School mapping in ESRI imagery

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Recap from last meeting

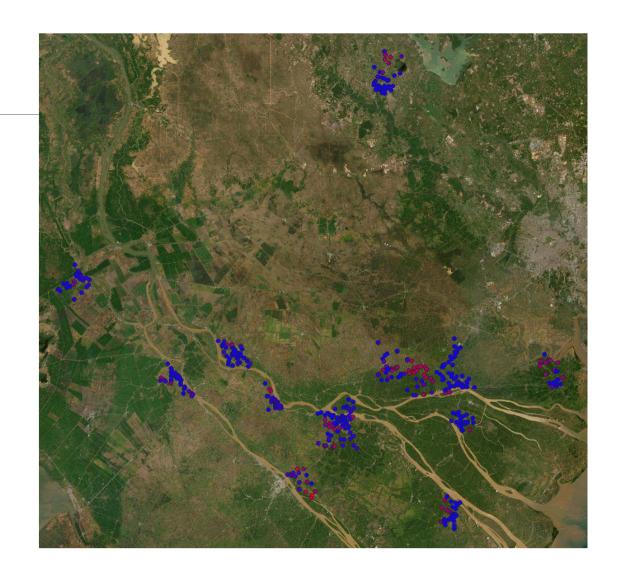
2-stage training, fine-tune and eval on Anditi schools

- 2-fold cross-validation
 - 50:50 train/val split of school locations
 - Add equal number of non-school locations
 - Sampled randomly throughout Vietnam
 - Unusually high results F1: 93.91%
 - In spite of potentially problematic outdated imagery

Potential problems

Outdated imagery

- Schools visible on Google Maps, but not in ESRI images
- Possible solutions:
 - Urban growth layer
 - ESRI metadata layer
 - Combination of the 2 methods
 - Compressed file size



Potential problems

- Many schools next to each other
 - For cross-validation experiments, we do a random 50:50 train/val split
 - Data leakage overlapping images get into both splits





Potential problems

Distinct appearance

• Images from different regions have large variations in appearance







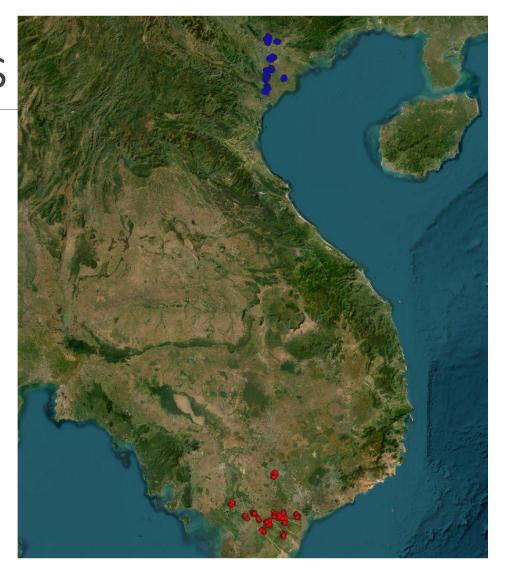
Solution – split by clusters

More realistic results

• F1: 81.55%

• P: 95.94%

• R: 73.97%



New contributions

Non-school sampling

Previously:

- Non-schools sampled throughout Vietnam
- Non-schools have no connection to the splits' schools

- Sample non-schools based on distance from schools
- Goal: train model only on non-school images geographically close to corresponding school images

- Schools are split into two clusters
- For each cluster, calculate the corresponding centroid
- For each non-school (OSM Vietnam data), calculate the Euclidean distance from both centroids

$$d((x,y),(a,b)) = \sqrt{(x-a)^2 + (y-b)^2}$$

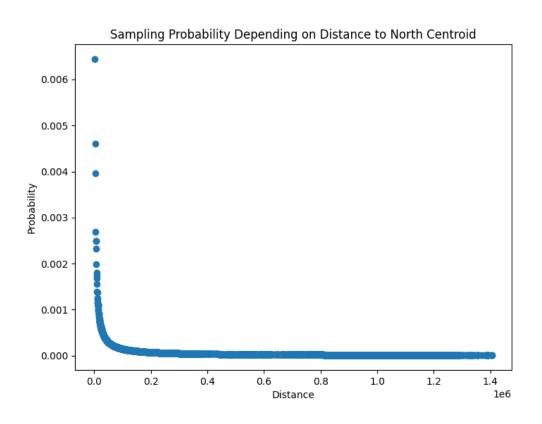
Convert distances to probabilities of sampling

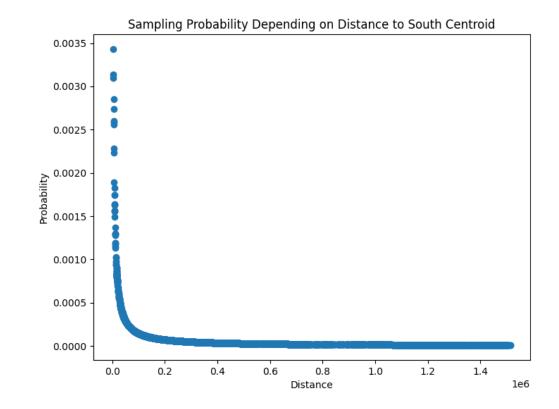
$$p_c(x) = \frac{1}{d_{c,x} + \varepsilon}$$
 , $\varepsilon = 1 * 10^{-10}$

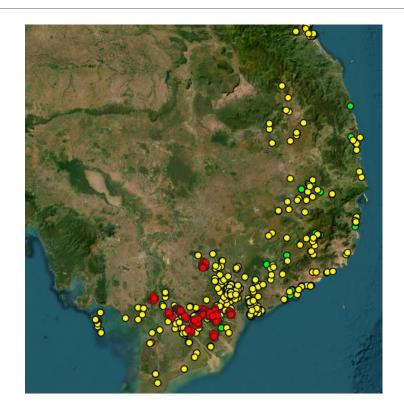
Sample non-schools for each cluster individually (no repetition)

Algorithm 1 Distance-based non-school sampling $X_N = \{\text{North Cluster School Data}\}$

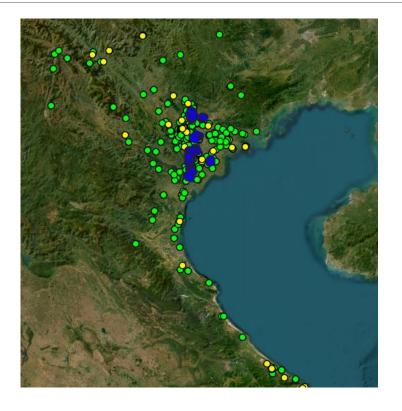
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X_S = \{ \text{South Cluster School Data} \}
X_{NS} = \{ \text{Non-school Data} \}
\epsilon = 1 \cdot 10^{-10}
C_N = (\text{mean}(X_N.long), \text{mean}(X_N.lat))
C_S = (\text{mean}(X_S.long), \text{mean}(X_S.lat))
for (X_i, C_i) in ((X_N, C_N), (X_S, C_S)) do
    for (X_c \text{ in } X_{NS}) do
        X_c.d = \sqrt{(X_c.long - C_i.long)^2 + (X_c.lat - C_i.lat)^2}
        X_c.p = \frac{1}{X_c.d+\epsilon}
    end for
   p_{sum} = \operatorname{sum}(X_{NS}.p)
   for (X_c \text{ in } X_{NS}) do
        X_c.p /= p_{sum}
    end for
    X_{i-NS} = sample_with_probs(data=X_{NS}, size=length(X_i),
replace=False)
    X_{NS} = X_{NS} \setminus X_{i-NS}
end for
```







- South School Cluster
- South Sampled Non-Schools

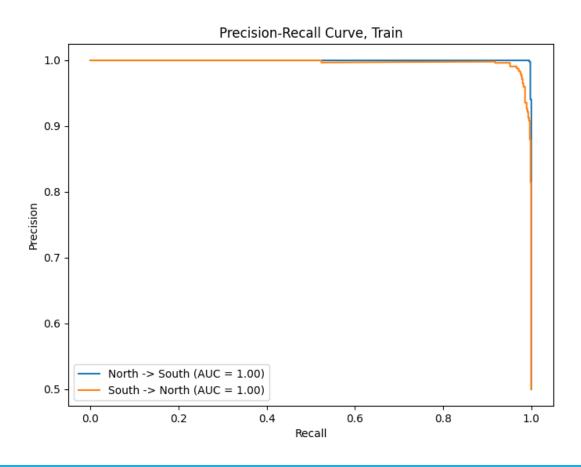


- North School Cluster
- North Sampled Non-Schools

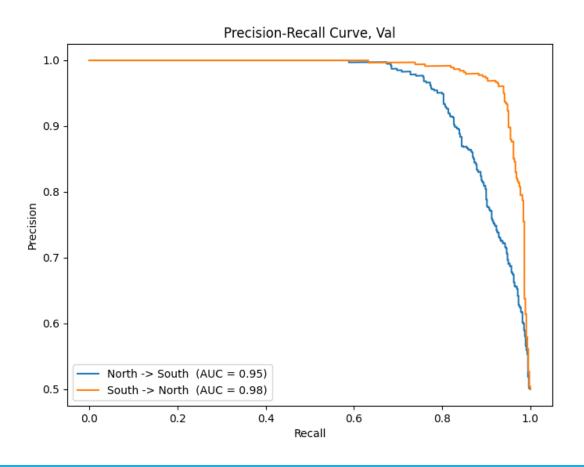
Results comparison

- Random non-school sampling
 - F1: 81.55%
 - P: 95.94%
 - R: 73.97%
- Distance-based non-school sampling
 - F1: 89.03%
 - P: 97.38%
 - R: 82.53%

Precision-recall curve



Precision-recall curve



Future work

Dense inference (run newly fine-tuned model on tiles covering the chosen 26 districts)