Stochastic

Harvard John A. Paulson School of Engineering and Applied Sciences

A Scalable Bayesian Inference Accelerator for Unsupervised Learning

Glenn Ko (Harvard University / Stochastic)

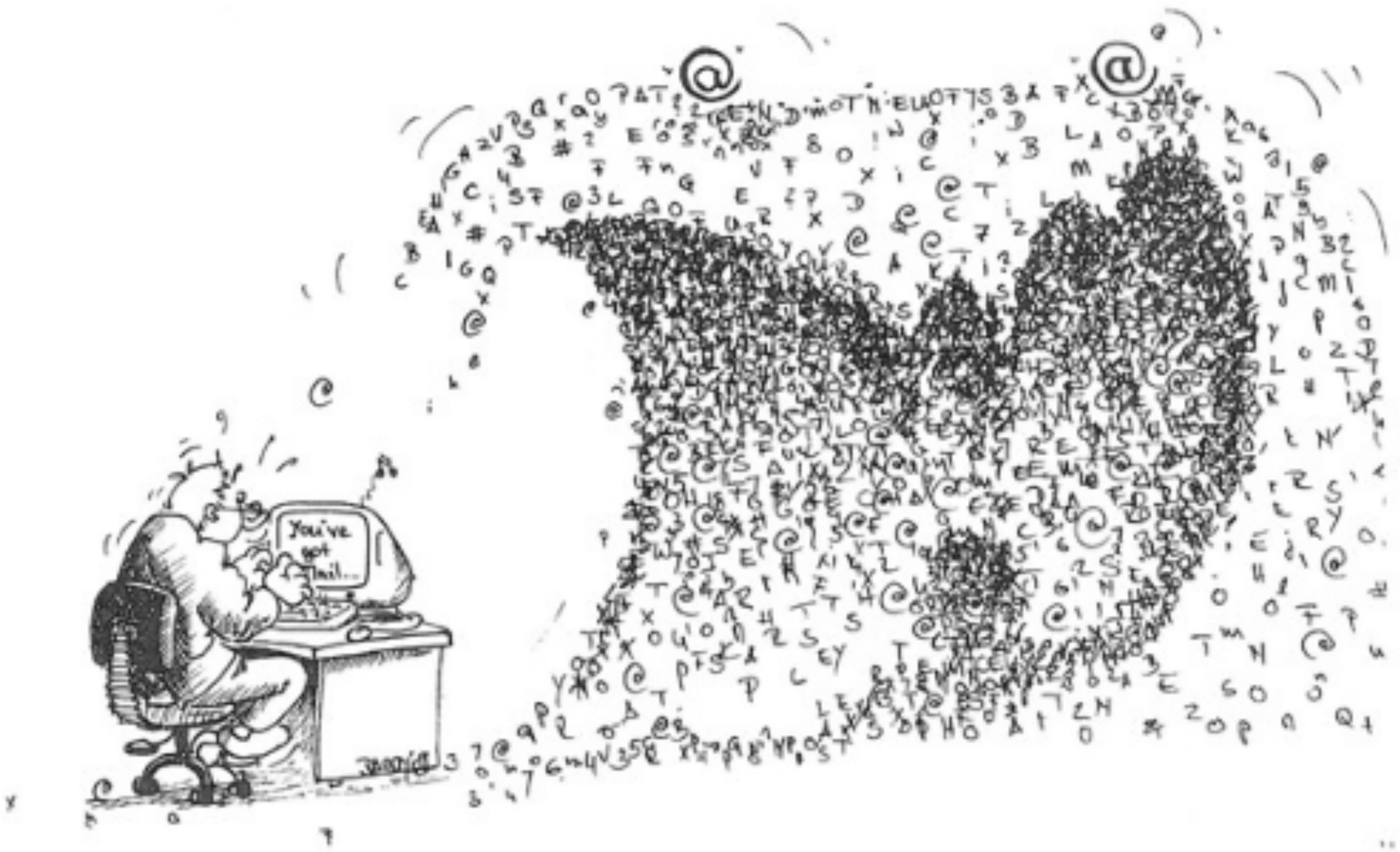
Yuji Chai[1], Marco Donato[1,2], Paul N. Whatmough[1,3], Thierry Tambe[1], Rob A. Rutenbar[4], Gu-Yeon Wei[1] and David Brooks[1]

Harvard University[1], Tufts University[2], Arm Research[3] , University of Pittsburgh[4]

The exponential data growth problem

Humans are generating data at an exponentially increasing rate.

Machine learning allows us to extract useful information from data **without much human intervention**.



Did we solve the problem?

Up to

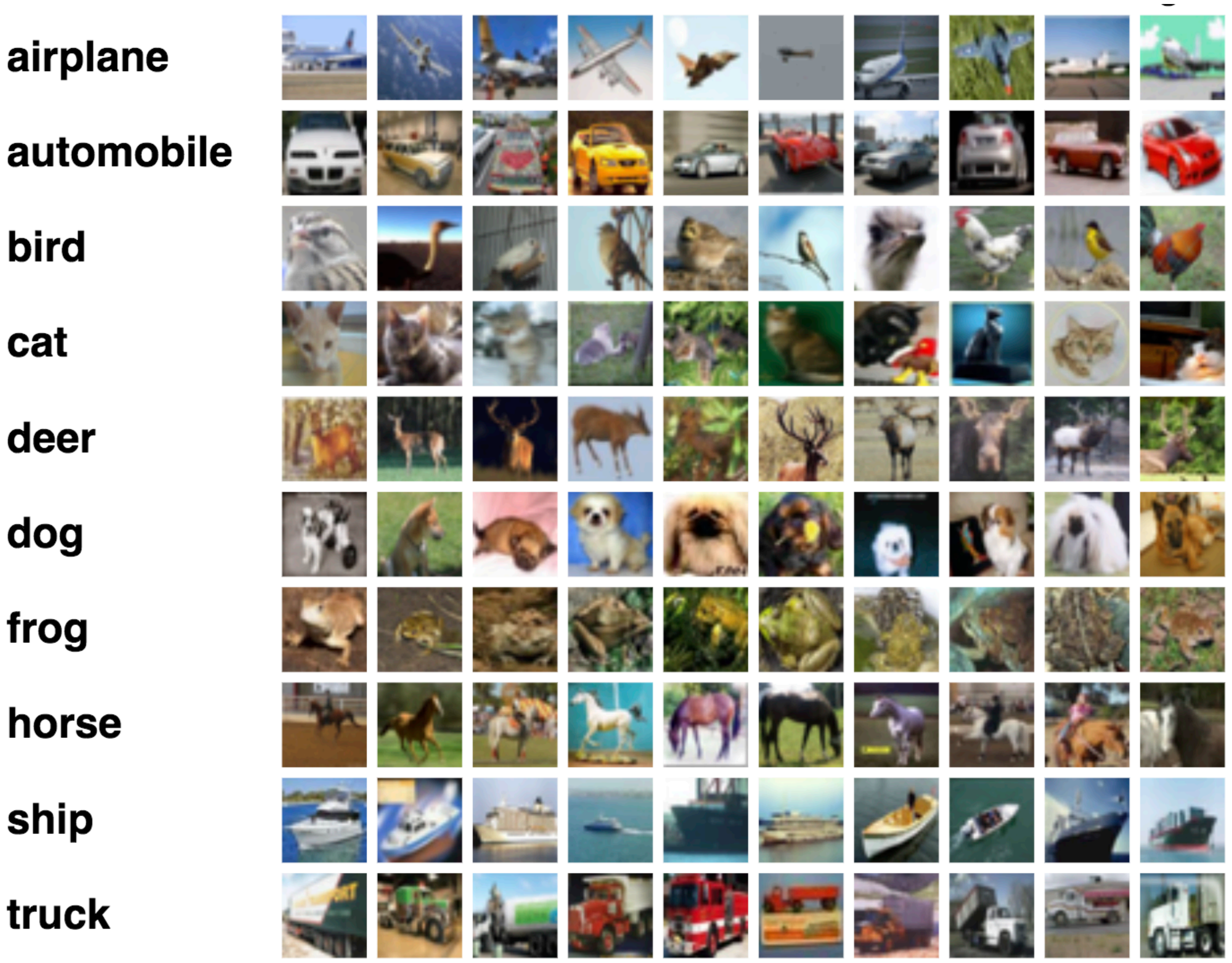
80% of time

of a data scientist is spent on sourcing and cleaning data

Deep learning requires

large labeled

datasets
(via data annotation services)



“The future of AI will be about less data, not more”

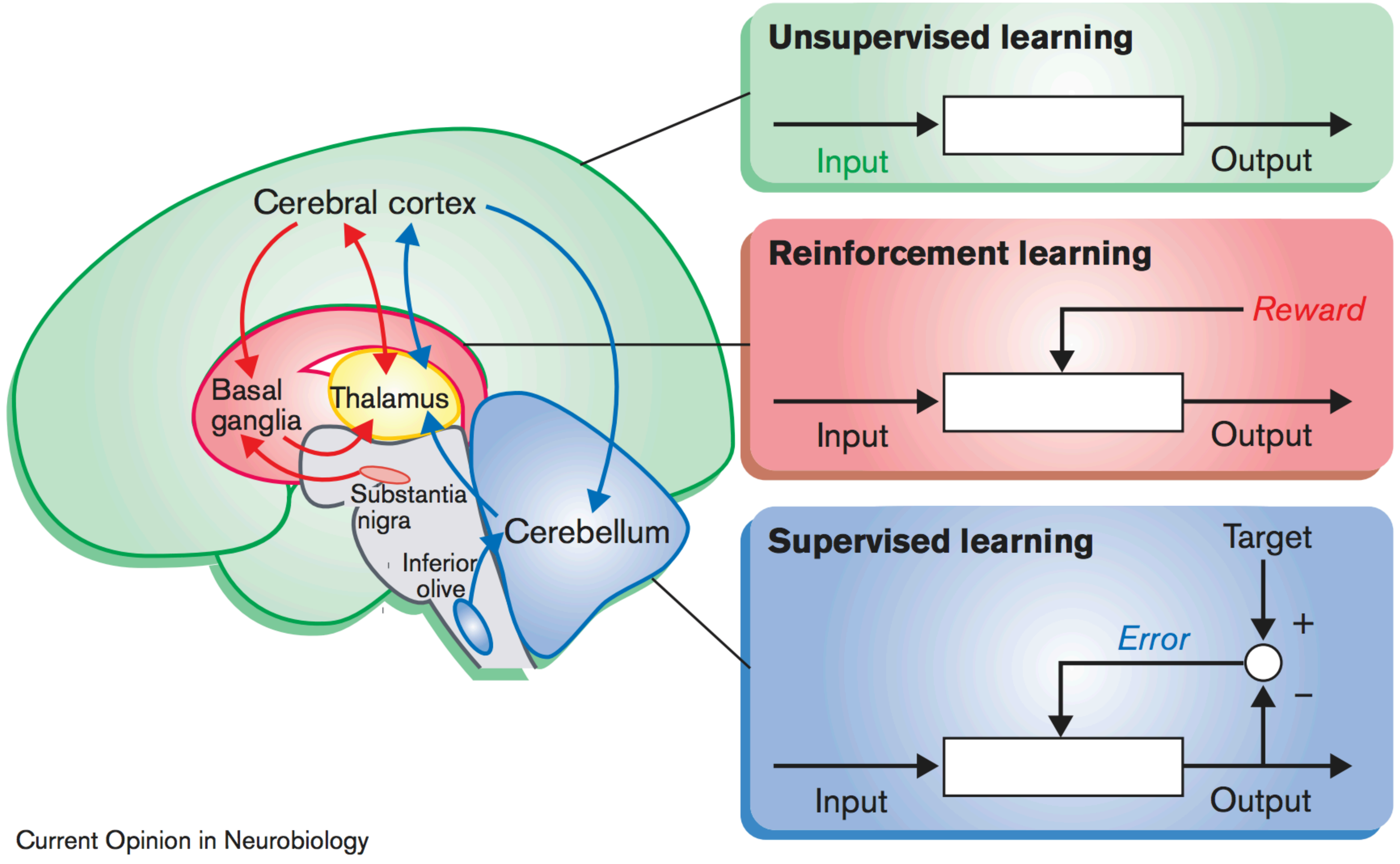
- Jan 19’ Harvard Business Review

Ref: CIFAR-10

Humans need a lot less data than machines

to generalize about and draw conclusions.

Babies can learn by crawling around and playing with toys or simply observing the behavior of adults.



Ref: https://babyology.com.au/; Doya et al. Curr Opin Neurobiol. 2000

Probabilistic Machine Learning

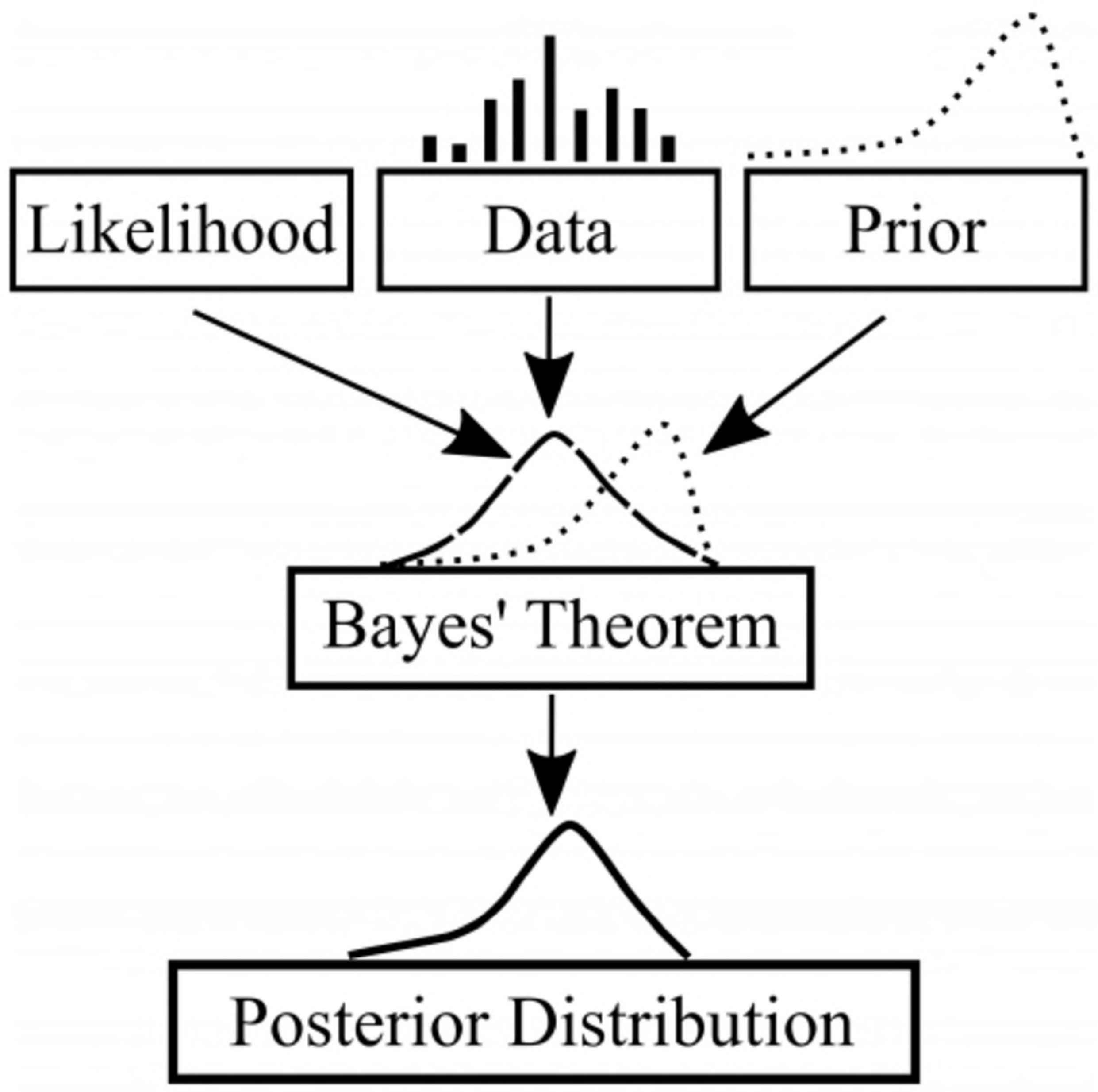
Or also called Bayesian learning

Probability is used to represent uncertainty about the relationship being learned.
Our beliefs about the true relationship are expressed in a probability distribution.

For learning and prediction,

<u>Bayesian Inference</u>:

How one should update one's beliefs upon observing data.



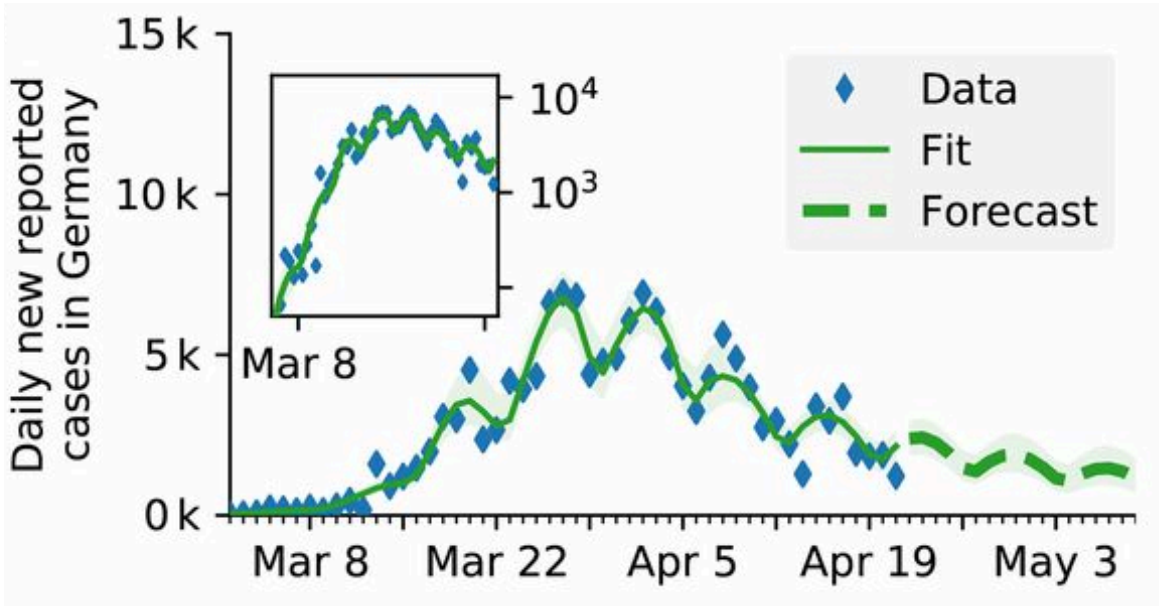
Bayes' theorem:

$$P(Hypothesis|Data) = \frac{P(Data|Hypothesis)P(Hypothesis)}{P(Data)}$$

Known to be More Powerful for

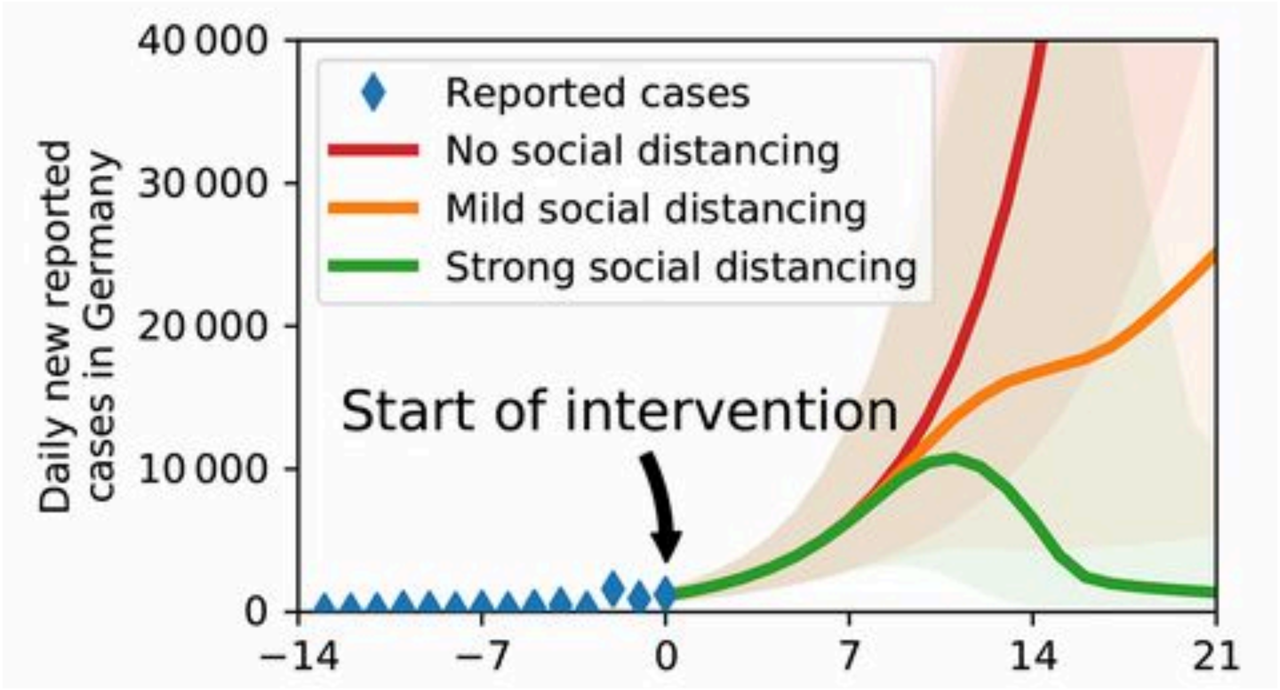
1. Online learning from small chunks of scarcely or unlabeled data

COVID-19 Predictions



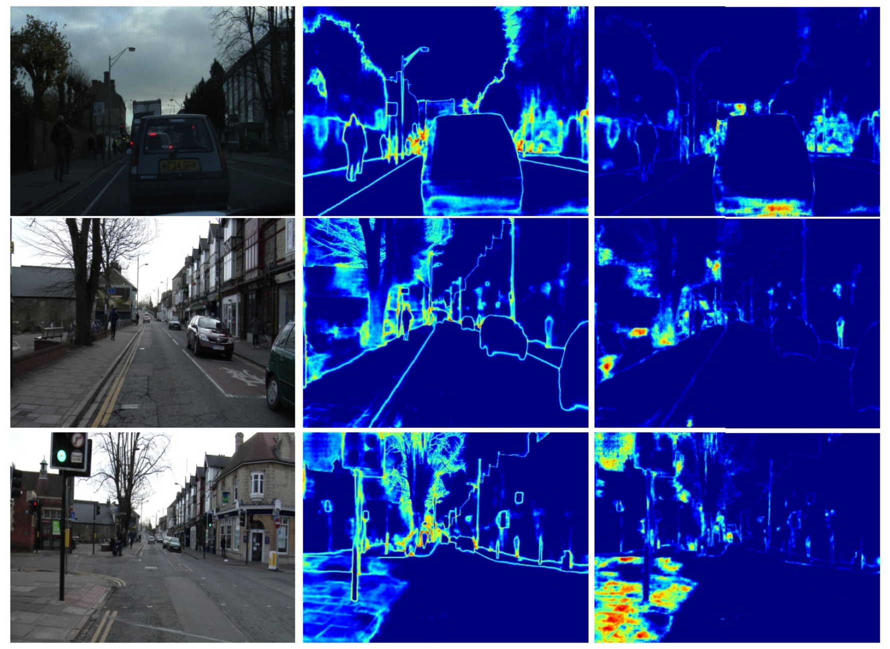
2. Finding a distribution instead of a point estimate

COVID-19 Predictions



3. Representing and computing with uncertainty

Autonomous Driving



Applications
- Biomedical
- Robotics
- Autonomous driving
- Finance

Problem

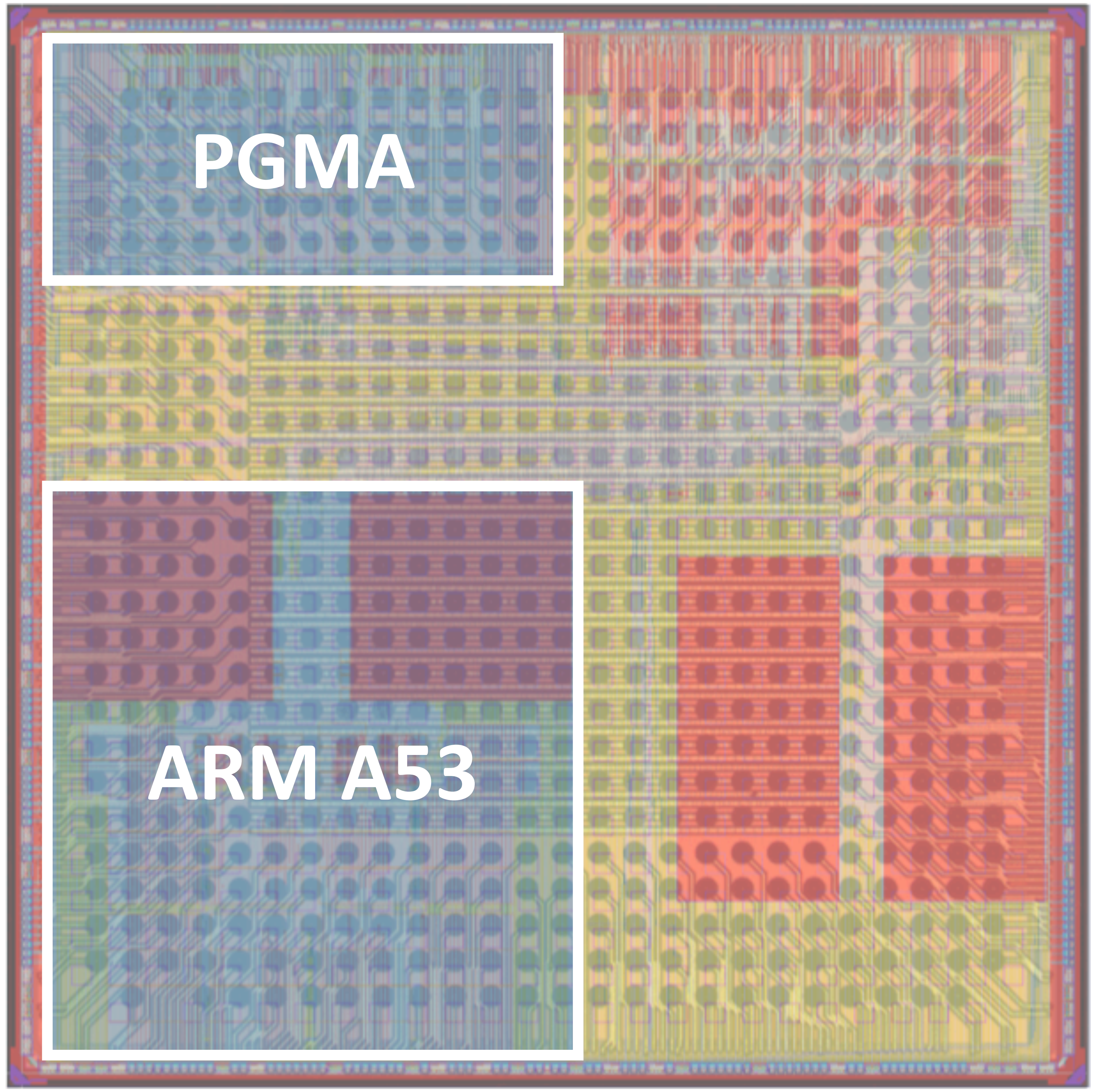
CPUs and GPUs are inefficient for Bayesian inference

Ref: Dehning et al. Science 2020, Kendell et al. NeurIPS 2017

PGMA: Probabilistic Graphical Models Accelerator

- First silicon accelerator for Bayesian inference
- Algorithm-hardware co-design for parallel MCMC inference
- To demonstrates efficient mobile implementation of Bayesian inference using unsupervised perceptual tasks
  - Stereo matching
  - Image restoration
  - Image segmentation
  - Sound source separation

SM5: A 16nm SoC for ML-Powered IoT Devices



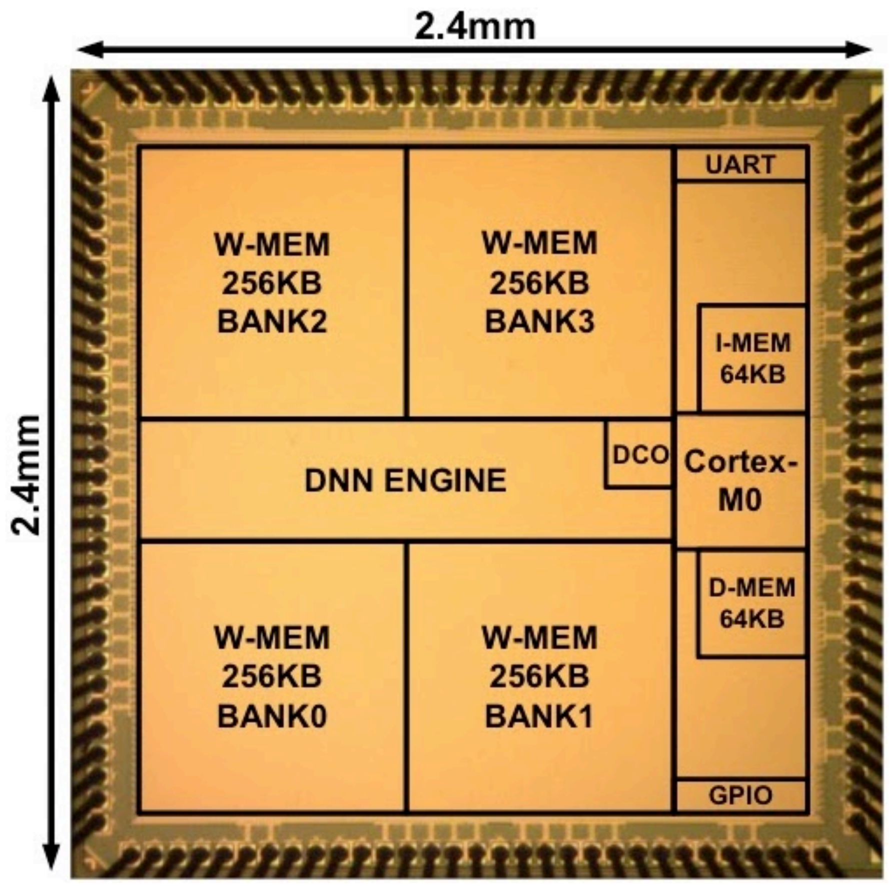
- TSMC 16nm FFC
- 25mm² (5mm x 5mm) SoC
- PGMA die area: 2.3mm x 1.3mm
- Designed using CHIPKIT
- Short design cycle: RTL to tape-out in 3 months by 5 people (2 postdocs + 3 PhDs)

Ref: Ko et al., VLSI 2020. Whatmough et al. IEEE Micro, 2020.

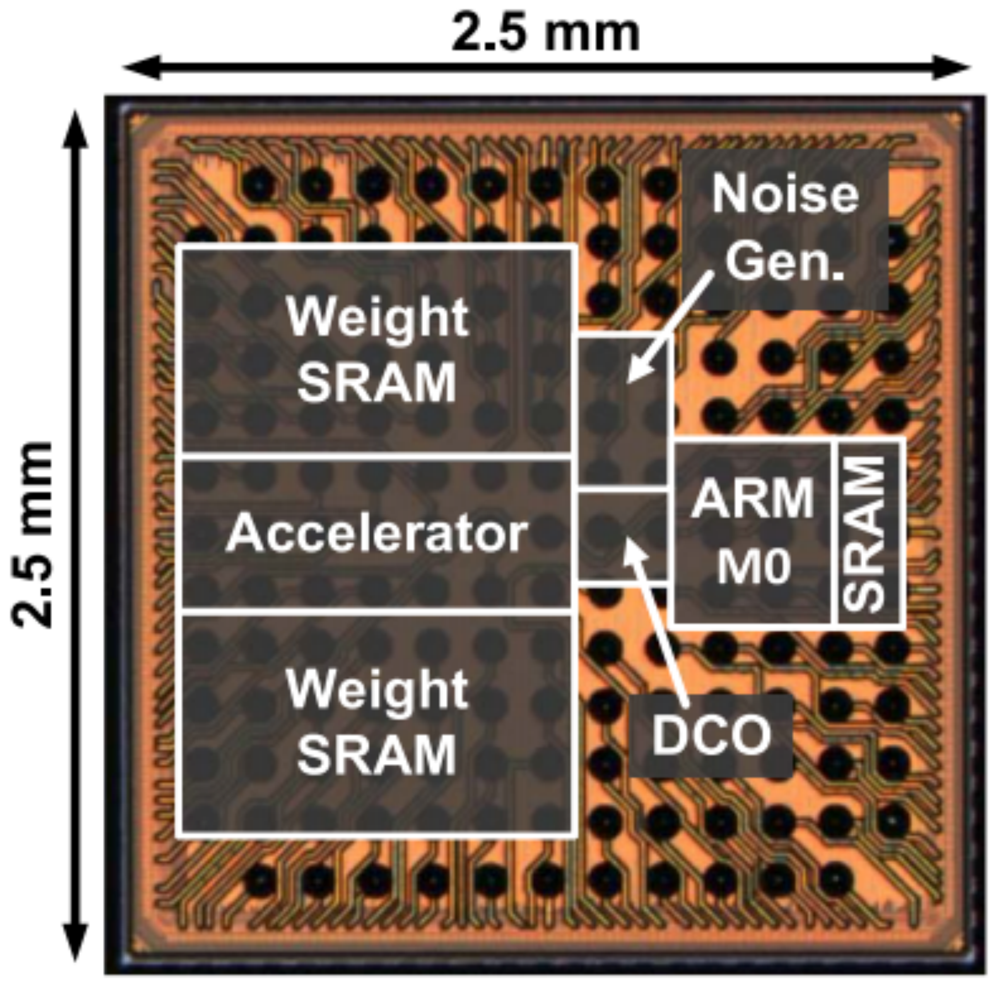
Harvard ML Research Platform + CHIPKIT

Arm M-class

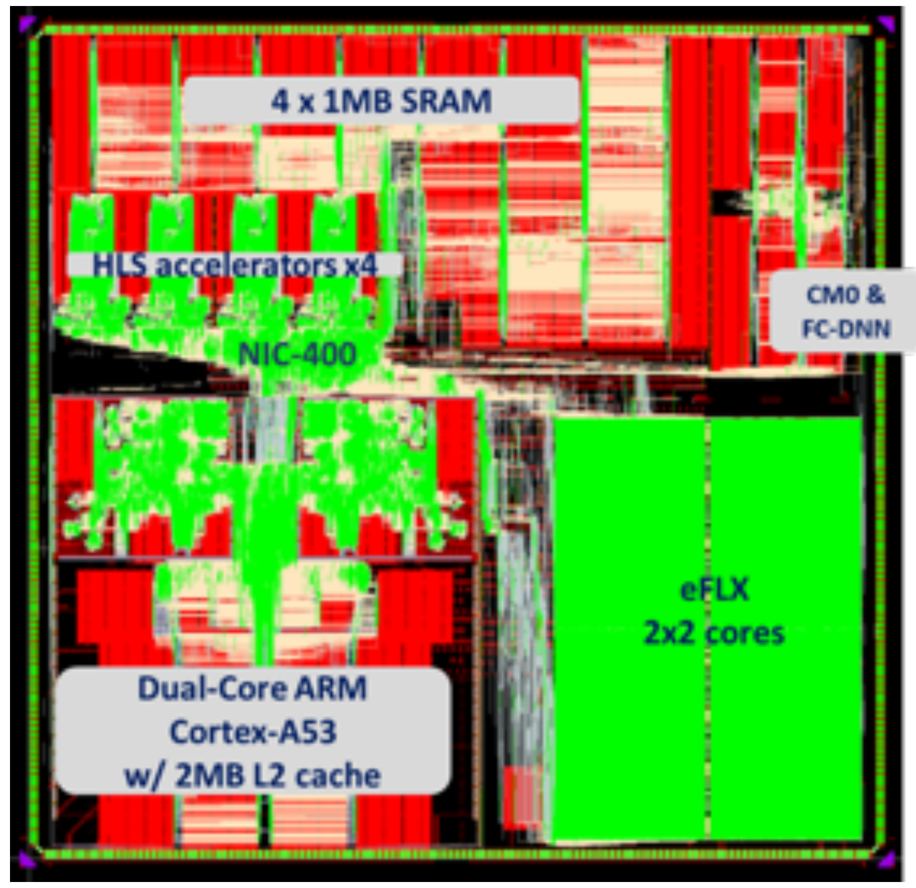
Arm A-class



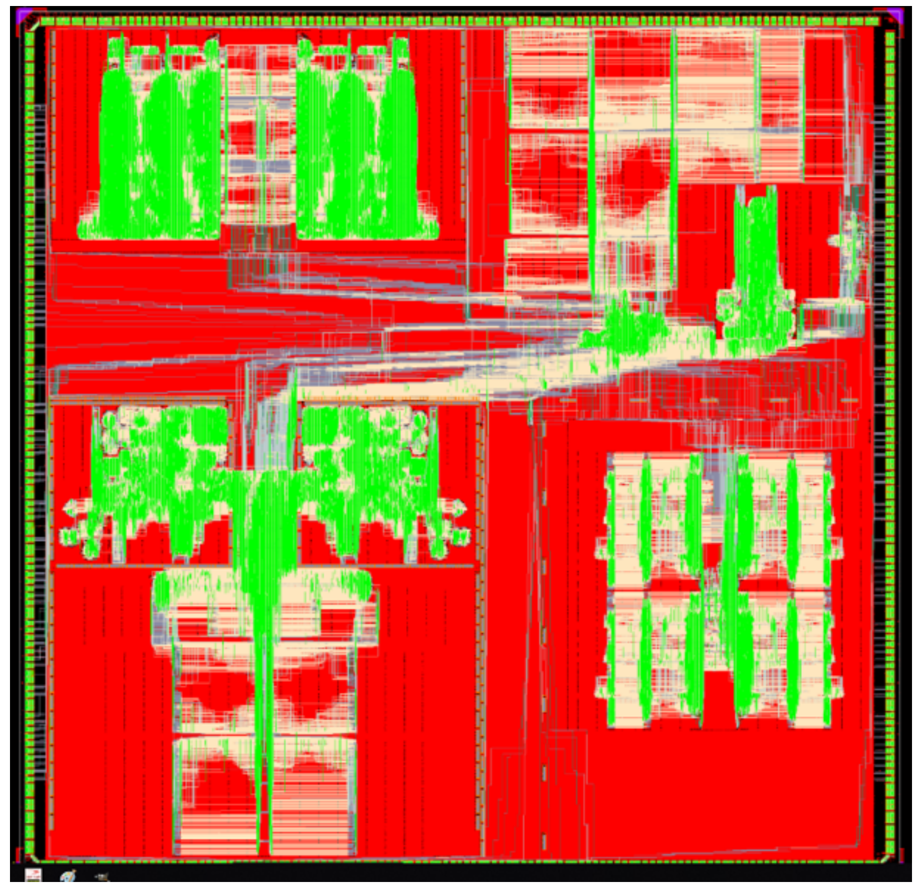
SM2



SM3



SMIV

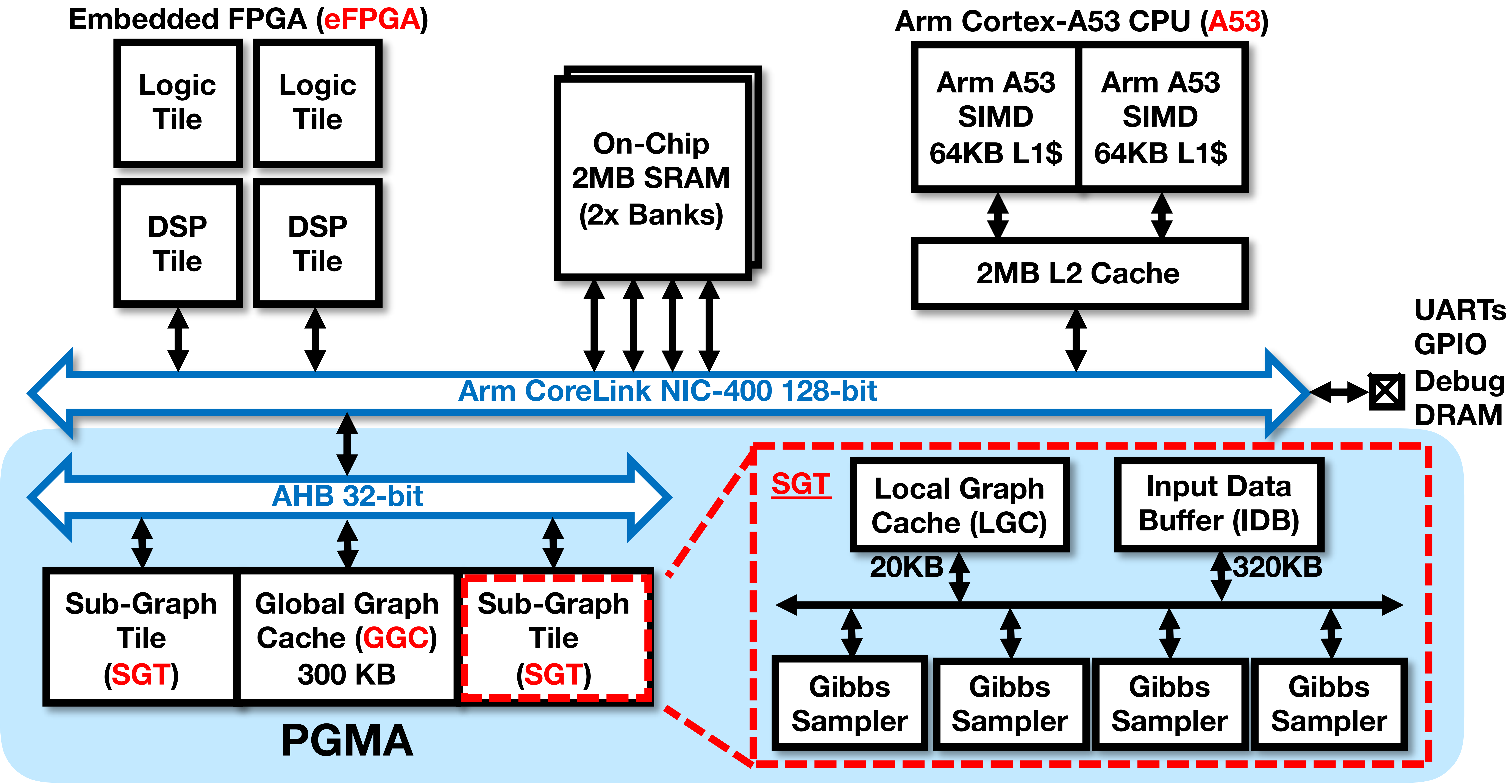


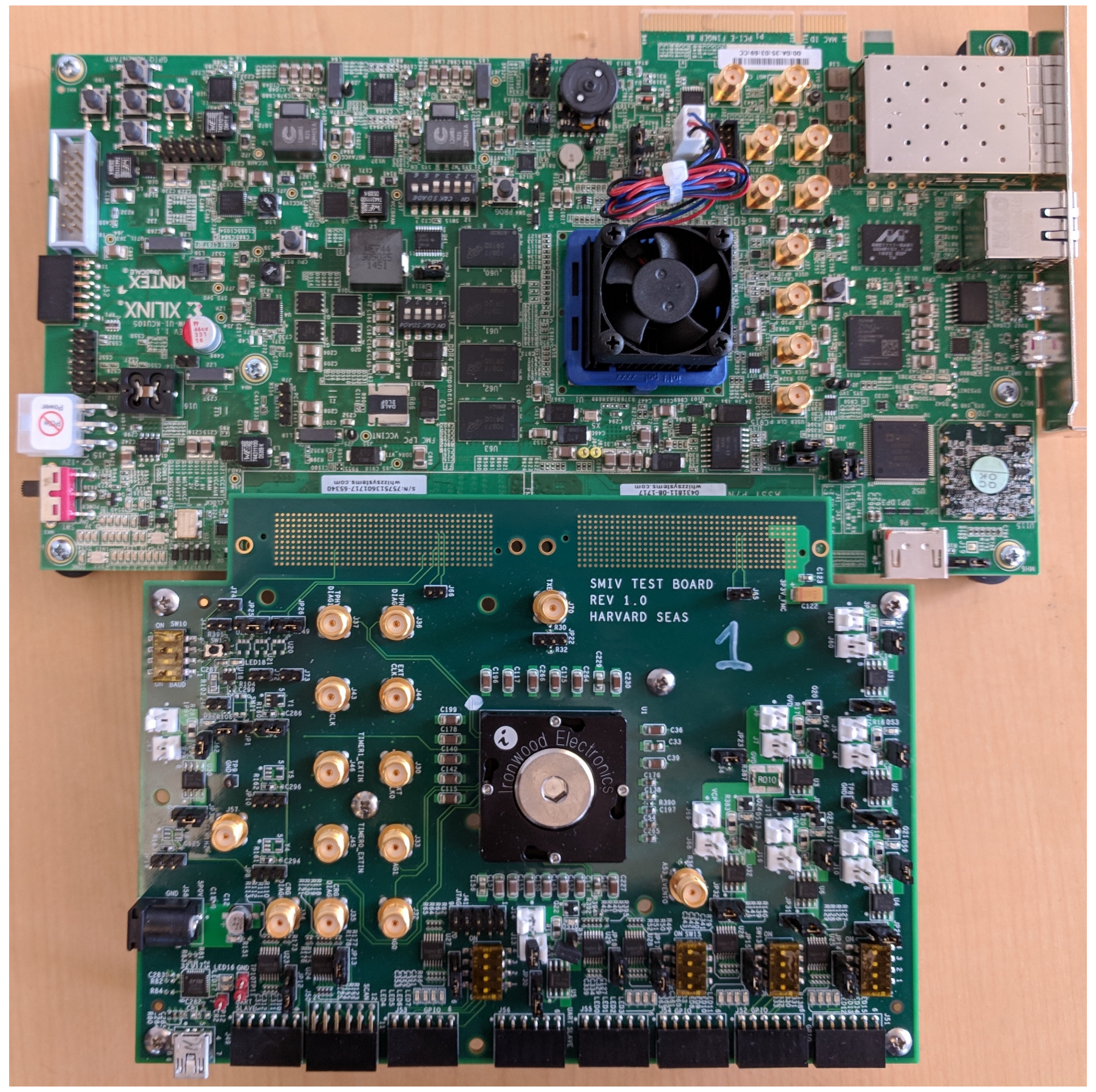
SM5

- SoC platform for architecture and systems research
- CHIPKIT: Agile research test chip design methodology

Ref: Whatmough et al., VLSI, 2019. Whatmough et al., HotChips, 2018. Whatmough et al. IEEE Micro, 2020.

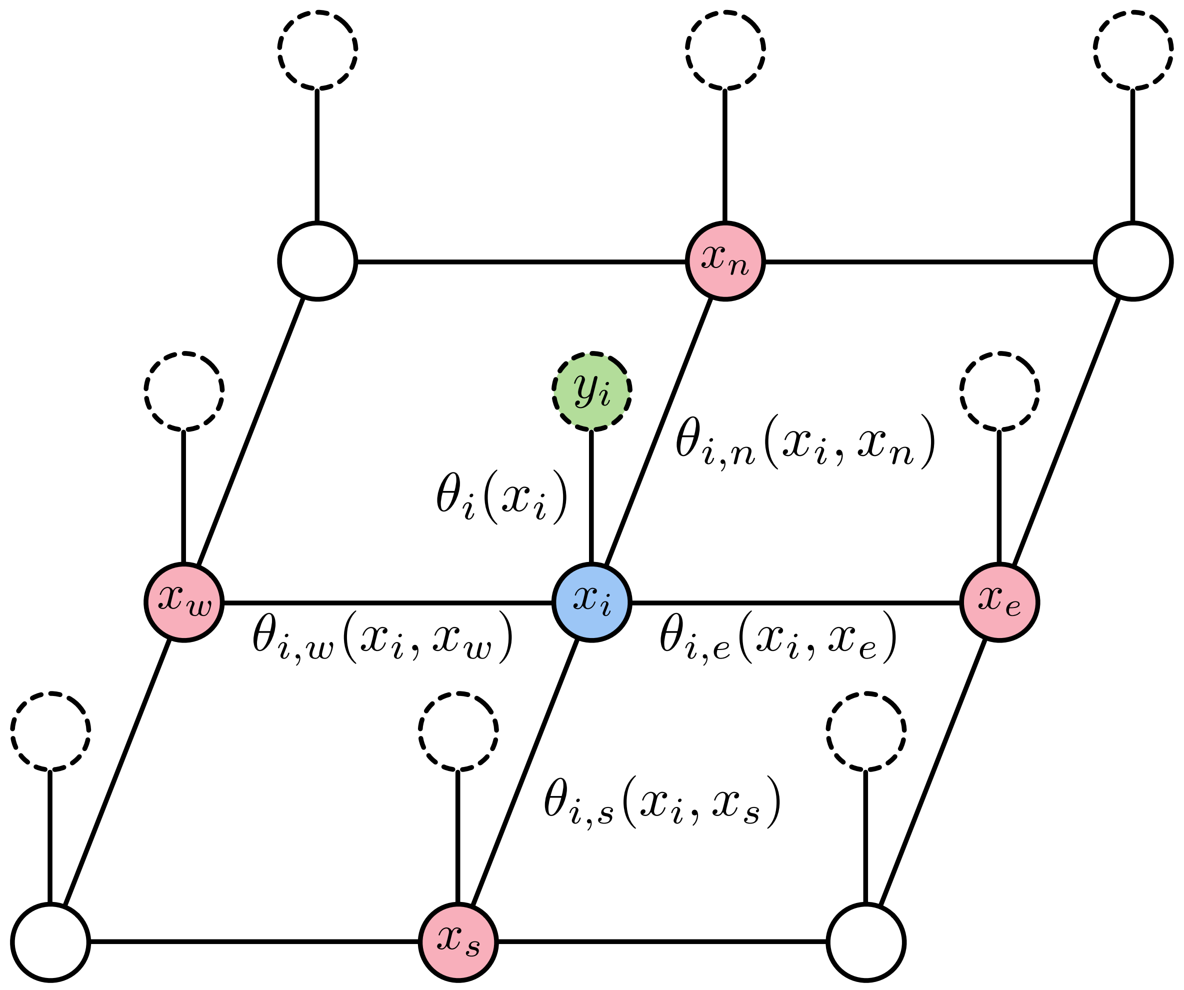
SM5 SoC Architecture





Ref: Ko et al., VLSI 2020

Models, Inference and Applications



Model

Markov Random Field (MRF) - A generalization over Ising model

Various other probabilistic models (HMM, regression, etc.)

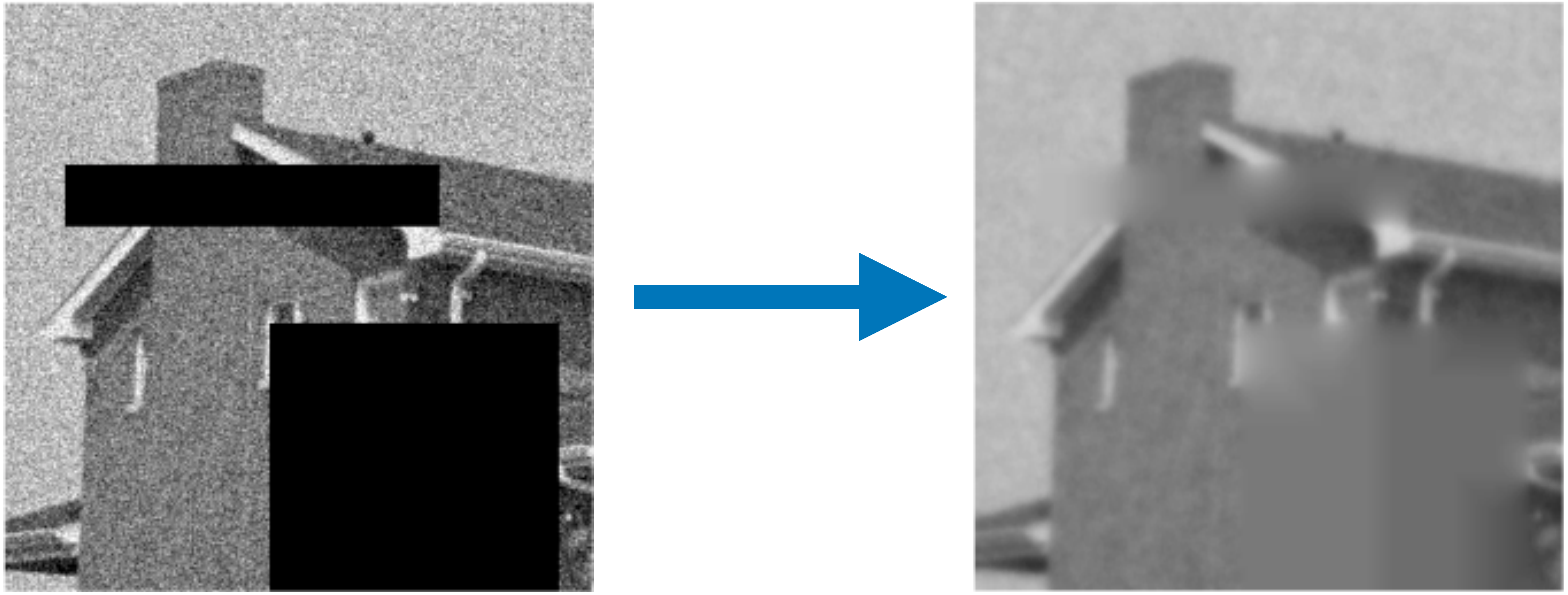
Inference

Gibbs sampling - A Markov Chain Monte Carlo (MCMC) algorithm derived from statistical physics

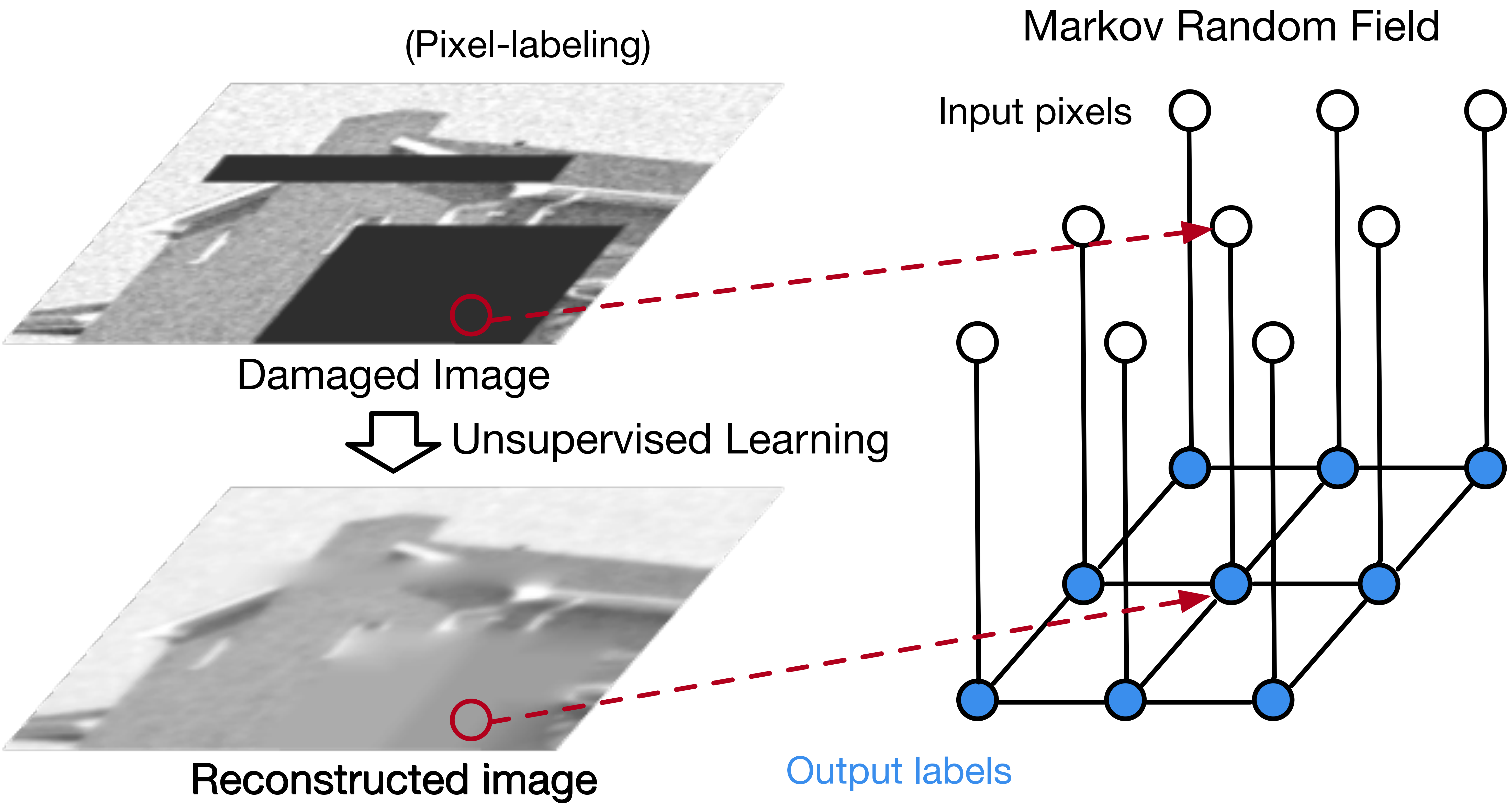
Application

computer vision, audio processing, combinatorial optimization, computational biology, recommender system, topic modeling, etc.

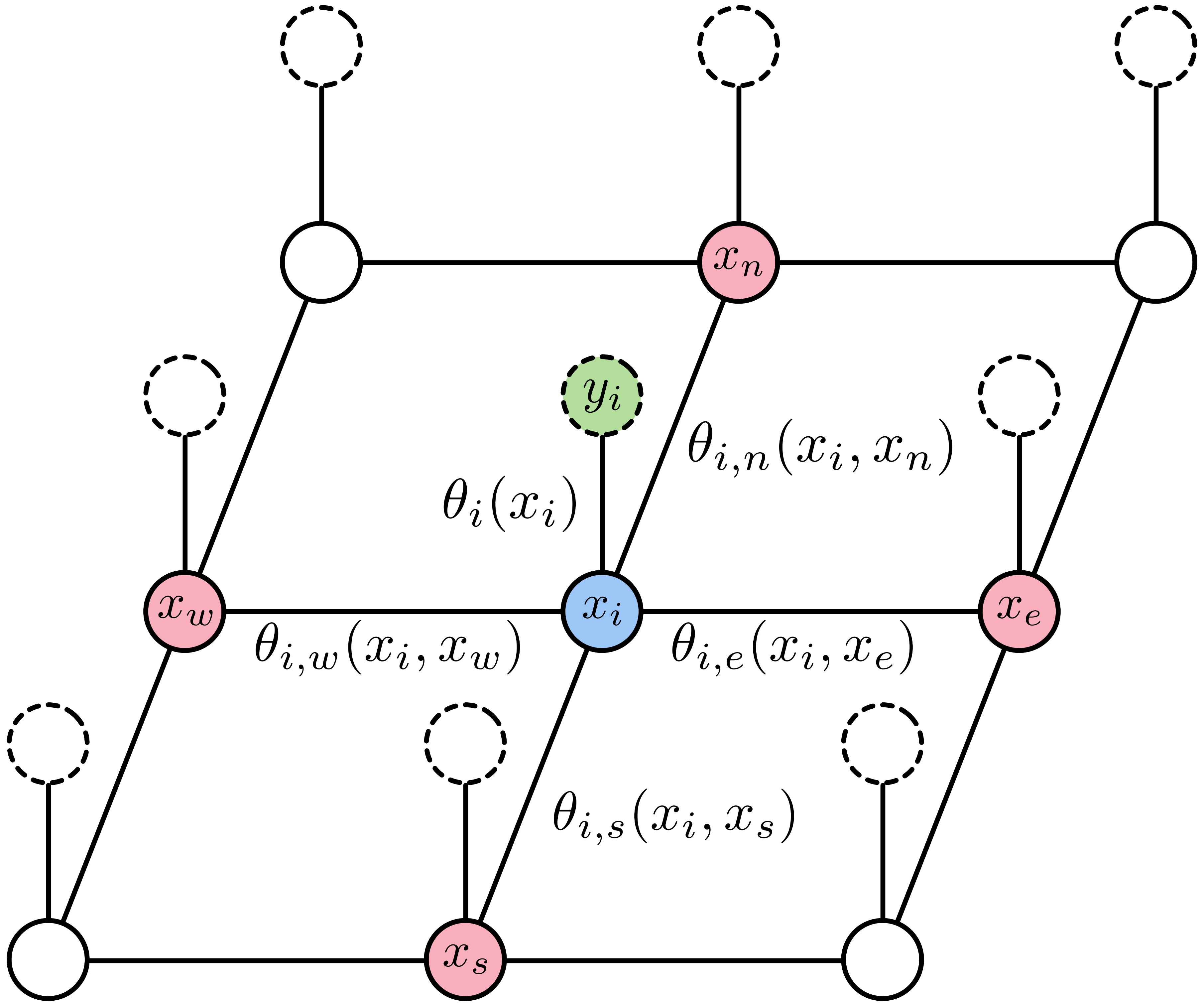
Example: Image restoration

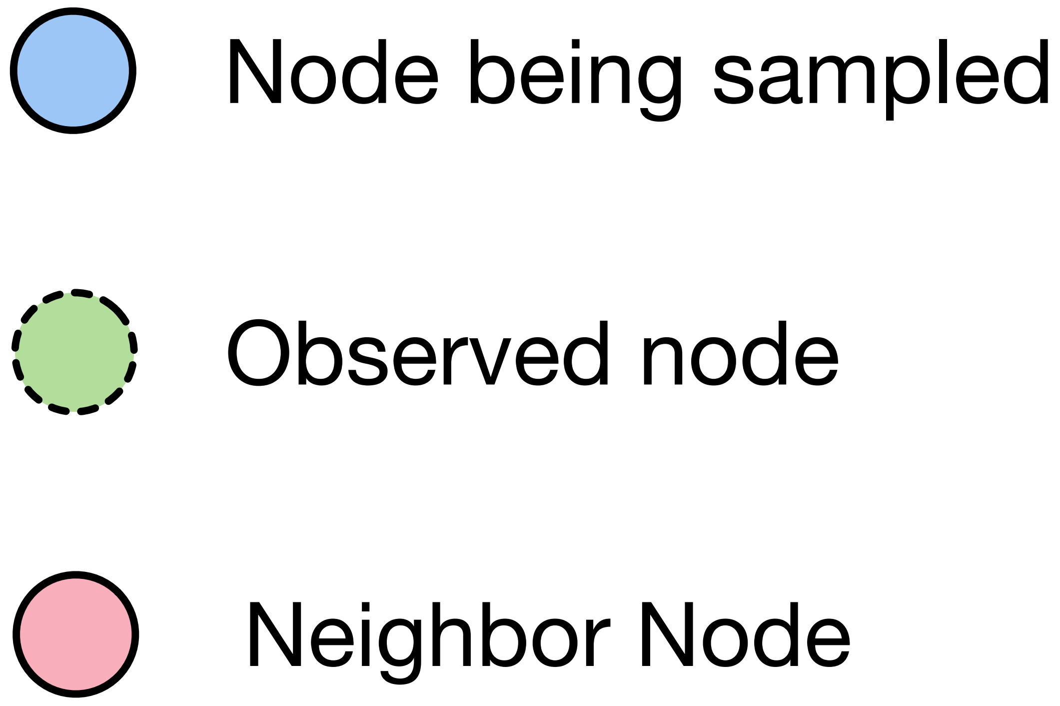


Mapping to Markov Random Field (MRF)



Gibbs sampling on MRF





Sequential Gibbs Sampling

while (< max Gibbs sampling iterations)
    for each node in an image
        sample()

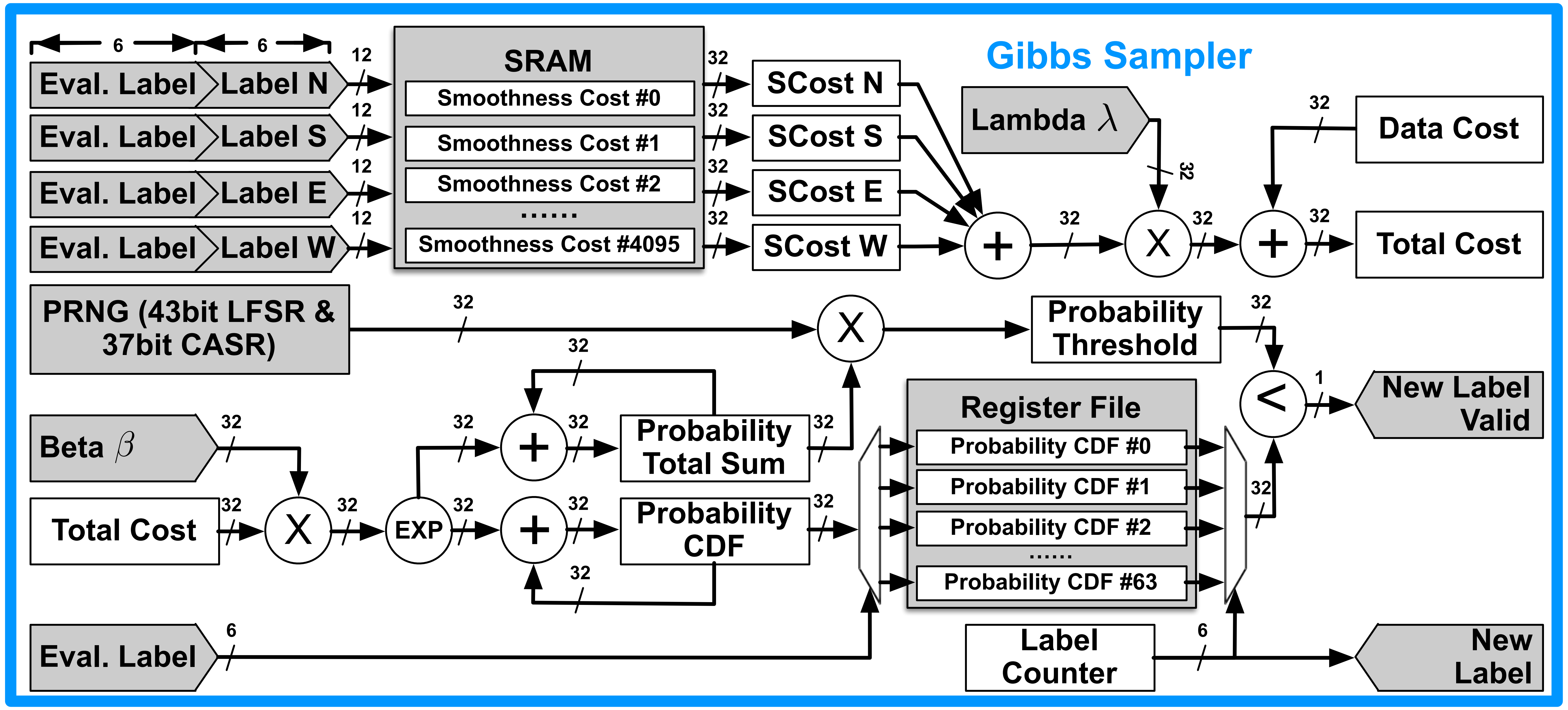
Why is it hard to accelerate?

Gibbs sampling on MRF

Initialize x^0
for $t = 0$ to T **do**
  for $i = 0$ to N **do**
    $x_i^{(t+1)} \sim P(x_i | x_{north}^{(t)}, x_{south}^{(t)}, x_{west}^{(t)}, x_{east}^{(t)})$
  end for
end for
return x

Sampling depends on the previous state and the dependency on previous loop iteration makes parallel programming hard

Gibbs Sampler (GS)



- Supports up to 64 states (labels) per node
- 32b variable fixed point arithmetic
- Tightly coupled PRNG
- Iterative architecture for minimal footprint

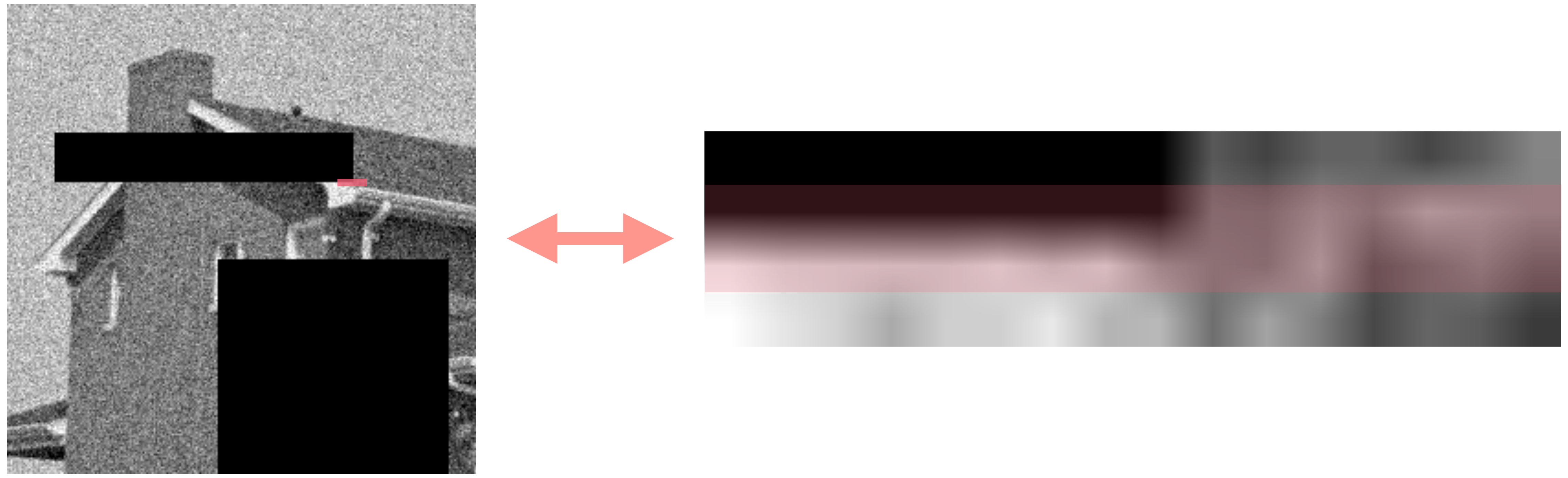
Ref: Ko et al., VLSI 2020

Two-levels of parallelism

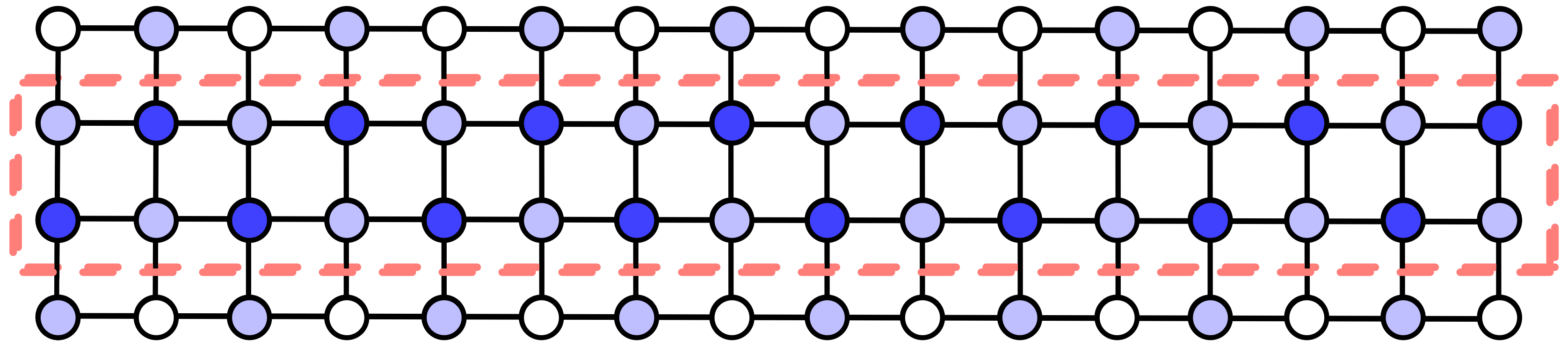
Two-level Parallel Gibbs Sampling

```
while ( < max Gibbs sampling iterations)
    for each tile in an image
        while ( < max tile sampling iterations )
            for each node in a tile
                sample()
```

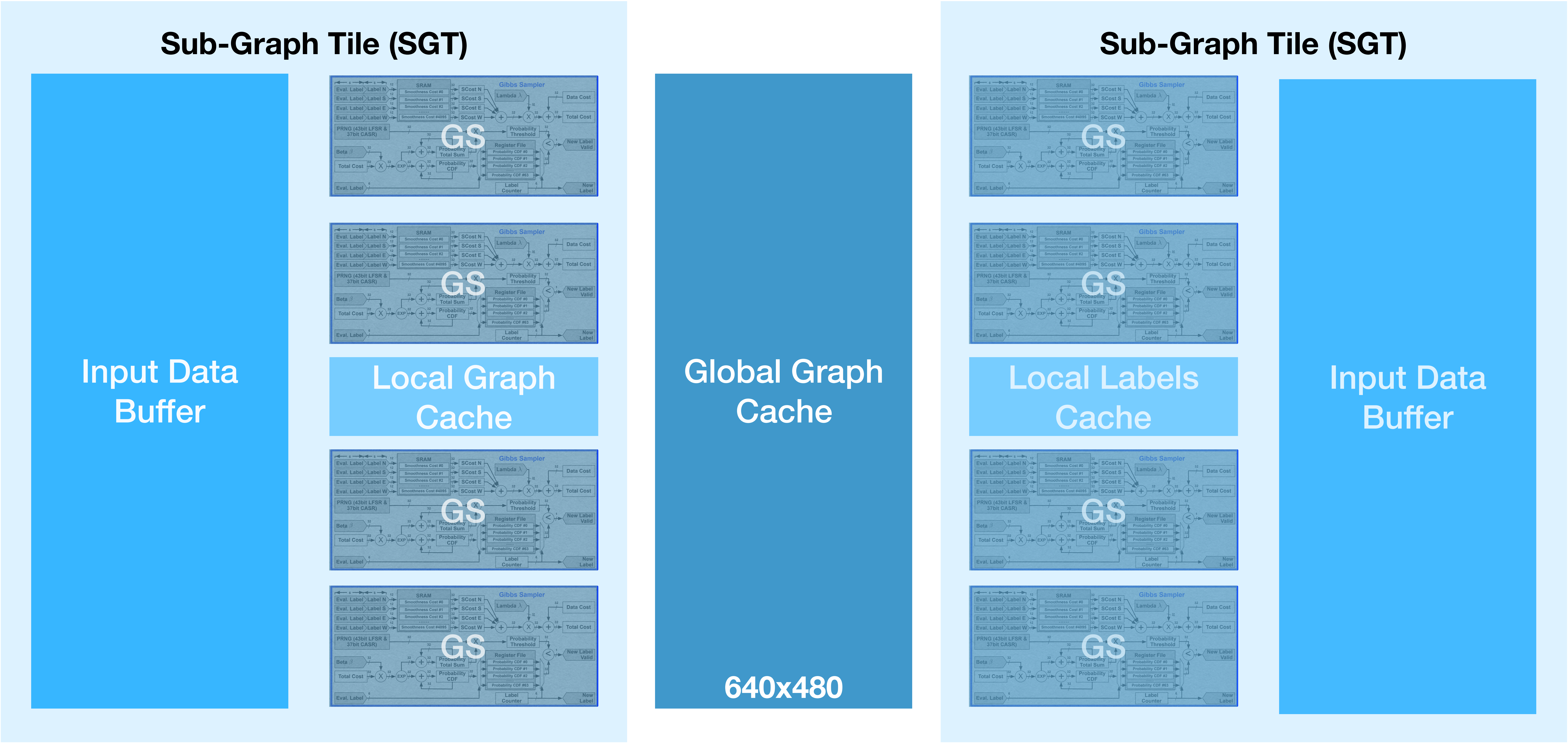
Asynchronous Gibbs sampling:
Sample different tiles in parallel as if they are separate images



Chromatic Gibbs sampling:
Sample conditionally independent nodes concurrently

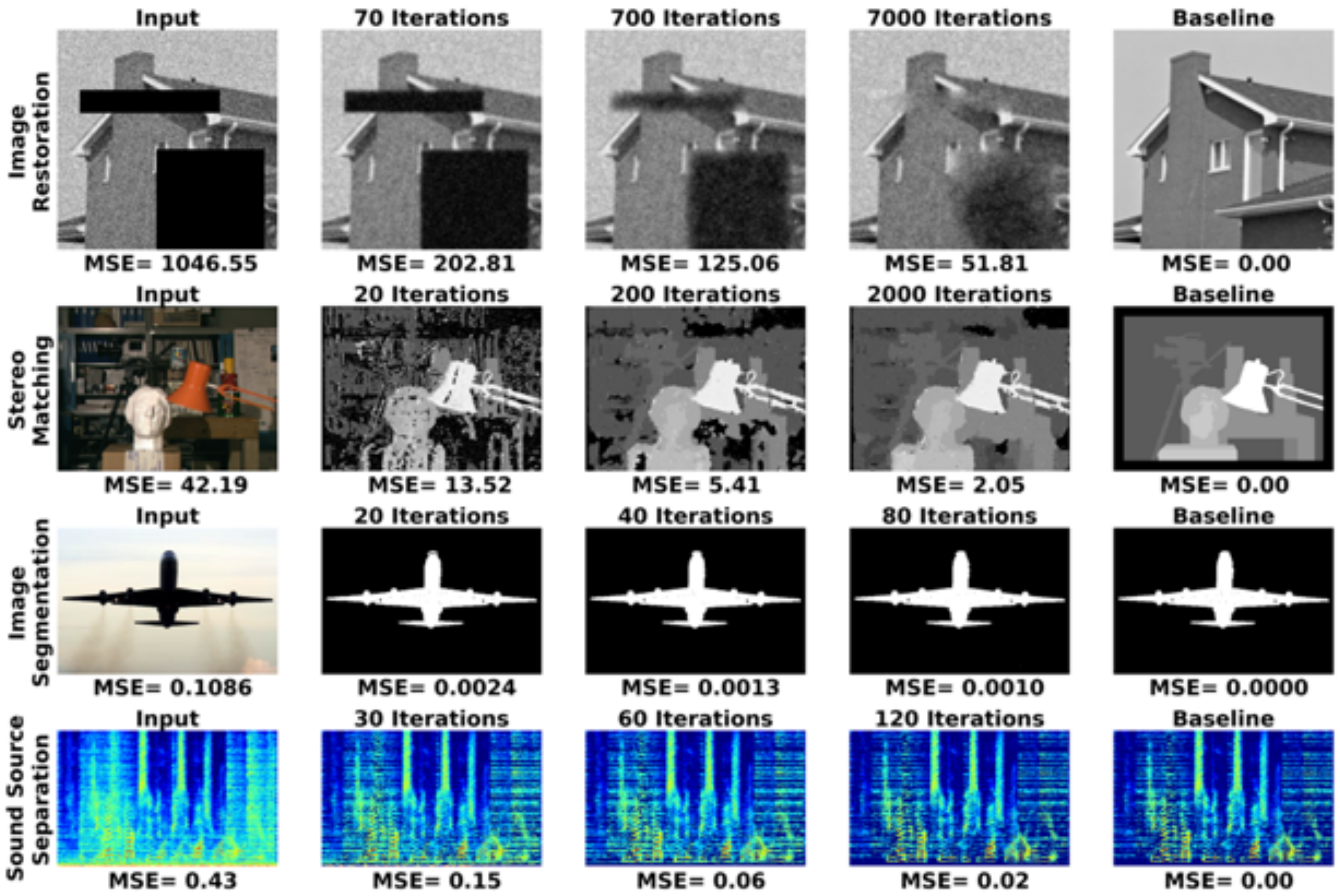


PGMA: Probabilistic Graphical Models Accelerator



Ref: Ko et al., VLSI 2020

Unsupervised perceptual tasks



Four example applications:

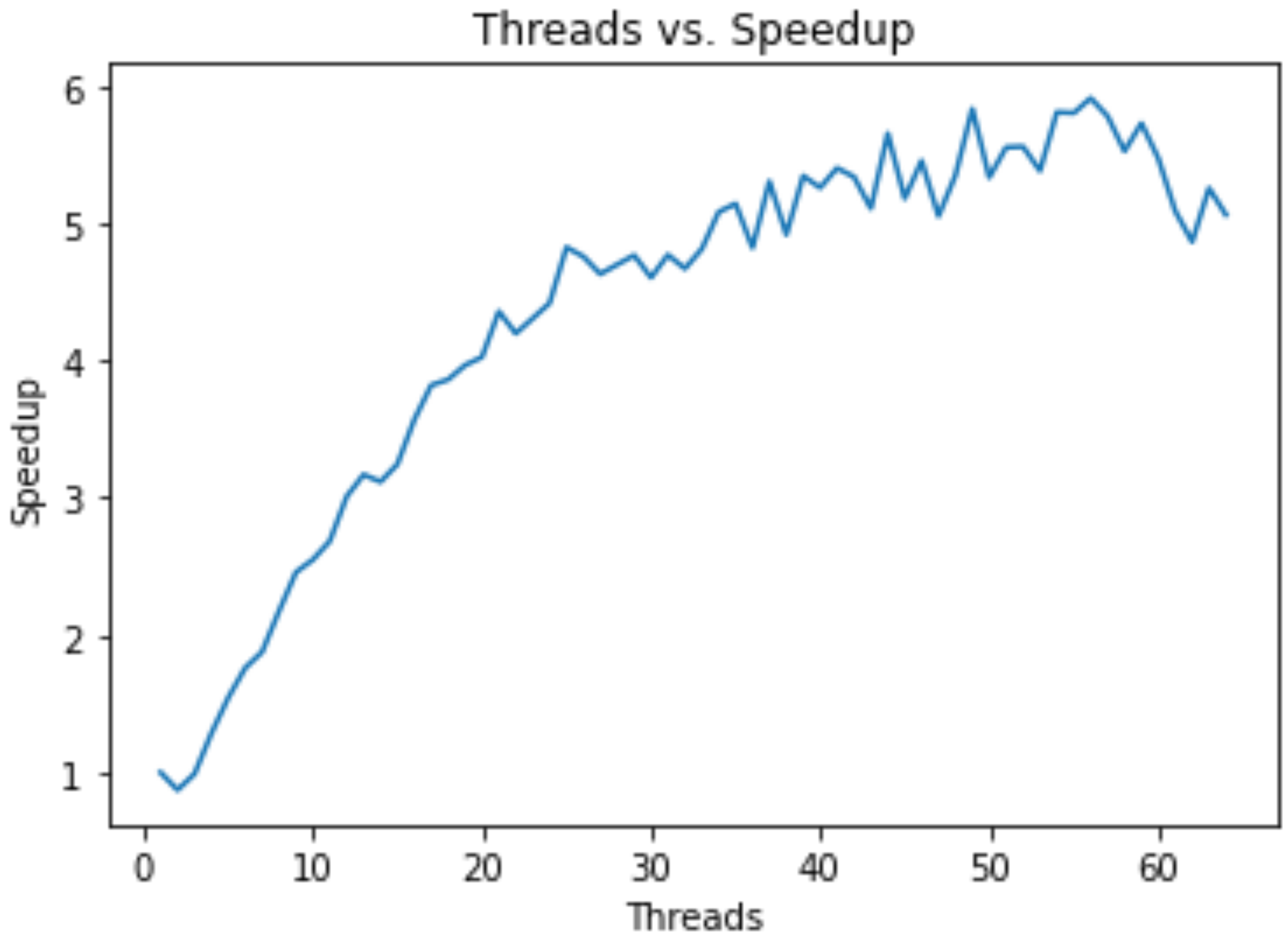
- **Image restoration**
- **Stereo matching**
- **Image segmentation**
- **Sound source separation**

Features:

- **No labeled dataset**
- **Completely unsupervised**
- **Both training and inference on-the-fly**

Ref: Ko et al., VLSI 2020

Multi-threaded Server-Class CPU

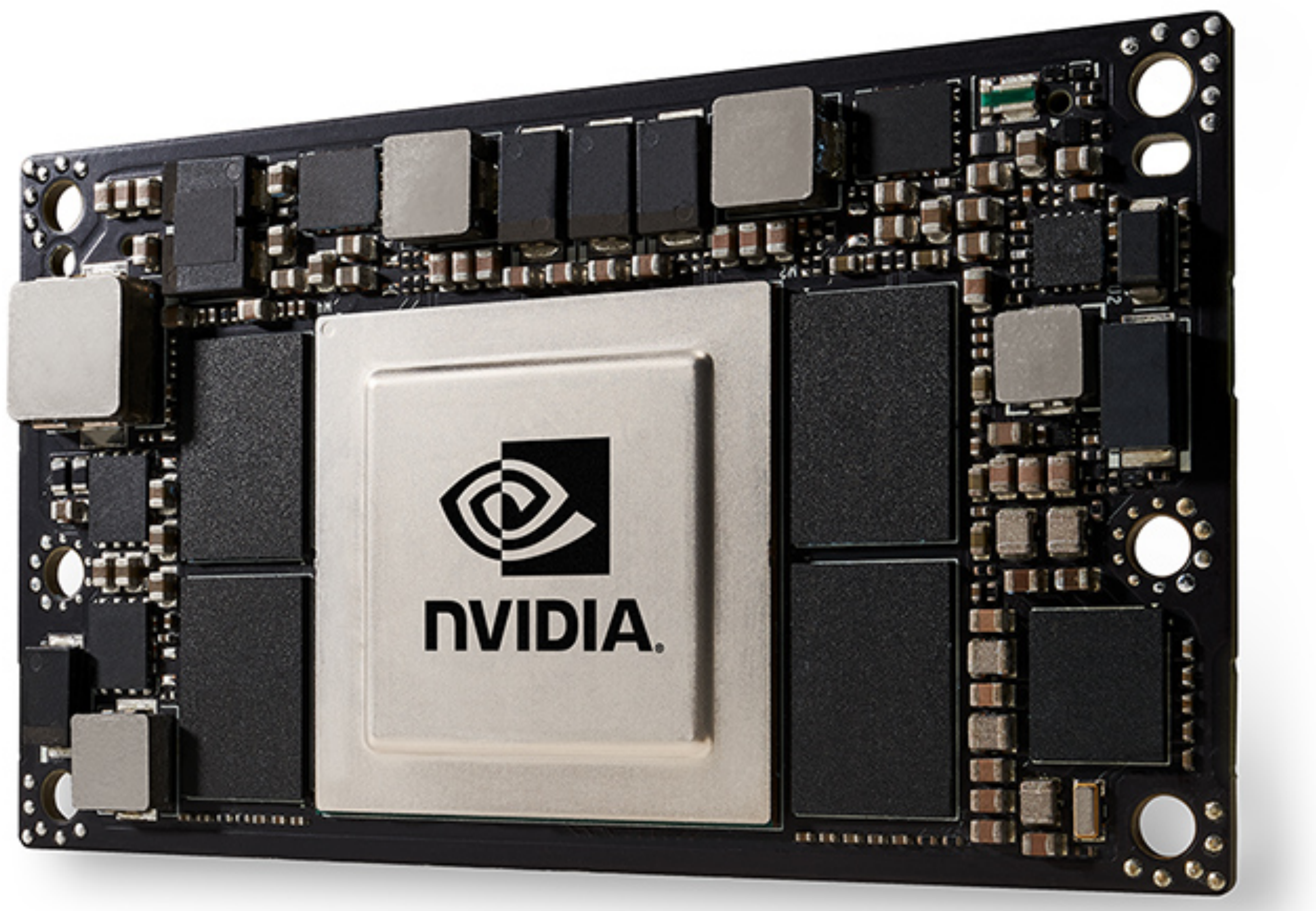


< 6X speedup

Machine: Intel(R) Xeon(R) CPU E5-2697A v4
Parallelism: Chromatic Gibbs sampling
Application: Stereo matching - 16 labels

Comparison with off-the-self embedded platforms

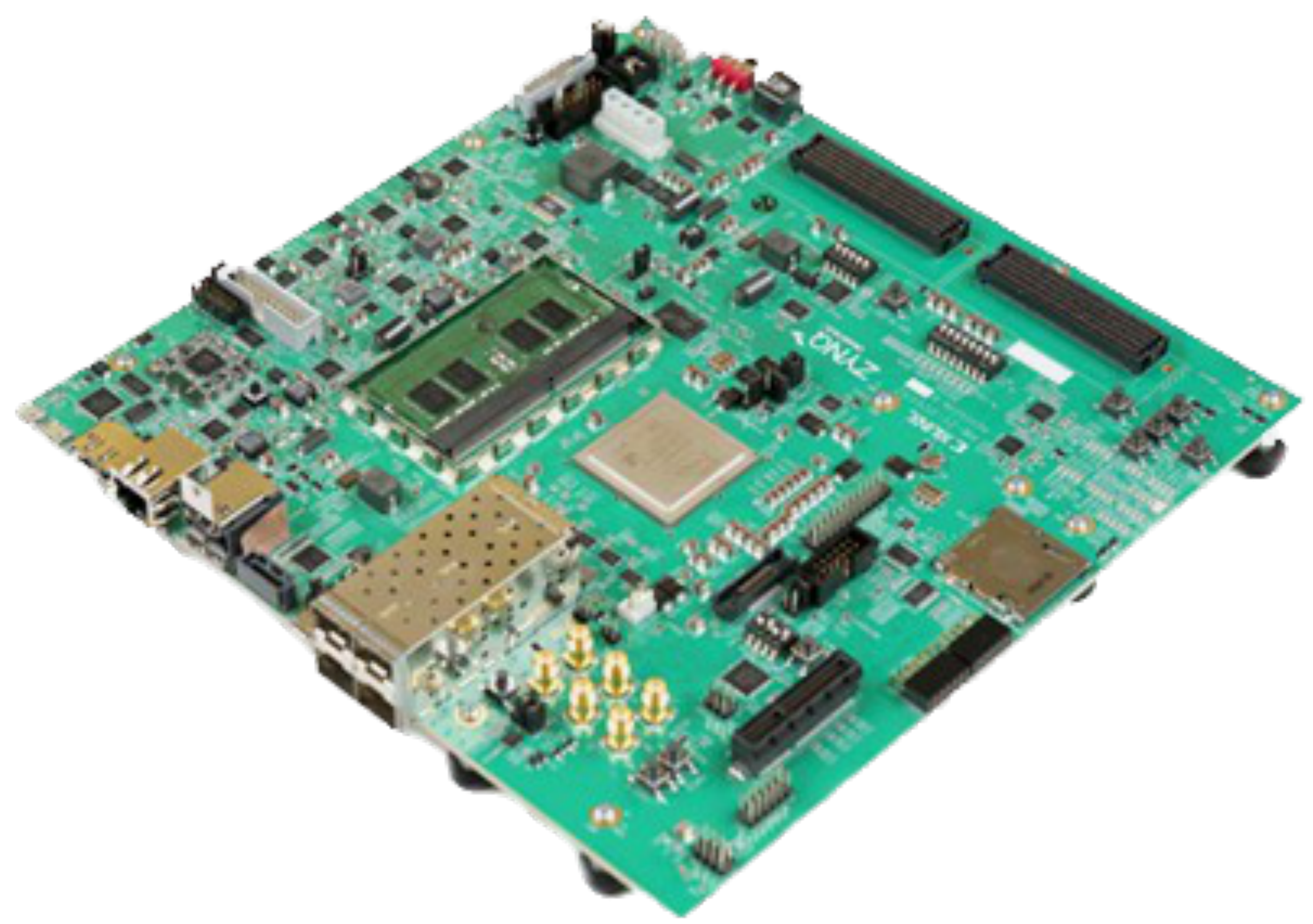
Nvidia Jetson TX2



48x throughput improvement per Watt

(2108x vs Arm A57, single-thread)

Xilinx Zynq ZCU102

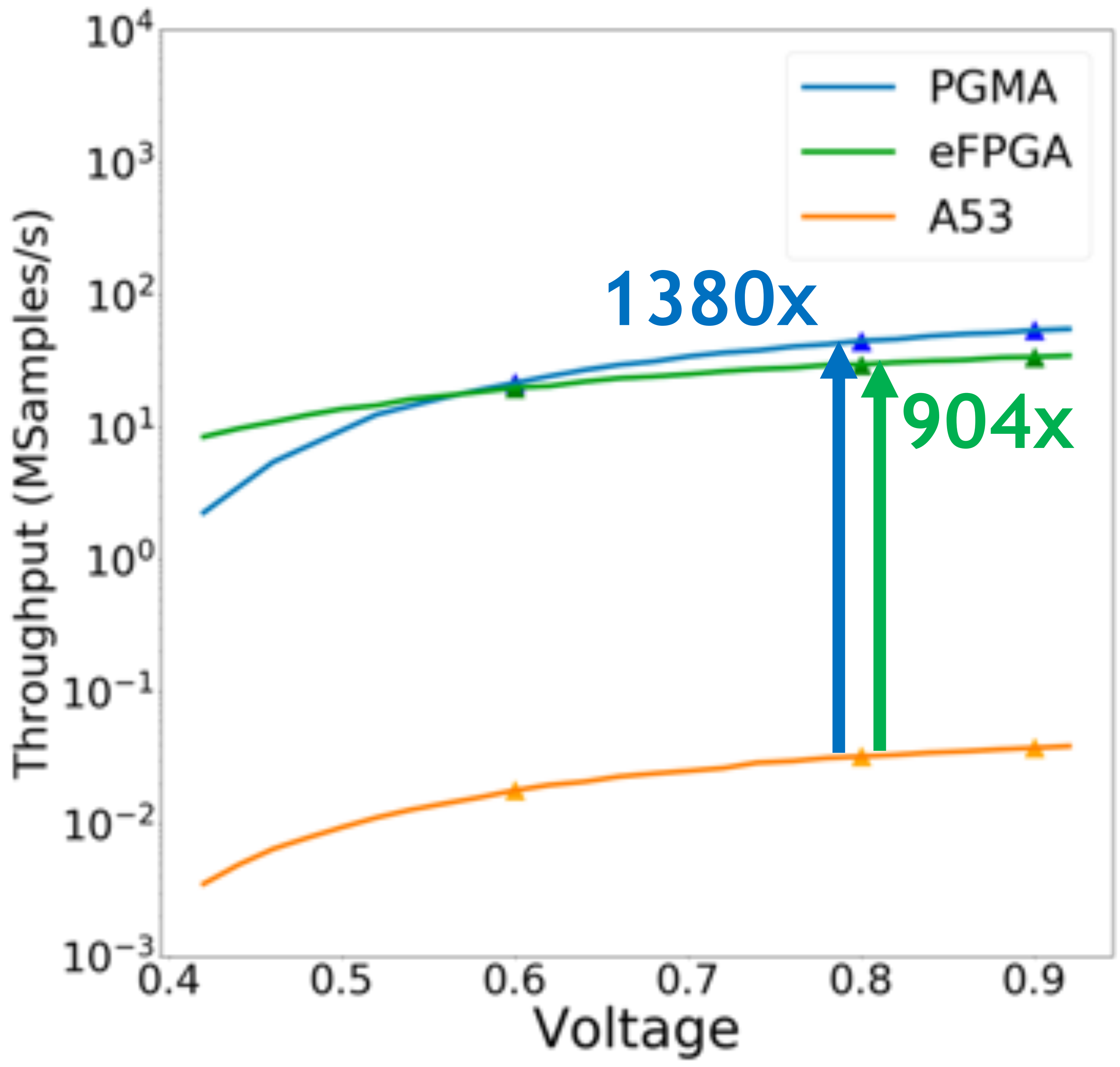


247x throughput improvement per Watt

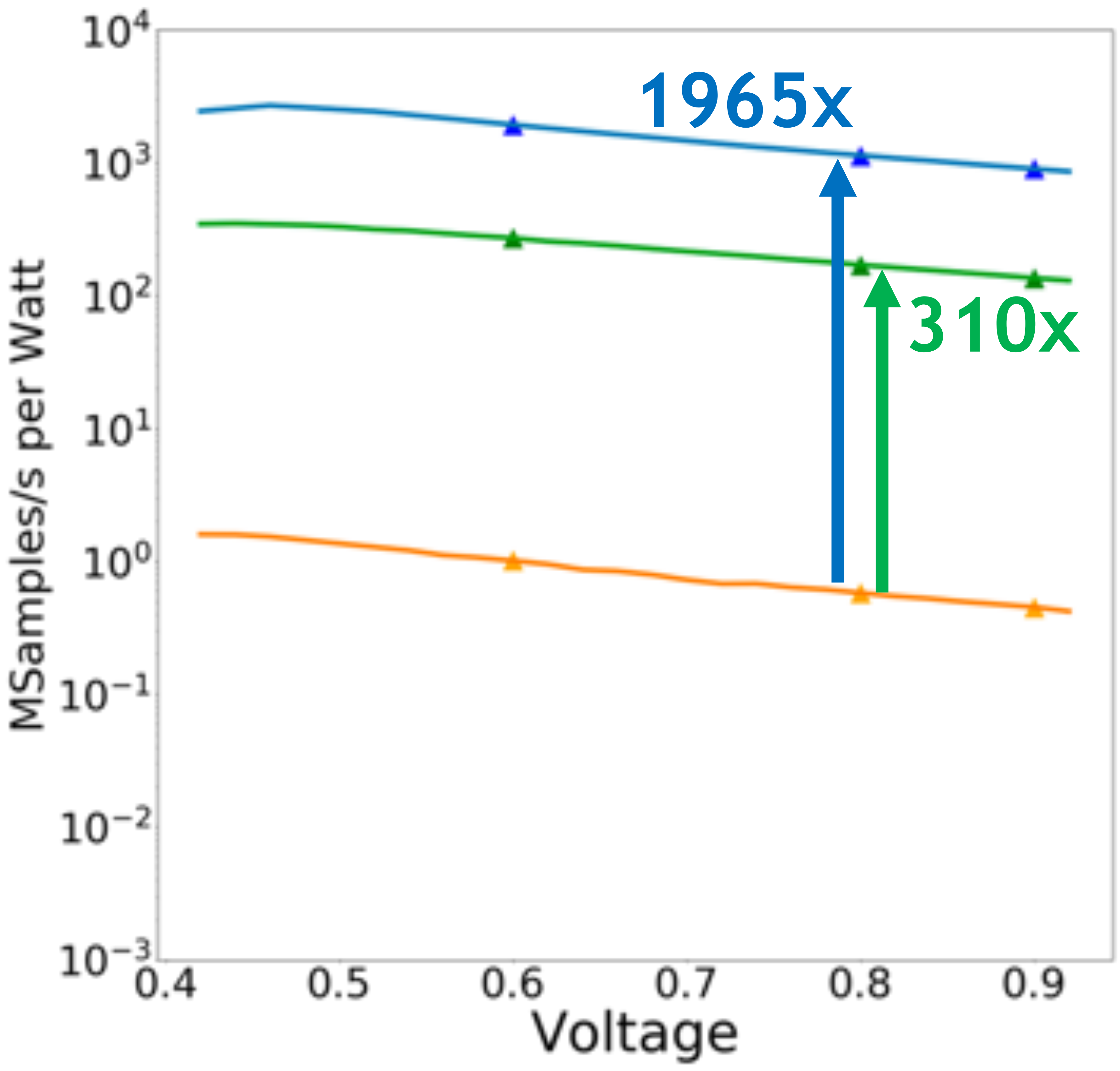
Parallelism: Chromatic Gibbs sampling

Ref: Ko et al., FPL, 2020. Ko et al. VLSI, 2020

SoC Results: vs. A53 and eFPGA



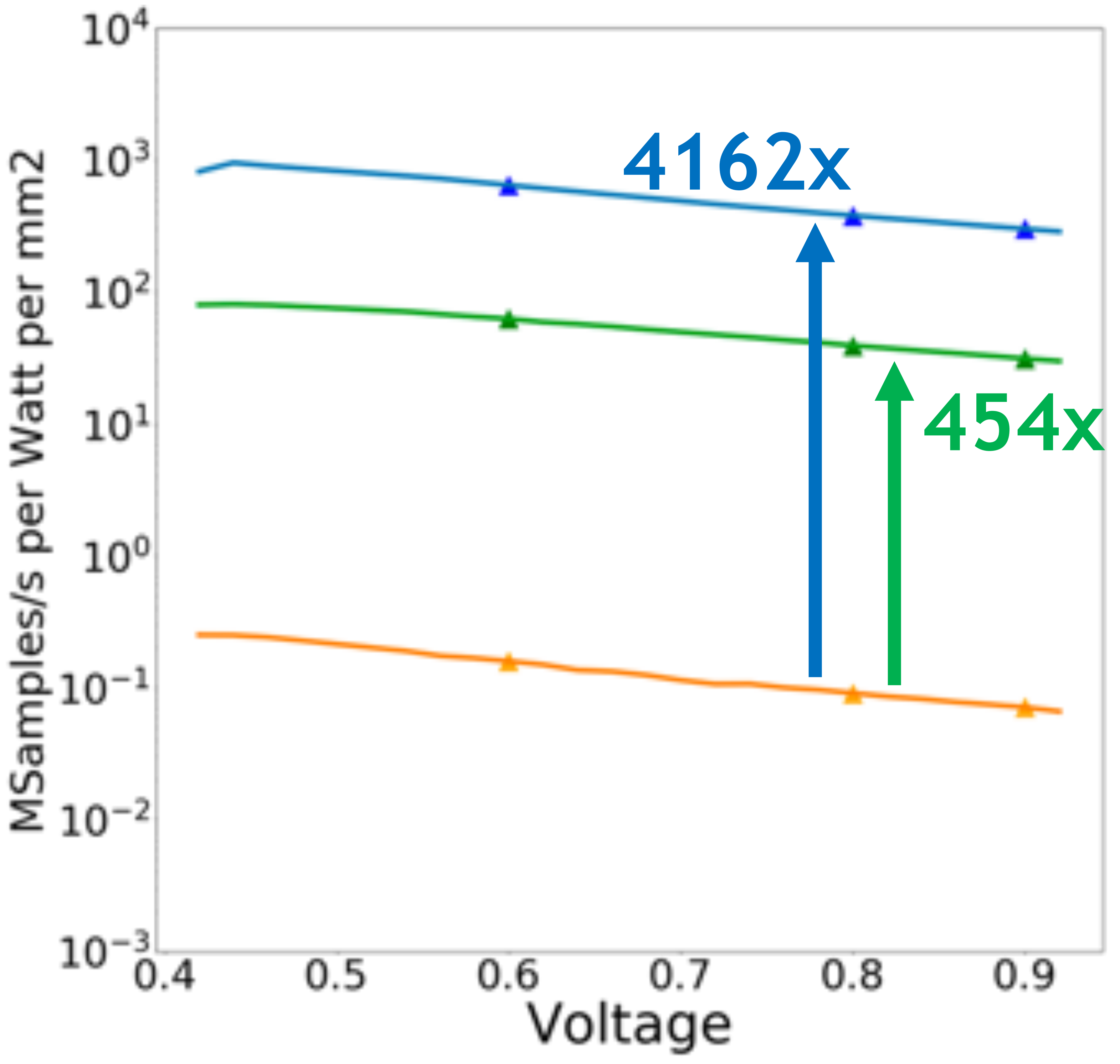
Achieves 1380x throughput improvements over Arm A53



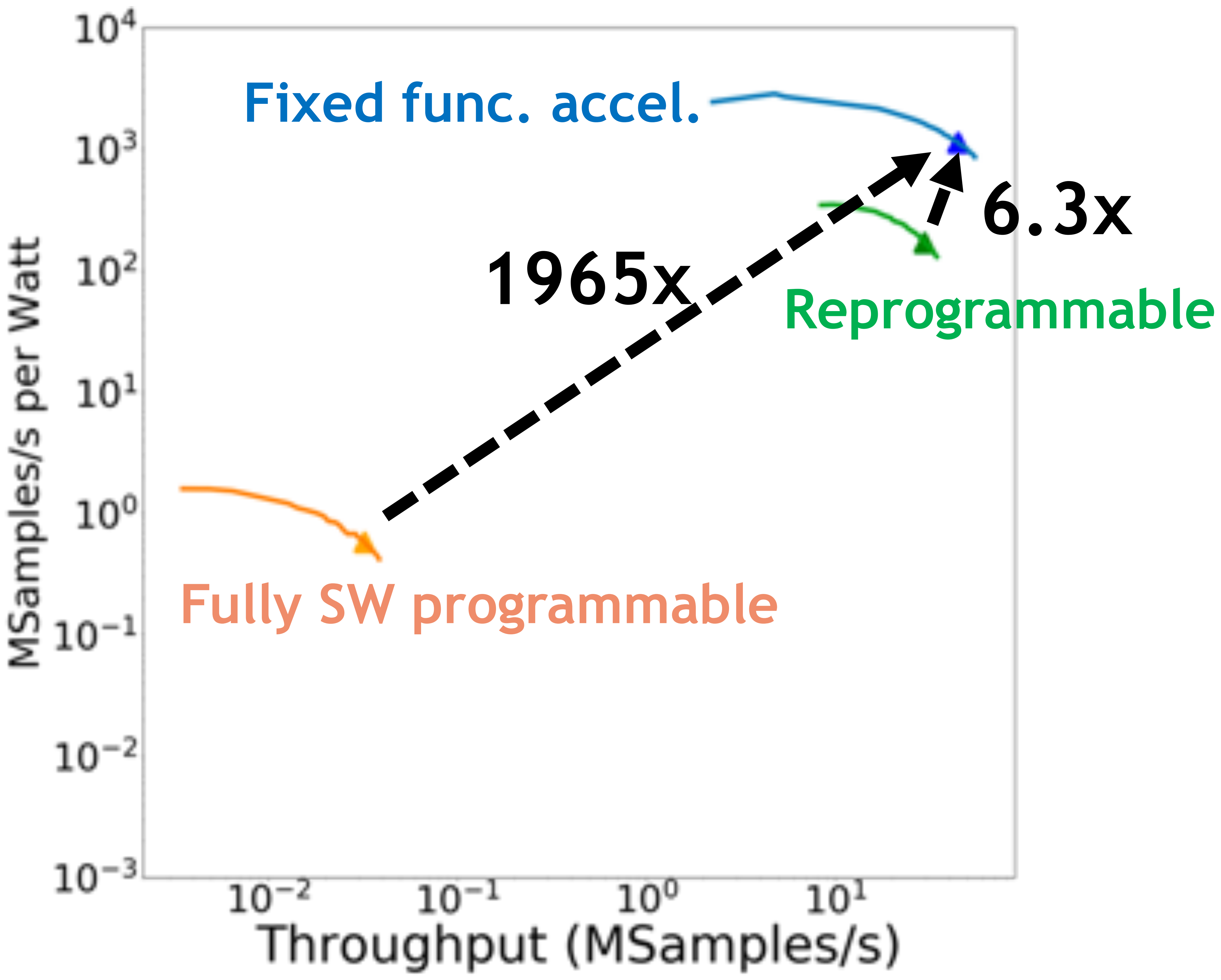
Achieves 1965x throughput per Watt improvements over Arm A53

Ref: Ko et al., VLSI 2020

SoC Results: vs. A53 and eFPGA



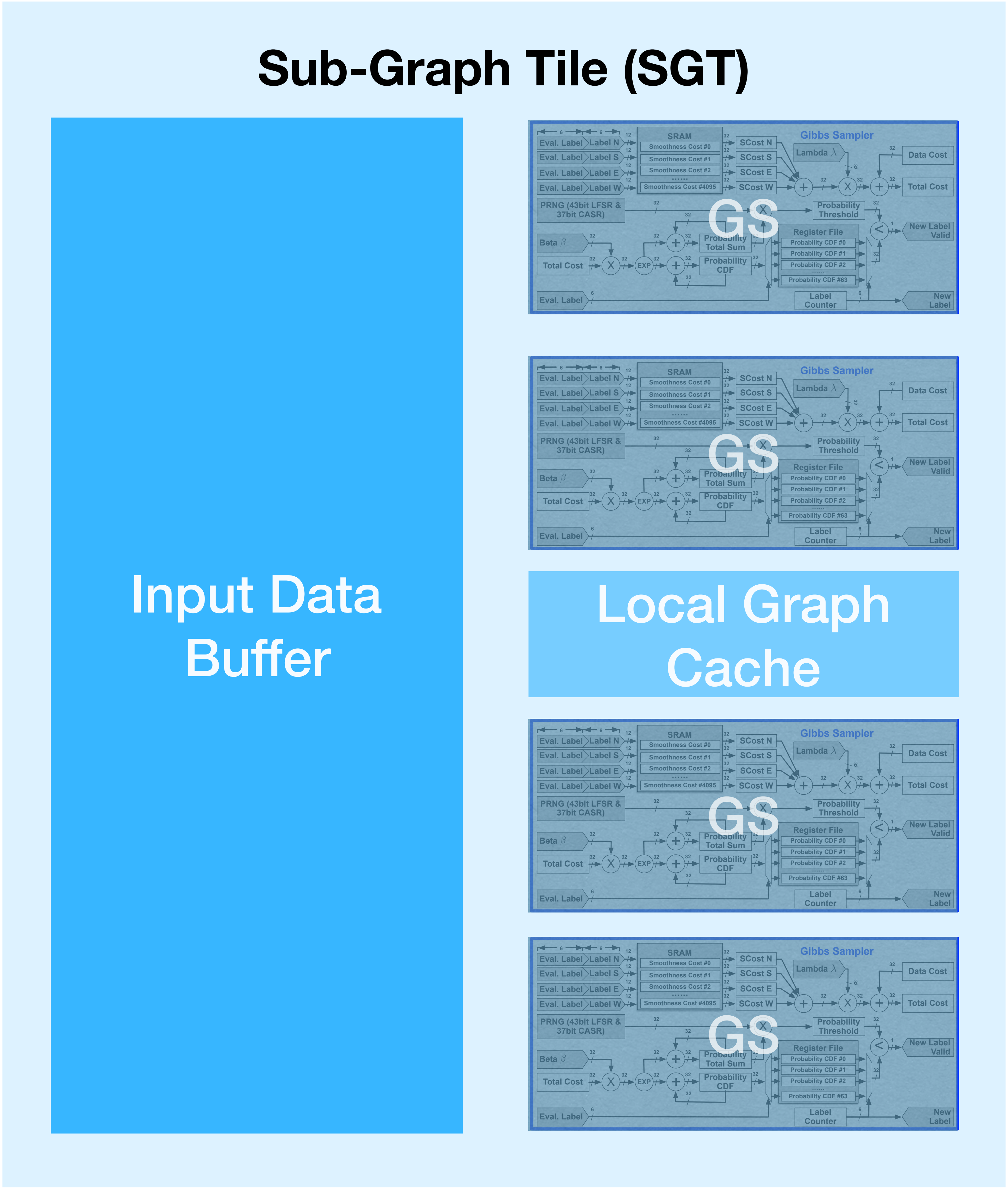
Achieves 4162x throughput per Watt per mm2 over Arm A53



PGMA achieves 1965x throughput per Watt improvements over Arm A53

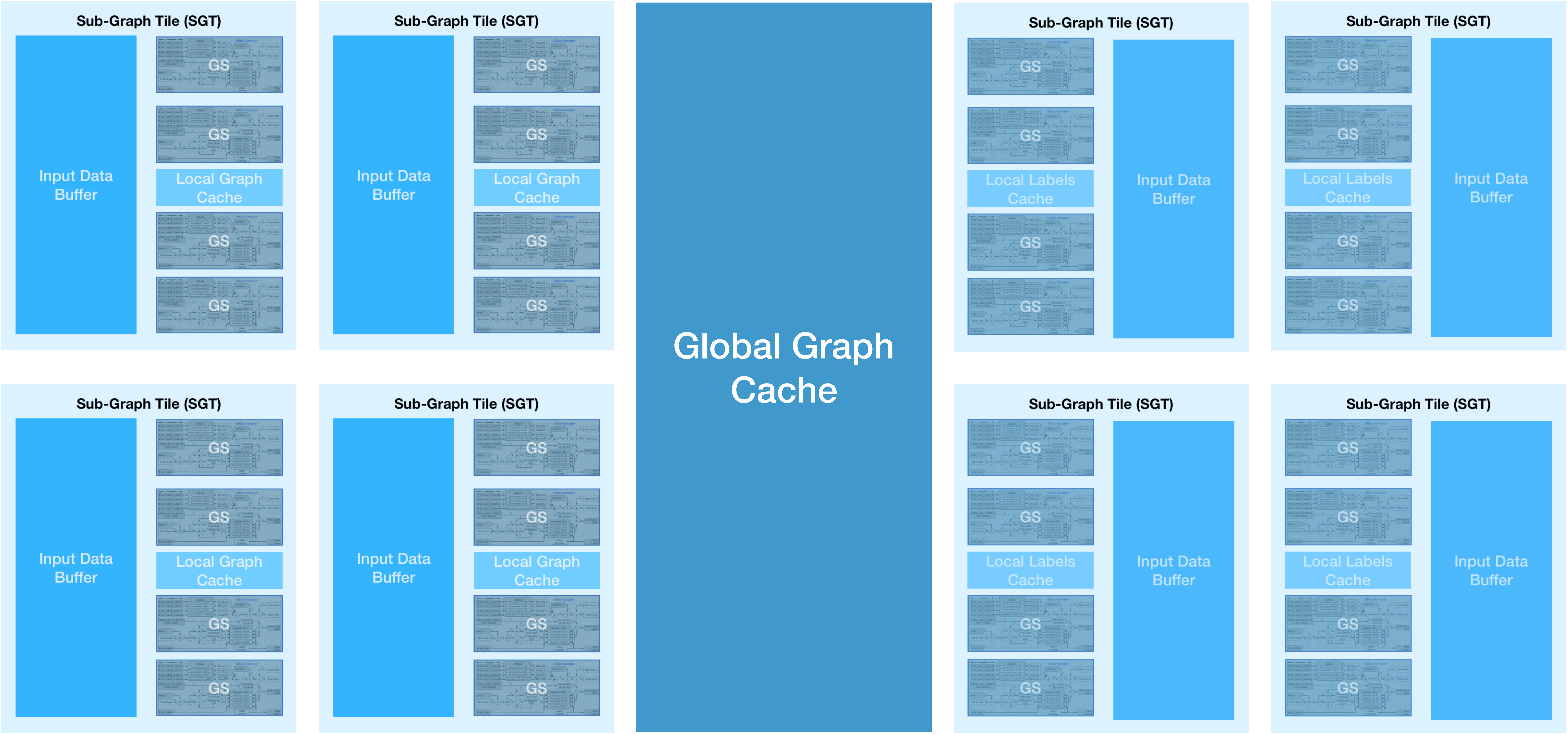
Ref: Ko et al., VLSI 2020

Scaling within SGT



Can add GS's for linear increase in throughput

Scaling with more SGT



Can add SGT's for linear increase in throughput

Summary

•**PGMA - Probabilistic Graphical Models Accelerator**

- First silicon Bayesian inference accelerator.
- Can run various probabilistic models including MRF, HMM and more.
- Solves various applications including computer vision, audio processing, recommender systems, topic modeling, combinatorial optimization, etc.

•**Scalable Bayesian inference accelerator architecture**

- Algorithm-hardware co-design to enable parallelism in natively sequential algorithm.
- Hierarchical architecture with two-levels of parallelism.
- Energy-efficient mobile implementation for real-time unsupervised perceptual tasks.
- *Stay tuned for server-class version for cloud applications.*

•**Rapid research SoC design and implementation using CHIPKIT**

- Harvard's open-source framework for chip design and testing.

Acknowledgments

- **Contributors:** Yuji Chai, Marco Donato, Paul N. Whatmough, Thierry Tambe, Rob A. Rutenbar, David Brooks and Gu-Yeon Wei

- Research sponsored by DARPA CRAFT and DSSoC programs, SRC JUMP ADA, Intel and Arm