Low-latency Noise Mitigation Techniques in Gravitational-wave Detector Data Using Auxiliary Sensor Information

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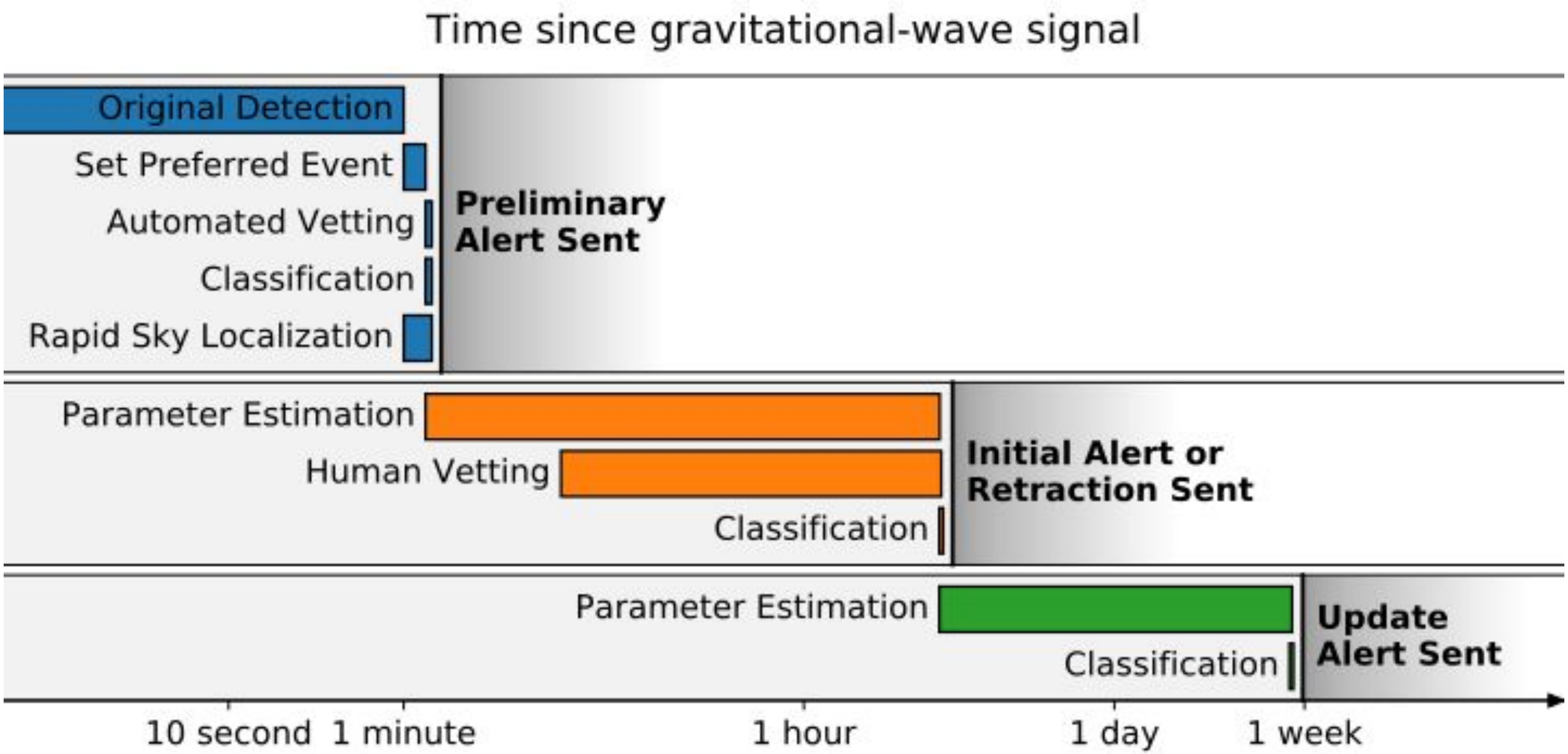
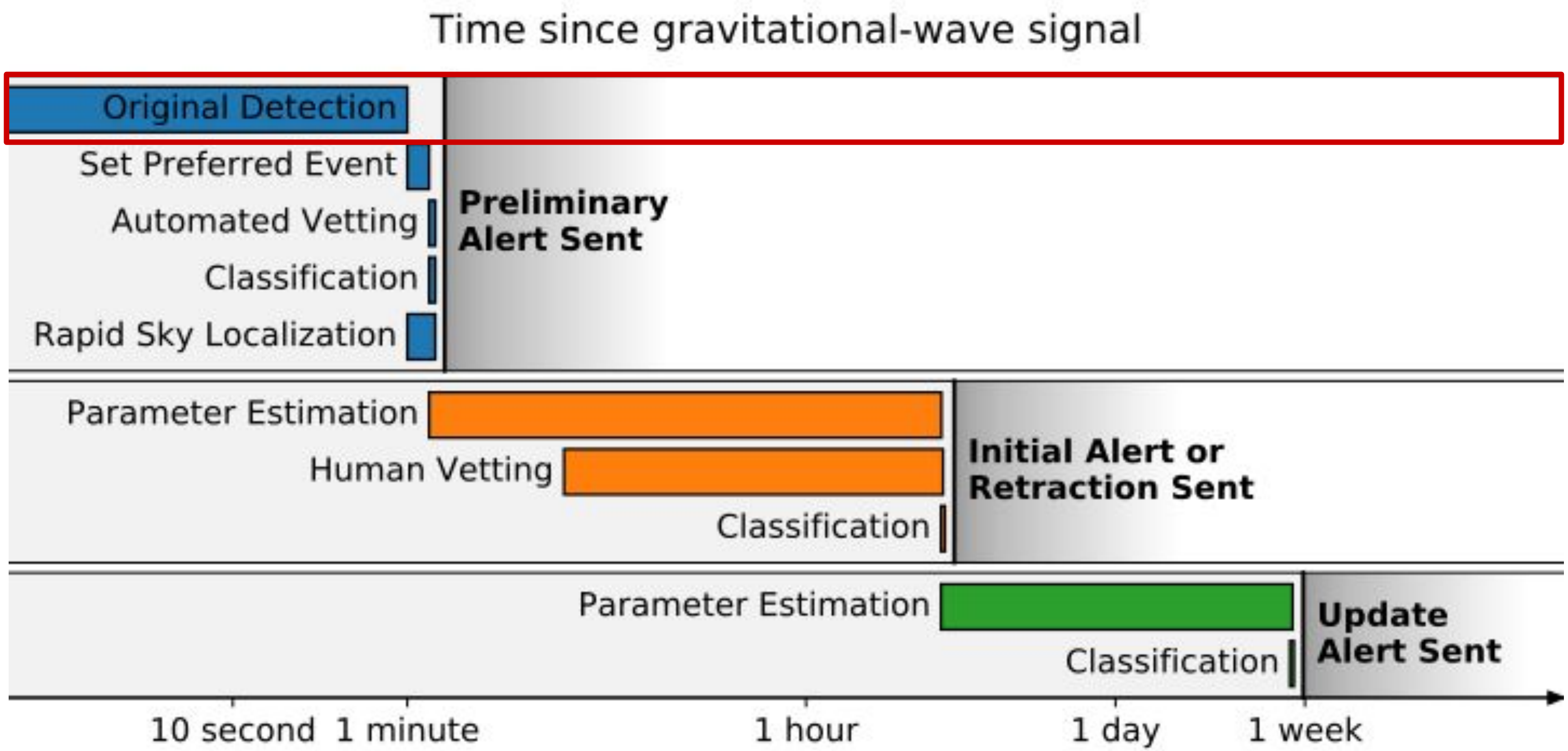
Open Public Alert Timeline



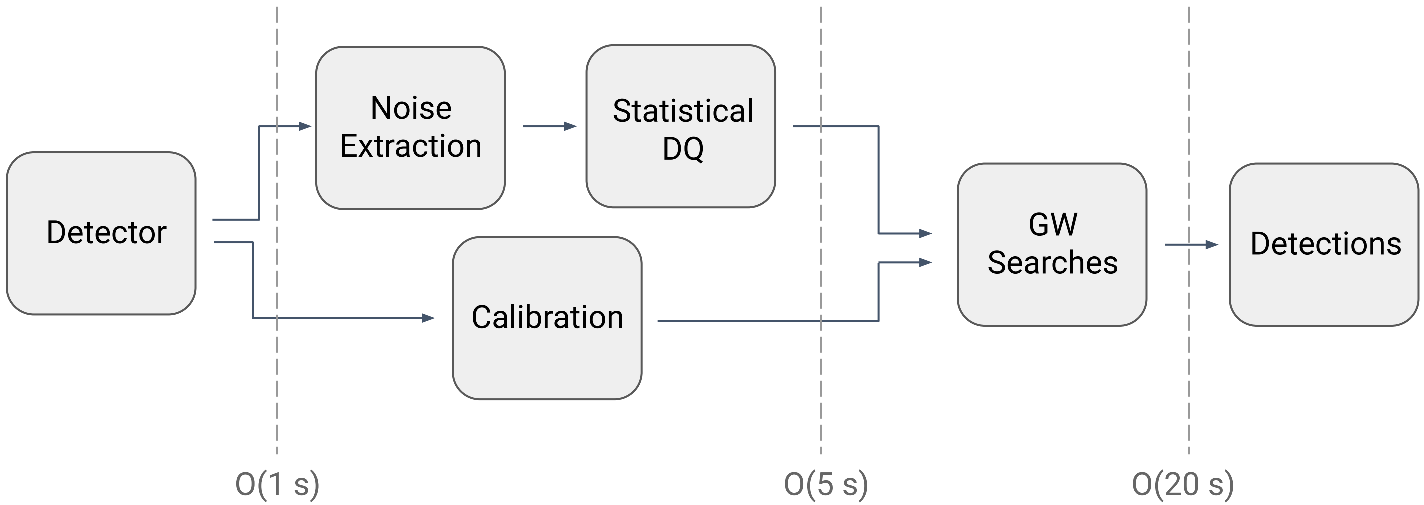
LSC Public Alerts User Guide, Version 12 (2019)

Open Public Alert Timeline

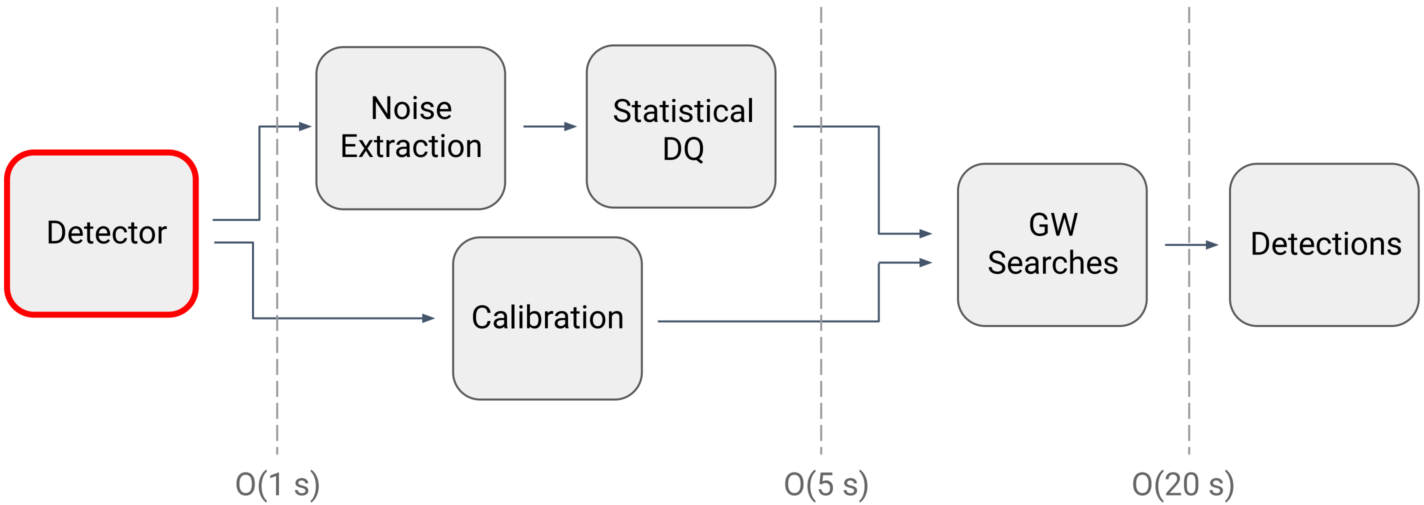


LSC Public Alerts User Guide, Version 12 (2019)

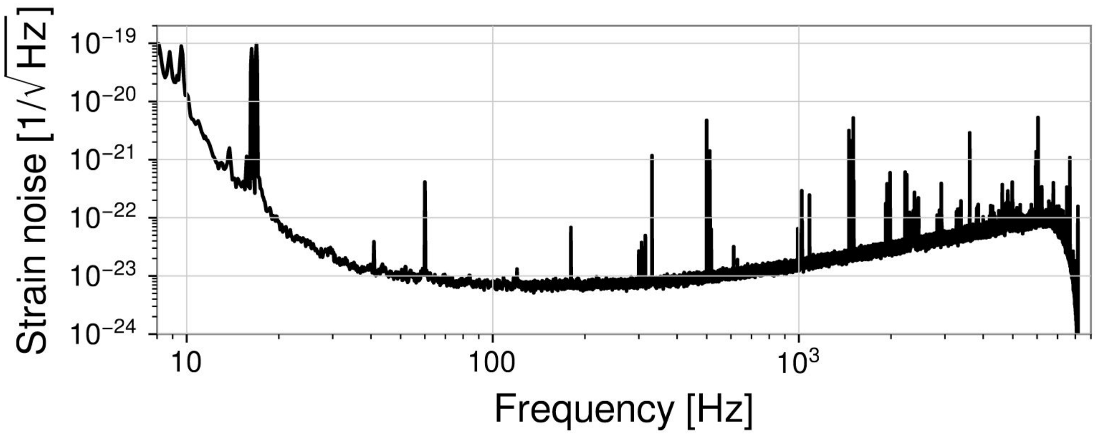
Simplified Low-Latency Dataflow: O3

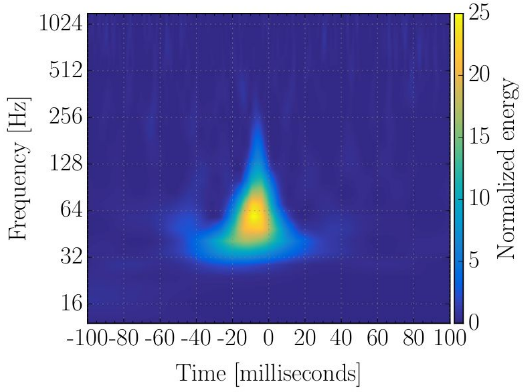


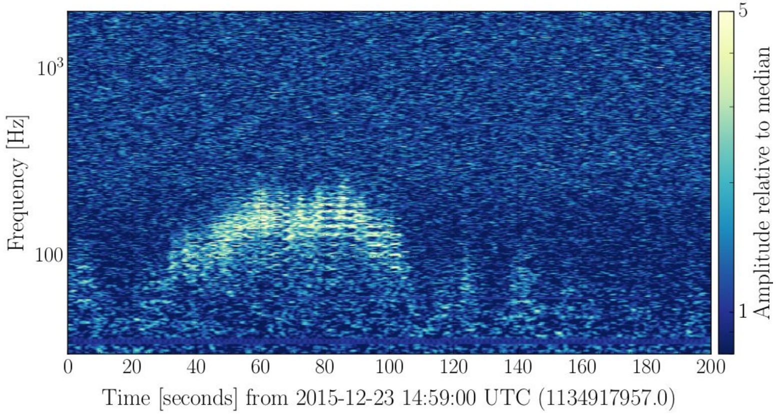
Detector Noise



Noise Types

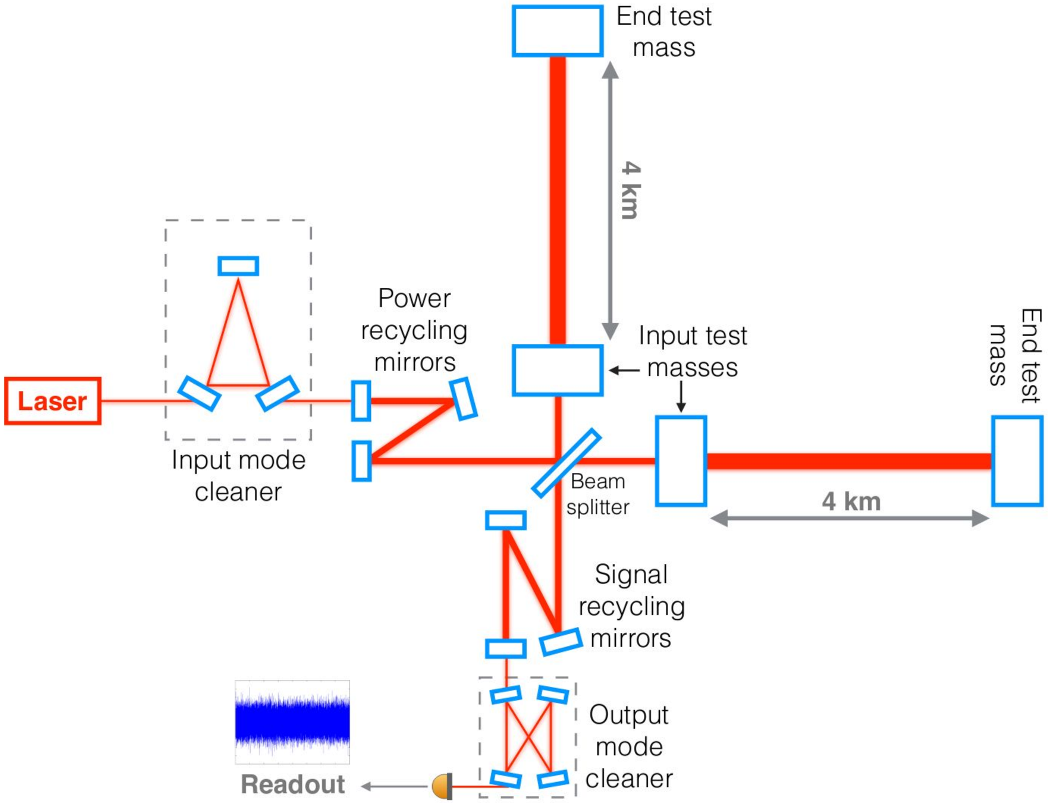




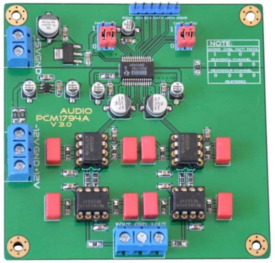


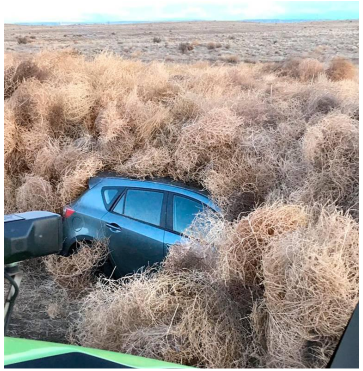
arXiv:1908.11170v2 + arXiv:1710.02185v4

Noise Sources

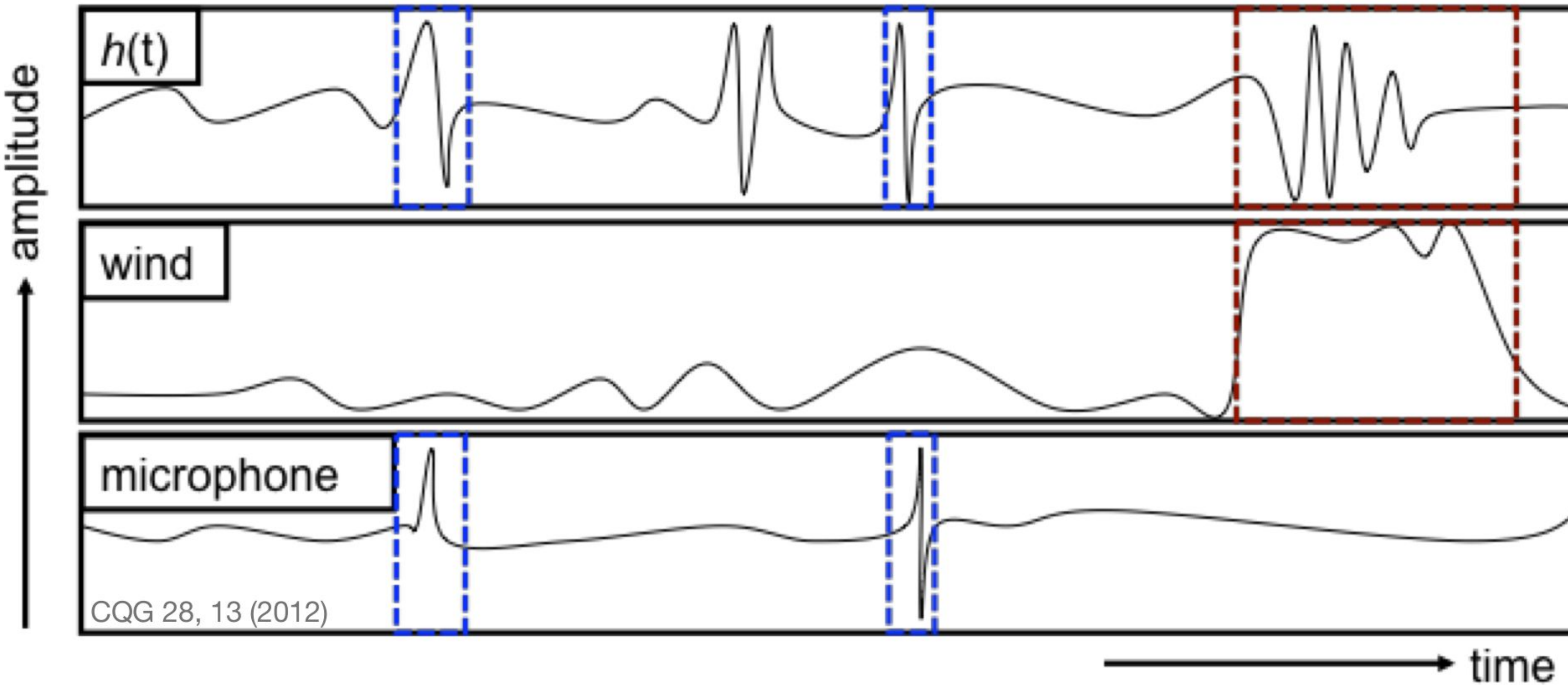


arXiv:1901.05093v2





Auxiliary Sensors



Auxiliary Sensors: A Big Data Challenge

- ~250k auxiliary channels
  - ~5k “fast” channels (≥ 256 Hz timeseries)
  - Rest are “slow” channels (16 Hz timeseries)
- Data rate: ~50 MB/s
- Data storage: ~ 1.5 PB/yr

Noise Mitigation Techniques

In order of preference:

1. Noise Source Removal
2. Noise Subtraction
3. Noise Identification
4. Search-Specific Mitigation

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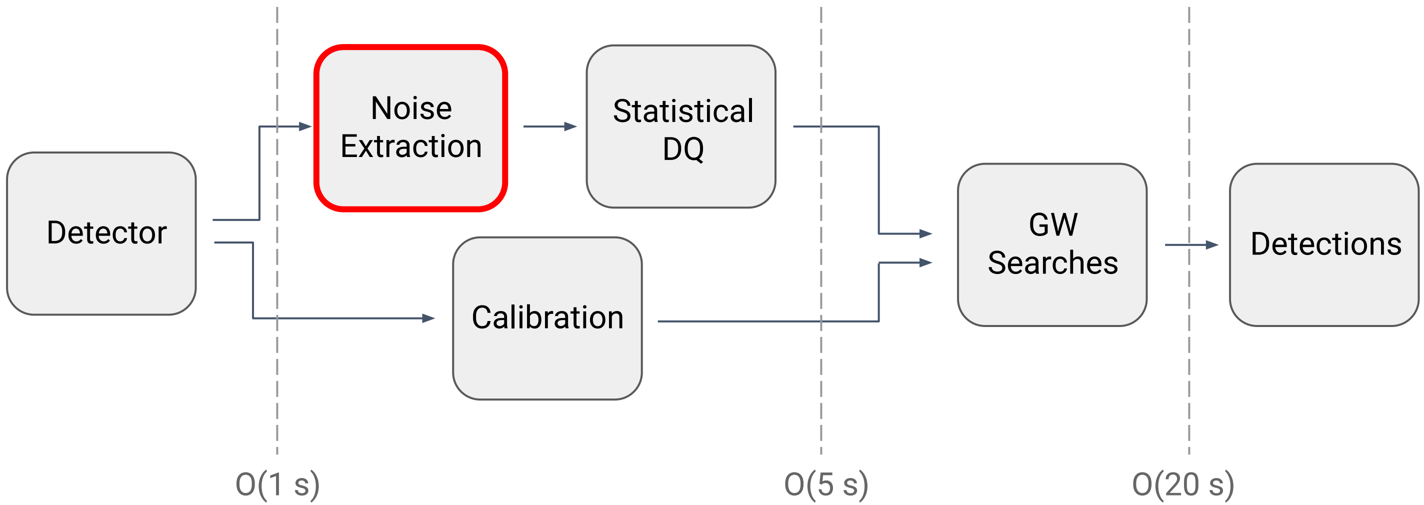
SNAX Toolkit



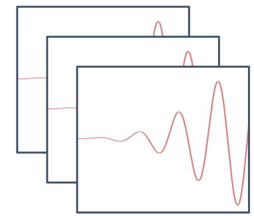
SNAX Toolkit: Overview

- Stream-based Noise Acquisition and eXtraction
- Extract non-stationary noise features in low-latency
- Sine-Gaussian basis
- **Output**: Multivariate timeseries data containing non-stationary noise features:

$$\vec{a}(t) = (\vec{a}_1(t), \ldots, \vec{a}_n(t))$$

feature vector

Auxiliary channel timeseries



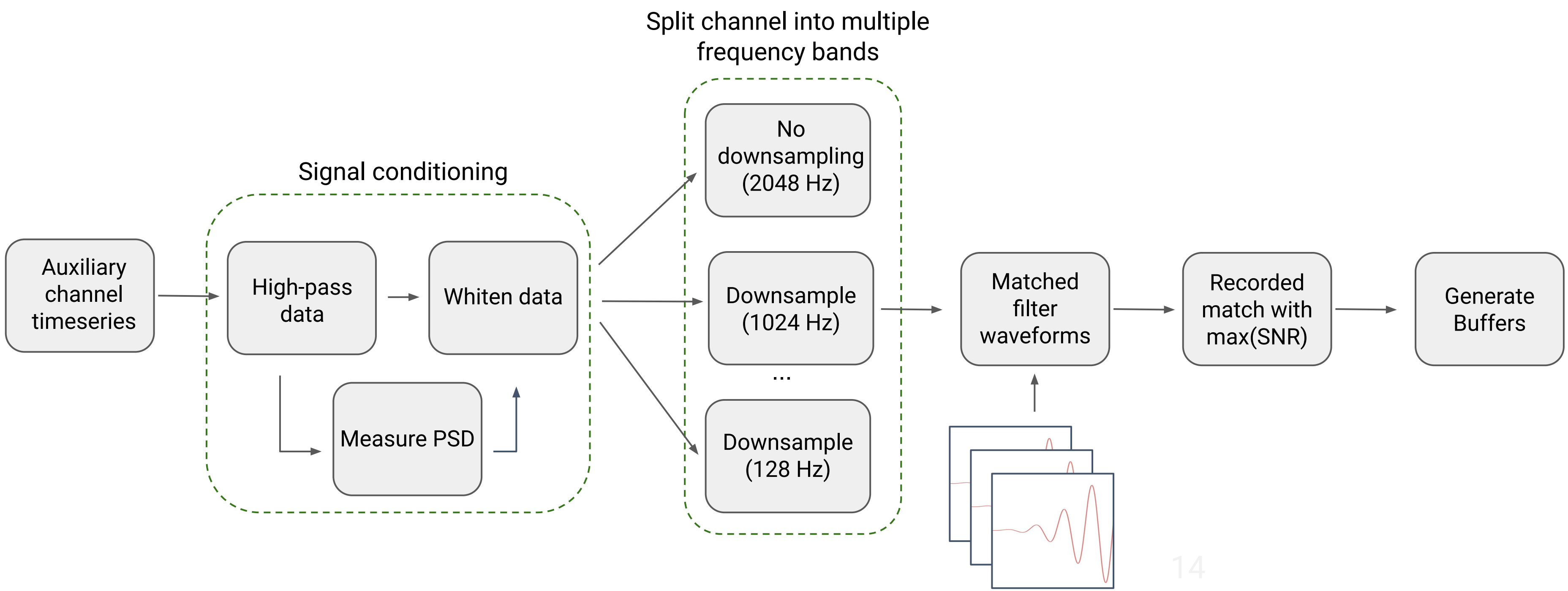
Matched filter waveforms

Record match with max(SNR) → $\vec{a}_i(t)$

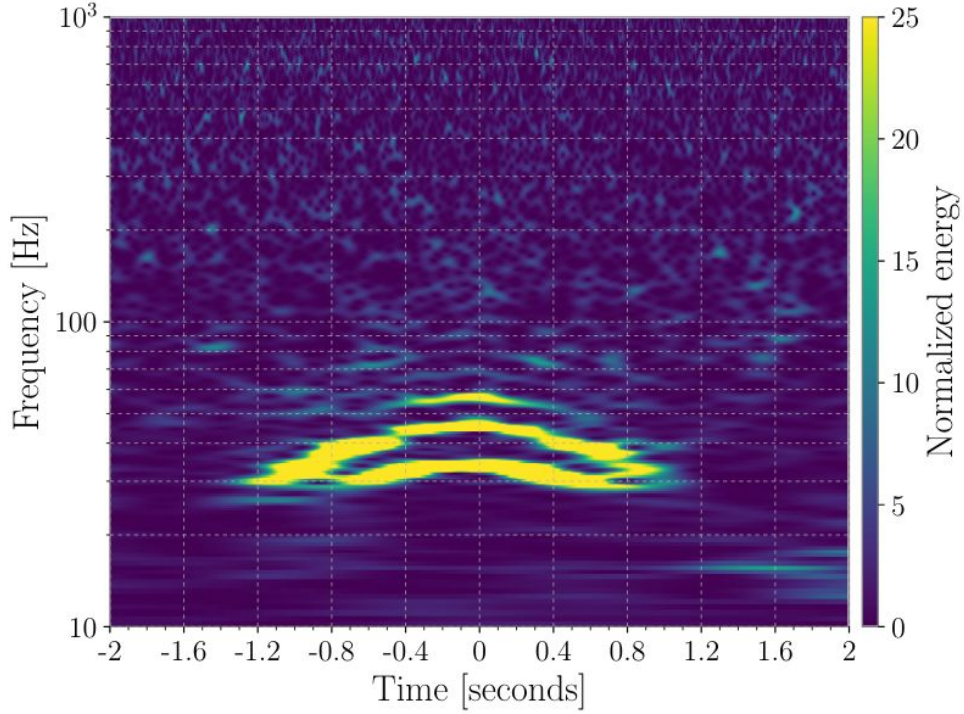
$$\vec{a}_i(t) = (\rho, \phi, t_{\mathrm{match}}, f, Q)$$

features

SNAX Toolkit: Workflow

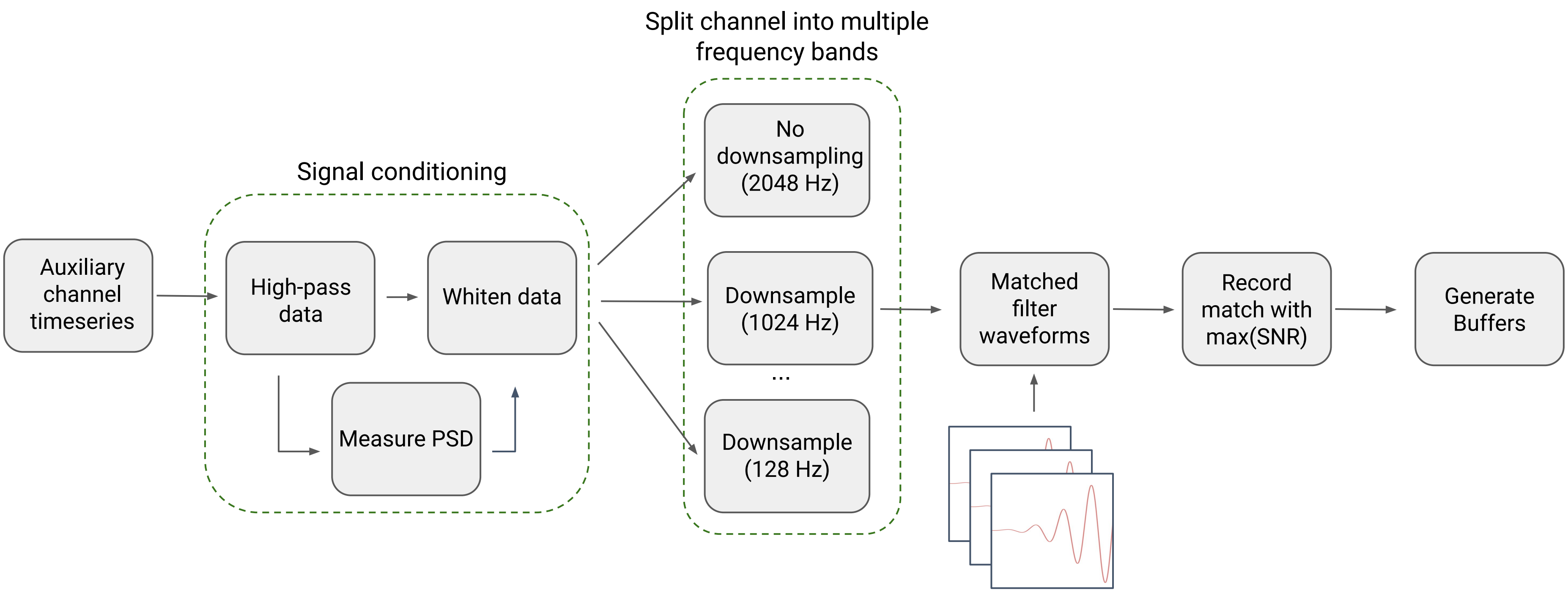


About Latency

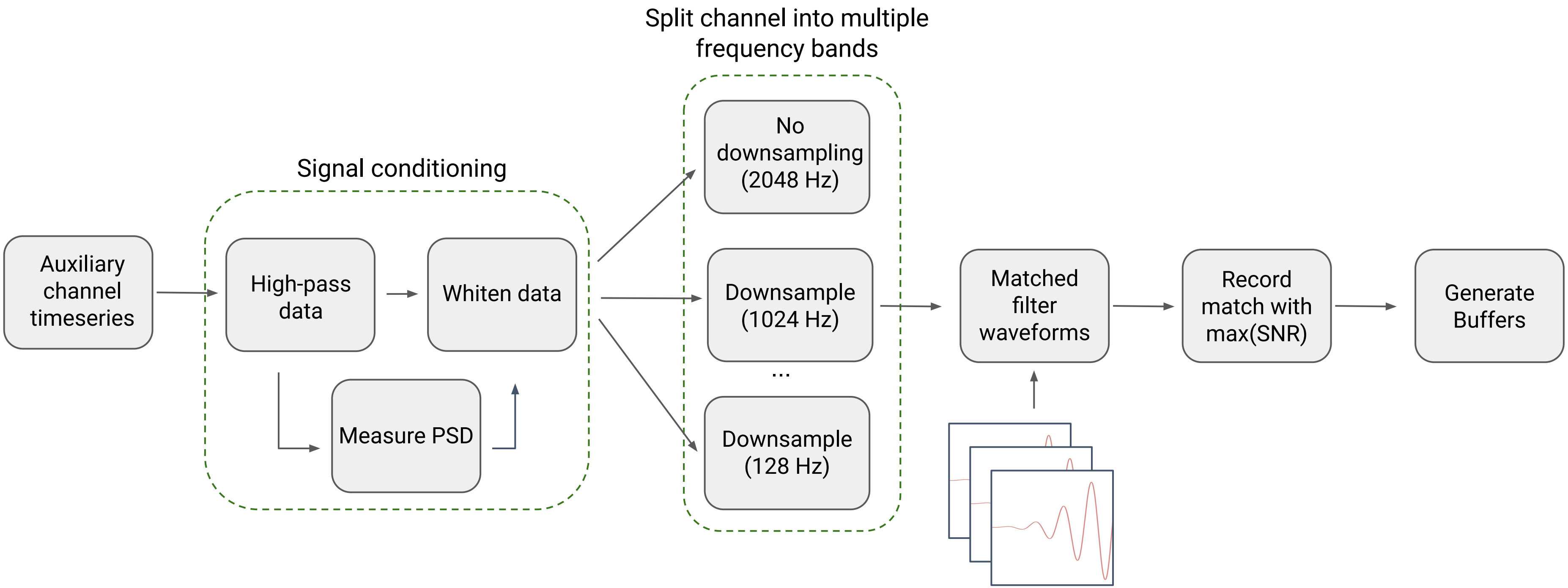


arXiv:1303.7159v1

SNAX Toolkit: Latency Budget

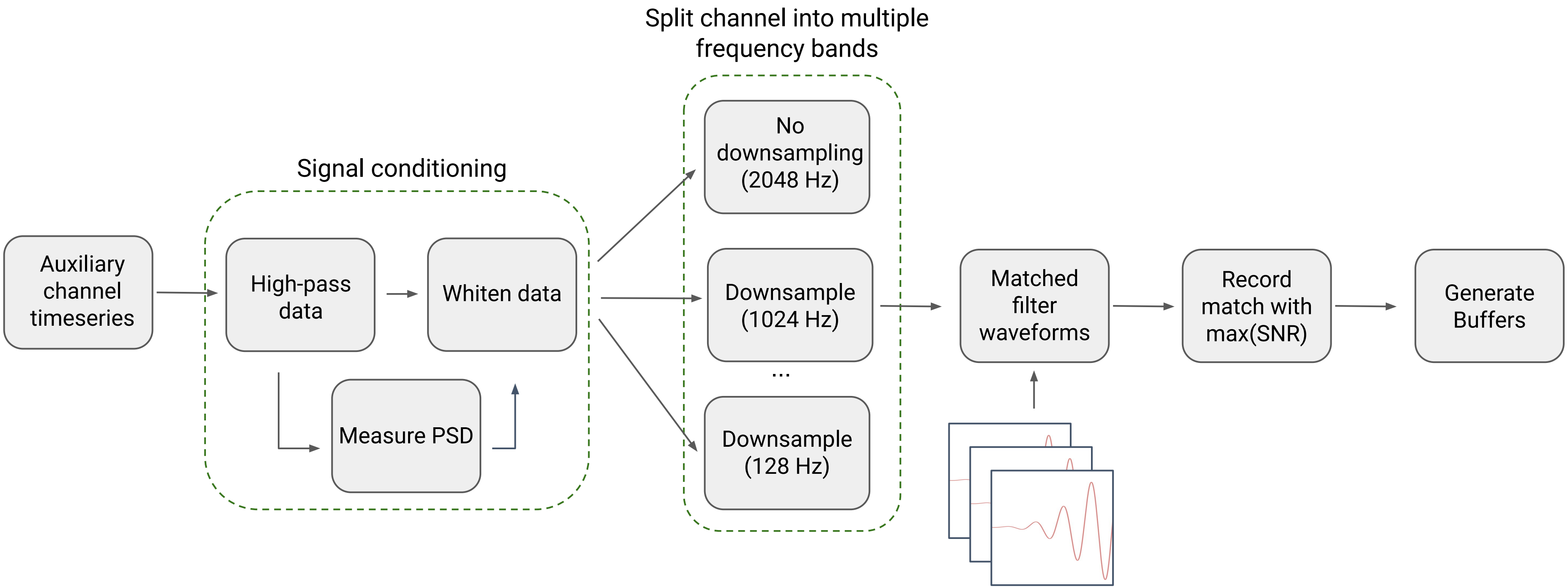


SNAX Toolkit: Latency Budget



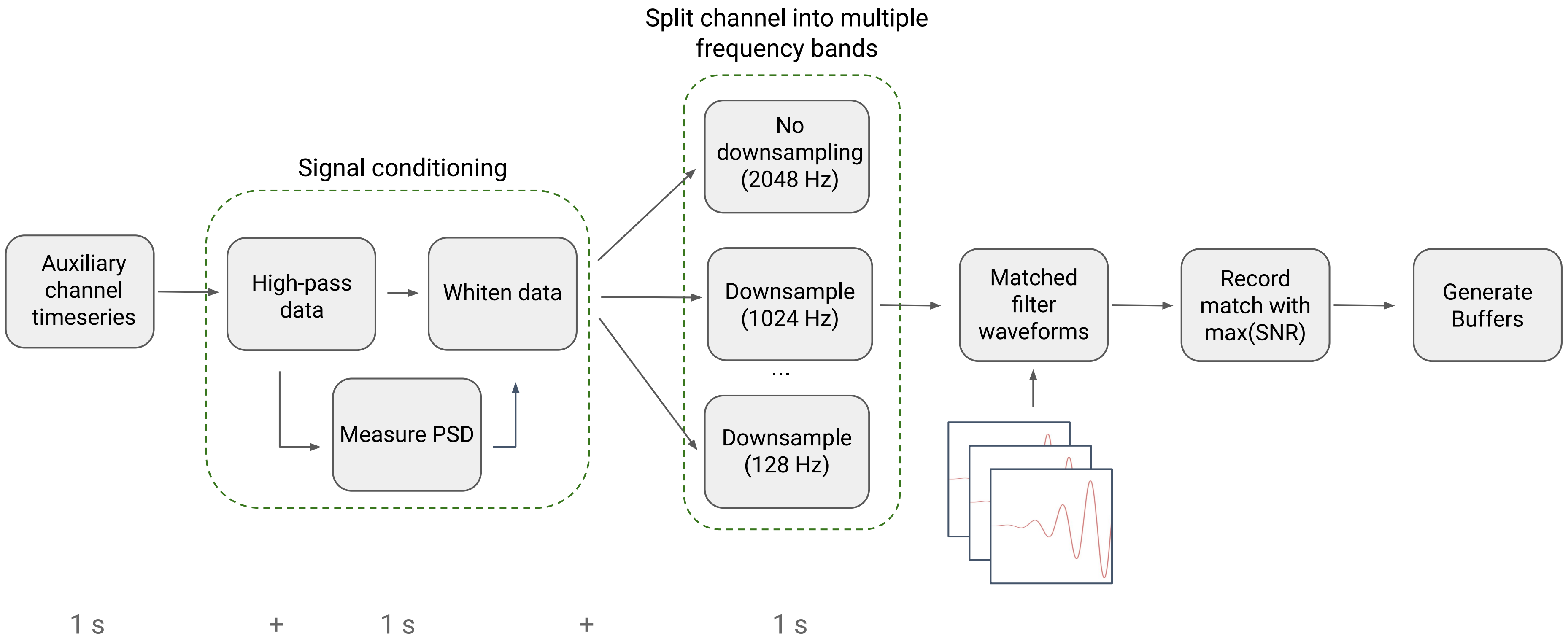
1 s

SNAX Toolkit: Latency Budget

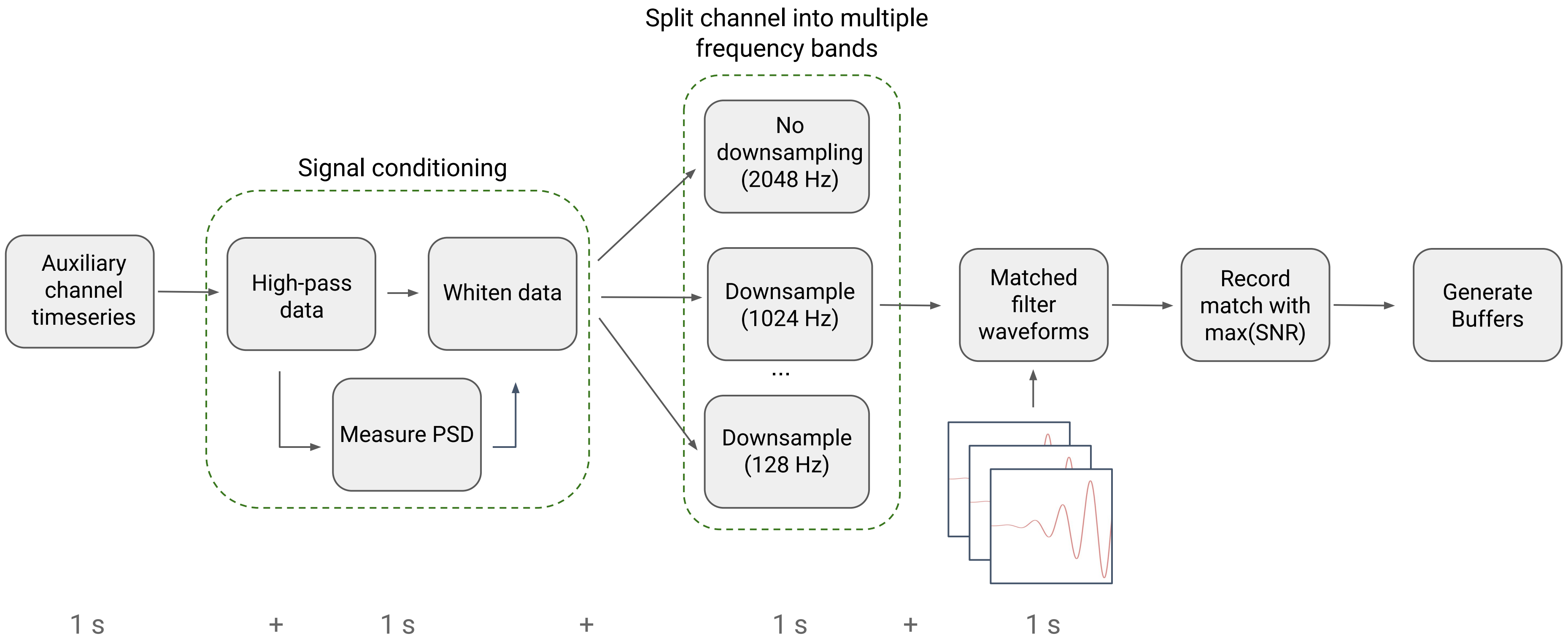


1 s + 1 s

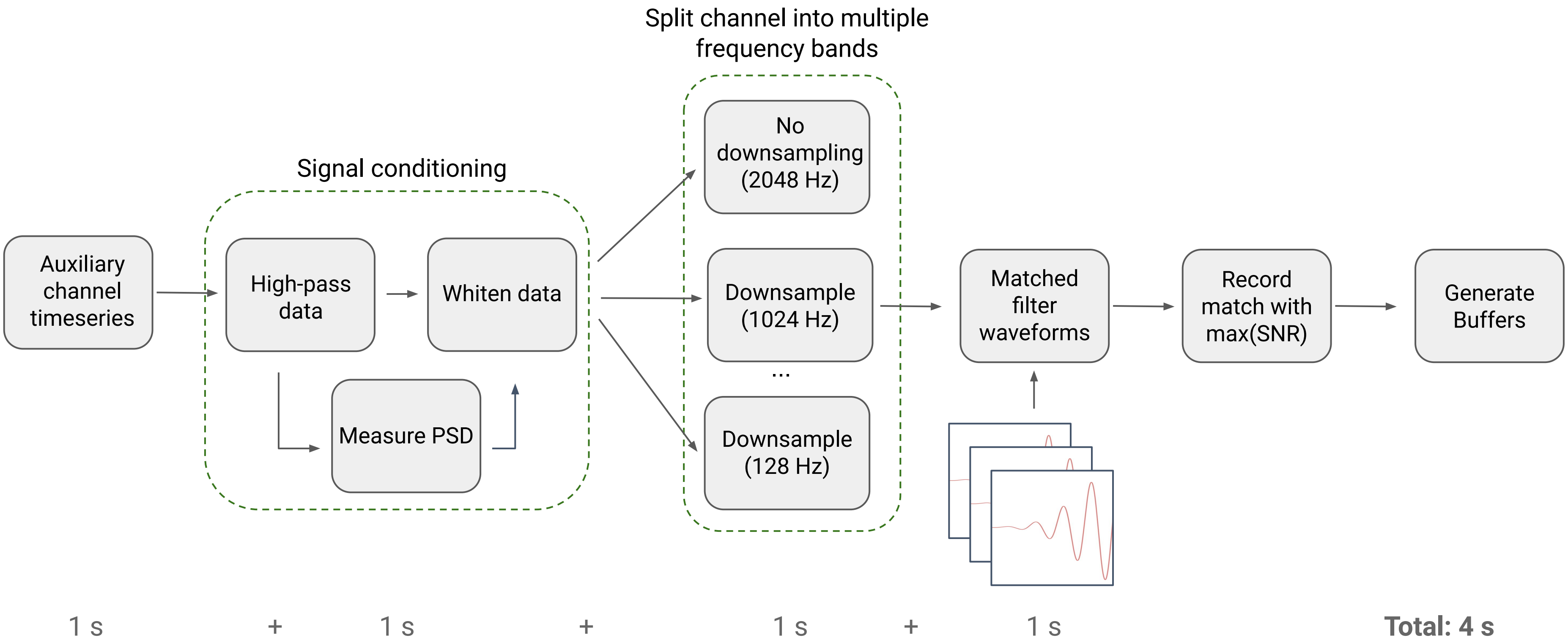
SNAX Toolkit: Latency Budget



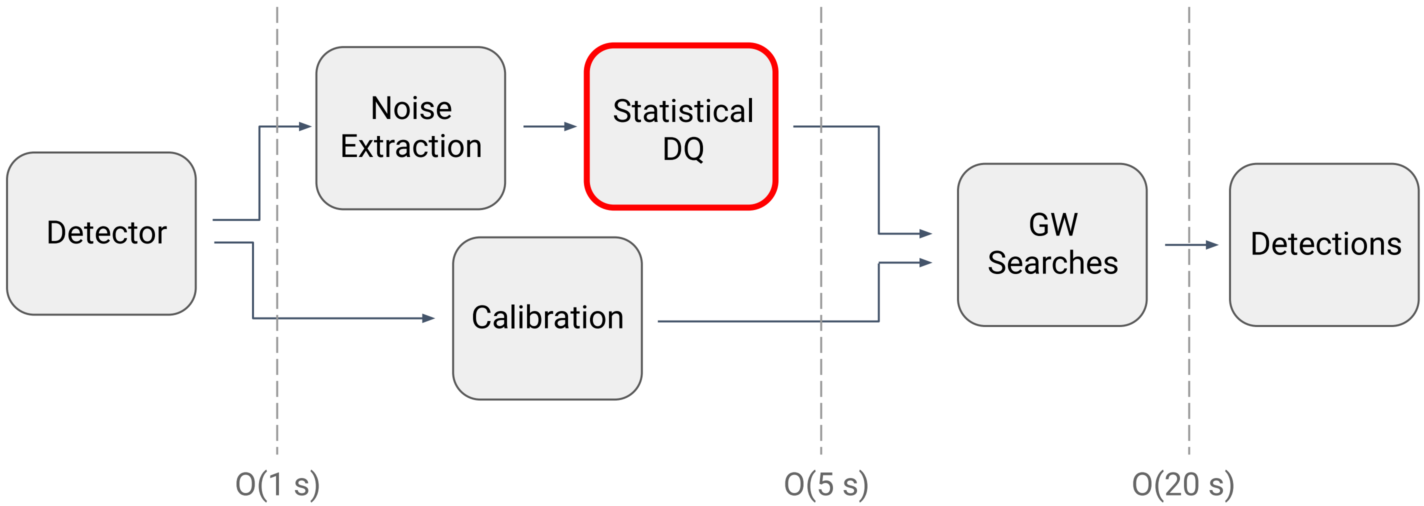
SNAX Toolkit: Latency Budget



SNAX Toolkit: Latency Budget



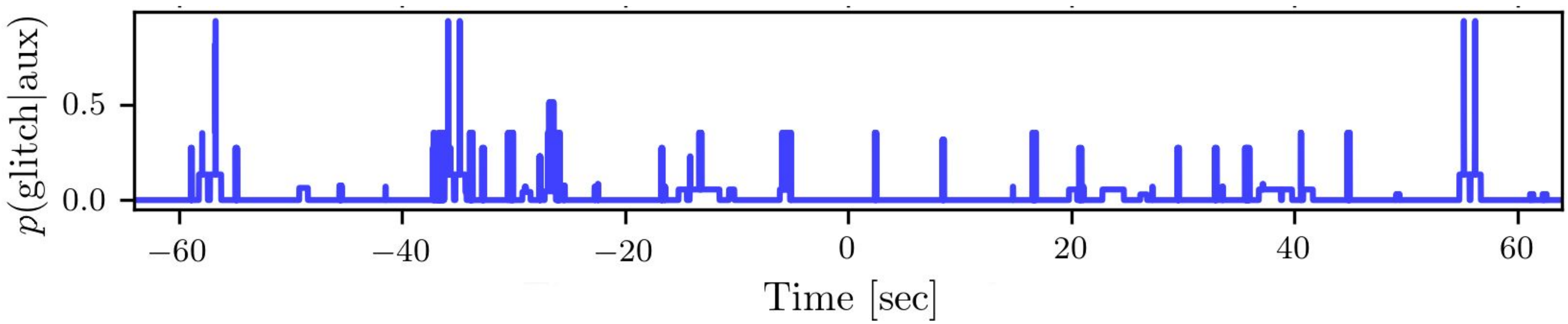
iDQ


Detector
Noise Extraction
Statistical DQ
Calibration
GW Searches
Detections
O(1 s)
O(5 s)
O(20 s)

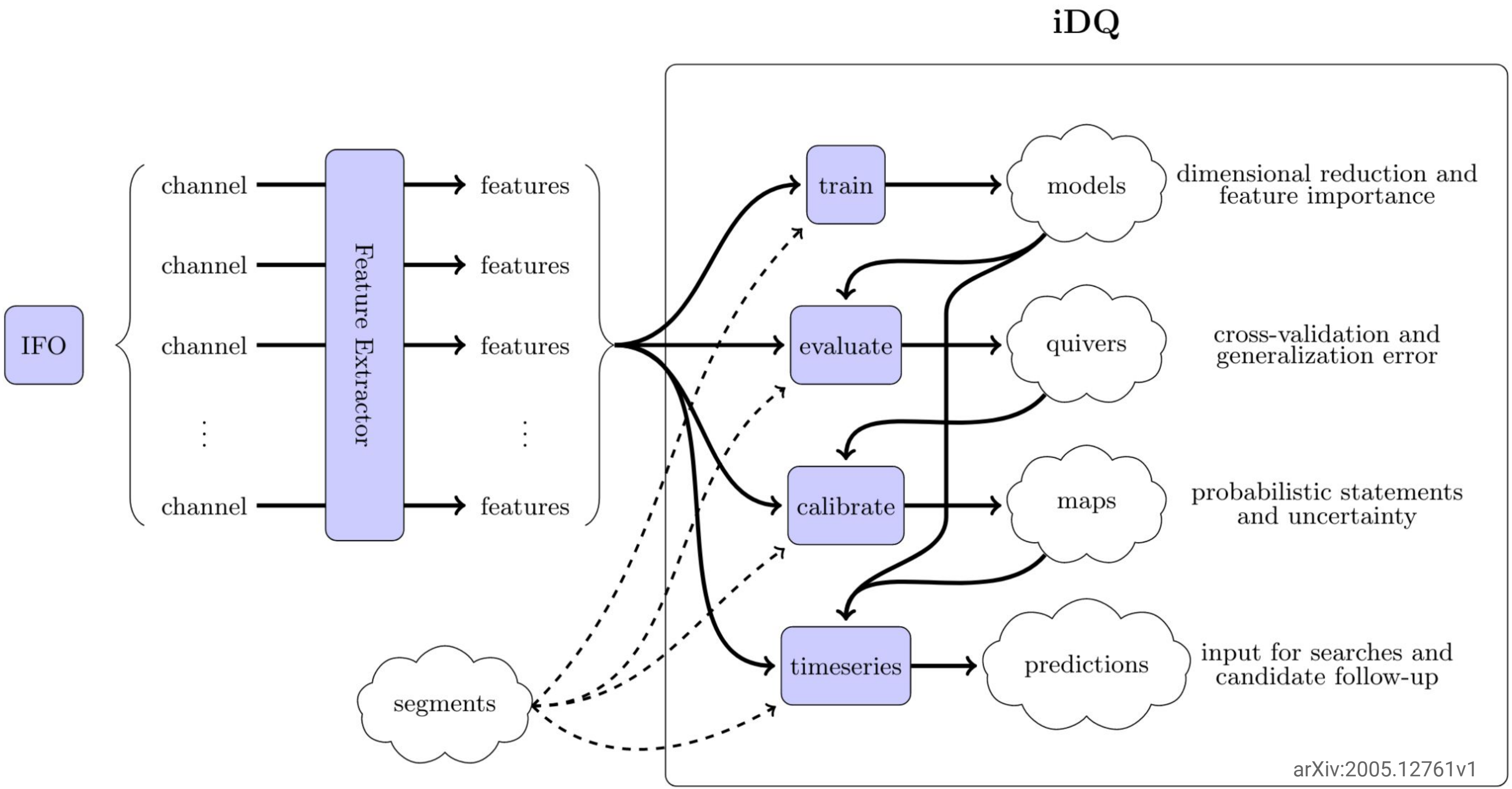
iDQ: Overview

- Search for correlations between auxiliary channels and *h(t)*
- **Output**: Probability that there is a glitch in *h(t)* as a function of time:

$$p_G(t) = p(G|\vec{a}(t)) = \frac{p(\vec{a}|G)p(G)}{p(\vec{a}|G)p(G) + p(\vec{a}|C)p(C)}$$



iDQ: Workflow



iDQ: Workflow

Features

$$\vec{a} \in \mathcal{R}^N$$

Models

$$\mathcal{M}_\alpha : \vec{a} \in \mathcal{R}^N \to r_\alpha \in [0, 1]$$

Maps

$$p(r_\alpha | G)$$

$$p(r_\alpha | C)$$

Predictions

$$\Lambda^G_C(r_\alpha) = \frac{p(r_\alpha|G)}{p(r_\alpha|C)}$$

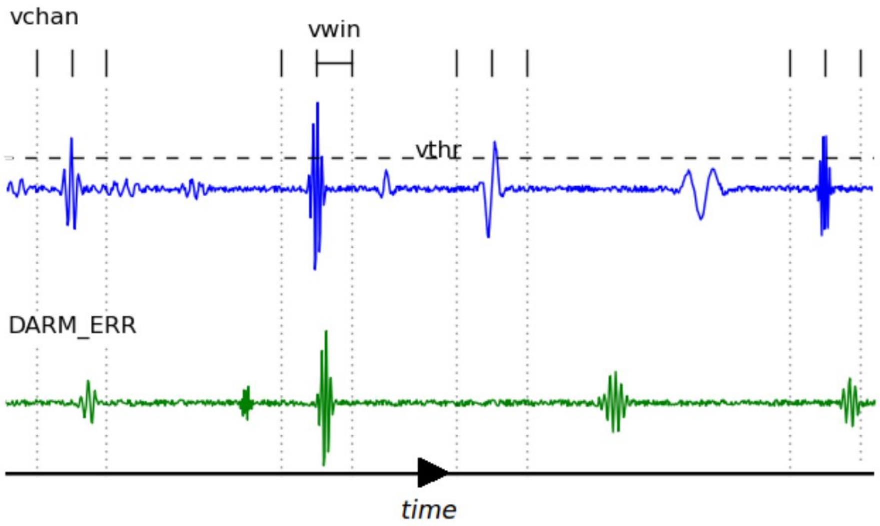
$$p_G = \frac{p(r_\alpha|G)p(G)}{p(r_\alpha|G)p(G) + p(r_\alpha|C)p(C)}$$

iDQ: Features

- Automatic retraining to deal with detector non-stationarity
- Provenance tracking
- Input features are relatively backend agnostic (SNAX, Omicron, etc)
- Supports variety of supervised classifiers
  - Statistical veto algorithms (OVL)
  - Classical ML classifiers (scikit-learn)
  - Gradient boosting (XGBoost)
  - Deep learning (Keras, PyTorch)

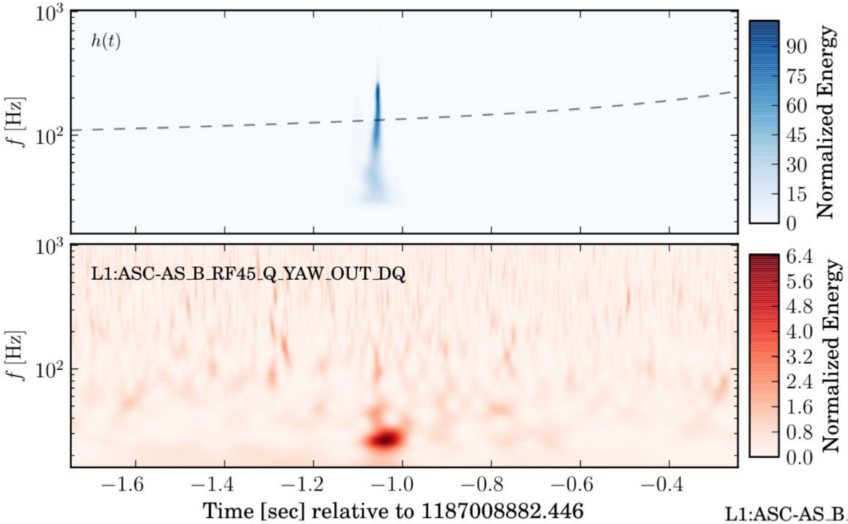
Ordered Veto List

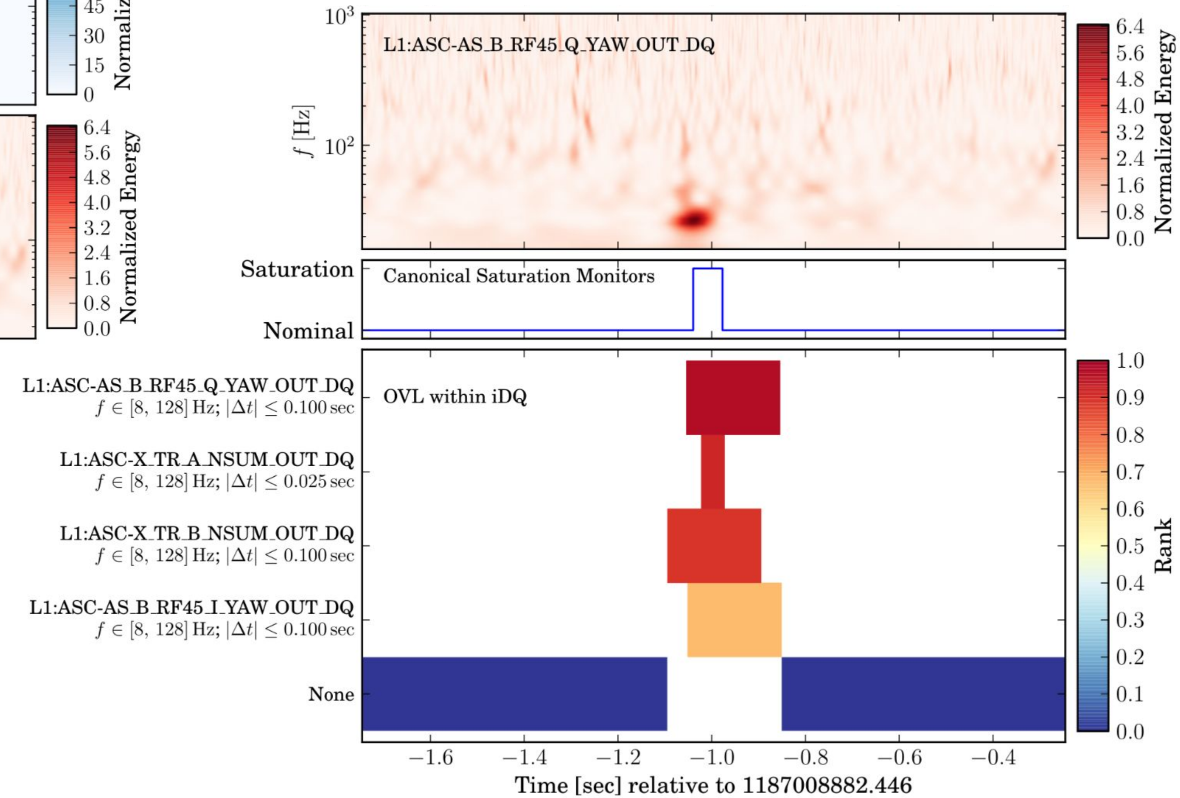
1. Apply veto configuration with a given threshold/window
2. Calculate veto efficiency for said configuration
3. Repeat for all threshold/window combinations for all auxiliary channels
4. Trim down set of veto configurations hierarchically



arXiv:1303.7159v2

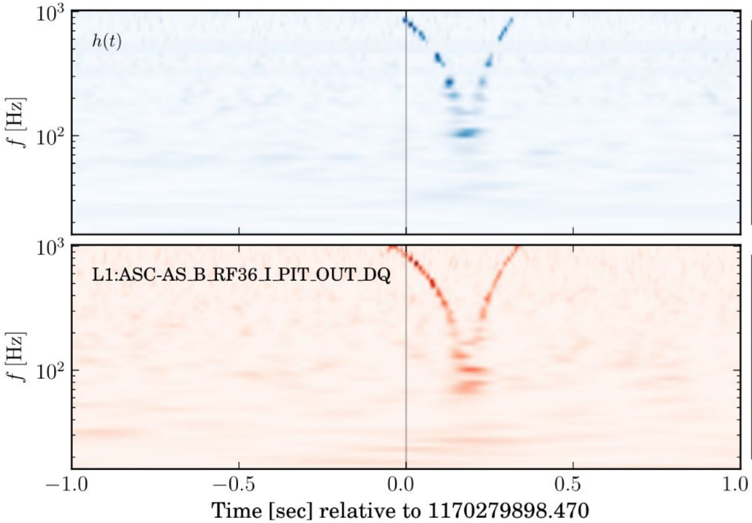
iDQ: GW170817

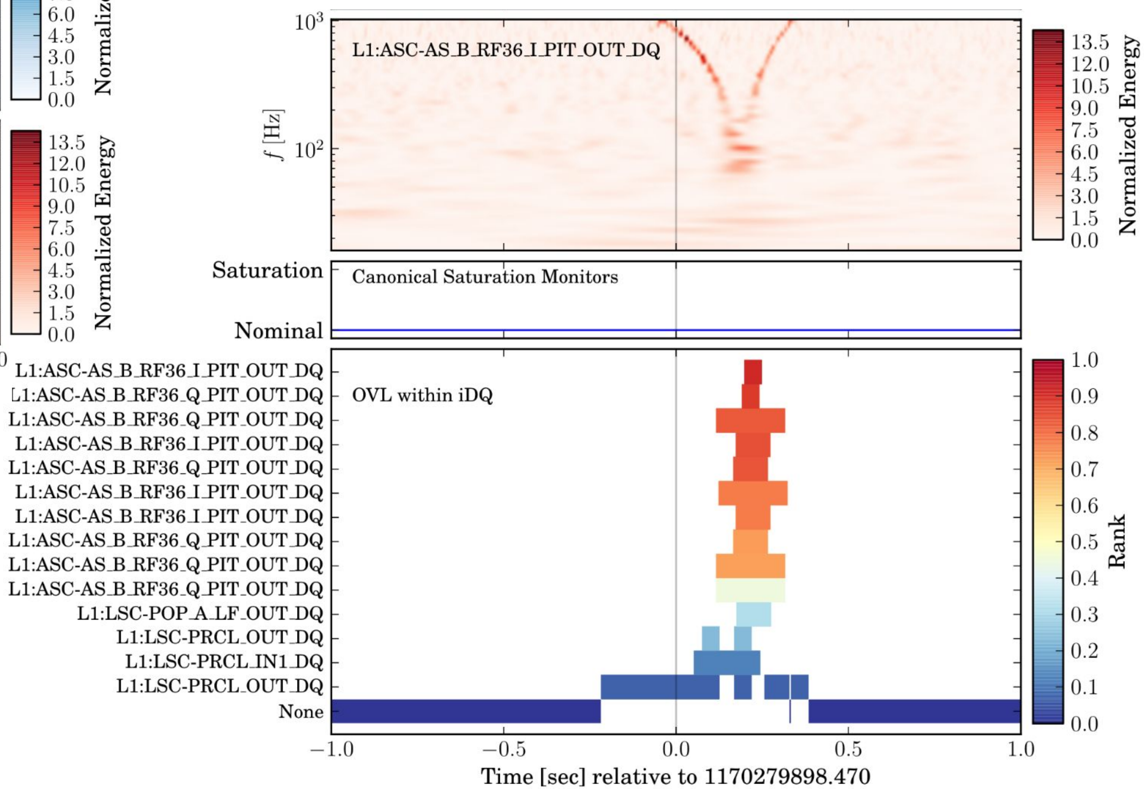




arXiv:2005.12761v1

iDQ: RF Whistle





arXiv:2005.12761v1

Wishlist For Online DQ

- Automated noise identification + mitigation (<5 second latency)
    - Medium-duration noise mitigation
    - Strain-only noise transient source mitigation
    - Noise subtraction for short duration transients
- Incorporation of non-binary DQ information into online searches
- Lock loss prediction