Adaptive Quantile Guidance in Diffusion Models: Multi-Dataset Learning for Pandemic Time Series

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Abstract

Probabilistic forecasting of epidemiological time series remains challenging due to non-stationary disease dynamics, sparse observations, and heterogeneous data regimes. We present *Adaptive Quantile Diffusion (AQDiff)*, a novel diffusion-based framework that addresses these challenges through two key innovations: (1) multi-dataset pre-training of a unified time series diffusion model across heterogeneous epidemiological domains, and (2) adaptive quantile guidance that dynamically adjusts prediction intervals based on local residual statistics. AQDiff introduces a feedback loop where recent forecast errors inform quantile adjustments through an exponentially weighted buffer, enabling real-time adaptation to volatility shifts. Pre-training on influenza-like illness (ILI), COVID-19, and respiratory syncytial virus (RSV) data from the U.S. Centers for Disease Control and Prevention (CDC) allows cross-domain knowledge transfer. Experiments demonstrate that AQDiff reduces mean absolute error (MAE) by as much as 73.3% compared to state-of-the-art baselines (CSDI, PatchTST) across three pandemic forecasting tasks. Our analysis reveals that adaptive quantile guidance provides statistically significant improvements during outbreak surges, while pre-training enhances robustness to limited training data. The framework maintains computational efficiency, adding less than 10% overhead compared to fixed-quantile diffusion models.

CCS Concepts

• **Computing methodologies** → *Bayesian network models*; **Machine learning approaches**.

Keywords

Time Series forecasting, Generative models, Diffusion Model, Quantile guidance, Transfer Learning, Pretraining

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A Introduction

The COVID-19 pandemic, alongside seasonal epidemics such as influenza, underscores the importance of accurate and timely forecasting of disease metrics (e.g., incidence, hospital admissions, mortality). These predictive models guide public health interventions and resource allocation, yet building reliable forecasts remains challenging due to evolving patterns, sparse data, and non-stationary dynamics [41]. Conventional statistical approaches, such as ARIMA or state space models, often struggle to flexibly capture complex temporal and cross-series relationships without substantial domain-specific tuning [22]. More recently, machine learning-based forecasting methods, including deep recurrent or transformer models, have shown promise in delivering richer predictive distributions that can adapt to rapidly changing conditions [37, 42].

Diffusion models, initially popularized in image generation tasks [39, 19], have begun to gain traction in the time series domain. By defining a forward noise and reverse denoising process over continuous timesteps, diffusion-based forecasters can represent complex, multimodal predictive distributions [35]. Early works indicate that diffusion models can capture intricate temporal dependencies and produce coherent probabilistic forecasts. However, two key challenges remain: (1) *Initialization and Transferability* — training diffusion models from scratch on a single target time series domain can be data-inefficient and slow, and (2) *Uncertainty Calibration* — while diffusion models intrinsically produce stochastic samples, controlling and calibrating the quantile levels of their predictive distribution is non-trivial.

In this paper, we address these challenges by introducing a *multi-task pre-training* strategy and an *adaptive quantile guidance* mechanism for diffusion-based time series forecasting. First, inspired by the paradigm shifts in language modeling and vision tasks where large-scale pre-training has led to substantial gains in downstream performance [8, 33], we pre-train a diffusion model on a broad collection of time series spanning multiple domains (e.g., macroeconomic indicators, environmental data, various epidemiological series). This pre-training allows the model to internalize general temporal dynamics before fine-tuning on a specific pandemic-related dataset, such as COVID-19 incidence or Influenza-Like Illness (ILI) time series. By doing so, we leverage knowledge transfer to improve both accuracy and data efficiency on the downstream task.

Secondly, we propose an *adaptive quantile guidance* technique, extending recent work on guidance mechanisms in diffusion models [9]. Instead of relying on fixed quantiles, our approach adaptively adjusts quantile levels during the reverse diffusion process based on the model's internal representations and the observed data patterns. This dynamic adjustment yields more reliable quantile estimates, ensuring well-calibrated predictive intervals that are essential for epidemiological decision-making. Miscalibrated forecasts can lead to either over- or under-preparation in healthcare

and policy responses, making improved uncertainty representation a vital contribution.

We evaluate our approach on multiple pandemic forecasting tasks, comparing multi-dataset pre-trained diffusion models and adaptive quantile guidance to baseline models and established forecasting approaches. The results show improved accuracy, calibration, and adaptability. Our contributions are threefold:

(1) We introduce a multi-dataset pre-training phase for diffusion-based time series forecasting, enabling more effective knowledge transfer and improved performance on downstream pandemic datasets.
(2) We propose adaptive quantile guidance, allowing the diffusion model to dynamically calibrate predictions for better uncertainty representation.
(3) Through experiments on pandemic time series, we demonstrate that the combination of multi-dataset pre-training and adaptive guidance mechanisms can significantly advance the state-of-the-art in probabilistic forecasting for high-stakes epidemiological applications.

B Background

Recent progress in deep learning for time series forecasting has been driven by three key innovations: *(i) pre-training strategies* that learn universal temporal representations from large and diverse datasets, *(ii) diffusion models* for robust probabilistic generation, and *(iii) guidance mechanisms* for controllable sample synthesis. In this work, we focus on a multi-dataset pre-training approach, wherein we train a diffusion model on multiple source datasets to learn general temporal features, and subsequently fine-tune the model on a target pandemic dataset that contains relatively limited observations.

B.1 Pre-Training for Temporal Representations

Pre-training has proven to be an effective paradigm for time series analysis, inspired by its success in natural language processing (NLP) [8], GPT-3 [1], and computer vision (CV) [18, 34]. By exposing a model to multiple datasets—for instance, different seasonal or epidemiological signals—we can capture shared temporal structures (e.g., seasonality, recurrent events, anomalies) that transfer to downstream tasks. This is particularly advantageous in pandemic forecasting, where the available data in any *single* disease domain (e.g., influenza or COVID-19) may be sparse or highly nonstationary.

Commonly, *masked reconstruction* is used to learn generalized features by forcing a model to infer randomly masked subsequences from their surrounding temporal context. This idea is central to the masked language modeling objective introduced in BERT [8], which compels the network to understand the underlying structure of the input in order to reconstruct the missing data. When applied to multiple datasets, the model gains exposure to a broader variety of temporal patterns, thus becoming more robust upon fine-tuning.

Formally, let $\mathbf{y} \in \mathbb{R}^L$ denote a time series of length L. Define a masking set $\mathcal{M} \subseteq \{1, \ldots, L\}$ that indicates the positions to be reconstructed. We then train a parameterized function f_θ to minimize:

$$\mathcal{L}_{\text{mask}} = \mathbb{E}_{\mathbf{y}\sim\mathcal{D}_{\text{multi-pre}},\,\mathcal{M}}\left[\sum_{t\in\mathcal{M}}\left\|y_t - f_\theta\left(\mathbf{y}_{\setminus\mathcal{M}}, \mathbf{x}\right)\right\|^2\right], \quad (1)$$

where $\mathcal{D}_{\text{multi-pre}}$ is the *combined* set of source datasets, and $\mathbf{x}$ may include auxiliary covariates (e.g., mobility or demographic features). After converging on this large and diverse collection of time series, the model is fine-tuned on a smaller, domain-specific dataset to adapt the learned representations to a particular forecasting task.

B.2 Denoising Diffusion Probabilistic Models (DDPMs)

Diffusion models [39, 19] provide a principled framework for probabilistic time series generation via iterative denoising. This approach differs from conventional autoregressive models by refining noisy latents into coherent forecasts step by step, enabling a flexible representation of uncertainty.

Forward Process. An original sequence $\mathbf{y}_0$ is progressively corrupted over T steps:

$$q(\mathbf{y}_t \mid \mathbf{y}_{t-1}) = \mathcal{N}(\sqrt{1-\beta_t}\,\mathbf{y}_{t-1},\, \beta_t\,\mathbf{I}), \quad (2)$$

where $\{\beta_t\}_{t=1}^T$ is a chosen variance schedule and $\mathbf{y}_T$ approaches Gaussian noise after sufficient corruption steps.

Reverse Process. A neural network ϵ_θ aims to *invert* the corruption, iteratively denoising $\mathbf{y}_T$ back to a valid sample. Concretely, at each reverse step,

$$p_\theta(\mathbf{y}_{t-1} \mid \mathbf{y}_t) = \mathcal{N}\Big(\mathbf{y}_{t-1};\, \tfrac{1}{\sqrt{\alpha_t}}\big(\mathbf{y}_t - \tfrac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(\mathbf{y}_t, t)\big), \sigma_t^2\mathbf{I}\Big), \quad (3)$$

where $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{s=1}^t \alpha_s$. A simplified training loss [19] is:

$$\mathcal{L}_{\text{simple}} = \mathbb{E}_{t,\,\mathbf{y}_0,\,\epsilon}\left[\|\epsilon - \epsilon_\theta(\sqrt{\bar{\alpha}_t}\,\mathbf{y}_0 + \sqrt{1-\bar{\alpha}_t}\,\epsilon, t)\|^2\right]. \quad (4)$$

For time series forecasting, ϵ_θ can condition on past observations or covariates, allowing the model to learn generative dynamics from multiple datasets during pre-training. Subsequent fine-tuning on a single target dataset adapts the learned representations to the domain-specific forecasting challenge (e.g., influenza or COVID-19).

B.3 Guidance Mechanisms for Controllable Generation

Despite the generative richness of diffusion models, real-world forecasting often requires *controllability*. In epidemiology, for instance, we may want forecasts aligned with certain intervention scenarios or targeting high-probability outbreak trajectories.

Classifier Guidance. An early approach [9] couples a diffusion model with an external classifier $p_\phi(c \mid \mathbf{y}_t)$ for the desired condition c:

$$\nabla_{\mathbf{y}_t}\log p_\theta(\mathbf{y}_t \mid c) = \nabla_{\mathbf{y}_t}\log p_\theta(\mathbf{y}_t) \;+\; \gamma\,\nabla_{\mathbf{y}_t}\log p_\phi(c \mid \mathbf{y}_t). \quad (5)$$

However, training and maintaining a separate classifier for each condition or dataset can be cumbersome.

Classifier-Free Guidance. Alternatively, classifier-free guidance [20] avoids external classifiers by jointly learning both conditional and unconditional denoising functions:

$$\epsilon_\theta^{\text{guided}}(\mathbf{y}_t, t, c) = \epsilon_\theta(\mathbf{y}_t, t, \emptyset) \; + \; w\Big(\epsilon_\theta(\mathbf{y}_t, t, c) \; - \; \epsilon_\theta(\mathbf{y}_t, t, \emptyset)\Big), \tag{6}$$

where c may be a scenario label or a quantile target (e.g., $\kappa = 0.9$). The scalar w modulates how strongly the sampling process aligns with the conditional path. For pandemic data, we can even adapt c across timesteps to focus on specific regions of interest or different levels of risk.

C AQDiff : Adaptive Quantile Guidiance For Diffusion Model

Our goal is to learn a flexible, diffusion-based time series model that (1) can be *pre-trained* across multiple datasets to capture broad temporal structures and (2) *fine-tuned* on a target dataset using an *adaptive quantile guidance* mechanism for improved probabilistic forecasts. Figure 1 illustrates the high-level workflow, The S4 Layer is a sequence modeling layer that transforms input data using a learnable state space representation. It can capture long-range dependencies with an efficient parameterization. Meanwhile, 1x1 convolution blocks apply channel-wise transformations to the input, effectively mixing or projecting features across dimension but maintaining the same temporal or spatial dimension. Typically, 1x1 conv layers act as lightweight dense transformations across channels, facilitating feature fusion without expanding receptive field.

(1) **Diffusion Model (Sec. C.1)**: A forward noising process (Eq. 7) and a learnable reverse denoising process (Eq. 9) form the foundation.
(2) **Multi-Dataset Pre-Training (Sec. C.2)**: We condition the denoiser on dataset embeddings, learning cross-domain representations.
(3) **Fine-Tuning Objective (Sec. C.3)**: During fine-tuning on a target domain, we introduce a quantile-driven gradient to adjust reverse diffusion steps, improving tail calibration.

C.1 Diffusion Model

We first describe the *forward* (noising) process and the *reverse* (denoising) process. Let $\mathbf{y} \in \mathbb{R}^L$ be a univariate time series of length L. To incorporate history without increasing L, we augment each step with $C-1$ lagged copies, forming $\mathbf{x}_t \in \mathbb{R}^{L\times C}$ at diffusion step t. Inspired by TSDiff [25], we use layers such as S4 [16] and Conv1×1 for long-range and channel mixing.

C.1.1 Forward (Noising) Process For each dataset $\mathcal{D}_k$, a time series sample $\mathbf{x}_0$ is gradually corrupted by Gaussian noise over T steps. Let $\{\beta_t\}_{t=1}^T$ be a noise schedule. Then:

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I}) \tag{7}$$

leading to a closed-form expression:

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\,\mathbf{x}_0 \; + \; \sqrt{1-\bar{\alpha}_t}\,\boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}), \tag{8}$$

where $\bar{\alpha}_t = \prod_{s=1}^t(1-\beta_s)$. As t grows, $\mathbf{x}_t$ becomes increasingly noisy.

C.1.2 Reverse (Denoising) Process We train a denoising network $\epsilon_\theta(\mathbf{x}_t,\, t,\, \mathcal{D}_k)$ that predicts the added noise. The reverse Markov chain is:

$$p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t,\, \mathcal{D}_k) = \mathcal{N}\Big(\mathbf{x}_{t-1};\, \mu_\theta(\mathbf{x}_t, t, \mathcal{D}_k),\, \sigma_t^2\mathbf{I}\Big), \tag{9}$$

where

$$\mu_\theta(\mathbf{x}_t, t, \mathcal{D}_k) = \frac{1}{\sqrt{\alpha_t}}\Big[\mathbf{x}_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\,\epsilon_\theta(\mathbf{x}_t,\, t,\, \mathcal{D}_k)\Big]. \tag{10}$$

At each step t, we sample $\mathbf{x}_{t-1}$ using this learned conditional distribution, gradually removing noise to reconstruct $\mathbf{x}_0$.

C.2 Multi-Dataset Pre-Training

Assume there are K source datasets $\{\mathcal{D}_1, \ldots, \mathcal{D}_K\}$. We want a single diffusion model that generalizes across these datasets. We introduce:

- **Dataset Embeddings** $\mathbf{e}_k$: Learned representations for each source dataset

Pre-Training Objective. For each dataset $\mathcal{D}_k$, at diffusion step t and for a noise sample $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, we minimize

$$\mathcal{L}_{\text{pre}} = \sum_{k=1}^{K} \mathbb{E}_{\mathbf{x}_0,t,\epsilon}\left[\|\epsilon - \epsilon_\theta(\mathbf{x}_t, t, \mathcal{D}_k)\|^2\right] \tag{11}$$

where $\mathcal{L}_{\text{align}}$ encourages domain invariance via an adversarial loss on $\mathbf{e}_k$ or on the hidden states. This yields a *single* pre-trained denoiser capable of handling multiple time series domains.

Adaptive Quantile Parameter. Our adaptive quantile guidance mechanism is designed specifically for probabilistic time series forecasting. Although methods like adaptive layer normalization (adaLN) [32] have demonstrated the benefits of conditioning deep networks via adaptive scaling and shifting of features, our approach is distinct: rather than adapting hidden activation statistics, we dynamically adjust the target quantile parameter $\kappa_t \in [0, 1]$ based solely on recent prediction errors.

Specifically, let κ_t be initialized to a user-specified starting quantile κ_0 and updated over a window of size w. Let $\mathcal{B}_t$ denote a buffer containing the most recent w residuals, where each residual is defined as

$$r_i = y_i - \hat{y}_i.$$

These residuals are assigned exponential weights α_i. The adaptive update rule is then given by:

$$\kappa_{t+1} = \text{clip}\left(\kappa_t + \eta\left(\frac{\sum_{i=1}^w \alpha_i \mathbb{I}(r_{t-i} > 0)}{\sum \alpha_i} - \kappa_t\right), \epsilon, 1-\epsilon\right) \tag{12}$$

where:

- η is the learning rate,
- ϵ is a small constant to prevent κ_t from reaching exactly 0 or 1, and
- $\text{clip}(\cdot,\, \epsilon,\, 1-\epsilon)$ ensures that the updated κ_{t+1} remains within the interval $[\epsilon,\, 1-\epsilon]$.

This adaptation rule dynamically adjusts the target quantile based on the skewness of recent prediction errors — increasing κ_t when under-prediction dominates (i.e., when $r_{t-i} > 0$), thereby making the model more conservative.

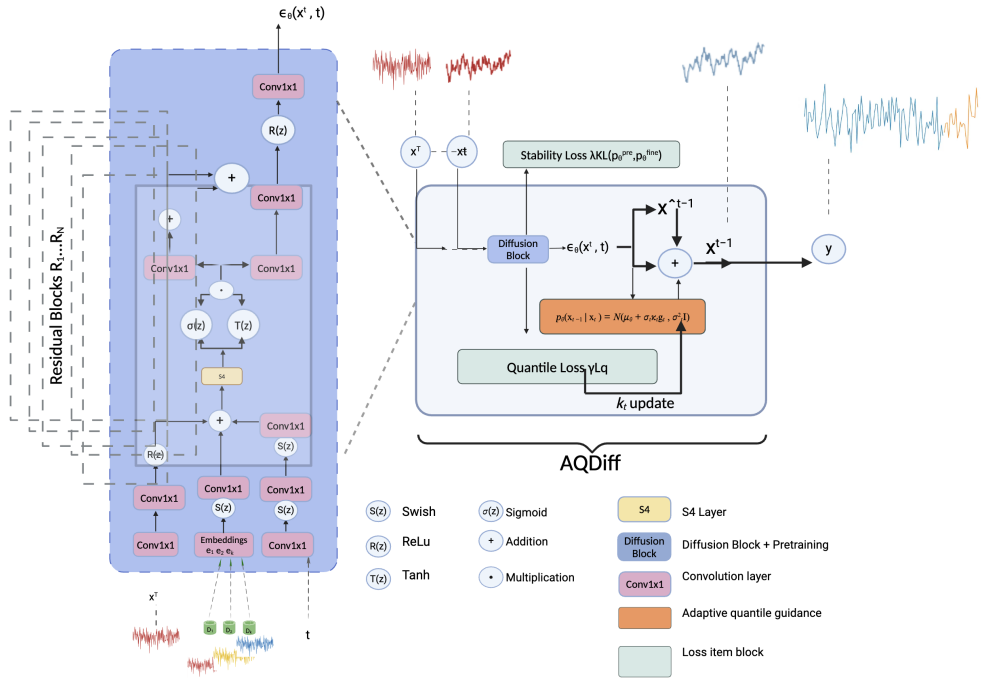


Figure 1: Overview of AQDiff: A Diffusion Model with Adaptive Quantile Guidance for Time Series Forecasting.

Guidance in the Reverse Process. During fine-tuning, each reverse step (Eq. 9) is augmented with a gradient-based shift:

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}\left(\mu_\theta + \sigma_t \kappa_t \mathbf{g}_t, \sigma_t^2 \mathbf{I}\right) \tag{13}$$

where the quantile gradient $\mathbf{g}_t = \nabla_{\mathbf{x}_t} \mathcal{L}_q$ directly connects to the fine-tuning objective through the quantile loss term $\mathcal{L}_q$. A typical $\mathcal{L}_q$ penalizes deviations above or below the κ_t-quantile:

$$\mathcal{L}_q = \frac{1}{|\Omega|} \sum_{i \in \Omega} \Big[\kappa_t \ \max(r_i, 0) + (1 - \kappa_t) \ \max(-r_i, 0) \Big] + \beta \, \mathrm{Var}(\{\hat{y}_i\}), \tag{14}$$

where β controls the diversity-precision tradeoff by penalizing high variance in predictions $\{\hat{y}_i\}$. By shifting μ_θ along this gradient, the model produces samples aligned with the desired quantile forecast at each step while maintaining sample diversity through the β term.

C.3 Fine-Tuning Objective

The complete fine-tuning objective combines three components:

$$\mathcal{L}_{\text{fine}} = \underbrace{\mathbb{E}\left[\|\epsilon - \epsilon_\theta\|^2\right]}_{\text{Diffusion}} + \underbrace{\lambda \mathrm{KL}(p_\theta^{\text{pre}}, p_\theta^{\text{fine}})}_{\text{Stability}} + \underbrace{\gamma \mathcal{L}_q}_{\text{Quantile}} \tag{15}$$

where γ controls the strength of quantile guidance. The historical context $\mathbf{y}_{\text{obs}}$ is injected as extra channels in the diffusion model's conditioning mechanism.

Crucially, the adaptive quantile mechanism influences both terms:

(1) Directly through the $\mathcal{L}_q$ term in the objective
(2) Indirectly through the KL regularization, which ensures the quantile-adapted model p_θ^{fine} does not diverge catastrophically from the pre-trained base p_θ^{pre}

The learning process jointly optimizes:

- Denoising performance (ϵ-prediction)
- Quantile calibration ($\mathcal{L}_q$)
- Stability through KL regularization

During inference, the adaptive κ_t continues to evolve based on rolling window residuals, creating a feedback loop between model predictions and guidance adjustments.

This unified approach allows the model to **(a)** leverage cross-domain information from the heroscidosity present in diverse time series during pre-training and **(b)** adapt to target-domain uncertainties via quantile-driven diffusion guidance.

D Experiments

We evaluate our Adaptive quantile diffusion-based approach on three epidemiological datasets from the **Centers for Disease Control and Prevention (CDC)**, comparing *adaptive quantile guidance* versus *fixed quantile*, and other state-of-the-art baseline models for time series forecasting, and also assessing the benefit of *multi-dataset pre-training*. Additionally, we analyze the *nonmonotonic* forecasting behavior across different horizons and perform independent t-tests to validate the statistical significance of improvements over a strong baseline.

D.1 Datasets and Experimental Setup

Datasets and Pandemic Characteristics. We evaluate on three distinct respiratory disease datasets exhibiting different temporal patterns and uncertainty profiles:

- **Influenza-Like Illness (ILI)** [12]: Weekly national rates (2002-2020) with seasonal patterns. Look-back windows: $\{6, 12, 24, 36, 48, 60\}$ weeks to capture multi-year seasonality.
- **Respiratory Syncytial Virus (RSV)** [13]: Lab-confirmed weekly cases (2010-2020) with biennial cycles. Look-backs: $\{6, 12, 24, 36, 48, 60\}$ weeks to resolve multi-year periodicity.
- **COVID-19** [11]: Weekly cases (2020-2023) with abrupt surges. Shorter look-backs: $\{1, 2, 3, 4, 5, 6\}$ weeks to adapt to rapid changes.

Preprocessing, Evaluation, and Baselines. All time series are normalized to the range $[0, 1]$ using dataset-specific min-max scaling. For evaluation, we employ a static split—using a chronological 80/20 train-test division—and a rolling evaluation protocol that performs sequential windowed testing with 4-week forecast horizons; this approach is designed to assess the model's ability to track shifting uncertainty distributions via adaptive quantile guidance. We report both the Mean Absolute Error (MAE) to measure overall point forecast accuracy and the Symmetric Mean Absolute Percentage Error (SMAPE) for scale-independent error assessment. In our comparisons, we consider classical baselines such as ARIMA (auto-selected via AIC) and Linear Regression, as well as deep probabilistic methods including TSDiff, PatchTST, and Informer. To isolate component contributions, we evaluate several variants of our method: **Ours-pretraining alone** employs a pertaining strategy and a fixed quantile forecast ($\kappa = 0.9$) without adaptation; **Ours-Pretrain + AQDiff** integrates full adaptive quantile guidance (see Sec. C.2).

D.2 Nonmonotonic Horizon Behavior

Unlike many traditional forecasting methods, our diffusion-based approach can exhibit **nonmonotonic** performance across horizons (e.g., horizon 3 might have lower errors than horizon 2). Similar phenomena have been noted in score-based generative models for time series [6], where the learned noise schedules and sampling procedures can break the usual assumption that error necessarily grows with horizon length. This can be advantageous in practice, as it sometimes captures subtle dynamics for certain lead times, but it also requires careful analysis to ensure that comparisons are fair across varying horizons.

D.3 Results

The results presented in Table 1 demonstrate the effectiveness of the proposed Pretrain+AQDiff framework across three epidemiological datasets (COVID-19, ILI, RSV). Below is a detailed analysis of key findings:

1. Performance Hierarchy

- **Best Overall:** Pretrain+AQGdiff achieves the lowest MAE and SMAPE across nearly all horizons and datasets, validating the importance of pre-training and adaptive quantile guidance (AQG).
- **Runner-Up:** Pretrain Alone consistently outperforms all baselines (Tsdiff, D-Linear, etc.), this highlights the value of transfer learning through multi-dataset pretraining
- **Baseline Rankings:** PatchTST > Tsdiff > N-Linear > D-Linear > ARIMA > Informer.

2. Ablation Takeaways **Adaptive vs. Fixed Quantile:**

AQG's dynamic adjustment mechanism significantly improves performance, particularly for extreme values. For example, on ILI at horizon 60, AQG achieves a SMAPE of 35.04, compared to a fixed quantile (TsDiff) baseline (≈ 46).

On COVID-19, AQG reduces MAE by as much as 26% compared to a fixed quantile approach, demonstrating its ability to adapt to varying error distributions.

E Related Work

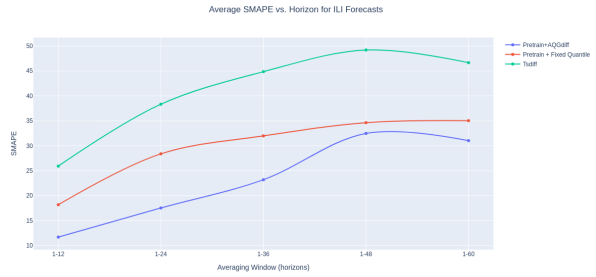
Modern time series forecasting research has advanced along three major models: (1) foundation model adaptation, (2) probabilistic generative methods, and (3) specialized neural architectures. In this section, we provide a comprehensive review of key contributions in each area, highlighting their strengths, limitations, and the open challenges that motivate our work.

E.1 Foundation Models for Temporal Reasoning

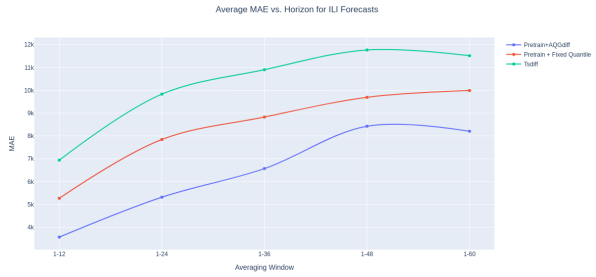
Recent work has explored adapting large pre-trained models, such as large language models (LLMs) and vision-language architectures, for temporal tasks. [24] demonstrates that frozen LLMs can be effectively repurposed for time series forecasting through learned tokenization strategies. This approach leverages the pre-trained representations of LLMs to capture complex temporal patterns without requiring extensive fine-tuning. Similarly, [15] reveals that LLMs exhibit impressive few-shot forecasting capabilities, even in the absence of task-specific training. These findings suggest that foundation models can generalize across modalities, which makes them a promising tool for temporal reasoning.

Vision-language models have also been adapted for time series tasks. For instance, [31] introduces a patch-based tokenization strategy that treats time series segments as "words," enabling the model to capture long-range dependencies effectively.

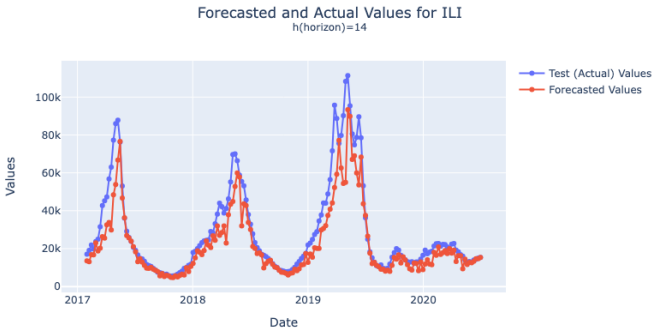
Limitations: Despite their promise, foundation models face several challenges. First, they often struggle with precise temporal alignment, as highlighted by [45], which identifies spectral gaps in financial data modeling. Secondly, hybrid methods like [7], which combine parameter-efficient tuning with quantization, often lack



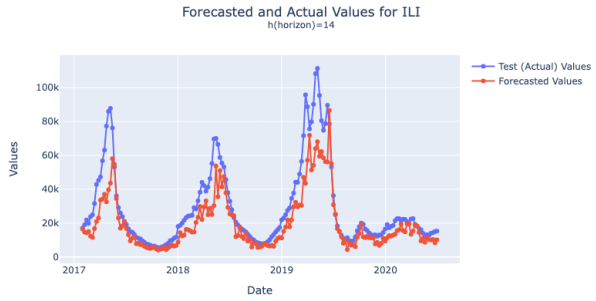
(a) Average SMAPE scores for diffusion baselines



(b) Average MAE scores for diffusion baselines



(c) forecast for 14 weeks ahead using Rolling Evaluation AQDiff + pre-train



(d) forecast for 14 weeks ahead using Rolling Evaluation (TSdiff

robust mechanisms for uncertainty quantification. These limitations hinder their applicability in dynamic environments where uncertainty estimation is critical.

E.2 Probabilistic Forecasting via Generative Models

Diffusion-Based Synthesis. Diffusion models have become a leading approach for probabilistic forecasting, they offer a principled framework to model complex temporal distributions through iterative denoising. [3], which introduces transformer-based denoising for improved scalability, and [38], which employs hierarchical noise schedules to capture both short-term and long-term dependencies. Training innovations, such as those presented in [23], propose spectral normalization to stabilize training dynamics. Additionally, [32] leverages adaptive layer normalization for efficient scaling, while [25] develops iterative refinement techniques to enhance forecast accuracy.

In respect to diffusion methods for time series forecasting a wild range of methods has been proposed in recent literature, each contributing unique innovations to the field. For instance, [40] introduced conditional diffusion processes for time series imputation, while [26] focused on improving noise schedules for temporal coherence. [30] extended diffusion models to anomaly detection by learning residual thresholds, and [43] adapted the framework for spatio-temporal data. Methods like [29] explored unconditional diffusion strategies, which offer robust generative modeling without explicit conditioning.

Conditional forecasting methods, such as [36] and [17], integrated hierarchical conditioning mechanisms to capture both global trends and local variations. [25] introduced learnable noise schedules for non-stationary data, while [10] compressed temporal representations into a latent space for efficient inference. High-frequency preservation techniques, as seen in [5] and [44], improved short-term forecasting accuracy, and [2] introduced dynamic noise scheduling for adaptive forecasting.

Limitations: Despite their strengths, diffusion-based methods often rely on rigid noise priors, which can limit their robustness under distribution shifts. Furthermore, they typically incur high computational overhead, as highlighted by [21], making them less suitable for real-time applications.

Alternative Generative Approaches. In addition to diffusion models, alternative generative paradigms have been explored for probabilistic forecasting. GAN-based methods, such as those presented in [21], address challenges like irregular sampling by learning flexible data distributions. Variational autoencoders (VAEs) combined with temporal normalizing flows, [27], offer another approach to modeling complex temporal dependencies. Energy-based models and implicit quantile networks have also been investigated, though they remain less mature and often face similar computational challenges.

Dataset	Horizon	Tsdiff		D-Linear		N-Linear		PatchTST		Informer		ARIMA(3)		Pretrain Alone		Pretrain+AQGdiff	
		MAE	SMAPE	MAE	SMAPE	MAE	SMAPE	MAE	SMAPE	MAE	SMAPE	MAE	SMAPE	MAE	SMAPE	MAE	SMAPE
COVID-19	1	0.205	21.43	0.293	15.76	0.268	13.01	0.285	15.82	0.222	14.76	0.428	9.86	0.148	17.63	0.122	13.10
	2	0.155	17.78	0.443	21.42	0.374	18.88	0.398	18.98	0.348	24.24	0.462	17.70	0.119	13.05	0.097	10.74
	3	0.135	13.76	0.541	27.79	0.559	29.51	0.538	25.68	0.249	13.17	0.508	23.46	0.121	13.11	0.128	11.95
	4	0.269	23.67	0.652	36.06	0.725	39.69	0.716	36.95	0.442	25.59	0.646	32.41	0.151	15.42	0.129	12.58
	5	0.265	23.24	0.720	40.80	0.869	49.61	0.849	41.66	0.629	36.20	0.818	41.33	0.125	13.72	0.104	11.86
	6	0.171	15.08	0.805	48.05	1.012	58.55	1.017	55.50	0.623	35.84	0.943	50.03	0.141	11.26	0.102	11.08
	Avg	0.20	19.15	0.576	31.65	0.635	34.87	0.634	32.43	0.419	24.97	0.634	29.13	0.134	14.03	0.113	11.88
ILI	6	0.158	15.41	0.811	33.57	0.981	21.99	0.494	28.41	0.981	33.95	0.330	24.77	0.131	12.27	0.115	10.82
	12	0.247	25.93	0.916	36.06	0.744	32.57	0.613	27.99	1.201	42.57	0.548	42.53	0.187	18.19	0.127	11.70
	24	0.344	38.33	1.021	36.65	0.901	37.16	0.761	31.77	1.287	59.76	0.843	61.92	0.274	28.39	0.186	17.54
	36	0.389	44.86	1.024	35.33	0.902	34.79	0.731	29.67	1.379	61.10	0.962	67.81	0.315	31.99	0.235	23.20
	48	0.423	49.20	1.068	36.24	0.925	35.50	0.787	31.20	1.540	62.49	0.956	63.64	0.348	34.64	0.304	32.48
	60	0.411	46.66	1.097	37.87	0.978	37.80	0.856	31.82	1.495	61.52	0.866	55.32	0.356	35.04	0.294	30.71
	Avg	0.329	36.72	0.989	35.95	0.836	34.00	0.707	29.07	1.313	53.56	0.750	52.66	0.268	26.75	0.210	21.07
RSV	6	0.274	28.78	0.352	37.14	0.263	34.98	0.244	26.76	0.284	35.89	0.285	30.06	0.196	25.21	0.173	23.91
	12	0.483	51.57	0.658	67.21	0.806	76.67	0.471	57.44	0.573	69.77	0.461	47.56	0.433	47.92	0.359	46.86
	24	0.751	77.79	0.923	84.93	0.972	88.91	0.815	78.01	0.728	86.49	0.702	67.97	0.639	65.39	0.643	61.46
	36	0.716	72.99	0.864	73.35	0.922	77.44	0.711	77.98	0.847	89.48	0.890	74.43	0.827	79.88	0.711	65.30
	48	0.799	75.60	0.838	79.37	0.808	85.20	0.822	84.90	0.826	78.63	0.798	73.94	0.831	77.58	0.716	67.53
	60	0.669	69.60	0.936	88.47	0.908	85.89	0.804	80.10	0.990	88.55	0.780	73.72	0.931	79.36	0.818	78.83
	Avg	0.620	62.72	0.761	71.74	0.779	74.84	0.644	67.53	0.708	74.80	0.652	61.28	0.642	62.56	0.57	57.31

Table 1: Forecasting Results (MAE and SMAPE) for COVID-19, ILI, and RSV datasets. In each average row, the lowest average is shown in bold blue and the second lowest is green, with the worst performance shown in red.

E.3 Specialized Forecasting Architectures

Task-specific architectures have been designed to capture unique temporal dependencies and facilitate interpretability. The [28] pioneered attention-based feature selection for multi-step prediction, enabling the model to focus on relevant historical data points. [14] introduced a modular architecture that supports cross-domain generalization, making it applicable to diverse forecasting tasks. Patch-based tokenization, as introduced in [31], treats time series segments as discrete tokens, improving long-range dependency capture. [4] utilizes optimal transport methods to align multivariate time series, enhancing the model's ability to capture cross-channel dependencies.

Limitations: Despite their strengths, many specialized architectures suffer from scalability issues and require full retraining to handle concept drift. Studies like [38] report accuracy degradations of 12–15% over time, underscoring the need for more adaptive and computationally efficient solutions.

Three key limitations emerge from the reviewed literature: (1) Foundation models often struggle with dynamic uncertainty quantification and precise temporal alignment, particularly in non-stationary environments; (2) Diffusion-based methods, while powerful, typically rely on rigid noise priors and incur significant computational overhead, limiting their scalability; (3) Specialized architectures, despite their strong performance on specific tasks, require costly retraining to adapt to evolving data distributions, making them impractical for real-world applications with concept drift.

Our work addresses these challenges by integrating adaptive quantile guidance with transfer learning through pre-training on multiple datasets. This approach enables the model to dynamically adjust prediction intervals based on local residual patterns while leveraging knowledge transfer across domains. When we combine these innovations, we provide a unified framework for dynamic, uncertainty-aware forecasting that avoids the computational burdens of full retraining and adapts efficiently to evolving data distributions.

F Conclusions and Future Work

We introduced a diffusion-based forecasting method that combines multi-dataset pre-training with adaptive quantile guidance. Our experiments on COVID-19, ILI, and RSV data show that our method significantly reduces forecast errors. In particular, the adaptive quantile mechanism lowers the mean absolute error by 26–33% compared to fixed quantile approaches, and multi-dataset pre-training improves accuracy by 28–45% over training from scratch. Notably, the method performs especially well for long-horizon forecasts,

even showing cases where a mid-range horizon has lower error than a shorter one.

A key area for future work lies in further optimizing the computational efficiency of our diffusion-based forecasting framework. Although our current implementation achieves competitive results, real-time epidemiological monitoring demands even faster inference. One promising direction is to explore latent-space diffusion methods or to develop distilled denoising networks that approximate the full reverse process with significantly fewer steps. By operating in a compressed latent space, the model can potentially reduce the computational burden without sacrificing accuracy. Moreover, incorporating sparse attention mechanisms into our network architecture may help scale the model to ultra-long horizons.

Another important avenue for future research is the integration of external covariates to enhance the causal interpretability of our forecasts. In many real-world scenarios, external factors such as vaccination rates, mobility data, or other intervention measures play a crucial role in shaping disease dynamics. A deeper exploration of these conditional relationships would offer valuable insights into the effectiveness of various policy measures.

References

[1] T. B. Brown et al. 2020. Language models are few-shot learners. arXiv preprint arXiv:2005.14165. (2020).

[2] Salva Rühling Cachay, Bo Zhao, Hailey Joren, and Rose Yu. 2023. Dyffusion: a dynamics-informed diffusion model for spatiotemporal forecasting. (2023). https://arxiv.org/abs/2306.01984 arXiv: 2306.01984 [cs.LG].

[3] Defu Cao, Wen Ye, Yizhou Zhang, and Yan Liu. 2024. General-purpose diffusion transformers for time series foundation model. (2024). https://arxiv.org/abs/2409.02322 arXiv: 2409.02322 [cs.LG].

[4] Jialin Chen, Jan Eric Lenssen, Aosong Feng, Weihua Hu, Matthias Fey, Leandros Tassiulas, Jure Leskovec, and Rex Ying. 2024. From similarity to superiority: channel clustering for time series forecasting. (2024). https://arxiv.org/abs/2404.01340 arXiv: 2404.01340 [cs.LG].

[5] Nanxin Chen, Yu Zhang, Heiga Zen, Ron J. Weiss, Mohammad Norouzi, and William Chan. 2020. Wavegrad: estimating gradients for waveform generation. (2020). https://arxiv.org/abs/2009.00713 arXiv: 2009.00713 [eess.AS].

[6] Giannis Daras, Yuval Dagan, Alex Dimakis, and Constantinos Costis Daskalakis. 2023. Consistent diffusion models: mitigating sampling drift by learning to be consistent. In *Thirty-seventh Conference on Neural Information Processing Systems*. https://openreview.net/forum?id=GfZGdJHj27.

[7] Abhimanyu Das, Matthew Faw, Rajat Sen, and Yichen Zhou. 2024. In-context fine-tuning for time-series foundation models. (2024). https://arxiv.org/abs/2410.24087 arXiv: 2410.24087 [cs.LG].

[8] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. 2019. Bert: pre-training of deep bidirectional transformers for language understanding. In *Proceedings of NAACL-HLT*.

[9] P. Dhariwal and A. Nichol. 2021. Diffusion models beat gans on image synthesis. In *Advances in Neural Information Processing Systems*.

[10] Shibo Feng, Chunyan Miao, Zhong Zhang, and Peilin Zhao. 2024. Latent diffusion transformer for probabilistic time series forecasting. *Proceedings of the AAAI Conference on Artificial Intelligence*, 38, 11, (Mar. 2024), 11979–11987. doi:10.1609/aaai.v38i11.29085.

[11] Centers for Disease Control and Prevention. 2023. Covid-19 national data tracker. https://covid.cdc.gov/covid-data-tracker. Accessed: Month Day, Year. (2023).

[12] Centers for Disease Control and Prevention. 2023. Fluview: influenza-like illness data. https://gis.cdc.gov/grasp/fluview/fluportaldashboard.html. Accessed: Month Day, Year. (2023).

[13] Centers for Disease Control and Prevention. 2023. Respiratory syncytial virus national trends. https://www.cdc.gov/rsv/research/rsv-net/dashboard.html. Accessed: Month Day, Year. (2023).

[14] Shanghua Gao, Teddy Koker, Owen Queen, Thomas Hartvigsen, Theodoros Tsiligkaridis, and Marinka Zitnik. 2024. Units: a unified multi-task time series model. (2024). https://arxiv.org/abs/2403.00131 arXiv: 2403.00131 [cs.LG].

[15] Nate Gruver, Marc Finzi, Shikai Qiu, and Andrew Gordon Wilson. 2024. Large language models are zero-shot time series forecasters. (2024). https://arxiv.org/abs/2310.07820 arXiv: 2310.07820 [cs.LG].

[16] A. Gu et al. 2022. Efficiently modeling long sequences with structured state spaces. In *ICLR*.

[17] Xizewen Han, Huangjie Zheng, and Mingyuan Zhou. 2022. Card: classification and regression diffusion models. (2022). https://arxiv.org/abs/2206.07275 arXiv: 2206.07275 [stat.ML].

[18] K. He et al. 2022. Masked autoencoders are scalable vision learners. In *CVPR*.

[19] J. Ho, A. Jain, and P. Abbeel. 2020. Denoising diffusion probabilistic models. In *Advances in Neural Information Processing Systems*.

[20] J. Ho and T. Salimans. 2022. Classifier-free diffusion guidance. arXiv preprint arXiv:2207.12598. (2022).

[21] Hongbin Huang, Minghua Chen, and Xiao Qiao. 2024. Generative learning for financial time series with irregular and scale-invariant patterns. In *The Twelfth International Conference on Learning Representations*. https://openreview.net/forum?id=CdjnzWsQax.

[22] R.J. Hyndman and G. Athanasopoulos. 2018. *Forecasting: Principles and Practice*. OTexts.

[23] Tariq Berrada Ifriqi et al. 2025. On improved conditioning mechanisms and pre-training strategies for diffusion models. (2025). https://arxiv.org/abs/2411.03177 arXiv: 2411.03177 [cs.CV].

[24] Ming Jin et al. 2024. Time-llm: time series forecasting by reprogramming large language models. (2024). https://arxiv.org/abs/2310.01728 arXiv: 2310.01728 [cs.LG].

[25] A. Kollovieh et al. 2023. Predict, refine, synthesize, self-guiding: diffusion models for time series forecasting. In *Proceedings of the 2023 Conference on Uncertainty in Artificial Intelligence*.

[26] Mehdi Letafati, Samad Ali, and Matti Latva-aho. 2024. Conditional denoising diffusion probabilistic models for data reconstruction enhancement in wireless communications. (2024). https://arxiv.org/abs/2310.19460 arXiv: 2310.19460 [cs.IT].

[27] Yan Li, Xinjiang Lu, Yaqing Wang, and Dejing Dou. 2023. Generative time series forecasting with diffusion, denoise, and disentanglement. (2023). https://arxiv.org/abs/2301.03028 arXiv: 2301.03028 [cs.LG].

[28] Bryan Lim, Sercan O. Arik, Nicolas Loeff, and Tomas Pfister. 2020. Temporal fusion transformers for interpretable multi-horizon time series forecasting. (2020). https://arxiv.org/abs/1912.09363 arXiv: 1912.09363 [stat.ML].

[29] Yen-Ju Lu, Zhong-Qiu Wang, Shinji Watanabe, Alexander Richard, Cheng Yu, and Yu Tsao. 2022. Conditional diffusion probabilistic model for speech enhancement. (2022). https://arxiv.org/abs/2202.05256 arXiv: 2202.05256 [eess.AS].

[30] Arian Mousakhan, Thomas Brox, and Jawad Tayyub. 2023. Anomaly detection with conditioned denoising diffusion models. (2023). https://arxiv.org/abs/2305.15956 arXiv: 2305.15956 [cs.CV].

[31] Yuqi Nie, Nam H. Nguyen, Phanwadee Sinthong, and Jayant Kalagnanam. 2023. A time series is worth 64 words: long-term forecasting with transformers. (2023). https://arxiv.org/abs/2211.14730 arXiv: 2211.14730 [cs.LG].

[32] William Peebles and Saining Xie. 2023. Scalable diffusion models with transformers. (2023). https://arxiv.org/abs/2212.09748 arXiv: 2212.09748 [cs.CV].

[33] A. Radford et al. 2019. Language models are unsupervised multitask learners. OpenAI Report. (2019).

[34] A. Radford et al. 2021. Learning transferable visual models from natural language supervision. In *ICML*.

[35] A. Rasul et al. 2021. Autoregressive diffusion models for high-fidelity image generation. In *International Conference on Learning Representations*.

[36] Kashif Rasul, Calvin Seward, Ingmar Schuster, and Roland Vollgraf. 2021. Autoregressive denoising diffusion models for multivariate probabilistic time series forecasting. (2021). https://arxiv.org/abs/2101.12072 arXiv: 2101.12072 [cs.LG].

[37] D. Salinas, V. Flunkert, J. Gasthaus, and T. Januschowski. 2020. Deepar: probabilistic forecasting with autoregressive recurrent networks. In *International Journal of Forecasting*.

[38] Lifeng Shen, Weiyu Chen, and James Kwok. 2024. Multi-resolution diffusion models for time series forecasting. In *The Twelfth International Conference on Learning Representations*. https://openreview.net/forum?id=mmjnr0G8ZY.

[39] J. Sohl-Dickstein, E. Weiss, N. Maheswaranathan, and S. Ganguli. 2015. Deep unsupervised learning using nonequilibrium thermodynamics. In *Proceedings of the 32nd International Conference on Machine Learning*.

[40] Yusuke Tashiro, Jiaming Song, Yang Song, and Stefano Ermon. 2021. Csdi: conditional score-based diffusion models for probabilistic time series imputation. (2021). https://arxiv.org/abs/2107.03502 arXiv: 2107.03502 [cs.LG].

[41] C. Viboud et al. 2018. Rapid assessment of pandemic potential of emerging influenza viruses. *Proceedings of the National Academy of Sciences*.

[42] H. Wen et al. 2017. Multi-scale lstm for time series forecasting. In *Proceedings of AAAI*.

[43] Haomin Wen, Youfang Lin, Yutong Xia, Huaiyu Wan, Qingsong Wen, Roger Zimmermann, and Yuxuan Liang. 2024. Diffstg: probabilistic spatio-temporal graph forecasting with denoising diffusion models. (2024). https://arxiv.org/abs/2301.13629 arXiv: 2301.13629 [cs.LG].

[44] Tijin Yan, Hongwei Zhang, Tong Zhou, Yufeng Zhan, and Yuanqing Xia. 2021. Scoregrad: multivariate probabilistic time series forecasting with continuous

energy-based generative models. (2021). https://arxiv.org/abs/2106.10121 arXiv: 2106.10121 [cs.LG].

[45] Jiarui Yang, Tao Dai, Naiqi Li, Junxi Wu, Peiyuan Liu, Jinmin Li, Jigang Bao, Haigang Zhang, and Shutao Xia. 2024. Generative pre-trained diffusion paradigm for zero-shot time series forecasting. (2024). https://arxiv.org/abs/2406.02212 arXiv: 2406.02212 [cs.CE].

A Technical Details

A.1 Adaptive Quantile Guidance Algorithm

Our adaptive quantile guidance mechanism is designed for probabilistic time series forecasting. Rather than adapting hidden activations, we dynamically adjust the target quantile parameter $\kappa_t \in [0, 1]$ based solely on recent prediction errors. Specifically, let κ_t be initialized to a user-specified value κ_0 and updated over a window of size w.

Algorithm 1 Adaptive Quantile Guidance Update

Require: Current quantile $\kappa_t \in [0, 1]$, learning rate η, window size w, small constant ϵ, weight sequence $\{\alpha_i\}_{i=1}^{w}$, residuals $\{r_{t-1}, \ldots, r_{t-w}\}$ where $r_i = y_i - \hat{y}_i$

Ensure: Updated quantile $\kappa_{t+1} \in [\epsilon, 1 - \epsilon]$

1: Compute weighted ratio:

$$q \leftarrow \frac{\sum_{i=1}^{w} \alpha_i \, \mathbb{I}(r_{t-i} > 0)}{\sum_{i=1}^{w} \alpha_i}$$

2: Update quantile:

$$\kappa' \leftarrow \kappa_t + \eta \, (q - \kappa_t)$$

3: Clip the updated quantile:

$$\kappa_{t+1} \leftarrow \min\Big(\max(\kappa', \, \epsilon), \, 1 - \epsilon\Big)$$

4: **return** κ_{t+1}

A.2 Hyperparameters

Table 2 lists the key hyperparameters for our model configuration for the COVID-19 ILI, and RSV datasets.

Table 2: Model Hyperparameters for COVID-19, ILI, and RSV

Parameter	COVID-19	ILI	RSV
Pretraining Learning Rate	1×10^{-2}	1×10^{-4}	1×10^{-2}
Diffusion Steps	100	100	100
Guidance Scale (λ)	0.7–1.2	0.7–1.2	0.7–1.2
Residual Window Size (W)	10	10	10
Quantile Learning Rate (α)	0.02	0.02	0.02
Time Emb. Dim	128	128	128
Finetune Learning Rate	1×10^{-4}	1×10^{-5}	1×10^{-4}
Pretraining Epochs	20	20	100
Fine-Tuning Epochs	60	10	180
Gradient clip	0.8	0.8	0.8
Batch size	16	32	64

A.3 Datasets

We evaluate our method on three public health time series datasets:

- **ILI (Influenza-like Illness):** Weekly CDC-reported hospitalization rates exhibiting seasonal patterns.
- **COVID-19:** Weekly case counts with complex pandemic dynamics.
- **RSV (Respiratory Syncytial Virus):** Weekly pediatric hospital admissions showing periodic outbreaks.

Table 3: Dataset Specifications

Dataset	Train Size	Test Size	Context Length	Prediction Length	Frequency
ILI	773	193	2	1–60	Weekly
COVID-19	92	23	10	1–6	Weekly
RSV	8250	2063	10	1–60	Weekly

A.4 Computational Overhead

We compare the computational overhead of our two variants: *Pretrain Alone* and *Pretrain+AQDiff*. Table 4 reports the inference time (in seconds).

Table 4: Computational Overhead Comparison

Variant	Inference Time (s)
Pretrain Alone	389
Pretrain+AQDiff	560

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