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GANexo v2.0: Enhancing Exoplanetary Transit Signal Analysis with Real Data Integration

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Abstract. GANexo v2.0 extends our previous framework for exoplanet transit analysis by moving from synthetic signal generation to direct application on real observational data. The new version combines autoencoder-based noise reduction with Generative Adversarial Network (GAN) models, specifically a conditional GAN (cGAN) used for regression, to extract key transit parameters from noisy light curves. This integration improves robustness against observational noise, enhances parameter estimation accuracy, and provides a reliable AI-driven tool specially for ground-based exoplanet studies.

Keywords. Exoplanet Detection, Transit Method, Photometric Analysis, Machine Learning, Generative Adversarial Networks, Noise Reduction, Autoencoders.

1. Introduction

The transit method has become one of the most widely used techniques for detecting and characterizing exoplanets, not only for its sensitivity but also because transits can be observed from ground-based facilities Perryman (2018). However, it remains highly affected by instrumental noise, atmospheric distortions, and incomplete ground-based coverage, which introduce gaps and systematics that limit parameter accuracy.

To address these challenges, Generative AI offers promising tools for denoising and characterizing transit signals. Our previous framework, GANexo v1.0, was limited to synthetic transits, serving as a proof of concept for exoplanet analysis. In this work, we present preliminary results from GANexo v2.0, an improved framework that integrates real observational data and represents a critical step toward more robust and reliable exoplanet characterization. For a detailed description of GANEXO v1.0 architecture, we refer the reader to Meza-Obando & Crespo-Mariño (2024).

2. GANexo v2.0: Innovations and Architecture

Figure 1 compares GANexo v1.0 and v2.0. While v1.0 was limited to synthetic signal generation, v2.0 integrates real observational data, enabling operation under realistic conditions where noise and data gaps are unavoidable.The updated version includes fine-tuning of both the autoencoder and GAN components for improved noise reduction and generative stability, and introduces direct extraction of transit parameters through GAN-based regression.

The architecture is structured in two main stages. First, autoencoder-based filtering is applied to reduce both white and red noise, enhancing the clarity of transit signals.

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Table 1. Comparison of some exoplanet parameters from GANexo and the NASA Exoplanet Archive.

Exoplanet	GANEXO		NASA EXOPLANET DATABASE	
	Exoplanet Radius ($R_\oplus$)	Semi-major Axis (AU)	Exoplanet Radius ($R_\oplus$)	Semi-major Axis (AU)
HAT-P-3 b	10.96	0.040	10.53	0.038
XO-7 b	14.92	0.044	15.38	0.044
HAT-P-37 b	12.95	0.037	12.74	0.037

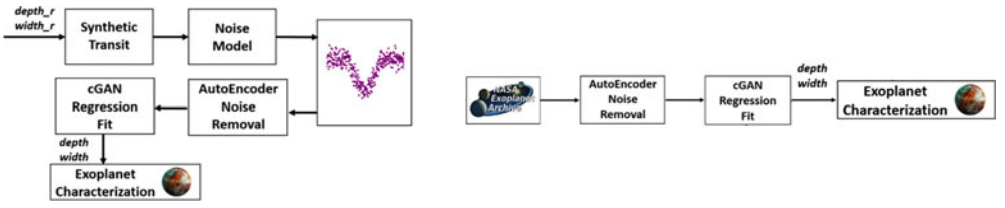


Figure 1. Comparison of GANexo v1.0 on the left with synthetic transits from Meza-Obando & Crespo-Mariño (2024), and GANexo v2.0 on the right with real data.

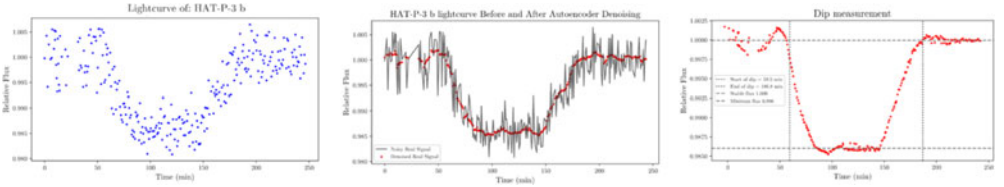


Figure 2. HAT-P-3 b transit: raw light curve (left), denoised signal with autoencoder (center), and cGAN regression for dip measurement (right).

Second, a one-dimensional conditional GAN performs generative regression to estimate critical planetary parameters such as transit depth and duration. Together, these stages improve robustness against observational noise and enhance the reliability of transit-based characterization. Data for this study were retrieved from the NASA Exoplanet Archive Akeson et al. (2013).

2.1. *Results*

GANexo v2.0 has so far been tested on three randomly selected exoplanet cases: HAT-P-3 b, XO-7 b, and HAT-P-37 b, focusing on the estimation of planetary radius and semi-major axis. Results are summarized in Table 1. Figure 2 shows HAT-P-3 b, where the original signal (left) is processed by the autoencoder to produce a denoised and more distinct transit profile (middle), and then refined through cGAN regression (right) for accurate characterization. Additional cases are currently being tested.

2.2. *Discussion*

GANexo v2.0 extends our earlier synthetic-based framework to real observational data, with fine-tuning of both the autoencoder and cGAN components yielding improved adaptation to noisy and incomplete light curves. These refinements enhance noise suppression and parameter regression, resulting in more accurate and robust exoplanet characterization under realistic observational conditions.

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Looking ahead, future developments will focus on extending GANexo v2.0 to multi-telescope datasets, adapting it for space-based missions, and conducting systematic tests with ongoing ground-based measurements. In parallel, the possibility of reintroducing synthetic generation is being explored as a way to reconstruct missing parts of ground-based transits when interruptions occur. Together, these directions aim to consolidate GANexo as a versatile and reliable tool for exoplanet transit analysis.

References

Akeson, R. L., Chen, X., et al. 2013, Publications of the Astronomical Society of the Pacific, 125, 989.

Meza-Obando, F., & Crespo-Mariño, J. L. 2024, IEEE 6th Int. Conf. on BioInspired Processing (BIP), 1-7.

Perryman, M. 2018, The Exoplanet Handbook, Cambridge University Press, 103-104.

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