# ADVERSARIAL AUTOENCODER FOR DENOISING AND SIGNAL RECOVERY IN QUANTUM GYROSCOPES

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TEMITOPE ADENIYI & DR SATHISH KUMAR

# OUTLINE

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# 1. INTRODUCTION

**Background of Study**

- For cognitive communication systems in space, highly accurate and precise gyroscope measurement is vital in enabling precise and reliable navigation [1]

- This also helps in determining and maintaining spacecraft orientation and attitude control [2]

- For achieving higher precision and accuracy in these measurements, quantum effects are being actively exploited

- This is to develop Quantum sensing devices like Quantum Gyroscopes (QGs) that can push beyond the limits of measurement capabilities [3]

# 1. INTRODUCTION

**Motivation: Noise Factor as a Limitation in QGs**

- There are a lot of factors that questions the superiority of Quantum Sensors over their classical counterpart
- QGs are heavily challenged by their susceptibility to various sources of noise
- This can be environmental disturbances, imperfections in measurement apparatus and decoherence
- This noise can severely compromise their performance and measurement accuracy[4]

# 1. INTRODUCTION

## The need for Stability in QGs – Past Solutions

- Constructing QGs with new schemes that exhibit optimal working conditions even in the presence of noise or with little or no decoherence
- Present Strategies to denoise the measurement obtained from QGs
  - New time-frequency analysis method [5]
  - Quantum Error Correction [6]
  - Quantum noise Cancellation processing [7]

# 1. INTRODUCTION

## AI model as a Solution – Adversarial Autoencoder Model (AAE)

- Low Complexity
- Not Model/Scheme Specific
- Adaptability
- Learning Capability

# 3. RESEARCH AIM AND OBJECTIVES

The aim of the research is to develop an Adversarial Autoencoder (AAE) model for denoising and signal recovery in QGs.

The Specific Objectives are to

1. Develop an AAE architecture capable of denoising and signal recovery in QGs
2. Analyze performance of model in denoising and signal recovery in QGs through reconstruction error loss
3. Use result to provide Insights into the application of AAEs to denoising and signal recovery in Quantum sensors

# 2. LITERATURE REVIEW

| Author and Topic | Research Background | Results |
|---|---|---|
| Denoising Autoencoder Aided Spectrum Reconstruction for Colloidal Quantum Dot Spectrometers (Zhang et al., 2021) | The research employed a denoising autoencoder to reduce noise in the filter raw measurements of synthetic and experimental colloidal quantum dot spectrometers | They demonstrated results with a reconstruction error of 10% and 40% respectively on synthetic and experimental datasets |
| Quantum Autoencoders to Denoise Quantum Data (Bandarenko and Feldmann, 2020) | The research used a Quantum autoencoder (quantum version of the classical autoencoder) to denoise Greenberger-Horne-Zeilinger states | Successfully denoised the Greenberger-Horne-Zeilinger states subject to spin-flip errors and random unitary noise. These states are entangled state which is an important resource for quantum communication and metrology. |
| Noise Prediction and Reduction of Single Electron Spin by Deep-Learning-Enhanced Feedforward Control (Thomas et al., 2021) | The paper introduced a deep learning approach to predict the trend of noise and compensating for delay in diamond-based nanoscale sensors. | They demonstrated that their approach can enhance the decoherence time of the electron spin in diamond-based nanoscale sensor |

# 4. METHODOLOGY

## A Noisy Gyroscope Scheme – Implemented on a Quantum Photonic System using Strawberry Fields

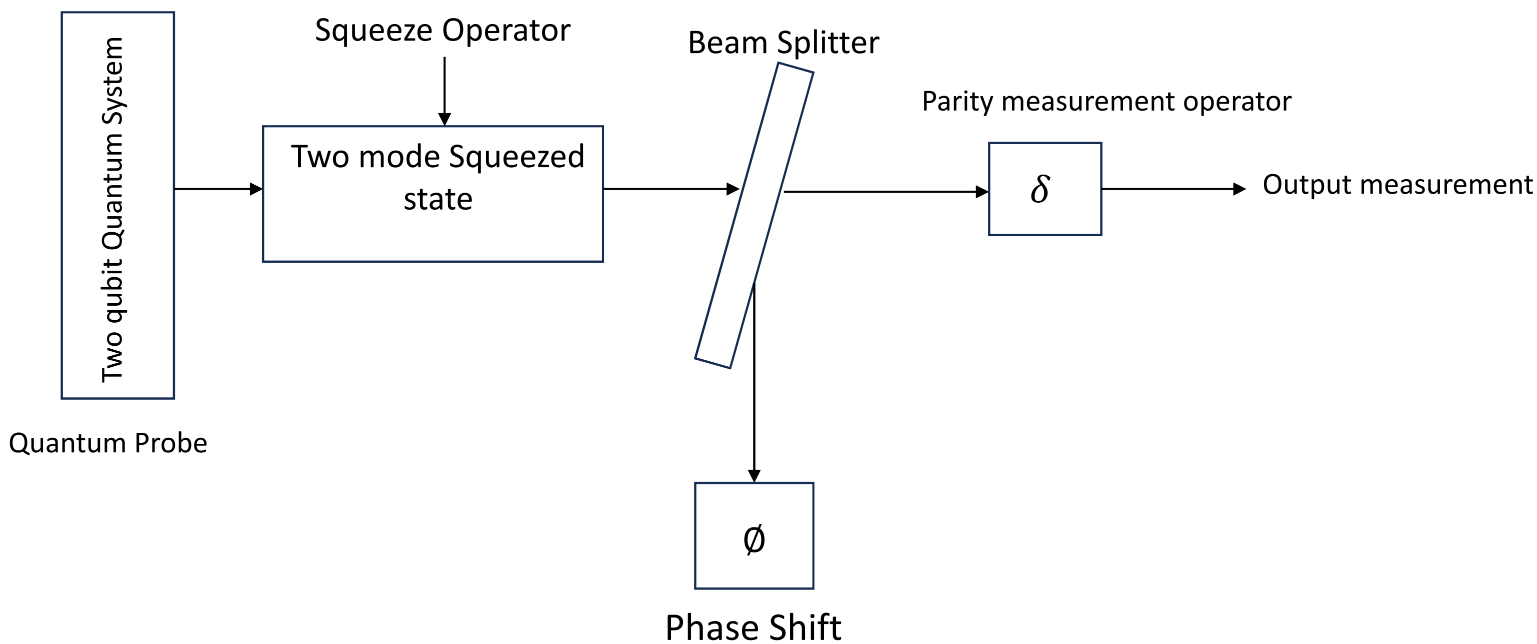
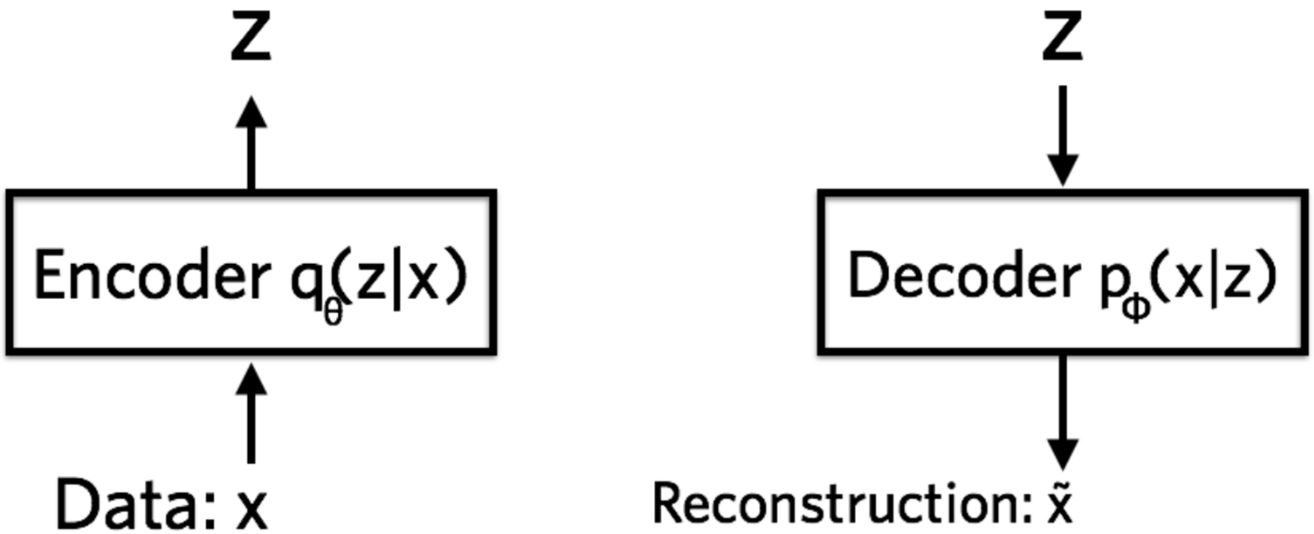



Fig 4a: A Sample Noisy Gyroscope Scheme, each of the components in the scheme are Implemented by Quantum Gates

# 4. METHODOLOGY

**Autoencoder**




Total loss is $\sum_{i=1}^{N} \mathcal{L}_i$ For N total datapoints

where $\mathcal{L} = ||\, x - x^{'} \,||^2$

# 4.METHODOLOGY

**Autoencoder: Training**

**The Encoder q$(\boldsymbol{z}|\boldsymbol{x})$**

$$P(z|x) = \frac{P(x|z)p(z)}{p(x)}$$

**The Decoder p$(\boldsymbol{x}|\boldsymbol{z})$**

$$P(x) = \int p(x|z)P(z)dz$$

- Training loss is is given by:

*Total loss = reconstruction loss + regularizer*

$$l_i(\theta, \phi) = -\mathrm{E}_{q_{(z|x)}} \log p(x|z) - \mathrm{KL} q(z|x)||p(z)$$

# 4. METHODOLOGY

## Generative Adversarial Network

The GAN consists of two parts: the discriminator (*D*), the generator (*G*)

- *G* maps the latent variable *z* to data space
- *D* distinguishes whether its input comes from the real data or the generated data
- The training function is given by:

$$V(G,D) \; = \; E_{x \sim p_{data}(x)}(log \; (D(x)) \; + \; E_{z \sim p_z(z)}(log(1-d(G(z)))))$$

# 4. METHODOLOGY

## Adversarial Autoencoder (AAE) – Autoencoder + a Discriminator

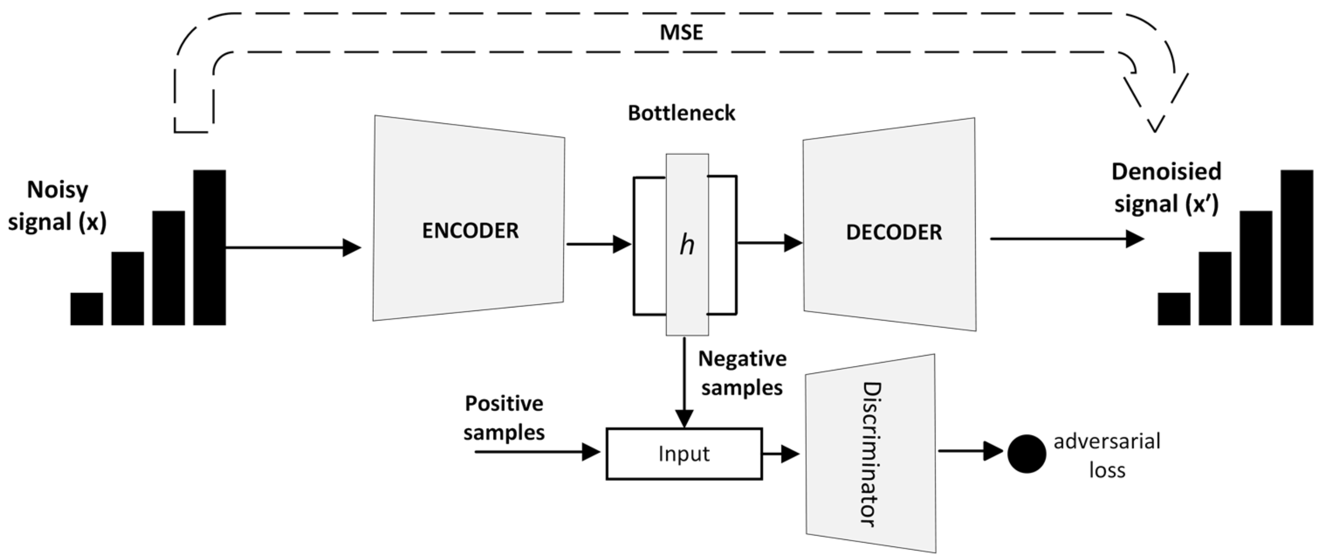



Fig 4a: Architecture for AAE

# 5.RESULT

**Signal graph for Original Gyroscope and Denoised Gyroscope Measurement for a noise factor of 0.1**

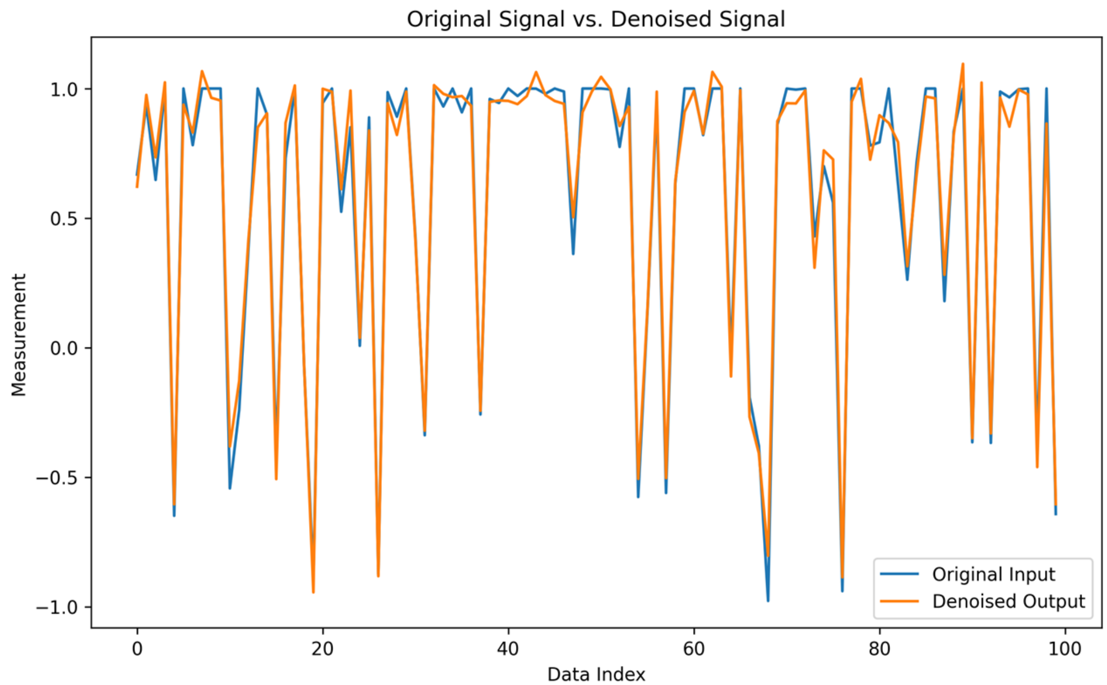



Fig 5a: *Plot of the correlation of the original and the denoised signal*

# 5.RESULT

**Signal graph for Original Gyroscope and Denoised Gyroscope Measurement for a noise factor of 0.5**

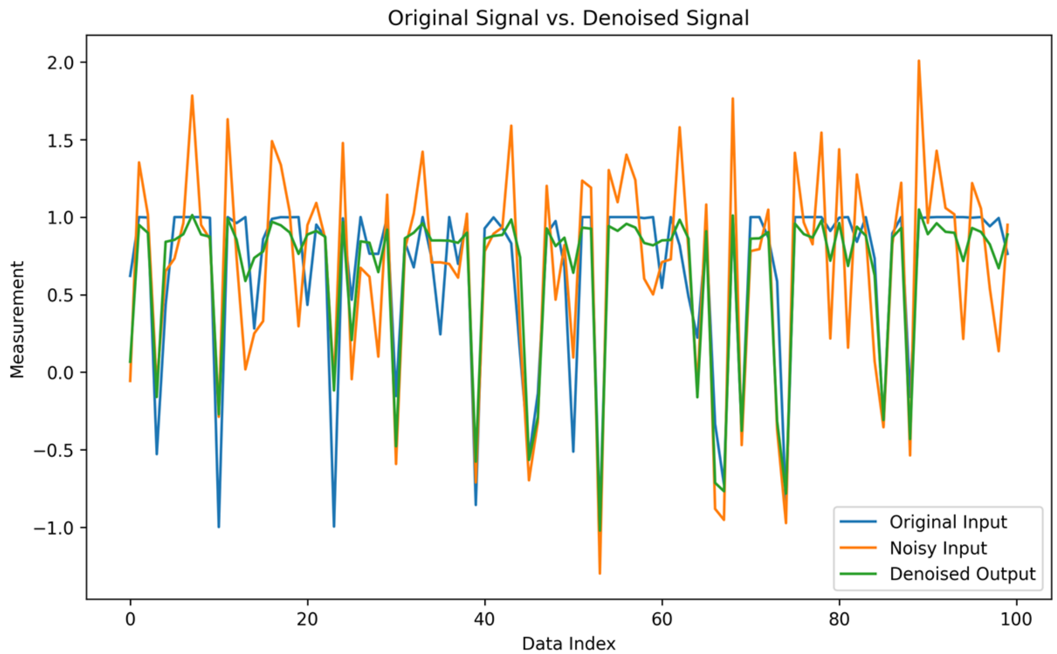



Fig 5b: *Plot of the correlation of the original and the denoised signal*

# 5.RESULT

**A subset of 15 dataset that shows the variation between the original, noisy and the corresponding denoised signal for a noise factor of 0.5. The blue dot represents the original signal, the red color represents the denoised signal and the green represents the noisy signal**

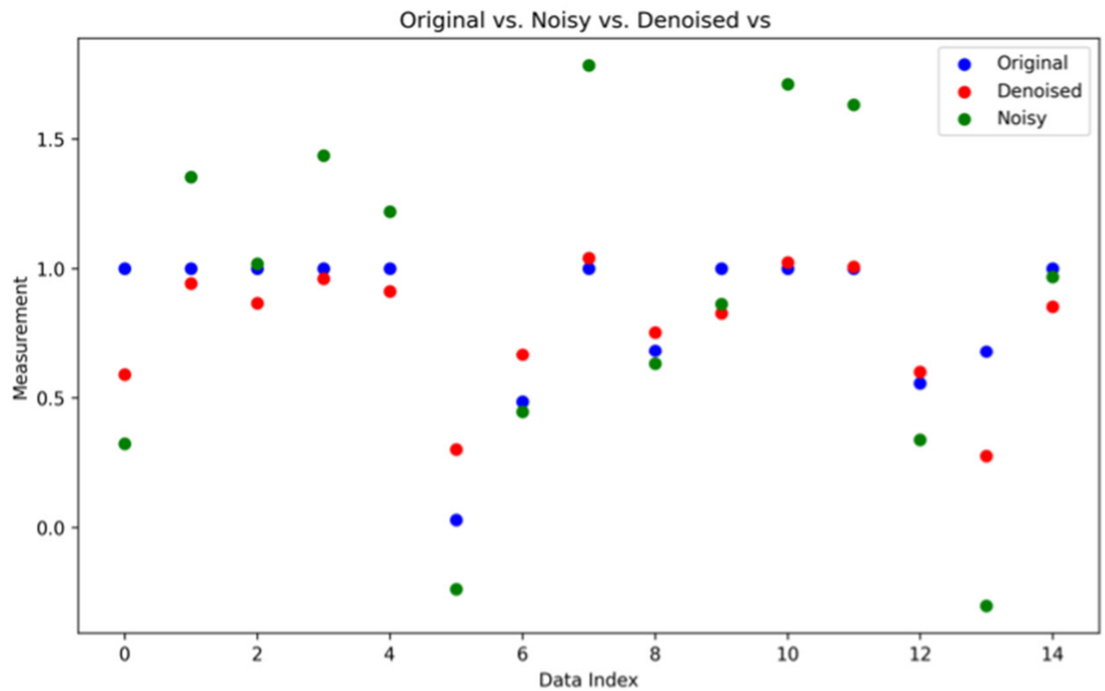



Fig 5c: *Plot of the correlation of the original, noisy and the denoised signal*

# 5.RESULT

**Residual graph shows how much of noise left after denoising for each dataset**

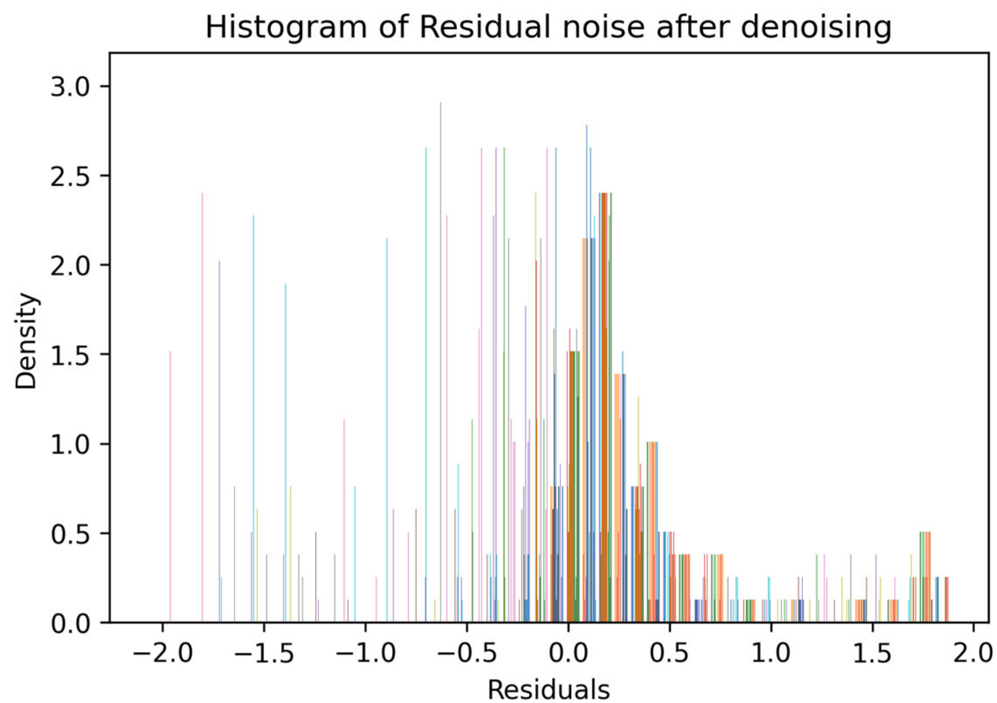



Fig 5d: Histogram of Residuals after denoising

# 5. FUTURE WORK

- Exploring the scalability of the AAE model for larger-scale quantum gyroscopes
- Investigating its performance in real-world space scenarios
- Exploring the robustness and resilience of our AAE model under various noise conditions encountered in space environments
- Exploring synergistic approaches that combine the strengths of AAE based denoising with quantum error correction techniques

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THANK YOU