Machine Learning for Failure Detection on RF Cavities

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DESY - MCS/CDCS

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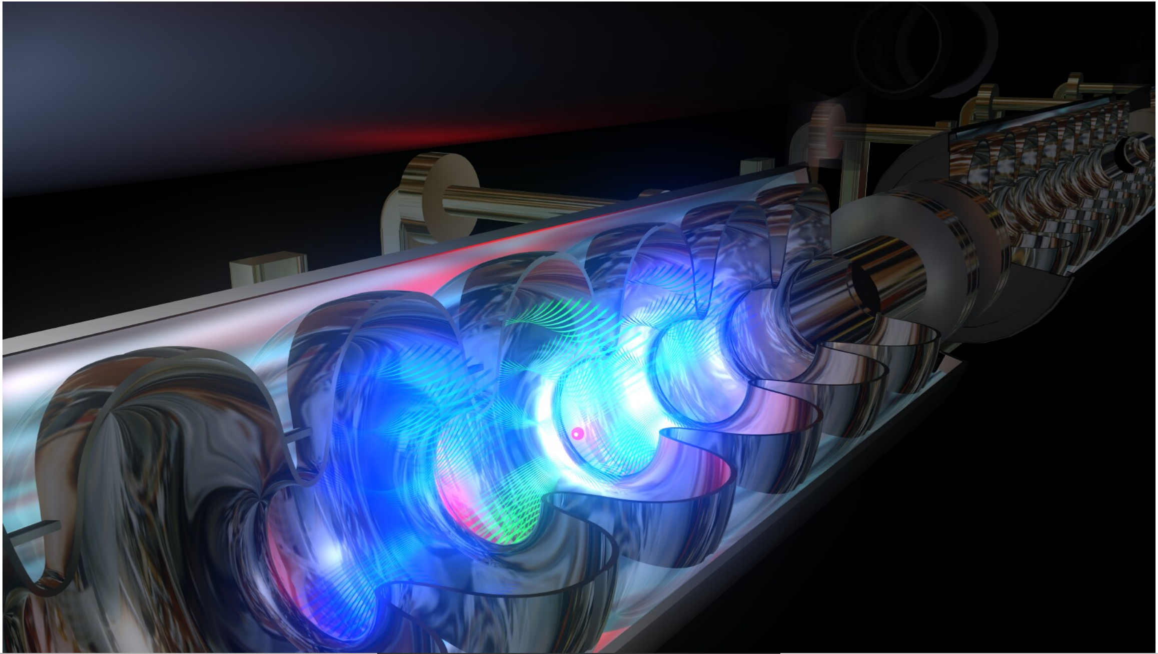
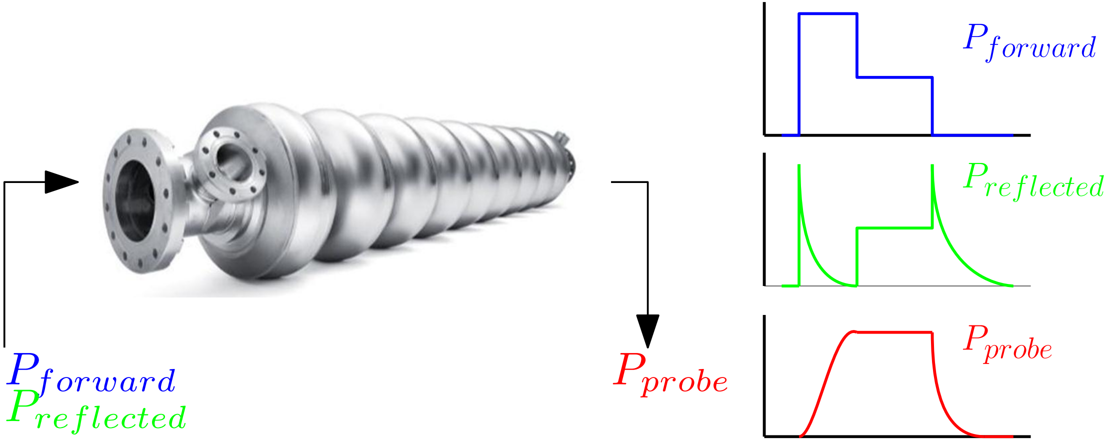
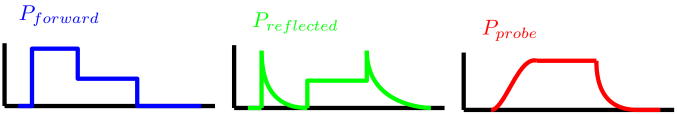


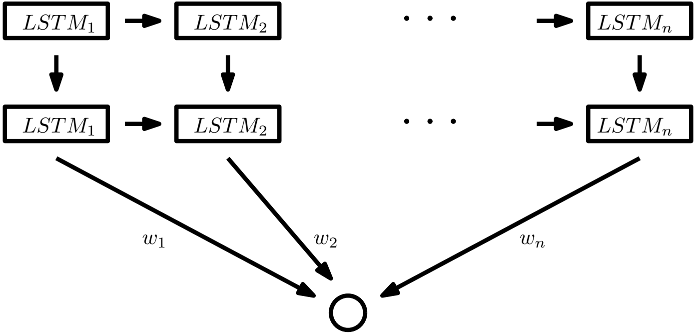
RF Cavities



Network Architecture - Fully Supervised

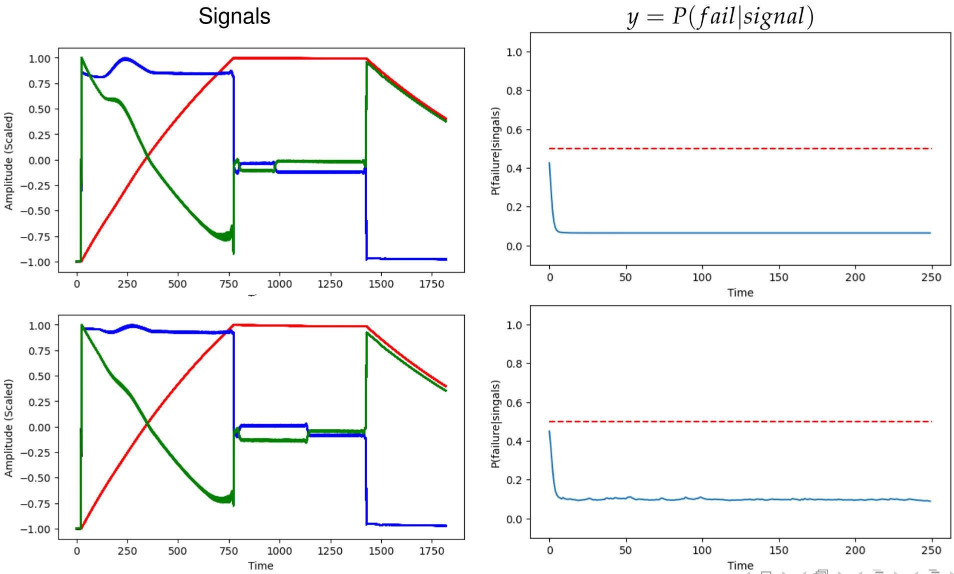


Input is a stacked vector $(6 \times 1820, \approx 250)$



$$y = P(fail|signals)$$

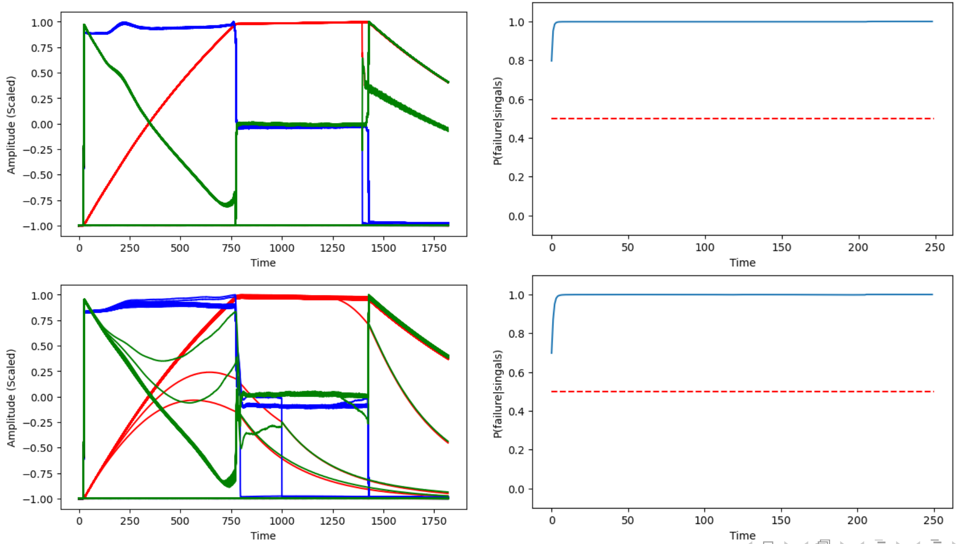
Results on the classifier - Properly Functioning



Results on the classifier - Failing Cavity

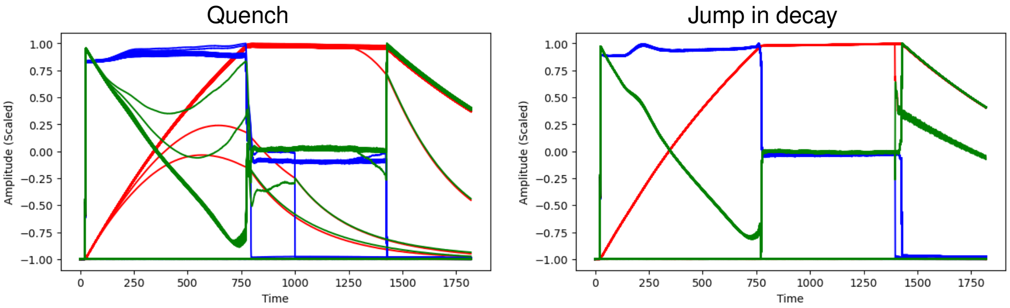
Signals

$y = P(fail|signal)$



Future Work

- Experimenting with different models like
  - one-class classifiers [RVG⁺18],
  - variational autoencoders for better interpretability of results [AC15]
  - or anomaly GANs for clear identification of failures [SSW⁺17])
- **Normalization** and **accurate labelling**.
- Classify different classes of failures.



References

[AC15] Jinwon An and Sungzoon Cho, *Variational autoencoder based anomaly detection using reconstruction probability*, Special Lecture on IE **2** (2015), no. 1, 1–18.

[NPLR18] Ayla Nawaz, Sven Pfeiffer, Gerwald Lichtenberg, and Philipp Rostalski, *Anomaly detection for the european xfel using a nonlinear parity space method*, IFAC-PapersOnLine **51** (2018), no. 24, 1379–1386.

[RVG+18] Lukas Ruff, Robert Vandermeulen, Nico Goernitz, Lucas Deecke, Shoaib Ahmed Siddiqui, Alexander Binder, Emmanuel Müller, and Marius Kloft, *Deep one-class classification*, International conference on machine learning, PMLR, 2018, pp. 4393–4402.

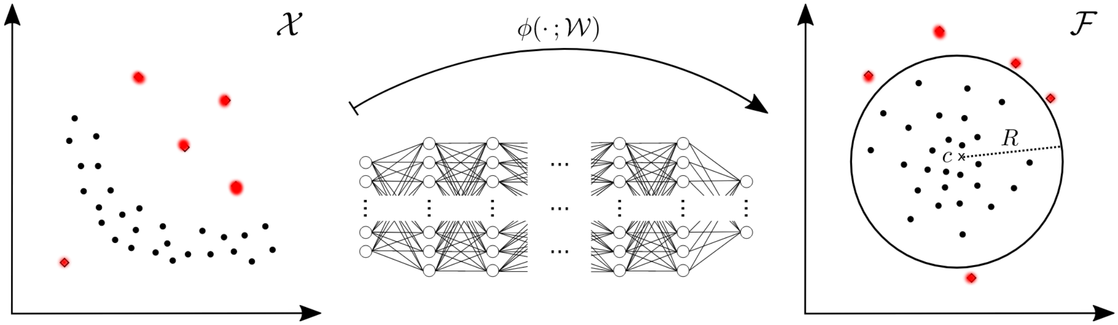
[RVG+19] Lukas Ruff, Robert A Vandermeulen, Nico Görnitz, Alexander Binder, Emmanuel Müller, Klaus-Robert Müller, and Marius Kloft, *Deep semi-supervised anomaly detection*, arXiv preprint arXiv:1906.02694 (2019).

References (cont.)

[SSW+17] Thomas Schlegl, Philipp Seeböck, Sebastian M Waldstein, Ursula Schmidt-Erfurth, and Georg Langs, *Unsupervised anomaly detection with generative adversarial networks to guide marker discovery*, International conference on information processing in medical imaging, Springer, 2017, pp. 146–157.

Spare slides

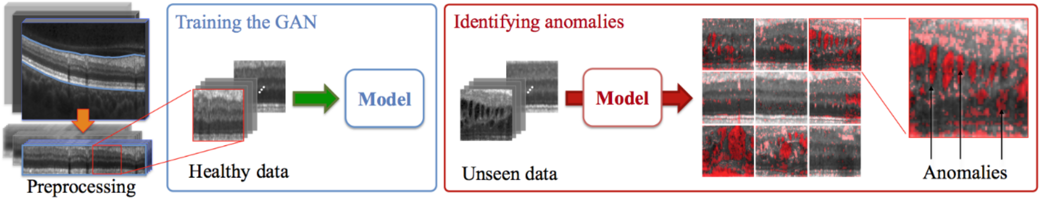
Future Work - Deep One Class Semi-Supervised Learning



$$\text{Loss} = \sum_{\mathbf{x}\in\mathbf{X}} \underbrace{\|\phi(\mathbf{x}) - \mathbf{c}\|}_{\text{searching a mapping } \phi \text{ to a common } \mathbf{c} \text{ [RVG}^+\text{18]}} + \sum_{\mathbf{x}\in\mathbf{X}} \underbrace{\|\phi(\mathbf{x}) - \mathbf{c}\|^{y}}_{\text{labelled samgples } \phi \text{ [RVG}^+\text{19]}}$$

Future Work - AnoGAN

Adveserial traning on healthly images [SSW+17].



- $\arg\min_{\mathbf{z}_\gamma} L(\mathbf{z}_\gamma) = \arg\min_{\mathbf{z}_\gamma} (1-\lambda) L_R(\mathbf{z}_\gamma) + \lambda L_D(\mathbf{z}_\gamma)$

where

$$L_R(\mathbf{z}_\gamma) = \sum |\mathbf{x} - G(\mathbf{z}_\gamma)| \quad \text{and} \quad L_D(\mathbf{z}_\gamma) = \sum |\mathbf{f}(\mathbf{x}) - \mathbf{f}(G(\mathbf{z}_\gamma))| \tag{1}$$

where $\mathbf{f}$ is discriminator feature layer.

- $|\mathbf{x} - G(\mathbf{z}_\gamma)|$ can be used to identify anomalous regions.
- Every test same must have their $\mathbf{z}_\gamma$ estimated.