

CIFAR 10 Classification by CNN

- From 79% to 90% Accuracy

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優化 CNN 的方法

- 改善 Gradient Vanishing 問題:
 - 1. Xavier Initialization \rightarrow He Initialization
 - 2. Batch Normalization
 - 3. Selu (Self-Normalizing ReLU, SNN)
- 讓 Dropout 比例不一: Differential Dropout
- 隨機打亂資料:Random Shuffling
- 考慮模型複雜度的懲罰值:L2 Regularization
- Learning rate decay
- NIN
- Data Augmentation

先講結論

• 使用 Xavier Initialization + Selu 讓 Accuracy 提升至 79%

method	architecture	epochs	batch_size	keep_probability	conv_num_outputs	conv_ksize	conv_strides	pool_ksize	pool_strides	fully_conn_num_outputs	testing accuracy
Orinial	1層CNN+ 1層FC	100	512	0.3	20	3 x 3	1 x 1	8 x 8	1 x 1	500	71.76%
Xavier+BN	1層CNN+ 1層FC	100	512	0.3	20	3 x 3	1 x 1	8 x 8	1 x 1	500	74.57%
Selu	1層CNN+ 1層FC	100	512	0.3	20	3 x 3	1 x 1	8 x 8	1 x 1	500	74.62%
Xavier+Selu	1層CNN+ 1層FC	100	128	0.3	24	3 x 3	1 x 1	2 x 2	1 x 1	512	74.72%
Xavier+BN with Multilayer	6層CNN+ 2層FC (每2層1個 dropout)	100	128	0.3	24	3 x 3	1 x 1	2 x 2	1 x 1	512	76.53%
Xavier+Selu with Multilayer	6層CNN+ 2層FC (每2層1個 dropout)	100	128	0.3	24 	3 x 3	1 x 1	2 x 2	1 x 1	512	79.31%
Constricted by OOM Problem											

Xavier Initialization

• 讓權重的初始值之高斯分布的變異數與 neuron 個數有關。

$$Var(W) = \frac{1}{n_{in}}$$

• 假設有一 linear neuron layer,希望讓 input 與 output 的變異數一樣。

$$Y = W_1 X_1 + W_1 X_1 + \dots + W_n X_n$$

$$\operatorname{Var}(W_i X_i) = E[X_i]^2 \operatorname{Var}(W_i) + E[W_i]^2 \operatorname{Var}(X_i) + \operatorname{Var}(W_i) \operatorname{Var}(i_i)$$

$$\operatorname{Var}(W_i X_i) = \operatorname{Var}(W_i) \operatorname{Var}(X_i)$$

$$\operatorname{Var}(Y) = \operatorname{Var}(W_1 X_1 + W_2 X_2 + \dots + W_n X_n) = n \operatorname{Var}(W_i) \operatorname{Var}(X_i)$$

$$\operatorname{Var}(W_i) = \frac{1}{n} = \frac{1}{n_{\text{in}}}$$

• 對於 non-linear , He 等人提出 He Initialization。

$$Var(W) = \frac{2}{n_{in}}$$

Selu (Self-Normalizing ReLU, SNN)

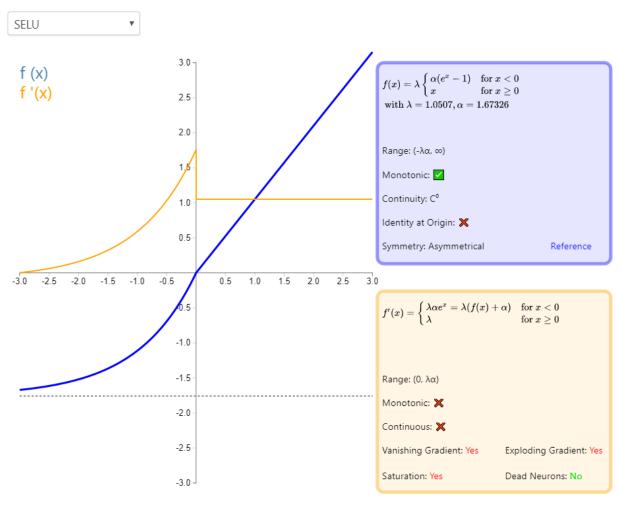
 Günter Klambaue et al., Andreas May. Self-Normalizing Neural Networks (2017)

$$Selu(x) = \lambda \begin{cases} x, & \text{if } x > 0 \\ \alpha e^x - \alpha, & \text{if } x \le 0 \end{cases}$$

$$\lambda = 1.0507009873554804934193349852946$$

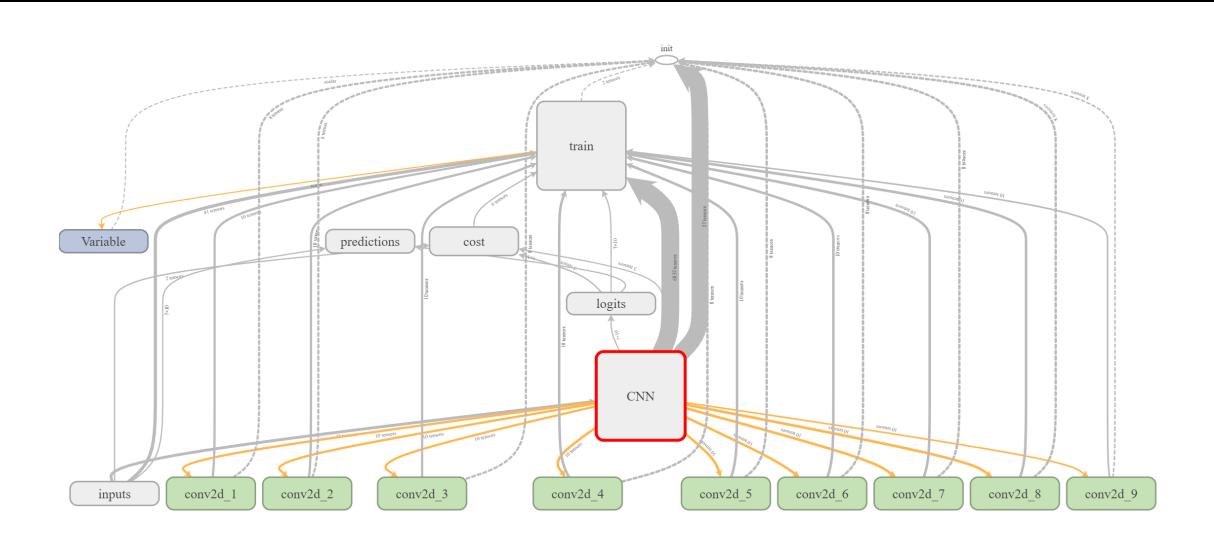
$$\alpha = 1.6732632423543772848170429916717$$

• 自動讓輸出值正規化。



Scaled Exponential Linear Unit (SELU) is simply a variation on the Exponetial Linear Unit (ELU) activation function, where λ and α have been fixed (to 1.0507 and 1.67326, respectively). The reasoning behind these values (zero mean/unit variance) forms the basis of Self-Normalising Neural Networks (SNNs- see the Reference link in the blue box for more information).

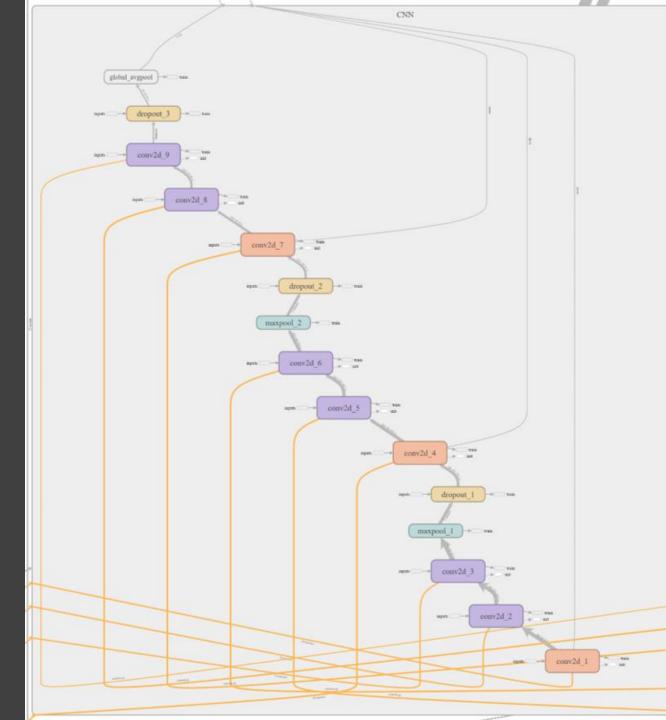
Final CNN Architecture



CNN Layers

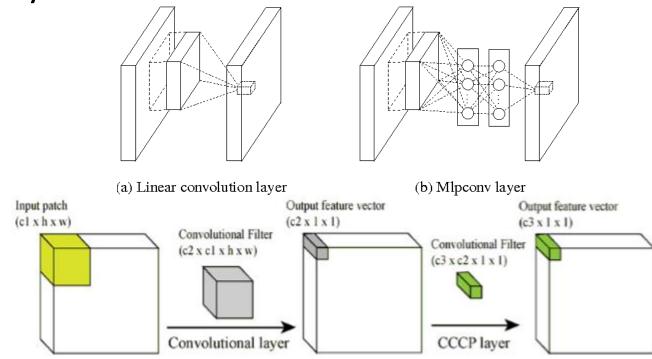
- NIN (Network in Network)

9 weight layers					
conv2d_1	3x3 conv 92 ReLU with I2 regularizer				
conv2d_2	3x3 conv 92 ReLU				
conv2d_3	3x3 conv 92 ReLU				
maxpool_1	maxpool with stride = 2				
dropout_1	dropout with keep-prob = 0.5				
conv2d_4	3x3 conv 192 ReLU with I2 regularizer				
conv2d_5	3x3 conv 192 ReLU				
conv2d_6	3x3 conv 192 ReLU				
maxpool_2	maxpool with stride = 2				
dropout_2	dropout with keep-prob = 0.5				
conv2d_7	3x3 conv 192 ReLU with I2 regularizer				
conv2d_8	1x1 conv 192 ReLU				
conv2d_9	1x1 conv 10 ReLU				
global_avgpool	global average pooling				



Mlpconv (multilayer perceptron convolution)

- 在 conv layers 中間加上多層的 fully connected layers。
- 實作上使用 1x1 conv (又稱 cascaded cross-channel pooling, CCCP)。
- 提高 conv layer 的非線性感知能力。



Global Average Pooling

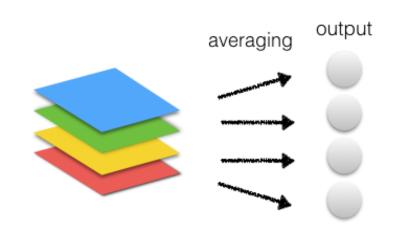
- 對整個 feature map 取平均值,直接作為output layer的結果。
- 取代 fully connected layers ,大幅減少 parameters 。

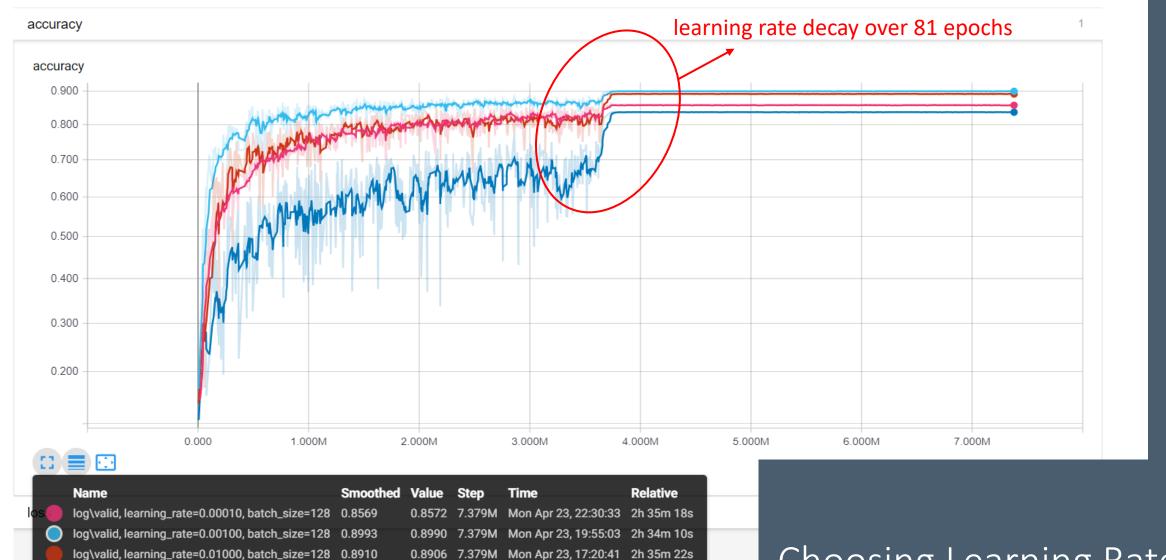
Fully Connected Layer

flatten output

fully connected

Global Average Pooling



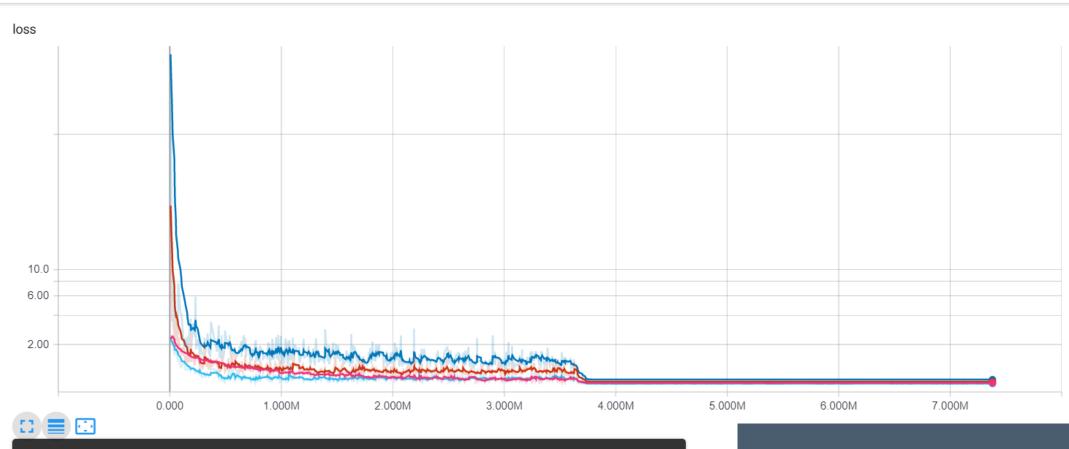


0.8358 7.379M Mon Apr 23, 14:45:06 2h 33m 32s

log\valid, learning_rate=0.10000, batch_size=128 0.8362

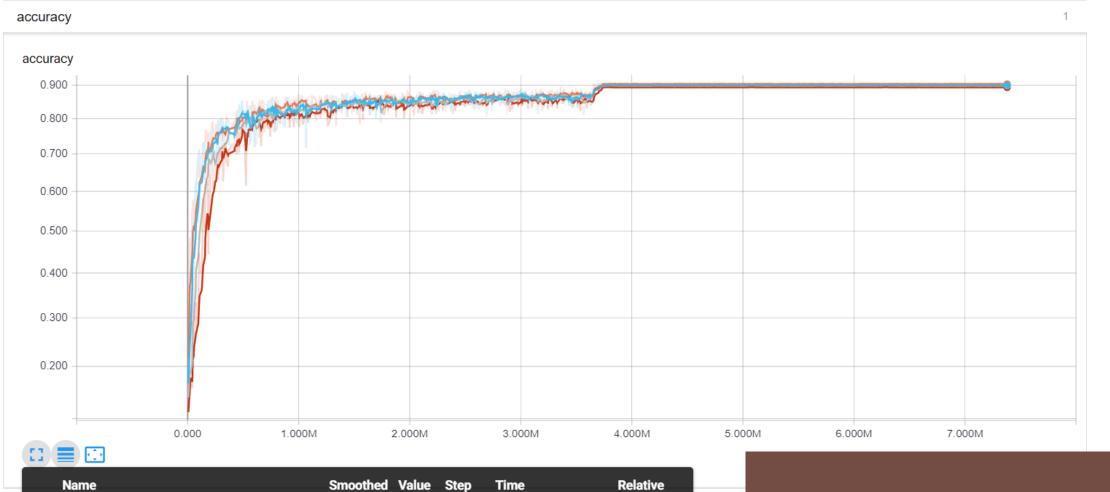
Choosing Learning Rate

loss 1



Name	Smoothed	Value	Step	Time	Relative
log\valid, learning_rate=0.00010, batch_size=128	0.5069	0.5071	7.379M	Mon Apr 23, 22:30:33	2h 35m 18s
log\valid, learning_rate=0.00100, batch_size=128	0.4865	0.4860	7.379M	Mon Apr 23, 19:55:03	2h 34m 10s
log\valid, learning_rate=0.01000, batch_size=128	0.5400	0.5397	7.379M	Mon Apr 23, 17:20:41	2h 35m 22s
log\valid, learning_rate=0.10000, batch_size=128	0.6011	0.6012	7.379M	Mon Apr 23, 14:45:06	2h 33m 32s

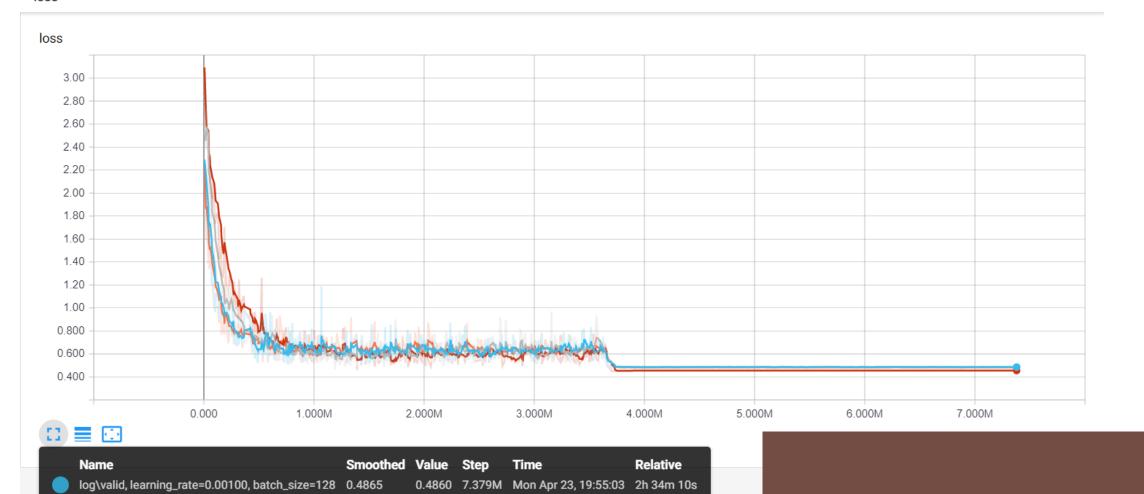
Choosing Learning Rate



	Name	Smoothed	Value	Step	Time	Relative
los	log\valid, learning_rate=0.00100, batch_size=128	0.8993	0.8990	7.379M	Mon Apr 23, 19:55:03	2h 34m 10s
	log\valid, learning_rate=0.00100, batch_size=256	0.8984	0.8982	7.379M	Mon Apr 23, 09:38:52	2h 31m 55s
	log\valid, learning_rate=0.00100, batch_size=512	0.8931	0.8932	7.379M	Sun Apr 22, 23:34:14	2h 29m 19s
	log\valid, learning_rate=0.00100, batch_size=64	0.9032	0.9032	7.379M	Tue Apr 24, 06:38:35	2h 42m 45s

Choosing Batch Size

loss



0.4866 7.379M Mon Apr 23, 09:38:52 2h 31m 55s

0.4556 7.379M Sun Apr 22, 23:34:14 2h 29m 19s

0.4839 7.379M Tue Apr 24, 06:38:35 2h 42m 45s

log\valid, learning_rate=0.00100, batch_size=256 0.4860

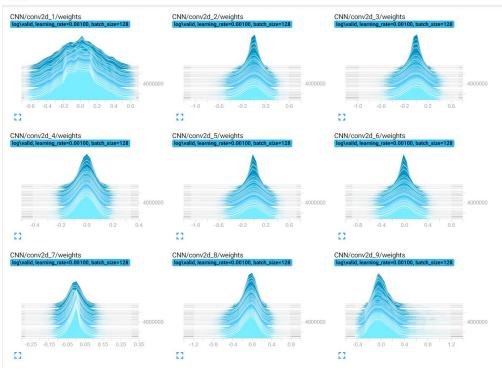
log\valid, learning_rate=0.00100, batch_size=512 0.4552

log\valid, learning_rate=0.00100, batch_size=64 0.4842

Choosing Batch Size







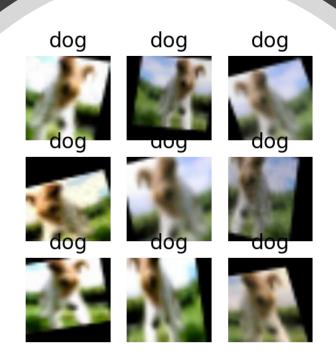
How to achieve 90% accuracy?

Data Augmentation

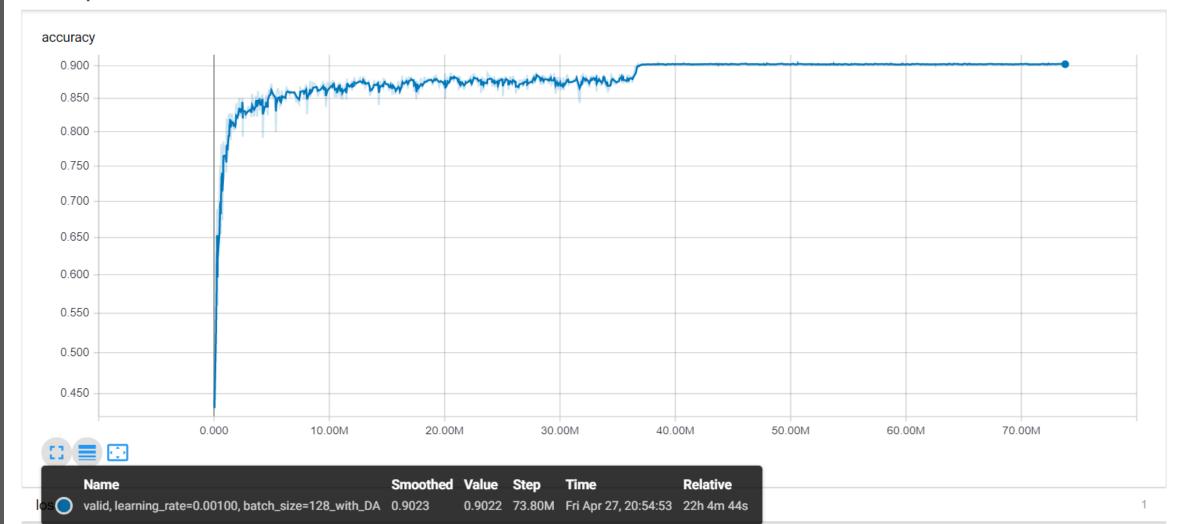
Kind		Method	Percentage of images	
Horizontal flip		Random	50%	
Crop from each side		Random	0 ~ 10%	
Gaussian blur		Random sigma 0 ~ 0.5	50%	
Contrast		0.75 ~ 1.5	100%	
		per pixel	50%	
Add gaussian noise		per pixel and per channel	50%	
Multiply		0.8 ~ 1.2	20%	
	scale	0.8 ~ 1.2x	100%	
Affine transformations	translate	$x = -0.2 \sim 0.2$ $y = -0.2 \sim 0.2$		
transiormations	rotate	-25 ~ 25 deg		
	shear	-8 ~ 8 deg		

https://github.com/aleju/imgaug

```
aug batch 1 shape: (81000, 32, 32, 3) aug batch 2 shape: (81000, 32, 32, 3) aug batch 3 shape: (81000, 32, 32, 3) aug batch 4 shape: (81000, 32, 32, 3) aug batch 5 shape: (81000, 32, 32, 3)
```

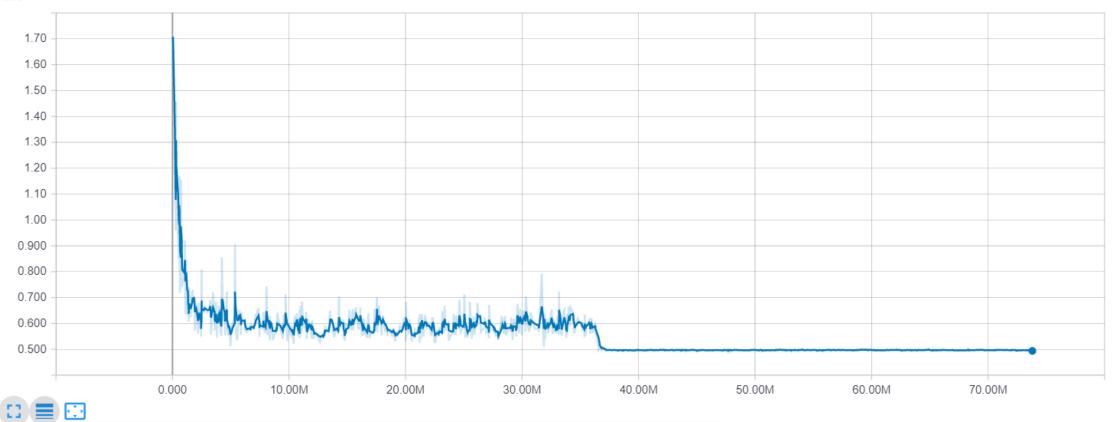


accuracy 1



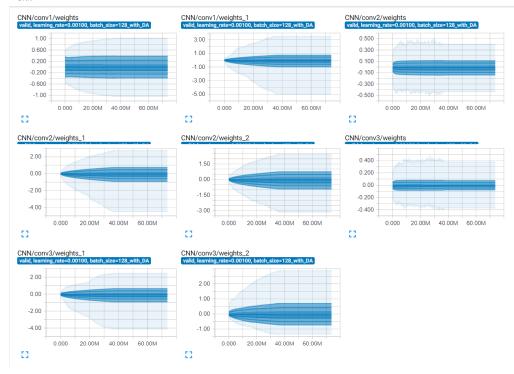
loss 1

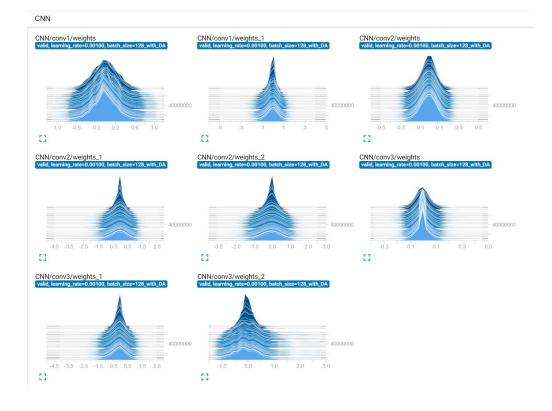
loss









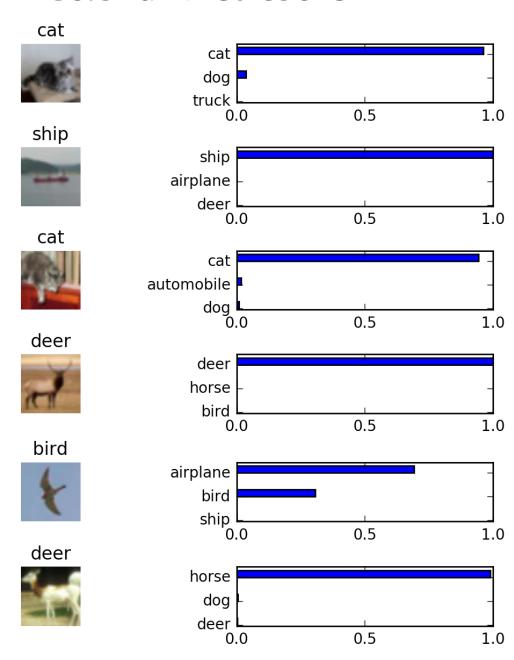


Final Testing Accuracy

- Batch size: 128
- Initial learning rate: 0.001
- Epochs : 164

Testing Accuracy: 0.8981408227848101

Softmax Predictions



Reference

- 《 Network In Network》
 https://arxiv.org/pdf/1312.4400.pdf
- «Striving For Simplicity: The All Convolutional Net »
 https://arxiv.org/pdf/1412.6806.pdf
- NIN

https://github.com/BIGBALLON/Deep-learning-and-practices/tree/master/Lab3-NIN

Xavier Initialization

http://andyljones.tumblr.com/post/110998971763/an-explanation-of-xavier-initialization

« Self-Normalizing Neural Networks »

https://arxiv.org/pdf/1706.02515.pdf