SUPPORT VECTOR DATA DESCRIPTION FOR RADAR DETECTION

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Radar Detection Problem

$$H_0 : \mathbf{z} = \mathbf{c} + \mathbf{n}, \quad H_1 : \mathbf{z} = \alpha\mathbf{p} + \mathbf{c} + \mathbf{n}$$

$\mathbf{p}$: steering vector, $\mathbf{c}$: clutter (Gaussian or compound Gaussian : texture $\sqrt{\tau}\mathbf{c}$), $\mathbf{n}$: thermal noise

Main state of the art

- **Matched Filter** (MF) and **Normalized Matched Filter** (NMF) assume **Gaussian clutter**.
- **Adaptive detectors** (AMF, ANMF) estimate the covariance matrix from secondary data using the **Sample Covariance Matrix** (SCM), which is sensitive to **non-Gaussian clutter**, or the **Tyler estimator**, which is more robust in such conditions.
- Their performance degrades with **additive thermal noise**.

Contributions

1. Adapt **SVDD** and **Deep SVDD** as **CFAR** detectors
2. Benchmark vs **AMF-SCM** and **ANMF-Tyler** and evaluation under **Gaussian + AWGN** and **Compound Gaussian + AWGN**

SVDD detector

Project H_0 data in a hypersphere

$$\min_{R,\mathbf{c},\xi} R^2 + \frac{1}{\nu N}\sum_{i=1}^{N}\xi_i\,, \tag{1}$$

subject to $\|\boldsymbol{\phi}_k(\mathbf{z}_i) - \mathbf{c}\|^2 \leq R^2 + \xi_i,\ \xi_i \geq 0$

- Kernel trick : Often radial basis function $k(\mathbf{x},\mathbf{y}) = \exp(\frac{\|\mathbf{x}-\mathbf{y}\|^2}{2\sigma^2}) = \langle \boldsymbol{\phi}_k(\mathbf{x}), \boldsymbol{\phi}_k(\mathbf{y})\rangle$
- Detection score : $\|\boldsymbol{\phi}_k(\mathbf{x}) - \mathbf{c}\|^2$

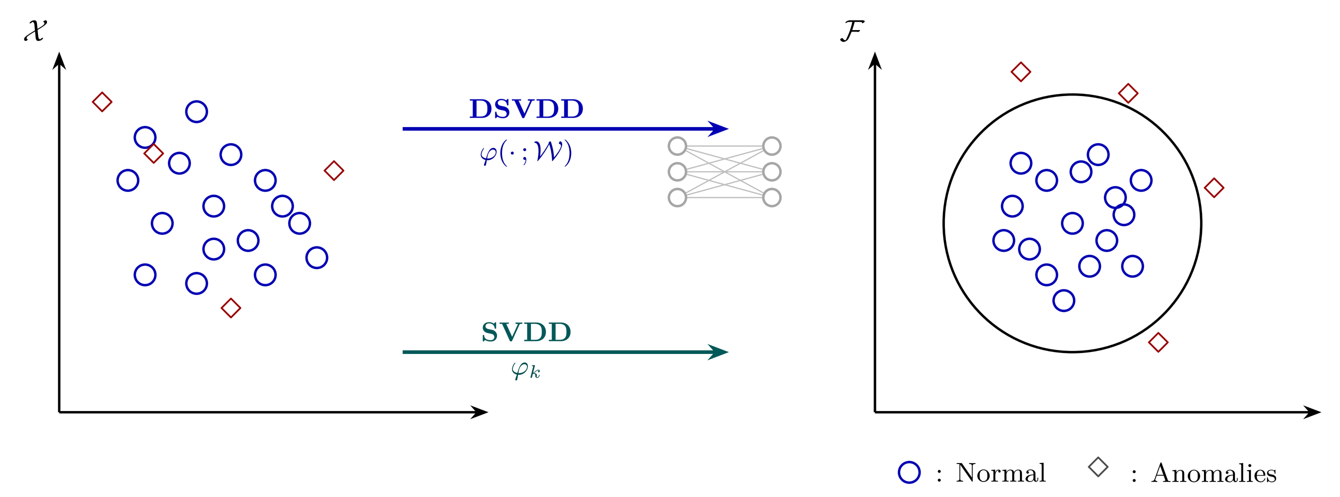
Deep SVDD detector

The network projects the data : $\psi(\mathbf{z};\mathcal{W})$ with loss :

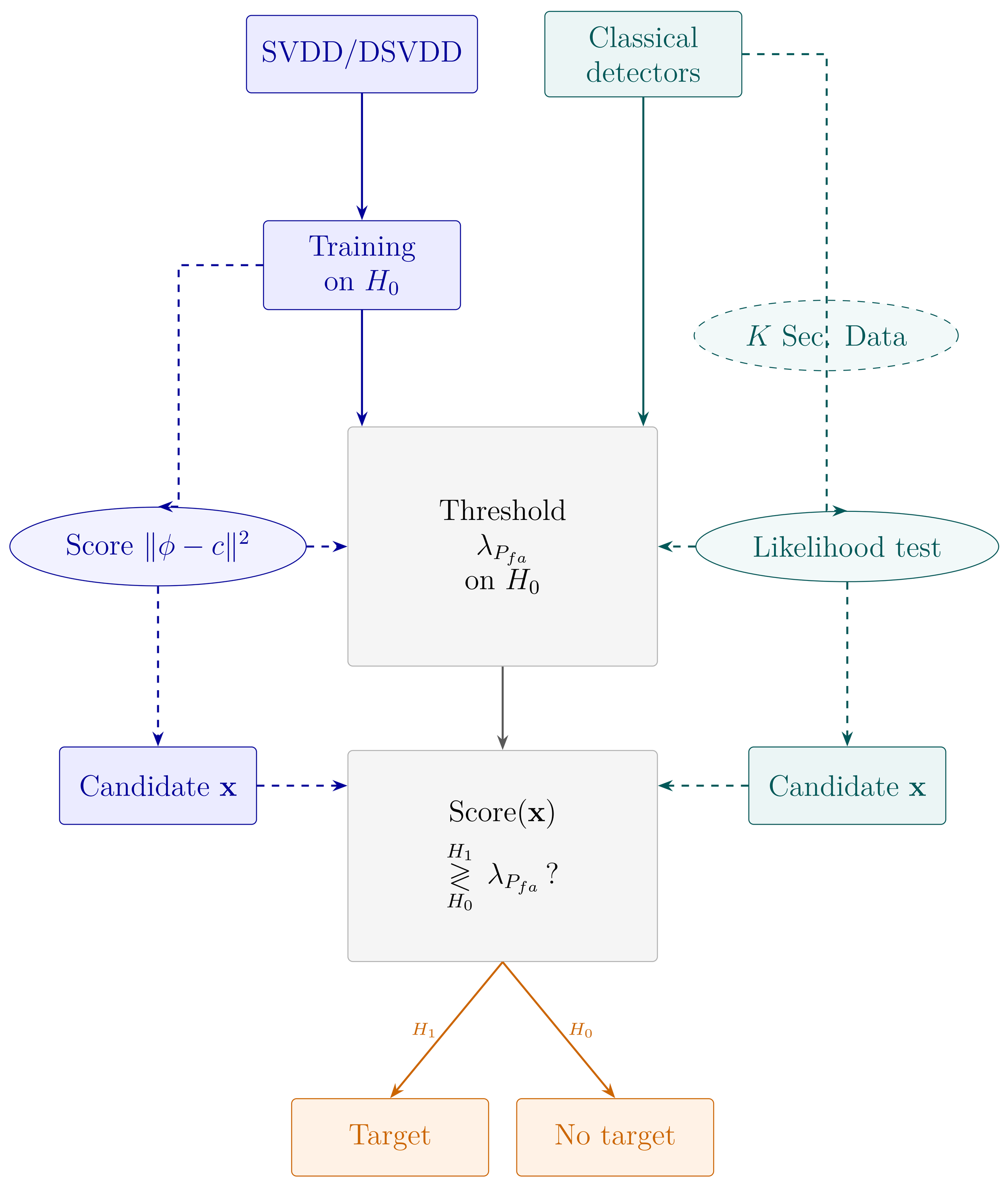
$$\min_{\mathcal{W}} \frac{1}{n}\sum_i \|\psi(\mathbf{z}_i;\mathcal{W}) - c\|^2 + \frac{\beta}{2}\sum_{l=1}^{L}\|\mathbf{W}^l\|^2,$$

- Learns compact representation, the center $\mathbf{c}$ is estimated beforehand to avoid collapse
- Detection score : $\|\psi(\mathbf{z}_i;\mathcal{W}) - c\|^2$

Principle of Support Vector Data Description



Detection pipeline



References

1 D. E. Tyler, "A Distribution-Free M-Estimator of Multivariate Scatter," *Annals of Statistics*, vol. 15, no. 1, pp. 234–251, 1987.
2 Ruff, L. et al . "Deep One-Class Classification Proceedings of the 35th International Conference on Machine Learning, 2018.
3 J.-P. Ovarlez, F. Pascal, and A. Breloy, "Asymptotic detection performance analysis of the robust adaptive normalized matched filter," in 2015 IEEE CAMSAP, 2015, pp. 137–140.

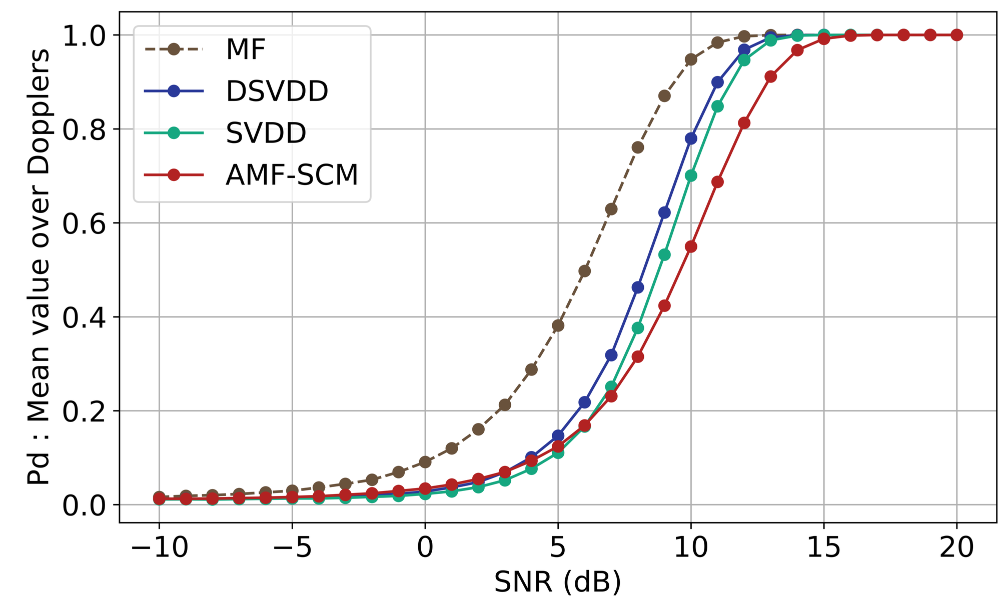
Data and protocol

- $m = 16$ Doppler bins, Toeplitz cov ($\rho = 0.5$), $P_{fa} = 0.01$
- SVDD and DSVDD training: $N = 5000$ clutter samples
- Classical detectors: $K = 32$ secondary data
- Threshold $\lambda_{P_{fa}}$ determined on 5000 H_0 samples.
- Target insertion : $\alpha = \sqrt{\frac{\text{SNR}}{m}}e^{j\phi}$, $\phi \sim \mathcal{U}[0, 2\pi)$ and $\mathbf{p} = \left(1, e^{j2\pi d/m}, \ldots, e^{j2\pi d(m-1)/m}\right)^T$

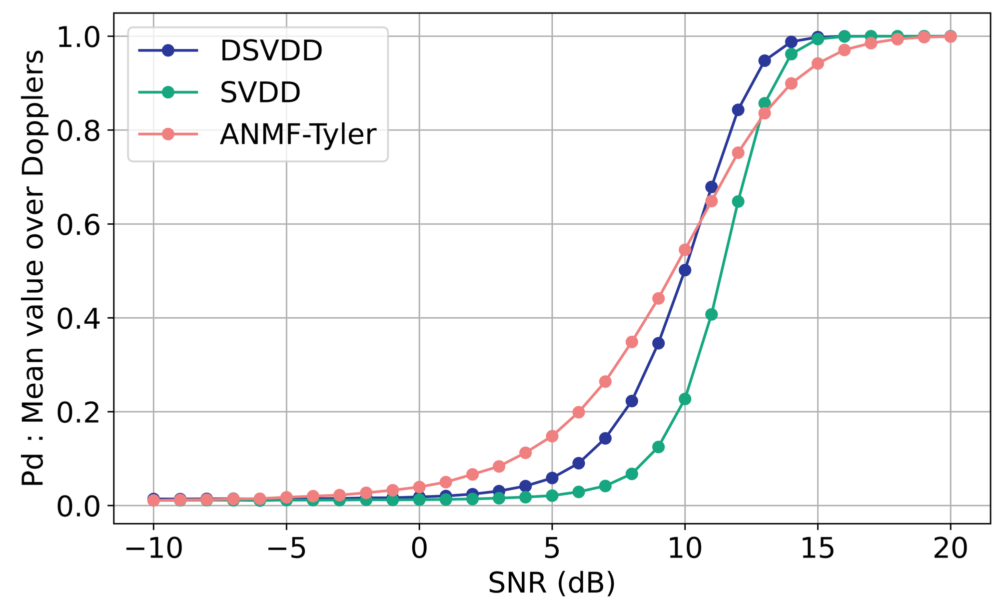
Architecture DSVDD

- 3 Conv1D layers (32, 64, 128)
- BatchNorm + LeakyReLU + pooling
- Final embedding: 128-dim
- Input: concatenated real and imaginary parts or magnitude
- Optimizer Adam, learning rate $= 0.001$

Detection performance

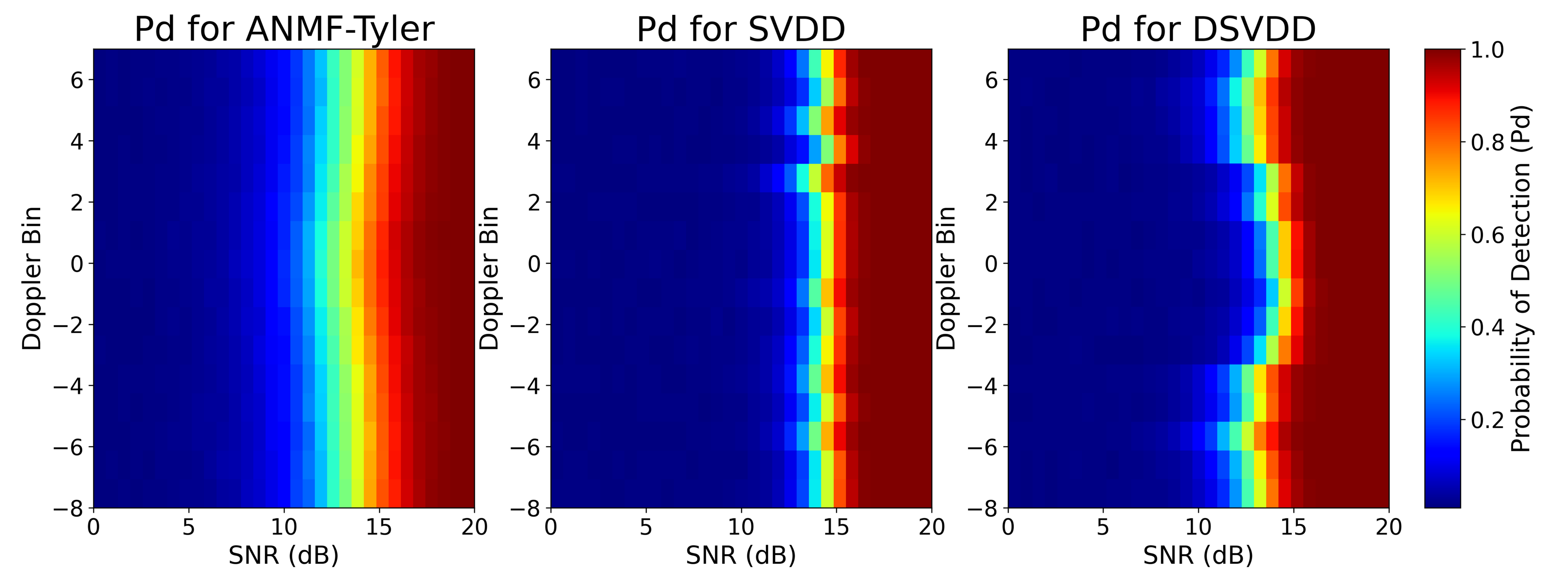


Gaussian clutter + AWGN



Compound Gaussian + AWGN

Doppler-SNR detection map : Compound Gaussian + AWGN



Conclusion

- Effective for Gaussian clutter (+ additive thermal noise) and high SNR
- Limitations remain at low SNR and in the Doppler-0 bin

Future work

- Test on CSIR database with synthetic target
- Latent space analysis
- Complex-valued algorithms