# Learning Latent Dynamics: A Unified Framework for Waveform Reconstruction and Inverse Modeling

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## Abstract

Modeling complex temporal dynamics in waveform data is a fundamental challenge in signal processing and time-series analysis. In this work, we present a deep learning framework designed to learn robust latent representations of waveform signals. We evaluate the model's performance across three distinct inference tasks: autoregressive forecasting, missing data imputation, and inverse parameter estimation. Our results demonstrate that the model achieves high-fidelity short-term predictions, maintaining phase and amplitude coherence for approximately 75 time steps before exhibiting characteristic autoregressive error accumulation. In imputation tasks, the model effectively reconstructs masked signal segments with a low and tightly distributed L1 loss, indicating strong generalization capabilities. Furthermore, analysis of parameter inference reveals a linear correlation between predicted and ground-truth governing variables, suggesting the model successfully disentangles the underlying physical factors of variation. These findings establish the architecture as a versatile tool for signal analysis, capable of both generating coherent future trajectories and recovering lost information with high consistency.

***K*eywords** Deep Learning · Time-Series Analysis · Waveform Prediction · Data Imputation · Parameter Inference · Autoregressive Modeling

## 1 Introduction

Although gravitational waves can be effectively detected using traditional Matched Filtering, this method becomes computationally expensive as detector sensitivity improves, often requiring the cross-correlation of data against millions of template waveforms [1]. The goal of this paper is to demonstrate how Transformer architectures [2] can address these computational bottlenecks. By leveraging the Transformer's ability to capture long-range dependencies in time-series data, we propose a unified approach for three critical tasks: parameter inference, waveform prediction, and signal imputation.

## 2 Tasks

In this section, we define the three distinct computational tasks that are addressed in this work. Each task focuses on a specific challenge in gravitational wave astronomy, ranging from physical characterization to signal recovery.

### 2.1 Parameter Inference

The primary goal of gravitational wave analysis is to infer the physical properties of the source system, denoted as the parameter vector $\theta$ (e.g., component masses $m_1, m_2$, luminosity distance $d_L$, and spin). Traditionally, this is performed using Bayesian inference methods like Markov Chain Monte Carlo (MCMC), which can be computationally expensive and slow [3].

We frame this problem as a direct regression task. A Transformer model processes the input strain time-series $h(t)$ and compresses the temporal information into a latent representation. A regression head attached to the final output layer then maps this representation to the continuous values of the source parameters. This approach aims to achieve "amortized inference" [4], where the computational cost is front-loaded during training, allowing millisecond-latency parameter estimation during inference [5].

### 2.2 Waveform Prediction

This task treats gravitational wave data as an autoregressive sequence modeling problem, analogous to "next-token prediction" in Large Language Models (LLMs) [6]. Given a sequence of observed strain values $x_0, \ldots, x_t$, the objective is to predict the subsequent value $x_{t+1}$.

By learning the temporal evolution of the waveform—specifically the frequency and amplitude evolution characteristic of compact binary coalescences—the model can be used recursively to generate the continuation of a signal. This capability is particularly relevant for "early warning" systems, where predicting the merger time and amplitude before it occurs allows for the rapid pointing of electromagnetic telescopes.

### 2.3 Missing Wave Imputation

Real-world detector data are frequently contaminated by non-Gaussian noise transients known as "glitches". A common mitigation strategy is "gating", where corrupted segments of the data are masked or removed, resulting in gaps in the time series.

Building on the work of Yıldız et al. [7], who demonstrated the efficacy of Transformers for multivariate time series imputation, we apply this methodology to gravitational waves. The task is formulated as a masked signal reconstruction problem: the model is presented with a waveform where random segments have been masked (replaced with a placeholder value). An encoder-only Transformer uses the bidirectional context—information before and after the gap—to reconstruct the missing waveform segment [8].

## 3 Model Structure and Training

In this section, we outline the neural network architectures employed for each task and the synthetic data generation process used to train them.

### 3.1 Architectures

We employ two distinct Transformer-based architectures tailored to the specific nature of each task:

- **Decoder-Only Transformer (Autoregressive Tasks):** For the tasks of *Parameter Inference* and *Waveform Prediction*, we utilize a decoder-only architecture similar to those used in Generative Pre-trained Transformers (GPT). This architecture is causal, employing masked self-attention to ensure that predictions at any given time step depend only on past information. This design is inherently suitable for sequential forecasting and processing time-series data, where temporal order is strictly preserved.
- **Encoder-Only Transformer (Reconstruction Task):** For *Missing Wave Imputation*, we employ an encoder-only architecture (analogous to BERT). Unlike the decoder, this model utilizes unmasked bidirectional attention, allowing every time step to attend to all other time steps in the sequence simultaneously. This global context—incorporating information before and after a gap—is critical for accurately reconstructing missing intervals.

For all tasks, the final hidden states of the Transformer are passed through a fully connected (dense) regression head to map the high-dimensional latent representations to the desired continuous output values.

### 3.2 Data Generation and Training Protocol

To validate the feasibility of these architectures for gravitational wave analysis, we generated synthetic training data designed to mimic key characteristics of astrophysical signals.

The training signals were constructed as a superposition of multiple sine waves with varying frequencies and amplitudes, rather than simple monotonic sinusoids. The frequency ranges were selected to align with the sensitive bandwidth of ground-based detectors (e.g. LIGO/Virgo). To facilitate efficient batch processing, all signals were discretized into fixed-length time windows with a constant sampling rate.

We implemented a dynamic data generation strategy within the training loop. Instead of training on a fixed static dataset, new synthetic waveforms were generated on-the-fly at the beginning of each epoch. This approach acts as an infinite source of data augmentation, effectively preventing the model from overfitting to a finite set of examples and encouraging it to learn the generalizable underlying physics of the waveforms.

While the core Transformer backbones remain consistent, the input-output definitions vary by task:

- **Parameter Inference:** The model processes the full time-series, and the regression head projects the final output vector to the dimensionality of the target parameter space.
- **Waveform Prediction:** The model is trained in a self-supervised manner to minimize the error between its output at step $t$ and the true signal value at step $t + 1$.
- **Imputation:** The input signal is corrupted by masking random contiguous segments with distinct placeholder values to represent missing data. The model is trained to output a complete reconstructed waveform, with the loss calculated specifically on the reconstruction error of the masked regions.

# 4 Model evaluation

In this section, we present a quantitative and qualitative analysis of the proposed Transformer models. We evaluate the performance of each architecture on the three distinct tasks defined previously: parameter inference, auto-regressive waveform prediction, and missing signal imputation.

To assess the models' efficacy, we utilize standard regression metrics, specifically L1 loss (Mean Absolute Error), to quantify the deviation between predicted values and the ground truth. Furthermore, we provide visual comparisons of the predicted and reconstructed waveforms against the true signals to demonstrate the model's ability to capture the underlying frequency and amplitude evolution of the gravitational waves.

## 4.1 Parameter Inference

We evaluated the model's ability to infer the underlying governing parameters of the waveform. This assesses whether the model has learned a disentangled representation of the physical factors of variation (such as frequency or amplitude) rather than simply memorizing surface-level patterns.

Figure 1 presents the regression analysis that compares the ground truth parameters with the predictions of the model on a generated test set.

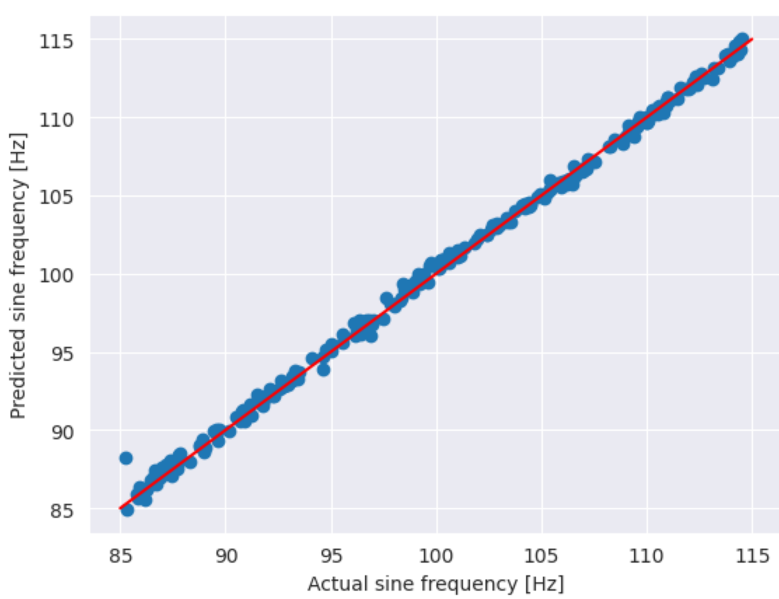



Figure 1: Scatter plot of Actual vs. Predicted parameter values. The red line represents the ideal identity relationship.

As illustrated in Figure 1, the data points cluster tightly along the identity line, demonstrating high predictive accuracy across the parameter space.

Quantitatively, the model achieved a Mean Absolute Error of $0.286$, confirming that it captures the majority of the variance in the underlying parameters. The lack of significant heteroscedasticity (widening of errors) at the upper or lower bounds suggests the model remains robust even at the extremes of the parameter range.

### 4.2 Waveform Prediction

Figure 2 demonstrates the model's capability to extrapolate a waveform beyond the training sequence. This inference is performed autoregressively: the model predicts a single time step, and this output is appended to the input sequence to generate the subsequent value.

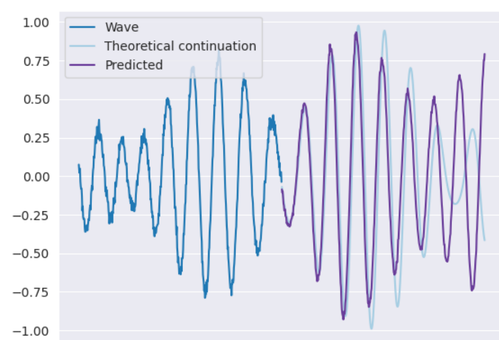
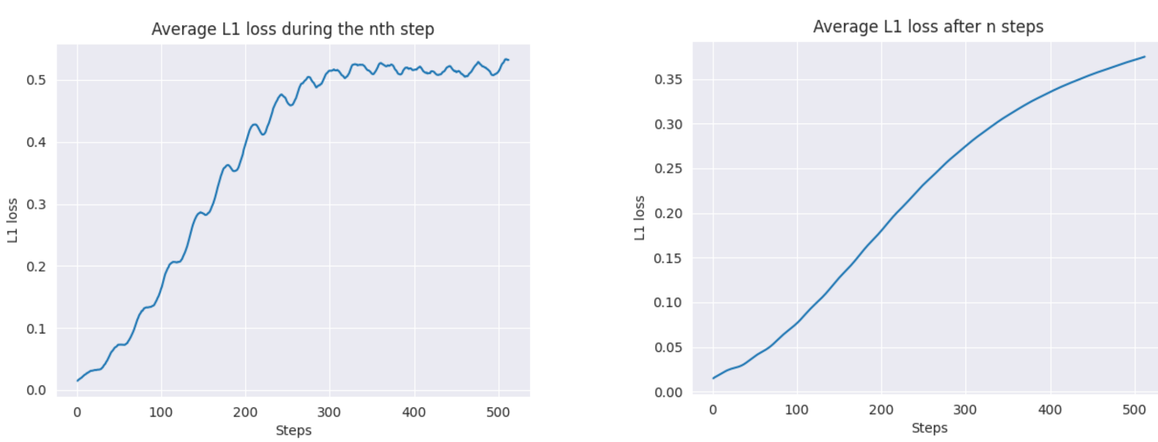



Figure 2: Qualitative comparison of the ground truth wave (blue) versus the model's autoregressive continuation (purple).

As observed in Figure 2, the generated sequence initially maintains phase and amplitude fidelity. However, as the prediction horizon extends, the signal degrades. This deterioration is characteristic of recursive prediction, where minor errors in early steps compound, causing the model's trajectory to diverge from the ground truth.

To quantify this degradation, Figure 3 presents the error analysis over time.




(a) Instantaneous Loss ($L_t$)

(b) Loss rolling average ($\frac{\sum L_t}{n}$)

Figure 3: Analysis of prediction stability over time. The error remains low for the initial ≈75 steps before cascading errors render the prediction unreliable.

The quantitative results confirm the visual assessment: for approximately the first 75 time steps, the model maintains high accuracy. Beyond this point, the accumulating variance pushes the inputs into regions of the latent space the model cannot handle robustly, resulting in a rapid loss of coherence.

### 4.3 Missing Wave Imputation

To evaluate the model's ability to recover missing information, we masked segments of the input data and tasked the model with reconstructing the original signal. Figure 4 illustrates a representative example of this imputation process.

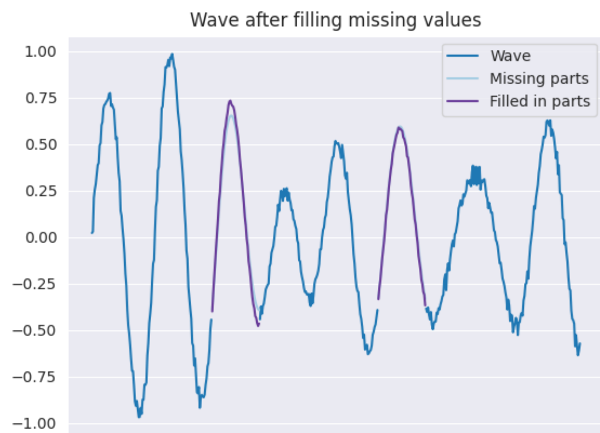



Figure 4: Example of signal reconstruction. The blue region indicates the masked input, the light blue line represents the ground truth, and the purple line shows the model's imputation.

Qualitatively, the model shows a strong capacity to infer the underlying dynamics of the missing segment. As shown in Figure 4, the reconstructed trajectory maintains continuity with the known boundary values and preserves the local frequency characteristics of the wave, rather than collapsing into a simple mean or linear interpolation.

To quantify this performance across the entire test set, we calculated the average L1 loss (Mean Absolute Error) for each imputed sequence. Figure 5 displays the distribution of these losses.

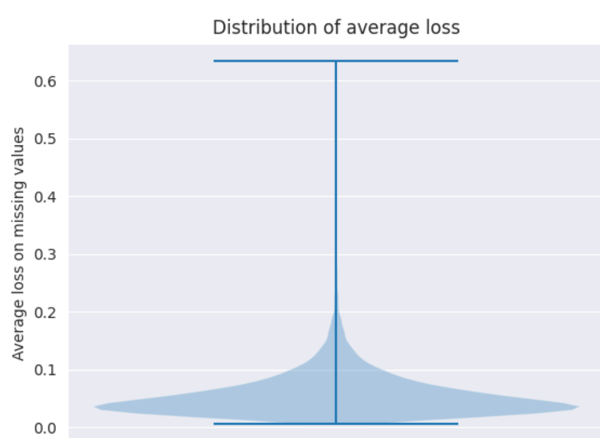



Figure 5: Violin plot showing the density distribution of average L1 losses across the test set

The violin plot reveals a highly concentrated error distribution with a median L1 loss of approximately $0.0465$. The probability density is widest near zero, indicating that, for the majority of samples, the reconstruction error is negligible. The narrow shape of the distribution suggests consistent performance, while the thin upper tail indicates that significant reconstruction failures (outliers) are rare. This low variance in error confirms that the model generalizes well across different waveform shapes.

## 5 Conclusion

In this work, we presented a deep learning framework capable of modeling complex waveform dynamics for parameter inference, future value prediction, and missing data imputation. Our experiments demonstrate that the model successfully learns the underlying latent representations of the signal, enabling it to perform robustly across distinct inference tasks.

The **parameter inference** results indicate that the model performs effective inverse mapping. The strong correlation between predicted and actual parameters suggests that the network has not only learned to mimic temporal patterns but has successfully encoded the governing dynamics of the waveform. This implies that the learned latent space is structurally informative and captures the physical factors of variation required for interpretable signal analysis.

In the context of **waveform prediction**, the model exhibits high fidelity in the short-to-medium term. As detailed in our error analysis, the autoregressive generation remains stable for approximately the first 75 time steps. Beyond this horizon, we observed the expected phenomenon of error accumulation, where minor deviations cascade into a loss of coherence. Despite this limitation in long-horizon forecasting, the immediate predictive capability is precise and effectively captures phase and amplitude shifts.

Regarding **missing value imputation**, the model demonstrated exceptional consistency. The reconstruction results, quantified by the distribution of L1 losses, show that the model can infer missing segments with high accuracy, preserving boundary continuity and local frequency characteristics. The narrow variance in the error distribution suggests that the model generalizes well to unseen data and is not merely memorizing training examples.

Future work will focus on mitigating the autoregressive drift observed in long-term predictions, potentially through curriculum learning [9]. Nevertheless, the current results establish the proposed architecture as a viable tool for signal processing tasks that require high-accuracy interpolation and short-term forecasting.

## References

[1] Benjamin J. Owen and B. S. Sathyaprakash. Matched filtering of gravitational waves from inspiraling compact binaries: Computational cost and template placement. *Physical Review D*, 60(2), June 1999.

[2] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. *CoRR*, abs/1706.03762, 2017.

[3] J. Veitch, V. Raymond, B. Farr, W. Farr, P. Graff, S. Vitale, B. Aylott, K. Blackburn, N. Christensen, M. Coughlin, W. Del Pozzo, F. Feroz, J. Gair, C.-J. Haster, V. Kalogera, T. Littenberg, I. Mandel, R. O'Shaughnessy, M. Pitkin, C. Rodriguez, C. Röver, T. Sidery, R. Smith, M. Van Der Sluys, A. Vecchio, W. Vousden, and L. Wade. Parameter estimation for compact binaries with ground-based gravitational-wave observations using the lalinference software library. *Physical Review D*, 91(4), February 2015.

[4] Stephen R. Green and Jonathan Gair. Complete parameter inference for gw150914 using deep learning, 2020.

[5] Maximilian Dax, Stephen R. Green, Jonathan Gair, Jakob H. Macke, Alessandra Buonanno, and Bernhard Schölkopf. Real-time gravitational wave science with neural posterior estimation. *Physical Review Letters*, 127(24), December 2021.

[6] Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever, et al. Improving language understanding by generative pre-training. *OpenAI Blog*, 2018.

[7] A. Yarkın Yıldız, Emirhan Koç, and Aykut Koç. Multivariate time series imputation with transformers. *IEEE Signal Processing Letters*, 29:2517–2521, 2022.

[8] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding, 2019.

[9] Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. Curriculum learning. In *Proceedings of the 26th Annual International Conference on Machine Learning - ICML '09*, pages 1–8, Montreal, Quebec, Canada, 2009. ACM Press.