Humanitarian Mapping with Deep Learning and Volunteered Geographic Information (VGI)

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Humanitarian Mapping

- Putting the Word’s Vulnerable People on the Map
  - Open Source, Open Data Sharing, Volunteers, OpenStreetMap (OSM)

Before

After

Haiti Earthquake 2010

Mapping events in Heidelberg
MapSwipe is a mobile application developed by Missing Maps Project that allows volunteers to label level 18 256pt × 256pt Bing Map satellite images with houses, roads, etc.

15144 volunteers
50 events (each for an area)
Over 20 million images (each is labeled by at least three volunteers)

Event 922, South Malawi District, House Mapping, over 170,000 positive images and over 135,000 negative images
Satellite Observation

Maps

Poverty Mapping

Population Mapping
“Connecting the World with Better Maps”, Facebook’s Connectivity Lab

Aerosol Optical Depth and Public Health
“Atmospheric Aerosols: What Are They, and Why Are They So Important?” NASA
Deep Learning

Input (Images)
- Satellite Images
- Benchmarks

Learning (Networks)
- Feature Representation
- GD, Adam, etc.
- AE
- SC
- RBM
- CNN
- MLP
- DBN
- GAN

Output (Labels)
- Pixel Classification
- Object Recognition
- Sense Understanding

### Popular Benchmarks

<table>
<thead>
<tr>
<th>Name</th>
<th>Classes &amp; Size</th>
<th>Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>UC Merced Land Use</td>
<td>21 classes, each with 100 images</td>
<td>Urban Areas in USA</td>
</tr>
<tr>
<td>Brazilian Coffee Sense Dataset</td>
<td>Coffee crops and none coffee crops, each with 1438 images</td>
<td>Four counties in the State of Gerais, Brazil</td>
</tr>
<tr>
<td>UCI Statlog Landsat Satellite Dataset</td>
<td>7 classes with totally 6435 samples</td>
<td>/</td>
</tr>
<tr>
<td>SpaceNet Dataset</td>
<td>220,594 building footprints</td>
<td>Rio De Janeiro, Brazil</td>
</tr>
</tbody>
</table>

- **Limited Size**
- **Limited Spatial Coverage**
- **Limited Semantics**

Big 2017, Co-event of WWW2017, 4 April, 2017, Perth
Learning from The Crowds

OSM Labels
- Vector Knowledge: Contours and Tags
- Building: Commercial Shop: Car Wheelchair: limited

MapSwipe Labels
- Binary Satellite Image Labels
- Local Knowledge for Specific Areas

GPX Labels
- Event 922 for South Malawi

Deep Models
- Forecarish, Guinea

Global Knowledge
- Spatial Distribution

Granularity

(1) Vector Knowledge: GPS Tracks of Red Cross Volunteers
(2) Local Knowledge of Specific Areas
VGI Data Quality and Noise

VGI Data Quality Issues
- Geometry Inaccuracy
- Attribute Inaccuracy
- Semantic Inaccuracy
- Incompleteness
- Logic Inconsistence
- Temporal Inaccuracy
- Lineage Missing

Training Data Noise
- Omission Noise
- Registration Noise
- Semantic Noise
Related Work

**Github/trailbehind/DeepOSM**: predict if the center 9px of a 64px tile contains road using neural networks and OSM labels only, with an overall accuracy of 75%~80%

**Github/geometalab/OSMDeepOD**: detect crosswalks over 50px × 50px satellite images with convolutional neural networks trained by OSM labels only

**[Mnih and Hinton ICML-12]**: deep road and building detection models with more robust loss functions to deal with the registration noise and missing noise considered

*The ideas of DeepOSM and OSMDeepOD are similar, and are named as Deep-OSM for simplicity in this presentation*
Problem

Task:
- train the networks with OSM labels
- predict the label of the MapSwipe images (256pt * 256pt), to save the volunteers’ labor

Problem:
- Open knowledge (lacking accurate negative labels)
- Missing noise (difference between OSM domain and MapSwipe domain)
Step 1: Train

ANN-S1

ANN-S4

Positive Labels from OSM

Negative Labels from MapSwipe

Satellite Images

Step 2: Predict

MapSwipe Labels

Satellite Images

Right

MapSwipe-Consistent Images $S^C$

Wrong

MapSwipe-Inconsistent Images $S'$

VIG-based Active Sampling Strategy

Step 3: Labeling

Type II Error Images

Step 4: Re-train

(\(s, y^+ \mid y^-\))

Satellite Images

Manual Labels

(\(s', y'_+ \))

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In the primary evaluation, we use 1590 MapSwipe images for training.

320 MapSwipe images that are re-labeled by experts with third part data (costs much time) for testing.

All the images come from South Malawi area in Africa (including downtown and rural areas).
The VGI-based active learning strategy outperforms the uncertainty-based for building detection with ANNs (LeNet and MLN).

<table>
<thead>
<tr>
<th></th>
<th>Precision</th>
<th>Recall</th>
<th>F1 Score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>DeepVGI</td>
<td>0.775</td>
<td>0.737</td>
<td>0.756</td>
<td>0.841</td>
</tr>
<tr>
<td>Deep-OSM</td>
<td>0.632</td>
<td>0.875</td>
<td>0.734</td>
<td>0.788</td>
</tr>
<tr>
<td>MapSwipe</td>
<td>0.738</td>
<td>0.938</td>
<td>0.826</td>
<td>0.868</td>
</tr>
</tbody>
</table>

DeepVGI with 10 actively sampled tiles outperforms the baseline Deep-OSM and achieves close accuracy as the MapSwipe volunteers.
Shortcomings

- Only a very small part of the data are used in this primary evaluation (ongoing work)
- Sliding window strategy: adjusting more hyper-parameters
- Human intervelment
Future Work

How to learn from multiple crowds: OSM, MapSwipe, GPS, etc.?

How to learn from multiple semantics: OSM tags, WikiData, etc.?

How can our model cooperate with the volunteers?
Other Supporting Projects

- Temporal Analysis of OSM
  - An Ignite-based big data infrastructure with temporal analysis of OpenStreetMap
  - By HeiGIT, Heidelberg University (Leaded by Alexander Zipf)

- OSM-WikiData Link Analysis
  - Linking entities of OSM and WikiData, to enrich the semantic of OSM and improve OSM data quality
  - HeiGIT, Heidelberg University (Jiaoyan Chen) and Zhejiang University (Huajun Chen)
Conclusion

- Humanitarian mapping with Volunteered Geographic Information (VGI)
- Deep learning with VGI for satellite image classification
- Primary study: an active learning solution
- Problems to deal with in our future work
Thanks for Your Attention

Any Questions or Comments are Very Welcomed

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