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Minimization At HCAL, Iteratively

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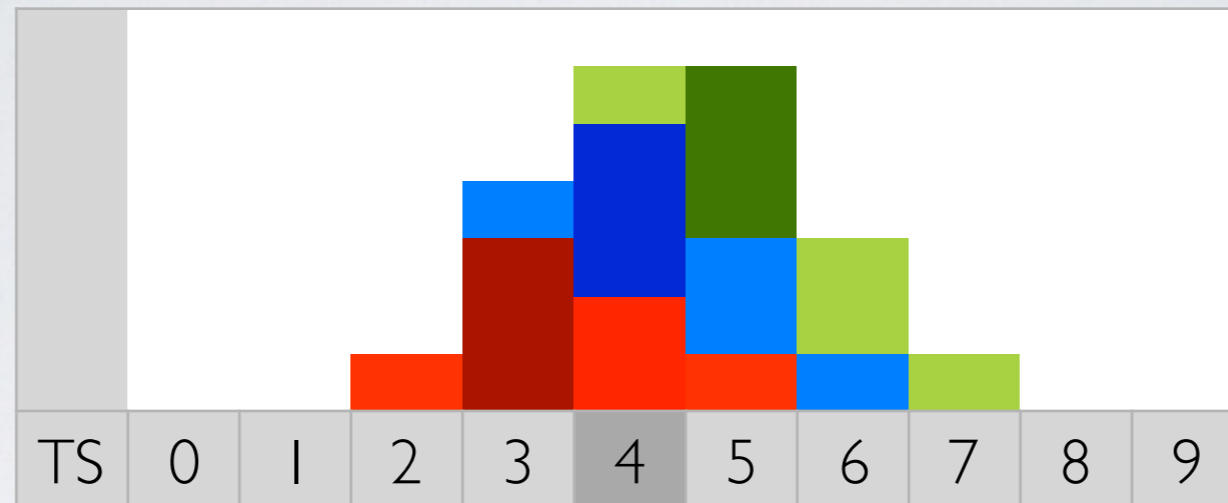
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HCAL Detector Performance Group

8.12.2017

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HBHE Local Reconstruction



- Inputs

- 10 pedestal-subtracted data samples (TS)
 - Not much we can do with just this, also need models of
 - Signal behavior (pulse shape, arrival time)
 - Noise/fluctuations/background (electronics, digitization, photo statistics, SiPM dark current)
-
- Can apply corrections to measured charge using this info (Method 0)
 - Or fit for the signal charge (Method 2, Method 3, Mahi)

Covariance matrices

Time Slice	0	1	2	3	4	5	6	7	8	9
0	Red				Grey					
1		Red			Grey					
2			Red		Grey	Blue				
3				Red	Grey					
4	Grey	Grey	Grey	Grey	Red	Grey	Grey	Grey	Grey	Grey
5			Blue		Grey	Red				
6					Grey		Red			
7					Grey			Red		
8					Grey				Red	
9					Grey					Red

- Build our detector description in terms of covariance matrices
- Diagonal terms are standard deviations σ_{ii}
- Off-diagonals are covariances
 - i.e. $\sigma_{25} = \langle (TS2 - \langle TS2 \rangle)(TS5 - \langle TS5 \rangle) \rangle$

- Start with empty detector and build up each component

Empty detector

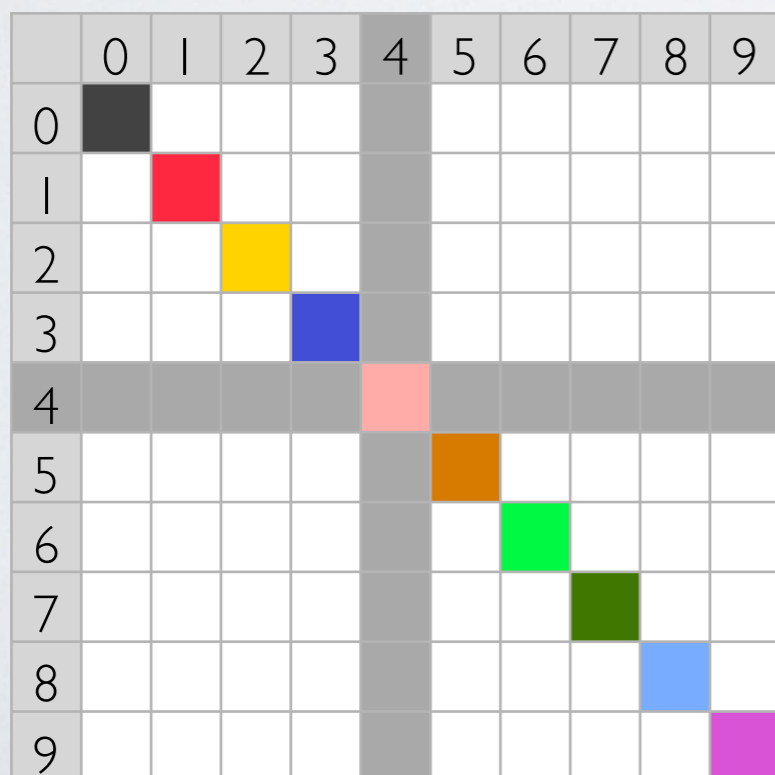


Electronics pedestal and dark current

- take average over CapIDs as fully correlated across time slices,
- and the value for each TS as uncorrelated (inflate uncertainties to help convergence)

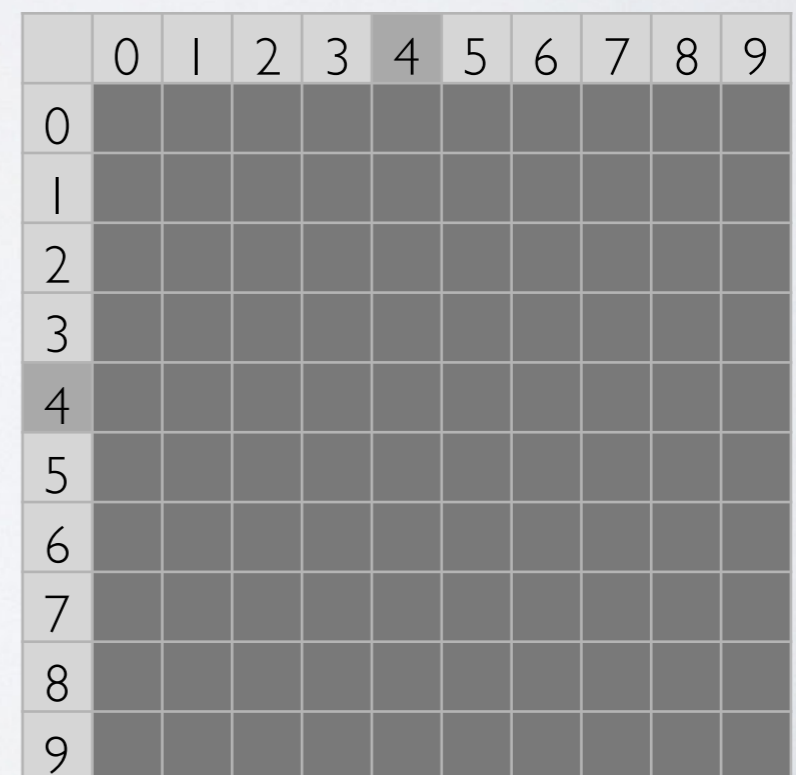
ADC granularity and photo statistics

- take as uncorrelated for each TS



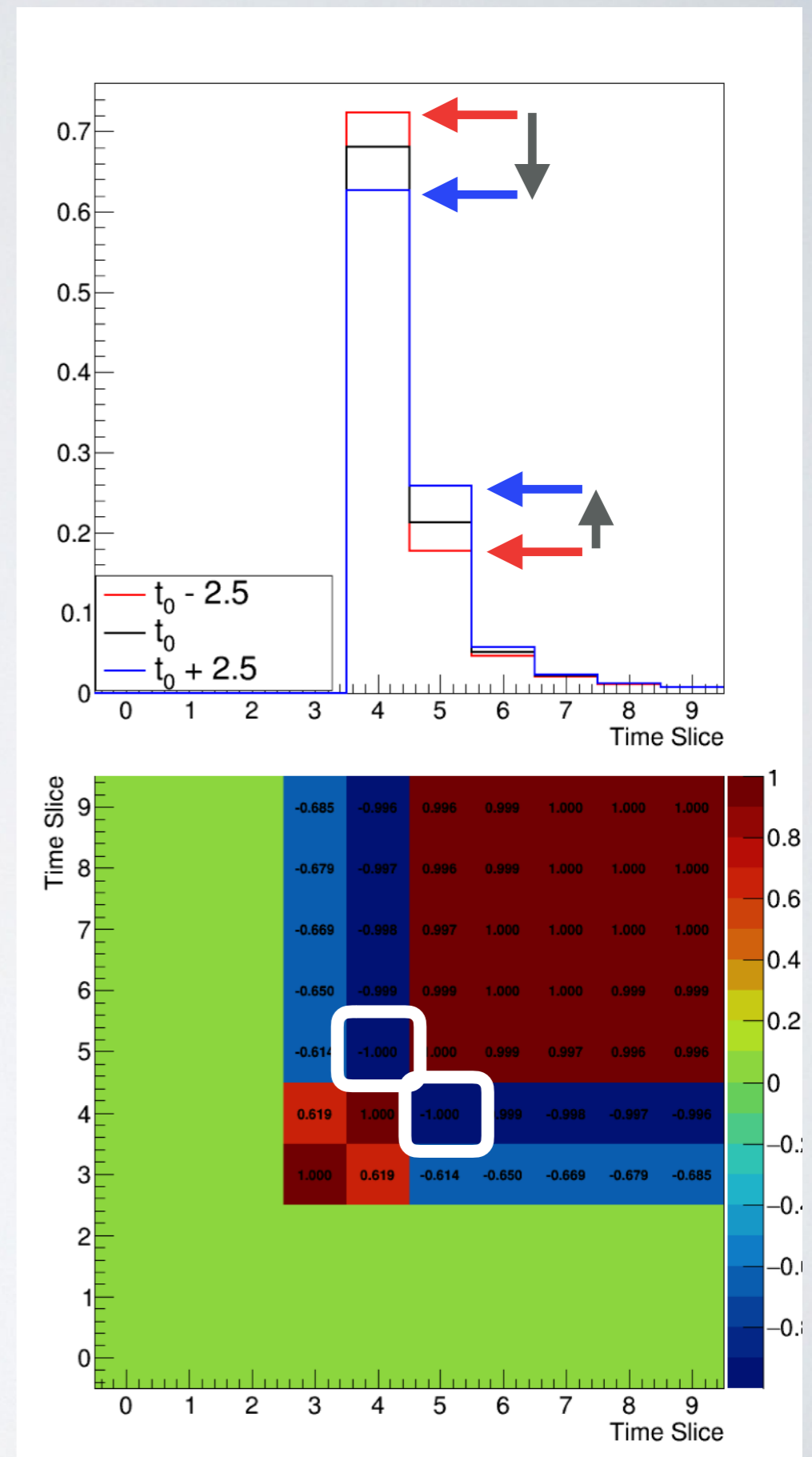
← uncorrelated

correlated →



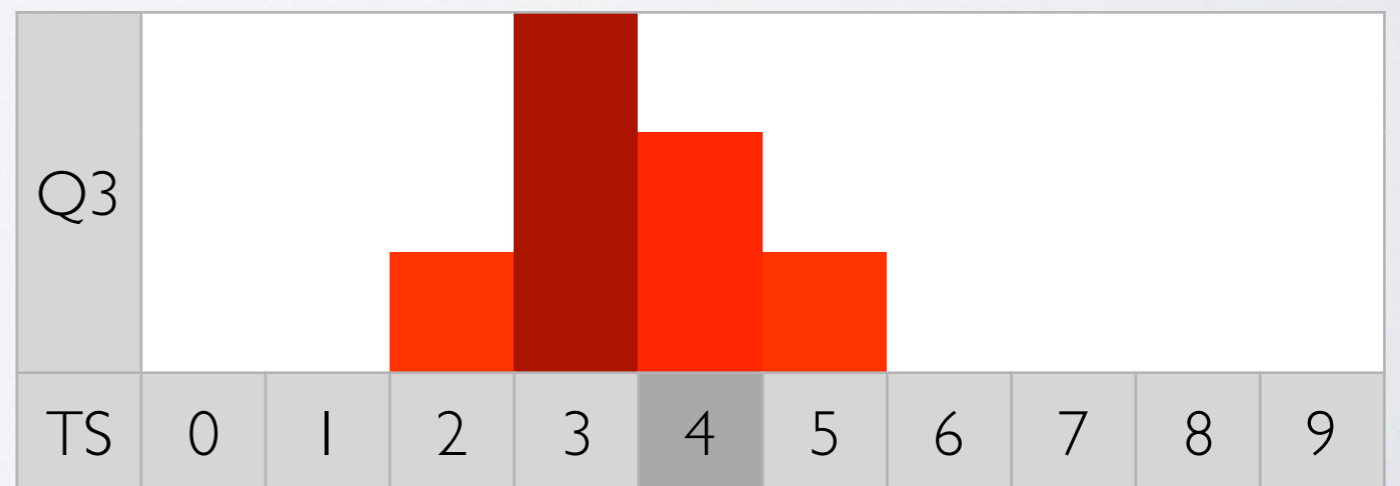
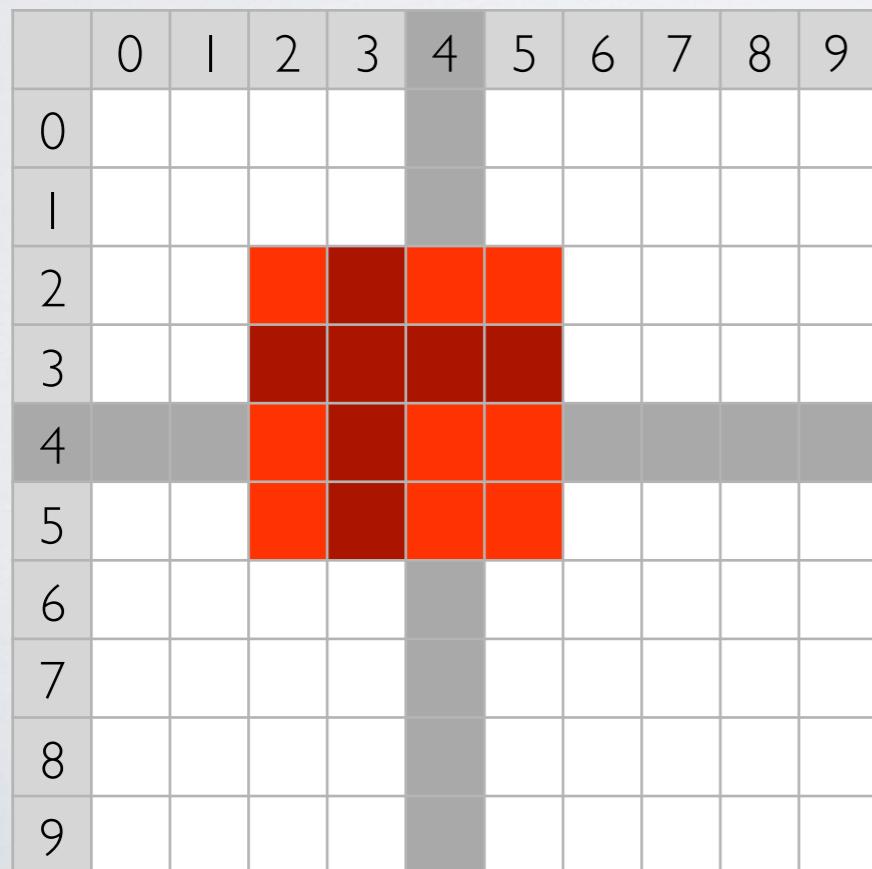
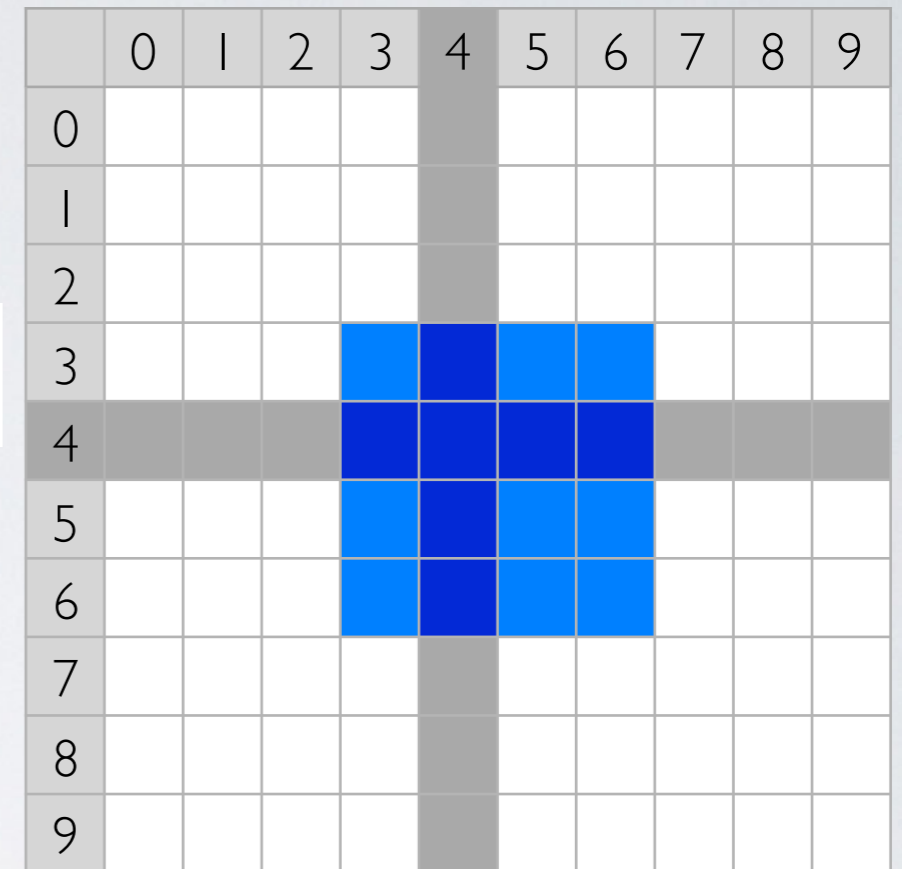
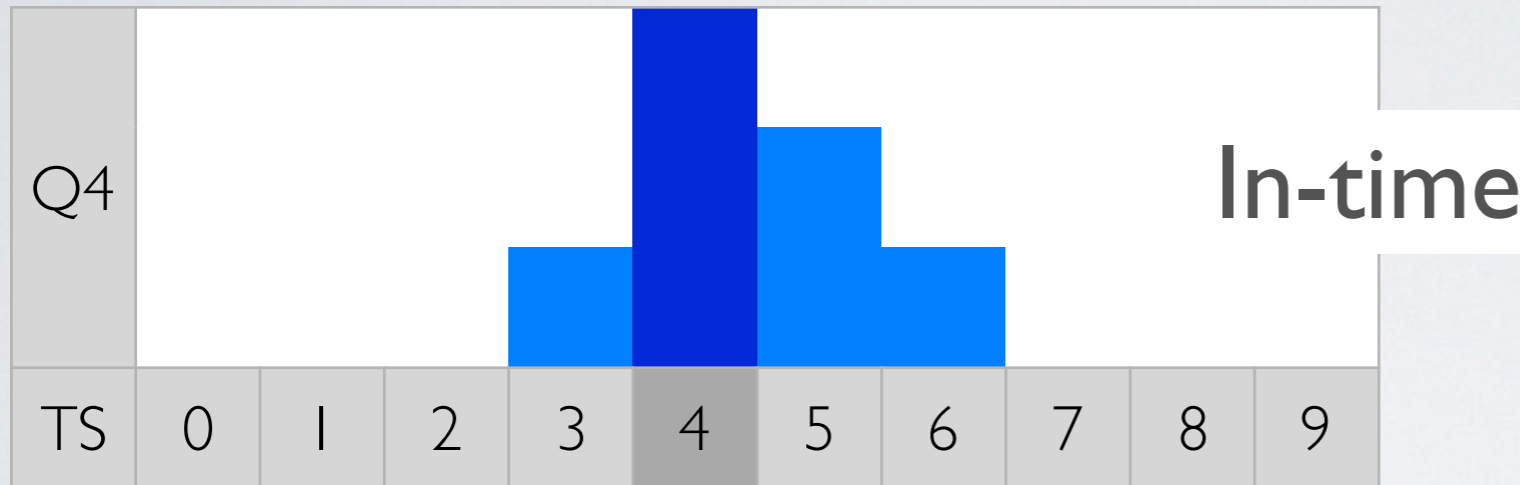
Signal model

- Pulse shape templates (nominal shape and time slew model) and uncertainties in terms of arrival time
- Build covariance matrix by shifting the template forward and backwards in time by 1σ variation
 - 2.5 ns for SiPM, 5.0 ns for HPD
- Covariance matrix encodes relative behavior of pulse shape as it is shifted



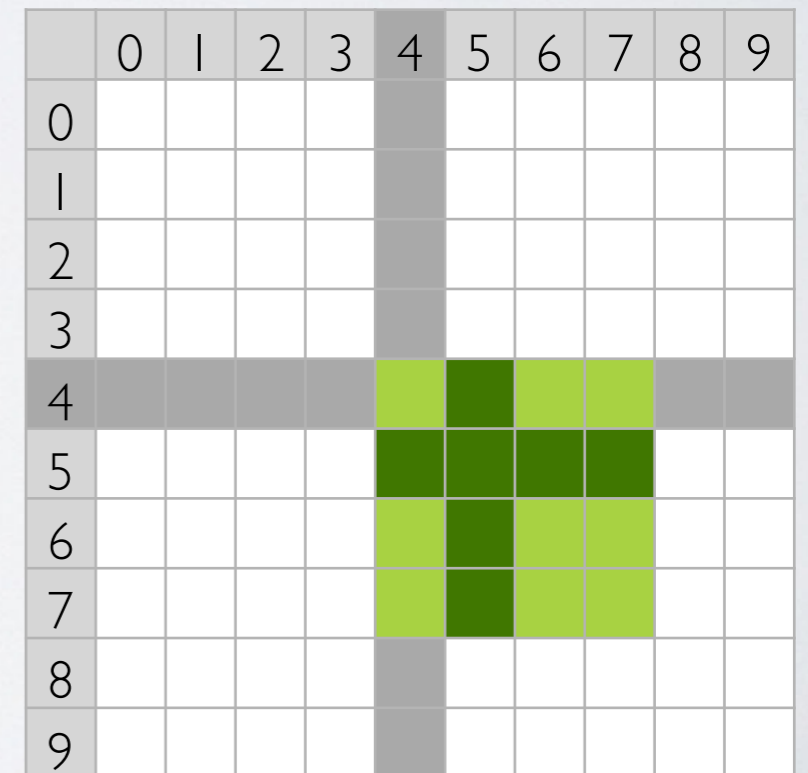
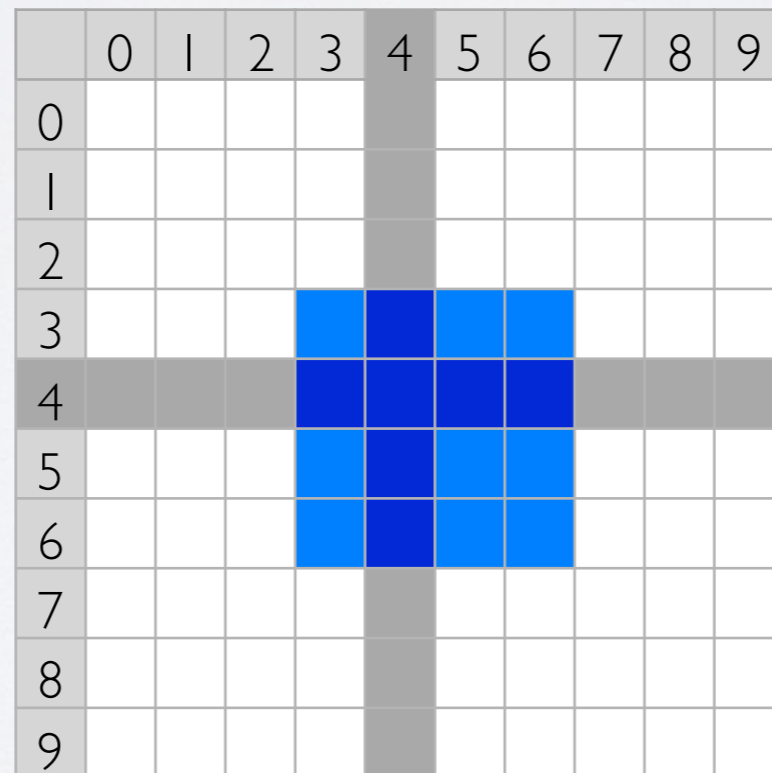
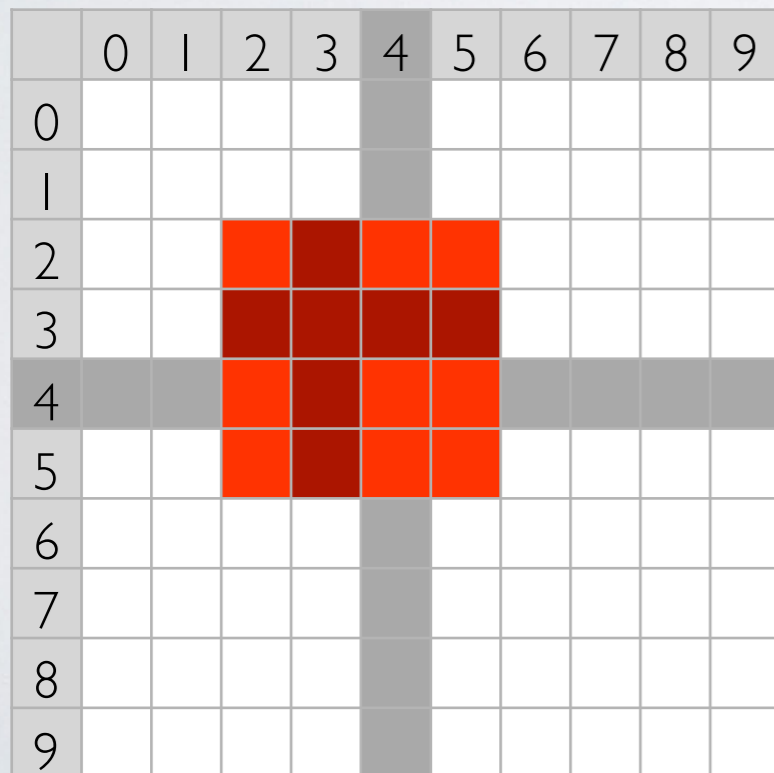
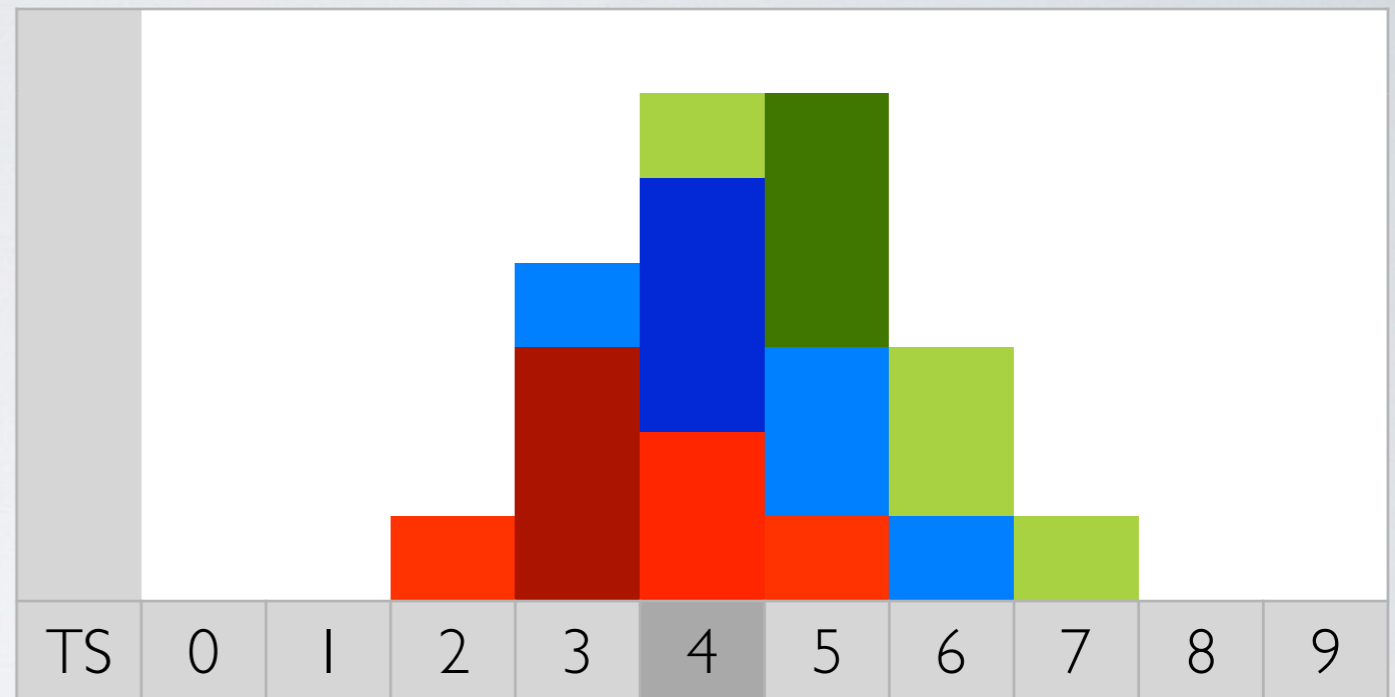
Building the signal covariance matrix

- Need covariance matrix for each pulse:

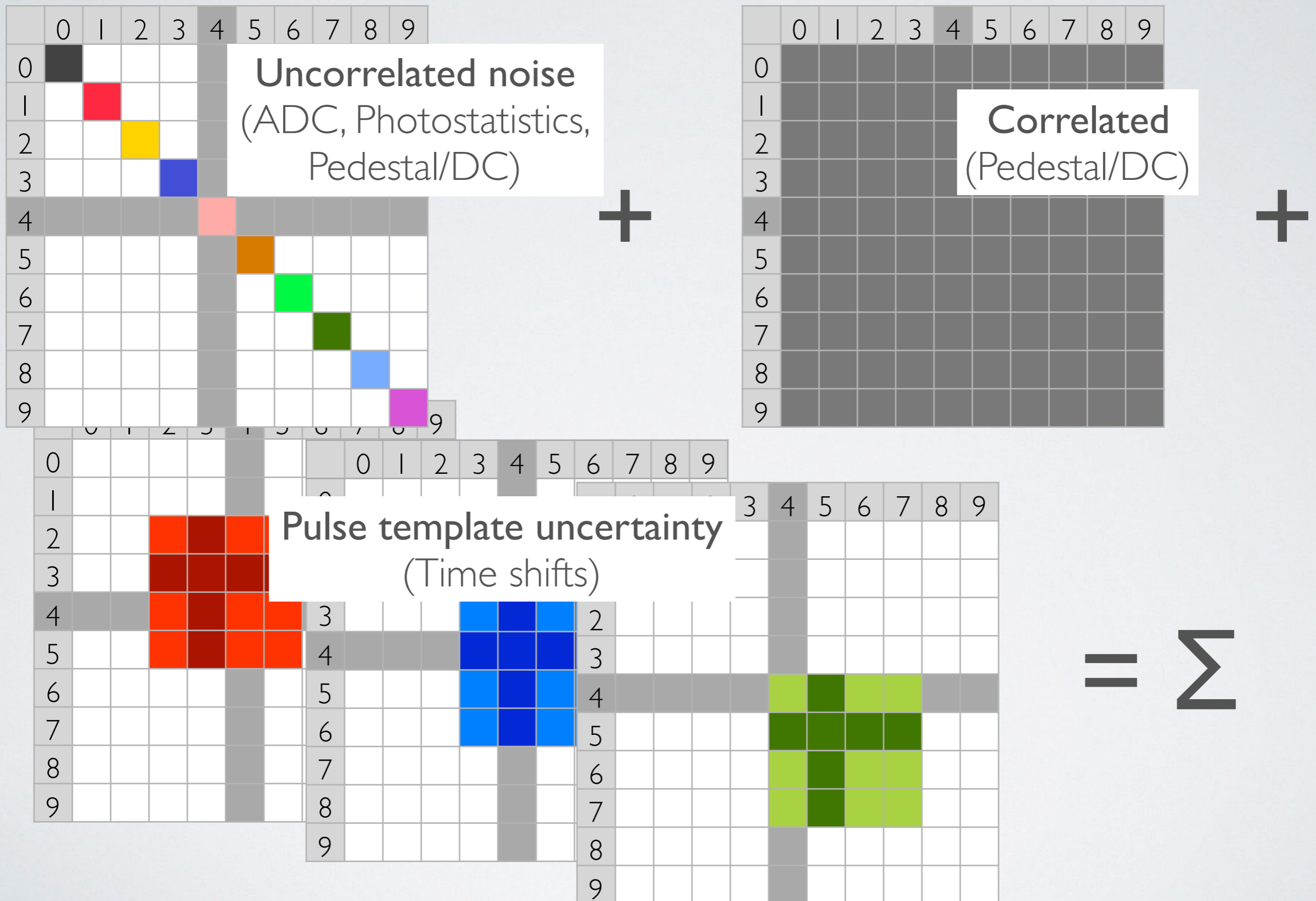


Overlapping signals

- For 3-pulse model, have 3 unique pulse shape covariance matrices:



Putting it all together

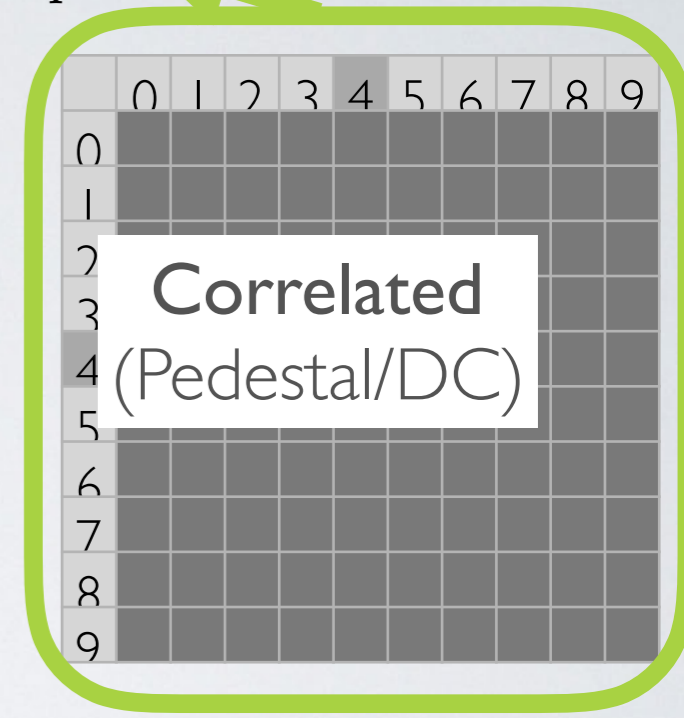


Method 2

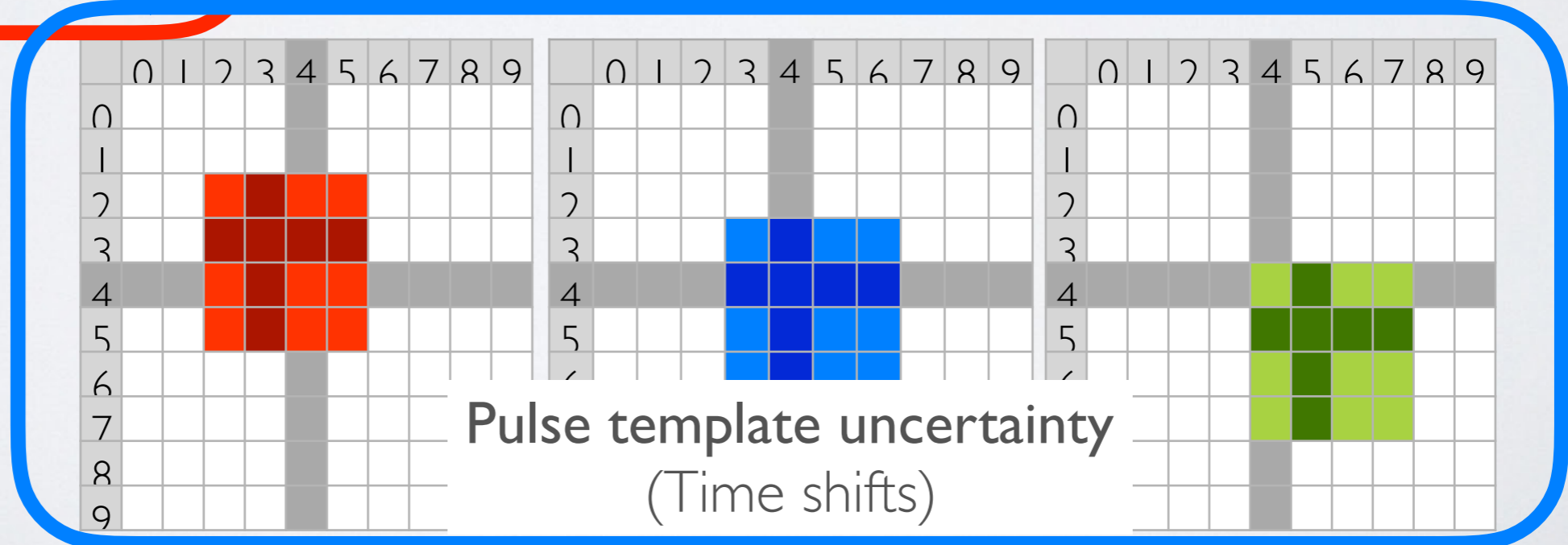
$$\chi^2 = \sum_{i=0}^9 \frac{(TS_i - A_i)^2}{\sigma_{p,i}^2} + \sum_{j=0}^3 \frac{(t_j - \langle t \rangle)^2}{\sigma_t^2} + \frac{(\text{ped} - \langle \text{ped} \rangle)^2}{\sigma_{\text{ped}}^2}$$



Uncorrelated noise
(ADC, Photostatistics,
Pedestal/DC)

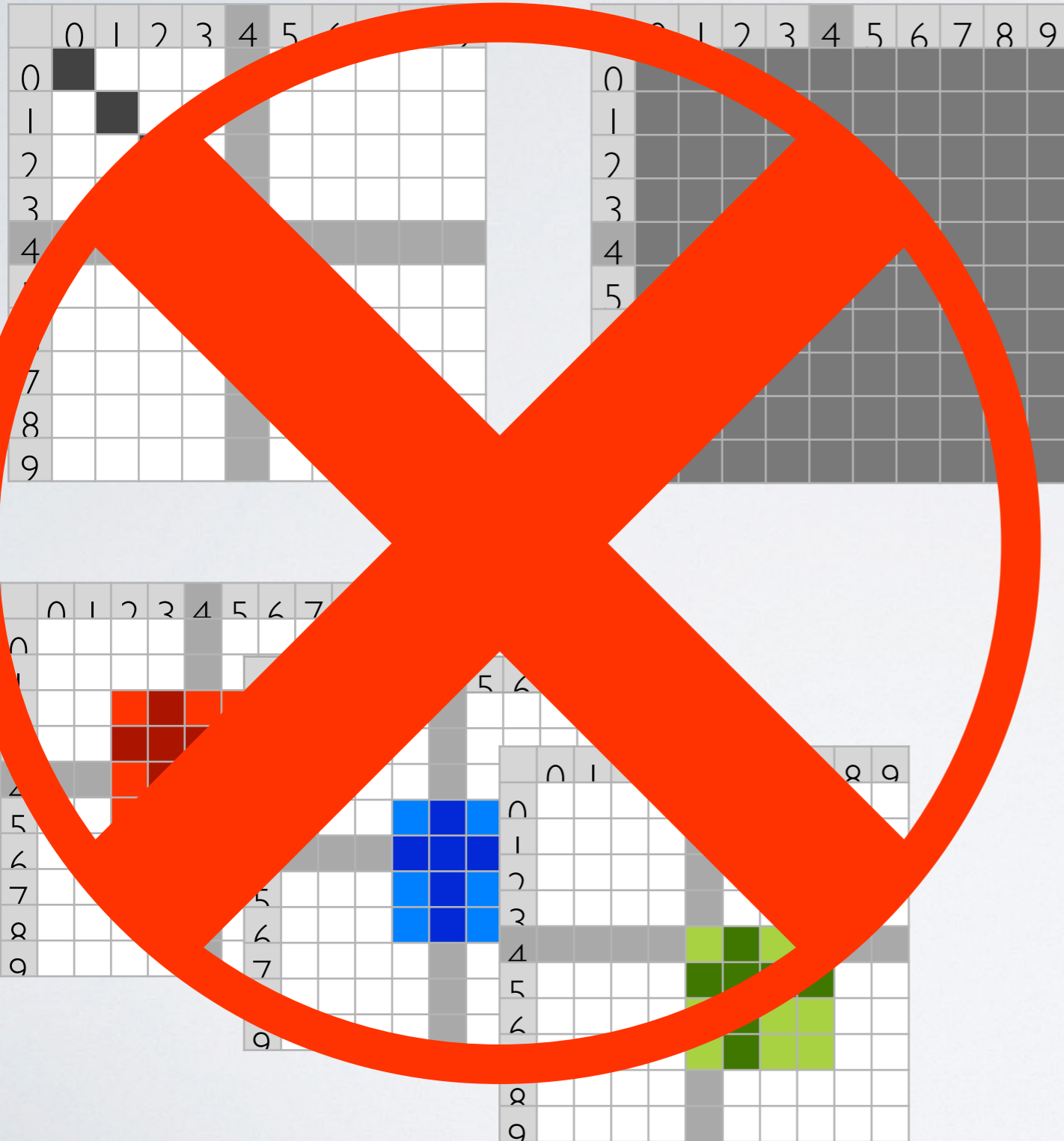


Correlated
(Pedestal/DC)



Pulse template uncertainty
(Time shifts)

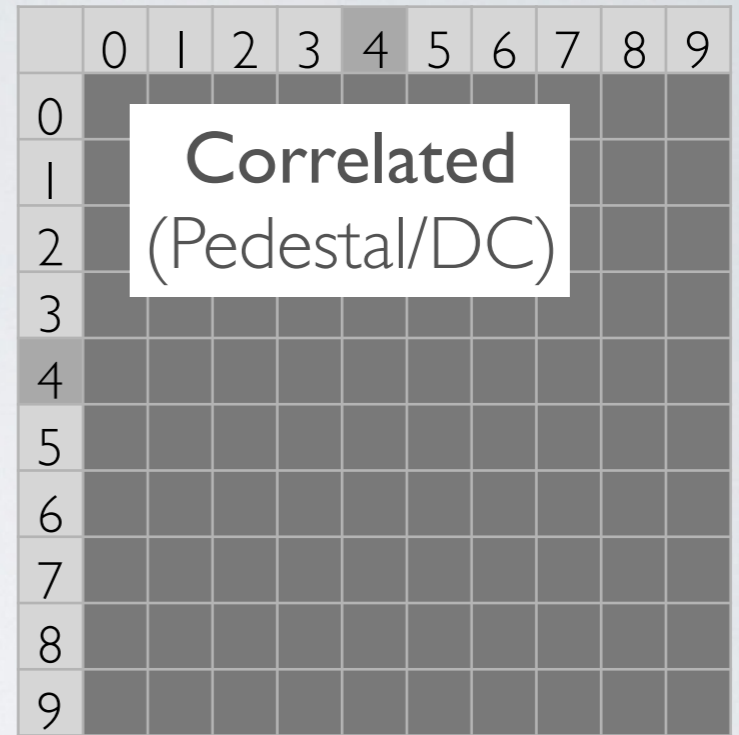
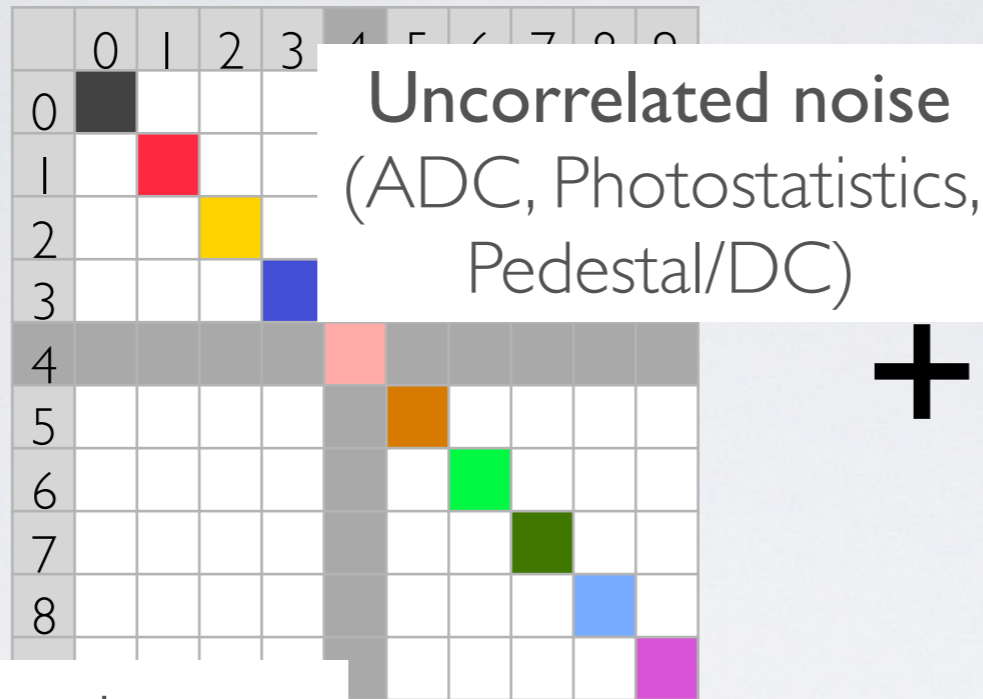
Method 3



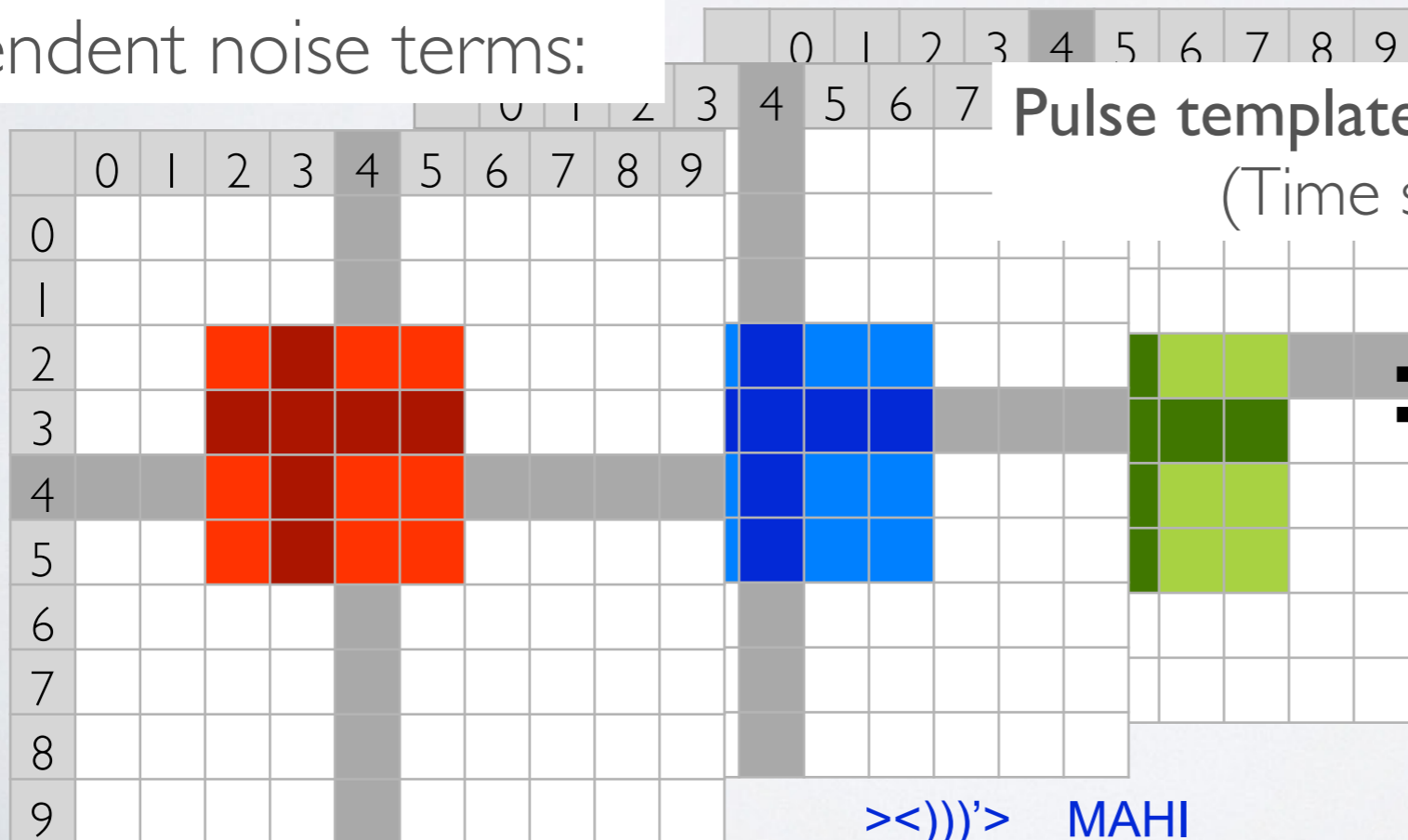
- Reduce problem to single matrix inversion
- No floating time/pulse template, pedestal
- Fully deterministic, no fit, no uncertainties considered

Mahi

- Σ_d : “dark” noise term:



- Σ_{p_i} : pulse amplitude-dependent noise terms:



$$= \left(\Sigma_d + \sum A_i^2 \Sigma_{p_i} \right)$$

Building the problem

- Have $X^2 =$

$$\left(\sum A_i \mathbf{p}_i - \mathbf{TS} \right)^T \left(\Sigma_d + \sum A_i^2 \Sigma_{\mathbf{p}_i} \right)^{-1} \left(\sum A_i \mathbf{p}_i - \mathbf{TS} \right)$$

- Now what?

- A_i : amplitudes
- \mathbf{p}_i : the pulse shapes
- \mathbf{TS} : observed data

- fast Non-Negative Least Squares (NNLS) minimizer
- But quickly, a word about current initialization:
 - Allow for a pulse arriving in TS3, TS4, and TS5 (as in Method 2)
 - All pulse amplitudes 0 except for TS4 which is set to charge in TS4 with pulse shape containment correction

Minimization

- **For each iteration:**

- **Update covariance matrix**

$$\left(\Sigma_{\mathbf{d}} + \sum A_i^2 \Sigma_{\mathbf{p}_i} \right)$$

- $\Sigma_{\mathbf{d}}$ and $\Sigma_{\mathbf{p}_i}$ don't change, just accessed
 - A_i^2 are updated based on previous iteration
 - sum of all terms calculated
 - invert result
 - **Run NNLS**
 - Calculate X^2
 - If $dX^2 < 1E-3$ or maxlts reached, **return result.**
 - Else, **repeat.**

Fast NNLS Algorithm

from *Nonnegativity constraints in numerical analysis*,
Chen and Plemmons

Algorithm *fnnls* :

Input: $\mathbf{A} \in \mathbf{R}^{m \times n}$, $\mathbf{b} \in \mathbf{R}^m$

Output: $\mathbf{x}^* \geq 0$ such that $\mathbf{x}^* = \arg \min \|\mathbf{Ax} - \mathbf{b}\|^2$.

Initialization: $P = \emptyset$, $R = \{1, 2, \dots, n\}$, $\mathbf{x} = \mathbf{0}$, $\mathbf{w} = \mathbf{A}^T \mathbf{b} - (\mathbf{A}^T \mathbf{A}) \mathbf{x}$

repeat

1. Proceed if $R \neq \emptyset \wedge [\max_{i \in R}(w_i) > tolerance]$
 2. $j = \arg \max_{i \in R}(w_i)$
 3. Include the index j in P and remove it from R
 4. $\mathbf{s}^P = [(\mathbf{A}^T \mathbf{A})^P]^{-1} (\mathbf{A}^T \mathbf{b})^P$
 - 4.1. Proceed if $\min(\mathbf{s}^P) \leq 0$
 - 4.2. $\alpha = -\min_{i \in P}[x_i / (x_i - s_i)]$
 - 4.3. $\mathbf{x} := \mathbf{x} + \alpha(\mathbf{s} - \mathbf{x})$
 - 4.4. Update R and P
 - 4.5. $\mathbf{s}^P = [(\mathbf{A}^T \mathbf{A})^P]^{-1} (\mathbf{A}^T \mathbf{b})^P$
 - 4.6. $\mathbf{s}^R = \mathbf{0}$
 5. $\mathbf{x} = \mathbf{s}$
 6. $\mathbf{w} = \mathbf{A}^T (\mathbf{b} - \mathbf{Ax})$
-

Details

- If in-time charge above `TS4Thresh_(0)`:
 - If `chisSqSwitch_(10)` is positive:
 - do 1 pulse fit
 - if 1 pulse `chiSq` greater than `chisSqSwitch_(10)`:
 - repeat fit with `activeBXs_` (filling scheme from config)
 - Else:
 - do fit with `activeBXs_`
- No energy-threshold for 1 vs 3 pulse switch as in Method 3

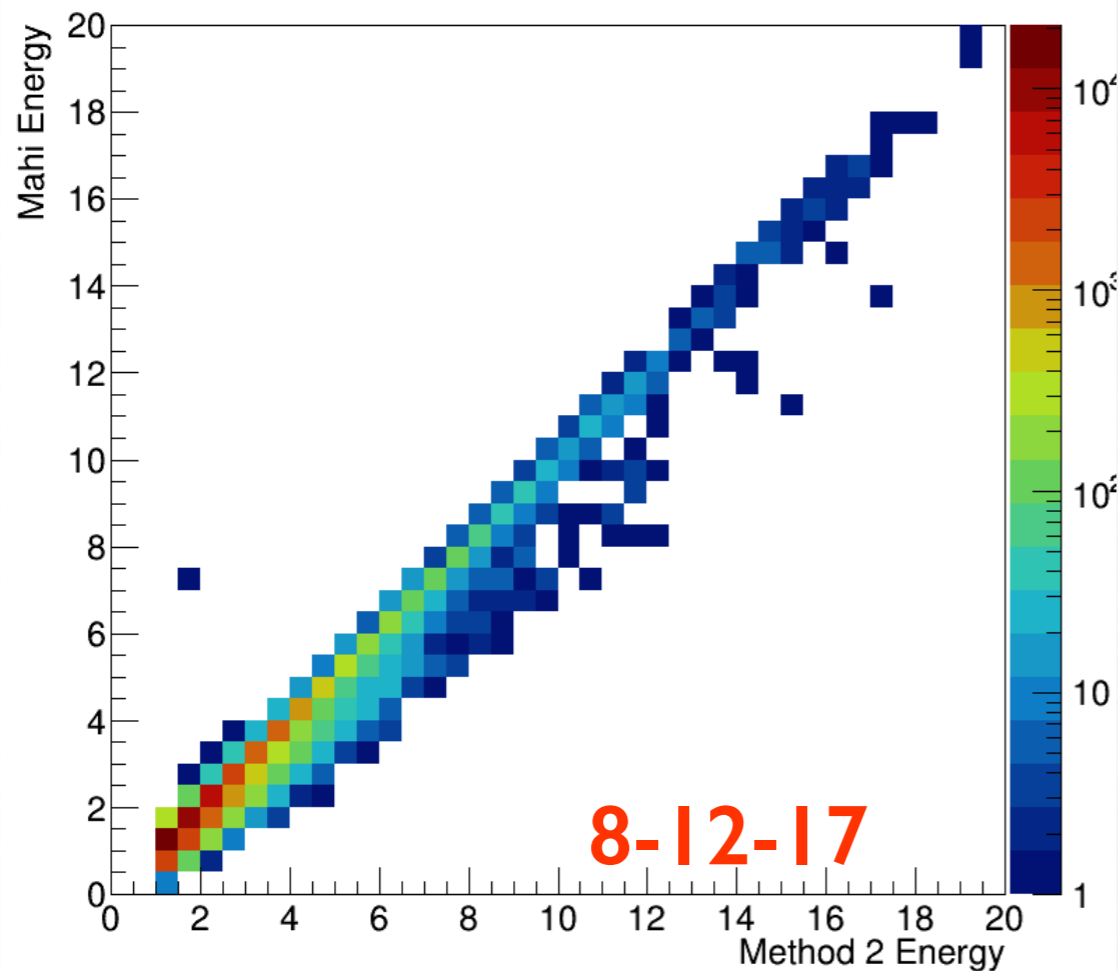
Performance

Performance: Single bunches

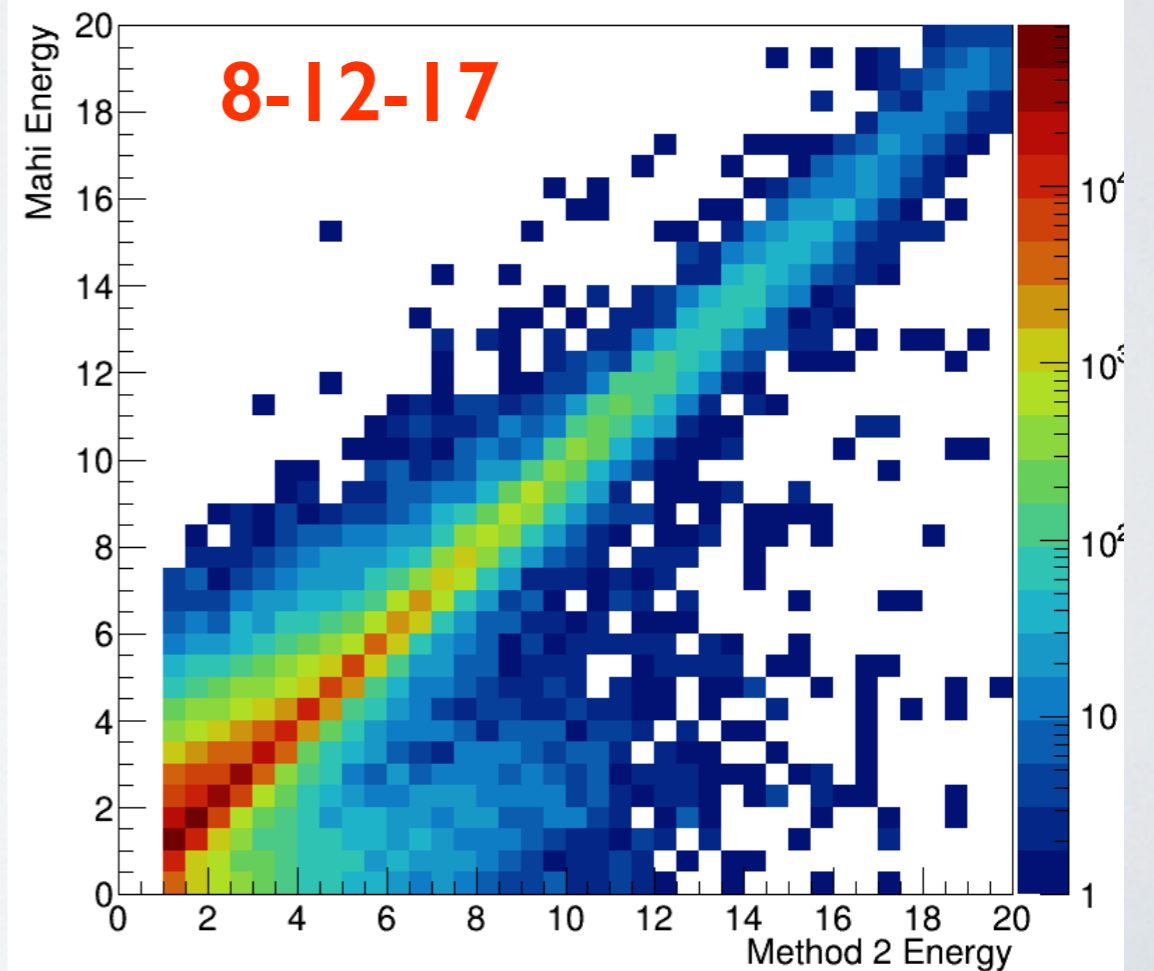
Compare Mahi energy to Method 2 energy in single bunch collisions:

Data from Run 296642 (Fill 5822)
Filling scheme Single_10b_9...
Post-HEP17 phase alignment
Using SiPM shape 205

SiPM



HPD

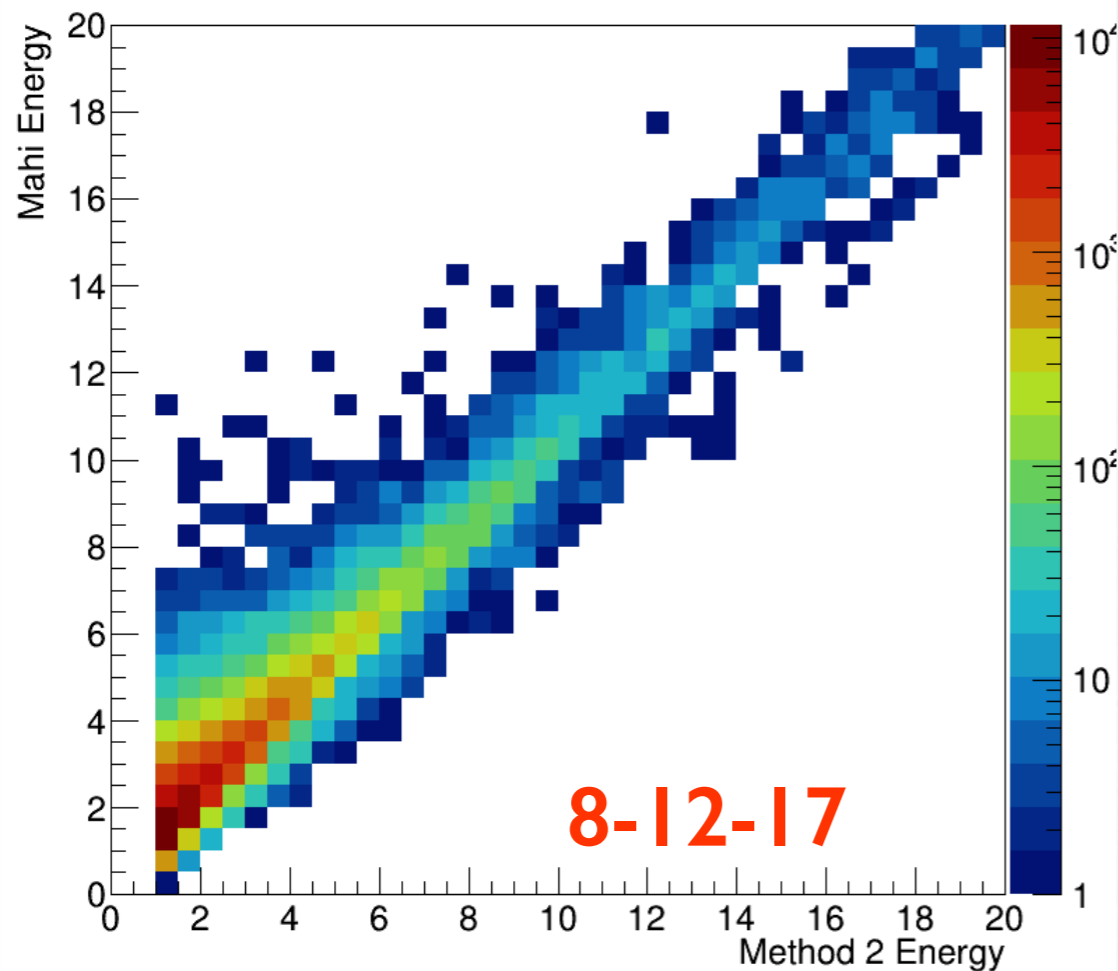


Performance: Bunch trains

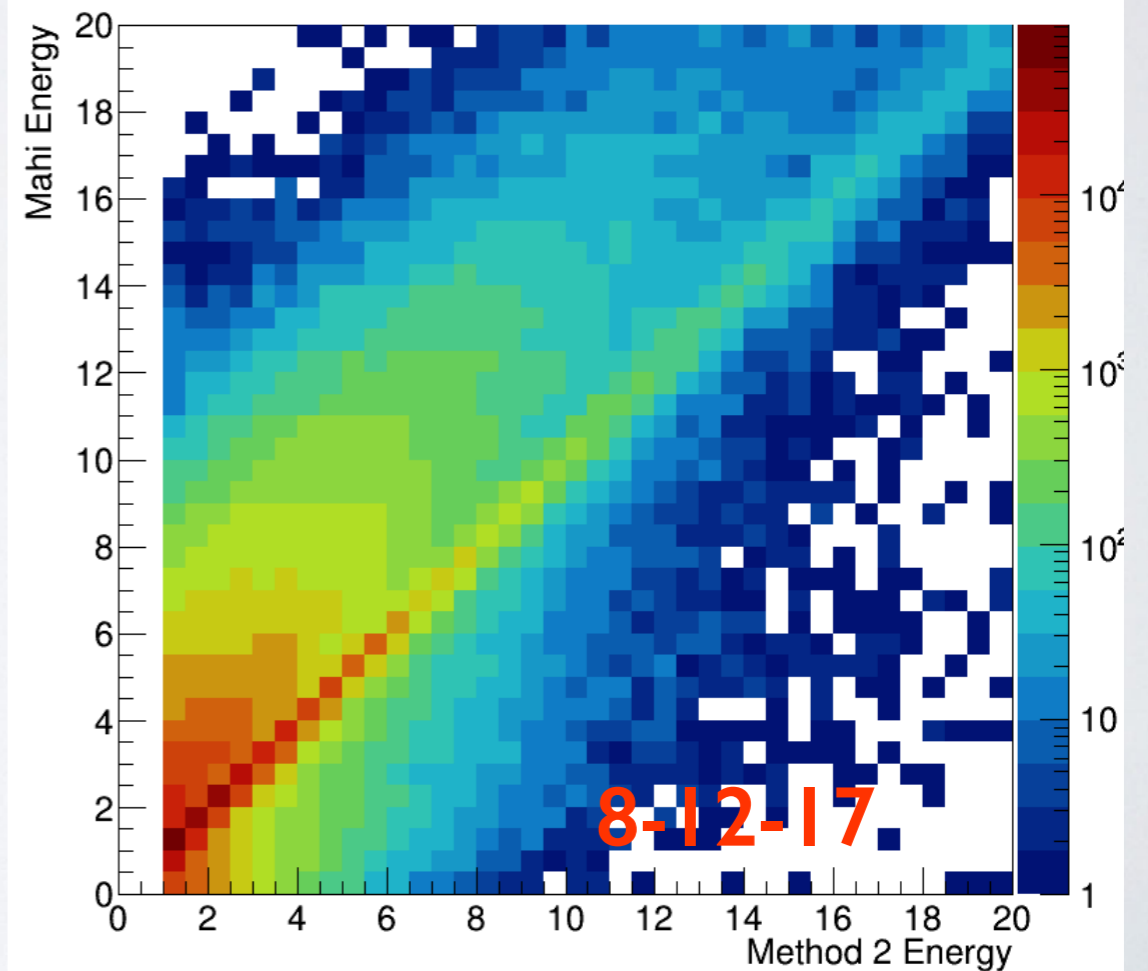
Compare Mahi energy to
Method 2 energy with
out of time pileup:

Data from Run 305809 (Fill 6341)
Filling scheme 25ns_1868b...
128bpi_17i8b4e
 $\langle n \rangle = 58$

SiPM



HPD

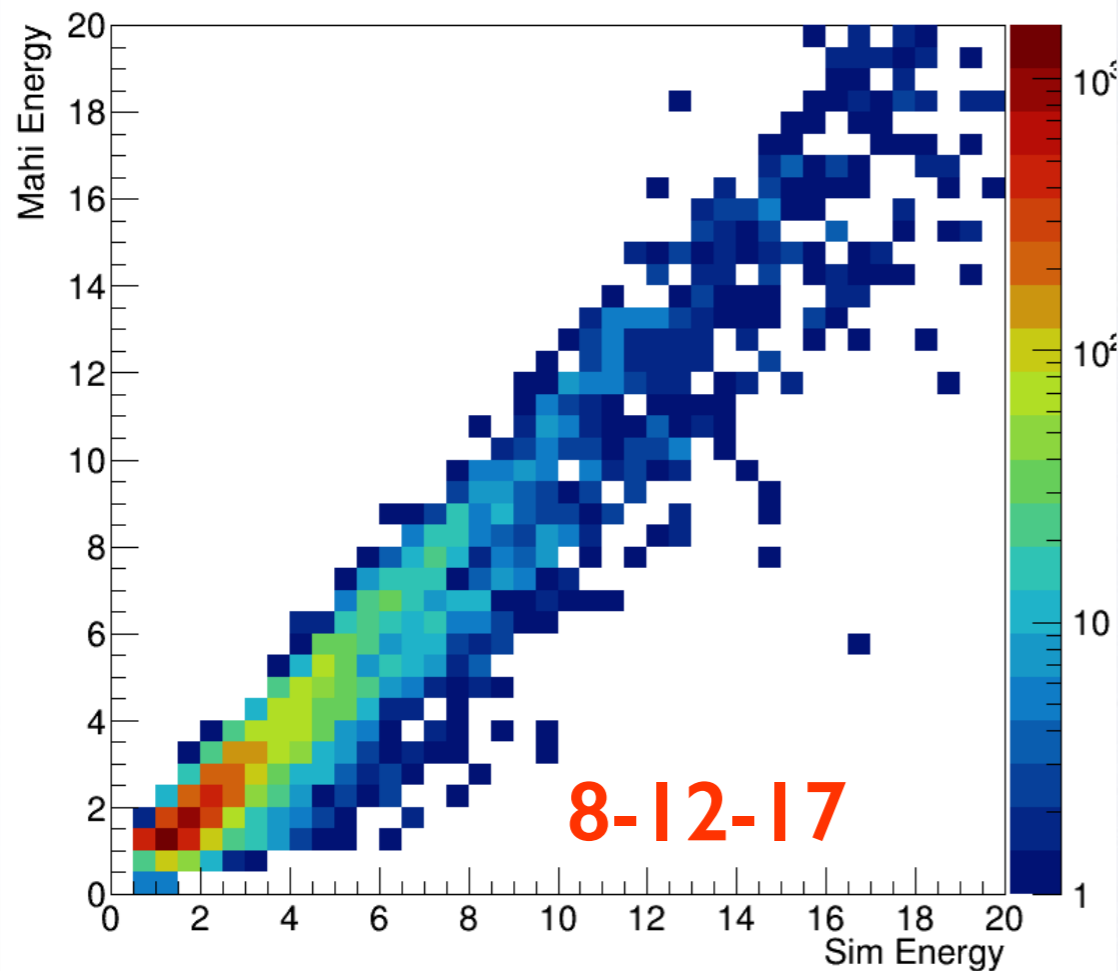


Performance: NoPU Simulation

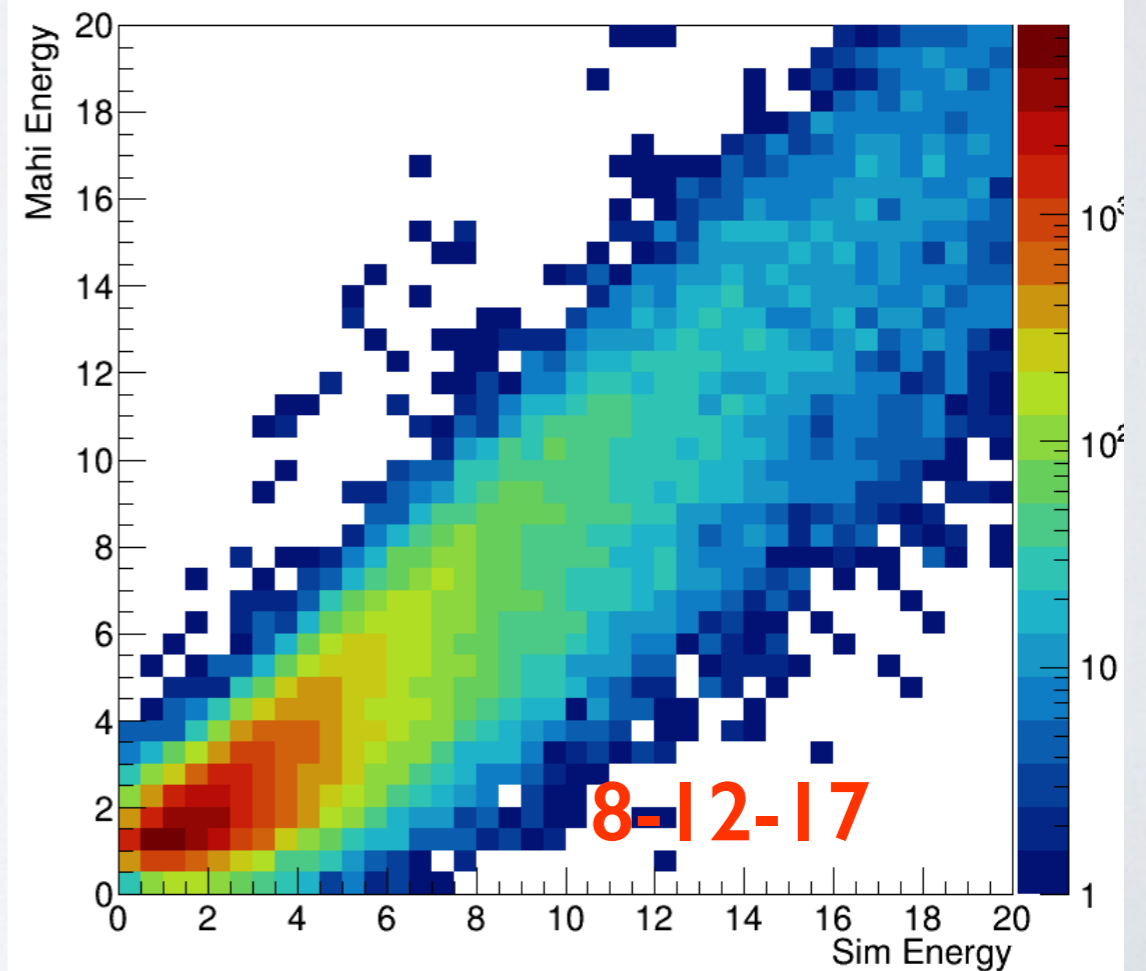
Compare Mahi energy to Sim-level energy in no pileup MC:

No pileup monte carlo

SiPM



HPD

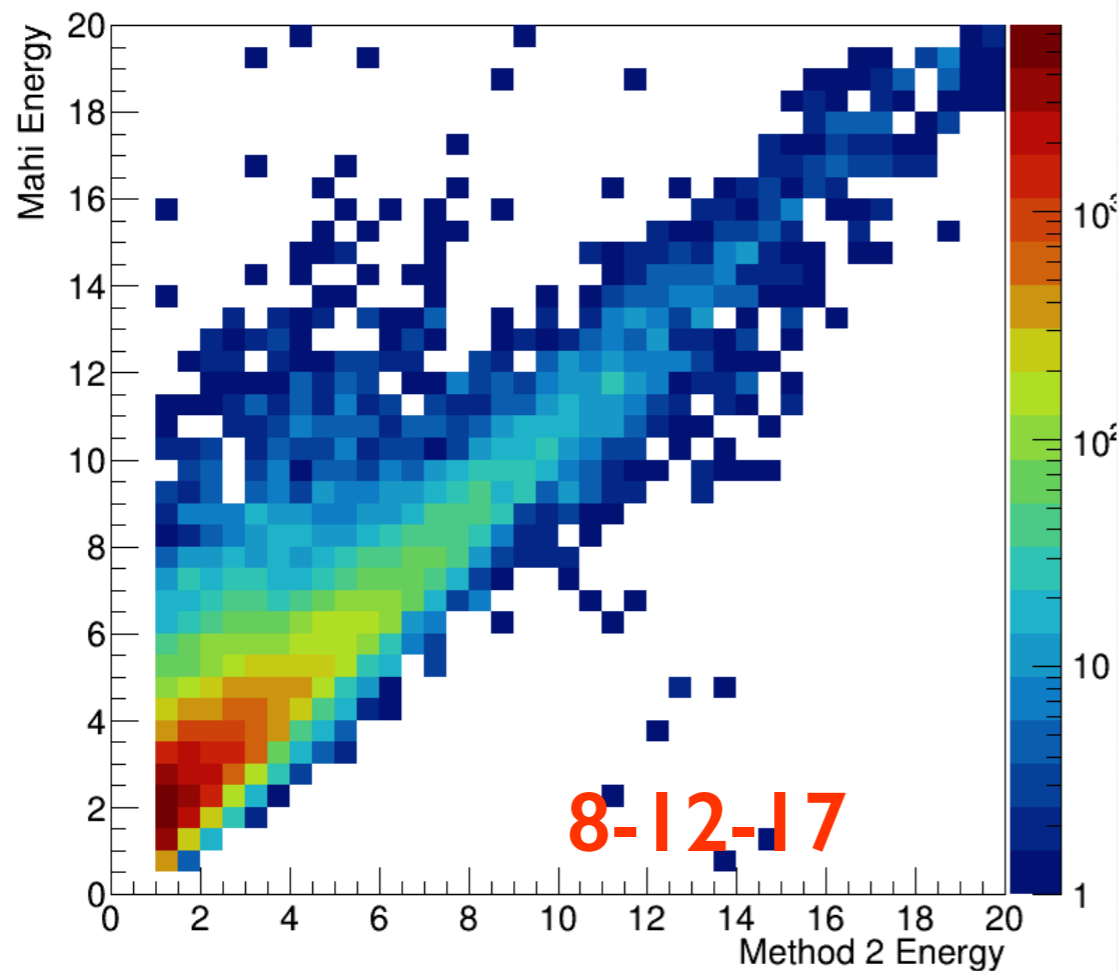


Performance: PU Simulation

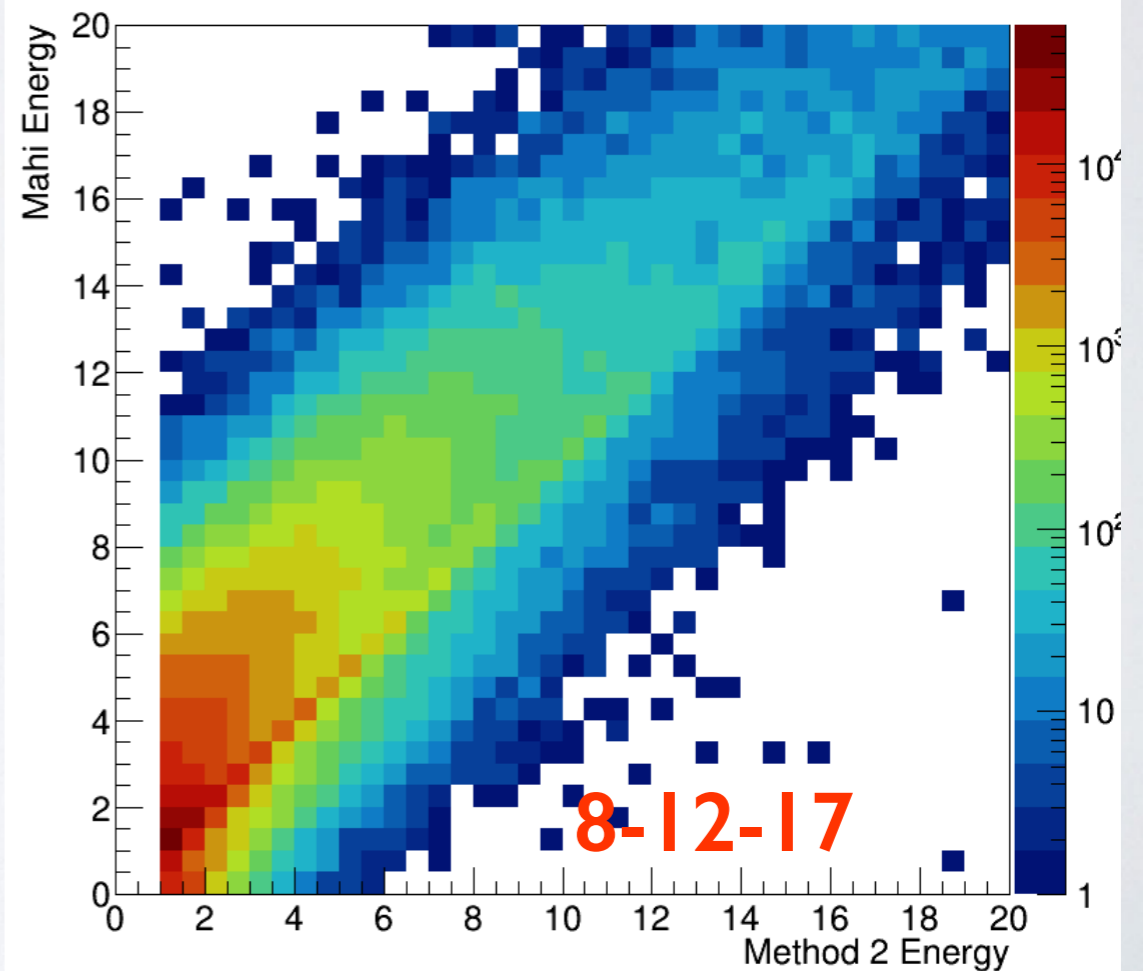
Compare Mahi energy to Method 2 energy with out of time pileup simulation:

ReValQCD PU25ns

SiPM



HPD



CPU timing

- In $\langle n \rangle = 58$ data, Mahi is
 - ~10 times faster than Method 2,
 - ~6 times slower than Method 3
- In single bunch data, Mahi is
 - ~6 times faster than Method 2,
 - ~5 times slower than Method 3
- Timing results from igprof using 1000 events per scenario
- CPU timing critical for use at HLT, will need TSG feedback

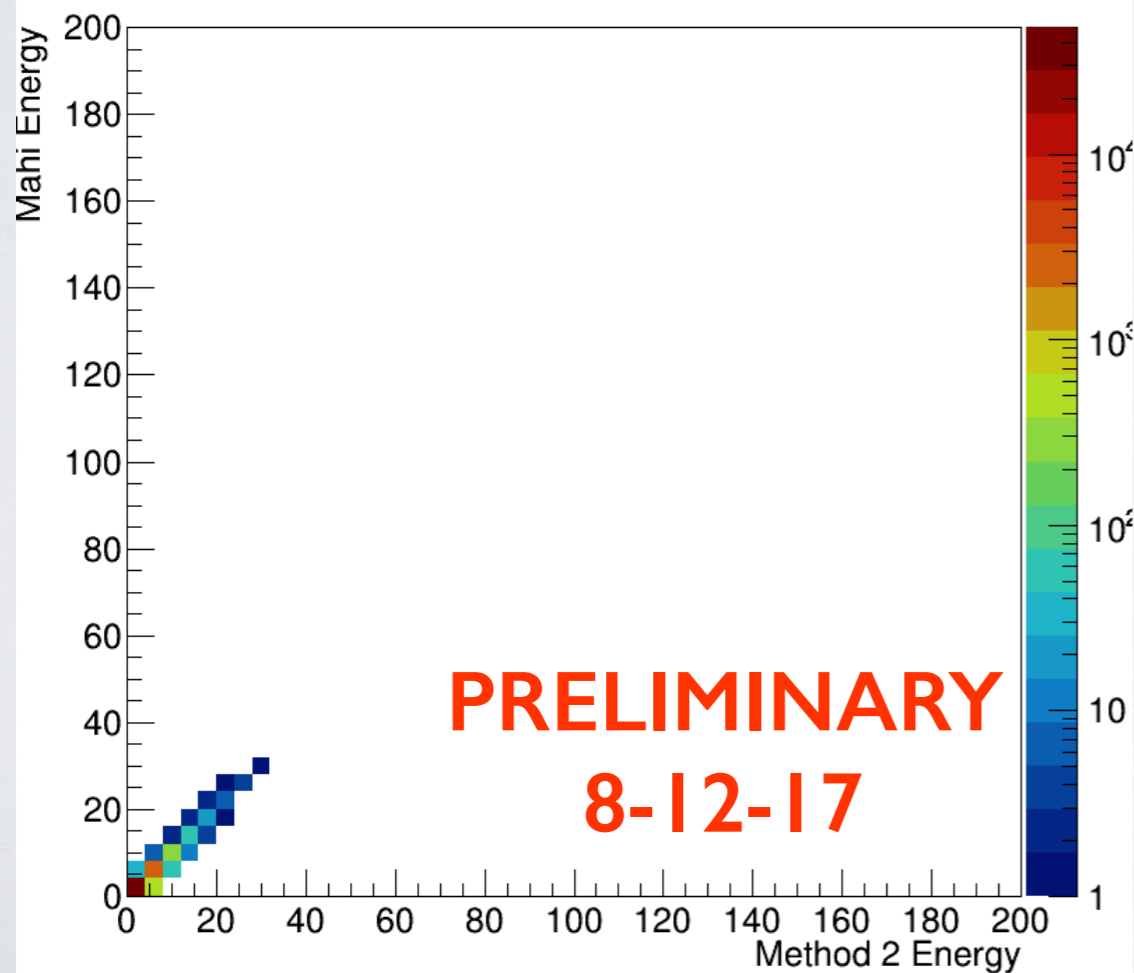
Backup

Single bunches vs Method 2

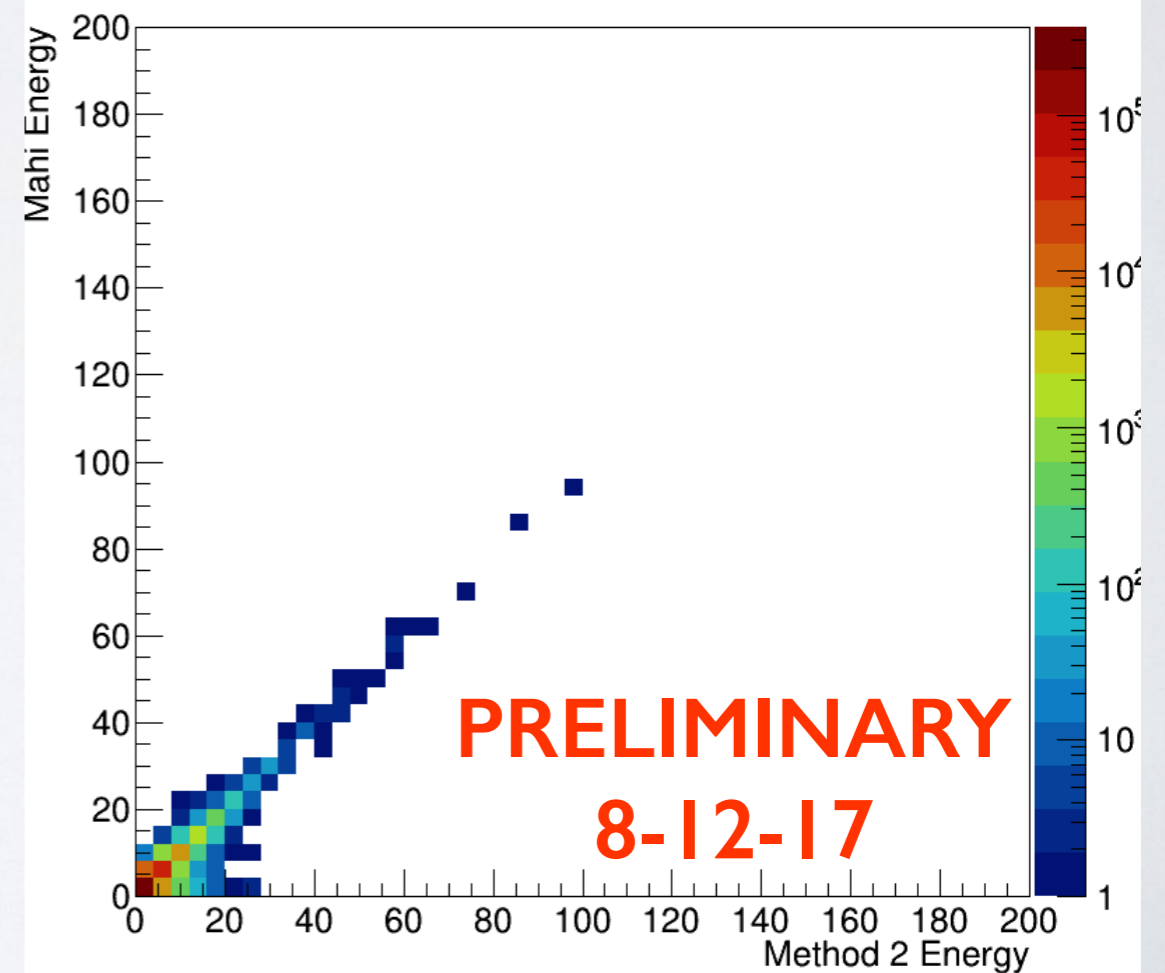
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SiPM



HPD

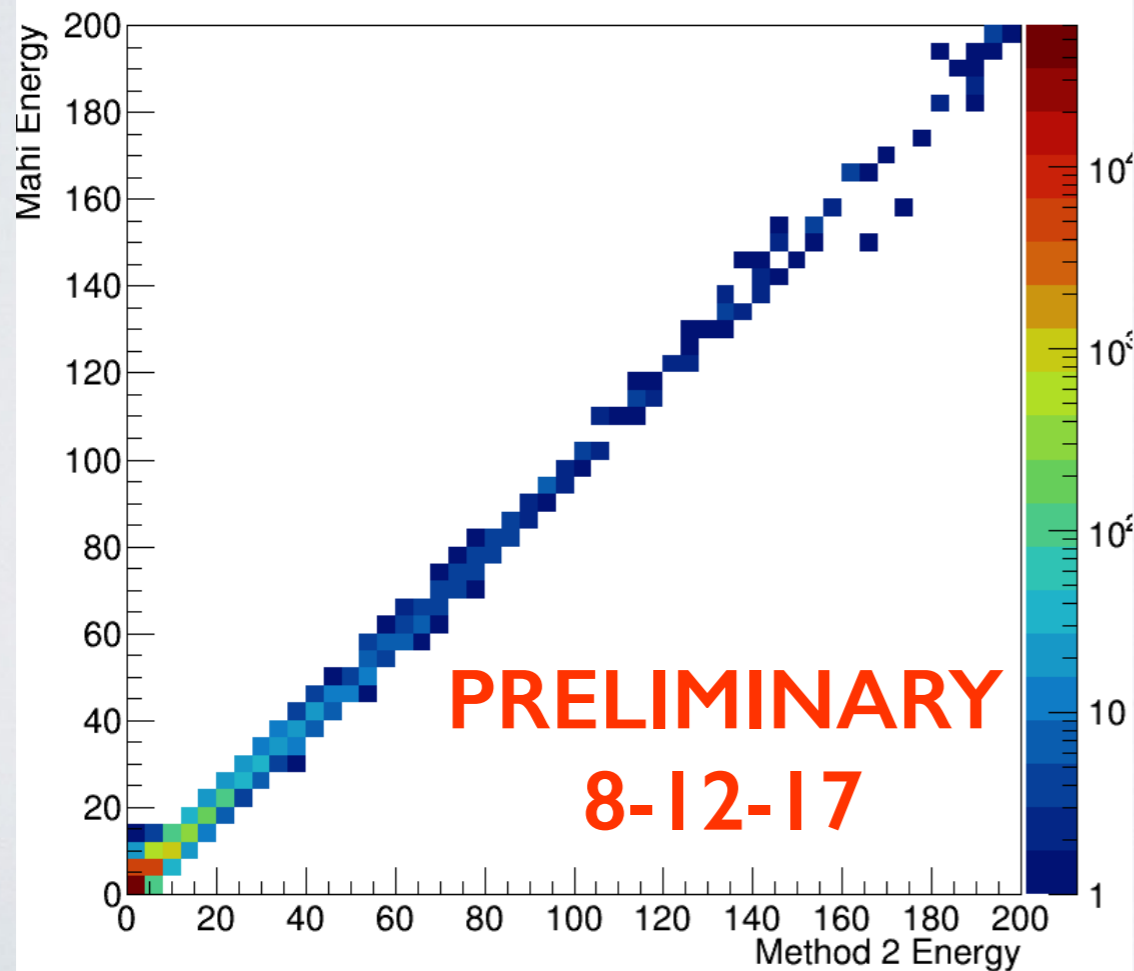


Bunch Trains vs Method 2

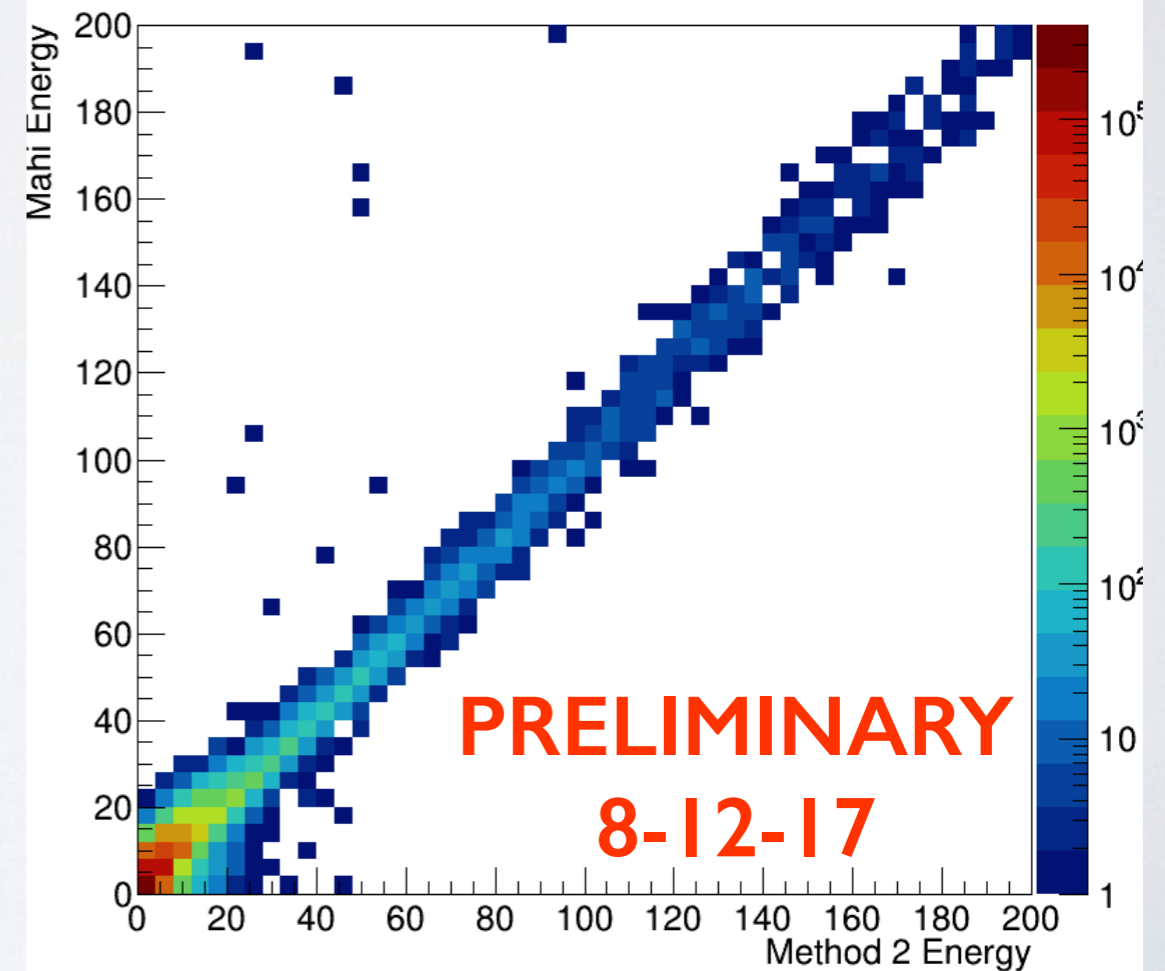
Compare Mahi energy to Method 2 energy with out of time pileup:

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Filling scheme 25ns_1868b...
128bpi_17i8b4e
 $\langle n \rangle = 58$

SiPM



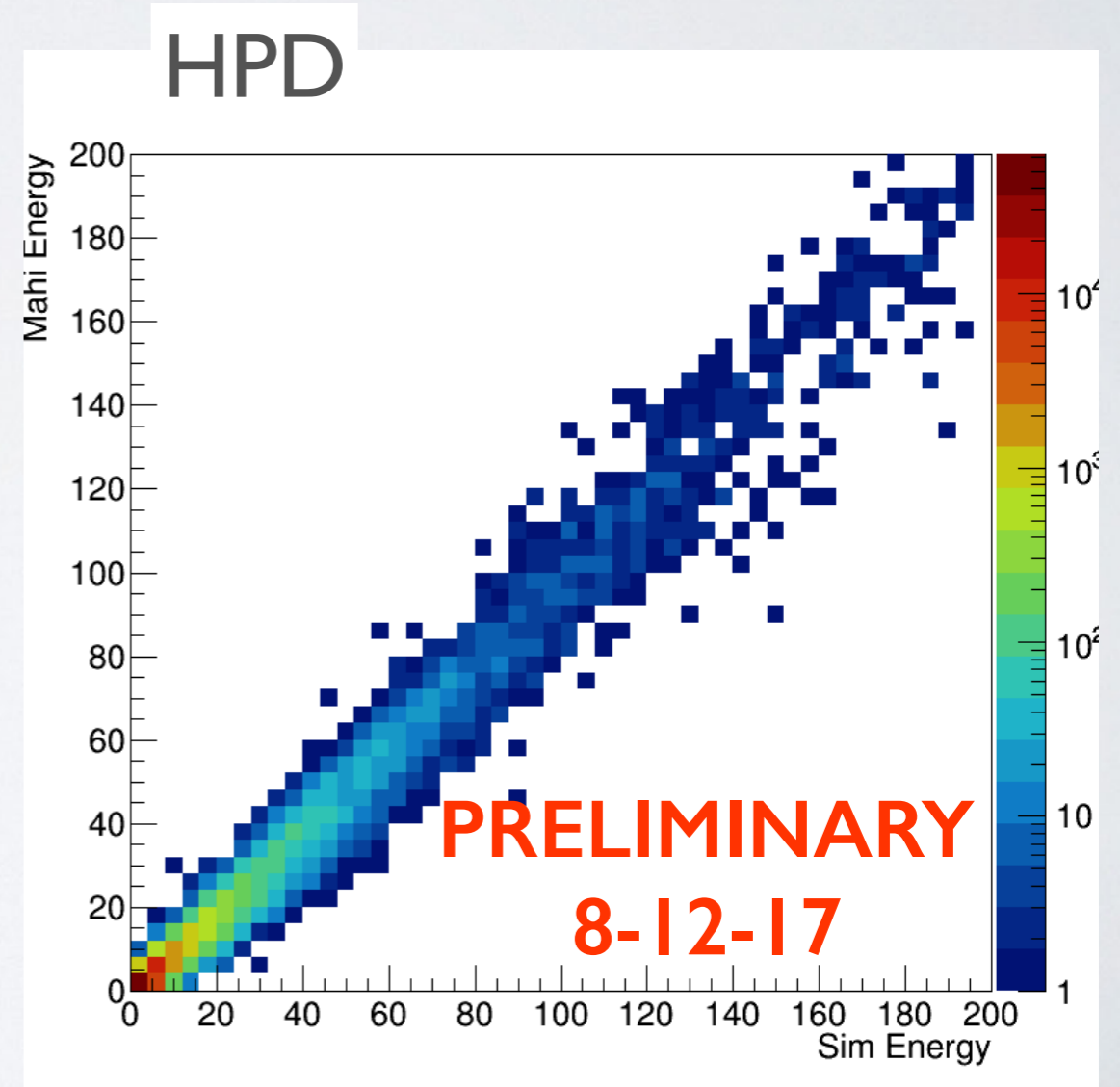
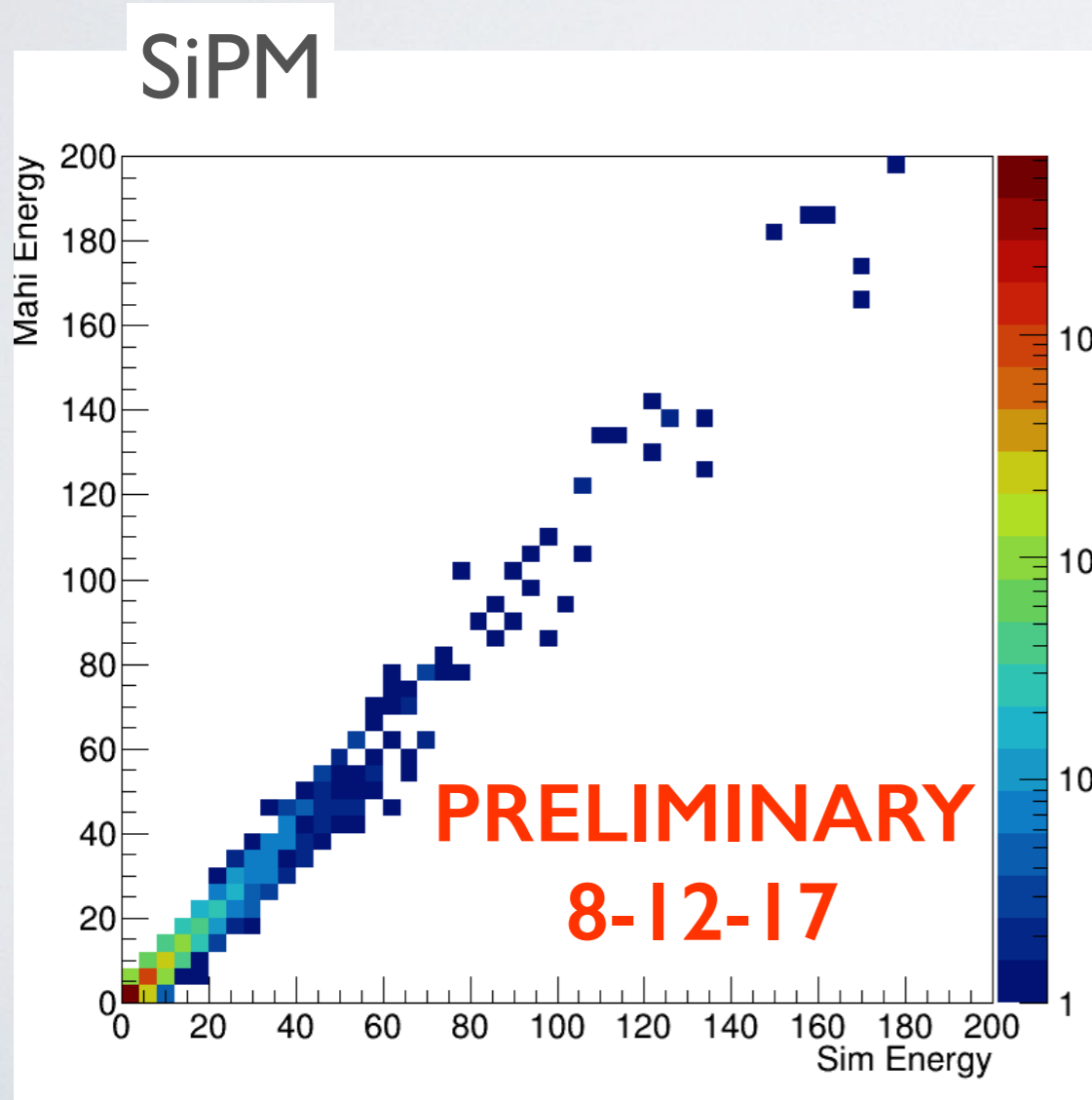
HPD



NoPU vs Sim

Compare Mahi energy to Sim-level energy in no pileup MC:

No pileup monte carlo

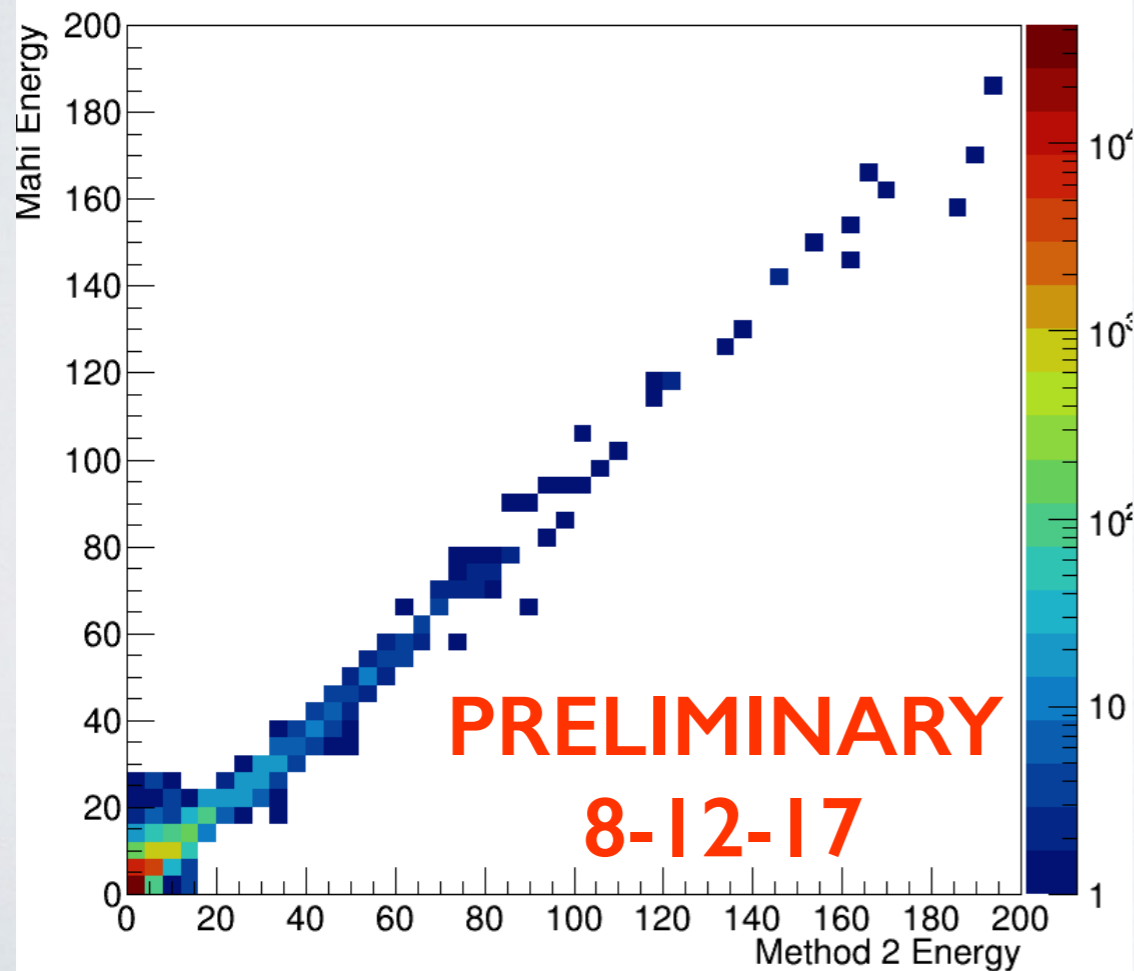


PU vs Method 2

Compare Mahi energy to Method 2 energy with out of time pileup simulation:

RelValQCD PU25ns

SiPM



HPD

