Summary of rbc project

Apr. 15, 2018

Datasets

Our research goal is to find out how region-specific data help us increase the classification accuracy. As a result, we need both general data that are collected globally and specific data that are unique to area of our interest in order to establish a meaningful comparison. In our research, we used two distinct datasets: Functional Map of the World(fMoW) and Wake County Dataset(Wake). fMoW is a publicly available dataset that contains houses all over the world while Wake is privately collected data specific to Wake County. Model trained on fMoW will serve as the baseline to which we compare the improvement in accuracy from model fine-tuned with Wake data.

Functional Map of the World

These were satellite images of various buildings around the world. This dataset was taken from Functional Map of the World. In the dataset provided by the paper, the buildings were categorized into about 20 categories (eg. single-unit residential, multi-unit residential, office, place of worship, etc.). We classified single-unit and multi-unit residential buildings into our category of "Residential", and all of the other categories from the paper were categorized as "Non-residential". There were about 180,000 total buildings in the dataset and about 18,000 residential buildings.

Wake County

We also collected images of Wake County buildings using Google Maps and QGIS. We had a GIS file containing the location and shape of about 300,000 buildings in Wake County. We used

a feature on QGIS called Atlas, which allows the user to automatically cycle through every

building identified on the gis file and capture an image of the building. There were about

300,000 total buildings and about 19,000 non-residential.

Methodology

To observe the effect of fine tuning based on region-specific data, we first establish a base

model trained from global data. We then test the model directly on regional (Wake County) data

without fine tuning. After obtaining the benchmark accuracy, we train the model further with a

varying amount of regional data and observe the improvement on regional accuracy.

1. We trained a DenseNet on fMoW to classify the buildings into residential and

non-residential. We used a total of 50000 images from fMoW with 13000 residential and

37000 non-residential images. We then tested the classification accuracy on Wake data.

2. We then fine-tuned the base model using images from Wake. In order to qualitatively

assess the improvement of testing accuracy with respect to number of images used for fine-tuning, we used different number of fine-tuning images and record the testing

accuracy for each. In the end we obtained a relationship between testing accuracy and

number of images from Wake used for fine tuning.

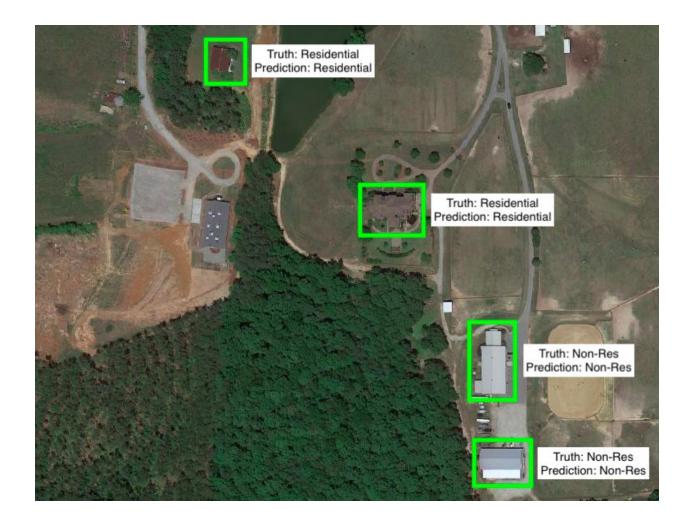
Observation

Wake Testing Sample Size: 2000

fMoW Testing Sample Size: 10000

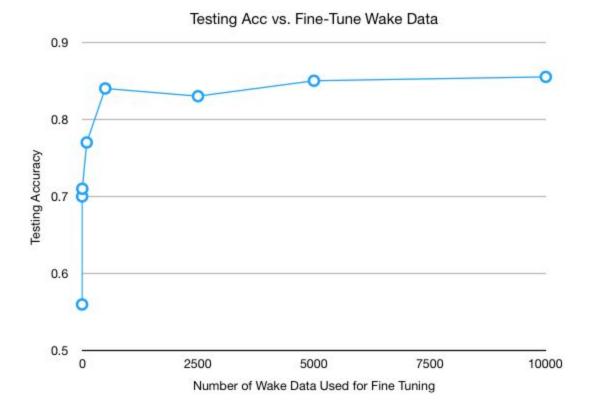






Improvement on Classification Accuracy

Fine-tuning base model on Wake data increases testing accuracy by a huge margin, with a decreasing amount of improvement when there is saturating amount of fine-tune data.



Number of Wake Fine Tuning Data	Testing Accuracy on Wake	
0(Base Model trained on fMoW)	0.5638	
1	0.7034	
5	0.7132	
100	0.7719	
500	0.8317	
2500	0.8273	
5000	0.8496	
10000	0.8543	

We also provide the testing accuracy on Wake with a model trained exclusively on Wake data.

Number of training Wake data	Testing Accuracy on Wake
5000	0.8571
10000	0.8738
12000	0.8734

Significantly Shorter Training Time

The above charts show that training exclusively on Wake data provide a similar testing accuracy in comparison to fine-tuning based on a pre-trained model from fMoW. However, a major advantage of transfer learning is faster convergence. Here, we show that it takes much less time for the pre-trained model to achieve the same level of testing accuracy than model trained from scratch on Wake.

Testing Accuracy	Time for Train from Scratch	Time for Fine Tune
0.83	14 min	5 min
0.85	20 min	15 min
0.87	120 min	-