# Automated Neural Network Acceleration on Edge:
## from Convolutional Networks to Transformers


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**Research Areas:**
AI： Deep learning acceleration, AutoML, Computer Vision, NLP
Distributed Systems: Federated Learning, Edge and Cloud computing, Parallel Computing Systems
Data Mining: graph mining and reasoning, GNNs

**PhD students （11）**
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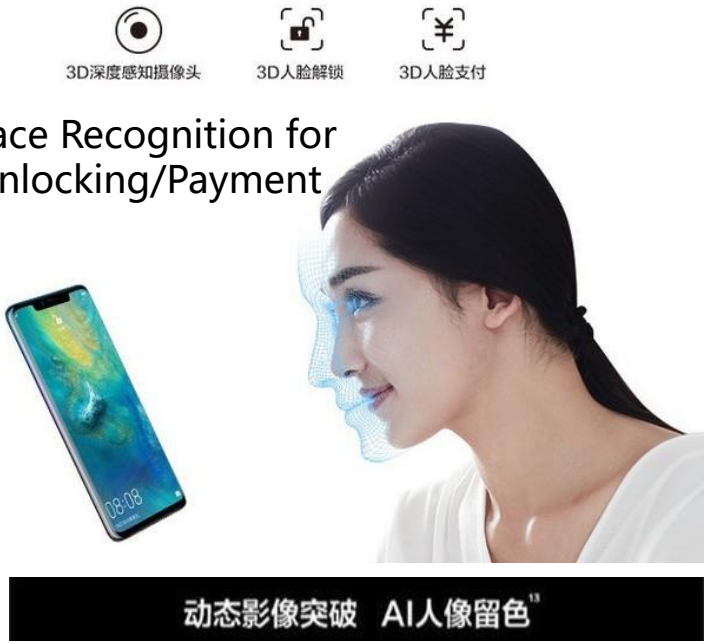
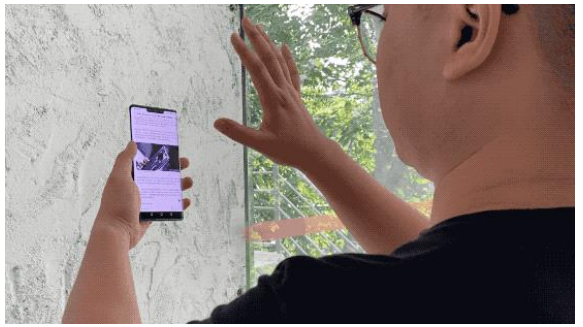
# DNNs are widely used in AI Applications on various Edge Devices


Semantic Segmentation
Photo Credit: Ambarella AI Vision Processor for edge applications




Face Recognition for Unlocking/Payment

Gesture Control



Assistant with Bard

Magic Editor

Video Boost


Best Take

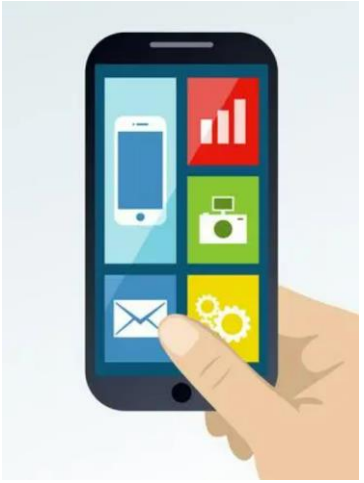
**DNN is most widely used on edge devices, including Phones, Cameras, Cars, etc.**

# Generative AI has changed Cellphone Usage

**SmartPhone -> Mobile Internet**

## Smart Phone

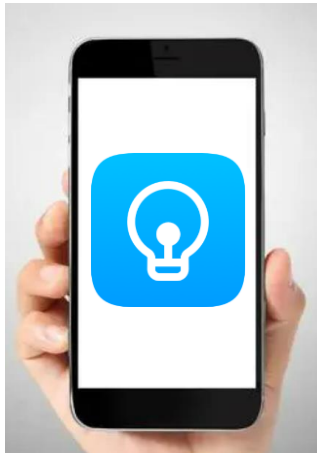
- 5hours per day
- Content acquisition
  - Short video/Long video
  - News / Search
  - Listening to music
- Shoppers
- Social Networking
- Games



**Generative AI -> a New Era**

## AI Phone

- >5hours per day
- Understanding:
  - Dealing with unstructured data
  - Diversified interaction modes
  - Natural language instead of programming language
- Generation:
  - Expert level beyond ordinary humans
- Reasoning: self-learning



Bard

文心一言

通义千问 阿里巴巴

Stable Diffusion

Midjourney

Tencent 腾讯

文心一格 AI艺术和创意辅助平台

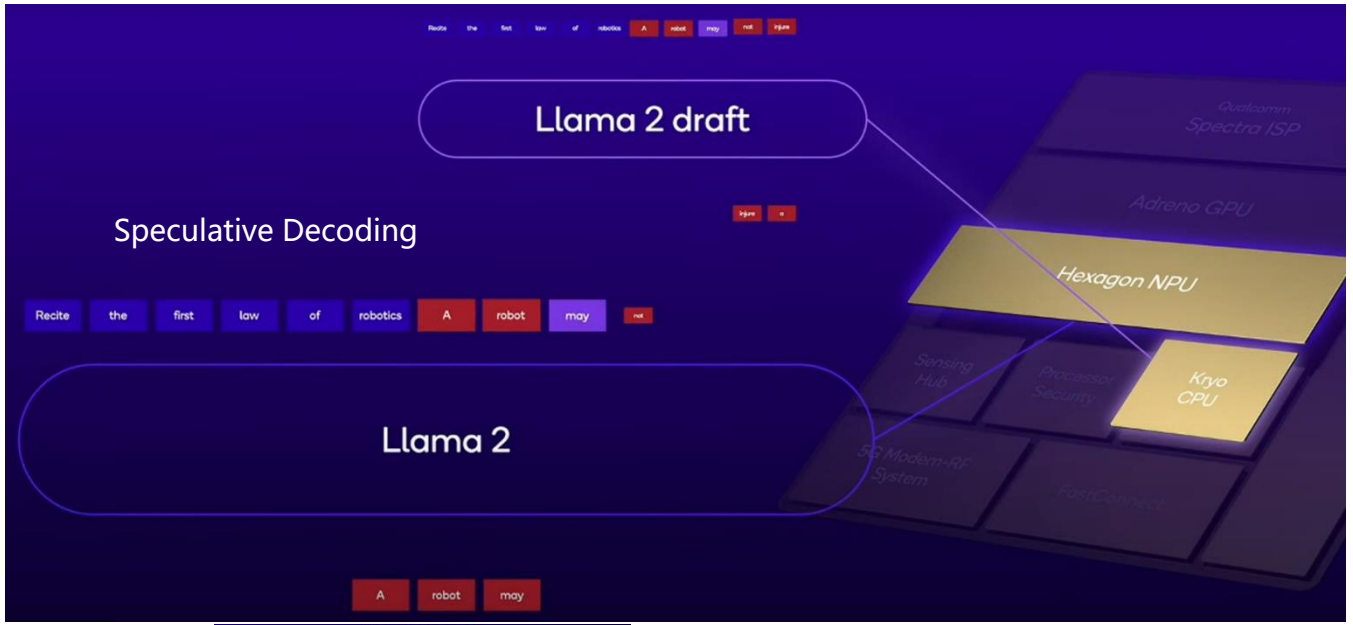
**Search → Push → GenAI → ?**

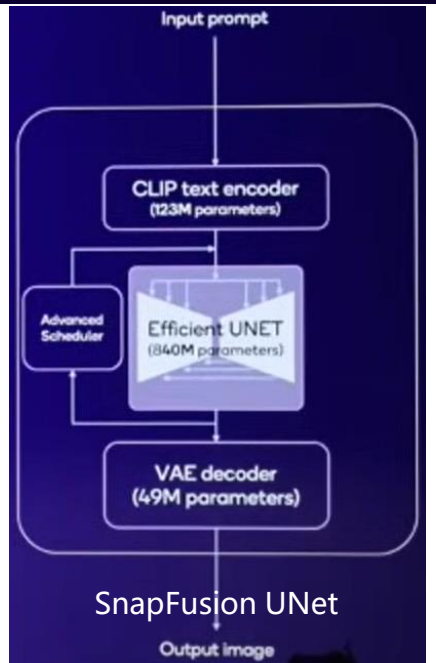
# Example: SnapDragon 8 Gen 3 Key Technologies for Edge AI

Snapdragon 8 Gen3 AI Capabilities

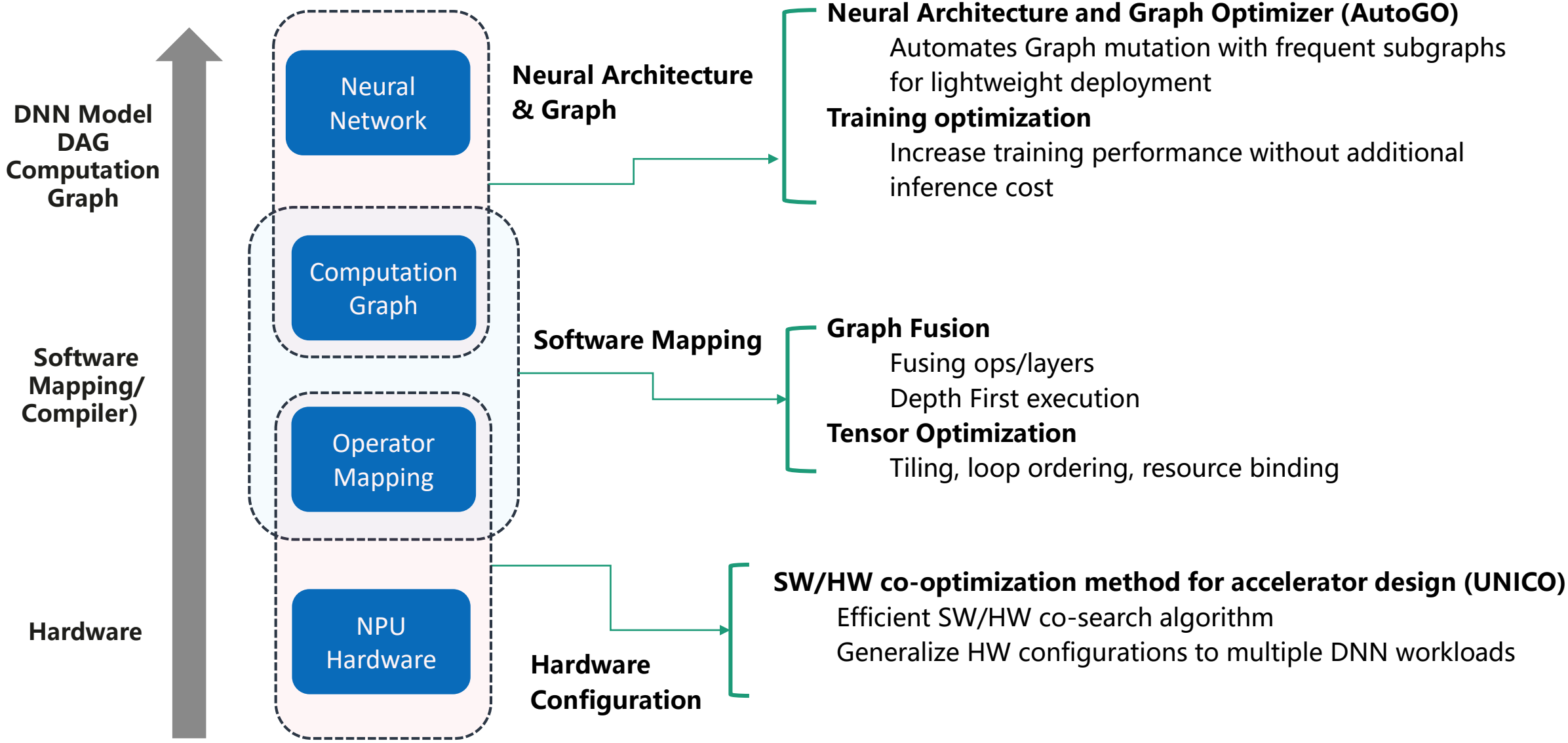
- Run LLAMA2 and Baichuan model on the device and implement LLM voice assistant function on device
- Run Stable Diffusion Text-to-Image model on the device and generate a 512x512 picture in 0.57s.
- Stable Diffusion Outpainting on the device, 8-steps, ~8s

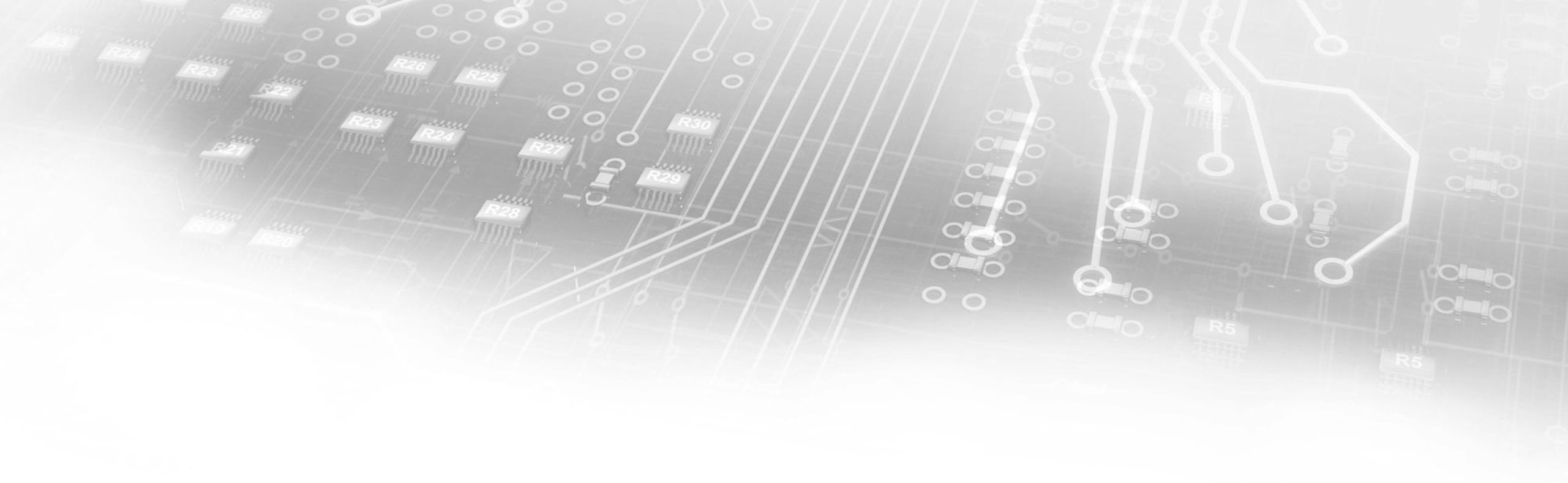
| | 8Gen3 |
|---|---|
| SD | Text to image 0.57s |
| LLM | 20 tokens/s LLAMA2 |
| LLM quantization | INT4 Weights, INT8 Act |
| SD quantization | INT4 Weights, INT8 Act |
| Software mapping | Micro-tile inference |
| NAS for SD | SnapFusion: NAS+Robust Training for Unet，NAS for VAE decoder |
| SD Step Distillation | Progressive Step Distillation |
| Heterogeneous Computing | **Speculative Decoding**，CPU run small model to predict k tokens，NPU run big model for verification, enhance token rate by 2x |



# Our Contributions to Full-Stack DNN Acceleration 2020-2023





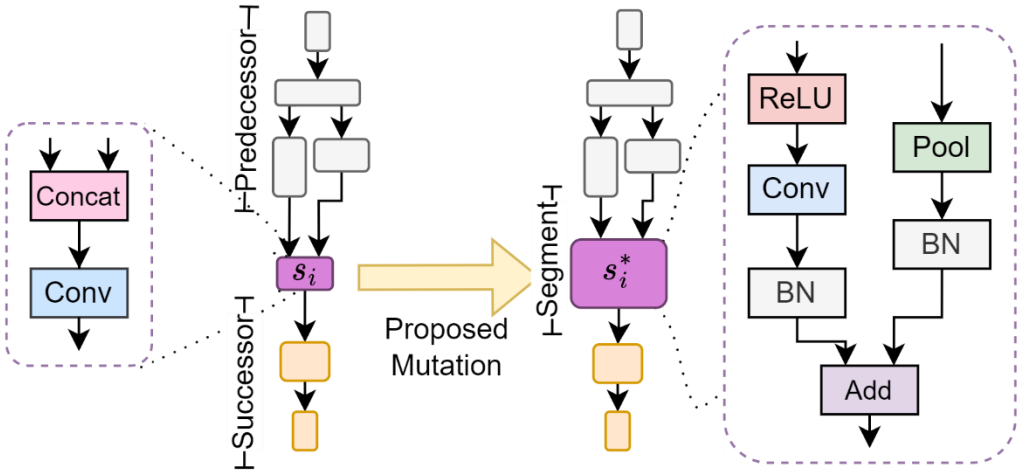

# Computation Graph Optimization

# AutoGO: Automated Computation Graph Optimization for Neural Network Evolution

Mohammad Salameh[1]*, Keith G. Mills[1,2*†], Negar Hassanpour[1], Fred X. Han[1], Shuting Zhang[3], Wei Lu[1], Shangling Jui[3], Chunhua Zhou[3], Fengyu Sun[3], Di Niu[2]
[1]Huawei Technologies Canada. [2]Dept. ECE, University of Alberta. [3]Huawei Kirin Solution, China.

## NeurIPS 2023

- **Replaces manual optimization efforts by ML engineers for deploying ML on (edge) devices** for hardware friendliness and higher task accuracy
  - NOT by searching in a large design space
  - But given a **computation graph** of an existing NN, mutating it by subgraph replacement.
- Maintain a database of "well performing" subgraphs and segments (prior knowledge management)
- Leverages a pretrained neural architecture capacity predictor for different tasks
- Can explore 1000 mutated architectures in 15 minutes




**Our Recent Publications on Computation Graph Optimization for Neural Architecture enhancement/compression:**

- Mohammad Salameh, Keith G. Mills, Negar Hassanpour, Fred X. Han, Shuting Zhang, Wei Lu, Shangling Jui, Fengyu Sun, Di Niu. "**AutoGO: Automated Computation Graph Optimization for Neural Network Evolution**," in Proceedings of **NeurIPS 2023**.
- Keith G. Mills, Di Niu, Mohammad Salameh, Weichen Qiu, Fred X. Han, Puyuan Liu, Jialin Zhang, Wei Lu, Shangling Jui. "**AIO-P: Expanding Neural Performance Predictors Beyond Image Classification**," in Proceedings of **AAAI 2023**.
- Keith G. Mills, Fred X. Han, Jialin Zhang, Fabian Chudak, Ali Safari, Mohammad Salameh, Wei Lu, Shangling Jui, Di Niu. "**GENNAPE: Towards Generalized Neural Architecture Performance Estimators**," in Proceedings of **AAAI 2023**.

# AutoGO: Automated Computation Graph Optimization

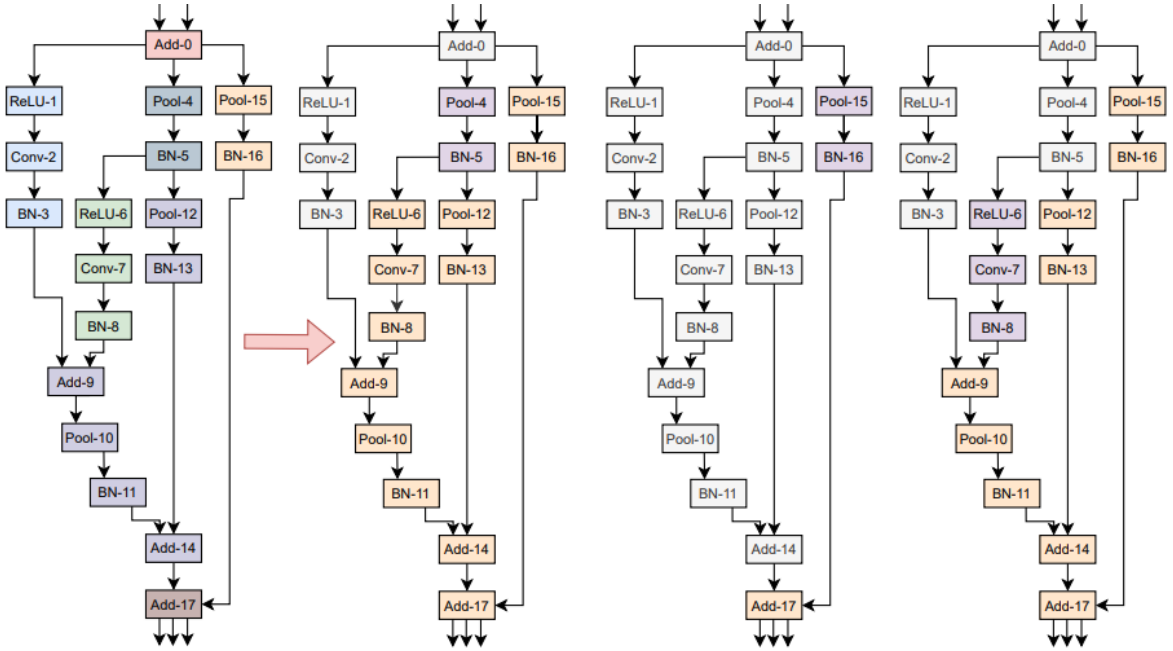
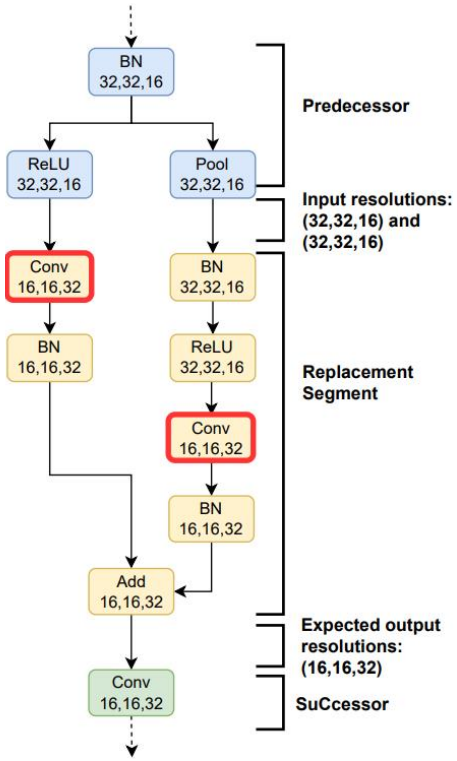



Figure 7: Example of how the BPE-segmented graph in Figure 6(b) is partitioned into Predecessor, Segment and suCcessor subgraphs based on the selected segment. Specifically, we highlight nodes of the selected segment in purple, the predecessor in grey and the successor in yellow.




Key Innovations

**Build a database of frequent subgraphs using a NLP tokenization technique (BPE)** based on several architectural families of >400k+ architectures including

- NB101, NB201, Inception, Two-path, HiAML benchmarks, etc.

**Pretrain a P-S-C predictor** to estimate the reward of each segment mutation Use Transfer Learning (**AIO-P** and **GENNAPE in AAAI 2023**) to transfer accuracy predictor to different CV tasks

**CG Optimizer:**

- Segment Mutation
- Channel Resolution Propagation
- Topology Optimizer

**(a) Convert a model to ONNX format (Computation Graph)**

**(b) Partition CG into Predecessor (P), Segment (S), suCcessor (C)**

**(c) Mutate the graph with a segment from a database and perform resolution propagation**

**(d) Evaluate Task Accuracy with a pretrained P-S-C predictor**

# AIO-P: Pretraining NN Performance Predictor for Various CV Tasks

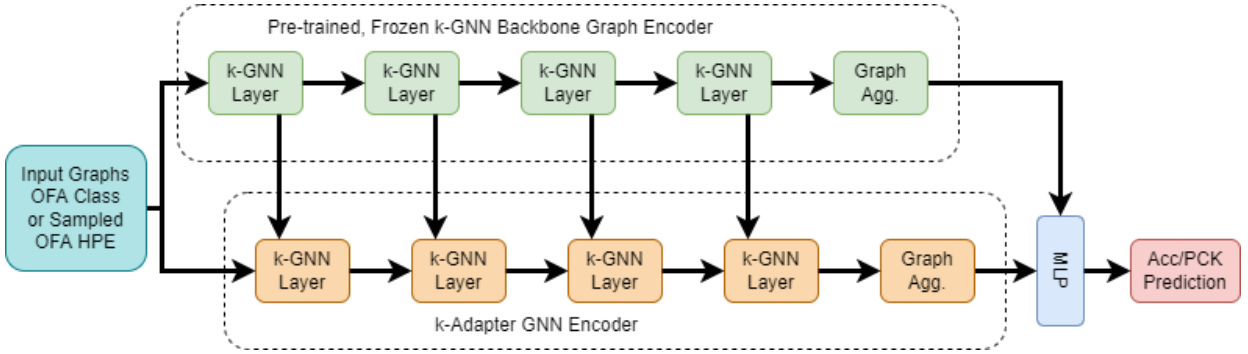
- **Current Issues**: Predictors in NAS are task (ImageClassification), dataset (CIFAR10) and metric (accuracy) dependent
- **Goal**: provide a generalizable predictor that
  - learns representations of graph structures of a neural network
  - transfer the learning among different CV tasks, datasets and metric
- **Challenges**: scarcity in NAS benchmark datasets for Dense CV Prediction tasks
  - Human Pose Estimation, SuperResolution, Image Segmentation, …

## Generalizable to different CV tasks with k-Adapter

- First, pretrain a predictor on Image Classification architectures and labels
- We infuse the pretrained predictor with knowledge from a new task with k-adapters layers
- For example, we infuse PCK of models for Human Pose estimation to enable the predictor to handle new HPE architectures.

Performance prediction for ProxylessNAS architectures for Panoptic Segmentation on MS-COCO.

| Scheme | Zero-Shot Inference | With Fine-tuning (20 samples) |
|---|---|---|
| Baseline *k*-GNN Predictor | MAE: 56.19%<br>SRCC: 0.562 | MAE: 0.53%<br>SRCC: 0.741 |
| + Label Scaling | MAE: 0.76%<br>SRCC: 0.119 | MAE: 0.62%<br>SRCC: 0.297 |
| + Double k-Adapter (Pose Estimation & Obj. Detection) | MAE: 0.50%<br>SRCC: 0.732 | MAE: 0.33%<br>SRCC: 0.868 |




Keith G. Mills, Di Niu, Mohammad Salameh, Weichen Qiu, Fred X. Han, Puyuan Liu, Jialin Zhang, Wei Lu, Shangling Jui. "**AIO-P: Expanding Neural Performance Predictors Beyond Image Classification**," in Proceedings of **AAAI 2023**.

# AutoGO Experiment Results on ImageNet

**AutoGO results on popular DNNs including ResNet-50, ResNet-101, VCG-16:**

- ✓ Can improve ImageNet Top-1 accuracy by 1%, without using new operations or increasing FLOPs
- ✓ Can optimize network performance when it is used as backbone for semantic segmentation and Human Pose Estimation
- ✓ Allow customized optimization objectives (accuracy, FLOPs, latency, power)

**Improve performance with latency reduction(GPU) on Classification, Segmentation, Human Pose Estimation**

| Architecture | ImageNet Top-1/5 | Cityscapes mIoU | MPII PCK | FLOPs [1e9] | Lat. [ms] |
|---|---|---|---|---|---|
| ResNet-50 Original | 74.02%/91.22% | 63.42% | 82.36% | 6.29 | 7.18 |
| ResNet-50 AutoGO Arch 1 | 75.34%/92.16% | 65.88% | **84.07%** | 6.71 | 7.50 |
| ResNet-50 AutoGO Arch 2 | **75.66%/92.45%** | **66.65%** | 82.70% | 5.88 | 6.92 |
| ResNet-101 Original | 75.09%/91.94% | 65.92% | 82.77% | 13.76 | 15.86 |
| ResNet-101 AutoGO Arch 1 | **76.56%/93.09%** | **67.12%** | 83.59% | 13.66 | 15.56 |
| ResNet-101 AutoGO Arch 2 | 75.69%/92.15% | 66.38% | **84.64%** | 13.35 | 15.36 |
| VGG-16 Original | 74.18%/91.83% | 65.36% | 85.92% | 30.81 | 4.65 |
| VGG-16 AutoGO | **74.91%/93.23%** | **66.91%** | **85.99%** | 24.34 | 4.20 |

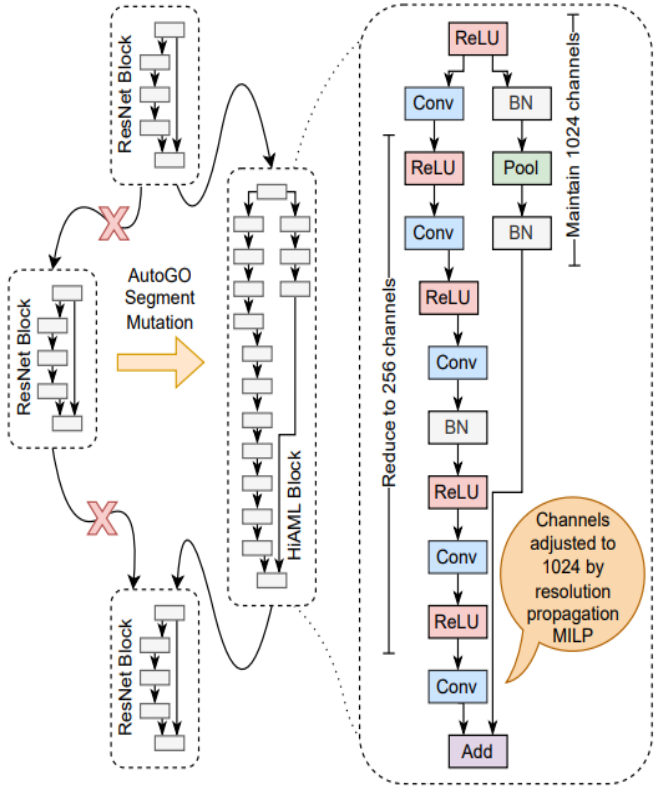



**Figure 5: Example of a segment mutation that helped create ResNet-50 AutoGO Arch 2 from Table 3. A ResNet residual block is replaced by a HiAML block.**

Mohammad Salameh, Keith G. Mills, Negar Hassanpour, Fred X. Han, Shuting Zhang, Wei Lu, Shangling Jui, Fengyu Sun, Di Niu. "**AutoGO: Automated Computation Graph Optimization for Neural Network Evolution**," in Proceedings of **NeurIPS 2023.**

# AutoGO Results on Other Tasks (e.g., Super Resolution)

Table 4: Peak Signal-to-Noise Ratio (PSNR) for EDSR on the DIV2K validation set and several SR benchmarks in the 2x upscaling setting. Higher is better. We measure latency on an RTX 2080 Ti.

| SR Architecture | DIV2K | Set5 | Set14 | BSD100 | Urban100 | Manga109 | FLOPs [1e9] | Lat. [ms] |
|---|---|---|---|---|---|---|---|---|
| EDSR Original | 36.19 | 36.86 | 32.57 | 31.39 | 29.14 | 36.09 | 141 | 18.04 |
| EDSR AutoGO Arch 1 | **37.28** | **38.01** | **33.62** | **32.18** | **31.56** | **38.49** | 118 | 15.38 |
| EDSR AutoGO Arch 2 | 37.27 | 37.97 | 33.55 | 32.16 | 31.53 | 38.47 | 110 | 14.52 |
| EDSR AutoGO Arch 3 | 37.25 | **38.01** | 33.58 | 32.16 | 31.46 | 38.44 | 105 | 13.81 |

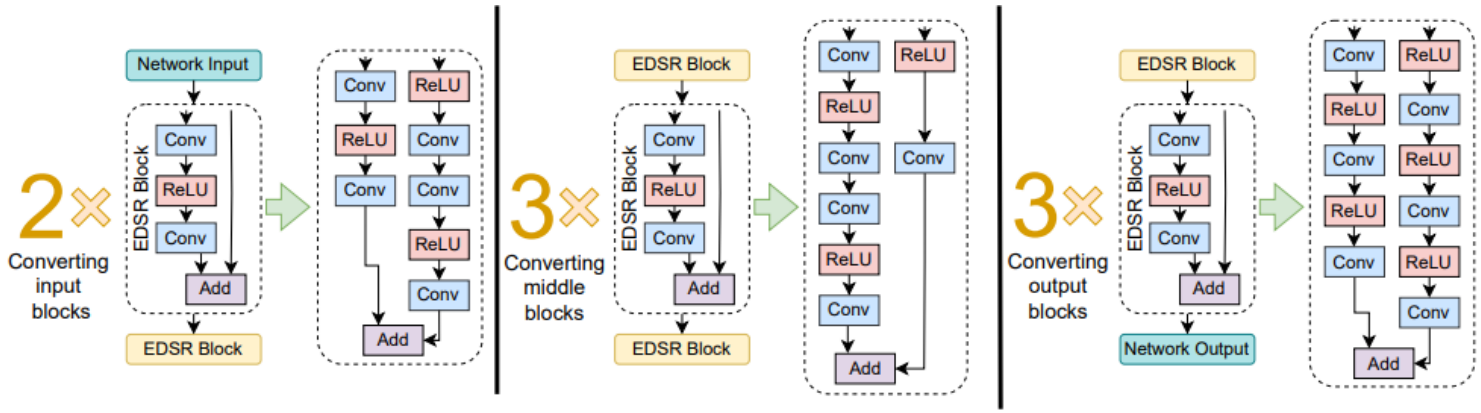
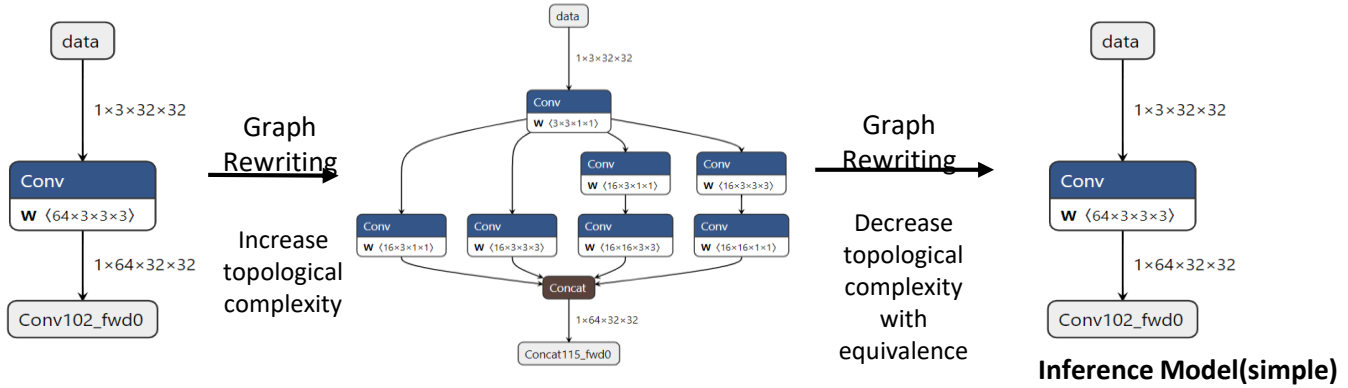



Figure 9: Example mutations performed by AutoGO to create EDSR Arch 2 in Table 4 by swapping out 8 EDSR blocks. Specifically, AutoGO will swap out multiple, simple 'Conv-ReLU-Conv' residual blocks for larger blocks that have operations on both branches.

Mohammad Salameh, Keith G. Mills, Negar Hassanpour, Fred X. Han, Shuting Zhang, Wei Lu, Shangling Jui, Fengyu Sun, Di Niu. "**AutoGO: Automated Computation Graph Optimization for Neural Network Evolution**," in Proceedings of **NeurIPS 2023.**

# Spatial Gradient Scaling: Deep Learning Optimization

- **Reparameterization**: replacing a subgraph with a computationally equivalent subgraph by algebraic manipulation of the weights.
- **Goal:**
  - increase accuracy
  - help the model to learn and generalize better




**Original Model (simple)**

**Training Model (complex)**
more complex to train but has "higher capacity" than starting model.

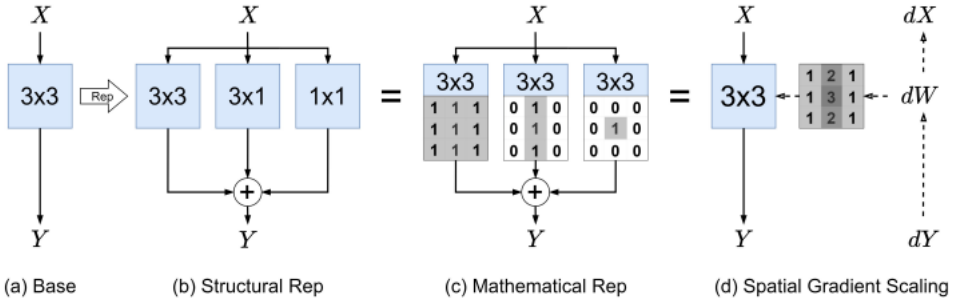
**Inference Model(simple)**

Same inference result but faster

**We discovered an equivalence between Branched Reparametrization and Spatial Gradient Scaling**

| Model | Rep method | Cost (GPU days) | Avg. FLOPs (G) | Avg. params (M) | Acc (%) |
|---|---|---|---|---|---|
| ResNet-18 | Origin | 4.8 | 1.81 | 11.7 | $71.13_{\pm 0.04}$ |
| | DBB* | 8.1 | 4.13 | 26.3 | 70.99 |
| | DyRep* | 6.3 | 2.42 | 16.9 | 71.58 |
| | DyRep | 9.1 | 2.92 | 22.1 | $71.50_{\pm 0.03}$ |
| | SGS (ours) | 5.1 | 1.81 | 11.7 | $71.65_{\pm 0.05}$ |
| ResNet-34 | Origin | 5.3 | 3.66 | 21.8 | $74.17_{\pm 0.05}$ |
| | DBB* | 12.8 | 8.44 | 49.9 | 74.33 |
| | DyRep* | 7.7 | 4.72 | 33.1 | 74.68 |
| | DyRep | 10.6 | 4.95 | 38.3 | $74.40_{\pm 0.03}$ |
| | SGS (ours) | 5.8 | 3.66 | 21.8 | $74.62_{\pm 0.05}$ |
| ResNet-50 | Origin | 7.5 | 4.09 | 25.6 | $76.95_{\pm 0.05}$ |
| | DBB* | 13.7 | 6.79 | 40.7 | 76.71 |
| | DyRep* | 8.5 | 5.05 | 31.5 | 77.08 |
| | DyRep | 11.0 | 5.84 | 38.3 | $77.11_{\pm 0.03}$ |
| | SGS (ours) | 7.9 | 4.09 | 25.6 | $77.10_{\pm 0.01}$ |

Table 2: Results on ImageNet dataset. We use the official implementation of DyRep (Huang et al., 2022) on 8 NVIDIA Tesla V100 GPUs. FLOPs and Parameters are averaged across DyRep runs. Results marked with * are taken from DyRep paper; the rest are our runs averaged over 3 seeds.




**Original Training**

$$K'_{11} \Leftarrow K'_{11} - \alpha \frac{\partial L}{\partial K_{11}}$$

$$K'_{22} \Leftarrow K'_{22} - \alpha \frac{\partial L}{\partial K_{22}}$$

**Spatial Gradient Scaling**

$$K'_{11} \Leftarrow K'_{11} - \alpha \frac{\partial L}{\partial K_{11}}$$

$$K'_{22} \Leftarrow K'_{22} - 2\alpha \frac{\partial L}{\partial K_{22}}$$


Alexander Detkov, Mohammad Salameh, Muhammad Fetrat, Jialin Zhang, Robin Luwei, Shangling Jui, Di Niu. "**Reparameterization through Spatial Gradient Scaling**," in Proceedings of the Eleventh International Conference on Learning Representations (**ICLR 2023**).

# Lightweight Diffusion on Edge (Text to Image)

**Method:**

- Performed finetuning for velocity prediction on Midjourney dataset
- Neural Architecture Search with AutoGO
- Step Distillation on MidJourney 1.3M dataset to reduce inference steps
- Generation performance improvement with:
  - Adaptive Jump Step-Distillation and Semantic Alignment with Attention
  - Faithful and Realistic Text-to-Image Generation with Adaptive prompt-weighting

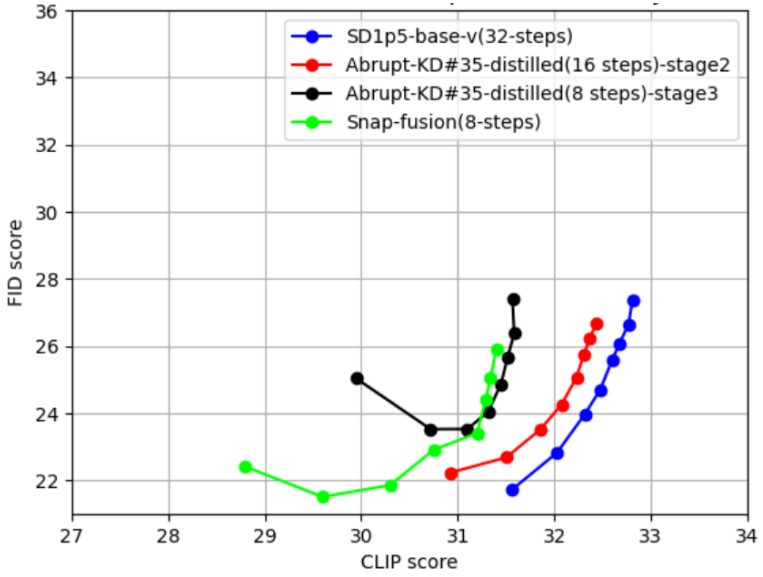
**Achievements**

- Reduced architecture latency by 78% with AutoGO
- We beat SnapFusion on 6k MS-COCO in terms of generation quality
  - CLIP score denoting better semantics (higher is better)
  - While maintaining comparable FID i.e generation quality (lower is better)

**SnapFusion** | **Our model**

A photo of an astronaut riding a horse on mars

SnapFusion is able to generate a 512-by-512-pixel image, requires 8 steps




Prompt: "***Lion riding a bike in Paris***

**Original (32steps, 55.9sec)**

Original (8steps, 14sec)

**Our reduced and optimized (8steps, <3sec)**

# SD (Text-to-Image) for Edge

**8-step model compared to SnapFusion (8 steps)**

- Better Quality and Semantics

Ours – 8 steps

A photo of an astronaut riding a horse on mars

SnapFusion

Ours (8 steps)

3d render of voxel pink elephant

SnapFusion (8 steps)

A beautiful image of a cute animal surrounded by natural light, capturing their delicate beauty and charm

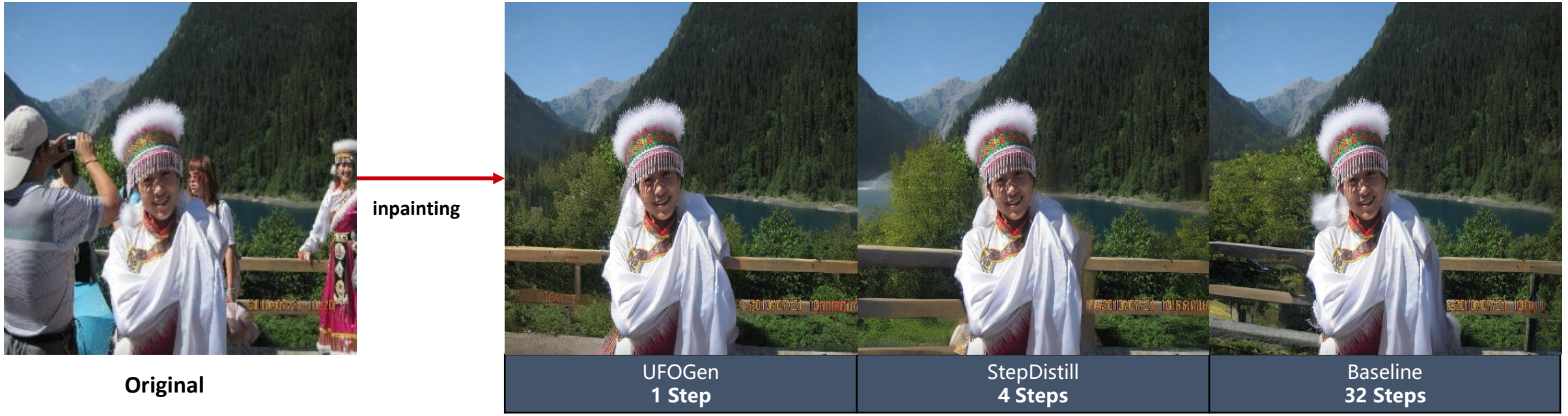
# SD-based Inpainting for Edge

Optimize diffusion-based inpainting model for edge deployment

- Used **Progressive Step Distillation** to reduce UNet inference to 1-4 steps, while maintaining comparable output quality
- Used **UFOGen** to distill a 50-step model to a few-step generator following Generative Adversarial training
  - with minimal drop in output quality
  - Estimated <1 second inference for 512 x 512 resolution

| Metric<br>Eval | Curation Score<br>Two numbers closer = comparable PQ to baseline |
|---|---|
| UFOGen 1 Step | [159, 201] |
| StepDistill 4 Steps | [148, 167] |

| Human<br>Eval | # Good PQ | # Acceptable, but has minor issues | # Bad PQ |
|---|---|---|---|
| Baseline 20 Steps | 248 | 68 | 113 |
| StepDistill 4 Steps | 236 | 83 | 110 |



# Software Mapping (Tensor Fusion)

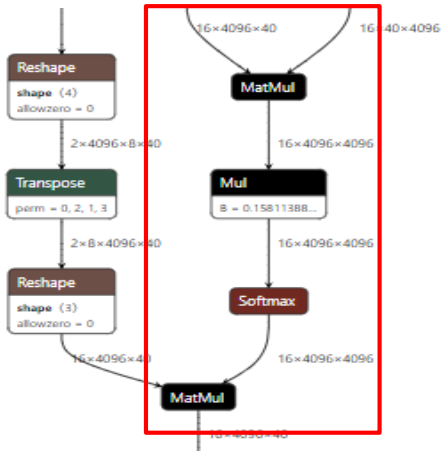
# Tiling and Fusion: Software Mapping Techniques to Reduce Memory Access

**Operational intensity** is the number of compute operations an algorithm takes divided by the number of byte accesses it requires and is a hardware-agnostic measurement.

The most computationally expensive parts of a 7B parameter LLM are the **Attention layers**, which ensure next token predictions are weighted based on the relevance of previous tokens.

Attention Block

1. $Matmul(Q, K^T); Q, K \in R^{head_{size} \times Seq_{size} \times Emb_{size}}$
2. $Mul\left(QK^T, \frac{1}{\sqrt{d_{emb}}}\right); d_{emb} \in R$
3. $Softmax\left(\frac{QK^T}{\sqrt{d_{emb}}}\right)$
4. $Matmul(softmax, V)$




- $Latency = MatMul$ + Mul + Softmax + MatMul
- Issues: Memory bound, low compute utilization

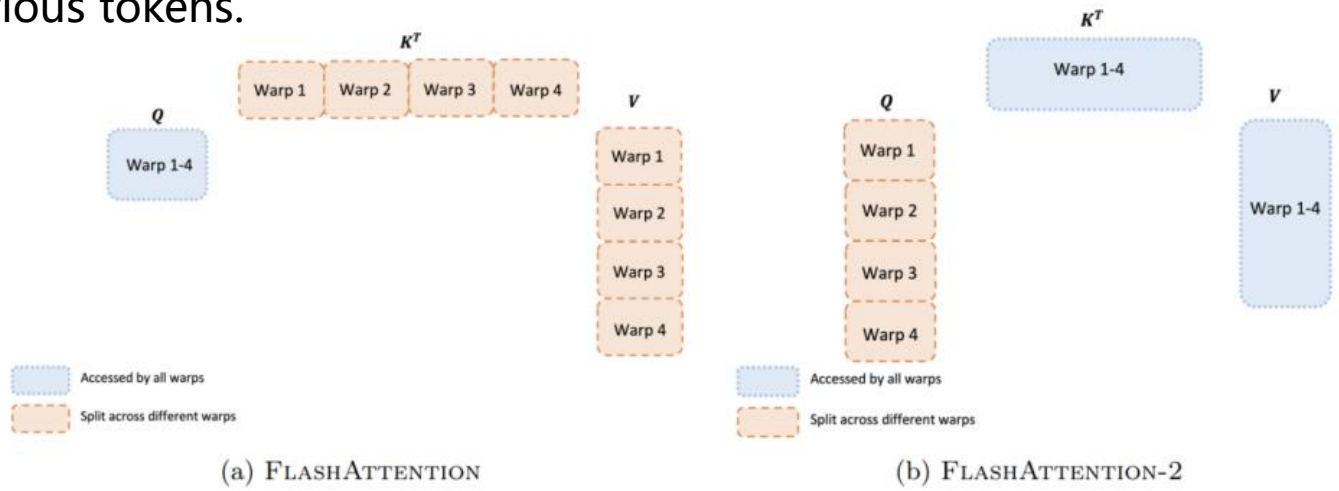



Figure 3: Work partitioning between different warps in the forward pass

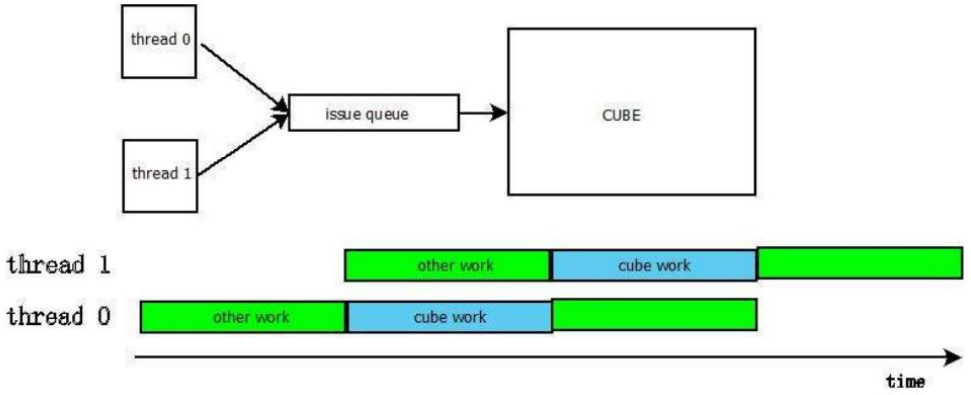
**FlashAttention (& v2):** For the GPU, perform tiling on K or Q, and allocate the fused tile computation to different Warps.

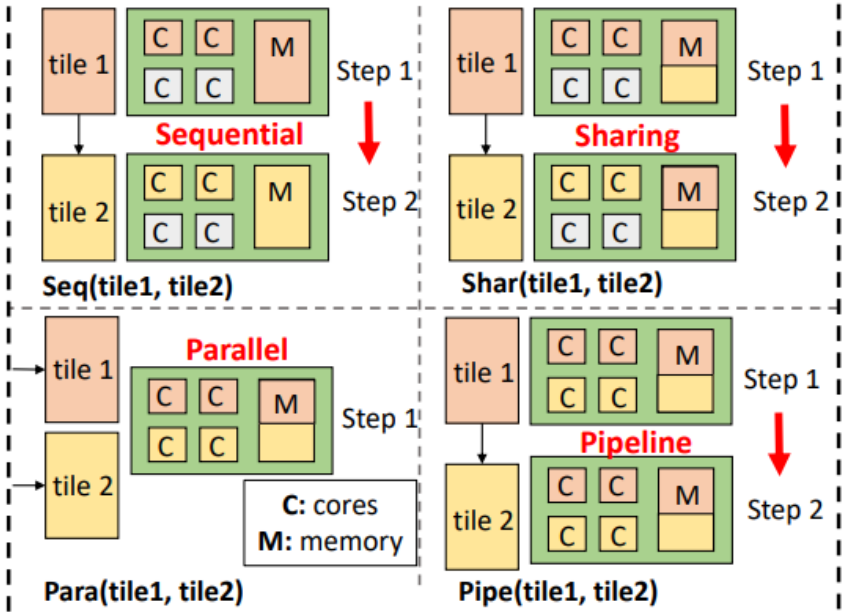
However, FlashAttention cannot directly benefit the edge devices.

- Different hardware architecture: resource binding is different but less explored in the literature
- Different parallelism: aim more aggressively at hiding memory operations

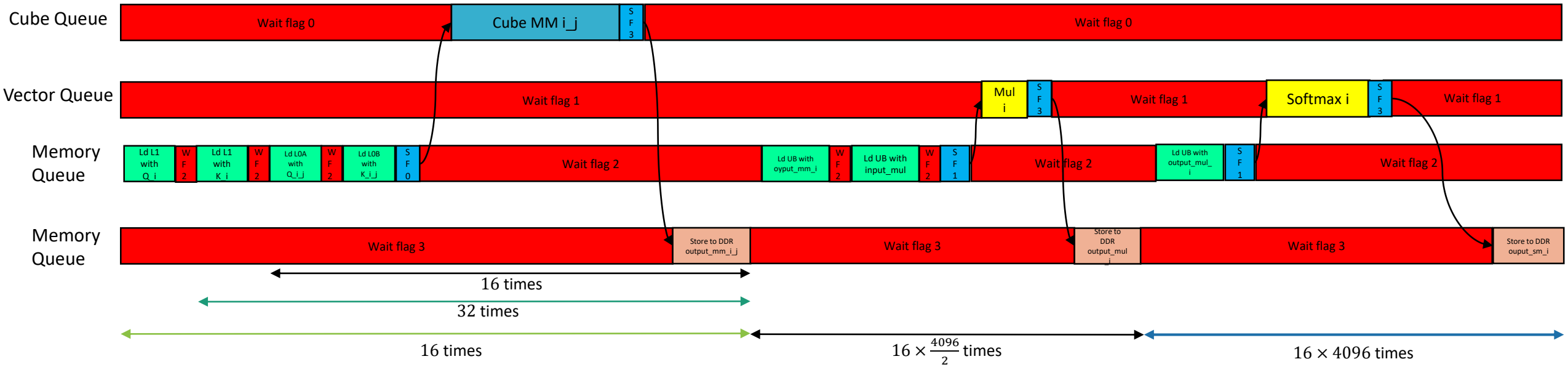
# Tiling and Resource Binding as a Scheduling Problem

Given the accelerator HW configuration, resource binding optimization is to bind the flow of compute and mem operations for each tile onto hardware components, while reducing DDR memory access and parallelizing the operations.



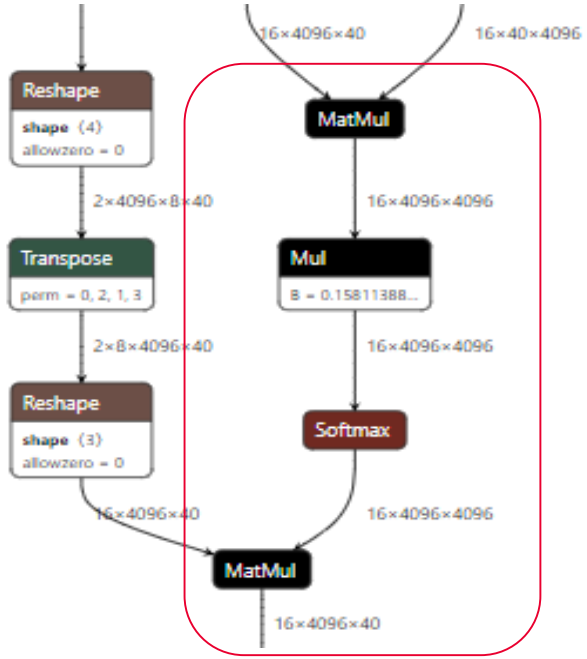

Figue credit: TileFlow (MICRO 2023)



# Tiling and Resource Binding as a Scheduling Problem

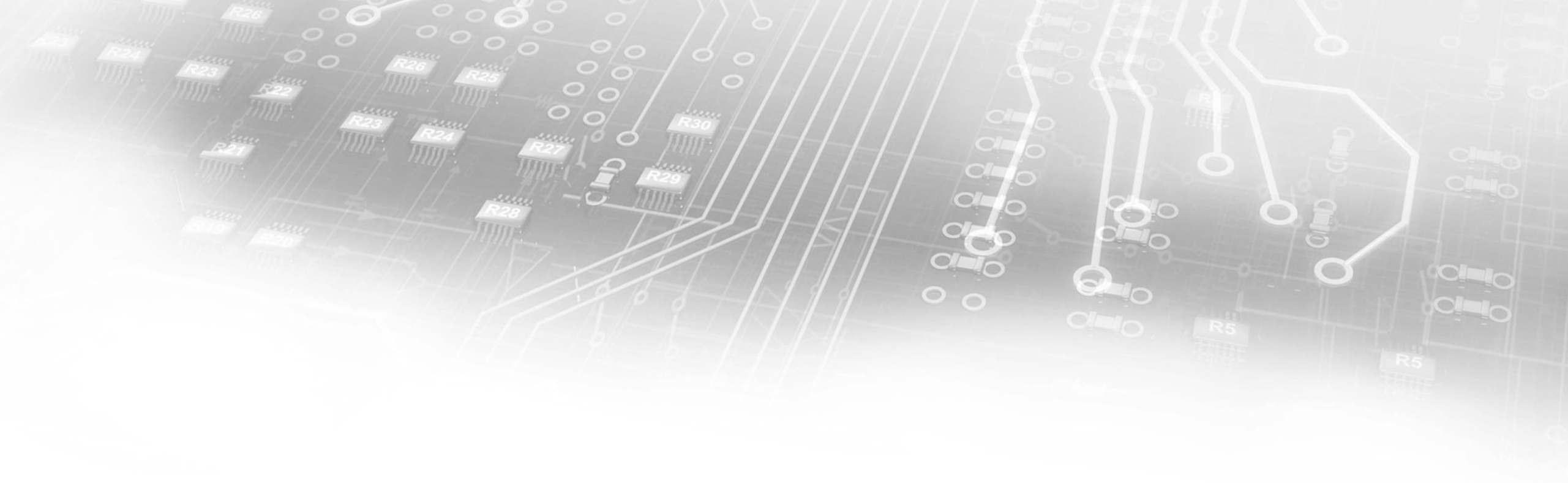
❖ Use optimization to solve the following scheduling problem:

1. Pipeline the operations:
   - $Matmul(Q, K^T); Q, K \in R^{head_{size} \times Seq_{size} \times Emb_{size}}$
   - $Mul\left(QK^T, \frac{1}{\sqrt{d_{emb}}}\right); d_{emb} \in R$
   - $Softmax\left(\frac{QK^T}{\sqrt{d_{emb}}}\right)$
2. Find the optimal split factor "$\boldsymbol{m}$" to split $Q$
3. Find the optimal number of consecutive pipelined chunks of $Softmax\left(\frac{QK^T}{\sqrt{d_{emb}}}\right)$ to be sent to the last *Matmul* operator.




❖ Example inference time for certain choices:
- The best parameters for Pipelined-Attention should be searched for

| Method | $Q, K, V_{shape}$ | $l_{factor}$ | $m_{factor}$ | Latency Reduction for Attention |
|---|---|---|---|---|
| Baseline (no fusion) | $(16, 4096, 40)$ | - | - | - |
| PipelinedAttention-v1 | $(16, 4096, 40)$ | - | 16 | 24.1% |
| PipelinedAttention-v2.1 | $(16, 4096, 40)$ | 512 | 16 | **31.15%** |

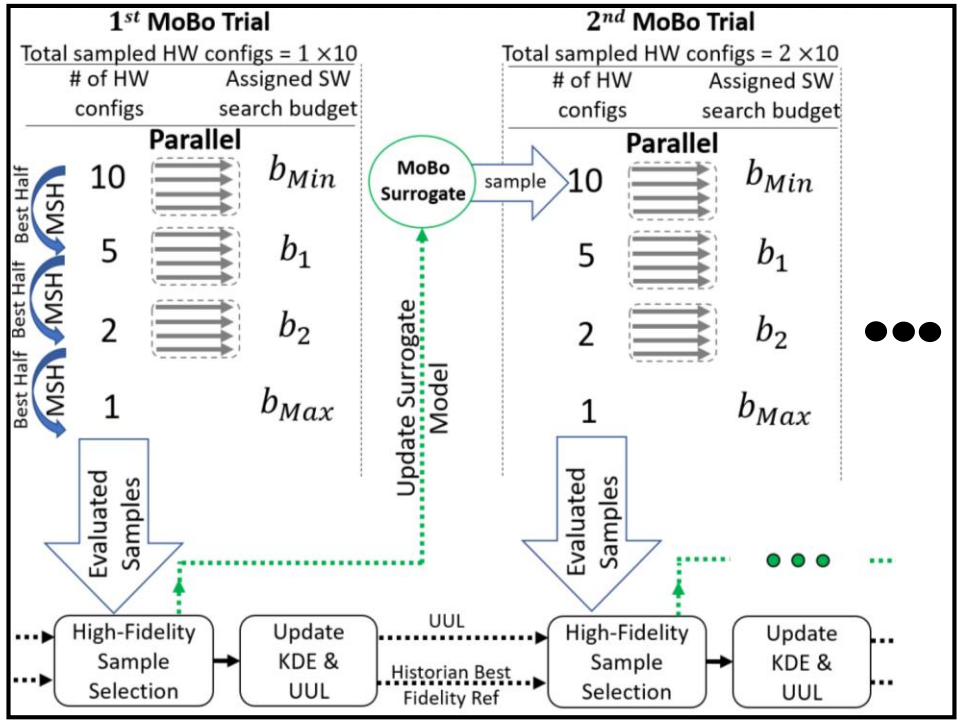



# Hardware Configuration

# UNICO: Robust Accelerator Hardware Configuration Search

## Innovation:

- Use Successive halving to reduce SW search budget for some "bad" HW parameters
- Proposed robust HW search, based on power/latency sensitivity to SW, to improve generalization of the found HW to different unseen DNNs




## On open-source platform:

- Training NN: MobileNetV2, ResNet, SRGAN, VGG;
- Tested on 7 new NNs: UNICO vs HASCO, 44% improvement
- Both convergence speed and robustness to new DNN workloads outperform HASCO

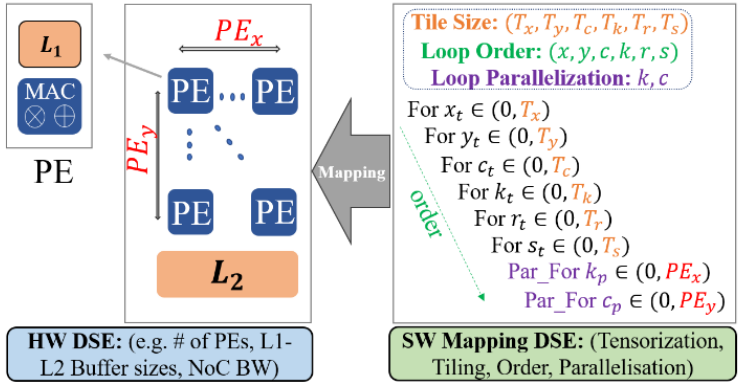



Figure 1: A typical 2D spatial accelerator HW design components (e.g. $(PE_x, PE_y)$, $L_1$ and $L_2$ buffer sizes)

**UNICO HW config. Vs. Original DaVinci HW Config**

| HW | L0A | L0B | L0C | … | Cube | Area |
|---|---|---|---|---|---|---|
| Original | 32 | 32 | 64 | unchanged | unchanged | unchanged |
| UNICO found | 128 | 8 | 16 | unchanged | unchanged | unchanged |

## DaVinci NPU verification:

- Model: Denoise U-Net, 6 variants of FSRCNN, DLSS
- Search: Use Power as the main target
- By adjusting L0A/B/C buffer parameters, on DLSS can achieve 54% power reduction;
- On all other NNs, there is no power or lateny degradation


Bahador Rashidi, Chao Gao, Shan Lu, Zhisheng Wang, Di Niu, Fengyu Sun. "**UNICO: Unified Hardware Software Co-Optimization for Robust Neural Network Acceleration**", in IEEE/ACM International Symposium on Microarchitecture (**MICRO 2023**)