

Sunday, September 13, 2020 9:32 AM

- [NOTE 9/13/20: To be added after competition winners publish their code and I can review it. At this point I've only seen the one solution from the end of competition webinar from leading teams.]

- This was a pretty straightforward binary image classification task classifying venomous vs non-venomous snakes <https://www.aicrowd.com/challenges/ai-for-good-ai-blitz-3/problems/snake>
 - The only wrinkle is that in reality what the model was learning was a multiclass classification before then separating those classes into the two binary classes
 - i.e. venomous: rattlesnake, cobra, black mamba; non-venomous: python, garter, king
 - But unless I'm very mistaken these sufficiently deep NNs should handle this perfectly fine.
 - Which is not to say that there aren't different approaches which could take further advantage of this (I was thinking about clustering approaches)
- My models performed worse on the test set than on the training and validation sets suggesting that either I was having some overfitting (I think unlikely) or there was some aspects of the test set which weren't well reflected in the training data
 - I'm very curious to see if the competition winners did anything drastically different than me. In the webinar the solution presented was extremely similar to mine

- For this competition I boosted a bunch of CNN models together with a gradient-boosting metaclassifier
- The CNNs were all fastai transfer learning models with different architectures and trained on three different cv-splits. All models used imagenet weights for the pre-trained models
 - Models used were [resnet34, xresnet34, resnet50, xresnet50, densenet121, densenet201]
 - At the time of the competition fastai didn't have efficientnet easily accessible, otherwise I would have used it
- Models were trained using fastai's factory fine tuning method with the following parameters:

NOTE: The `aug_transforms` function has a ton of augmentations, the arguments shown are the ones where I'm changing from the default.

- I would therefore characterize this model as having extensive augmentation

After training I exported the models for later use

For boosting I ran every training and test image through every classifier and trained a gradient boosting machine on the training data and then made predictions with it on the test data.

This is where I got fucked. Something happened, possibly with `fastai's get_image_files` function or possibly with Colab's varied backends, but the predictions (which were saved in a simple numpy array, and not a labeled dataframe or something smart) got out of order between different

models which made using the boosting model impossible and I had to rerun all of the predictions over again using a robustly deterministic ordering of the images

- Because the competition was so fast, I ran out of time and compute to do as much test-time augmentation (tta) as I wanted to and in the end only used between 2-4 rounds of tta for each image. I think being in the 4-10 range is much better and that this likely hurt me quite a bit.

Postmortem

- The boosting classifier reached $f1=0.98$ on a validation set but only achieved an $f1=0.865$ on the test set which put me in 16th place. The first place solution had $f1=0.906$.
<https://www.aicrowd.com/challenges/ai-for-good-ai-blitz-3/problems/snake/leaderboards>
 - All things considered an $f1$ difference of .041 isn't a lot. From a competitive standpoint it's huge, but from the perspective of the classifier's efficacy it's fairly small
- The boosting classifier didn't have a true validation set, because the individual NNs had been trained on the data. To really measure the performance of the boosting classifier a true test set would have been needed, but I didn't have time to do that experiment AND train the models on as much data as possible.
 - Just means that the $f1=0.98$ isn't the whole story
- I think I would have benefited a lot from further time and compute to do more tta
- I didn't cv optimize pretty much any hyperparameters, I just found ones that worked very well and stuck with them. This may have helped slightly, but I think it was right to not spend time on this
 - The learning curves from training showed convergence and no overfitting, so the only thing I might have gotten was slight better accuracy
- I would have liked to use some better CNN architectures (efficientnet, others?) and explored other pretrained weights.
- I really suffered here from time and compute constraints, it probably would have helped me out a lot to try and optimize around those considerations