

Detection and Estimation Theory Project Presentation

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Introduction

- H_0 - Null hypothesis, H_1 - Alternative Hypothesis. NP rule: $\Lambda(\mathbf{z}) = \frac{f(\mathbf{z}|H_1)}{f(\mathbf{z}|H_0)} \stackrel{H_1}{\underset{H_0}{\gtrless}} \eta(P_{\text{FA}})$
- For the NP detector to be implemented, both likelihood functions must be known and so, statistical models are assumed and parameters are estimated. Losses are calculated when this statistical model varies from the design.
- For the proposed approach, no statistical model is assumed and a good approximation for the optimal NP detector is obtained from choosing a relevant error function while training the ML model.
- Drawback of the approach is the difficulty of obtaining training samples, and defining the most suitable learning machine architecture.

Previous Works

- Basic NP Detector Approximation: Use a **single-output learning machine** compared to a **threshold** to decide between null (H_0) and alternative (H_1) hypotheses. The threshold sets the desired **Probability of False Alarm (P_{FA})**.
- Alternative Implementations: Varies the **bias** of a single output neuron. Utilizes a **two-output NN** (outputs in (0,1)), comparing their subtraction to a threshold, which is equivalent to a single output with desired outputs {-1,1}.
- Advanced Techniques: **Radial Basis Function Neural Networks (RBFNN)**, **Support Vector Machines (SVMs)**, and **Committee Machines** have also been applied for detection.
- Supervised Training: Adaptive systems (learning machines) can approximate the **Neyman-Pearson (NP) detector** when trained in a supervised manner.
- Suitable Error Functions: The **Sum-of-Squares error** is suitable for approximating the NP detector (and optimal for **Gaussian signals**). The **Minkowski error** with R=1 (Mean Absolute Deviation) is suitable for approximating the **minimum probability of error classifier**.
- Future Work: Investigating **alternative error functions** suitable for non-Gaussian interference, ensuring they meet the sufficient condition for NP detector approximation.

Problem Statement

- Consider a learning machine with one output, that is used to classify input vectors $z = [z_1, z_2, \dots, z_L]^T$ into two hypotheses H_0 and H_1 , that represent absence of target and its presence, respectively, in radar detection problems.
- Given a decision rule, let Z_i be the set of all possible input vectors that will be assigned to hypothesis H_i , and $Z_0 \cup Z_1 = Z$ the ensemble of all possible input vectors. The output of the learning machine is represented by $F(z)$, and the desired output by t_{Hi} . A training set, $Z = Z_0 \cup Z_1$, where Z_1 is composed of N_1 training patterns from hypothesis H_1 , and Z_0 is composed of N_0 training patterns from hypothesis H_0 ($N = N_1 + N_0$), is available.
- The function the learning machine approximates to after training is obtained (as a function of the likelihood functions and the prior probabilities) and the implemented detector compares the learning machine output to a threshold η_0 , which varies to fix the P_{FA} . The NP detector is usually implemented by comparing the likelihood ratio to a threshold η_{lr} , fixed according to the required P_{FA} .

Proof of Concept

This section explains how the MLP's output can be treated as an approximation of the NP detector

Law of Large Numbers

The law of large numbers states that given a sample of independent and identically distributed values, the sample mean converges to the true mean.

- Equation three here denotes the cross entropy loss function at an MLP's output.
- For N tends to infinity, the sample mean of the function becomes true expected value of the function as shown in equation 5.

$$E = -\frac{1}{N} \left[\sum_{\mathbf{z} \in H_1} \ln[F(\mathbf{z})] + \sum_{\mathbf{z} \in H_0} \ln[1 - F(\mathbf{z})] \right] \quad (3)$$

If the number of patterns tends to infinity ($N \rightarrow \infty$), the error can be expressed as follows:

$$E_m = -\lim_{N \rightarrow \infty} \left[\frac{N_1}{N} \frac{1}{N_1} \sum_{\mathbf{z} \in H_1} \ln[F(\mathbf{z})] + \frac{N_0}{N} \frac{1}{N_0} \sum_{\mathbf{z} \in H_0} \ln[1 - F(\mathbf{z})] \right] \quad (4)$$

Applying the strong law of large numbers, expression (5) is obtained:

$$\begin{aligned} E_m &= - \int_{\mathcal{Z}} (P(H_1)f(\mathbf{z}|H_1) \ln(F(\mathbf{z})) \\ &\quad + P(H_0)f(\mathbf{z}|H_0) \ln(1 - F(\mathbf{z})) d\mathbf{z} \end{aligned} \quad (5)$$

Proof of Concept

By Calculus of Variations, a function $F_0(z)$ which minimizes the function/loss E_m can be written using Euler-Lagrange:

$$\frac{\partial I}{\partial F} - \sum_{k=1}^L \frac{\partial}{\partial z_k} \left(\frac{\partial I}{\partial F'_k} \right) = 0$$

Here the function I is the function inside the integral of the loss E_m , Solving further we get $F_0(z)$ as follows:

$$\frac{\partial}{\partial F} \left(-P(H_1)f(\mathbf{z}|H_1) \ln(F(\mathbf{z})) - P(H_0)f(\mathbf{z}|H_0) \ln(1 - F(\mathbf{z})) \right) = 0 \quad (8)$$

$$F_0(\mathbf{z}) = \frac{P(H_1)f(\mathbf{z}|H_1)}{P(H_1)f(\mathbf{z}|H_1) + P(H_0)f(\mathbf{z}|H_0)}$$

$$\frac{P(H_1)f(\mathbf{z}|H_1)}{P(H_1)f(\mathbf{z}|H_1) + P(H_0)f(\mathbf{z}|H_0)} \stackrel{H_1}{\underset{H_0}{\gtrless}} \eta_0$$

Proof of Concept

Extracting the Likelihood ratio from the above $F_o(z)$ equation we get our new NP detector threshold as given below:

$$\Lambda(\mathbf{z}) \stackrel{H_1}{\gtrless} \frac{P(H_0)\eta_0}{P(H_1)(1 - \eta_0)} = \eta_{lr}$$

$$\eta_0 = \frac{\eta_{lr}P(H_1)}{P(H_0) + \eta_{lr}P(H_1)}$$

Experiments

Objective: Design **Multilayer Perceptrons (MLPs)** to approximate the performance of the **optimum NP detector**.

Challenge: Target parameters are **unknown**; therefore, the NP detector is approximated using an **Average-Likelihood Ratio** compared against a threshold.

MLP Structure: Real arithmetic MLP with **L/M/1** architecture.

- **Input Layer (L=16):** 8 complex radar echoes → 16 real inputs (in-phase and quadrature).
- **Hidden Layer (M):** Number of neurons (M) is a studied parameter.
- **Output Layer (1):** Compared to a hard threshold for detection.
- **Activation Function:** Sigmoid.

Experiments

Three Case Studies of Detection Problems: The studies assess the MLP's ability to approximate the NP optimum detector, focusing on:

Case Study	Target Type & Interference	Sub-Cases (Target Unknowns)
Case 1	Gaussian Fluctuating Target in AWGN (Clear Conditions)	Unknown correlation coefficient OR Unknown Doppler shift (Swerling I).
Case 2	Gaussian Fluctuating Target in Correlated Gaussian Clutter + AWGN (Sea/Land Clutter, Low Resolution)	Unknown correlation coefficient OR Unknown Doppler shift (Swerling I).
Case 3	Non-Fluctuating (Swerling V) Target in K-distributed Clutter ($\nu = 0.5$) (Spiky Clutter, High Resolution, Low Grazing Angle)	Unknown Doppler shift .

Experiments

Performance Comparison Strategies

The proposed MLP detectors are benchmarked using two primary strategies:

1. **MLP vs. NP Approximation:**
 - MLP detectors (trained via supervised learning) are compared against the optimum **NP Detector approximation**.
 - The NP approximation uses a **Constrained Generalized Likelihood Ratio (CGLR)**.
 - **Metric:** Receiver Operating Characteristic (**ROC** curves) are used to show validity (Probability of Detection (P_D) vs. Probability of False Alarm (P_{FA})).
2. **MLP Error Function Comparison:**
 - Compare detectors trained with **Cross-Entropy Error** against those trained with:
 - **Sum-of-Squares Error**
 - **Minkowski Error ($R=1$)**
 - **Note:** This comparison is performed only for **Case Study 1** due to space limitations, but similar trends were observed for the other cases.
 - **Metric:** PD versus Signal-to-Noise Ratio (SNR) for the best detectors.

Experiments

II. Training and Testing Parameters

Parameter	Value / Method	Details
Training Set	50,000 patterns	Equal patterns for H_0 (No Target) and H_1 (Target).
Validation	10,000 patterns	Used for cross-validation ($k = 5$) to prevent overfitting.
Testing Set	2×10^7 (H_0) and 5×10^4 (H_1) patterns	Allows accurate estimation of very low P_{FA} values (down to 10^{-6}) and P_D .
Training Algorithm	Cross-Entropy: Algorithm from [43]	Sum-of-Squares/Minkowski: Conjugate Gradient method [44].

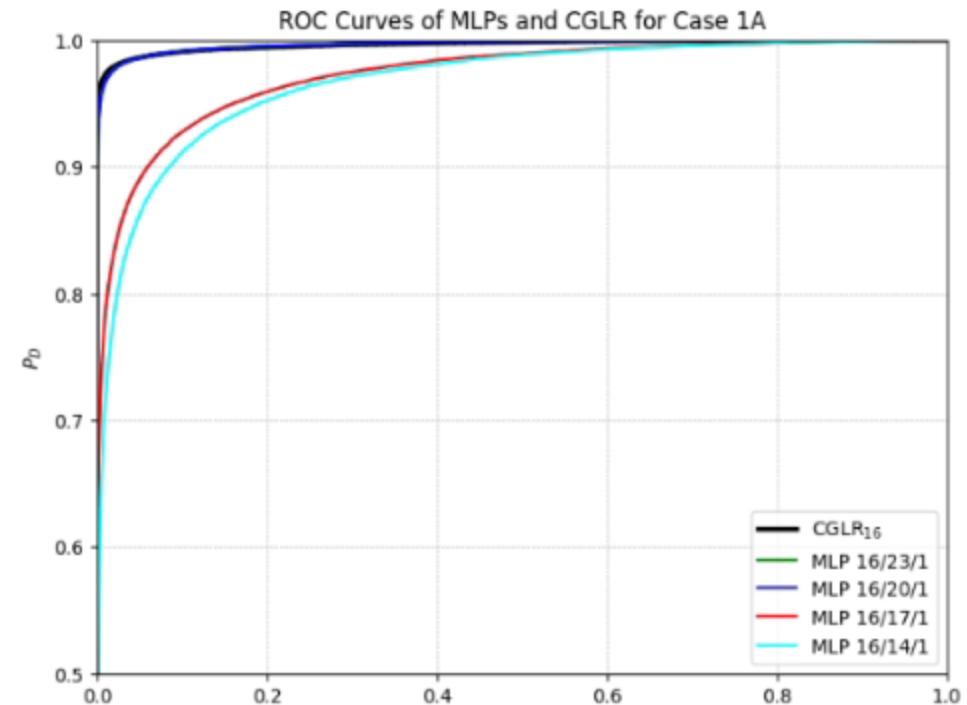
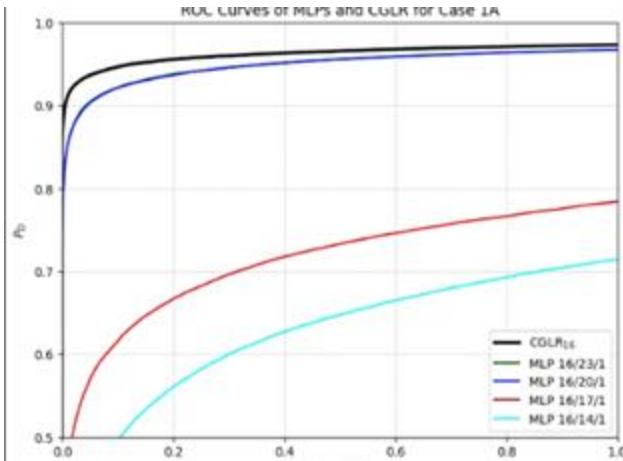
Experiments

- The final approximation error depends on the **error function**, **training/validation sets**, system **structure**, and **training algorithm**.
- For a good approximation, the training set must be a subset of the input, the predicted function (implemented by the learning machine) must be **sufficiently general** to minimize the error function and the **learning algorithm** must effectively find the **minimum** of the error function.

Results: Case 1A

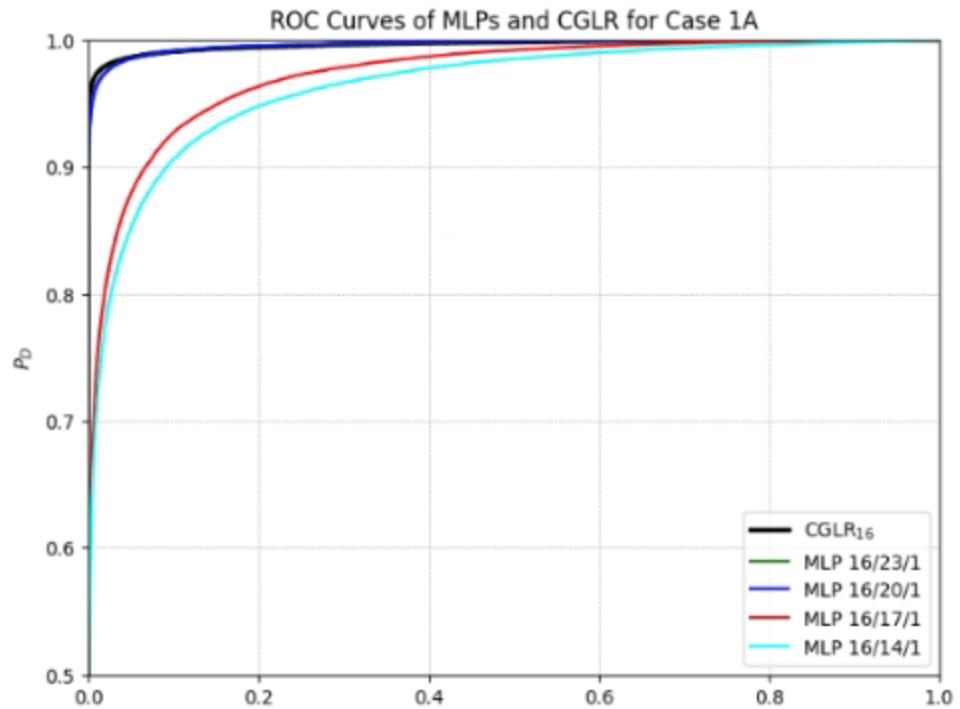
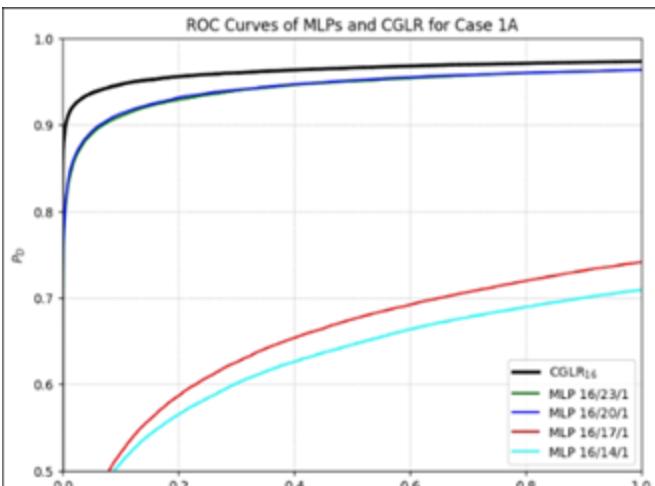
ROC curve for Gaussian Targets with
Cross-Entropy error

Zoomed version given below



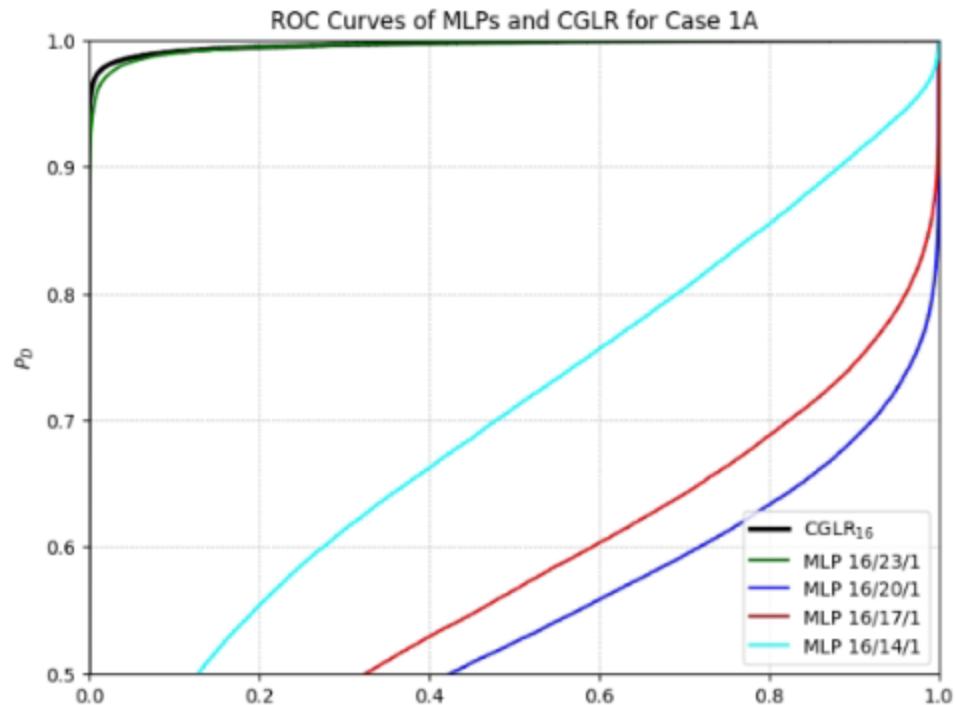
Results: Case 1A

ROC curve for Gaussian Targets with
Sum of Squared Error



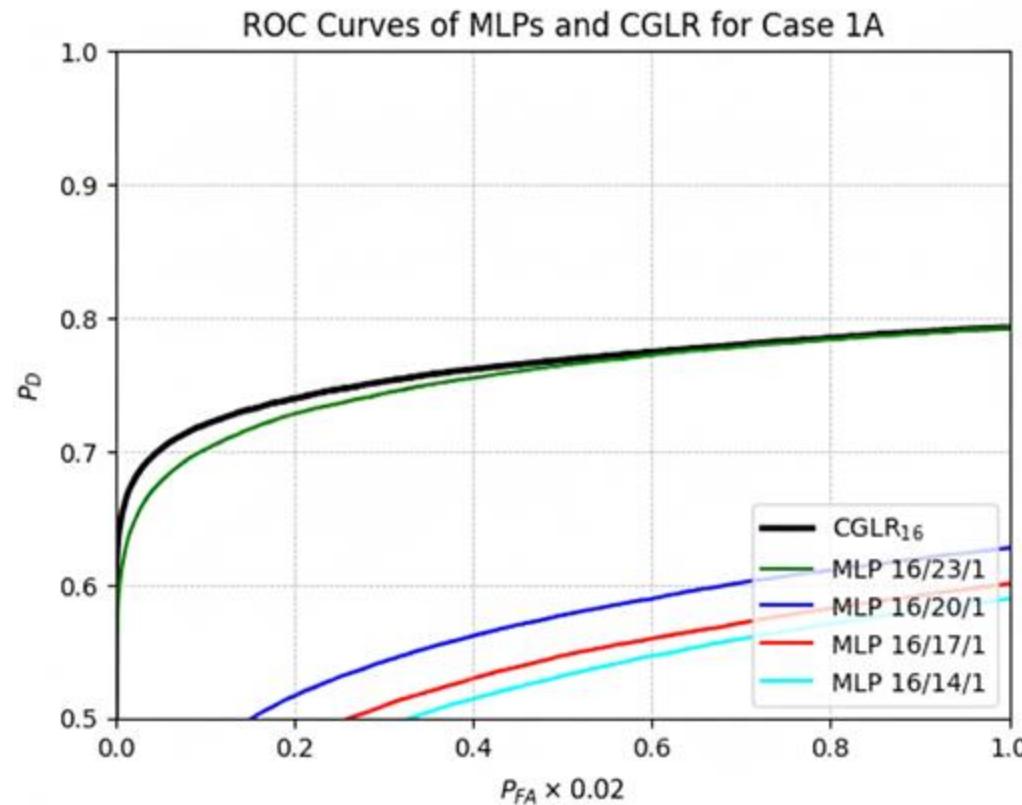
Results: Case 1A

ROC curve for Gaussian Targets with
Minkowski error R = 1



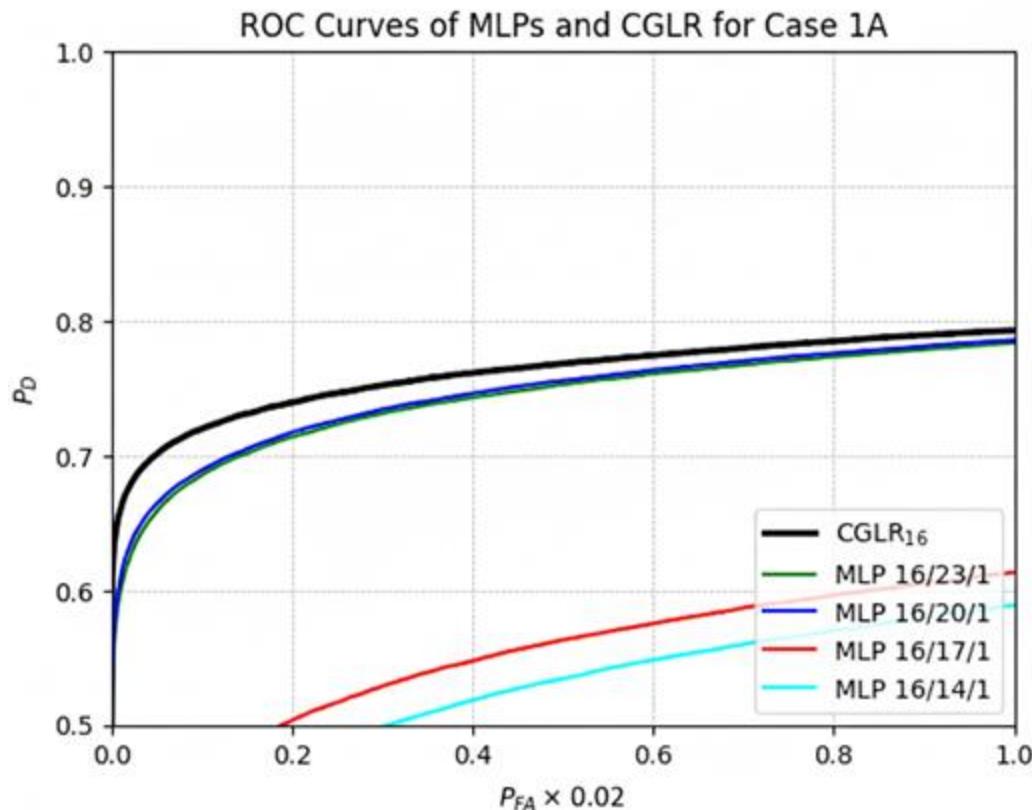
Case 1B: ROC curve for SW1 with Cross-Entropy Error

Local Trend (Zoomed Version)



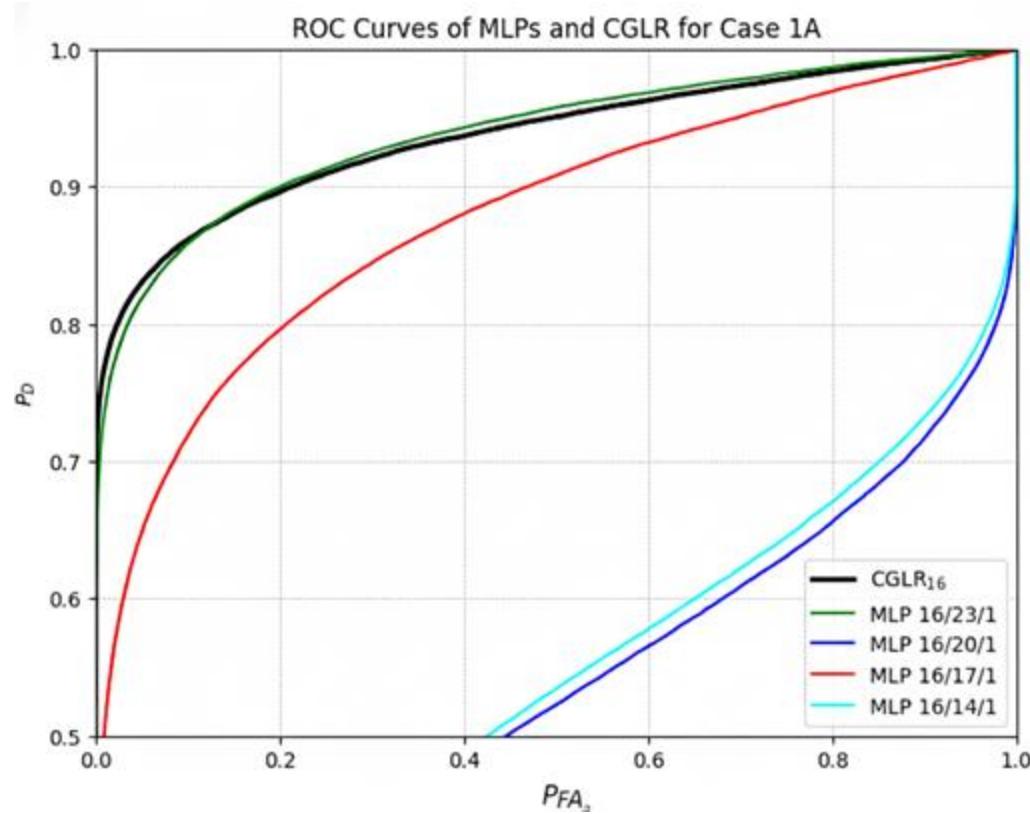
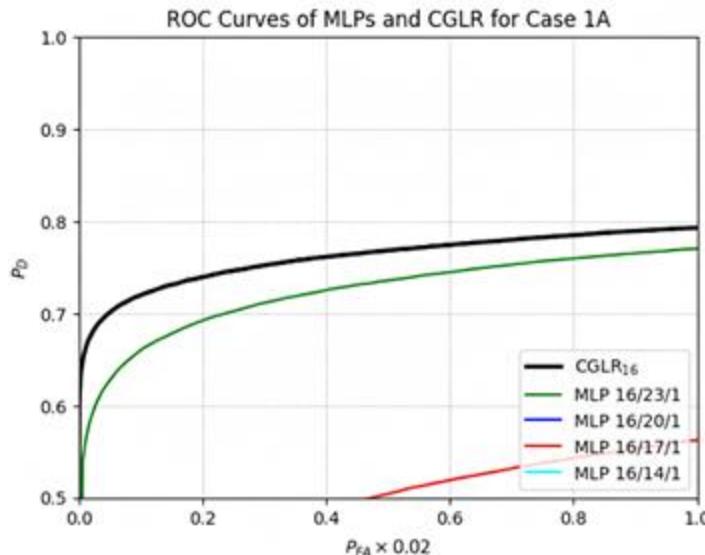
Case 1B: ROC curve for SW1 with Sum-of-Squares Error

Local Trend (zoomed version)



Case 1B: ROC curve for SW1 with Minkowski Error (for R=1)

Local Trend (zoomed version)



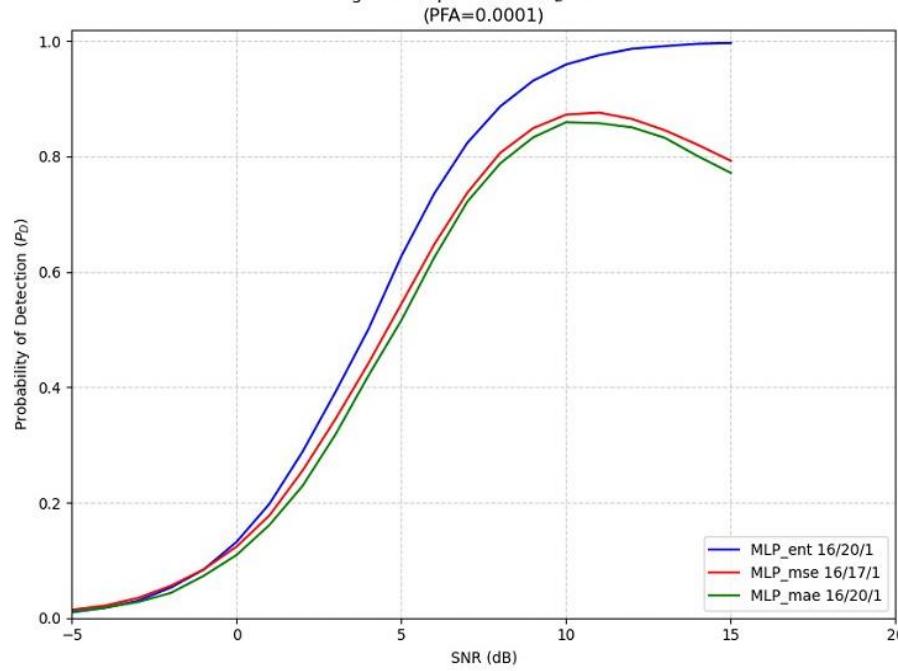
Future Works

- Generate the ROC plots for Case-2 and Case-3 for A and B subcases.
- Plot P_D VS SNR for all the 3 types of error
- Finding an innovation for this proposal.

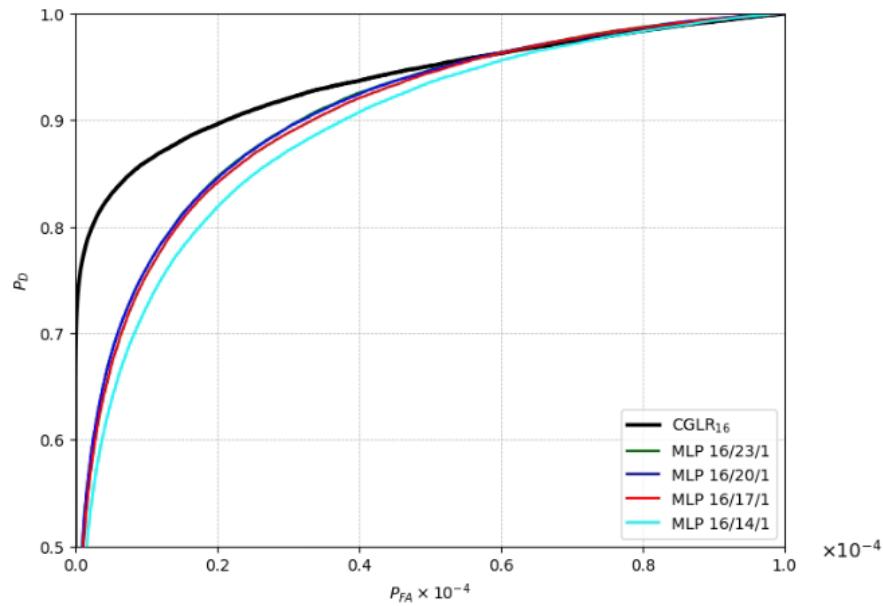
TILL MIDTERM

POST-MIDTERM PROGRESS

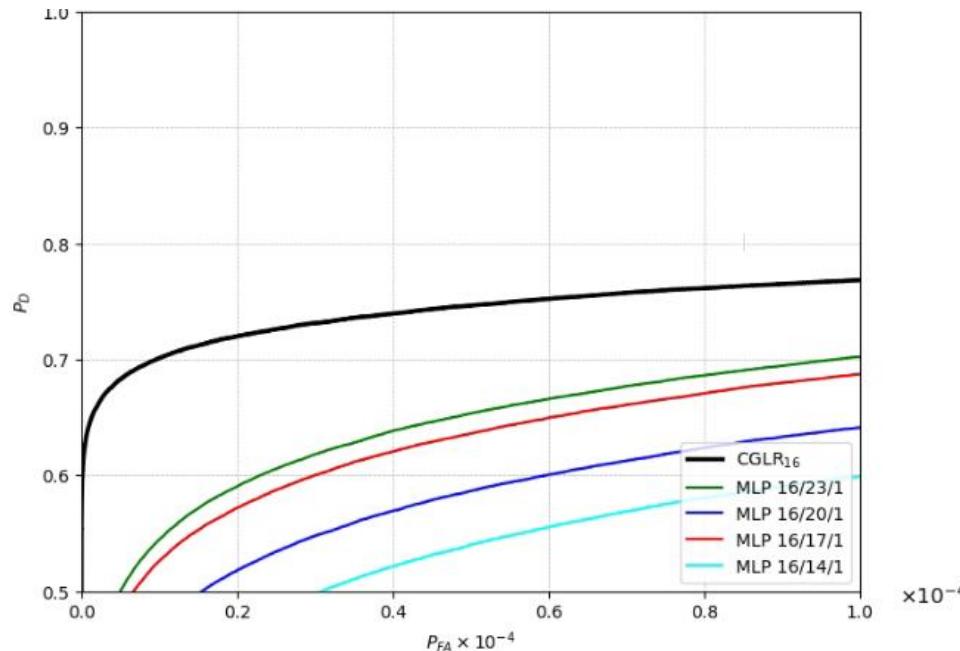
Variation of P_d vs SNR



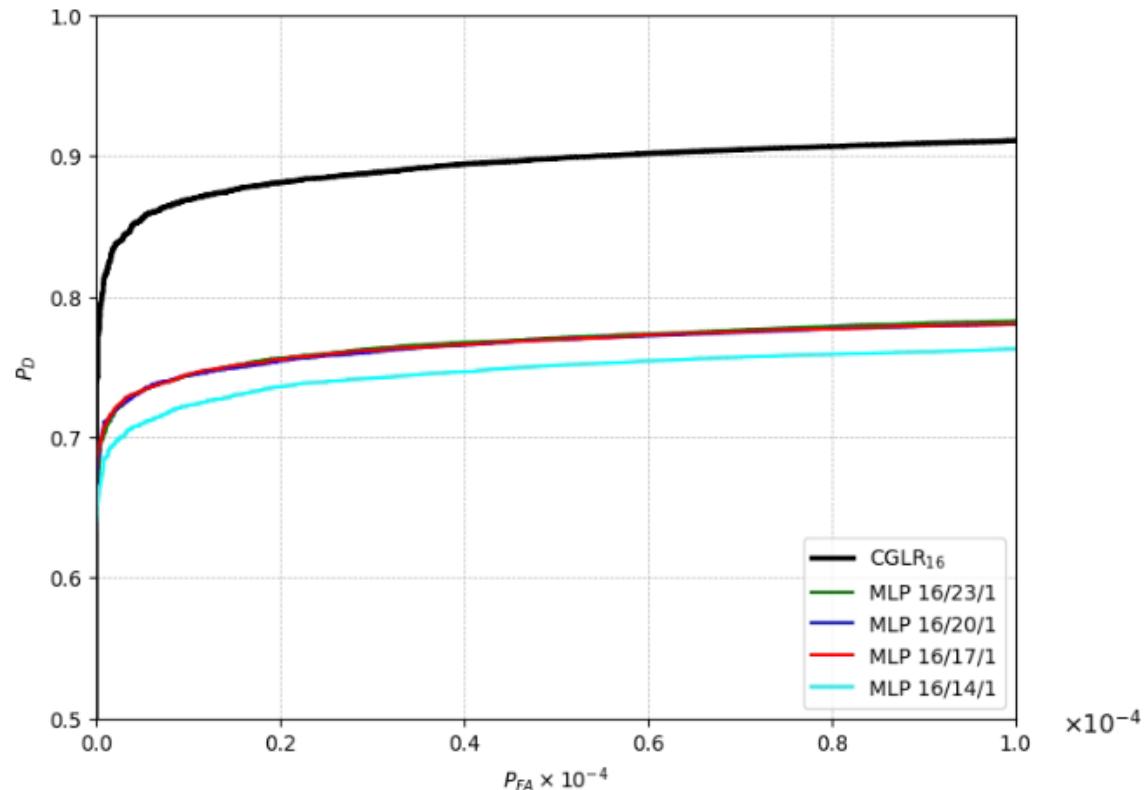
Detection of Gaussian fluctuating targets in presence
of correlated Gaussian clutter and AWGN (CNR = 20 dB, ρ_c = 0.7, SIR = 0 dB)



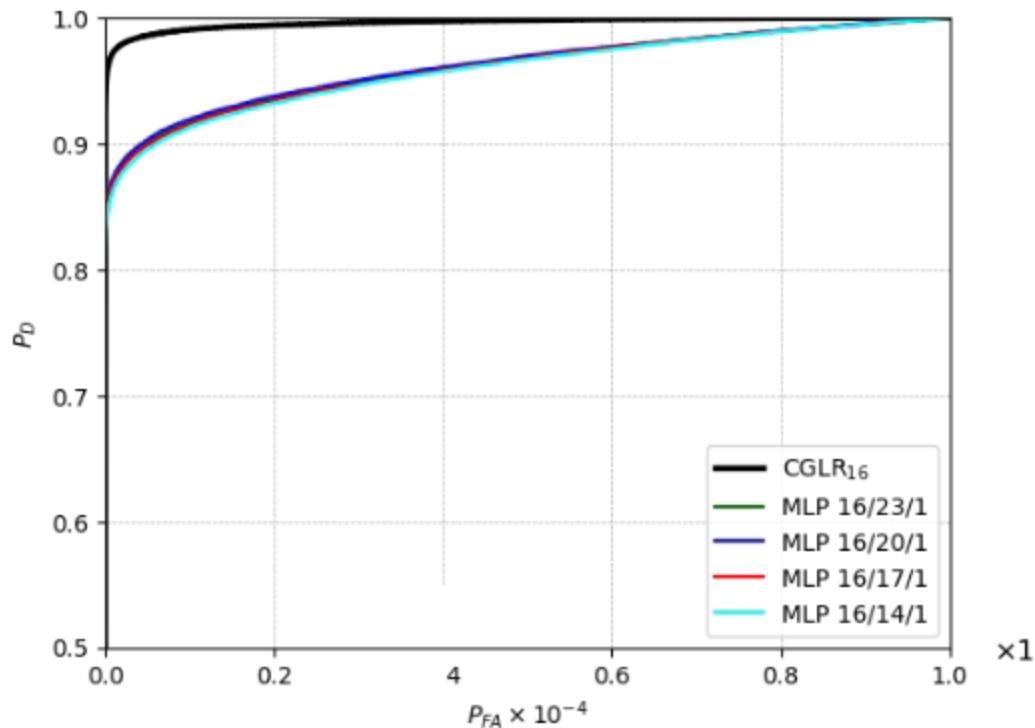
Detection of Gaussian fluctuating targets in presence
of correlated Gaussian clutter and AWGN (CNR = 20 dB, ρ_c = 0.995, SIR = -10 dB)



Detection of Gaussian fluctuating SW targets in presence of correlated Gaussian clutter and AWGN (CNR = 20 dB, $\rho_c = 0.7$, SIR = 13 dB)



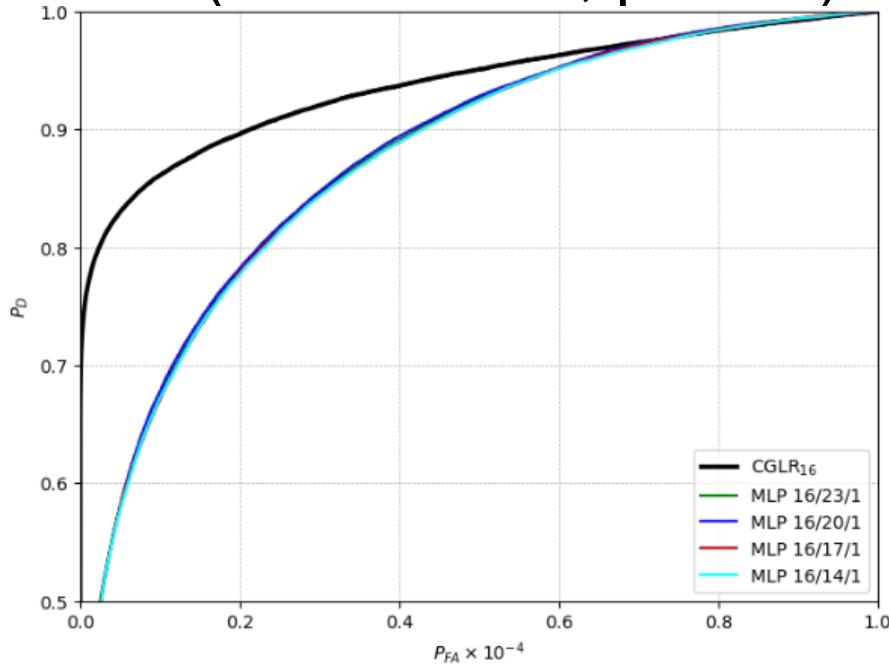
Detection of Gaussian fluctuating SW targets in presence of correlated Gaussian clutter and AWGN (CNR = 20 dB, $\rho_c = 0.995$, SIR = 1 dB)



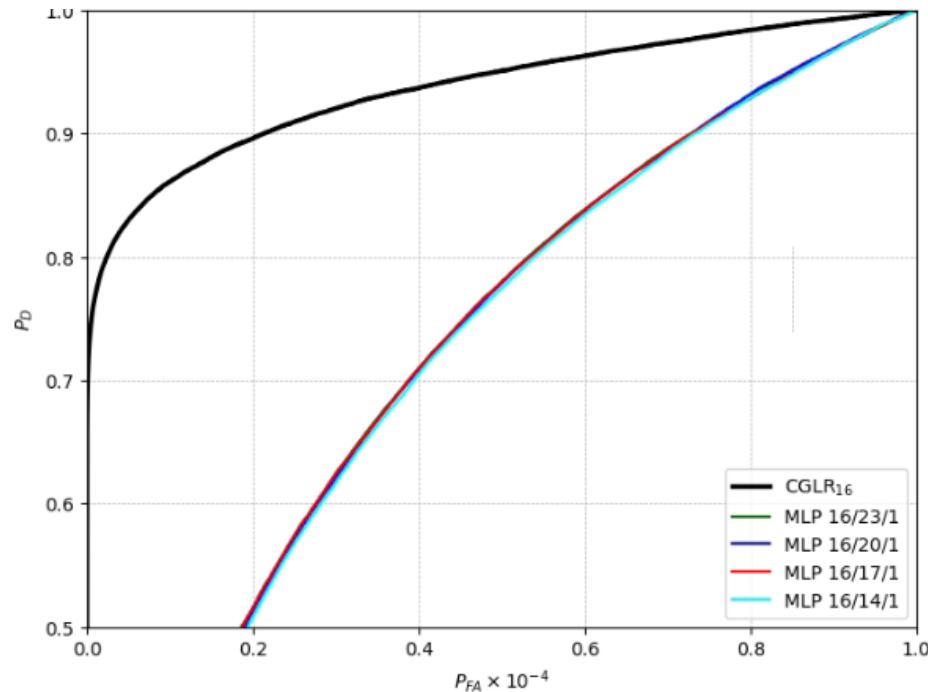
Spiky K-distributed clutter

Detection of non fluctuating targets in presence of spiky K -distributed clutter ($v = 0.5$, where v is the shape parameter of the K -distribution): This model is suitable for target detection in sea/land clutter with high resolution radar systems and low grazing angles. In this case, the problem of detecting Swerling V (SWV) targets with unknown Doppler shift is considered.

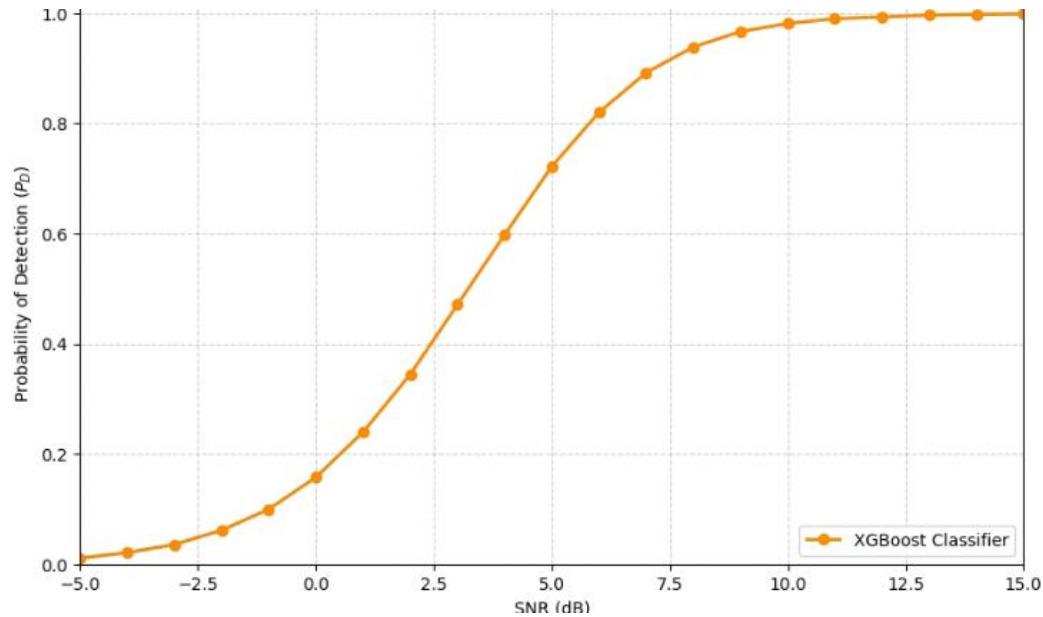
Detection of non fluctuating targets in presence of spiky K-distributed clutter (SCR = 9 dB, $\rho_c = 0$)



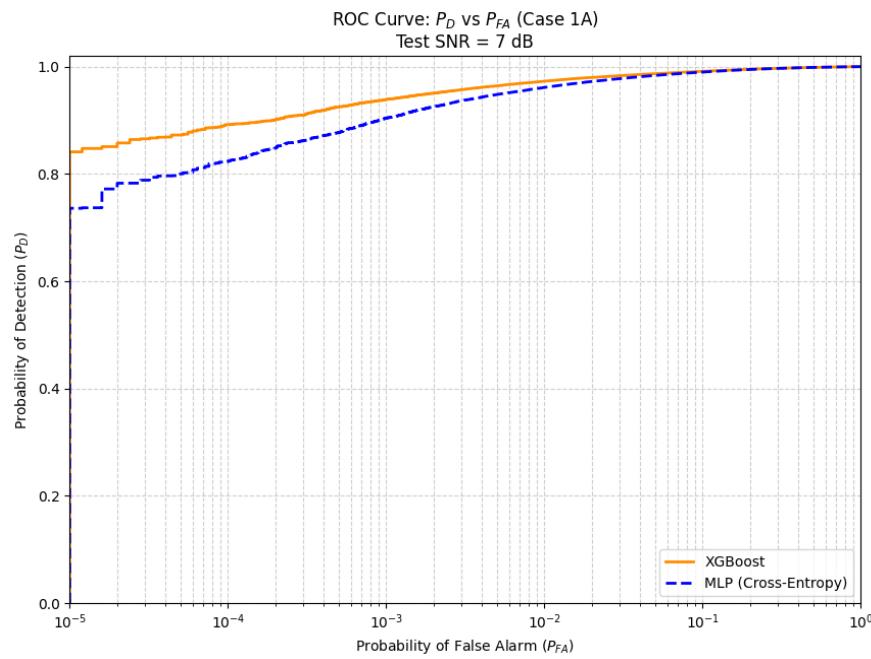
Detection of non fluctuating targets in presence of spiky K-distributed clutter (SCR = -3 dB, $\rho_c = 0.9$)



XGBOOST (Novelty)



XGBOOST (P_d vs P_{fa})



GitHub Repository link

Repo link : https://github.com/Shannon2004/Radar-detection-with-the-Neyman-Pearson-criterion-using-supervised-ML-/tree/main/DET_Project

THANK YOU