

Noise mitigation with iDQ in MBTA

Amazigh OUZRIAT

PhD Candidate – Institut des 2 Infinis de Lyon

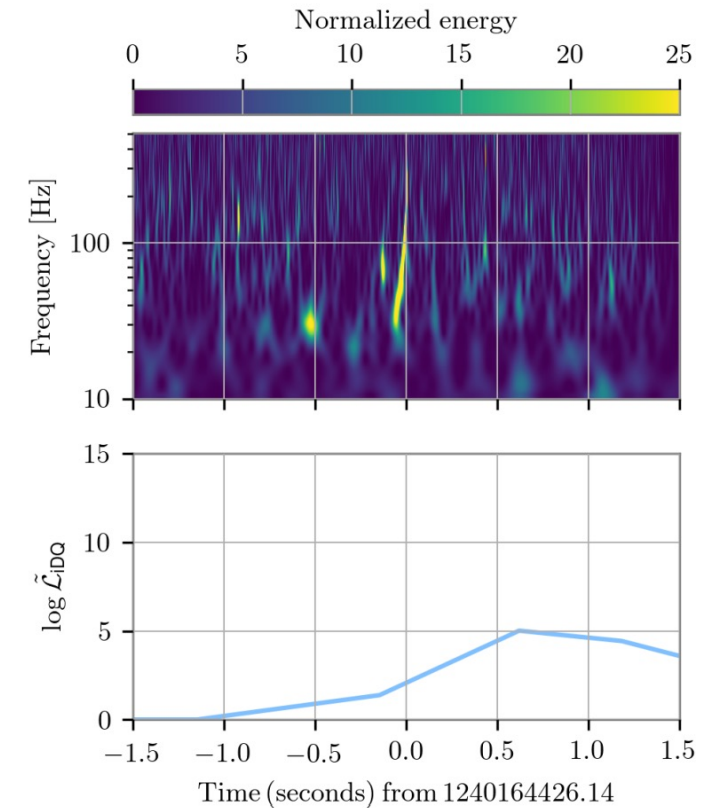


iDQ : Framework for statistical inference of glitches

- Used offline at Hanford & Livingston in O3, to be used at Virgo in O4
- iDQ correlates auxiliary data information and strain data
- Trains safe auxiliary channels only
- The iDQ timeseries are machine-learning based data quality products
 - => Probabilistic quantities to estimate glitch presence in $h(t)$
- Incorporated as DQ flag in PyCBC & GstLAL

Motivation

- Use iDQ outputs to flag DQ problems => improve search sensitivity
- MBTA used CAT2 in O3, will not be produced by DetChar in O4
- Instead of vetoing : reranking events, allowing detection of loud signal during flagged times (Example: GW190424A)
- Current strategy : reweighting SNR single triggers using iDQ, expected improvement of VT



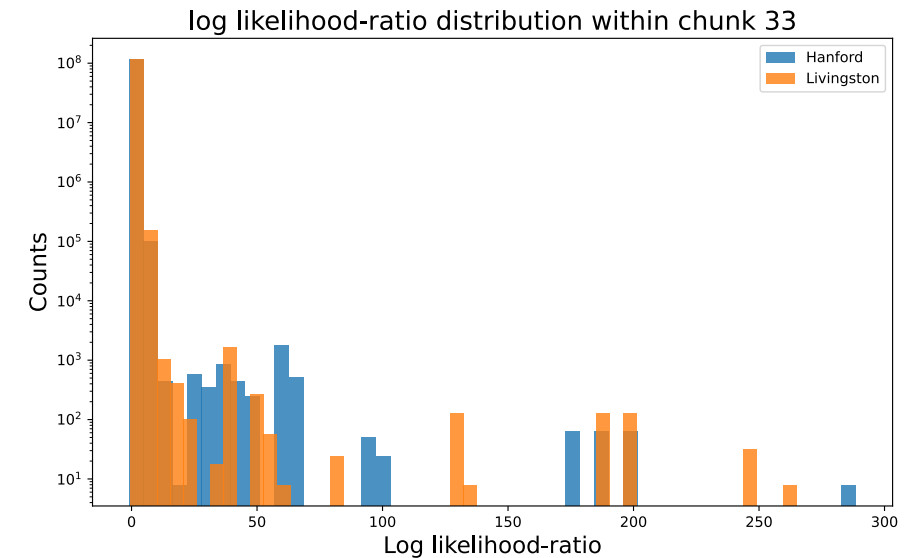
Time surrounding GW190424A vetoed by CAT2
Recovered after iDQ incorporation into GstLAL

iDQ timeseries

- 5 outputs : Rank, FAP, Eff/FAP, P_{glitch} , $\log(\mathcal{L})$
- Sampled at 128Hz
- P_{glitch} will not be produced during O4
- GstLAL uses $\log(\mathcal{L})$ to downgrade triggers : $\mathcal{L} = \frac{\mathcal{L}(glitch)}{\mathcal{L}(clean)}$
- PyCBC uses $\log(\mathcal{L})$ to correct trigger rate in the time dependent noise model

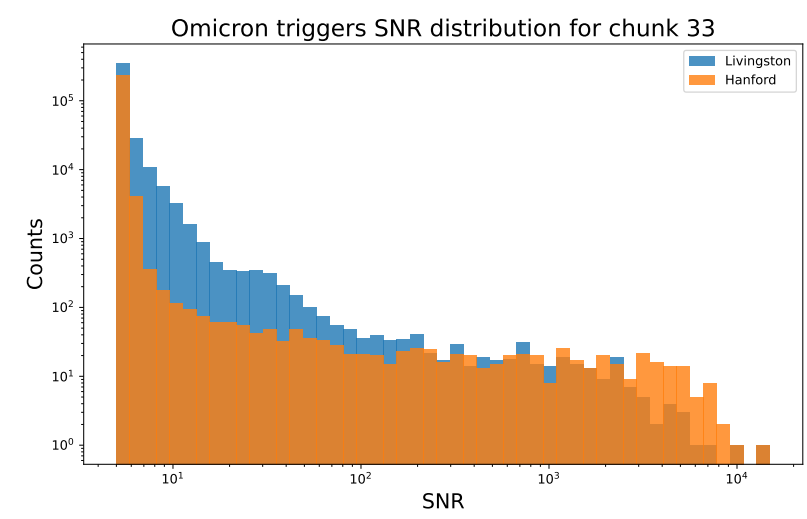
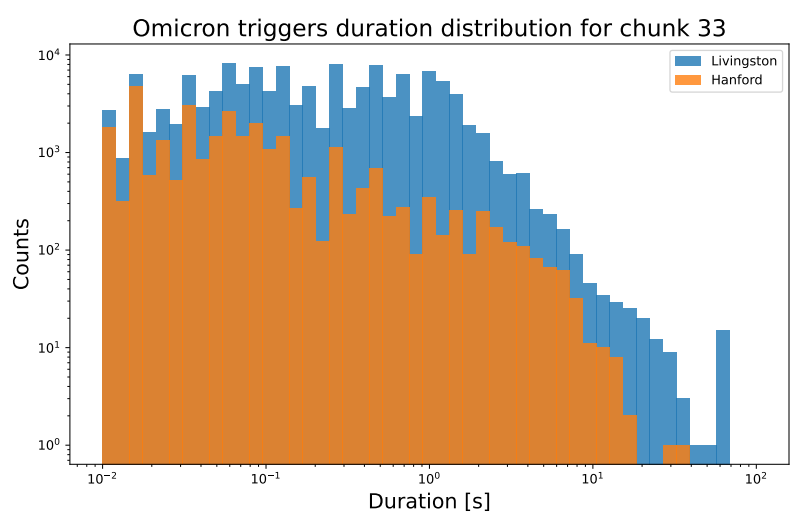
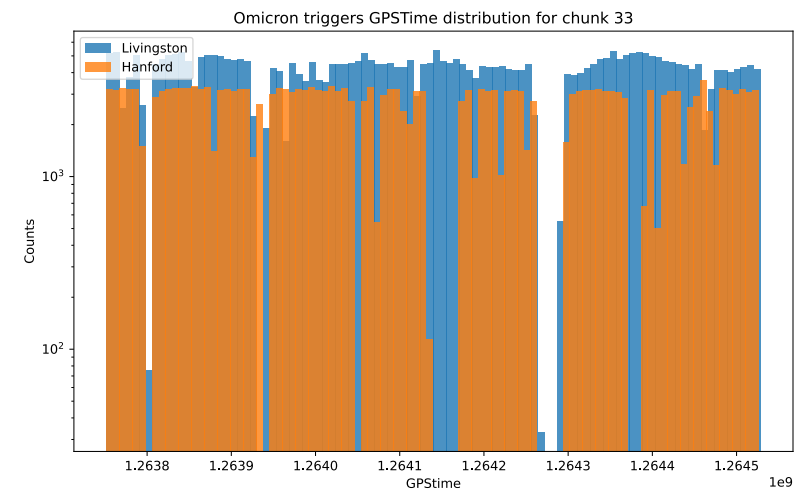
iDQ timeseries – Chunk 33

- We study MDC chunks (32-36)
- In these slides chunk 33, GPS Time within [1263751884, 1264528208]
- Use $\log(\mathcal{L})$ as DQ flag.
- Conservative approach : $\log(\mathcal{L}) < 0 \rightarrow \log(\mathcal{L}) = 0$
- Downsample from 128Hz to 1Hz
- 3 $\log(L)$ trend timeseries :
 - Maximum 1Hz $\log(\mathcal{L})$
 - Median 1Hz $\log(\mathcal{L})$
 - Mean 1Hz $\log(\mathcal{L})$



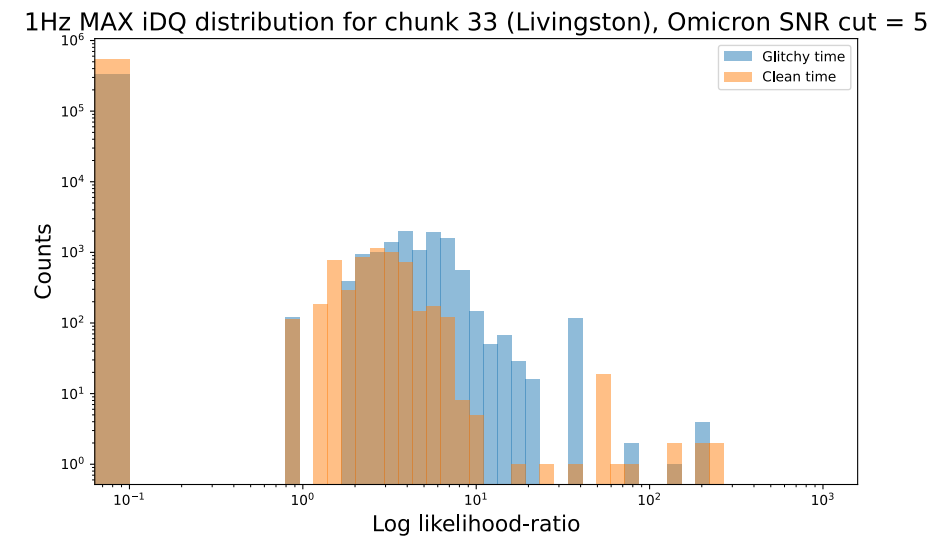
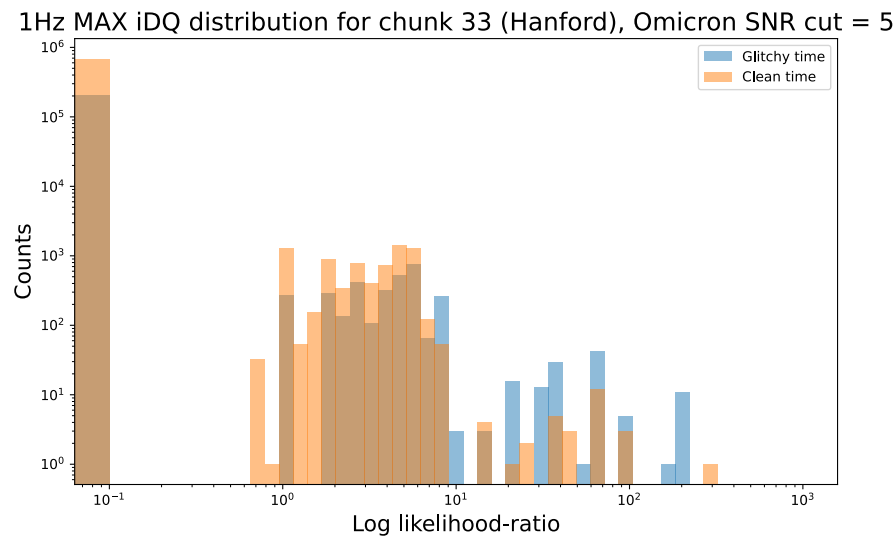
Omicron pipeline – Chunk 33

- Omicron is a glitch search pipeline used as input to train iDQ
- We use $\text{SNR} > 5$ triggers in $h(t)$ with 0.1 clustering time
- Over 250k (400k) glitches in Hanford (Livingston)
- Sub-second glitches are dominant



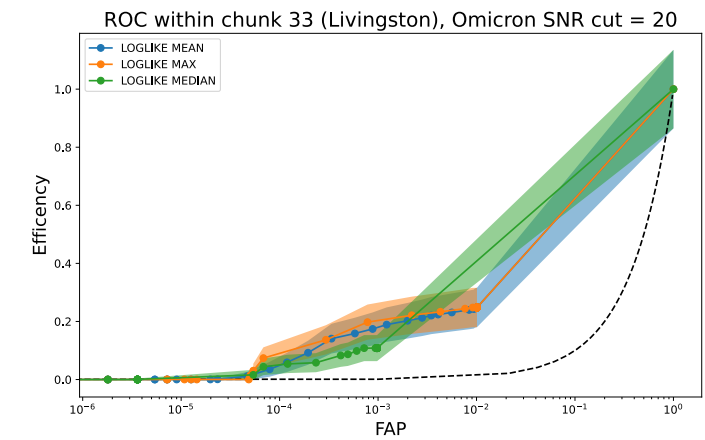
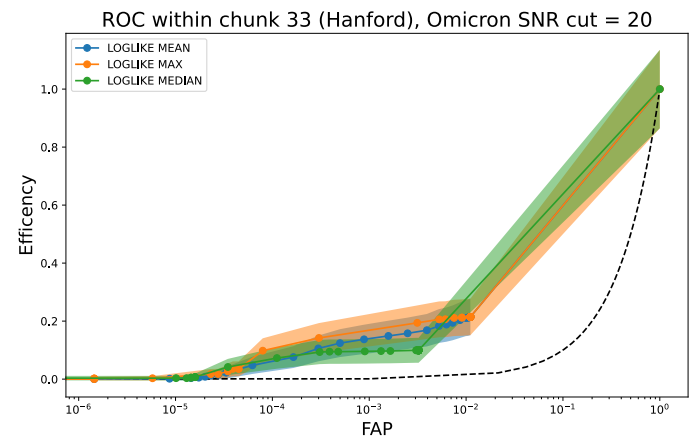
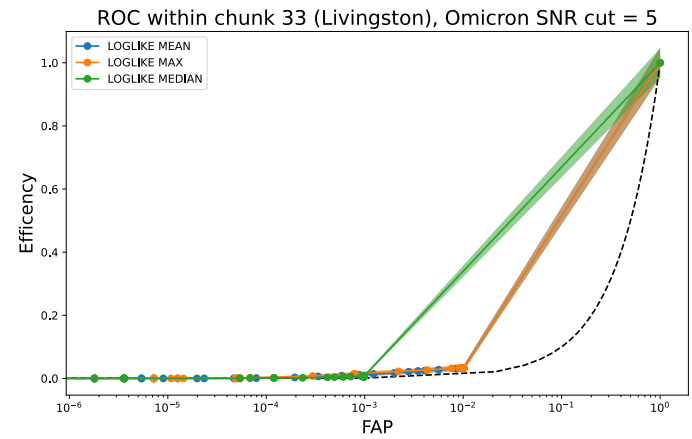
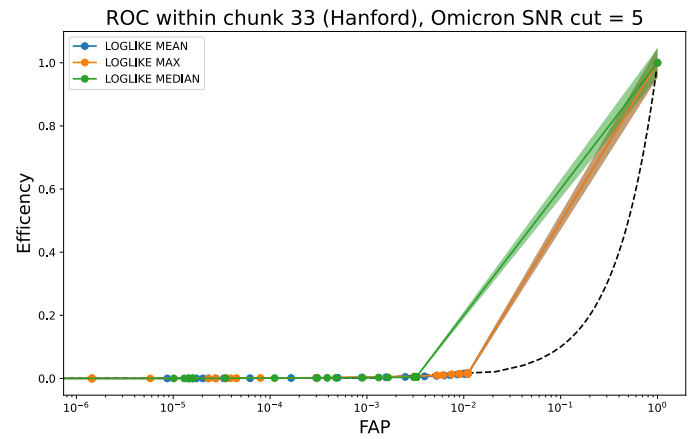
iDQ vs Omicron – Chunk 33

- Divide chunk 33 into two distinct timeseries (1Hz) : clean region (segments containing no Omicron triggers with SNR > 5), glitchy regions (segments containing at least a Omicron trigger with SNR > chosen SNR cut)
- Define several glitchy regions with different SNR cut
- For each segment we calculate Max/Mean/Median $\log(\mathcal{L})$



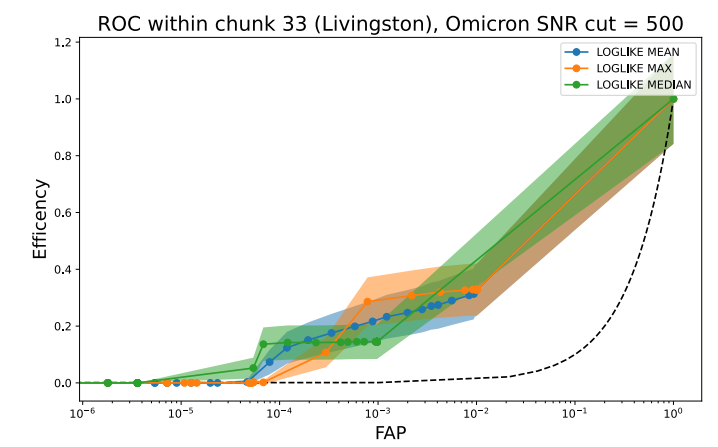
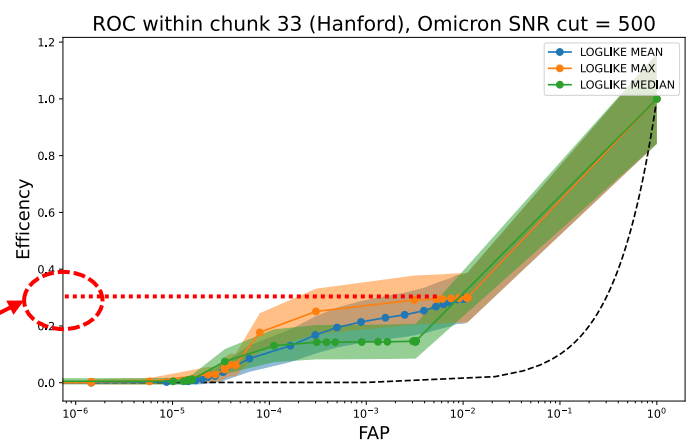
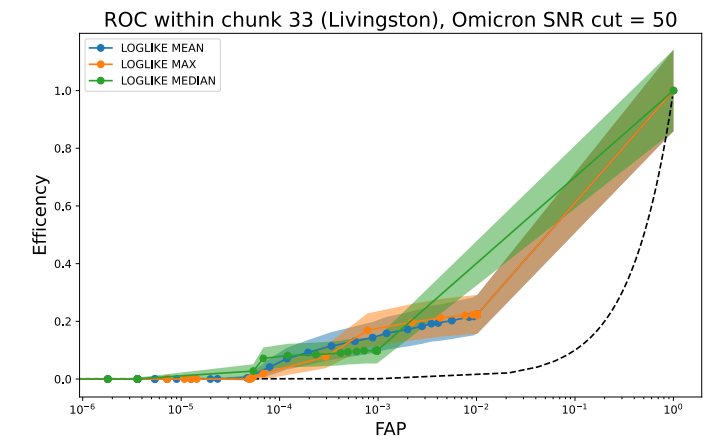
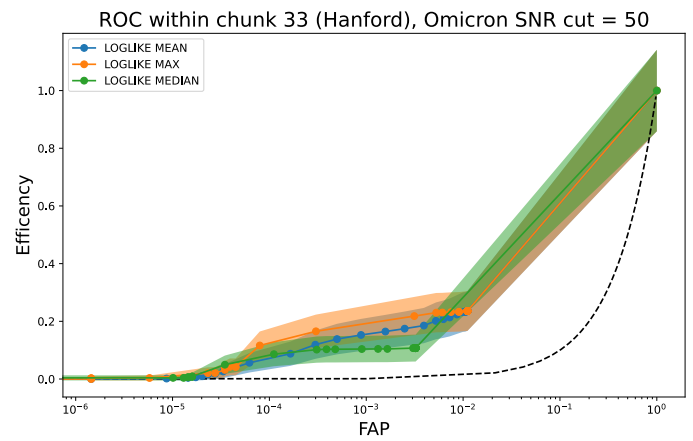
iDQ vs Omicron – Chunk 33

- ROC curves : Efficiency vs FAP
- **Efficiency** : fraction of glitchy samples removed by cut on $\log(\mathcal{L})$
- **FAP** : fraction of clean samples removed by cut on $\log(\mathcal{L})$
- SNR>5 poor efficiency/FAP
- Improvement when defined with SNR>10
- Using Maximum 1Hz $\log(\mathcal{L})$ more efficient



iDQ vs Omicron – Chunk 33

- For SNR>50 Omicron glitches, a cut at $\log(\mathcal{L}) = 5$:
 - 22% Eff vs 0.3% FAP in H for max $\log(\mathcal{L})$
 - 17% Eff vs 0.08% FAP in L for max $\log(\mathcal{L})$
- For SNR>500 Omicron glitches, a cut at $\log(\mathcal{L}) = 5$:
 - 29% Eff vs 0.3% FAP in H for max $\log(\mathcal{L})$
 - 29% Eff vs 0.08% FAP in L for max $\log(\mathcal{L})$
- Only a small fraction of triggers have $\log(\mathcal{L}) > 0$, meaning only this fraction can be rejected by iDQ

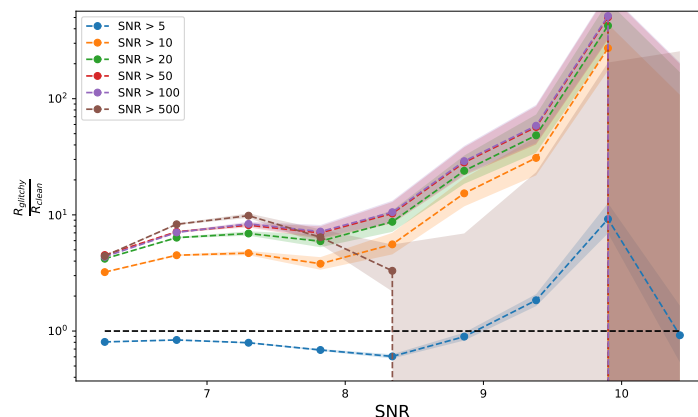


MBTA BBH triggers vs Omicron – Chunk 33

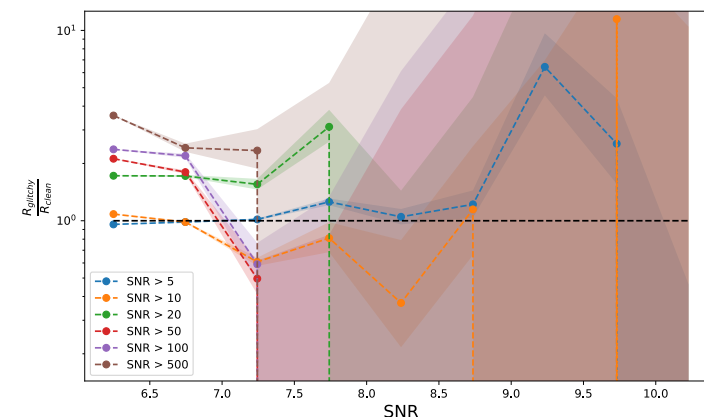
- We run MBTA to get single detector triggers in Hanford & Livingston
- We select only events with $rwSNR > 6$ (~200k triggers, enough stats)
- Separate the triggers into 2 populations:
 - Triggers in regions defined as glitchy by Omicron (at least an Omicron trigger with $SNR >$ given SNR cut)
 - Triggers in clean region
- Calculate the MBTA triggers rate in both regions

$$: \frac{R_{glitchy}}{R_{clean}} \text{ in H} > \frac{R_{glitchy}}{R_{clean}} \text{ in L}$$
- Higher cuts on Omicron SNR \Rightarrow ~ higher $\frac{R_{glitchy}}{R_{clean}}$
- No clear dependency on MBTA SNR

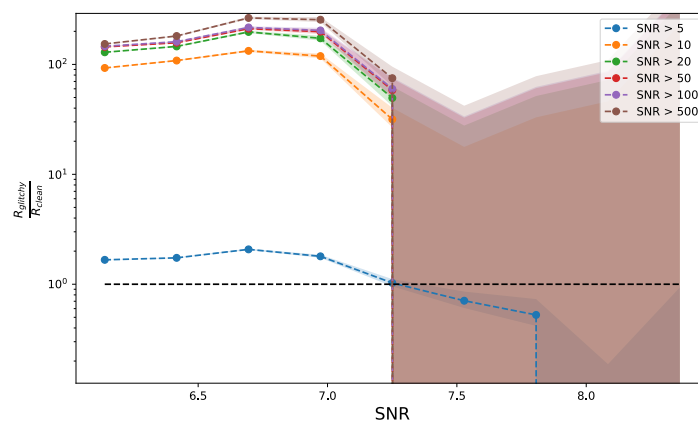
BBH MBTA triggers distribution for chunk 33 (Hanford)



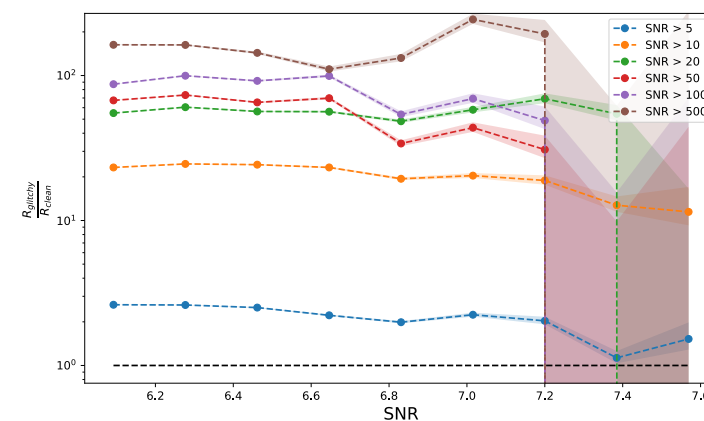
BBH MBTA triggers distribution for chunk 33 (Livingston)



BBH MBTA triggers distribution for chunk 33 (Hanford) with MAX LOG>0



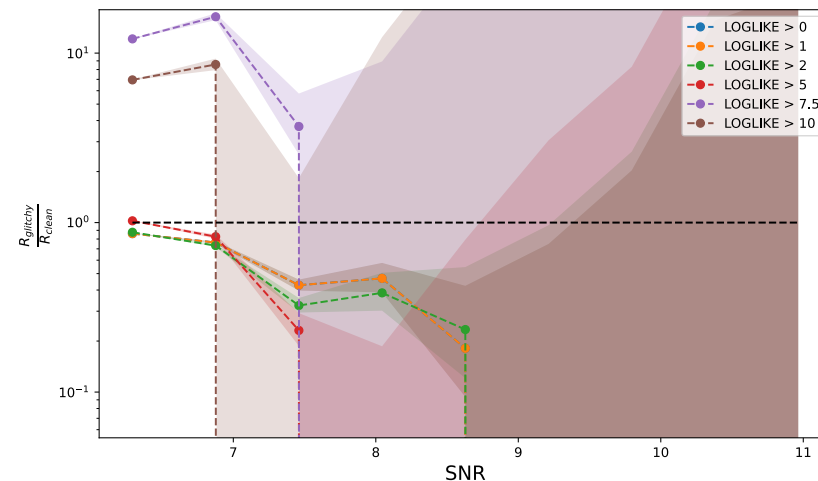
BBH MBTA triggers distribution for chunk 33 (Livingston) with MAX LOG>0



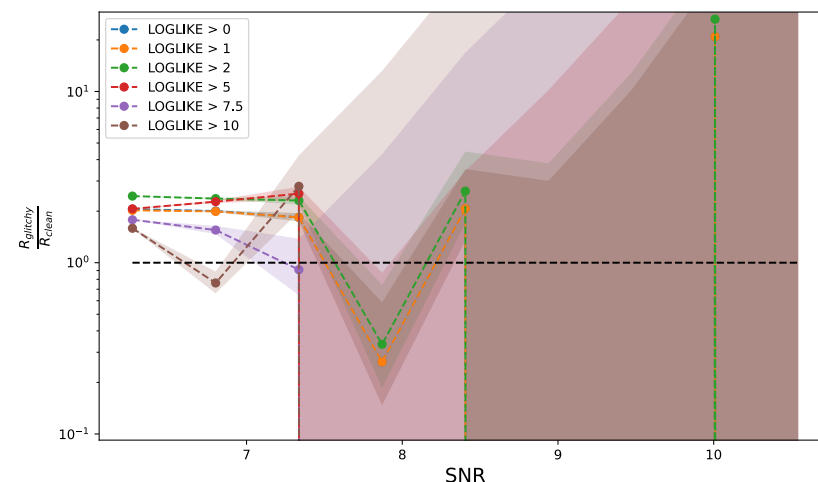
MBTA BBH triggers vs iDQ – Chunk 33

- We run MBTA to get single detector triggers in Hanford & Livingston
- We select only events with $rwSNR > 6$ (~200k triggers, enough stats)
- Separate the triggers into 2 populations:
 - Triggers in regions defined as glitchy by iDQ (samples with $\log(\mathcal{L}) >$ given $\log(\mathcal{L})$ cut)
 - Triggers in clean region ($\log(\mathcal{L}) = 0$)
- Calculate the MBTA triggers rate in both regions
- No clear dependency on MBTA SNR
- Higher cuts on $\log(\mathcal{L}) \Rightarrow \sim$ higher $\frac{R_{glitchy}}{R_{clean}}$

BBH MBTA triggers distribution for chunk 33 (Hanford)



BBH MBTA triggers distribution for chunk 33 (Livingston)



iDQ incorporation into MBTA

- Reweight single detector triggers SNR :

$$SNR_{iDQ} = \sqrt{SNR^2 - \alpha \log(\mathcal{L})}$$

- Run MBTA with injections, study efficiency & VT changes after reweighting SNR using iDQ
- iDQ useful if it globally improves (reduces) FAR of injections
- Calculation of new FAR requires editing MBTA code (coming soon)
- Meanwhile : Approximative method to calculate new FAR of injections

$FAR_{iDQ}(\alpha)$ calculation

- First MBTA run over chunk 33 without injections (noise only)

- $SNR_{iDQ} = \sqrt{SNR_{old}^2 - \alpha * \log(\mathcal{L})}$

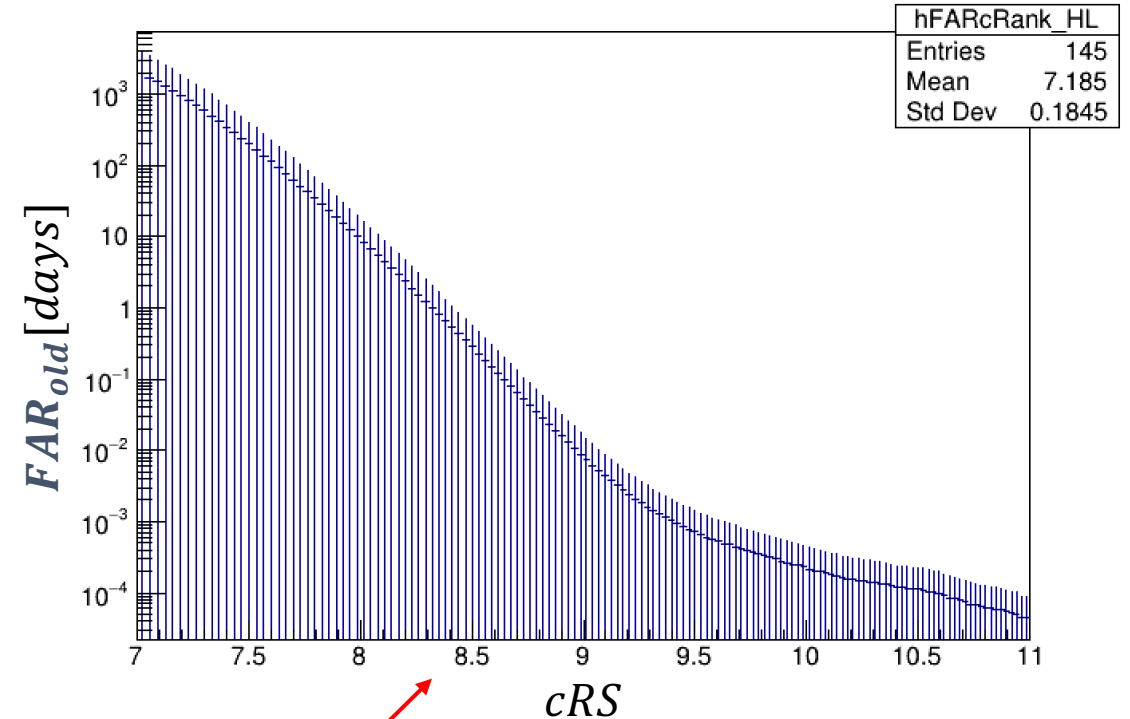
- $R_H = \frac{N \text{ singles triggers in Hanf. with } SNR_{iDQ} > 6}{N \text{ singles triggers in Hanf. with } SNR_{old} > 6}$

- $R_L = \frac{N \text{ singles triggers in Liv. with } SNR_{iDQ} > 6}{N \text{ singles triggers in Liv. with } SNR_{old} > 6}$

- Second MBTA run over chunk 33 with injections

$$FAR_{iDQ} = FAR_{old} * R_H * R_L * \frac{FAR_{old}(SNR_{iDQ})}{FAR_{old}(SNR_{old})}$$

chunk33
hFARcRank_HL



$FAR_{iDQ}(\alpha)$ calculation – chunk33

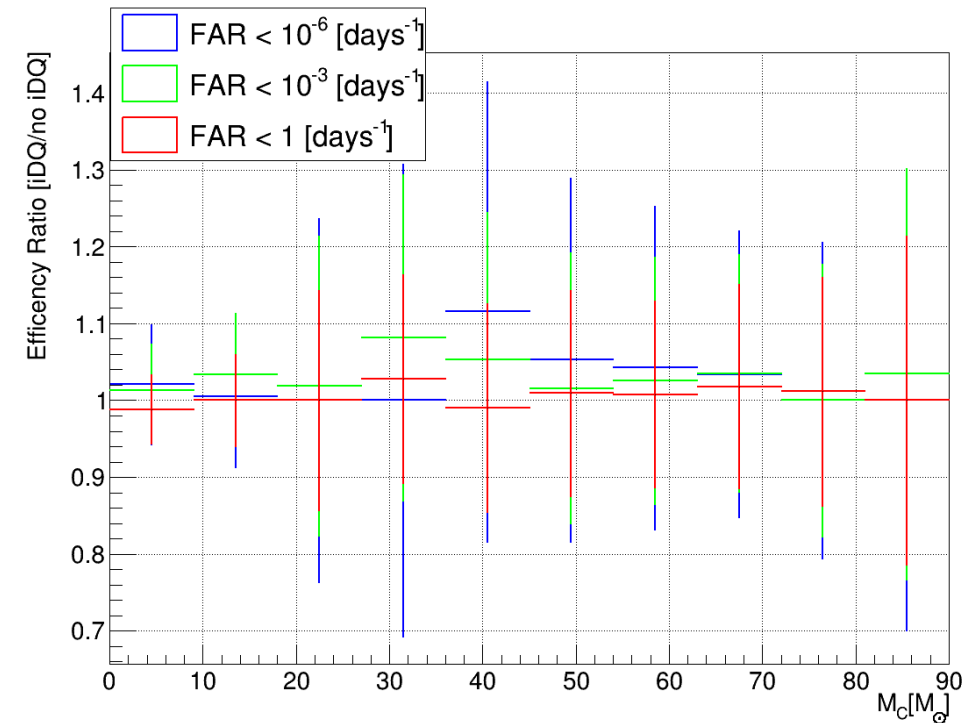
- α from 0 to 3 by step of 0.5
- $\forall \alpha$: max log(L) over template duration more efficient

$\Rightarrow \alpha = 1.5$ best choice so far

- $FAR < 10^{-3} [days^{-1}]$: 1218 injections recovered without iDQ
- $FAR < 10^{-3} [days^{-1}]$: 1248

$\Rightarrow +2.5\% \sim +31$ injections recovered

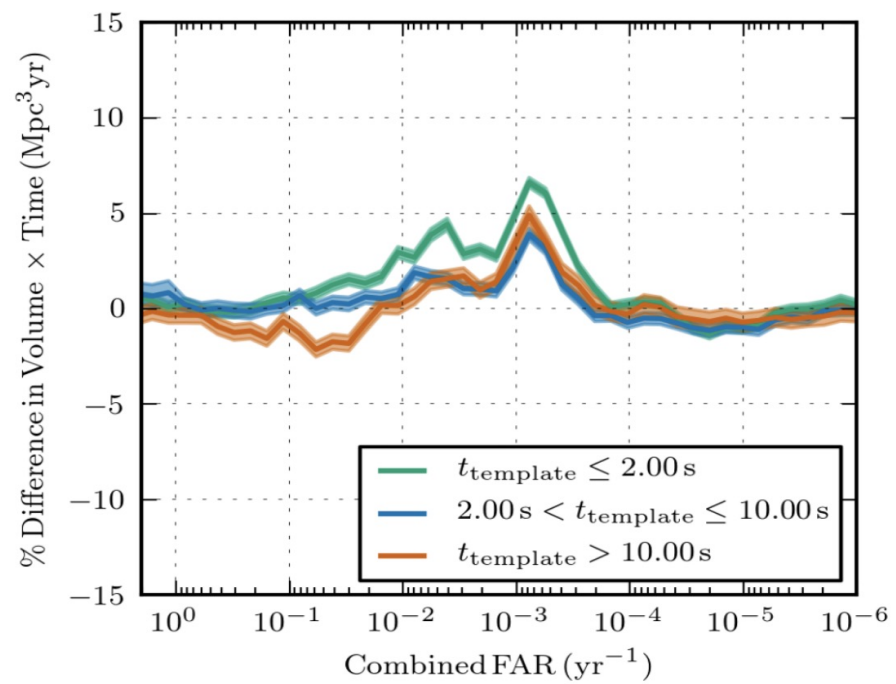
- Dependency on chirp mass : more data needed



iDQ results in PyCBC & GstLAL

GstLAL

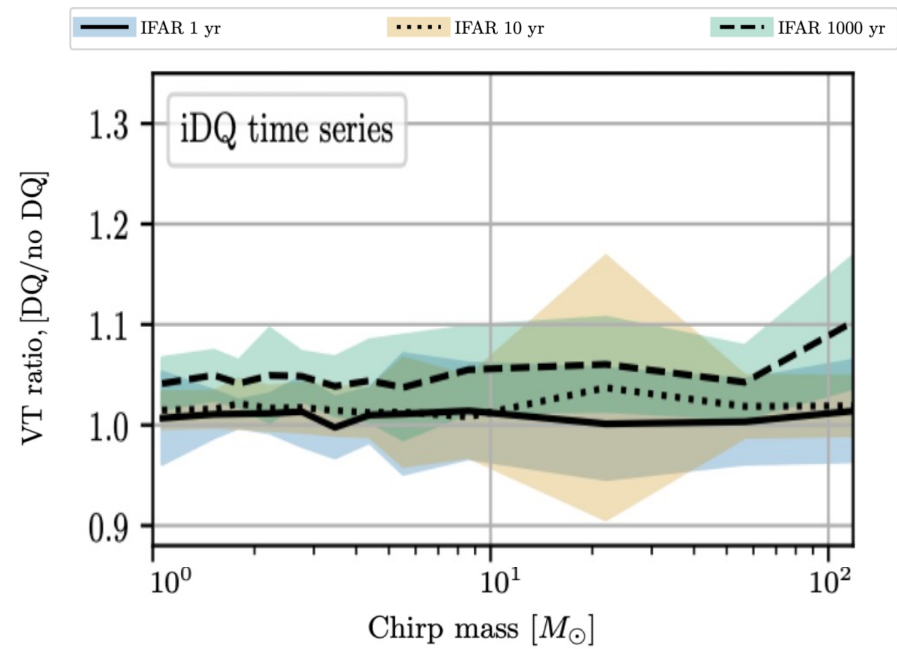
At most +6% in VT at $FAR \sim 10^{-6} [days^{-1}]$



PyCBC

Average of +5% in VT at $FAR \sim 10^{-6} [days^{-1}]$

At most +10% for very high chirp mass



Conclusion

- Preliminary results for chunk 33 :
 - Using 1Hz Maximum trend of $\log(\mathcal{L})$ more efficient than Mean/Median
 - Large fraction of Omicron glitches are not flagged by iDQ
- Lower mass template can have large durations: consider iDQ on all template duration or some Δt around trigger time ?
 - Maximum $\log(\mathcal{L})$ over long durations could be overestimated \rightarrow falsely downgrading events
 - Should iDQ be used for short BBH only ? BHNS/BNS events ?
- Reweight single detector triggers SNR : $SNR_{iDQ} = \sqrt{SNR^2 - \alpha \log(\mathcal{L})}$
- Approximative new FAR calculation : $\alpha = 1.5$ & using max $\log(\mathcal{L})$ more efficient
- Reach +2.5% of efficiency at FAR = 10^{-3} [$days^{-1}$]
- Need to run MBTA once again after implementing iDQ reweighted SNR