Machine Learning approaches for gravitational wave detection

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Outline

1. Motivation
2. Inception networks
3. Data generation
4. Training and results
5. Outlook

The ASFAE's research projects acknowledge the financial support from the MCIU with funding from the European Union NextGenerationEU and Generalitat Valenciana.

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Motivation

PHYSICAL REVIEW D **107,** 023021 (2023)

First machine learning gravitational-wave search mock data challenge

Marlin B. Schäfer,[1,2] Ondřej Zelenka,[3,4] Alexander H. Nitz,[1,2] He Wang,[5] Shichao Wu,[1,2] Zong-Kuan Guo, Zhoujian Cao,[6] Zhixiang Ren,[7] Paraskevi Nousi,[8] Nikolaos Stergioulas,[9] Panagiotis Iosif,[10,9] Alexandra E. Koloniari,[9] Anastasios Tefas,[8] Nikolaos Passalis,[8] Francesco Salemi,[11,12] Gabriele Vedovato,[13] Sergey Klimenko,[14] Tanmaya Mishra,[14] Bernd Brügmann,[3,4] Elena Cuoco,[15,16,17] E. A. Huerta,[18,19] Chris Messenger,[20] and Frank Ohme[1,2]

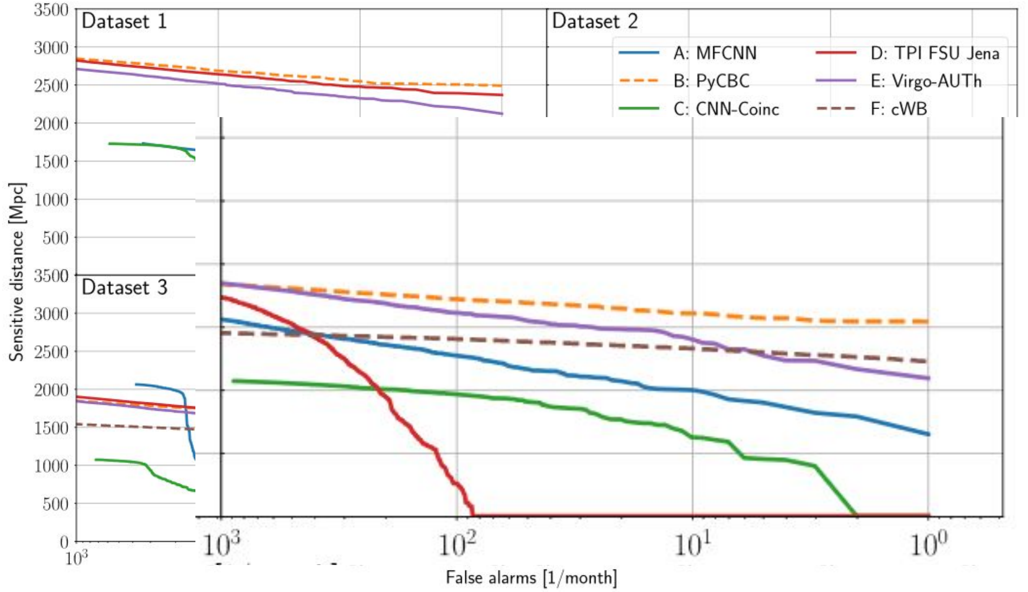

FIG. 2. The sensitive distances of all submissions and all four datasets as functions of the FAR. Submissions that made use of a machine learning algorithm at their core are shown with solid lines, others with dashed lines. The FAR was calculated on a background set that does not contain any injections.

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Motivation

VI. CONCLUSIONS

[...]

We also want to mention that we did not receive a submission utilizing one of the most promising neural network architectures for GW detection of the recent past. A WaveNet based architecture, that uses dilated convolutions, has been reported to do well for this kind of task [65,68,133]. We also did not receive submission based on many other neural network architectures that have been used in the past, such as autoencoders [74,81,82,134], inception networks [47,69], or two-dimensional convolutions that analyze time-frequency decompositions [70]. We hope that some of these approaches will be adapted to the requirements of this challenge and evaluated on the datasets presented here, to allow for a quantitative comparison.

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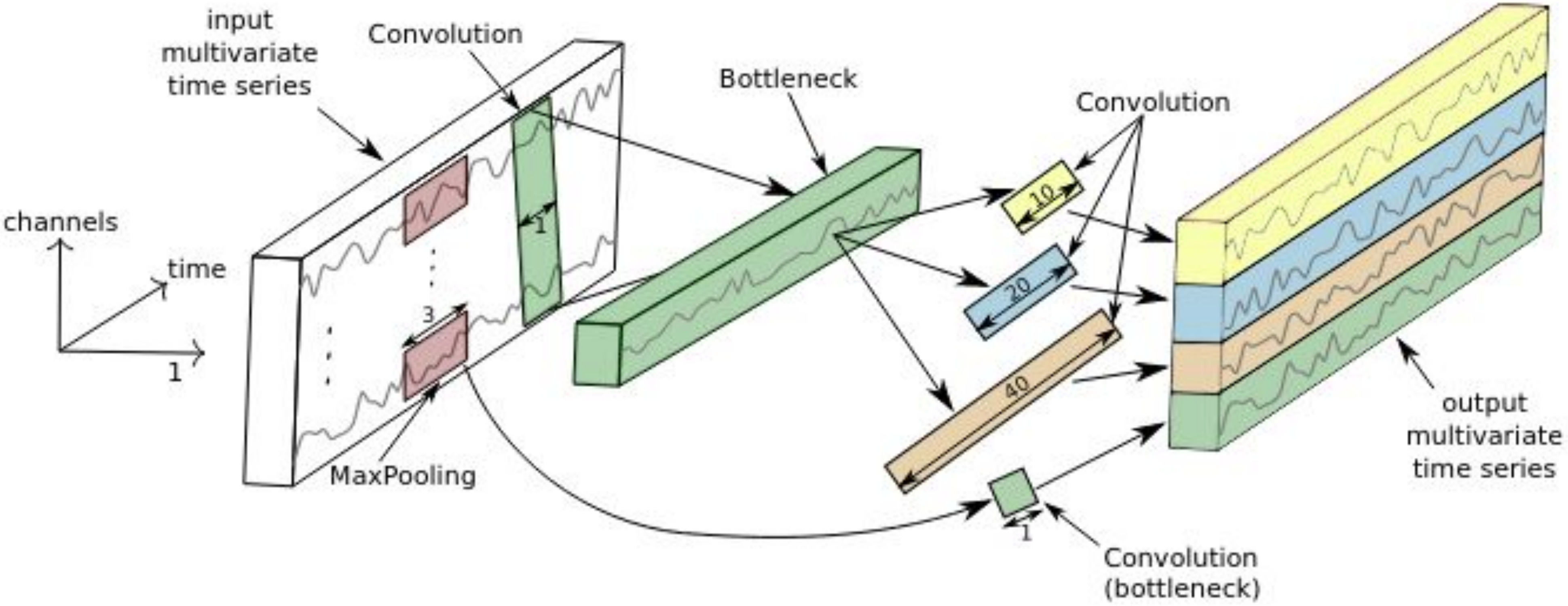
Inception module architecture



(From doi.org/10.1007/s10618-020-00710-y)

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Inception network implementation

- PyTorch implementation from TimeseriesAI (timeseriesai.github.io/tsai)
- 5 Inception modules
- 18 convolutional kernels per block
- Inception result is pooled and a linear layer outputs the classification (float between 0 and 1)

```
==========================================================================================
Layer (type:depth-idx)                                            Param #
==========================================================================================
InceptionTimePlus                                                 --
├─Sequential: 1-1                                                 --
│    └─InceptionBlockPlus: 2-1                                    --
│    │    └─ModuleList: 3-1                                       --
│    │    │    └─InceptionModulePlus: 4-1                         21,924
│    │    │    └─InceptionModulePlus: 4-2                         24,444
│    │    │    └─InceptionModulePlus: 4-3                         24,444
│    │    │    └─InceptionModulePlus: 4-4                         24,444
│    │    │    └─InceptionModulePlus: 4-5                         24,444
│    │    └─ModuleList: 3-2                                       --
│    │    │    └─ConvBlock: 4-6                                   288
│    │    └─ModuleList: 3-3                                       --
│    │    │    └─ReLU: 4-7                                        --
│    │    └─Add: 3-4                                              --
├─Sequential: 1-2                                                 --
│    └─Sequential: 2-2                                            --
│    │    └─GAP1d: 3-5                                            --
│    │    │    └─AdaptiveAvgPool1d: 4-8                           --
│    │    │    └─Reshape: 4-9                                     --
│    │    └─LinBnDrop: 3-6                                        --
│    │    │    └─Linear: 4-10                                     73
==========================================================================================
Total params: 120,061
Trainable params: 120,061
Non-trainable params: 0
==========================================================================================
```

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Dataset composition

- Injections into noise
  - Using NRHybSur3dq8 GW approximant
  - Component masses between 5 and 100 solar masses
  - Aligned spins
  - Target signal to noise ratio (SNR) is sampled uniformly between 8 and 30. Injection distance adjusted until calculated SNR = target SNR

- 11 datasets (10 training/validation, 1 test) created with 102,400 4-second H1-L1 strain samples (50% injections, 50% background)

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Training the network

- The 10 training/validation datasets are cycled for use in each epoch
- Minimization of weighted binary crossentropy:

$$\mathcal{L}_{wBCE} = -\mathbb{E}\left[w_1 \cdot y_{\text{true}} \cdot \log\left(y_{\text{pred}}\right) + w_0 \cdot \left(1 - y_{\text{true}}\right) \cdot \log\left(1 - y_{\text{pred}}\right)\right]$$

- Steps are taken to minimize false alarm rate (FAR)
  - Loss on background samples is weighted by a factor 10
  - Injection labels are set to 0.75 rather than 1 (“label smoothing”)
- Training for 100 epochs (~20 hrs)
- In the first 10 epochs, the dataset is sorted by decreasing SNR

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Results: FAR and TPR

- Best network chosen by lowest FAR (primary criterion) and highest True Positive Rate (TPR)

$$FAR = \frac{FP}{FP+TN} \cdot (\#samples/year) \qquad TPR = \frac{TP}{TP+FN}$$

- Best network in training process reached at epoch 57, with FAR=0 and TPR~0.87
- FAR
  - The FAR is calculated using the challenge's "dataset 4" background: a month's worth of data where no events are present
- TPR
  - The true positive rate is calculated using the test dataset generated

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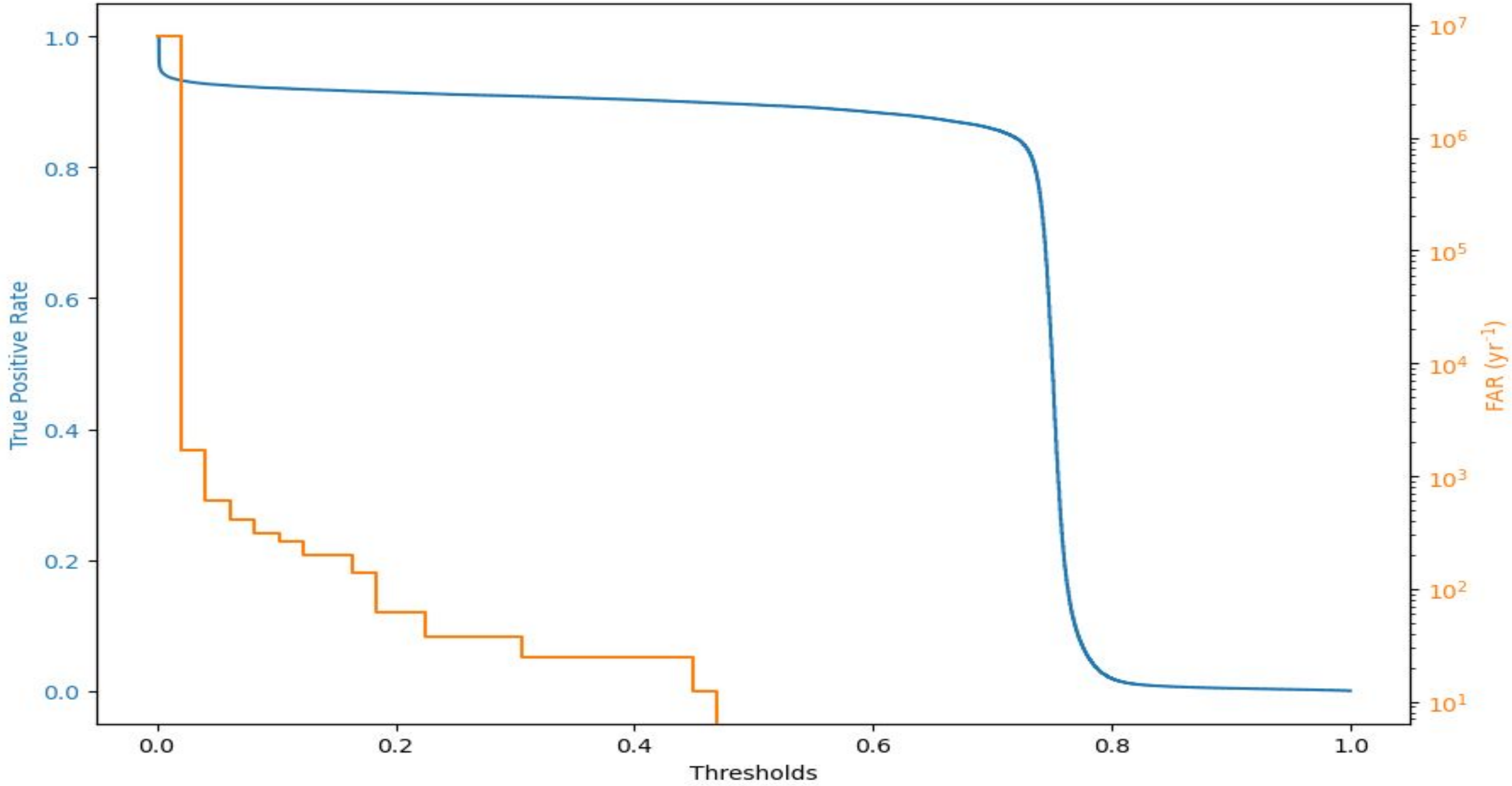
Results: FAR and TPR



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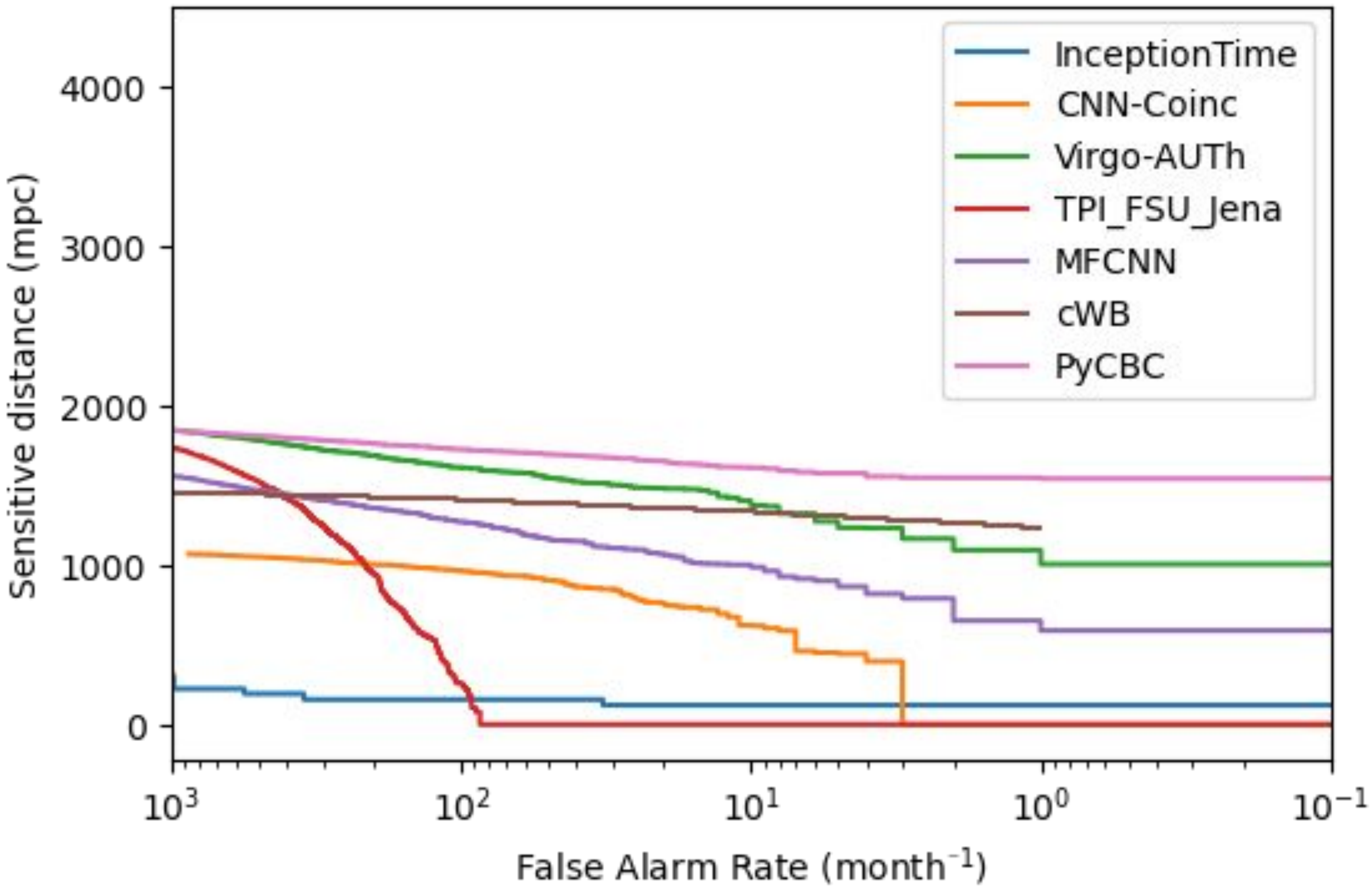
Results: mock data challenge



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Results: mock data challenge

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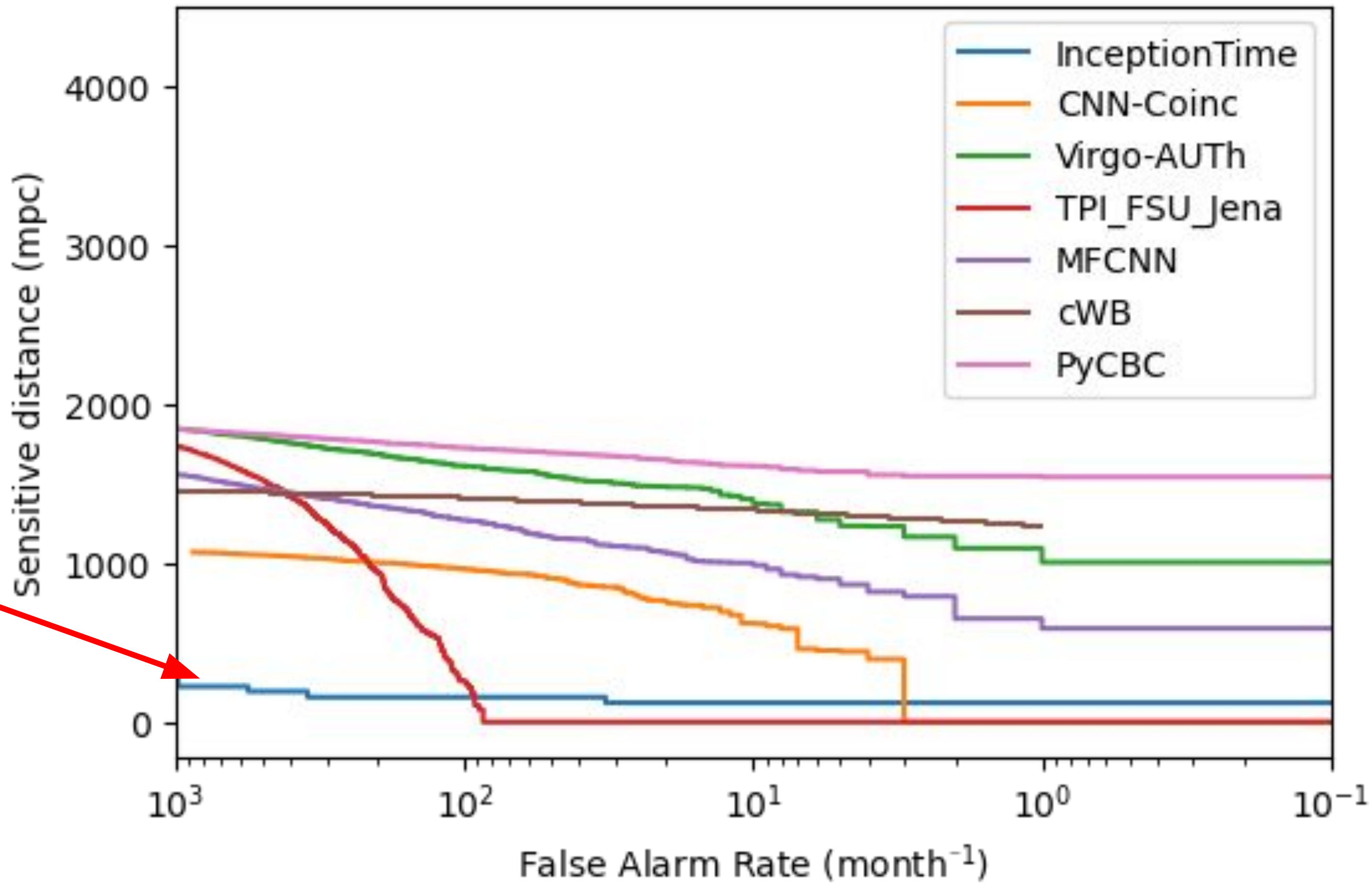

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Conclusions and outlook

- What is causing this issue?
  - Most likely: the SNR trained on, though realistic, is too high for the mock data challenge conditions
- Next steps:
  - Re-produce datasets with lower snr's and a distribution weighted to lower values
  - Simpler path: train similar network and hope for the best
  - More complex path: Implement a two-stage pipeline to filter out trivial false positives

Thank you

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