Architecting a Stochastic Computing Unit with Molecular Optical Devices

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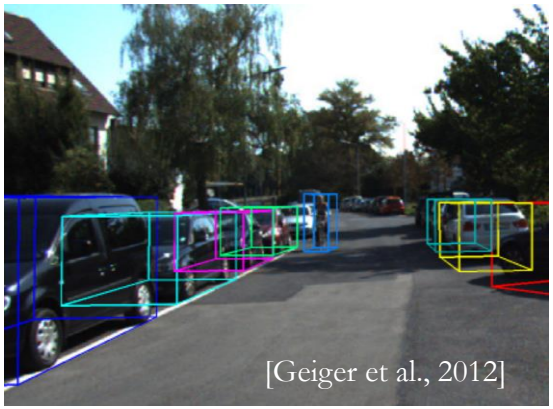
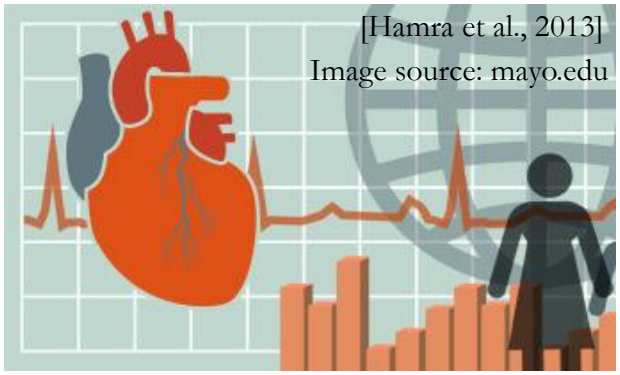
Chris Dwyer*, Alvin R. Lebeck

Duke University *Parabon Labs

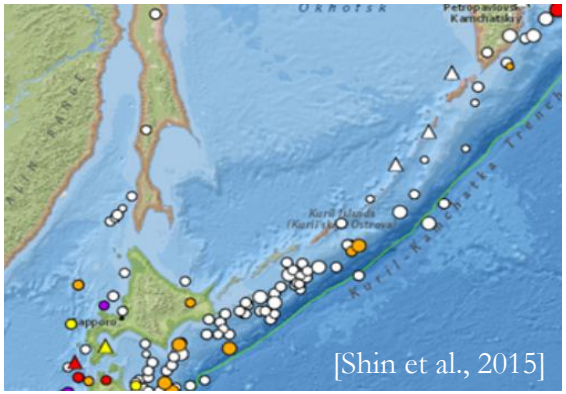
Stochastic (Probabilistic) Computing



Computer vision



Medical statistics



Earthquake prediction

Statistical Machine Learning

- Probabilistic algorithms (e.g. Markov Chain Monte Carlo):
  - Key to performance: generating samples.
- **Problem: Sampling overhead is TOO HIGH:**
  - A sample from a simple distribution: >500 cycles.

Using Markov Chain Monte Carlo method

Left image

Right image

- Stereo Vision: reconstruct the depth information from image pairs.
  - Matching corresponding pixels.
  - Calculate disparity: location difference $x_l - x_r$.

Using Markov Chain Monte Carlo method

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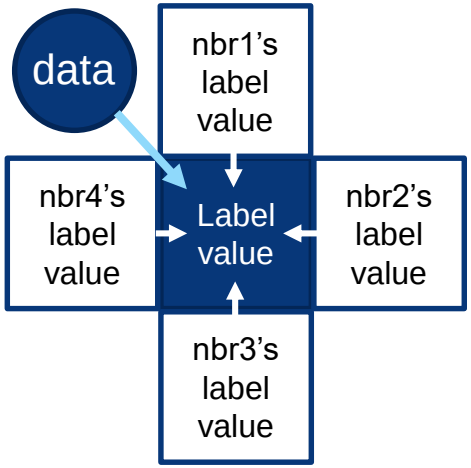

Label dependency

Energy function:

$E(Data, Lables)$

- Label: disparity on that pixel.

```
while(not converged) {
        for each pixel {
                Gibbs Sampling
        }
}
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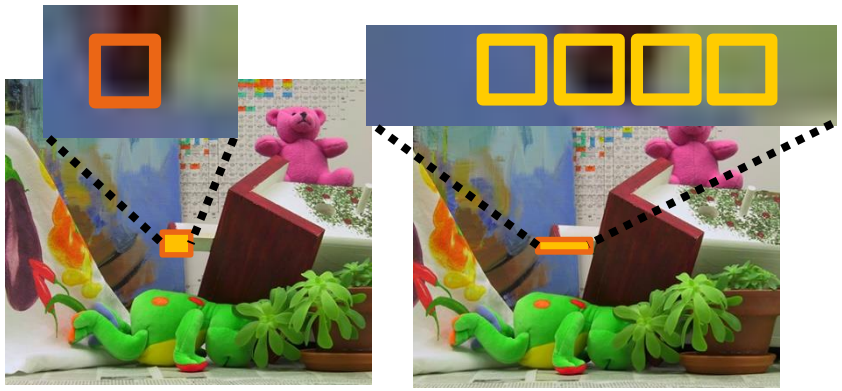
Using Markov Chain Monte Carlo method



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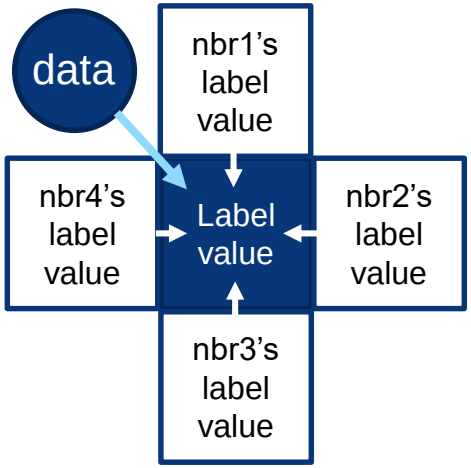
Pixel

Possible Matchings



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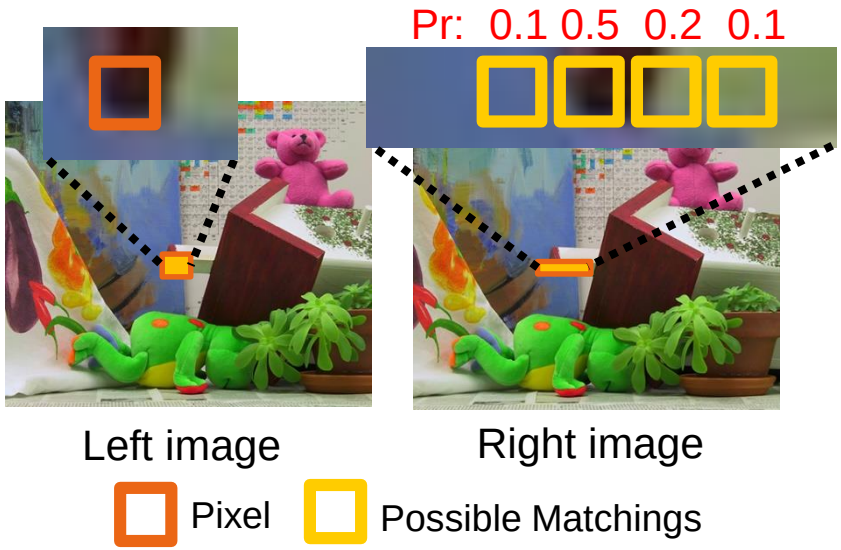

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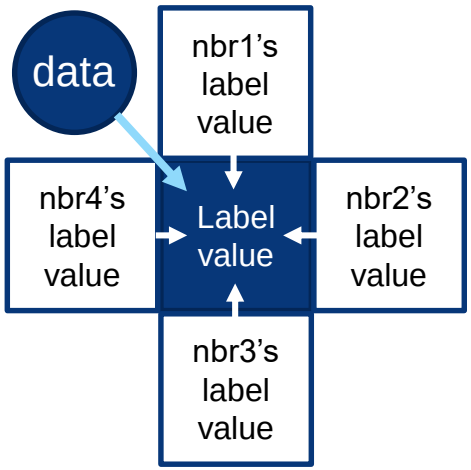

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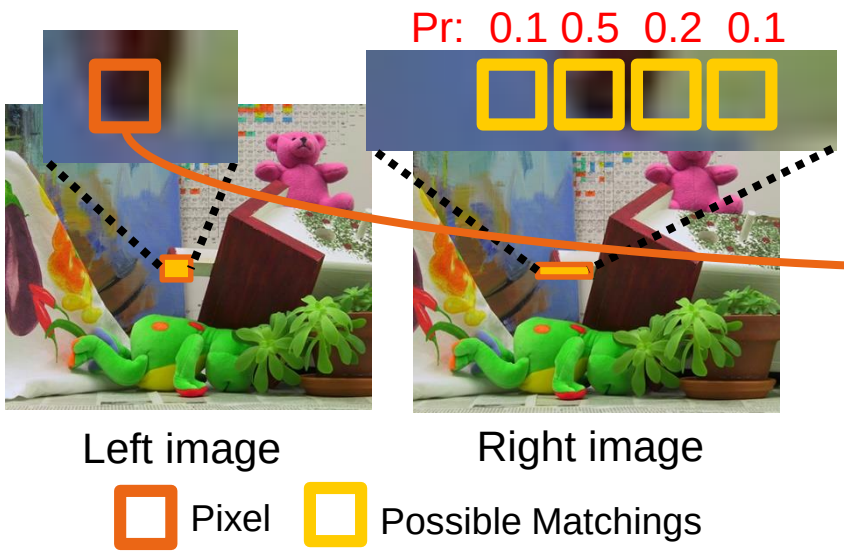

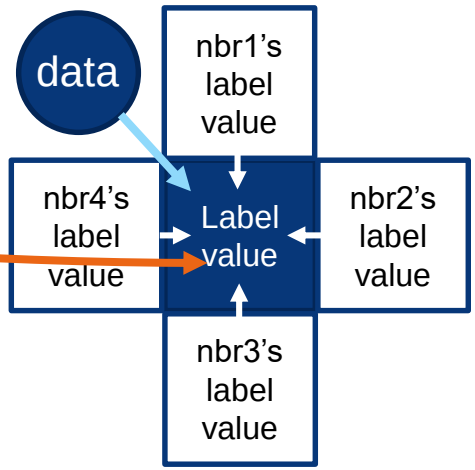

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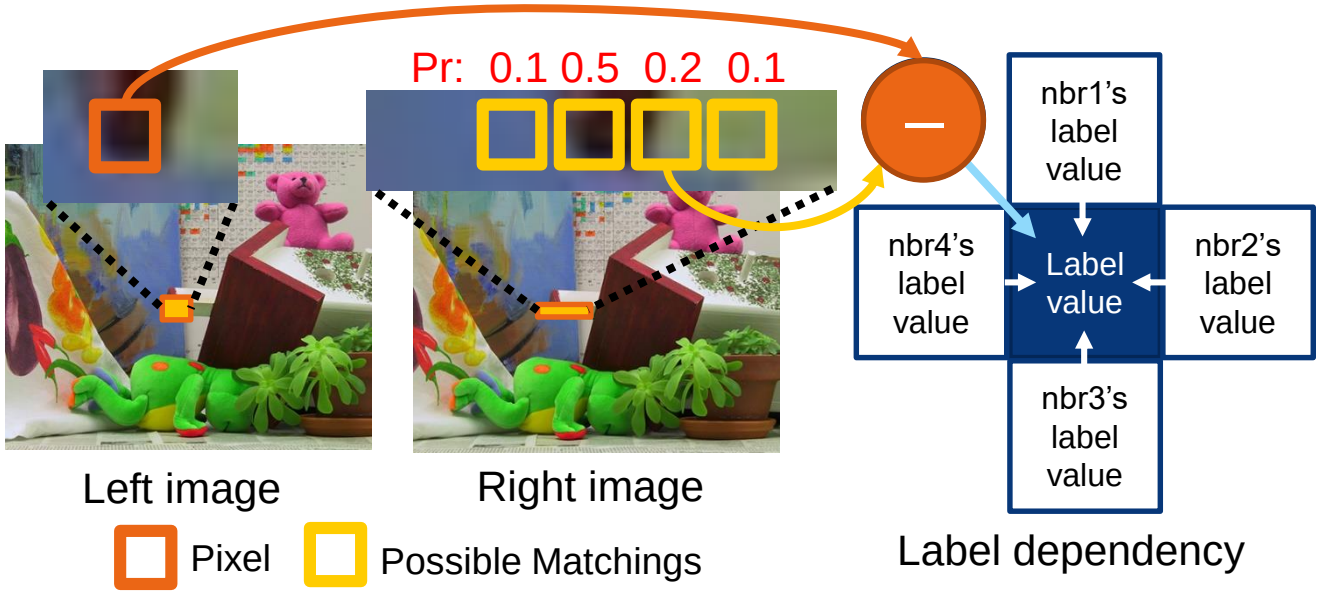

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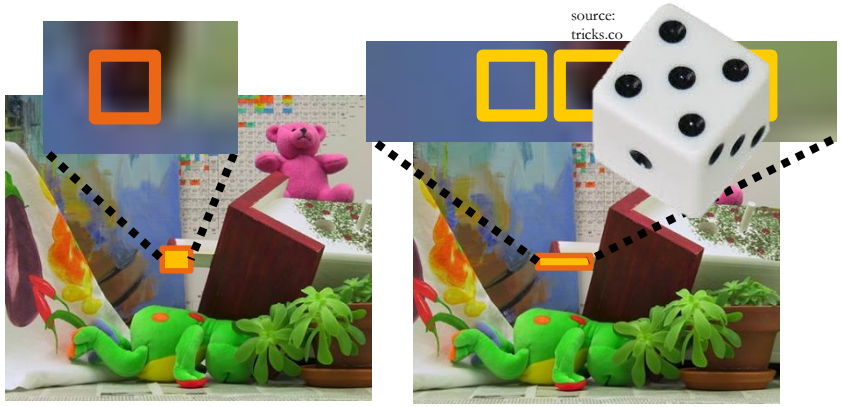

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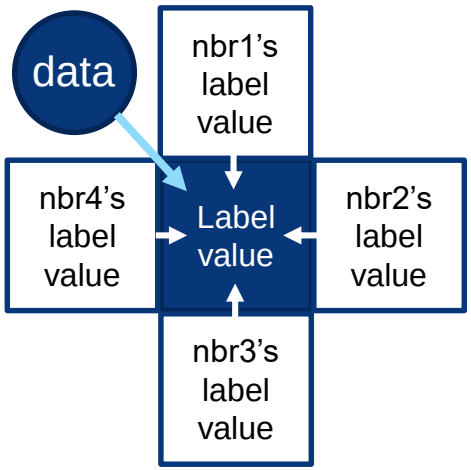

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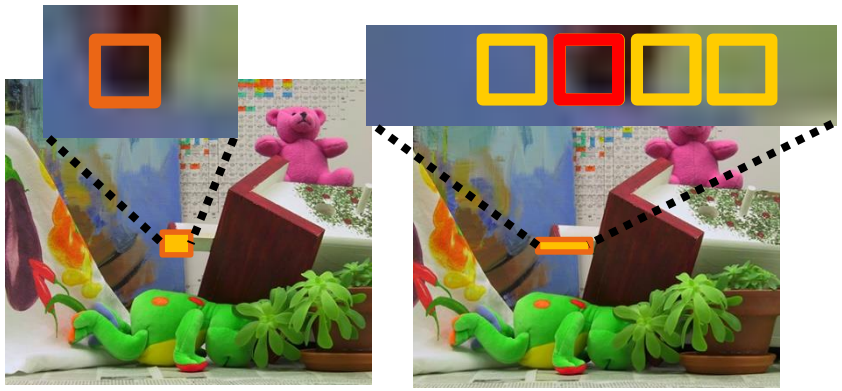

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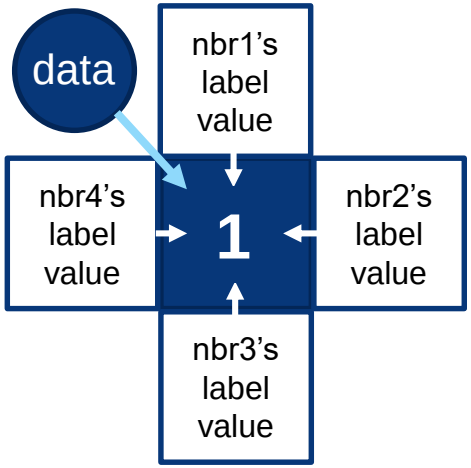

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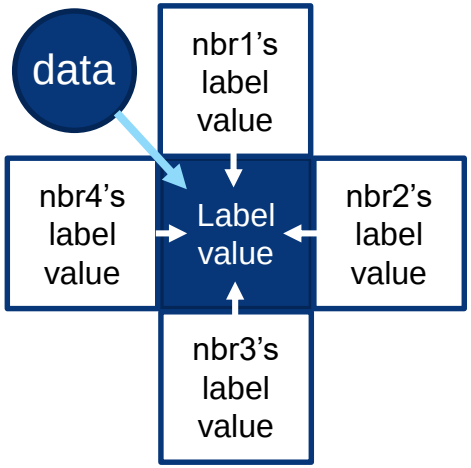

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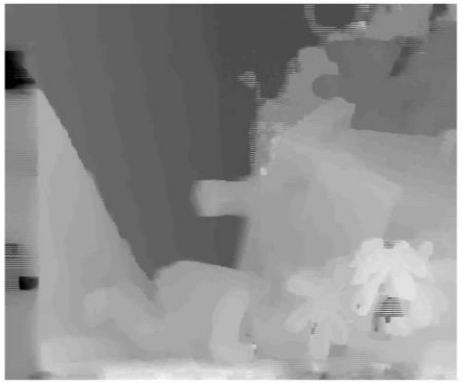

Disparity map
(lighter is closer)

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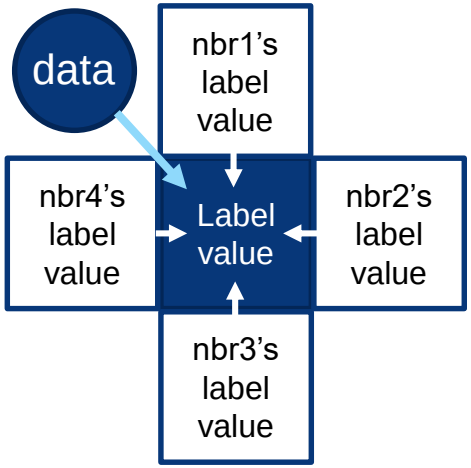

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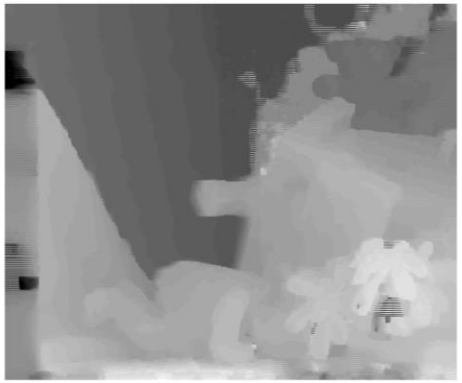

Disparity map
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- Label: disparity on that pixel.

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while(not converged) {
        for each pixel {
                1) compute probabilities over each possible label;
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        }
}
```

Slow!

Using Markov Chain Monte Carlo method

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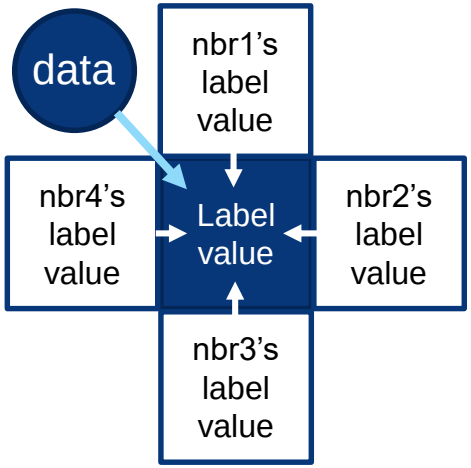

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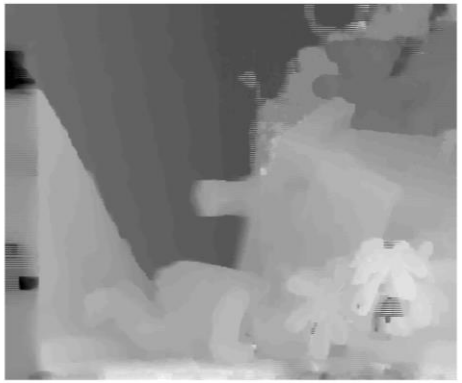

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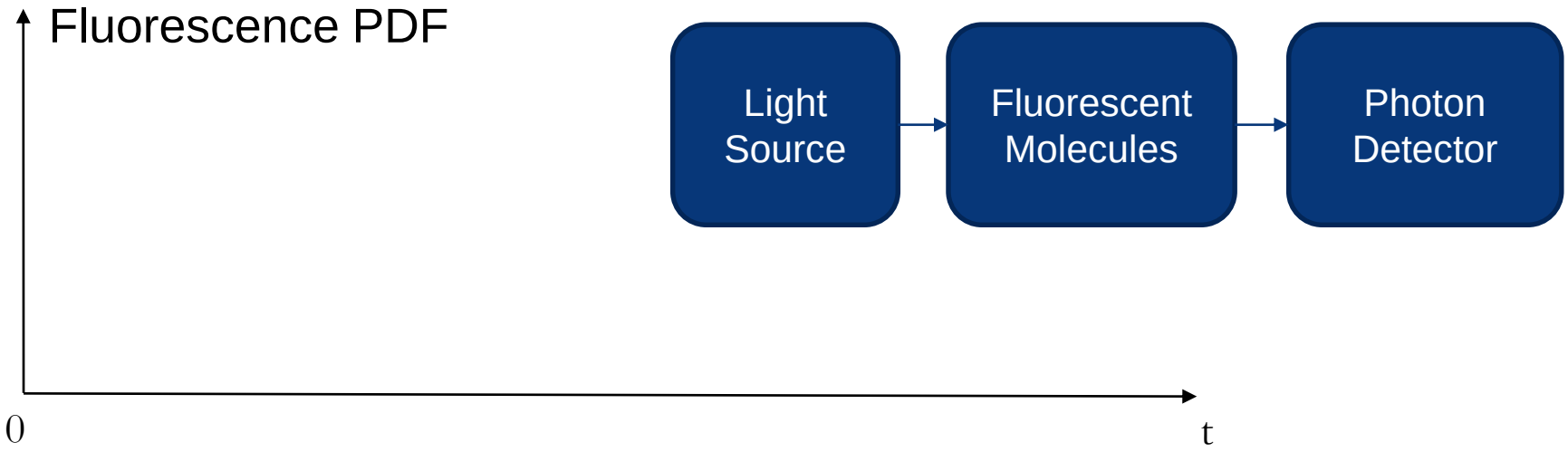
Emerging Technology + Hardware specialization
[Wang et al., 2016]

Review: Sampling Using Molecules



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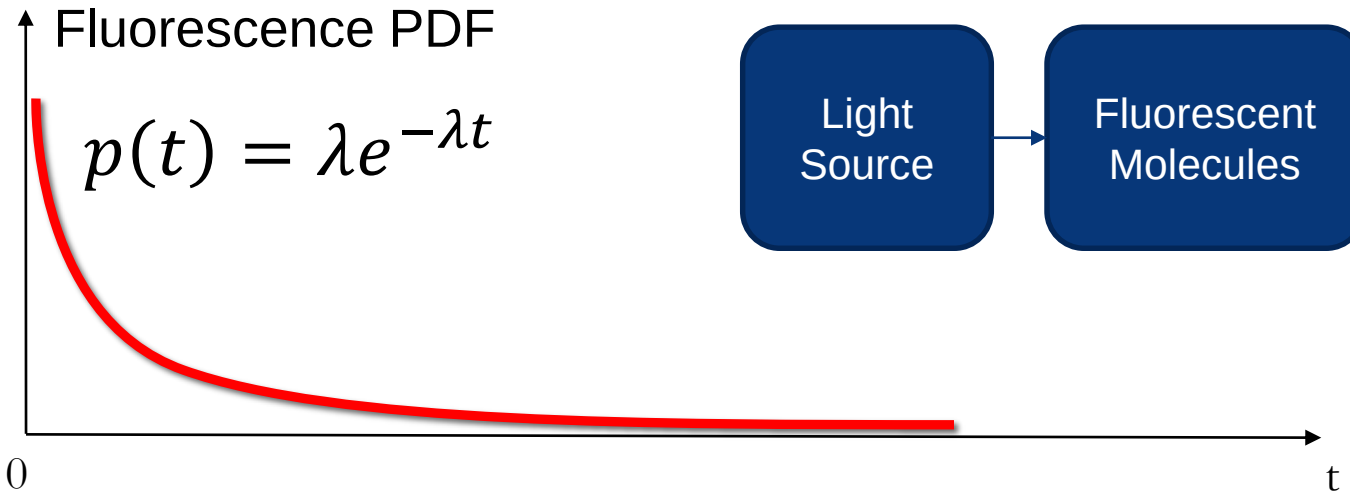

- Single fluorophore: exponential distribution.

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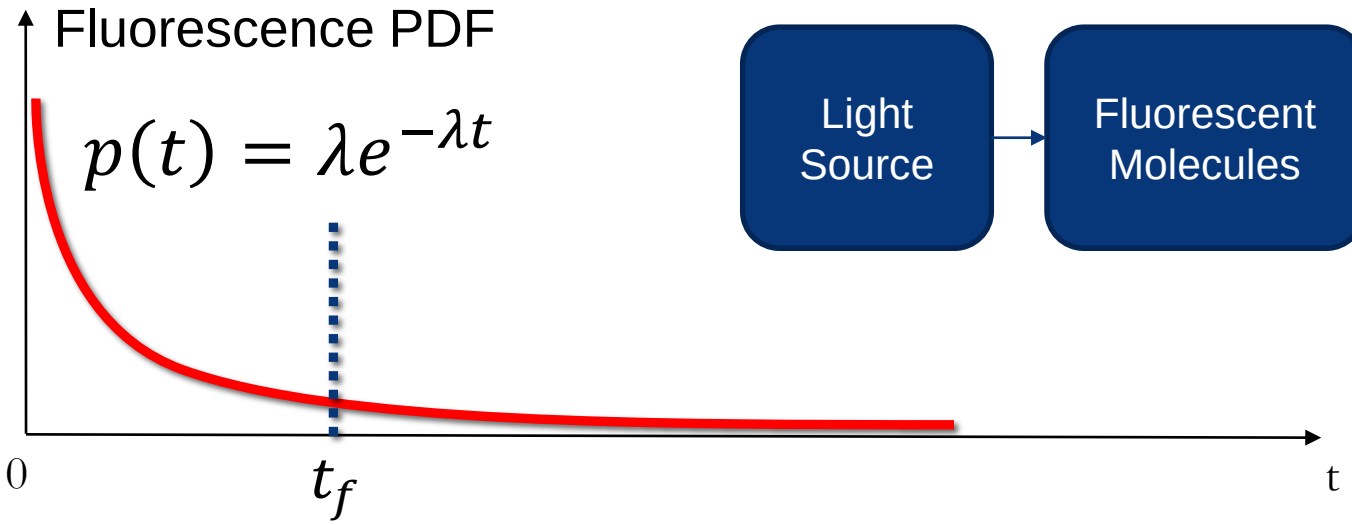

- Single fluorophore: exponential distribution.
- Record Time to Fluorescence t_f.

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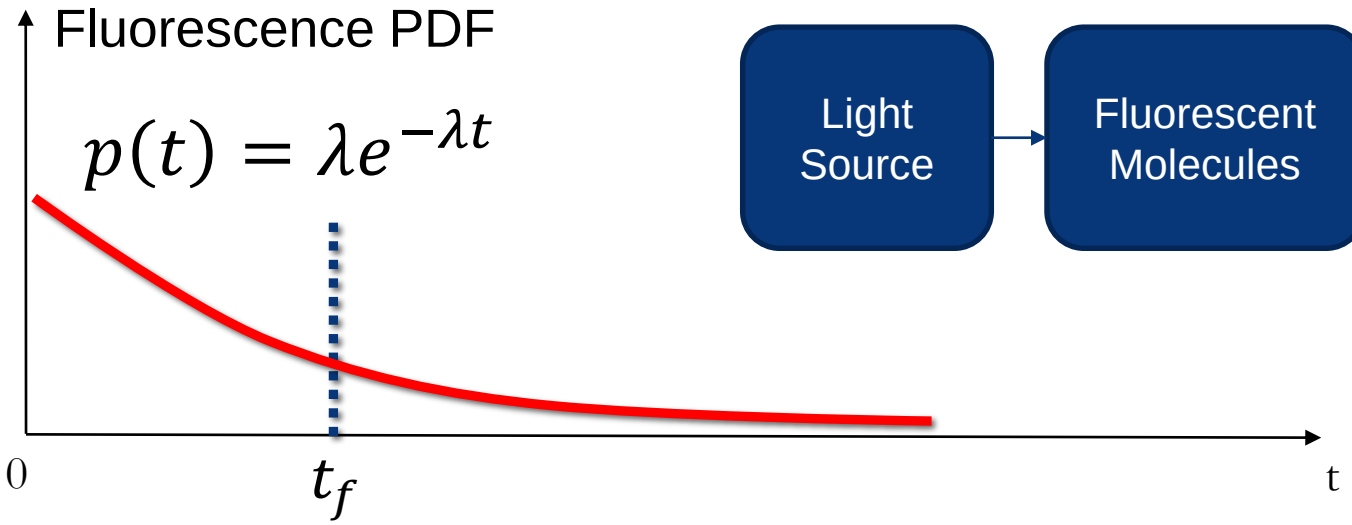

- Single fluorophore: exponential distribution.
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- Parameterize distributions by decay rate (λ):

$$\lambda \propto \frac{1}{2}\,\text{intensity} \times \text{concentration}$$

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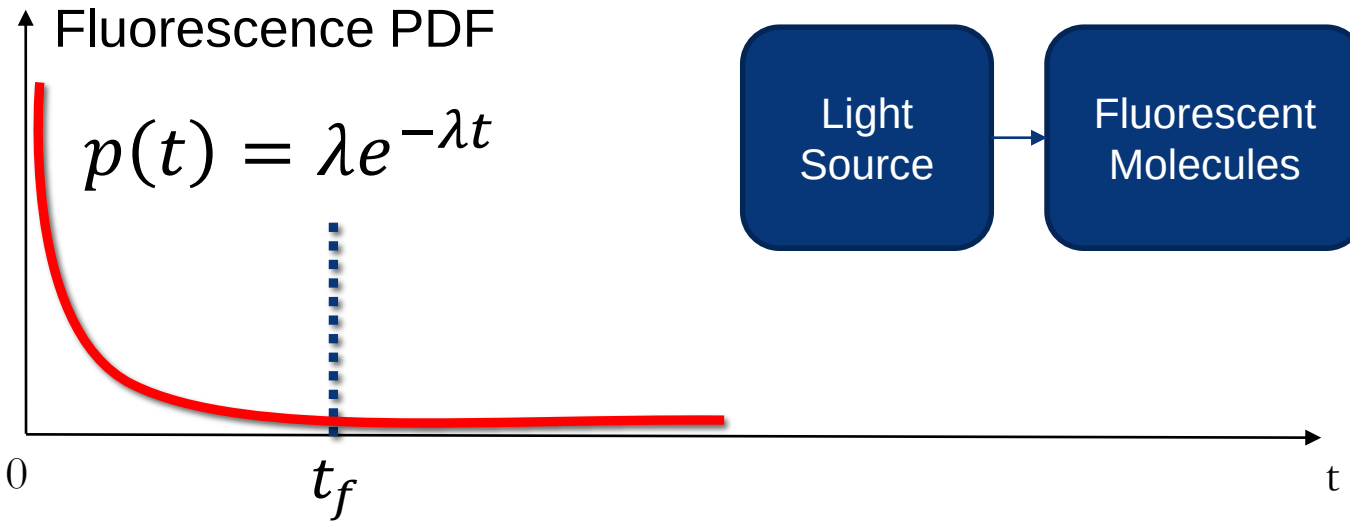

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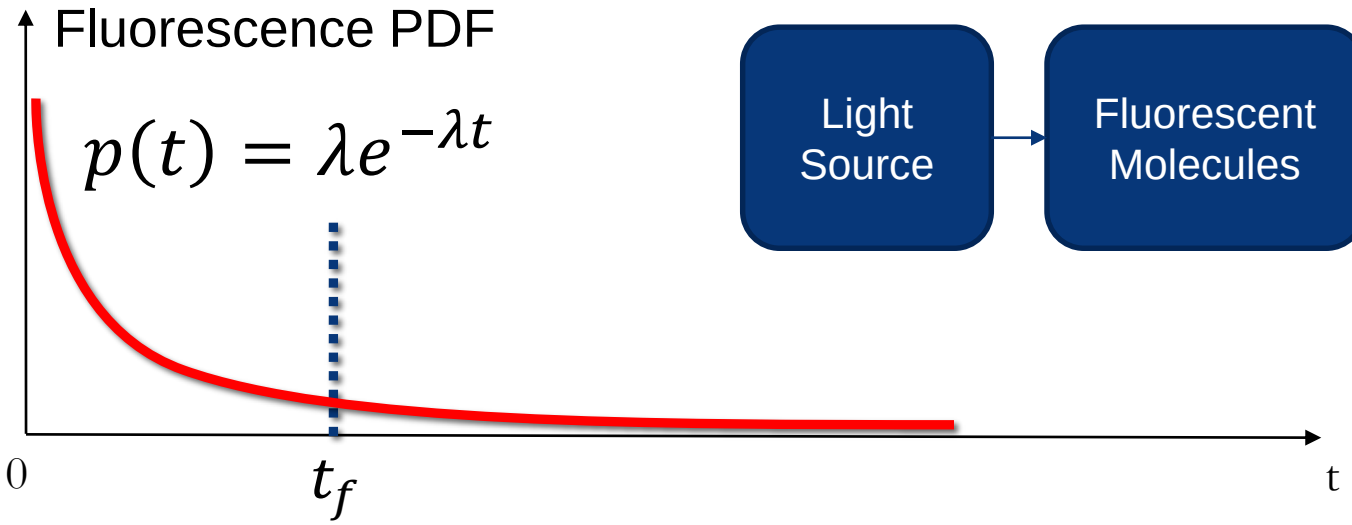

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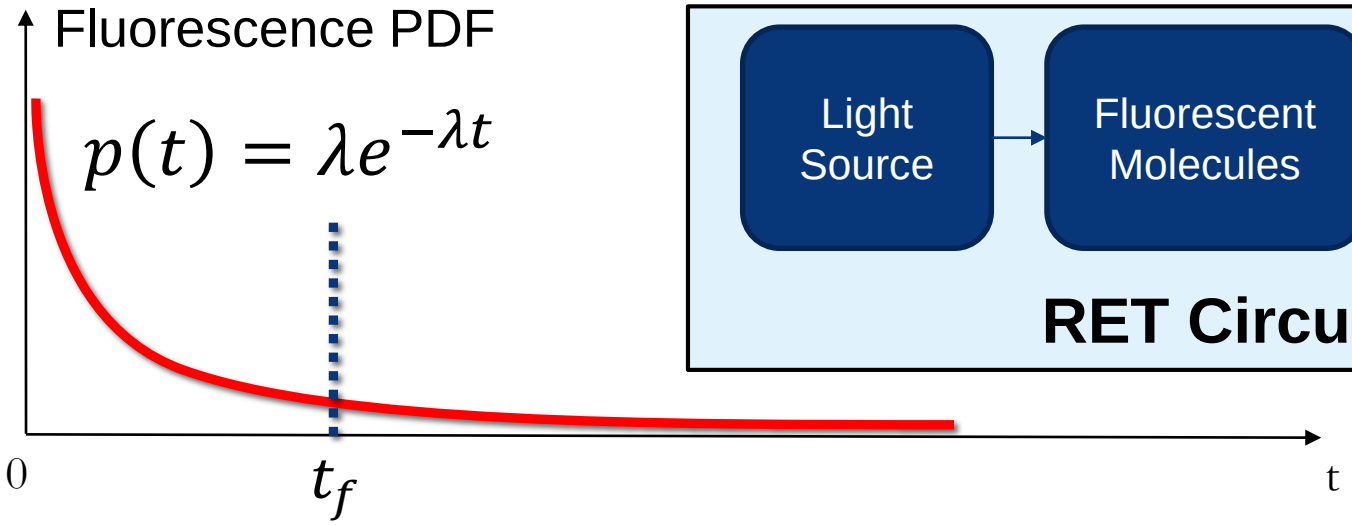

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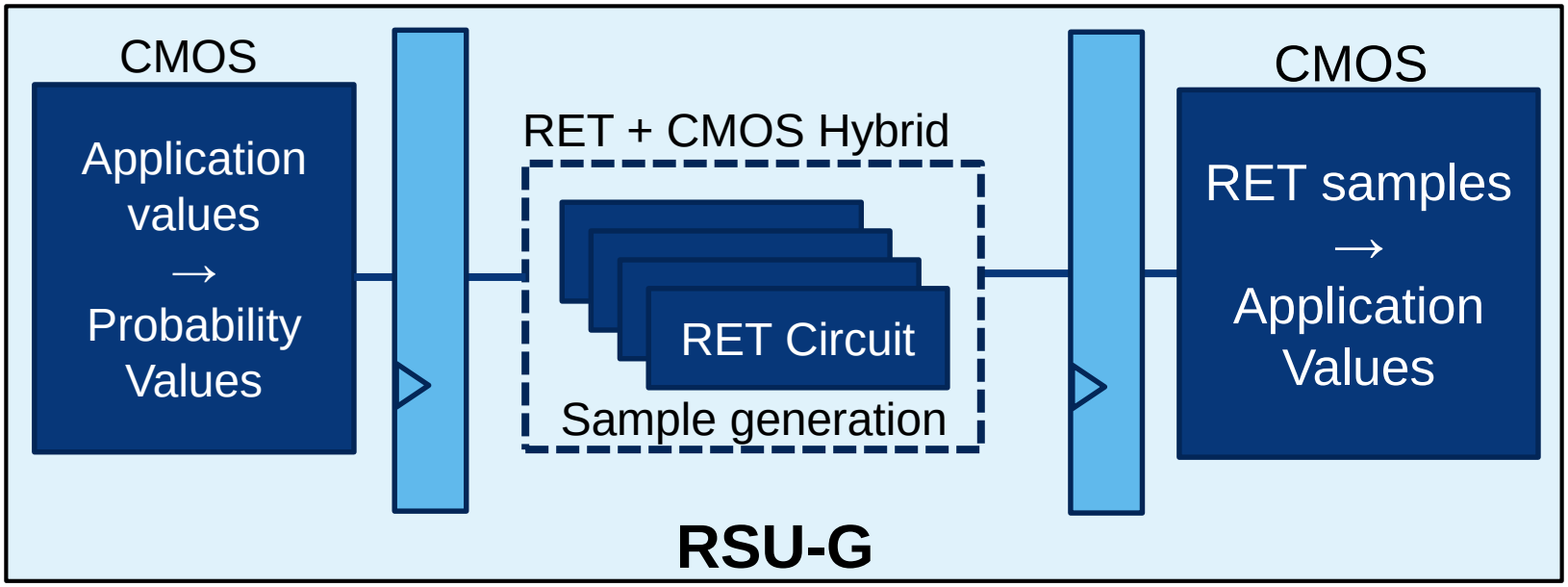
- Implemented in Resonance Energy Transfer (RET) circuit.

Review: RET-based Gibbs Sampling Unit (RSU-G)



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1) compute probabilities of each possible label;
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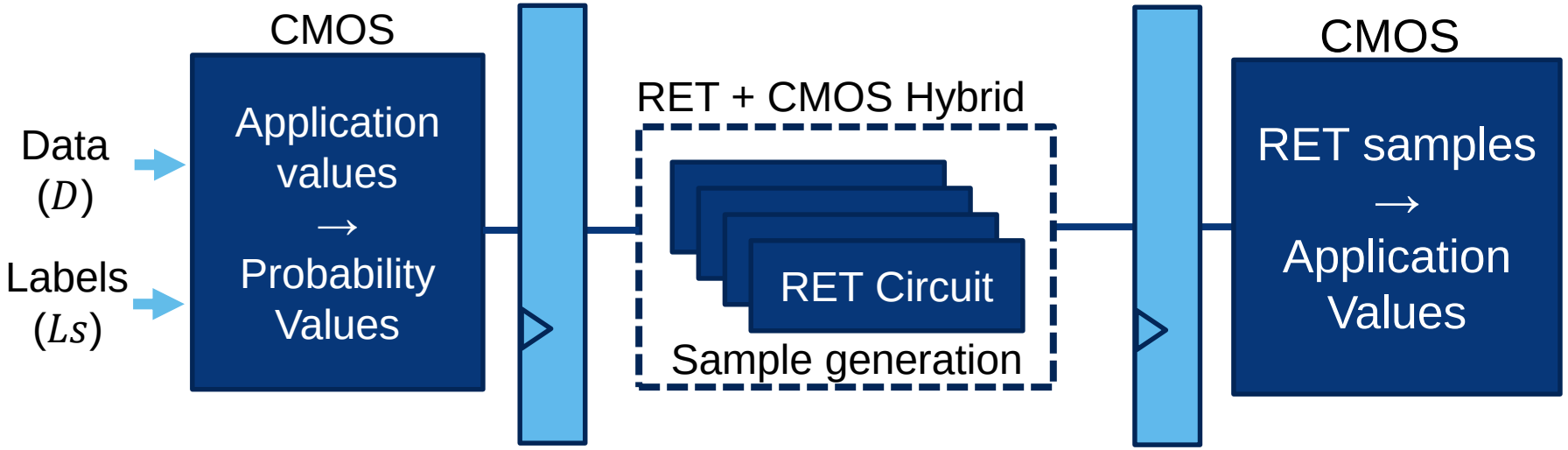

$$\lambda = \exp(-E(D, L))$$

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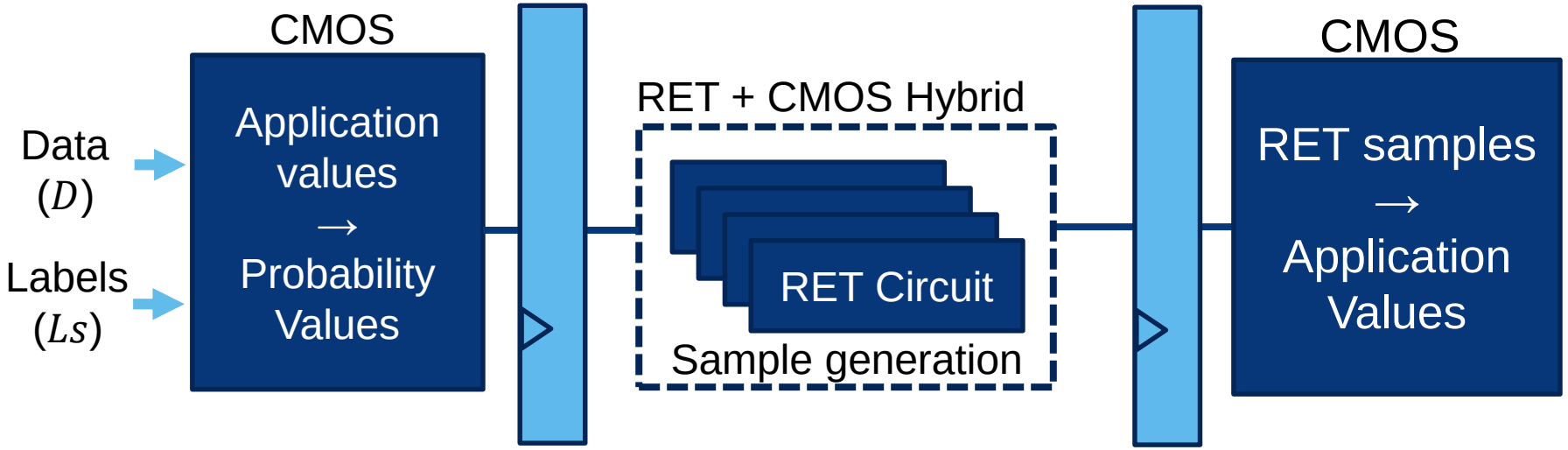

$$\lambda = \exp(-E(D,L)) \qquad p(t) = \lambda\exp(-\lambda t) \qquad L = argmin(t_1, t_2, \dots)$$

"First-to-fire" [Wang et al., 2015]

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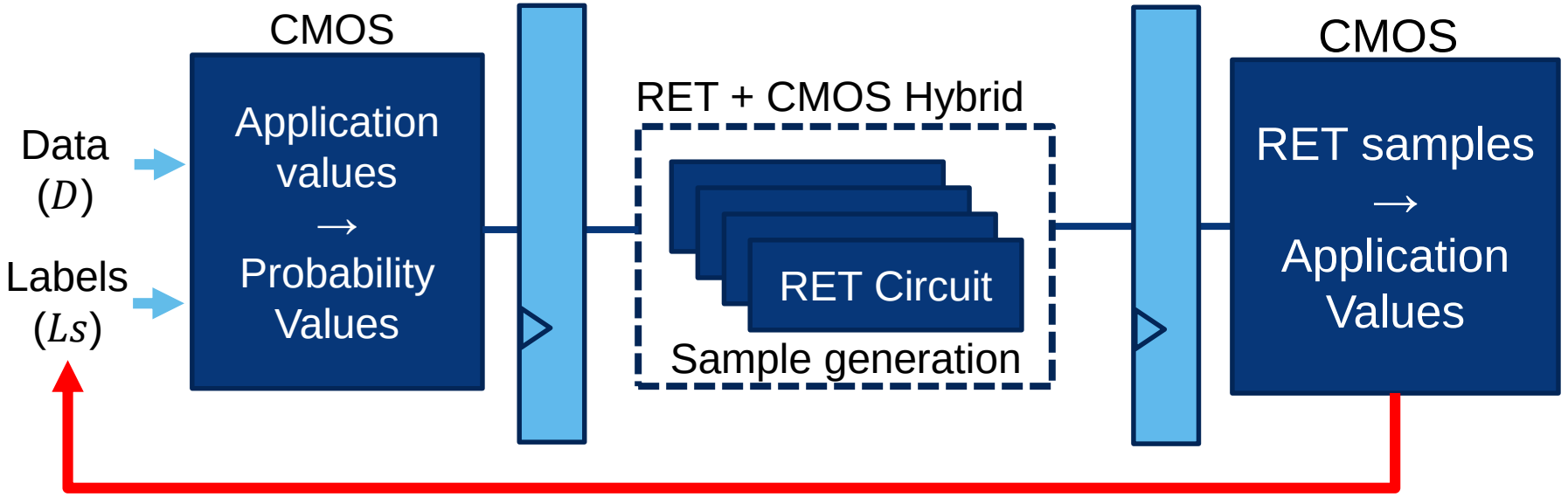

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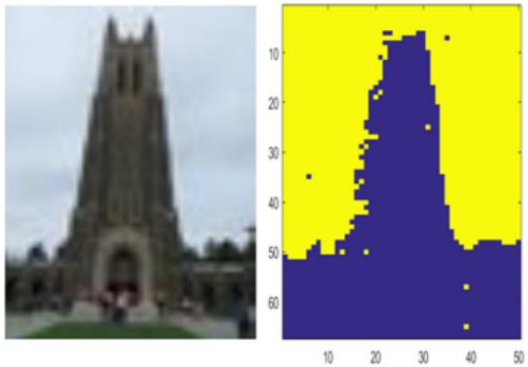

Original Prototype result

Image Segmentation

[Wang et al., 2016]

- Speedups over GPU:
  - Augmented GPU 3-34x
  - Discrete Accelerator 21-84x
- First experimental demonstration of RSU-G.

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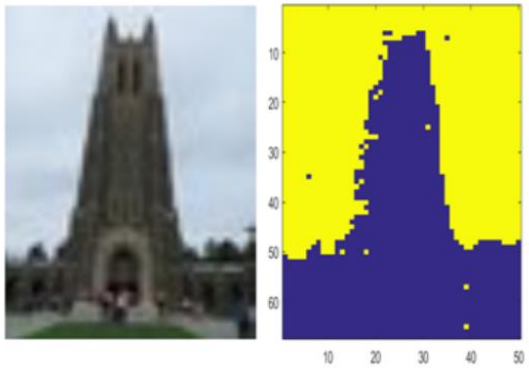

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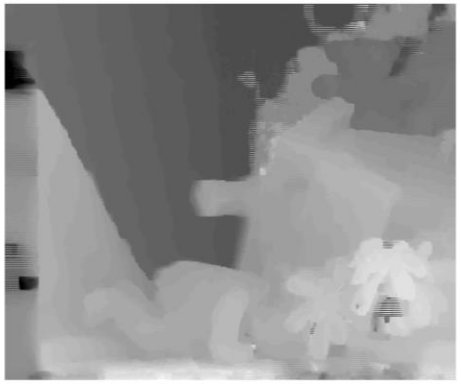
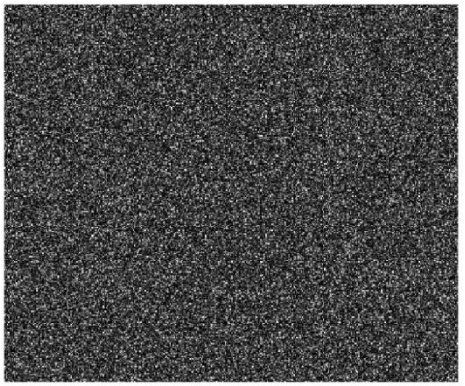


Software disparity map



RSU-G disparity map

Stereo vision *teddy* dataset

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- Result quality: doesn't reach the level we need!

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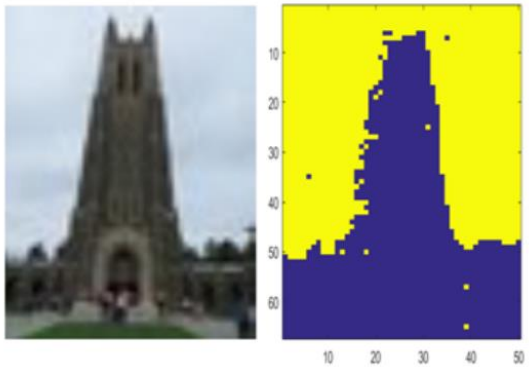

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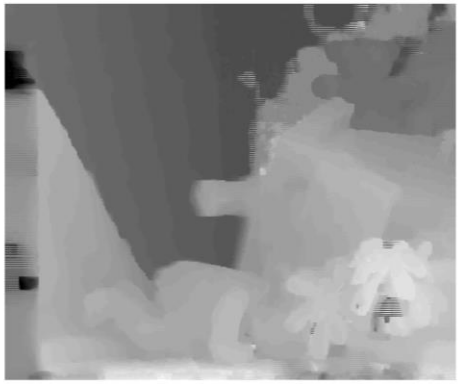

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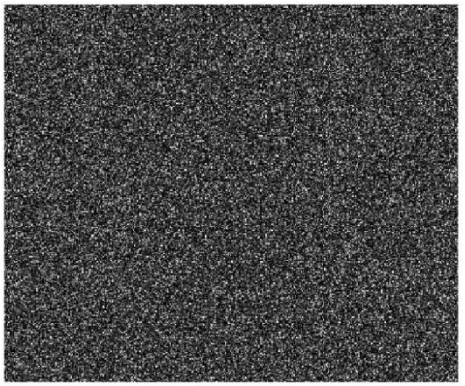

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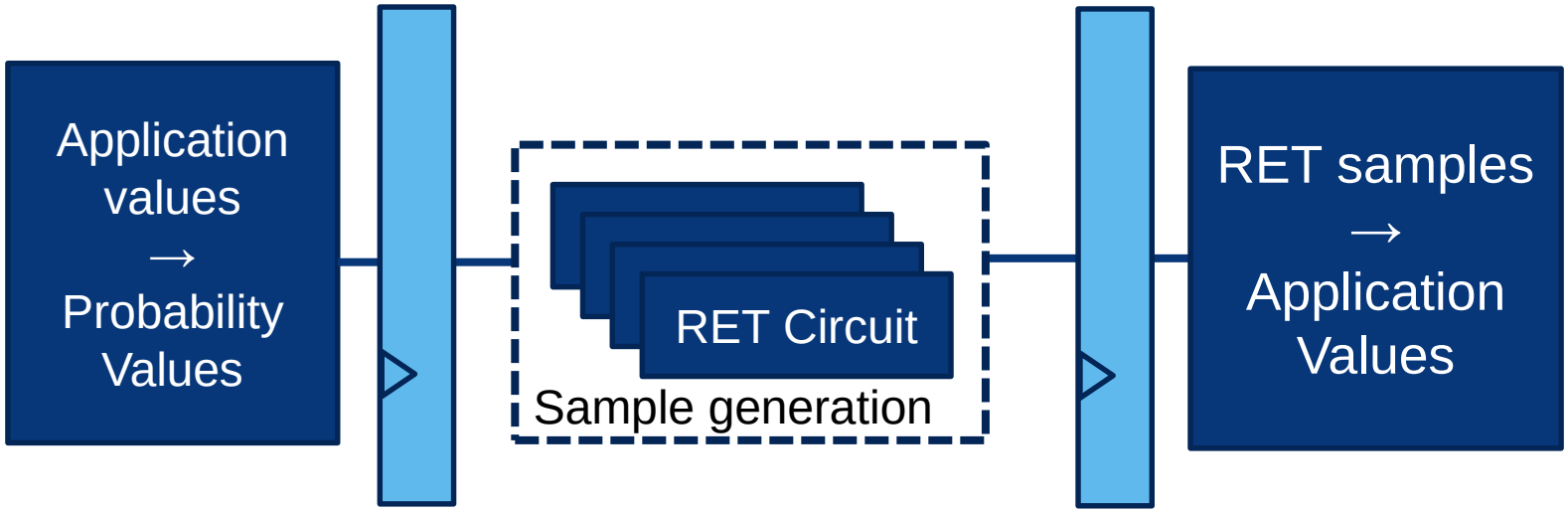
How to preserve result quality?

How to do this? Naïve Approach



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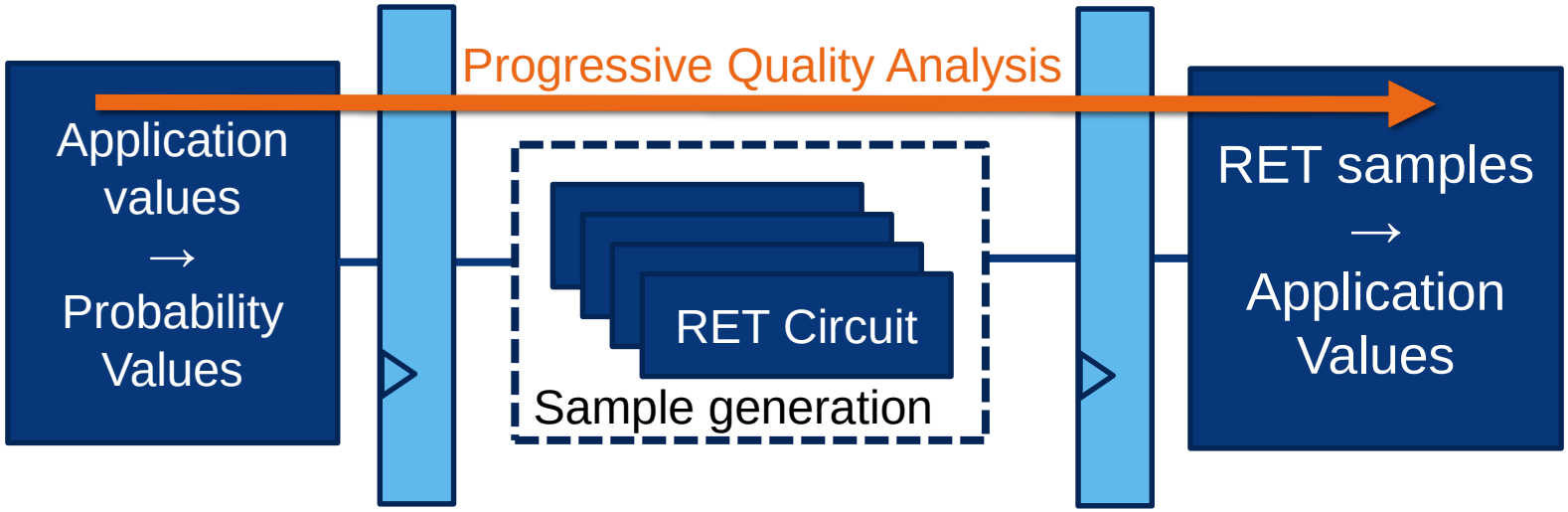

- Lacks both precision and dynamic range.

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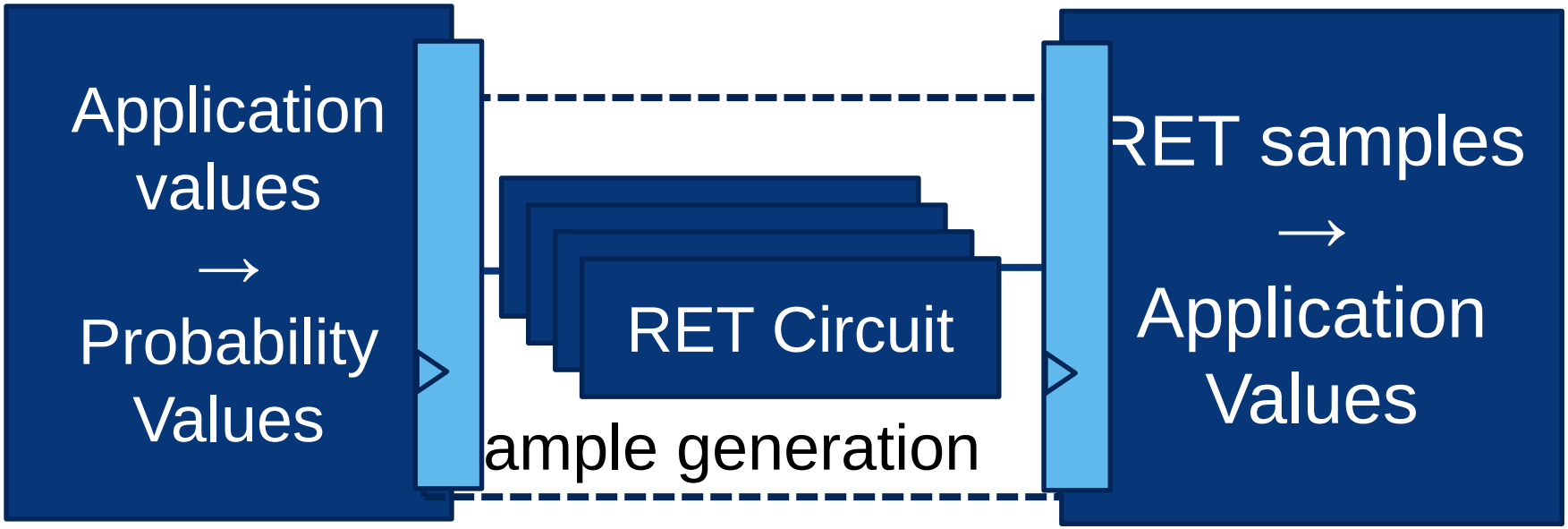

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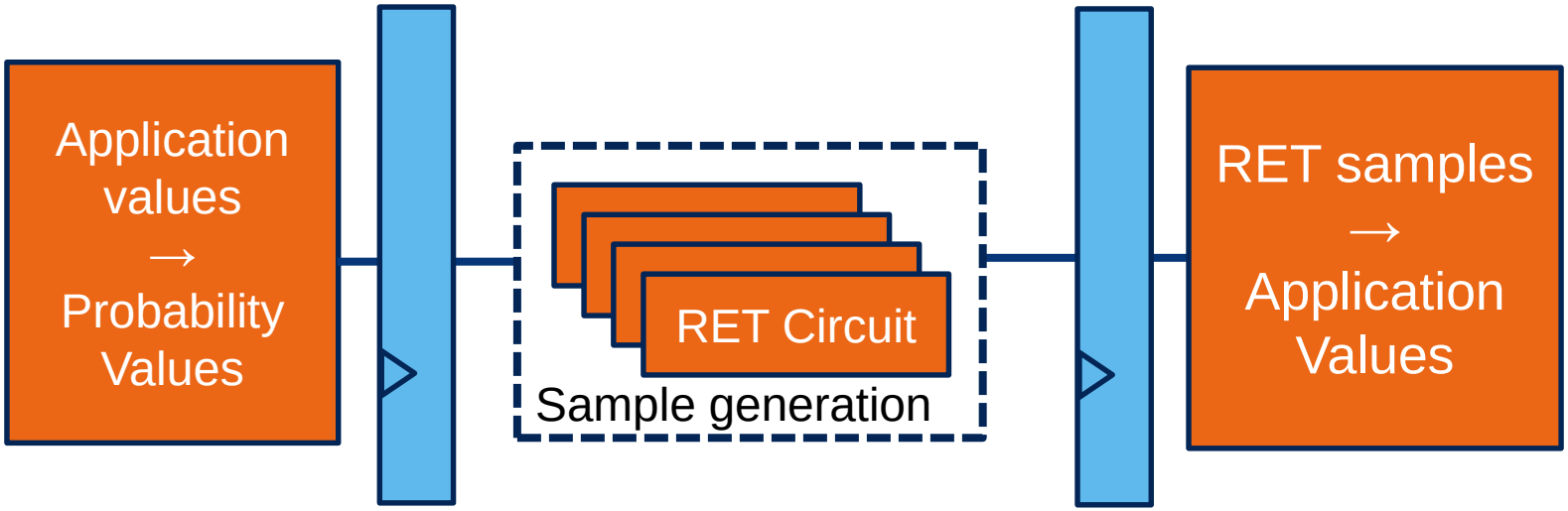
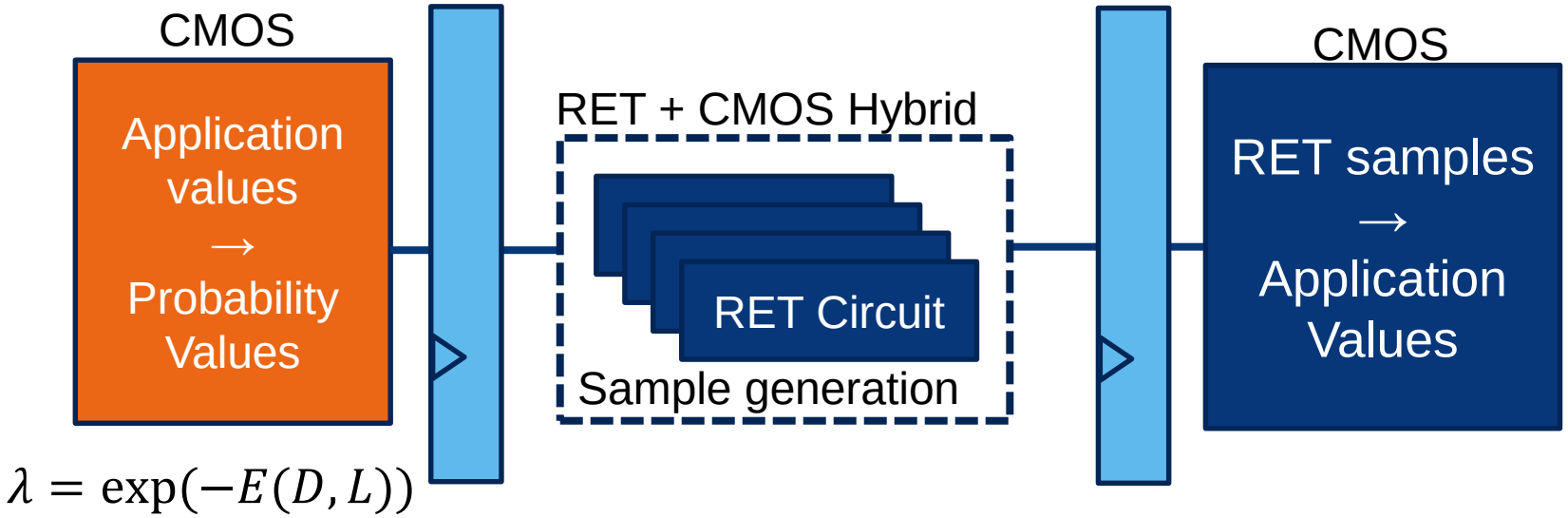


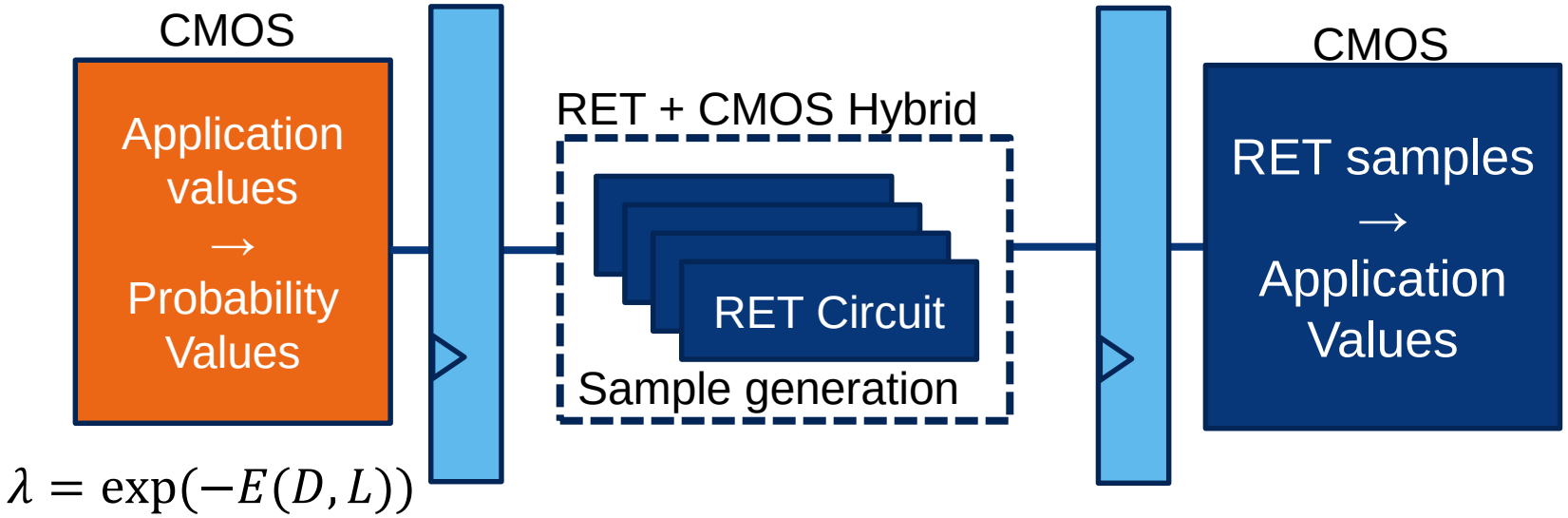
- Lacks both precision and dynamic range.
- Naively increase #bits: too much area/power.
- Need new microarchitecture to achieve:
  - **High** result quality.
  - **Sizable** performance benefits.
  - **Minimal** area/power.
  - **More** flexibility.

Improving Decay Rate (λ) Dynamic Ranges



- New microarchitectural techniques:
  - Decay rate scaling.
  - Probability cut-off.
  - 2^n approximation.
- Requires only 4 unique decay rates.
- Detail described in the paper.

Improving Decay Rate (λ) Dynamic Ranges



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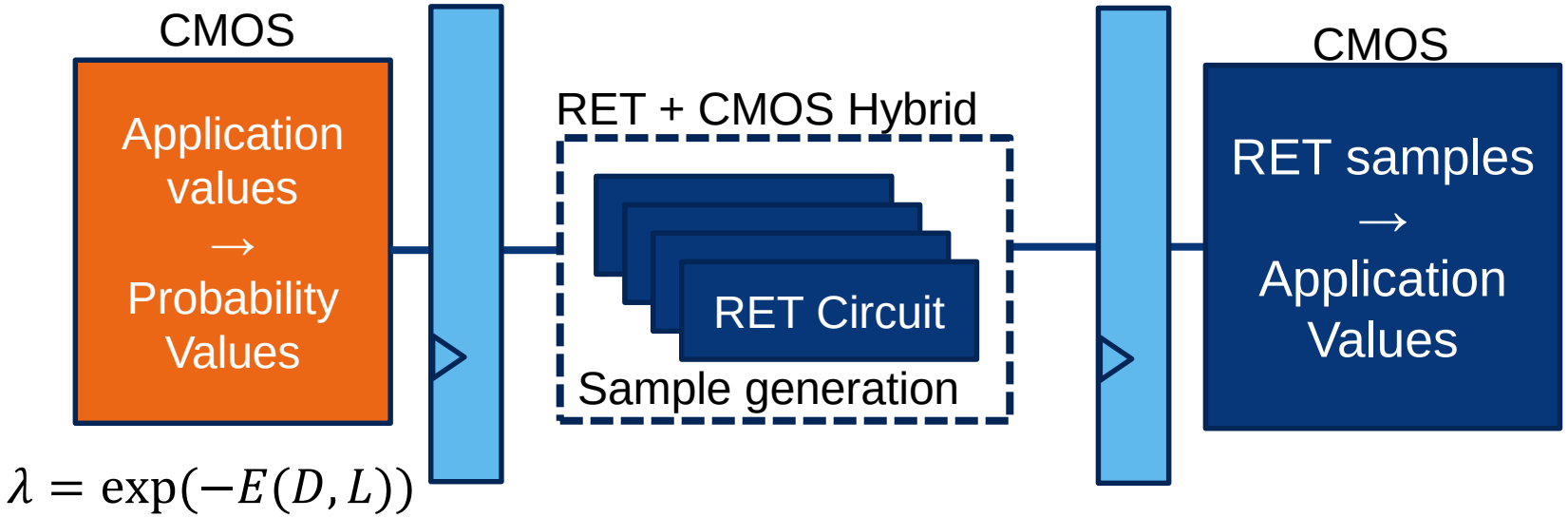

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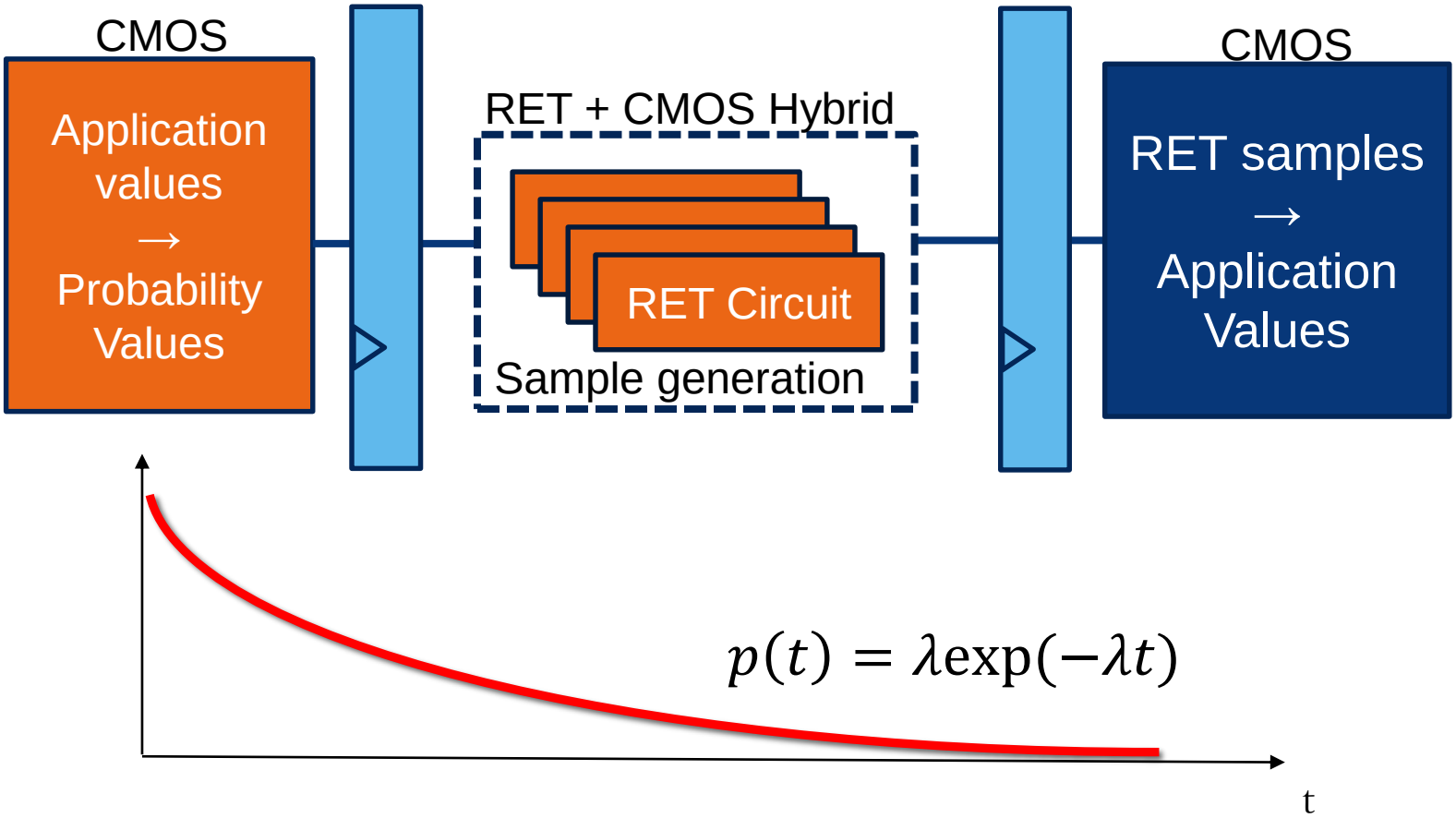
Exploring Sample Generation



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- Two Parameters:
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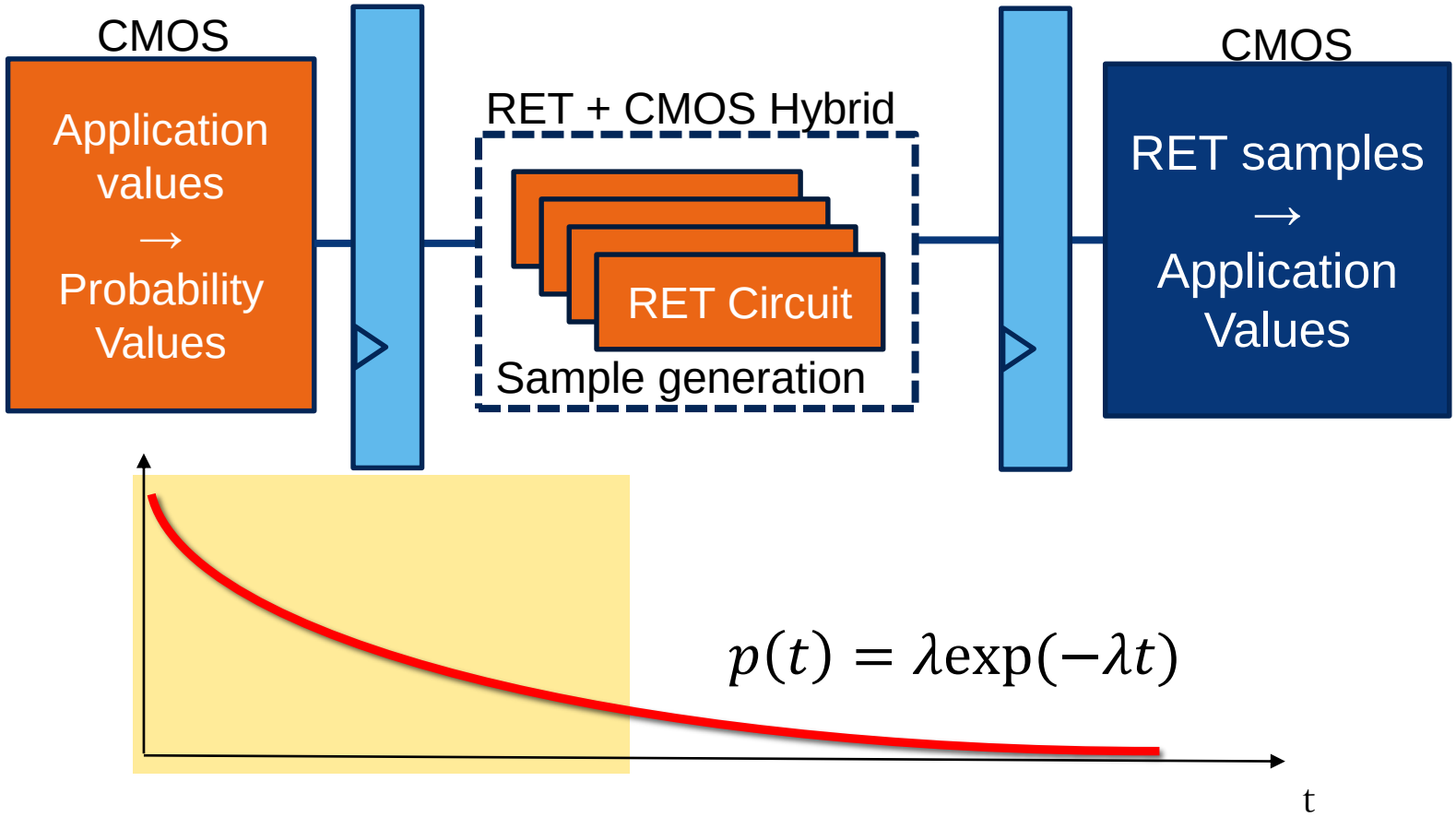

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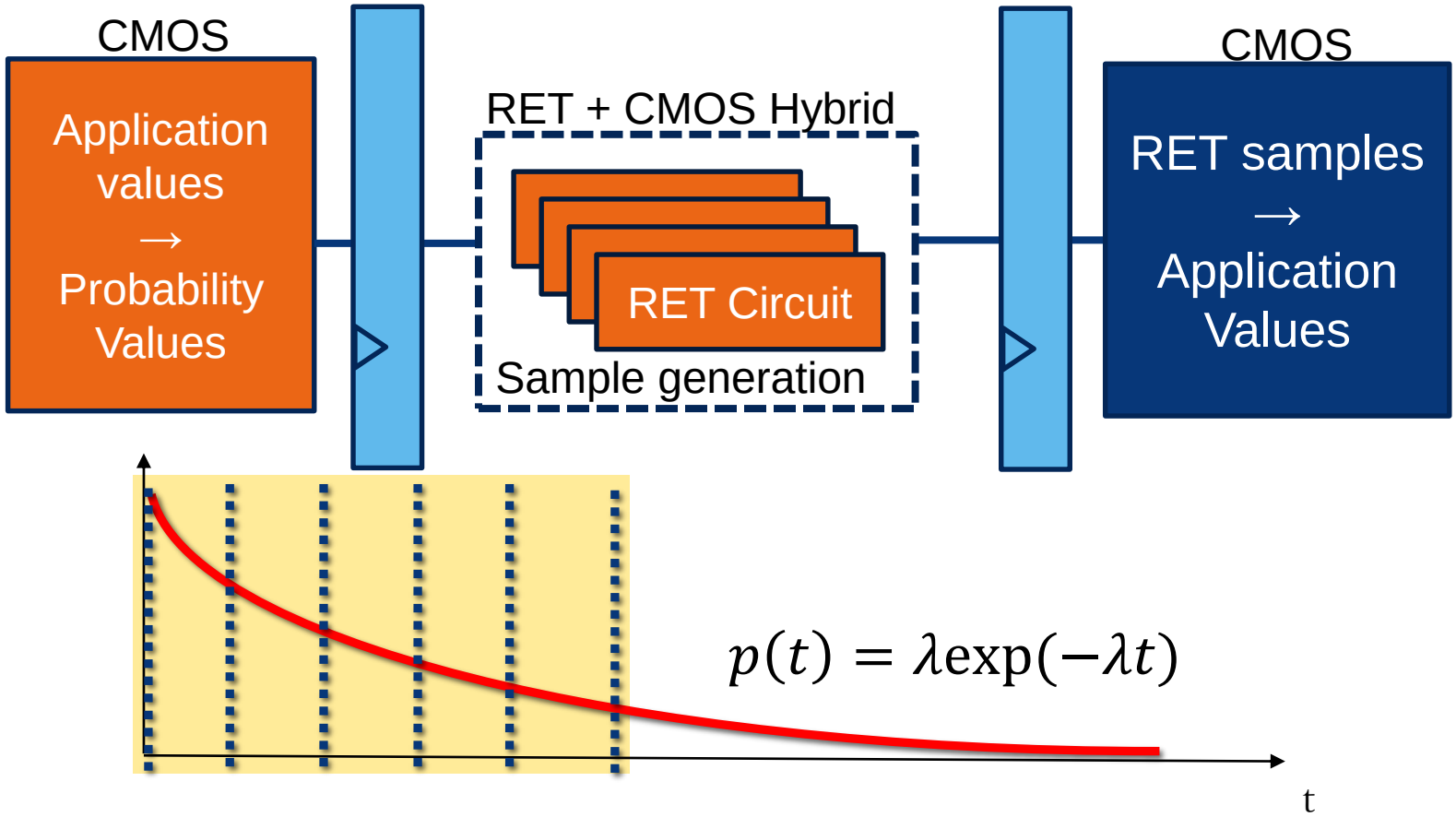

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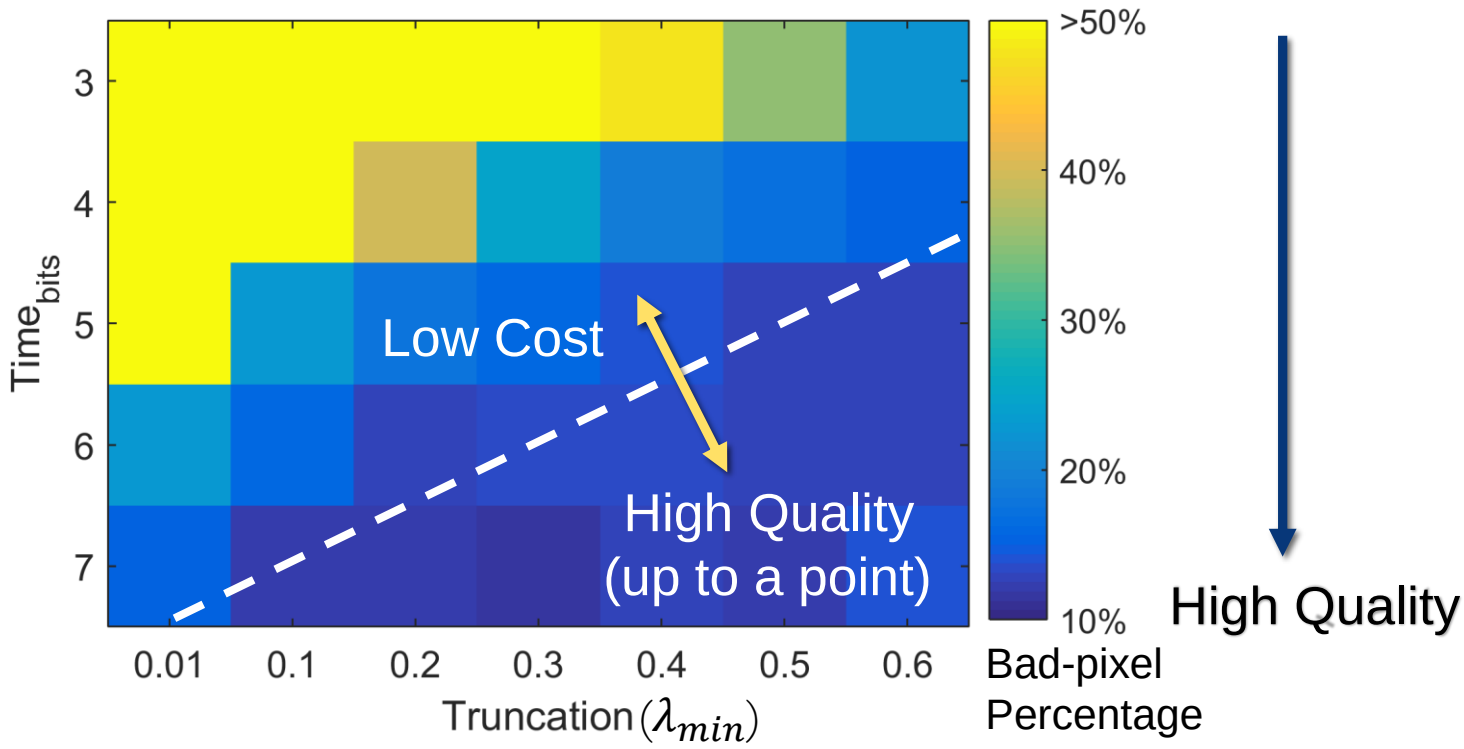
Timing Resolution vs. Truncation Probability



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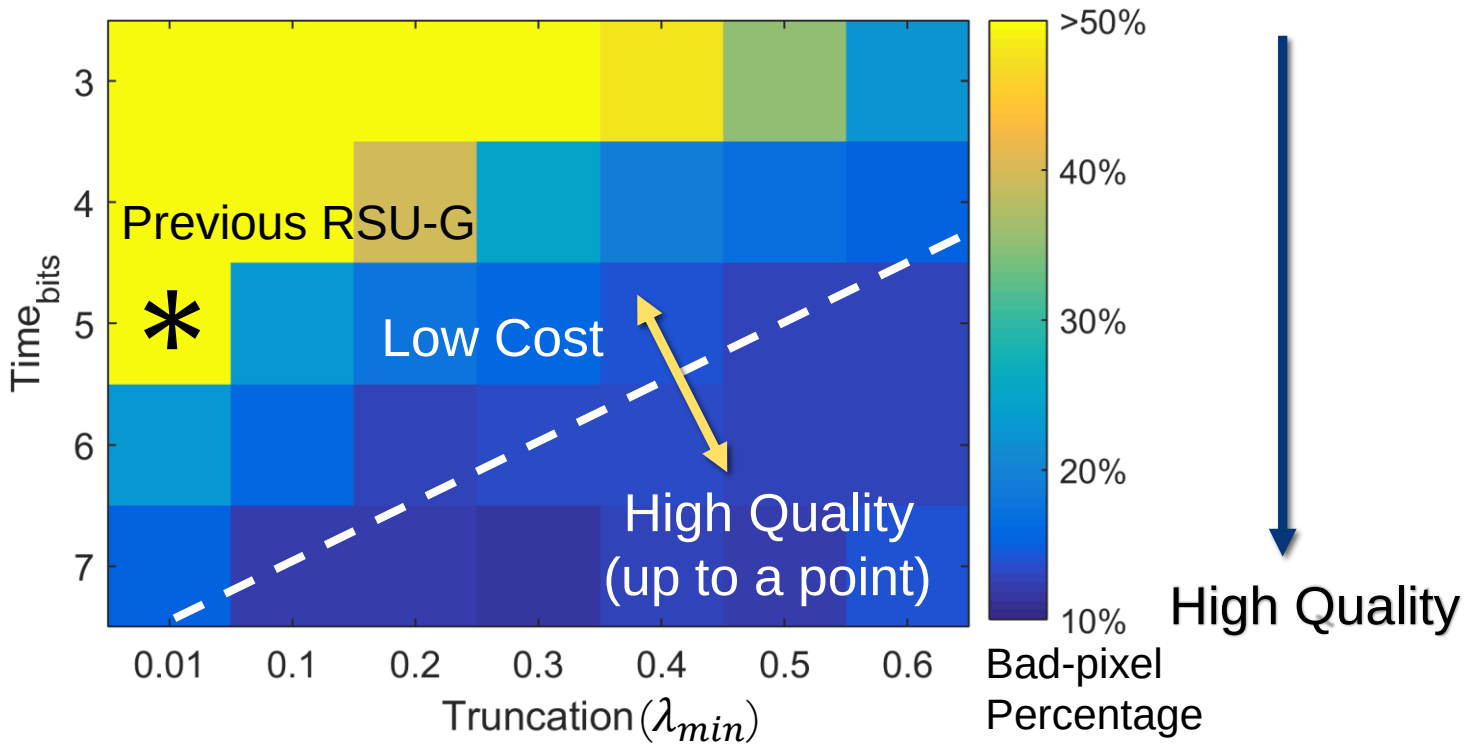

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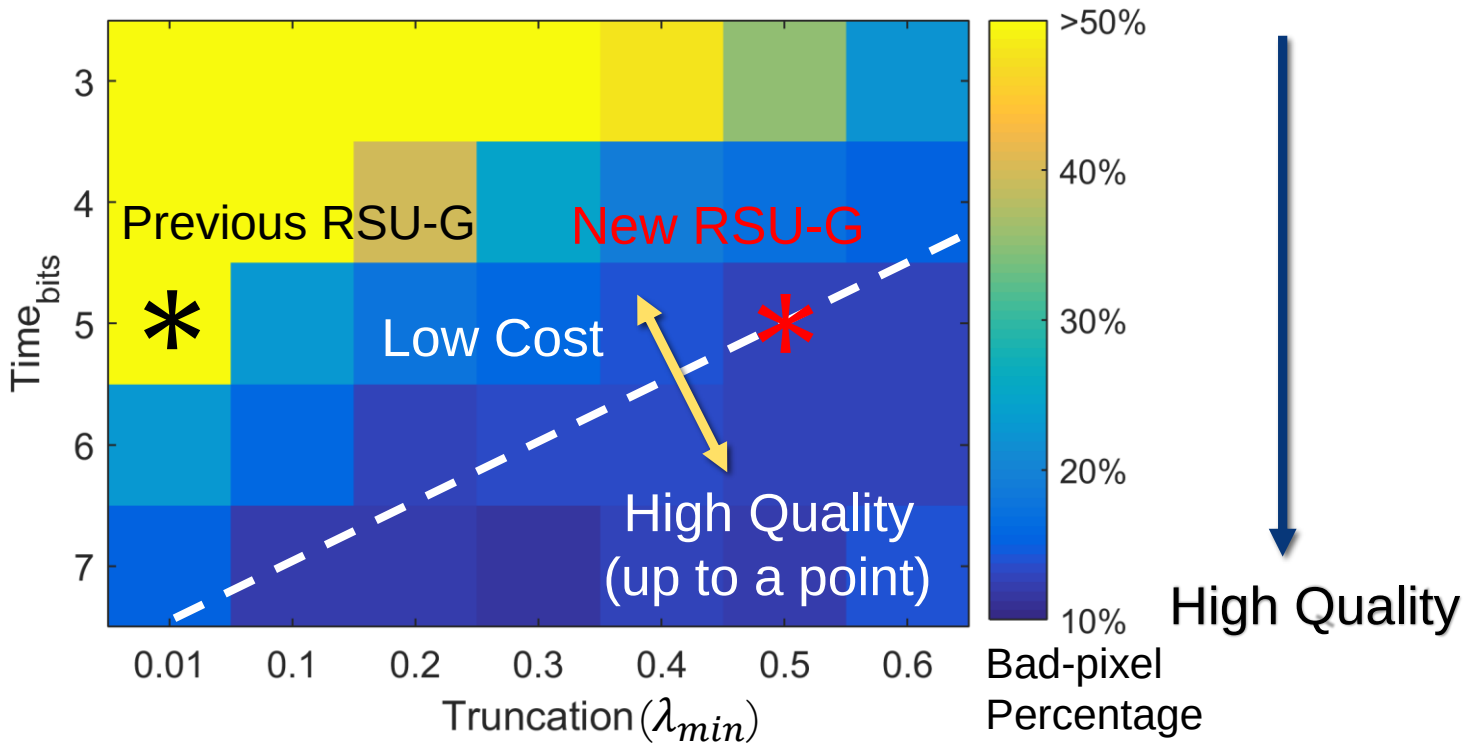

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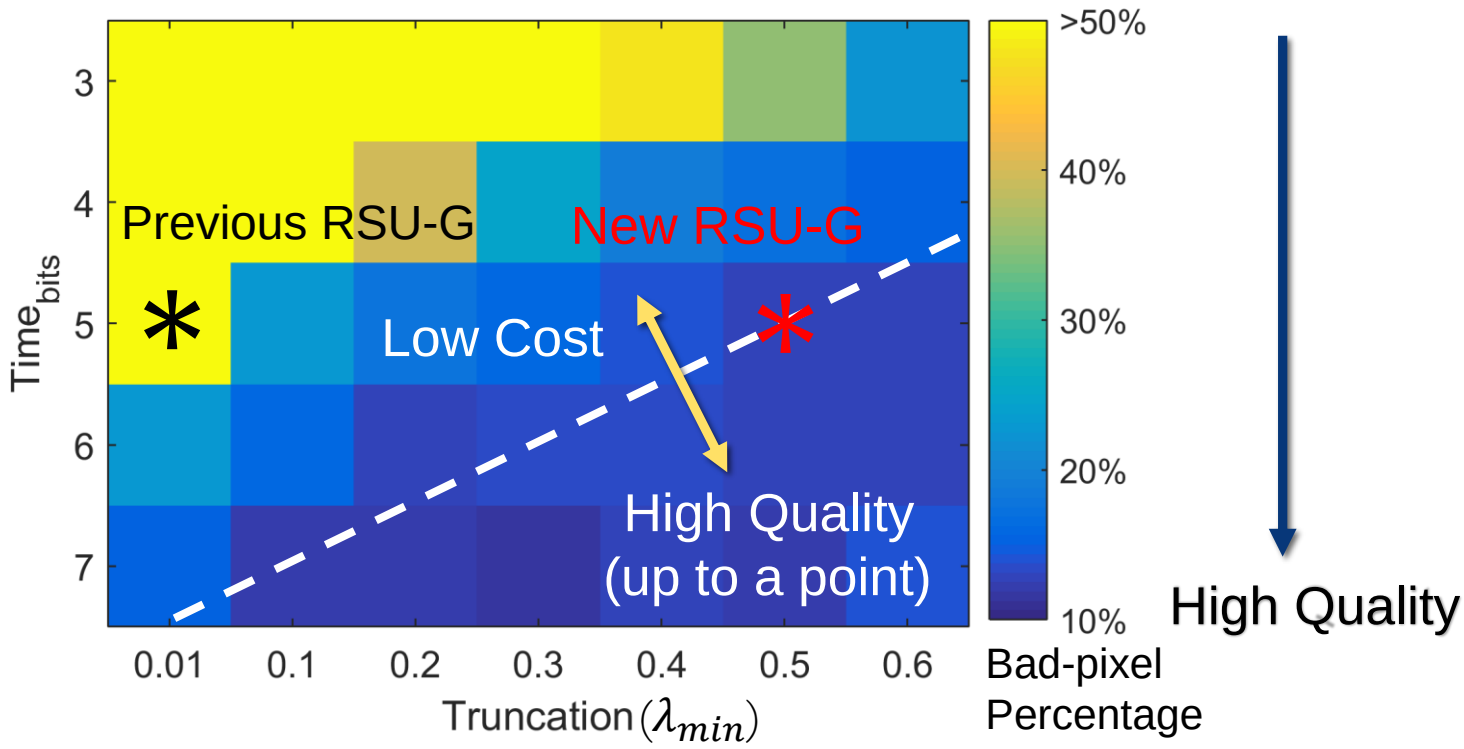

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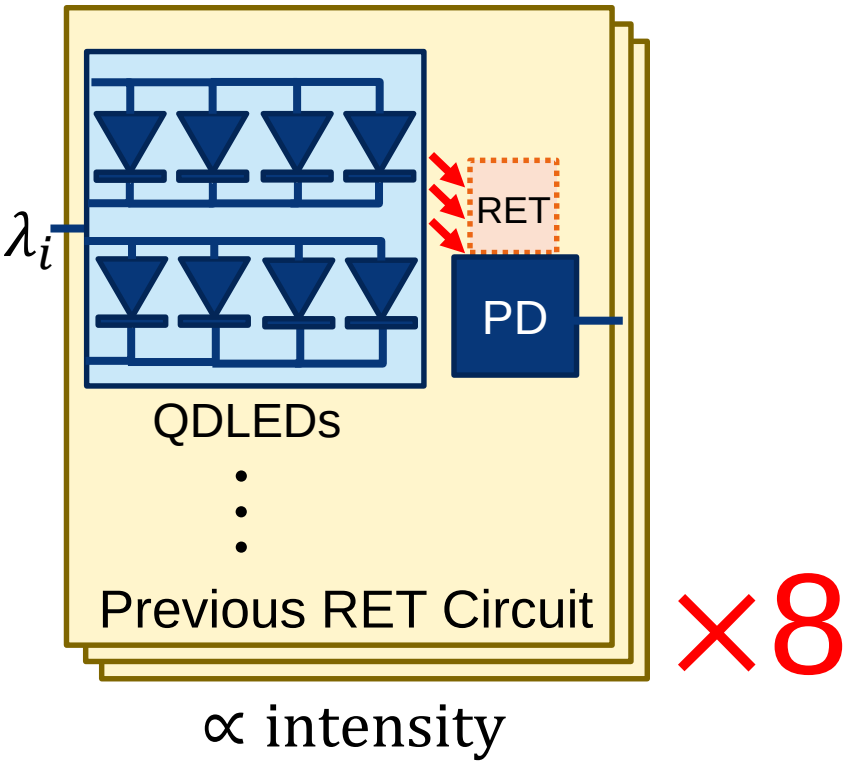
- Pr ($t \geq t_{max}$) = 0.5 for λ_{min} (< 0.5 for other λs).
- Fluorophores can emit photons beyond max detection time.
- Need 8 RET replica to avoid structural hazard.

Re-design RET Circuit



×8

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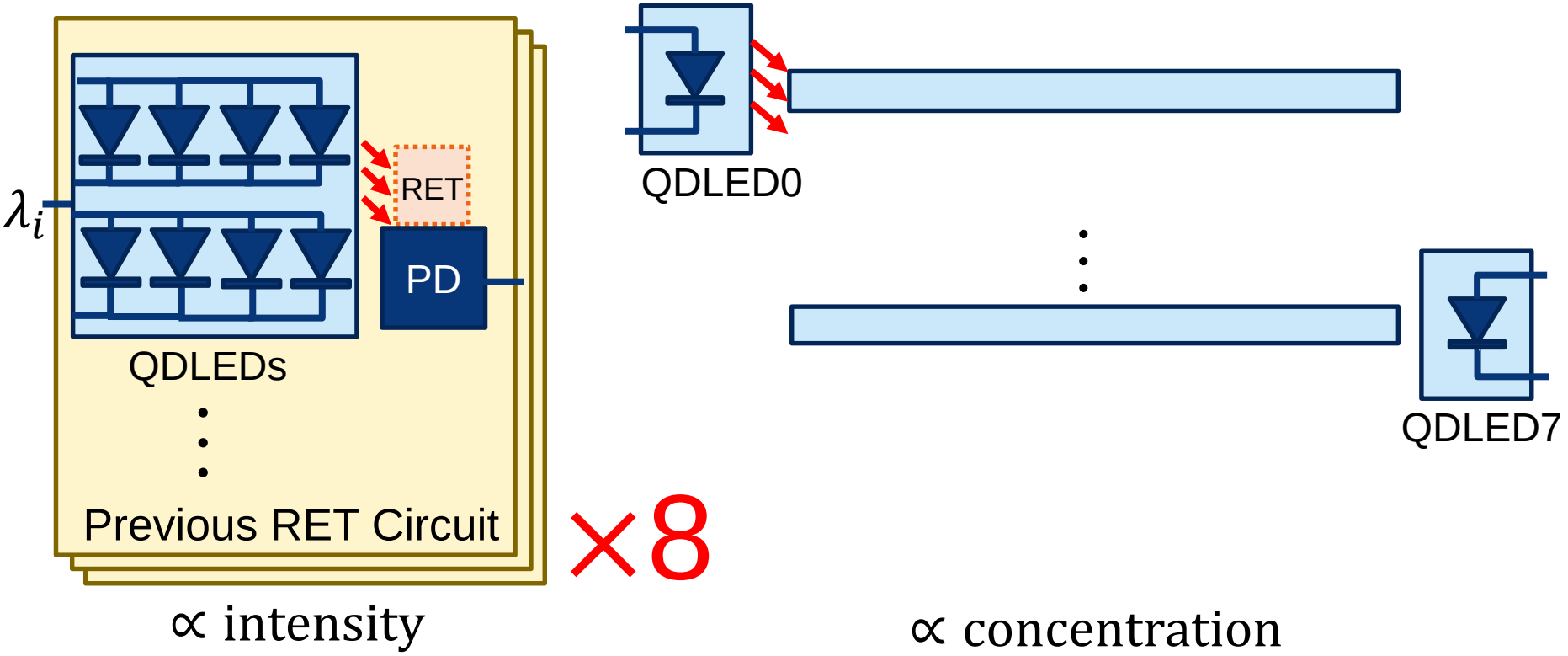

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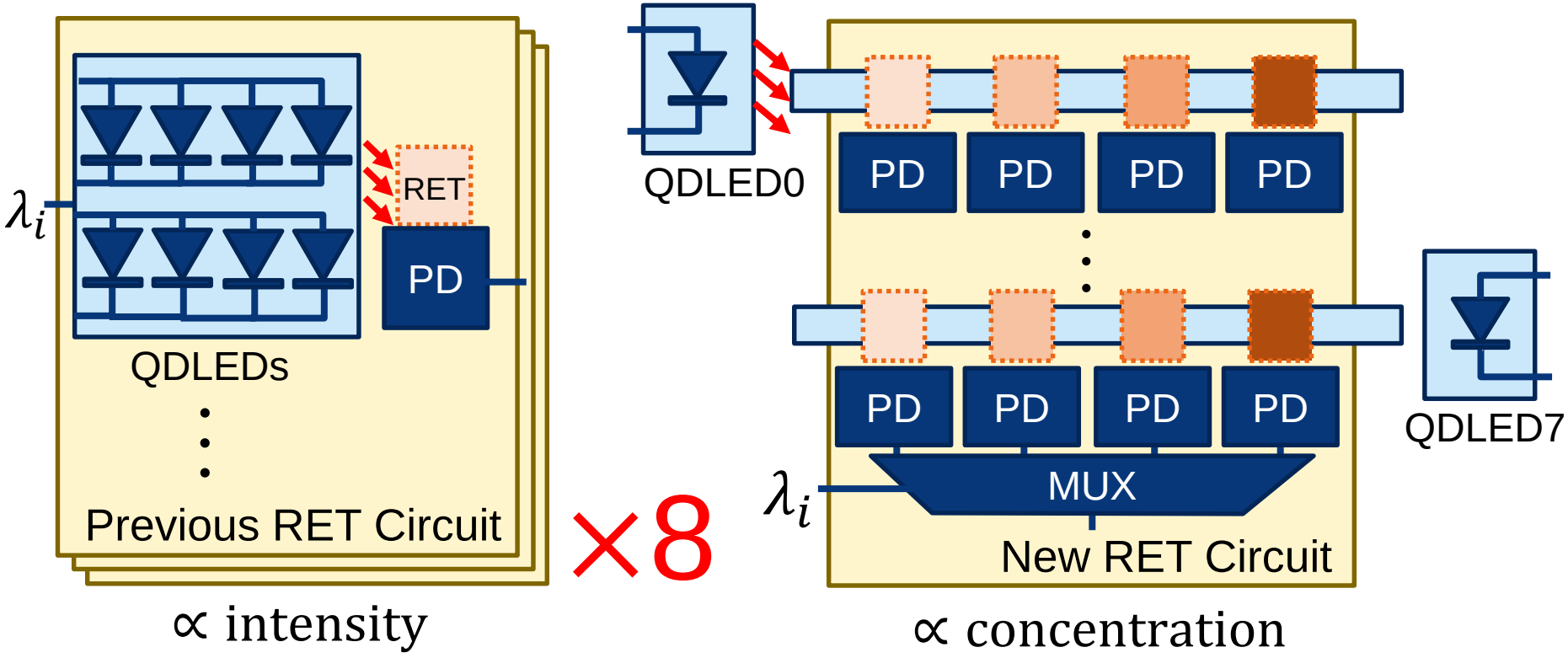
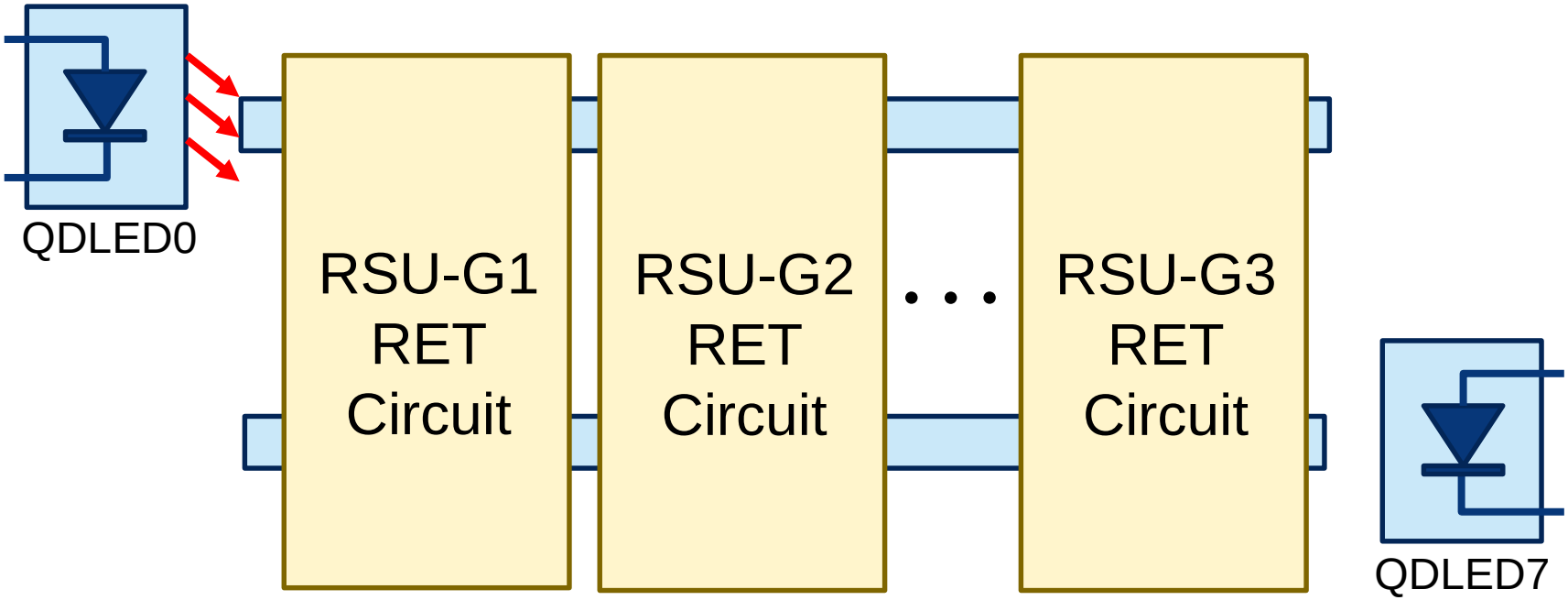


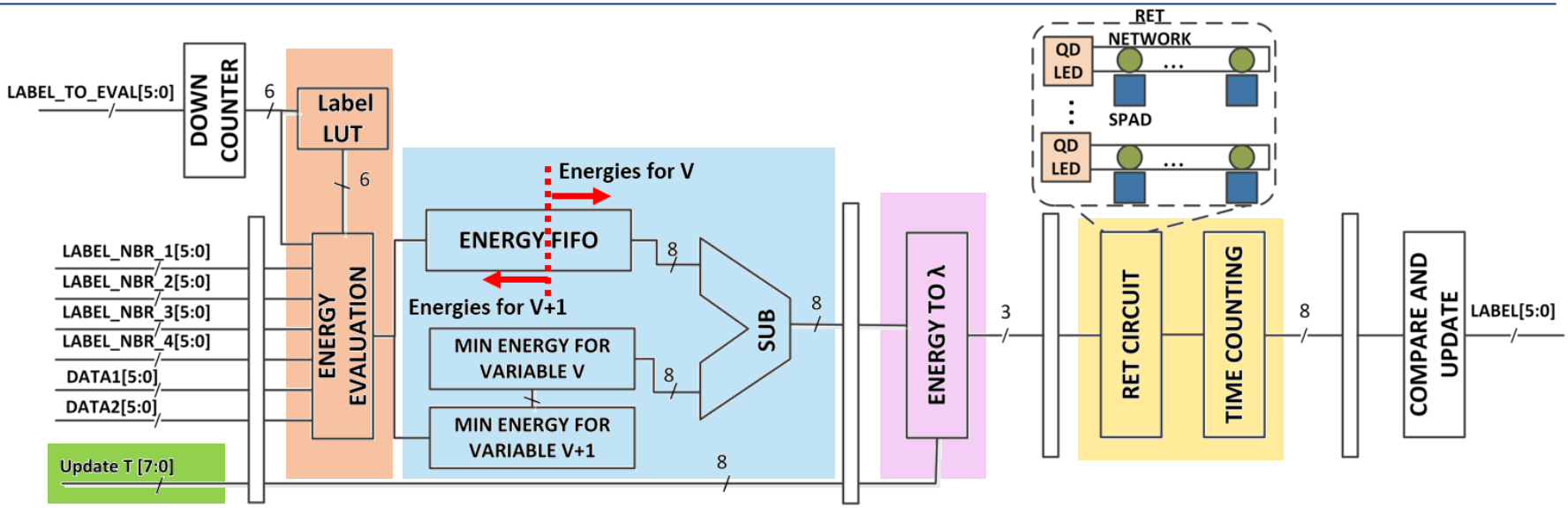
- Previous RET Circuit: QDLEDs dominates the area.
- New RET Circuit:
  - Fixed intensity, 8 waveguides lighted in round robin.
  - Exploit 4 unique decay rates -> 4 unique concentrations.

Sharing Light Sources



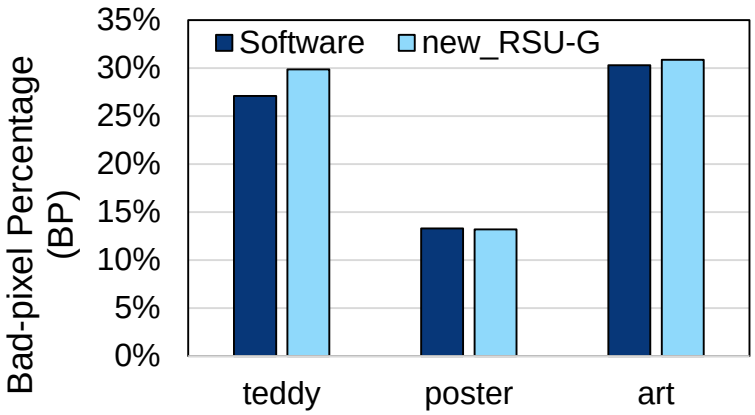
- Multiple RET circuits can share light sources.
- Further reduces area/power.
- Opportunities to use one light source per chip.

New RSU-G

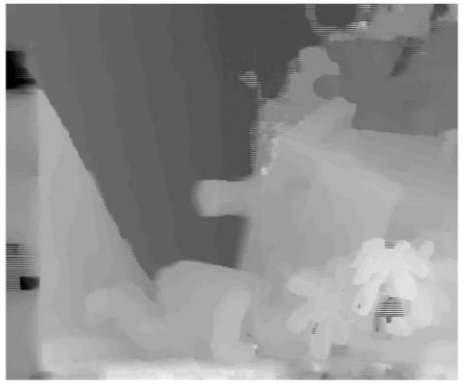


- Circuit and microarchitecture changes:
  - Improved decay rate (λ) dynamic ranges.
  - New RET circuit and peripheral circuits.
  - Support multiple energy function $E(D, L)$ for more applications.
  - Efficient λ conversion.
- Software visible (ISA) change:
  - Addition interface for simulated annealing.
- Details of the pipeline in the paper.

Result Quality



Stereo vision result quality
(lower is better)



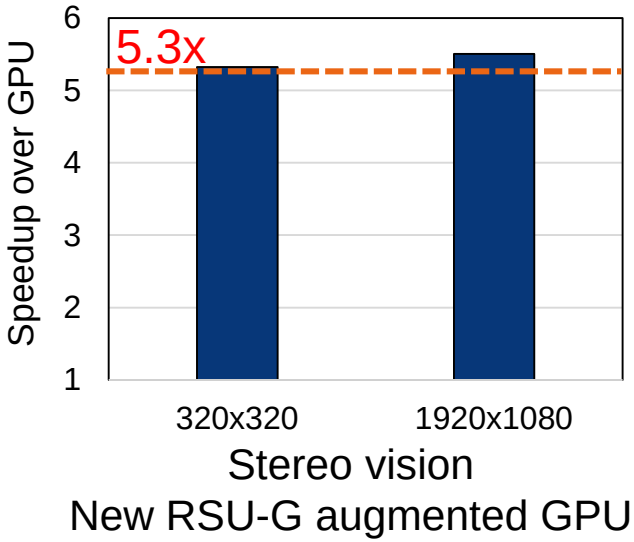
Software disparity map

New RSU-G disparity map

Stereo vision ***teddy*** **dataset**

- Standard benchmarks and metrics:
  - Stereo vision.
  - Motion estimation.
  - Image segmentation.
- New RSU-G provides same result quality as software.
- Other two application results in the paper.

Performance / Area / Power



- Preserve speedups.

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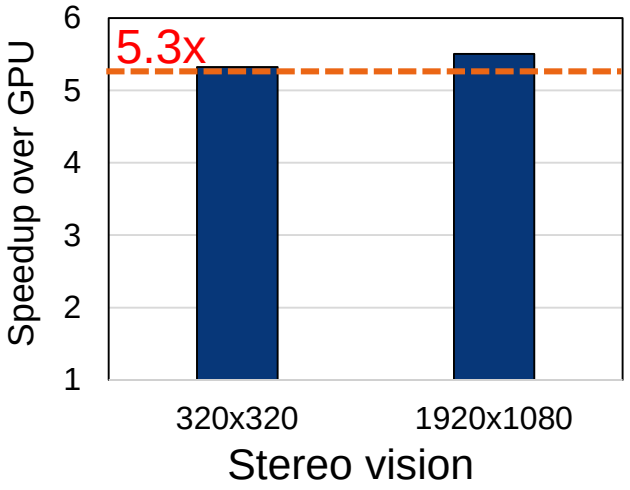
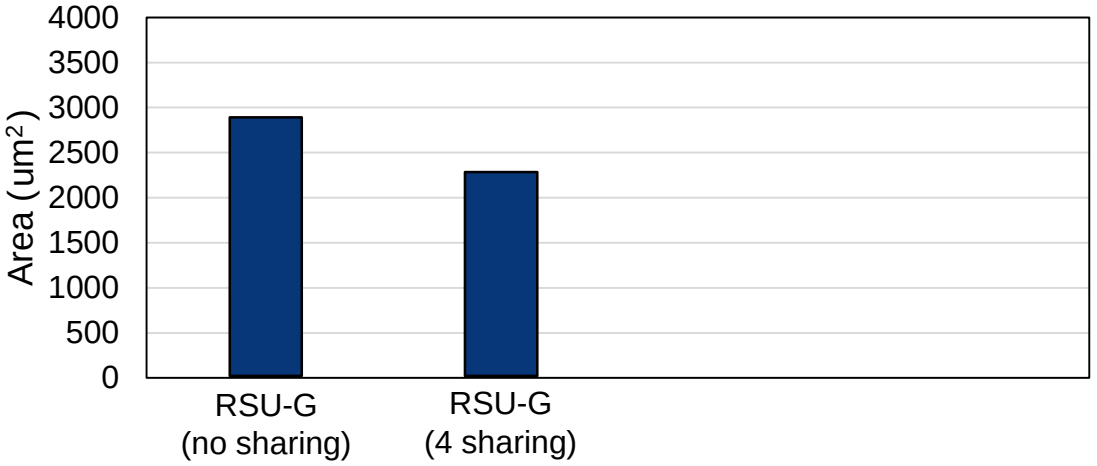


New RSU-G augmented GPU



Area: RSU-G

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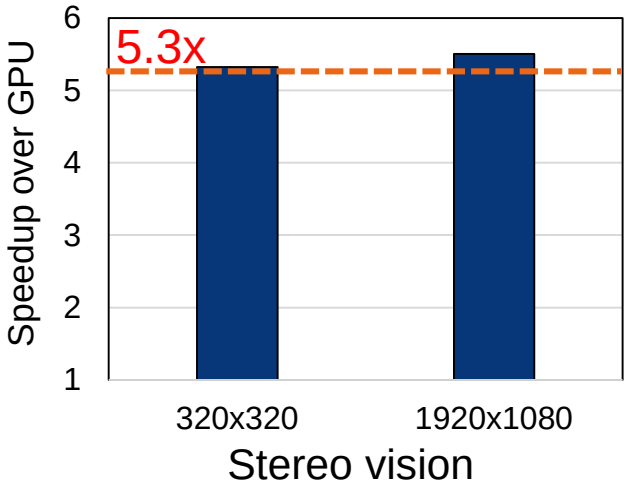

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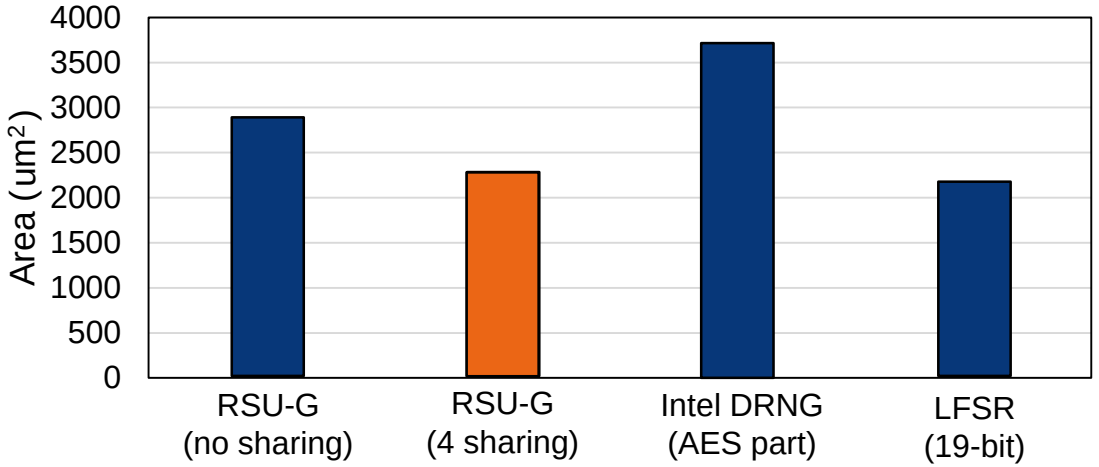

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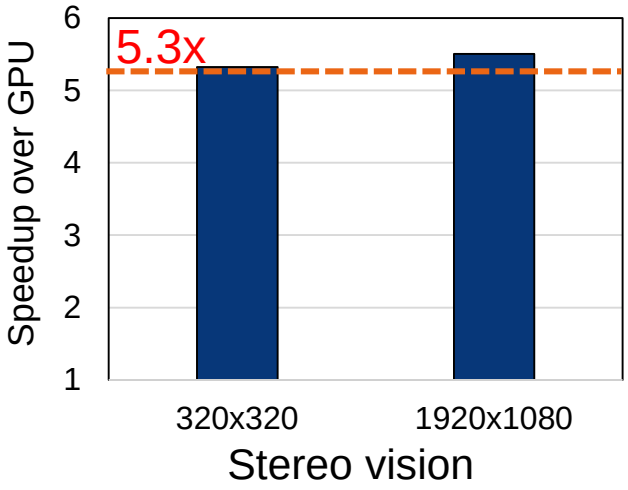

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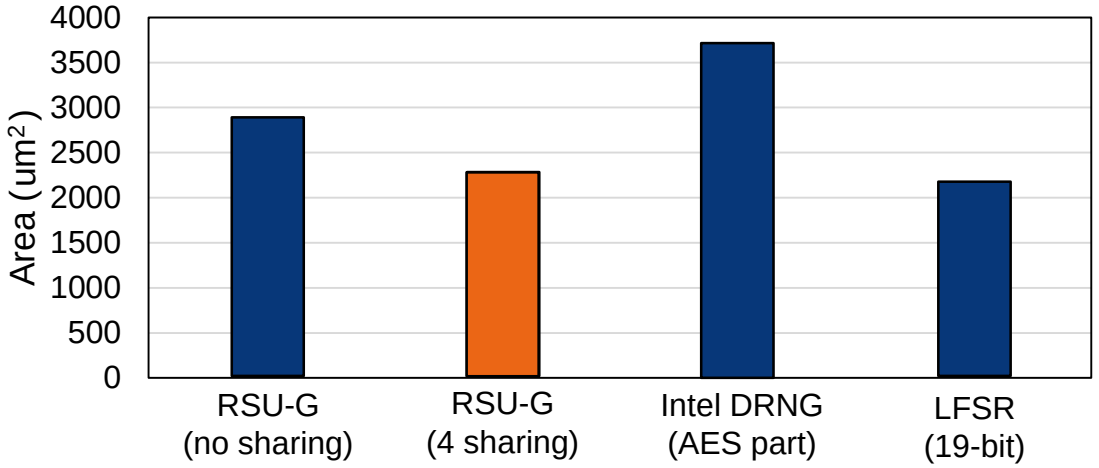

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- Future Work:
  - Supporting more mathematical MCMC models.
  - Quality analysis on wider application domains.

Thank you

- Q&A