Sampling Frequency for Machine Learning to Separate Monitoring Artifact from Instability

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- No commercial conflict of interest

Motivation

We know: Vital sign (VS) data collected every 20s can be used to adjudicate alerts, classifying them as either artifacts or real instabilities.

We asked: Would sampling VS data less frequently impair ability to define real vs. artifact alerts?

Hypothesis:

Models using data sampled less frequently can be used to adjudicate alerts.

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Why evaluate lower sampling frequencies?

- 20s resolution is often not available in deployed systems.
    - *How far can we downsample without losing clinical utility?*
- Higher data frequencies entail higher collection and storage costs.
- In retrospective analysis existing data repositories may have only low frequency data.

Importance of Artifact Detection

For Clinicians:

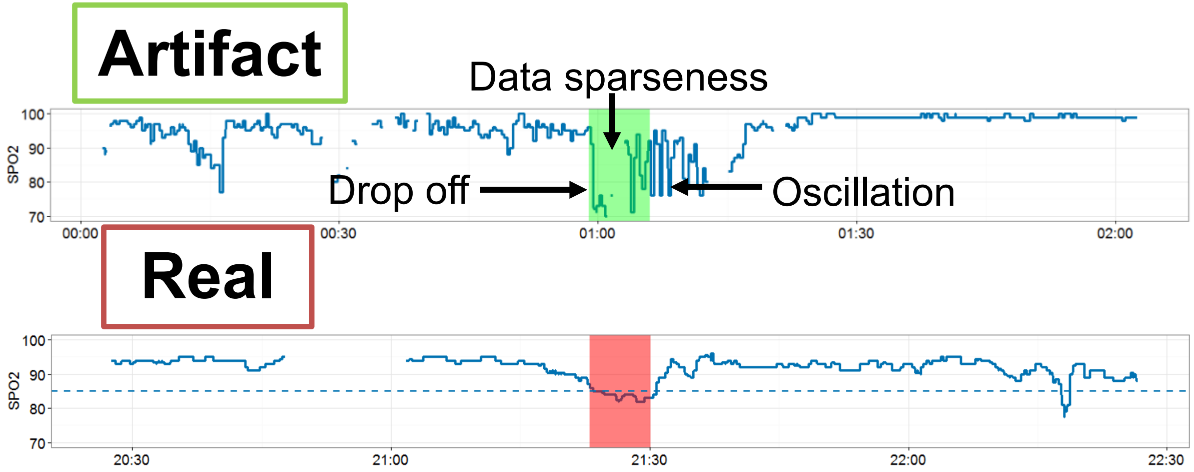
- Treat artifact vs instability differently.
- Delayed response time due to alarm fatigue.

  Bonafide et al. J Hosp Med. 2015; 10(6):345-51

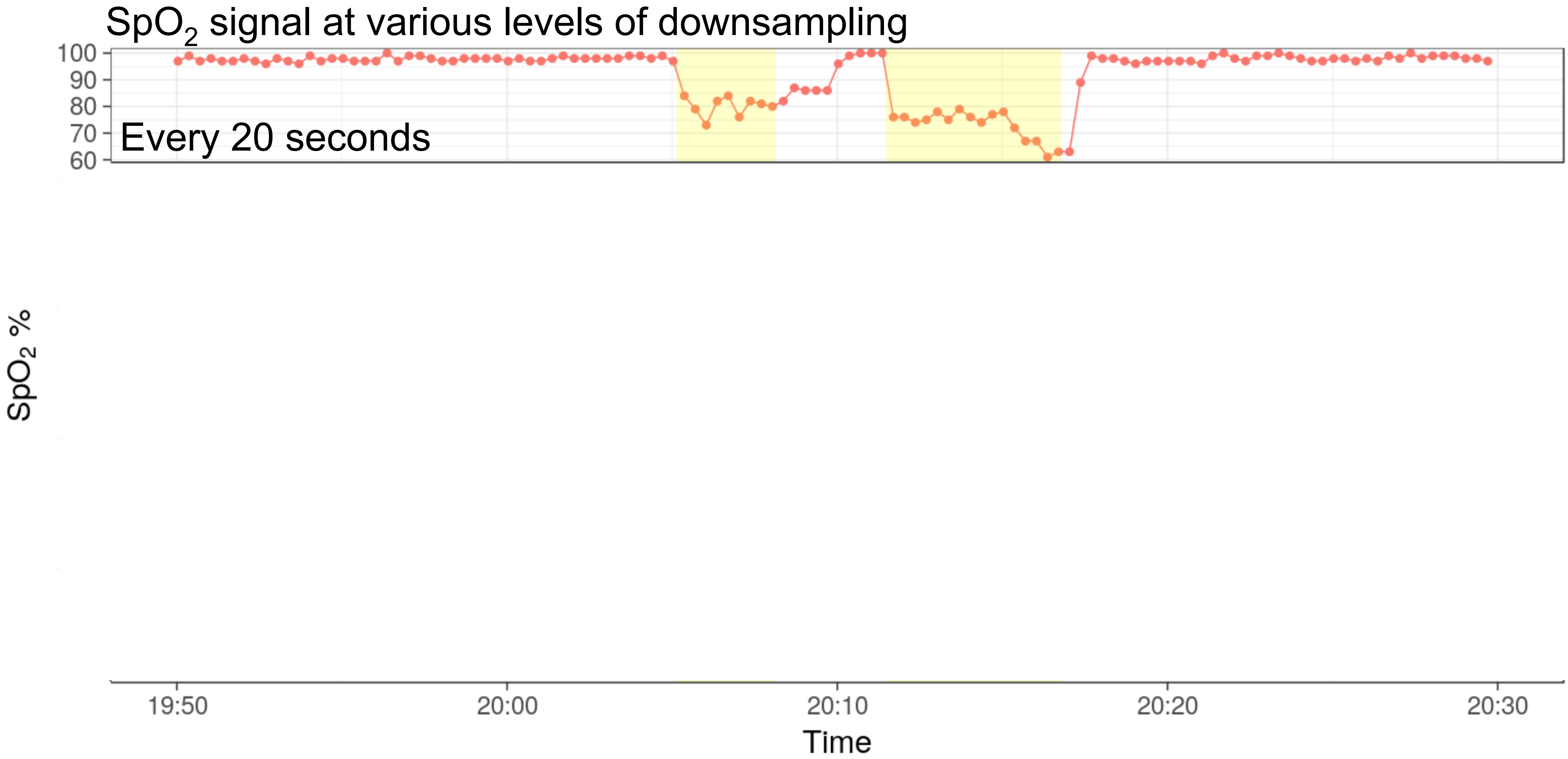
For Modelling Instability:

- More difficult in the presence of artifacts.
- Might end up modeling the artifact instead

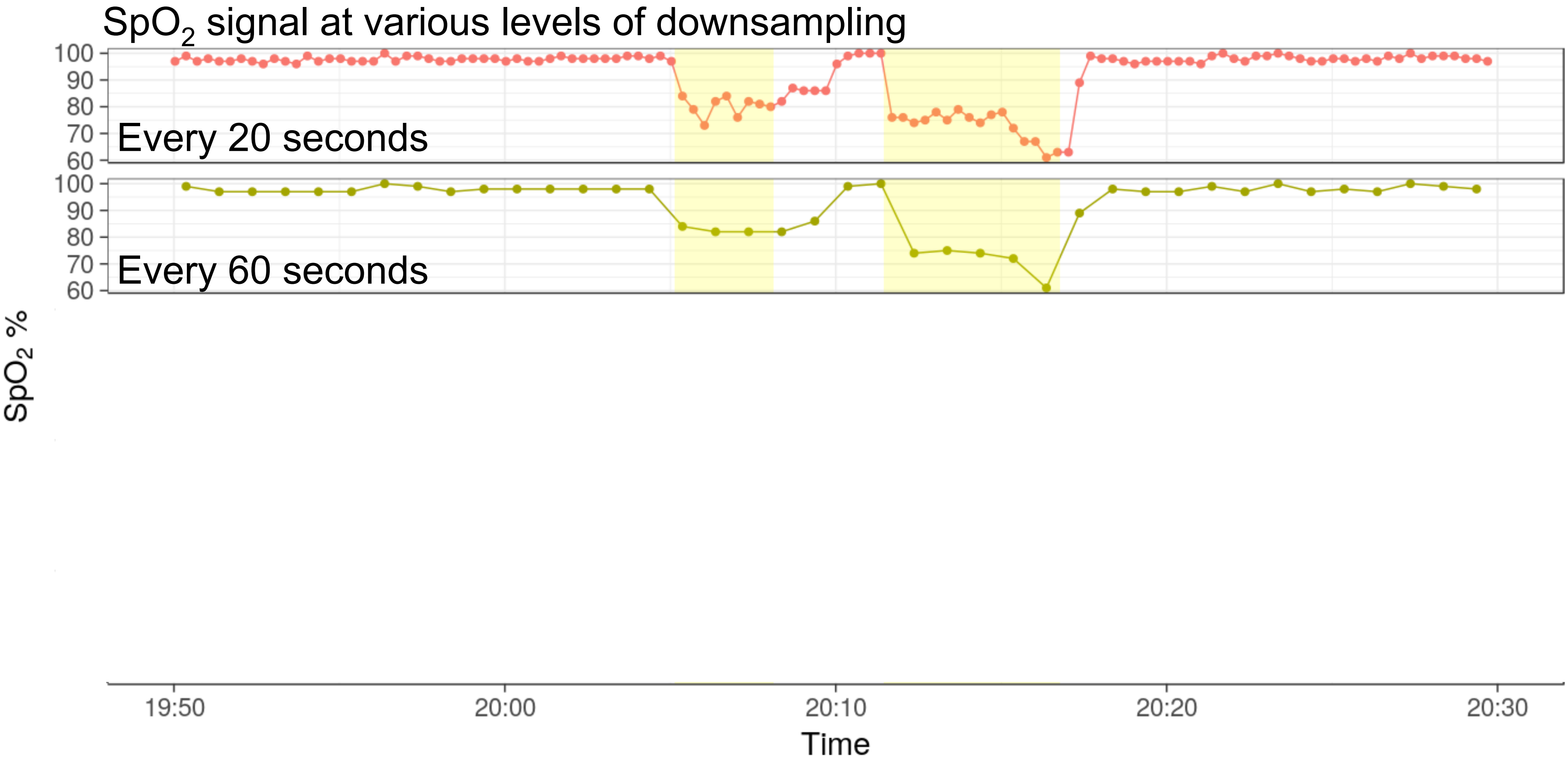
Alerts versus Artifacts



Original Vital Sign Data Collected Every 20s



Downsampling Reduces Number of Observations



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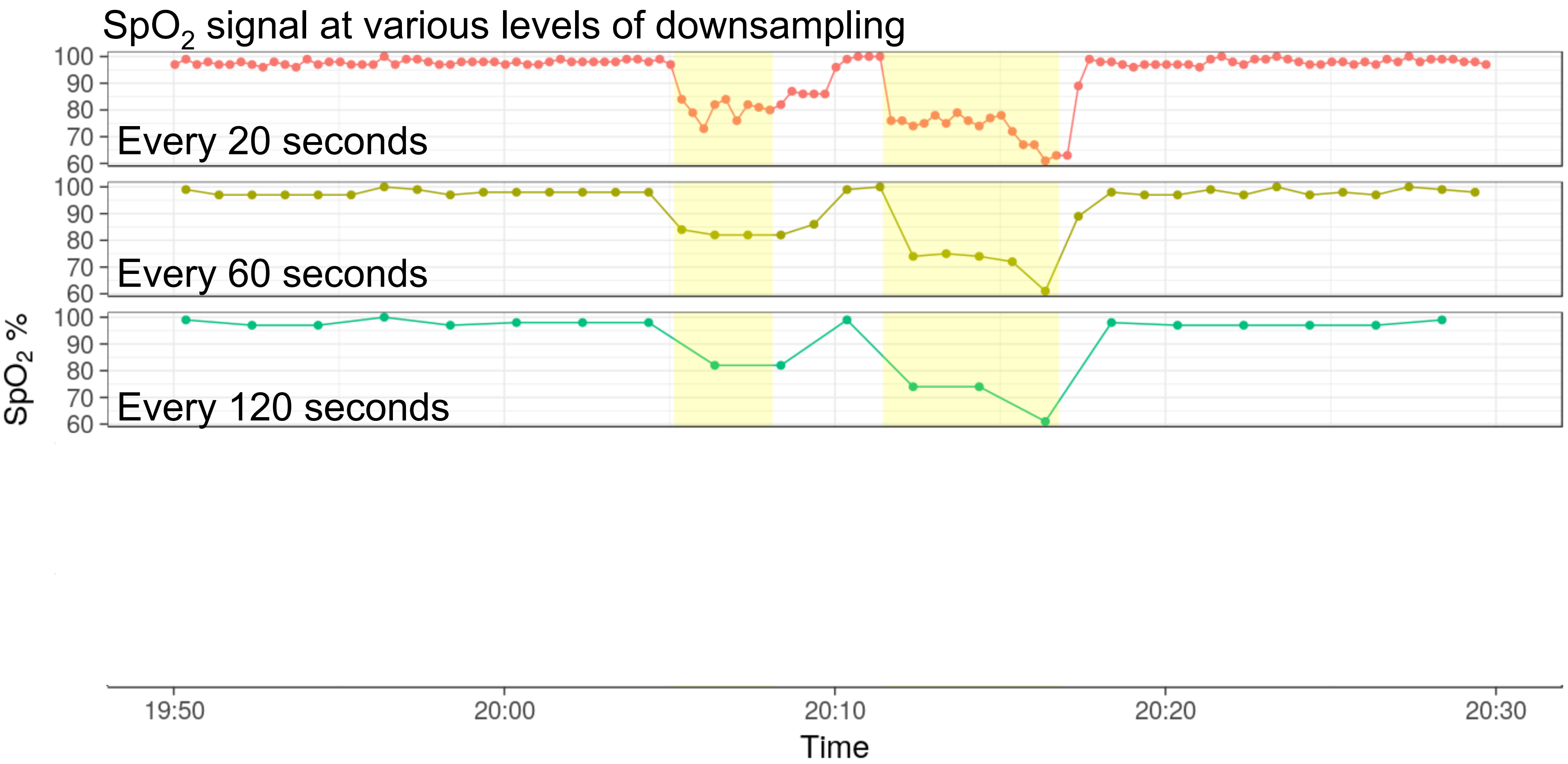

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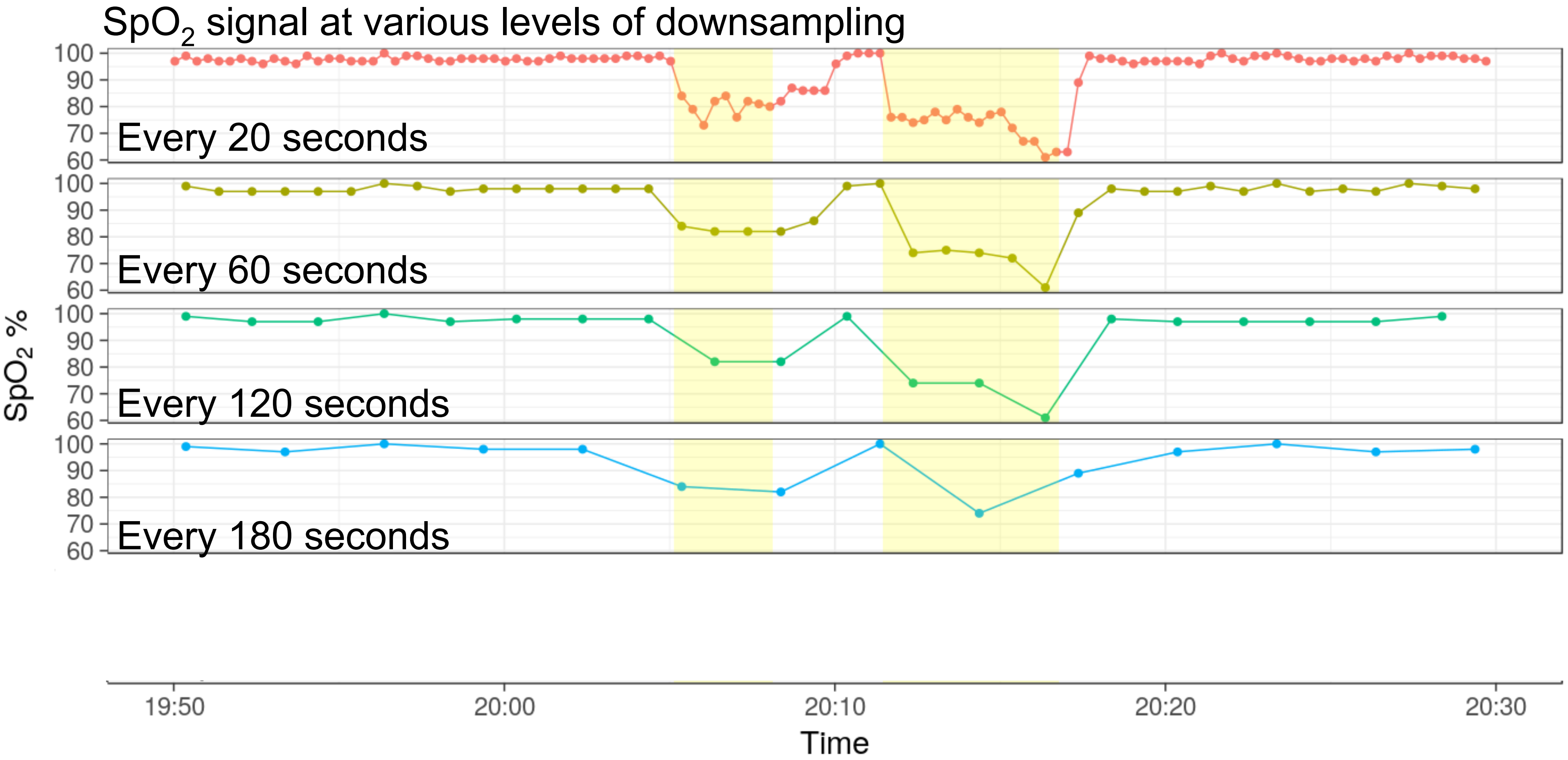
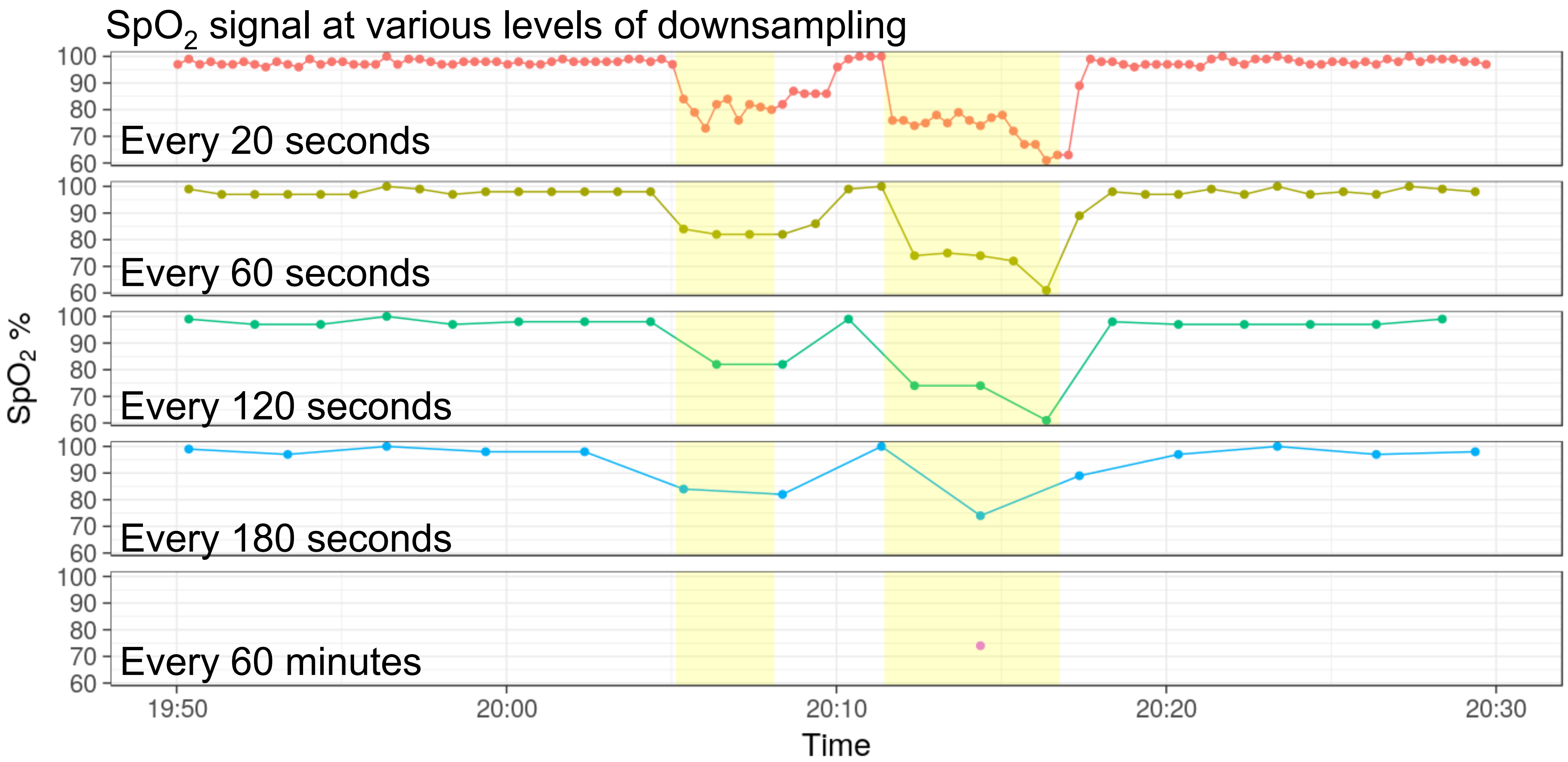


Excessive Downsampling May Leave Too Little Data



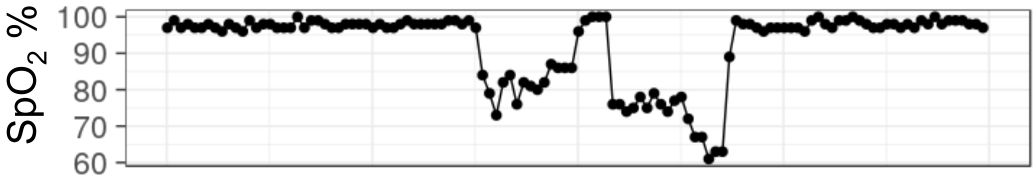
Dataset Collected from Step Down Unit Patients

- Collected continuous vital sign (VS) data streams from 200 step-down unit (SDU) patients.
  - Heart rate (HR) - 3-lead ECG.
  - Respiratory rate (RR) - bioimpedance signaling.
  - Pulse O_2 saturation (SpO_2) - pulse oximeter.
  - Intermittent noninvasive blood pressure (BP) - sphygmomanometer.
- Cardiorespiratory instability (CRI) alerts generated when VS signals are outside defined thresholds.
- Alerts labeled "real" or "artifact" by clinical investigators as previously reported.

Hravnak et al. J Clin Monit Comp 2016; 30:875-88

Alerts Generated as Vital Signs Move Outside Thresholds

- Alerts *generated* using established process. *



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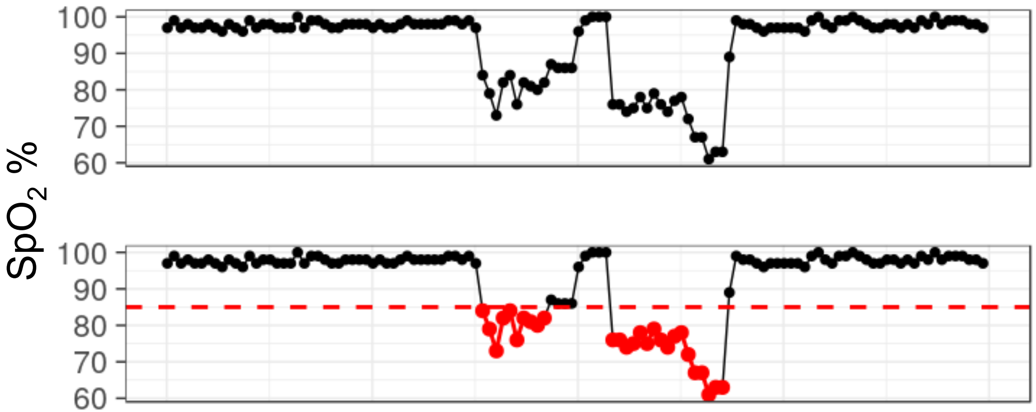

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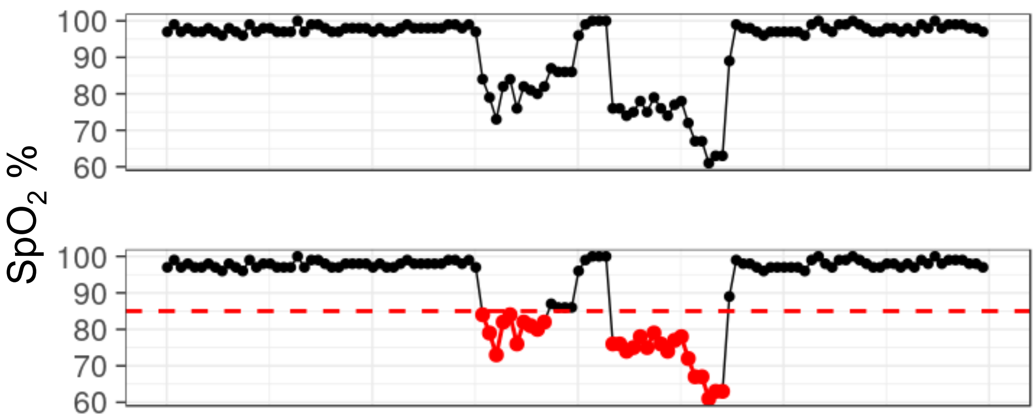
- Alert thresholds: **

HR	<	40	*OR*	HR	>	140
RR	<	9	*OR*	RR	>	36
SpO_2	<	85				
Sys	<	80	*OR*	Sys	>	200
Dia	>	110				



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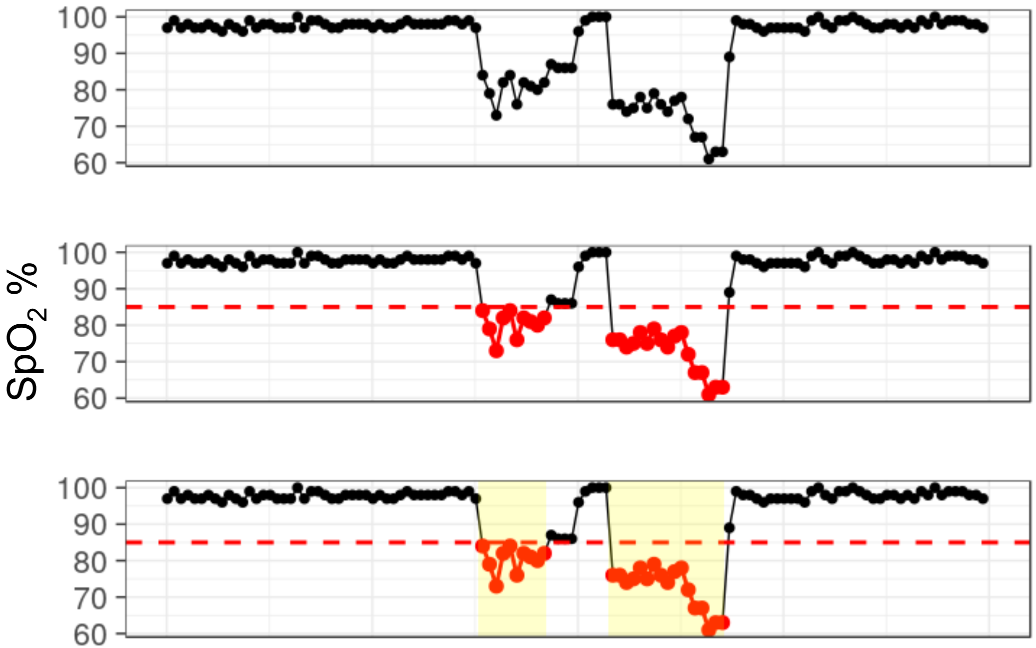
- Alert if out of bounds for at least 3 minutes.



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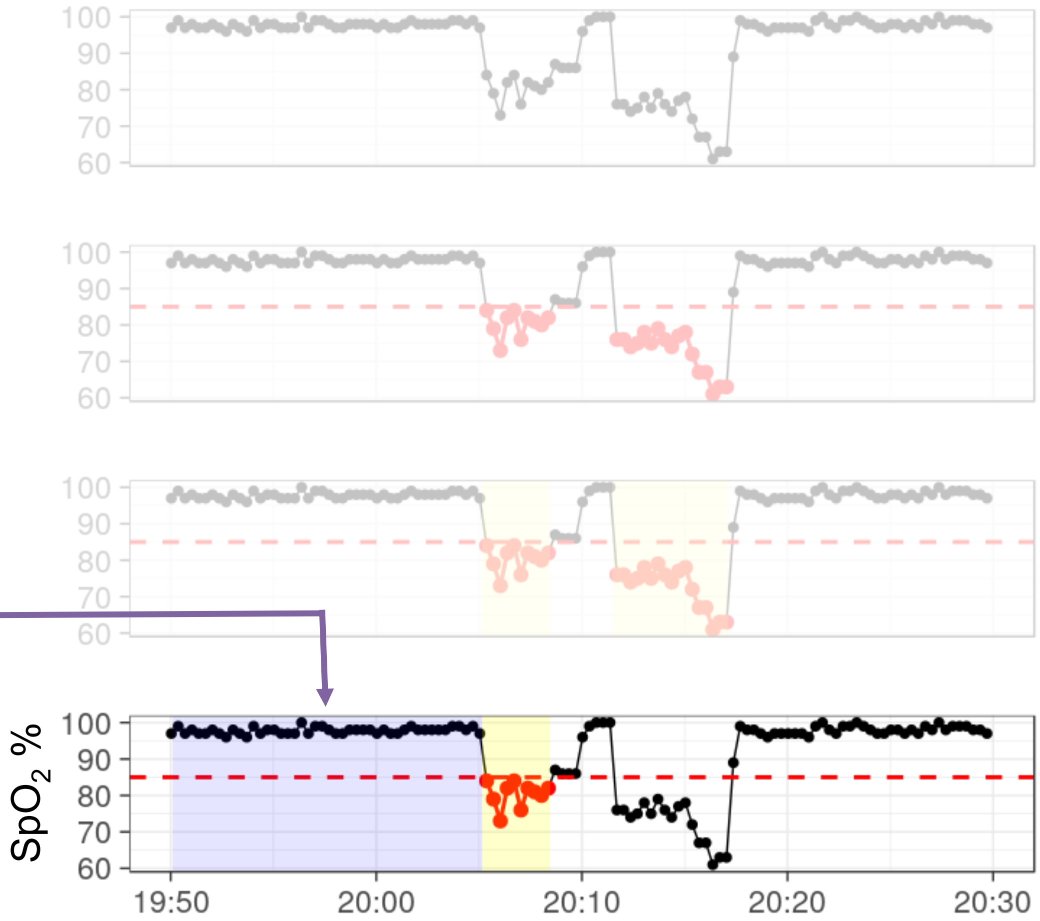
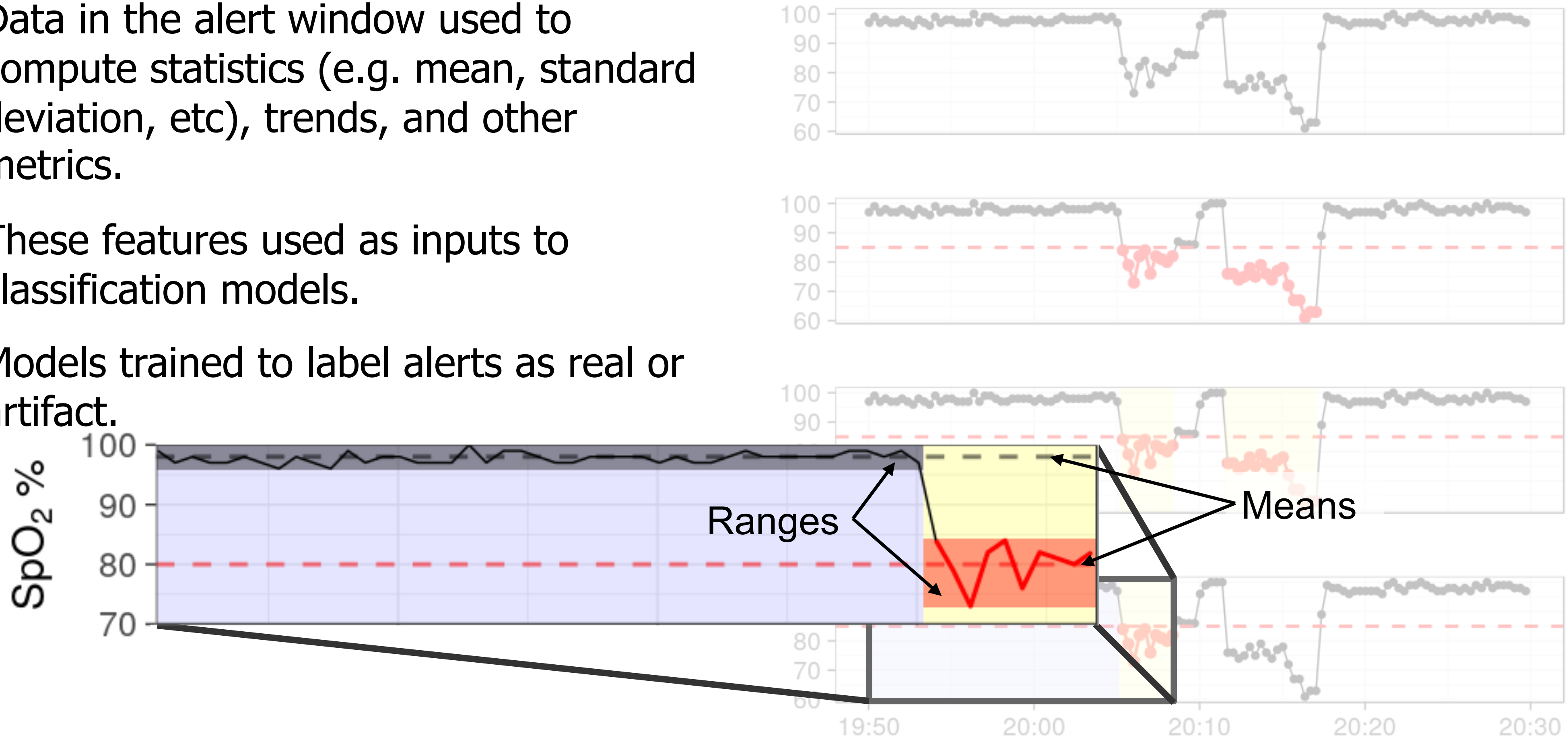
Features Generated from Downsampled Vital Sign Data

- VS data downsampled to one observation every 20 seconds (original), 60s, 120s, 180s, and 60 minutes.
- Features generated using data in alert window (featurization).
    - Feature: Secondary variable generated from original signal.
- 15 minutes prior to the alert used as a baseline.
- Raw VS along with generated features are the inputs to the models.



Featurizing Time Series by Evaluating Data Near Event

- Data in the alert window used to compute statistics (e.g. mean, standard deviation, etc), trends, and other metrics.
- These features used as inputs to classification models.
- Models trained to label alerts as real or artifact.



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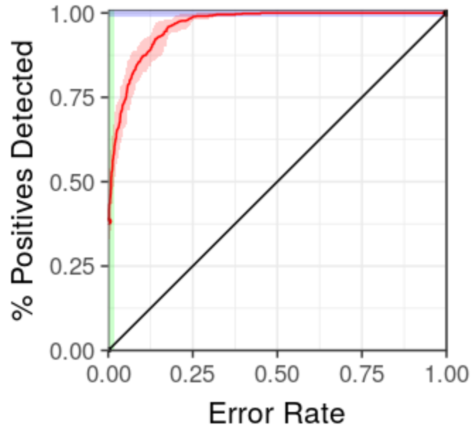
Negative class: Real instability



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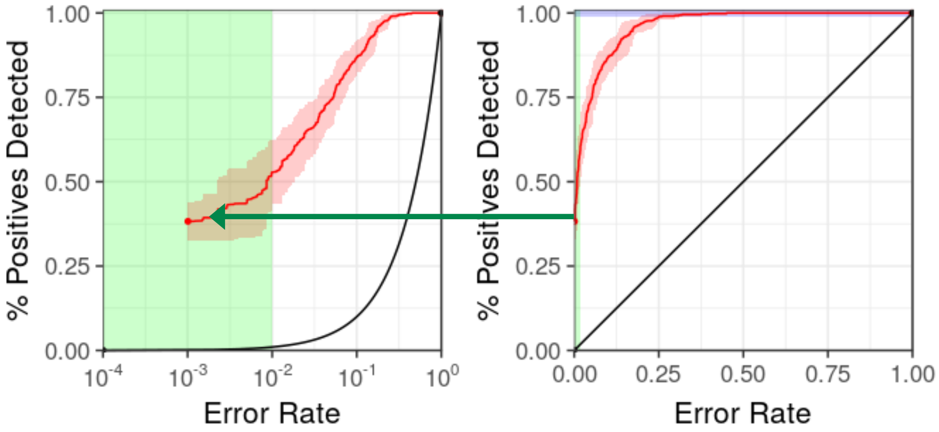

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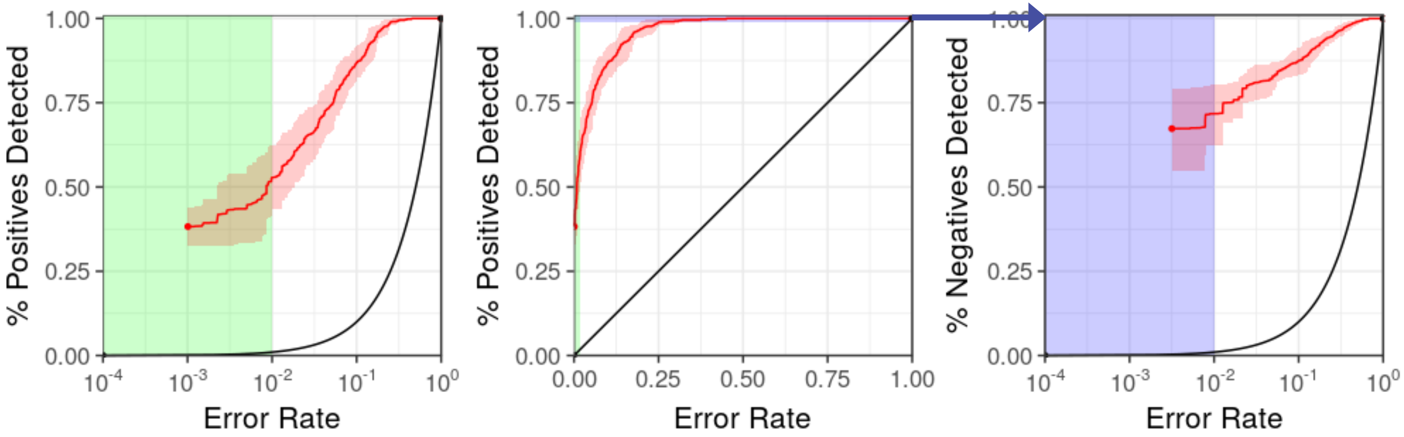

Performance of Original 20s Model

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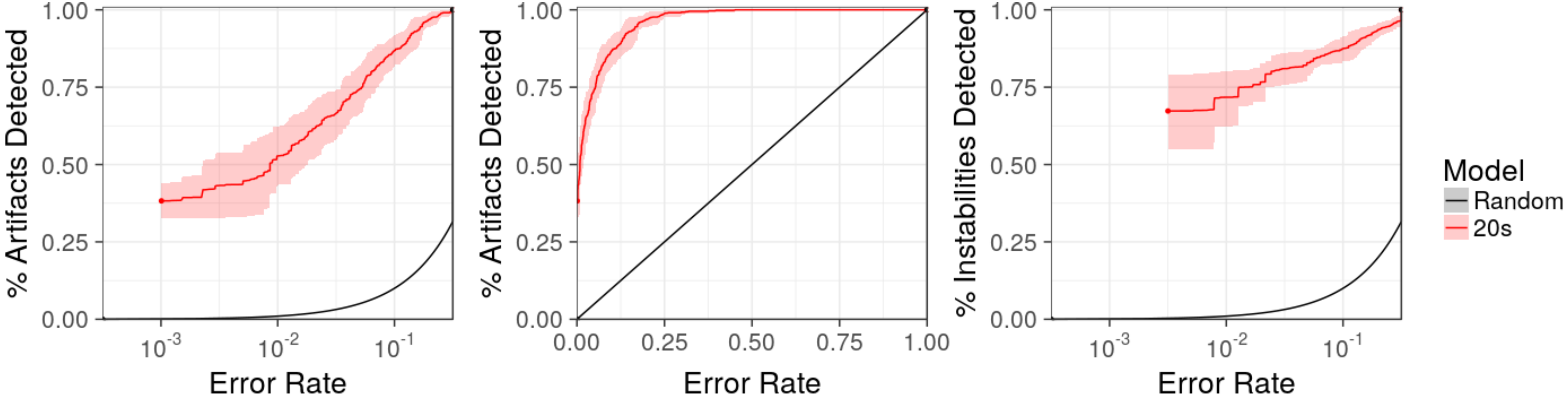
Negative class: Real instability



Detect 40% of Artifacts

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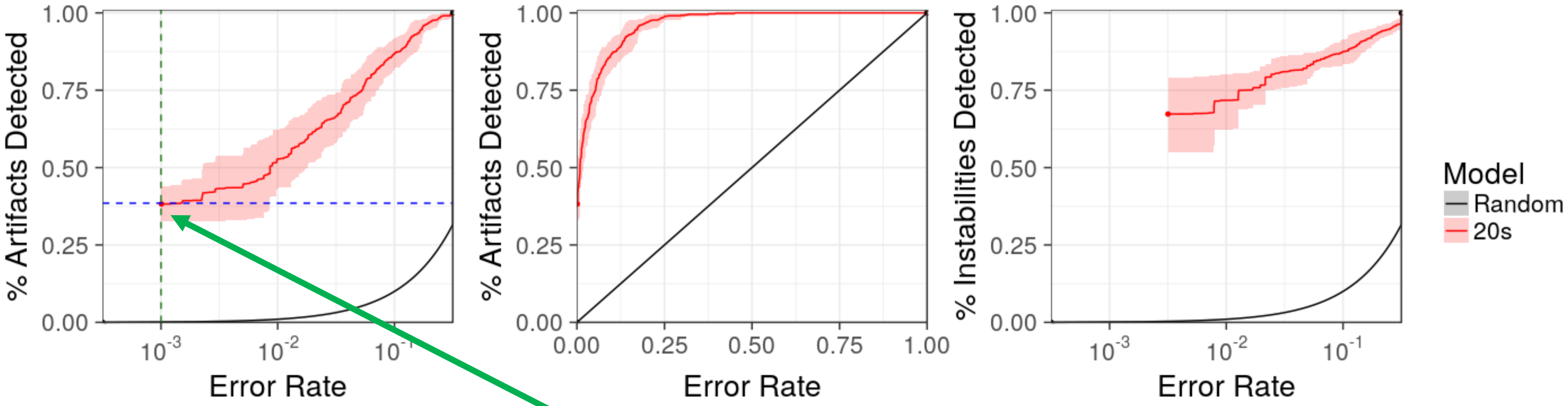
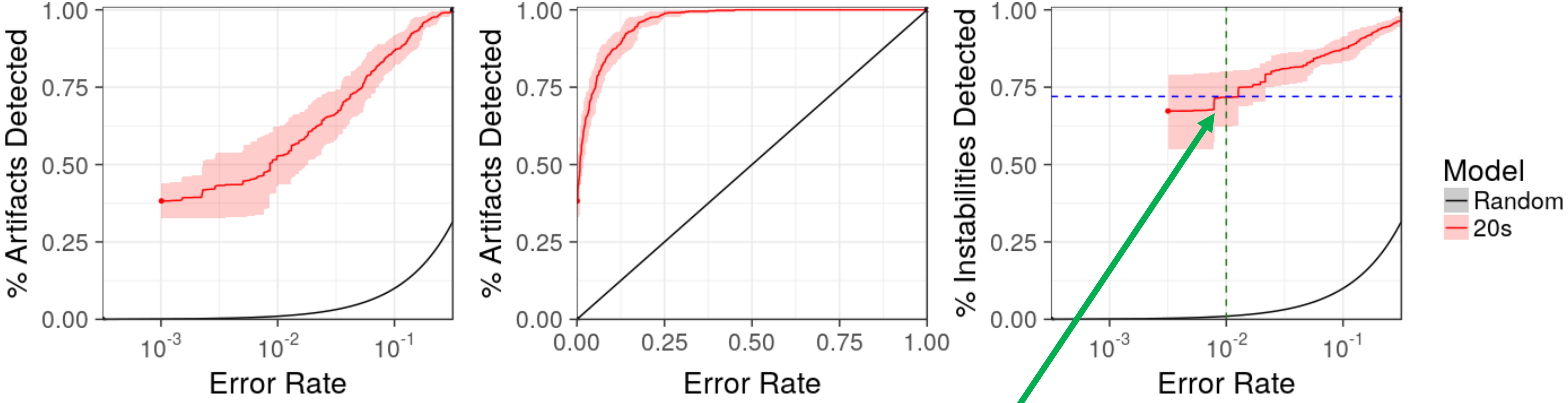
Negative class: Real instability



Using this threshold we correctly detect 40% of artifacts with only 1 error in 1000 decisions.

Detect 72% of Real Instabilities

Positive class: Artifact
Negative class: Real instability



Using this threshold we correctly detect 72% of artifacts with only 1 error in 100 decisions.

For Uncertain Predictions Fall Back To Standard Practice

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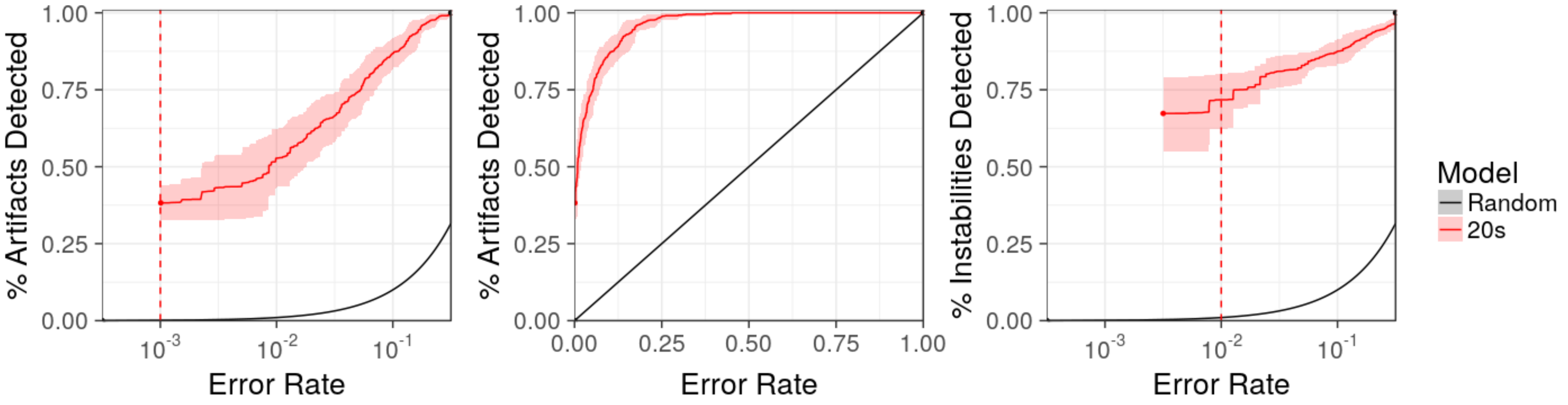
Negative class: Real instability



For predictions in between the model is less certain.
Fall back on current standard practice.

Nearly Identical Performance Sampling Every 60s

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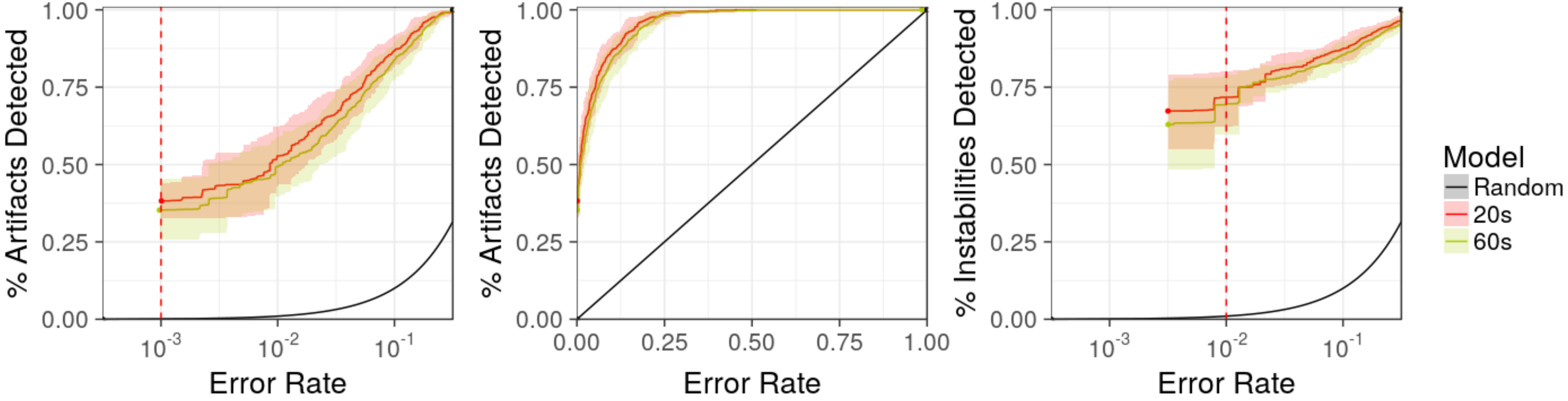
Negative class: Real instability



120s Model Still Differs Insignificantly

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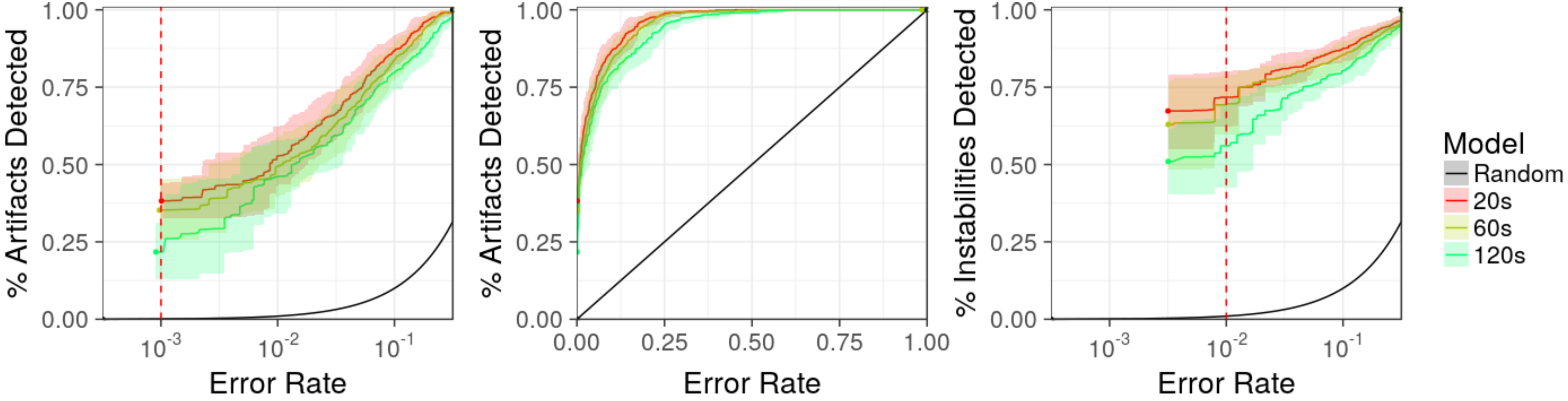

180s Model Degrades Significantly

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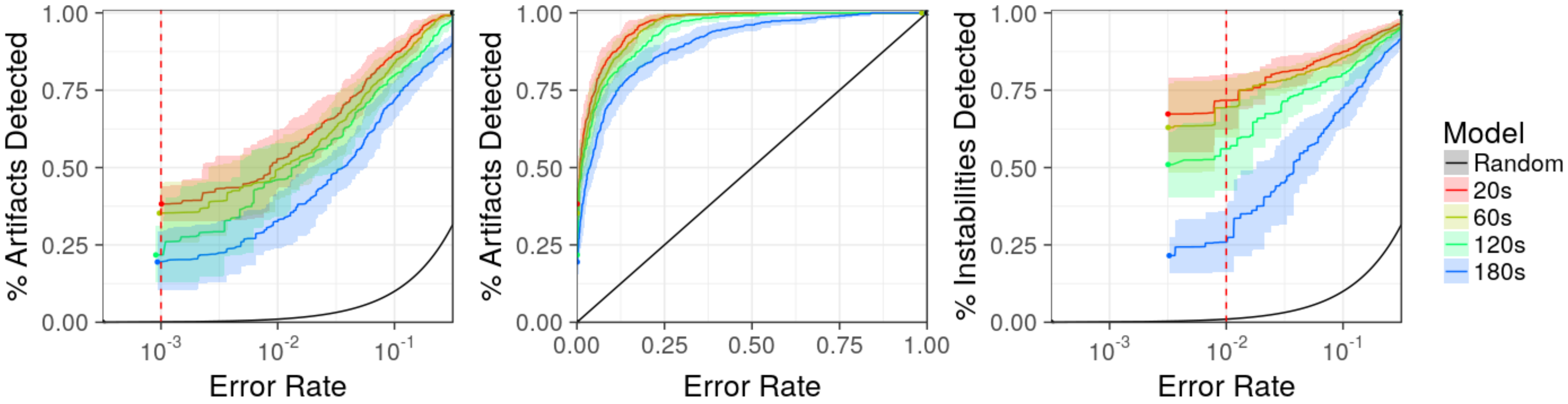

Sampling Every 60m is Detrimental to Performance

Positive class: Artifact
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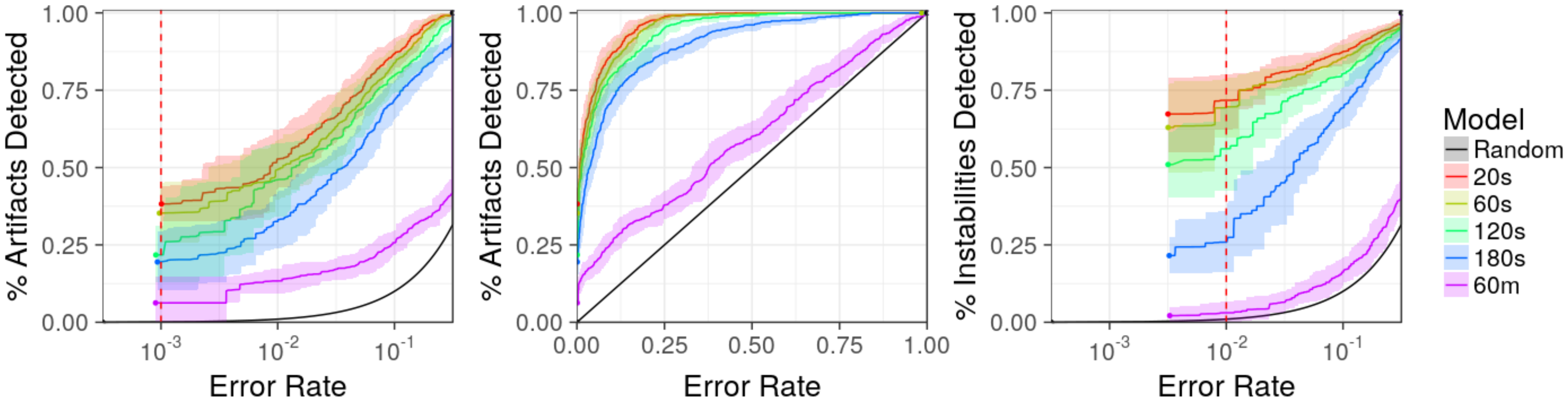

Good Model Performance if Sampling Every 1 or 2 Minutes

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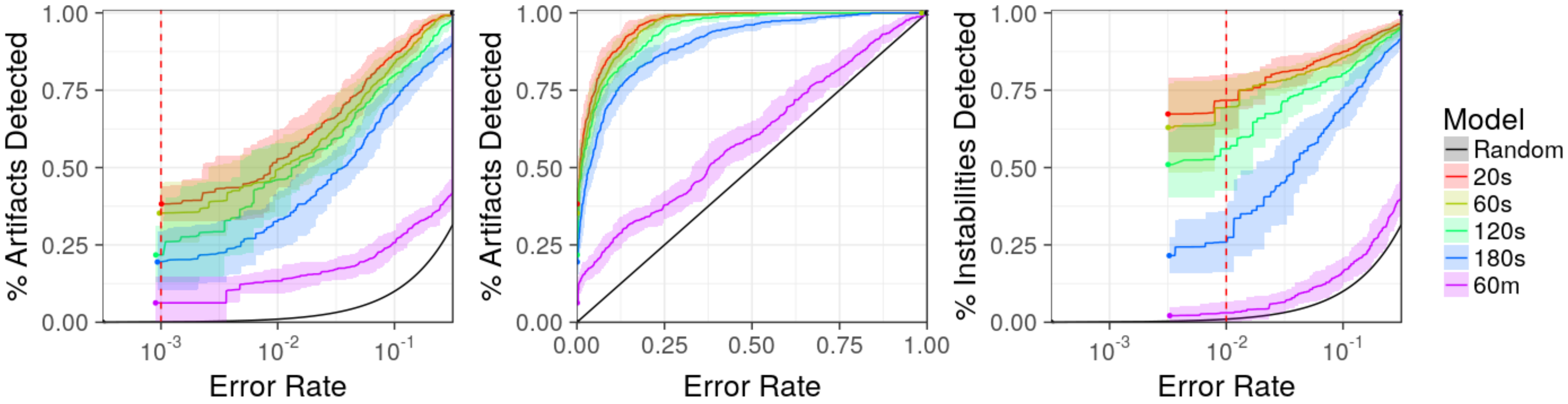

Key Finding: Data sampled every one or two minutes can be used to adjudicate alerts.

Lower Frequency Data Can Be Used to Classify Alerts

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Vital sign data collected as infrequently as every 120 seconds can be used to adjudicate alerts without significantly sacrificing model performance.

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Impact (Why we care)

Analysis applicable to a wider range of existing systems which sample at lower rates.

Helps understand trade offs between sampling frequency and clinical utility of the models.

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Next Steps

Does sampling more frequently improve performance?

Work on similar projects suggests we can derive more descriptive features when higher frequency data is available.