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Visual Inspection for Aircraft & Power Lines

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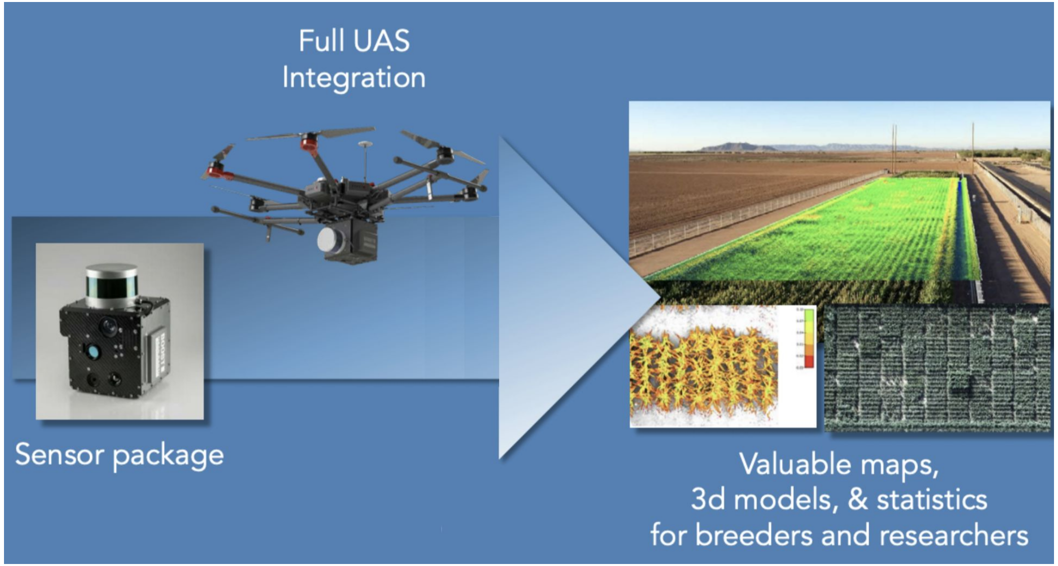
Summary



Motivation

Automate asset inspection with sensor data

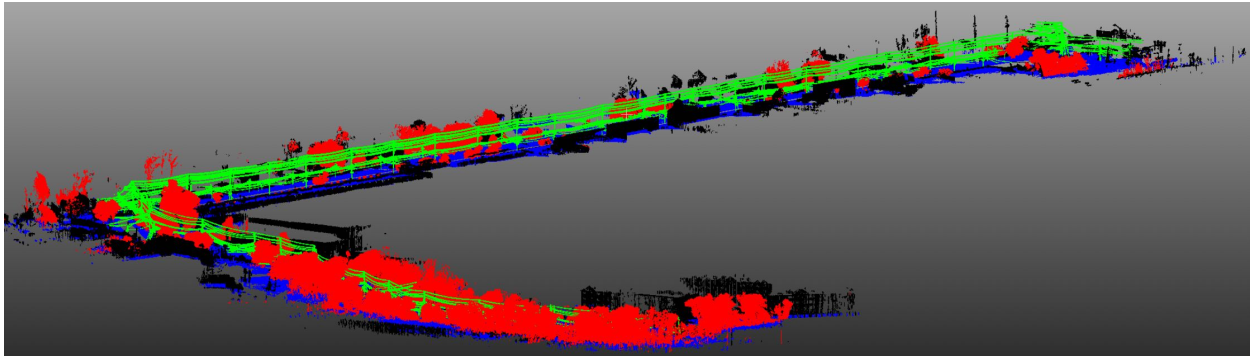
Problem

Powerline inspection & aircraft defect detection

Solution

Semantic segmentation & object detection

First Semester: Powerline Inspection



3D Semantic Segmentation Results

Green = Power lines

Red = Trees

Black = Houses

Blue & **Black** = Ground

New task: Aircraft Defect Detection

Sample defect images with bounding boxes

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Aircraft Defect Detection

1. Problem overview
2. Dataset study
3. Proposed approaches
4. Experimental results
5. Conclusion

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Problem Overview

For airplane companies and airport managers

- Planes need to be inspected before taking off
- It takes a long time and many workers

Proposed solution

- Just let drones fly around and take pictures
- Perform defect detection on these pictures

We now have the dataset collected from pictures taken around planes

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Dataset

Dataset

Key findings

Approach: Object Detection

Why object detection?

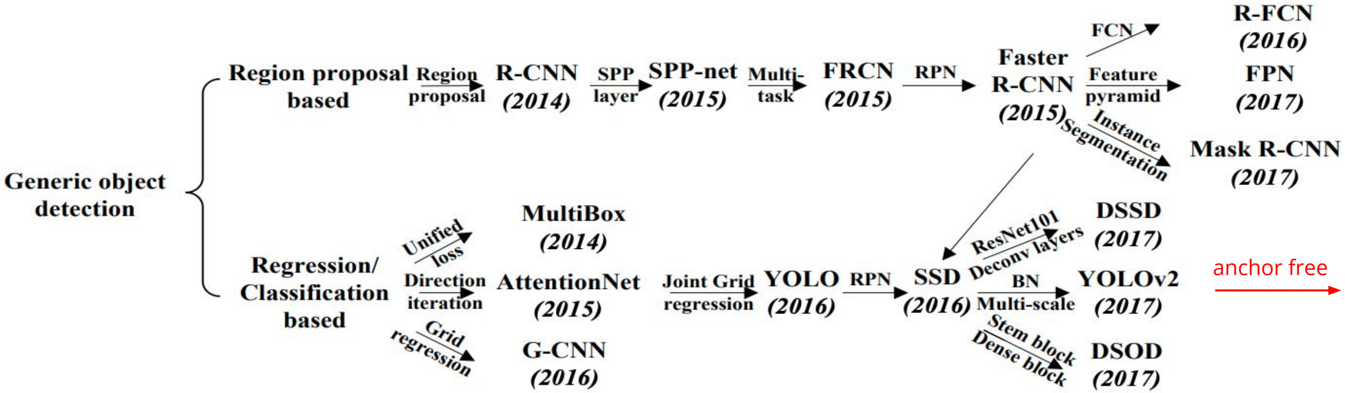
- Bounding boxes already provided as ground-truth
- Direct approach to solve the problem

What type of object detection?

- Speed & Feasibility to train and evaluate -> one stage over two stage
- Variant ratio of bounding box sizes -> anchor-free models

Literature Review

Object detection roadgraph

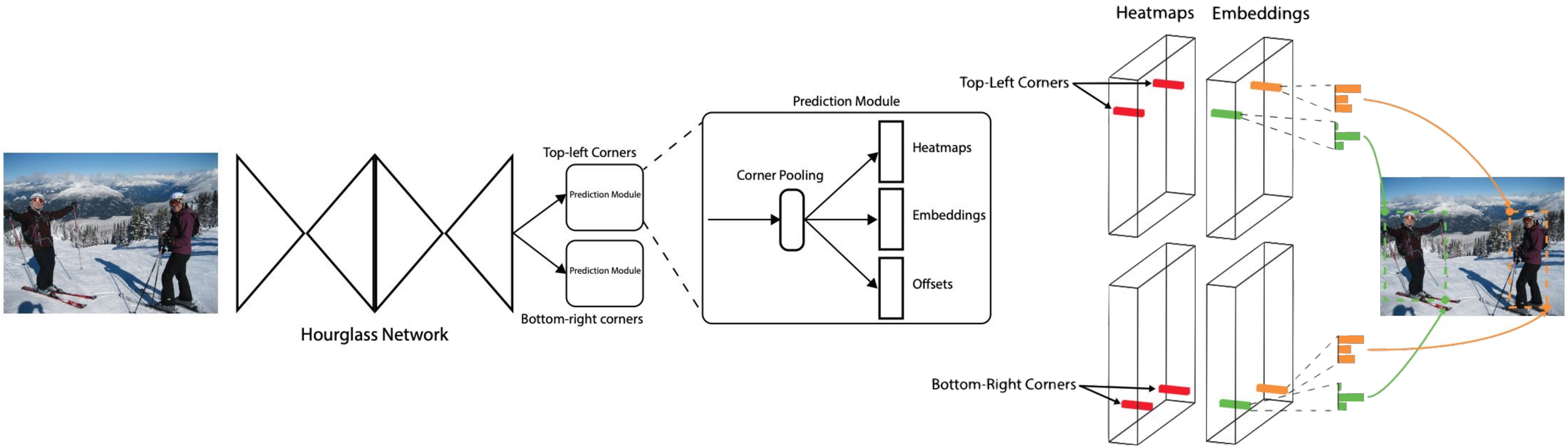


anchor free →

CornerNet (2018)
CenterNet (2019)
FCOS (2019)

Literature Review: CornerNet

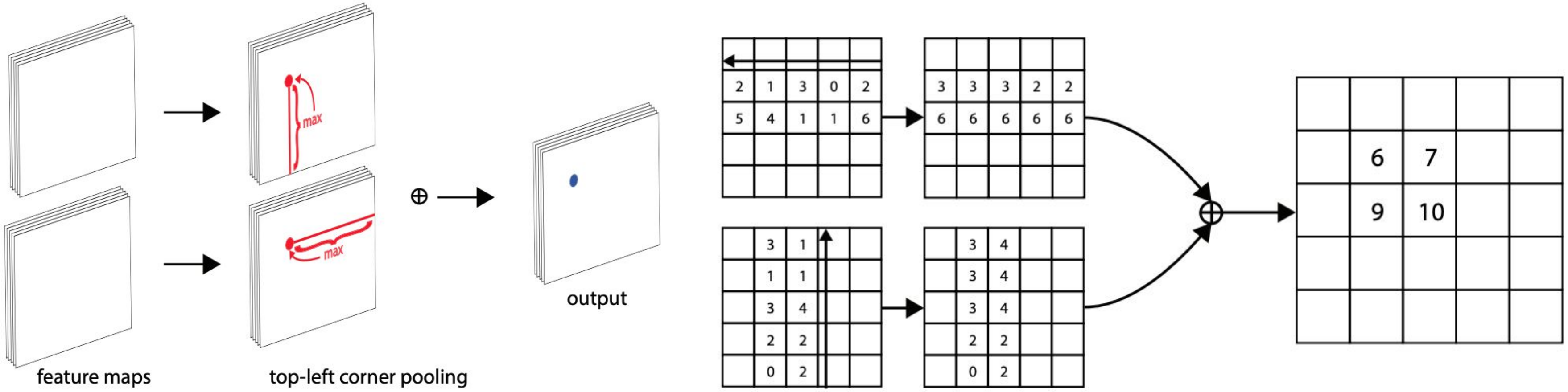
CornerNet Architecture



Law, Hei, and Jia Deng. "Cornernet: Detecting objects as paired keypoints." ECCV 2018.

Literature Review: CornerNet

Corner Pooling Module



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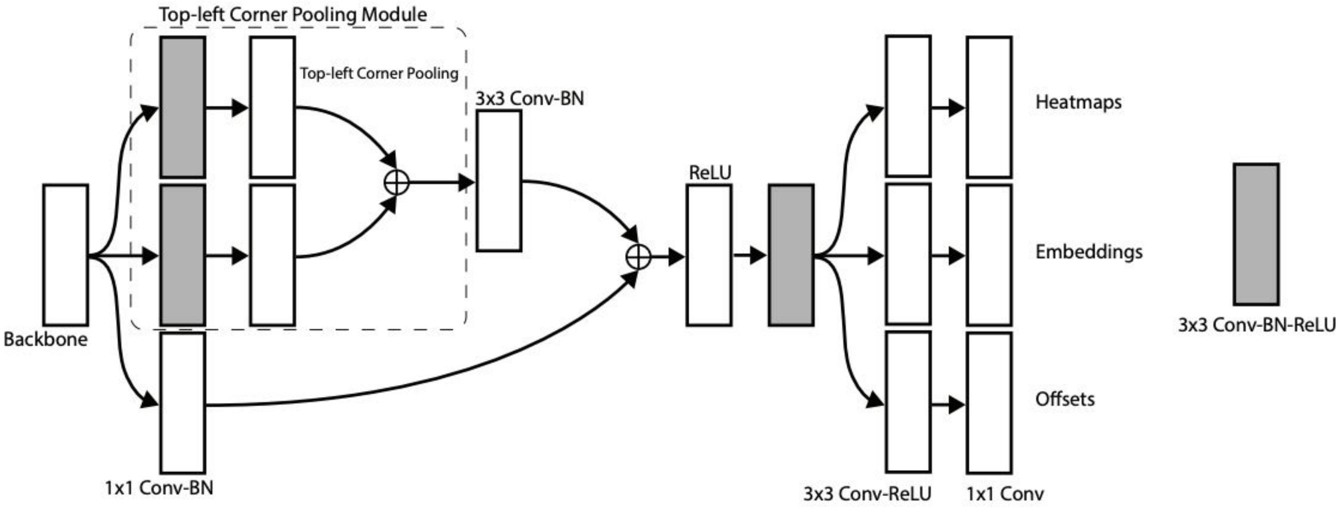
Literature Review: CornerNet

Bounding Box Prediction Module (Top-left branch)



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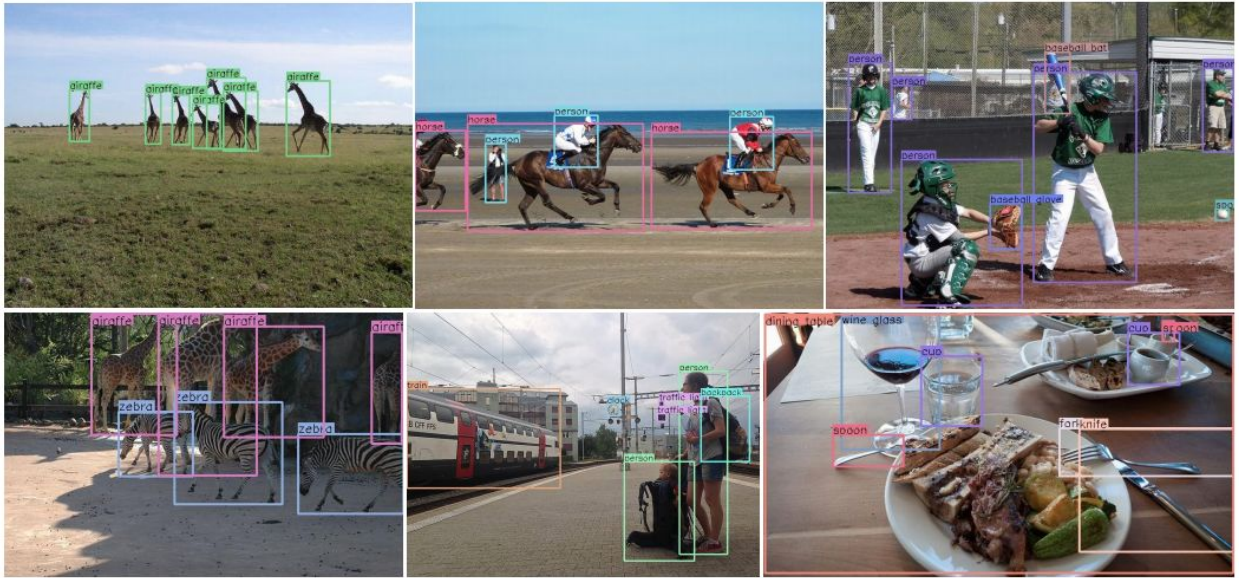
Literature Review: CornerNet

Qualitative Examples on MSCOCO



Law, Hei, and Jia Deng. "Cornernet: Detecting objects as paired keypoints." ECCV 2018.

Literature Review: CenterNet

Improvements from CornerNet:

- Center pooling module: inherits the functionality of RoI pooling
- Cascade corner pooling: perceives internal information

Duan, Kaiwen, et al. "CenterNet: Keypoint Triplets for Object Detection." ICCV 2019.

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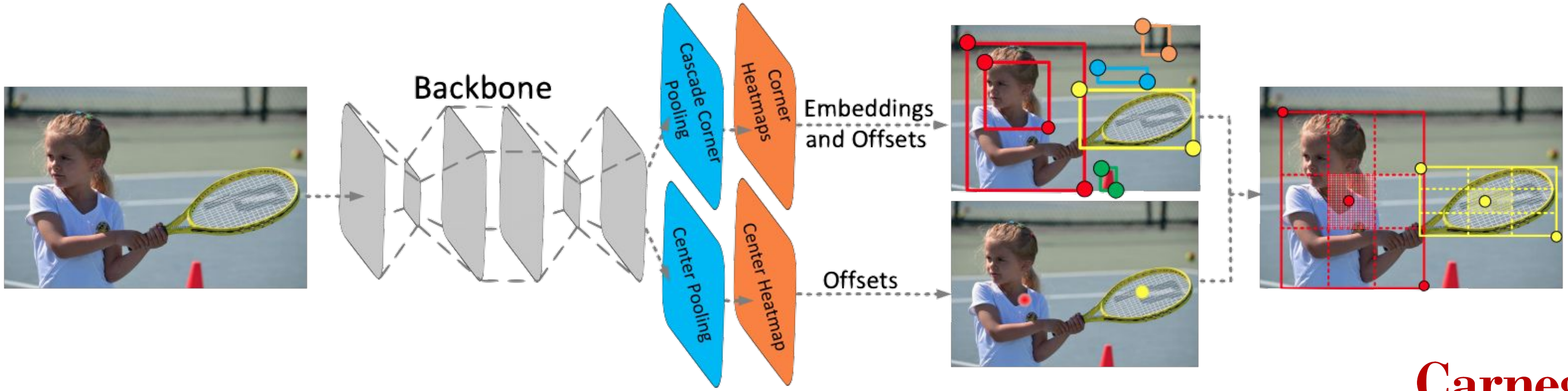
Literature Review: CenterNet

CenterNet Architecture

- Similar to CornerNet, a pair of detected corners and the similar embeddings are used to detect a potential bounding box. Then the detected center keypoints are used to determine the final bounding boxes.



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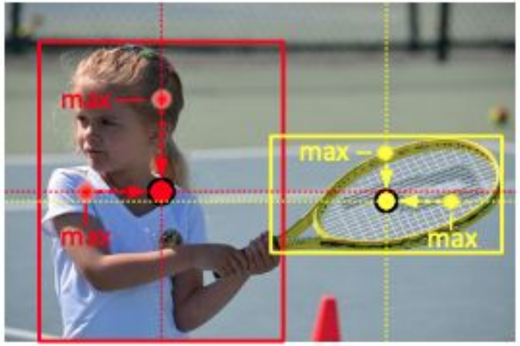
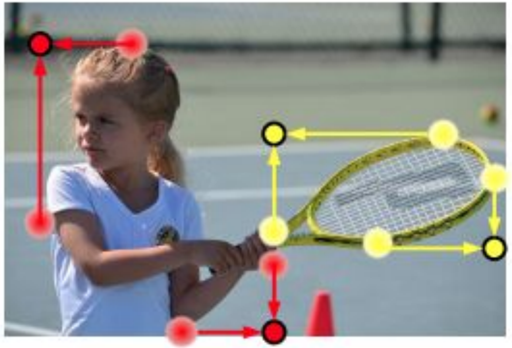
Literature Review: CenterNet

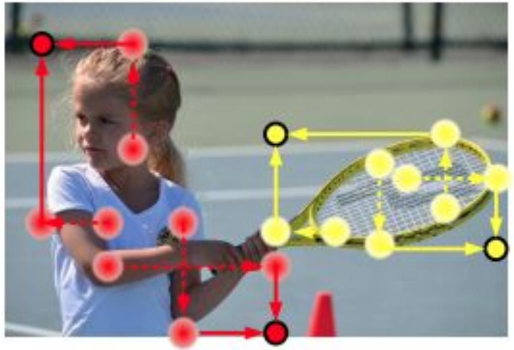
Center pooling & cascade corner pooling module



Center Pooling



Corner Pooling



Cascade Corner Pooling

Duan, Kaiwen, et al. "CenterNet: Keypoint Triplets for Object Detection." ICCV 2019.

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Literature Review: CenterNet

Quantitative Results on MSCOCO (Apr 2019)

		Average Precision
Two-stage Models	Mask R-CNN	39.8
	PANet (SOTA)	47.4
One-stage Models	RetinaNet800	39.1
	CornerNet	42.1
	CornerNet-Saccade	43.2
	CenterNet-104	47.0

Duan, Kaiwen, et al. "CenterNet: Keypoint Triplets for Object Detection." ICCV 2019.

Network Training & Evaluation

- We use CenterNet-52 as our network structure (52-layer Hourglass Network)
- Multi-scale training
- batch size of 4 on each of 2 Nvidia 1080 Ti GPUs
- 4K as training set and 1K as evaluation set

Experimental Results: Quantitative

Training set (NMS threshold = 50%, proposal confidence = 30%):

- mAP = 92.2301%
- Foreground overall recall [1] = 97.7200%
- Foreground overall precision [2] = 71.7203%
- CenterNet-52 successfully converged on the training set

[1] A ground-truth bounding box is considered recalled if it is predicted as any foreground class.
[2] A predicted bounding box is considered correct if any foreground ground-truth bounding box overlaps it larger than a threshold (default is 50%).
* We also define image level recall and precision in following slides, which denotes an image as positive if there is at least a bounding box provided or predicted.

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Experimental Results: Quantitative

Validation set (NMS threshold = 50%, proposal confidence = 30%):

- mAP = 18.1666%
- Foreground overall recall = 49.3571%
- Foreground overall precision = 49.3860%
- Severe overfitting effect observed!

Experimental Results: Quantitative

Validation set (NMS threshold = 50%, proposal confidence = 30%):

- Class-wise confusion matrix
- Findings: P/R among each class is good, P/R against background is terrible

Experimental Results: Qualitative

Why overfitting is so severe?

1. Ground-truth labels are actually ill-posed

Ground-truth Predicted

Experimental Results: Qualitative

More ill-posed or bad bounding boxes and labels

Experimental Results: Qualitative

We sometimes, not too rarely, performs better than the ground-truth!

Ground-truth

Predicted

Experimental Results: Qualitative

Why overfitting is so severe?

1. Ground-truth labels are actually ill-posed
    - Possible solution: Lower overlapping threshold
    - With overlapping threshold changed from 50% to 30%
    - mAP = 18.1666% -> 25.6855%
    - Foreground overall recall = 49.3571% -> 55.8153%
    - Foreground overall precision = 49.3860% -> 55.7909%

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Experimental Results: Qualitative

Why overfitting is so severe?

2. Too few training data (only ~4000 images)
   - It is really hard to train a supervised detection model given limited data
   - We apply anti-overfitting techniques, including
     1. random rescaling, random cropping, color jittering
     2. gaussian bump of corner/center ground-truth
     3. class-balanced weights for losses [1]
     4. download similar images online

[1] Cui, Yin, et al. "Class-balanced loss based on effective number of samples." CVPR 2019.

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Experimental Results: Qualitative

Download similar images online

- Search for images with captions “airplane close up”, “aircraft zoom in”, etc
- We tried our best and downloaded ~1500 images, yet not many of them are in the same domain as the provided dataset, and some of them look completely different

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Experimental Results: Qualitative

Download similar images online

- Add around online 700 images to the training set, with no ground truth bounding boxes
- Add around online 700 images to the test set, with no ground truth bounding boxes

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Experimental Results: Qualitative

Why overfitting is so severe?

2. Apply more data augmentation techniques:
   - mAP: 25.6855% -> 26.4279%
     - Adding online data is the main contributor
   - To consider the online data, we also evaluated image-level recall and precision
   - On the test set with both original and online images
     - Image-level recall = 96.5368%
     - Image-level precision = 95.0554%
   - Although the domain is likely different, we perform fairly good on detecting whether a region has defects or not

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Experimental Results: Qualitative

Why overfitting is so severe?

3. Model complexity is too high
   - Reduce channel sizes and layers
   - Apply dropouts
   - Result: None of these methods work, probably because given too few images, we do not have enough features to learn

More Qualitative Examples

Conclusion

1. On a new image domain with limited data, our detection model performs fare on detecting bounding boxes and performs well on detecting image-level defects
2. The provided data is ill-posed and is hard to learn itself, and we sometimes perform better than the labeler
3. In future, one could possibly use weakly-supervised methods to perform segmentation instead of bounding box detections to reduce the ambiguity in the labels

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