

# Unconventional Compute Architectures for Enabling the Roll-Out of Deep Learning

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# Background

## > Xilinx



- » Fabless semiconductor company
- » Founded in Silicon Valley in 1984
- » Today:
  - 3,500 employees
  - \$2.5B revenue
- » Invented the FPGA



1<sup>st</sup> FPGA in 1985: XC2064  
128 3-input LUTs

# What are FPGAs?

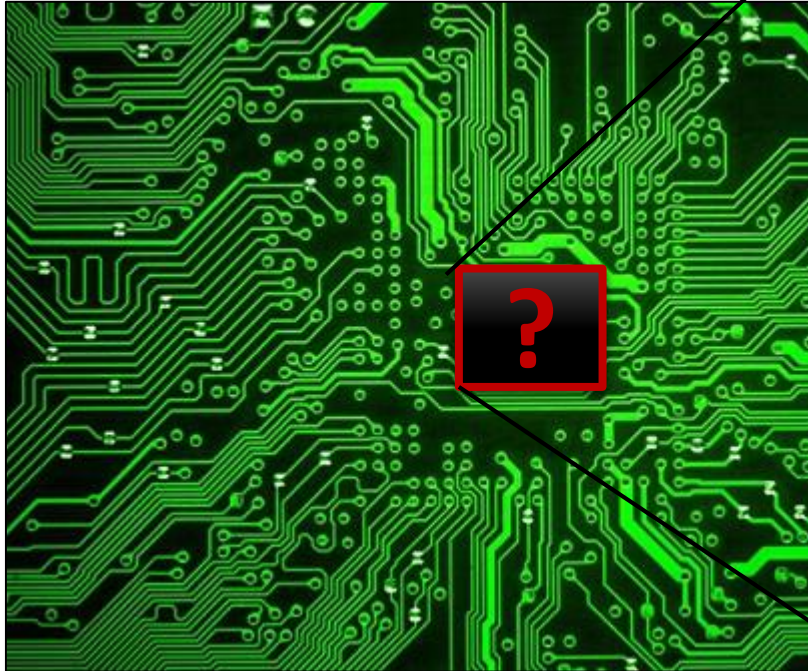
## *Customizable, Programmable Hardware Architectures*

- > The **chameleon** amongst the semiconductors... 
  - >> Customizes IO interfaces, compute architectures, memory subsystems to meet the application
- > **Classic use case:** Nothing else works, and you want to avoid ASIC implementation
- > **Recent use cases:** Custom hardware architecture for performance or efficiency required 

Non-standard IOs

Different functionality?

Higher performance or  
efficiency metrics?



HONEY, WAIT !  
I CAN CHANGE !





# Trends Meet Technological Reality



Roll-out of machine learning  
“Potential to solve the unsolved”

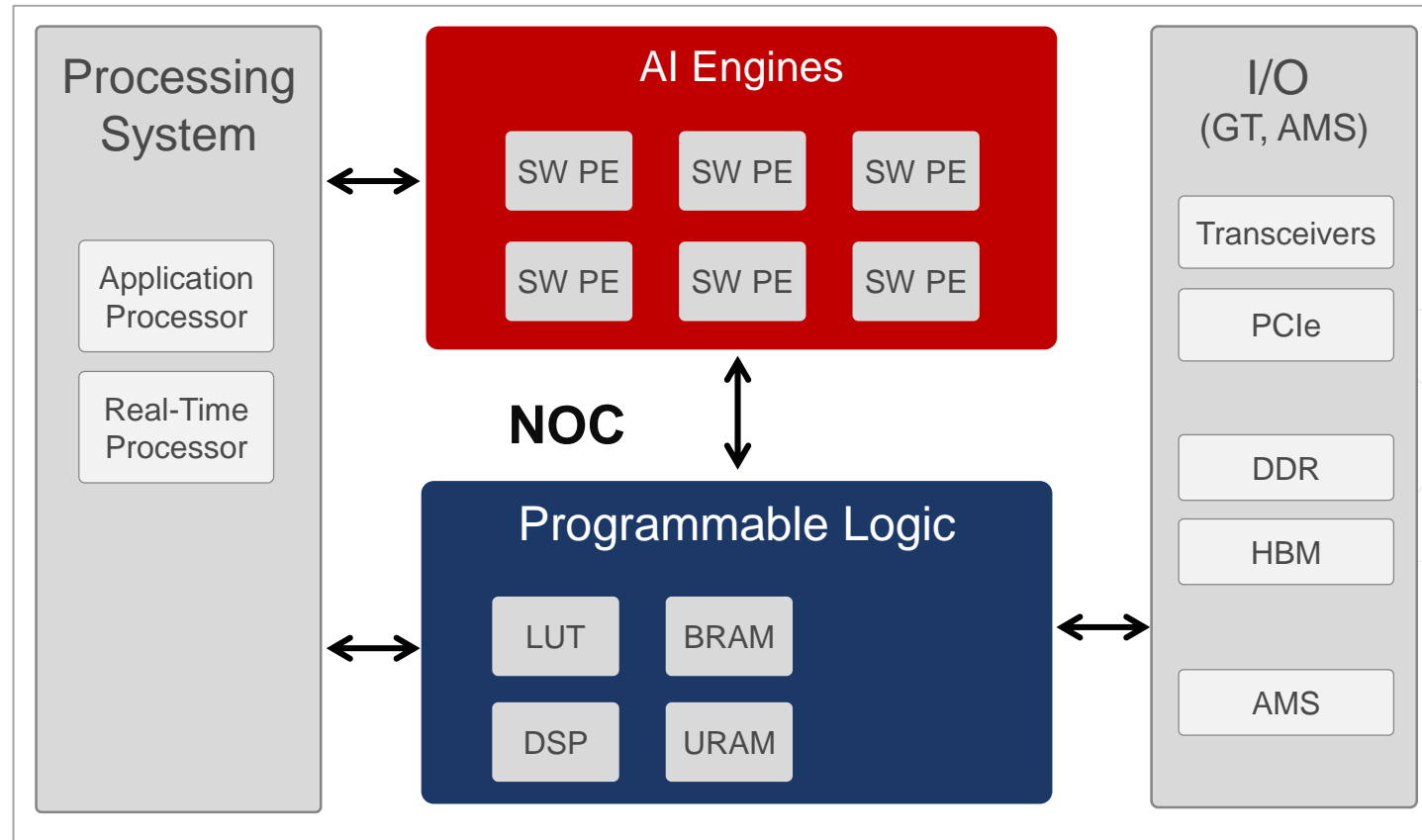
Explosion of Data  
“genomical”

End of Moore’s Law  
End of Dennard Scaling

## Era of heterogeneous computing has begun

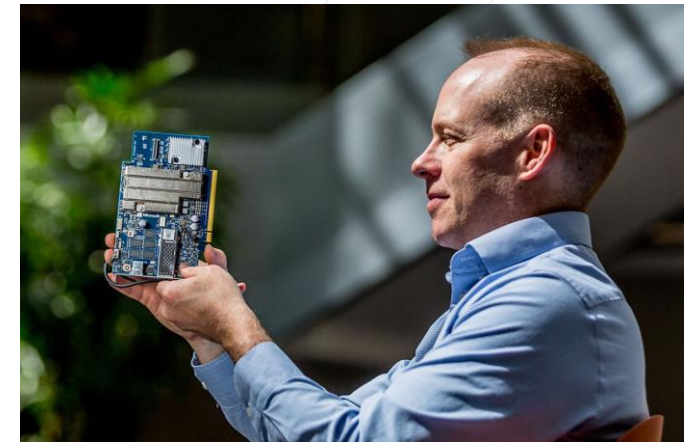
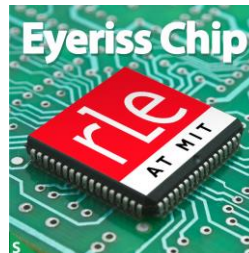
- Diversification of increasingly heterogeneous “unconventional” devices
- Moving away from van Neumann architectures
- Architectural and algorithmic innovation is needed

# Increasingly Heterogeneous Devices From the Xilinx World: Evolution of FPGAs to **ACAPs**

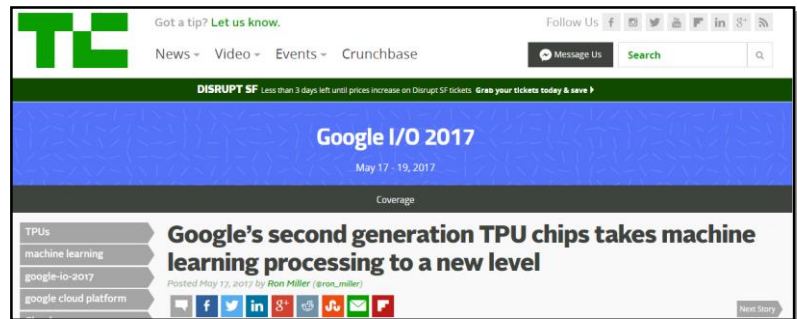


# *More Unconventional:* Customized Hardware for AI *DPU: Deep Learning Processing Unit*

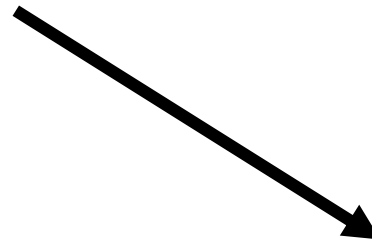
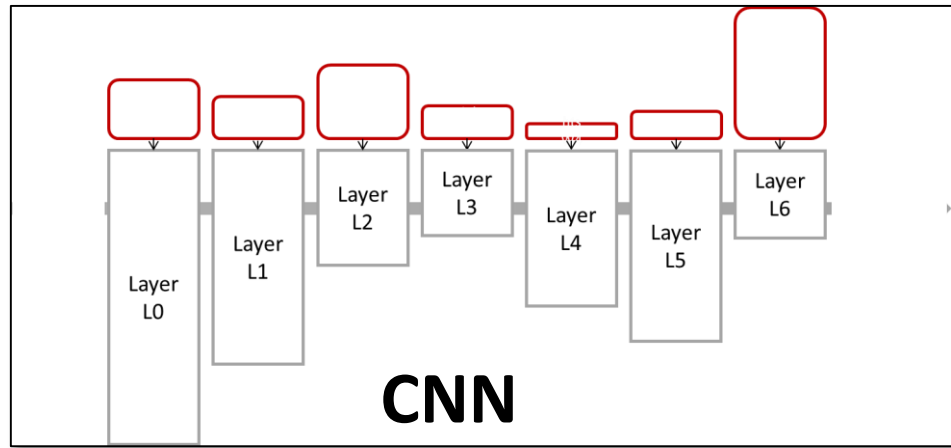
> Custom AI Accelerators (soft in FPGA and hard in ASICS)



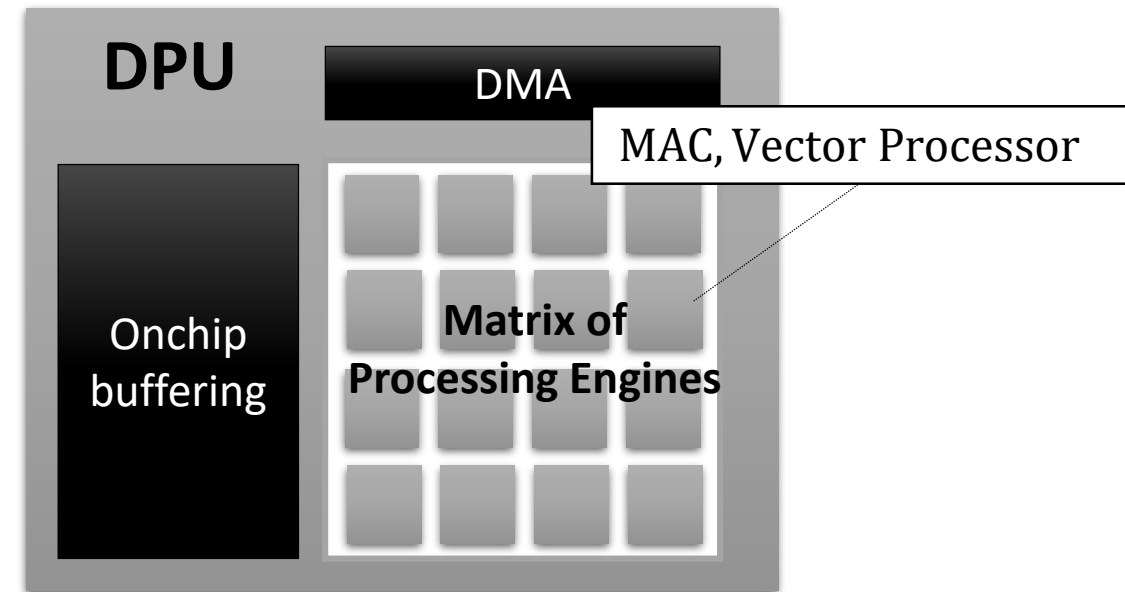
Microsoft Brainwave



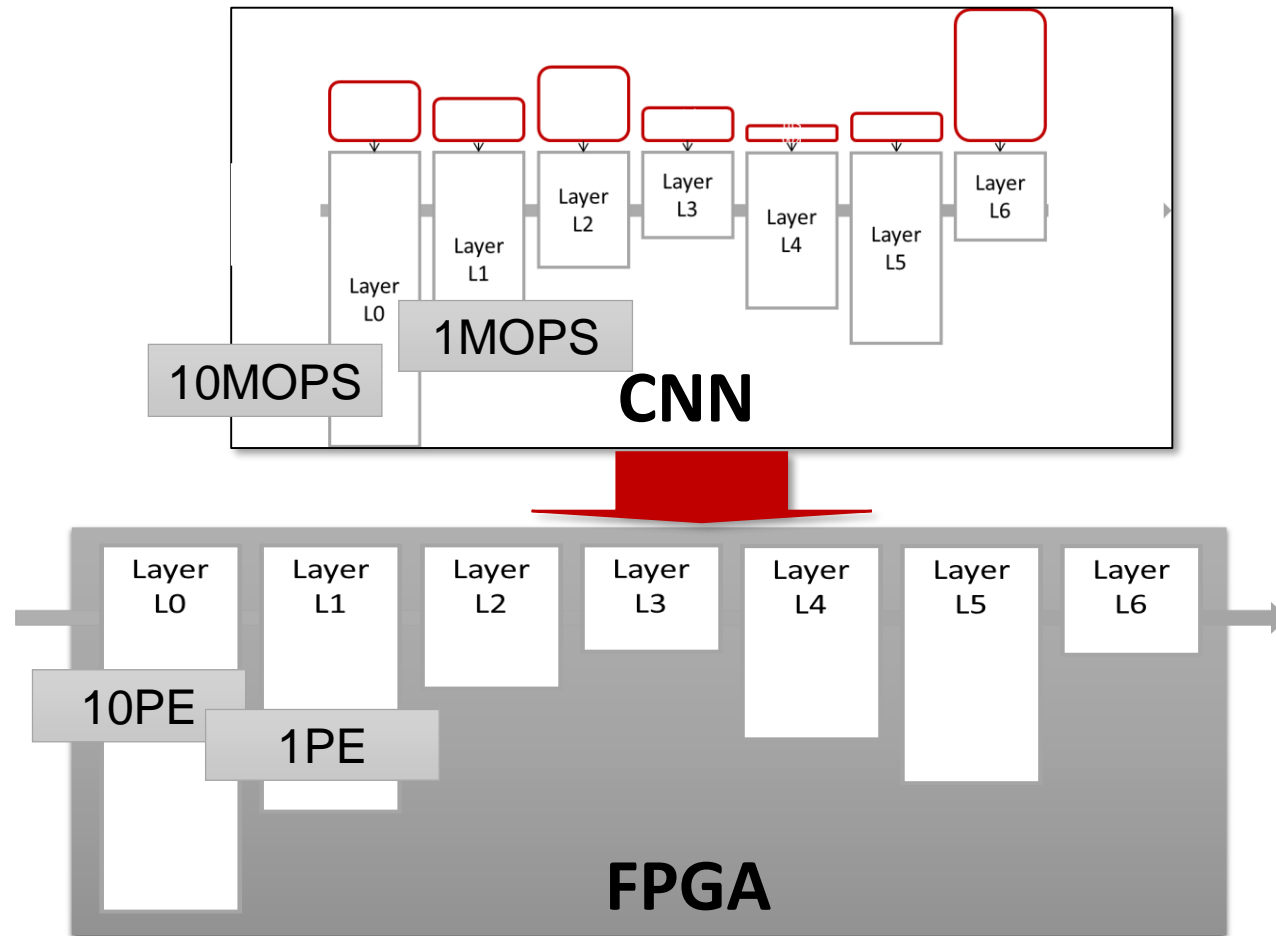
# Popular DPU Architecture



***"Layer by layer compute"***



***Even more unconventional:***  
**Custom-Tailored Hardware Architectures (Macro-Level)**  
***Synchronous Dataflow***

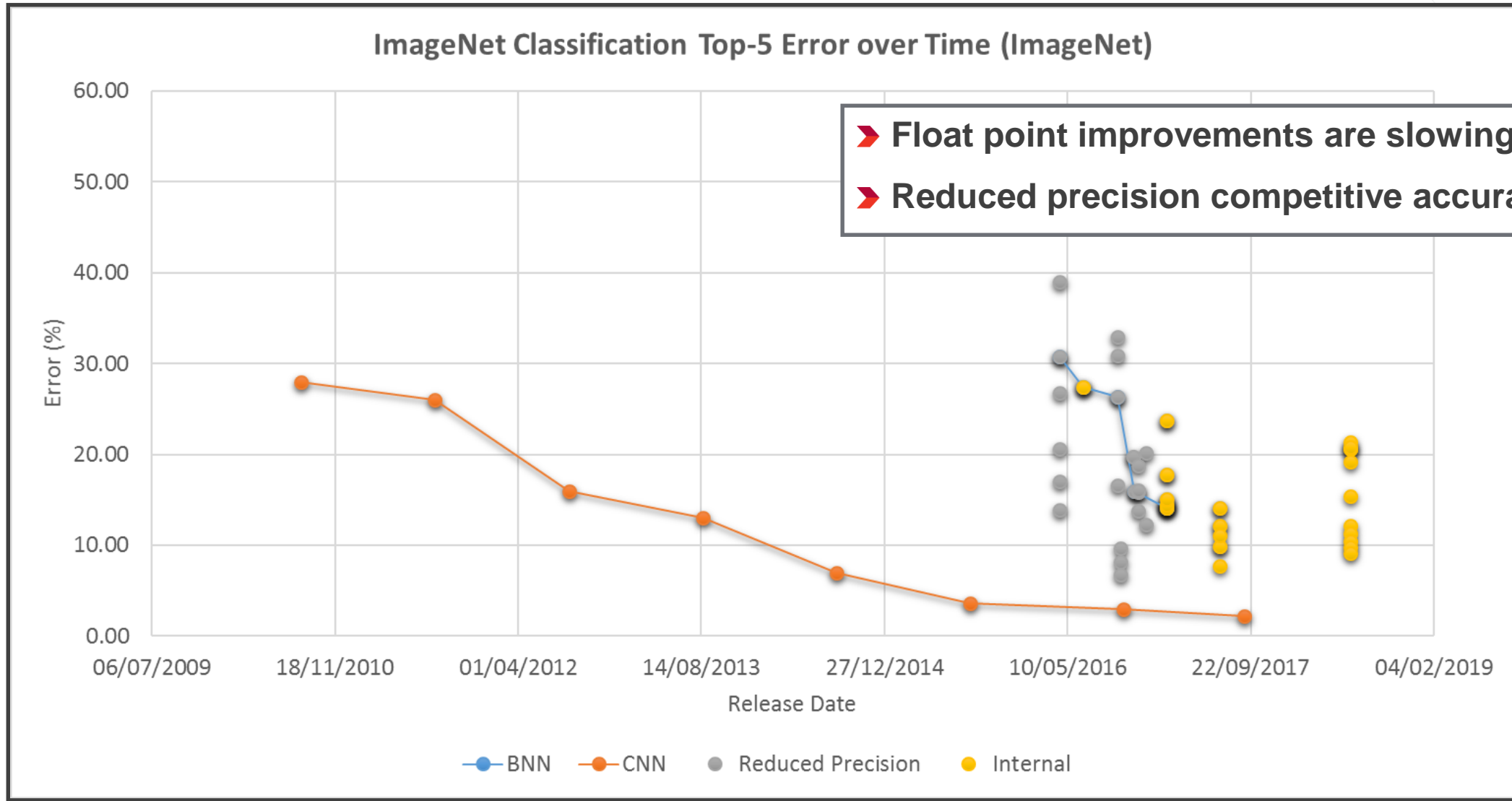


***“Hardware Architecture Mimics the NN Topology”***

- > Customized feed-forward dataflow architecture to match network topology
- > Higher compute and memory efficiency



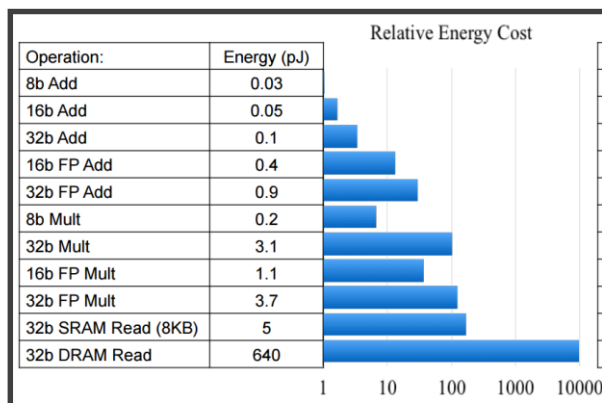
# *Further unconventional at the Micro-Architecture, leveraging Floating Point to Reduced Precision Neural Networks*



# Reducing Precision

## *Scales Performance & Reduces Memory*

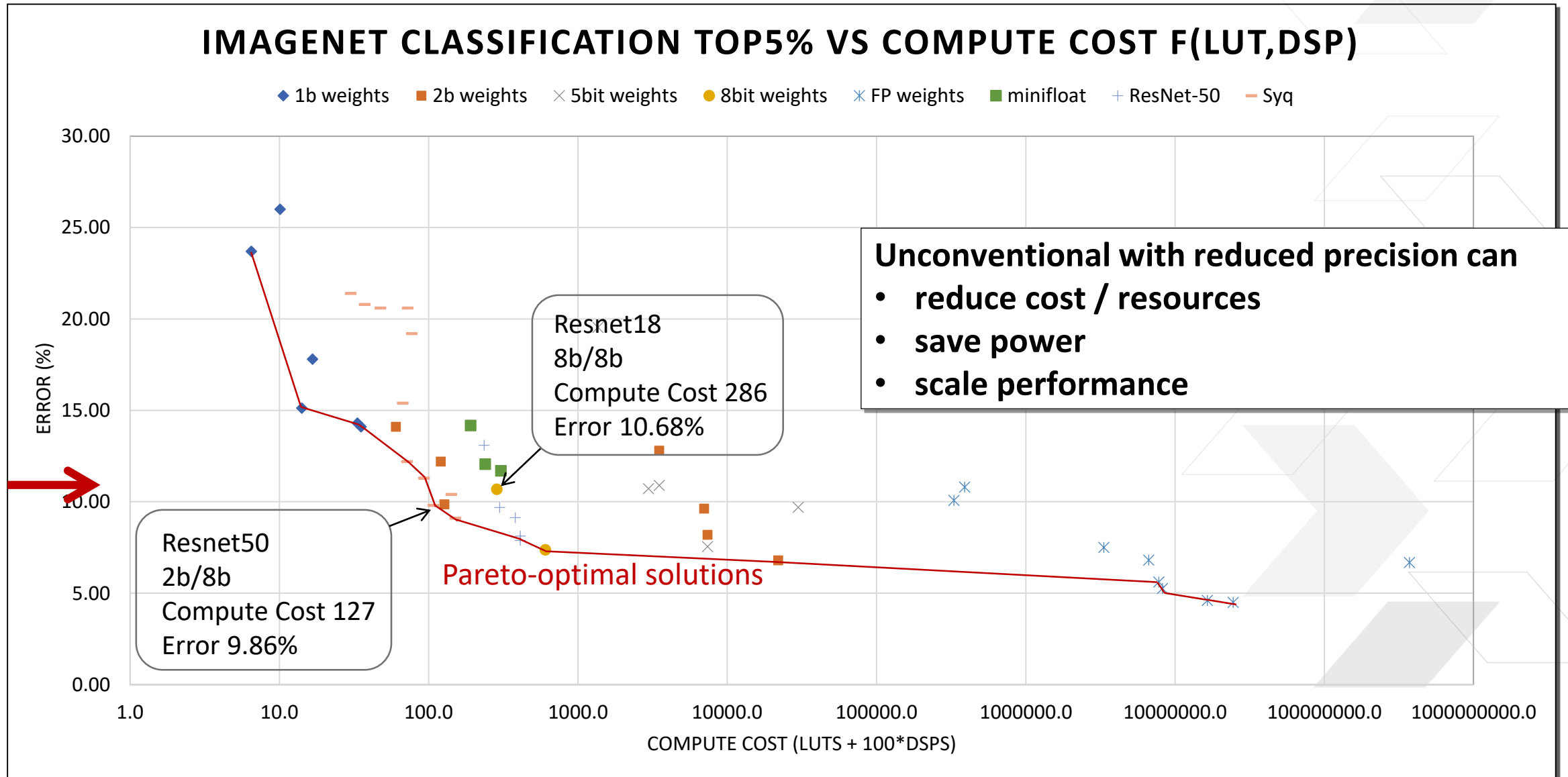
- > Reducing precision shrinks hardware cost
  - >> Instantiate **100x** more compute within the same fabric
  - >> Thereby scale performance **100x**
- > Potential to reduce memory footprint
  - >> NN model can stay on-chip => no memory bottlenecks
- > Reducing precision inherently saves power



Precision	Modelsize [MB] (ResNet50)
1b	3.2
8b	25.5
32b	102.5

Source: Bill Dally (Stanford), Cadence Embedded Neural Network Summit, February 1, 2017

# Design Space Trade-Offs



# Summary

- **Unconventional computing architectures emerge to help with the roll-out of deep learning**
- **Customized dataflow architectures and precisions provide dramatic performance scaling and energy efficiency**
- **Providing new exciting trade-offs within the design space**

**More information can be found at:**  
**<http://www.pynq.io/ml>**

# Adaptable. Intelligent.



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