Turn on, Tune in, Listen up

Maximizing Side-Channel Recovery in Time-to-Digital Converters

Colin Drewes[1], Olivia Weng[1], Keegan Ryan[1], Bill Hunter[2], Christopher McCarty[2], Ryan Kastner[1], and Dustin Richmond[3]

[1]UCSD, [2]GTRI, [3]UCSC

February 13, 2023

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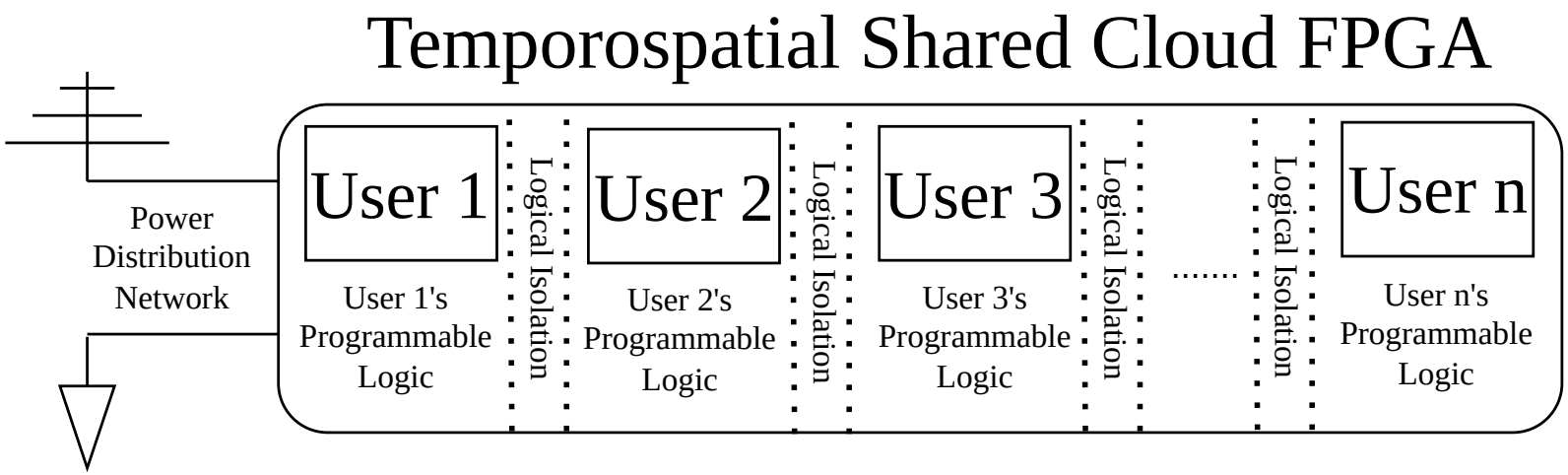

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- Detect round 7 of AES to introduce a power fault into the system

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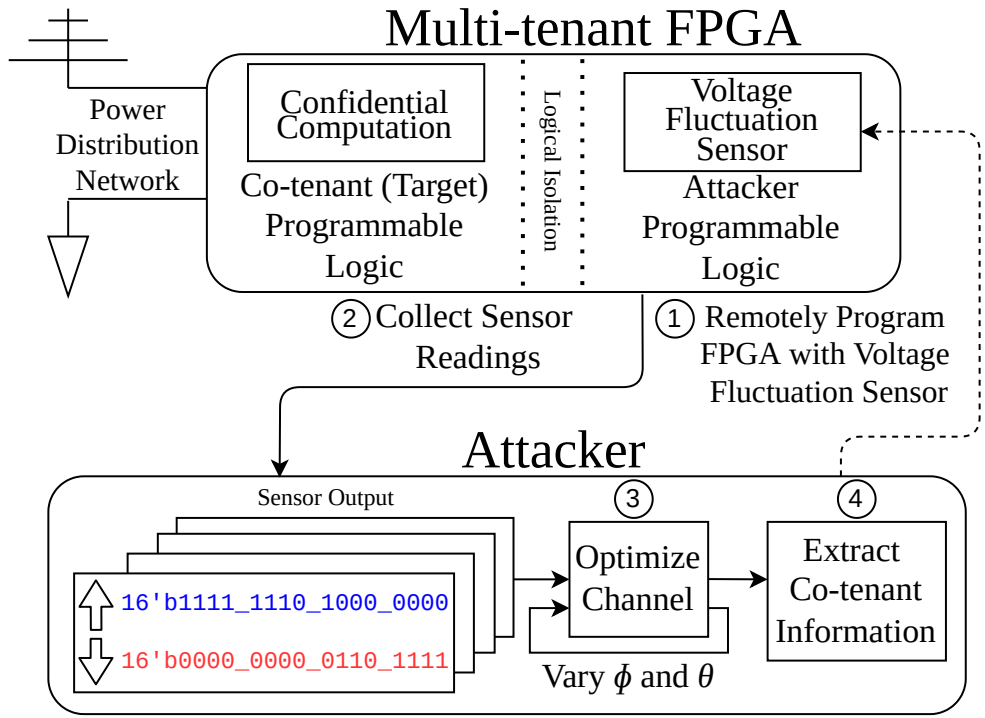

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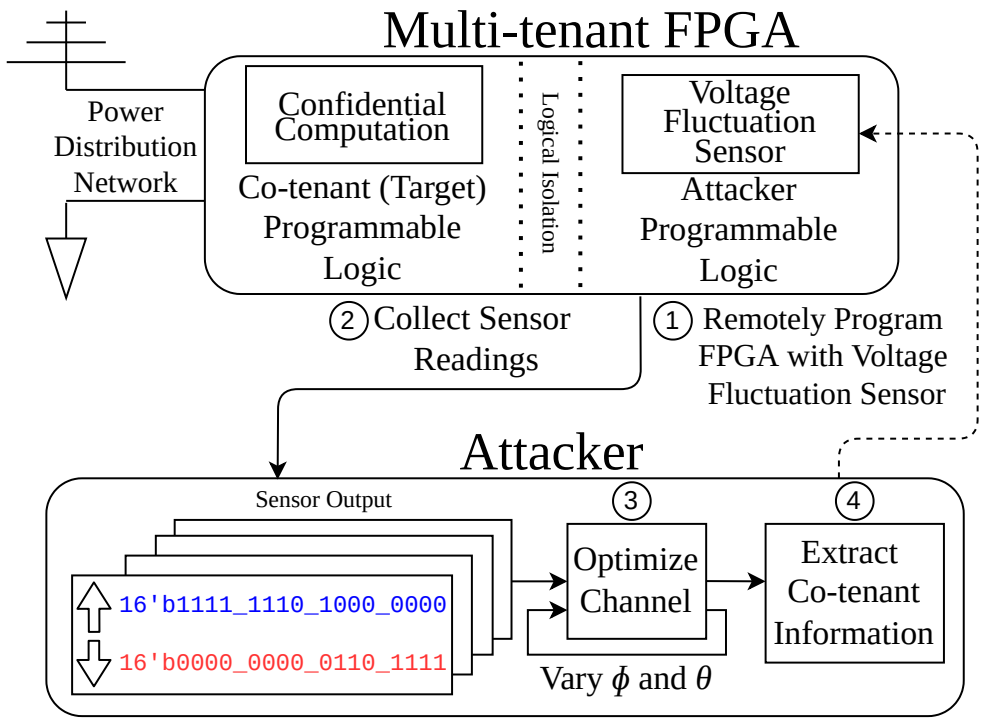

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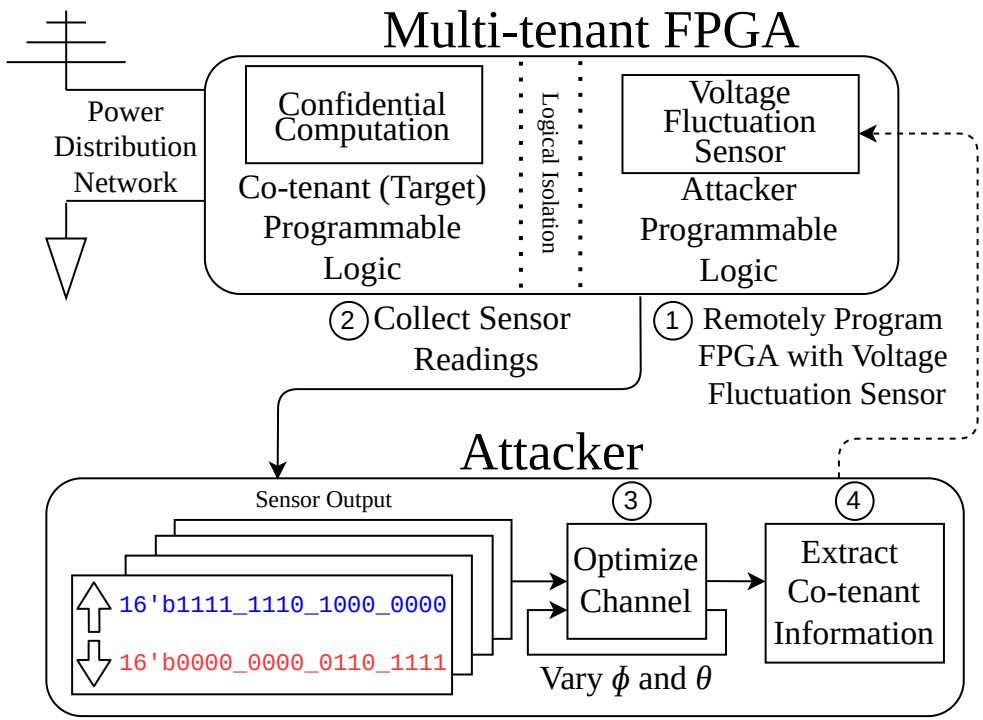

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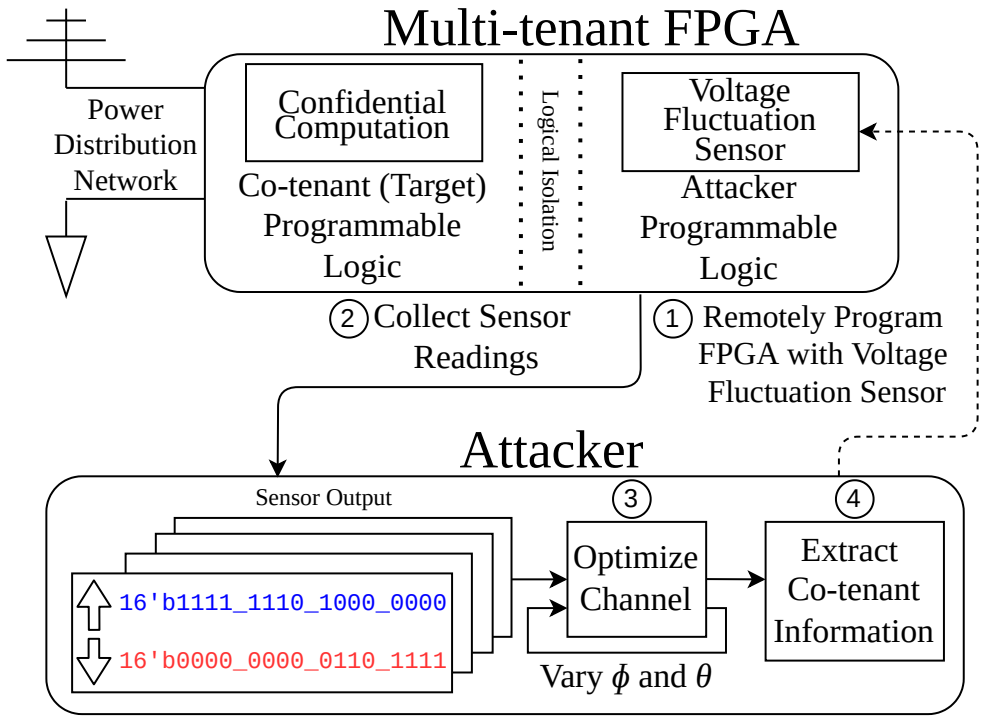

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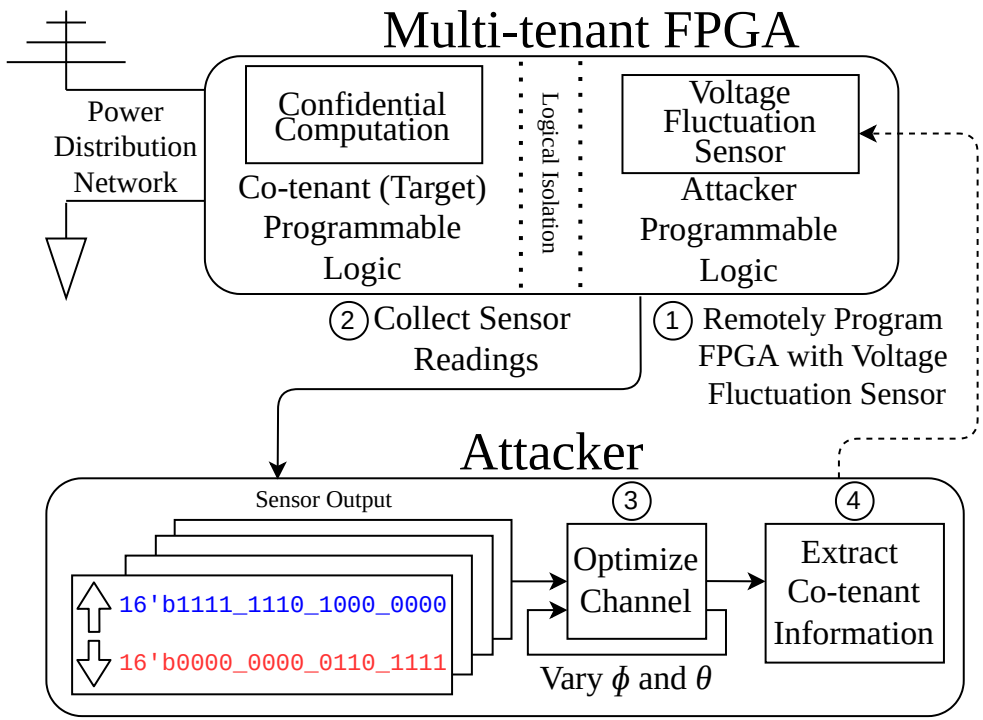

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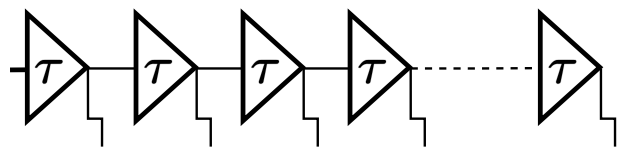

*An array of elements with uniform delay

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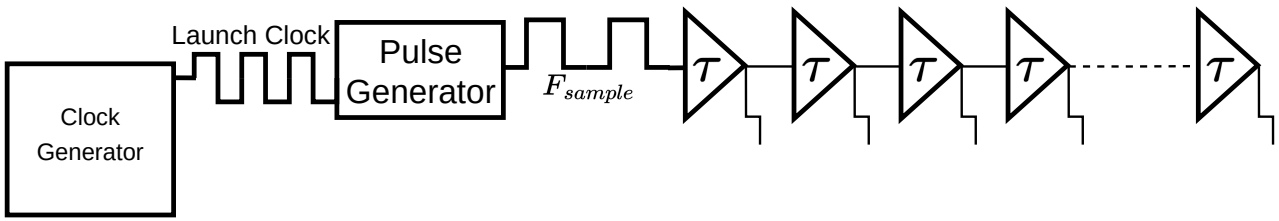

*Launch clock sends rising/falling pulses through delay elements

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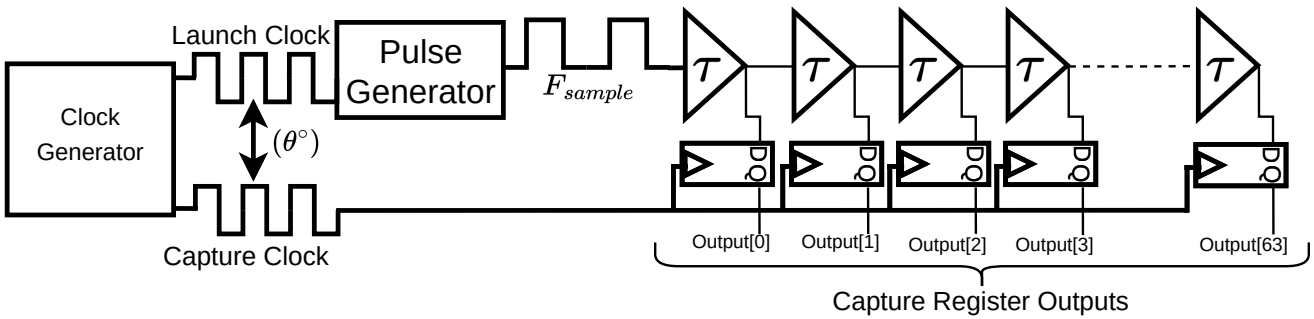

*Capture clock, which is phase offset a constant value from the launch, captures how far signals propagated through delay elements

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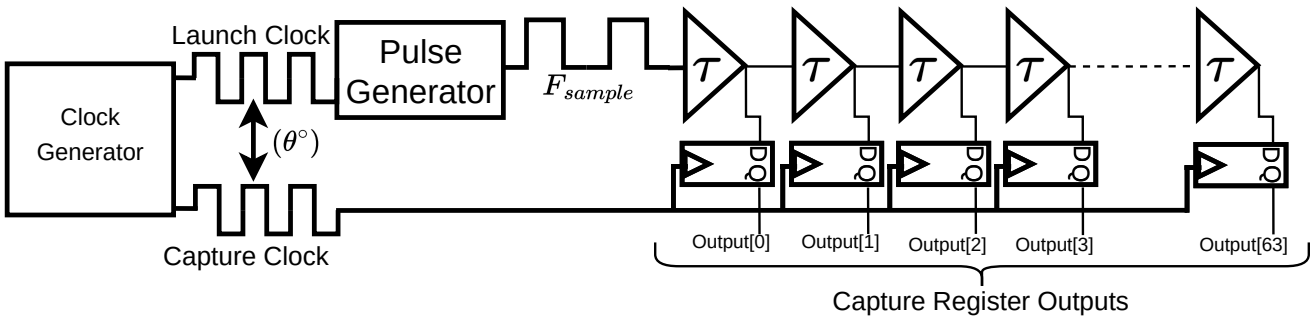

Capture output distance $\propto$ state of the PDN

Known Problems: Architectural Irregularities

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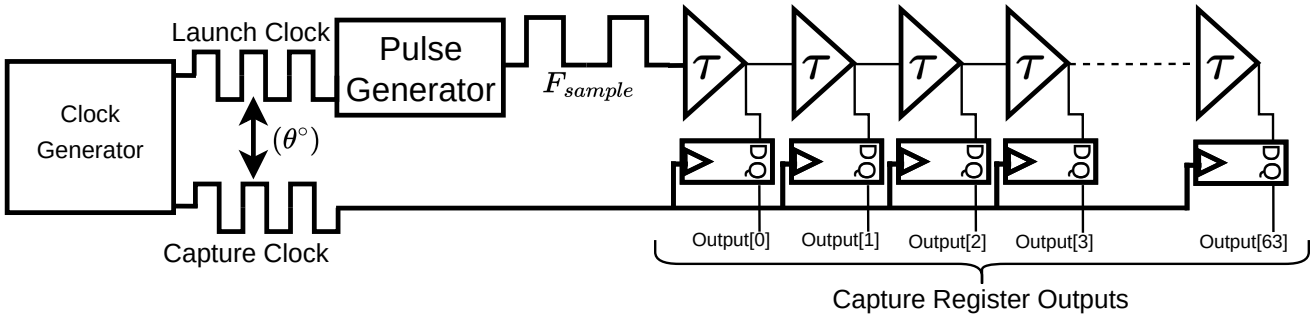

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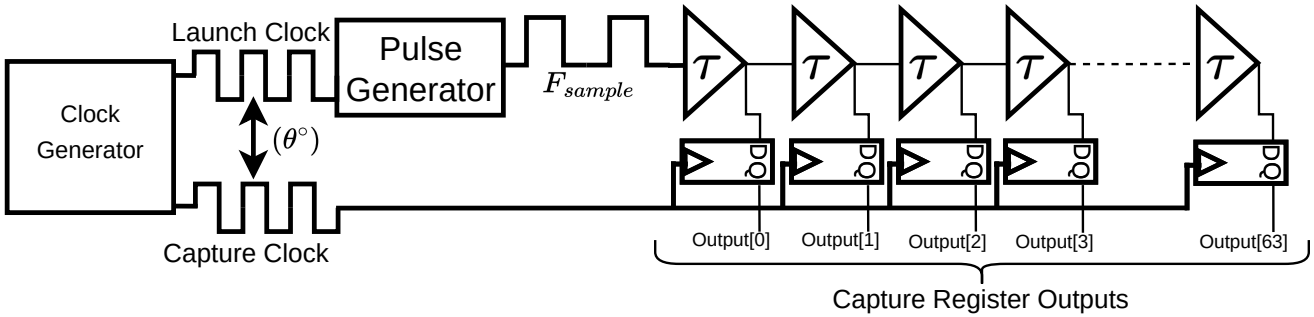

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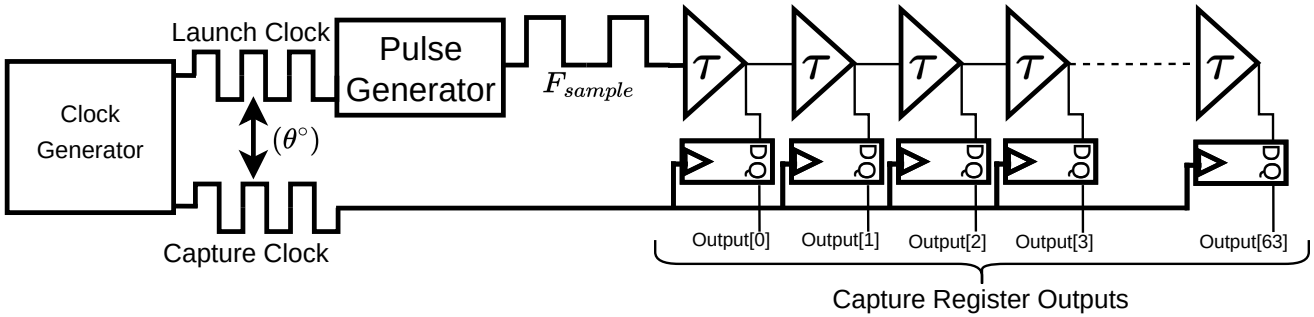

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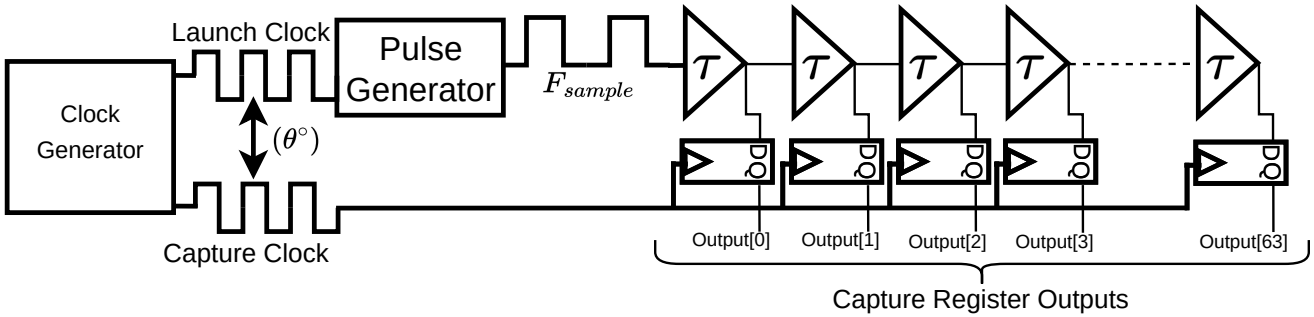

Perfect delay line doesn't exist:

- More linear propagation = more responsive to fluctuations
- Faster propagation = higher resolution

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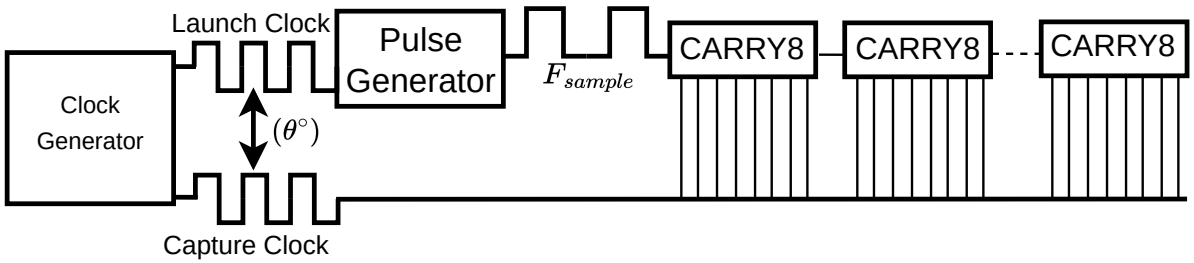

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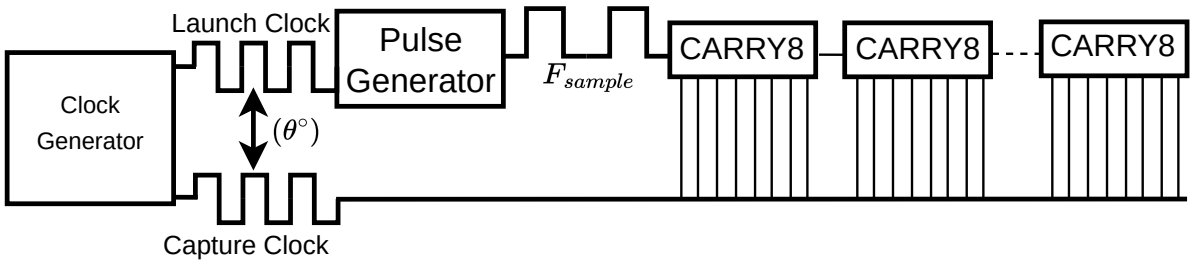

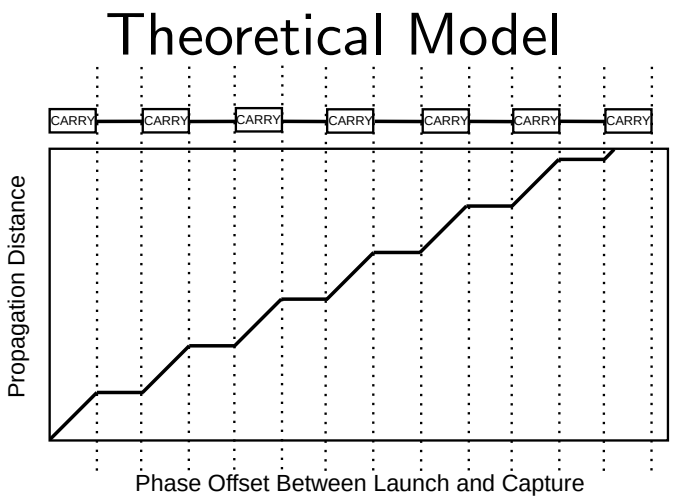

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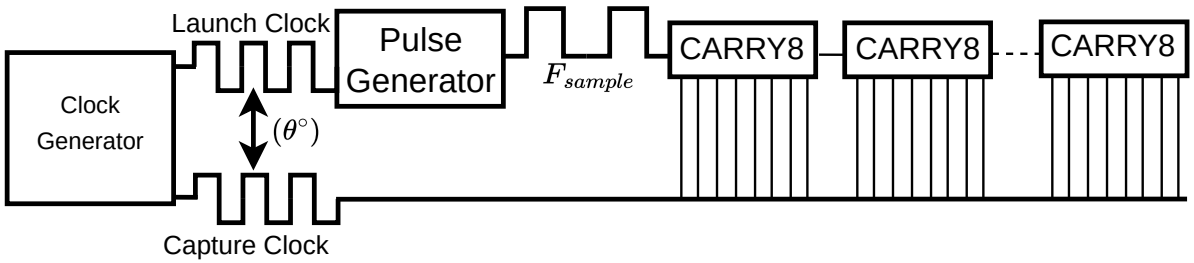

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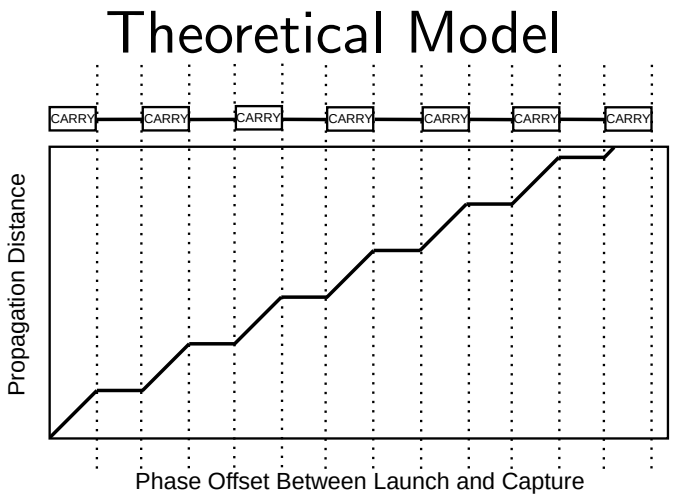

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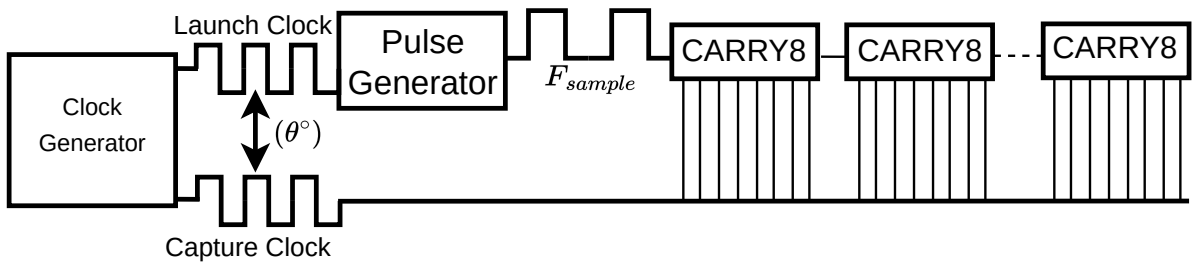

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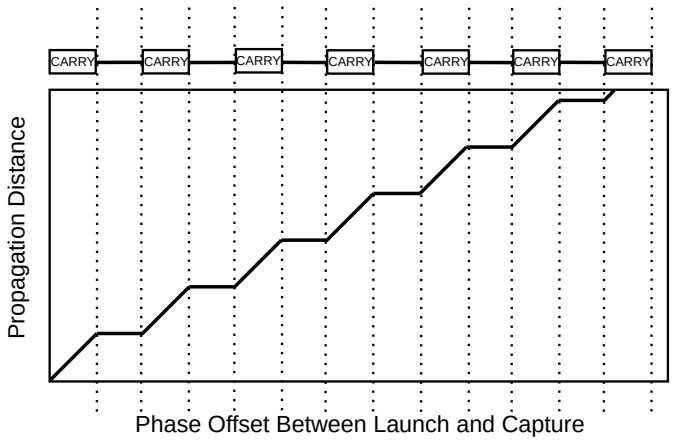

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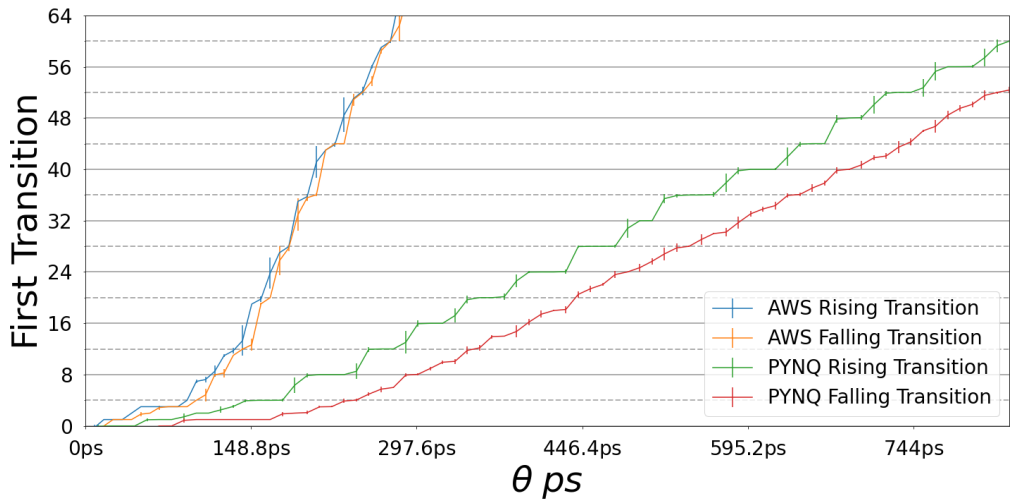
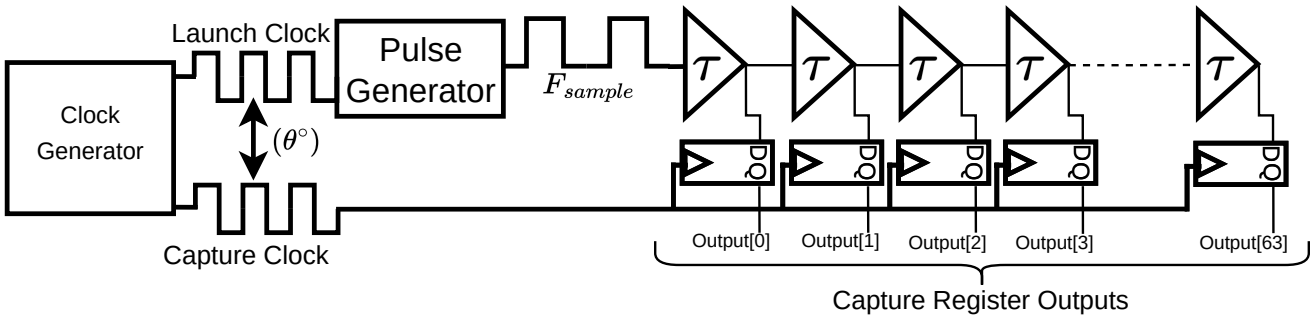


Solution: Dynamic Tuning

Constant phase offset.



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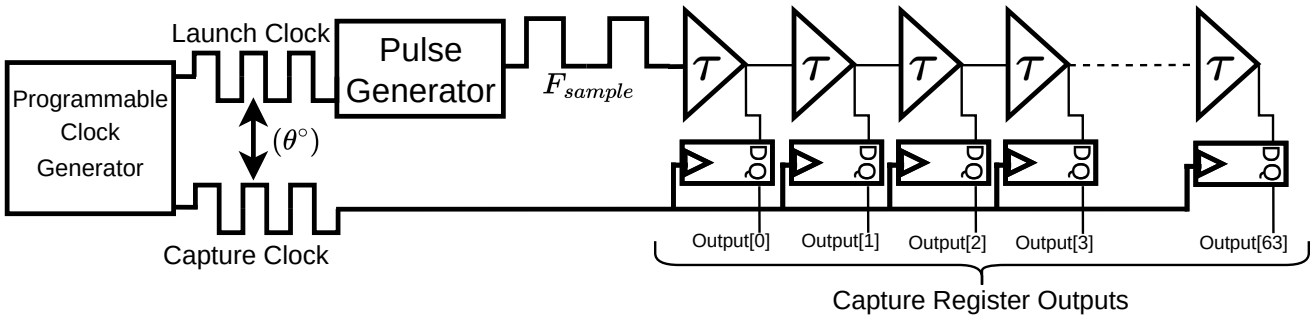

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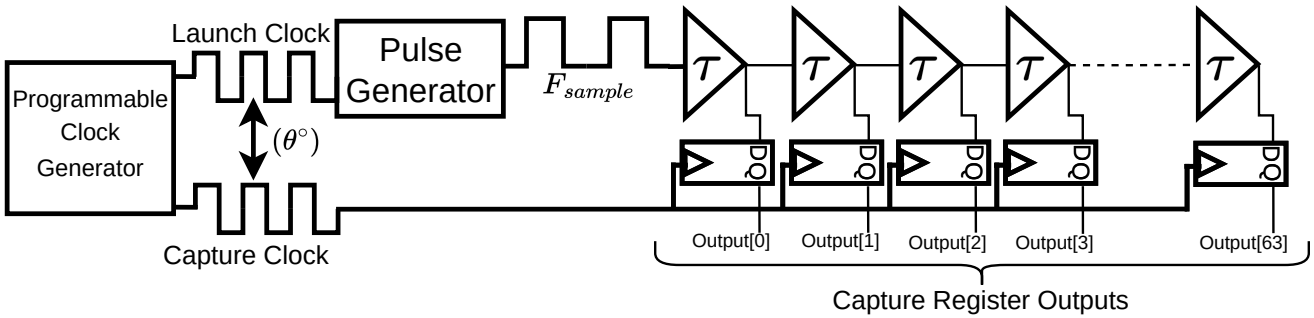

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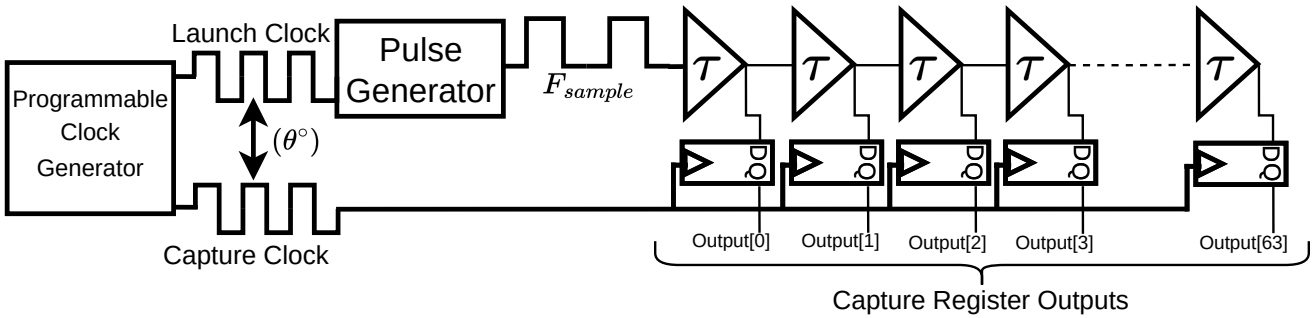

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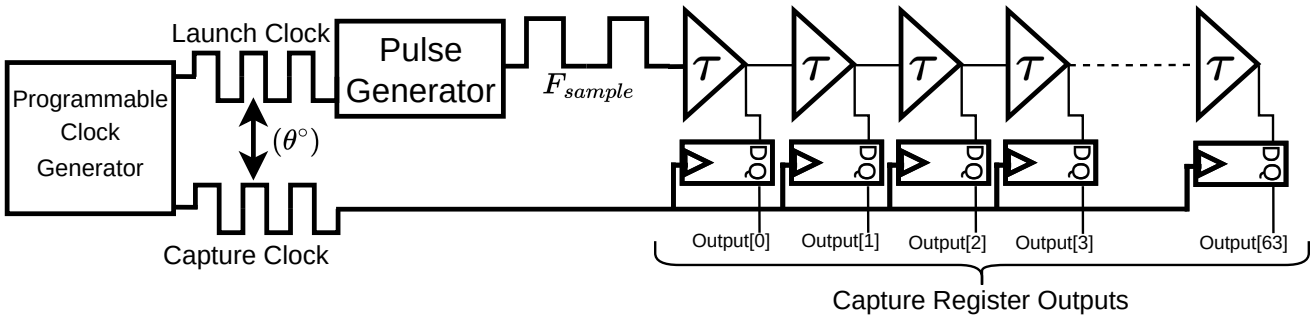

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- Attacker can place transition at ideal point within CARRY primitive, improving sensor response to power fluctuations.

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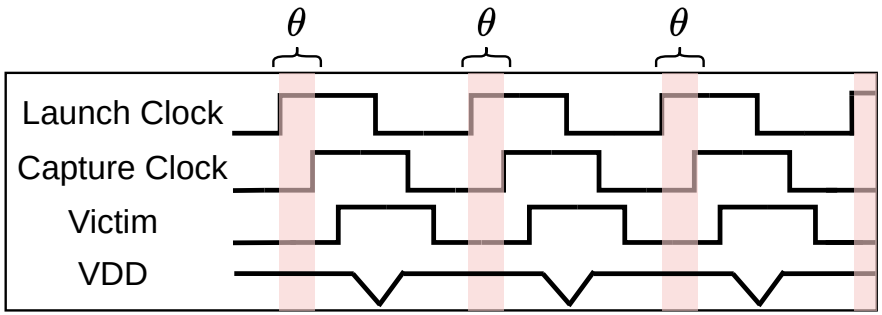

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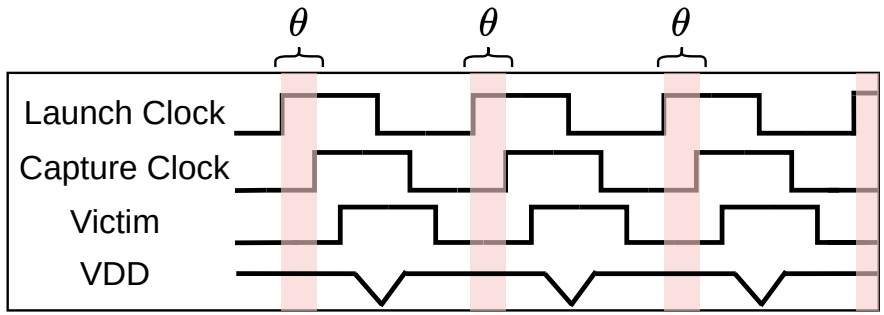

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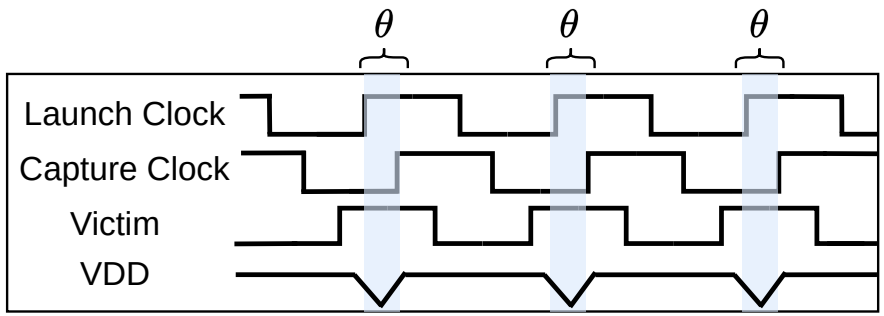

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- Lets phase shift launch and capture clock together, wrt victim computation

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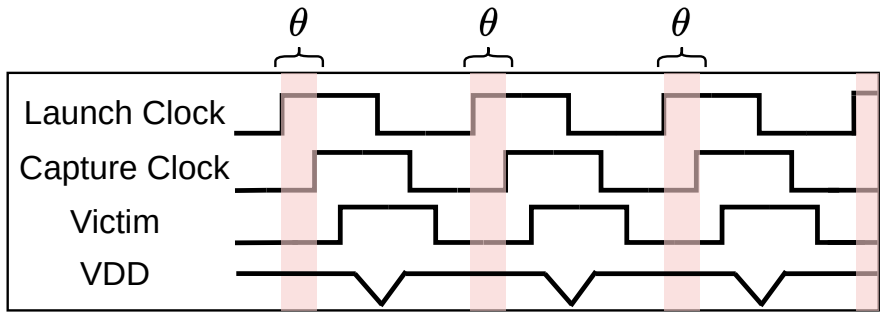

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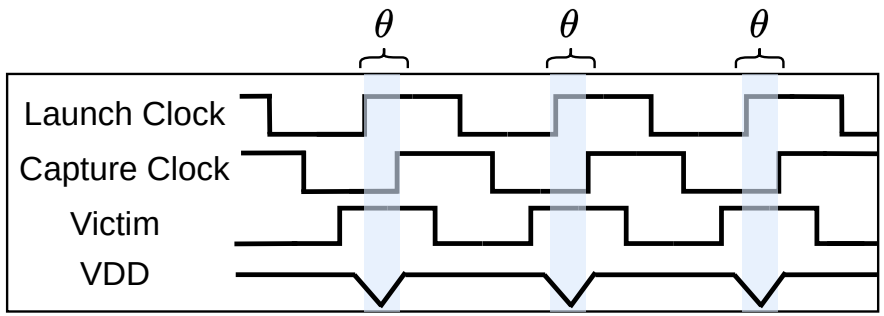

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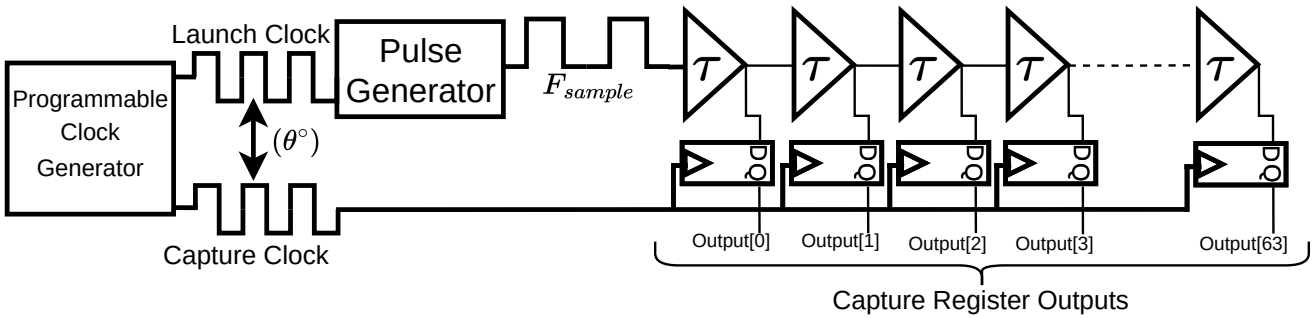

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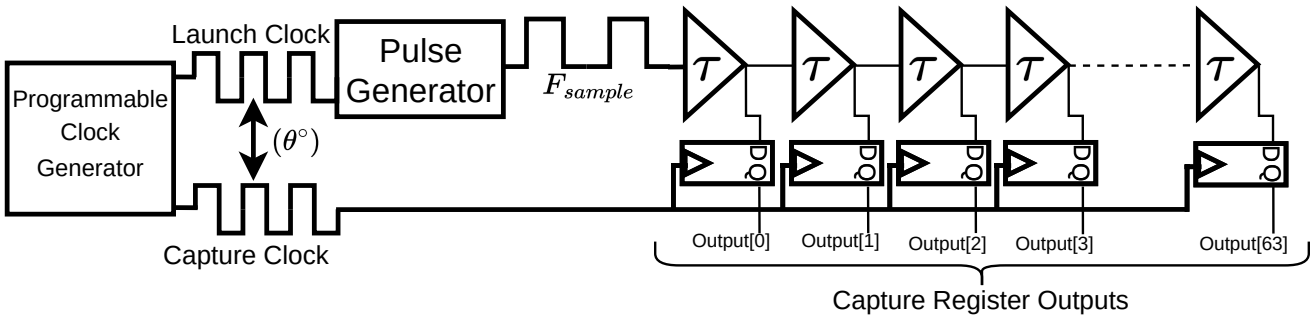

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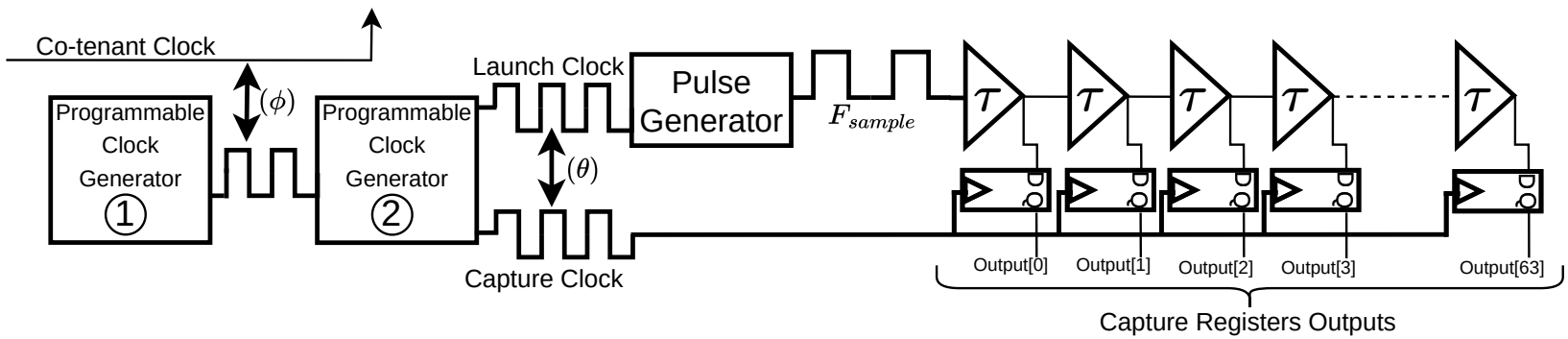

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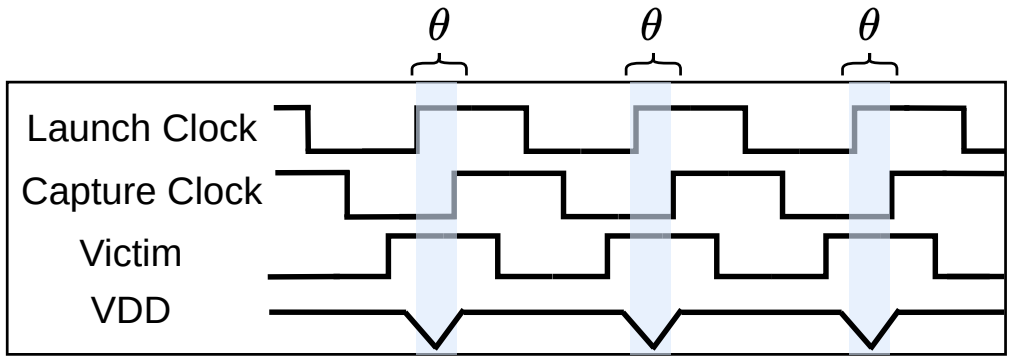

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- Rotate by two periods with processor disabled and measure.
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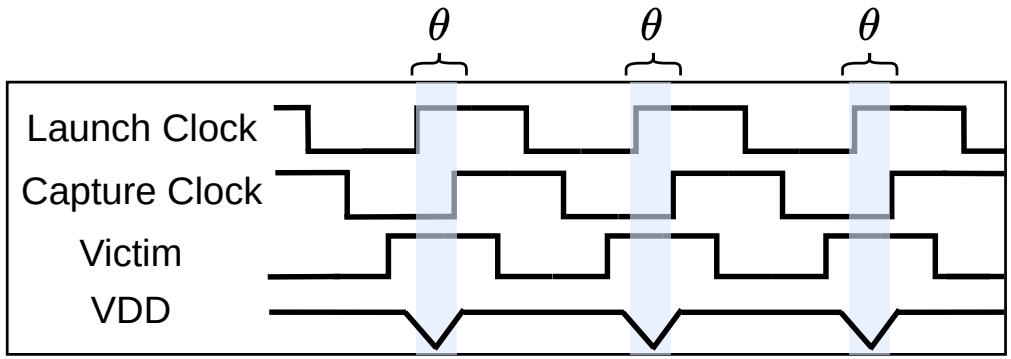
Expect to see a single optimal



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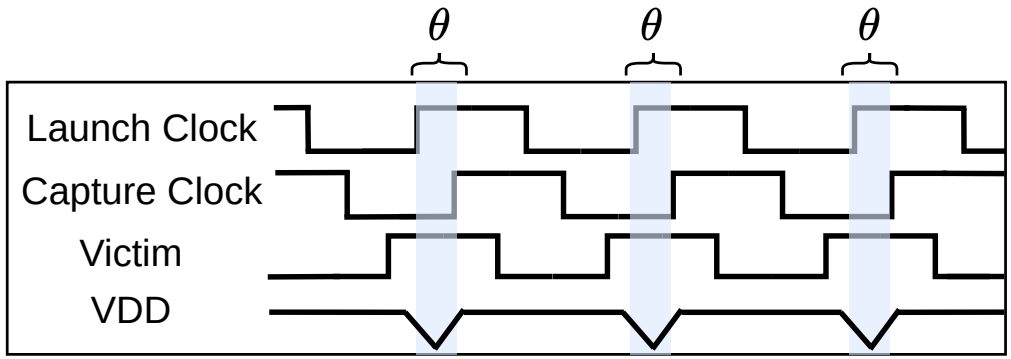

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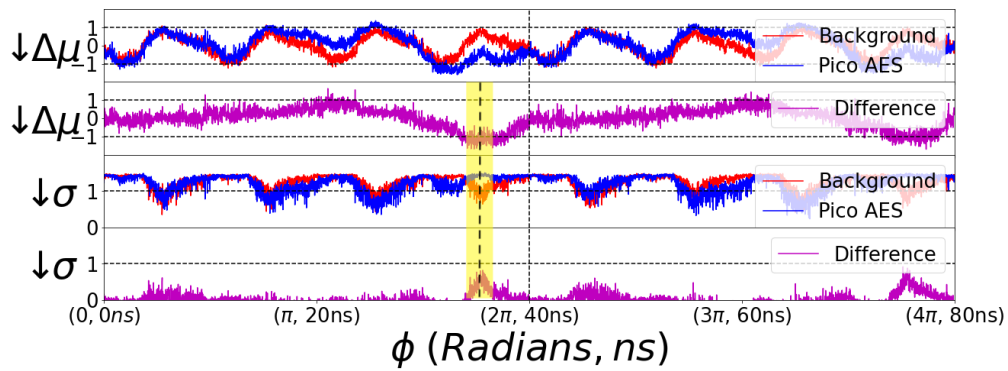

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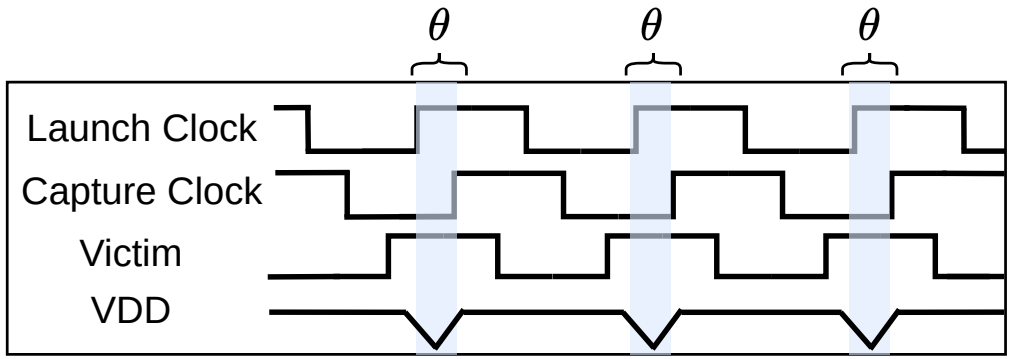

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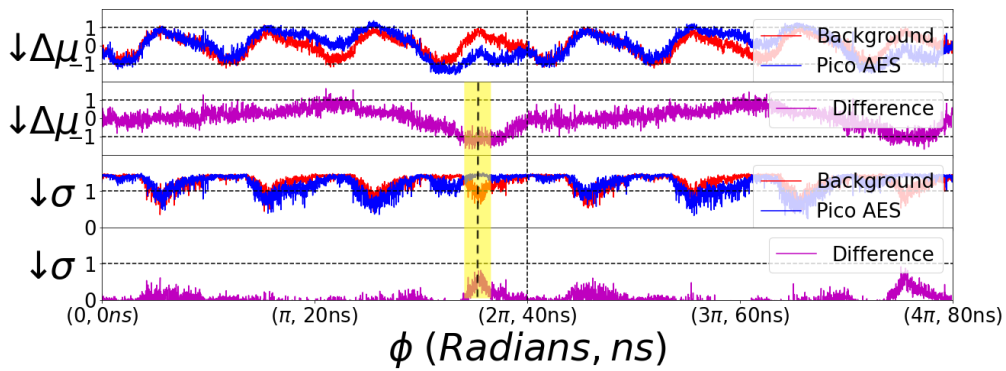

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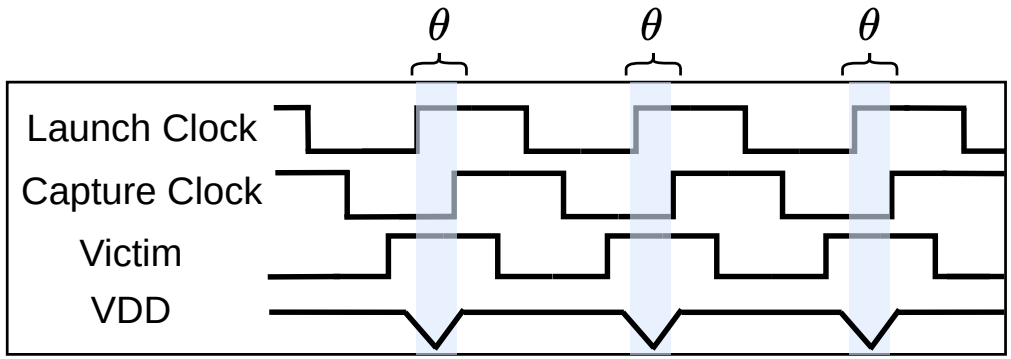

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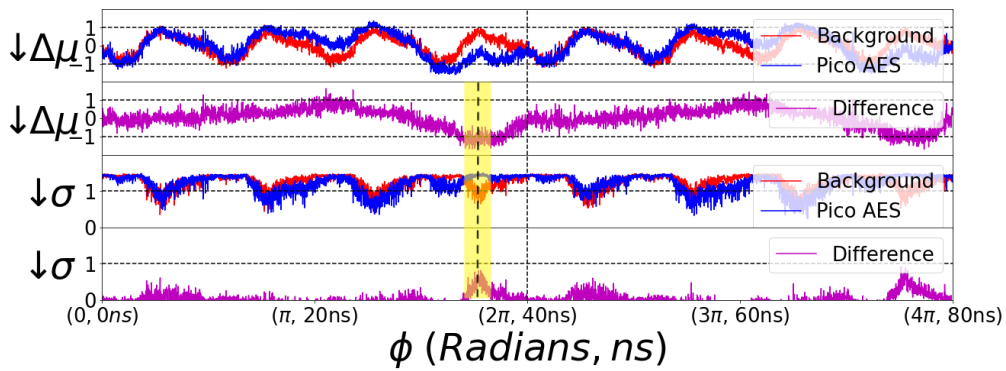

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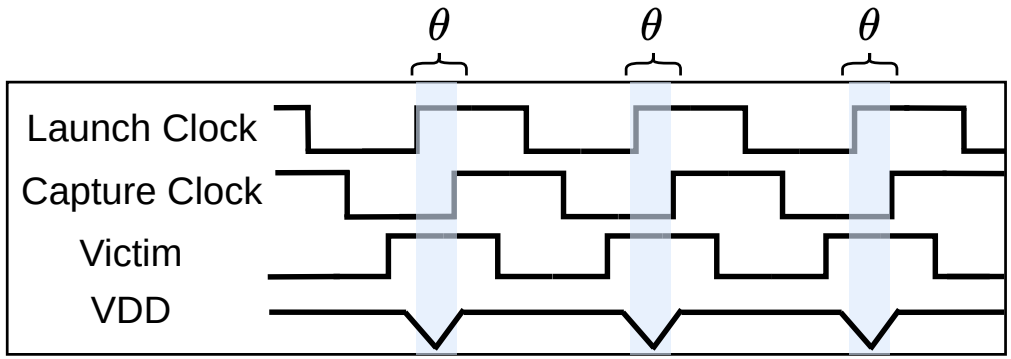

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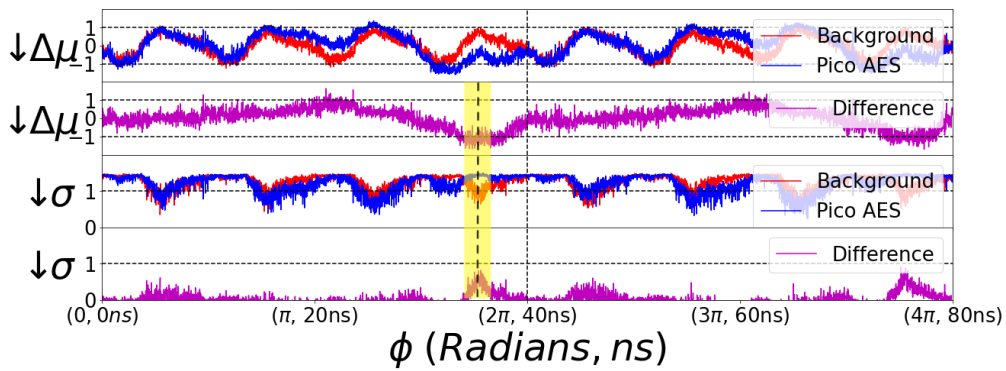

Taking the di erence from the background exposes optimal to capture power uctuations induced by victim.

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- Sensor co-located with each of 13 victim computations on multiple boards

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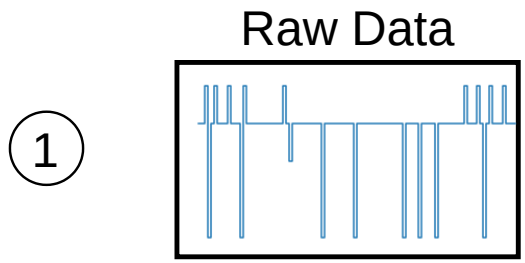

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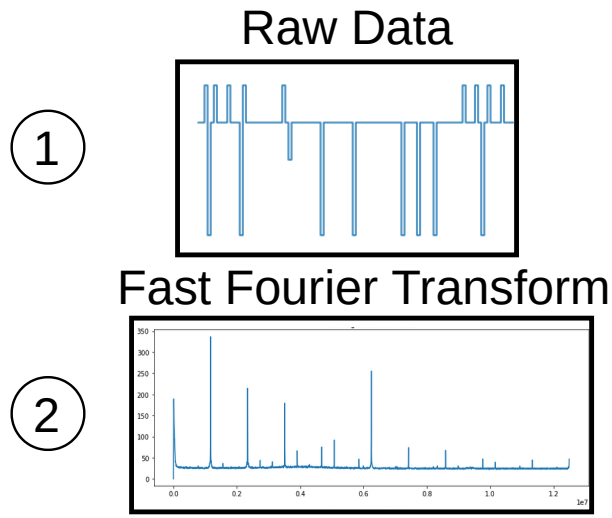

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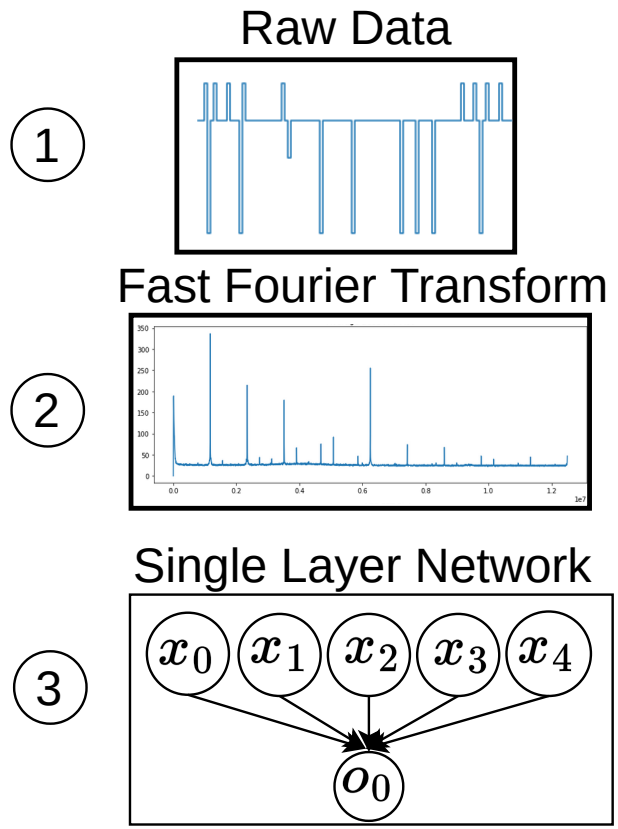

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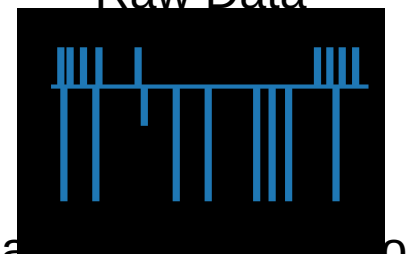

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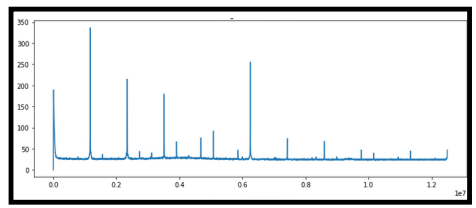

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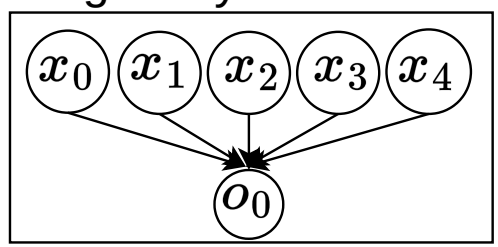

4

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Good and with bg: 75.552%

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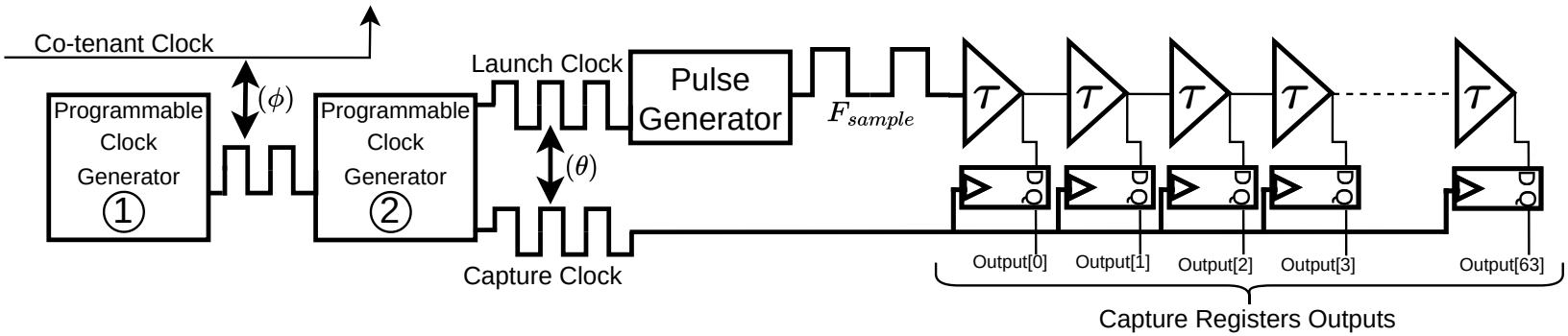
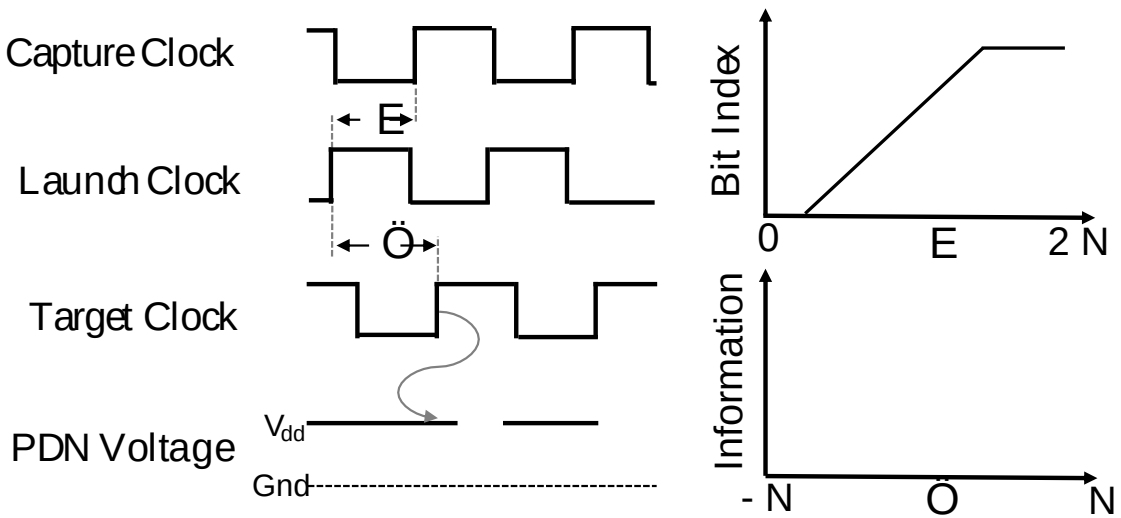
Background Subtraction is Out-of-Distribution Generalization!

Conclusion/Questions

Don't let and assume a random value!





Thanks!