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Automated Synthetic-to-Real Generalization

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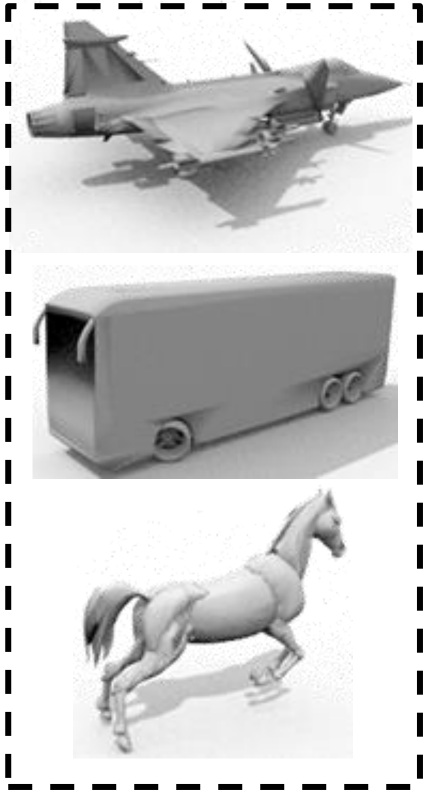
Syn-to-Real Generalization: Problem & Challenge

Pretrained Model e.g. ImageNet

Fine-tune

Labeled Training (Synthetic Data)



Visda17

Test

Unseen Test (Real Data)

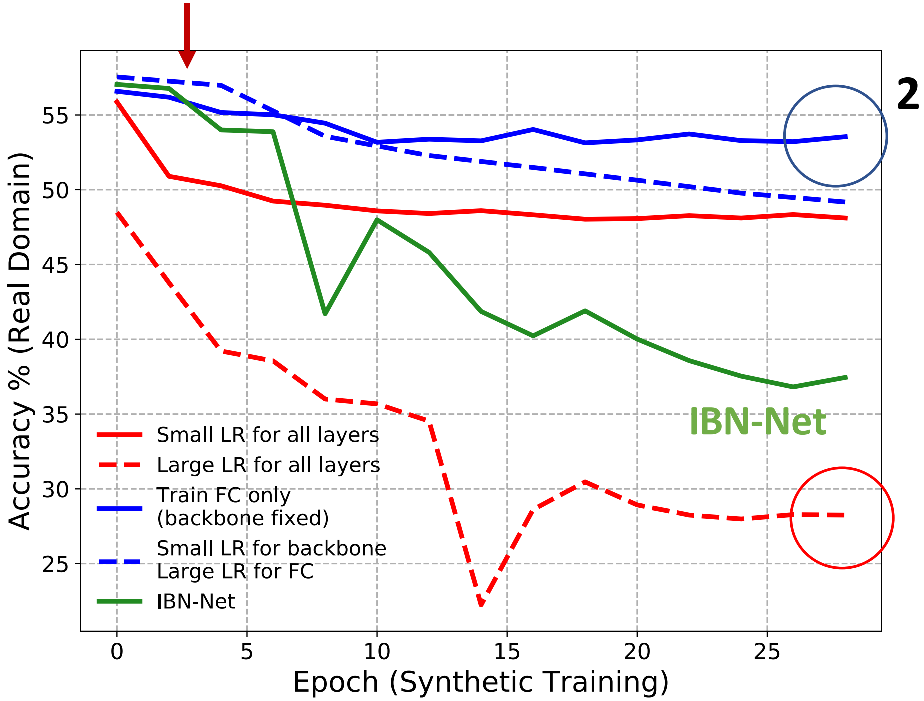
COCO

Challenge:

Large domain gap b/w synthetic and real data

Prior solutions:

1) Early stopping



2) Small LR

Large LR

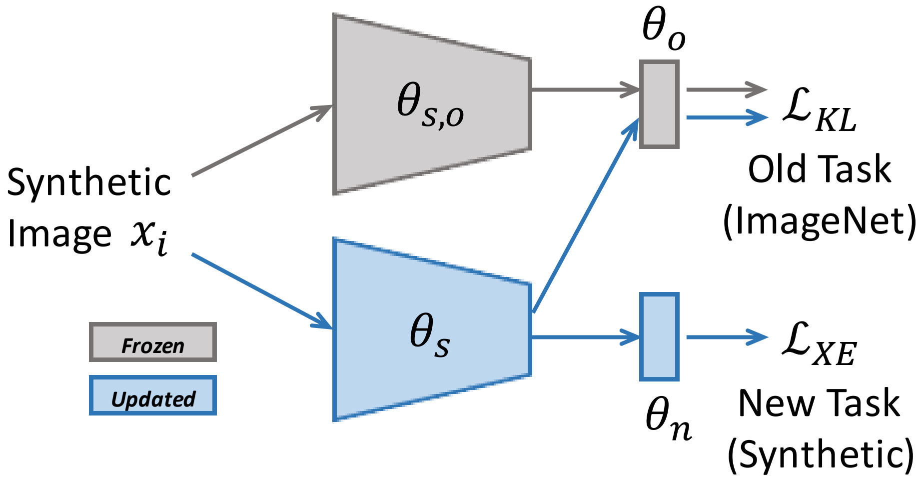
Syn-to-Real Generalization with Proxy Guidance

- Why people do **early stopping**?

➔ Do not train too far from initialization (ImageNet pretrained weight).

- We minimize KL divergence $\mathcal{L}_{KL}$ b/w new model and initialization.

➔ ImageNet pretrained weight as proxy guidance in syn2real training.



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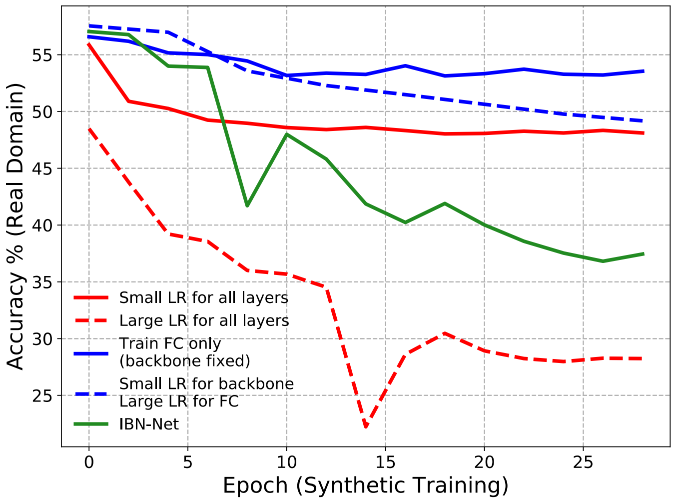
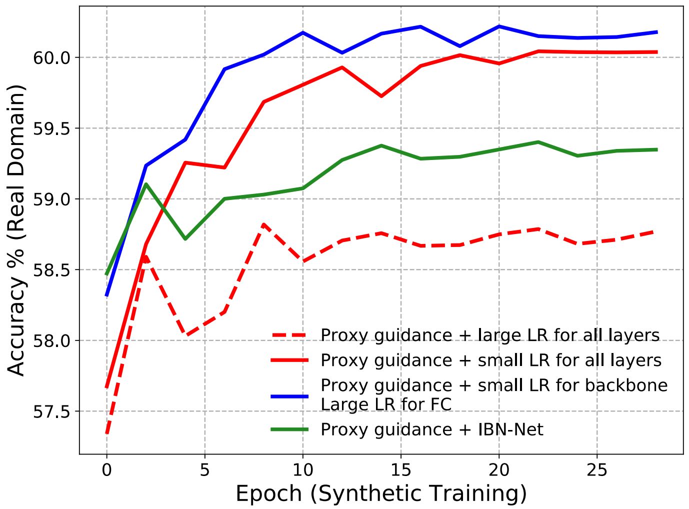


Proxy Guidance



Visda17 → COCO

Automated Synthetic-to-Real Generalization (**ASG**)

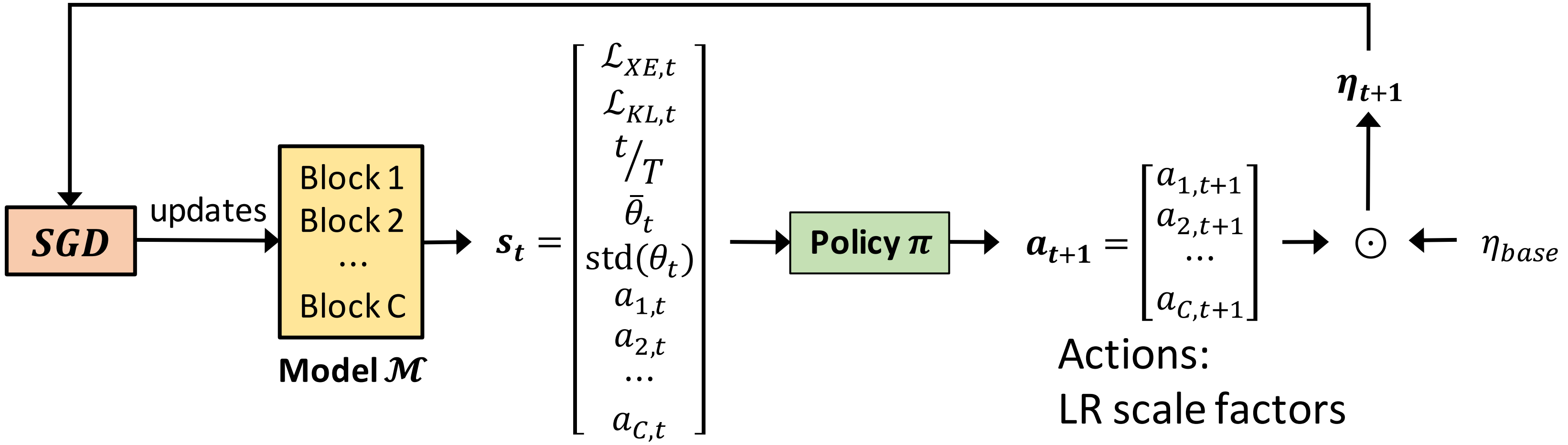
- Why people use **<u>small learning rate</u>**?

➔ Carefully fine-tune to avoid being far from initialization (ImageNet pretrained weight).

- But how small for which layer?

➔ **L2O** (learning-to-optimize): automatic control of layer-wise learning rate.

  - Train L2O policy π with REINFORCE to produce learning rate actions.



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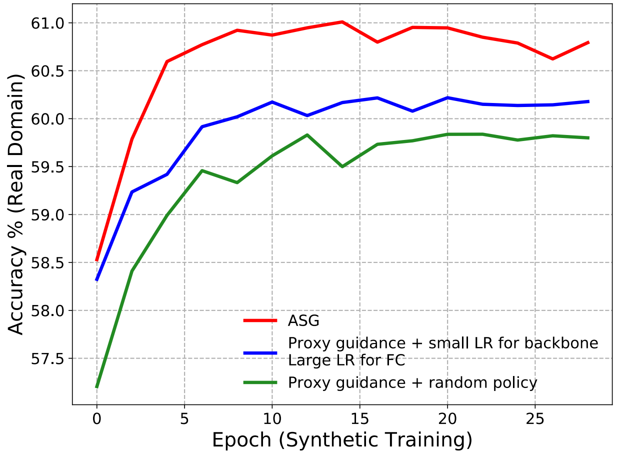
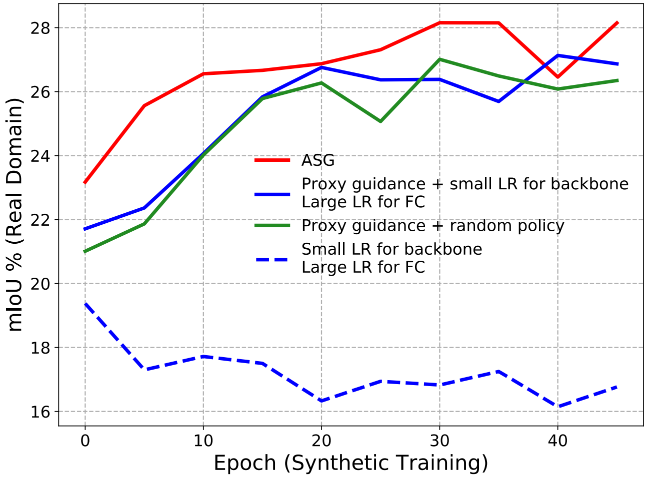


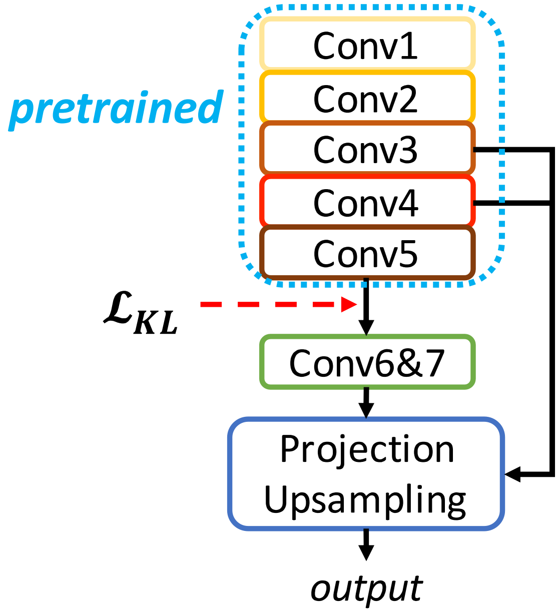
Classification: Visda17 ➔ COCO



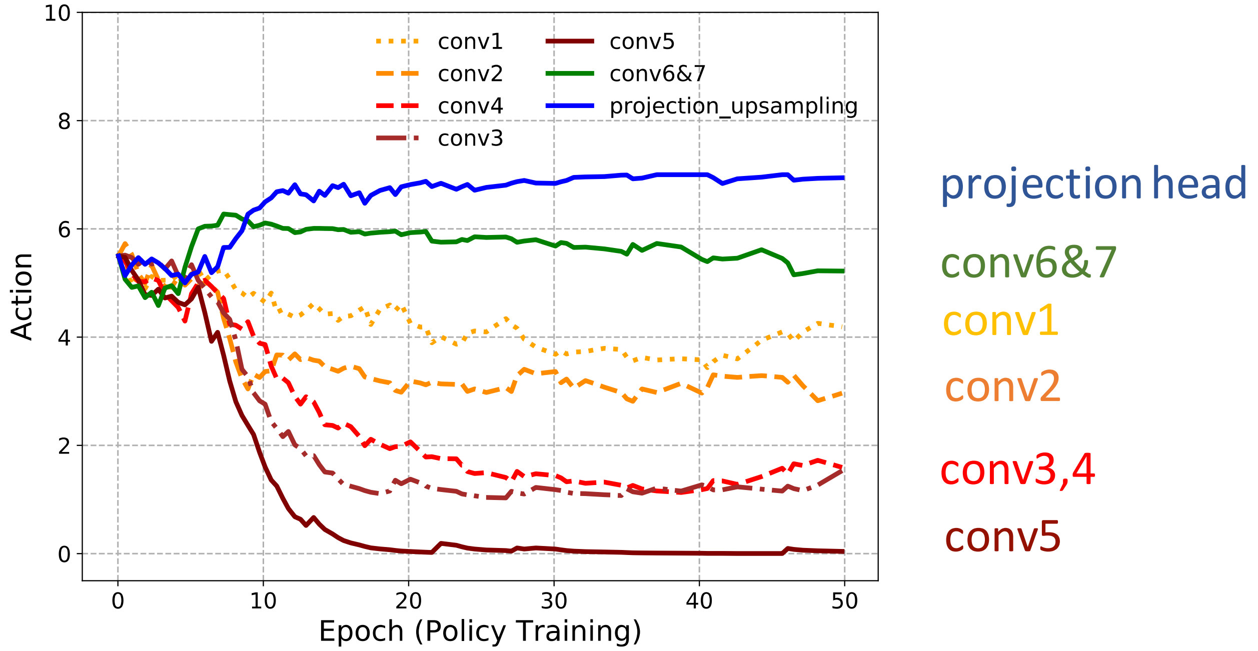
Segmentation: GTA5 ➔ Cityscapes

Action Behavior of RL-L2O Policy

- Backbone (ImageNet pretrained): closer to $\mathcal{L}_{KL}$ → smaller LR.
- Projection head: large LR.



Vgg16-FCN8s



Segmentation: GTA5 → Cityscapes

Why ASG Works? Retaining ImageNet Information

- ImageNet is a large-scale real-world dataset, it provides rich information about real domain.

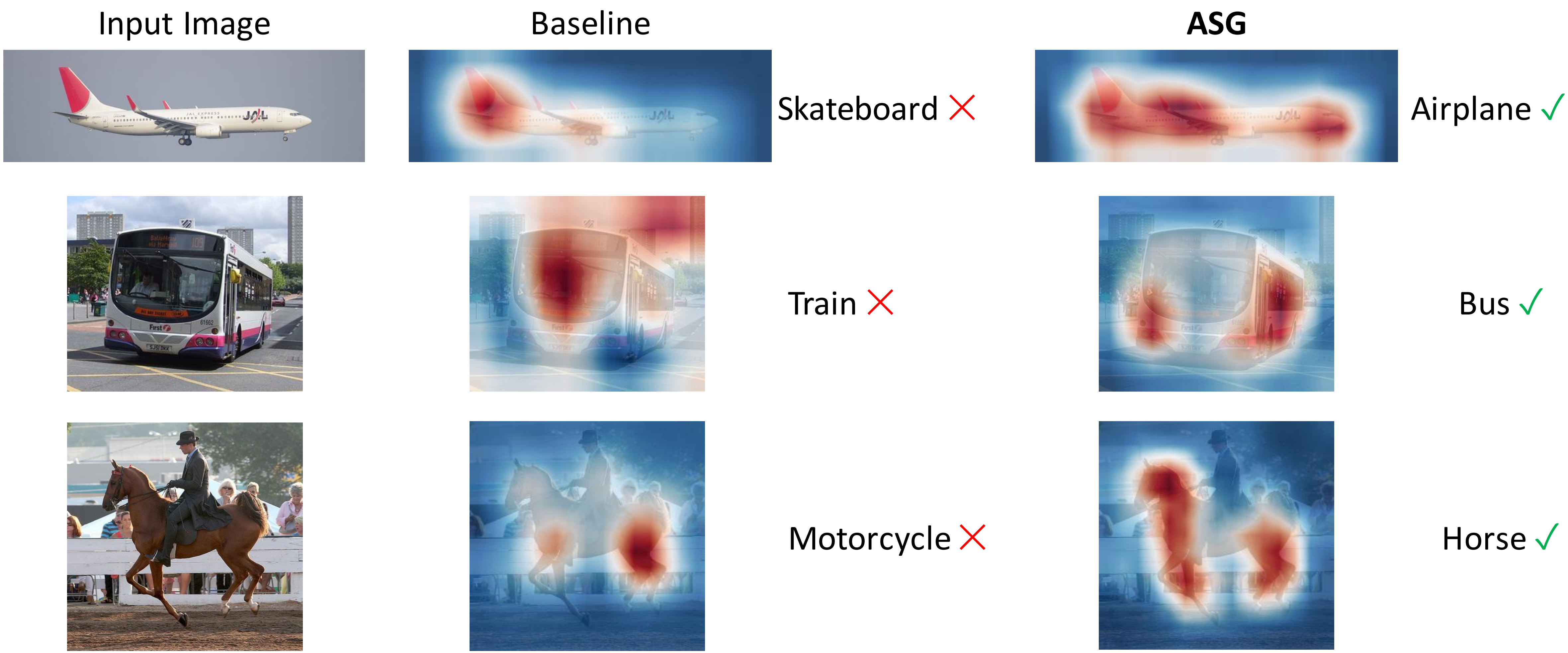
#	Model	Visda-17	ImageNet
1.	Large LR for all layers	28.2	0.8
2.	+ our Proxy Guidance	58.7 (+30.5)	76.2 (+75.4)
3.	Small LR for backbone and large LR for FC	49.3	33.1
4.	+ our Proxy Guidance	60.2 (+10.9)	76.5 (+43.4)
5.	Oracle on ImageNet[2]	53.3 (+4.0)	**77.4**
6.	ROAD (Chen et al., 2018)	57.1 (+7.8)	**77.4**
7.	Vanilla L2 distance	56.4 (+7.1)	49.1
8.	SI (Zenke et al., 2017)	57.6 (+8.3)	53.9
9.	ASG (ours)	**61.5**	76.7

ASG Benefits Domain Adaptation

- ASG as initialization for domain adaptation methods.

Method	Tgt Img	Accuracy
Source (Saito et al., 2017)	✗	52.4
MCD (Saito et al., 2018)	✓	71.9
ADR (Saito et al., 2017)	✓	74.8
SimNet-Res152 (Pinheiro, 2018)	✓	72.9
GTA-Res152 (Sankaranarayanan et al., 2018)	✓	77.1
Source-Res101 (Zou et al., 2019)	✗	51.6
CBST (Zou et al., 2018)	✓	76.4 (0.9)
MRKLD (Zou et al., 2019)	✓	77.9 (0.5)
MRKLD + LRENT (Zou et al., 2019)	✓	78.1 (0.2)
ASG (ours)	✗	61.5
ASG + CBST	✓	82.5 (0.7)
ASG + MRKLD	✓	**84.6** (0.4)
ASG + MRKLD + LRENT	✓	84.5 (0.4)

ASG Improves Model Attention (GradCAM)



Thank you!