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Vision Transformer Adapters for Generalizable Multitask Learning

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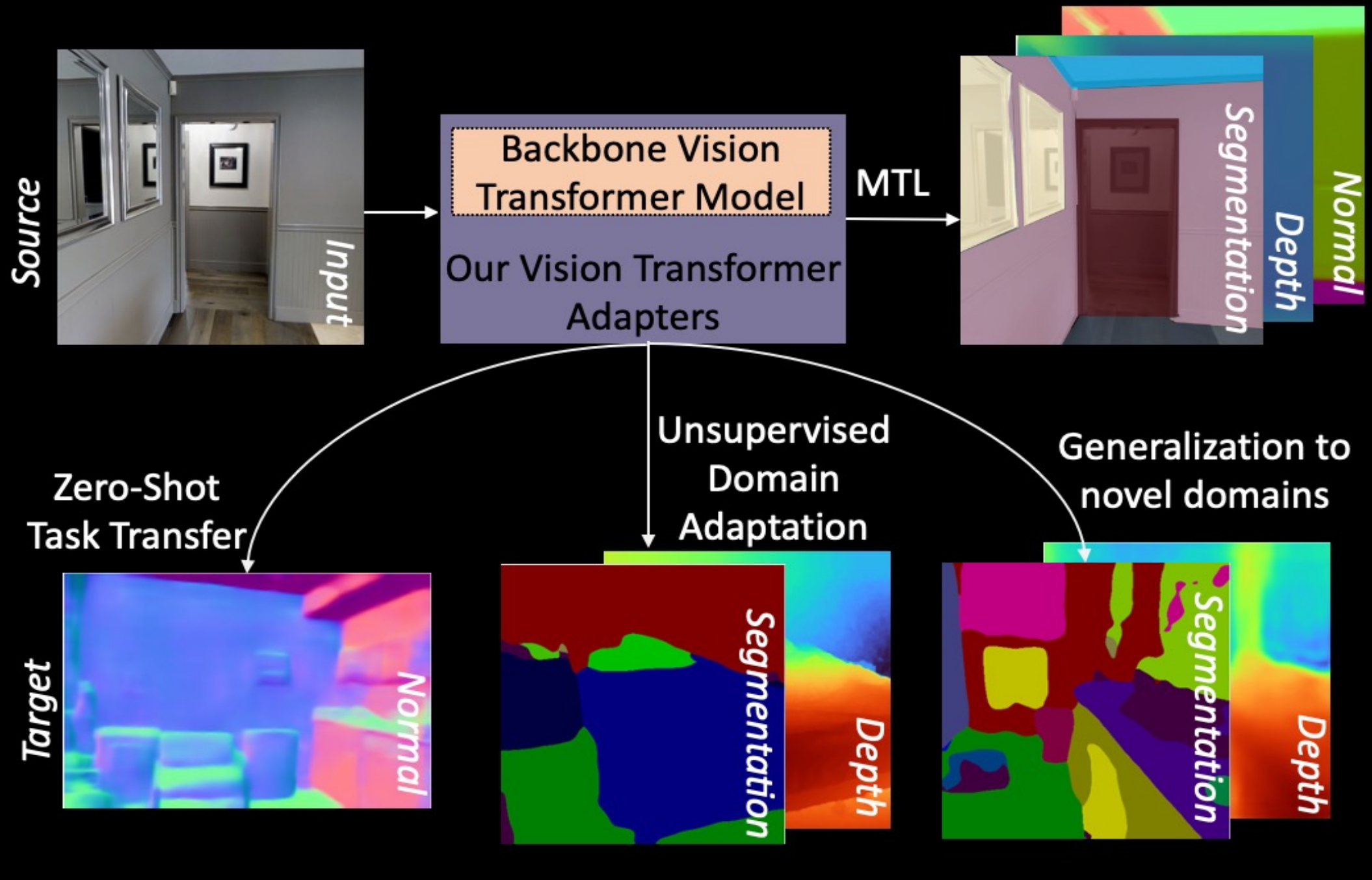

Source
Input
Backbone Vision Transformer Model
Our Vision Transformer Adapters
MTL
Normal
Depth
Segmentation
Zero-Shot Task Transfer
Target
Normal
Unsupervised Domain Adaptation
Segmentation
Depth
Generalization to novel domains
Segmentation
Depth

Method Overview

H xWx 3

$Batch - size = 128$

TROA input: Encoded batch embeddings

TROA

T1 T2 T1 T2 T1 T15 T18 T1 T2

Stage 1 $\frac{H}{4}$ x $\frac{W}{4}$ x 192

Stage 2 $\frac{H}{8}$ x $\frac{W}{8}$ x 384

Stage 3 $\frac{H}{16}$ x $\frac{W}{16}$ x 768

Stage 4 $\frac{H}{32}$ x $\frac{W}{32}$ x 1536

Task head 1

Task head n

Task head N

$\frac{H}{32}$ x $\frac{W}{32}$ x 1536 $\frac{H}{16}$ x $\frac{W}{16}$ x 768 $\frac{H}{8}$ x $\frac{W}{8}$ x 384 $\frac{H}{4}$ x $\frac{W}{4}$ x 192

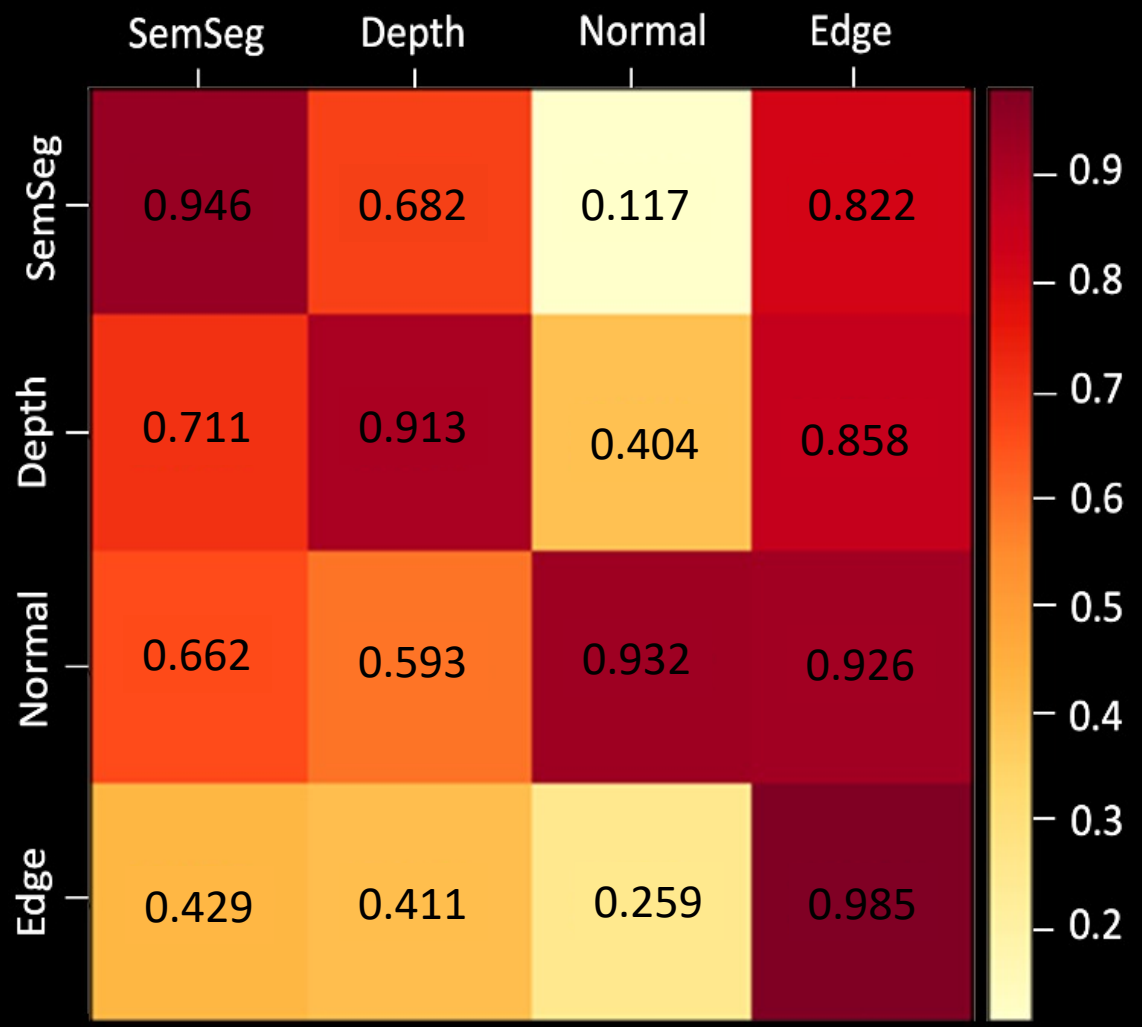
Legend

- Frozen Swin encoder
- Swin decoders trained
- Vision Adapter trained
- Task heads trained
- TROA trained
- Skip connection

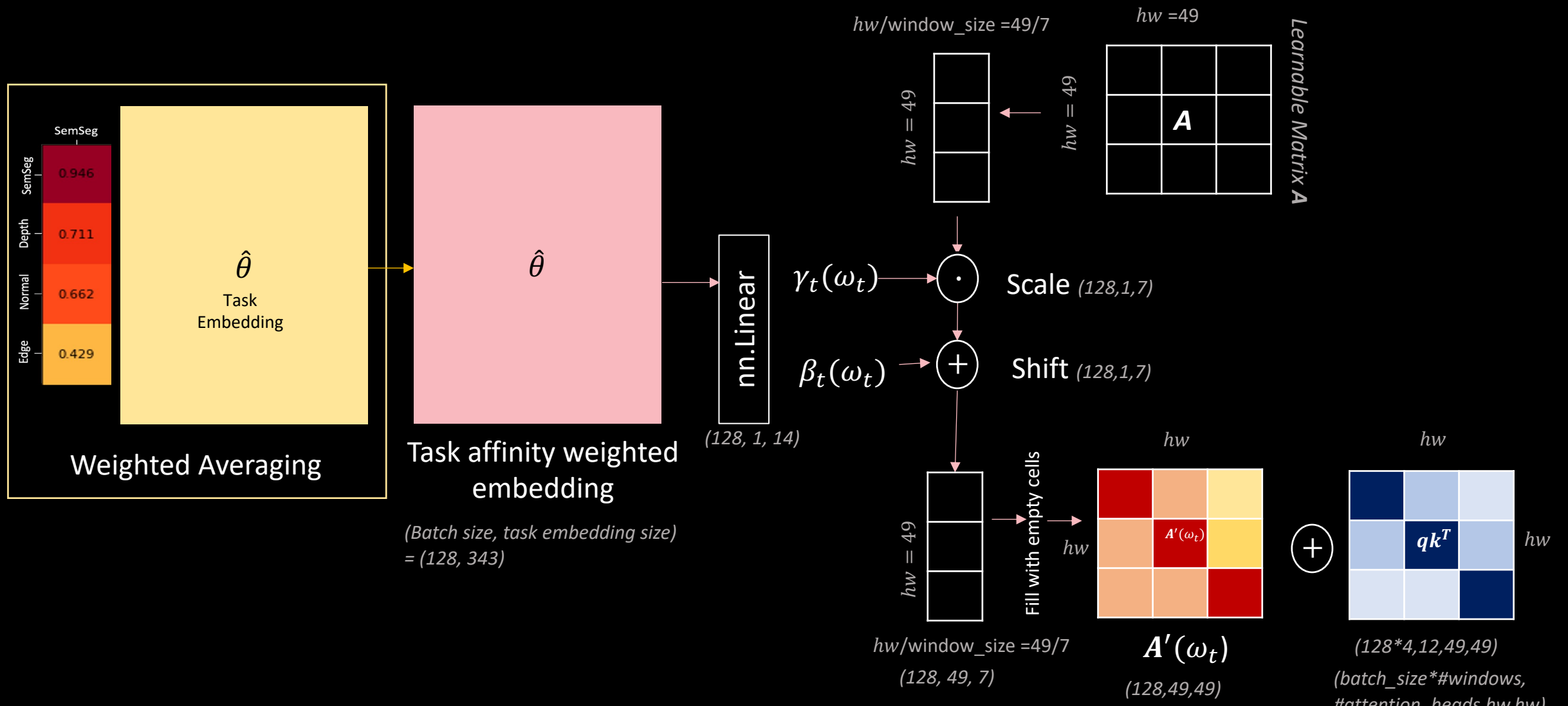
Motivation: Learning generalizable task affinities in a parameter-efficient way

Task Representation Optimization Algorithm (TROA)

Motivation: Finds gradient-based task affinities



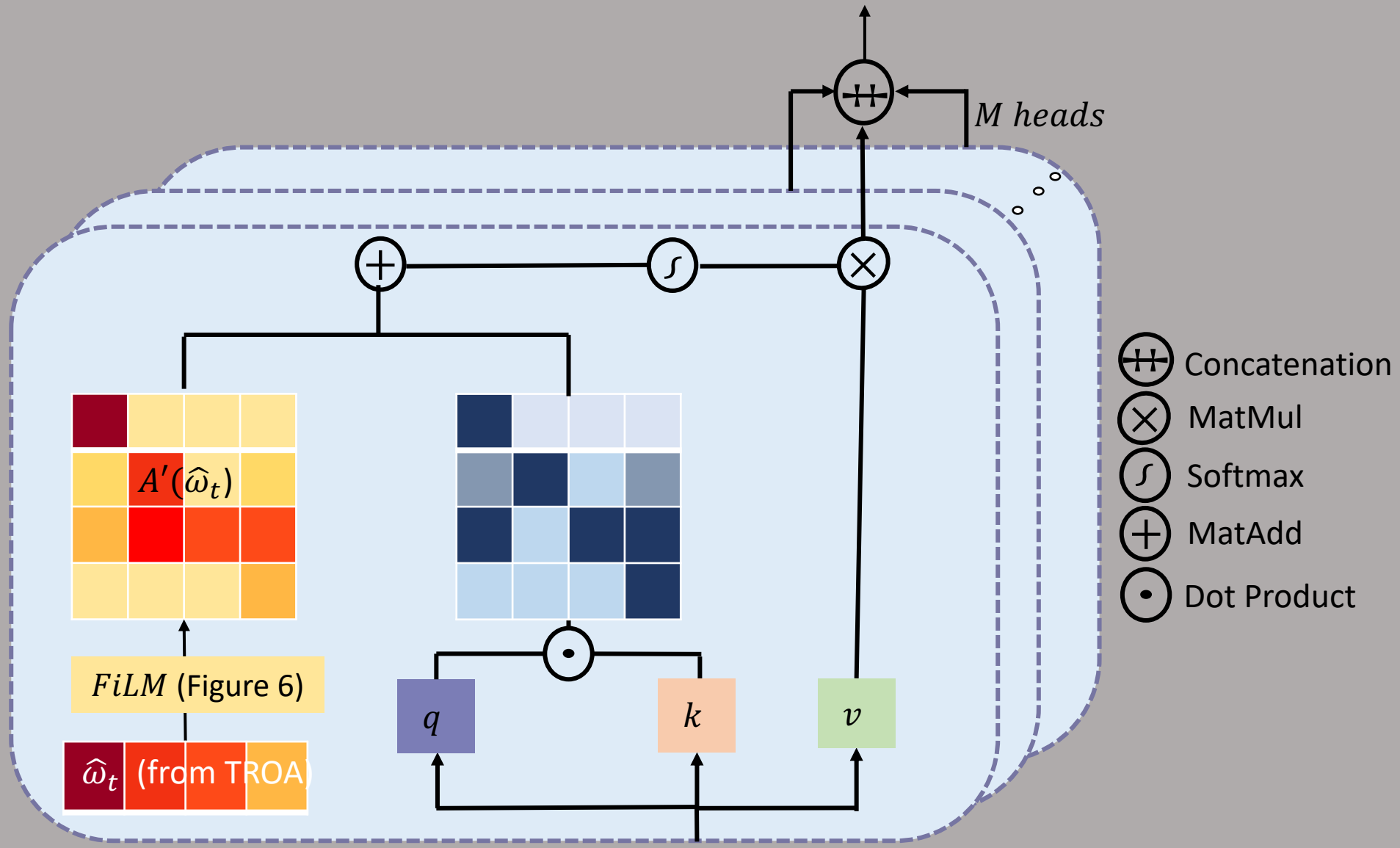
Feature-wise Linear Modulation



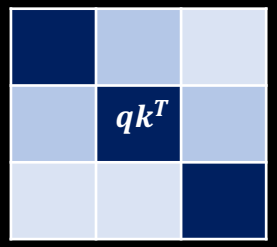
Perez et.al, MILA, published at AAAI 2018

Task-Adapted Attention (TAA)

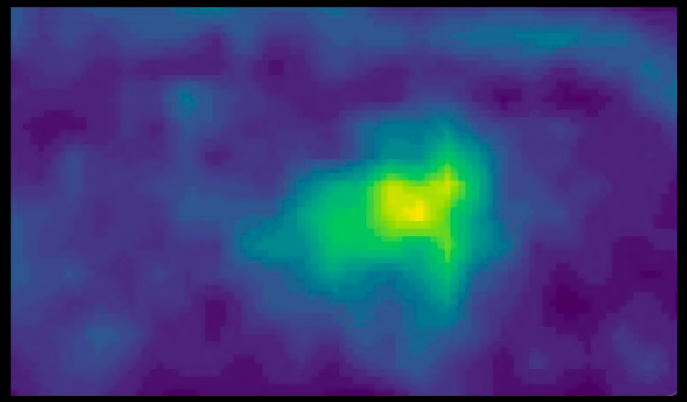
Motivation: Combines task affinities with image attention



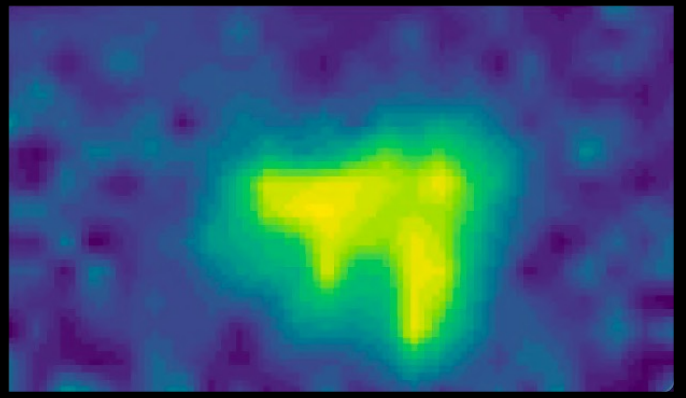
Task-Adapted Attention (TAA)



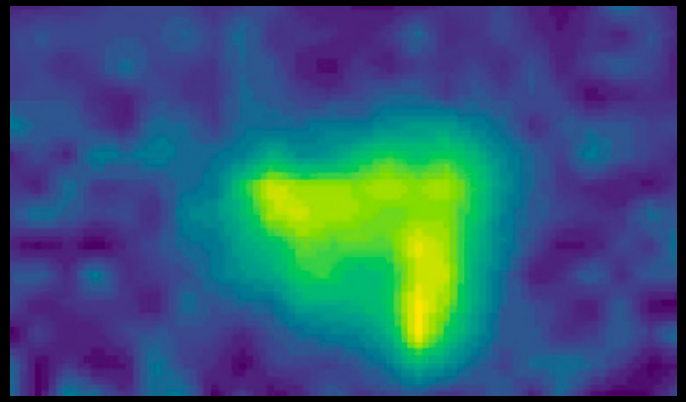
Example Image



Regular Self-Attention



SemSeg-TAA



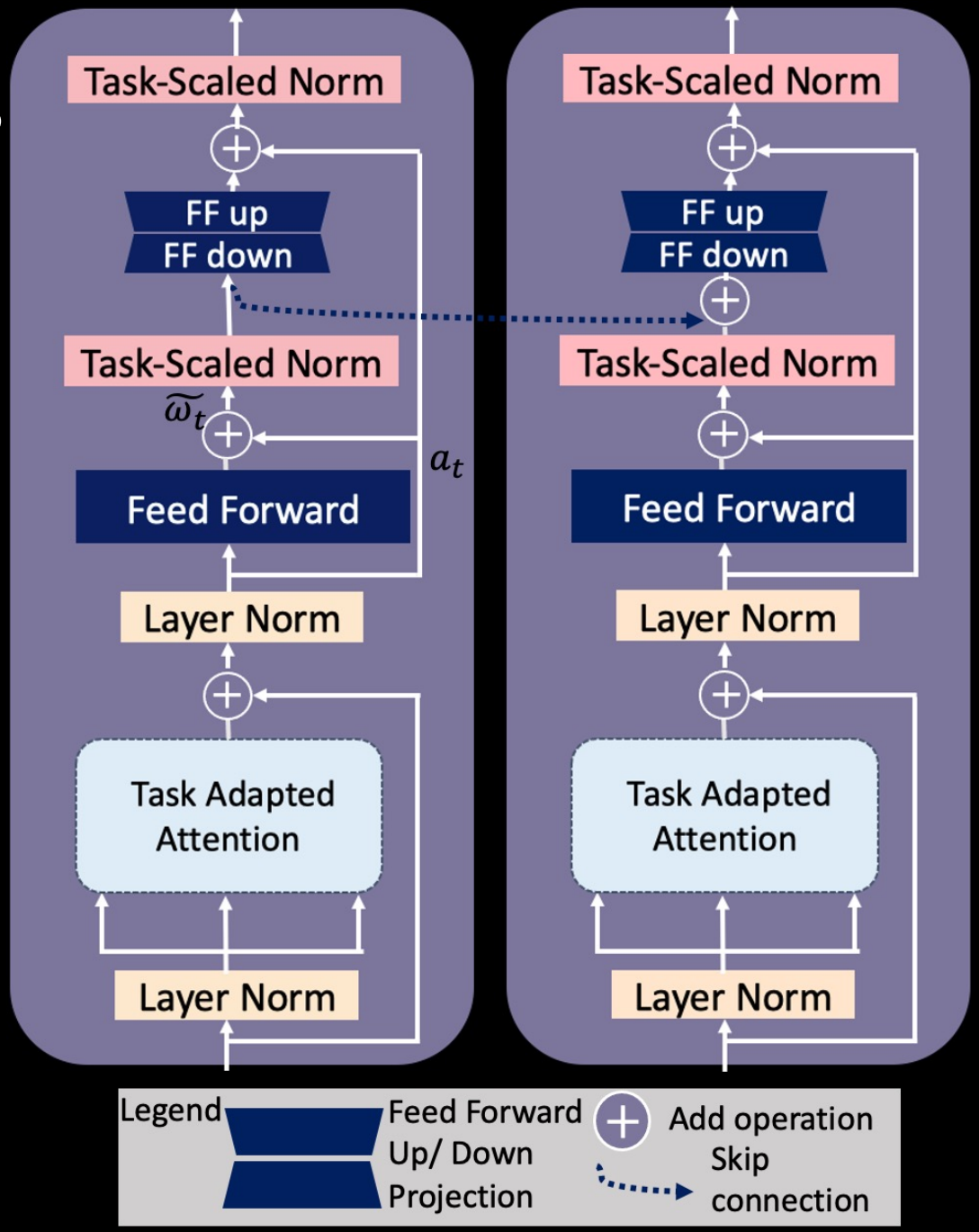
Depth-TAA

Vision Transformer Adapters

Motivation: Learns to perform multitasking in a parameter-efficient way; learns transferrable task affinities

To match the scales of different tasks

Normalizes across all features, more stable



Task-Scaled Norm

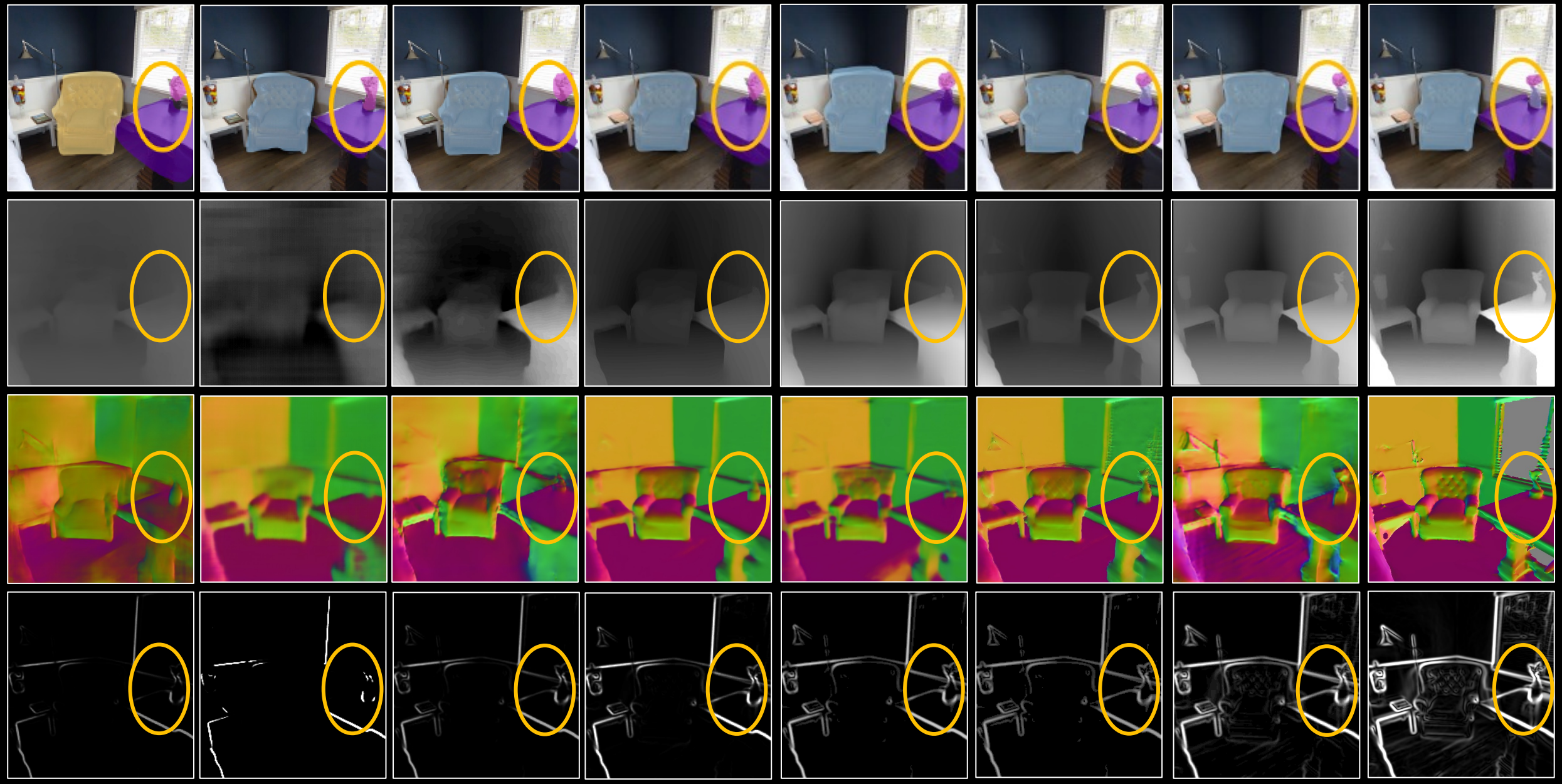
Motivation: TSN balances the different scales of the tasks. Balancing the task scales is necessary to avoid learning interference in MTL.

$$TSN_t = \frac{1}{\sigma}\left(a_t - \mu\right)\hat{\gamma}_t\left(\tilde{\omega}_t\right) + \beta_t\left(\tilde{\omega}_t\right)$$

$$\hat{\gamma}_t\left(\tilde{\omega}_t\right) = \gamma'\,\gamma_t\left(\tilde{\omega}_t\right) + \beta'$$

Swin's layer norm weights (for initialization)

Swin's Layer Norm: Fixed
Ours: Trained, based on the equation above



STL | MTL-baseline (CNN) | Consistency (CNN) | XTAM (CNN) | TAWT + MTL-baseline (CNN) | MulT (Transformer) | Adapters (transformer) | Ground-truth

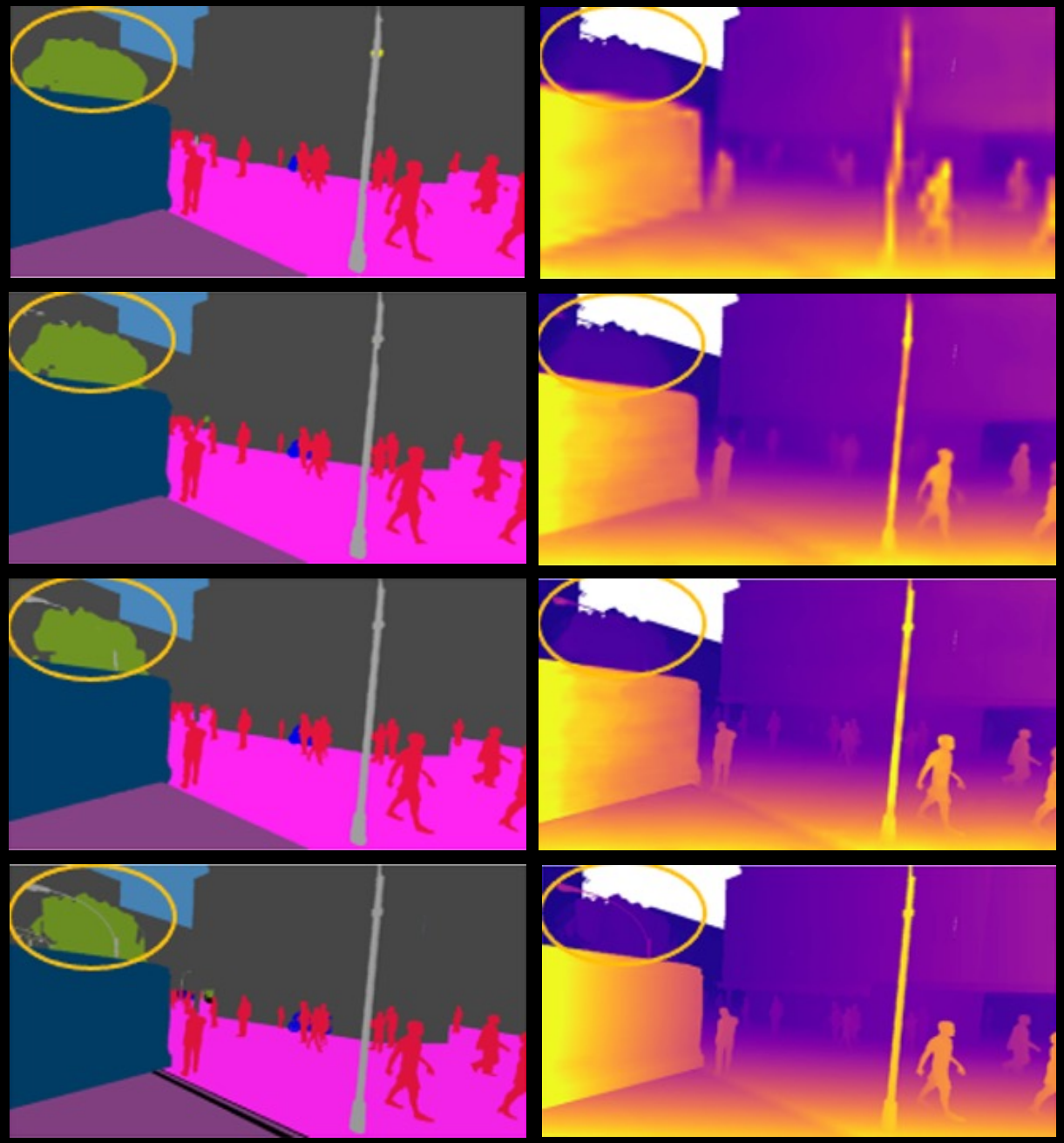
Zero-shot Task Transfer

TAWT + MTL-baseline

MulT

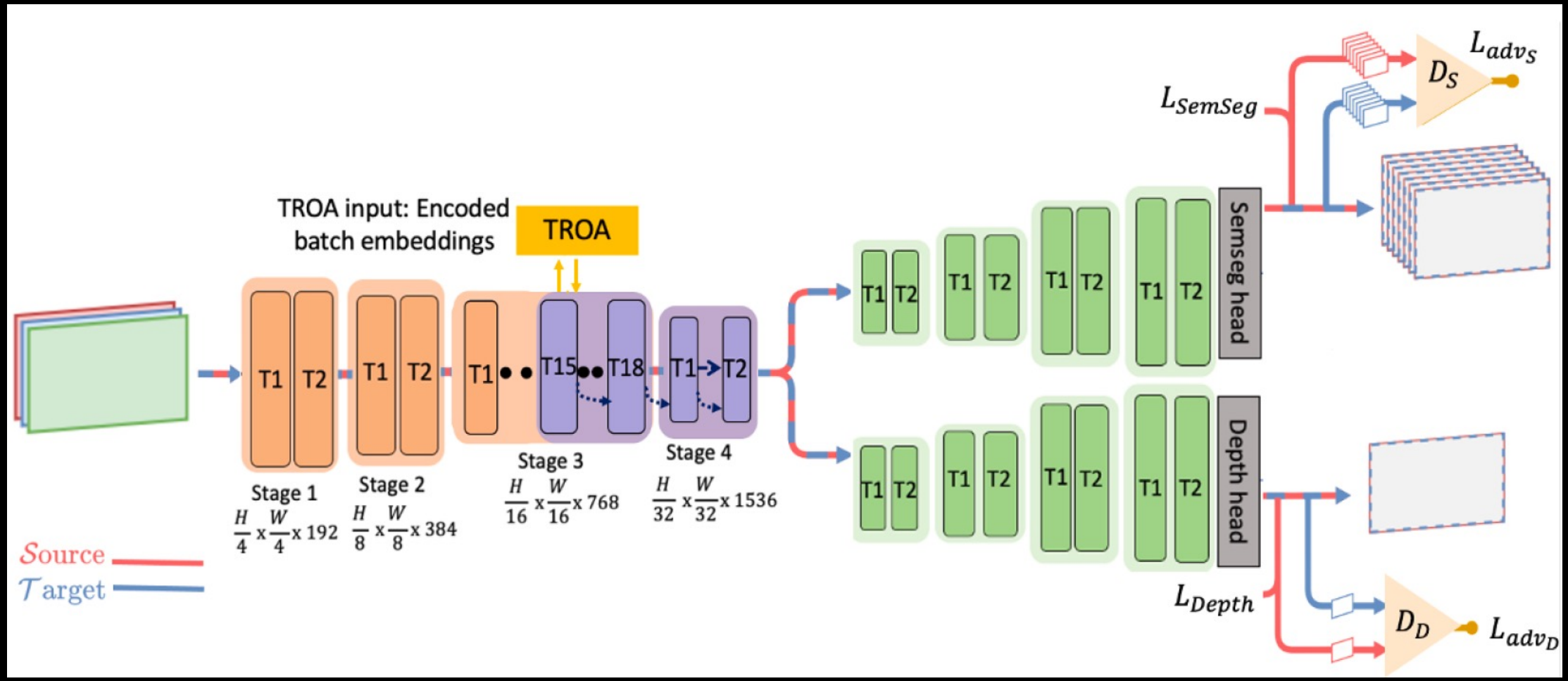
Adapters

Ground-truth

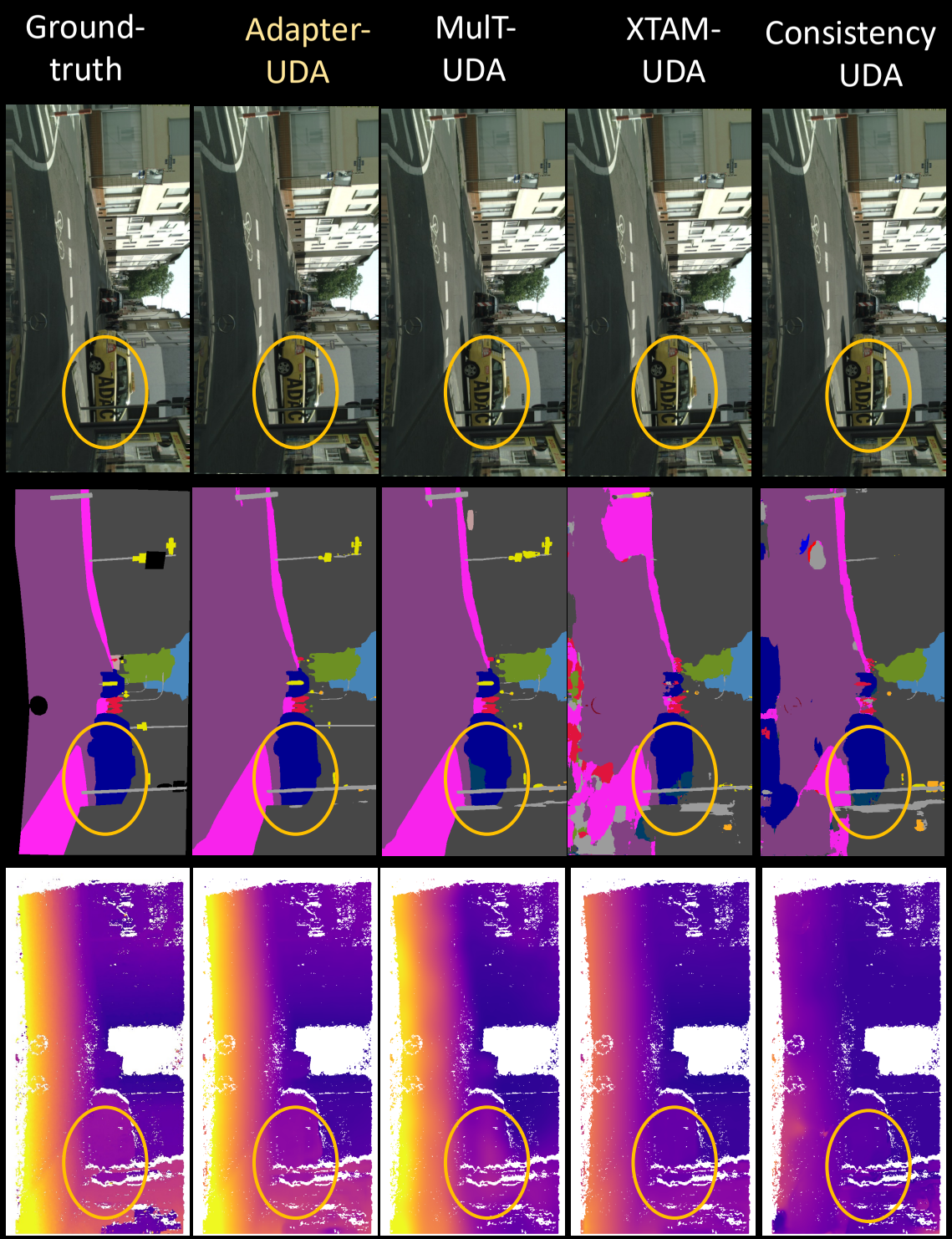


Normal is the zero-shot task

Unsupervised Domain Adaptation Method



Unsupervised Domain Adaptation



TEAM

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Thank you!

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