

Medusa: Universal Feature Learning via Attentional Multitasking

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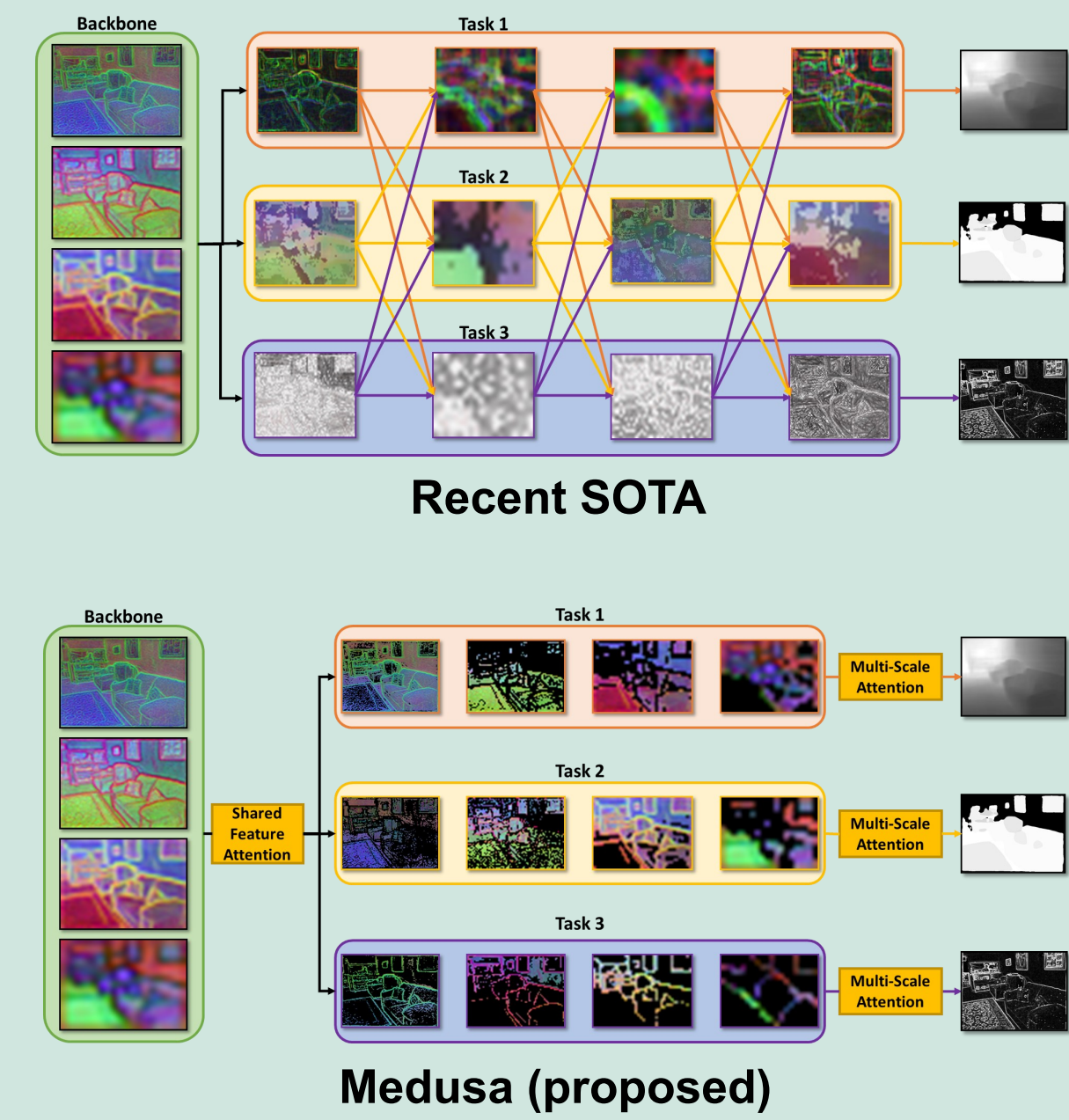
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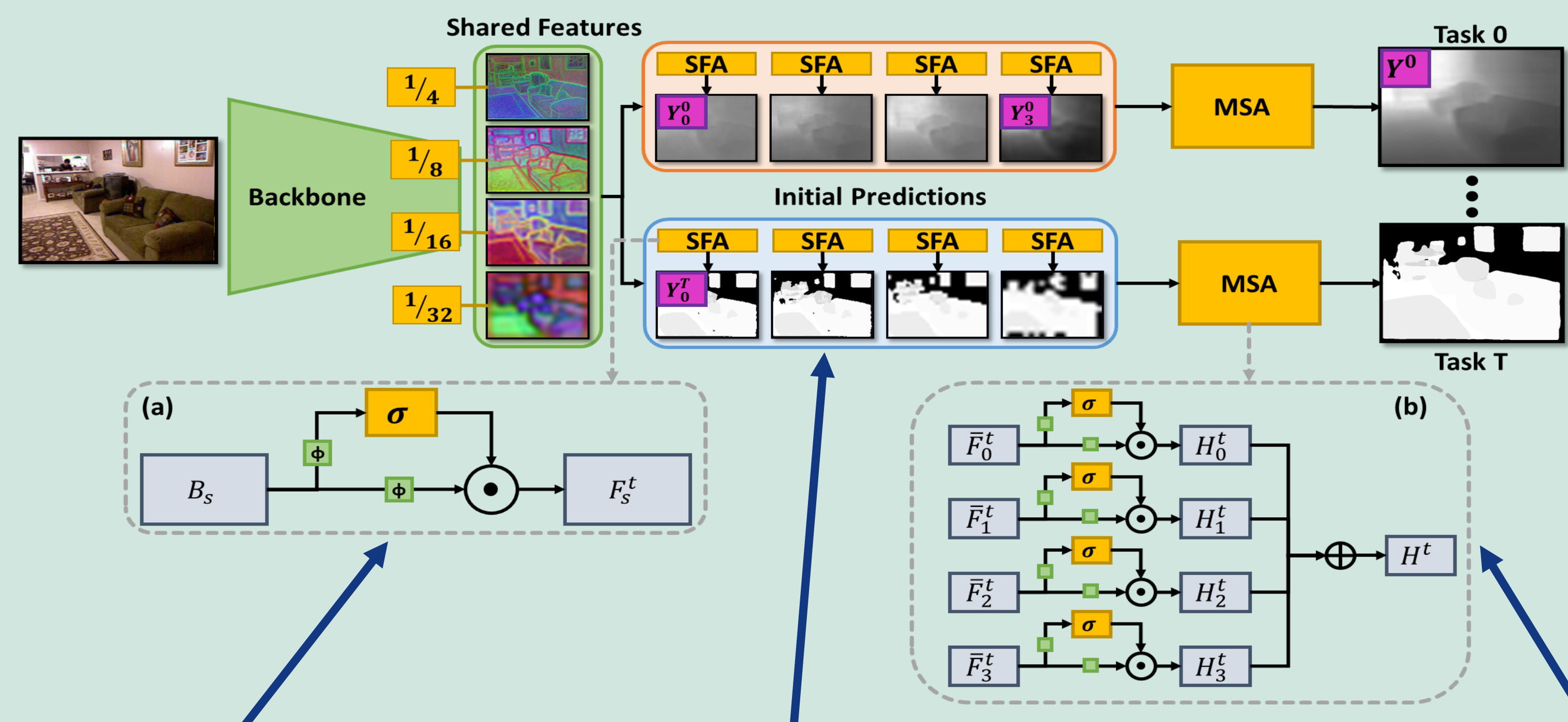
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1. Overview

- We present **Medusa**, an efficient approach to learning **generic features for multitasking**
- Recent multi-task learning (MTL) networks model connections between all pairs of tasks
 - Requires **retraining** when adding tasks... ♦ **Quadratic** complexity...
- Objective should be learning generic features capable of **adapting to tasks** not seen during training
 - ♦ **Universal Feature Learning (UFL)**
- Medusa uses **dual spatial attention** mechanisms
 - ♦ **Improved generalization capabilities!** ♦ **Linear** complexity!



2. Methodology



Shared Feature Attention

- Connects multi-scale shared backbone to each task head
- Backbone** learns **generic features** for all tasks
- Each **task & scale** filters relevant features via **spatial attention**
- Alleviates negative transfer** between unrelated tasks

Multi-scale Initial Predictions

- Each task makes an **initial prediction** at each **backbone scale**
- Guides each scale** to produce useful features for the final task
- Discarded during evaluation** for increased efficiency

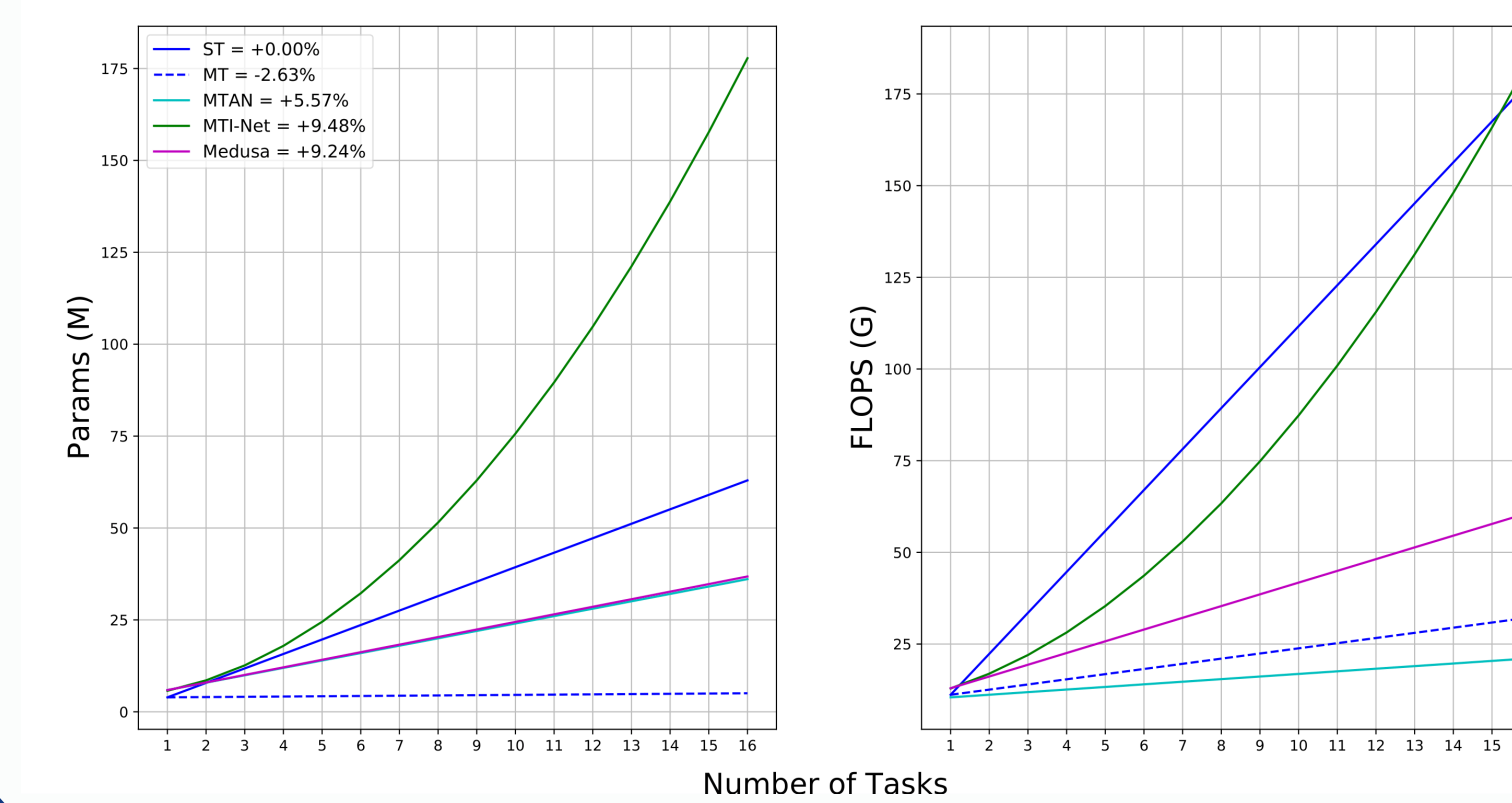
Multi-scale Attention Task Head

- Combines **multi-scale features** from each task prior to making final prediction
- Each scale has **different roles**, trading **global consistency** and **accurate boundaries**
- Spatial attention lets network **learn how to best combine features** from each scale

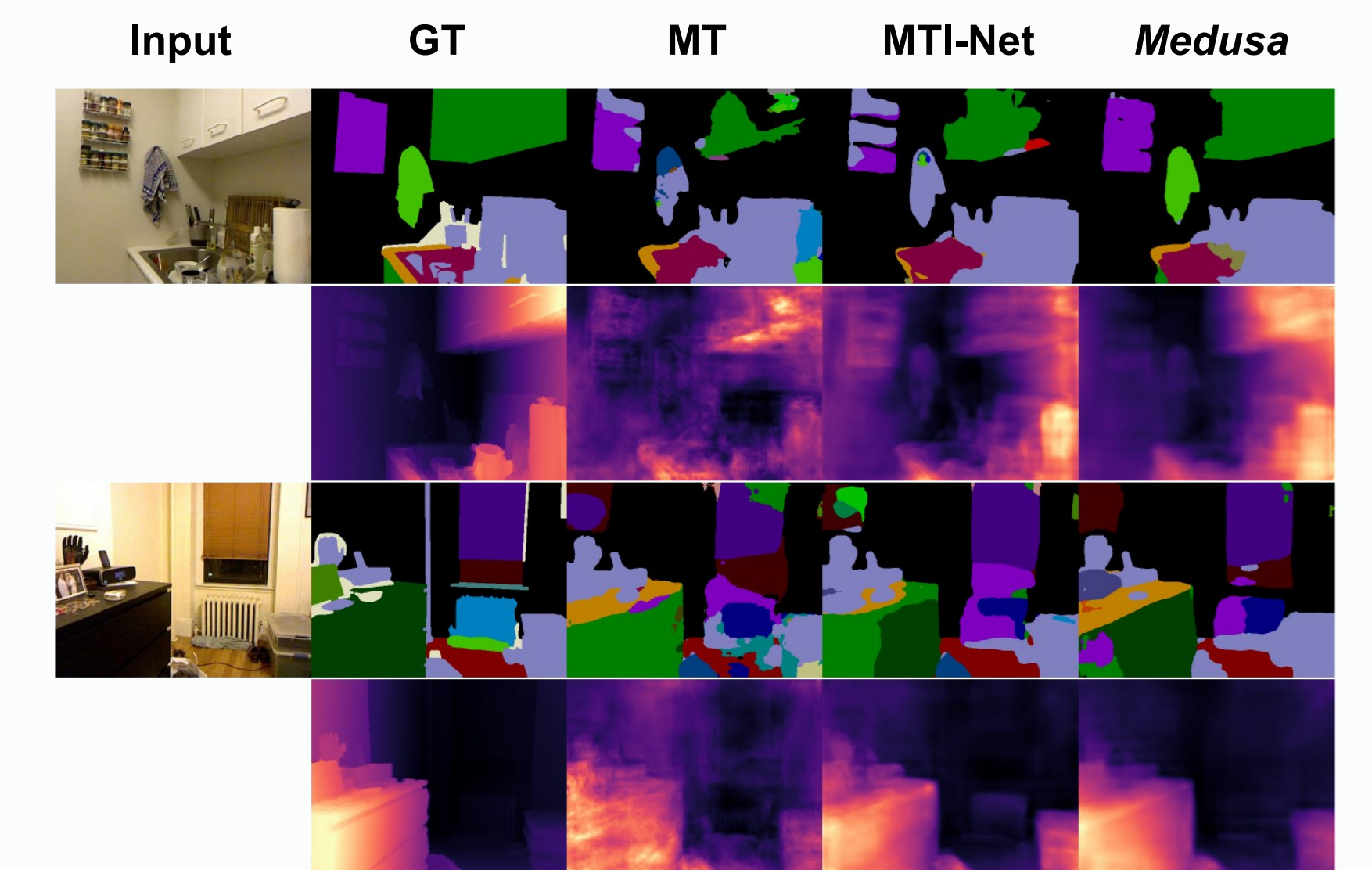
3. Results

Resource Usage

- Independent task heads** results in higher efficiency with **linear scaling**
- Quadratic scaling (MTI-Net) is **less efficient** than training a **separate network for each task**



Visualizations



Multi-task Learning

- Train on NYUD using edges & normal as auxiliary
- $\Delta_m\%$ reports **average performance improvement** across all tasks
- Medusa is comparable to MTI-Net** while being **more efficient**

	Backbone	Head	N+E	Seg \uparrow	Depth \downarrow	$\Delta_m\% \uparrow$
ST Baseline	HRNet-18	HRHead		34.57	0.606	+0.00
MT Baseline	HRNet-18	HRHead		33.21	0.614	-2.63
MTAN [23]	HRNet-18	DeepLab-v3+		35.25	0.581	+3.02
MTAN	HRNet-18	DeepLab-v3+	✓	36.19	0.567	+5.57
PAD-Net [43]	HRNet-18	HRHead		34.39	0.617	-1.23
PAD-Net	HRNet-18	HRHead	✓	35.46	0.604	+1.43
MTI-Net [42]	HRNet-18	HRHead		36.94	0.559	+7.26
MTI-Net	HRNet-18	HRHead	✓	37.40	0.540	+9.48
Medusa (ours)	HRNet-18	MSA (ours)		36.99	0.573	+6.19
Medusa	HRNet-18	MSA	✓	37.48	0.545	+9.24

Universal Feature Learning

- Use **frozen pretrained backbones** from NYUD
- Train **only task heads** on PASCAL
- Medusa's features transfer better** to unseen tasks
- Since backbone is frozen, **previous tasks are not forgotten**

	NYUD-v2			PASCAL-Context		
	Seg \uparrow	Depth \downarrow	$\Delta_m\% \uparrow$	Parts \uparrow	Sal \uparrow	$\Delta_m\% \uparrow$
ST Baseline	34.57	0.606	+0.00	48.73	56.44	+0.00
MT Baseline	33.21	0.614	-2.63	36.13	51.96	-12.93
MTAN [23]	36.19	0.567	+5.57	47.37	57.84	+4.26
MTI-Net [42]	37.40	0.540	+9.48	51.50	60.19	+10.76
Medusa	37.48	0.545	+9.24	52.24	61.91	+13.18

4. Conclusions

- We introduced **Medusa** and showed its effectiveness in both **MTL** and **UFL**
- Focus on **independent task heads**
 - More **efficient** network (parameters & FLOPS)
 - Improved **feature generalization**
- Improve on previous models with independent task heads by introducing **dual attention mechanisms**
 - MTL** performance is **comparable with current SOTA**, while providing **25% parameter reduction** and **linear scaling**
 - UFL** performance improves on **SOTA** due to focus on shared features