

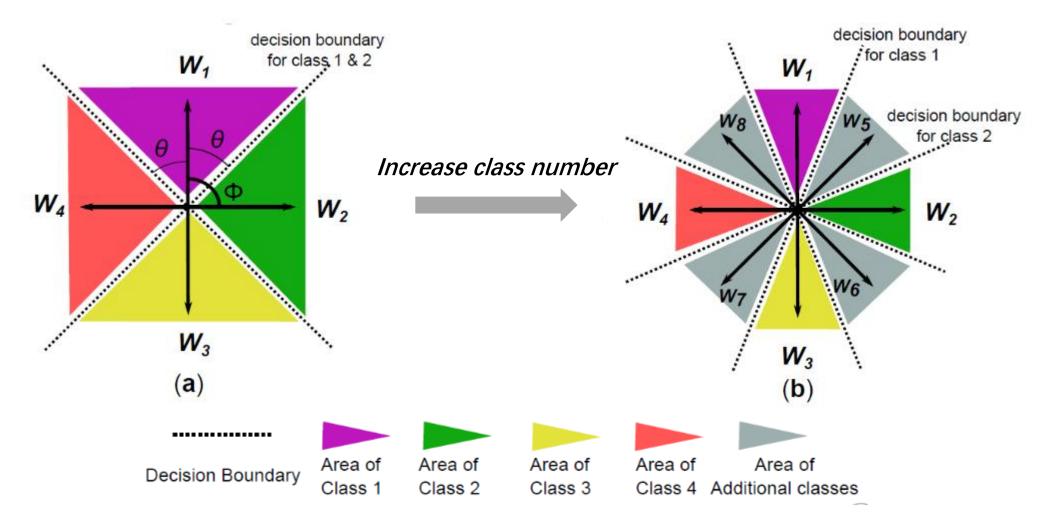
Virtual Class Enhanced Discriminative Embedding Learning

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Observation & Motivation

• For d-dimensional feature space under Softmax classifier, the feature region of each class is inversely proportional to the number of class.

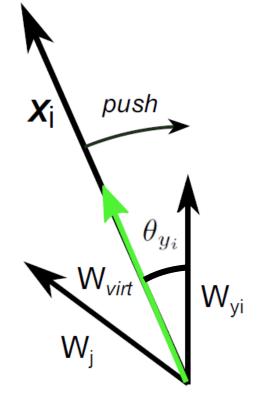


Virtual Softmax :

Learning towards discriminative image features

- Formulation: inject a dynamic virtual negative class

$$L = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{e^{W_{y_i}^T X_i}}{\sum_{j=1}^{C} e^{W_j^T X_i} + e^{W_{virt}^T X_i}}$$
where $W_{virt} = \frac{\|W_{y_i}\|X_i}{\|X_i\|}$
- Optimization goal:



$$W_{y_i}^T X_i \ge \max_{j \in C+1} (W_j^T X_i) = W_{virt}^T X_i$$
i.e. $\|W_{y_i}\| \|X_i\| \cos \theta_{y_i} \ge \|W_{y_i}\| \|X_i\|$

$$\theta_{y_i} = 0$$

- Optimization goal of Virtual Softmax:

- The conventional Softmax learns towards a weaker goal:

$$||W_{y_i}|| \cos \theta_{y_i} \ge \max_{j \in C} (||W_j|| \cos \theta_j)$$

$$\theta_{y_i} \le \min_{j \in C} (\arccos \left(\frac{||W_j||}{||W_{y_i}||} \cos \theta_j\right)) \checkmark$$

Objective comparison

Discussion :

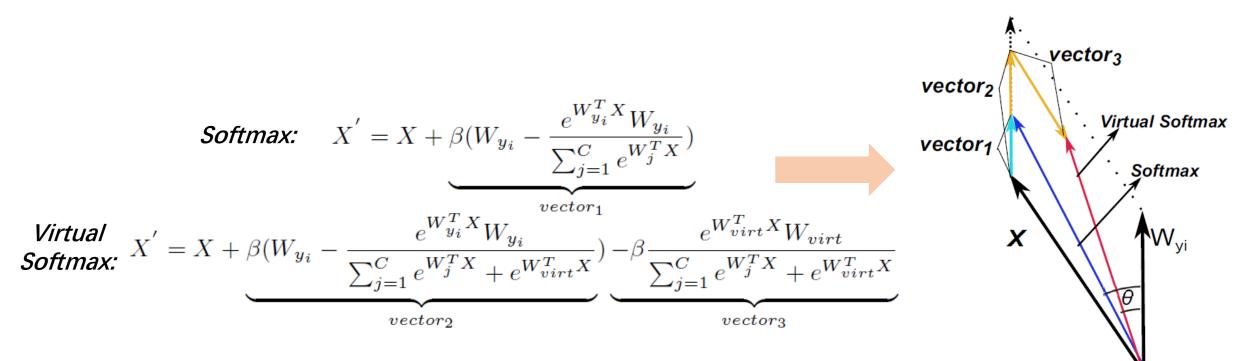
- Interpretation from *Coupling Decay*:

$$L_{i} = -\log \frac{e^{W_{y_{i}}^{T}X_{i}}}{\sum_{j=1}^{C} e^{W_{j}^{T}X_{i}} + e^{W_{virt}^{T}X_{i}}}$$
(1)
$$L_{i} = -W_{y_{i}}^{T}X_{i} + \log \left(\sum_{j=1}^{C} e^{W_{j}^{T}X_{i}} + e^{\|W_{y_{i}}\|\|X_{i}\|}\right)$$
(2)

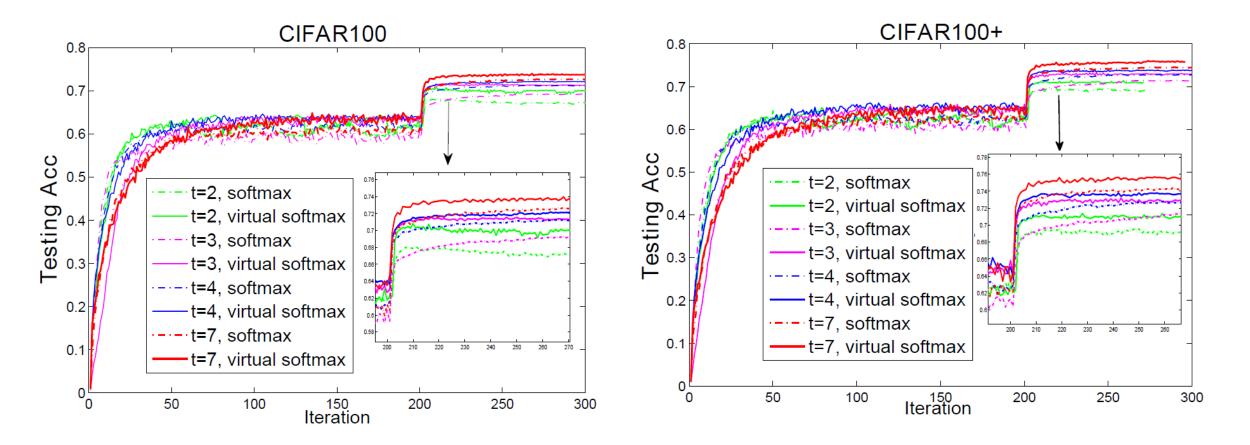
perform the first order Taylor Expansion for the second log-term in Eq.2, a term of $||W_{y_i}|| ||X_i||$ shows up. Therefore, minimizing the above equation is to minimize $||W_{y_i}|| ||X_i||$ to some extend, and this can be viewed as a coupling decay term, i.e. **Data-Dependent Weight Decay** and **Weight-Dependent Data Decay**.

- Interpretation from *Feature Update*:

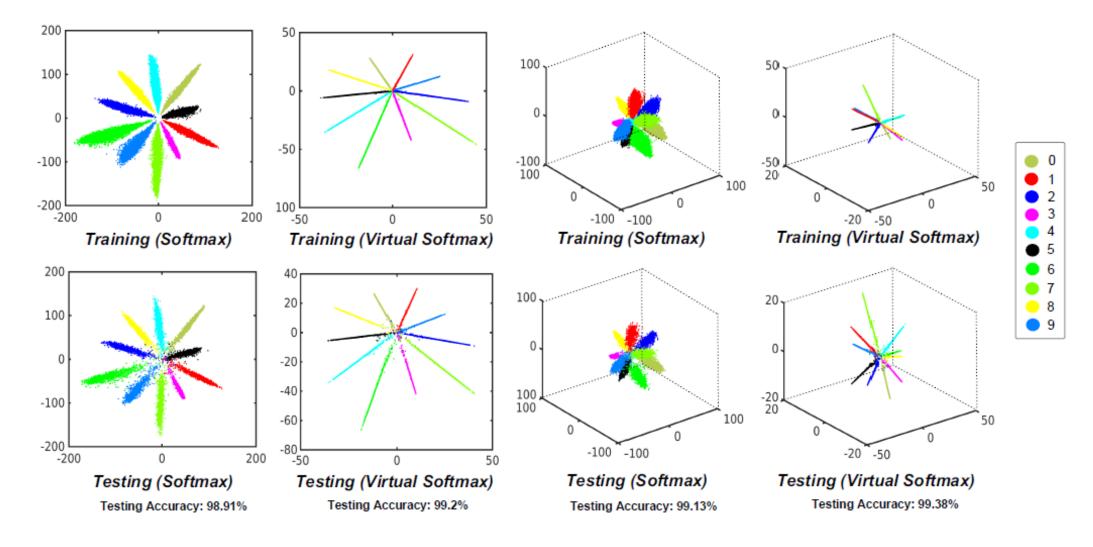
For a linear neural layer, the *Feature Update* by Softmax and our Virtual Softmax is like:



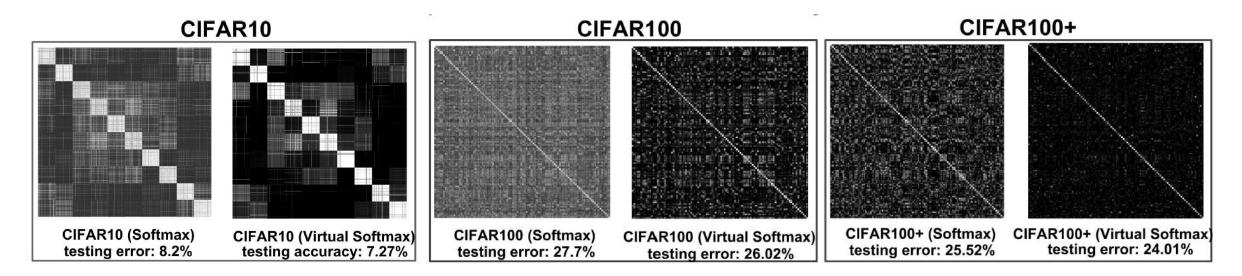
- Similar convergence and higher accuracy on CIFAR100:



- Visualization of Feature Compactness and Separability on MNIST :



- Visualization of intra-class and inter-class similarities on CIFAR10, CIFAR100:



- Performances on small-scale object classification datasets:

Method	MNIST(%)	SVHN(%)	Method	CIFAR10(%)	CIFAR100(%)	CIFAR100+(%)
Maxout [7]	0.45	2.47				CIFAK100+(%)
DSN [19]	0.39	1.92	GenPool [18]	7.62	32.37	-
			DisturbLabel 38	9.45	32.99	26.63
R-CNN 20	0.31	1.77	Noisy Softmax 3	7.39	28.48	-
WRN [39]	-	1.85	L-Softmax 22	7.58	29.53	-
DisturbLabel [38]	0.33	2.19	ACU 13	7.12	27.47	-
Noisy Softmax [3]	0.33	-	ResNet-110 9	-	-	25.16
L-Softmax [22]	0.31	-	Densenet-40 [11]	7.00	27.55	24.42
Softmax	0.35	2.11	Softmax	7.15	27.7	25.52
NS*[3]	0.32	2.04	NS*[3]	6.91	26.33	25.20
LS*[22]	0.30	2.01	LS*[22]	6.77	26.18	24.32
	0.30	2.01	AS* 21	6.83	26.09	24.11
AS*[21]			Virtual Softmax	6.68	26.02	24.01
Virtual Softmax	0.28	1.93	<i>.</i>			
T-11-2 D		MALLOT 1	Table 4: Recogniti	on error rates	on CIFAK dat	asets. + denotes

SVHN. * denotes our reproducing.

Table 3: Recognition error rates on MNIST and data augmentation. * denotes our reproducing.

- Performances on large-scale object classification and face verification

Top5

73.14

73.25

73.82 73.57

74.06

48.84

1		
datasets:	Method	Top1
	Softmax	47.63
	NS*[3]	47.96
	LS*[22]	48.59
	AS*[21]	48.66

Softmax	1	99.10	94.59
NS*[3]	1	99.16	94.75
LS*[22]	1	99.37	95.58
AS*[21]+Normface*[33]	1	99.57	96.45
Virtual Softmax	1	99.46	95.85
Table 6: Verification results (%) on LF	W/SLLFW	. * denote
our reproducing.			

Table 7: Acc (%) on ImageNet32

Virtual Softmax



Thanks!

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