Maritime Asset Protection using Deep Learning

Nicholas Warren, Jelena Tešić
Computer Science Department, Texas State University

State of the are advances in Deep Learning for Object Detection do not extend beyond consumer domain. We have developed a robust Deep Learning pipeline for Asset Protection in Maritime environment

Research Problem

How effective is Deep Learning for Maritime domain

Why not just apply a current object detection algorithm?

[Examples of Detectron visualizing on personal images]

A: *Machine Learning algorithms do exactly what you tell them to do . Deep Learning system was trained for consumer images in controlled environments with large objects in focus*

How is the Maritime Domain Different?

A: *Objects not centered or in focus with a large range of scale. Sensitive to weather conditions including high variability of lighting i.e. rain, fog, glare, overhead view,…*

Methodology

Train, evaluate, and tune Mask R-CNN pipeline

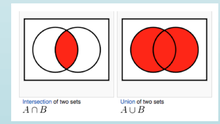
Deep Learning Architecture
- Mask R-CNN - Near real time
- ResNet
- [10.1109/ICCV.2017.322]

DATASET

- Base Training Set - Common Objects in Context(COCO), 860k object instances in training set, **10,800** annotations of boats in training set
- Control Set
  - COCO Training Set
  - IPATCH Low Level Challenge data - 3,581 boat annotations from 12,928 frames
- Validation Set
  - IPATCH Mid Level Challenge – 7,070 boat annotations from 31,706 frames. From separate scenarios and instances of Low Level Challenge.

Tuning Parameters

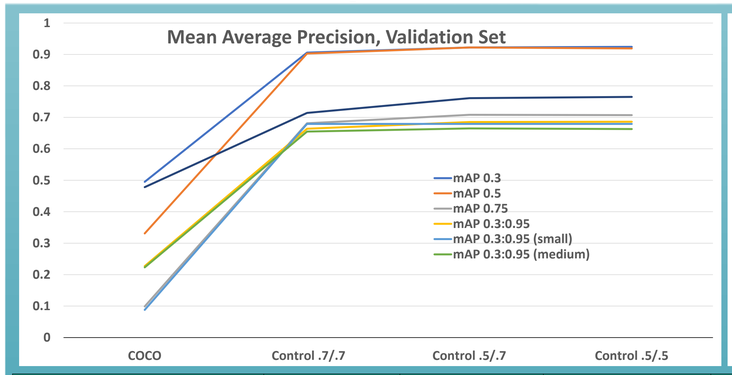
- Intersection of Union(IoU)

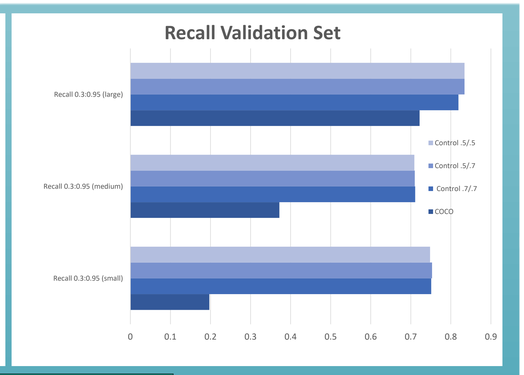


- RPN – region proposal network
- Model Threshold – lowered to 0.4 from default 0.7

Server
- Linux version 4.15.0
- CPU Intel® Xeon® Gold 5120 CPU @2.20GHz x2
- NVIDIA GeForce GTX 1080 GPU x4
- 376 GiB System memory

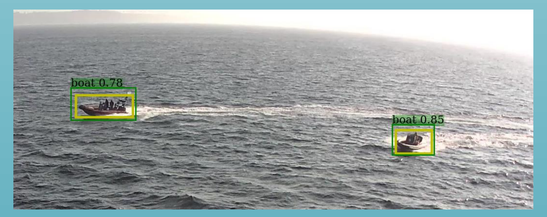
Experimental Results

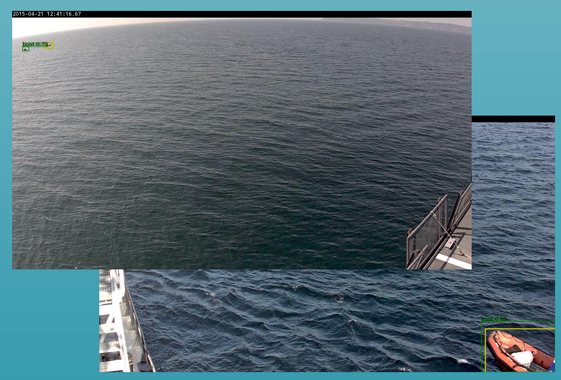




Model Trained On	Base	Control	Control	Control
RPN Train/RPN Test	0.7/0.7	0.7/0.7	0.5/0.7	0.5/0.5
mAP 0.75/0.5/0.3	**0.1/0.33/0.5**	**0.68/0.9/.91**	**0.71/0.92/0.92**	**0.71/.92/.92**
mAP 0.3:0.95	**0.49**	**0.66**	**0.685**	**0.68**
Recall 0.3:0.95	**.42**	**.74**	**.71**	**0.71**
mAP 0.3:0.95 (small)	**0.09**	**0.68**	**0.68**	**0.68**
Recall 0.3:0.95 (small)	**0.2**	**0.75**	**0.75**	**0.75**

Conclusion





Domain transition requires that the model be trained on data from that domain. Training on even large amounts of data seem not make up for the variables not captured within its training set. However, when adding a relatively small amount of data from the new domain, the robustness of the model is improved. Further adjustments may increase precision and recall (IoU, Region Proposal Network.

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Contact Info: ndw30@txstate.edu