

Multigrid Neural Architectures

Tsung-Wei Ke

UC Berkeley / ICSI

Michael Maire

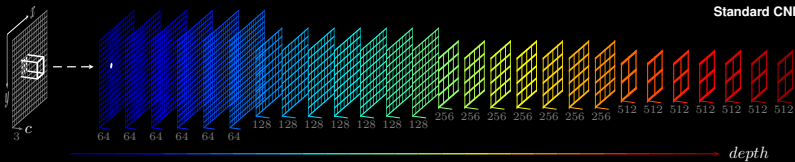
TTI Chicago

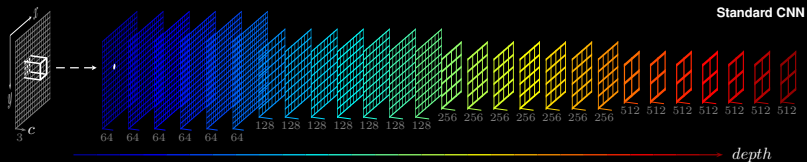
Stella X. Yu

UC Berkeley / ICSI

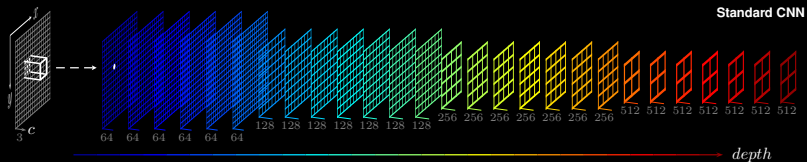
arXiv:1611.07661 & CVPR 2017

Standard CNN



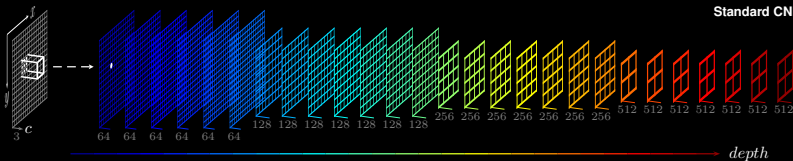


- ▶ Conflates abstraction & scale

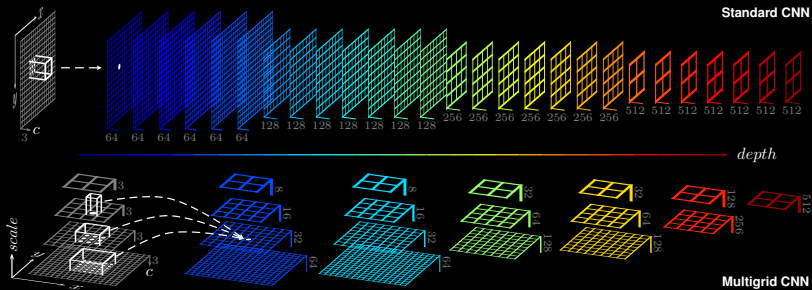


- ▶ Conflates abstraction & scale
- ▶ Fine-to-coarse

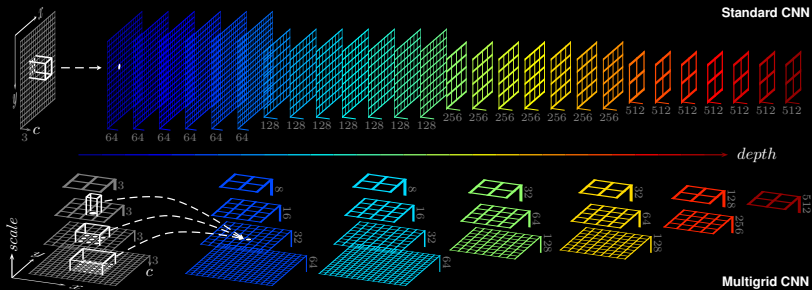
Standard CNN



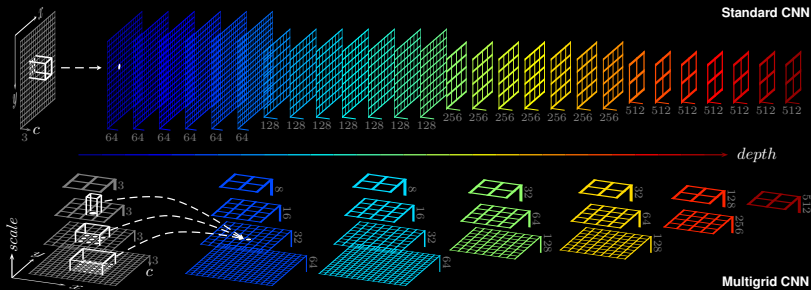
- ▶ Conflates abstraction & scale
- ▶ Fine-to-coarse
- ▶ Slow receptive field growth



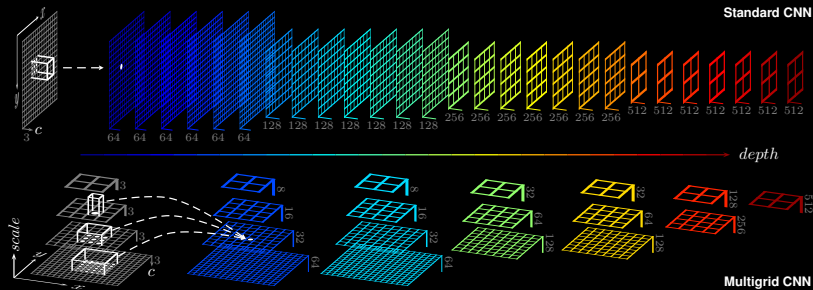
- ▶ Conflates abstraction & scale
- ▶ Fine-to-coarse
- ▶ Slow receptive field growth



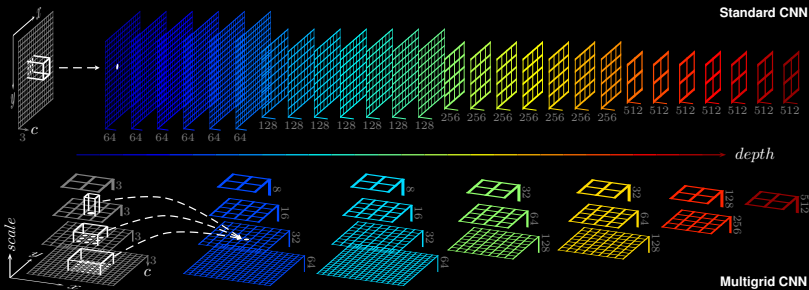
- ▶ Conflates abstraction & scale → disentangles them
- ▶ Fine-to-coarse
- ▶ Slow receptive field growth



- ▶ Conflates abstraction & scale → **disentangles them**
- ▶ Fine-to-coarse → **coarse & fine** (optionally progressive)
- ▶ Slow receptive field growth



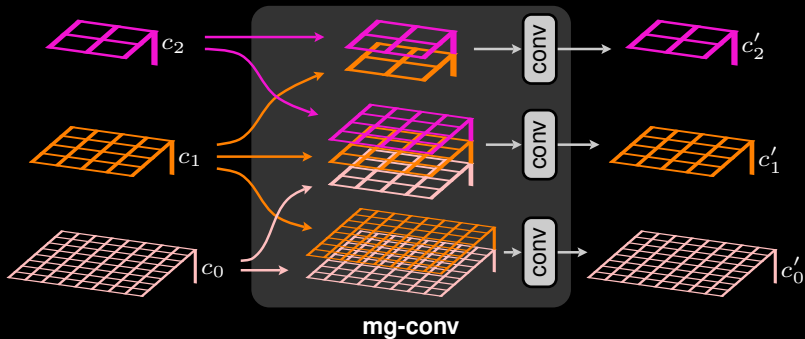
- ▶ Conflates abstraction & scale → **disentangles them**
- ▶ Fine-to-coarse → **coarse & fine** (optionally progressive)
- ▶ Slow receptive field growth → **efficient communication**



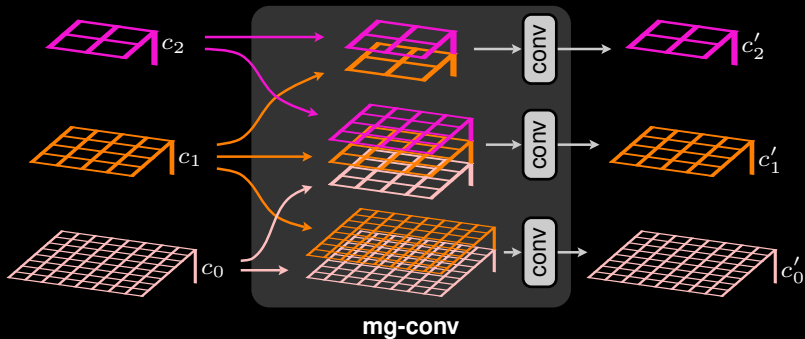
- ▶ Conflates abstraction & scale → **disentangles them**
- ▶ Fine-to-coarse → **coarse & fine** (optionally progressive)
- ▶ Slow receptive field growth → **efficient communication**

Multigrid destroys the notion of receptive field

Multigrid Convolution

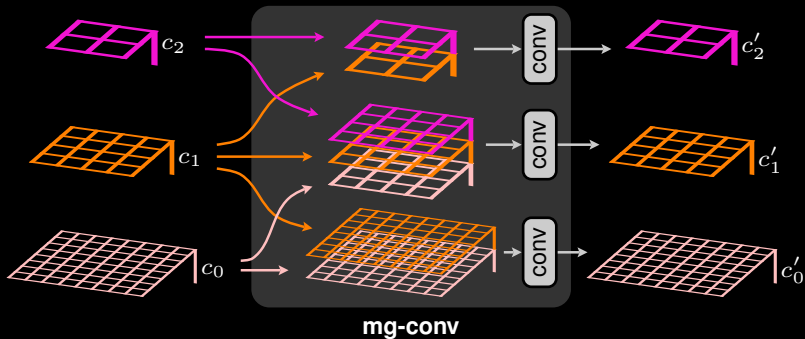


Multigrid Convolution



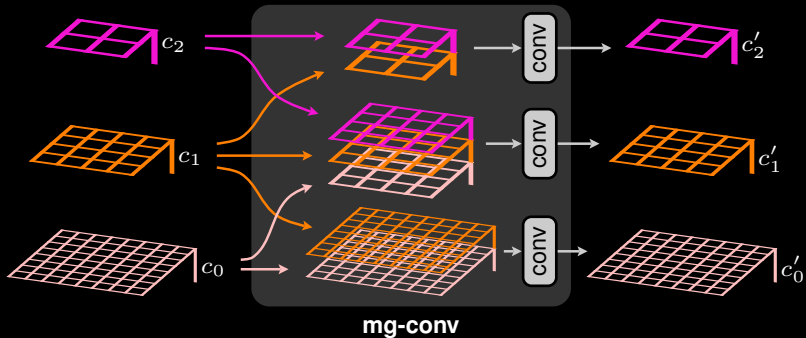
- Upsampling: nearest neighbor

Multigrid Convolution



- ▶ Upsampling: nearest neighbor
- ▶ Downsampling: max-pooling

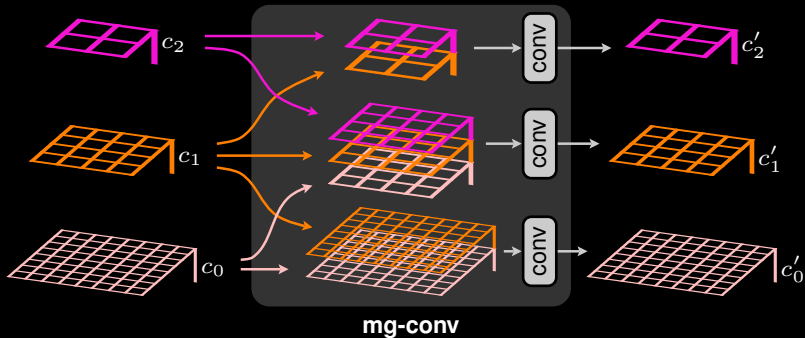
Multigrid Convolution



- ▶ Upsampling: nearest neighbor
- ▶ Downsampling: max-pooling

Rethink pooling: communication, not summarization

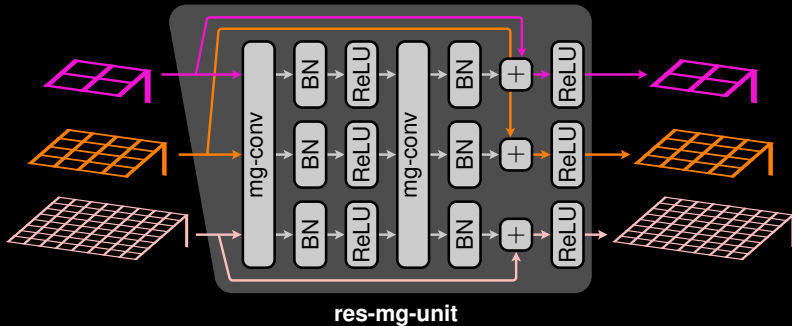
Multigrid Convolution



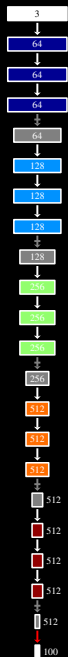
- ▶ Upsampling: nearest neighbor
- ▶ Downsampling: max-pooling

CNN evolves representation on pyramid

Multigrid Residual Unit



VGG-16



Layers:

↓ conv+BN+ReLU

↻ residual unit

↓ mg-conv+BN+ReLU

↻ residual-mg unit

↓ pool & subsample

up ↓ upsample


⚡ concatenation


↓ prediction (output)


Grids:


 $64 \times 64 \times c$


 32×32

 16×16

 8×8

 4×4

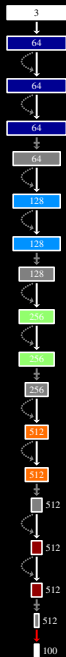
 2×2

 1×1

VGG-16



RES-22



Layers:

- ↓ conv+BN+ReLU
- ↪ residual unit
- ↘ mg-conv+BN+ReLU
- ↘ residual-mg unit
- ↓ pool & subsample
- up ↓ upsample
- ⚡ concatenation
- ↓ prediction (output)

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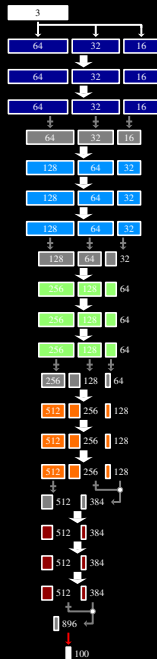
VGG-16



RES-22



MG-16



Layers:

- ↓ conv+BN+ReLU
- ↪ residual unit
- ↘ mg-conv+BN+ReLU
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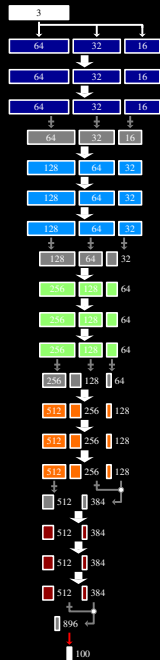
VGG-16



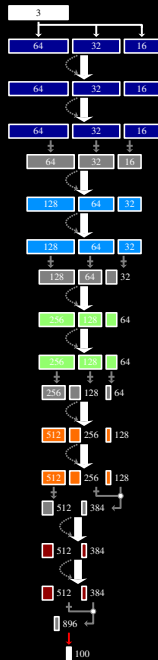
RES-22



MG-16



R-MG-22



Layers:

- ↓ conv+BN+ReLU
- ↪ residual unit
- ↘ mg-conv+BN+ReLU
- ↘ residual-mg unit
- ↓ pool & subsample
- ↑↓ upsample
- ⚡ concatenation
- ↓ prediction (output)

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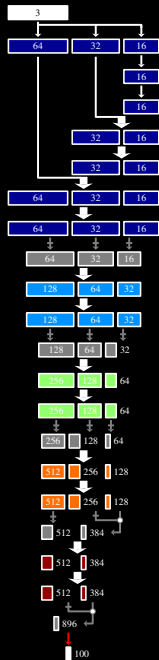
VGG-16



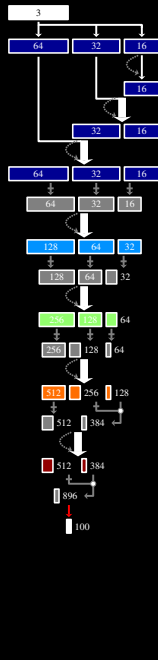
RES-22



PMG-16



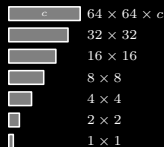
R-PMG-16



Layers:

- ↓ conv+BN+ReLU
- ↪ residual unit
- ⇩ mg-conv+BN+ReLU
- ⇩ residual-mg unit
- ⇩ pool & subsample
- up ↓ upsample
- ⤵ concatenation
- ↓ prediction (output)

Grids:



Results: CIFAR 100 Classification

Method	Params ($\times 10^6$)	FLOPs ($\times 10^6$)	Error (%)
VGG-6	3.96	67.88	32.15
VGG-11	9.46	228.31	30.26
VGG-16	14.96	388.75	30.47
VGG-21	20.46	549.18	31.89
MG-6	8.34	116.63	32.08
MG-11	20.46	391.88	28.39
MG-16	32.58	667.13	29.91
MG-21	44.69	942.38	30.03
PMG-9	8.46	186.21	30.61
PMG-16	20.60	468.09	28.11
PMG-30	32.74	749.98	29.89
<hr/>			
RES-12	9.50	266.02	28.64
RES-22	20.49	586.93	28.05
RES-32	31.49	907.79	27.12
RES-42	42.48	1228.65	27.60
R-MG-12	20.56	457.20	27.84
R-MG-22	44.79	1007.70	26.79
R-MG-32	69.02	1558.20	25.29
R-MG-42	93.26	2108.71	26.32
R-PMG-16	20.60	468.09	27.35
R-PMG-30	44.88	1031.87	26.44
R-PMG-44	69.16	1595.64	26.68

Results: CIFAR 100 Classification

- Multigrid capacity useful, improves performance

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Results: CIFAR 100 Classification

- ▶ Multigrid capacity useful, **improves performance**
- ▶ Synergistic with **residual** connections

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Results: CIFAR 100 Classification

- ▶ Multigrid capacity useful, **improves performance**
- ▶ Synergistic with **residual** connections
- ▶ **Progressive** versions:
 - ▶ save params
 - ▶ save FLOPs

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Results: ImageNet Classification

Method	Params ($\times 10^6$)	FLOPs ($\times 10^9$)	val, 10-crop	
			Top-1	Top-5
VGG-16 (Simonyan and Zisserman, 2015)	138.0	15.47	28.07	9.33
ResNet-34 C (He et al., 2016)	21.8	3.66	24.19	7.40
ResNet-50 (He et al., 2016)	25.6	4.46	22.85	6.71
WRN-34 (2.0) (Zagoruyko and Komodakis, 2016)	48.6	14.09	-	-
R-MG-34	32.9	5.76	22.42	6.12
R-PMG-30-SEG	31.9	2.77	23.60	6.89

ImageNet validation set error, 10-crop

R-MG-34 outperforms ResNet-50

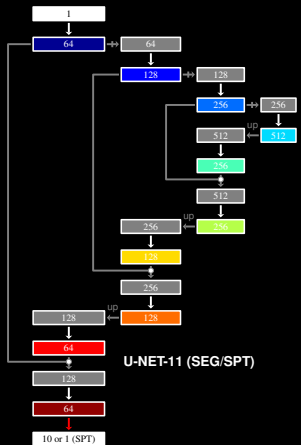
Results: ImageNet Classification

Method	Params ($\times 10^6$)	FLOPs ($\times 10^9$)	val, 1-crop	
			Top-1	Top-5
VGG-16 (Simonyan and Zisserman, 2015)	138.0	15.47	-	-
ResNet-34 C (He et al., 2016)	21.8	3.66	-	-
ResNet-50 (He et al., 2016)	25.6	4.46	-	-
WRN-34 (2.0) (Zagoruyko and Komodakis, 2016)	48.6	14.09	24.50	7.58
R-MG-34	32.9	5.76	24.51	7.46
R-PMG-30-SEG	31.9	2.77	26.50	8.63

ImageNet validation set error, single-crop

R-MG-34 matches WRN-34, using fewer params and FLOPs

Networks for Semantic Segmentation

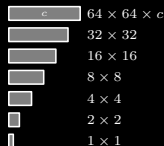


U-NET-11 (SEG/SPT)

Layers:

- ↓ conv+BN+ReLU
- ↻ residual unit
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- ↻ residual-mg unit
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- up ↓ upsample
- ⚡ concatenation
- ↓ prediction (output)

Grids:

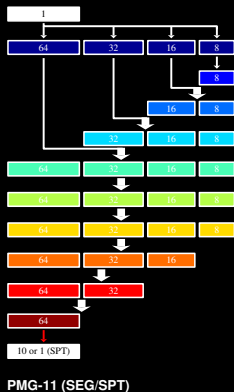
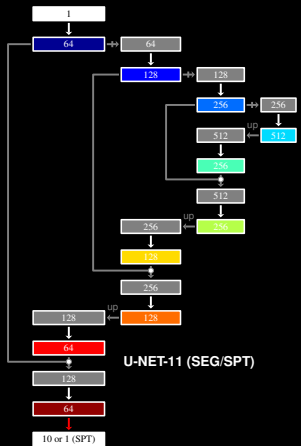


U-NET: Ronneberger et al. (2015)

similar: autoencoders; Badrinarayanan et al. (2015);

Hu and Ramanan (2016); Newell et al. (2016)

Networks for Semantic Segmentation



Layers:






























































- ↓ conv+BN+ReLU
- ↻ residual unit
- ⇓ mg-conv+BN+ReLU
- ↻ residual-mg unit
- ⇓ pool & subsample
- ↑ upsample
- ⚡ concatenation
- ↓ prediction (output)

Grids:

- $64 \times 64 \times c$
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U-NET: Ronneberger et al. (2015)
 similar: autoencoders; Badrinarayanan et al. (2015);
 Hu and Ramanan (2016); Newell et al. (2016)

MNIST Synthetic Semantic Segmentation

Input	Digit: 0	1	2	3	4	5	6	7	8	9	
											True
											U-NET
											SG
											R-SG
											PMG
											R-PMG

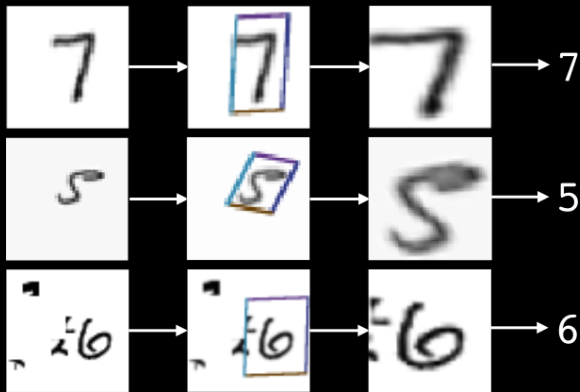
MNIST Synthetic Semantic Segmentation

Input	Digit: 0	1	2	3	4	5	6	7	8	9	
											True
											U-NET
											SG
											R-SG
											PMG
											R-PMG

MNIST Synthetic Semantic Segmentation

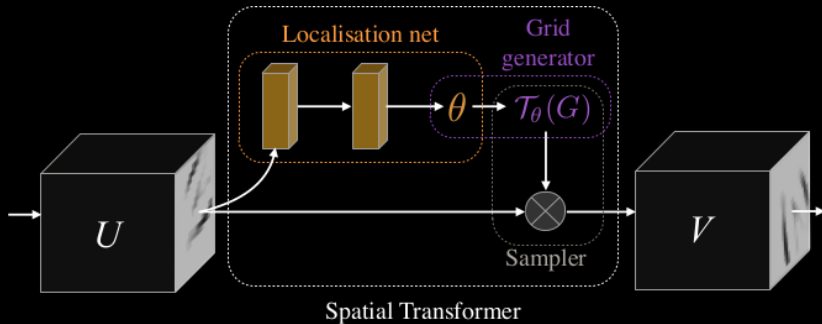
Method	Params ($\times 10^6$)	IoU (%)	Error (%)
U-NET-11	3.79	58.46	22.14
U-MG-11	5.90	58.02	21.45
SG-11	0.23	32.21	22.33
R-SG-20	0.45	69.86	14.43
PMG-11	0.61	61.88	14.75
R-PMG-20	1.20	81.91	8.89

Spatial Transformations



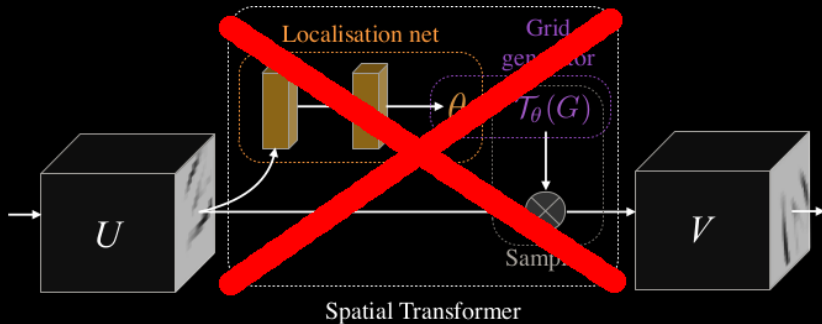
Jaderberg et al. (2015)

Spatial Transformations






































Jaderberg et al. (2015)

Spatial Transformations



Replace with Multigrid CNN

MNIST Spatial Transformation Task

Input	True	U-NET	SG	R-SG	PMG	R-PMG
						
						
						
						
						

MNIST Spatial Transformation Task

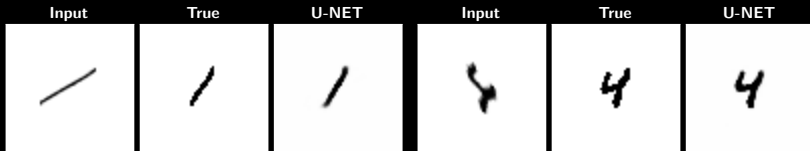
Method	Params ($\times 10^6$)	IoU (%)	Error (%)
U-NET-11	3.79	12.20	37.55
SG-11	0.23	0	100.00
R-SG-20	0.45	0	82.98
PMG-11	0.61	50.64	29.20
R-PMG-20	1.20	55.61	25.59

Multigrid necessary!

MNIST Spatial Transformation Task



Rotation Only



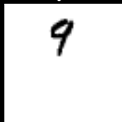
Affine Only



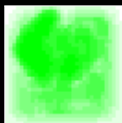
Translation Only

Multigrid Enables Learned Attention

Input

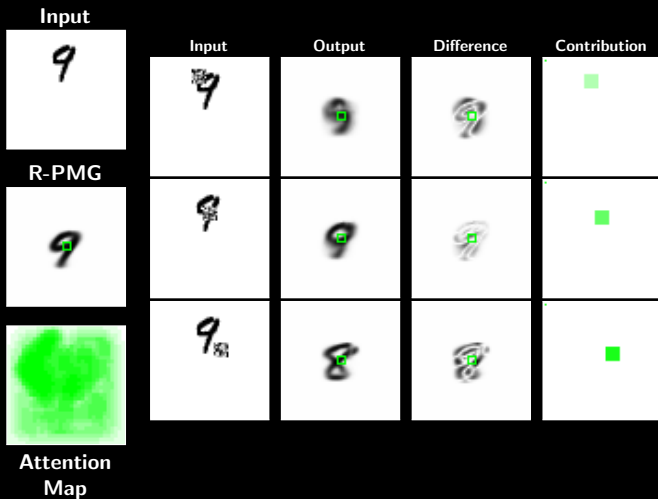


R-PMG

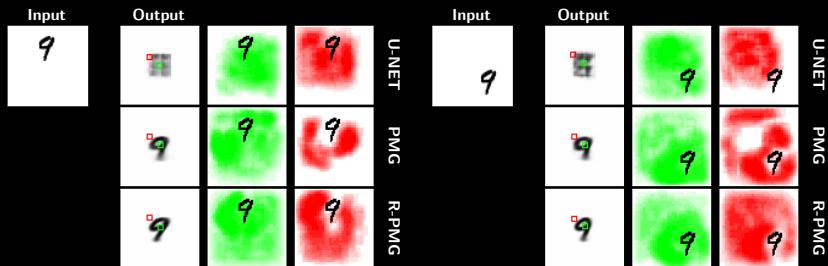


Attention
Map

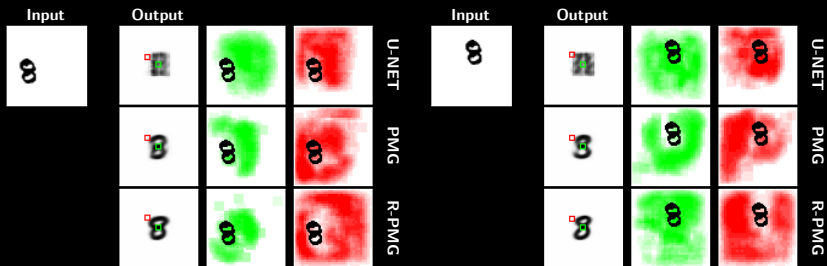
Multigrid Enables Learned Attention

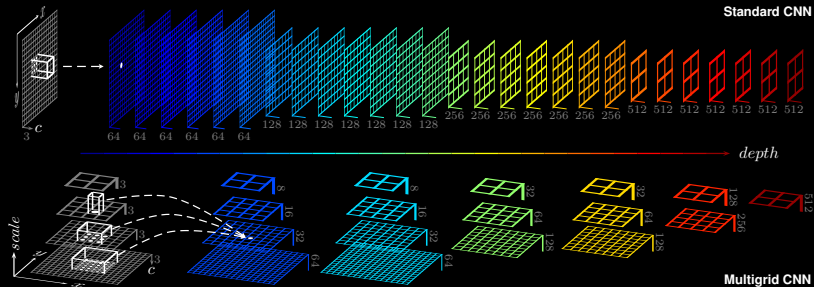


Multigrid Enables Learned Attention



Multigrid Enables Learned Attention





- ▶ Representation: evolve scale-space features
- ▶ Computation: progressive coarse-to-fine
- ▶ Communication: enable dynamic routing & attention

