AWS Machine Learning Engineer Nanodegree

Capstone Project

Inventory Monitoring at Distribution Centers

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I. Definition

Project Overview

In the recent times, Artificial Intelligence and Machine Learning technologies have been adopted by different verticals. One of the reason that they have become popular now a days is that we now have increased computing power to train large machine learning models and more data to train our models to get an increase in accuracy.

Modern supply chain management can greatly benefit by adopting these technologies. Machine learning in supply chain management can especially impact inventory levels, quality, supply and demand, production planning and transport management. This is important for supply chain management moving forward, particularly when applied to warehouse management.

A smart warehouse combines various interconnected technologies to form an ecosystem whereby an entire business operation, from supply to delivery, is governed by Artificial Inteligence. Goods are received at the warehouse, identified and sorted, processed, packaged, and pulled for shipment, all automatically and with minimal margin for error.

Incase of amazon, the distribution centers like Amazon Fulfillment Centers play an important role in delivering millions of products all over the world. These centers often use robots to move objects as a part of their operations. These products are randomly placed in bins, which are carried by robots. Occasionally, items are misplaced while being handled, resulting in a mismatch between the recorded bin inventory and its actual content.

This problem of mismatched inventory bins can be detected by adopting the Machine learning techniques, which will definetly help further in improving the productivity and efficiency of the distribution centre.

Problem Statement

Amazon uses a random storage scheme where items are placed into accessible bins with available space, so the contents of each bin are random, rather than organized by specific product types. Thus, each bin image may show only one type of product or a diverse range of products. Occasionally, items are misplaced while being handled, so the contents of some bin images may not match the recorded inventory of that bin.

The proposed solution is to train and build a Deep Learning model using a pretrained model that can classify the image based on the number of objects in the bin. The input to the model is an image of a bin with the products in it and the output is list of predicted scores for each category type in this case the number of objects in the bin. Individual instances need to be counted separately, which means if there are two same objects in the bin, count them as two.

Metrics

The model predictions are evaluated by a standrad metric called precision for each class as this is a multiclass image classification problem. This metric is choosen because the classes of dataset are bit imbalanced.

$$Precision = \frac{True\ \ Positive}{True\ \ Positivie + False\ \ Positive}$$

The precision is calculated for each class (number of objects in the bin). The precision tells how many images are correctly labeled as ‘x’ out of total images that are labeled as ‘x’.

II. Analysis

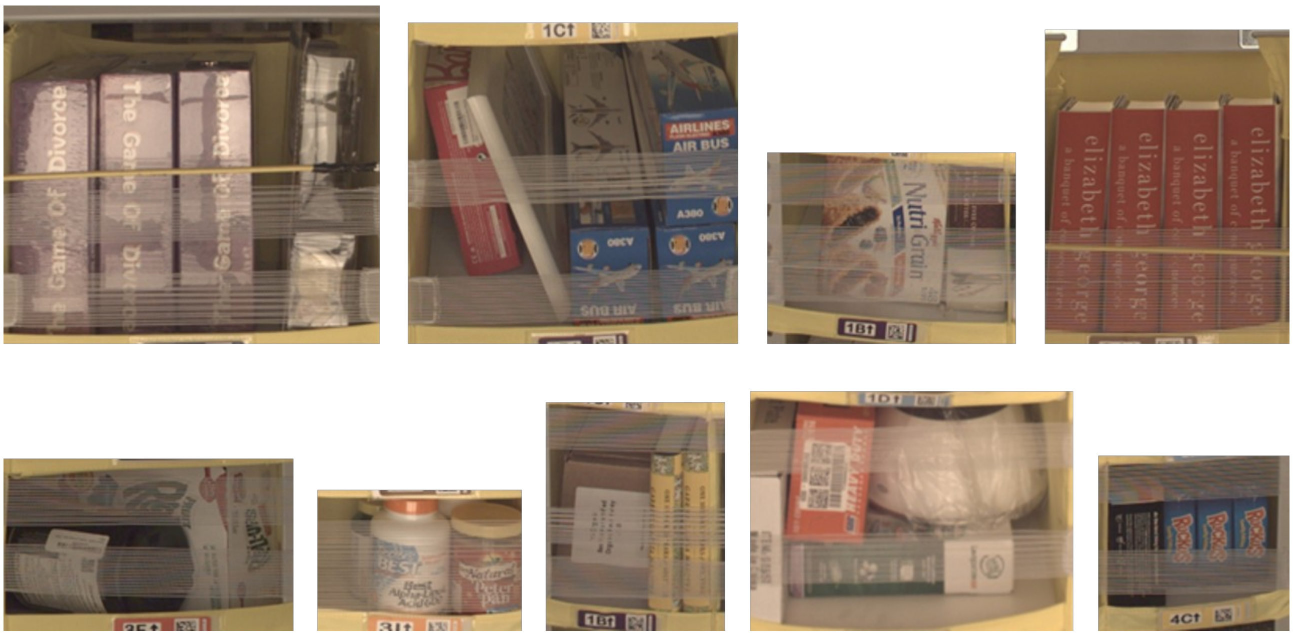
Data Exploration

For this project a subset of Amazon Bin Image Dataset[1] will be used.

The Amazon Bin Image Dataset contains over 500,000 images and metadata from bins of a pod in an operating Amazon Fulfillment Center. The bin images in this dataset are captured as robot units carry pods as part of normal Amazon Fulfillment Center operations.

The contents of each bin are random, rather than organized by specific product types. Thus, each bin image may show only one type of product or a diverse range of products.

Sample images from the dataset;



A bin contains multiple object categories and various number of instances.The size of bins are various depending on the size of objects in it. The tapes in front of the bins are for preventing the items from falling out of the bins and sometimes it might make the objects unclear. Objects are sometimes heavily occluded by other objects or limited viewpoint of the images.

The corresponding metadata exists for each bin image and it includes the object category identification(Amazon Standard Identification Number, ASIN), quantity, size of objects, weights, and so on.

Since this is a large dataset, only a subset of the data has been used for this project. The subset of bin images dataset were choosen so that the number of objects in a bin range from ‘1’ to ‘5’ only.

The subset of data created are arranged in subfolders. Each of these subfolders contain images where the number of objects is equal to the name of the folder. For instance, all images in folder 3 has images with 3 objects in them. The number of objects will serve as the categories for classification of bin images.

The list of file names to be downloaded is collected in file_list.json. The metadata(json) filenames are arranged in json object using number of images in bin as the ‘key’.

Eg:

```
{
      “1”: ["data/metadata/100313.json",
             "data/metadata/09915.json",.....],

      “2”: ["data/metadata/102489.json",
             "data/metadata/104982.json",.....],

      .........


      “5”: ["data/metadata/03858.json",
             "data/metadata/101598.json",......]
}
```

The dataset is available on Amazon S3[1]. Images are located in the bin-images directory, and metadata for each image is located in the metadata directory.

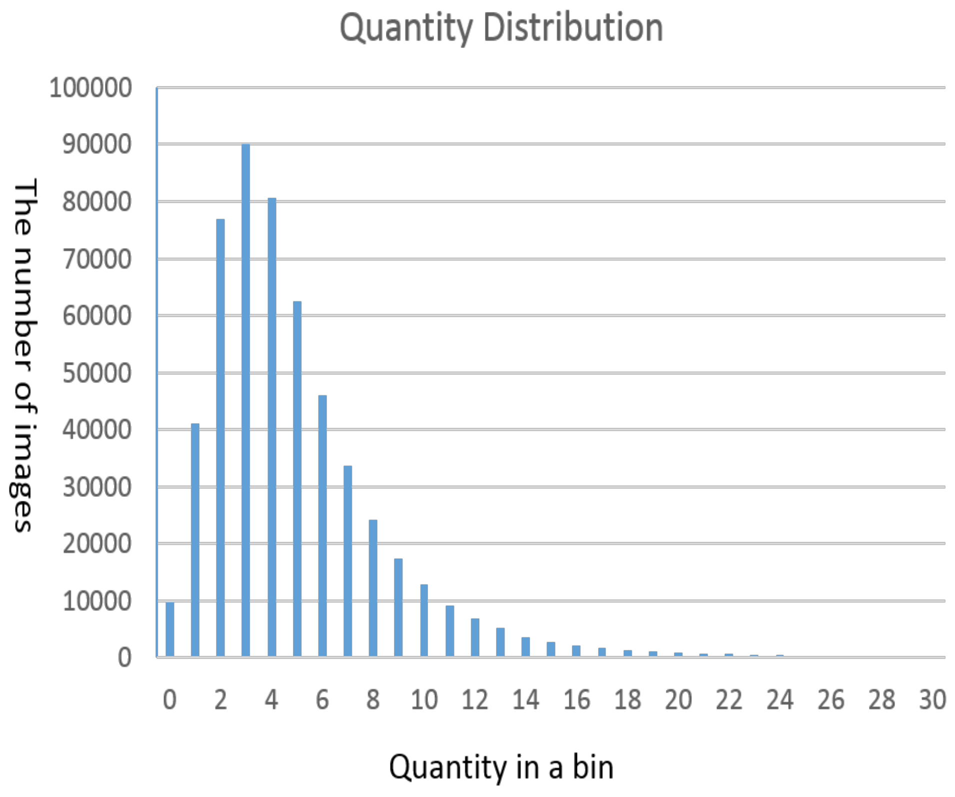
Exploratory Visualization

Amzon bin images dataset

The plot below shows the distribution of number of products in a bin. Here we can see 90% of bin images contains less than 10 object instances in a bin and the average quantity in a bin is 5.1[3].

Data Statistics:

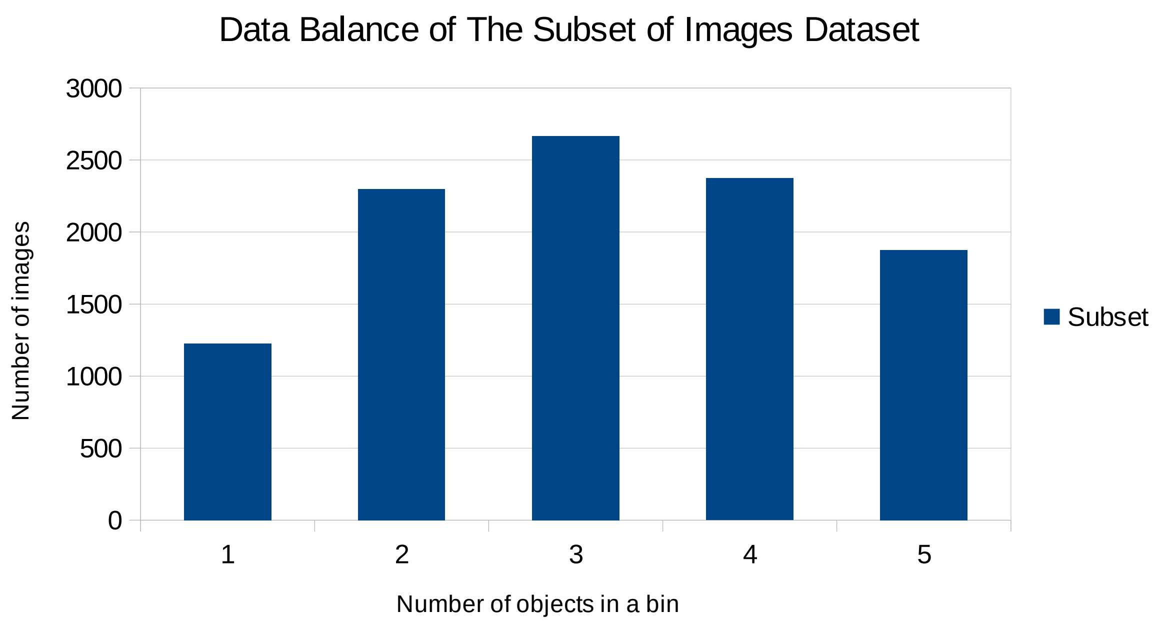
Description	Total
The number of images	535,234
Average quantity in a bin	5.1



Subset of the images dataset

The subset of the images dataset has total **10441** images. The number of images in each class are as below;

Category (number of objects in a bin)	**Total Images**
1	1228
2	2299
3	2666
4	2373
5	1875



Algorithms and Techniques

Image classification is a comlex task. So, an advanced neural network like a Convolutional Neural Network(CNN) is the popular choice for image classification tasks. One of the advantage with CNN is pretrained models can be used and fine tuned for other tasks. There are different types of CNN models available like; LeNet, AlexNet, VGG, Inception, ResNet etc.

ResNet short for Residual Network is one of the modern model with impressive performance in computer vision tasks.

Here, a pretrained model of '**resnet50**' has been used to fine tune on the amazon bin image dataset.

To finetune the resnet50 CNN, following steps are performed:

- create or load the pre-trained model
- freeze all the convolutional layers
- add a fully connected layer and train it.

In this training paradigm, the forward pass will run for the whole network and since the convolutional layers are frozen, the backward pass (and update weights) will run for only the fully connected layers.

The following hyperparameters are used during tuning and training;

- training length (number of epochs)
- batch size (number of images to look at once during a single training step)
- learning rate (how fast to learn)

As this is a multi class classification problem **Cross entropy loss** function is used as the cost function and **Adaptive Moment Estimation (Adam)** method is used as an optimizer.

Benchmark

The benchmark for this project is to be able to get the per class precisions as mentioned below;

Quantity	Per class precision(%)
0	97.7
1	83.4
2	67.2
3	54.9
4	42.6
5	44.9

These values were taken from the Amazon Bin Image Dataset Challenge[3].

III. Methodology

Data Preprocessing

This dataset is split into training, testing and validation sets in ratio of 8:1:1.

The images come in different sizes. The pretrained model resnet50 takes the input images of size 224 X 224. So, all the images are resized to 224 X 224 and then the input values are normalized.

I observed, some of the images are of very poor quality and the objects are not at all visible to human eye. So, some images may need to be deleted to improve the training performance.

Implementation

The AWS SageMaker, S3, Cloudwatch etc. have been used to carry out the implementation of the project. The code is implemented using python and its libraries like pytorch, torchvision etc.

The pretrained model resnet50 is adopted from torchvision library. This model is trained on the ImageNet dataset.

Setup AWS SageMaker Notebook instance

Create and open a Sagemaker instance, I have chosen 'ml.t2.medium' instance type. This instance comes with 2vCPUs and 4GiB memory. This configuration is good enough for running the project jupyter notebook and the price is also one of the least.

Then create or load the project files required to your workspace.

Training Script (*train.py / hpo.py / inference.py*)

The training script takes the hyperparameters as arguments and reads, loads and preprocesses the train, test and validation data. Then after creating and loading the pretrained 'resnet50' model it trains the model using the given parameters.

hpo.py: used for hyperparameter tuning job.

train.py: used for fine tuning the model with best hyperparameters.

inference.py: used for deploying the trained model.

Submission Script (*sagemaker.ipynb*)

This jupyter notebook has the code cells to interface with the sagemaker and submit all the jobs to it. The following jobs are done using this script;

- Data download and preparation: Download the subset of the Amazon bin image dataset[1]. The *file_list.json* has the list of files to download. The dataset is split into train, test and validation directories in the ratio of 8:1:1.
- Data Upload to S3: Upload the downloaded data to the required S3 bucket.
- Setup the Hyperparameter search space
- Setup the model debugging and profiling rules
- Create the model estimator
- Create the Hyperparameter tuning job
- Submit the tuning job
- Fetch the best training job and the hyperparameters

- Finetune the model with the best hyperparameters
- Deploy the model
- Query the model with a bin image and get prediction

Refinement

In this project, I created a deep learning work flow using AWS SageMaker, which we can use to train the image classification model on Amazon bin image dataset. With minimal changes in the scripts the training process can be performed iteratively with various parameters and larger datasets. So that, we can get the better performing model.

In the first iteration I used below hyerparameter ranges for hyperparameter tuning;

```
hyperparameter_ranges = {
    "lr": ContinuousParameter(0.001, 0.1),
    "batch-size": CategoricalParameter([32, 64, 128, 256]),
    "epochs": IntegerParameter(2, 10)
}
```

The returned best performing hyperparameters are;

```
{       'batch-size': '"256"',
        'epochs': '8',
        'lr': '0.003820049499119736',
        'test-batch-size': '"100"'
}
```

The model test set loss and accuracy are;

```
Test set: Average loss: 1.5935008831864572
Testing Accuracy: 0.22701148688793182
```

Model predictions:

```
[-0.1935795694589615,
    0.01356017217040062,
    0.010463185608386993,
    0.06341414898633957,
    -0.06604141741991043]
```

** The same prediction result is returned for all the images irrespective of number of objects in the bin.

In the second iteration, I changed the number of epochs range as (**10, 40**)

The returned best performing hyperparameters are;

```
{'test-batch-size': '100',
 'epochs': '15',
 'batch-size': 256,
 'lr': '0.005400944277147078'}
```

The model test set loss and accuracy are;

```
Test set: Average loss: 1.5811538189307026
Testing Accuracy: 0.25574710965156555
```

Model predictions:

```
[-0.3486097455024719,
    0.06472239643335342,
    0.20118021965026855,
    0.10767237097024918,
    -0.06968116760253906]
```

** The same prediction result is being returned for all the images irrespective of number of objects in the bin.

IV. Results

Model Evaluation and Validation

The final model has been deployed with the best performing hyperparameters. I used PyTorchModel for deploying the model.

Once the model is successfully deployed on Endpoint, queried the endpoint usig the predict() method.

Screenshot of the endpoint results;

```
In [60]: from PIL import Image
         import io
         Image.open(io.BytesIO(img_bytes))
Out[60]:
```

```
In [61]: response = predictor.predict(img_bytes, initial_args={"ContentType": "image/jpeg"})

In [62]: type(response)
Out[62]: list

In [63]: response
Out[63]: [[-0.1935795694589615,
           0.01356017217040062,
           0.010463185608386993,
           0.06341414898633957,
           -0.06604141741991043]]

In [64]: import numpy as np
         np.argmax(response, 1)
Out[64]: array([3])
```

The model prediction results for this image is correct, but the accuracy percentage is low.

When I queried the endpoint with different images, for all of the images it is returning the same response.

The overall workflow of the model training looks robust but the model needs more training with larger datasets and also need to explore iteratively for better performing CNN models and hyperparameters.

The one important thing to consider is using the larger dataset and cleanup of images with the wrong label and unclear bin images.

Justification

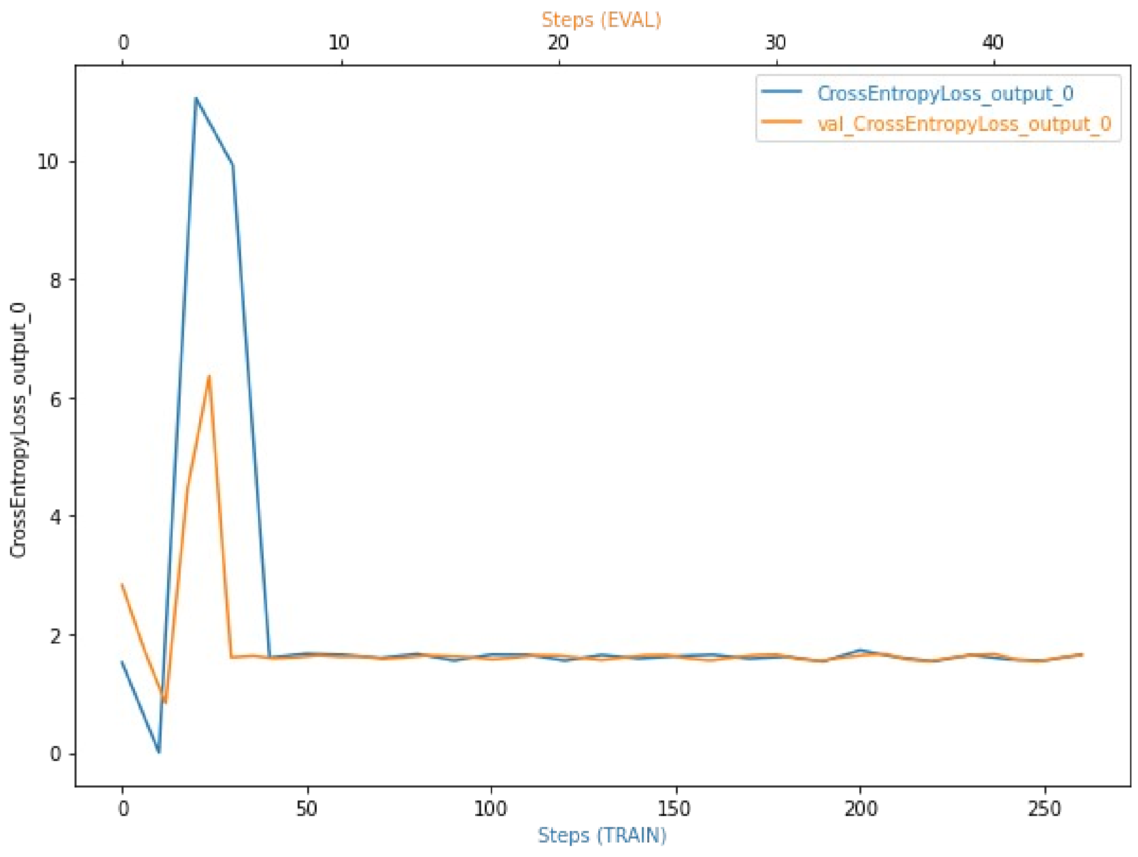
With the small subset of images dataset the model's accuracy reached saturation point and reached the testing accuracy of 0.25574710965156555 and is below the bench mark result mentioned earlier.

Using the AWS ML work flow that's been built more training can be performed to achieve better accuracy.

V. Conclusion

Free-Form Visualization

Below is the plot of CrossEntropyLoss captured against number of epochs during the model training;



The AWS SageMaker provides robust platform for developing machine learning models. There are debugger and profiling libraries or services which can be used in debugging and analysing the model training process.

To build an ML model some of the important things to take care include but not limited to are accuracy and quantity of the dataset, neural network model architecture, different parameters, the loss function, optimizer functions and cost of the resources.

Also, I think things like increasing the training time, using larger datasets and model architectures with more number of layers blindly may not work, one has to find the optimum values or resources when building an ML model.

Resources and references:

1. Amazon Bin Image Dataset : https://registry.opendata.aws/amazon-bin-imagery/

2. Documentaions : https://github.com/awslabs/open-data-docs/tree/main/docs/aft-vbi-pds

3. Amazon Bin Image Dataset(ABID) Challenge : https://github.com/silverbottlep/abid_challenge

4. Amazon Inventory Reconciliation using AI : https://github.com/pablo-tech/Image-Inventory-Reconciliation-with-SVM-and-CNN

5. Project Starter files : https://github.com/udacity/nd009t-capstone-starter

6. https://towardsdatascience.com/

7. https://supplychaingamechanger.com/

Thank You