Generating Building Exterior Wall Material Estimates Using Google Street View Imagery

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AAG Annual Meeting, 2017
Boston, MA

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Overview

- Global Building Characterization Project
  - Learning about buildings is important
  - No global building characterization database with exterior wall material, height, occupancy, etc.
  - Several problems with coverage and validation
- Google Street View API and Imagery
  - Imprecise sampling of buildings to determine building characteristics
  - Leveraging current data with Google Street View API to obtain imagery
  - Limitations of Google Street View coverage
- Image Classification
  - Opportunity to concentrate on exterior wall material
  - A hypothetical framework for creating building exterior wall material estimates
- Future Work and Considerations
  - Other exterior wall materials, other building characteristics

Earthquakes don’t kill people, buildings do.

- Someone said this

Nepal
April 25th, 2015, over 2,000 dead

Photo by Athit Perawongmetha via Reuters

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Japan
March 11th, 2011, over 18,000 dead or missing

Photo by Yasushi Kanno, Yomiuri Shimbun, via AP

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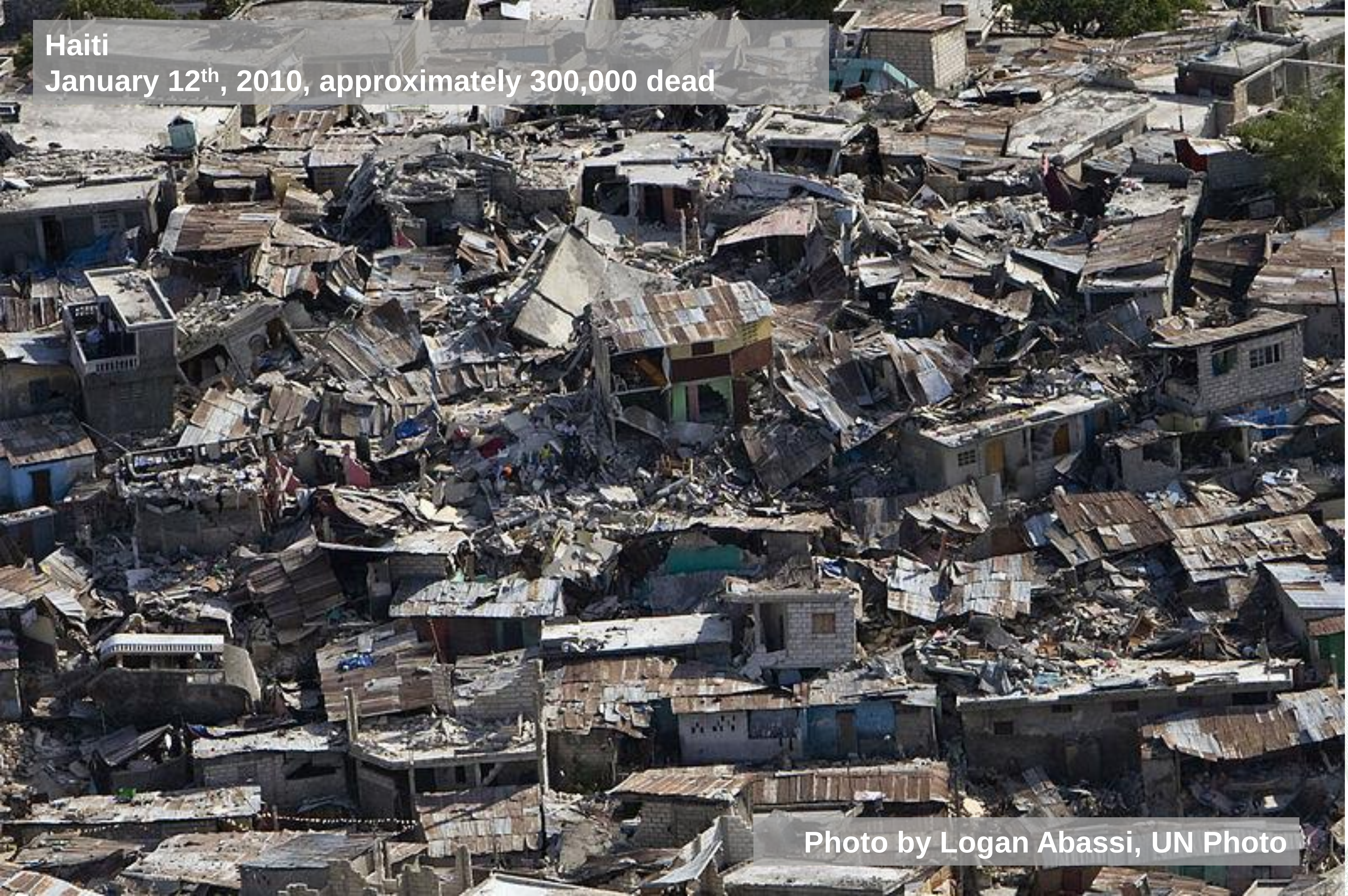

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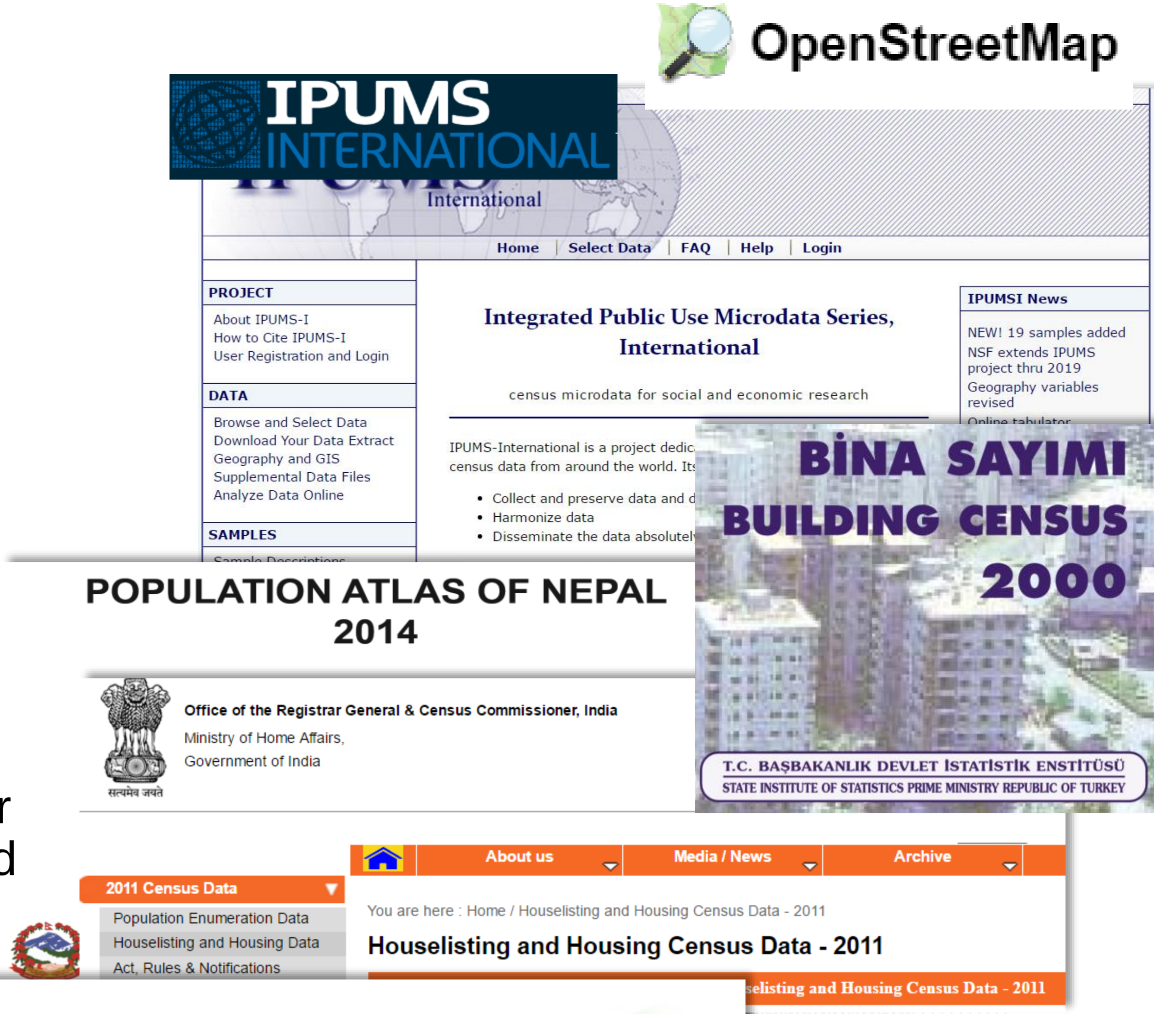
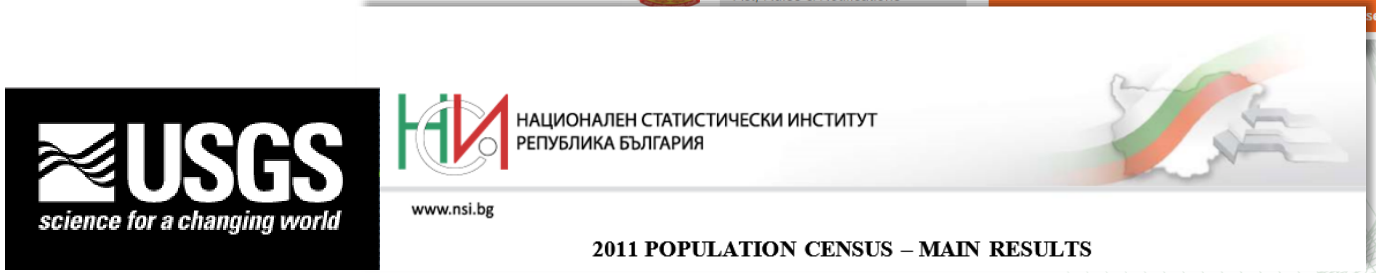
Global Building Characterization

Data Collection

Data sources including IPUMS, PAGER, OSM, and national censuses are checked for relevant building information.

- IPUMS (Integrated Public Use Microdata Series) International provides microdata for countries of interest
- Search for national census data that might be published after or might be more illustrative than IPUMS microdata
- Use PAGER (Prompt Assessment of Global Earthquakes for Response) and OSM (Open Street Map) data where needed





Global Building Characterization

GEM NEXUS working together to assess risk

Data Translation

Though we always try to obtain as much building information for a country as possible, we focus our efforts on key variables:

- **Exterior wall material**
- **Height**
- **Occupancy**

All of the variables of interest are:

- Direction of the building
- Material of the lateral load-resisting system
- Lateral load-resisting system
- Height
- Date of construction/retrofit
- Occupancy
- Building position within a block
- Shape of the building plan
- Structural irregularities
- Exterior wall material
- Roof material
- Floor material
- Foundation system

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Global Building Characterization

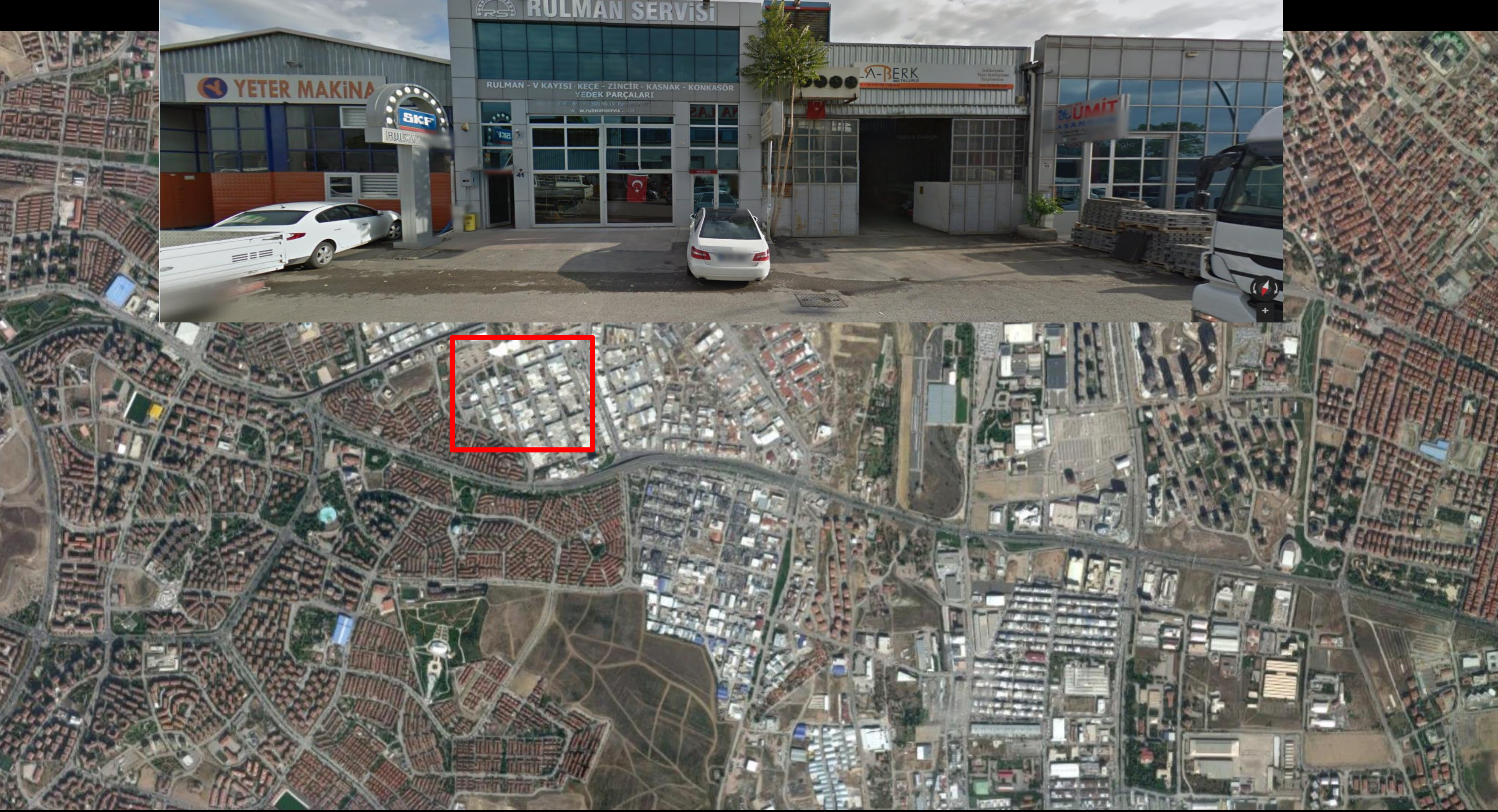
Coverage/Validation Issues

When translating building characteristics for a country, we encountered some challenges:

- Unclear translations
- Omission of an area
- Skeptical numbers or data inconsistent with other data sources

Solution?

- Check out Google Maps!


RULMAN SERVİSİ
YETER MAKİNA
RULMAN - V KAYISI - KEÇE - ZİNCİR - KASNAK - KONKASÖR
YEDEK PARÇALARI
SKF
ÜMİT


Hide imagery

Google Street View API and Imagery

Pros:

- Acts as “ground truth”—can validate census data or microdata
- Imagery is already there, free to access
- Can build distributions of building exterior wall material

Cons:

- Limited by Google Street View coverage
- Limited by API request cap of 25,000 images a day
- Must create a framework for sampling images and extracting information
- Create labelled dataset, knowledge of machine learning

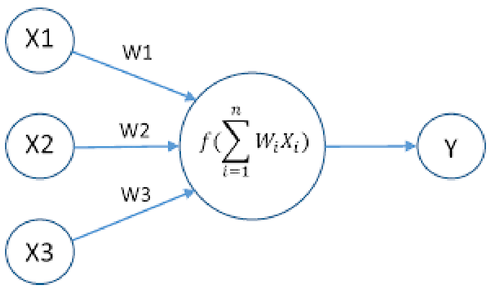
Image Classification

Proposed Methodology

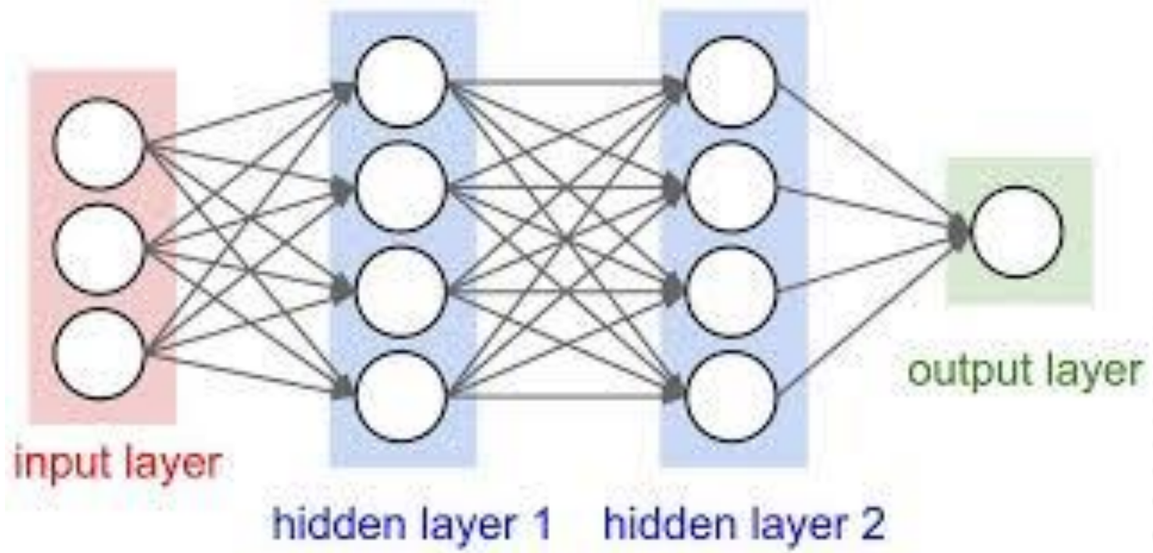
1. Leverage ORNL resources to create labelled dataset
   - Parcel centroids of all the buildings in the United States
   - High-performance computing for running the model (GPU)
2. Run a small Convolutional Neural Network (CNN) to detect exterior wall material
   - Start with open source software—LeNet
   - Concentrate on one building material type at first: brick versus non-brick
3. Analyze the results, make changes as necessary
   - Assess the model’s performance
   - Consider how to improve the model

Image Classification

Short Introduction into Neural Networks



- **What is a neural network?**
  - A neural network is the computer simulation of the human brain: it attempts to “learn things” on its own through copious training.
  - A neural network consists of:
    - Input units
    - Layers
    - Output units



- **What is a convolutional neural network (CNN)?**
  - A CNN is a neural network that processes input images in portions (performing “convolutions”) so that the output is a higher-resolution representation of the original image.

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Image Classification

Great resources:
Image Classification
http://neuralnetworksanddeeplearning.com/chap1.html
http://cs231n.github.io/classification/ (left text and image below)
http://people.csail.mit.edu/torralba/shortCourseRLOC/index.html
http://docs.opencv.org/2.4/modules/ml/doc/neural_networks.html
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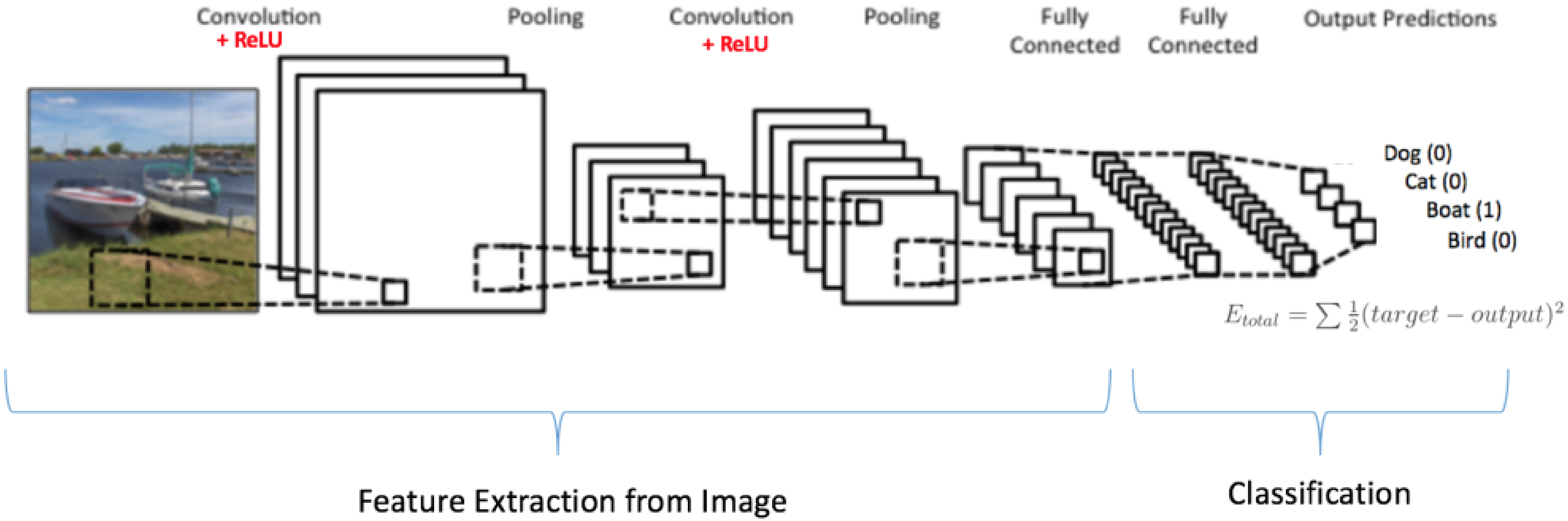
http://caffe.berkeleyvision.org/gathered/examples/mnist.html

LeNet

Convolution Non-Linearity (ReLU) Pooling or Subsampling Classification



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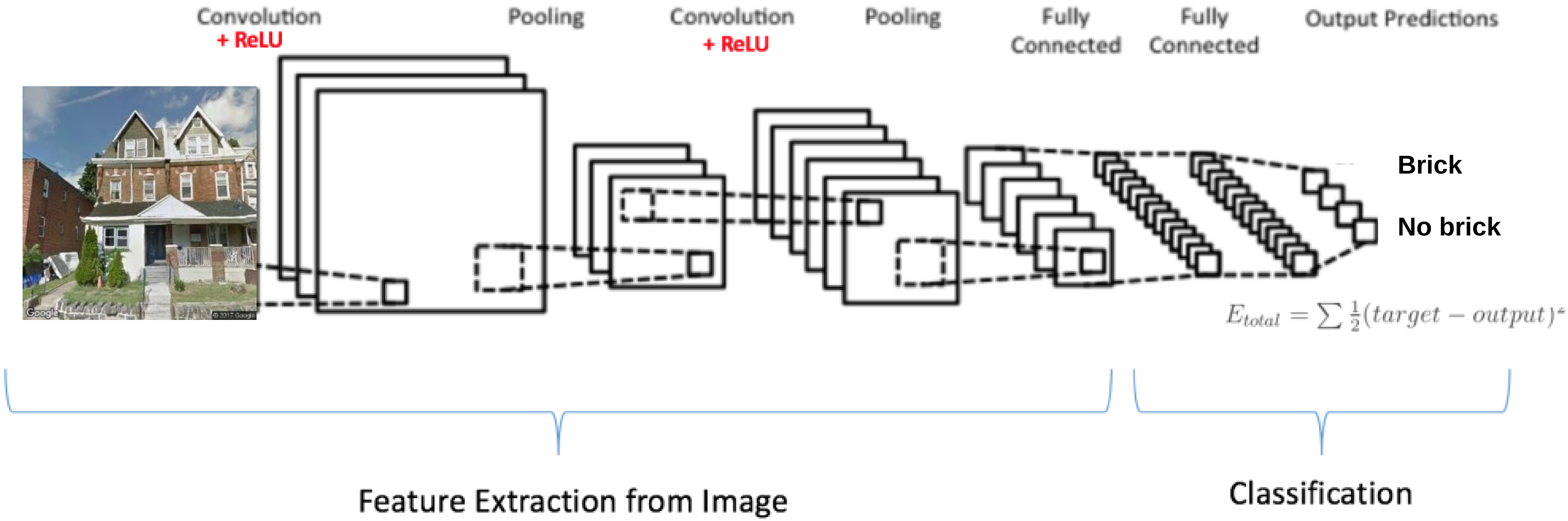

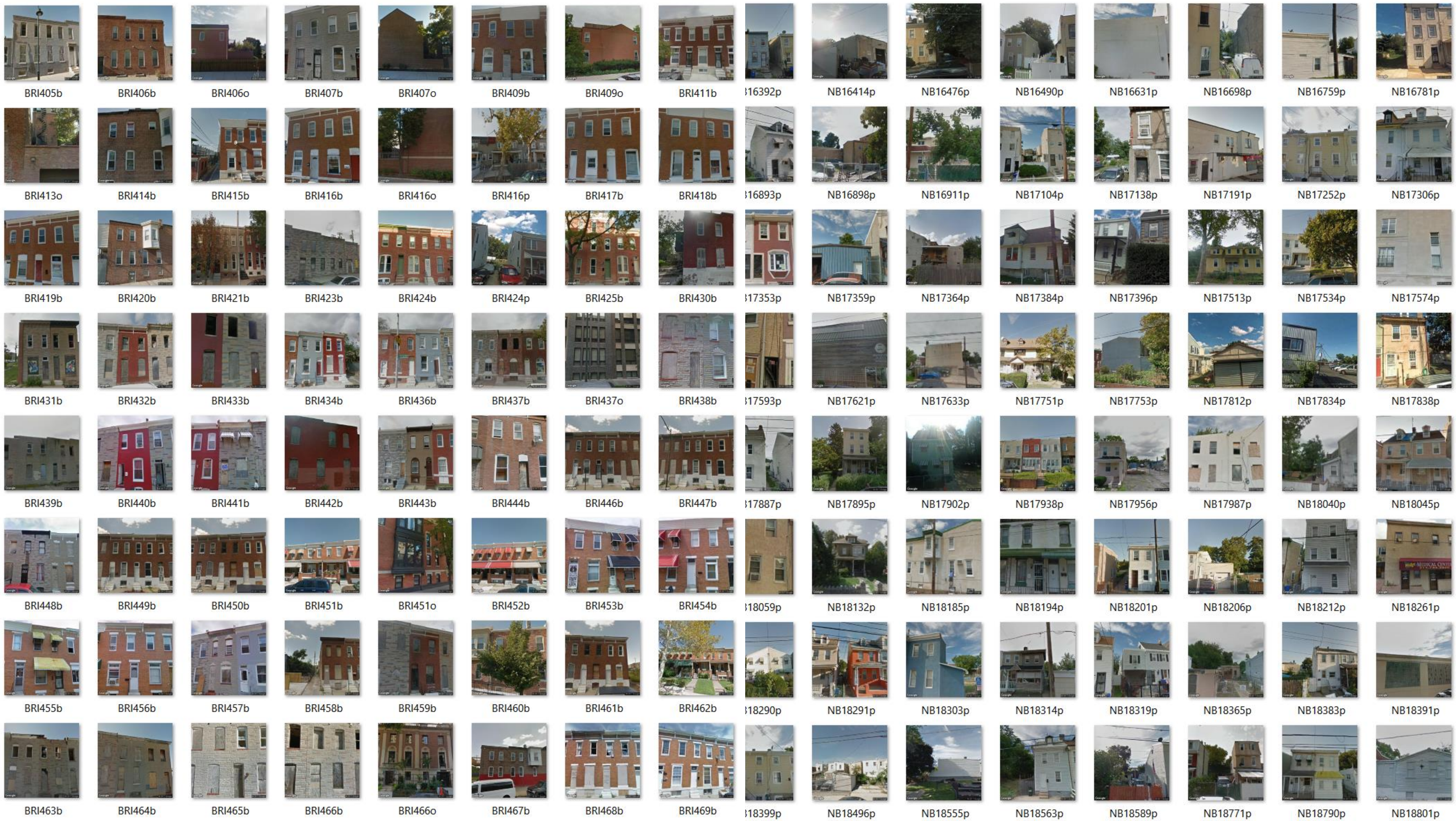
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BRI431b BRI432b BRI433b BRI434b BRI436b BRI437b BRI437o BRI438b 17593p NB17621p NB17633p NB17751p NB17753p NB17812p NB17834p NB17838p
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Results

Training Model
(~8,000 images)

Validation Set
(~2,000 images)

- Model creation ~4 hours on 1 GPU
- Model validation < 1 hour

Statistic	Accuracy (%)
Grand Average	0.5785
Minimum	0.46
Median	0.575
Maximum	0.67

Encouraging initial results, but still a somewhat low accuracy rate.

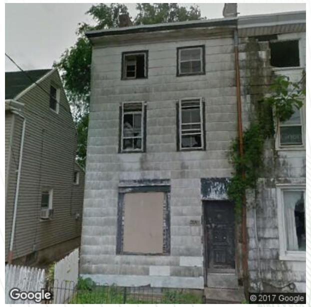
Considerations

How can we improve this model?

- Modify the learning rate?
- Modify the image size (decrease field of view)?
- Improve images labels?
- Increase number of images?

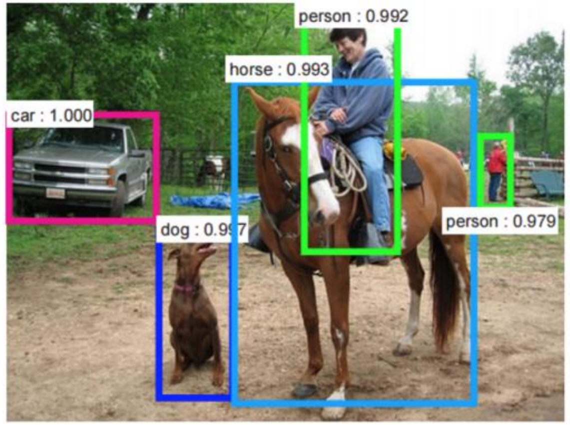
- Are there elements in both sets of images (trees) that are confusing the model?
    - Is the binary classification too narrow?

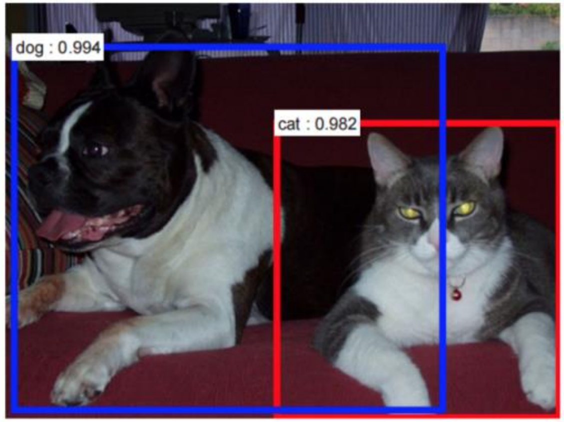
Lots of room for future work.



Too similar? → Non brick | Brick

Future Work

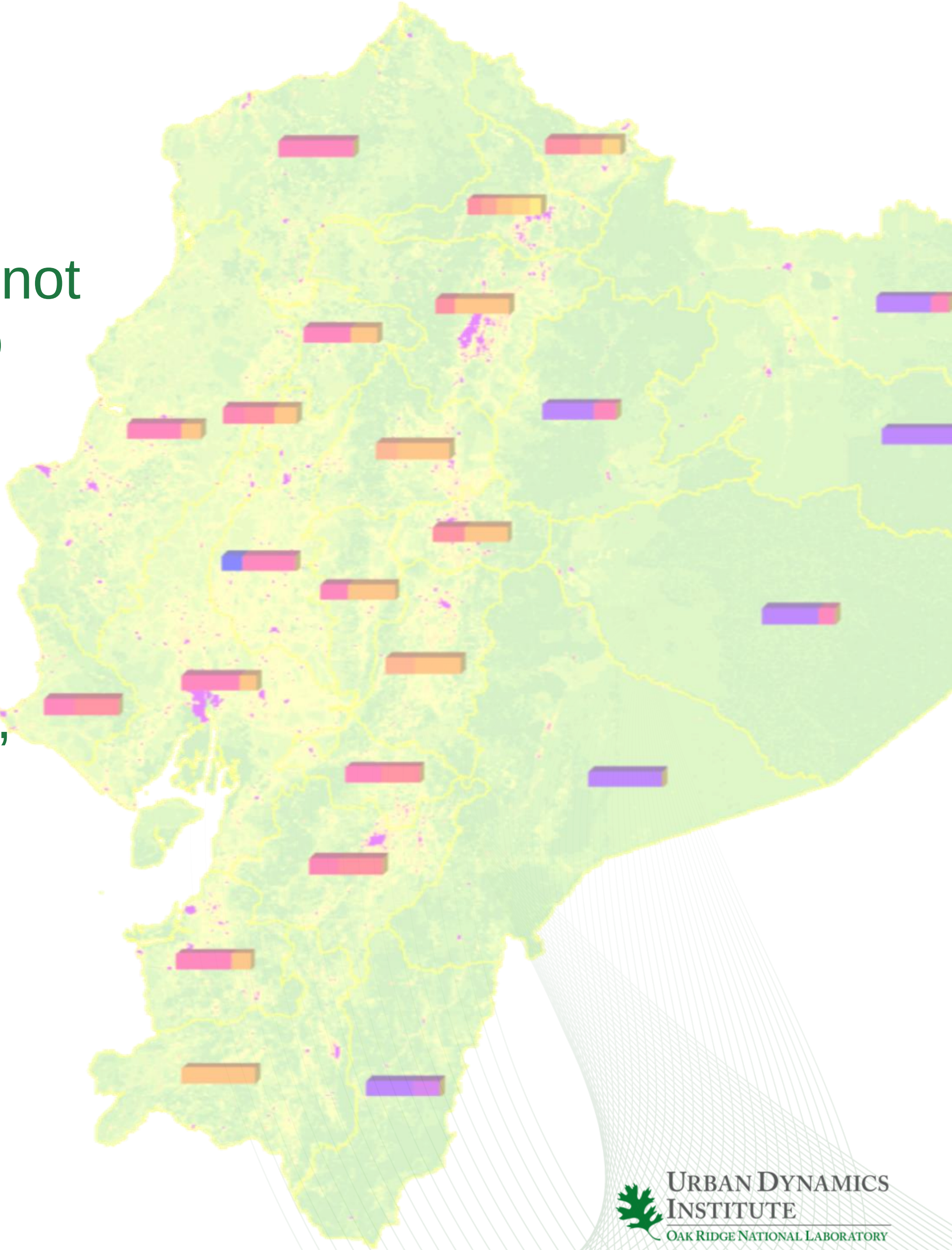




- Multiple classifications, more models
  - Improved image translations and more defined classes
- Way to assess which images Google Street View API pulls
  - Create better distance thresholds
  - Urban model has shorter FOV, rural model has longer FOV
- Explore the use of other neural networks or CNNs
  - AlexNet, GoogleNet, imageNet, etc.
- Estimate building distributions in unknown area using model created from known areas
  - Additional framework for assessing model accuracy

Conclusion

- No global building characteristics database, but not much can be done for areas in which there is no data
- As Google Street View Imagery coverage increases, therein lies an opportunity to characterize buildings
- The results of the LeNet model are encouraging, but there is much more work to be done until building exterior wall estimates can be made



Acknowledgements

ORNL Staff Scientists and Research Associates

Travis Johnston

Byung Park

David Hughes

Jessica Moehl

Lexie Yang

Jake McKee

Lora Meadows

Jared Cleghorn

Thank you!

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Questions?

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Thank you for listening!