LOCO-Reg

Locality-Promoting Representation Learning

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Weights in Convolutional Networks

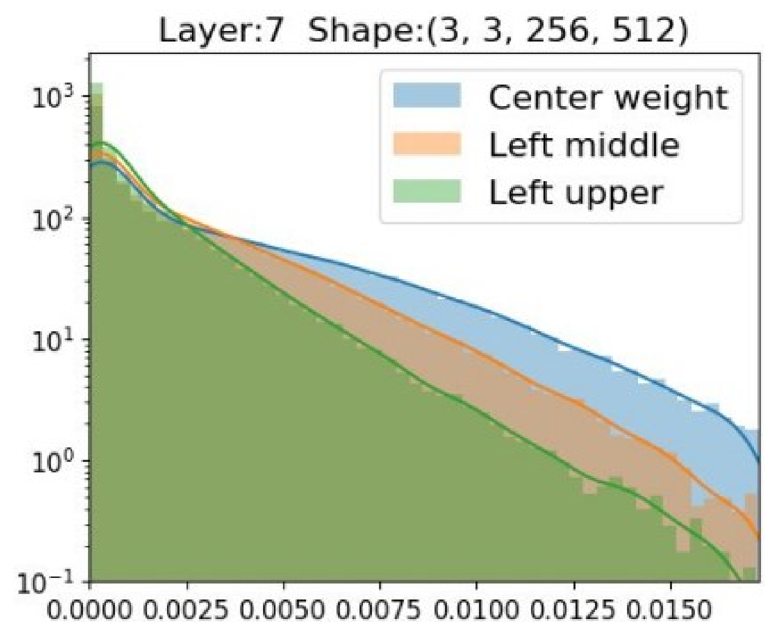
Architecture
VGG16
ResNet50
InceptionV3
Xception
MobileNet

… are not of the same magnitude

On average weights near the center are larger

3x3 Filter

S(mall)	M(edium)	S
M	Large	M
S	M	S



Distribution in log-scale of absolute weights of 3x3 filters at center, left middle and left upper

Let us think about that…

Filter = common pattern in feature maps

Red or **violet**? **Red** preferred because they have a large center

$\Rightarrow$ More robust (to noise, variation)

3x3 spatial filter

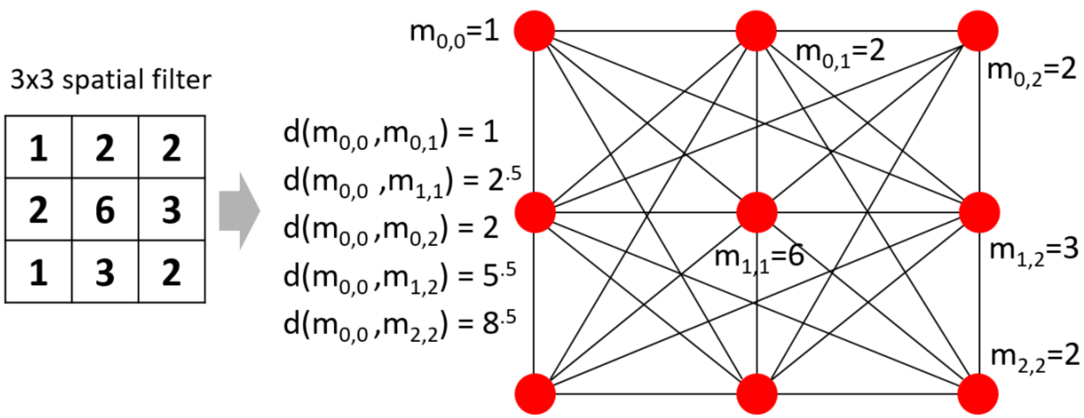
1	2	2
2	6	3
1	3	2

?

0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0
0	0	1	0	0	1	2	2	1	0	2	3	1	1	1	0
1	0	0	0	1	2	6	3	1	1	2	5	1	2	1	0
0	0	0	0	1	1	3	2	2	3	2	3	2	0	0	0
0	1	0	0	0	1	2	2	2	2	3	2	2	1	0	0
0	0	0	1	0	1	1	1	2	3	3	2	1	1	0	0

Model from Physics

- We want maximal feature cohesion
- Activation, weight = Mass
- Cohesion = Gravitational Force



Theorem 1. *For any feature strength distribution* $m' \leq m_c, m_{co}, m_n < (1+\epsilon)m'$ *with* $\epsilon \in [0, 0.675[$, *the cohesion* F_{tot} *of the feature is increased most by increasing* m_c, *and more by increasing any* $m_n \in M_n$ *than any* $m_{co} \in M_{co}$ *for arbitrary* m', *center* $m_c = m_{1,1}$, *direct neighbors* $M_n := \{m_{1,0}, m_{0,1}, m_{2,1}, m_{1,2}\}$ *and corners* $M_{co} := \{m_{0,0}, m_{2,0}, m_{2,2}, m_{0,2}\}$ *(Figure 3).*

Implementation: LOCO-Reg

Standard L2-regularization pushes all weights to be equal

$\Rightarrow$ This reduces central weights too much

LOCO-Reg: Regularize outer weights more than more central weights

Base L2 Regularization Constant

λ *

LOCO- Regularization weights

γ > η	η > 1	γ > η
η > 1	1	η > 1
γ > η	η > 1	γ > η

Dataset	Architecture	(η, γ)	Avg. Accuracy for different λ				Best Acc.
			.00025	.0005	.001	.002	
cifar10	MobileNet	(1,1)	.8611	.8686	.8688	.8647	.8688
cifar10	MobileNet	(1.4,1.56)	.8618	**.8701***	.8714	.8657	.8714
cifar10	MobileNet	(1.8,2.13)	**.8619**	.8692	**.8721***	**.8668***	**.8721***
cifar10	ResNet	(1,1)	.9191	.9227	.9236	.9222	.9236
cifar10	ResNet	(1.4,1.56)	**.921**	**.9253***	**.9242**	.9224	**.9253***
cifar10	ResNet	(1.8,2.13)	.9186	.9244*	.9237	**.9236**	.9244*
cifar10	VGG	(1,1)	.8754	.8761	.882	.8858	.8858
cifar10	VGG	(1.4,1.56)	.8722	**.884****	.8858**	.8869	.8869
cifar10	VGG	(1.8,2.13)	**.8808****	.8816*	**.8875*****	**.8884***	**.8884***
cifar100	MobileNet	(1,1)	.5926	.6116	.6182	.6155	.6182
cifar100	MobileNet	(1.4,1.56)	**.5941**	.6124	.6182	.6149	.6182
cifar100	MobileNet	(1.8,2.13)	.5935	**.6144**	**.6199**	**.6184***	**.6199**
cifar100	ResNet	(1,1)	.702	.71	.7156	.7124	.7156
cifar100	ResNet	(1.4,1.56)	.702	**.7129***	.7163	**.7146**	.7163
cifar100	ResNet	(1.8,2.13)	**.7022**	.7116	**.7198****	.7142	**.7198****
cifar100	VGG	(1,1)	.6415	.6551	.6597	.6599	.6599
cifar100	VGG	(1.4,1.56)	.6432	.6583*	**.6665*****	.6645*	.6665***
cifar100	VGG	(1.8,2.13)	**.6449***	**.6629*****	.6653**	**.6671*****	**.6671*****
fashion	MobileNet	(1,1)	**.9403**	.9402	.939	.9369	.9403
fashion	MobileNet	(1.4,1.56)	.9398	.9406	.9385	**.9372**	.9406
fashion	MobileNet	(1.8,2.13)	.9402	**.9408**	**.9398**	.9371	**.9408**
fashion	ResNet	(1,1)	.9501	.9504	.9494	.9492	.9504
fashion	ResNet	(1.4,1.56)	.9496	**.951**	.9506*	.9489	.951
fashion	ResNet	(1.8,2.13)	**.9509***	.9505	**.9515***	**.9494**	**.9515***
fashion	VGG	(1,1)	.9404	**.942**	.9417	.9426	.9426
fashion	VGG	(1.4,1.56)	.941	.9414	.9419	.9436*	.9436*
fashion	VGG	(1.8,2.13)	**.9423**	.9417	**.9436***	**.9437***	**.9437***

THANKS

S(mall)	M(edium)	S
M	Large	M
S	M	S

0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0
0	0	1	0	0	1	2	2	1	0	2	3	1	1	1	0
1	0	0	0	1	2	6	3	1	1	2	5	1	2	1	0
0	0	0	0	1	1	3	2	2	3	2	3	2	0	0	0
0	1	0	0	0	1	2	2	2	2	3	2	2	1	0	0
0	0	0	1	0	1	1	1	2	3	3	2	1	1	0	0