Searching for BurgerFormer with Micro-Meso-Macro Space Design

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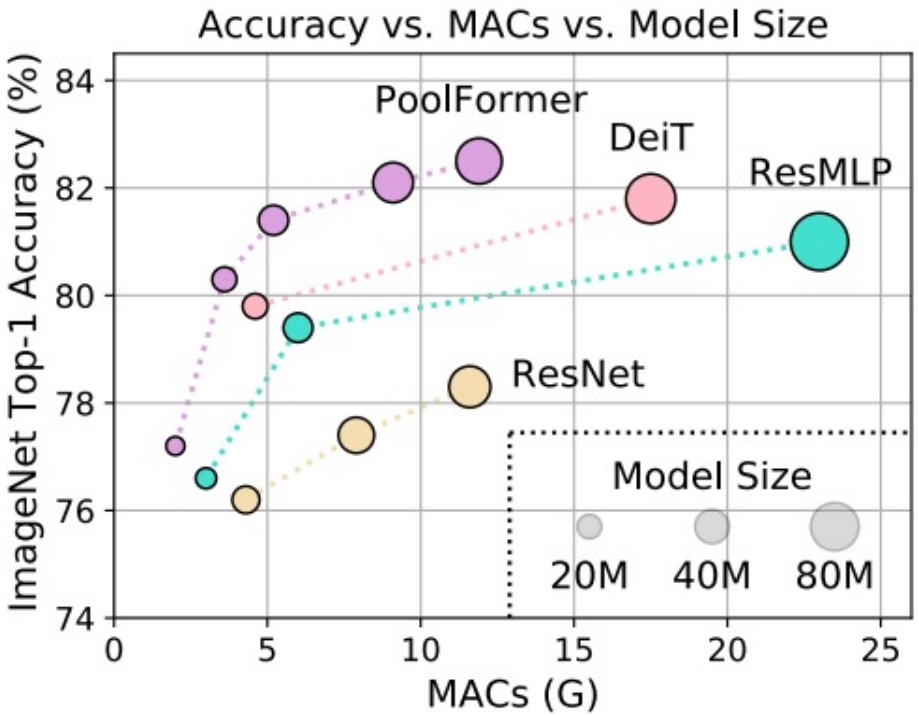
Motivation

Hot Vision Transformers

Simple Pooling can achieve impressive performance

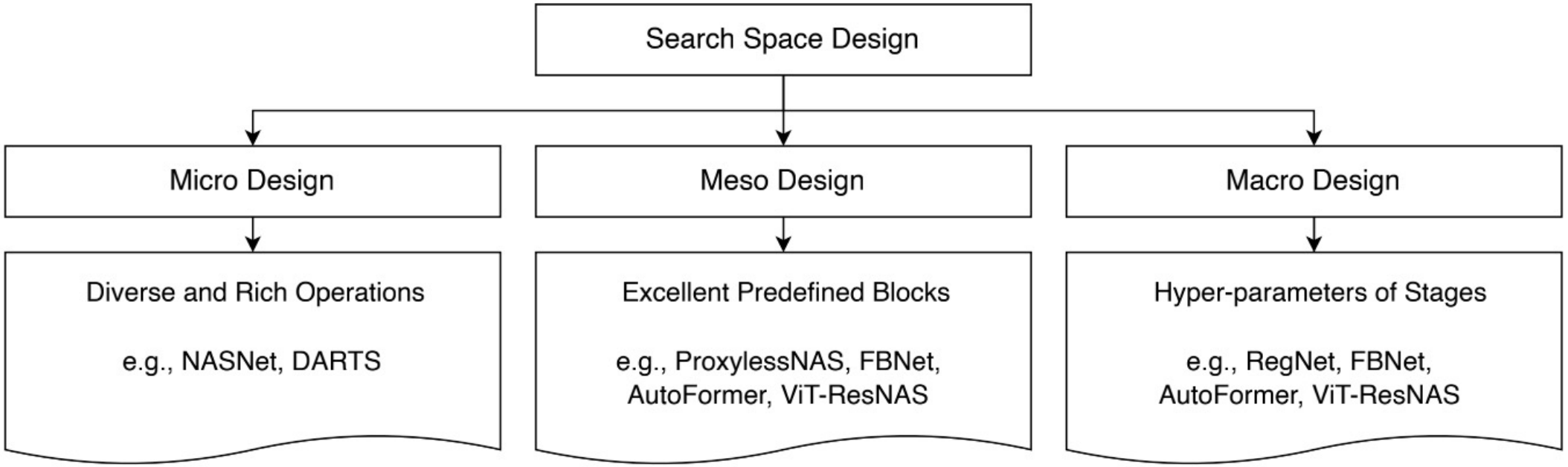


Transformers + Neural Architecture Search

How to design a generic search space to search high-performance Transformer-like architectures ?

[1] Yu, W., Luo, M., Zhou, P., Si, C., Zhou, Y., Wang, X., Feng, J., and Yan, S. MetaFormer is Actually What You Need for Vision. CVPR 2022 Oral.

Typical Search Space Design



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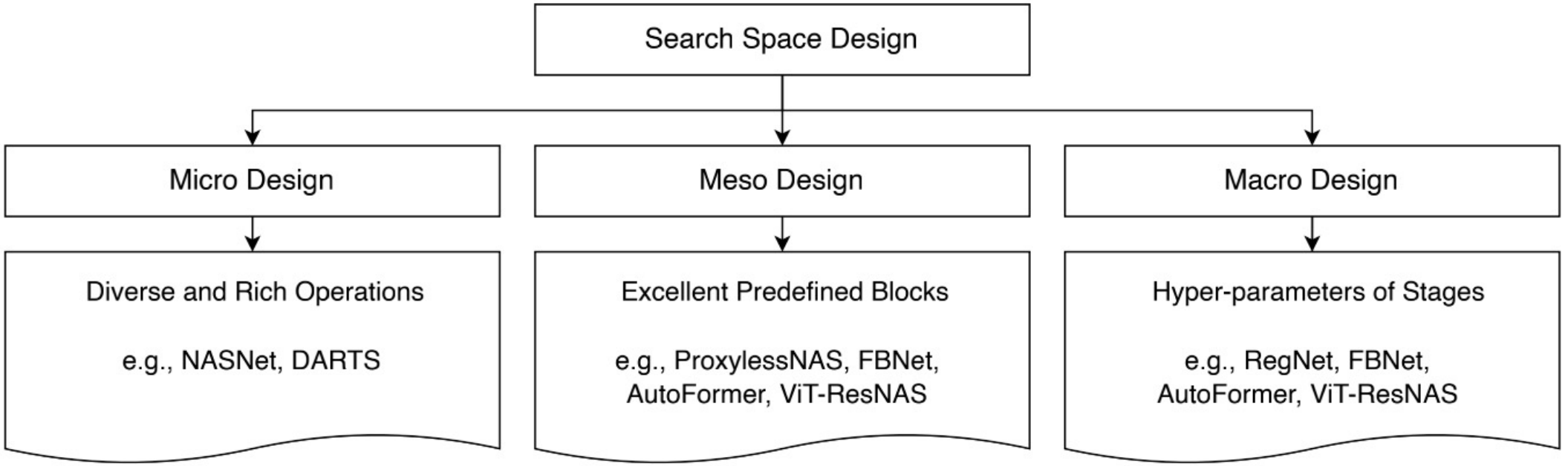

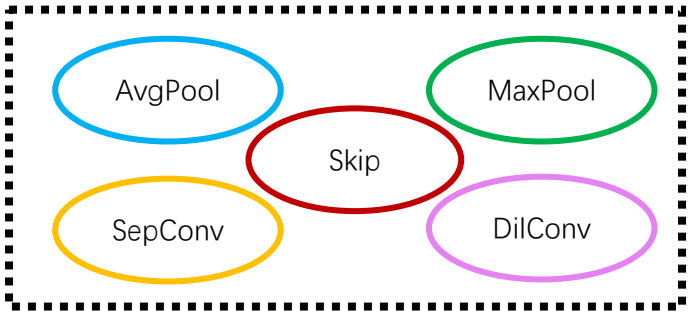

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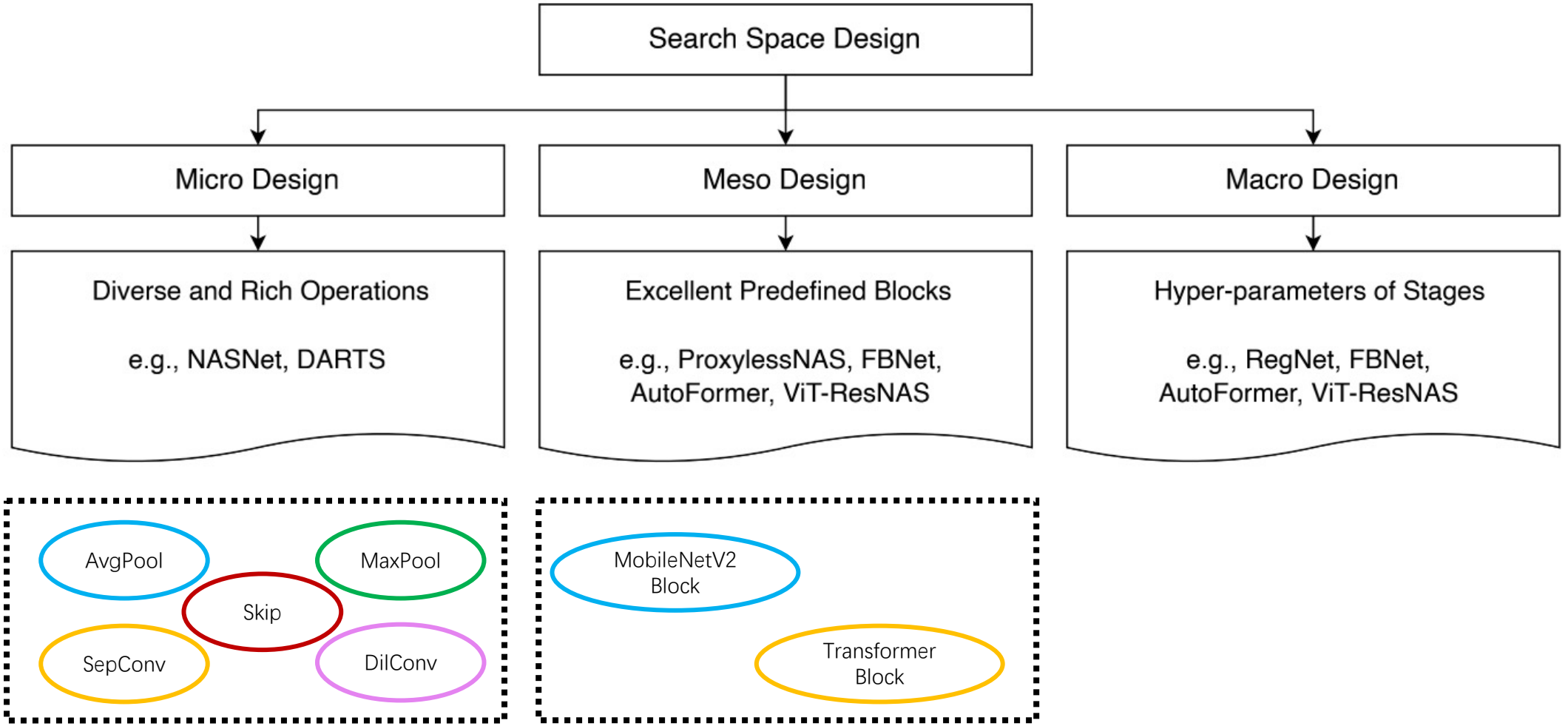

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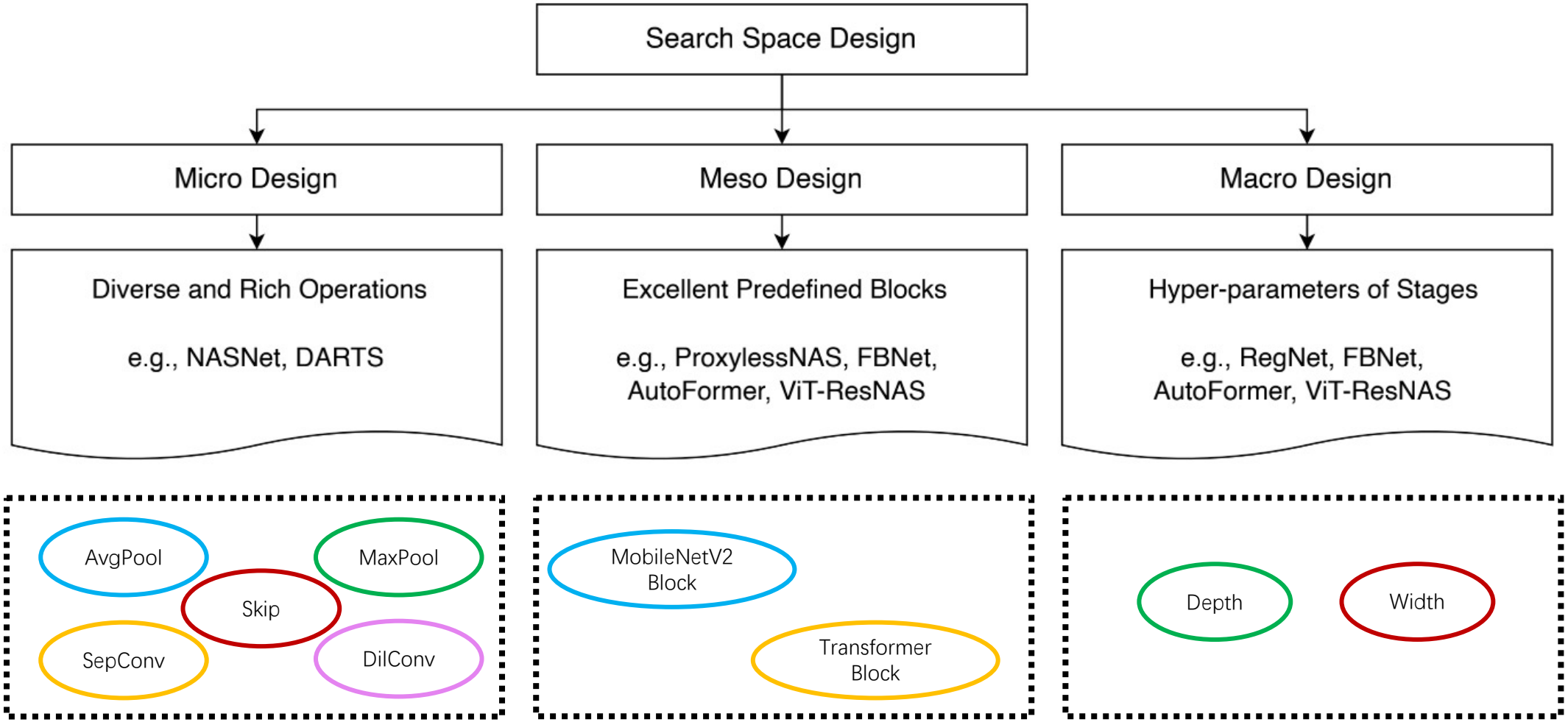

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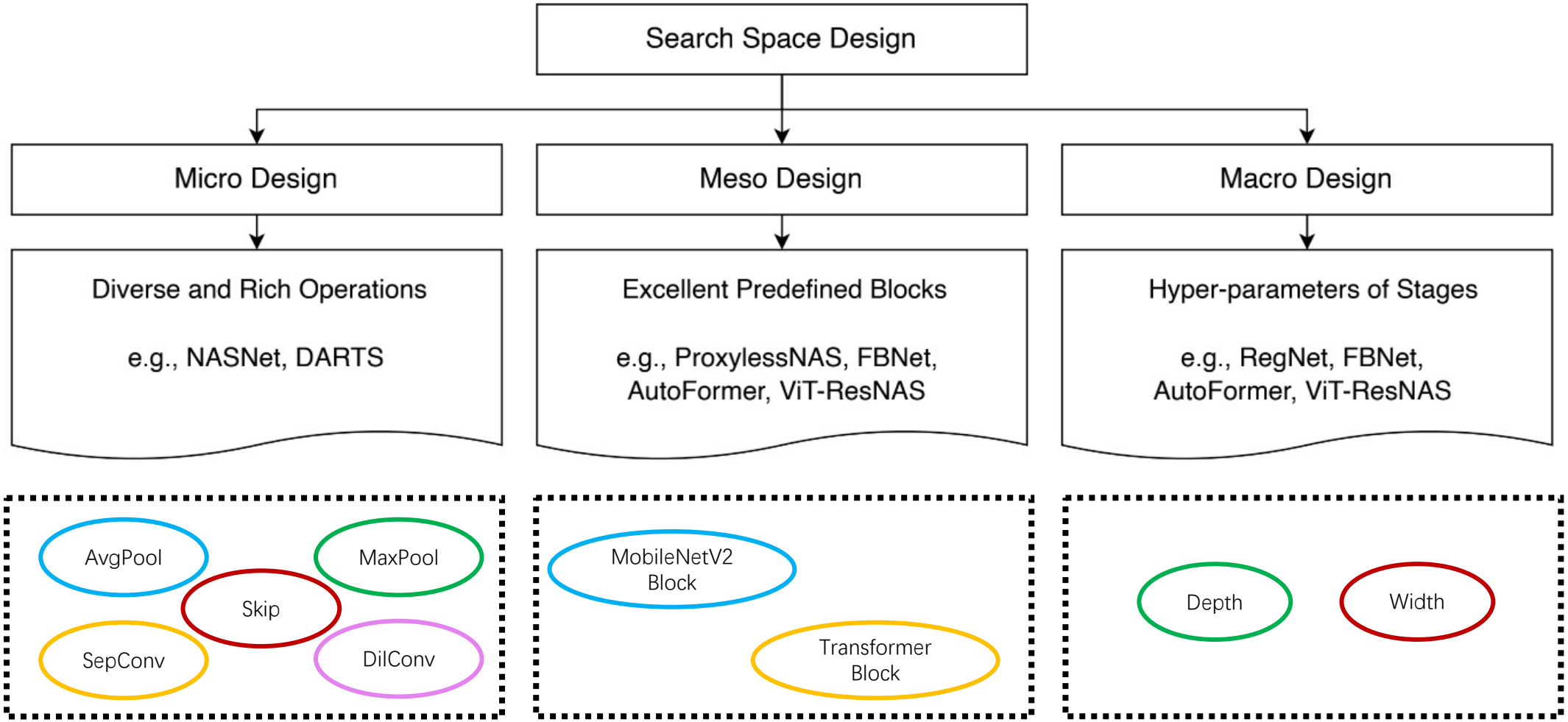
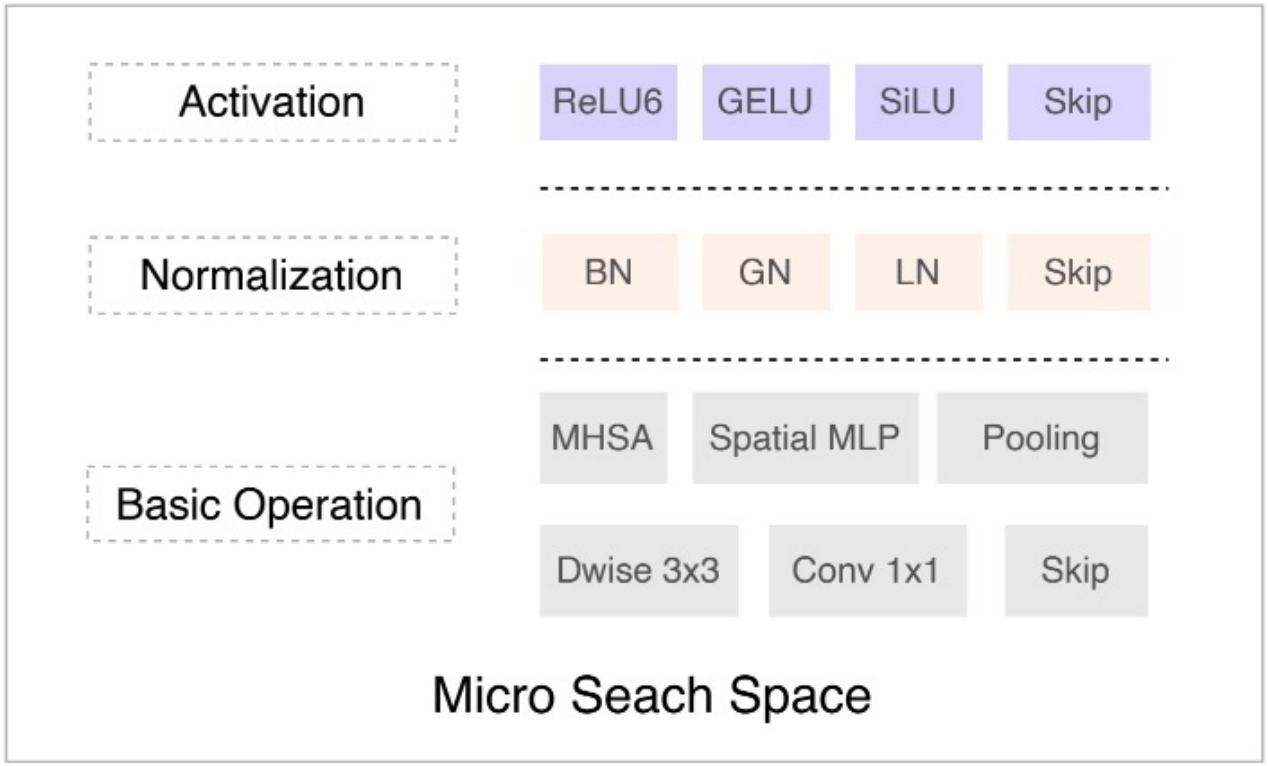


Transformers NAS: Lacking a Search Space Constructed from Three Granularities

Contributions

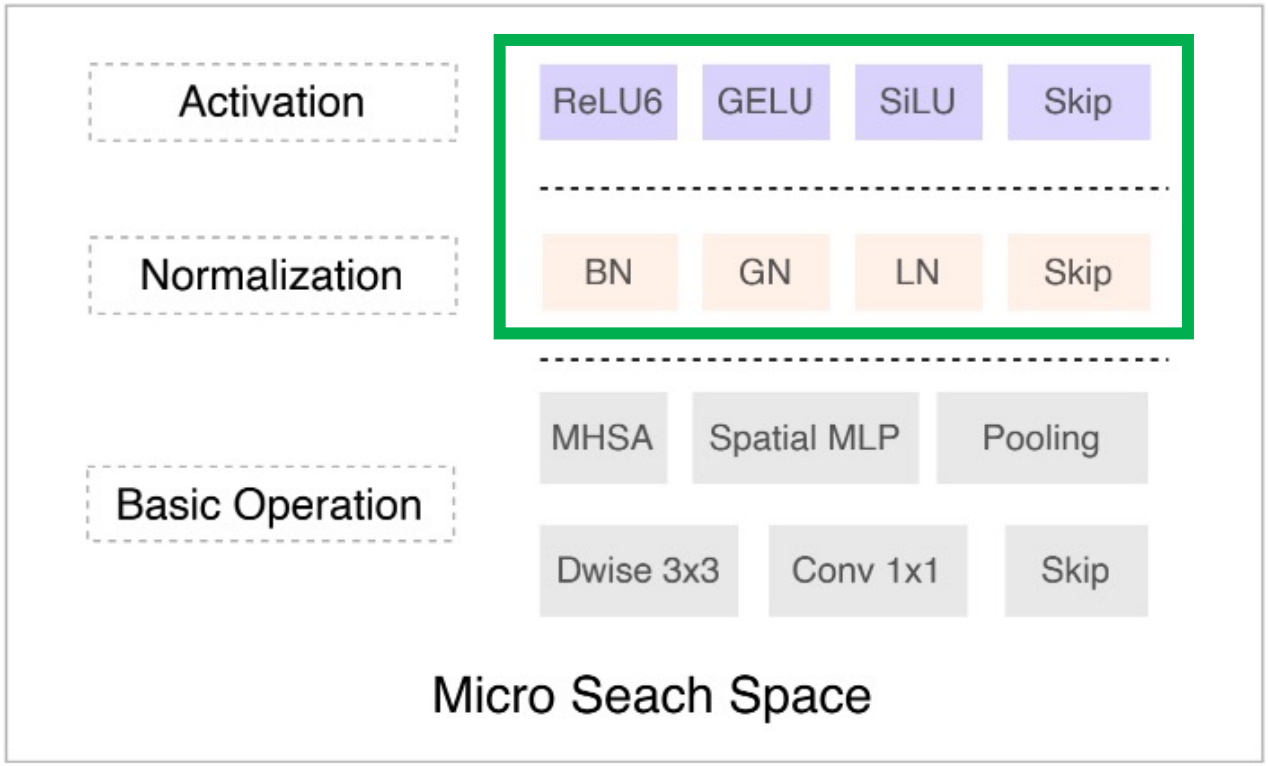
- A Micro-Meso-Macro Search Space for Transformer-Like Architectures
- A Hybrid Sampling Method for Effective One-Shot NAS
- Good Experiment Results on ImageNet and COCO Datasets

Micro Search Space



- Transformers and CNN employ different activation and normalization.
- Following Transformer-like architectures, MHSA, Spatial MLP, and Pooling are searched.
- We extend Dwise 3x3, Conv 1x1 for more locality.

Micro Search Space



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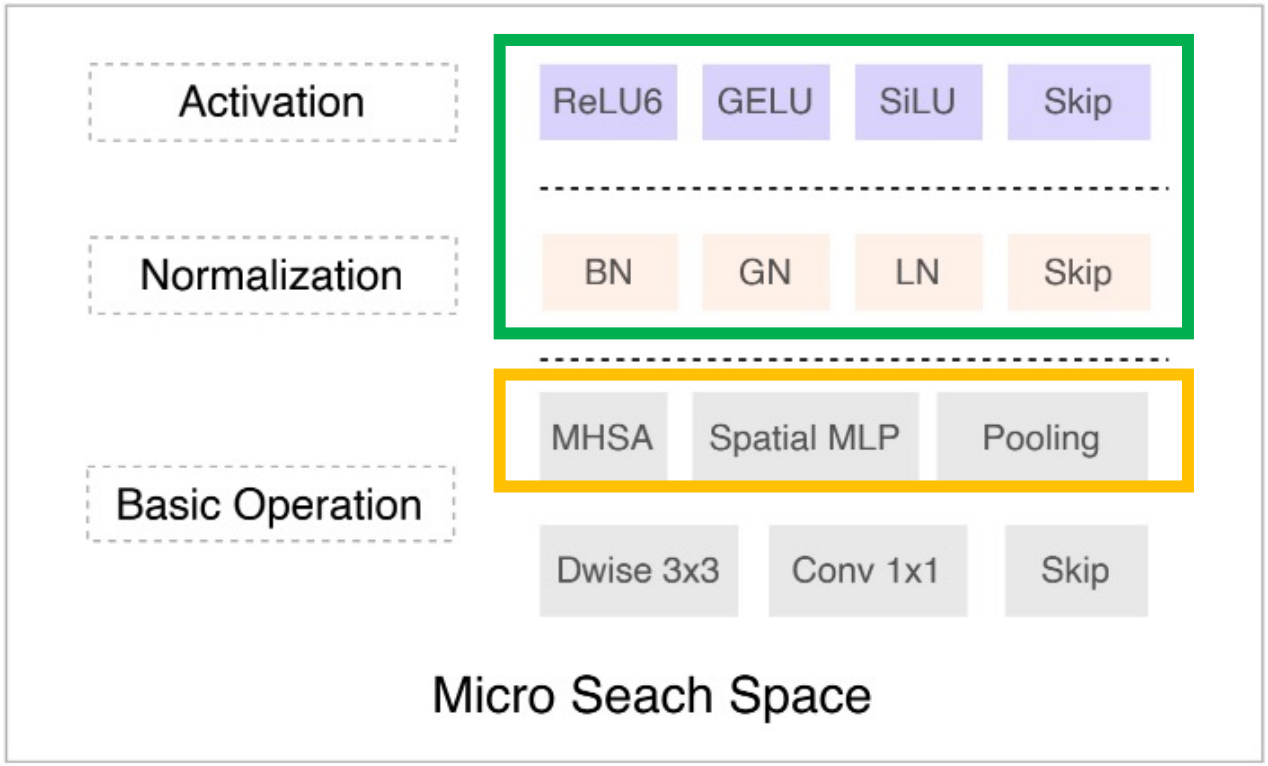

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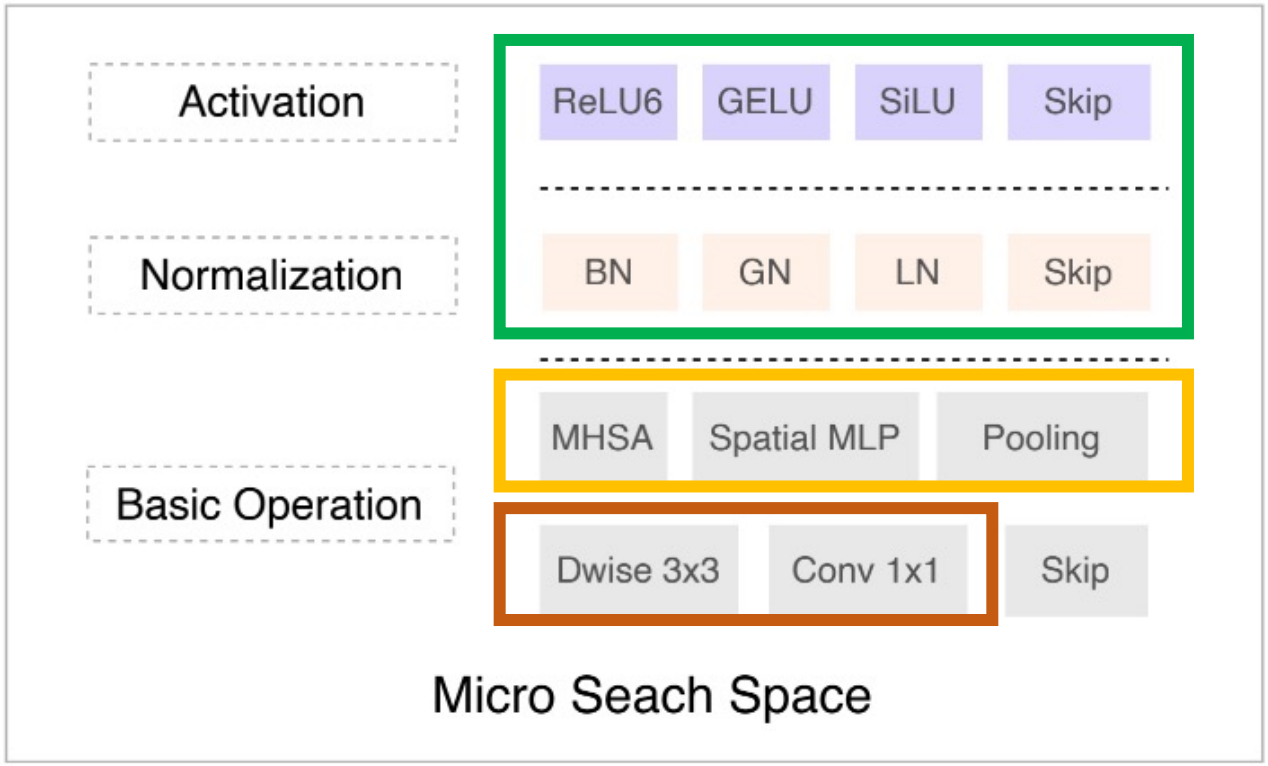

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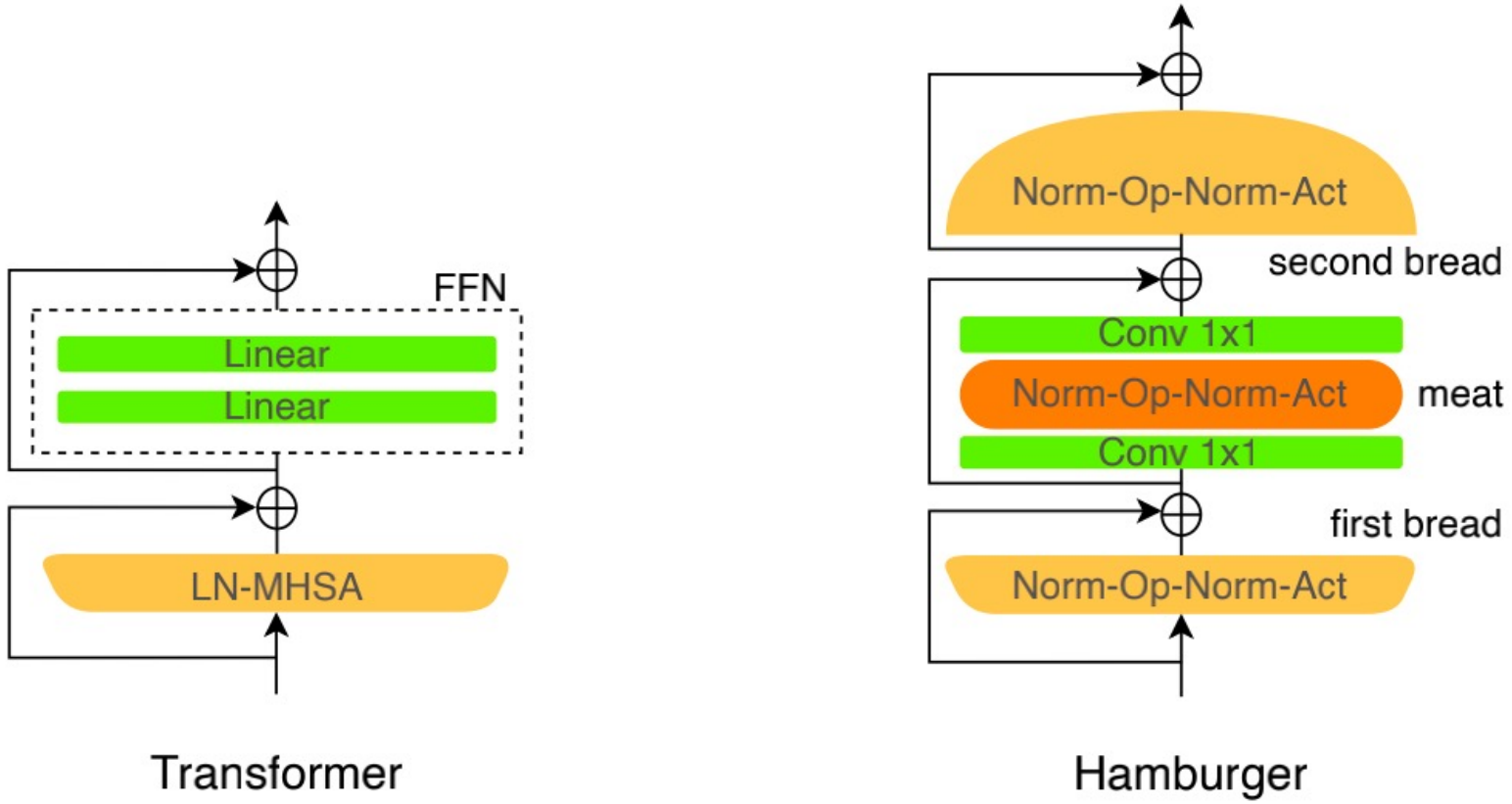
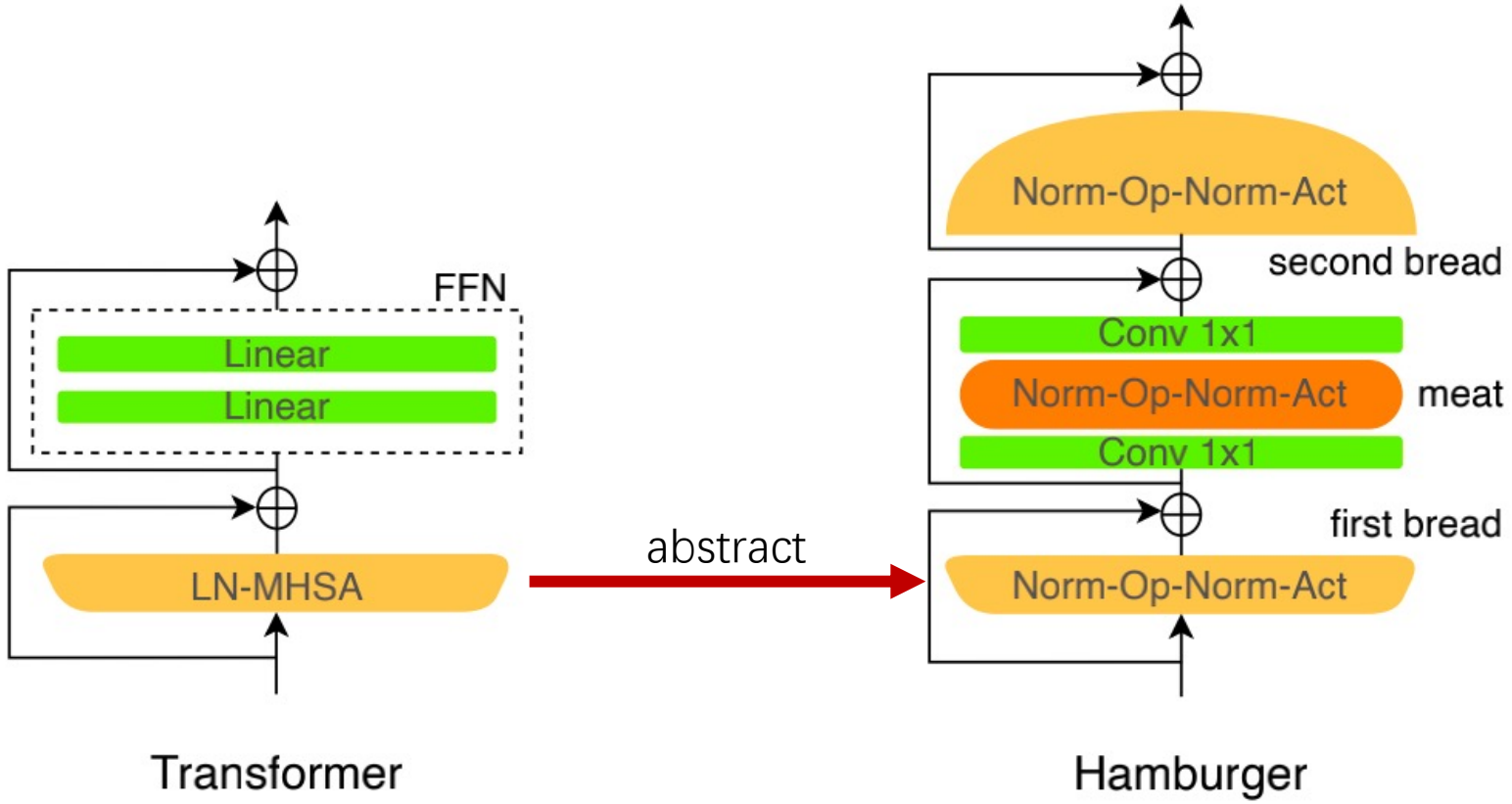
Meso Search Space



- Abstract the combination of LN and MHSA as a Norm-Op-Norm-Act Structure.
- Split FFN into two Conv 1x1 for keeping inverse bottleneck structures.
- Symmetrical design for more diverse meso blocks.

Meso Search Space



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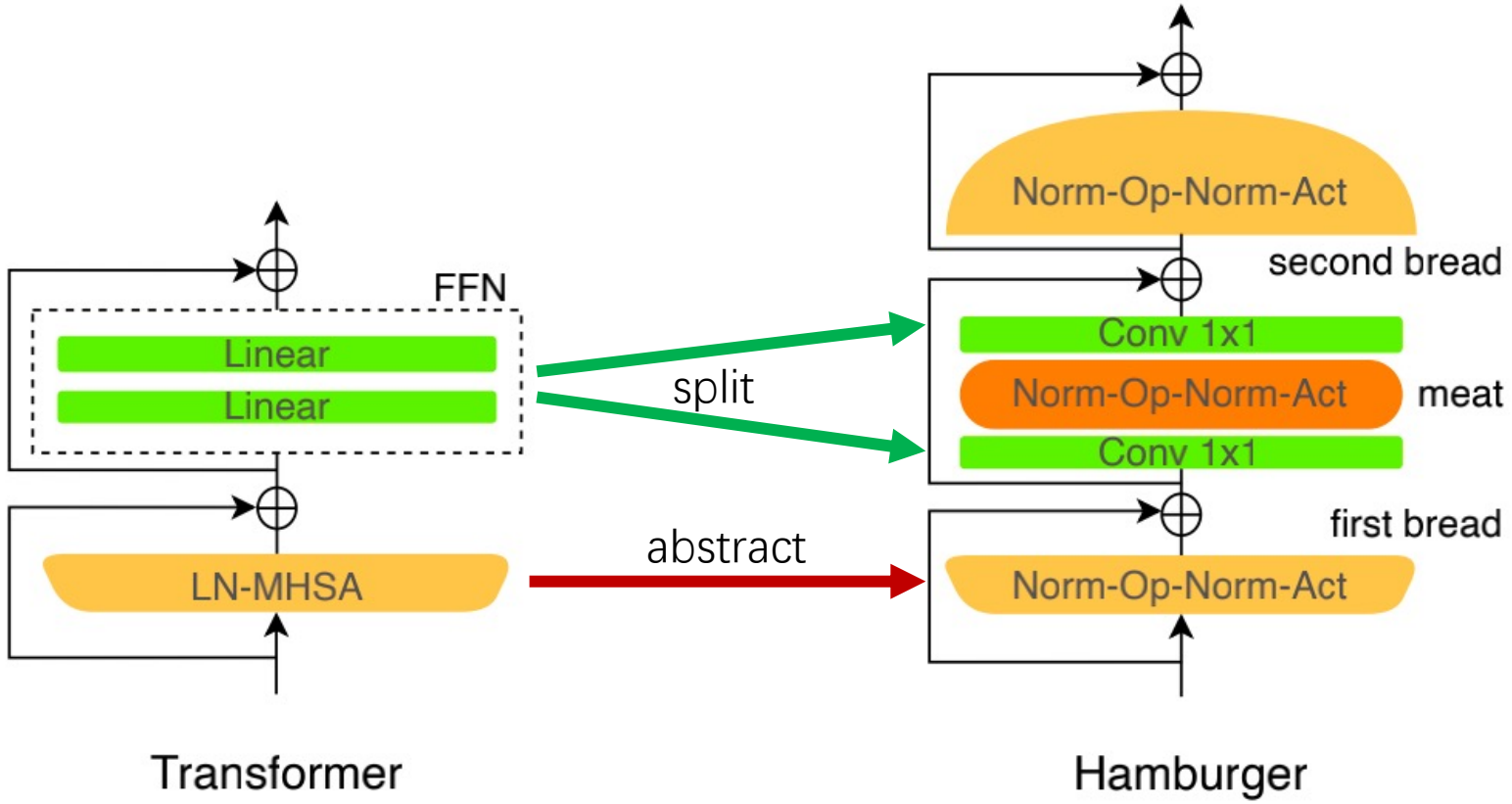

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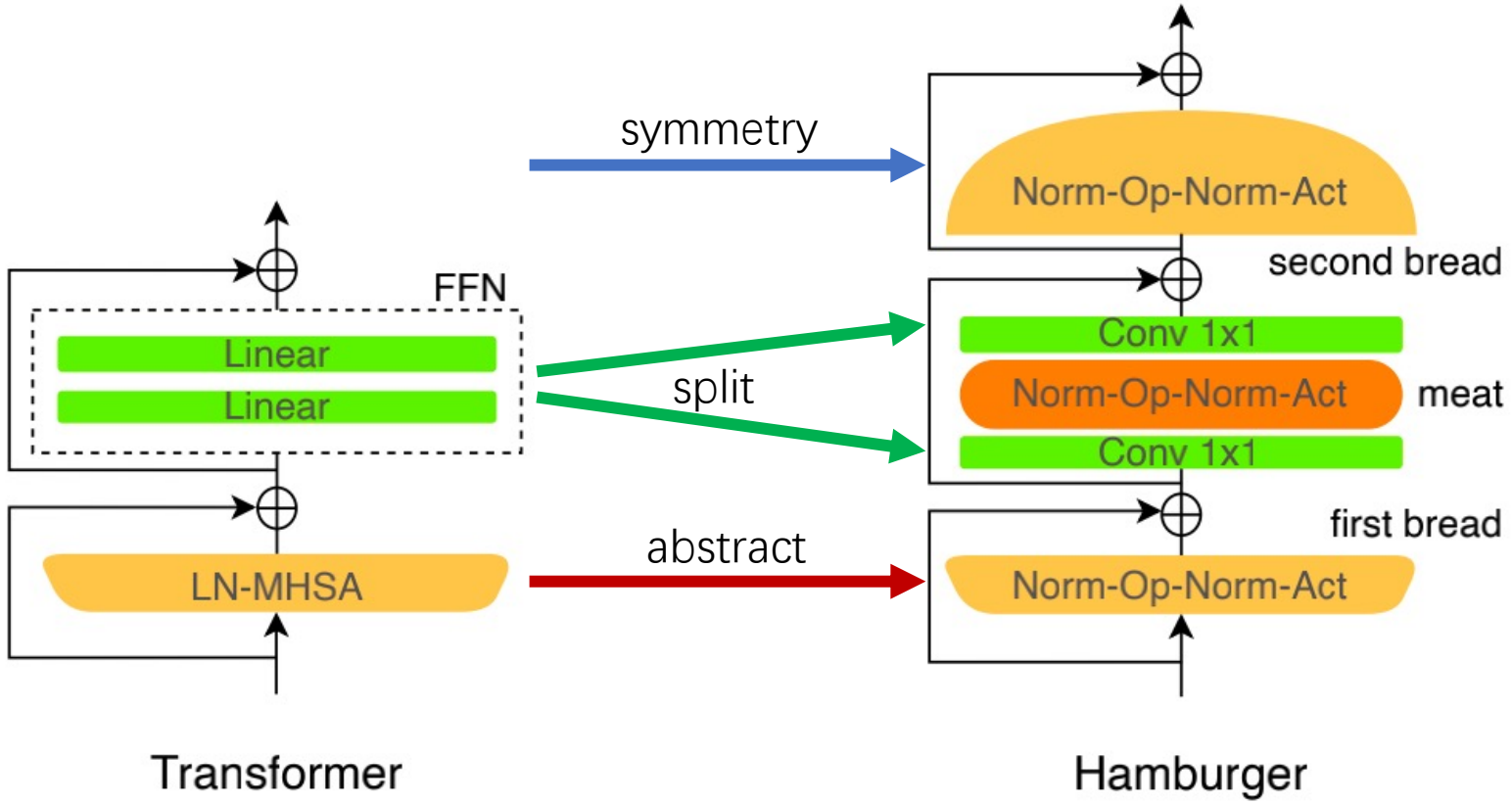

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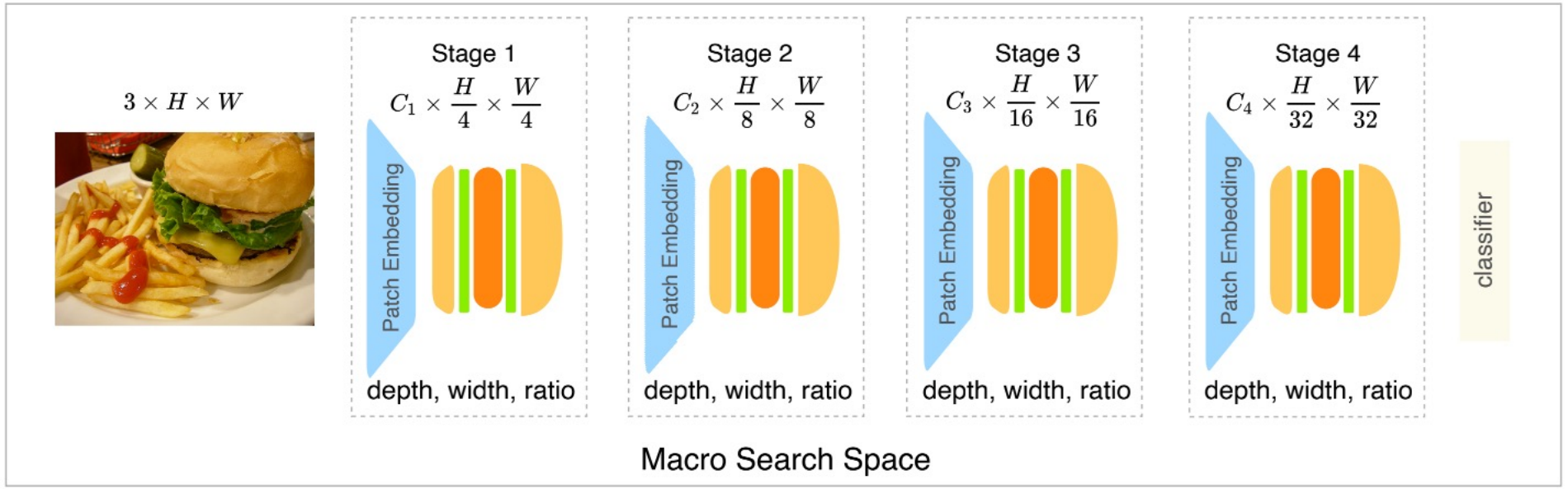
Macro Search Space



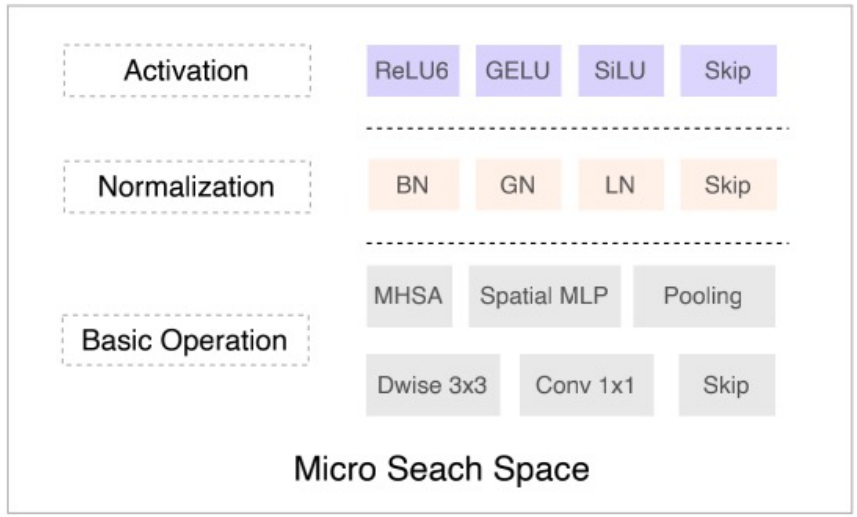
- Multi-Stage Architecture
- Search for Depth, Width, Ratio

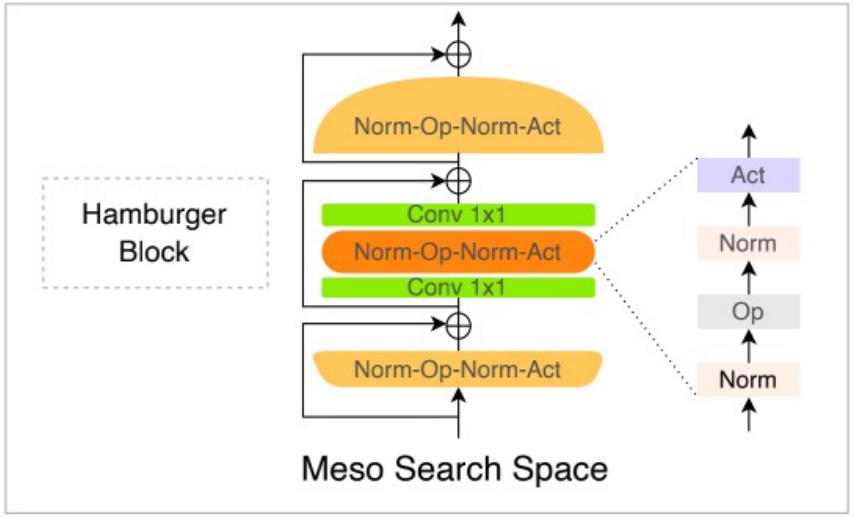
Stage	Depth	Width	Ratio
1	$\{1, 2, 3, 4\}$	$\{32, 64, 96\}$	$\{1, 2, 4, 6\}$
2	$\{1, 2, 3, 4\}$	$\{64, 96, 128\}$	$\{1, 2, 4, 6\}$
3	$\{1, 2, 3, 4, 5, 6, 7, 8\}$	$\{128, 192, 256, 320\}$	$\{1, 2, 4, 6\}$
4	$\{1, 2, 3, 4\}$	$\{128, 256, 384, 512\}$	$\{1, 2, 4, 6\}$

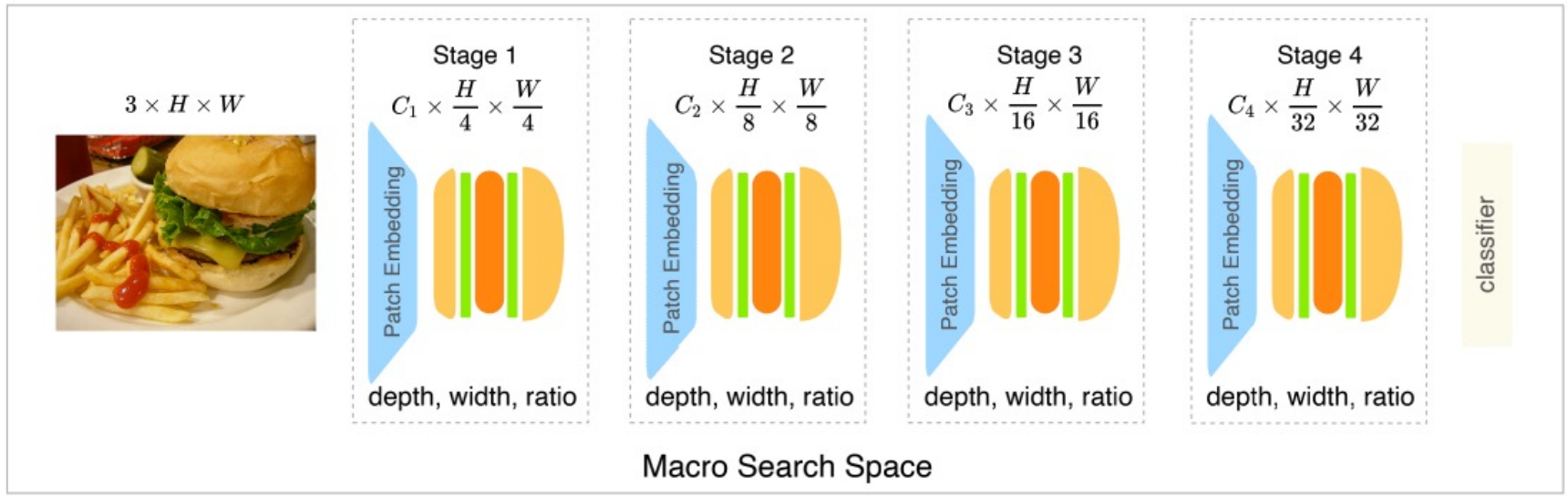
[2] Wang, W., Xie, E., Li, X., Fan, D.-P., Song, K., Liang, D., Lu, T., Luo, P., and Shao, L. Pyramid vision transformer: A versatile backbone for dense prediction without convolutions. ICCV 2021 Oral.

[3] Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., Lin, S., and Guo, B. Swin transformer: Hierarchical vision transformer using shifted windows. ICCV 2021 Best Paper.

Micro-Meso-Macro Search Space







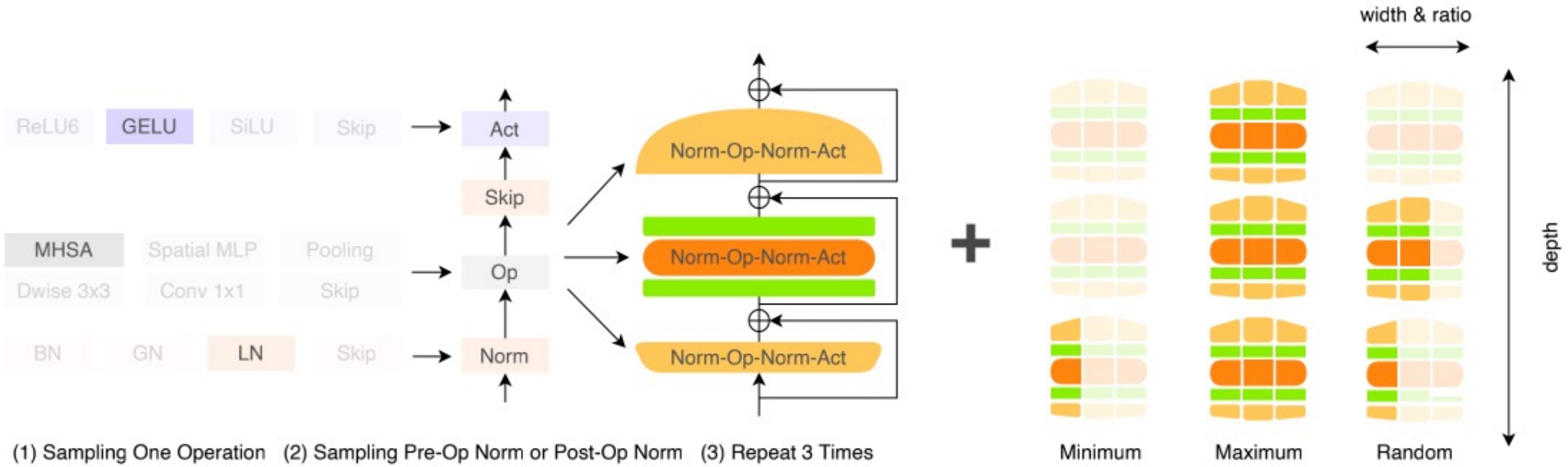
Size: 4.5×10^{28} FLOPs: $0.2G \sim 7.4G$ Parameters: $0.5M \sim 41.6M$

One-Shot NAS & Hybrid Sampling

One-Shot NAS:

$$W_A^* = \arg\min_A L_{train}(N(A, W)),$$
$$\alpha^* = \arg\max_{a \in A} Acc_{val}(N(\alpha, W^*)),$$
$$s.t.\ Resource(N(\alpha, W_{\alpha^*})) \leq C,$$

Hybrid Sampling:



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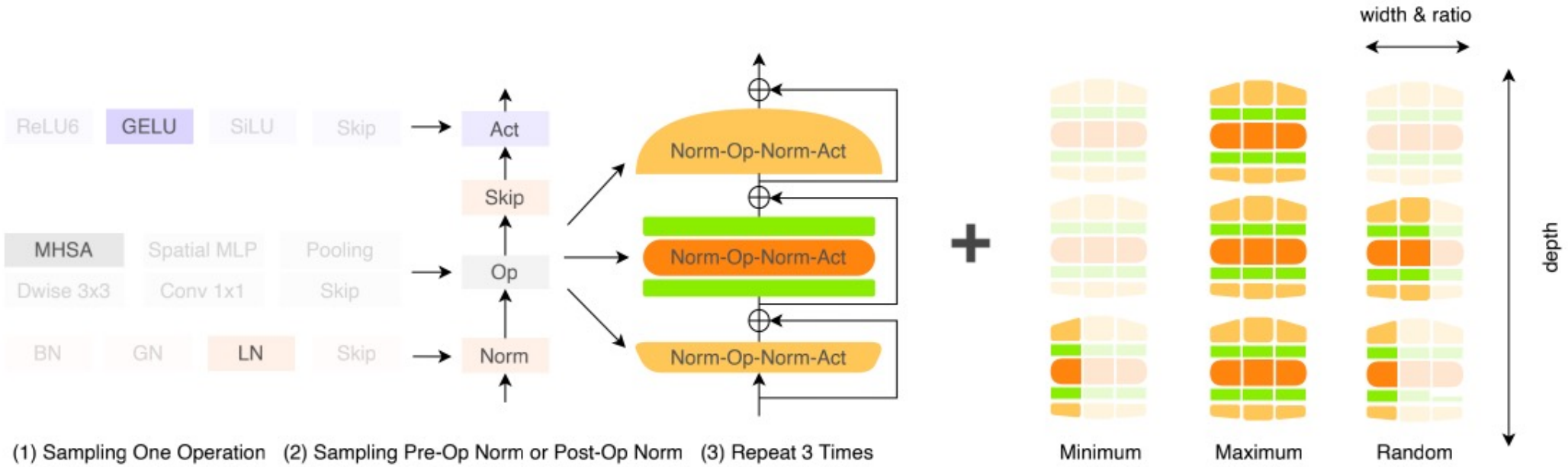
Methods	FLOPs (G)	Top-1 acc. (%)
Random Search	1.0	75.6
SPOS	1.0	77.0
Sandwich	1.0	77.5
Hybrid Sampling	1.0	78.0

Hybrid Sampling:



ImageNet Results

Model	Params. (M)	FLOPs (G)	Top-1 acc. (%)	Top-5 acc. (%)	Design Type
DeiT-Ti (Touvron et al., 2021b)	6	1.3	72.2	91.1	Manual
TNT-Ti (Han et al., 2021)	6	1.4	73.9	-	Manual
CeiT-T (Yuan et al., 2021)	6	1.2	76.4	-	Manual
AutoFormer-tiny (Chen et al., 2021b)	6	1.3	74.7	92.6	Auto
GLiT-Tiny (Chen et al., 2021a)	7	1.4	76.3	91.1	Auto
ViTAS-DeiT-A (Su et al., 2021)	7	1.4	75.6	92.5	Auto
BurgerFormer-Tiny	10	1.0	78.0	93.7	Auto
ConVi-Ti+ (d'Ascoli et al., 2021)	10	2.0	76.7	93.6	Manual
PVT-Tiny (Wang et al., 2021)	13	1.9	75.1	-	Manual
PoolFormer-S12 (Yu et al., 2022)	12	2.0	77.2		Manual
BurgerFormer-Small	14	2.1	80.4	95.0	Auto
Deit-S (Touvron et al., 2021b)	22	4.7	79.9	-	Manual
Swin-T (Liu et al., 2021)	29	4.5	81.3	-	Manual
CvT-13 (Haiping et al., 2021)	20	4.5	81.6	-	Manual
TNT-S (Han et al., 2021)	24	5.2	81.5	95.7	Manual
PVT-Small (Wang et al., 2021)	25	3.8	79.8	-	Manual
ViL-Small (Pengchuan et al., 2021)	25	4.9	82.0	-	Manual
ResMLP-S12 (Touvron et al., 2021a)	31	6.0	79.4	-	Manual
Twins-PCPVT-S (Xiangxiang et al., 2021)	24	3.8	81.2	-	Manual
PoolFormer-S36 (Yu et al., 2022)	31	5.2	81.4	-	Manual
RegNetY-4G (Ilija et al., 2020)	21	4.0	80.0	-	Auto
AutoFormer-small (Chen et al., 2021b)	23	5.1	81.7	-	Auto
GLiT-Small (Chen et al., 2021a)	25	4.4	80.5	-	Auto
ViTAS-DeiT-B (Su et al., 2021)	23	4.9	80.2	95.1	Auto
S3-T (Minghao et al., 2021)	28	4.7	82.1	95.8	Auto
ViT-ResNAS-Medium (Liao et al., 2021)	97	4.5	82.4	-	Auto
BurgerFormer-Base	26	3.9	82.7	96.2	Auto
Swin-S (Liu et al., 2021)	50	8.7	83.0	-	Manual
Twins-PCPVT-B (Xiangxiang et al., 2021)	44	6.4	82.7	-	Manual
CvT-21 (Haiping et al., 2021)	32	7.1	82.5	-	Manual
BoTNet-S1-59 (A. et al., 2021)	34	7.3	81.7	-	Manual
RegNetY-8G (Ilija et al., 2020)	39	8.0	81.7	-	Auto
BossNet-T1 (Changlin et al., 2021)	-	7.9	82.2	95.8	Auto
BurgerFormer-Large	36	6.5	83.0	96.8	Auto

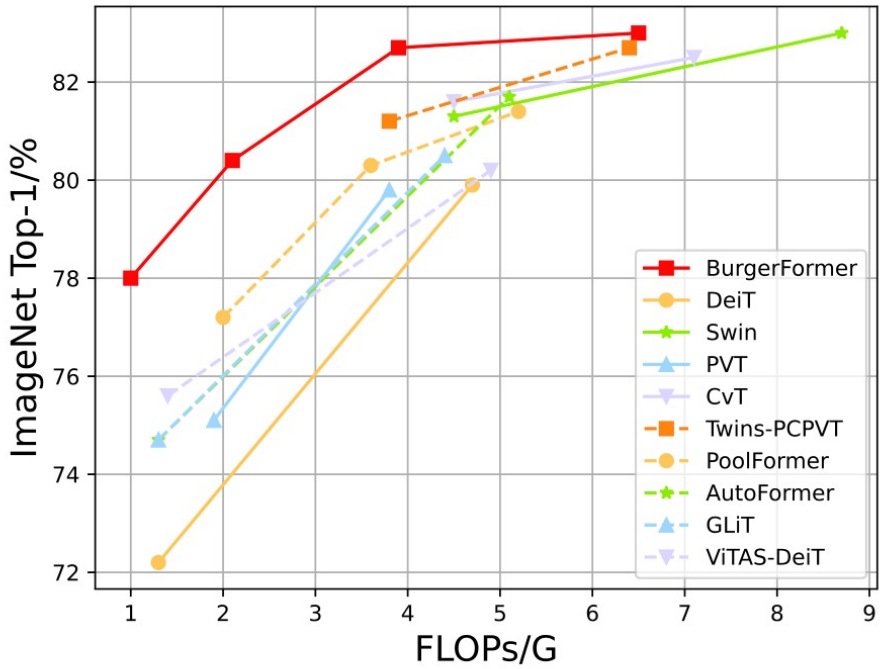


Figure 5. Comparison between BurgerFormer and efficient vision transformers, in terms of ImageNet Top-1 over FLOPs.

COCO Results

BackBone	RetinaNet 1x						
	Param. (M)	AP^b	AP^b_{50}	AP^b_{75}	AP_S	AP_M	AP_L
ResNet50 (He et al., 2016)	37.7	36.3	55.3	38.6	19.3	40.0	48.8
PVT-Small (Wang et al., 2021)	34.2	40.4	61.3	43.0	25.0	42.9	55.7
PoolFormer-S24 (Yu et al., 2022)	31.1	38.9	59.7	41.3	23.3	42.1	51.8
BurgerFormer-Base	35.9	41.2	61.3	43.9	24.2	44.4	55.4
BackBone	**Mask R-CNN 1x**						
	Param. (M)	AP^b	AP^b_{50}	AP^b_{75}	AP^M	AP^M_{50}	AP^M_{75}
ResNet50 (He et al., 2016)	44.2	38.0	58.6	41.4	34.4	55.1	36.7
PVT-Small (Wang et al., 2021)	44.1	40.4	62.9	43.8	37.8	60.1	40.3
PoolFormer-S24 (Yu et al., 2022)	41.0	40.1	62.2	43.4	37.0	59.1	36.9
Swin-T (Liu et al., 2021)	48.0	43.7	66.6	47.7	39.8	63.3	42.7
BurgerFormer-Base	45.9	44.0	65.6	48.1	40.2	62.7	43.4

Table 3. Comparison with state-of-the-art models on COCO.

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Thank You!

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