Foundational mapping of Uganda to assist American Red Cross disaster response to floods and pandemics

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1 Problem Description

Preparing and responding to humanitarian disasters requires accurate and timely mapping of affected regions. Foundational data such as roads, waterways, population settlements are critical in mapping evacuation routes, community gathering points, and resource allocation.

Current approaches require time-intensive manual labeling from teams of crowdsource human volunteers, such as the Humanitarian OpenStreetMap Team (HOT). We are partnering with the American Red Cross to explore how machine learning techniques can be leveraged to automate the generation of accurate foundational maps from remote sensing data. Here, we describe two critical Red Cross missions in Uganda, our proposed application of machine learning, and the constraints and challenges we anticipate to encounter in deployment and evaluation.

The American Red Cross described two missions where effectiveness is hampered by the lack of accurate foundational data:

- Pandemic Response: Containing outbreaks of diseases endemic to the region, such as viral hemorrhagic fevers, requires accessible facilities to act as local outposts to coordinate the response, and train healthcare workers.
- Severe flooding: Heavy rainfall can cause disruptive flooding in Uganda, rendering transportation infrastructure unusable and displacing hundreds of thousands of people, who often rely on emergency relief for food and clean water [1]. These events are expected to become more frequent due to climate change. Flooding that coincides with outbreaks could exacerbate pandemics by disrupting communities' evacuation routes and hindering aid organizations' ability to bring in needed supplies. Quickly identifying viable infrastructure after flooding would accelerate the ability of aid organizations to respond.

For both types of emergencies, well-annotated, reliable maps can provide emergency preparedness teams with crucial information needed to successfully and hastily conduct their missions.

2 Proposed Deliverables

- Pandemic response time: we propose applying computer vision to help augment the existing maps of schools that can be used as aid-worker facilities during outbreak response. Red Cross teams currently invest substantial time visiting villages to identify and update school locations, while also educating village leaders about ways to prepare for pandemics. Existing school annotations are either incorrect or missing, in turn our deliverable is: (1) List of school locations in Uganda that are missing or incorrect in OpenStreetMap (OSM), and (2) the model used to generate these annotations, and details for how it can be rerun on updated data for future versions of the OSM.

Submitted to 32nd Conference on Neural Information Processing Systems (NIPS 2018). Do not distribute.

- Severe flooding response: As part of local community outreach, Red Cross teams prepare evacuation routes in case of disasters such as flooding. An accurate mapping of bridges is critical to effective route planning, because bridges are often at risk of being washed out or becoming impassable during floods. Proposed deliverables here would be (1) geographic coordinates for all road bridges that cross rivers, and (2) algorithm for reproducing the results in order to run inference after a flood event.

3 Machine Learning Feasibility

Various sources of data are potentially relevant to these tasks, some of which are public, and others of which we are purchasing from DigitalGlobe. These are summarized below:

- **Satellite imagery**: Satellite imagery are available through DigitalGlobe and Planet. Data from Planet are available through an education and research license, and we have access to data from DigitalGlobe. This imagery includes 8 band multi-spectral data across various collect times.
- **OSM Annotations**: Roads, rivers, and schools in Uganda have been annotated by OSM volunteers, with varying degrees of coverage and accuracy. For example, the Uganda Bureau of Statistics has begun an effort to import $>$ 24,000 school coordinates [2].
- **Complementary school information**: In addition to coordinates already uploaded to the OpenStreetMap, the Education Department of Uganda has uploaded a list of all primary and secondary school names and their Parish locations, which are potentially geocodable [3]. Some data may also be accessible via ProjectConnect [4], a UN project to map schools which leveraged broadband internet provider data.
- **Purchased Annotations**: In addition to these public data, we will be using a third-party provider to gather gold standard annotations relevant to both tasks.

The specific machine learning formulations most useful to these tasks still need to be identified. For example, we could use semantic segmentation to determine rivers and roads from annotated satellite imagery, and use intersection points as proposals for bridges. For school labels, we could attempt to infer ground truth coordinates based on noisy labelings from the heterogeneous sources described above.

4 Constraints and Challenges

Beyond machine learning, important challenges we face include (1) integration with the existing OSM data and (2) ensuring sustainable training data creation and system deployment. Any machine learning model will propose incorrect annotations, and presenting results in a way that makes the best use of OSM volunteers time will be important. For example, it might be possible to build an interface that lets volunteers import a large collection of confident machine annotations at once, or a system to easily introduce small adjustments to proposed labels. For sustainable training data, we have considered leveraging the Red Cross' volunteer annotation team through Missing Maps [5], and adapting a model initially trained on one set of expert labels to these noisier, but more up-to-date ones.

Ultimately, we hope that this system contributes to concrete improvements in the Red Cross' efforts to prepare for emergencies in Uganda. We also believe that this exercise in improving map annotations by leveraging various data sources can both motivate the development of practical tools and novel abstractions for blending crowdsourcing with machine learning during crisis response in many other places.

References

[1] Floods continue to ravage Uganda: Thousands risk lives as they cross cut off flooded areas. *International Federation of Red Cross and Red Crescent Societies*, Sep 2007. `http://www.ifrc.org/en/news-and-media/news-stories/africa/uganda/floods-continue-to-ravage-uganda/`.

[2] Wikiproject Uganda / Import Uganda Bureau of Statistics education facilities. *Wiki OpenStreetMap*. https://wiki.openstreetmap.org/wiki/WikiProject_Uganda/Import_Uganda_Bureau_Of_Statistics_Education_Facilities.

[3] List of government primary schools. *Uganda Ministry of Education*. http://www.education.go.ug/files/downloads/List%20of%20Government%20Primary%20Schools%202016.pdf.

[4] Project connect. *Unicef Project Connect*. https://www.projectconnect.world/.

[5] Missing maps. https://missingmaps.org.