

# Honey Bee Image Classification

DATS6203 Machine Learning 2, Prof: Amir Jafari

Group 4: Ruyue Zhang

This project goal is to use deep learning network to classify Bees Subspecies and Hive Health. The data is from Kaggle: <https://www.kaggle.com/jenny18/honey-bee-annotated-images/kernels> In this project, we first explore the dataset and operate data preprocessing. Then we use 2 different neural network frameworks to classify Bee Subspecies and Hive Health. In this project, we use Gradient Descent Algorithm to optimize the network. In the end we evaluate the result by f1 score, AUC and ROC and test accuracy. Yijia did the load image function and worked with Phoebe on Pytorch CNN model for health and subspecies. Xiaochi did the Keras cnn model for health. Phoebe and Xiaochi together finished EDA. I finished the Keras cnn model for subspecies first testing most models with hyperparameters then offering advice for health Keras model and Pytorch model. In terms of portion, I suppose is 1/4.

Basically after preprocessing the data, I experimented with building cnn models for subspecies with different hyperparameters .

I started a basic convolutional neural(with 2 conv total 8 layers ) network then adding layers, changing kernel size, trying different optimizers, learning rate, loss function, weight initialization, and activation. I tested around 19 models.

The initial training algorithm I used is Adam. It belongs to gradient descent but with adaptive learning rate. I tried sgd as well but not the standard sgd. Transfer function tried: softmax, relu, sigmoid. Loss function tried: binary\_cross\_entropy, categorical\_cross\_entropy, two custom loss function (weighted cross entropy, focal loss). Metrics used to measure accuracy: F1 score, Cohen kappa score .

cohen kappa score

$$k = \frac{p_o - p_e}{1 - p_e}$$

## Adam

- As  $m_t$  and  $v_t$  are initialized as vectors of 0's, they are biased towards zero.
  - Especially during the initial time steps
  - Especially when the decay rates are small
    - (i.e.  $\beta_1$  and  $\beta_2$  are close to 1).
- Counteracting these biases in Adam

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$
$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

Adam

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$$

Note : default values of 0.9 for  $\beta_1$ , 0.999 for  $\beta_2$ , and  $10^{-8}$  for  $\epsilon$

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

$$H_p(q) = -\frac{1}{N} \sum_{i=1}^N y_i \cdot \log(p(y_i)) + (1 - y_i) \cdot \log(1 - p(y_i))$$

Binary Cross-Entropy / Log Loss



$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}}\right)$$

$$H(p, q) = -\sum_x p(x) \log q(x)$$

SuperDataScience

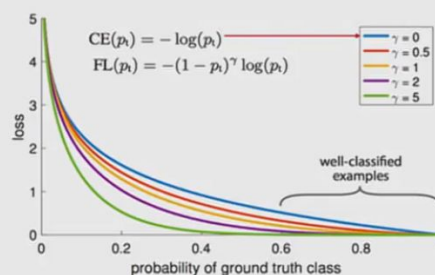


Convolutional Neural Networks (CNN): Softmax & Cross-Entropy

Focal loss




## Focal Loss



loss falls back to the standard cross entropy with






### Prior

- $\alpha$ -balanced Cross entropy  
 $CE(p_k) = -\alpha_k \log(p_k)$
- $\alpha$ -balanced Focal Loss  
 $FL(p_k) = -\alpha_k (1 - p_k)^\gamma \log(p_k)$
- $\gamma$ : focus more on hard examples
- $\alpha$ : offset class imbalance of number of examples

distribution of foreground and background classes



### Workflow:

Basic cnn model ---- trying different epochs (20,30,50)---- trying activation (softmax,relu,sigmoid) ---- trying optimizers(adam, sgd) ----trying adding sample weights ---- trying adding convolutional layer (2-4) ----trying kernel size (5,3) ----trying different kernel initialization (glorot uniform,he\_normal) ----trying adding other layers(dropout, batch normalization) ---- trying custom loss function for imbalanced data(weighted CE loss, Focal loss) ---- pick the best model changing the learning rate and batch size

### Experiment data:

model_name	Layers	ACC	F1	Kappa	Kernel size	Kernel initialization	Optimizer	Loss func	Activation	Time (s)	Epoch	Batch size
modelS	2 conv total 8	0.90	0.91	0.86	5,5,3,3	Glorot uniform	Adam	Categorical_CE	softmax	166	50	32
modelS	2 conv total 8	0.89	0.90	0.83	5,5,3,3	Glorot uniform	Adam	Categorical_CE	softmax	67	20	32
modelS	2 conv total 8	0.89	0.89	0.824	5,5,3,3	Glorot uniform	Adam	Categorical_CE	softmax	95	30	32
modelR	2 conv total 8	0.56	0.41	0.0	5,5,3,3	Glorot uniform	Adam	Categorical_CE	Relu	177	50	32

model_sg	2 conv total 8	0.97	0.91	0.86	5,5,3,3	Glorot uniform	Adam	binary _CE	sigmoid	179	50	32
modelS_S	2 conv total 8	0.77	0.72	0.059	5,5,3,3	Glorot uniform	SGD	Catego rical_ CE	softm ax	165	50	32
modelS_sa	2 conv total 8	0.91	0.91	0.86	5,5,3,3	Glorot uniform	Adam	Catego rical_ CE	softm ax	164	50	32
model45	4 conv total 15	0.91	0.91	0.86	5,5,3,3 3,3, 2,2,	Glorot uniform	Adam	Catego rical_ CE	softm ax	134	37	32
model43	4 conv total 15	0.92	0.93	0.88	3,3,3, 3,3,3, 2,2	Glorot uniform	Adam	Catego rical_ CE	softm ax	178	50	32
model43_h	4 conv total 15	0.91 6	0.92	0.867	3,3,3, 3,3,3, 2,2,	he_normal	Adam	Catego rical_ CE	softm ax	83	27	32
model43_d	4 conv total 15	0.91 8	0.92	0.873	3,3,3, 3,3,3, 2,2,	Glorot uniform	Adam	Catego rical_ CE	softm ax		33	32
model33_b	3 conv total 18	0.88	0.89	0.82	3,3,3, 3,2,2	Glorot uniform	Adam	Catego rical_ CE	softm ax	187	30	32
model43_b	3 conv total 23	0.90	0.91	0.859	3,3,3, 3,3,3, 2,2	Glorot uniform	Adam	Catego rical_ CE	softm ax	263	47	232
model43_bdr	4 conv total 23	0.92	0.93	0.88	3,3,3, 3,3,3 2,2	Glorot uniform	Adam	Catego rical_ CE	softm ax	314	48	32
model43_w	4 conv total 15	0.89	0.89	0.82	3,3,3, 3,3,3, 2,2	Glorot uniform	Adam	weighte d_categ orical_ CE	softm ax	83	22	32
model43_f	4 conv total 15	0.93	0.93	0.89	3,3,3, 3,3,3 2,2	Glorot uniform	Adam	Focal loss	sigmoid	180	50	32
model43lr005	4 conv total 15	0.86	0.86	0.77	3,3,3, 3,3,3, 2,2,	Glorot uniform	Adam	Catego rical_ CE	softm ax	185	50	32

model431 r0007	4 conv total 15	0.92	0.93	0.88	3,3,3, 3,3,3, 2,2,	Glorot uniform	Adam	Catego rical_ CE	softm ax	178	50	32
model431 rchaing	4 conv total 15	0.74	0.70	0.54	3,3,3, 3,3,3, 2,2,	Glorot uniform	SGD	Catego rical_ CE	softm ax	171	50	32
tmodel43 64	4 conv total 15	0.91	0.92	0.86	3,3,3, 3,3,3, 2,2	Glorot uniform	Adam	Catego rical_ CE	softm ax	164	48	64

In terms of transfer function, for this dataset, according to f1, softmax>sigmoid>relu. For batch\_size, 32 performs better than 64. For Kernel initialization, the default Glorot uniform is better than he\_normal. Initial kernel size 3 is better than 5. Adding more convolutional layers reaches higher f1 score. Adam performs way better than SGD.

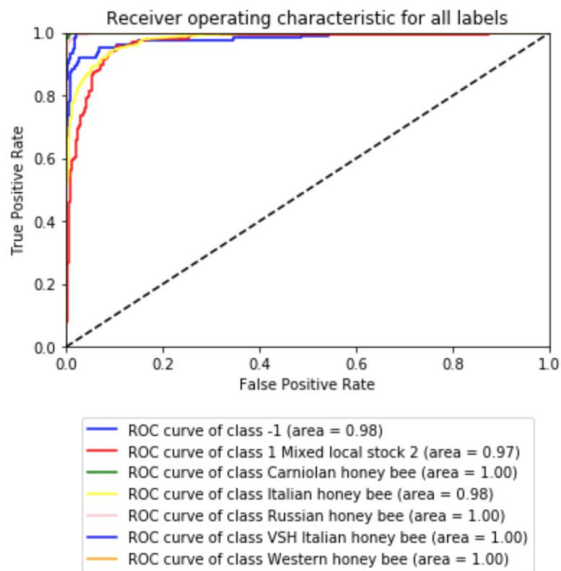
Since our data is imbalanced, also tried adding weights to sample, using custom weighted cross entropy loss and Focal loss function to handle it and compared each model. Meanwhile, due to the imbalance, the accuracy can not be counted as “accurate”. F1 score is much more important. Adapting Cohen Kappa score to decide how much better the classifier is comparing with random guessing.

### Conclusion:

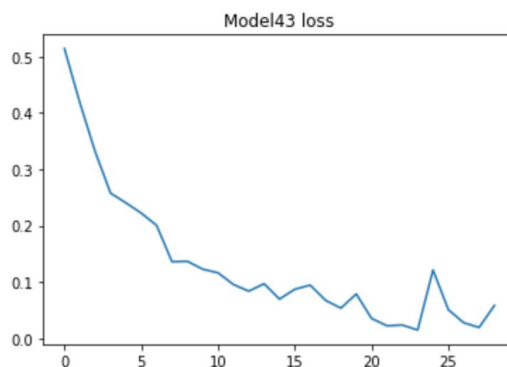
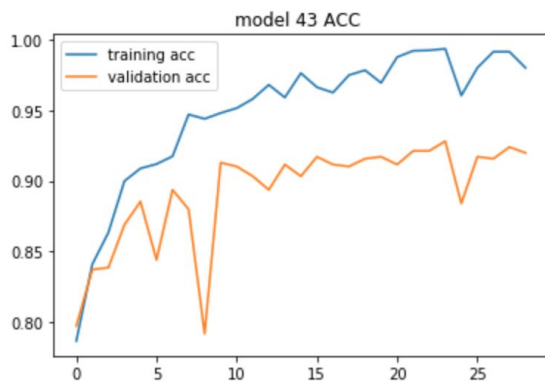
After trying, the best model are model43 and model43\_f with focal loss according to f1 score, kappa score and time(model43 2s faster than model43\_f). Then Compare them with ROC\_AUC, model43\_f did not outperform model43. Therefore focal loss seems not outperform CE in terms of traditional classification when dealing with this imbalanced data. Except for imbalance, another defect for our dataset is data size. We only have around 5000 images. The training size is only around 36000. In the future, I should try with keras image generator then use fit\_generator to train the model. It can be used for image augmentation. Through keras image generator images can be flipped, shifted then act as new training samples. This way the training data could be increased.

- ROC AUC Loss ACC

Model 43

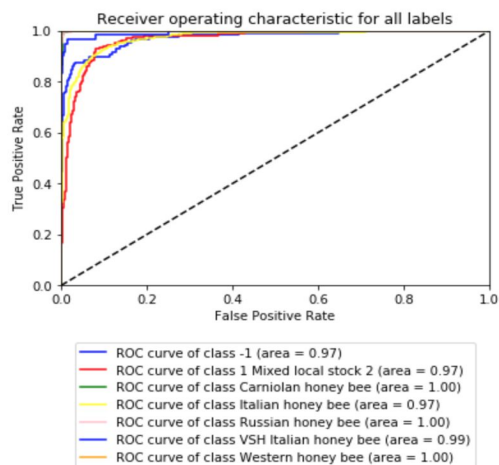


Text(0.5, 1.0, 'model 43 ACC ')

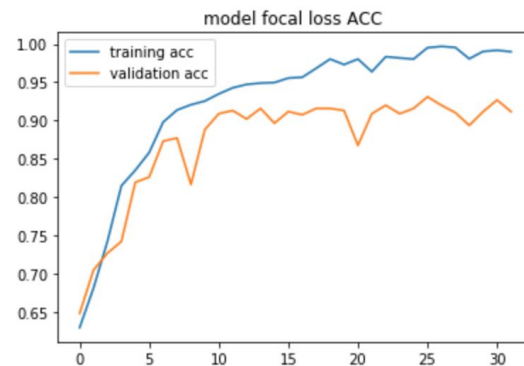


## Model43\_f

show\_roc\_auc(model43\_f)

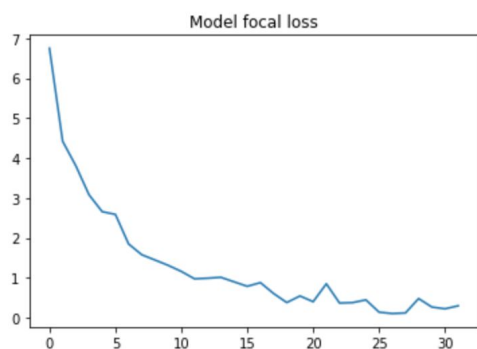


Text(0.5, 1.0, 'model focal loss ACC ')

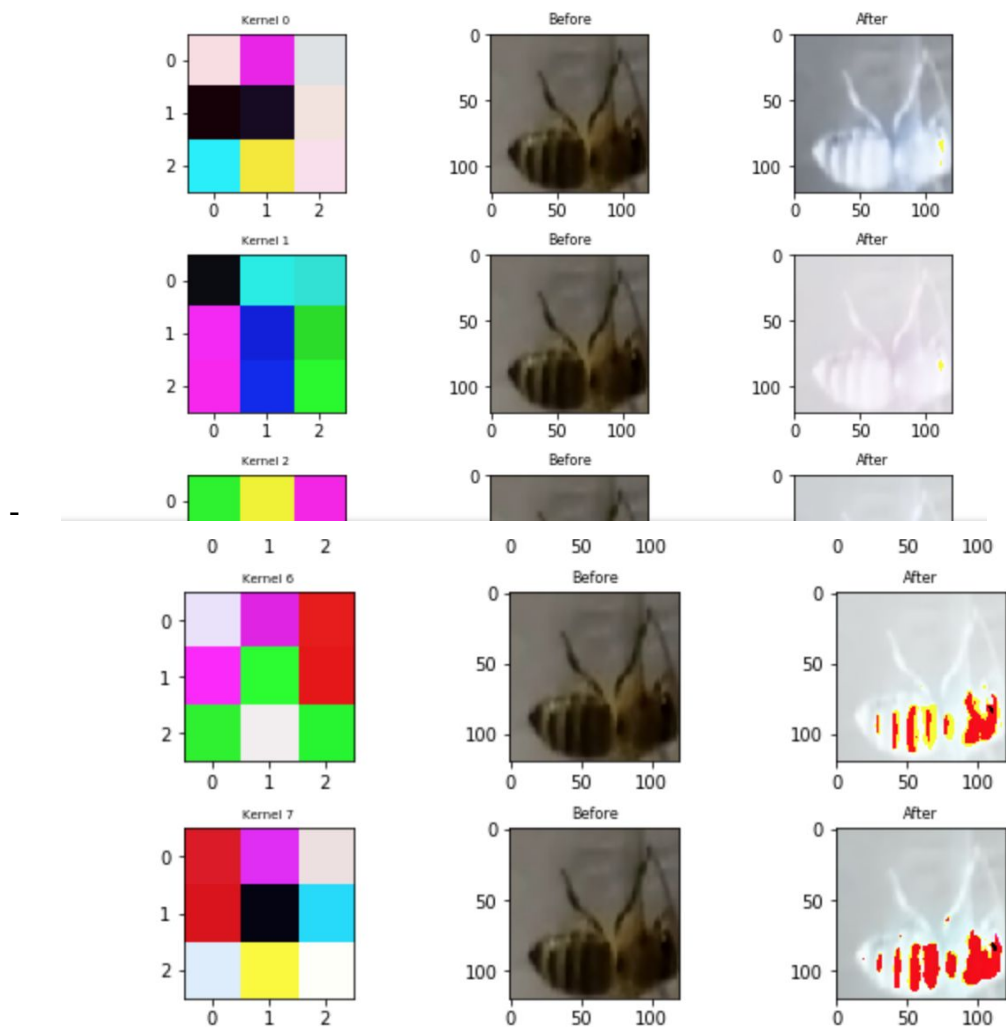


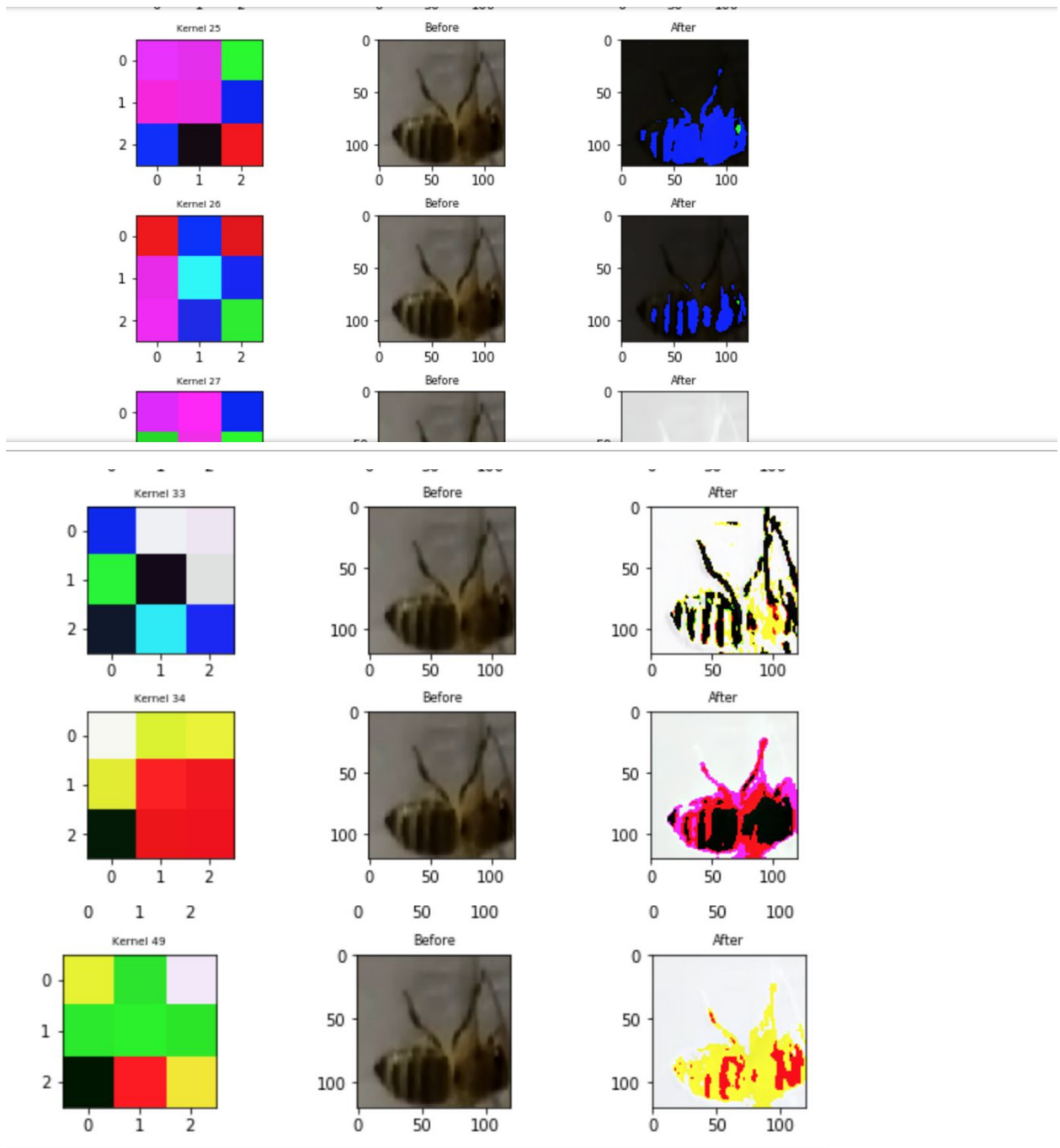
plt.plot(training\_focal\_loss\_f\_history['loss'],

Text(0.5, 1.0, 'Model focal loss')



### - Kernel visualization for one image



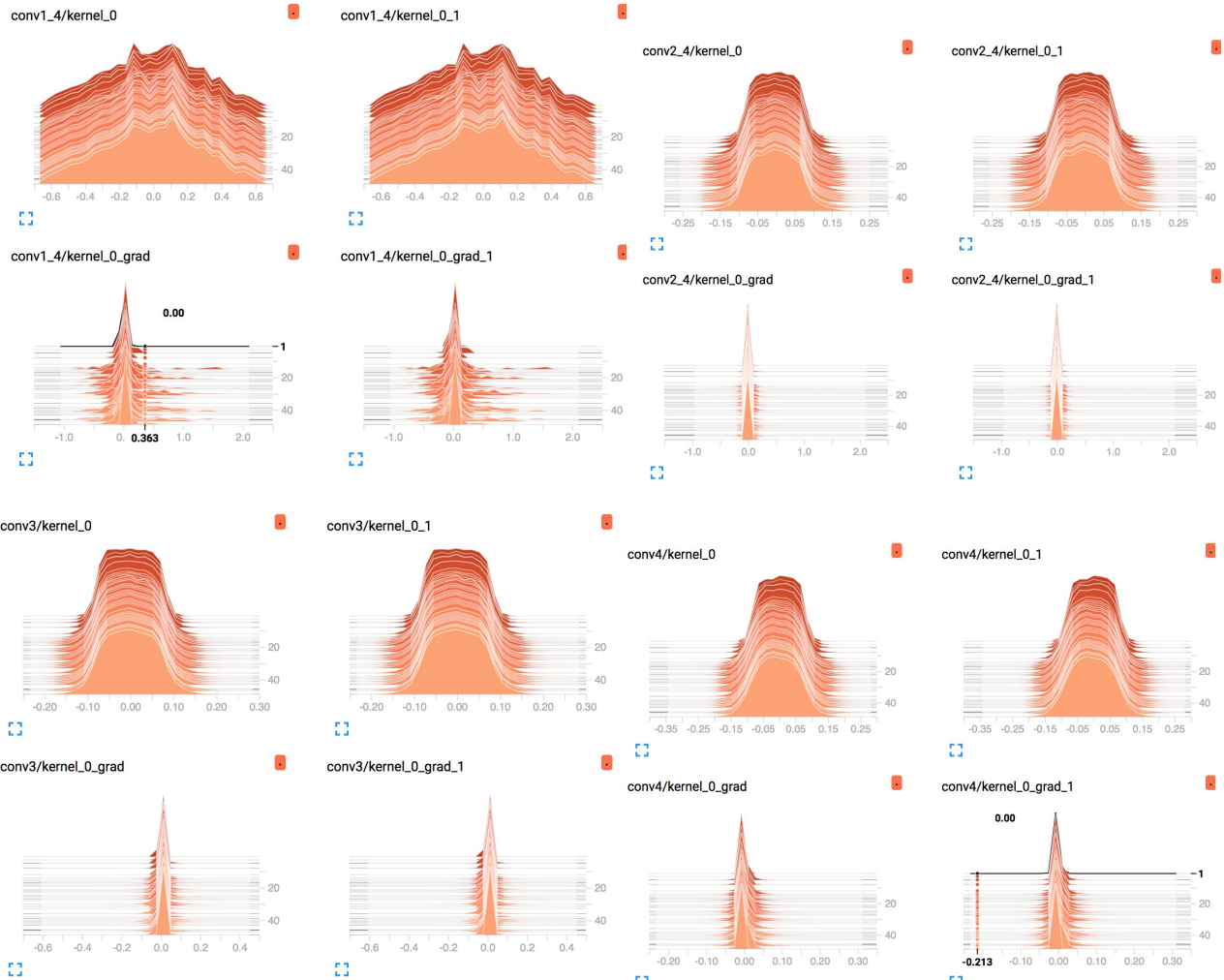


Most weights are applied on the back

#### - Tensorboard for model 43

tensorboard --logdir ./Graph





Comparing the variance, std for kernels at each convolution layer, it did get trained.

Code copy:

```
[zhangruyuedeMacBook-Pro:Ruyue_Zhang_individual_project zhangruyue$ cd code ]
[zhangruyuedeMacBook-Pro:code zhangruyue$ tokei
```

Language	Files	Lines	Code	Comments	Blanks
Python	1	1681	788	212	681
Total	1	1681	788	212	681

All code 788

img function: 9 all copy

Weighted loss function: 10 all copy

Focal loss: 8 all copy

Learningratescheduler: 7 modified 2

Show roc\_auc: 18 modified 5

Visualization kernel: 19 modified 5

Own Code : 788-9-10-8-7-18-19=717

Copy rate:10%

## Reference

Mkocabas, Muhammed. "Mkocabas/Focal-Loss-Keras." *GitHub*, 18 Mar. 2018, [github.com/mkocabas/focal-loss-keras](https://github.com/mkocabas/focal-loss-keras).

Shaoanlu. "Experiment: Applying Focal Loss on Cats-vs-Dogs Classification Task." *SALu*, 9 Nov. 2018, [shaoanlu.wordpress.com/2017/08/16/applying-focal-loss-on-cats-vs-dogs-classification-task/](https://shaoanlu.wordpress.com/2017/08/16/applying-focal-loss-on-cats-vs-dogs-classification-task/).

Shaikh, Faizan, and Faizan. "Essentials of Deep Learning: Visualizing Convolutional Neural Networks in Python." *Analytics Vidhya*, 22 Mar. 2018, [www.analyticsvidhya.com/blog/2018/03/essentials-of-deep-learning-visualizing-convolutional-neural-networks/](https://www.analyticsvidhya.com/blog/2018/03/essentials-of-deep-learning-visualizing-convolutional-neural-networks/).

Brownlee, Jason. "8 Tactics to Combat Imbalanced Classes in Your Machine Learning Dataset." *Machine Learning Mastery*, 7 June 2016, [machinelearningmastery.com/tactics-to-combat-imbalanced-classes-in-your-machine-learning-dataset/](https://machinelearningmastery.com/tactics-to-combat-imbalanced-classes-in-your-machine-learning-dataset/).

Pukhov, Dmitry. "Honey Bee Health Detection with CNN." *RSNA Pneumonia Detection Challenge* | *Kaggle*, 2018, [www.kaggle.com/dmitrypukhov/honey-bee-health-detection-with-cnn](https://www.kaggle.com/dmitrypukhov/honey-bee-health-detection-with-cnn).

BigMoyan. "初始化方法." *初始化方法* - *Keras 中文文档*, [keras-cn.readthedocs.io/en/latest/other/initializations/](https://keras-cn.readthedocs.io/en/latest/other/initializations/).

Godoy, Daniel. "Hyper-Parameters in Action! Part II - Weight Initializers." *Towards Data Science*, Towards Data Science, 18 June 2018, [towardsdatascience.com/hyper-parameters-in-action-part-ii-weight-initializers-35aee1a28404](https://towardsdatascience.com/hyper-parameters-in-action-part-ii-weight-initializers-35aee1a28404).

Dahal, Paras. "Classification and Loss Evaluation - Softmax and Cross Entropy Loss." *DeepNotes*, 28 May 2017, [deepnotes.io/softmax-crossentropy](https://deepnotes.io/softmax-crossentropy).

“Using sample\_weight in Keras for Sequence Labelling.” *Stack Overflow*, 2018, [stackoverflow.com/questions/48315094/using-sample-weight-in-keras-for-sequence-labeling](https://stackoverflow.com/questions/48315094/using-sample-weight-in-keras-for-sequence-labeling).

Benshetler, Jeff . “Why does the accuracy decreases after I did data normalization in CNN model?” 26 Aug 2016, <https://www.quora.com/Why-does-the-accuracy-decreases-after-I-did-data-normalization-in-CNN-model>