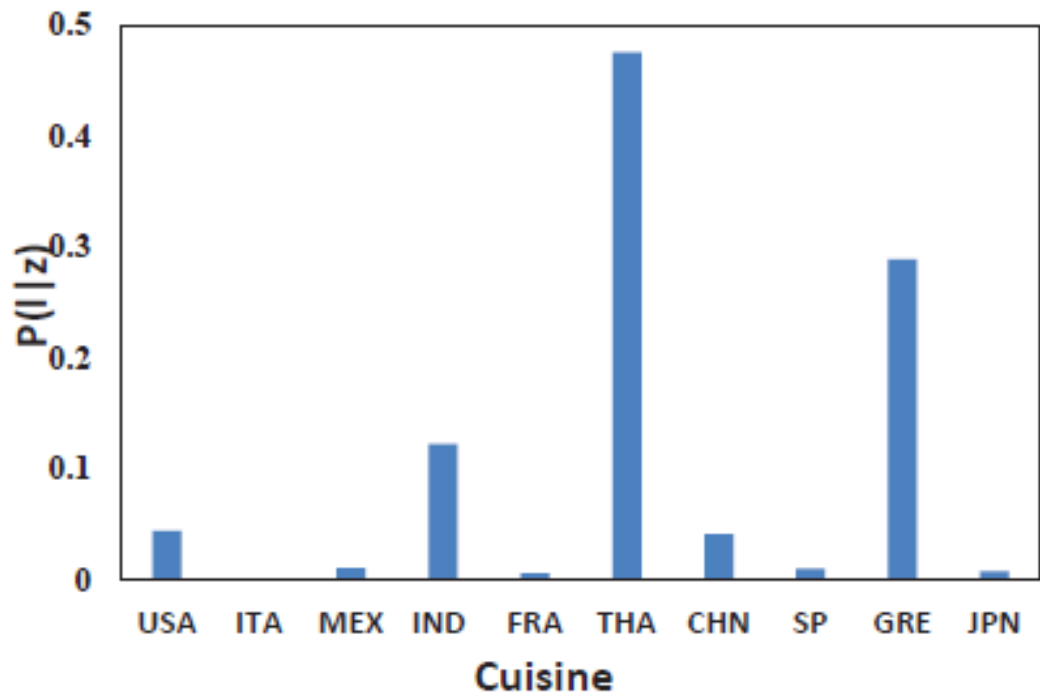


Cuisine-Course Pattern Analysis

- Cuisine distribution conditioned on certain theme

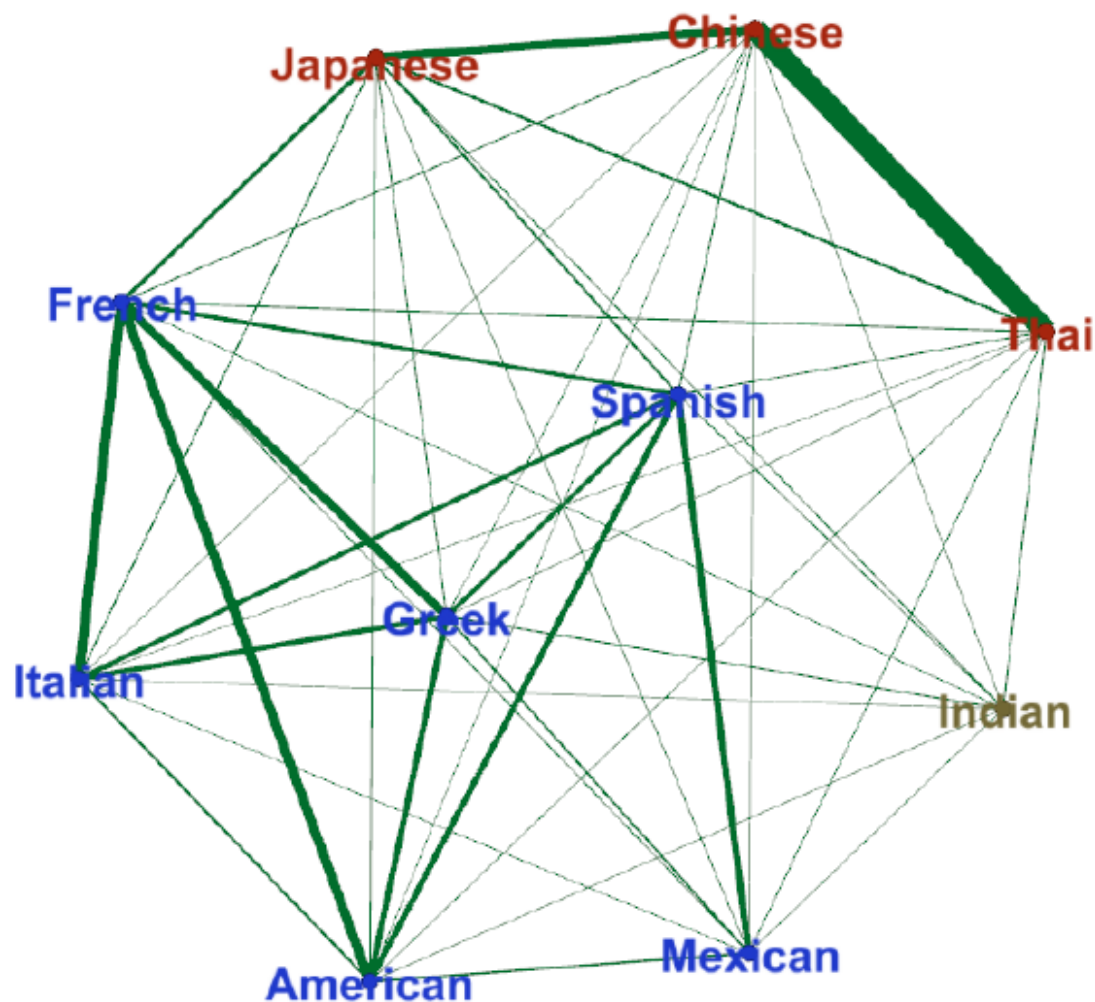
Theme #89

mango 0.093
coconut-milk 0.085
milk 0.080
ice-cube 0.0691
water 0.064
tea 0.0377
coconut 0.034
thai-basil 0.023
sticky-rice 0.022
banana 0.021



Cuisine Recommendation

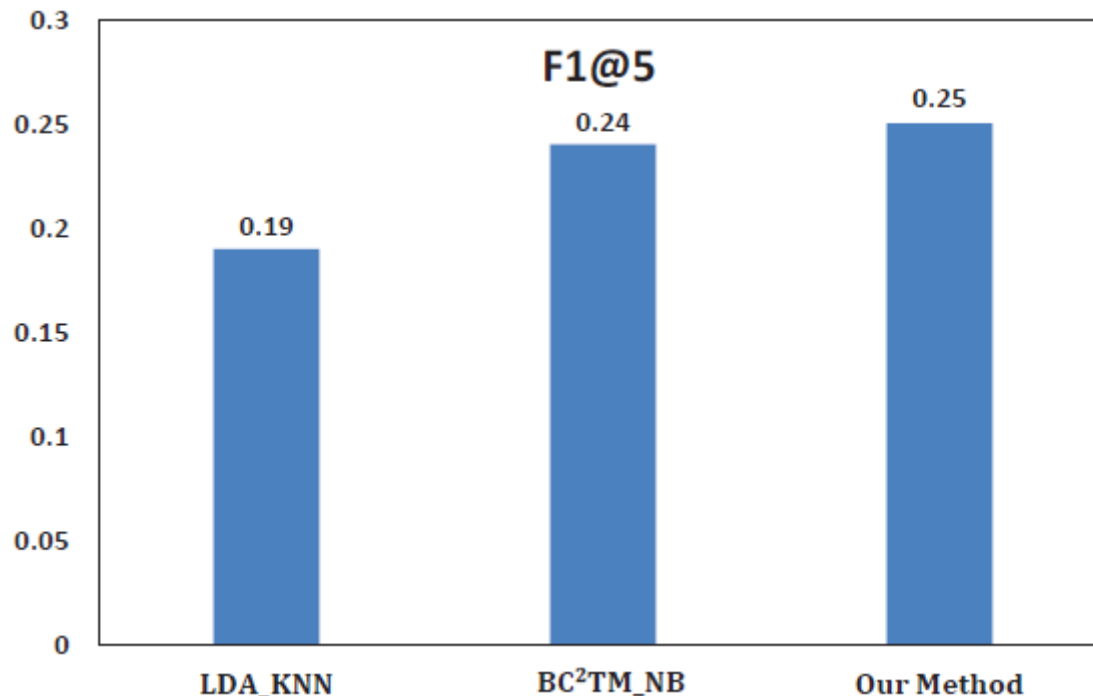
- Cuisine similarity graph





Cuisine Recommendation

- Recommend both relevant cuisine and course information give the ingredients.





Outline

- Introduction
- Two cases
 - Landmark Analysis
 - Cross-Region Food Analysis
- Conclusions



Conclusions

- propose a multi-modal multi-attribute topic modeling and analysis framework, which is capable of discovering themes conditioned on different attributes and visualizing them for landmarks and recipes.
- Collect a real-world multi-modal multi-attribute landmark/recipe dataset Landmark-20 and Yummly-66K (<http://isia.ict.ac.cn/dataset>)



Future Work

- Geo-multimedia computer vision: e.g. high-level attribute learning, large-scale visual feature learning
- Geo-multimedia knowledge graph construction and learning
- Cross-platform geo-multimedia correlation modeling
- Explore more interesting and useful applications in vertical fields and interdisciplinary fields



Reference

- **Weiqing Min**, Bing-kun Bao, Changsheng Xu. Multi-modal Spatio-Temporal Theme Modeling for Landmark Analysis. *IEEE Multimedia Magazine (IEEE MM)*. 21(3): 20-29 (2014) (**2017 Best Paper Award**)
- **Weiqing Min**, Shuqiang Jiang, Jitao Sang, et al. Being a Super Cook: Joint Food Attributes and Multi-Modal Content Modeling for Recipe Retrieval and Exploration. *IEEE Transactions on Multimedia(TMM)* 19(5): 1100-1113 (2017)
- **Weiqing Min**, Shuqiang Jiang, et al. A Delicious Recipe Analysis Framework for Exploring Multi-Modal Recipes with Various Attributes. *ACM Multimedia 2017* (accepted)
- **Weiqing Min**, Shuqiang Jiang, Bing-Kun Bao, Shuhuan Mei, Yaohui Zhu, Yong Rui : You Are What You Eat: Exploring Multi-modal and Multi-attribute Information from Recipes for Cross-Region Food Analysis. *Transactions on Multimedia (TMM) 2017* (Minor revision)



Thank you!