Large-Scale Twitter Food Photo Mining and Its Applications

The Fifth IEEE International Conference on Multimedia Big Data (BIGMM)
Sep. 11th 2019

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The Univ. of Electro-Communications, Tokyo, Japan
Overview of this talk

• Introducing our Twitter photo mining works since Feb. 2011 (one month before the big earthquake)
  – Geotagged tweet photo analysis
    • Real-time geo-tweet photo mapping system [2012]
    • Event photo mining from geo-tweet photos [2012–2016]
    • Finding regional tendency on Twitter photos [2019]
  – Twitter food photo mining
    • Statistics on food image collection for 8 years [2012–]
    • Regional tendency on Twitter food photos [2019]
    • Applications of a large-scale Twitter food photoDB [2018–]
      – Food image translation by GAN, mobile app., food VR
Background

- Various kinds of photos are posted to SNSs such as Twitter, Instagram, and Facebook every seconds.
- Photos on SNSs are posted with text messages and meta data such as geotags.
- SNSs can be regarded as useful data sources for multimedia research.
Why **twitter**? 

- **twitter** provides the API to watch the Tweet stream in the real time way.
  - Twitter API `statuses/filter` (formerly TW Streaming API (~2018/8))

- **Instagram** and **Facebook** do not provide real-time API.
  - Most of the Facebook msg. are not public.
  - Instagram msg. are public, but its API is highly restricted (mainly designed for mobile apps.)
Google images vs Twitter

- Typical, very relevant
- Distributed over the Web
  - Various purpose

- Everyday life
  - w/ tweet messages
  - Not describing

The biggest difference is instant or not.

- Appropriate for training CNN

- 30 million/day

Twitter photos are more helpful to understand the current state/trend of the worlds.
Many text mining works using twitter

• Text analysis ⇒ so many
  – Event detection
  – Trend mining
  – Positive/Negative reputation

• Photo analysis ⇒ limited before, but recently increasing due to CNN
  – Evaluation of relatedness between msg. and img.
  – Brand image mining, event photo detection
  – Fake News detection

Typhoon trajectory estimated by tweets [WWW 2010]
Characteristic of the Twitter photos

- **Normal condition: everyday life**
  - Food
  - Scene
  - People

- **Something special: event photos**
  - Artificial public events: sport games
  - Natural phenomena: earthquake, typhoon
  - Personal events
    - go hiking, travel, birthday
Mining two types of photos

- Event photo: special
- Food photo: everyday-life
Twitter photos: special event

Special big event photos on March 11th 2011 around Tokyo area
Twitter photos: normal event

Everyday-life photos on March 11th 2011 in the western part of Japan
World Seer: A Real-time Geo-Tweet Photo Mapping System

ICMR 2012
World Seer: Real-time Twitter Photo Mapping System [ICMR 2012]

Build geo-photo tweet database for research
Monitoring the TW stream & Recording Geo-Photo Tweets
demo

- http://mm.cs.uec.ac.jp/tw/
News: TW St API discon.

• Twitter Streaming API was discontinued officially Aug. 2018. But it was still available until the end of July. 2019. (When we wrote this review paper, it was still available.)

• Aug 1st 2019, a new connection to the Twitter Streaming API was not accepted anymore.
Still OK : realtime tweet API

• An alternative method is provided.
  – Twitter API statuses/filter

Unfortunately in our system (in fact My system) API is not update. So currently it does not work.

I will update it soon after completing reviewing five MMM papers.
Tweet photo database
2011/2~2019/7

• Since Feb. 2011, we have collected
  – several billion photo tweets
  – 321 million geo-photo tweets
    (5M geo-tweets/month before May 2015, 0.5M geo-tweets/month after May 2015)

• We used this data for
  – Event Photo Mining
  – Food Photo Mining
  – Visual Topic Tendency Analysis
  – Training of GANs for food image translation
Twitter Event Photo Mining

Yusuke Nakaji and Keiji Yanai: Visualization of Real World Events with Geotagged Tweet Photos, IEEE ICME Workshop on Social Media Computing (SMC), (2012).


Demo

- http://mm.cs.uec.ac.jp/kanekot/tw/jp/index.html
Twitter Event Photo Mining

- Mine the photos related to the events happened in the specific areas and times

The results of detected event photos in 2012
Twitter Event Photo Mining

• sunset January 13, 2012

Cluster No.1 num="53" bof="156.684" color="336.837" weight="10.757" score="61.224"
Objective

- Detect events from Twitter stream
  - Weather, natural events
  - Festivals, sport games
- Understand events visually
  - Select representative photos
  - Place event photos on a map

Mapping events with the photo
Processing flow

1. Event keyword detection
2. Keyword unification
3. Event photo clustering
4. Mapping event with photos
Event Keyword Burst Detection

- Examine change of daily frequency
Event Photo Clustering

• Hand-crafted image features (not CNN!)
  – Bag-of-Features with SURF
  – Color histograms

• Ward clustering method
  – a hierarchical clustering method
  – threshold is 300 (both)

\[
E(C) = \sum_{x \in C} ((x_{BOF} - \bar{x}_{BOF})^2 w_{BOF} + (x_{RGB} - \bar{x}_{RGB})^2 w_{RGB})
\]
Experiments

- **Japan Dataset**
  - Feb 10th, 2011 to Sep 30th, 2012
  - about 3 million geo-tweet photos

- **US Dataset**
  - Jan 1st, 2012 to Dec 31st, 2012
  - about 17 million geo-tweet photos
# Results of Keyword Detection

<table>
<thead>
<tr>
<th>Keyword</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>snow</td>
<td>11/02/2011</td>
</tr>
<tr>
<td>earthquake</td>
<td>11/03/2011</td>
</tr>
<tr>
<td>fireworks</td>
<td>06/08/2011</td>
</tr>
<tr>
<td>typhoon</td>
<td>21/09/2011</td>
</tr>
<tr>
<td>Mt. Fuji</td>
<td>24/09/2011</td>
</tr>
<tr>
<td>Apple</td>
<td>06/10/2011</td>
</tr>
<tr>
<td>eclipse</td>
<td>10/12/2011</td>
</tr>
<tr>
<td>illumination</td>
<td>10/12/2011</td>
</tr>
<tr>
<td>Christmas</td>
<td>24/12/2011</td>
</tr>
<tr>
<td>New years eve</td>
<td>31/12/2011</td>
</tr>
<tr>
<td>sunrise</td>
<td>01/01/2012</td>
</tr>
<tr>
<td>firefly</td>
<td>06/05/2012</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Keyword</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>snow</td>
<td>09/01/2012</td>
</tr>
<tr>
<td>sunset</td>
<td>13/01/2012</td>
</tr>
<tr>
<td>Grammy</td>
<td>12/02/2012</td>
</tr>
<tr>
<td>Valentines</td>
<td>14/02/2012</td>
</tr>
<tr>
<td>SXSW</td>
<td>09/03/2012</td>
</tr>
<tr>
<td>Easter</td>
<td>08/04/2012</td>
</tr>
<tr>
<td>shuttle</td>
<td>17/04/2012</td>
</tr>
<tr>
<td>WWDC</td>
<td>10/06/2012</td>
</tr>
<tr>
<td>hurricane</td>
<td>26/08/2012</td>
</tr>
<tr>
<td>rainbow</td>
<td>05/09/2012</td>
</tr>
<tr>
<td>49ers</td>
<td>18/10/2012</td>
</tr>
<tr>
<td>NYE</td>
<td>31/12/2012</td>
</tr>
</tbody>
</table>
“fireworks” photo clusters

Cluster No.1 num="40" b_score="127.5948" c_score="36.7071" weight="1" score="9.7382"

Cluster No.2 num="22" b_score="121.0945" c_score="58.4237" weight="1" score="2.6961"

Cluster No.3 num="25" b_score="114.3028" c_score="148.3092" weight="1" score="2.3799"

Cluster No.4 num="2" b_score="36.5067" c_score="10.0696" weight="1" score="0.0859"
“cherry blossoms” photo clusters

Cluster No.1 num="32" b_score="89.4698" c_score="127.6658" weight="1.9642" score="9.2631"

Cluster No.2 num="24" b_score="77.7001" c_score="90.9009" weight="1.9642" score="6.7104"

Cluster No.3 num="1" b_score="0" c_score="0" weight="1.9642" score="0.0002"
Mapping Results

• Map event in a map
  – Calculate coordinates of event
  – Correspond information and the photo

• Summary of results

<table>
<thead>
<tr>
<th></th>
<th>Japan</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td># events</td>
<td>258</td>
<td>1676</td>
</tr>
<tr>
<td>accuracy</td>
<td>65.5%</td>
<td>72.5%</td>
</tr>
</tbody>
</table>
fireworks
01/08/2012
lat: 33.5862
lng: 130.38237
Edward Jenkins @edwardjenkins
Awesome sunset photo here in the #Seattle area.

sunset January 13, 2012

Cluster No.1 num="53" bof="156.68" color="336.84" weight="10.76" score="61.22"

"sunset"
Visual Topic Analysis of Twitter Photo Analysis

Unpublished.
2million photo clustering using only visual features (no text)

- [http://mm.cs.uec.ac.jp/twimg/](http://mm.cs.uec.ac.jp/twimg/) (BOF features)
- [http://mm.cs.uec.ac.jp/twimg/dcnn.cgi](http://mm.cs.uec.ac.jp/twimg/dcnn.cgi) (CNN features)

Most of the tweet texts do not explain the attached images directly. So text-based analysis might restrict target images too much. ⇒ Twitter images with only visual analysis
Food is one of the major topics of Twitter photos.

- Visual topic analysis with half-million Twitter photos employing DCNN feature.

**Topic 2** Food-related topics

**Topic 3** Food-related topics
Finding regional tendency on Twitter photos using only image features

Regional tendency analysis on Twitter geotagged photos

- Apply visual clustering based photo topic analysis on each of the regions over the world.
Experiments

• Dataset
  – Collected from January to June in 2016
  – 2,161,000 geotagged Twitter images

• Feature
  – CNN (128-d compressed by PCA)

• K-means
  – K-means with one-tenth images
    • Assigned rest of images into the nearest clusters
  – K=100
Regions

- East Asia, North America, South America, Europe, Africa, Middle East, South Asia and South-East Asia, Oceania
Clustering results (CNN features)
Select five representative topics from observation of clusters

• pre-selected photo genres.
  – “people”
  – “building”
  – “document”
  – “scene”
  – “food”
### Ratio of five topics on each region

<table>
<thead>
<tr>
<th>Region</th>
<th>People</th>
<th>Building</th>
<th>Document</th>
<th>Scene</th>
<th>Food</th>
</tr>
</thead>
<tbody>
<tr>
<td>East Asia</td>
<td>1%</td>
<td>31%</td>
<td>14%</td>
<td>13%</td>
<td>42%</td>
</tr>
<tr>
<td>North America</td>
<td>32%</td>
<td>31%</td>
<td>10%</td>
<td>9%</td>
<td>18%</td>
</tr>
<tr>
<td>South America</td>
<td>67%</td>
<td>5%</td>
<td>21%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>Europe</td>
<td>35%</td>
<td>21%</td>
<td>19%</td>
<td>12%</td>
<td>14%</td>
</tr>
<tr>
<td>Africa</td>
<td>72%</td>
<td>1%</td>
<td>27%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>Middle East Asia</td>
<td>26%</td>
<td>23%</td>
<td>28%</td>
<td>9%</td>
<td>13%</td>
</tr>
<tr>
<td>South Asia</td>
<td>41%</td>
<td>2%</td>
<td>54%</td>
<td>9%</td>
<td>2%</td>
</tr>
<tr>
<td>East-South Asia</td>
<td>50%</td>
<td>11%</td>
<td>9%</td>
<td>3%</td>
<td>27%</td>
</tr>
<tr>
<td>Oceania</td>
<td>22%</td>
<td>3%</td>
<td>47%</td>
<td>20%</td>
<td>7%</td>
</tr>
</tbody>
</table>

© 2017 UEC Tokyo.
• East Asia

– No people photos
– Many building and food photos
– The total ratio of building and food photos were more than 70%
• North America

- The ratio of people and building were high more than 60%.
• **South America**

– People photos are the most popular genre (67%)
Analysis of Regional Tendency of Photo Genres

- **Europe**
  - The number of posted photos was the most large.
  - The genres were well balanced.

- **Africa**
  - Almost no building, scene and food photos were posted.
  - People photos occupied 70%.
• Middle East

– Although the number of posts were fewer than Europe, all the five genres were balanced as well.
Analysis of Regional Tendency regarding Photo Topics

- **South Asia**
  - More than half of the photos were document photos.
  - This tendency was not observed in other regions

- **SouthEast Asia**
  - People photos are the most and in addition food photos was the second most
South America: People
Africa : People
East Asia: Food
South East Asia: Food
Findings

• Tendency
  – East Asia and East-South Asia,
    • Food photos are relatively high
  – South America, South Asia and East-South Asia
    • people photos are exceptionally high.
  – Europe and MiddleEast
    • well balanced.

• East Asia enjoys posting food photos
• South America, South Asia and EastSouth Asia like to post people photos without caring privacy issue.
Food Twitter Photo mining
Why food?
Food is one of the major topics in Twitter photos. Especially in East Asia
We are actively working on food images.

FoodCam: [Kawano et al. MTA13]

- Real-time mobile food recognition
  Android application

http://foodcam.mobi/
UEC-FOOD 256
## UEC-FOOD 256

<table>
<thead>
<tr>
<th>Image</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><a href="#">Image</a></td>
<td><a href="#">Description</a></td>
</tr>
</tbody>
</table>

- **Loco moco**
- **Adobo**
- **Lumpia**
- **Apple pie**
- **Brownie**
- **Meat loaf**
- **Malasada**
- **マンゴーパudding (mango pudding)**
- **雑炊 (zoni)**
- **お吸い物 (clear soup)**
- **もずく (mizuko)**
- **ヒレカツ (pork filet cutlet)**
- **メンチカツ (minted meat cutlet)**
- **沖縄そば (oline wa soba)**
- **干し缶 (lamb kabab)**
- **焼肉 (roast duck)**
- **月餅 (moon cake)

- **沙拉酱 (pork cutlet)**
- **臭豆腐 (stinky tofu)**
- **炒面 (chow mein)**
- **Pork & pepper fried shrimp with chili**
- **Papaya salad (Thaipapaya salad)**
- **Arroz (Pork Sticky Rice)**
- **Braised (Bonied, seasoned ham-n-stars, style chicken & vegetables)**
- **凧焼き (pork satay)**
- **ロースカツ (pork loin cutlet)**
- **冬瓜汤 (winter melon soup)**
- **ねぎ (green onion)**
- **羅宋汤 (beet soup)**
- **minestrone**

- **green curry**
- **dak galbi**
- **dry curry**
- **vermicelli (汤面)**
- **yellow curry**
- **spaghetti**
- **rare cheese cake**
- **chop suery**
- **masuroum risotto**
- **fine white noodles**
- **chicken nugget**
- **namero**
- **French bread**
- **broiled eel bowl**
- **yudofu**
- **inari sushi**
- **baked salmon (鹽鰤)**

- **ham cutlet**
- **tortilla**
- **tacos**
- **scrambled egg**
- **lasagna**
- **ceasar salad**
- **oatmeal**
- **cream puff**
- **doughnut**
- **parfait**
- **hot pot**
- **Pork belly**
- **Minced pork rice**
- **glutinous oil rice**
- **Tramp Pudding**
- **lemon fig jelly**
- **Small cremmed Savory rice pancake**

- **noodles with fish curry (イカすり)**
- **Pancakes (パン)**
- **Curry with coconut (ココナッツ)**
- **vermicelli noodles with snail (貝べ)**
- **fried spring rolls (春巻き)**
- **shrimp patties (Bánh té)**
- **bauxia**
- **lau lau**
- **spam musubi**
- **oxtail soup**
- **nasi goreng**
- **nasi padang**
- **kaya toast**
- **bak kut teh**
- **curry puff**
- **been curry family style (家庭炊具)**
FoodRec: foodrec app with UECFOOD100
by Hamlyn Centre-Imperial College(UK)
Modelling Local Deep Convolutional Neural Network Features to Improve Fine-Grained Image Classification

ZongYuan Ge, Chris McCool, Conrad Sanderson, Peter Corke

(Submitted on 27 Feb 2015)

We propose a local modelling approach using deep convolutional neural networks (CNNs) for fine-grained image classification. Recently, deep CNNs trained from large datasets have considerably improved the performance of object recognition. However, to date there has been limited work using these deep CNNs as local feature extractors. This partly stems from CNNs having internal representations which are high dimensional, thereby making such representations difficult to model using stochastic models. To overcome this issue, we propose to reduce the dimensionality of one of the internal fully connected layers, in conjunction with layer-restricted retraining to avoid retraining the entire network. The distribution of low-dimensional features obtained from the modified layer is then modelled using a Gaussian mixture model. Comparative experiments show that considerable performance improvements can be achieved on the challenging Fish and UEC FOOD-100 datasets.
UECFOOD-256 is used in NVIDIA ICCV2019 paper


\[ x \rightarrow \text{style}(y_1, y_2) \rightarrow x' \]

food image translation
We are organizing food WS.

ACM MM Workshop related to “food multimedia”

5th International Workshop on Multimedia Assisted Dietary Management
In conjunction with the 27th ACM International Conference on Multimedia (ACMMM2019), Nice, France

Organization

Workshop chairs

Stavroula Mougiakakou, University of Bern, Switzerland
Giovanni Maria Farinella, University of Catania, Italy
Keiji Yanai, The University of Electro-Communications, Tokyo, Japan

Paper submission deadline: July 8th, 2019
Notification of acceptance: August 5th, 2019
Camera-ready deadline: August 12th, 2019
Workshop date: October 21th
Twitter Real-time Food Photo Mining

Keiji Yanai and Yoshiyuki Kawano: Twitter Food Image Mining and Analysis for One Hundred Kinds of Foods, Pacifit-Rim Conference on Multimedia (PCM), (2014).

Keiji Yanai, Kaimu Okamoto, Tetsuya Nagano and Daichi Horita: Large-Scale Twitter Food Photo Mining and Its Applications, IEEE International Conf. on Big Multimedia (BIGMM), (2019)
Twitter Real-time Food Photo Mining System ([mm.cs.uec.ac.jp/tw/](mm.cs.uec.ac.jp/tw/))

- What kinds of foods are being eaten in Japan?
Objective

- Which food is the most popular in Japan?
  - “Ramen vs Curry” problem ⇒ very controversial
  - I would like to put a period to this controversy by Twitter food photo mining !!!
Approach for food photo mining

• **Two-step food photo selection**
  – [1] *Keyword-based tweet selection*

  • 101-class (100 foods + non-food) classification (fine-tuned AlexNet)
Experiments

• Collect photo tweets via Twitter Streaming API
  – From 2011/5 to 2019/07/16 (8year 2month)
  – About several billion photo tweets

• Search for the tweets including any of 100–food names (in Japanese) and apply a food CNN
  – 16,044,090 images ⇐ Apply the 101–food CNN

• 2,308,988 food photos (14.4%)
  13,735,102 non–food photos (85.6%)
<table>
<thead>
<tr>
<th>rank</th>
<th>foods</th>
<th>#photos</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Ramen noodle</td>
<td>500,210</td>
</tr>
<tr>
<td>2</td>
<td>Curry</td>
<td>209,391</td>
</tr>
<tr>
<td>3</td>
<td>Sushi</td>
<td>130,501</td>
</tr>
<tr>
<td>4</td>
<td>Omelet</td>
<td>103,199</td>
</tr>
<tr>
<td>5</td>
<td>Dipping noodle (tsukemen)</td>
<td>96,482</td>
</tr>
<tr>
<td>6</td>
<td>Pizza</td>
<td>89,568</td>
</tr>
<tr>
<td>7</td>
<td>Jiaozi (Gyoza)</td>
<td>67,196</td>
</tr>
<tr>
<td>8</td>
<td>Okonomiyaki</td>
<td>61,919</td>
</tr>
</tbody>
</table>

Ramen noodle is the most popular food in Japan. I have solved “ramen vs curry” problem !!! (And I got a “ramen vs curry” expert !!)
# Precision of the top 5 foods
(May 2011–Aug. 2013)

<table>
<thead>
<tr>
<th>Food</th>
<th>(1) KW</th>
<th>(2) f/n</th>
<th>(3) spec.</th>
<th>(4) ALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>ramen</td>
<td>275,652</td>
<td>200,173</td>
<td>84,189</td>
<td>80,021</td>
</tr>
<tr>
<td></td>
<td><strong>72.0%</strong></td>
<td><strong>92.7%</strong></td>
<td><strong>95.0%</strong></td>
<td><strong>99.7%</strong></td>
</tr>
<tr>
<td>curry</td>
<td>224,685</td>
<td>163,047</td>
<td>62,824</td>
<td>59,264</td>
</tr>
<tr>
<td></td>
<td><strong>75.0%</strong></td>
<td><strong>95.0%</strong></td>
<td><strong>97.0%</strong></td>
<td><strong>99.3%</strong></td>
</tr>
<tr>
<td>sushi</td>
<td>86,509</td>
<td>43,536</td>
<td>48,019</td>
<td>25,898</td>
</tr>
<tr>
<td></td>
<td><strong>69.0%</strong></td>
<td><strong>86.0%</strong></td>
<td><strong>72.3%</strong></td>
<td><strong>92.7%</strong></td>
</tr>
<tr>
<td>tsukemen</td>
<td>33,165</td>
<td>24,896</td>
<td>28,846</td>
<td>22,158</td>
</tr>
<tr>
<td></td>
<td><strong>88.7%</strong></td>
<td><strong>96.3%</strong></td>
<td><strong>93.7%</strong></td>
<td><strong>99.0%</strong></td>
</tr>
<tr>
<td>omelet</td>
<td>34,125</td>
<td>28,887</td>
<td>18,370</td>
<td>17,520</td>
</tr>
<tr>
<td></td>
<td><strong>90.0%</strong></td>
<td><strong>96.3%</strong></td>
<td><strong>98.0%</strong></td>
<td><strong>99.0%</strong></td>
</tr>
</tbody>
</table>
Only keyword search (Ramen noodle) (72.0%)
After applying 100-class food classifier (final)(99.7%)
Only keyword search (curry) (75.0%)
Final results (curry) (99.3%)
Some interesting findings

• Letters or drawings are sometimes drawn on omelets with ketchup

• Fast-foods such as hamburger (rank 30th) and beef bowl (rank 27th) are ranked lower, since their appearance is always the same.

Not worth posting fastfood photos to Twitter
Omlet wall paper
Geographical-Temporal analysis on ramen vs curry

12.6% of the obtained food photos have geotag.

Whole year

Dec. (winter)
Ramen is popular.

Aug. (summer)
Curry gets more popular than ramen only in summer.
I appeared TV program in Japan (2018/11/1)
I commented on “ramen vs curry” problem as a “ramen vs curry” expert.
Ramen won !!!
Curry lost!
But the rank is second.
Regional Tendency Analysis on Twitter Food Photo

Method overview

The method is almost the same as the work on regional tendency analysis on generic images. The difference is using a food/non-food classifier at first.

[1] Classifying food and non-food photos
[2] Extracting food CNN features
[3] Clustering and analyzing of regional tendency
Experiments

• Selecting food images from Twitter images in 2016 for whole a year with the food/non-food classifier

• 190,000 food images from 3.78 million raw Twitter images
## Results

<table>
<thead>
<tr>
<th>Region</th>
<th>Noodles</th>
<th>Rice</th>
<th>Fried food</th>
<th>Sea food</th>
<th>Soup</th>
<th>Salad</th>
<th>Sweets</th>
<th>Bread</th>
<th>Fast food</th>
<th>Beverage</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>East Asia</strong></td>
<td>29.3</td>
<td>12.5%</td>
<td>14.5</td>
<td>5.8</td>
<td>5.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>South-East Asia</strong></td>
<td>16.6%</td>
<td>14.8</td>
<td>10.8</td>
<td>10.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>North America</strong></td>
<td>12.6%</td>
<td>10.3</td>
<td>18.6</td>
<td>15.4</td>
<td>8.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>South America</strong></td>
<td>6.7%</td>
<td>25.1</td>
<td>22.5</td>
<td>11.6</td>
<td>10.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Europe</strong></td>
<td>10.4%</td>
<td>17.6</td>
<td>18.7</td>
<td>12.1</td>
<td>11.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Middle East</strong></td>
<td>11.8%</td>
<td>23.2</td>
<td>17.7</td>
<td>22.2</td>
<td>6.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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Tendency analysis

- **East Asia**: “Noodles” and “Rice”, which are relatively rare in the other regions, are included at the top.
- **South-East Asia**: “Soup” is ranked at the top, and many dishes are made of vegetables and meats in soup.
- **North America, South America, Europe**: It turned out that 4 items of the top 5 items of the categories are the same.
- **Middle East**: The top five food categories are the same as Europe. However there are many brown coffee photos which are a unique type to Middle East.
Applications of Large-Scale Twitter Food Photo DB

[food image translation (food GAN)]

[Food VR]
Food Image Translation (FoodGAN)
Real-time Food Translation “MagicalRiceBowl”
Original StarGAN

- **Cycle Consistency Loss**
- **Adversarial Loss**
  - `fake` or `real`
- **Auxiliary Classifier Loss**

- **Real Image**
  - In domain A

- **Fake Image**
  - In domain B

- **Reconstructed Image**

- **Domain Selector**
  - `C[1, 0, 0, 0, 0, ...]`
  - `G_C`
  - `C[0, 1, 0, 0, 0, ...]`

- **Original StarGAN**
Experiments

• We use foods, which have similar dish plates as target food category for simplification.

Selected 10 kinds of food category.

Curry  Fried rice  Beef bowl  Chilled noodle  Meat spaghetti
Ramen  Rice  Buckwheat noodle  Eel bowl  Fried noodle
Experimanetal Data

- Total amount:
  - 230k images
  - Training : 0.9
  - Testing : 0.1

<table>
<thead>
<tr>
<th>Target category</th>
<th>Image number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chilled noodle</td>
<td>13,499</td>
</tr>
<tr>
<td>Meat spaghetti</td>
<td>7,138</td>
</tr>
<tr>
<td>Buckwheat noodle</td>
<td>3,530</td>
</tr>
<tr>
<td>Ramen</td>
<td>74,007</td>
</tr>
<tr>
<td>Fried noodle</td>
<td>24,760</td>
</tr>
<tr>
<td>Rice</td>
<td>21,324</td>
</tr>
<tr>
<td>Curry rice</td>
<td>34,216</td>
</tr>
<tr>
<td>Beef bowl</td>
<td>18,396</td>
</tr>
<tr>
<td>Eel bowl</td>
<td>5,329</td>
</tr>
<tr>
<td>Fried rice</td>
<td>27,854</td>
</tr>
<tr>
<td>total</td>
<td>230,053</td>
</tr>
</tbody>
</table>

Twitter Stream から収集
The number of training images affects quality.
Experimental results

• In case of one food included in an image
Experimental results

- In case of one food included in an image
• In case of multiple foods included in an image
Experimental results

• In case of multiple foods included in an image

input

ramen  rice  Buckwheat noodle  Eel bowl  Fried noodle
[extension] Attentional StarGAN (network of “MagicalRiceBowl”)
Attentional StarGAN

- w/o attention
- w/ attention

Background is also translated.

Background is almost unchanged.
MagicalRiceBowl with the model with attention
MagicalRiceBowl on iOS App Store

Only working on iPhone 8 or more (8/X/Xs/XR/11/11pro)

Using Neural Engine.
Food VR
Enchanting Your Noodles: GAN-based Real-time Food-to-Food Translation and Its Impact on Vision-induced Gustatory Manipulation

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Cybernetics & Reality Engineering
Cyber Interface Lab.
In the user study, subjects felt the taste of ramen noodles presented by our system when they were actually eating somen noodles.
食事変換＋HoloLens
(VR Restaurant)
カツオだしのそうめん
脳をダマして…"高カロリー"食べた気分に
Conclusions
Conclusions

- Introduced our Twitter photo mining works since Feb. 2011 (one month before the big earthquake)
  - Geotagged tweet photo analysis
    - Real-time geo-tweet photo mapping system [2012]
    - Event photo mining from geo-tweet photos [2012–2016]
    - Finding regional tendency on Twitter photos [2019]
  - Twitter food photo mining
    - Statistics on food image collection for 8 years [2012–]
    - Regional tendency on Twitter food photos [2019]
    - Applications of a large-scale Twitter food photoDB [2018–]
      - Food image translation by GAN, mobile app., food VR
“Thank you” by fake ramen images