ILLINOIS

CSL | Coordinated Science Lab

COLLEGE OF ENGINEERING

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Computer Science, Electrical and Computer Engineering

UIUC

AcMC^2: Accelerated Markov Chain Monte Carlo for Probabilistic Models

ASPLOS 2019

Probabilistic Models: Core of Many AI Apps

- Probabilistic modeling: integrates domain knowledge, quantifies uncertainties

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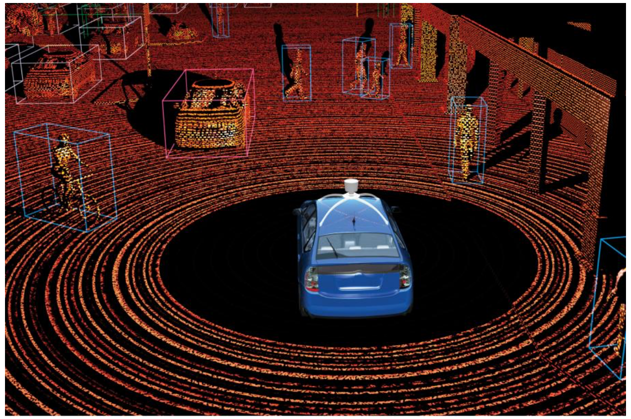
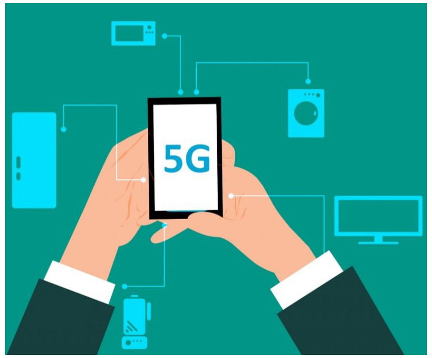


Sensor Fusion in Self Driving Vehicles

Skill Matching in Online Gaming (TrueSkill 1&2 from Microsoft)



4G or 5G Communication Devices (Turbo/LDPC Codes)

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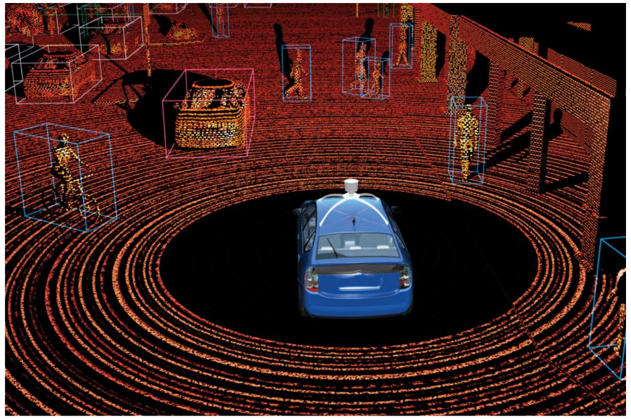

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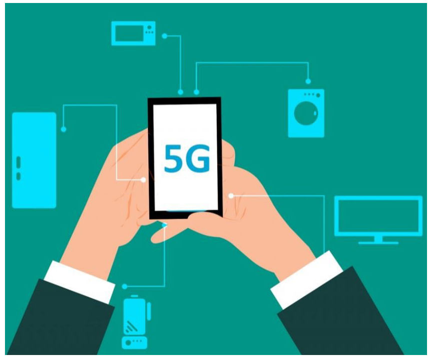

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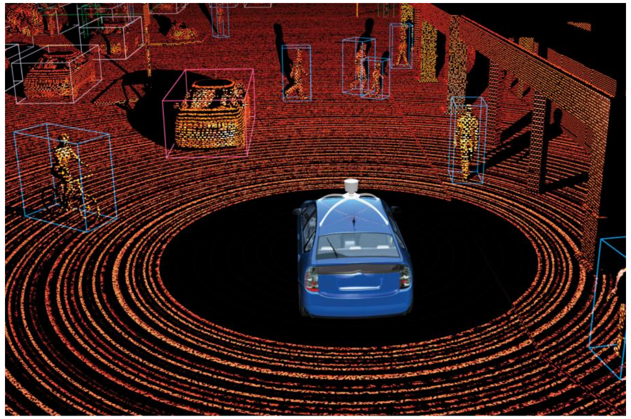

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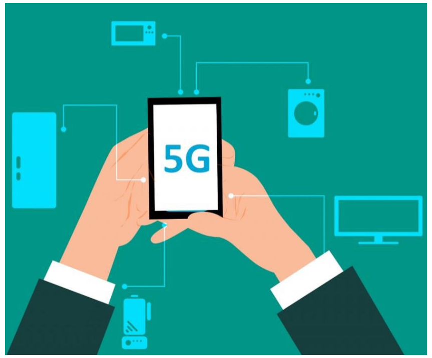

4G or 5G Communication Devices (Turbo/LDPC Codes)

- Inference: General solutions based on Markov Chain Monte Carlo
- Extremely compute intensive & real time constraints

Our Approach

Automatically generate efficient accelerator from high level description

1. Abstraction: Domain specific languages

2. Mapping abstractions to an architecture

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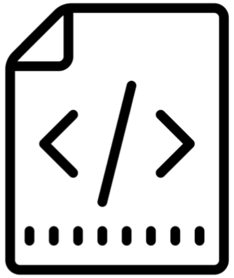

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Church
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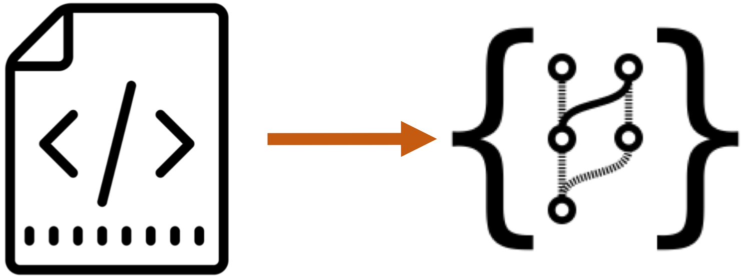
Probabilistic Graphical Model based IR



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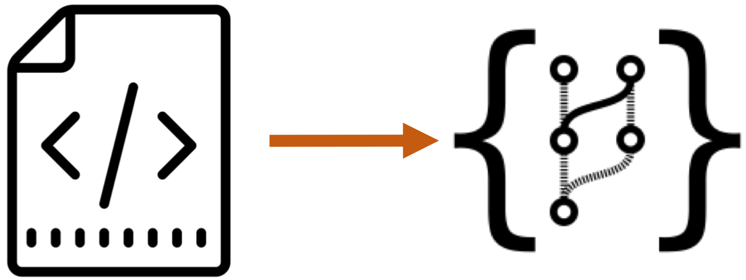

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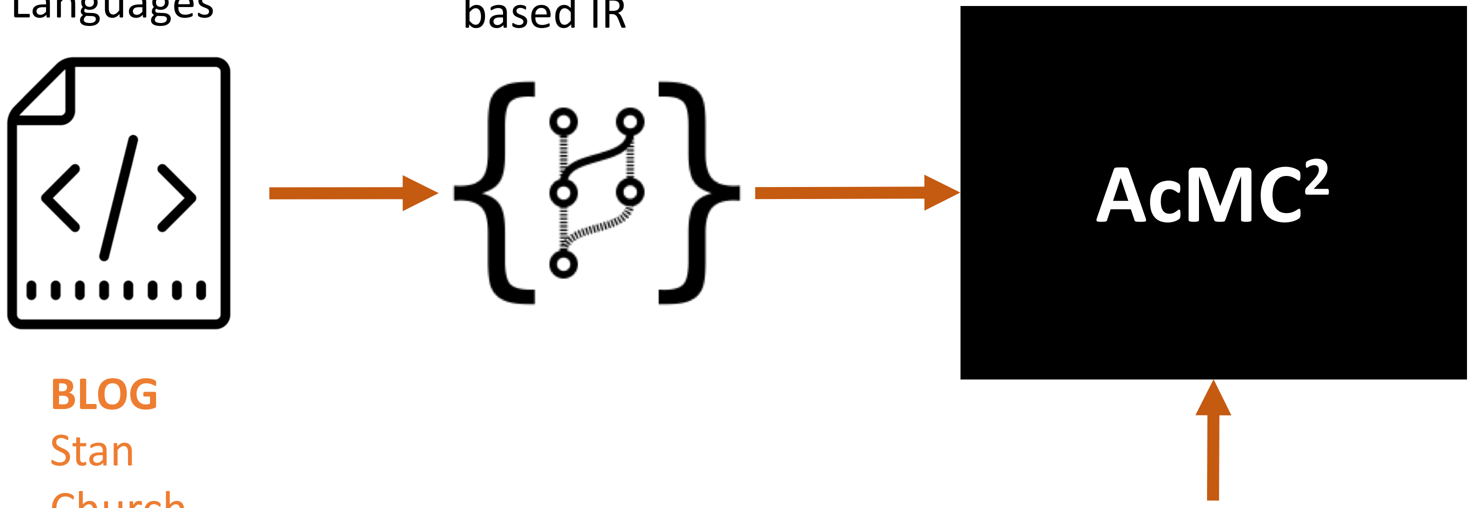

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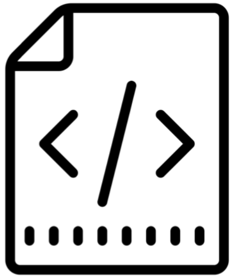

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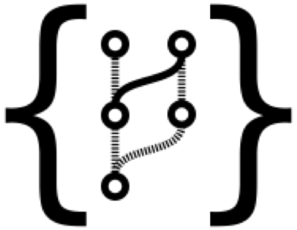


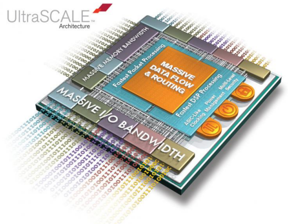
AcMC²

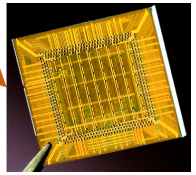
Inference Procedure
Markov Chain Monte Carlo

Traditional synthesis flow

CHISEL
VIVADO
SYNOPSYS

FPGAs





ASICs

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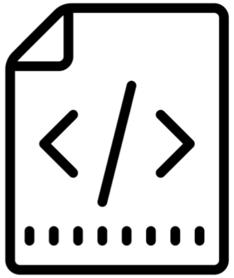
Contributions:

1. Identify accelerable kernels
2. Opportunities for parallelism
3. Knobs for trading off accuracy and performance

Probabilistic Programming Languages



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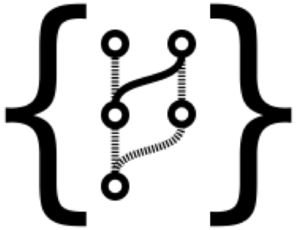

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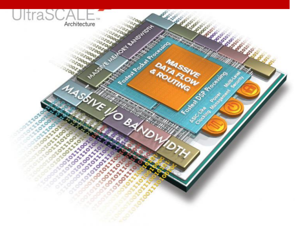

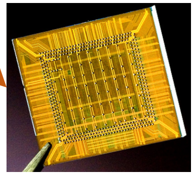

ASICs

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- Generic architecture for MCMC accelerators
  - Efficient high dimensional random number generators (samplers)
- Specializes architecture of accelerator given model, inference method

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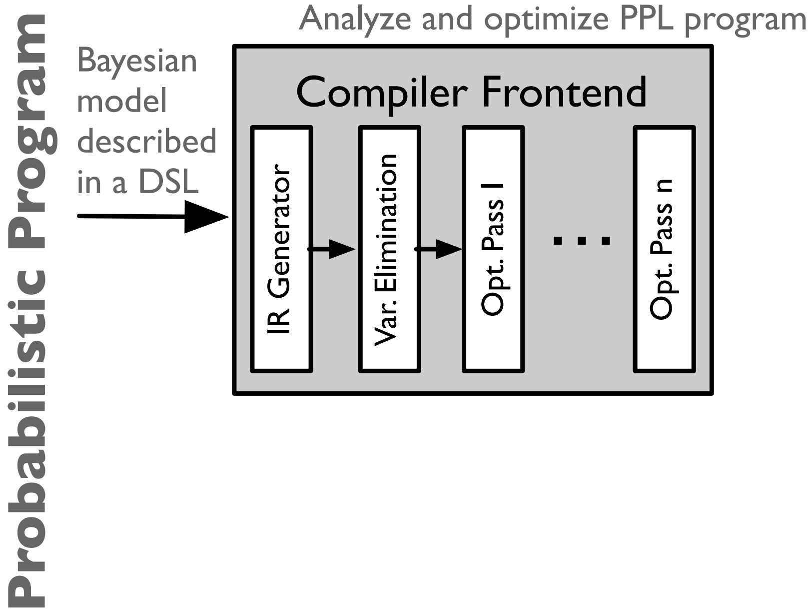

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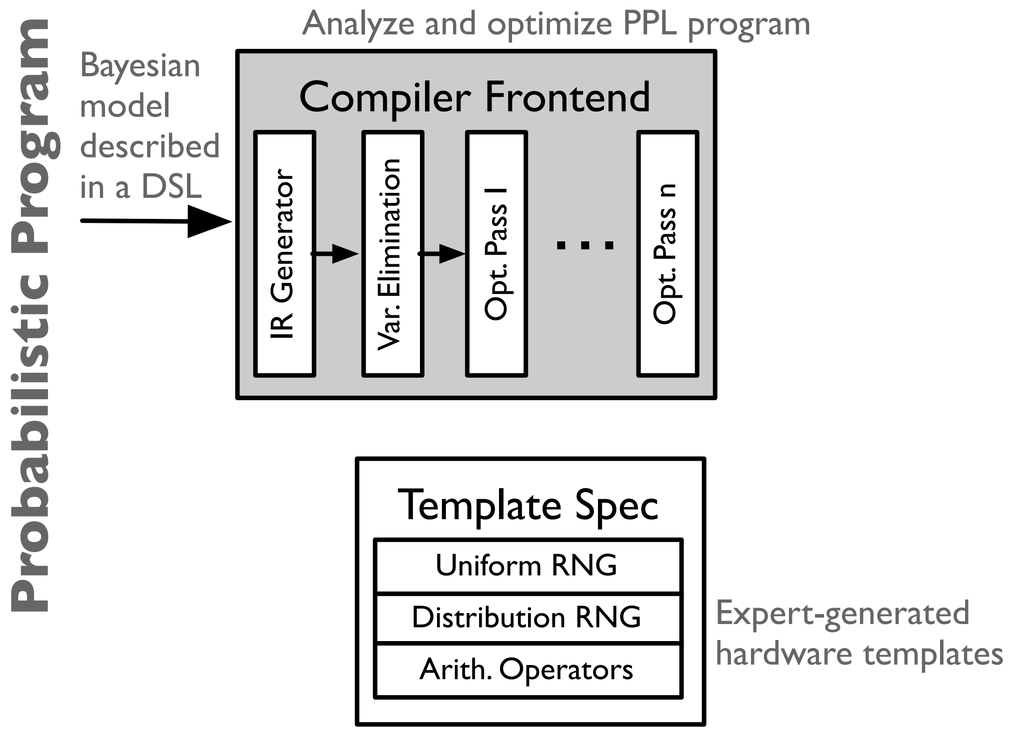

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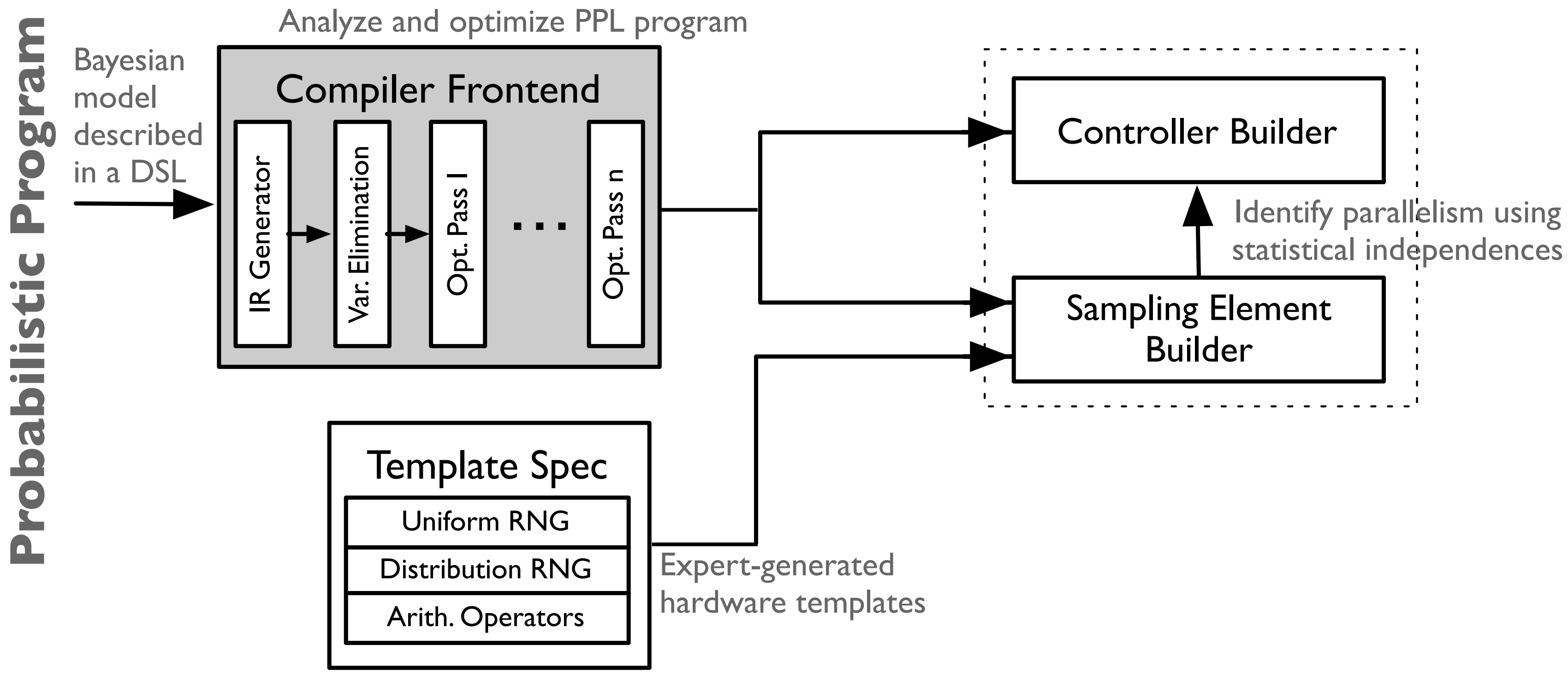

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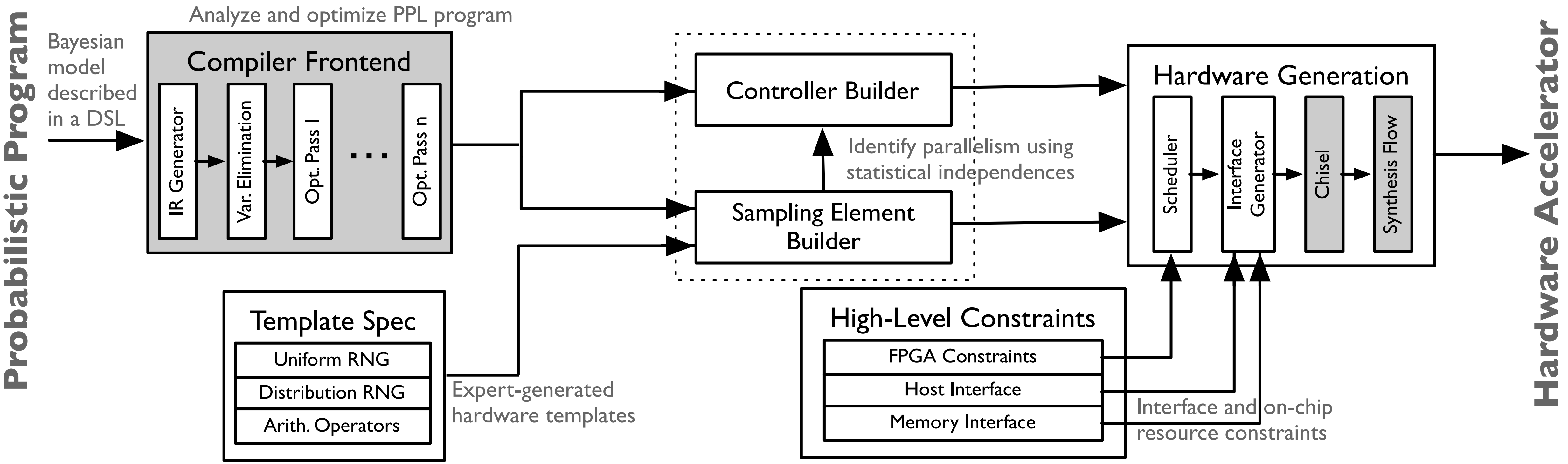

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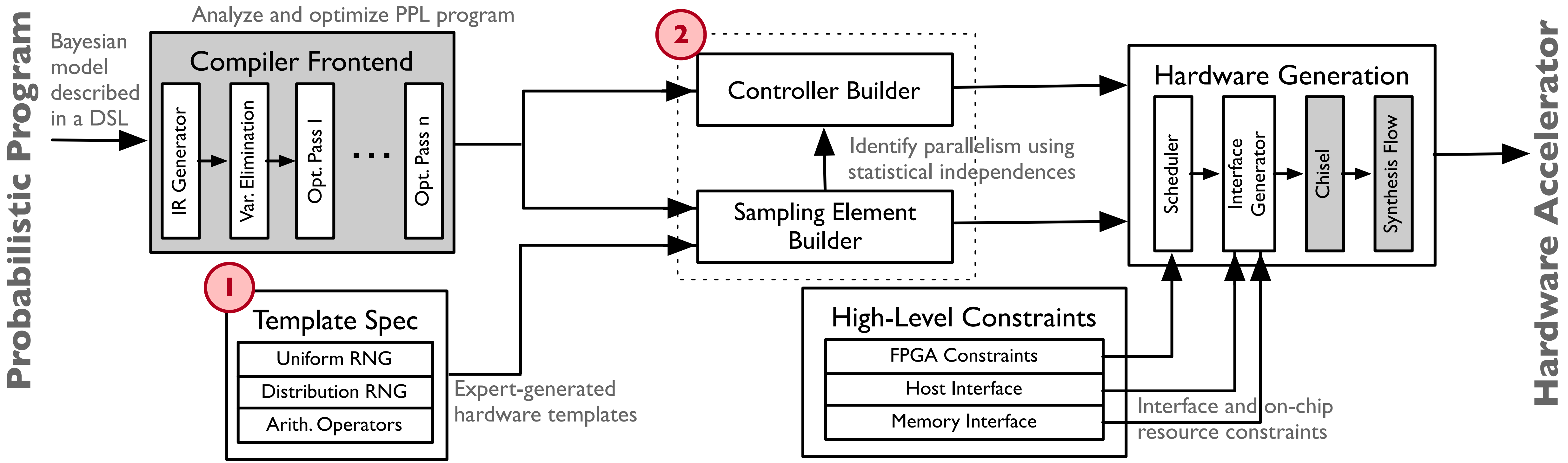
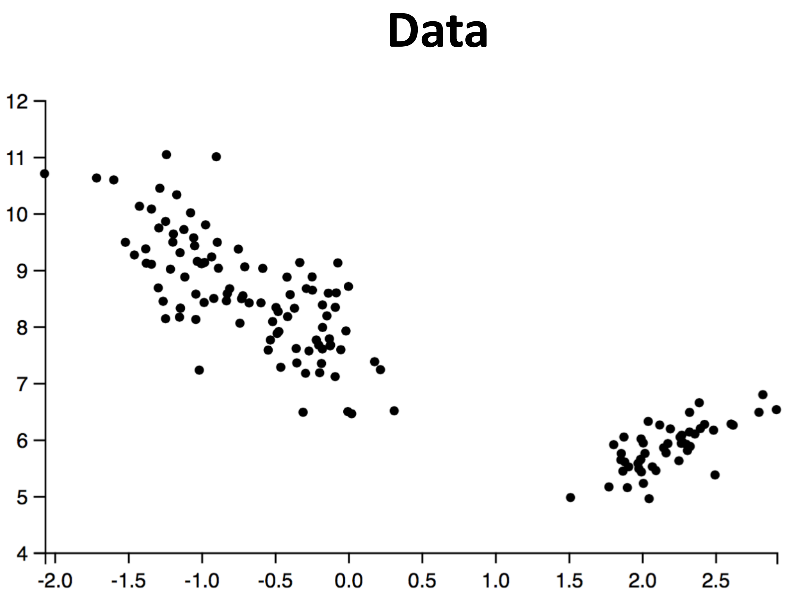


Example: GMM Clustering Data



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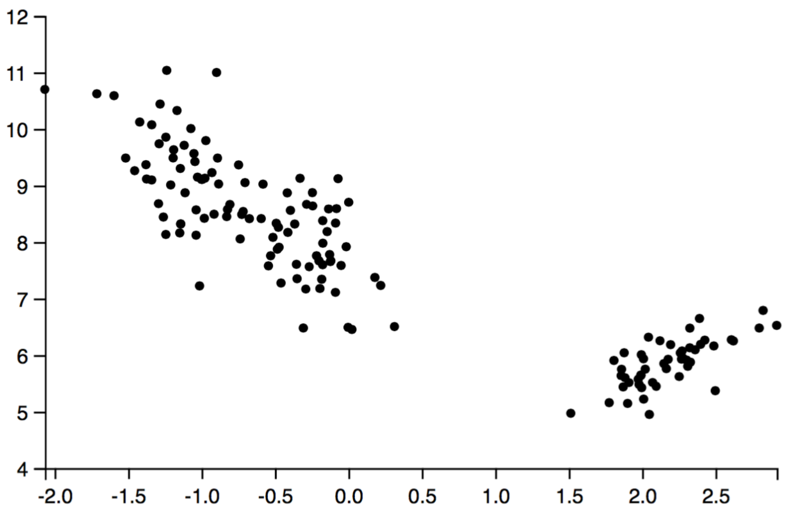
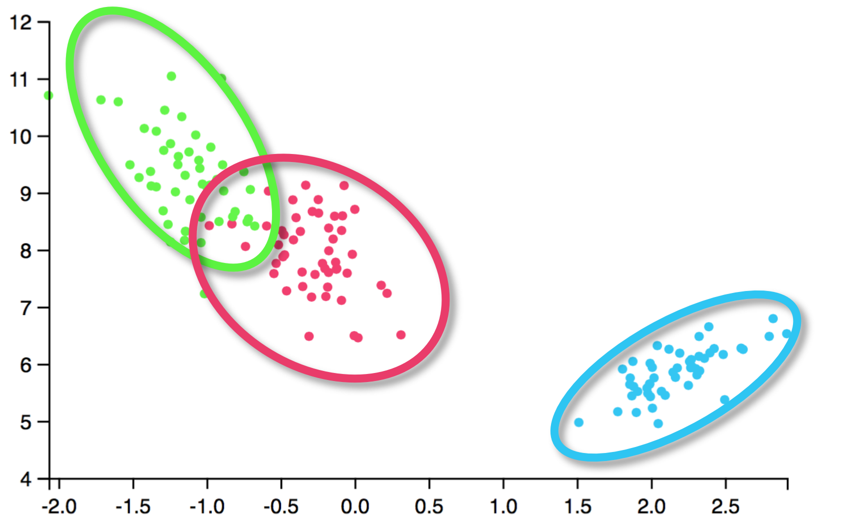


Inference



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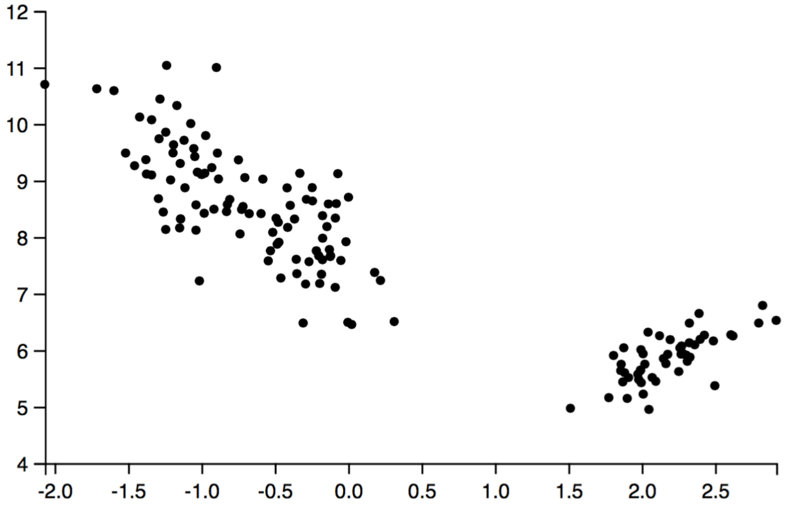
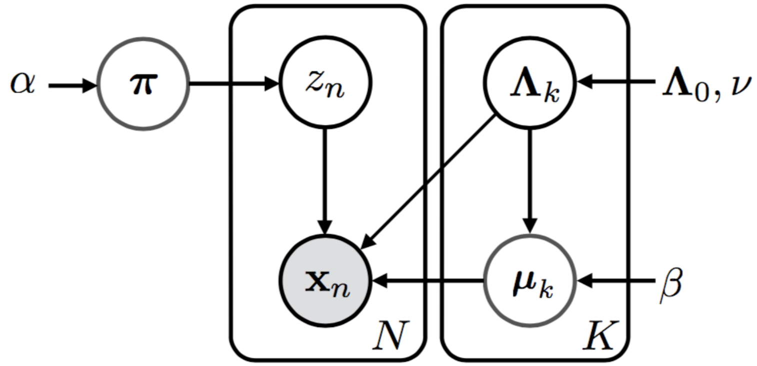


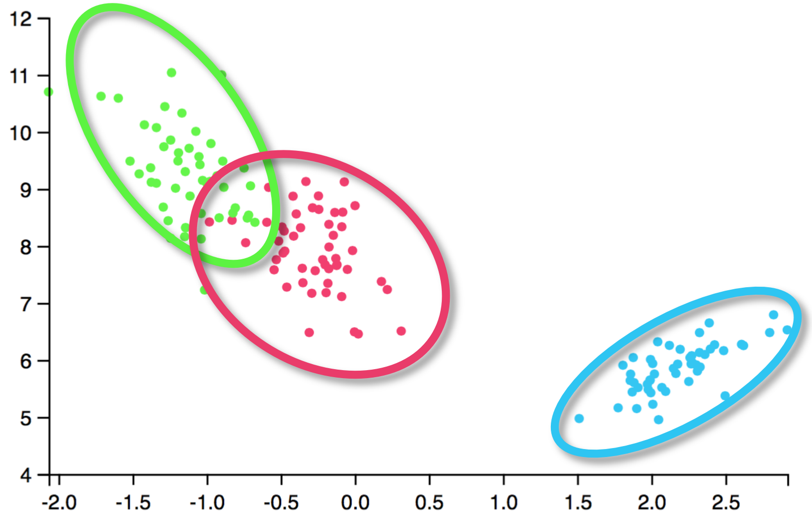
Generative Bayesian Model



$$\boldsymbol{\pi} \sim \text{Dirichlet}(\alpha)$$
$$\boldsymbol{\Lambda}_k \sim \text{Wishart}(\boldsymbol{\Lambda}_0, \nu)$$
$$\boldsymbol{\mu}_k | \boldsymbol{\Lambda}_k \sim \text{Normal}(\mathbf{0}, (\beta\boldsymbol{\Lambda}_k)^{-1})$$

$$z_n | \boldsymbol{\pi} \sim \text{Categorical}(\boldsymbol{\pi})$$
$$\mathbf{x}_n | z_n = k, \ \boldsymbol{\mu}_k, \ \boldsymbol{\Lambda}_k \sim \text{Normal}(\boldsymbol{\mu}_k, \boldsymbol{\Lambda}_k^{-1}) \, .$$

Inference



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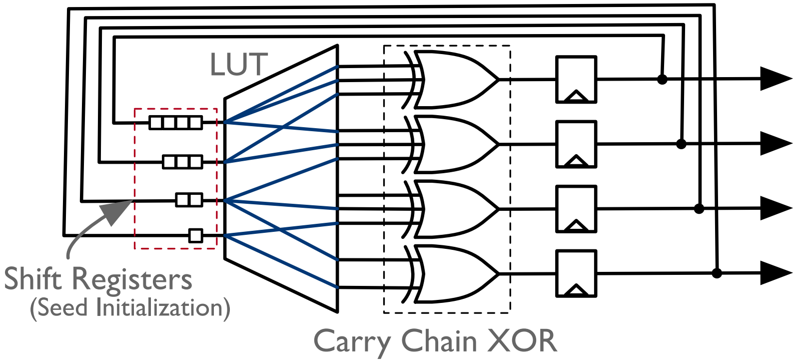
Uses single Logic Block for 4-bit RNG



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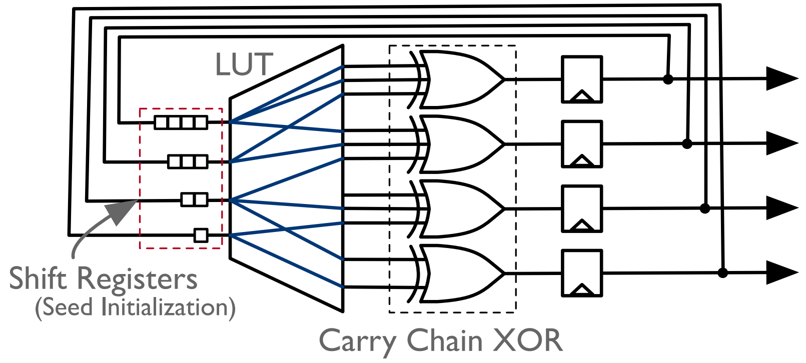

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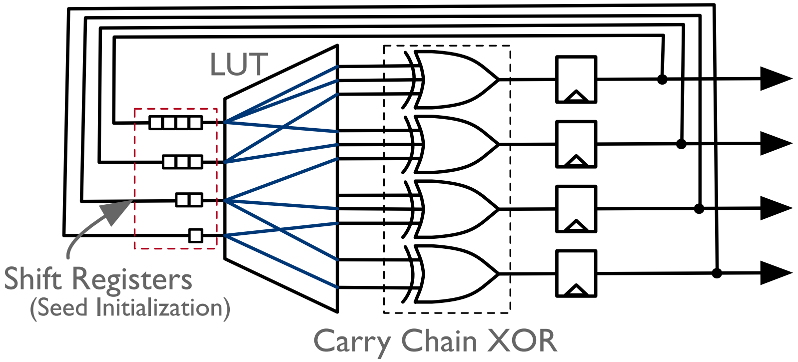
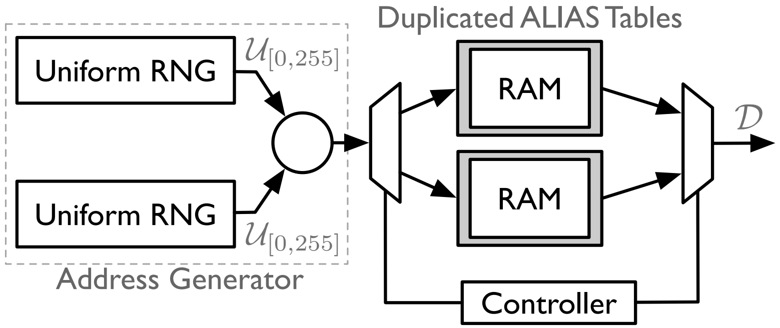
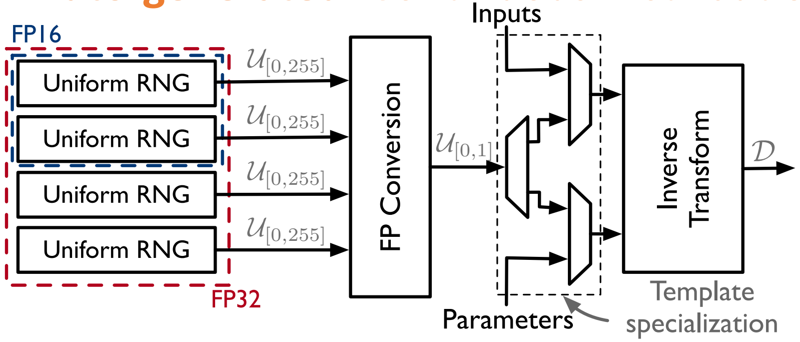


Auto-generated: Discrete Distributions



Auto-generated: Continuous Distributions



Identifying Parallelism: Enter Markov Blankets

- How do we compose the samplers?
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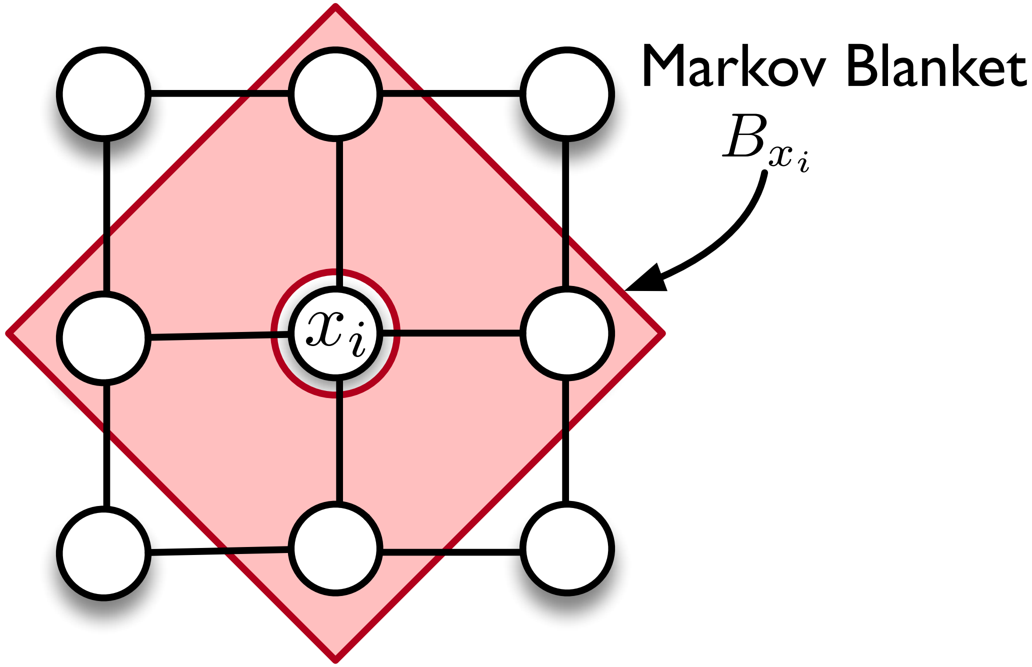
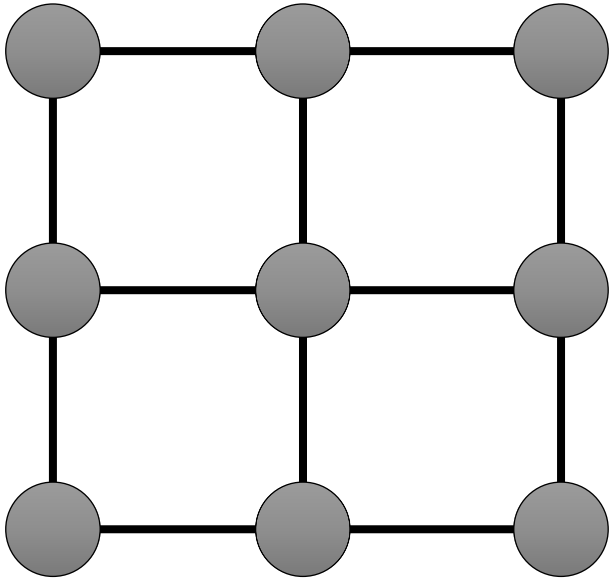
- How do we compose the samplers?
  - Program dataflow ordering is too conservative
- Use **conditional dependencies** to identify parallelism
- Set of nodes B_{x_i} for a node x_i such that:

$$\Pr(x_i | B_{x_i}, A) = \Pr(x_i | B_{x_i})$$

- **Markov blanket** is the only knowledge needed to predict behavior node.



Identifying Parallelism: k-Colorings



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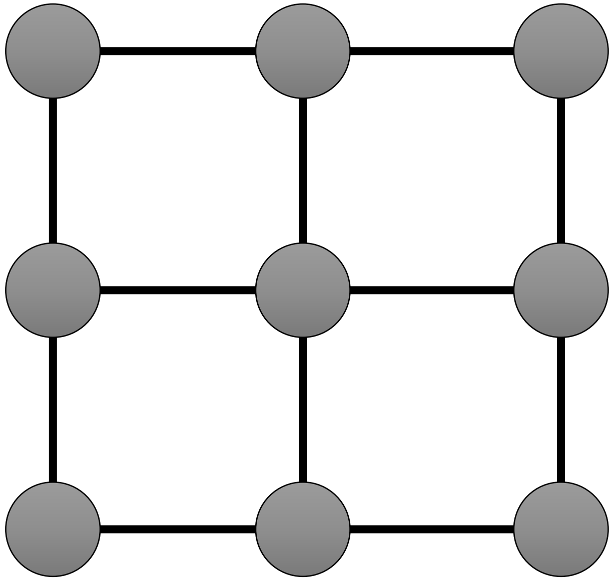

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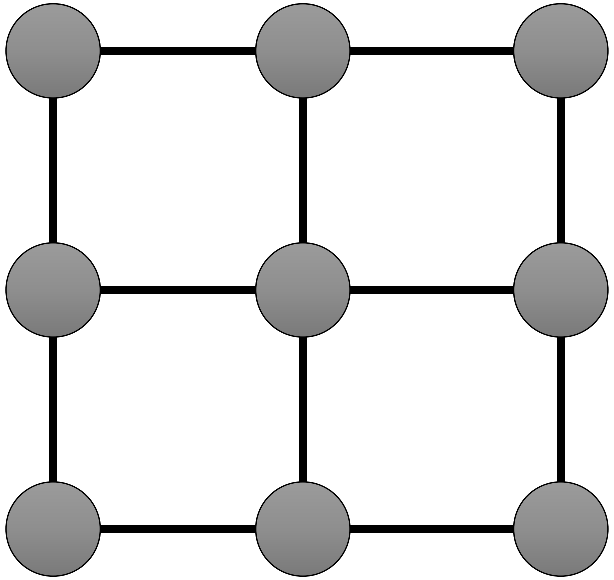

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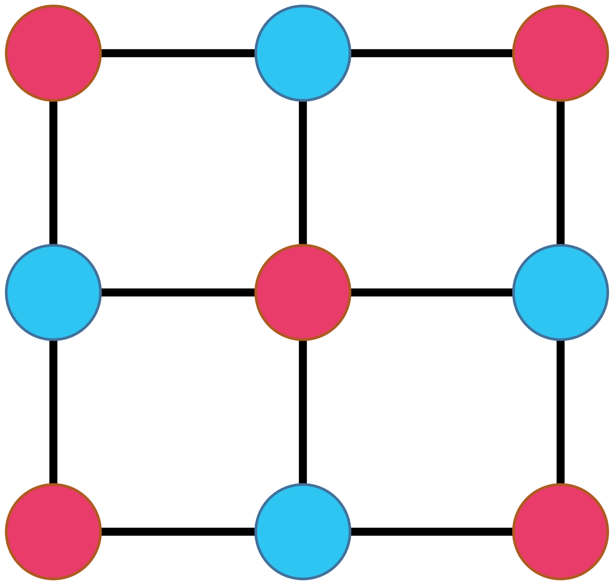

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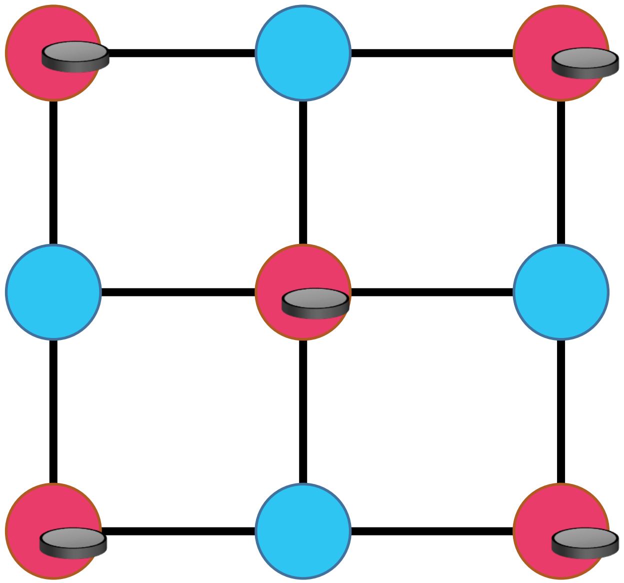

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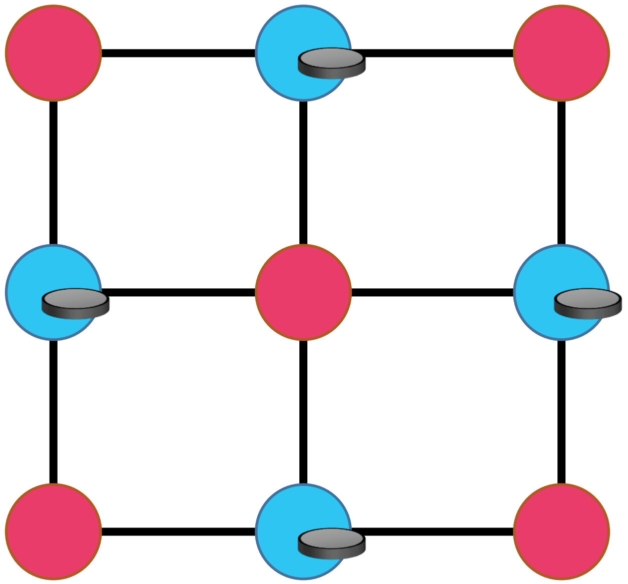

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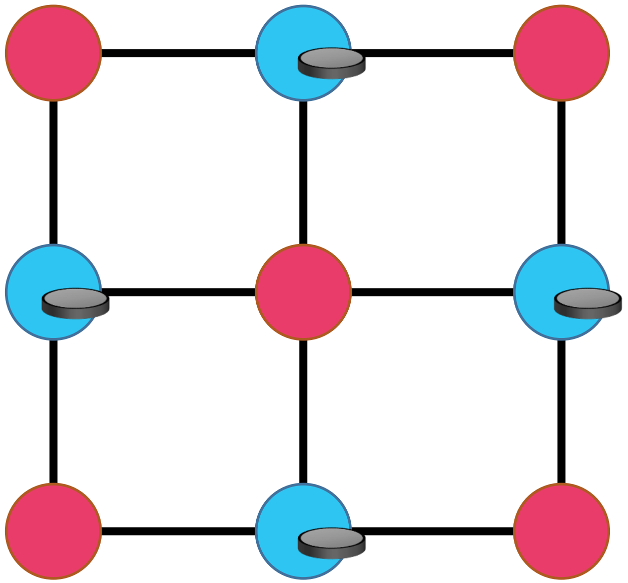

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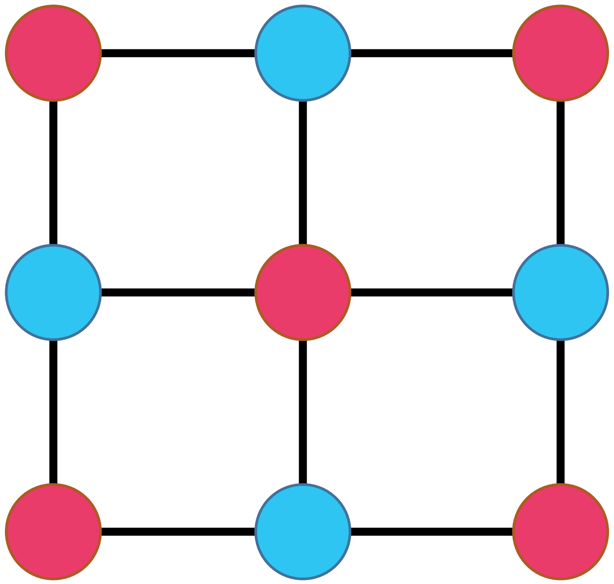

Identifying Parallelism: k-Colorings

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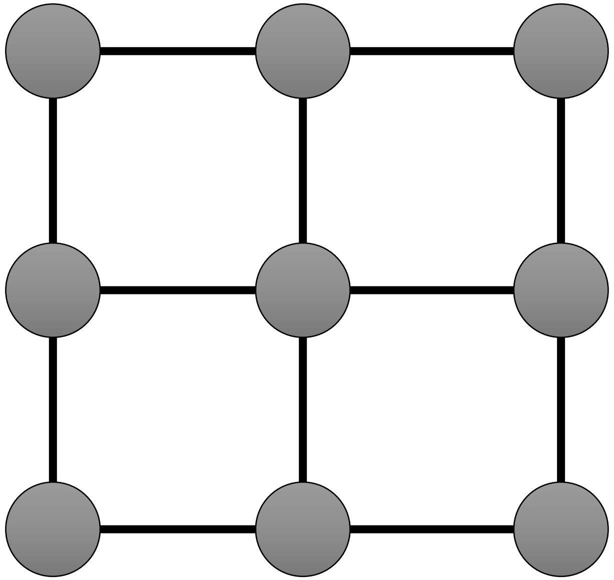
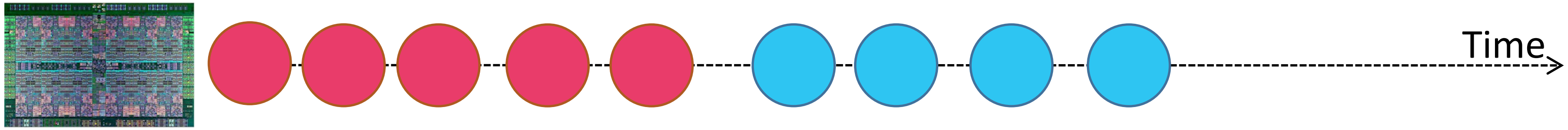
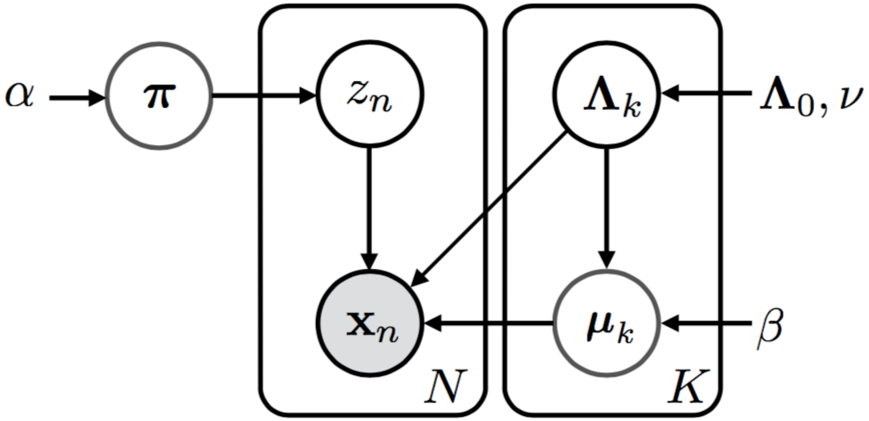
- Synthesize state machines corresponding to coloring
- Equivalent to sequential





Parallelism in the GMM Clustering Example



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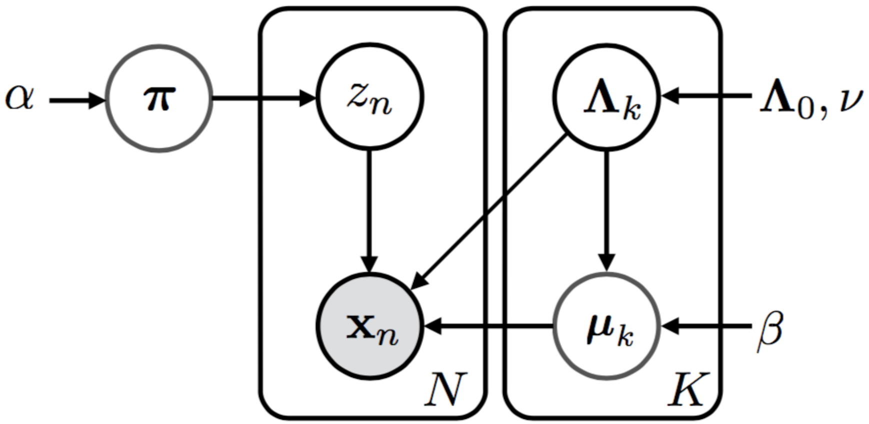

$\Pr(\alpha|\pi)$

$\Pr(\pi|\alpha, z_n)$

$\Pr(z_n|\pi, x_n, \Lambda_k, \mu_k)$

$\Pr(x_n|z_n, \Lambda_k, \mu_k)$

$\Pr(\mu_k|\beta, \Lambda_k, x_n)$

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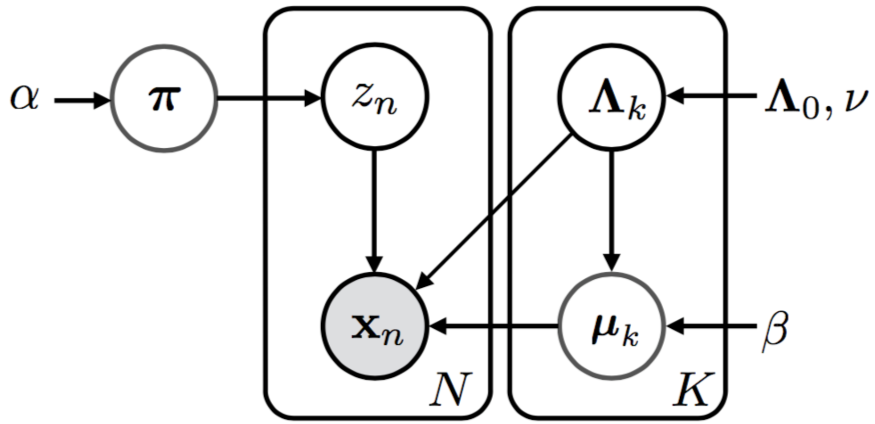

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Revisiting the GMM Clustering Example

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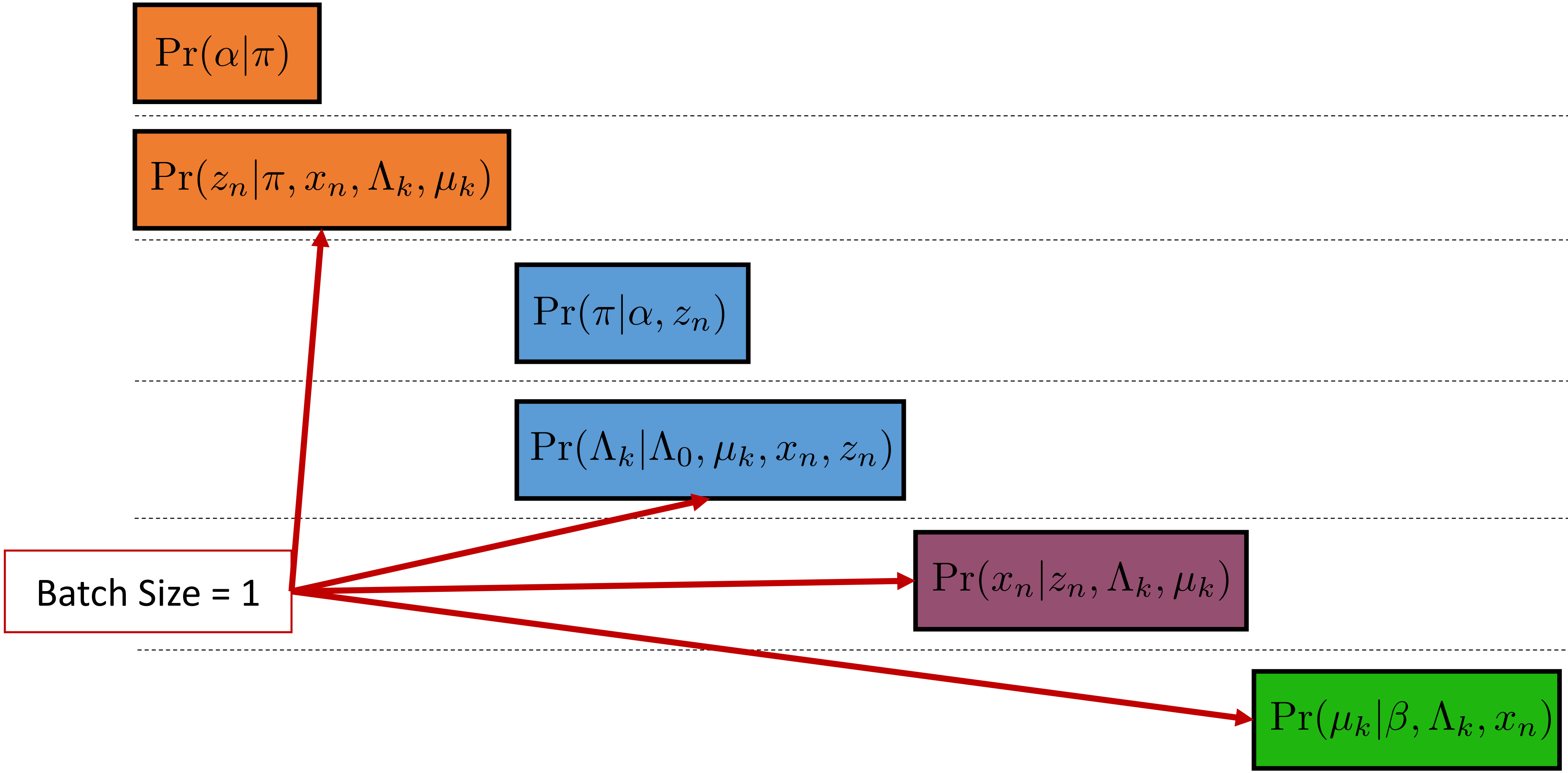
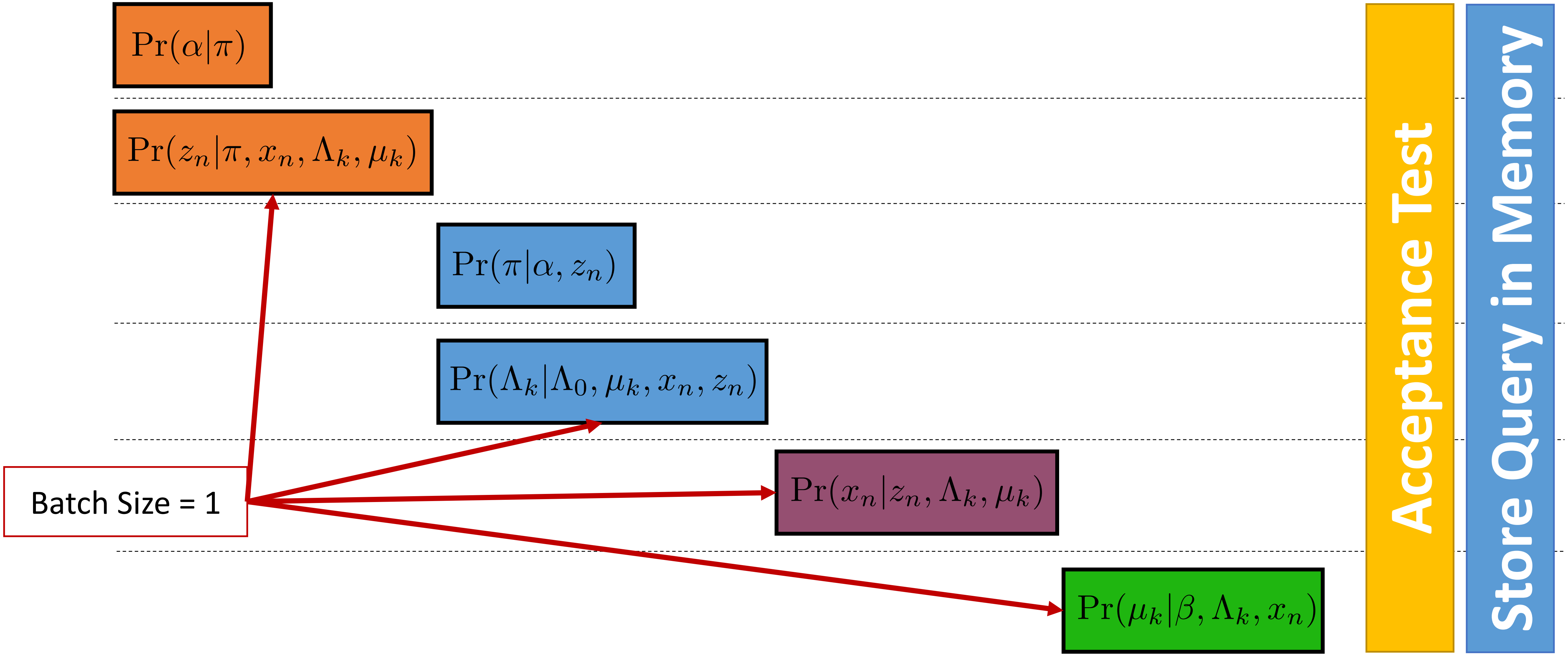


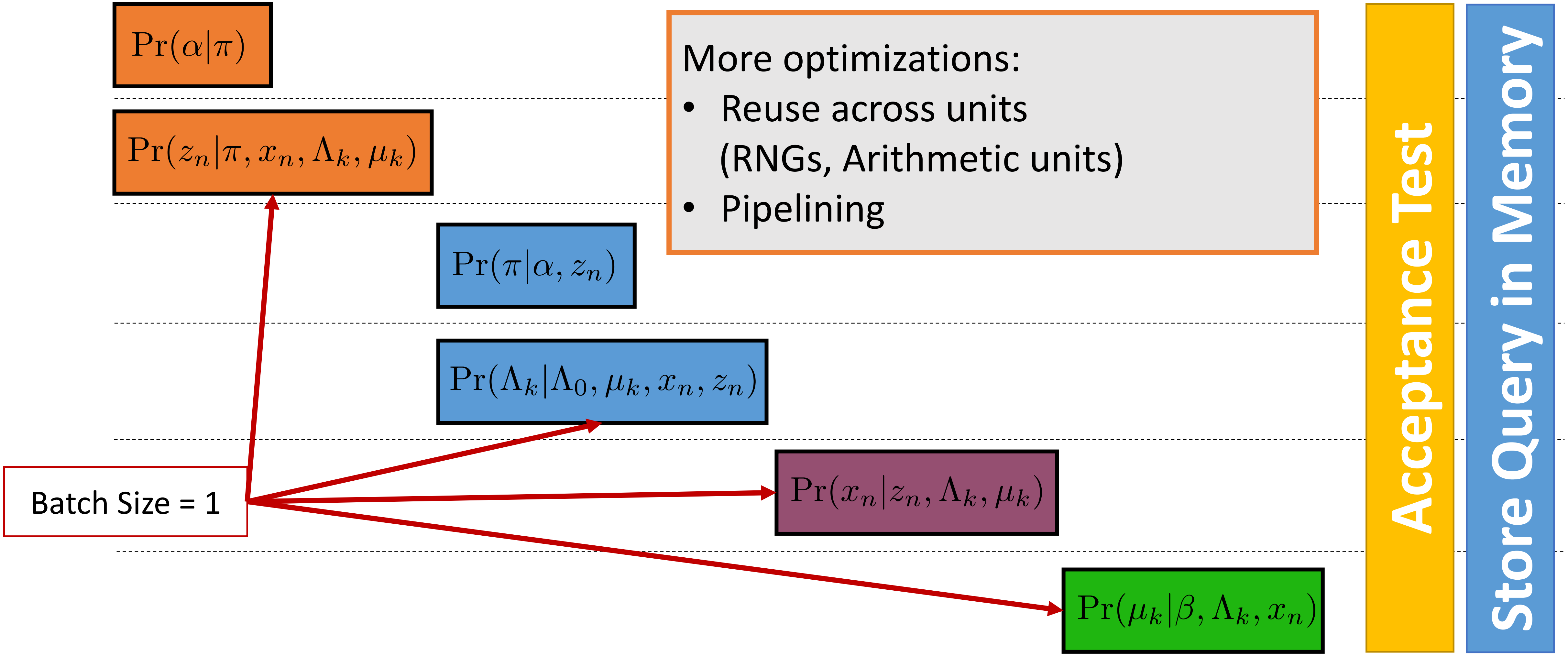
Revisiting the GMM Clustering Example



Revisiting the GMM Clustering Example

More optimizations:

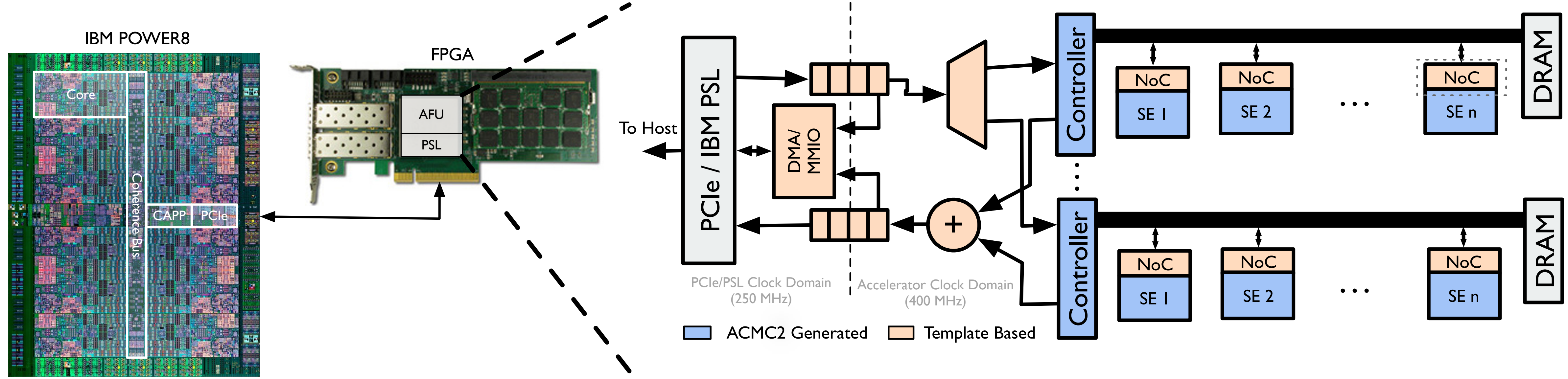
- Reuse across units (RNGs, Arithmetic units)
- Pipelining



Other Details in the Paper

- Compositional MCMC
  - Gibbs, Metropolis Hastings, Hamiltonian
- Speculative Execution
  - Speculate past rejected samples
- Accuracy – Performance Tradeoffs
  - Bloom Filters; Precision
- Generating IBM-CAPI based DMA Engine
  - Little’s Law

Implementation



6-core IBM POWER8

CAPI attached Virtex 7 FPGA

Sampling Element (SE) = RNGs + k-coloring controller

N x M sampling elements
N = 4 (4 DRAM channels on FPGA board)
M = max that can be fit on FPGA

Evaluation: AcMC^2 in Real World Models

Epilepsy/Neurosicnece: Identifying epilepsy affected brain regions [Varatharajah, NeurIPS17]

Security: Preempting advanced persistent threats using host/network IDSs [Cao, HOTSOS15]

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Embedded Medical Devices

Datacenter network monitoring tools

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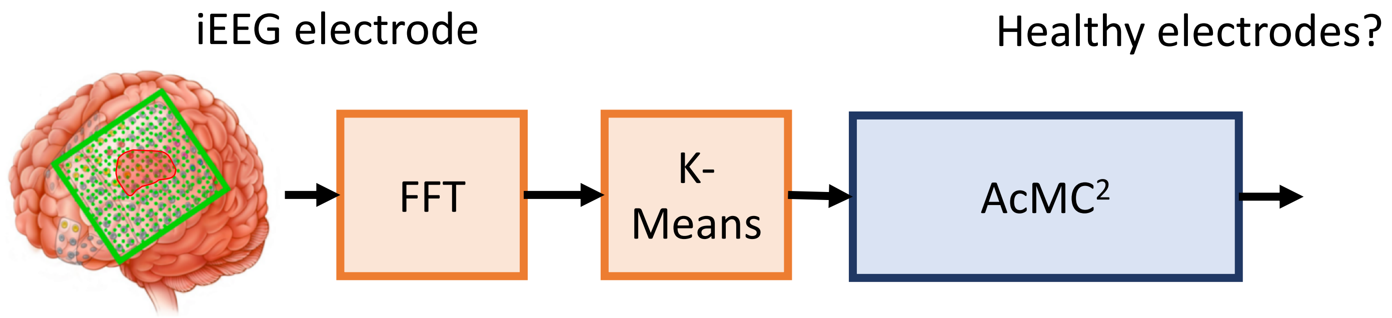
Embedded Medical Devices ⟷ **Datacenter network monitoring tools**



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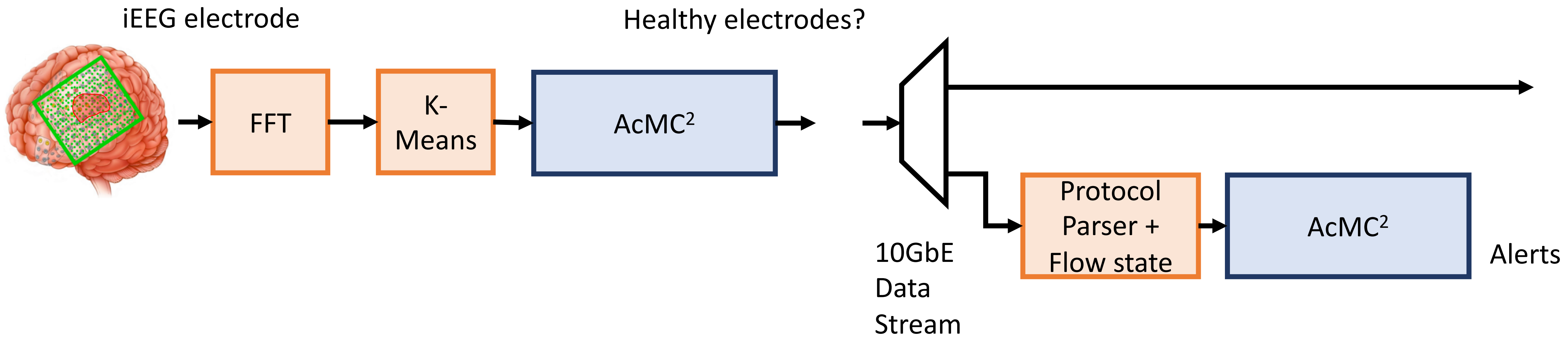
Embedded Medical Devices ⟷ **Datacenter network monitoring tools**



Evaluation: AcMC² in Real World Models

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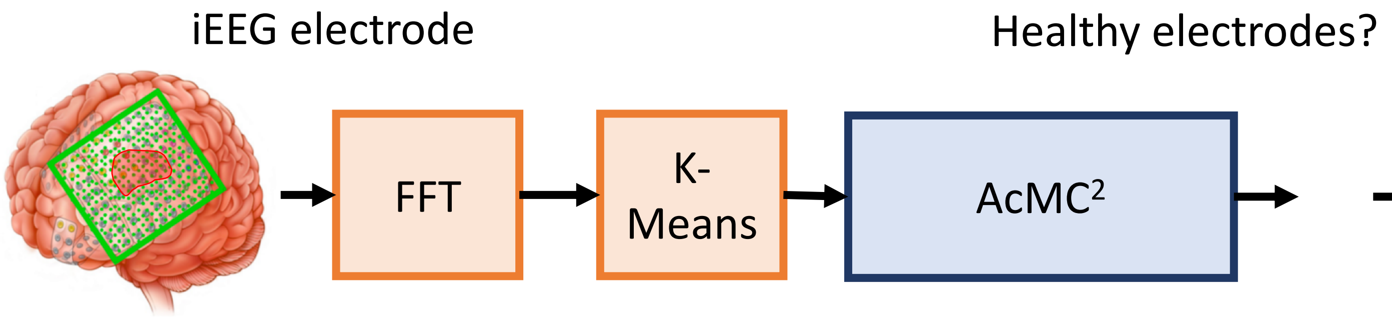
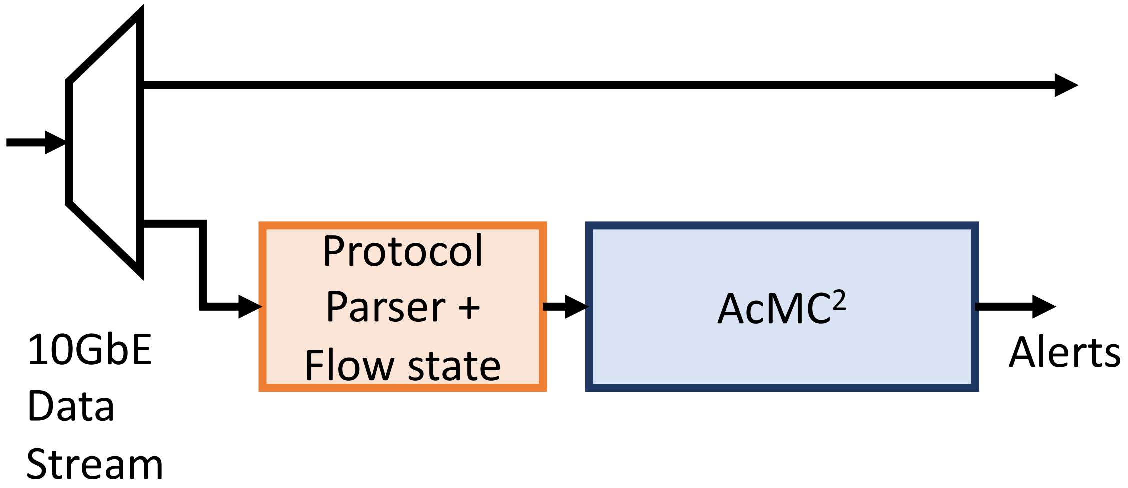
Embedded Medical Devices

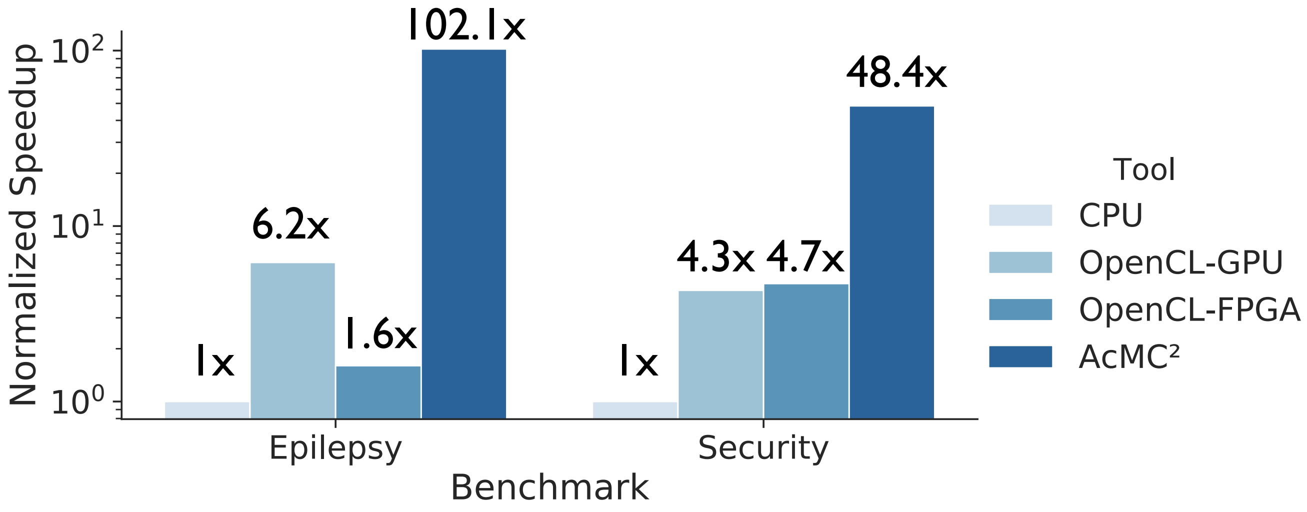
Datacenter network monitoring tools



Inference accounts for >90% of the latency



Results: Real World Case Studies



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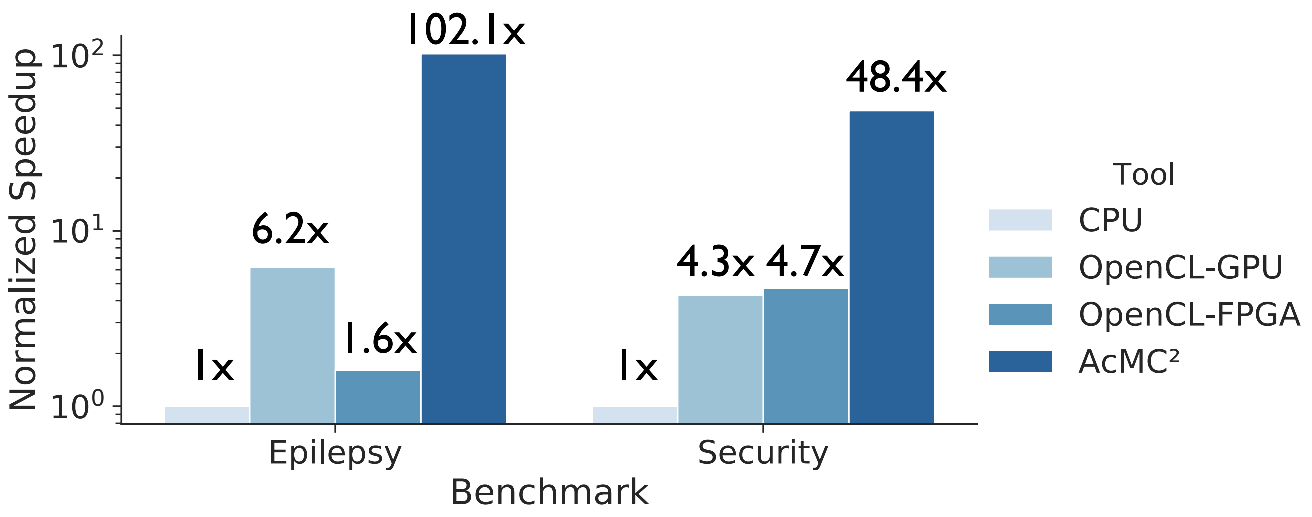

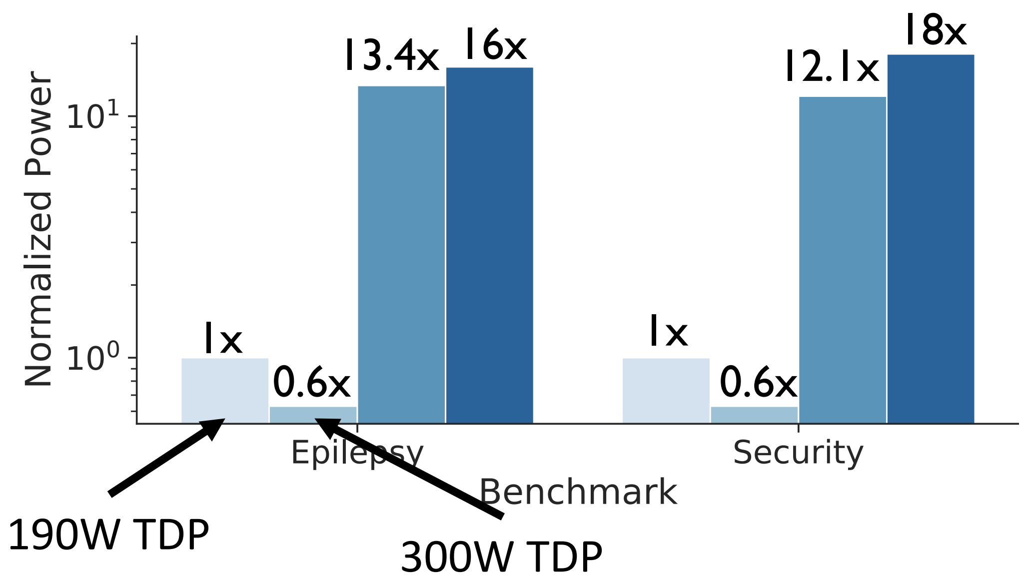

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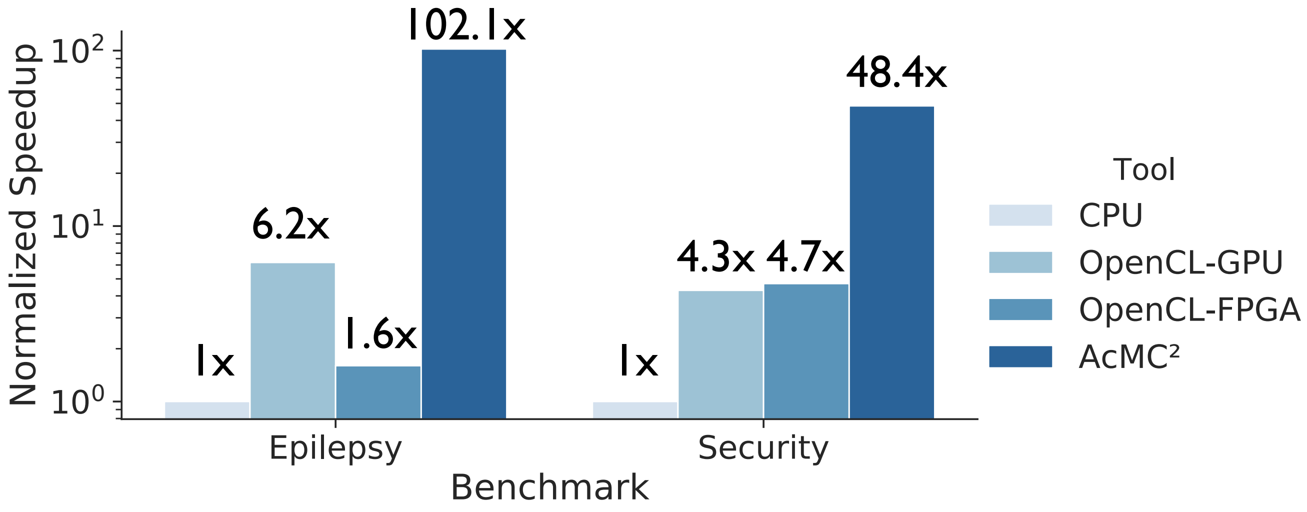

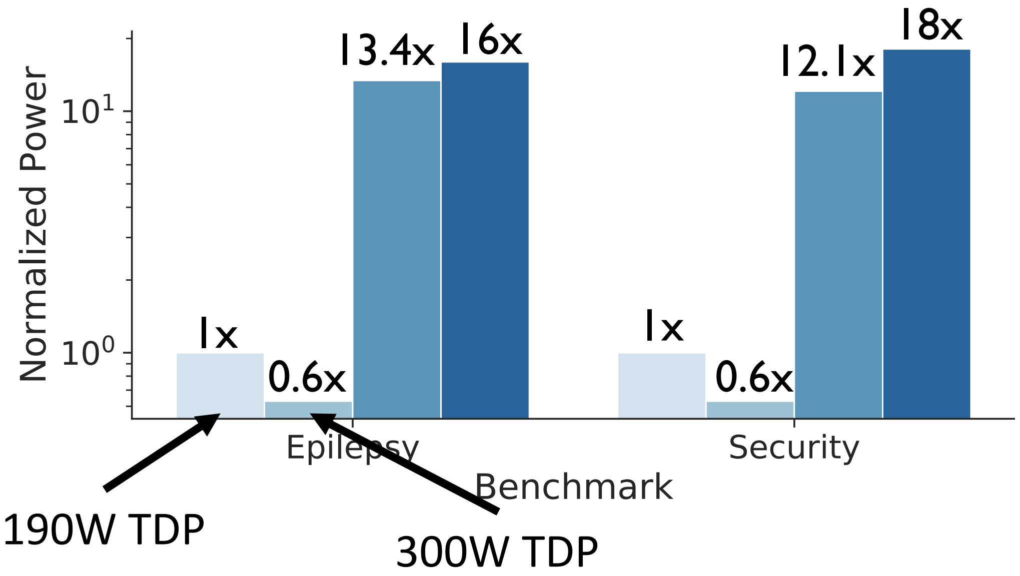

Significantly better results at much simpler code complexity
LoC AcMC² – 183 for C1 & 146 for C2
LoC OpenCL – 961 for C1 & 4861 for C2

Conclusion

- AcMC^2: A High Level Synthesis Compiler for Probabilistic Programs

- Code is open-source and available at https://gitlab.engr.Illinois.edu/DEPEND/AcMC2

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- Looking forward
  - How does these models fit in the context of Deep Learning? – Bayesian Deep Learning