Generalized Meta-Framework for Forecasting

Authors:
Theepana
Gowsigan
Pavadaran
Dr. Priyanga Dilini Talagala

Content

Introduction

- Time Series data

  Observations collected in a sequential order, where each data point is associated with a timestamp or a temporal context

- Importance of Forecasting

  Demand planning, Market trend analysis, Weather forecasting, Stock Market Analysis, Supply chain optimization

- Ensemble

  Collection of models from diverse AI approaches to be used to train on a given dataset

Introduction Cont.

- Meta-Learning

  Identifying the ensemble for a particular dataset which could be from any domain by using the Meta-Features which are the characteristics of time series dataset

- Stacking Approach

  Technique utilized to generate accurate final predictions by conditionally weighing the predictions derived from ensemble

- Generative Modeling

  Generative model learns the underlying probability distribution of the training data and generates new samples that resemble the original data

Motivation & Research Gap

- Time efficiency in forecasting has not been given equal consideration as accuracy
  - Khairuddin et al. In 2022 [1]
- Arithmetic average of the outputs from the ensemble reduces the contribution of the best performing models
  - Vaiciukynas E. et al. in 2021 [2]
- A diverse pool of models from different AI approaches has not been deployed for Meta-Learning approach
  - Montero-Manso P. et al. in 2020 [3]
- Potential value of applying generative models for time series forecasting is not clearly identified
  - Deecke L. et al. in 2019 [4]

Motivation & Research Gap Cont.

Research Gap	Novelty/Main Contribution
Time efficiency in forecasting has not been given equal consideration as accuracy	Custom algorithm to balance accuracy with time efficiency
Arithmetic average of the outputs from the ensemble reduces the contribution of the best performing models	Stacking Approach
A diverse pool of models from different AI approaches has not been deployed for Meta-Learning approach	Identify the forecasting models for the different AI approaches, perform automatic hyperparameter tuning, and retrieve required data from all training datasets Conventional Machine Learning Conventional Deep Learning Generative Modeling
Potential value of applying generative models for time series forecasting is not clearly identified	Applied generative models VAE and GAN

Research Objectives

- Perform a critical literature review and comprehensive comparative analysis on existing techniques for time series forecasting
- Identifying the research gap in the existing techniques
- Identifying the method to choose the member models for the ensemble approach for a given dataset
- Analyze the existing Meta-Learning methods
- Propose a generalized novel Meta-Framework for time series forecasting
- Critically evaluate the performance of the proposed framework

Project Approach

Phase I: Comparative Analysis and Selection of Models

Identify the most effective models for the diverse pool of forecasting models from below AI approaches, including automatic hyperparameter tuning technique for each model

- Conventional Machine Learning : Exponential Smoothing & XGBoost
- Conventional Deep Learning : LSTM & GRU
- Generative modeling : GAN & VAE

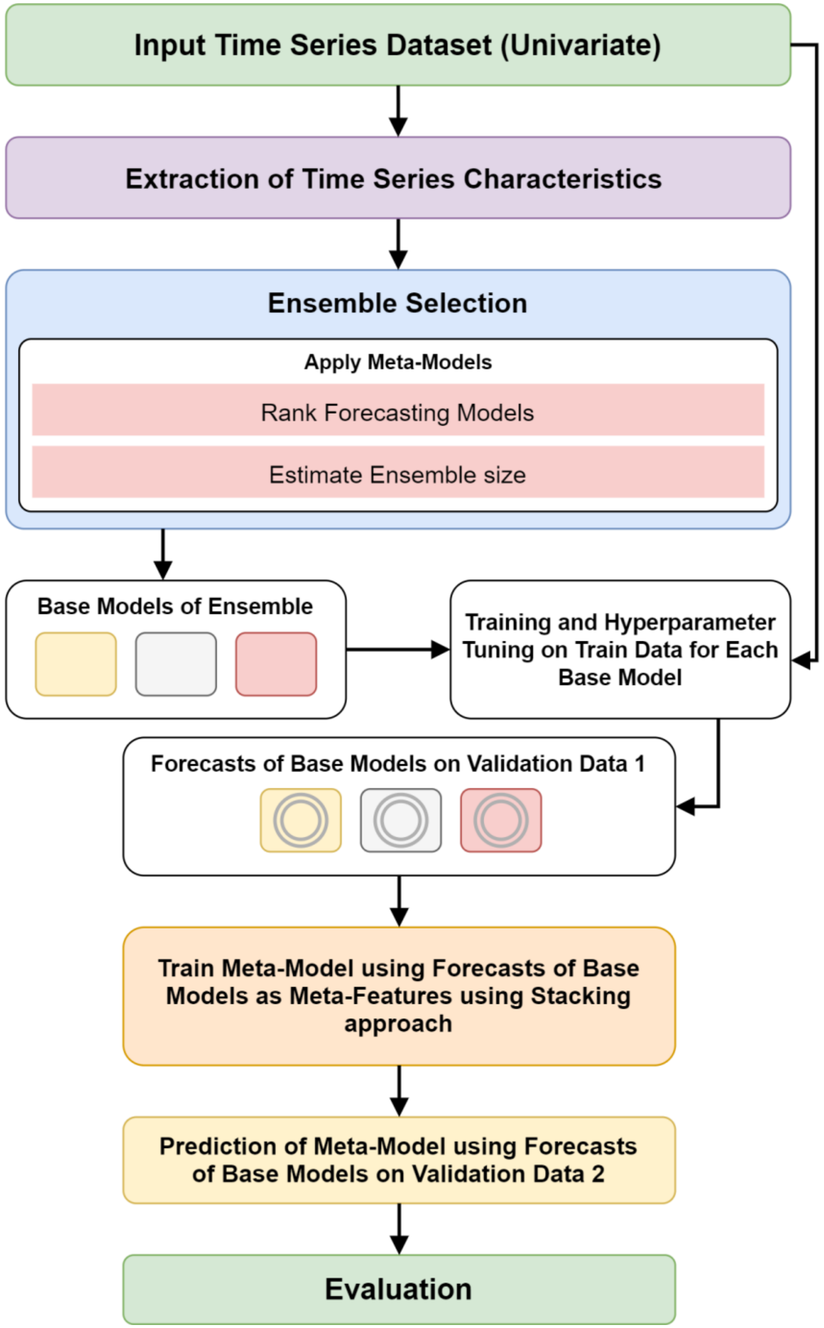
Project Approach Cont.

- **Phase II: Build a Generalized Novel Meta-Framework for Forecasting and Critical Evaluation**

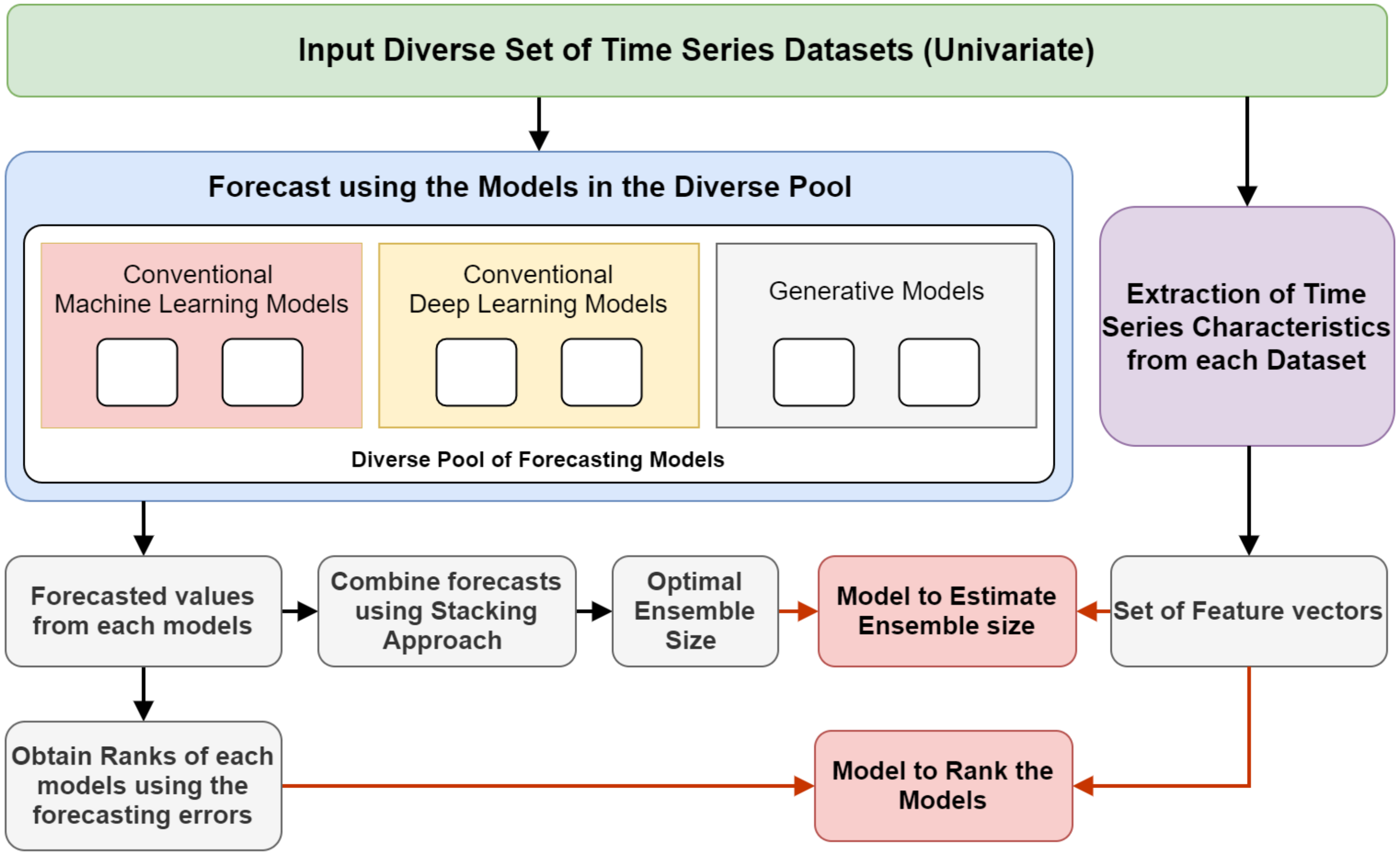
  Develop a generalized novel Meta-Framework using Meta-Learning techniques and stacking approach

  - Meta-Learning for Ensemble Selection
  - Obtain final forecasted value using stacking approach
  - Critical Evaluation

High Level Architecture of Proposed Solution



Meta-Learning for Ensemble Selection



Final Evaluation

Results of Individual Models

- a: realAdExchange/exchange-4_cpm_results
- b: realAWSCloudwatch/ec2_cpu_utilization_77c1ca
- c: realKnownCause/ambient_temperature_system_failure

Dataset	XGBoost	Exponential Smoothing	LSTM	GRU	VAE + LSTM	GAN + LSTM
a	0.177	0.172	0.168	0.169	0.174	0.177
b	5.83	5.73	5.72	5.73	5.75	5.75
c	1.32	1.30	1.27	1.29	1.34	1.34

Results of Stacking Approach

- a: realAdExchange/exchange-4_cpm_results
- b: realAWSCloudwatch/ec2_cpu_utilization_77c1ca
- c: realKnownCause/ambient_temperature_system_failure

Dataset	Best Model produced from meta-model	Stacking MAE
a	LSTM, GRU	0.164
b	LSTM, GRU, Exponential Smoothing, VAE	5.65
c	GRU, LSTM Exponential Smoothing	1.23

Project Requirements

- Dataset :
  - Numenta Anomaly Benchmark (NAB)

    Domains:

    - AWS server metrics as collected by the AmazonCloudwatch service. Example metrics include CPU Utilization, Network Bytes In, and Disk Read Bytes.
    - Online advertisement clicking rates, where the metrics are cost-per-click (CPC) and cost per thousand impressions (CPM).
    - The ambient temperature in an office setting.
    - Temperature sensor data of an internal component of a large, industrial machine
    - Number of NYC taxi passengers
    - Computer usage patterns for different users
    - Real time traffic data from the Twin Cities Metro area in Minnesota
    - collection of Twitter mentions of large publicly-traded companies such as Google and IBM
- Python Packages
  - Basic Packages: Pandas, Numpy, Scikit-learn, TensorFlow, Plotly
  - Hyperparameter Tuning: Random Search, Grid Search, Keras Tuner

Summary

- Forecasting in tabular time-series data proves challenging due to the distinct patterns found in diverse datasets
- The potential value returned by applying generative model approach for time series forecasting is not clearly identified
- This research will lead to a generalized novel meta framework for time series forecasting combining different AI approaches including generative modeling while deploying Meta-Learning for ensemble selection, stacking approach, and automatic hyperparameter tuning

List of References

- [1] Uswah Khairuddin, A. Ahmad, Mohamad, K. B. Chin, Siti Fairuz Zainudin, and A. M. Aris, “Clustering Time Series Data Using Kohonen Self-organizing Map (KSOM) for Classification of Sewage Treatment Plant Operations,” pp. 165–174, Jan. 2024, doi: https://doi.org/10.1007/978-3-031-70687-5_18.
- [2] E. Vaiciukynas, P. Danenas, V. Kontrimas, and R. Butleris, “Two-Step MetaLearning for Time-Series Forecasting Ensemble,” IEEE Access, vol. 9, pp. 62687– 62696, 2021, doi: 10.1109/ACCESS.2021.3074891
- [3] Montero-Manso, P., Athanasopoulos, G., Hyndman, R. J., and Talagala, T. S. (2020). FFORMA: Feature-based forecast model averaging. International Journal of Forecasting, 36(1):86{92. doi:10.1016/j.ijforecast.2019.02.011
- [4] L. Deecke, R. Vandermeulen, L. Ruff, S. Mandt, and M. Kloft, Image Anomaly Detection with Generative Adversarial Networks, vol. 1. Springer International Publishing

Thank you

Q & A