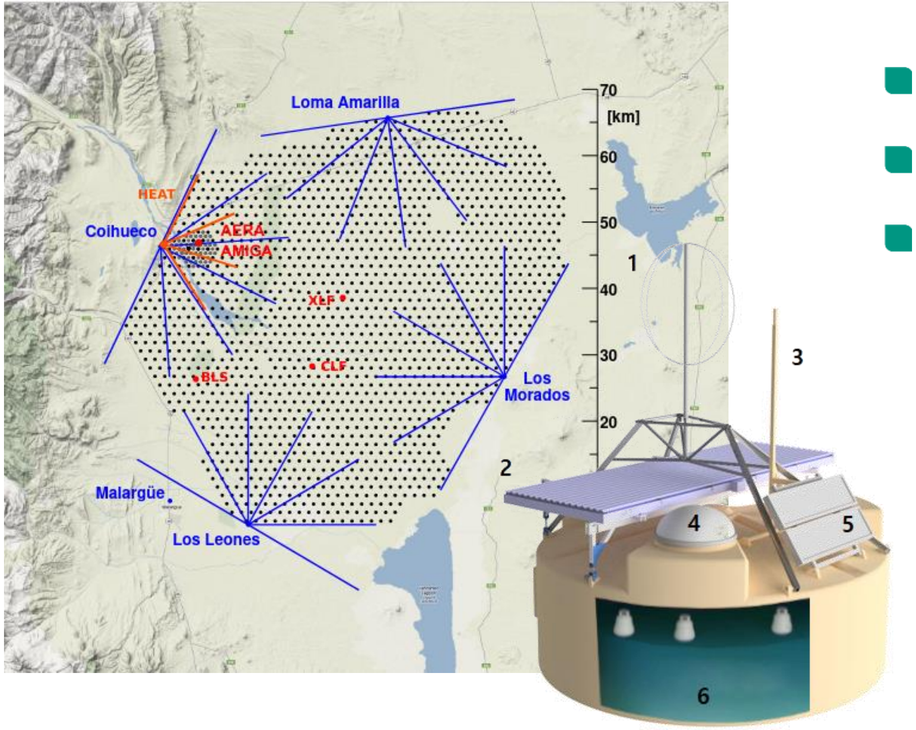
# Potential of neural network triggers for the Water-Cherenkov detector array of the Pierre Auger Observatory

Paul Filip - High Energy Universe seminar 01.06.23

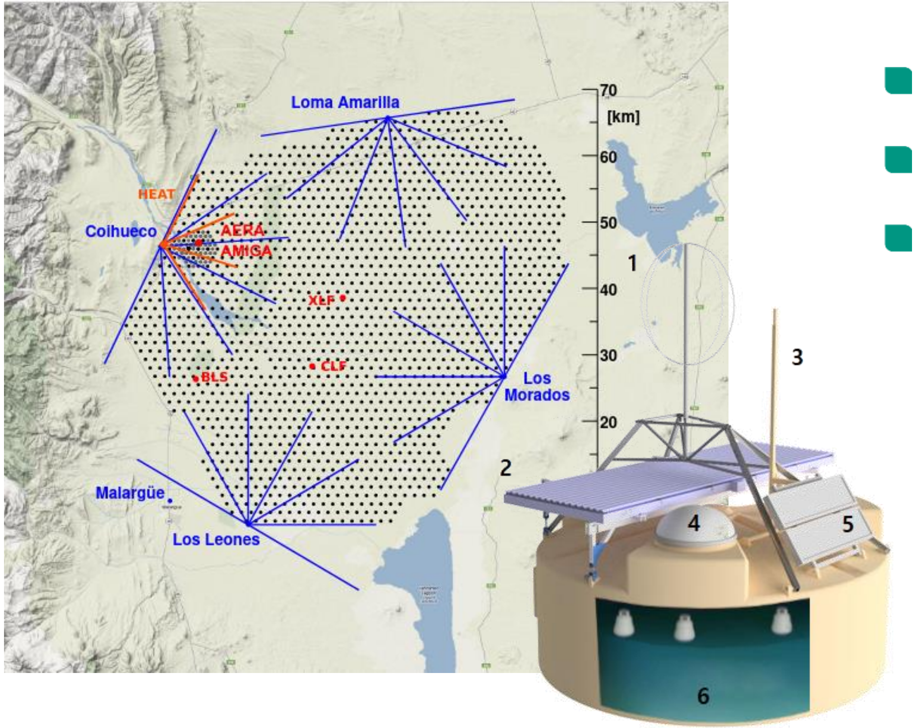
# SD Array / trigger hierarchy / WCD time traces

Karlsruhe Institute of Technology




- **Around ~1600 stations**
- **Triangular $1.5\ \mathrm{km}$ grid spacing**
- **Ongoing upgrade from UB → UUB**
  - **3 Water-Cherenkov detectors (WCD)**
  - 1 Surface scintillator detector (SSD)
  - 1 Radio antenna

# SD Array / trigger hierarchy / WCD time traces

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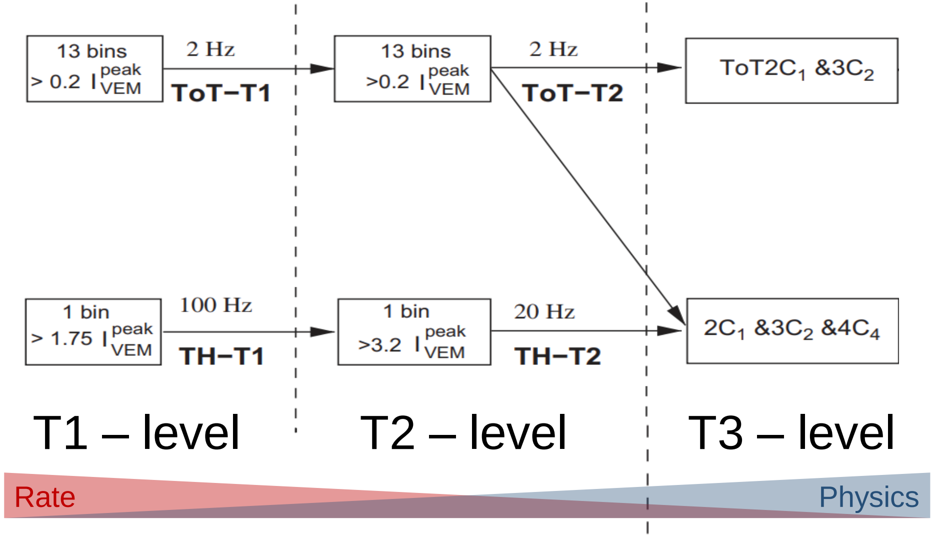
**Too comput. expensive to read all measured data at all times!**

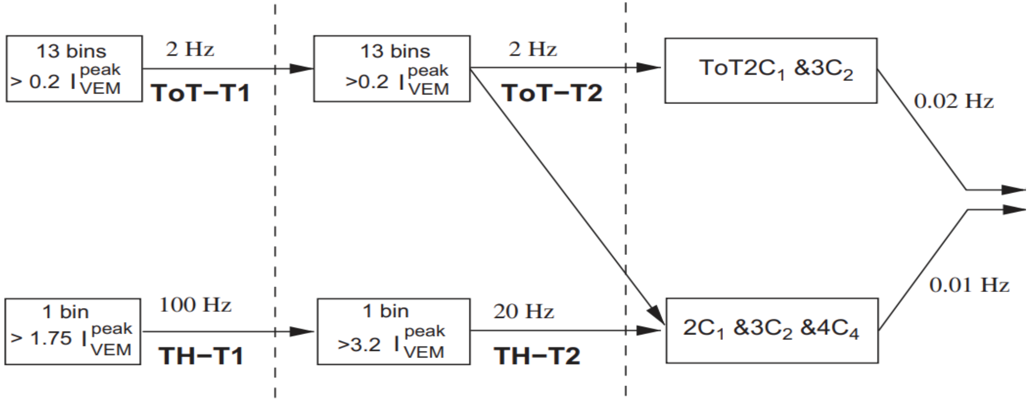
**→ Implement trigger hierarchy**

# SD Array / **trigger hierarchy** / WCD time traces




Raised at ...station-level ... CDAS level

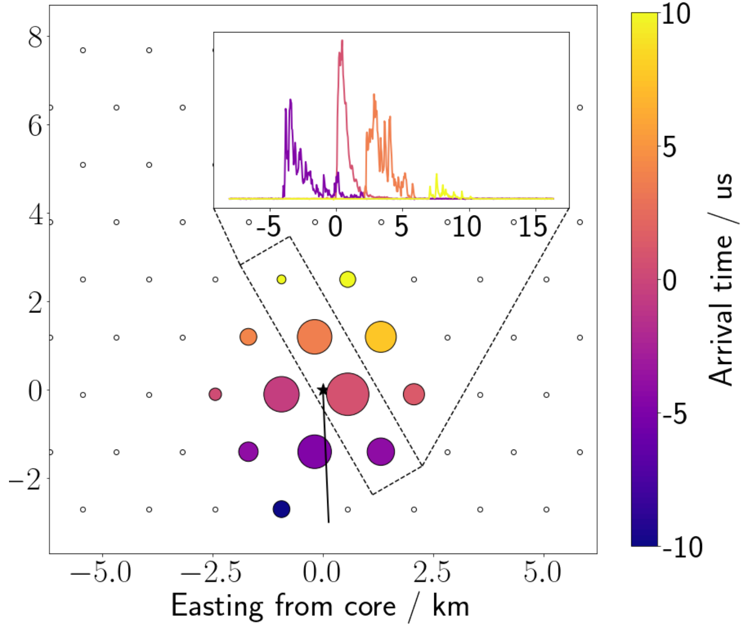
# SD Array / **trigger hierarchy** / WCD time traces




T1 – level | T2 – level | T3 – level

Rate | Physics

Raised at …station-level … CDAS level



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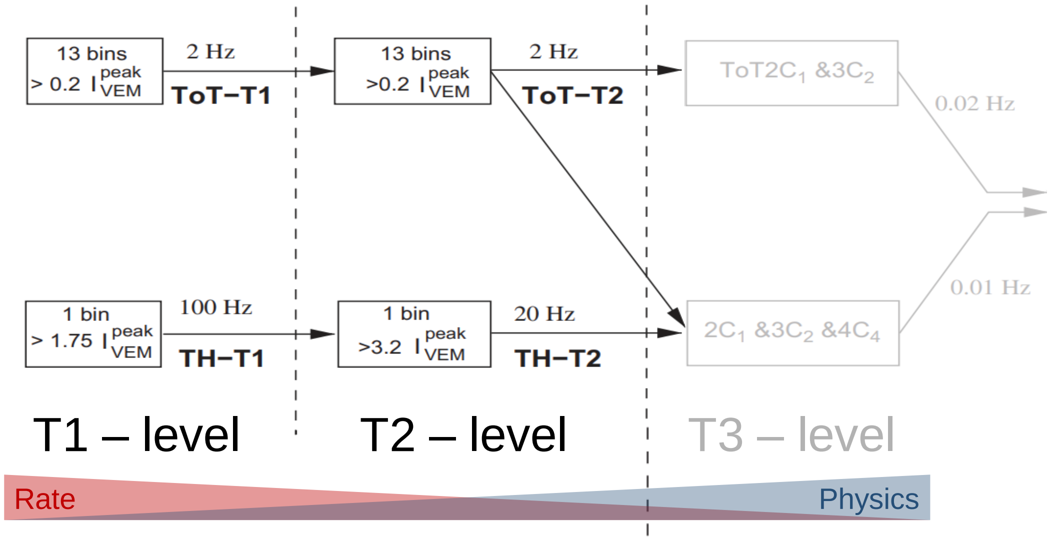


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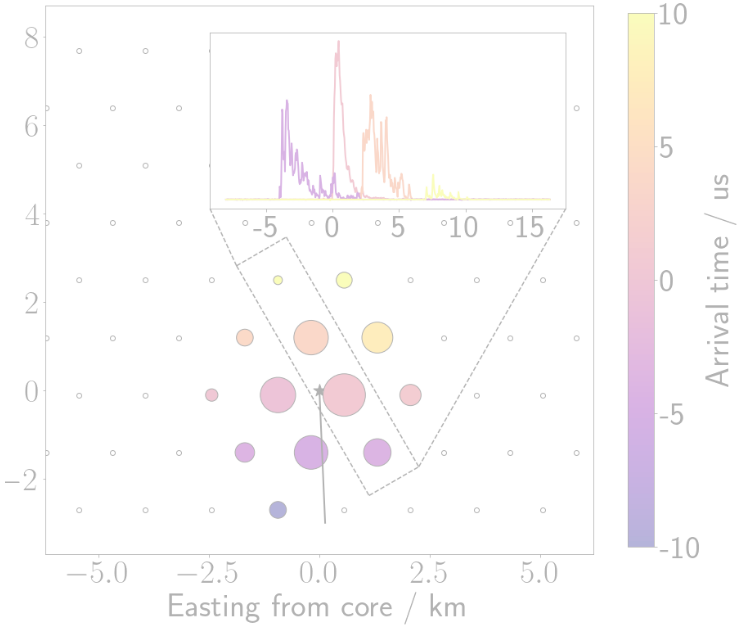
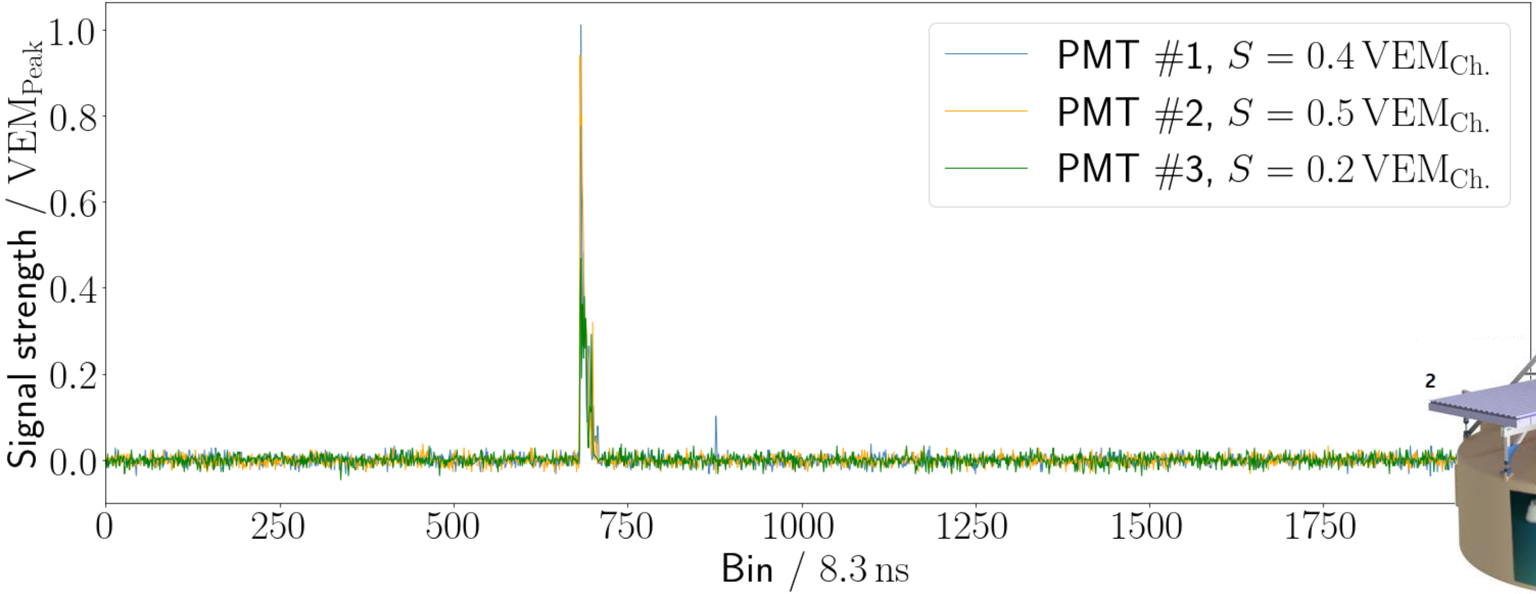
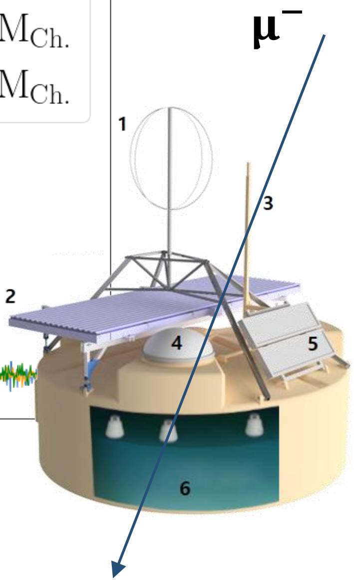



- **Threshold trigger (Th)**
- **Time over threshold (ToT) & ToT-like triggers**

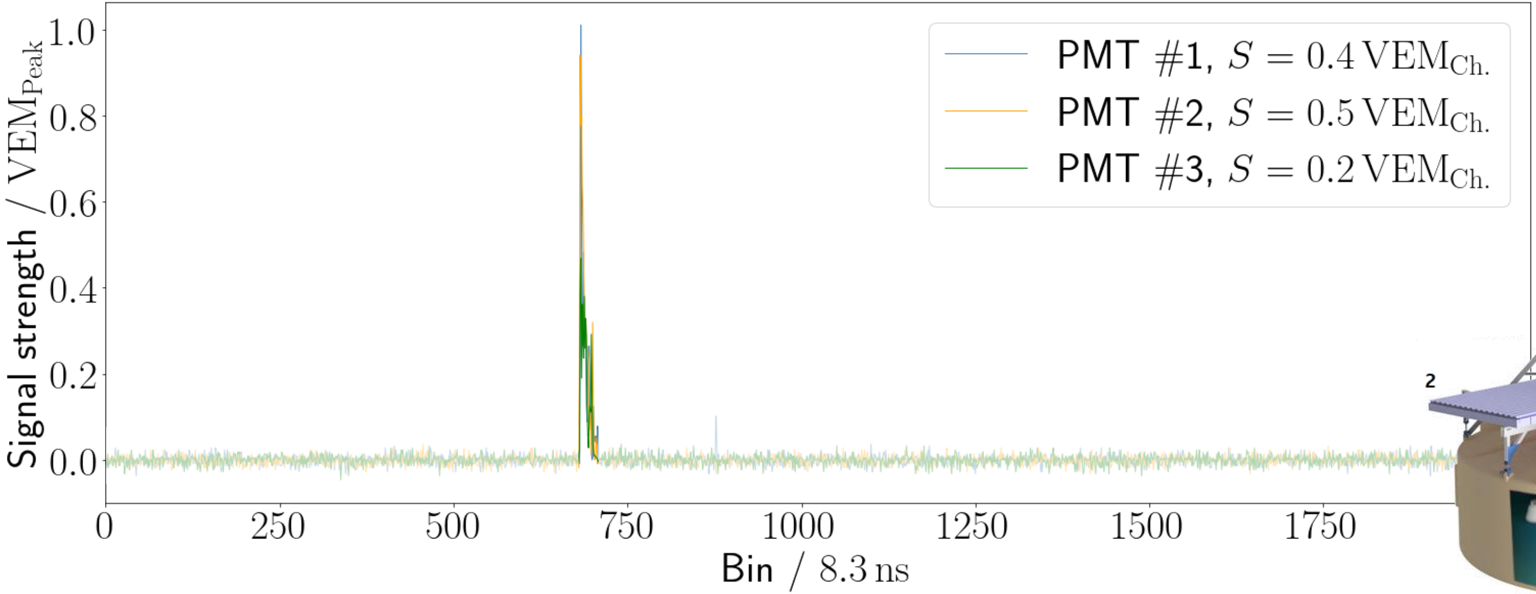
# SD Array / trigger hierarchy / WCD time traces

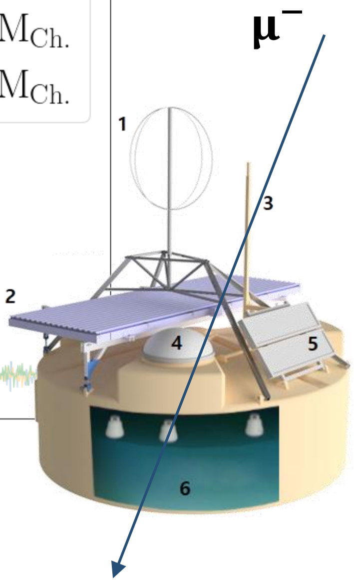



- **Measured in** $\mathrm{VEM_{Peak}}$ **/** $\mathrm{VEM_{Ch.}}$
- $120\ \mathrm{MHz}$ **sampling frequency**

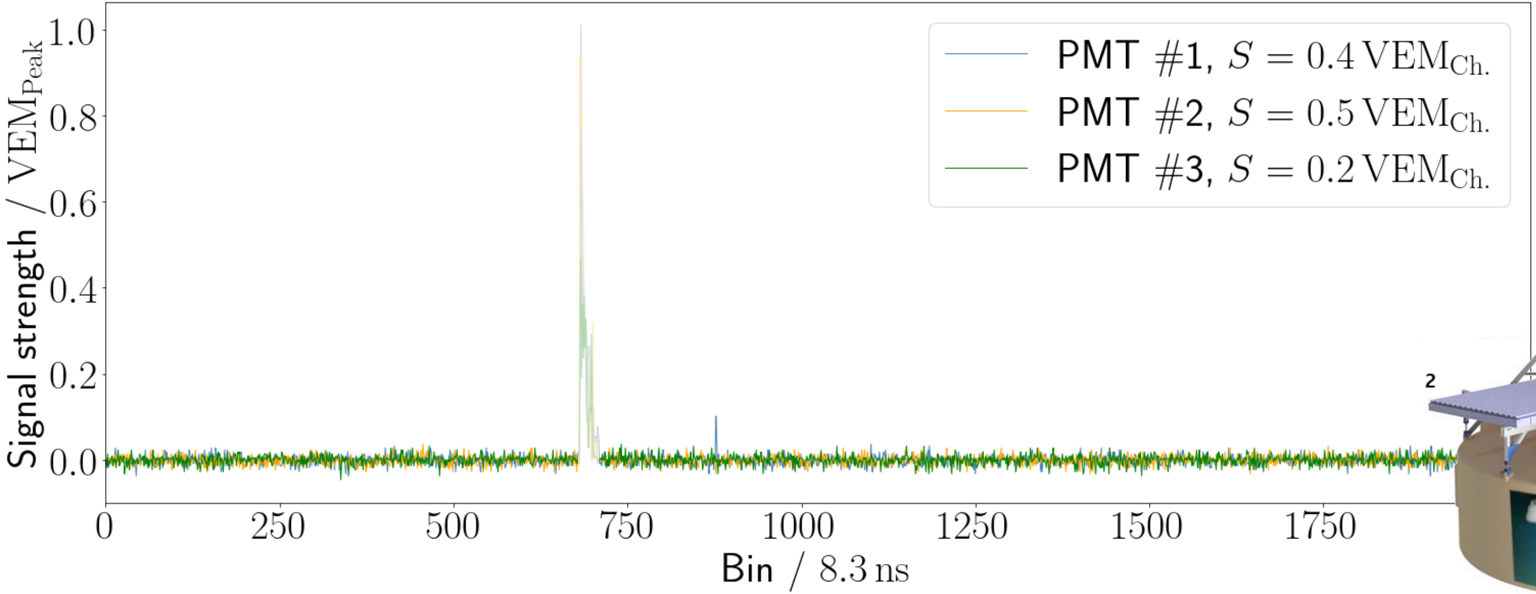
# SD Array / trigger hierarchy / WCD time traces

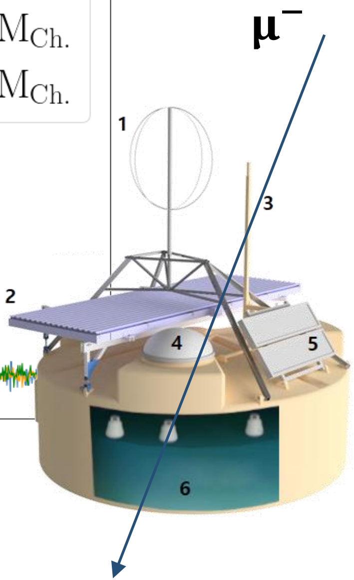



- **QGSJET-II.04 protons with** $16 \leq \log_{10}(\mathrm{E} / \mathrm{eV}) < 19.5$
- **Background electronic noise measured in field**

# SD Array / trigger hierarchy / **WCD time traces**

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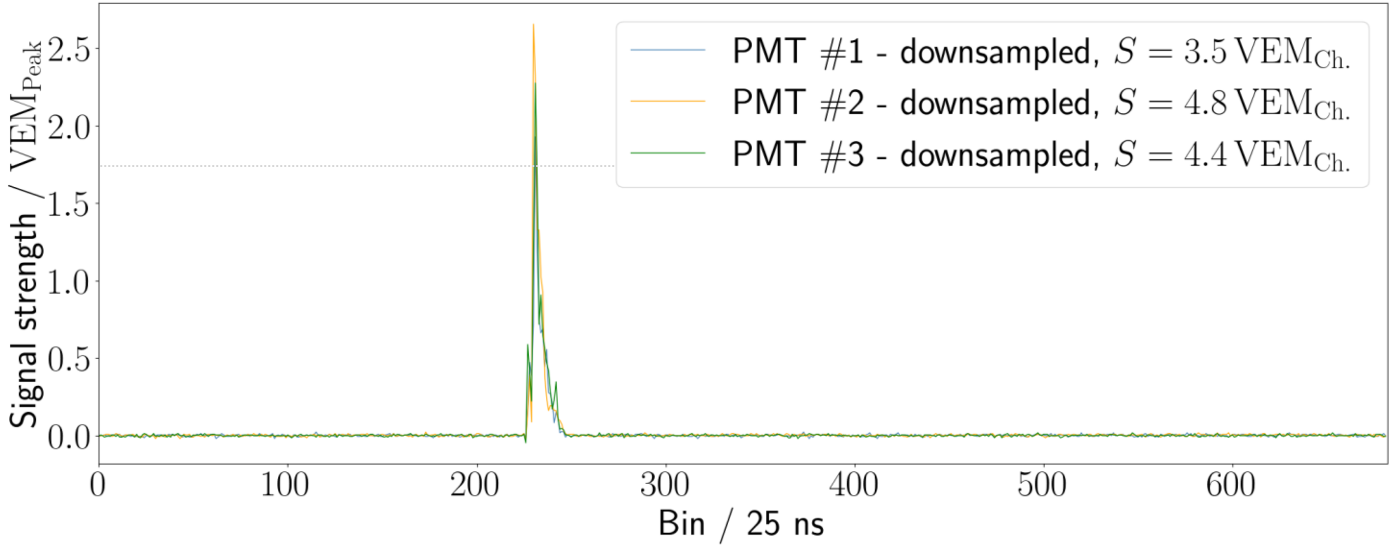
# Current station-level trigger algorithms

- **Threshold trigger (Th)**
  - **PMTs register signal** $S \geq 3.2\ \mathrm{VEM}_{\mathrm{Peak}}$ $(1.75\ \mathrm{VEM}_{\mathrm{Peak}}$ **for T1**)
  - **Threshold must be exceeded simultaneously for all PMTs**



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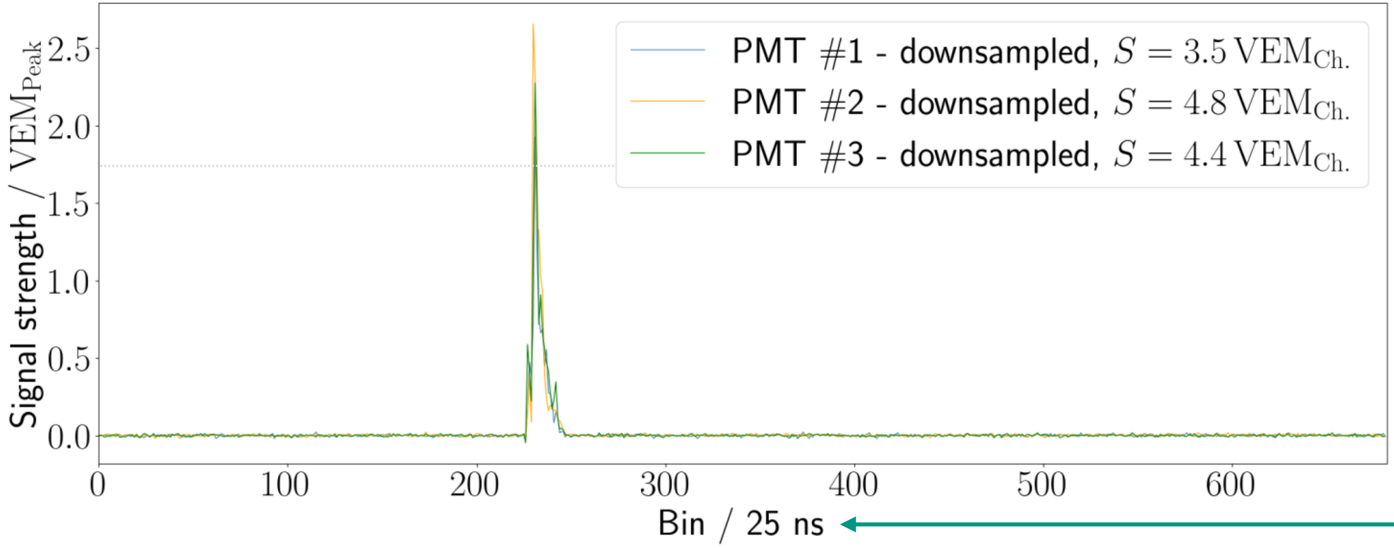
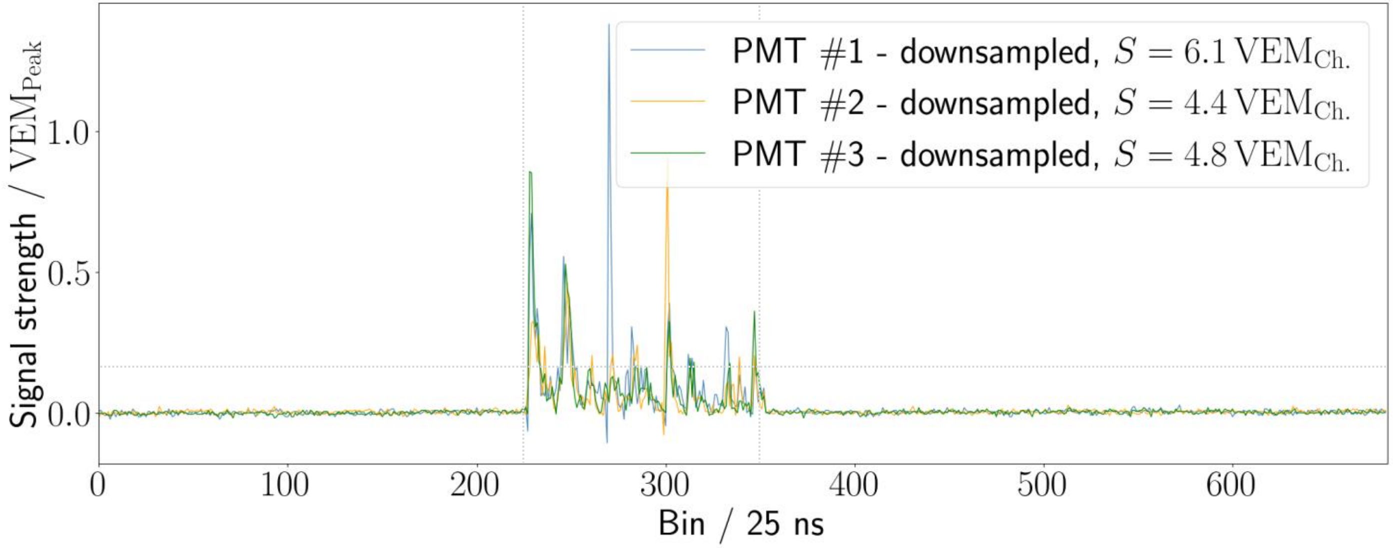



**Different binning!**

Trigger thresholds defined for **UB traces**; measured data must be filtered and downsampled

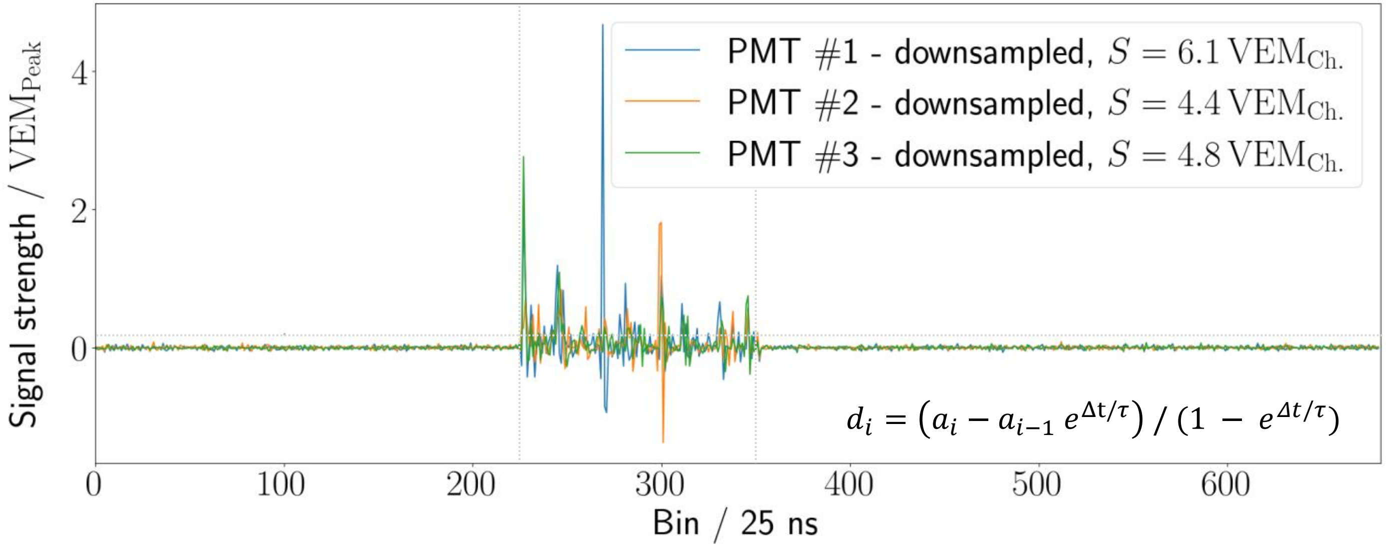
# Current station-level trigger algorithms

- **Time over threshold (ToT)**
  - **More than 12 bins with $S \geq 0.2\,\mathrm{VEM_{Peak}}$ in any 120 bin window**
  - **At least 2 out of 3 PMTs meet above critera**



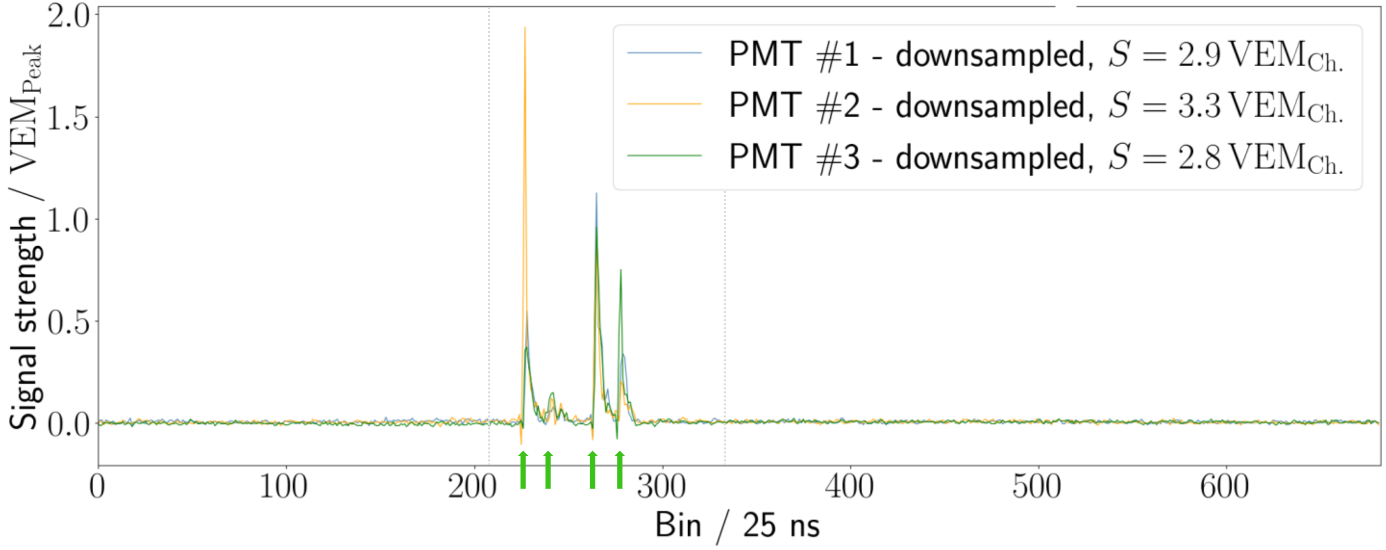
# Current station-level trigger algorithms

- **ToT deconvoluted (ToTd)**
  - **Deconvolute input data stream with exponential factor**
  - **Feed deconvoluted trace into ToT algorithm**

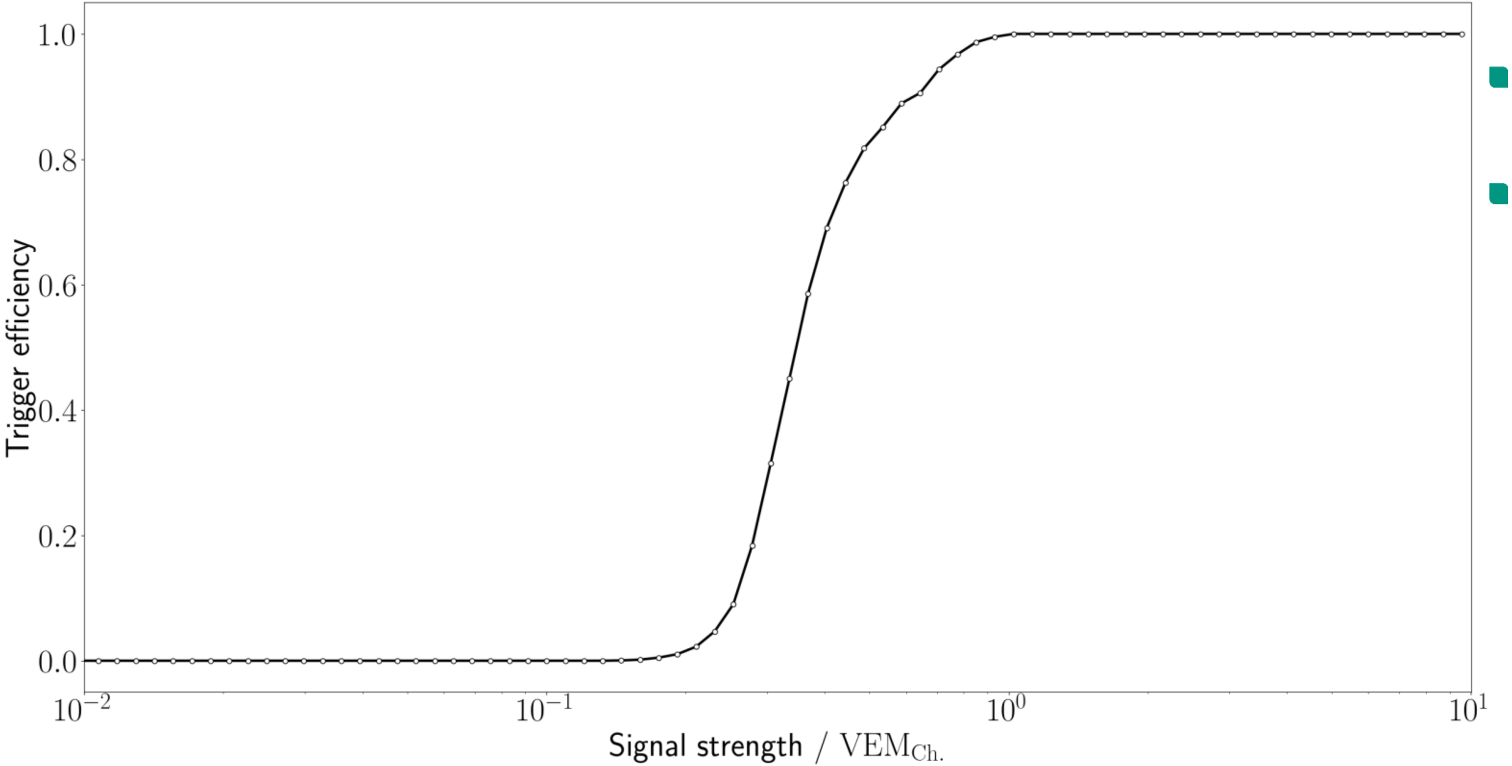


# Current station-level trigger algorithms

- **Multiplicity of positive steps (MoPS)**
  - **Count number of rising flanks within 120 bin window**
  - **At least 2 PMTs have 4 (or more) rising flanks**

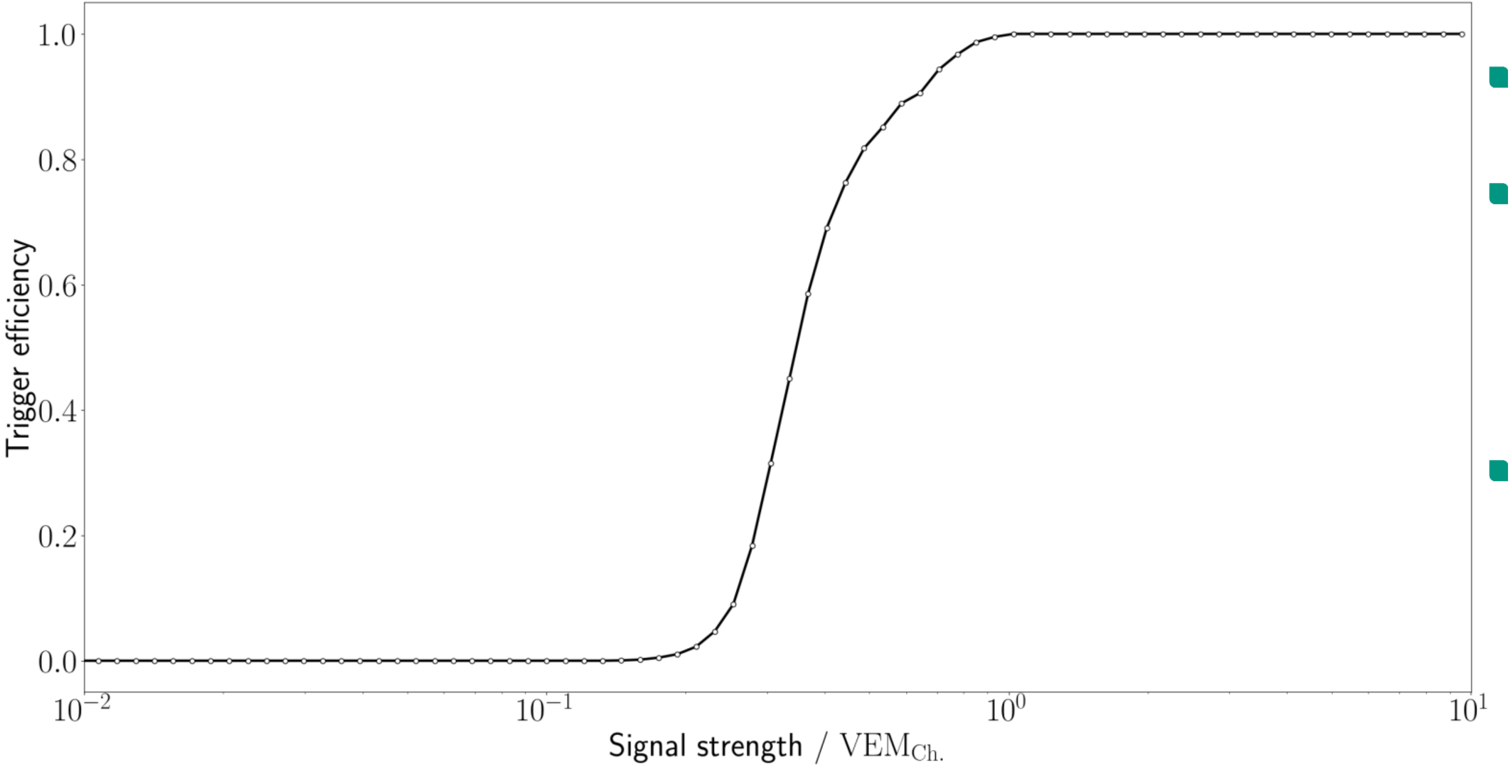


# Trigger performance




- **100% eff.** $\approx 1\ \mathrm{VEM_{Ch.}}$ $\Leftrightarrow 3\ \mathrm{EeV}\ (10^{18.5}\ \mathrm{eV})$
- **Can we do better?**
  - **Photon search**
  - **Neutrino search**
  - **GZ effect**
  - **…**

# Trigger performance

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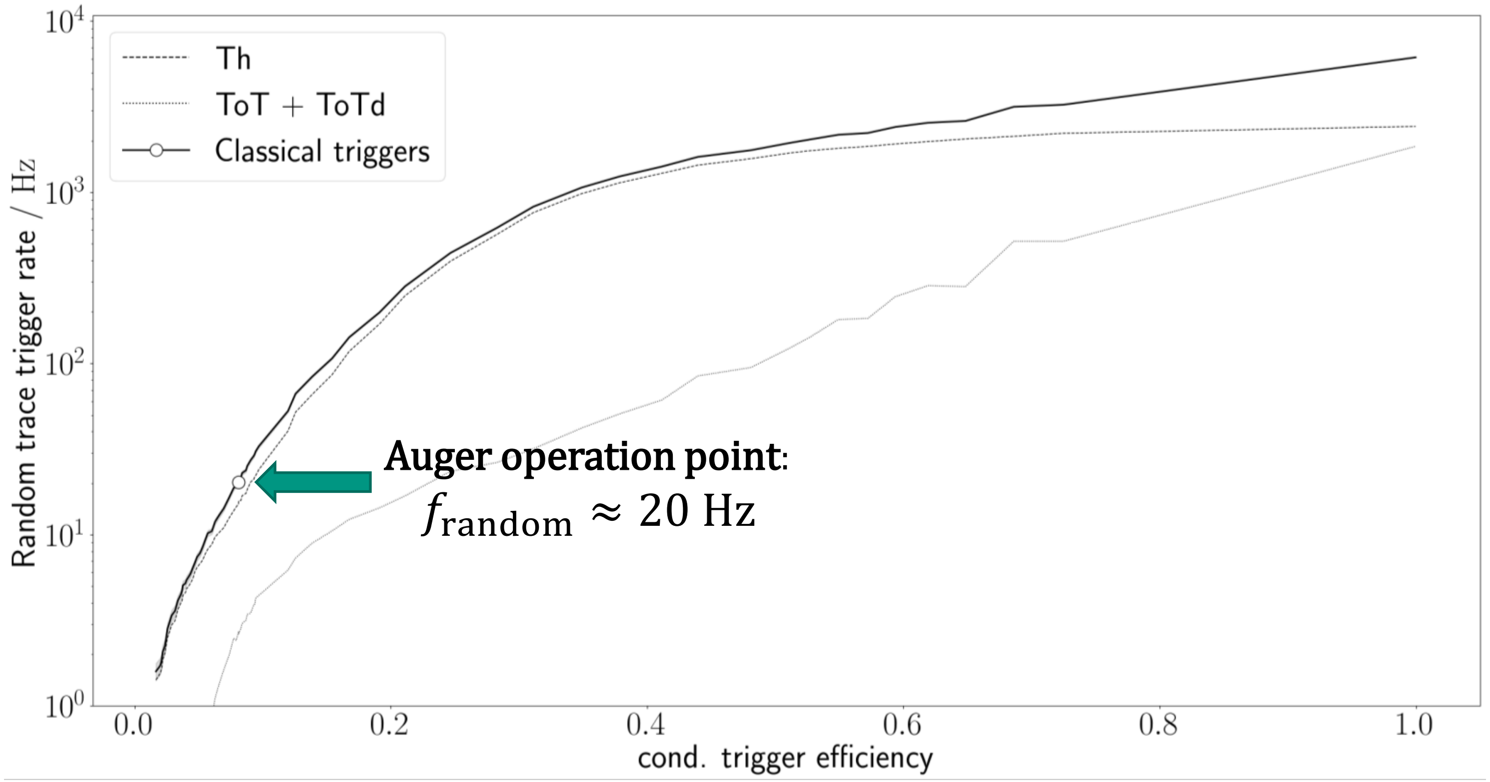
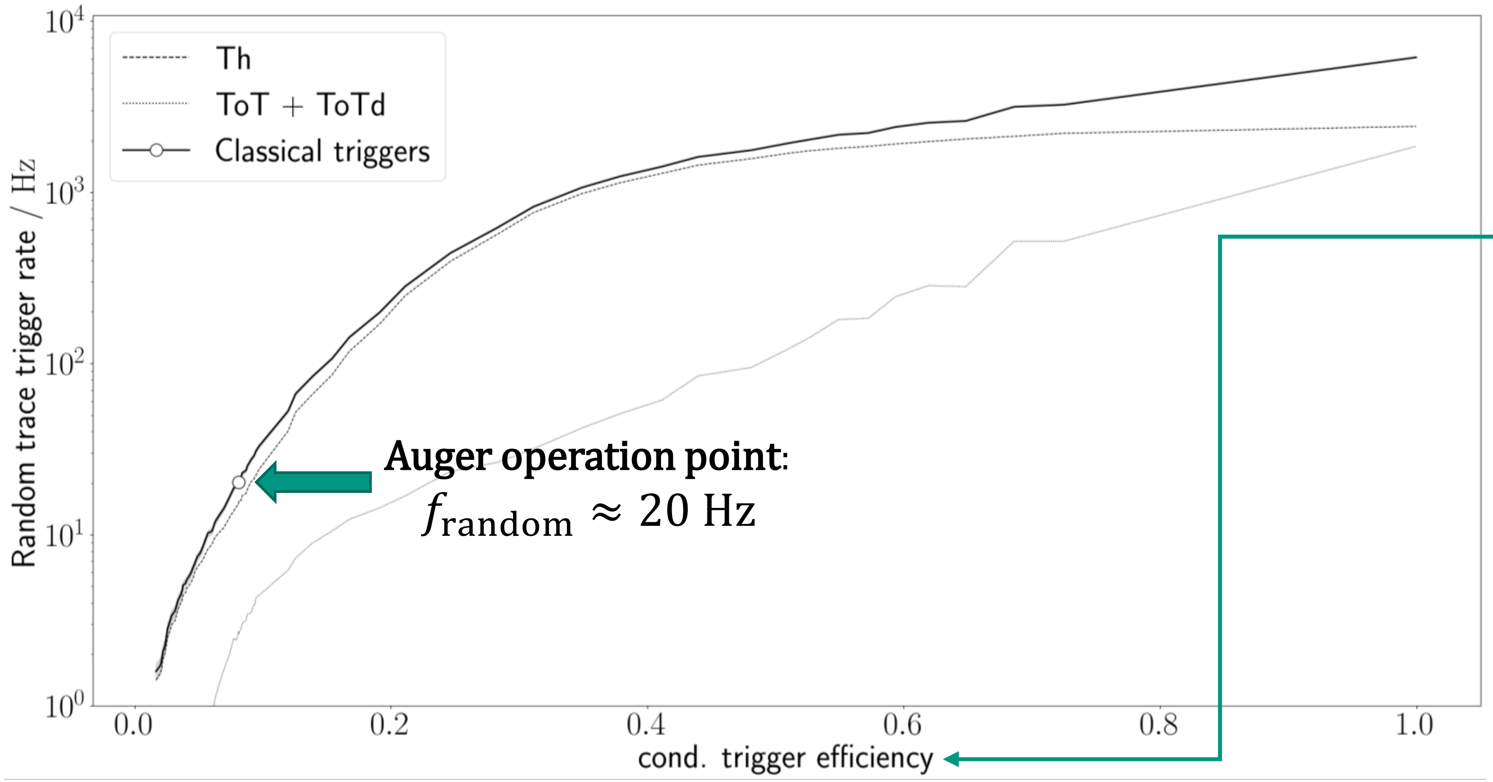
  - **Better sensitivity**
  - **Worse specificity**
  - **What about SNR?**

# Trigger performance




- Adjust thresholds
  - Better sensitivity
  - Worse specificity
  - What about SNR?
  - → gets way worse!
- Use ML triggers
  - Bayesian classifier
  - Neural networks
- Design limitation
  - Bandwidth limit
  - Performance limit
  - Storage limit

# Trigger performance




**Cond. trigger efficiency**

Ratio of air showers that ***are*** detected from all showers that ***can*** theoretically be detected

- **Use ML triggers**
  - **Bayesian classifier**
  - **Neural networks**
- **Design limitation**
  - **Bandwidth limit**
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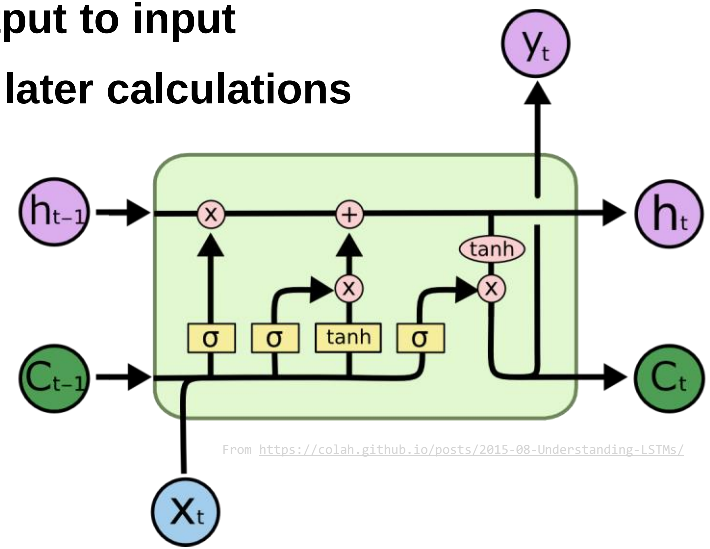
# Recurrent neural networks

- **Long-Short-Term-Memory (LSTM) architecture**
  - **Has internal connections that point from output to input**
  - **Earlier processed information can influence later calculations**
  - **Treat time series very efficiently / elegantly**




From https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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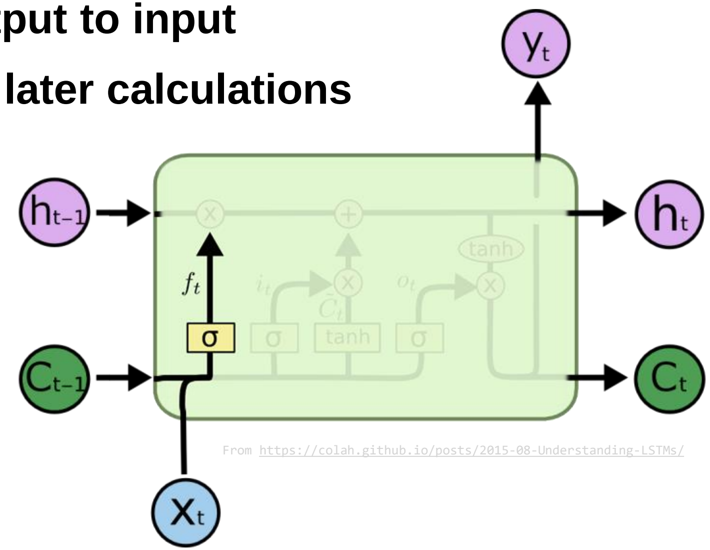
  - **What to keep from previous iterations**
- **Input-Gate**
  - **What to save from this iteration**
- **Output-Gate**
  - **What to output from (updated) cell state**

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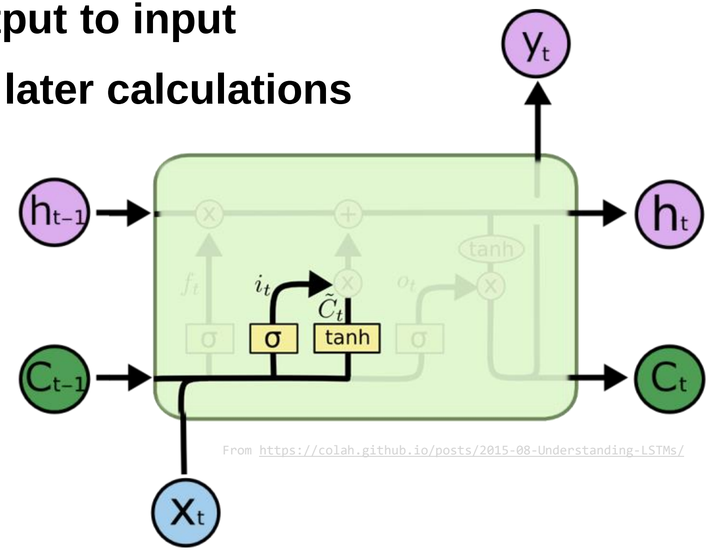


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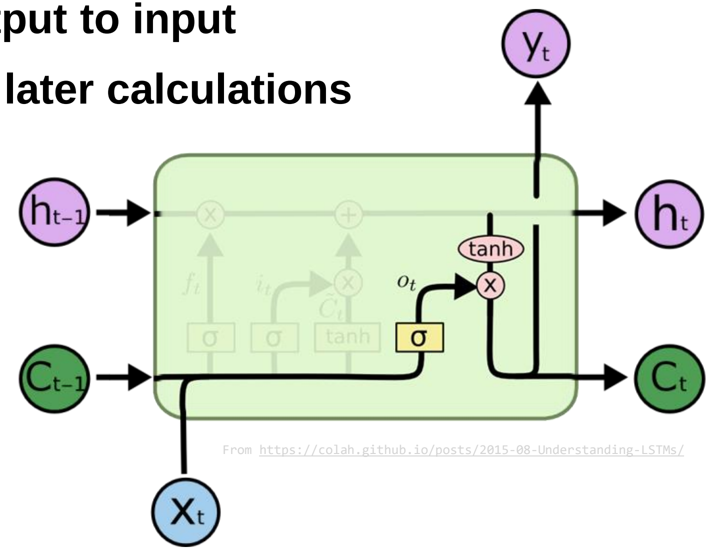


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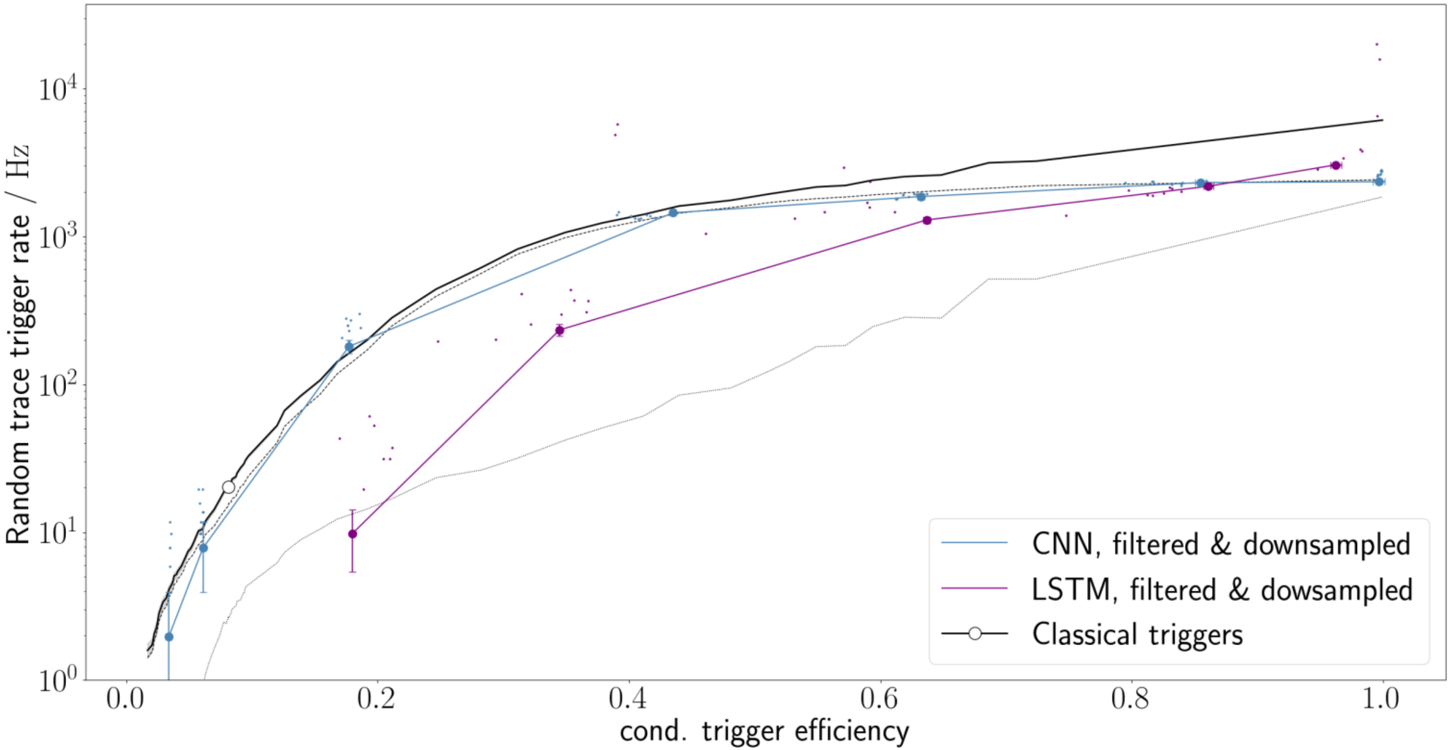
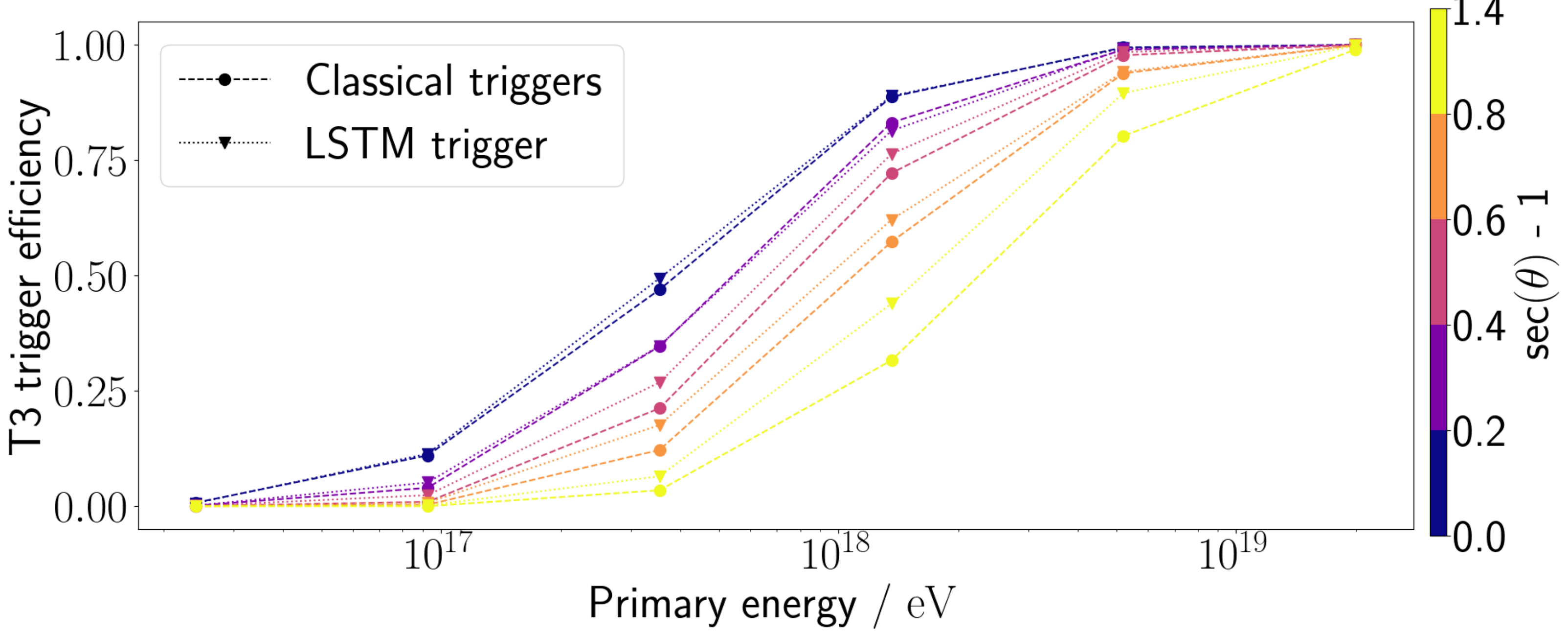



- LSTM performance better than Th trigger
- Can be better than ToT for $t_S = 0.5\ \mathrm{VEM_{Ch.}}$
- Just 44 parameters
- Effects on event level detection efficiency?

# Recurrent neural networks

- **Most drastic gains at inclinations** $\theta \approx 60°$ $(+16.5\%)$
- **Possibly higher gains at** $65° \leq \theta < 90°$ …



# Summary / Outlook

- Test data-driven, machine learning concepts
  - Bayesian classifier promising, but needs lots of finetuning
  - Neural networks work out of the box but „too efficient“
  - Control trigger rate by implementing charge cut
- Convolutional neural networks
  - Performance of simple CNN architectures on par with Th-Trigger
  - Filtered & downsampled data preferred over full bandwidth input
- LSTM / recurrent neural networks
  - First results indicate better performance than ToT
  - Large gains in event detection efficiency at high shower angles

# Summary / Outlook

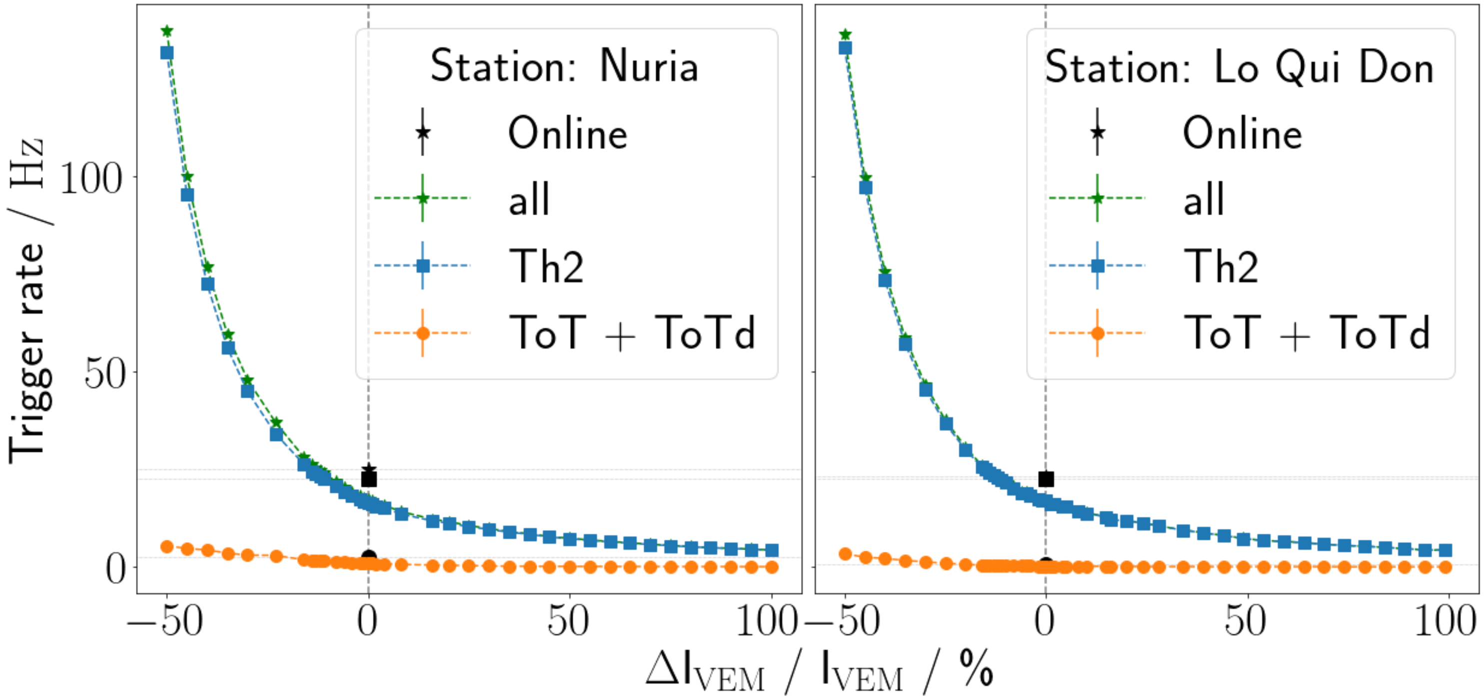
- **Lot of work needed until prototyping stage is left**
  - **Presented results stem from simulations only**
  - **No primary distinction, only data from protons considered**
  - **Only one hadronic interaction model (QGSJET-II.04)**

- **Ground work is completed**
  - **Key assumptions have been tested and verified to hold true**
  - **Analysis chain is implemented and ready to run**

- **Upcoming dataset of easily accessible ($.csv$) WCD time traces**
  - **40k (proton primary) events, tagged by $\theta,\ \phi,\ E,\ SPD$, $n_{\mu}$, …**
  - **Please tell us what other data you would be interested in**

# Backup

# Random traces – Calibration



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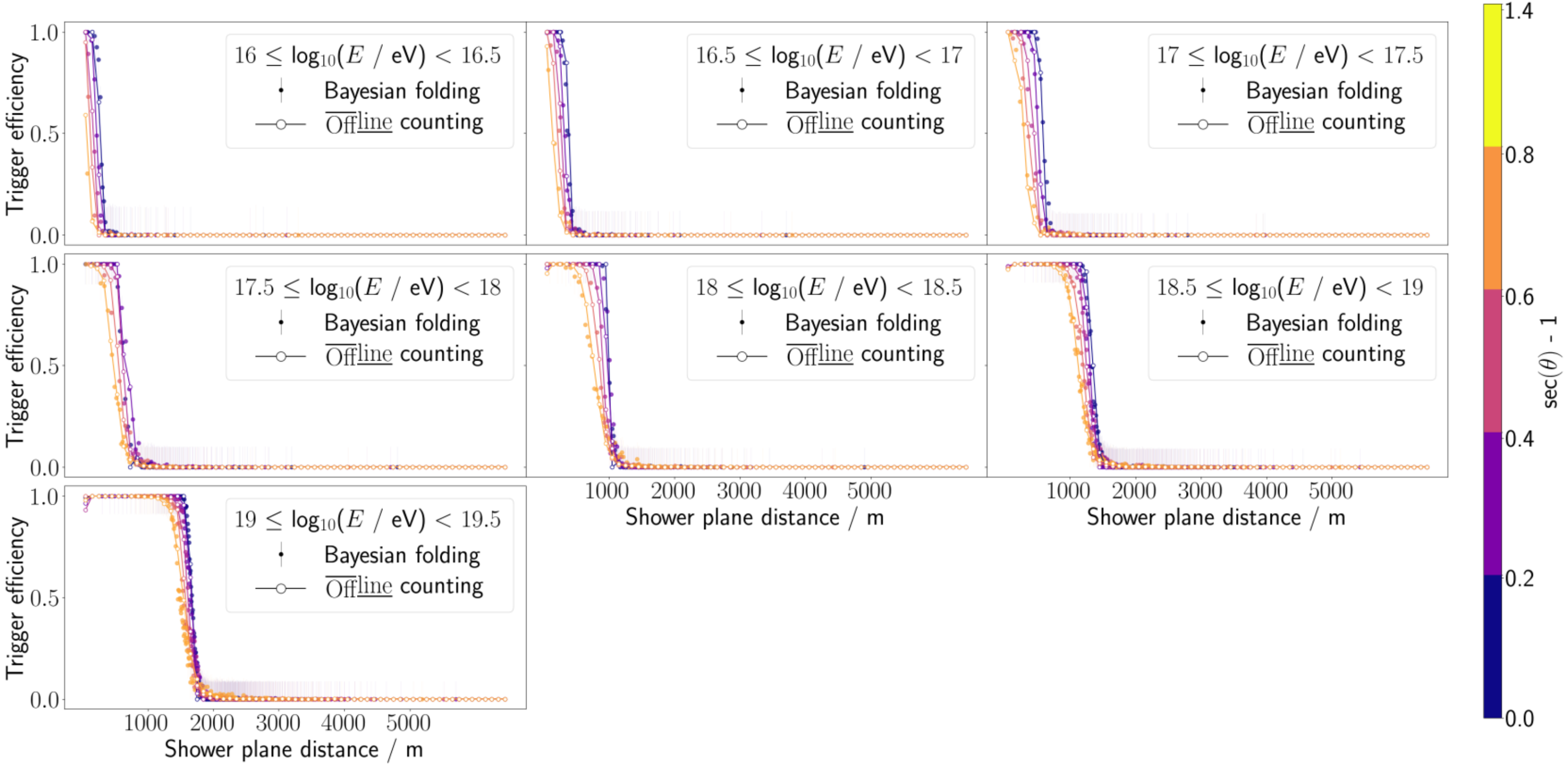

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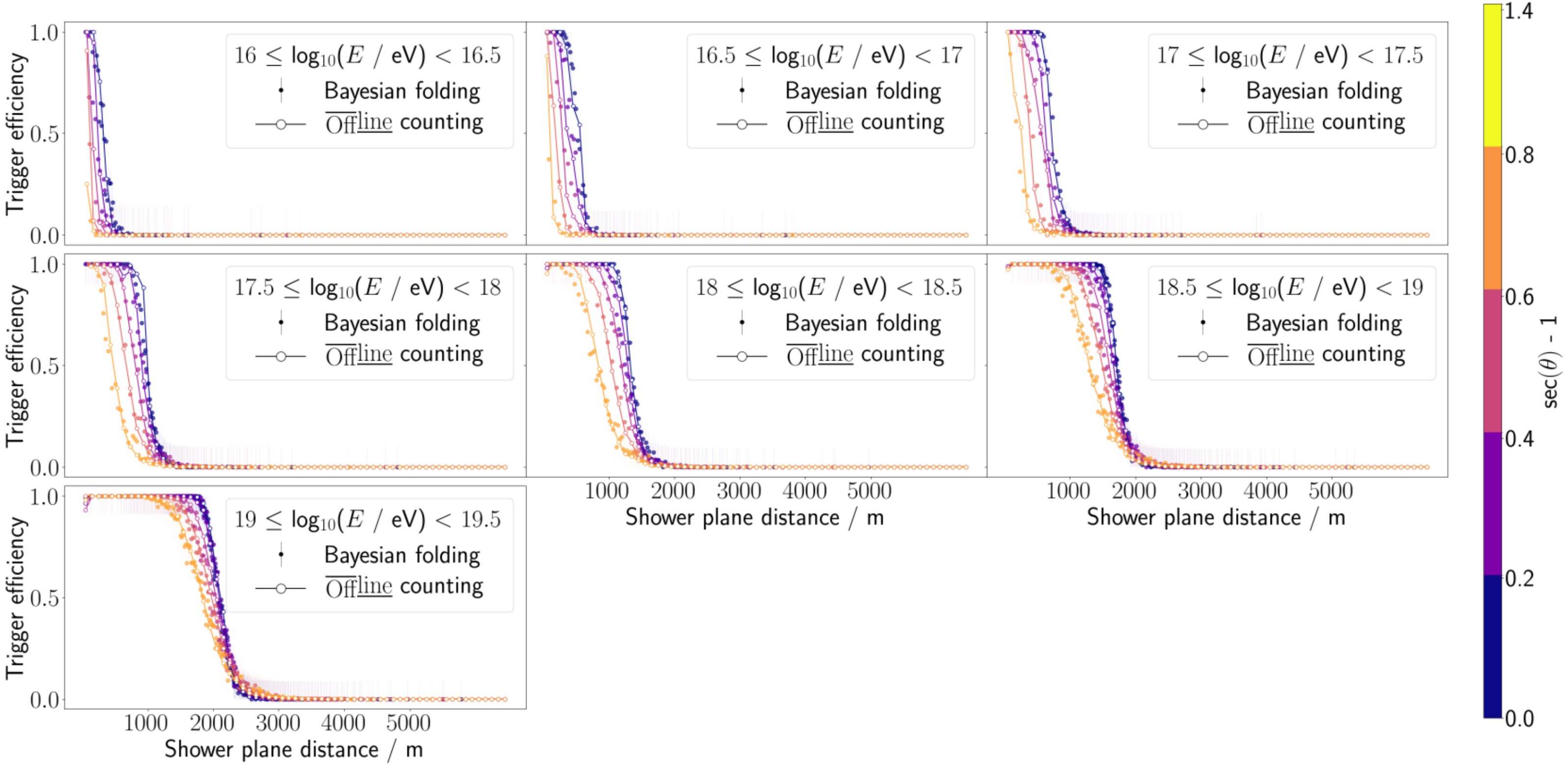

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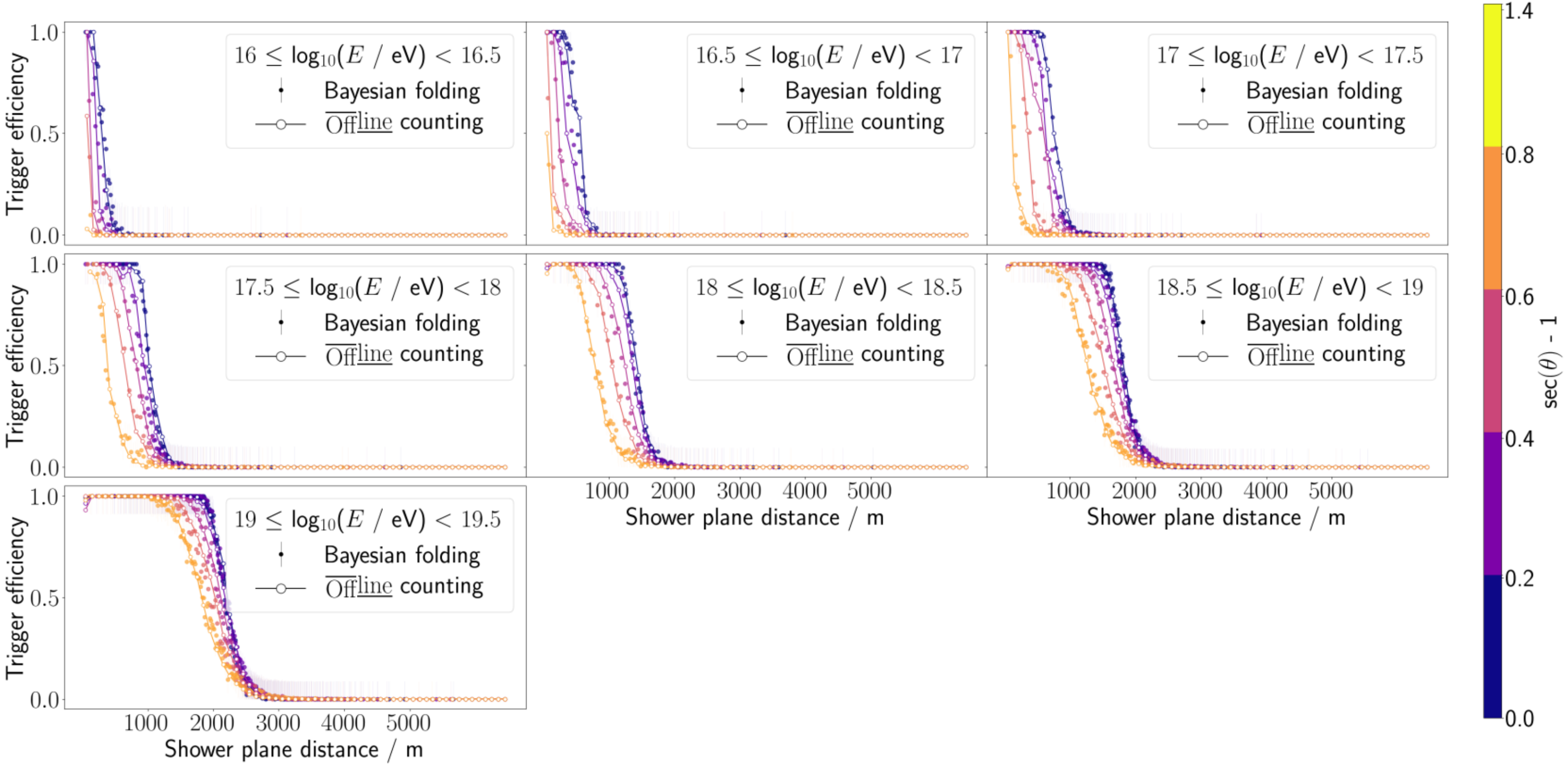
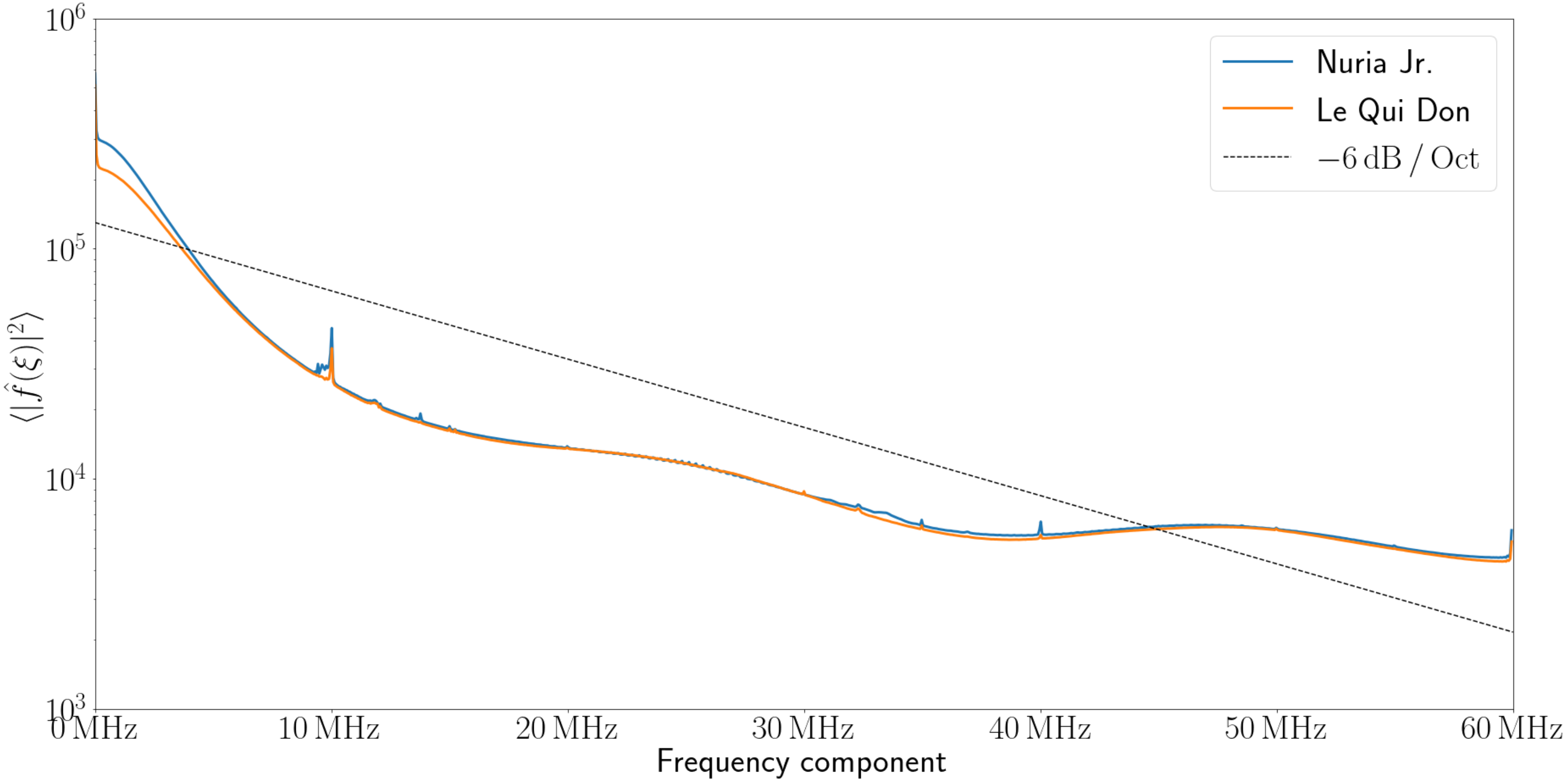
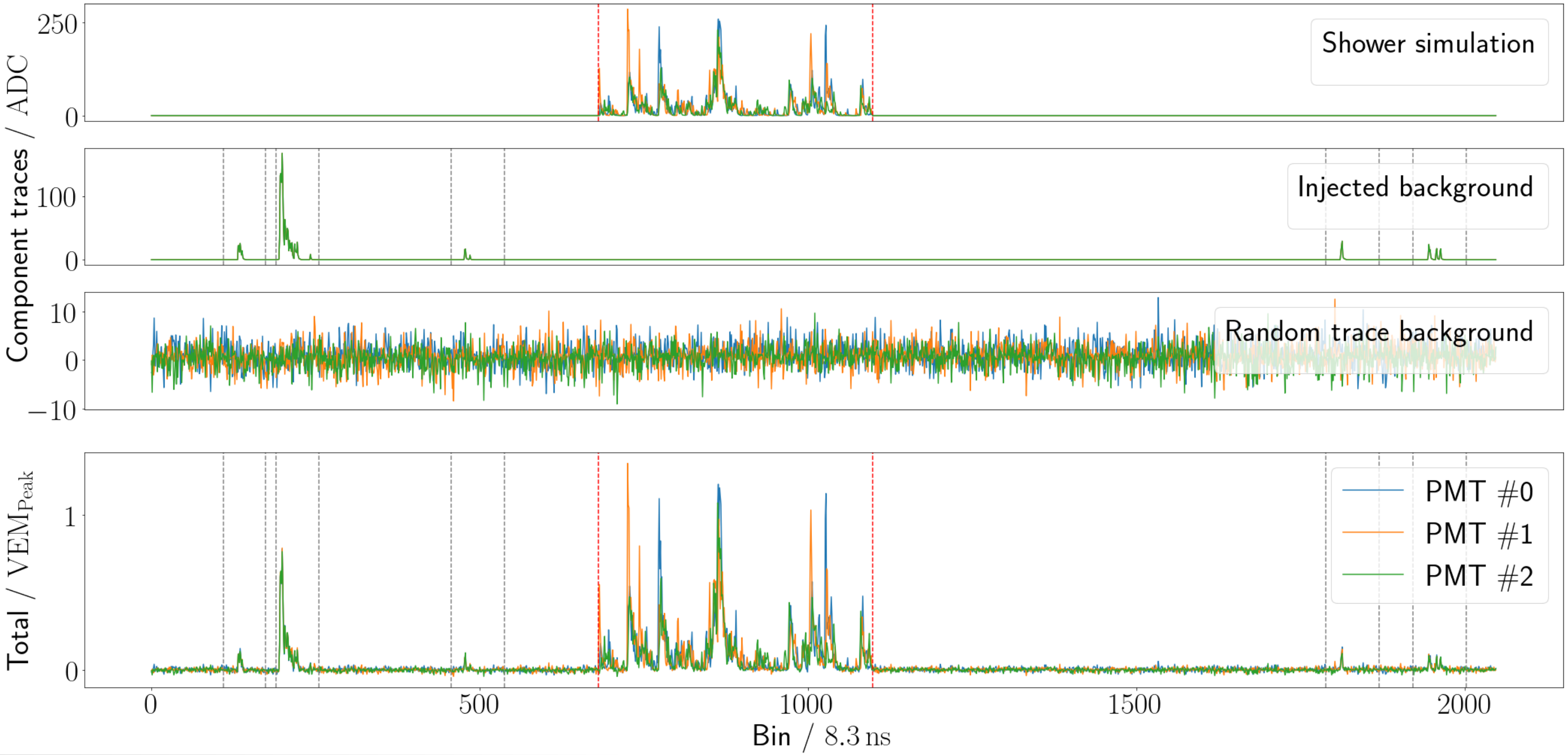


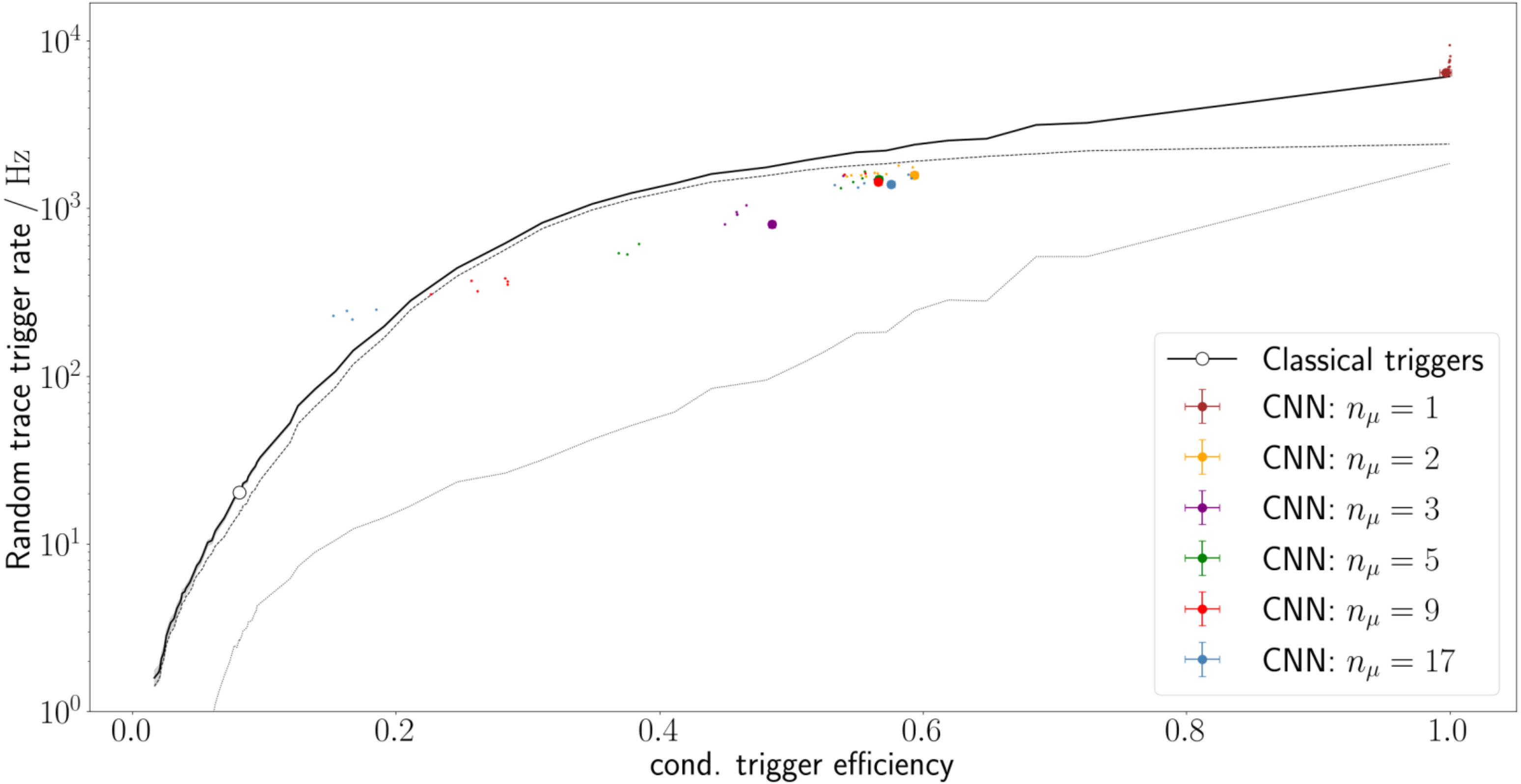
# Random traces – Power spectrum



# Trace building

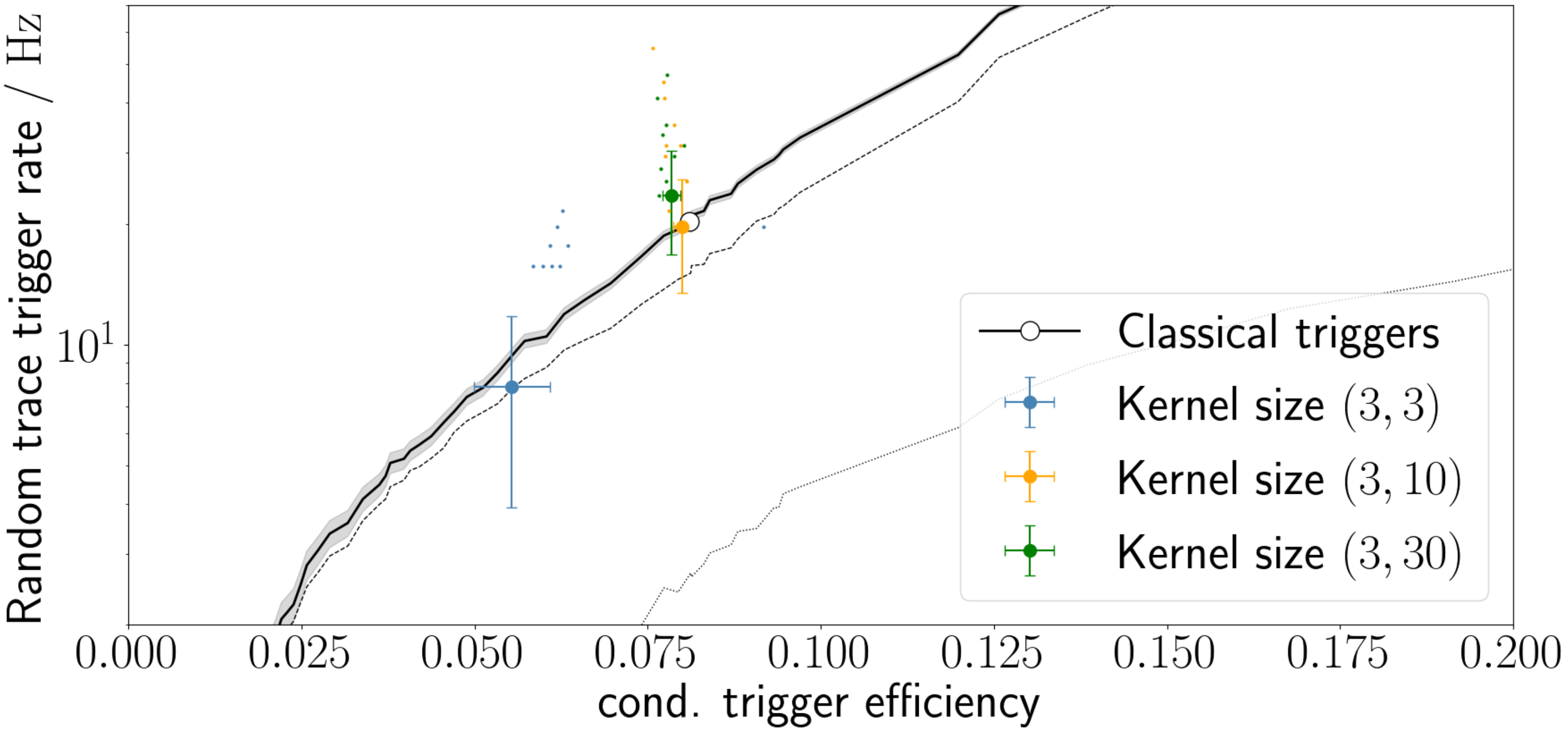


# Muon cut



Random trace trigger rate / Hz
cond. trigger efficiency
Classical triggers
CNN: $n_\mu = 1$
CNN: $n_\mu = 2$
CNN: $n_\mu = 3$
CNN: $n_\mu = 5$
CNN: $n_\mu = 9$
CNN: $n_\mu = 17$

# Kernel size



Random trace trigger rate / Hz
$10^1$
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
cond. trigger efficiency
Classical triggers
Kernel size $(3,3)$
Kernel size $(3,10)$
Kernel size $(3,30)$

# Network parameters

| Type | Input size | Kernel size | $n_{\text{train}}$ | w/ dense extension |
|---|---|---|---|---|
| CNN | $(3, 120)$ | $(3, 3)$ | **140** | **834** |
| CNN | $(3, 120)$ | $(3, 10)$ | **216** | **534** |
| CNN | $(3, 120)$ | $(3, 30)$ | **444** | **714** |
| CNN | $(3, 40)$ | $(3, 3)$ | **84** | **210** |
| CNN | $(3, 60)$ | $(3, 3)$ | **100** | **290** |
| CNN | $(3, 90)$ | $(3, 3)$ | **120** | **390** |
| CNN | $(3, 240)$ | $(3, 3)$ | **220** | **890** |
| LSTM | $(3, 120)$ | – | **12** | (single layer) |
| LSTM | $(3, 120)$ | – | (three layers) | **44** |

# LSTM permutations