Error Analysis of Object Detection Models with Interactive User Interfaces

DAYEON OH

Computer vision

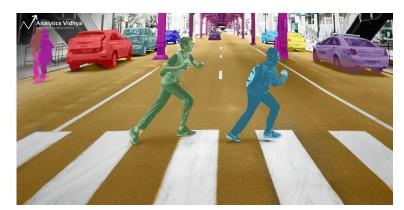


Image segmentation



Object detection

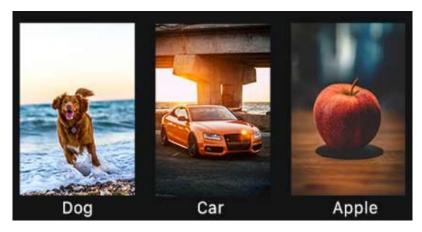
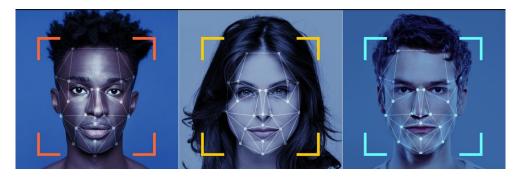
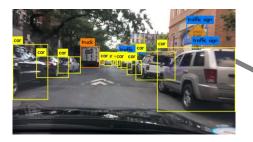


Image classification

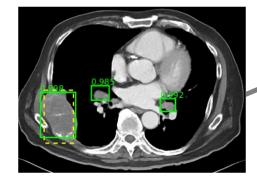


Facial recognition

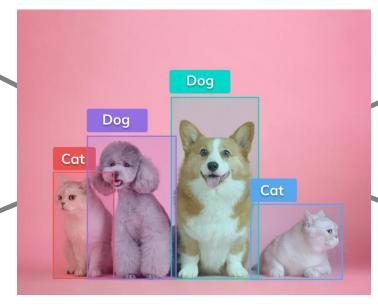
Object detection



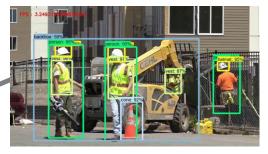
Self-driving cars



Cancer and tumor detection



Object Detections



Construction management



Drones and robots



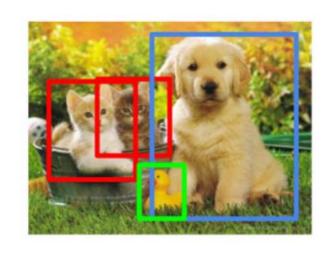
Object detection model evaluation

Classification



CAT

Object Detection



CAT, DOG, DUCK

Most of the images have several objects to be detected



Errors of object detection models



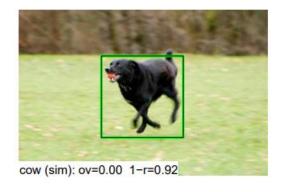
Not fully detecting the whole object



Detecting the background



Incorrectly classifying and not fully detecting the object

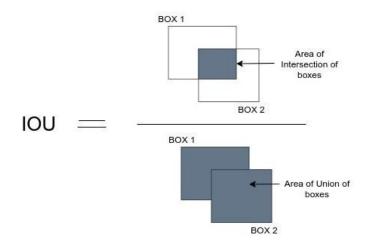


Incorrectly classifying the object

Different types of errors in object detection models



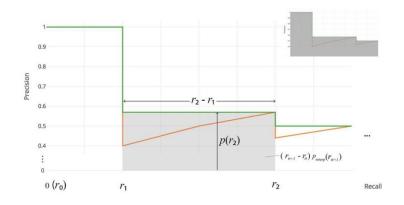
Object detection evaluation metrics



$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$



Intersection of Union

Precision and Recall

Mean average precision



Motivation

- Evaluating the performance of the object detection model is more complicated than other computer vision models such as image classification models.
- Most of the images have several objects to be detected, and the types of detections and their errors can be categorized in several different ways.

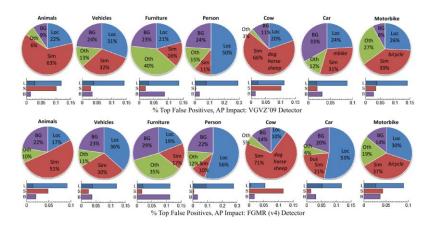


An effective performance evaluation method for the object detection model is needed.



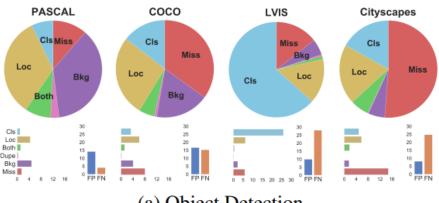
Related works

D. Hoiem, Y. Chodpathumwan, and Q. Dai



Diagnosing errors in object detectors

Hoiem, D., Chodpathumwan, Y., Dai, Q.: Diagnosing error in object detectors. In: ECCV (2012)



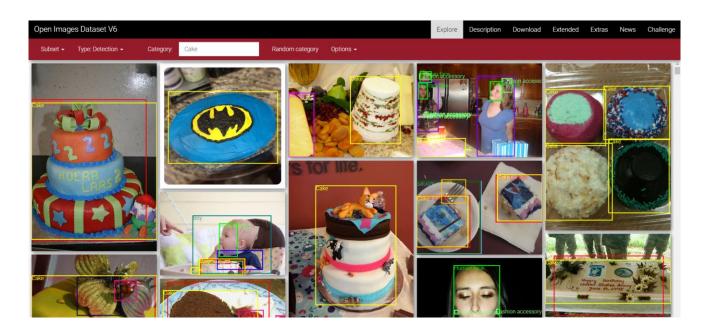
(a) Object Detection

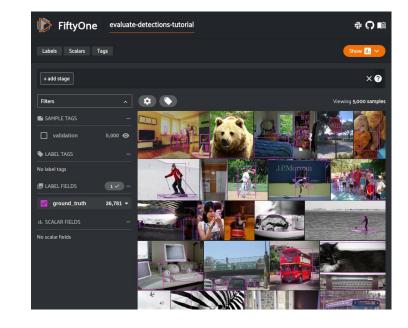
TIDE: A general toolbox for identifying object detection errors

Boyla D., Foley S., Hays J., Hoffman J.: TIDE: A General Toolbox for Identifying Object Detection Errors. In: ECCV (2020)

Categorized the errors into different types and visualized the result with charts

Related works





Google Open Images Dataset V6

https://storage.googleapis.com/openimages/web/index.html

Voxel 51
https://voxel51.com/

Showing individual images based on the filters like class



Related works



4 different false-positive error types and 6 error types do not contain all the detection result which limit the explanation of the results.

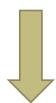


Showing summarized results with the chart is easy to check the percentage of each error type, but it is difficult to immediately check in detail which images and under what circumstances each error occurs.



Research Objectives

- The goal of this project is to develop a tool that enables browsing object detection models and verifies the features of the tool.
 - Design the tool as an interactive web application with the features to analyze and evaluate the object detection results.
 - Evaluate the function/features of the tool with a realistic user scenario.



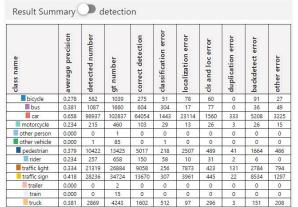
- Understand and evaluate the result of the object detection model.
- Helping users to make more critical decisions based on the results.

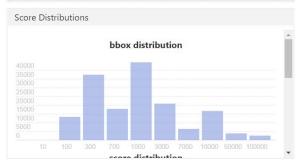
Method and Design

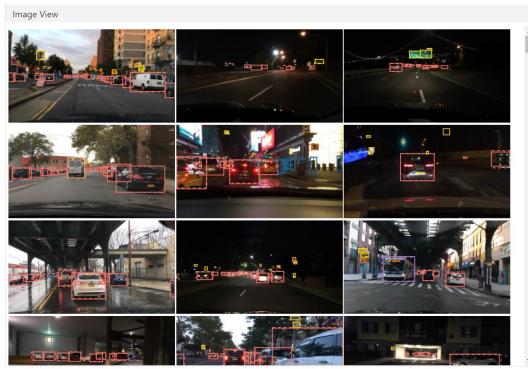


Object detection error explorer

Error Report





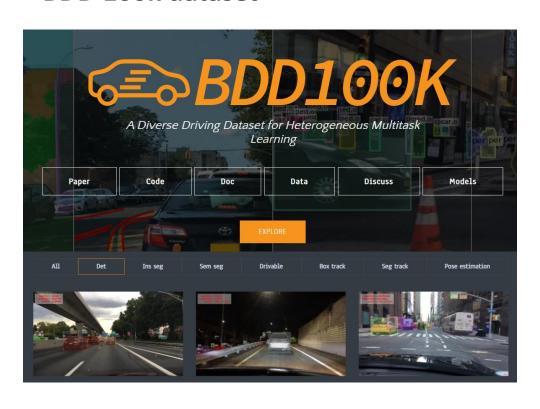


An interactive tool that supports the evaluation and analysis of the results of the detection model

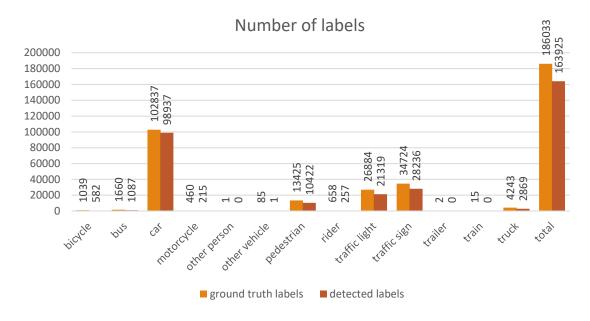


Dataset and model

BDD 100k dataset



Training (70K), validation (10K), and testing (20K) Number of classes: 13



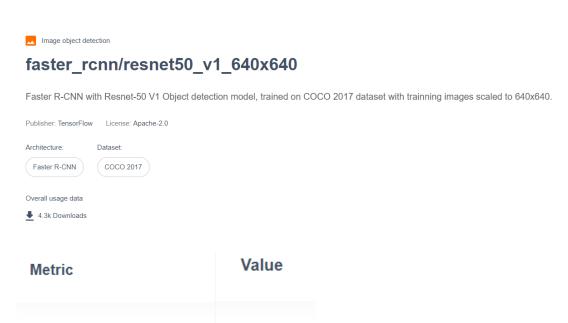
Method and Design



Dataset and model

Faster R-CNN

mAP on COCO 2017 test set



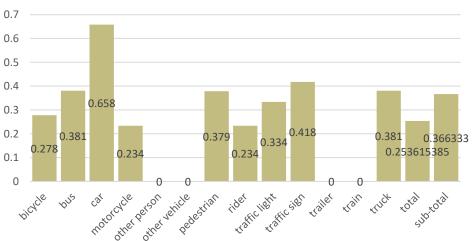
29.3

Trained on COCO 2017

Fine-tuned with BDD 100K training data (70K)

Used BDD 100K validation data (10K) for the experiment mAP on COCO: 29.3, mAP on fine-tuned: 25.3, 36.6

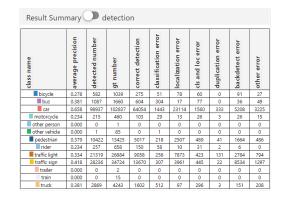
Mean average precision values





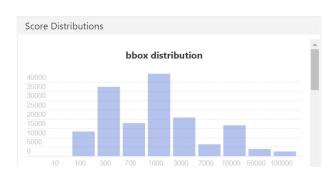
Object detection error explorer





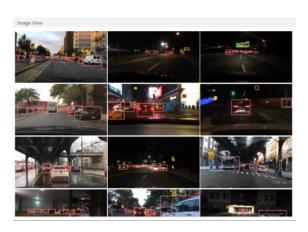






Summary of class and detection type

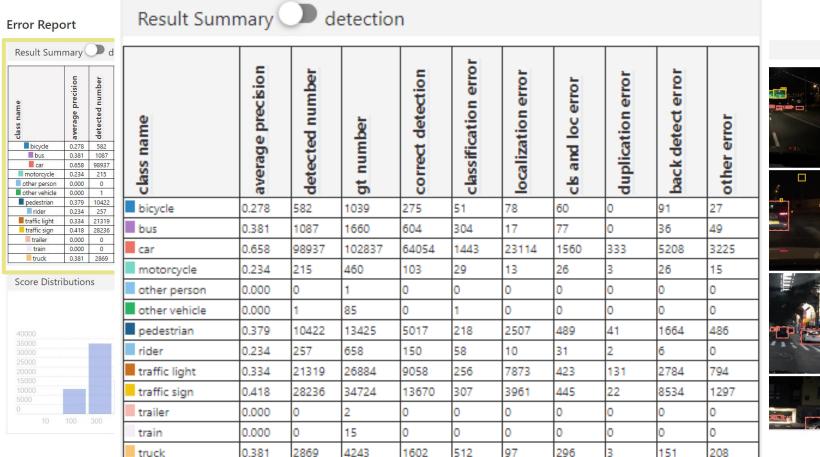


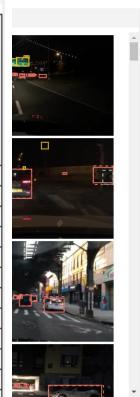


Individual image display



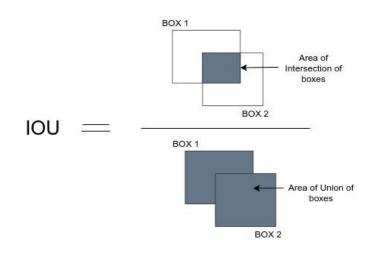
Summary view panel



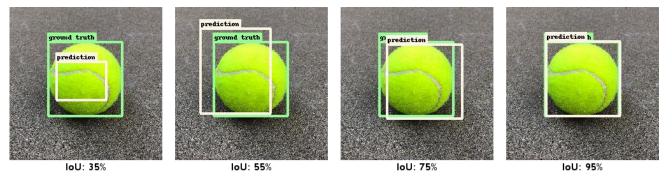




Object detection evaluation metrics



Intersection over Union



Examples of different IoU score

IoU Thresholds:

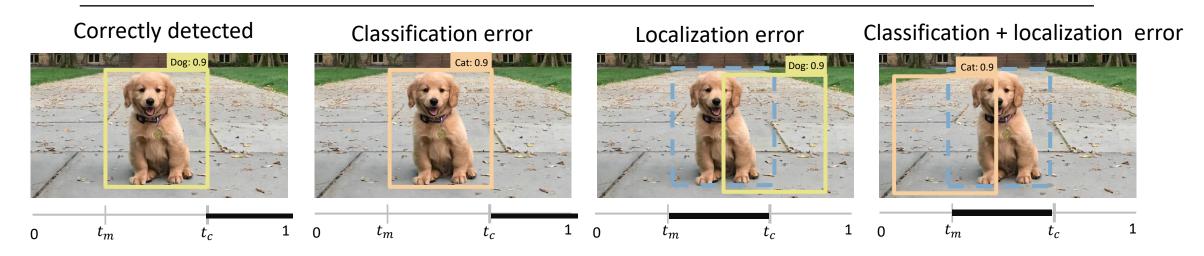
A value used in object detection to measure the overlap of a predicted versus actual bounding box for an object.

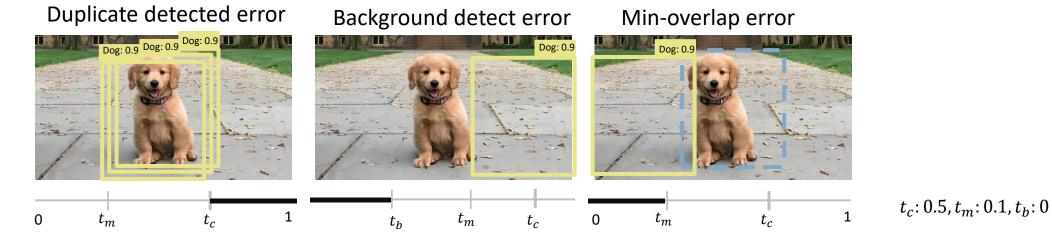
Thresholds for object detection result analyzer:

Correct threshold (0.5): if higher than 0.5, consider as correct overlapping Minimum threshold (0.1): if lower than 0.1, consider a non-meaningful overlapping Background threshold (0): if the score is 0, consider non-overlapping



Detected labels categories



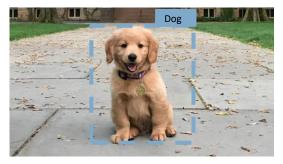




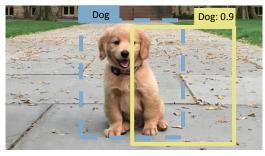
Ground truth labels categories

None or one matching label between the ground truth label and the detected label

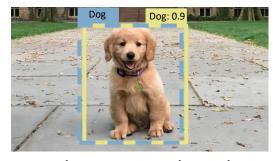
No matching label Missed detected error



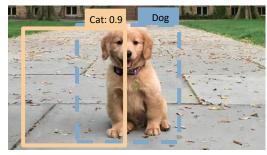
Only one match with localization error



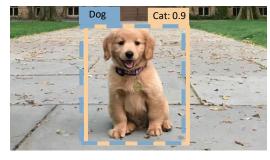
Only one match with correct detection



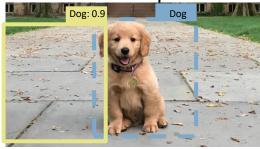
Only one match with classification + localization error



Only one match with classification error



Only one match with Min-overlap error

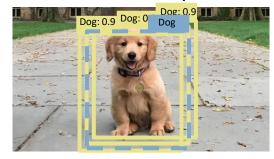




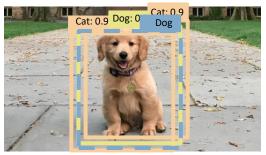
Ground truth labels categories

Multiple matching labels between the ground truth label and the detected label

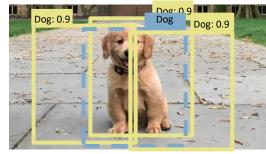
Multiple matches with Correct and duplication



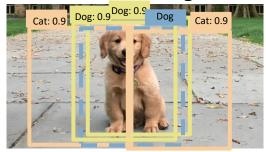
Multiple matches with Correct and classification



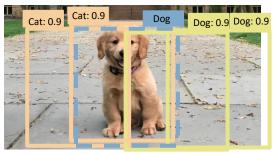
Multiple matches with Correct and localization



Multiple matches with errors and including correct



Multiple matches and all incorrect



Summary view panel

Detection result summary table

Result Summary detection											
class name	average precision	detected number	gt number	correct detection	classification error	localization error	ck and loc error	duplication error	back detect error	other error	
bicycle	0.278	582	1039	275	51	78	60	0	91	27	
bus	0.381	1087	1660	604	304	17	77	0	36	49	
car	0.658	98937	102837	64054	1443	23114	1560	333	5208	3225	
motorcycle	0.234	215	460	103	29	13	26	3	26	15	
other person	0.000	0	1	0	0	0	0	0	0	0	
other vehicle	0.000	1	85	0	1	0	0	0	0	0	
pedestrian	0.379	10422	13425	5017	218	2507	489	41	1664	486	
rider	0.234	257	658	150	58	10	31	2	6	0	
traffic light	0.334	21319	26884	9058	256	7873	423	131	2784	794	
traffic sign	0.418	28236	34724	13670	307	3961	445	22	8534	1297	
trailer	0.000	0	2	0	0	0	0	0	0	0	
tenin.	0.000	0	15	0	0	0	0	0	0	0	
olor of	0.381	2869	4243	1602	512	97	296	3	151	208	

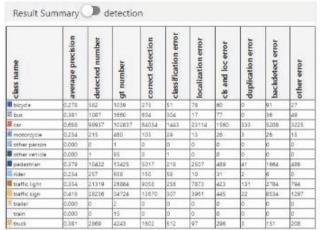
Ground truth summary table

Result Summary ground truth										N	Name of the		
					and loc	t	dnp	cls	loc	cor		categories	
class name	number	match + correct	match + cls	match + loc	match + cls ano	match + incorrect	matches + cor,	matches + cor,	matches + cor,	matches + with	matches + inco	missed detecte	
bicycle	1039	239	70	56	88	14	0	0	16	16	10	530	
bus	1660	558	408	9	170	25	0	0	3	43	64	380	
car	102837	56783	469	15153	317	513	221	4	4232	2594	674	21877	
motorcycle	460	93	91	11	65	4	2	0	0	8	19	167	
other person	1	0	0	0	1	0	0	0	0	0	0	0	
other vehicle	85	0	32	0	14	4	0	0	0	0	6	29	
pedestrian	13425	4282	139	1632	351	133	24	0	519	180	97	6068	
rider	658	140	114	8	83	12	1	0	0	9	13	278	
traffic light	26884	7100	232	5062	317	257	60	0	1598	259	270	11729	
traffic sign	34724	12743	265	3023	485	371	14	0	525	305	147	16846	
trailer	2	0	1	0	0	0	0	0	0	0	1	0	
train	15	0	2	0	3	3	0	0	0	0	0	7	
truck	4243	1438	985	56	437	59	1	2	11			r of lab	

Name and color of the classes

Summary view panel

Error Report









Potential user and User scenarios



- Amy
- Using object detection model for self-driving car research

User scenarios

- Finding similarities between certain errors
 - From localization errors
 - From classification errors
 - From background detection errors
- Finding example images for specific conditions
 - Misclassification cases between pedestrians and vehicles
 - Missed detection cases for pedestrians and vehicles



Demo



Findings

Similarities between errors

- Localization errors: small bounding boxes, densely located objects, or hard to observe
- Classification errors: small bounding boxes or misclassification between similar objects
- Background errors: frequently occurred in dark and blurry images

Find example images for specific conditions

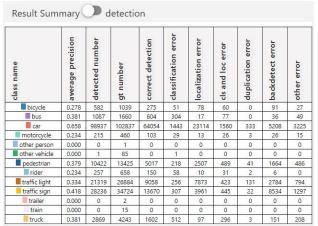
- Misclassification between pedestrians and vehicles: small bounding boxes, hard to distinguish, overlaps between the objects, and labeling errors
- Missed detected pedestrians and vehicles: small bounding boxes, densely located objects, on the opposite side of the driveway or on the sidewalk

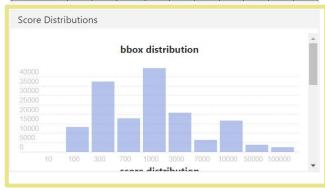
Discover labeling errors while browsing images

Labeling errors between cars and pedestrians

Chart view panel

Error Report





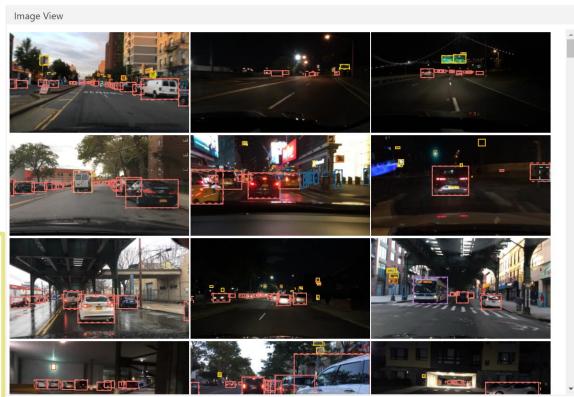
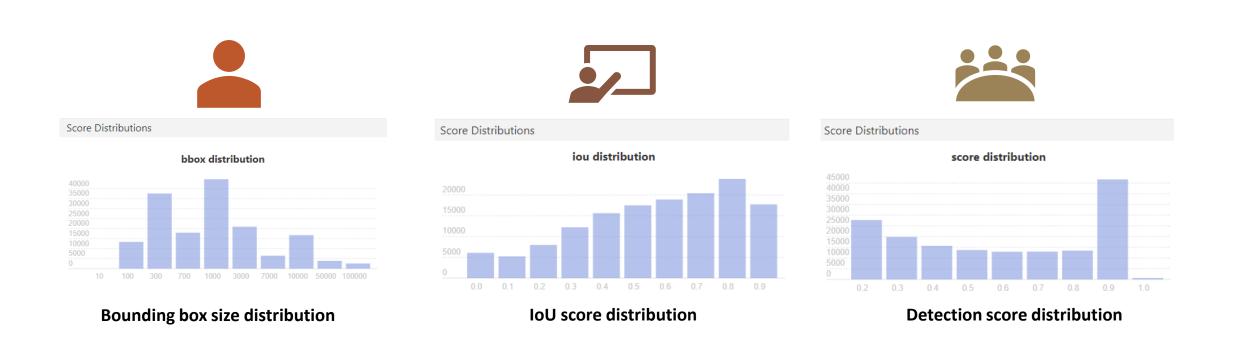




Chart view panel



- To find the relationship between the size of the bounding box, IoU score, detection score, and different detection types.
- To check the distribution difference between different detection types.

Chart view panel with detection type

Oregon State University
College of Engineering

Classification error

 Distribution chart for incorrectly classified classes

Background detection error

 Only bounding box size and detection score distribution charts



Classification error class distribution

Chart view panel

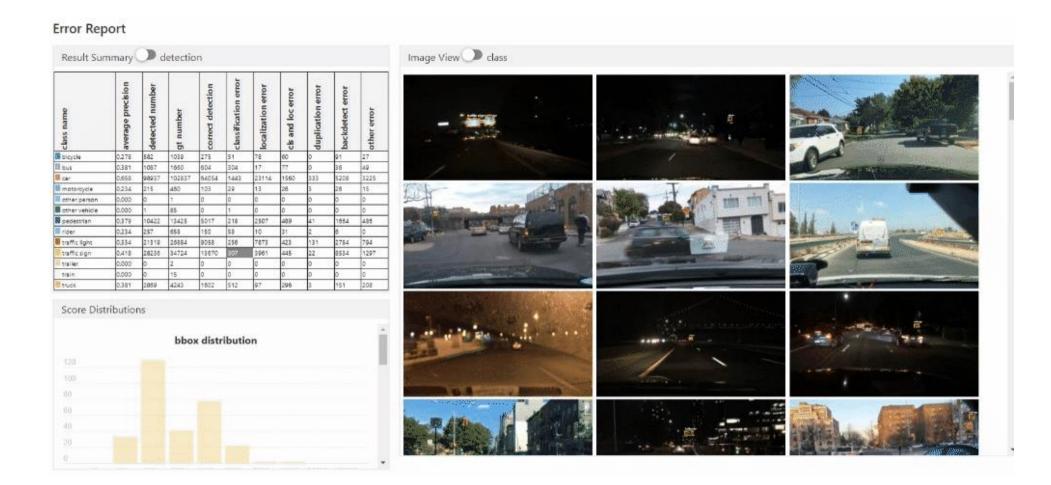
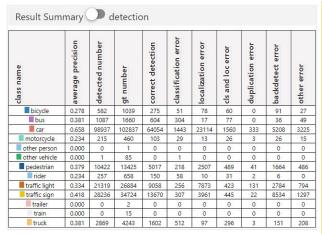
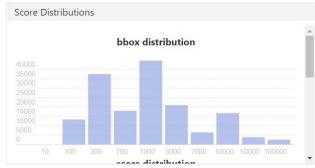
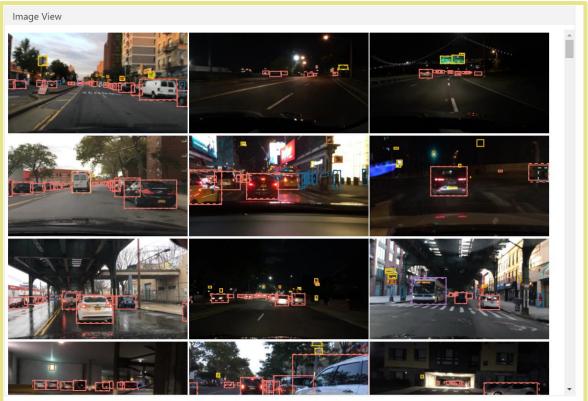


Image view panel

Error Report





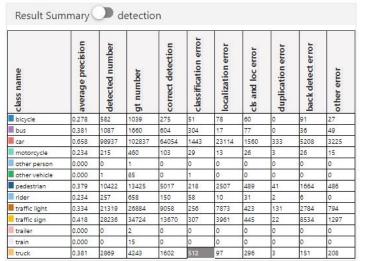


Method and Design

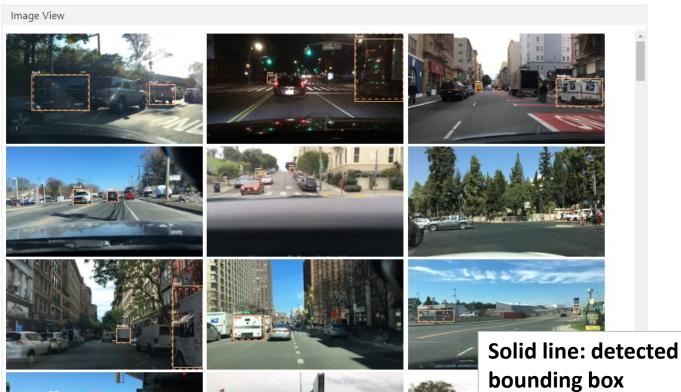


Image view panel

Error Report







Dotted line: ground truth

bounding box



Image view modal window

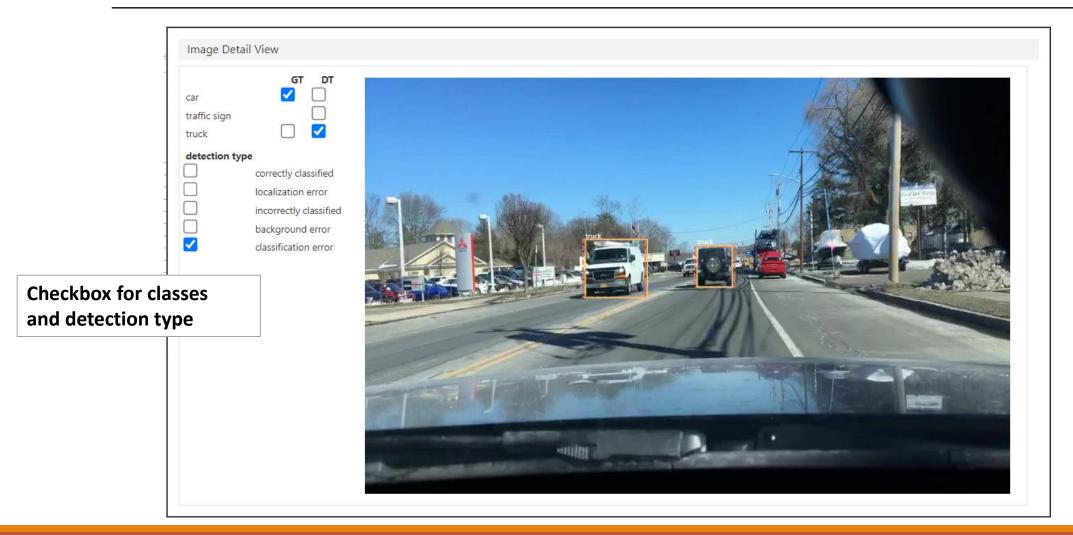
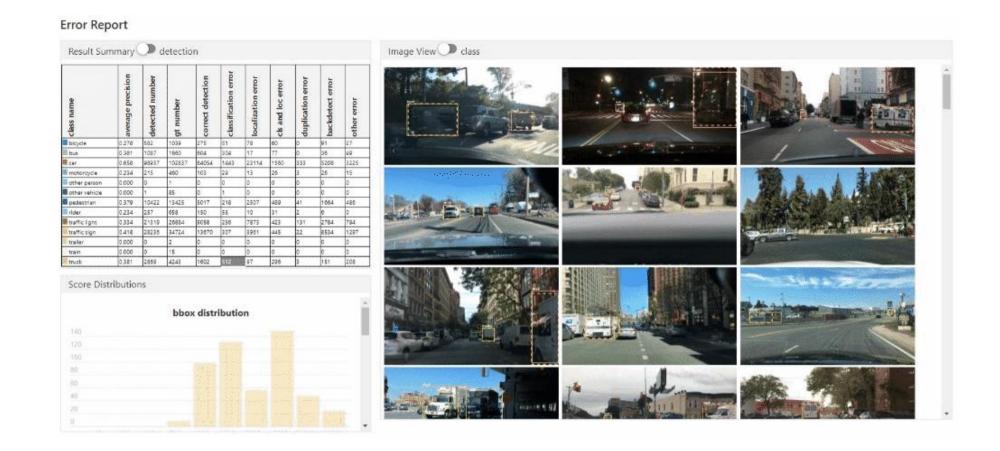




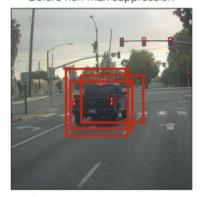
Image view panel





post-processing with results

Before non-max suppression





Non-maximum suppression to reduce the duplicated detection bounding boxes

Non-Max Suppression

type 1	type 2	type 3	type 4	type 5	type 6	type 7	type 8
326	131	153	132	63	124	530	34
746	768	34	141	18	45	380	70
70443	2381	38930	2475	6142	6931	21877	4964
127	78	26	48	15	45	167	23
0	0	0	0	0	0	0	0
0	5	0	0	0	0	29	0
5902	366	4067	782	832	2123	6068	831
180	185	27	77	14	13	278	3
11643	366	13156	621	1789	3608	11729	1206
14977	432	7130	645	1399	10223	16846	1820
0	0	0	0	0	0	0	0
0	0	0	0	0	0	7	0
1973	1566	211	475	79	187	913	263

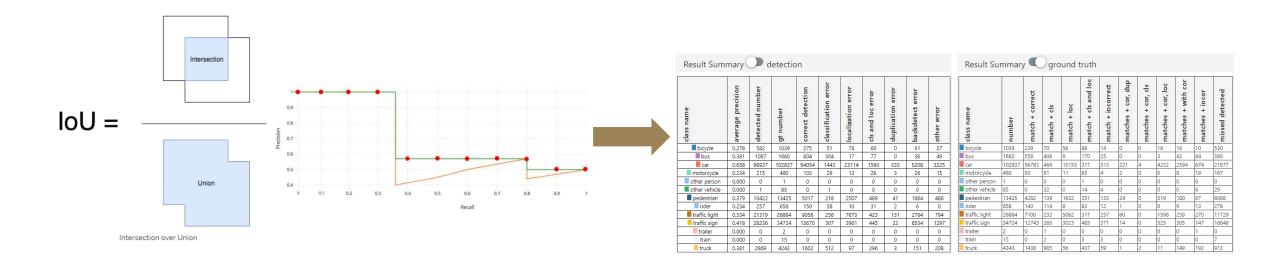
Before applying NMS methods

type 1	type 2	type 3	type 4	type 5	type 6	type 7	type 8
275	51	78	60	0	91	530	27
604	304	17	77	0	36	380	49
64054	1443	23114	1560	333	5208	21877	3225
103	29	13	26	3	26	167	15
0	0	0	0	0	0	0	0
0	1	0	0	0	0	29	0
5017	218	2507	489	41	1664	6068	486
150	58	10	31	2	6	278	0
9058	256	7873	423	131	2784	11729	794
13670	307	3961	445	22	8534	16846	1297
0	0	0	0	0	0	0	0
0	0	0	0	0	0	7	0
1602	512	97	296	3	151	913	208

After applying NMS methods



Post-processing with results



Calculate the IoU and average precision of detected labels

Categorized the labels into different types



Conclusion



- Develop an interactive tool that helps evaluate and analyze the results of the object detection model
- Can be helpful for non-computer science experts to evaluate the performance of the models and answer their research questions



FUTURE WORK

- Show the answers to 'why' with more enhanced explainability and interpretability
- Explore images intersecting with the ground truth and detected labels categories



References

- [1] Boyla D., Foley S., Hays J., Hoffman J.: TIDE: A General Toolbox for Identifying Object Detection Errors. In: ECCV (2020)
- [2] Hoiem, D., Chodpathumwan, Y., Dai, Q.: Diagnosing error in object detectors. In: ECCV (2012)
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- [9] Fisher et al.: BDD100K: A Diverse Driving Dataset for Heterogeneous Multitask Learning. arXiv: 1805.04687
- [10] Ren S., He K., Girshick., Sun J.: Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. arXiv: 1506.04197
- [11] TF2.0 Faster R-CNN with Resent-50 V1 Object detection model:
- [12] Google Open Image Dataset v6 https://storage.googleapis.com/openimages/web/index.html