

*Image generated by Microsoft Copilot.*

# NextGen Accelerators: Flexible, Scalable, Efficient – Together<sup>3</sup>

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Gothenburg, Sweden

# NextGen Accelerators: Flexible, Scalable, Efficient – Together<sup>3</sup>

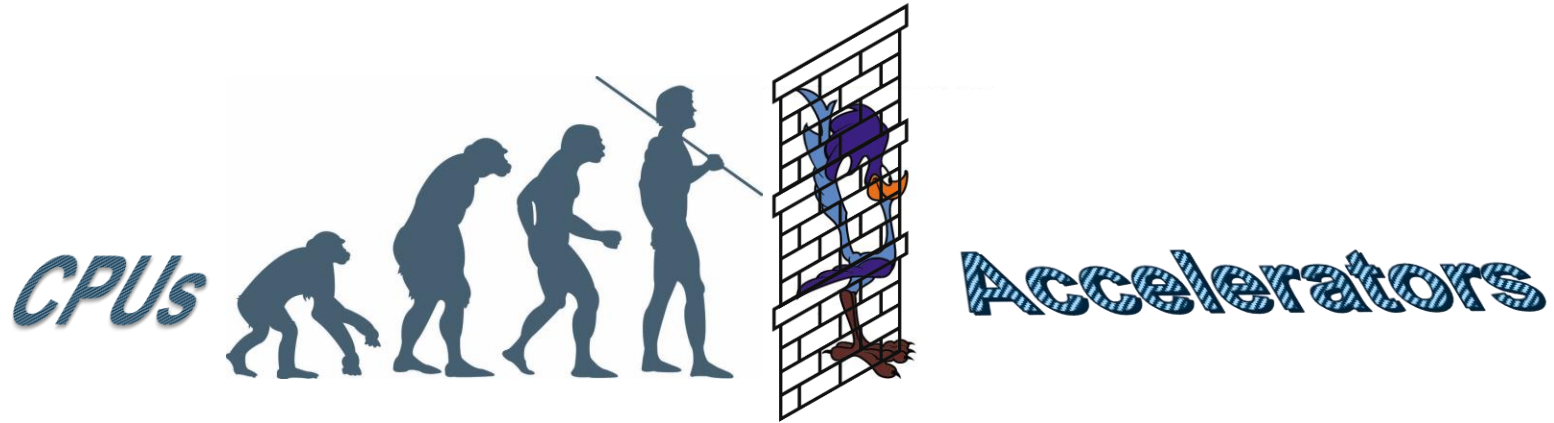


<https://www.scientificamerican.com/article/what-causes-the-feeling-of-deja-vu/>

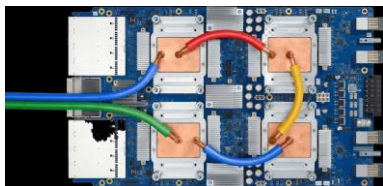
All has been said before!



# Motivation...



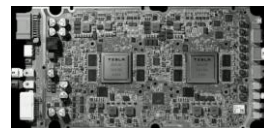
# Accelerators



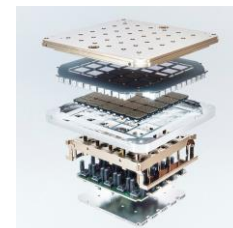
Google TPU



Amazon Inferentia & Tranium



Tesla FSD



Tesla Dojo D1



High-performance



NVIDIA Jetson Orin

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lan Graphcore IPU

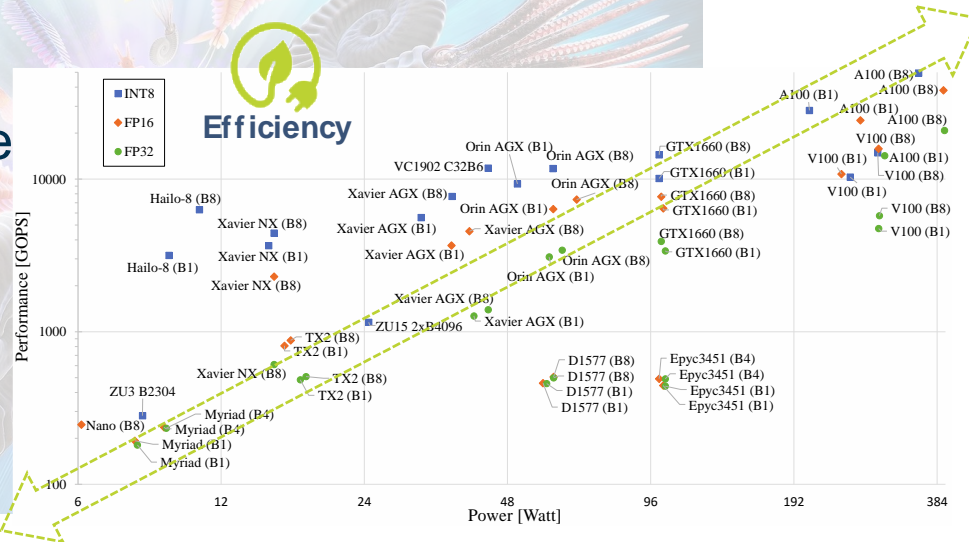


AMD Versal

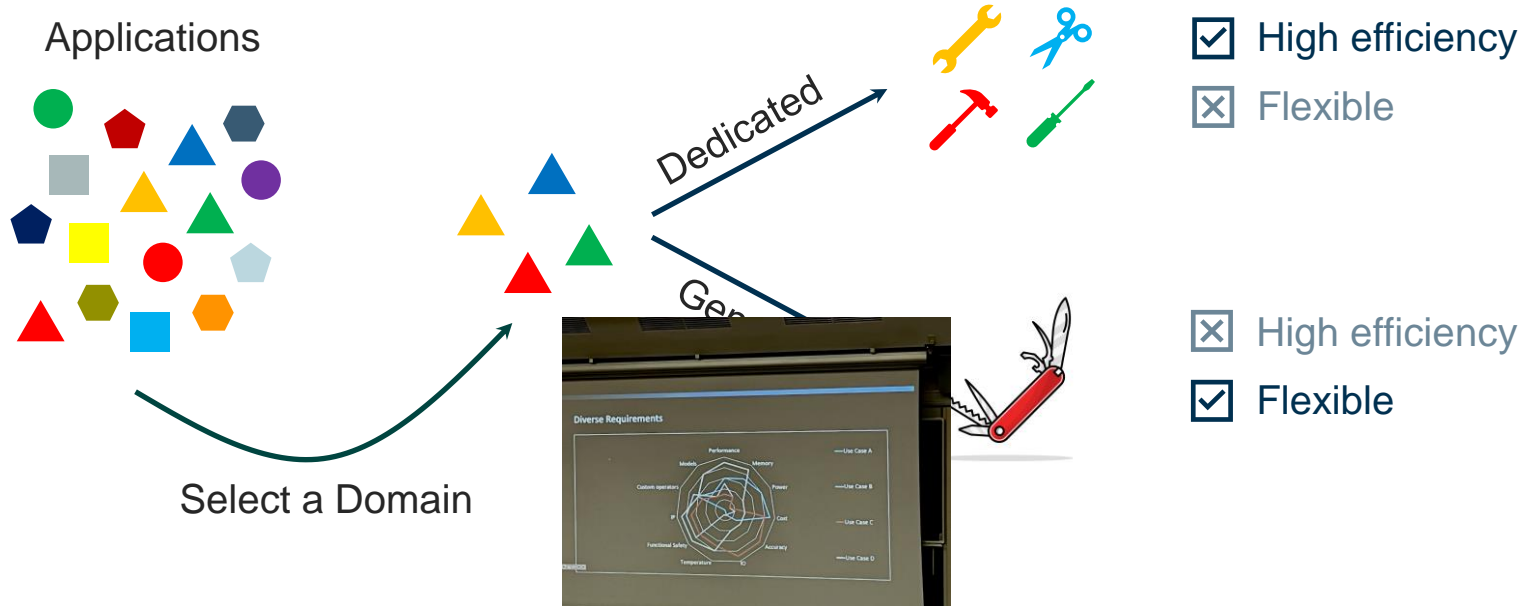


Hailo-8

Low power



# Accelerators design tradeoff



I WANT BOTH!!!





# Accelerators design



# Accelerators design how-to...

## IKEA MEATBALLS AT HÖME (SERVES 4)

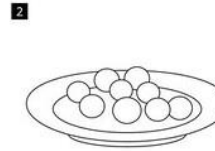


### INGREDIENTS - MEATBALLS

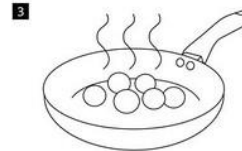
- 500g beef mince
- 250g pork mince
- 1 onion finely chopped
- 1 clove of garlic (crushed or minced)
- 100g breadcrumbs
- 1 egg
- 5 tablespoons of milk (whole milk)
- generous salt and pepper



**Meatballs:** Combine beef and pork mince and mix with your fingers to break up any lumps. Add finely chopped onion, garlic, breadcrumbs, egg and mix. Add milk and season well with salt and pepper.



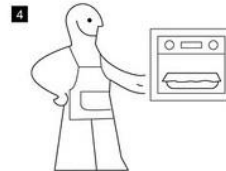
Shape mixture into small, round balls. Place on a clean plate, cover and store in the fridge for 2 hours (this will help them hold their shape whilst cooking).



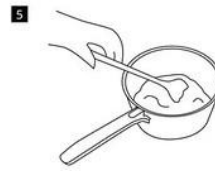
In a frying pan, heat oil on medium heat. When hot, gently add meatballs and brown on all sides.

### INGREDIENTS - CREAM SAUCE

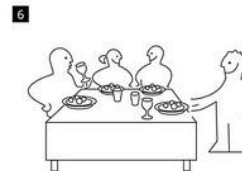
- dash of oil
- 40g butter
- 40g plain flour
- 150ml vegetable stock
- 150ml beef stock
- 150ml thick double cream
- 2 teaspoons soy sauce
- 1 teaspoon Dijon mustard



When browned, add to an ovenproof dish and cover. Place in a hot oven (180°C conventional or 160°C fan).



**Iconic Swedish cream sauce:** Melt 40g of butter in a pan. Whisk in 40g of plain flour and stir for 2 mins.

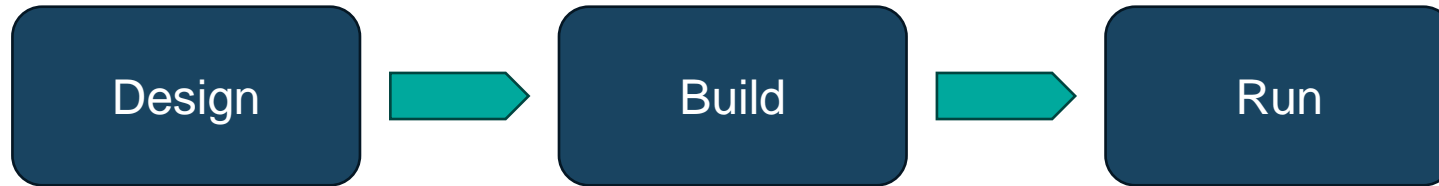


When ready to eat, serve with your favourite potatoes - either creamy mash or mini new boiled potatoes. Enjoy!

[https://twitter.com/IKEAUK/status/1252269467515617280?ref\\_src=twsrc%5Etfw%7Ctwcamp%5Etweetembed%7Ctwterm%5E1252269467515617280%7Ctwgr%5E%7Ctwcon%5Es1\\_c10](https://twitter.com/IKEAUK/status/1252269467515617280?ref_src=twsrc%5Etfw%7Ctwcamp%5Etweetembed%7Ctwterm%5E1252269467515617280%7Ctwgr%5E%7Ctwcon%5Es1_c10)

# Our work (so far...)

## Deep Learning accelerators





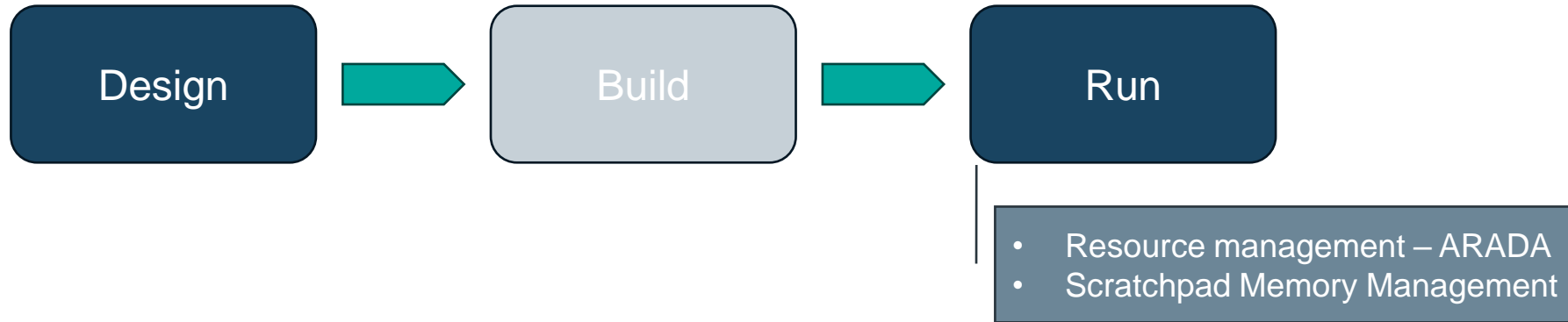
# Our work (so far...)

## Deep Learning accelerators



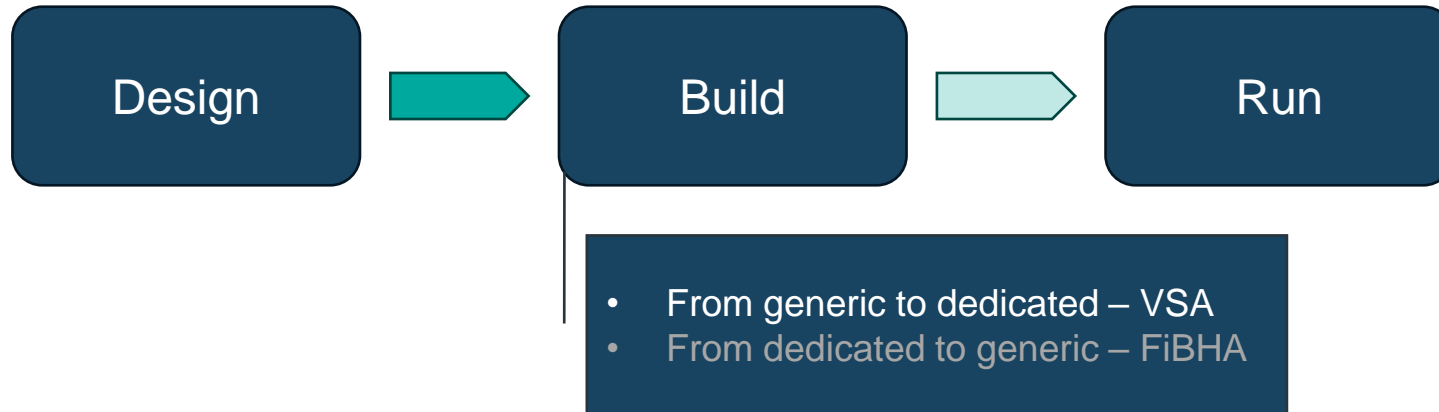
# Our work (so far...)

## Deep Learning accelerators



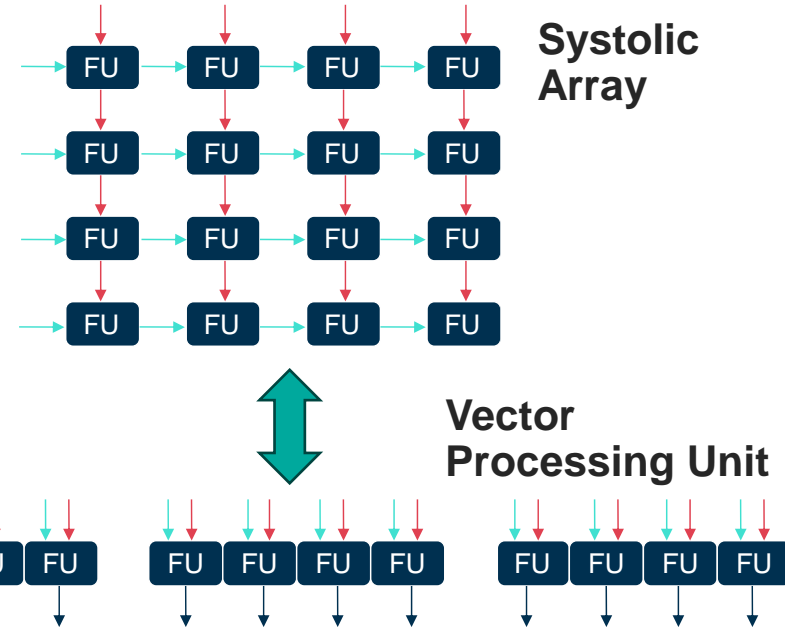
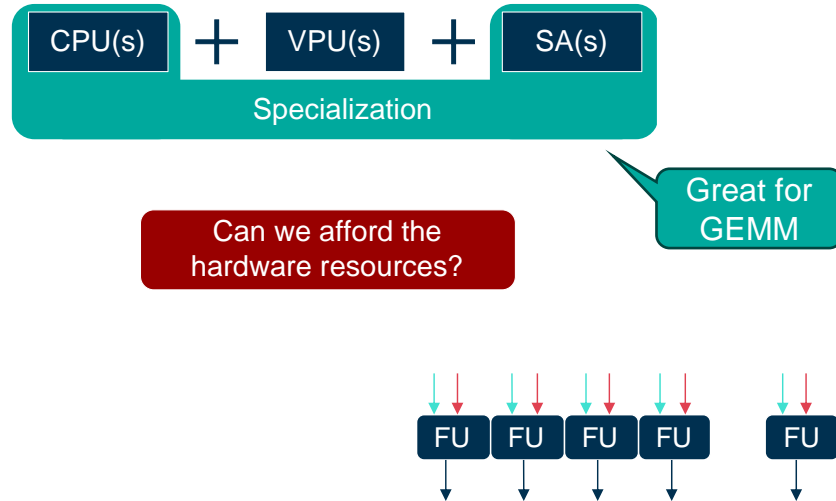
# Our work (so far...)

## Deep Learning accelerators



# From generic to dedicated

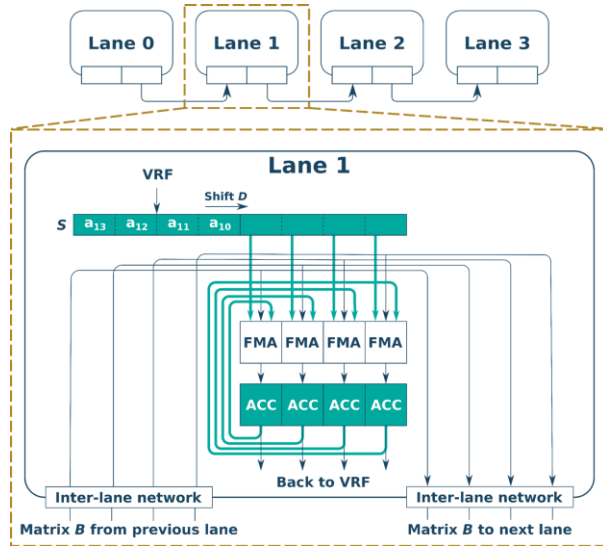
## VSA: A Hybrid Vector-Systolic Architecture



- M. V. Maceiras, M. Waqar Azhar and P. Trancoso, "VSA: A Hybrid Vector-Systolic Architecture," *2022 IEEE 40th International Conference on Computer Design (ICCD)*, Olympic Valley, CA, USA, 2022, pp. 368-376
- M. V. Maceiras, M. W. Azhar and P. Trancoso, "Exploiting the Potential of Flexible Processing Units." In *Proc. of the IEEE 35th International Symposium on Computer Architecture and High Performance Computing (SBAC-PAD 2023)*, pp. 1-12

# From generic to dedicated

## VSA hardware, software, experimental setup



“Magic sauce” – hardware overhead < 0.1% area



Algorithm 2 GEMM using custom instruction

```

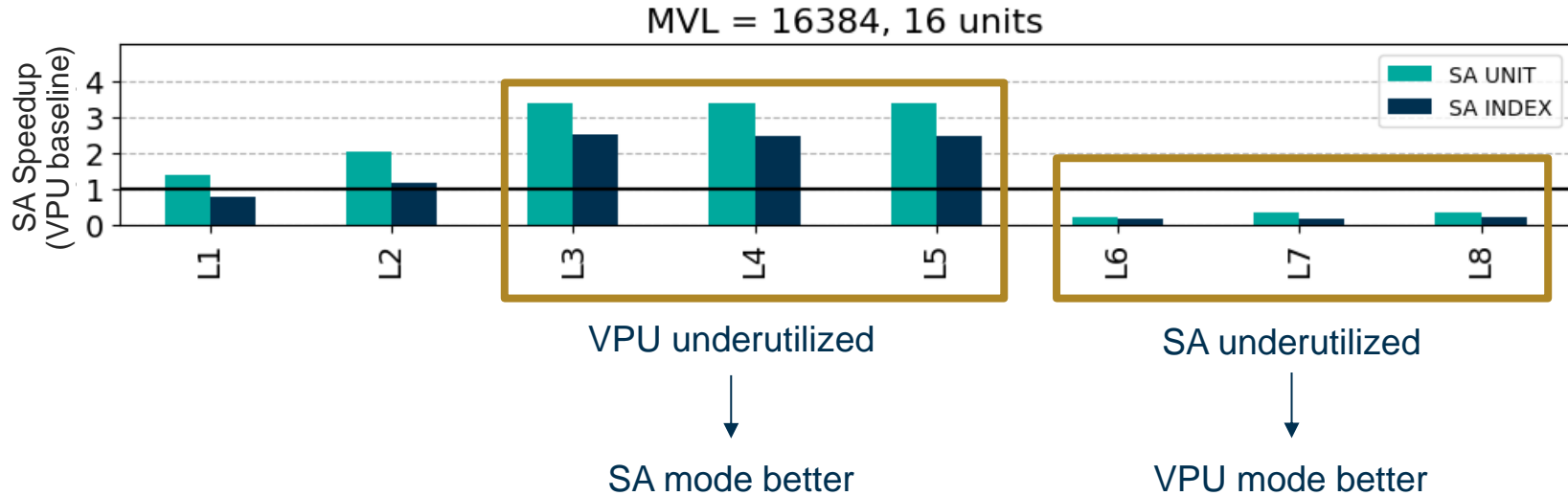
1: for all  $i \in \{1, \dots, M/SA\_R\}$  do
2:    $v\_r = \text{LOAD\_ROW\_SET}(i)$ 
3:   for all  $j \in \{1, \dots, N/SA\_C\}$  do
4:      $v\_c = \text{LOAD\_COL\_SET}(i)$ 
5:      $v\_t = \text{INIT\_TILE}(i, j)$ 
6:      $v\_t = \text{SA}(v\_r, v\_c, v\_t)$ 
7:   end for
8:    $\text{STORE}(v\_t)$ 
9: end for
  
```

### Experimental Setup:

- RISC-V VPU
- Simulation: gem5+McPAT
- Implementation (eProcessor / 65nm)
- Index and unitary data load
- Workloads: AlexNet, ResNet18/50, Skin (DeepHealth)

# From generic to dedicated

## Vector Processing Unit vs. Systolic Array

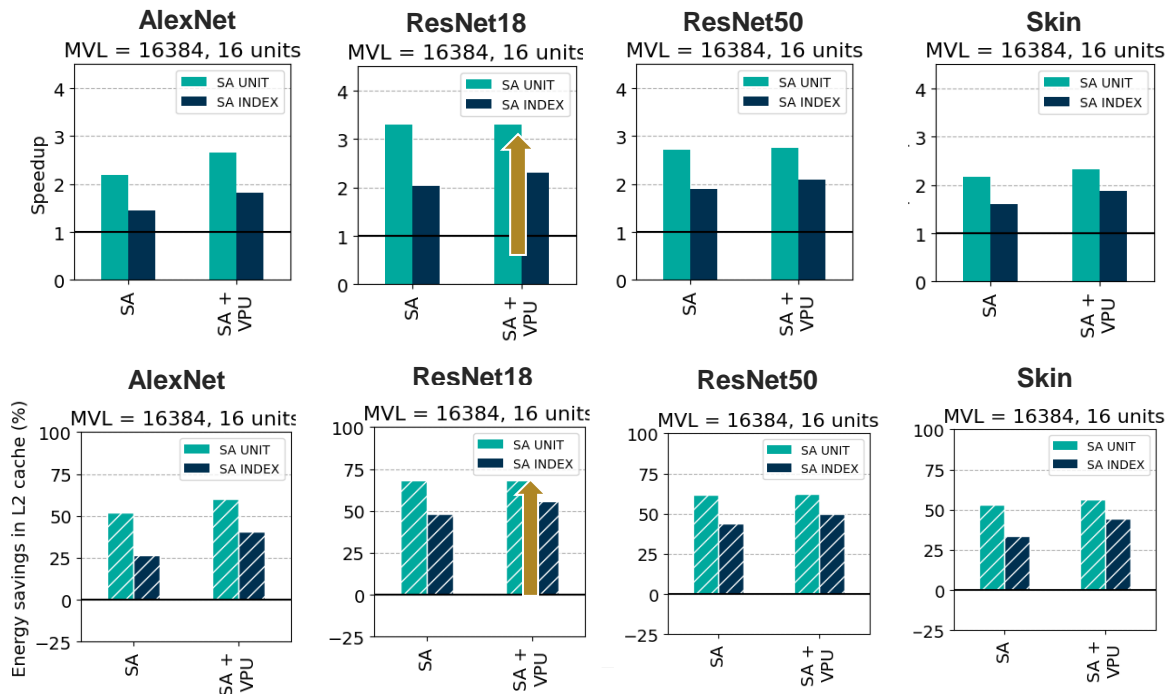


Different phases of same application benefit differently from VPU or SA – Hybrid can achieve the best of both worlds!



# From generic to dedicated

## VSA speedup and energy savings



Minimal area  
overhead of 0.1%

Up to 3.5x  
speedup

Up to 70% energy  
savings in cache

# From generic to dedicated

## Open questions...

Which extensions make sense?

Which are quality metrics?  
(performance/area)

???

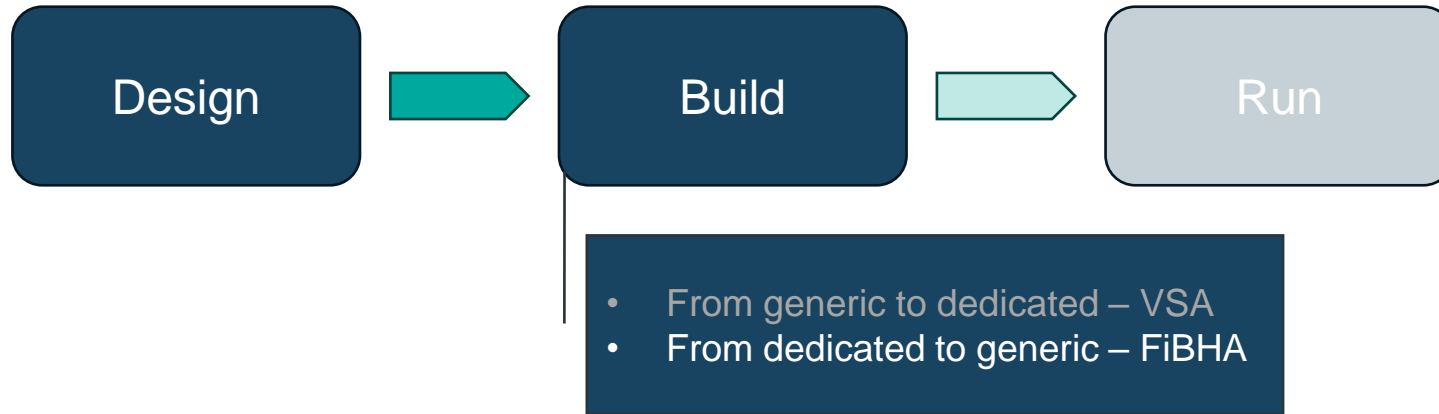
How many extensions to be supported at the same time?

How should we configure a multi-engine accelerator?

How dedicated should a generic engine be?

# Our work (so far...)

## Deep Learning accelerators



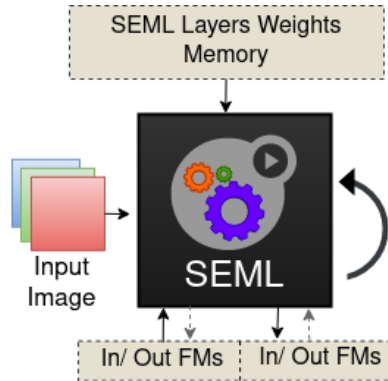
# From dedicated to generic

## FiBHA: Fixed Budget Hybrid CNN Accelerator

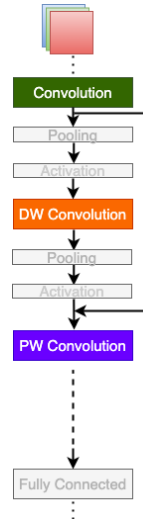
**Observation:** ML Models are increasingly and more heterogeneous



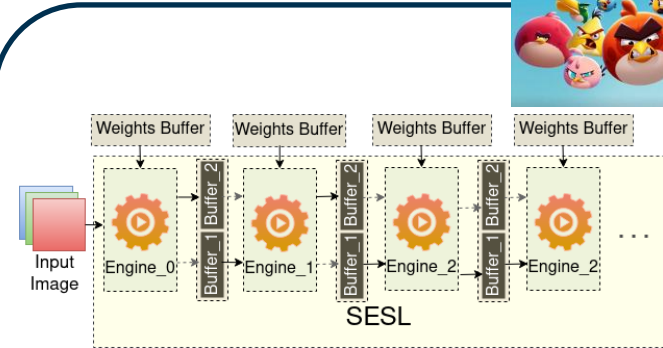
Option A



All layers are executed by the same engine  
Single Engine Multiple Layers (SEML)



Option B



Each layer is executed by a different engine  
Single Engine Single Layer (SESL)

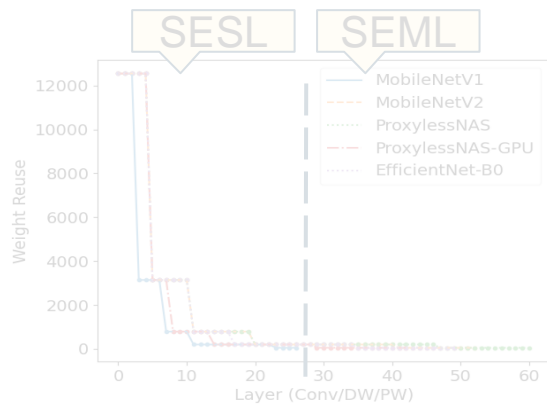


- F. Qararyah, M. W. Azhar and P. Trancoso, "FiBHA: Fixed Budget Hybrid CNN Accelerator," *2022 IEEE 34th International Symposium on Computer Architecture and High Performance Computing (SBAC-PAD)*, Bordeaux, France, 2022, pp. 180-190
- F. Qararyah, M. W. Azhar, and P. Trancoso, "An Efficient Hybrid Deep Learning Accelerator for Compact and Heterogeneous CNNs," *ACM Transactions on Architecture and Code Optimization (TACO)* 21(2), Article 25 (June 2024), 26 pages.

# From dedicated to generic

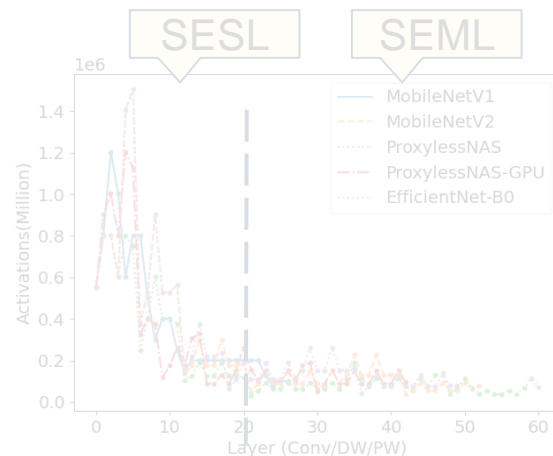
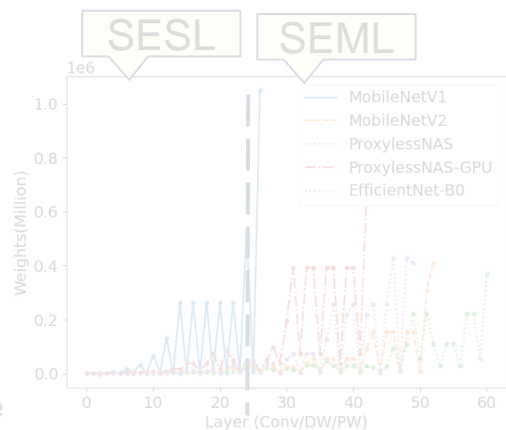
## SESL & SEML: When to use which?

# SplitCNN



Keep weights in  
local memory

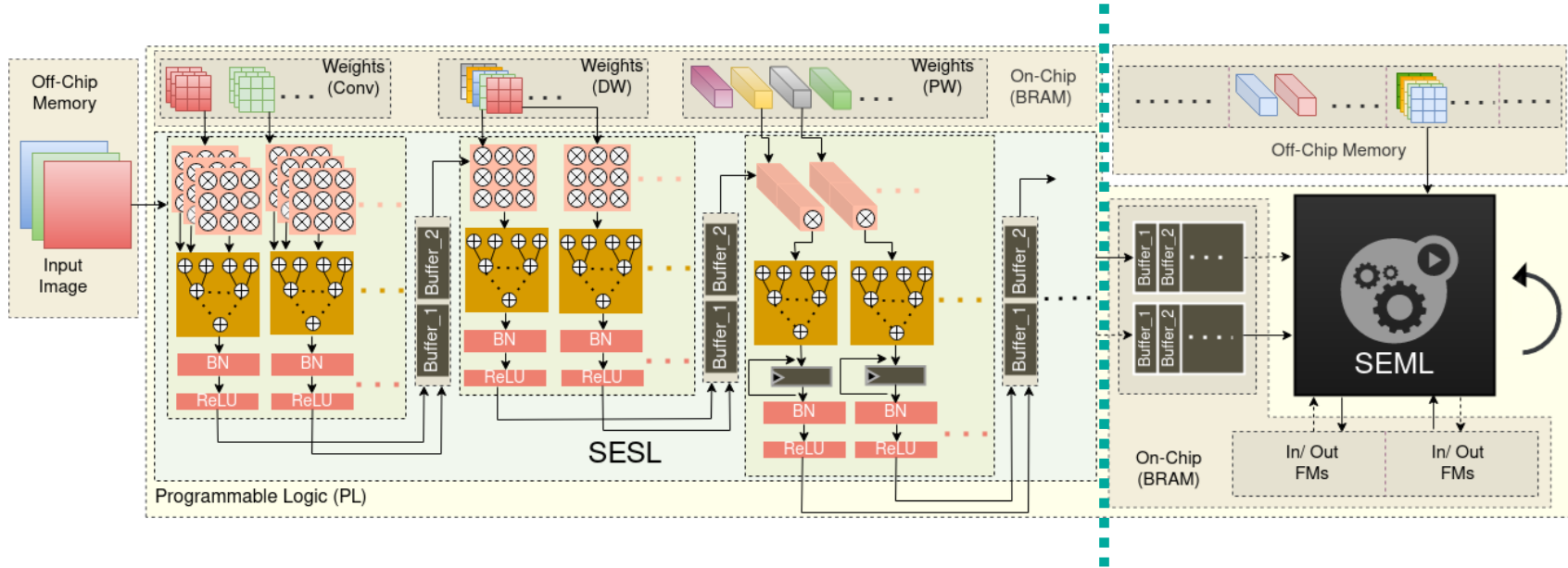
Limited local  
memory space



Dataflow reduce  
temporary storage

# From dedicated to generic

## FiBHA example

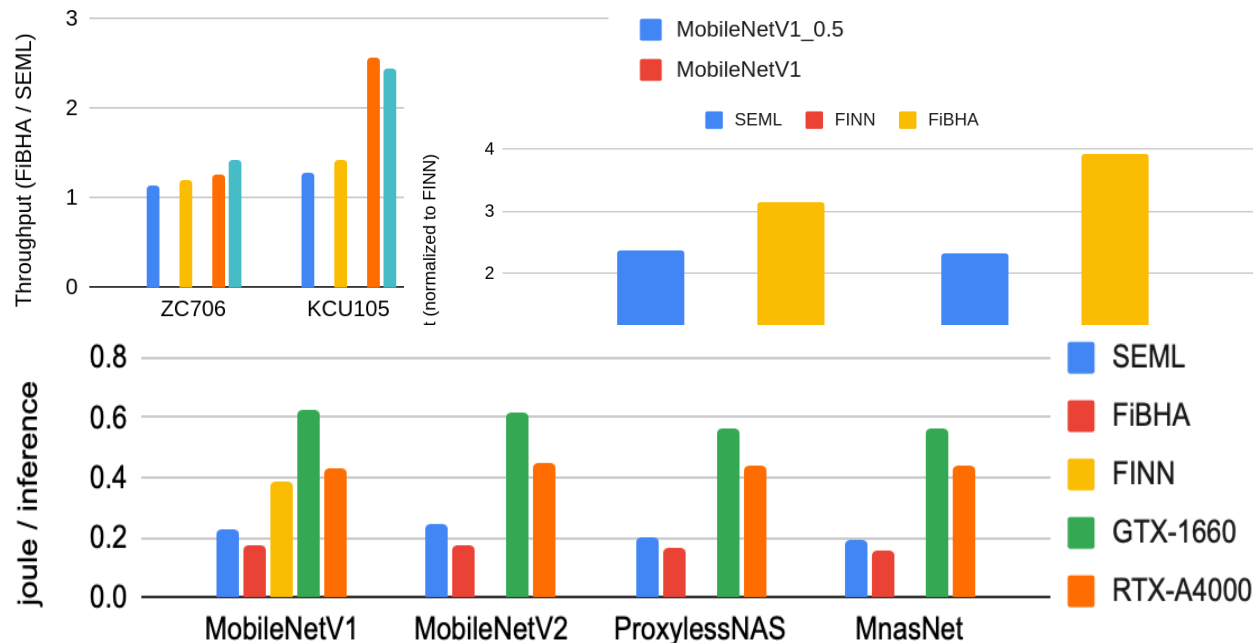


Implemented in HLS, evaluated on FPGA!



# From dedicated to generic

## Results



FiBHA hybrid accelerator balances heterogeneity & resource budget

$\cong 4\times$  Throughput improvement

$\cong 2\times$  Energy efficiency

# From dedicated to generic

## Open questions...

Which engines should  
be made available?

Which combinations of engines  
and configurations into a multi-  
engine accelerator?

???

Which configurations  
depending on goals?

How generic  
should a dedicated  
engine be?

# “Science Fiction” => The Vision

Flexible, Scalable, Efficient – Together<sup>1-2-3</sup>

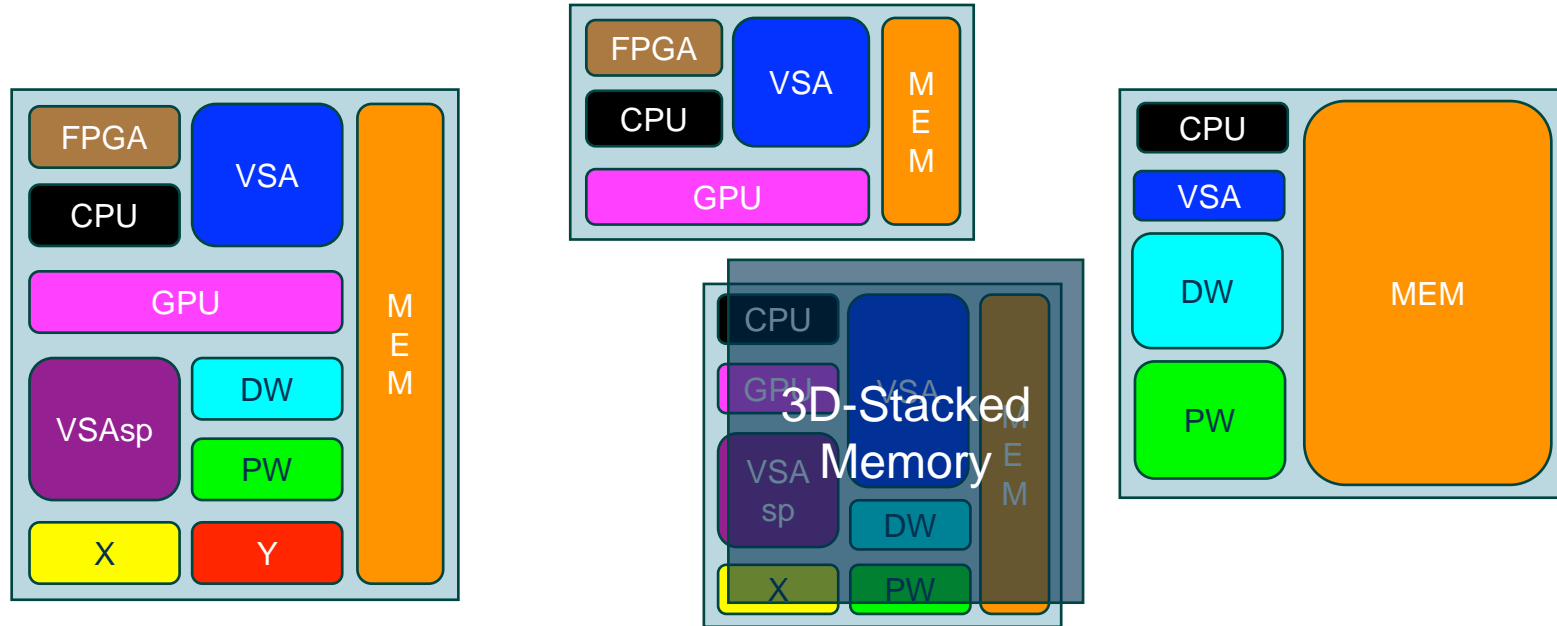


Volvo Museum, Gothenburg, Sweden



# The Vision

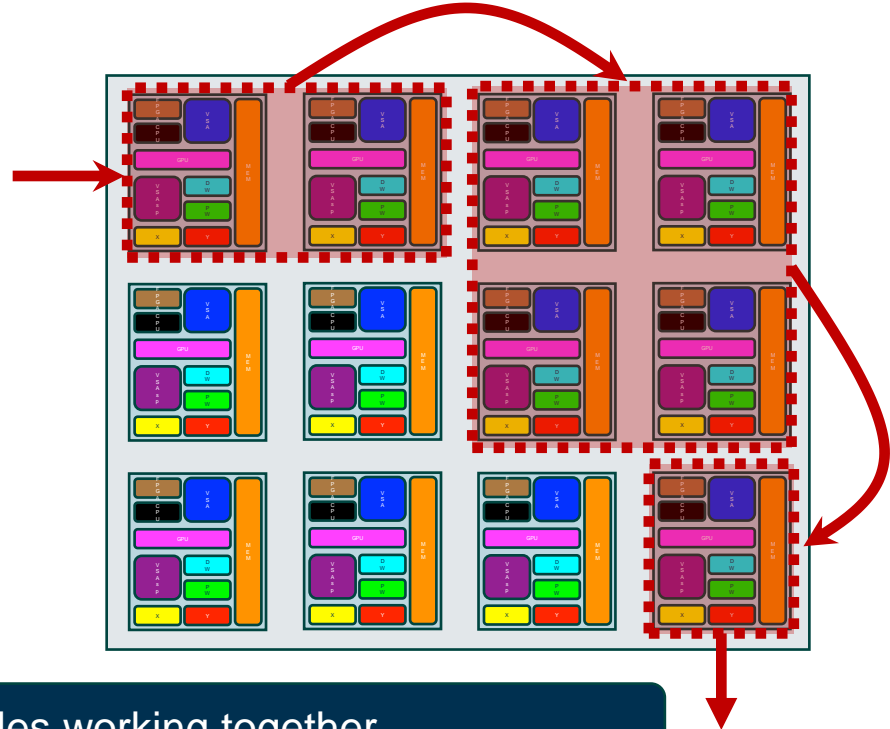
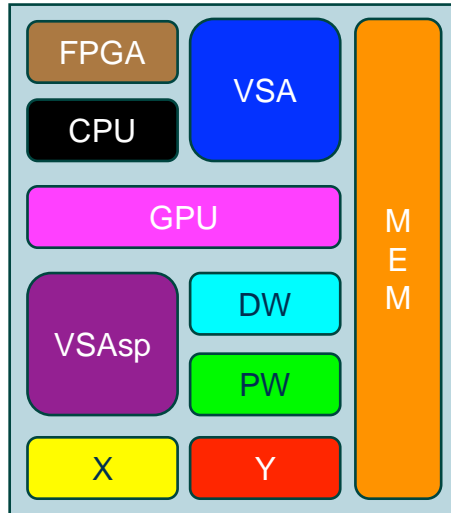
Flexible, Scalable, Efficient – Together<sup>1</sup>



Units working together

# The Vision

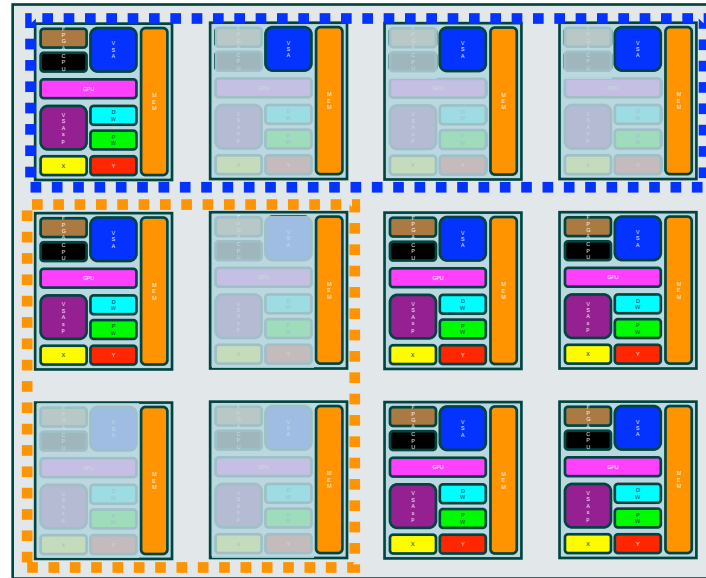
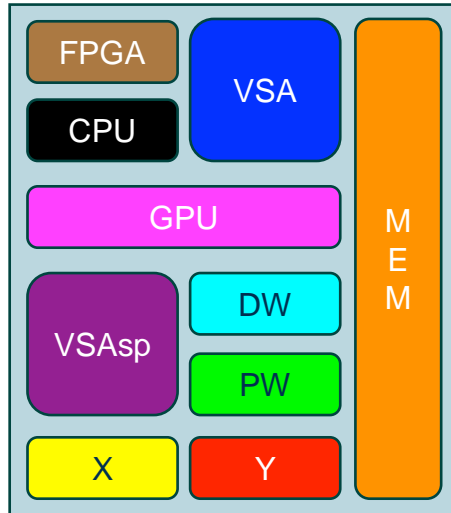
Flexible, Scalable, Efficient – Together<sup>2</sup>



Tiles working together

# The Vision

## Flexible, Scalable, Efficient – Together<sup>3</sup>



Resources shared together

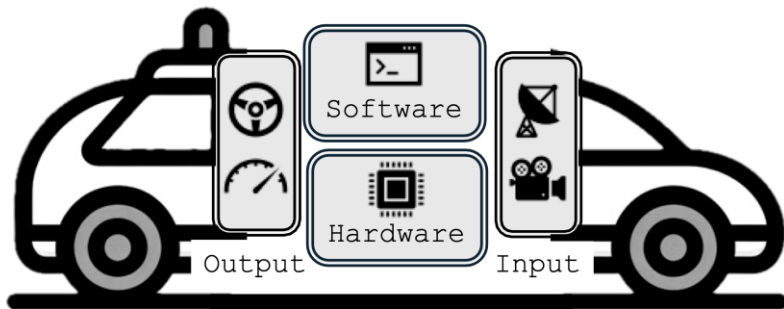




Swedish Foundation  
for Strategic Research



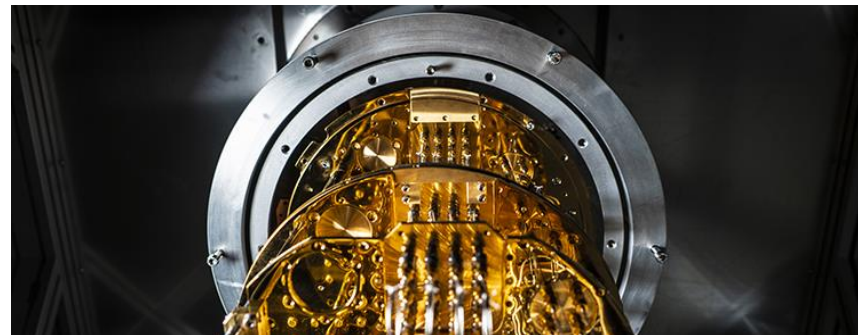
# We also accelerate...



## SSF-AutoPiM

- Develop energy-efficient hardware accelerators for autonomous vehicles
- Deep learning application
- Novelty: combine near- and in-memory proc.
- Our contribution: near-memory processing
- Collaboration: Bar-Ilan University

X. Wang, M. A. Maleki, M. W. Azhar, P. Stenström, and P. Trancoso, "Challenges and Directions for Autonomous Driving Hardware Accelerators", ACACES 2024, Italy, July 2024

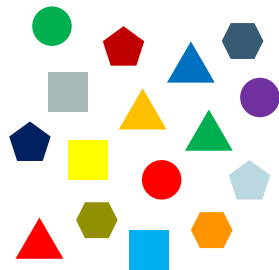


## SSF-QuantumStack

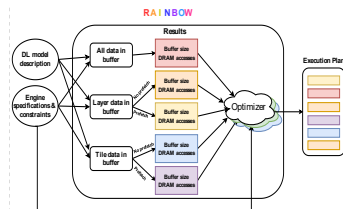
- Develop a full software stack for programming quantum computers
- Novelty: Bring all together – physics, computer science and engineering; improve programmability for QC
- Our contribution: hardware acceleration for QC simulation and error correction
- Collaboration: CSE and WACQT

# Conclusions

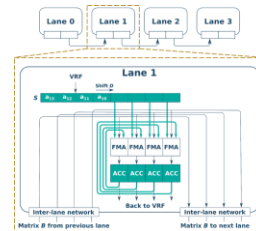
Applications



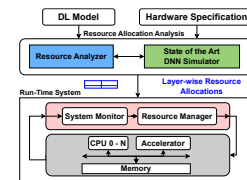
RAINBOW



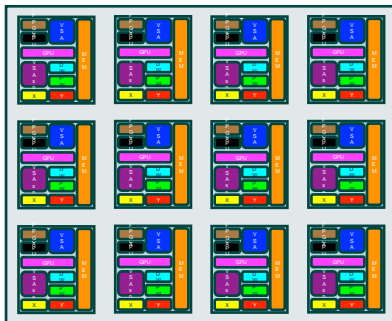
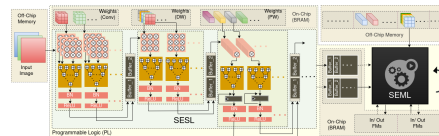
VSA



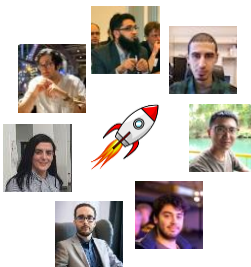
ARADA



FIBHA



**Flexible, Scalable,  
Efficient – Together<sup>3</sup>**





**CHALMERS**