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

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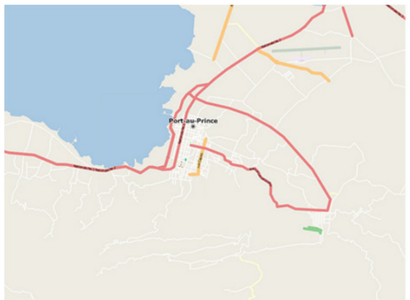
Contents

Humanitarian Mapping

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



Before

After

Haiti Earthquake 2010

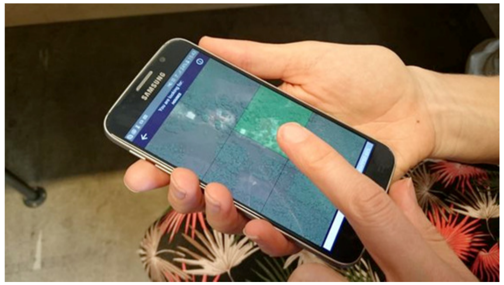
HOT Humanitarian OpenStreetMap Team

Mapping events in Heidelberg

MISSING MAPS

MapSwipe

- 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

MapSwipe https://mapswipe.org/

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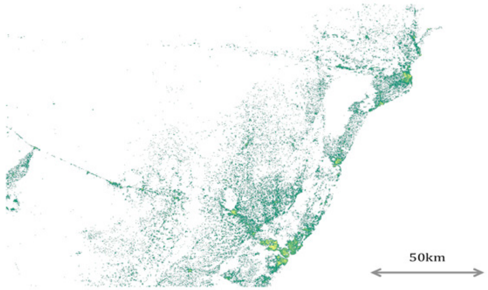
Satellite Observation

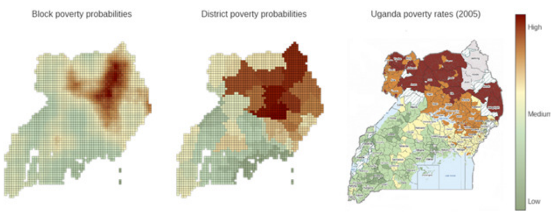
Maps



Population Mapping

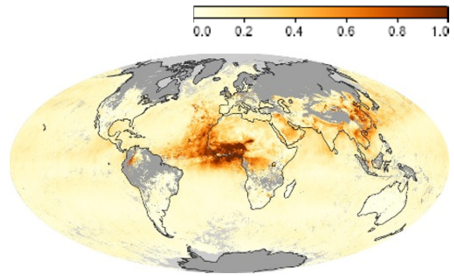
"Connecting the World with Better Maps", Facebook's Connectivity Lab

Satellite Observation



Poverty Mapping

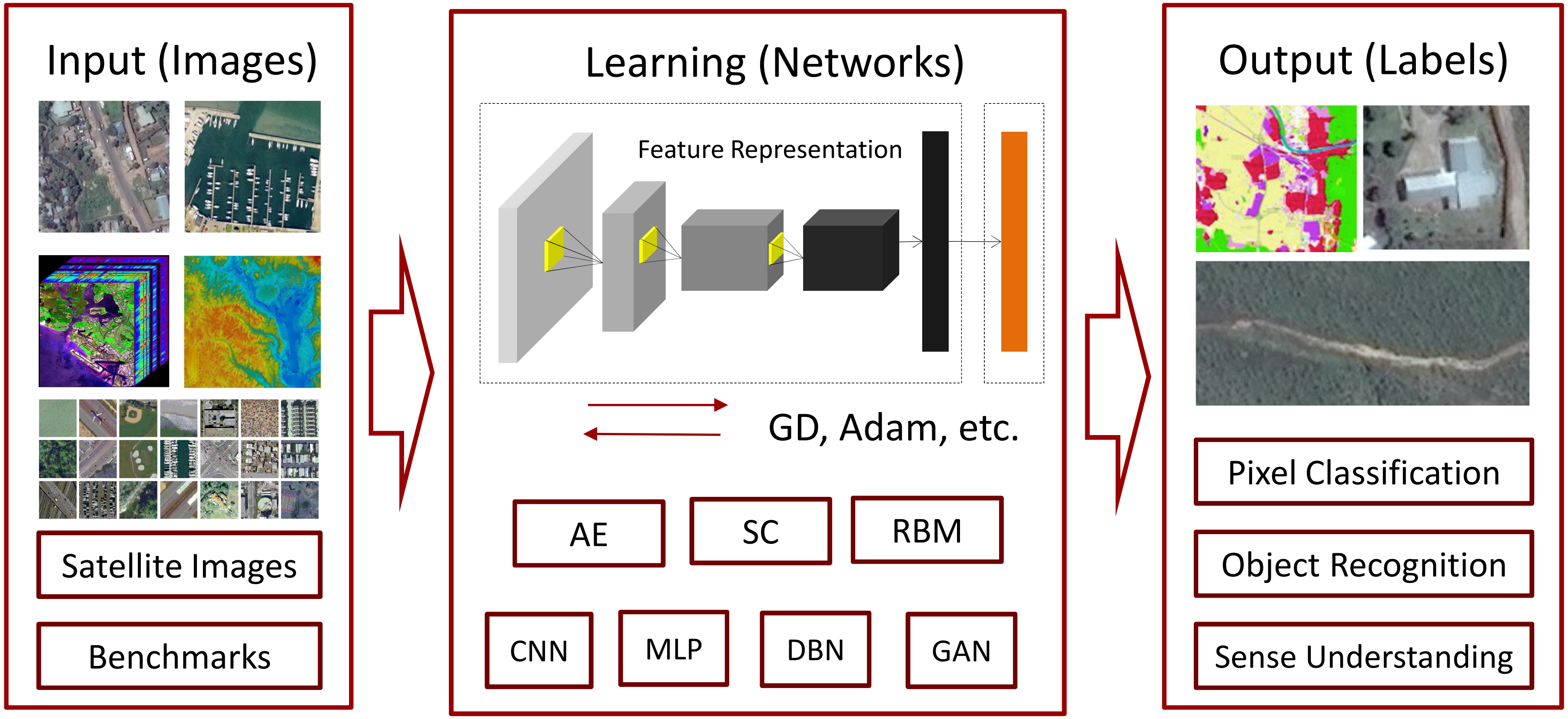
M. Xie, N. Jean, M. Burke, D. Lobell, and S. Ermon, "Transfer Learning from Deep Features for Remote Sensing and Poverty Mapping," AAAI 2016.



Aerosol Optical Depth and Public Health

"Atmospheric Aerosols: What Are They, and Why Are They So Important?" NASA

Deep Learning



Zhang, L., Zhang, L., & Kumar, V. (2016). “Deep learning for Remote Sensing Data, A Technical Tutorial on the State-of-The-Art” IEEE Geoscience and Remote Sensing Magazine, (June), 18

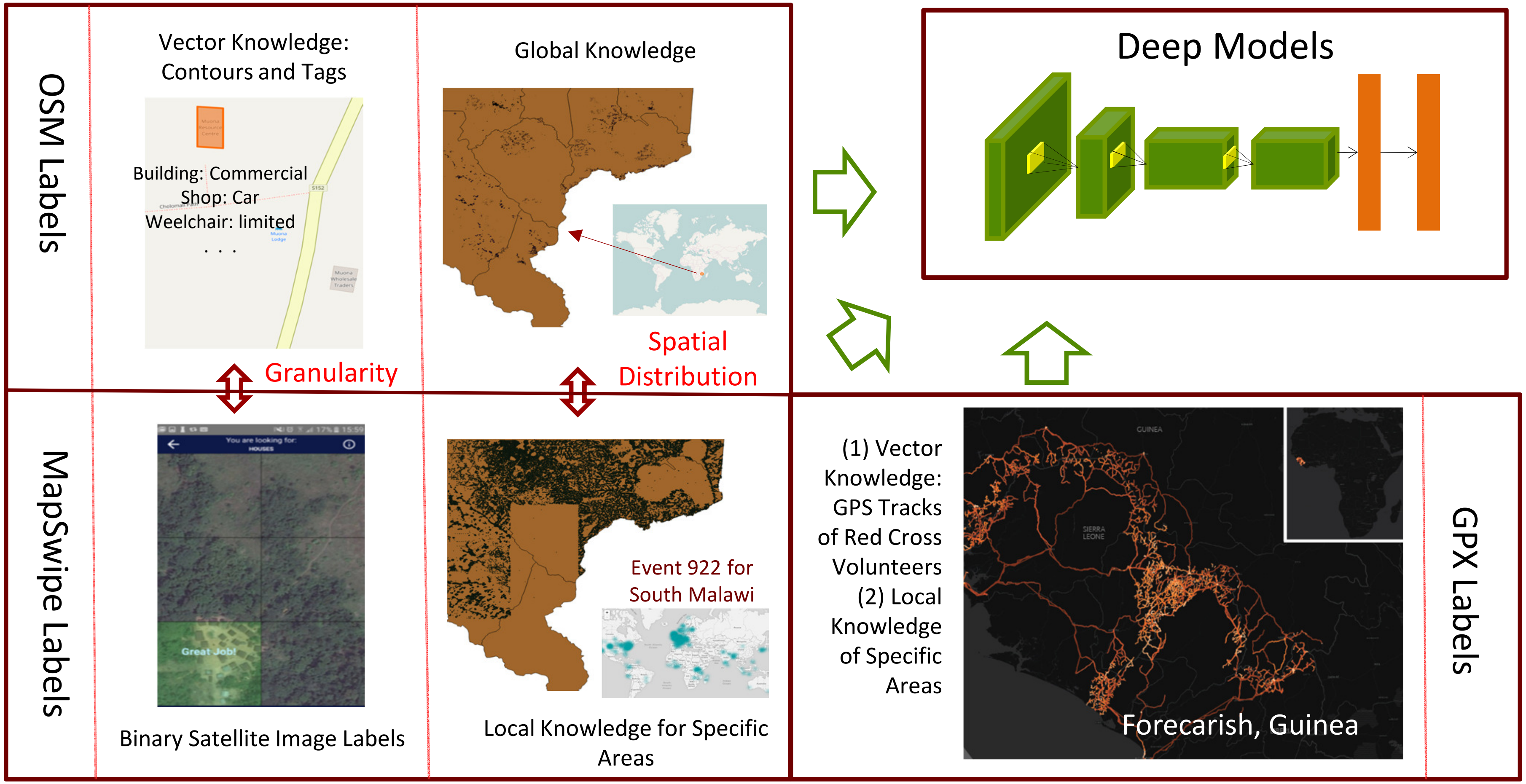
Training Data Challenge

Popular Benchmarks

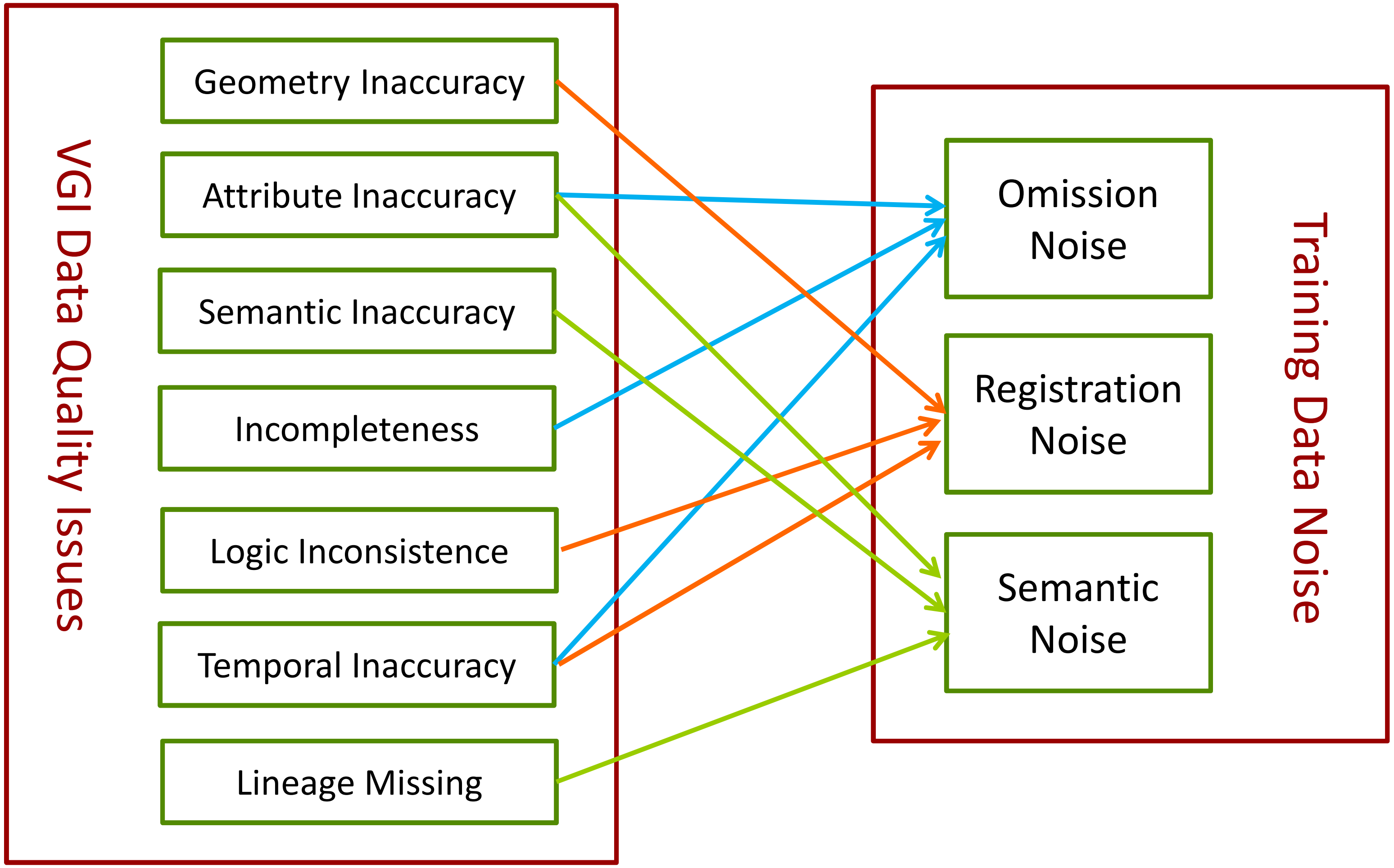
Name	Classes & Size	Coverage
UC Merced Land Use	21 classes, each with 100 images	Urban Areas in USA
Brazilian Coffee Sense Dataset	Coffee crops and none coffee crops, each with 1438 images	Four counties in the State of Gerais, Brazil
UCI Statlog Landsat Satellite Dataset	7 classes with totally 6435 samples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

Limited Size → Limited Spatial Coverage → Limited Semantics

Learning from The Crowds



VGI Data Quality and 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]:

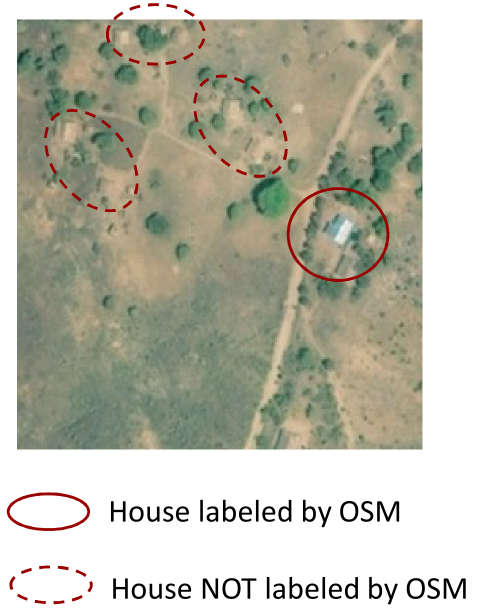
deep road and building detection models with more robust loss functions to deal with the registration noise and missing noise considered

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

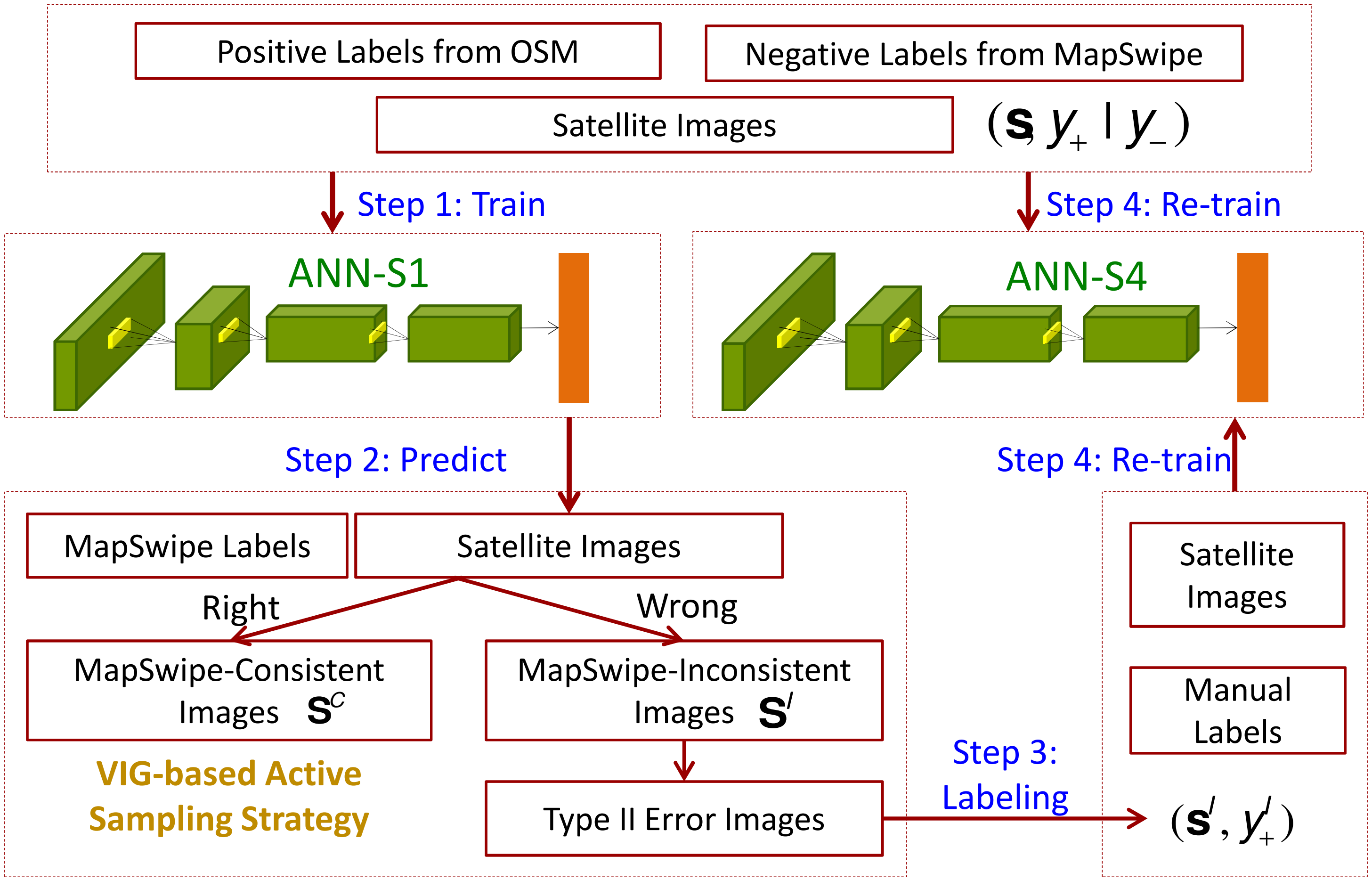
Contents

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)



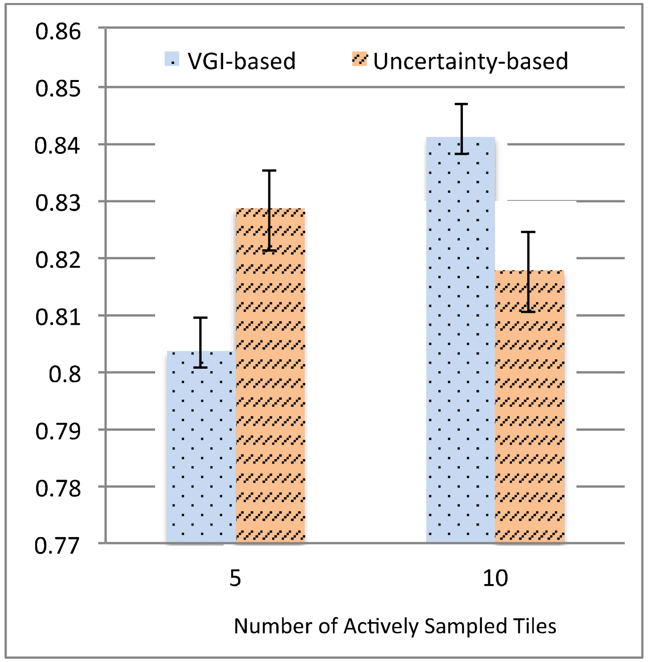
Technical Framework



Evaluation

- 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)

Evaluation



The VGI-based active learning strategy outperforms the uncertainty-based for building detection with ANNs (LeNet and MLN)

	Precision	Recall	F1 Score	Accuracy
DeepVGI	0.775	0.737	0.756	0.841
Deep-OSM	0.632	0.875	0.734	0.788
MapSwipe	0.738	0.938	0.826	0.868

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

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Future Work

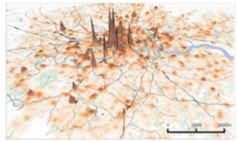
How to learn from multiple crowds: OSM, MapSwipe, GPS, etc.?

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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