Multi-Exit Semantic Segmentation Networks

Alexandros Kouris[1], Stylianos I. Venieris*,[1], Stefanos Laskaridis*,[1], Nicholas D. Lane[1,2]

[1] *Samsung AI Center - Cambridge, UK* [2] *University of Cambridge* **Indicates Equal Contribution*

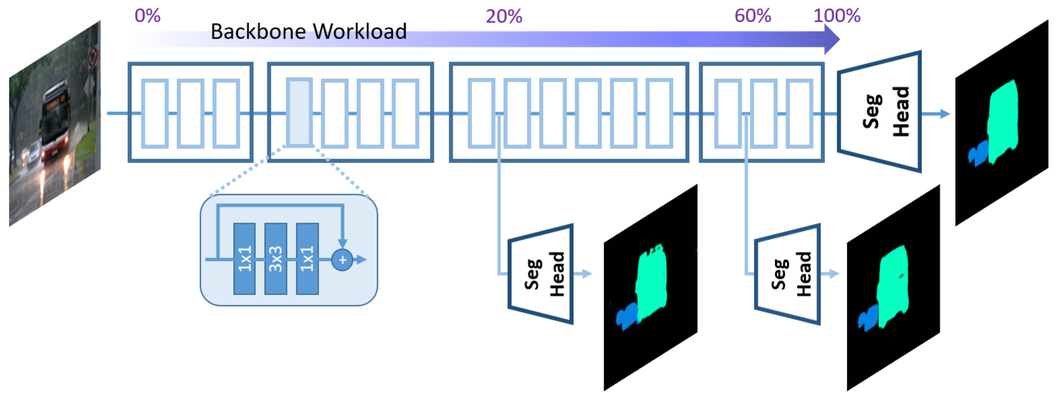
Overview

MESS is a framework that converts segmentation CNNs to multi-exit models:

- Specially trained models that employ parametrised exits along their depth.
- This allows to dynamically save computation during inference on easier samples.
- MESS jointly optimises the number, placement and architecture of early-exits.
- Saves training and maintenance cost by allowing post-training adaptation.

To enable this we also introduce:

- A novel two-stage training scheme for MESS networks, combining exit-aware backbone pre-training, with a selective self-distillation loss for the exits.
- An input-dependent inference pipeline for MESS networks, introducing a novel exit-policy, tailored to dense-output models, such as semantic segmentation.



Key findings

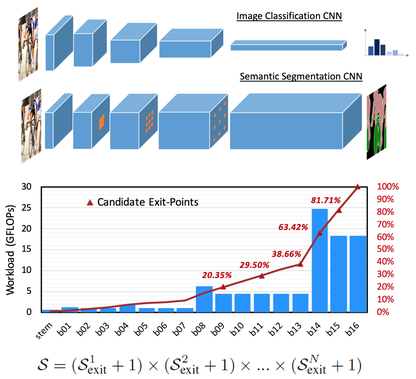
MESS networks are able to achieve: (compared to their respective backbones):

- Up to 2.8x faster inference, with the same accuracy
- Up to 5.3 pp higher accuracy, for the same computation budget

- Better (but comparable) speed-accuracy trade-off than SOTA NAS-crafted models, while being 10x faster to train.
- Up to 3x faster inference than uniform-exit MESS instances (status-quo).
- Gains that translate to realistic latency speed-ups out-of-the-box.
- Remain adaptable post-training via search (<1GPUh).

Candidate Exit-Points

Given a (user-provided) semantic segmentation model, MESS framework measures the workload/latency of each layer to identify N candidate exit-points with approximately equidistant workload distribution.



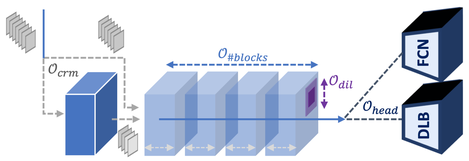
$$\mathcal{S} = (\mathcal{S}^1_{\text{exit}} + 1) \times (\mathcal{S}^2_{\text{exit}} + 1) \times \ldots \times (\mathcal{S}^N_{\text{exit}} + 1)$$

Exit Architecture

Different exit-point (depths) benefit from different architectural configuration of exits. Shallow exits suffer from limited receptive field and weak semantics, whereas deeper ones can introduce significant computational overhead due to large incoming feature volume. Early-exits can incorporate:

1. ***Channel Reduction module:*** reducing the number of channels and this computational overhead.
2. ***Extra Trainable Blocks:*** To remedy weak semantics.
3. ***Rapid Distillation Increase:*** To increase receptive field.
4. ***Segmentation head:*** FCN and DeepLab-based segmentation output layers supported.

$$\mathcal{S}^i_{exit} = \mathcal{O}_{crm} \times \mathcal{O}_{\#blocks} \times \mathcal{O}_{dil} \times \mathcal{O}_{head}$$



MESS Training

MESS networks are trained by a novel 2-stage scheme:
Stage1 - Exit-aware pre-training: trains the backbone in an exit-aware manner, pushing the extraction of semantically strong features to shallow layers, without committing to any exit configuration, or affecting the accuracy of deeper exits:

$$\mathcal{L}^{\text{batch}(j)}_{\text{pretrain}} = \sum_{i=1}^{N-1} \mathbb{1}(j \bmod i = 0) \cdot \mathcal{L}_{\text{CE}}(\boldsymbol{y}_i, \hat{\boldsymbol{y}}) + \mathcal{L}_{\text{CE}}(\boldsymbol{y}_N, \hat{\boldsymbol{y}})$$

Stage2 – Frozen backbone KD: Trains all candidate exit configurations, without any interference with the backbone (or between them). Allows massive parallelism during training, and easy interchange of exits upon deployment. Backed by a novel self-distillation scheme that filters the information propagating from the final exit to the earlier ones (allowing only "easy" pixels through).

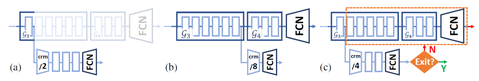
$$\mathcal{L}_{\text{PFD}} = \sum_{i=1}^{N} \alpha \cdot \mathbb{1}(\hat{\boldsymbol{y}}_N = \hat{\boldsymbol{y}}) \mathcal{L}_{\text{CE}}(\boldsymbol{y}_i, \hat{\boldsymbol{y}}) + (1 - \alpha) \cdot \mathcal{L}_{\text{KL}}(\boldsymbol{y}_i, \boldsymbol{y}_N)$$

Search and Deployment

Upon deployment, MESS support different settings:
(a) Budgeted Inference: static workload-lighter sub-models (up to an exit) are extracted and deployed.
(b) Anytime Inference: every sample goes through several exits sequentially, providing an early actionable result while progressively refining its prediction.
(c) Input-Dependent Inference: similar to anytime, but each sample dynamically finalises its output at a different depth, based on a difficulty-aware exit policy.

MESS instances can be optimised to:

- Minimise cost, given an accuracy constraint:
$$s^\star = \arg\min_{s \in \mathcal{S}} \{\text{cost}(s) \mid \text{acc}(s) \geq th_{\text{acc}}\}$$
- Maximise accuracy, given a cost constraint:
$$s^\star = \arg\max_{s \in \mathcal{S}} \{\text{acc}(s) \mid \text{cost}(s) \leq th_{\text{cost}}\}$$



Exit-Policy

We establish a mechanism to capture segmentation confidence on a *per-image* granularity, reducing the *per-pixel* confidence values provided with the model prediction. Our metric considers the percentage of pixels with high prediction confidence (above a tunable threshold) in the dense output (instead of naïve avg.).

$$c^{\text{img}}_i = \frac{1}{RC} \sum_{r=1}^{R} \sum_{c=1}^{C} \mathbb{1}(\boldsymbol{c}^{\text{map}}_{r,c}(\boldsymbol{y}_i) \geq th^{\text{pix}}_i)$$

It is observed that predictions in pixel along the semantic boundaries of each object are naturally under confident. Thus we introduce a mechanism to down-weight the contribution of these pixels to the final result.

$$\mathcal{M} = \text{erode}(\text{cannyEdge}(\hat{\boldsymbol{y}}_i), s_i)$$

$$\widehat{\boldsymbol{c}^{\text{map}}_{r,c}}(y_i) = \begin{cases} \text{median}(\boldsymbol{c}^{\text{map}}_{w_r, w_c}(\boldsymbol{y}_i)) & \text{if } \mathcal{M}_{r,c} = 1 \\ \boldsymbol{c}^{\text{map}}_{r,c}(\boldsymbol{y}_i) & \text{otherwise} \end{cases}$$

At runtime, a per-exit tunable threshold is used to evaluate whether each sample should exit-early or continuer to the next (deeper) exit: $c^{\text{img}}_i \geq th^{\text{img}}_i$

Results

MESS End-to-End Evaluation

Method		Backbone*	Head	Search Targets		Results: MS COCO			Results: PASCAL VOC		
				Error	GFLOPs	mIoU	GFLOPs	Latency†	mIoU	GFLOPs	Latency†
DRN [68]	(i)	ResNet50	FCN	–Baseline–		59.02%	138.63	39.96ms	72.23%	138.63	39.93ms
Ours	(ii)	ResNet50	FCN	min	$\leq 1\times$	64.35%	113.65	37.53ms	79.09%	113.65	37.59ms
Ours	(iii)	ResNet50	FCN	$\leq 0.1\%$	min	58.91%	41.17	17.92ms	72.16%	44.81	18.63ms
Ours	(iv)	ResNet50	FCN	$\leq 1\%$	min	58.12%	34.53	15.11ms	71.29%	38.51	16.80ms
DLBV3 [6]	(v)	ResNet50	DLB	–Baseline–		64.94%	163.86	59.05ms	80.32%	163.86	59.06ms
Ours	(vi)	ResNet50	DLB	min	$\leq 1\times$	65.52%	124.10	43.29ms	82.32%	124.11	43.30ms
Ours	(vii)	ResNet50	DLB	$\leq 0.1\%$	min	64.86%	69.84	24.81ms	80.21%	65.29	24.14ms
Ours	(viii)	ResNet50	DLB	$\leq 1\%$	min	64.03%	57.01	20.83ms	79.30%	50.29	20.11ms
segMBNetV2 [50]	(ix)	MobileNetV2	FCN	–Baseline–		54.24%	8.78	67.04ms	69.68%	8.78	67.06ms
Ours	(x)	MobileNetV2	FCN	min	$\leq 1\times$	57.49%	8.10	56.05ms	74.22%	8.10	56.09ms
Ours	(xi)	MobileNetV2	FCN	$\leq 0.1\%$	min	54.18%	4.05	40.97ms	69.61%	3.92	32.79ms
Ours	(xii)	MobileNetV2	FCN	$\leq 1\%$	min	53.24%	3.48	38.83ms	68.80%	3.60	31.40ms

*Dilated network [68] based on backbone CNN. †Measured on: GTX for ResNet50 and AGX for MobileNetV2 backbone.

MESS Training Evaluation

stage 1:

Method	Init.	Loss	$\mathcal{E}_1$	$\mathcal{E}_2$	$\mathcal{E}_3$	$\mathcal{E}_4$	$\mathcal{E}_5$	$\mathcal{E}_6$
(i) Baseline Init.	ImageNet	$\mathcal{L}_{\text{CE}}(\mathcal{E}_6)$	-	-	-	-	-	59.02%
(ii) **E2E** [21,53]	ImageNet	$\mathcal{L}_{\text{CE}}(\mathcal{E}_1) + ... + \mathcal{L}_{\text{CE}}(\mathcal{E}_6)$	29.02%	40.67%	48.64%	51.69%	55.34%	58.33%
(iii) Exit-aware Init.	ImageNet	Eq. (2) **(Ours)**	28.21%	39.61%	47.13%	50.81%	56.11%	**59.90%**
(iv) **Frozen** [25,28]	(i)	$\mathcal{L}_{\text{CE}}(\mathcal{E}_1), ..., \mathcal{L}_{\text{CE}}(\mathcal{E}_5)$	23.94%	31.50%	38.24%	44.73%	54.32%	59.02%
(v) **Ours (§4.3)**	(iii)	$\mathcal{L}_{\text{CE}}(\mathcal{E}_1), ..., \mathcal{L}_{\text{CE}}(\mathcal{E}_5)$	**32.40%**	**43.34%**	**50.81%**	**53.73%**	**57.9%**	**59.90%**

* Experiments repeated 3 times. The sample stdev in mean IoU is at most ± 0.09 in all cases.

stage 2:

Method	Loss	DRN-50			MobileNetV2		
		$\mathcal{E}_1$	$\mathcal{E}_2$	$\mathcal{E}_3$	$\mathcal{E}_1$	$\mathcal{E}_2$	$\mathcal{E}_3$
E2E [21,53]	CE	49.96%	55.40%	58.96%	31.56%	41.57%	51.59%
KD [19]	KD	50.33%	55.67%	59.08%	31.04%	41.93%	51.66%
SelfDistill [73,48,72]	CE+KD	50.66%	55.91%	58.84%	32.08%	41.96%	51.58%
Ours (§4.3)	PFD	**51.02%**	**56.21%**	**59.36%**	**33.36%**	**42.95%**	**52.20%**

CE=Cross-entropy, KD=Knowledge Distillation, PFD=Positive Filtering Distillation