FORECASTPFN: UNIVERSAL FORECASTING FOR HEALTHCARE

Anonymous authors
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ABSTRACT

With the proliferation of time-series analysis in the healthcare sector, each new time series requires a new model to be fit and trained on those specific data. The vast majority of time-series forecasting approaches require a training dataset. There is very recent work on zero-shot forecasting—pretraining on one series and evaluating on another—yet its performance is inconsistent depending on the training dataset. In this work, we take a different approach and devise ForecastPFN, the first universal zero-shot model, pretrained purely on synthetic data. Drawing inspiration from TabPFN, a recent breakthrough in tabular data, ForecastPFN is the first forecasting model to approximate Bayesian inference. To accomplish this, we design a synthetic time-series distribution with local and global trends, and noise. Through experiments on multiple datasets, we show that ForecastPFN achieves competitive performance without ever seeing the training datasets, compared to popular methods that were fully trained on the training dataset.

1 INTRODUCTION

Time-series forecasting problems are an important class of problems with applications in healthcare, such as diagnosing diseases, predicting disease progression, and online monitoring (Harutyunyan et al., 2019; Chimmula & Zhang, 2020), in addition to other areas such as forecasting financial metrics, supply and demand, and cloud computation monitoring (Sezer et al., 2020; Krollner et al., 2010). The vast majority of time-series forecasting approaches require training on a training dataset, however, many real-world forecasting applications have very few initial observations, sometimes just one hundred or less. While there is recent work on zero-shot forecasting (Oreshkin et al., 2021) by training on one time series and evaluating on another, its performance is inconsistent depending on which dataset it is trained on. As in prior work (Oreshkin et al., 2021), we use the term "zero-shot forecasting" when the number of available observations for the target time series is so small (such as 100 or less) that training a deep learning model is not possible.

In this work, we take a different approach and devise ForecastPFN, the first *universal zero-shot method*, pretrained purely on synthetic data. We draw inspiration from TabPFN (Hollmann et al., 2022), a recent breakthrough in tabular data, which is trained offline to approximate Bayesian inference using prior-data fitted networks (PFNs). However, there are significant challenges when designing a general and flexible PFN in the forecasting setting. First, we design a novel synthetic time-series distribution with global trends, multi-scale seasonal trends, and noise. Next, we design a scheme for dynamically scaling across a wide range of time-series values. Finally, we design a flexible transformer architecture that can query values at any timestep in the future.

We show that by carefully designing a prior-data fitted network for forecasting, unlike TabPFN, our model achieves competitive performance *without ever seeing the training datasets*, compared to popular methods that were fully trained on the training datasets. This remarkable result is due to the structure of our synthetic priors: by encoding multi-scale seasonal trends, global trends, and noise, across a variety of parameters, our model is able to learn how to forecast general time series. Our codebase and all raw results will be open-sourced after the double-blind review process.

2 RELATED WORK

Time-series forecasting problems have numerous applications in healthcare (Harutyunyan et al., 2019; Chimmula & Zhang, 2020) and other areas (Sezer et al., 2020; Krollner et al., 2010). Already in the 1970s, ARIMA builds an autoregressive model based on Markov processes (Box & Pierce, 1970). A popular method in practice is Prophet (Taylor & Letham, 2018), which incorporates non-linear trends and multi-scale seasonality via traditional methods. Recently, researchers have turned to deep learning to model highly nonlinear time series. DeepAR (Salinas et al., 2020) is a popular deep learning method which makes use of autoregressive methods and RNNs. Recently, many works have applied transformer models to time-series forecasting (Zhou et al., 2021; Kitaev et al., 2020; Wu et al., 2021), following the success of transformers on NLP (Vaswani et al., 2017). FEDformer (Zhou et al., 2022) is a popular recent method that incorporates Fourier transforms and the seasonal trend decomposition method into a transformer architecture. For a survey on deep learning methods for time-series forecasting, see Mahmoud & Mohammed (2021).

There is much less work on zero-shot time-series forecasting. Oreshkin et al. (2021) use an MLP with residual connections to train on a (single) real-world time series and test on a different time series. However, it achieves substantially different performance based on which training dataset is used, and official code is not released. To the best of our knowledge, we are the first to design a *single, universal* model for zero-shot time-series forecasting, trained purely on synthetic data.

3 PRIOR-DATA FITTED NETWORKS FOR FORECASTING

In this section, we introduce prior-data fitted networks (PFNs) for forecasting, and then we introduce our ForecastPFN model. PFNs were first introduced by Hollmann et al. (2022); Müller et al. (2022) for classification, and we extend the idea of PFNs for time-series forecasting.

We define a prior Φ as a set of hypotheses. Each hypothesis $\phi \in \Phi$ defines a mechanism for generating a time series. Given a time series $D = \{x_1, \ldots, x_N\}$, it is typically split up into training data, test input, and test prediction: $D_{\text{train}} = \{x_1, \ldots, x_T\}$, $x_{\text{test}} = \{x_{T+1}, \ldots, x_{T+\ell}\}$, $y_{\text{test}} = \{x_{T+\ell+1}, \ldots, x_{T+\ell+h}\}$. A forecasting model typically trains on D_{train}, and at test time, given x_{test}, predicts y_{test}. However, we consider only much smaller time series of the form $D = x_{\text{test}} \cup y_{\text{test}}$, with no training data. The *posterior predictive distribution* (PPD) for a point $y \in y_{\text{test}}$ is the distribution of its values given the test input, $p\left(\cdot \mid x_{\text{test}}\right)$, and it is computed for a particular point y as follows:

$$p(y \mid D) \propto \int_{\Phi} p(y \mid \phi) p(D \mid \phi) p(\phi) d\phi. \tag{1}$$

We conduct synthetic prior-fitting as in Müller et al. (2022), adapted to the forecasting domain. Prior-fitting is the training of a prior-data fitted network (PFN) to approximate the PPD. As in (Hollmann et al., 2022), we use a prior-sampling scheme $p(D)$ which first samples a hypothesis $\phi \sim p(\phi)$ and then a dataset $D \sim p(D \mid \phi)$. In order to train the PFN, we repeatedly sample a dataset $D = x_{\text{test}} \cup y_{\text{test}}$ and use the PFN to predict y_{test} given x_{test}. The training loss is computed as the mean squared error for the predicted y_{test}. Prior work has proven that this trains the PFN to approximate Bayesian inference (Müller et al., 2022).

ForecastPFN. The majority of existing time-series forecasting methods work only for a fixed series length, horizon length, and frequency. In contrast, we design a PFN for forecasting, ForecastPFN, which can handle a wide variety of time series. We use an encoder-based transformer architecture, consisting of a multi-head attention layer and two feedforward layers. In contrast to prior work on zero-shot forecasting (Oreshkin et al., 2021), we do not use any residual connections.

The transformer accepts data in the form of tokens of (date, value). The transformer takes in a set of ℓ contiguous tokens, along with a query consisting of a future date without a value, and then it predicts the PPD of this query. This is in contrast to existing transformer models for forecasting, which are only set up to predict the next N steps in the current sequence.

When standard forecasting models are trained on the training data, it is typical to apply linear and non-linear transforms to put the data in a fixed range. However, ForecastPFN is designed to handle

scaling *dynamically*: we set a very relaxed scale based on the 99% percentile of the input, at the same time dealing with signal at small values by passing the input through a `tanh` layer at multiple orders of magnitude, allowing the model to concentrate on different scales in the same series.

We train ForecastPFN with a novel prior for time-series forecasting, described in the next section. We generate 100 000 synthetic daily, weekly, and monthly series, each of length 200, and we use a sliding window of size 100 to obtain 101 prediction tasks per series. We sample 1024 tasks in a training step, and there are 1000 training steps in an epoch. We trained the transformer for 300 epochs on a single Tesla V100 16GB GPU, which took 16 hours. Note that this training is done offline, and only once. The trained ForecastPFN was used for all experiments in our paper and can be used in the future on any new time series.

Synthetic Data Distribution. Unlike prior work in forecasting, our model is not trained on any real-world data; it is trained purely on synthetic data. We assume that there is a distribution of time series from which real-world time series are derived. We show that when we model data from the distribution described below, we can adequately capture aspects of time series data in order to produce high performance zero-shot forecasting models.

We model our synthetic data with the simple premise that time series data has three independent components: trends, seasonality, and noise. We see these at three independent aspects of time series data and model them as below, where the time series is the product of a trend, seasonality, and noise factor. The trend component is made up of a linear and exponential component with coefficients $m_{\text{lin}}, c_{\text{lin}}, m_{\text{exp}}, c_{\text{exp}}$. The seasonal component has a week, month, and year component where each comprises of of coefficients $m_{\text{week}}, m_{\text{month}}, m_{\text{year}}, c_i, d_i$ where the $c_i, d_i \sim N(0, 1/i)$. Finally, the noise in our model is derived from a Weibull distribution and is modeled such that the expected value of the noise model is 1, meaning in expectation the noise does not contribute to the seasonality or trend of the time series.

$$
\begin{aligned}
\text{series}(t) &= \text{noise}(t) \cdot \text{trend}(t) \cdot \text{seasonal}(t), \text{ where} \\
\text{noise}(t) &= 1 + m_{\text{noise}}\left(z - \bar{z}\right), \text{ where } z \sim \text{Weibull}(k),\ \bar{z} = \text{median}\left(\text{Weibull}(k)\right) \\
\text{trend}(t) &= \left(1 + m_{\text{lin}} \cdot t + c_{\text{lin}}\right)\left(m_{\text{exp}} \cdot c_{\text{exp}}^{t}\right) \\
\text{seasonal}(t) &= \text{seasonal}_{\text{week}}(t) \cdot \text{seasonal}_{\text{month}}(t) \cdot \text{seasonal}_{\text{year}}(t), \text{ where} \\
\text{seasonal}_{\text{per}}(t) &= 1 + m_{\text{per}} \sum_{i=1}^{k} \left[c_i \sin\left(2\pi i \frac{t \text{ Mod } p_{\text{per}}}{p_{\text{per}}}\right) + d_i \cos\left(2\pi i \frac{t \text{ Mod } p_{\text{per}}}{p_{\text{per}}}\right) \right], \\
&\text{where per} \in \{\text{week}, \text{month}, \text{year}\} \text{ and } p_{\text{week}} = 7,\ p_{\text{month}} = 30.5,\ p_{\text{year}} = 12.
\end{aligned}
$$

4 EXPERIMENTS

We run experiments with various forecasting models on different datasets. We compare against two high-performing traditional methods: ARIMA (Box & Pierce, 1970) and Prophet (Taylor & Letham, 2018), and three state-of-the-art transformer-based method: FEDformer (Zhou et al., 2022), Autoformer (Wu et al., 2021), and Informer (Zhou et al., 2021).

We evaluate our method on two datsets. Illness is a dataset [1]containing influenza-like illness patients in the United States. It contains 966 datapoints with 8 dimensions, spaced weekly. Exchange is a currency exchange dataset (Lai et al., 2018) across 8 countries, consisting of 7588 datapoints with 9 features, spaced daily.

Experimental setup and results. Following prior work (Zhou et al., 2022; Wu et al., 2021), for the Illness dataset, we fix the input length to be 36, and we predict the next sequences up to length 24, 36, 48, and 60. For the Exchange dataset, we fix the input length to 96, and we predict the next sequences up to length 96, 192, 336, and 720. We focus on the univariate case, leaving the mutlivariate case for future work. Additionally, we scale our datasets using the approach of (Zhou et al., 2022) where all data is scaled by removing the mean and scaling to unit variance of the

[1] `https://gis.cdc.gov/grasp/fluview/fluportaldashboard.html`

Table 1: Forecasting results on Illness and Exchange datasets with two budgets, 1 second and 1 minute, for training. A lower MSE indicates better performance. A black bold is for the best performance on 1 second budget, and blue bold is for the best performance on 1 minute budget.

Datasets		Illness				Exchange			
Methods	Budget	24	36	48	60	96	192	336	720
ForecastPFN	1s	**0.850**	**0.868**	**0.896**	**1.042**	**0.176**	**0.293**	**0.521**	1.266
	1m	0.850	0.868	0.896	1.042	0.176	0.293	**0.521**	1.266
FEDformer-w	1s	0.975	0.955	1.078	1.107	0.246	0.337	0.628	**1.081**
	1m	0.701	0.584	0.710	0.823	**0.130**	**0.263**	0.537	1.288
Autoformer	1s	0.905	1.031	0.968	1.201	0.280	0.642	0.623	2.062
	1m	0.795	0.622	0.738	0.897	0.167	0.342	0.974	1.205
Informer	1s	6.120	4.831	4.314	4.947	1.009	1.154	1.640	2.534
	1m	5.214	4.485	4.433	4.895	0.598	2.386	3.350	1.908
Prophet	1s	4.728	4.709	4.690	4.677	15.809	15.809	15.809	15.809
	1m	**0.588**	**0.568**	**0.548**	**0.535**	1.017	1.017	1.017	1.017
Arima	1s	2.915	2.892	2.872	2.860	2.445	2.444	2.444	2.444
	1m	0.779	0.783	0.789	0.792	0.917	0.917	0.917	**0.917**

training data. The same transformation is then applied to the test data. At inference on the test set, the data may not be scaled such that it has zero mean and unit variance, for example if the test data trends higher or lower than the training data. However, if a model expects input to be within the unit interval, we then scale the input sequence of the test sequence to be as such and then inverse the scaling on the prediction.

We compare a low budget (1 second) and moderate budget (1 minute) for training the baseline models. During this budget, we allow for each comparison baseline method to train for that budgeted amount of time on the dataset. Explicitly, we allow a baseline, like Prophet, to fit to the training data for 1 second (or 1 minute) by learning from the training dataset. We expect, and show, that the performance on the resource-constrained, small budget should yield worse performance (higher MSE) than performance when there is a longer training time. This contrasts to ForecastPFN which does not train on the given dataset and so performance on both budgets is the same.

We report mean squared error (MSE) for the evaluation. Our main results are presented in Table 1. We see that at the lowest budget (1 second of training time) and for every prediction length (except for one – 720 on the Exchange dataset), ForecastPFN achieves the lowest MSE. This confirms that ForecastPFN's strength rests in the ability to quickly perform well on a wide range of forecasting tasks, without ever seeing any part of the training time series for a given dataset. We also see that with a 1 minute budget, ForecastPFN still achieves competitive results, particularly on the Exchange dataset where it is the top-performing method at prediction length 336. We also note that the simple Prophet algorithm outperforms all transformer-based methods in the 1 minute setting, which is in line with recent work (Zeng et al., 2022).

5 Conclusions and Future Work

In this work, we introduced ForecastPFN, the first universal zero-shot model, trained purely on synthetic data. To accomplish this, we designed a novel synthetic time-series distribution and a new dynamic scaling method. Through experiments on multiple datasets, we show that ForecastPFN achieves competitive performance *without ever seeing the training datasets*, compared to popular methods that were trained on the training data.

In the domain of health, we see that ForecastPFN has wide potential to be applied to a variety of applications, particularly in low-resource settings. Given that ForecastPFN can achieve competitive results even without access to the training data, we propose further work in this area to extend its application to more healthcare applications. Designing ForecastPFN for multivariate time series, and training with a mix of synthetic and real datasets, are both exciting direction for future work.

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