
Supplementary material:

Deep Neural Nets with Interpolating Function as Output Activation

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A Proof of Theorem 1

Proof. Let $X_i, i = 1, 2, \dots, N$, be the number of additional data needed to obtain the i -type after $(i - 1)$ distinct types have been sampled. The total number of instances needed is:

$$X = X_1 + X_2 + \dots + X_N = \sum_{i=1}^N X_i.$$

For any i , $i - 1$ distinct types of instances have already been sampled. It follows that the probability of a new instance being of a different type is $1 - \frac{i-1}{N} = \frac{N-i+1}{N}$. Essentially, to obtain the i -th distinct type, the random variable X follows a geometric distribution with $p = \frac{N-i+1}{N}$ and $E[X_i] = \frac{N}{N-i+1}$. Thus, we have

$$E[X] = \sum_{i=1}^N E[X_i] = \sum_{i=1}^N \frac{N}{N-i+1}.$$

Asymptotically, $E[X] \approx N \ln N$ for sufficiently large N . □

B Results on SVHN data

For the SVHN recognition task, we simply test the performance when the full training data are used. Here we only test the performance of the ResNets and pre-activated ResNets. There is a relative 7%-10% error rate reduction for all these DNNs.

Table 1: Error rates of the vanilla DNNs v.s. the WNLL activated DNNs over the whole SVHN dataset. (Median of 5 independent trials)

Network	Vanilla DNNs	WNLL DNNs
ResNet20	3.76%	3.44%
ResNet32	3.28%	2.96%
ResNet44	2.84%	2.56%
ResNet56	2.64%	2.32%
ResNet110	2.55%	2.26%
ResNet18	3.96%	3.65%
ResNet34	3.81%	3.54%
PreActResNet18	4.03%	3.70%
PreActResNet34	3.66%	3.32%