### MC<sup>2</sup>RAM

# In-SRAM Markov Chain Monte Carlo Sampling for Fast Bayesian Inference

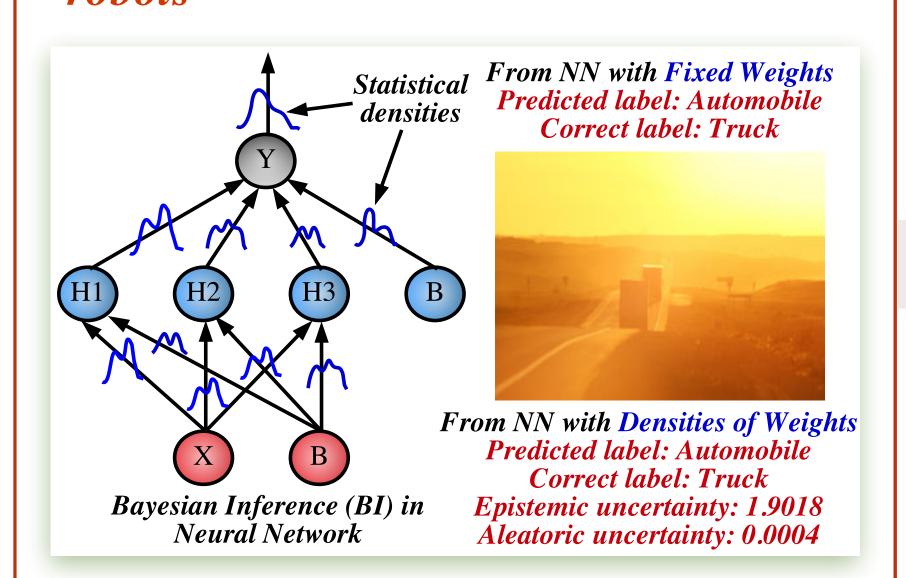
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In Bayesian Inference (BI), the predictions over different model parameters are weighted by how much we believe in

those parameter values given the data.

Accounting for these uncertainties in prediction is crucial for critical real-time decision making in settings like autonomous driving and surgical robots



 $\Theta$ : weight (w), bias (b)

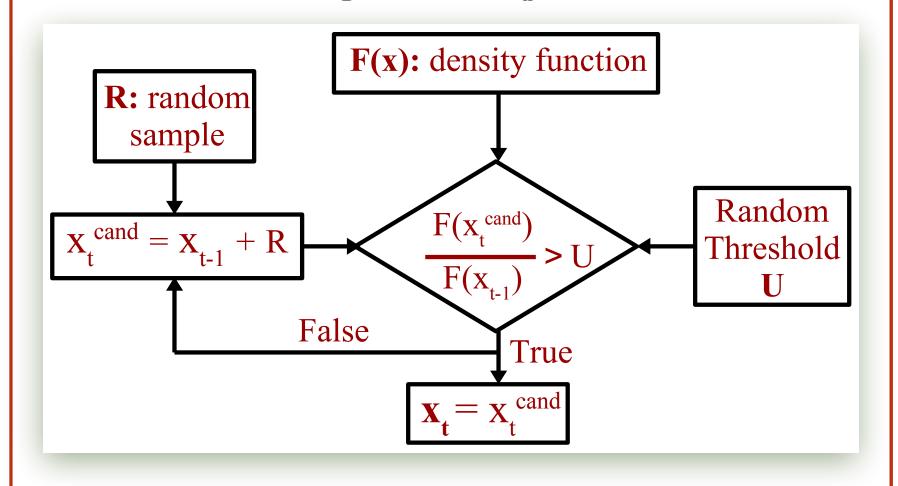
Bayes model:  $P(\theta|D) \propto P(D|\theta) \cdot P(\theta)$ 

Prediction:  $P(y|x,D) = \int P(y|x,\theta).P(\theta|D)d\theta$ (Intractable integral)

Using Monte Carlo approach to numerically compute these quantities  $\int G(x).F(x)dx \approx (1/T).\sum_{t}G(x_{F(x)})$ 

 $G(x) \equiv Mixture \ of \ Gaussians \ which \ is$   $proportional \ to \ Exponent \ computed \ as$   $E_i(t) = E_i(t-1) + (R/\sigma_i^2).R + 2.(R/\sigma_i^2)$ 

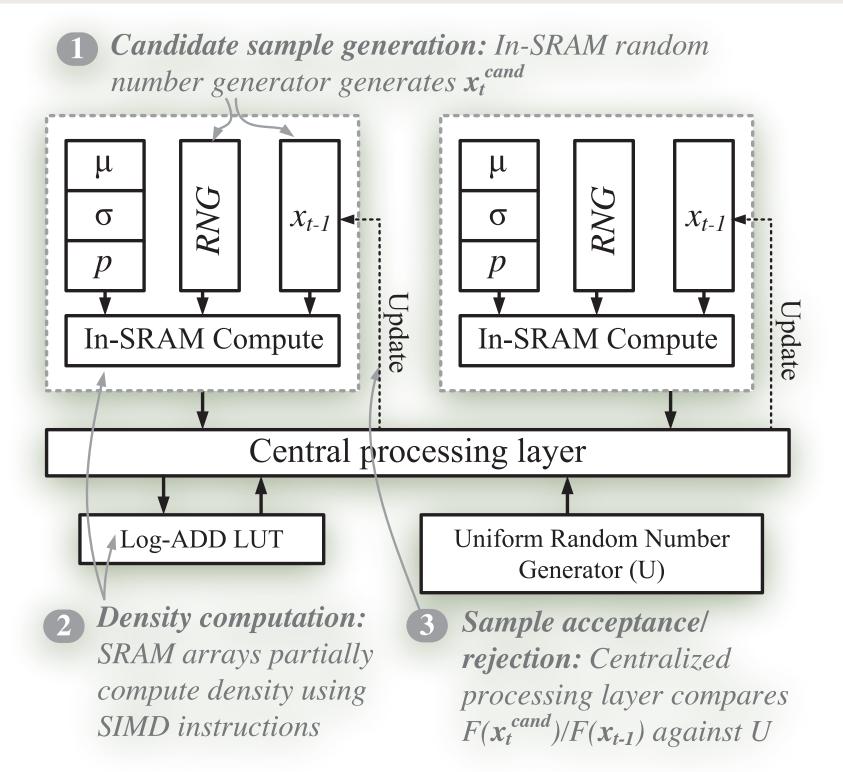
# Metropolis-Hastings sample acceptance/rejection



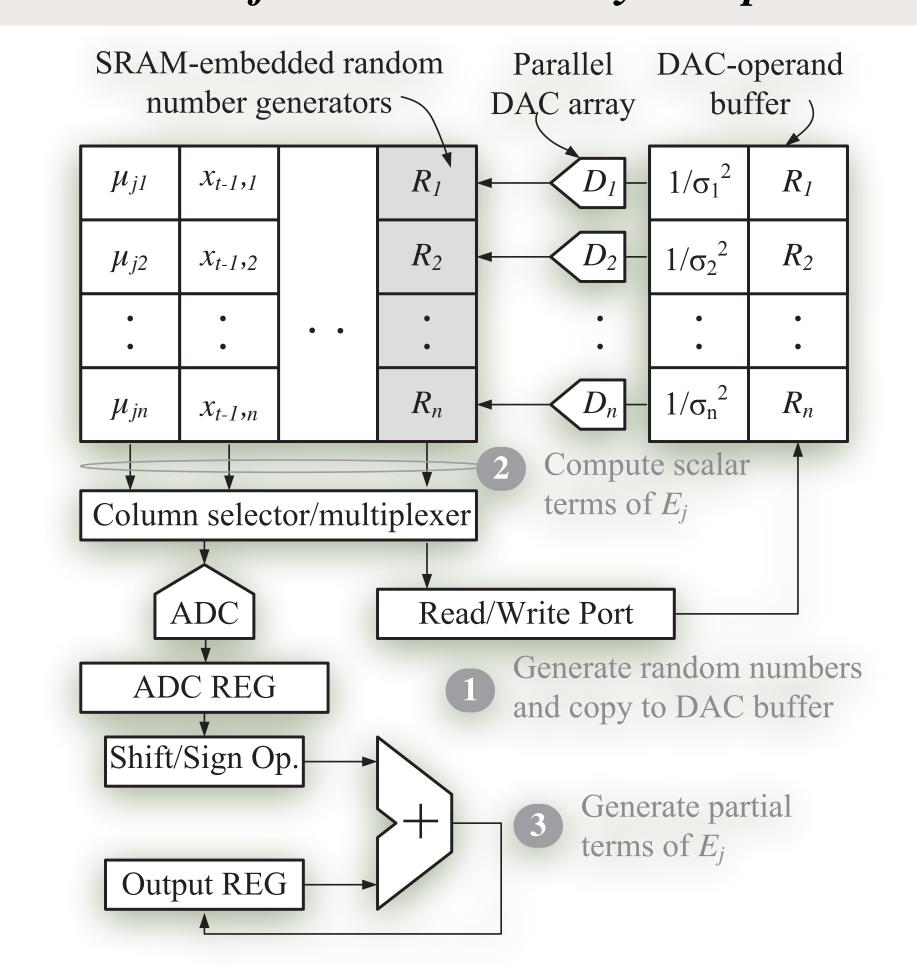
The posterior probability distribution of weights over data for a given model is a mixture of gaussian (GMM) components.

Bivariate GMM posterior of weights is sampled by MC<sup>2</sup>RAM using Metropolis-Hastings (MH) MCMC sampling criteria.

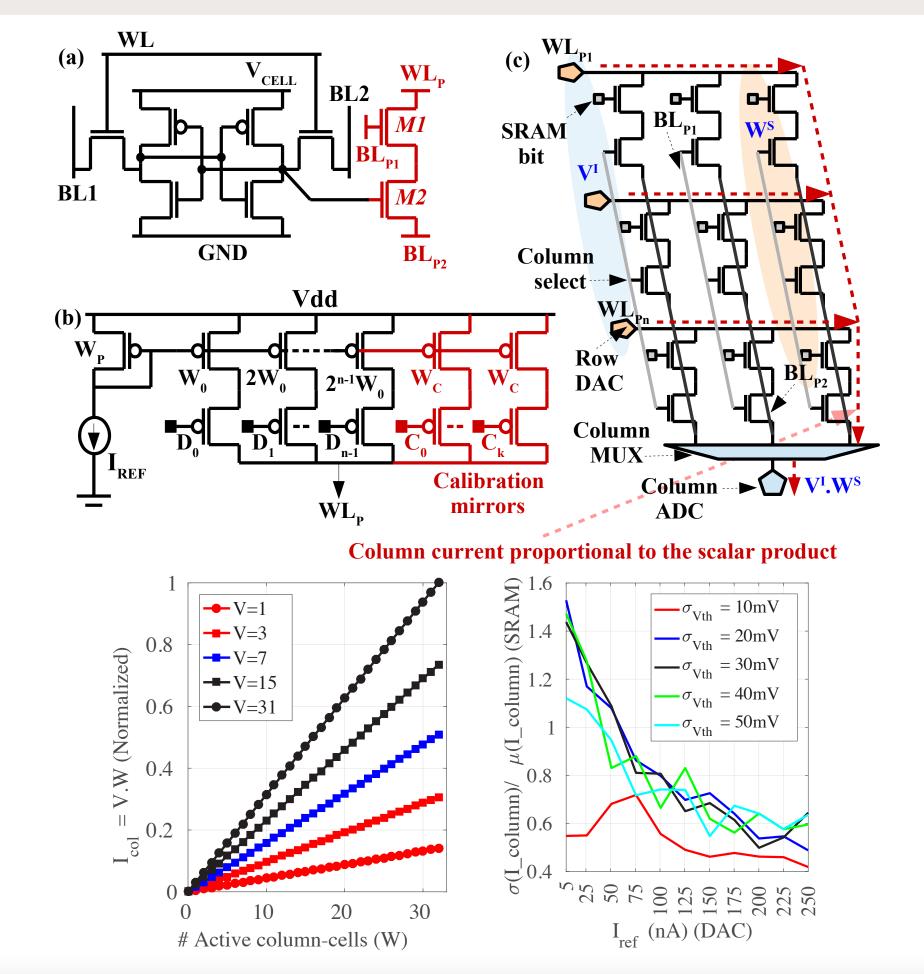
# A key framework to accelerate MCMC based sampling for BI



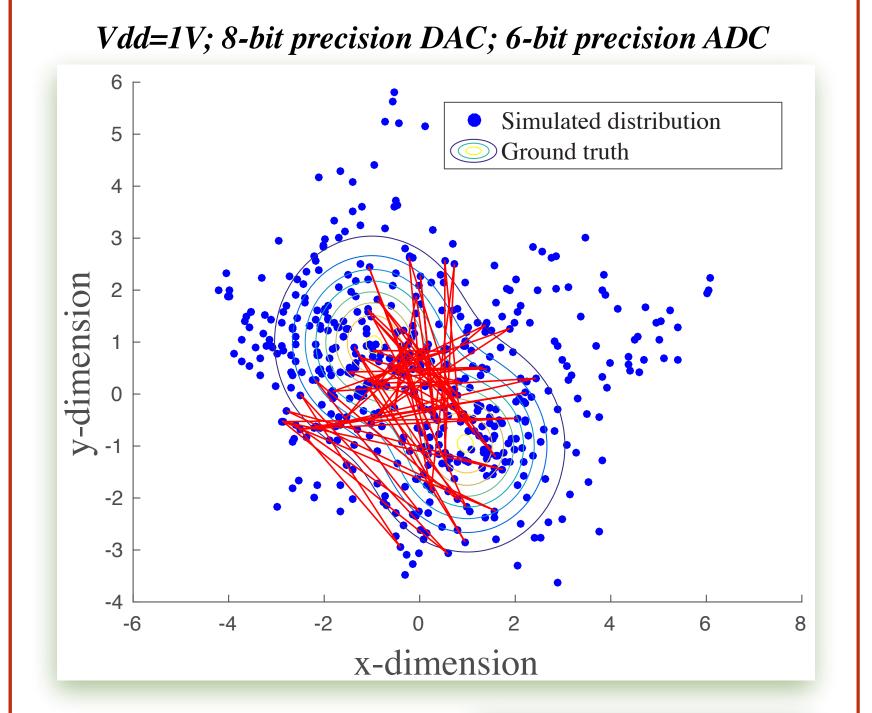
#### A Mixture-of-Gaussian Density Computation

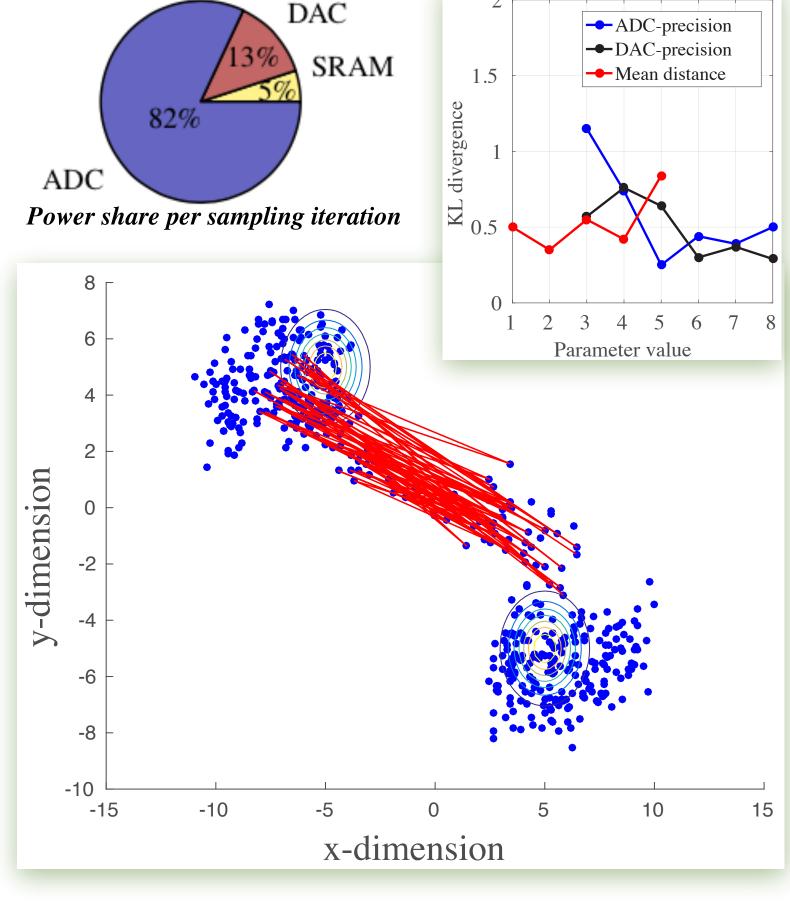


#### Co-located MC<sup>2</sup>RAM peripherals



## MCMC-MH based samples observed over ground truth posterior





- KL divergence figures illustrate the degree of deviation of sampled distribution from ground truth posterior
- MCMC sampling is imprecision tolerant to SRAM peripherals (DAC/ADC)
- Power share is greatly impacted by peripheral components in SRAM
- Sampling in higher dimensions call out for efficient and high degree of parallel operations using multiple SRAM banks

#### To Investigate...

Can peripherals be more efficient?

Is Metropolis-Hastings good enough for BI?

Can we efficiently accelerate sampling for 500-dimensional random variables?

Tapeout complexities?

#### Key References...

Blundell et. al, ICML 2015 Cai et. al, ASPLOS 2018 Zhang et. al, JSSC 2015 Kyle Dorman's Blogposts

