CS-583: Deep Learning

Final Project Report

Humpback Whale Identification Challenge on Kaggle

Team: Taru Tak, Amit Vadnere

May 18, 2019

1 Summary

We participated in an inactive with late submission competition of classifying humpback whale identification based on photos. The focus was to build an algorithm which can identify whale categories from the images. The final model we choose is ResNet50, a deep convolutional neural network architecture, which is initially trained with 224×224 images as input and later after oversampling, trained on 448*448. The output of the model for an image is a set of at most 5 labels in a priority sequence where each element of the set the category corresponding to the image. We implemented the convolutional neural network using fastai library and ran the code on a Google Cloud Platform with 12v CPU, 45 GB memory and 1 NVIDIA Tesla P4 GPU with 16GB GPU Memory. Performance is evaluated based on Mean Average Precision from at most 5 labels. In the public leaderboard, our score is 0.71991; we rank 1082 among the 2131 teams. In the private leaderboard, our score is 0.74815; we rank 1068 among the 2131 teams.

2 Problem Description

Problem:

The challenge was to develop an algorithm that identifies the whale category from the provided image that includes whale tail. The competition is a type of multi classification and image recognition problem. The size of the training dataset was 25000 images which were gathered from the research institutions and public contributors.

Competition link:

https://www.kaggle.com/c/humpback-whale-identification

Data:

The data are variable-sized JPEG images. The number of training samples is n = 25,000, test is 7003 Images. The number of classes is 5005. The training set is highly imbalanced.

Challenges: The greatest challenge is the imbalanced nature of dataset where 2000+ whales have just one image, about 30% of the whale categories consists of 4 or fewer images.Moreover 40% of the whale images belongs to new_whale category.

3 Solution

Model:

The model we finally choose is the ResNet50 , which is standard deep convolutional neural network architecture. We can read more about it on https://www.kaggle.com/keras/resnet50.

Implementation:

We implemented two models. Res-Net18 baseline model and Res-Net 50 final Model. The models used were ImageNet pretrained and were directly imported from FastAI library. Our code is available at https://github.com/tarutak/Humpback-Whale-Identification. This model was trained using Google Cloud Platform with 12v CPU, 45 GB memory and 1 NVIDIA Tesla P4 GPU with 16GB GPU Memory. It takes about 4.5 hours to train the model.

Settings

The loss function is categorical cross-entropy. The optimizer is ADAMs (by default). We trained our final model in a progressive manner. We first set our batch Size as 64, with cyclical learning rate of 1E-02, and Size of Image were 224. We fine tuned the pretrained model for 14 Epochs and then proceeded to unfreeze inner layers and trained them for 5 more epochs.

Next, we trained our model with 224 * 2 size images, and decreased batch size to 16. We train the for another 22 Epochs.

Next, we used an oversampled train set from Kaggle to increase the dataset size and low count categories and trained the model of the complete set for another 4 epochs.

Advanced tricks:

We used a pre-trained imageNet model by default and tuned it for our whale recognition challenge.

We used various image augmentation techniques such as crop, Zoom, Rotate, Sheer, Reflection Padding, Brightness, Contrast, etc using the transform function of FastAi.

We used progressive image sizing technique wherein we were training iteratively on higher dimension images to reduce overfitting and get better generalization.

Cyclical Learning rate and Differential LR for different layers of the Deep CNN models allows more fine tuned training of the model.

Lastly, we used over Sampling techniques to increase the low image count categories in the data.

4 Compared Methods

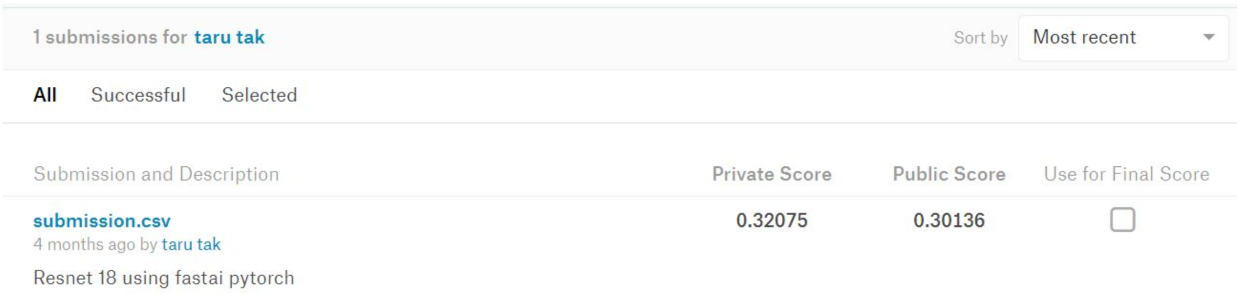
The first model we implemented was a simple ResNet-18 model where in we divided our training data to 90%-10% train and validation. The problem was that most a few categories was in validation set but not in test set and vice versa. It did not provide a good accuracy or LB scores. Normal default transformations were used for Image Augmentations using FastAI.

In the Final model, we trained the model by increase image sizes and learning rates so as to properly utilize our training data available. We used the kaggle leaderboard to understand the performance of the model and were able to get a LB of .719.

We were able to see that ResNet 50 was able to perform better than its smaller ResNet-18 architecture. We utilized over sampling in the final model so as to provide more training data to the Whale categories which had very few images. We saw a huge reduction in training loss also while using this model compared to the previous model.

The overall score of the model can be improved by using custom loss functions or ensemble models but they too expensive to train our on GCP cloud machine.

Result for BaseLine Model: Res-Net 18



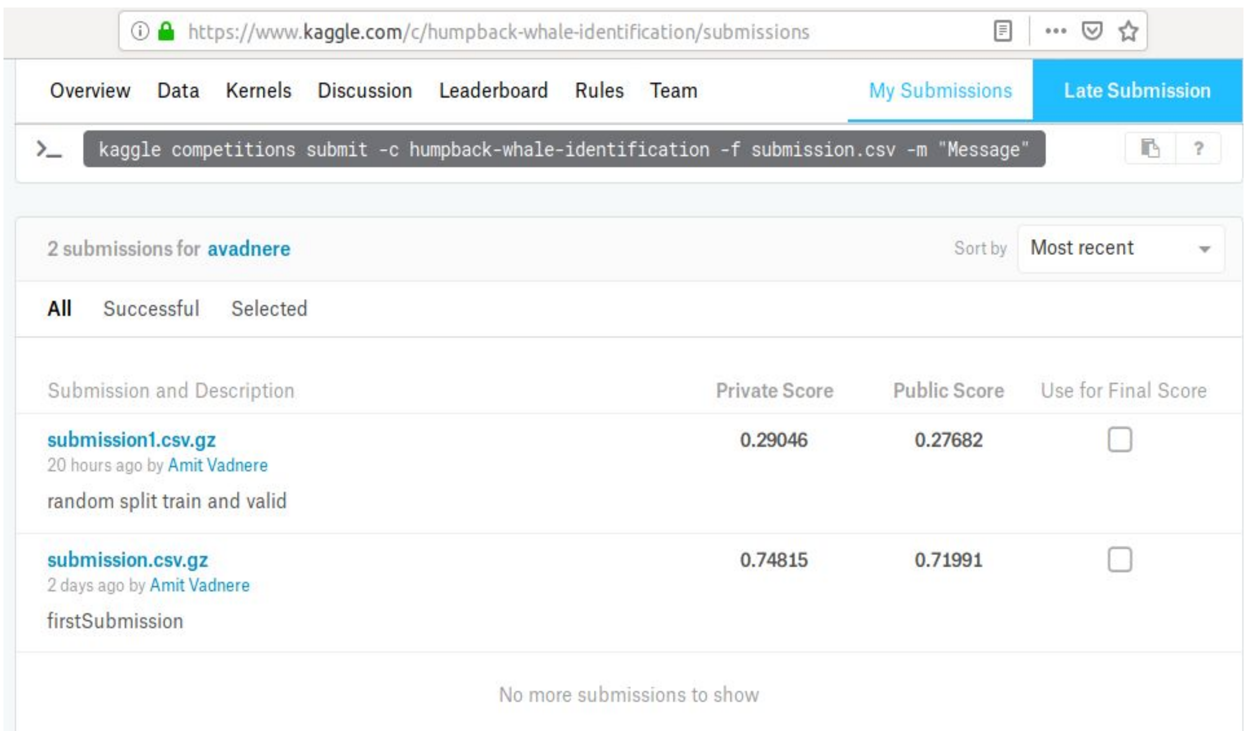
1 submissions for taru tak

Sort by Most recent

All Successful Selected

Submission and Description	Private Score	Public Score	Use for Final Score
submission.csv 4 months ago by taru tak Resnet 18 using fastai pytorch	0.32075	0.30136	

Result for Final Model : ResNet-50



https://www.kaggle.com/c/humpback-whale-identification/submissions

Overview Data Kernels Discussion Leaderboard Rules Team My Submissions Late Submission

```
kaggle competitions submit -c humpback-whale-identification -f submission.csv -m "Message"
```

2 submissions for avadnere

Sort by Most recent

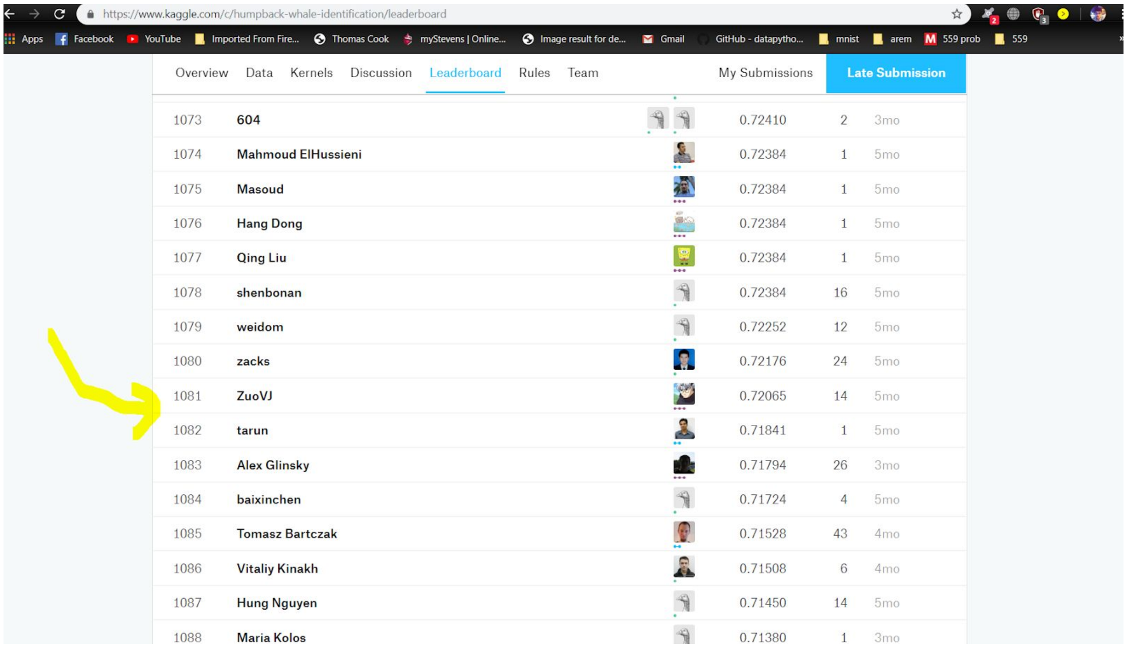
All Successful Selected

Submission and Description	Private Score	Public Score	Use for Final Score
submission1.csv.gz 20 hours ago by Amit Vadnere random split train and valid	0.29046	0.27682	
submission.csv.gz 2 days ago by Amit Vadnere firstSubmission	0.74815	0.71991	

No more submissions to show

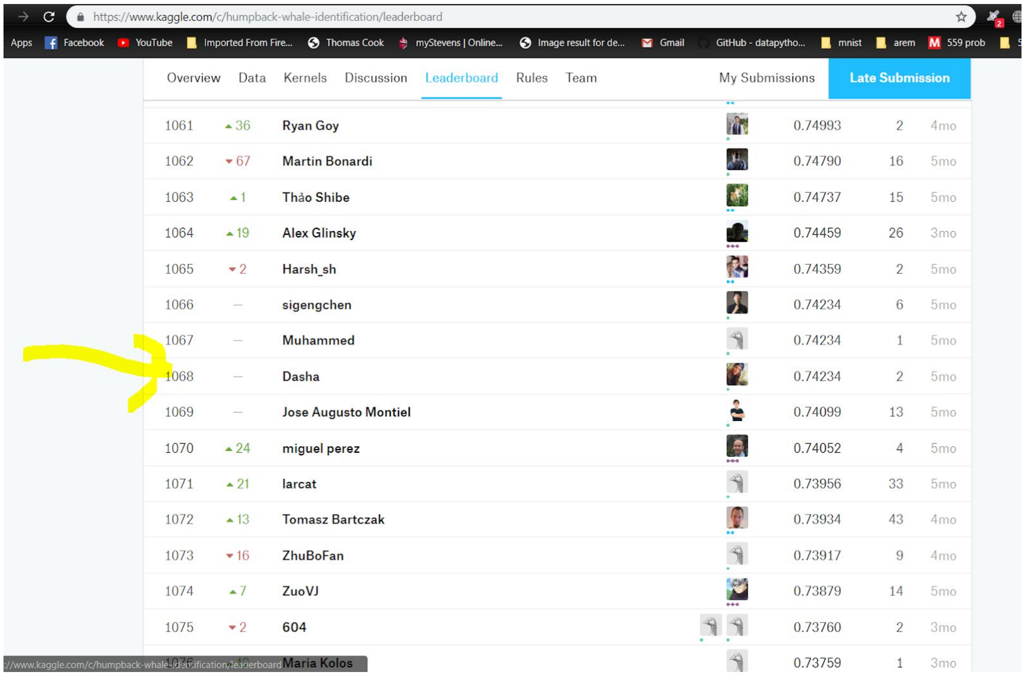
Leaderboard Rankings:

Public LB Rank (Tentative): 1082/2131



1073	604	0.72410	2	3mo
1074	Mahmoud ElHussieni	0.72384	1	5mo
1075	Masoud	0.72384	1	5mo
1076	Hang Dong	0.72384	1	5mo
1077	Qing Liu	0.72384	1	5mo
1078	shenbonan	0.72384	16	5mo
1079	weidom	0.72252	12	5mo
1080	zacks	0.72176	24	5mo
1081	ZuoVJ	0.72065	14	5mo
1082	tarun	0.71841	1	5mo
1083	Alex Glinsky	0.71794	26	3mo
1084	baixinchen	0.71724	4	5mo
1085	Tomasz Bartczak	0.71528	43	4mo
1086	Vitaliy Kinakh	0.71508	6	4mo
1087	Hung Nguyen	0.71450	14	5mo
1088	Maria Kolos	0.71380	1	3mo

Private LB Rank Rank : 1068/ 2131



https://www.kaggle.com/c/humpback-whale-identification/leaderboard

Overview Data Kernels Discussion Leaderboard Rules Team My Submissions Late Submission

1061	▲36	Ryan Goy	0.74993	2	4mo
1062	▼67	Martin Bonardi	0.74790	16	5mo
1063	▲1	Thảo Shibe	0.74737	15	5mo
1064	▲19	Alex Glinsky	0.74459	26	3mo
1065	▼2	Harsh_sh	0.74359	2	5mo
1066	—	sigengchen	0.74234	6	5mo
1067	—	Muhammed	0.74234	1	5mo
1068	—	Dasha	0.74234	2	5mo
1069	—	Jose Augusto Montiel	0.74099	13	5mo
1070	▲24	miguel perez	0.74052	4	5mo
1071	▲21	larcat	0.73956	33	5mo
1072	▲13	Tomasz Bartczak	0.73934	43	4mo
1073	▼16	ZhuBoFan	0.73917	9	4mo
1074	▲7	ZuoVJ	0.73879	14	5mo
1075	▼2	604	0.73760	2	3mo
1076	[illegible]	Maria Kolos	0.73759	1	3mo

5 Outcome

We participated in an inactive competition. On public leaderboard, our score is 0.71991; we rank 1098 among the 2131 teams (Tentative). In the private leaderboard, our score is 0.74815; we rank 1072 among the 2131 teams.

6 References

[1] Fastai Documentation -- https://docs.fast.ai/

[2] Radek Kernel - https://www.kaggle.com/c/humpback-whale-identification/discussion/82480

[3] https://github.com/radekosmulskai

[4] https://www.kaggle.com/c/humpback-whale-identification/

[5] https://www.kaggle.com/c/humpback-whale-identification/discussion/82352