Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences

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Master's Thesis

Out-of-distribution detection in 3D semantic segmentation

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Submitted to Hochschule Bonn-Rhein-Sieg,
Department of Computer Science
in partial fullfilment of the requirements for the degree
of Master of Science in Autonomous Systems

Supervised by

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Prof. Dr. Sebastian Houben

April 2022

I, the undersigned below, declare that this work has not previously been submitted to this or any other university and that it is, unless otherwise stated, entirely my own work.

Date

Lokesh Veeramacheneni

Abstract

Your abstract

Acknowledgements

Thanks to ....

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Introduction

The development of Deep Neural Networks (DNNs) made tasks such as object classification and object detection simple. These DNNs has seen their way to various real world scenarios such as autonomous driving [19], semi-autonomous robotic surgery [23] and also in space rovers [21], [4]. DNNs are majorly deployed in the perception stack in the autonomous pipeline. Figure 8.1 depicts the pipeline of the modules present in one of the open source autonomous driving platform called Apollo [8]. From this pipeline, we can infer that the most of the decisions regarding the vehicle control made by autonomous system is dependent on the output of the perception module. Since the perception module plays such significance, the developers of the perception stack must make sure that the output is flawless.

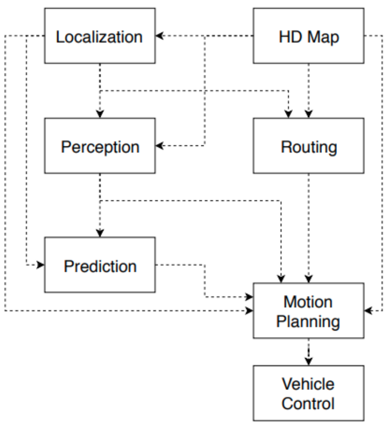
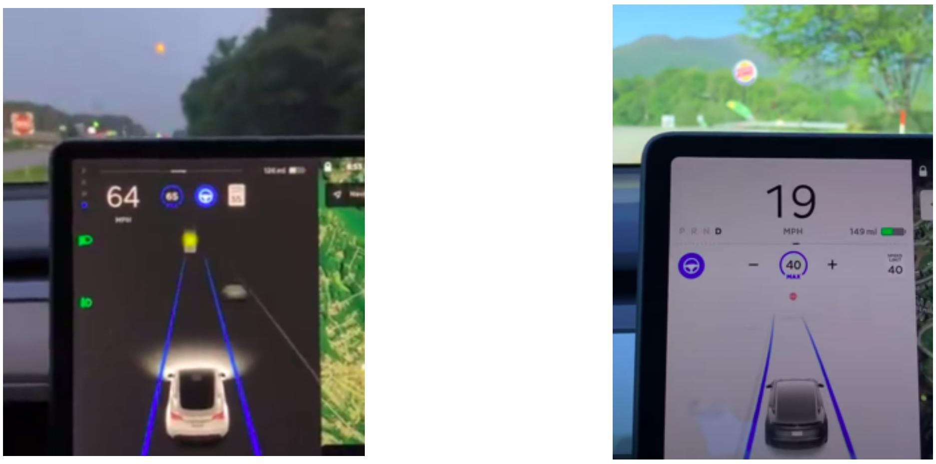


Figure 1.1: Module pipeline for Apollo autonomous driving platform. Image taken from [8]

The DNNs deployed in perception module are needed to be trained on the dataset which should be similar to area of its deployment. For example, an autonomous driving agent must be trained on dataset containing roads, vehicles, vegetation and other objects found around road. This closedness of the dataset i.e., fixed number of classes, will cause an issue when the DNN encounter an unknown object in real world. This unknown object is predicted as one of the class in the dataset, leading to radical decisions when this error is propogated down the pipeline in Figure 8.1. One such real world problem is encountered by the Tesla autonomous driving platform.



(a) (b)

Figure 1.2: Tesla fails. Images taken from [18]

Figures 8.2a and 8.2b depict the misdetections from the Tesla autonomous driving system. The problem with first one, is the moon is detected as the yellow signal light and second one has the problem of misdetection of burger king sign as stop signal. These misdetections of unknown objects might lead to consequences beyond imagination. This questions the safety of the Deep Neural Networks (DNNs) predictions. An effort has been made in this thesis to detect these unknown objects in 3D LiDAR data using uncertainty score. The unknown obejcts in the real world which are not present in the training dataset are called as out-of-distribution (OOD) class. More discussion on the OOD is presented in Section 8.2. More discussion on misdetections in a DNN trianed on MNIST and tested on USPS is presented in Section A.1 The contributions made in this thesis are

1. A survey on the available 3D LiDAR datasets and benchmark dataset for the OOD detection.

2. A survey on the 3D semantic segmentation models, uncertainty estimation methods and classical OOD methods.

3. Use of uncertainty for OOD detection in RandLA-Net

1.1 OOD/Anomaly/Distributional shift

Let us time travel back to 18^{th} century and assume that we had implemented a model to detect ships, the dataset images for the trained model will be similar to Figure 8.3a. 18^{th} century ships as in 8.3a can be defined as "*ship contains hull and sails*". Fast forward to present time, current ships are as shown in Figure 8.3b. Ship as in 8.3b can be defined as "*ship contains hull and passenger decks stacked upon each other*". Now if we want to deploy the old model trained with old ships to detect the present generation of ships, it is diffcult because of the change in definition and properties of ship. This change in data distribution over a period of time is called "*distributional shift*" of the data.

(a) (b) (c)

(d) (e) (f)

Figure 1.3: Illustration of distributional shift, anomaly and out of distribution examples using various kind of ships. 8.3a represents the sail ship during 18th century. 8.3b depicts the current training data. 8.3c, 8.3d represents the anamolous ship data and 8.3e, 8.3f represents the OOD data. Images are taken from [31], [16], [22], [32], [10], and [3] respectively in the order they appear.

Anomaly can be defined as the patterns that doesn't conform to the expected training behavior. By this definition, Figure 8.3c and Figure 8.3d can be considerd as anomalies. This is becuase Figure 8.3c is a container ship looking similar to Figure 8.3b instead of passenger decks we have containers stacked. Figure 8.3d is also anomaly because the Titanic also has a hull, passenger decks and chimneys. This additional chimnies as a fetures deviates this image from the definition of the ship and can be considered as "*anomaly*".

The input for out of distribution (OOD) is drawn from an unknown distribution of unknown data, which is not near to the trianing distribution. Figures 8.3e and 8.3f are submarine and ariship which are from unknown distribution and they doesn't adhere to the definition of ship by any means. In general, one can argue that OOD can be defined as inputs which doesn't belong to any class in the training data.

1.2 Problem Statement

In this thesis, we study the application of out-of-distribution (OOD) detection over the 3D semantic segmentation problem in the context of autonomous driving. Notably, we study the 3D semantic segmentation datasets available and create a benchmark for in-distribution and out-distribution for the OOD setting.

The other major issue, we address in this thesis is the OOD detection methods themselves. Existing OOD detection methods are developed on 2D classification tasks and applicability of these methods on 3D semantic segmentation tasks is not studied. This is also challenging because the existing OOD methods are not easily adaptable to the 3D segmentation models because segmentation involves multi class classification and moreover high dimensionality of the 3D data.

The research questions answered by this thesis are:

R1 How to create a benchmark over 3D segmentation datasets for the OOD setting?, i.e., create the in-distribution and out-distribution datasets.

R2 How to extend current OOD detection methods from 2D classification task to 3D semantic segmentation?

R3 Is uncertainty quantification an effective approach to classify OOD detection in 3D semantic segmentation models?

R4 How to evaluate the OOD detections over the 3D semantic segmentation task?

2

State of the Art

2.1 ....

Use as many sections as you need in your related work to group content into logical groups Don't forget to correctly cite your sources [**?**].

2.2 Limitations of previous work

3

Methodology

Dataset bechmarking is important any task because it allows future researchers to compare and validate their methods. In this thesis, we tried to formulate a benchmark for out of distribution (OOD) detection in 3D datasets and evaluated the benchmarked datasets over the baseline models. In this chapter, we discuss about the benchmarking of datasets particualry how is it done and experimental setup which includes models used and also a description about the process of OOD detection.

3.1 Dataset benchmark formulation

In this era, development of novel architectures in deep learning is made easy by improvement in frameworks such as Pytorch and Tensorflow. These rapidly developed architectures requires a standard benchmarked datasets to compare performance with existing architectures. The process of creating benchmarked datasets with high quality are tedious and requires Herculian effort. Moreover the benchmarking for OOD detection task in 2D is already available in [cite]. The benchmarked datasets in OOD detection for 2D classification setting are MNIST vs Fashion MNIST [cite] or CIFAR vs SUN datasets [cite]. Since this thesis deals with OOD detection in 3D segmentation task and it is first of its kind no such benchmarking is available as best of our knowledge. As discussed in [cite], we chose the datasets for in and out distributions based on the criteria of *relevance*, *representativeness*, *experimentally verified case*, *scalability* and *resuability*. As argued in [cite] one more criteria is *non-redundancy* was tried to maintain and its only possible with hard OOD scenarios where classes doesn't overlap between datasets. In case of soft OOD there are class overlaps but it should not be a problem in OOD detection task.

3.1.1 SemanticKITTI

The first benchmarked datasets are of LiDAR point annotation datasets for 3D semantic segmentation. This thesis also include the study of the available LiDAR datasets, a detailed descripton of datasets and their classes are availbale in appendix [cite]. The discussion here is only confined to the datasets used for benchmarking. For this study we chose the SemanticKITTI dataset [**?**] as an in distribution dataset. We adopted SemanticKITTI becuase of its wide usage in evaluation of 3D semantic segmentation model performance. Moreover the dataset consits of high qualitative and quantative scans. Also the sensor used is Velodyne HDL-64E which is widely used sensor for LiDAR scans as its used in other datasets such

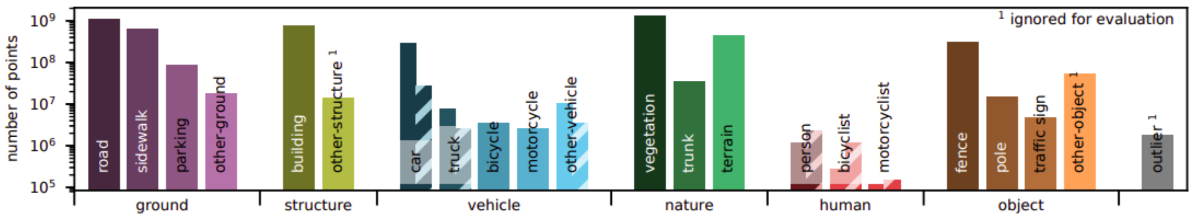


Figure 3.1: Classes in semanticKITTI datset and their distribution in dataset. The hatched bars means a mving object where as solid bar means a non movable object. Image taken from [**?**].

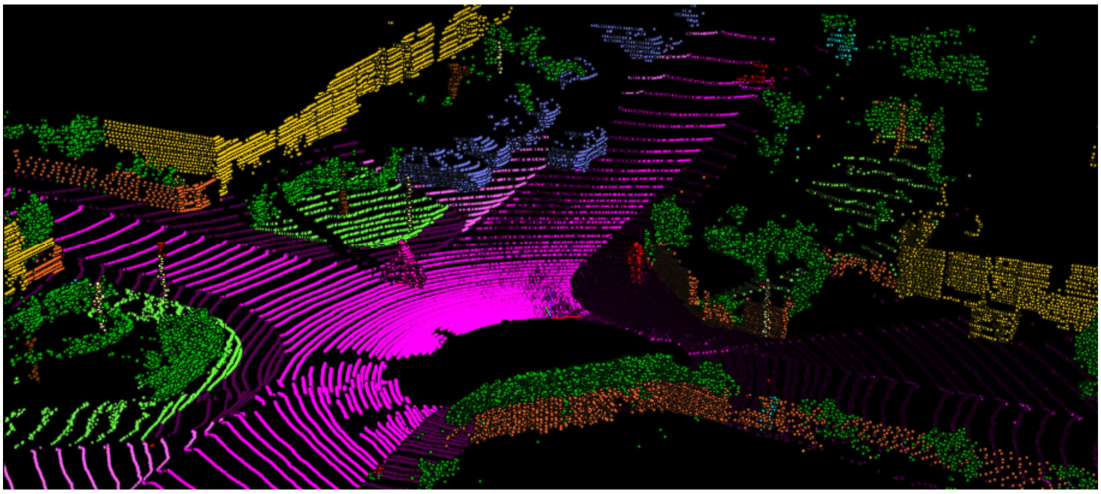


Figure 3.2: Ground truth example of a scan in SemanticKITTI dataset depicting various classes

as [cite]. SemanticKITTI [**?**] is a large dataset with 23201 and 20351 scans for training and testing respectively. The datasets has a gigantic 4549M number of points which are annotated individually. It has 28 classes annotated but only 25 are used for evaluation. The dataset is also publicly available at [cite] for download and API at [cite]. The available classes and their distribution in dataset is given in Figure 3.1. SemanticKITTI is an outdoor autonomous driving dataset as depicted in Figure 3.2.

3.1.2 Stanford 3D Indoor Scene Dataset (S3DIS)

4
Solution

Your main contributions go here

4.1 Proposed algorithm

4.2 Implementation details

5

Evaluation

Implementation and measurements.

6

Results

6.1 Use case 1

Describe results and analyse them

6.2 Use case 2

6.3 Use case 3

7

Conclusions

7.1 Contributions

7.2 Lessons learned

7.3 Future work

8

Notes/Remarks

8.1 Introduction

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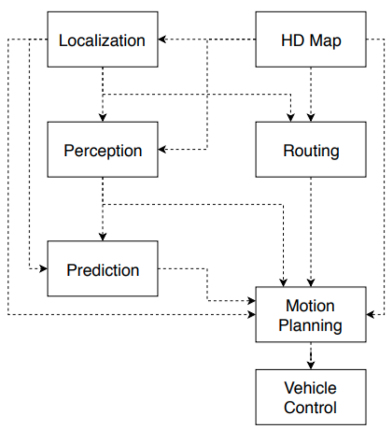

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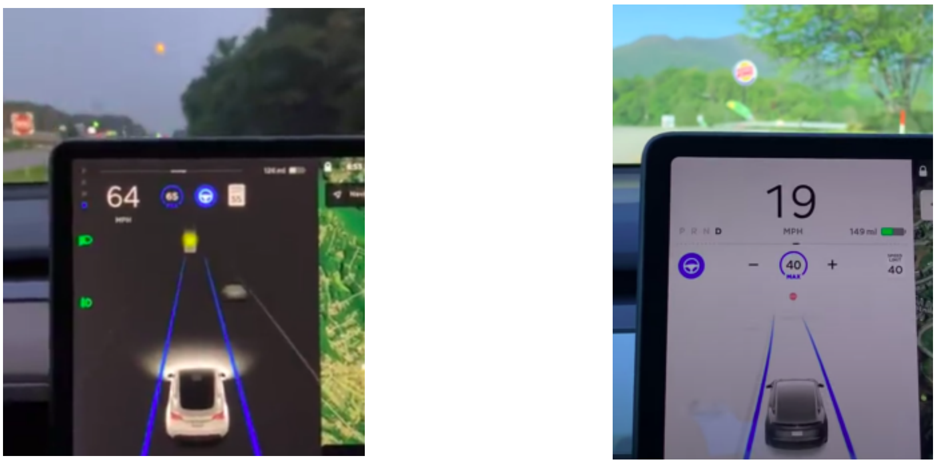

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8.4 Related work - Datasets

LiDAR is one of the central component in the sensor suite for SLAM system in robotic applications [34], [26], [15] and autonomous driving [20]. 3D LiDAR data is preferred because, it can provide the exact replica of 3D geometry of the real world represented in the form of 3D point clouds. Because of these rich features and widespread use of LiDAR sensors, tasks such as 3D object detection [42], [41] and 3D semantic segmentation [27], [1] are becoming more predominant area for research.

In this section, we will discuss about the available 3D LiDAR datasets for 3D semantic segmentation task and classify the datasets based on acquisition methods as in [9]. [9] classifies the available public datasets into three classes based on the data acquisition process. They are *Sequential*, *Static* and *Synthetic* datasets. The data for sequential datasets are collected as frame sequences where mechanical LiDAR is mounted on top of a autonomous driivng platform as in Figure 8.4. Most of the popular autonomous

Figure 8.4: Sequential mounted LiDAR for data collection of Lyft L5 dataset. Image from [17]

driving datasets are of sequential type, but these kind of datasets comes with a drawback of sparse points than other datasets.

Static datasets consists of data collected from a stationary view point by a terrestrial laser scanner. These kind of datasets capture the static information of the realworld whereas the sequential datasets capture the dynamic movements of the surrounding objects. Static datasets find their way in applications such as the urban planning, augmented reality and robotics. Figure 8.5 depcits a terrestrial laser scanner

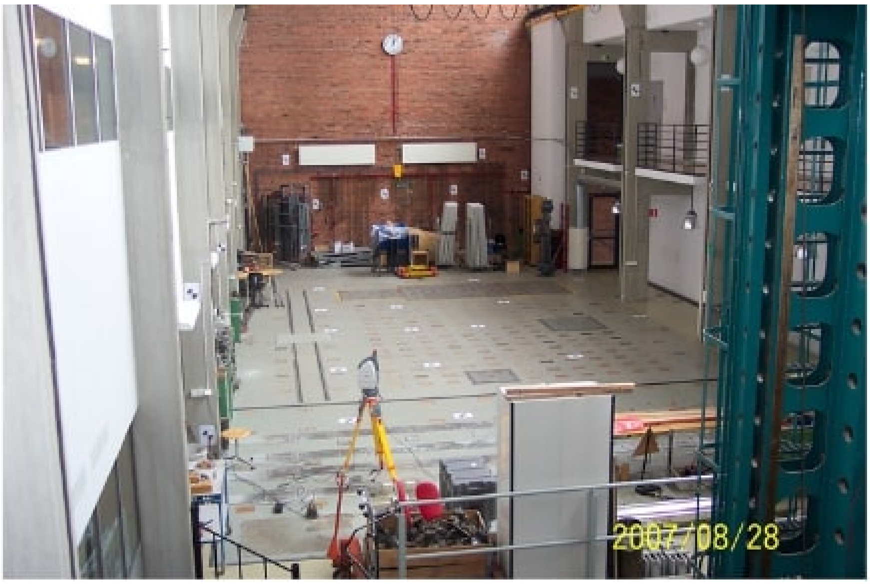


Figure 8.5: Terrestrial laser scanner in an industrial environment with the laser scanner mounted on a yellow tripod in the left corner of the floor. Image taken from [28]

used to capture point cloud of an industrial environment. An advantage with the static datasets, are they can produce highly dense point clouds leading to rich 3D geometric representations.

Last type of 3D LiDAR datasets are synthetic datasets. As the name suggests these datasets are generated from the computer simulation. Figure 8.6 depcits a simulated point cloud in a synthtic dataset called SynthCity. Eventhough synthetic datasets can be generated in large scale with cheap cost, they lack the accuracy in detail when compared to the point clouds generated from real world.

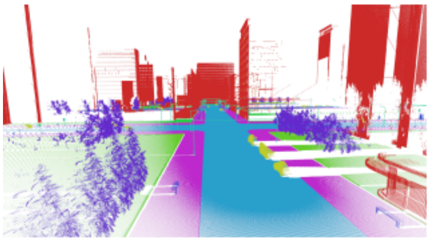


Figure 8.6: Illustration of a scene in synthetic dataset called SynthCity. Image taken from [13]

The datasets belonging to the each acquisition type are summed up in Table 8.1. Most of the datasets from the Table 8.1 are taken from [9] and also as a part of this study, additional new datasets were added to the list. The newly added datasets include DALES [37], ScanObjectNN [35] in static acquisition mode and AIO Drive [38], Toronto3D [33] are additions in the sequential mode. [9] also classifies GTAV (#cite) dataset as synthetic 3D LiDAR but the corresponding paper doesn't report any LiDAR dataset and proposed only 2D dataset for segmentation. The limited number of datasets in 3D LiDAR allowed us to study the characteristics of each individual datasets such as each class, data distribution and features of each point in point cloud. It is summarized in Table (#ref) in Appendix (#chapter number)

acquisition mode	dataset	frames	points (in million)	classes	scene type
static	Oakland[24]	17	1.6	44	outdoor
	Paris-lille-3D[29]	3	143	50	outdoor
	Paris-rue-Madame[30]	2	20	17	outdoor
	S3DIS[2]	5	215	12	indoor
	ScanObjectNN[35]	-	-	15	indoor
	Semantic3D[14]	30	4009	8	outdoor
	TerraMobilita/IQmulus[36]	10	12	15	outdoor
	TUM City Campus[11]	631	41	8	outdoor
	DALES[37]	40 (tiles)	492	8	outdoor
sequential	A2D2[12]	41277	1238	38	outdoor
	AIO Drive[38]	100	-	23	outdoor
	KITTI-360[40]	100K	18000	19	outdoor
	nuScenes-lidarseg[6]	40000	1400	32	outdoor
	PandaSet[39]	16000	1844	37	outdoor
	SemanticKITTI[5]	43552	4549	28	outdoor
	SemanticPOSS[25]	2988	216	14	outdoor
	Sydney Urban[7]	631	-	26	outdoor
	Toronto-3D[33]	4	78.3	8	outdoor
synthetic	SynthCity[13]	75000	367.9	9	outdoor

Table 8.1: 3D LiDAR datasets classified based on the acquisition type. Table updated from [9]

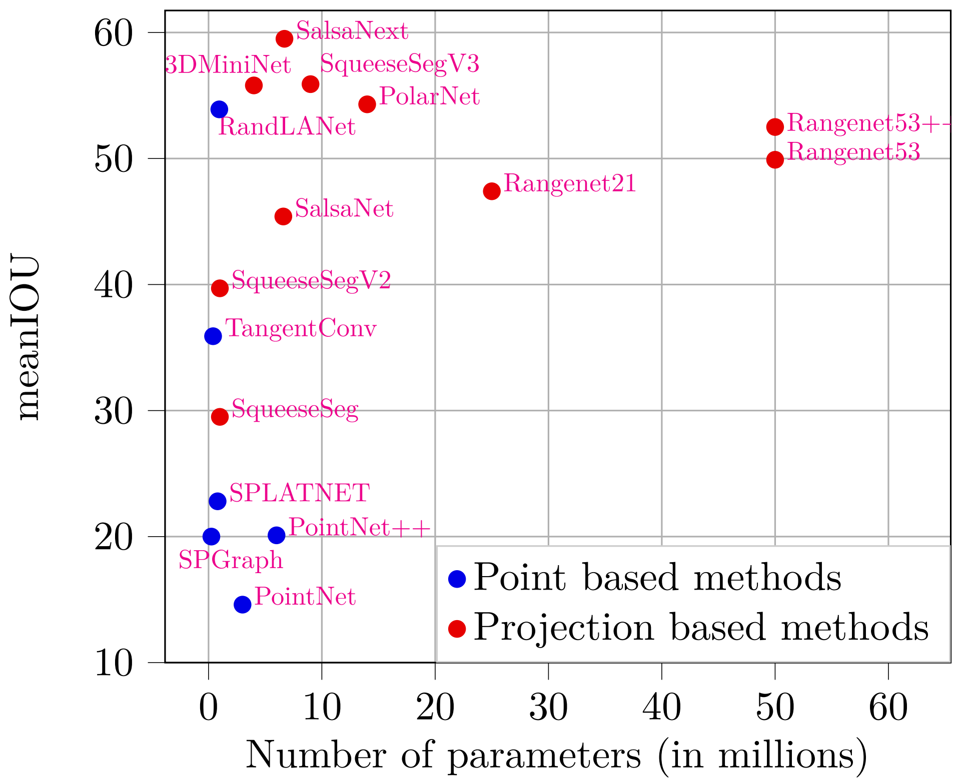


Figure 8.7: Comparison of 3D semantic segmentation methods performance on SemanticKITTI dataset against the number of parameters. Blue points represent point based methods and red represented projection based methods.

8.5 Related work - Models

A

DNN Safety

A.1 Safety of DNNs

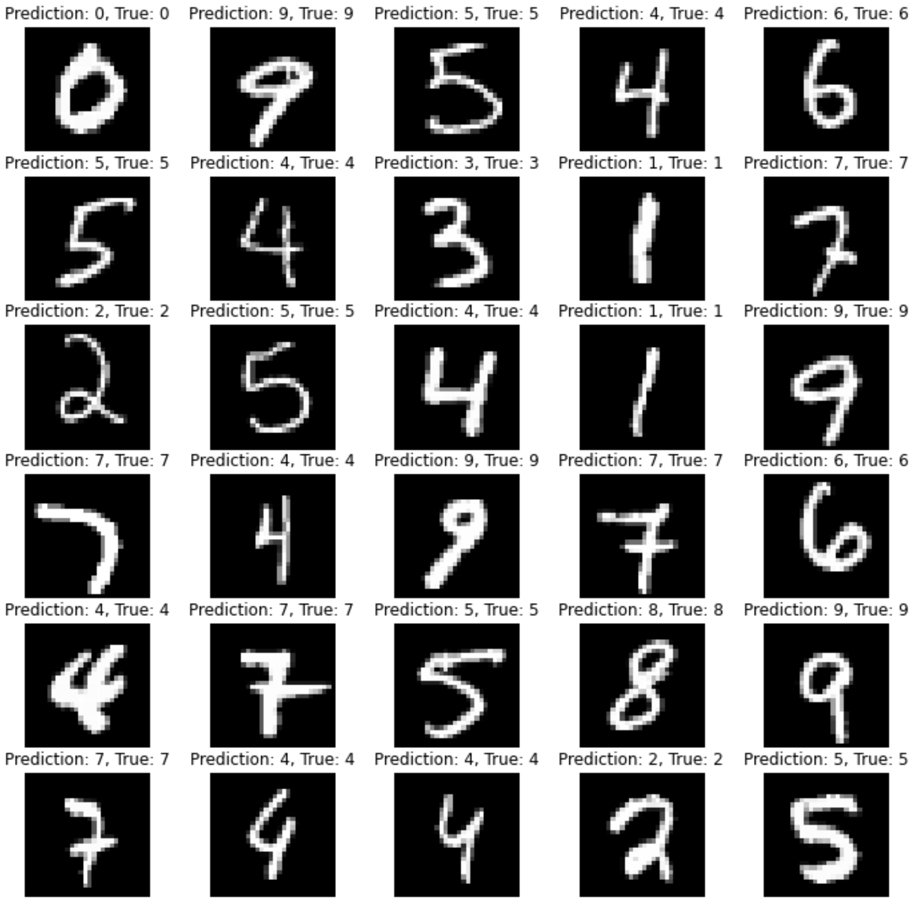
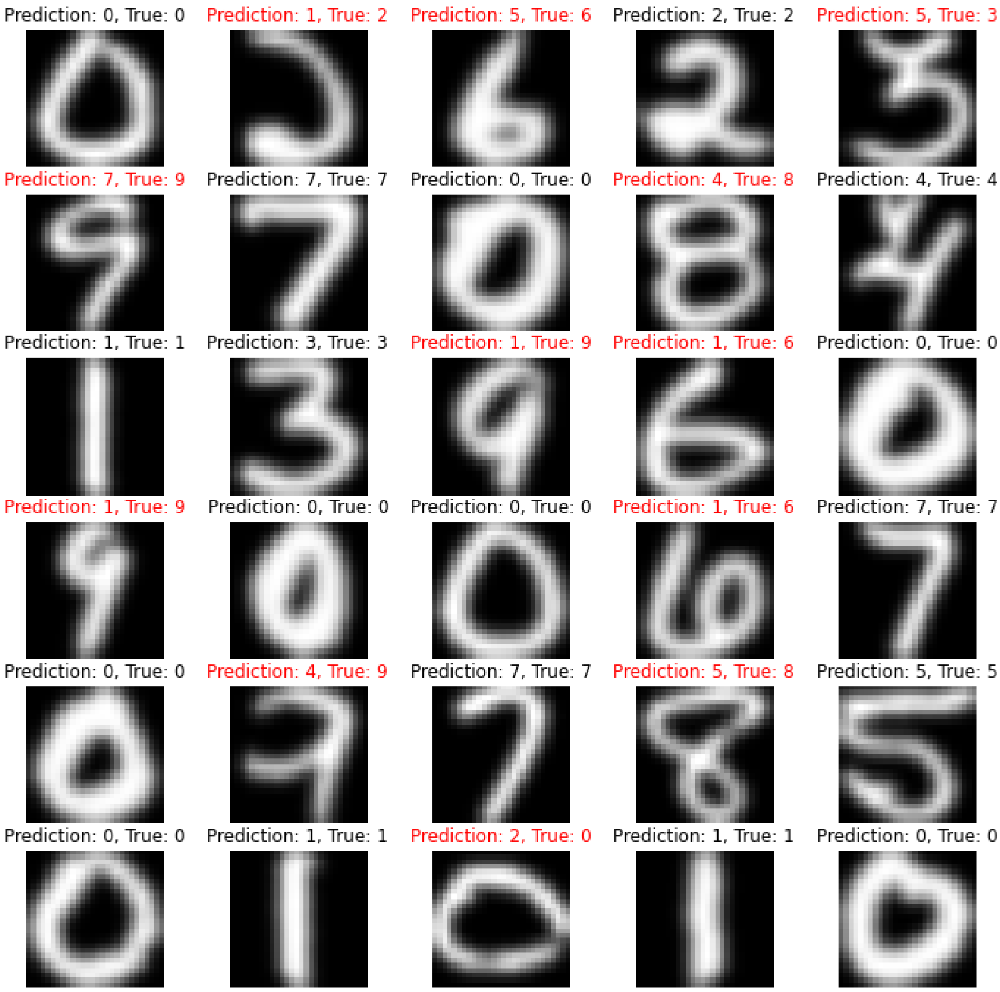

Prediction: 0, True: 0
Prediction: 9, True: 9
Prediction: 5, True: 5
Prediction: 4, True: 4
Prediction: 6, True: 6
Prediction: 5, True: 5
Prediction: 4, True: 4
Prediction: 3, True: 3
Prediction: 1, True: 1
Prediction: 7, True: 7
Prediction: 2, True: 2
Prediction: 5, True: 5
Prediction: 4, True: 4
Prediction: 1, True: 1
Prediction: 9, True: 9
Prediction: 7, True: 7
Prediction: 4, True: 4
Prediction: 9, True: 9
Prediction: 7, True: 7
Prediction: 6, True: 6
Prediction: 4, True: 4
Prediction: 7, True: 7
Prediction: 5, True: 5
Prediction: 8, True: 8
Prediction: 9, True: 9
Prediction: 7, True: 7
Prediction: 4, True: 4
Prediction: 4, True: 4
Prediction: 2, True: 2
Prediction: 5, True: 5

Figure A.1


Prediction: 0, True: 0
Prediction: 1, True: 2
Prediction: 5, True: 6
Prediction: 2, True: 2
Prediction: 5, True: 3
Prediction: 7, True: 9
Prediction: 7, True: 7
Prediction: 0, True: 0
Prediction: 4, True: 8
Prediction: 4, True: 4
Prediction: 1, True: 1
Prediction: 3, True: 3
Prediction: 1, True: 9
Prediction: 1, True: 6
Prediction: 0, True: 0
Prediction: 1, True: 9
Prediction: 0, True: 0
Prediction: 0, True: 0
Prediction: 1, True: 6
Prediction: 7, True: 7
Prediction: 0, True: 0
Prediction: 4, True: 9
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Prediction: 0, True: 0
Prediction: 1, True: 1
Prediction: 2, True: 0
Prediction: 1, True: 1
Prediction: 0, True: 0

Figure A.2

B

Parameters

Your second chapter appendix

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