Global Models for Time series Forecasting

Google Cloud, Machine Learning Group

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Presenter

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About Me

- 2015 Graduated in Computer Science from University of Colombo School of Computing, Sri Lanka
- 2015 Joined WSO2 Inc. as a Software Engineer
- 2016-2020 Ph.D. in Computer Science, Monash University, Australia
  - Topic: Forecasting In Big Data With Recurrent Neural Networks
  - Machine Learning for Time Series Forecasting
  - Research Internship at Walmart Labs, San Francisco, USA
  - Research Scientist at Turning Point, Melbourne, Australia
  - Data Science Tutor, Faculty of IT, Monash University
- 2021 Research Fellow, University of Melbourne

About Me (2)

- Research Interests
  - Global Forecasting Models
  - Hierarchical Forecasting
  - Retail sales/demand forecasting
  - Demand forecasting (Retail, Energy, Health-care)
- Competition Fanatic
  - Fuzz-IEEE Competition on Explainable Energy Prediction (**2nd Place**)
  - M5 Forecasting Competition (**Gold Medalist; World Rank 17/5500, Australia Rank 2nd**)
  - IEEE CIS Energy Forecasting Competition (**World Rank 4/100, Australia Rank 1st**)
  - Air-Liquide Energy Forecasting Competition (**World Rank 4/350, Australia Rank 1st**)
  - ANZ Customer Segmentation Challenge (**Top Performer**)

Outline

Time Series Forecasting

- Process of making temporal predictions of the future based on past and present data.
- Accurate and reliable time series prediction is crucial in many industries.
  - Retail, food, railway, mining, tourism, energy, traffic and cloud-computing.
- Impact of Accuracy
  - Poor forecasting can be costly, Accurate forecasting can be considerably lucrative.

Big Data in Time Series Forecasting

- Large quantities of related, similar time series are available.

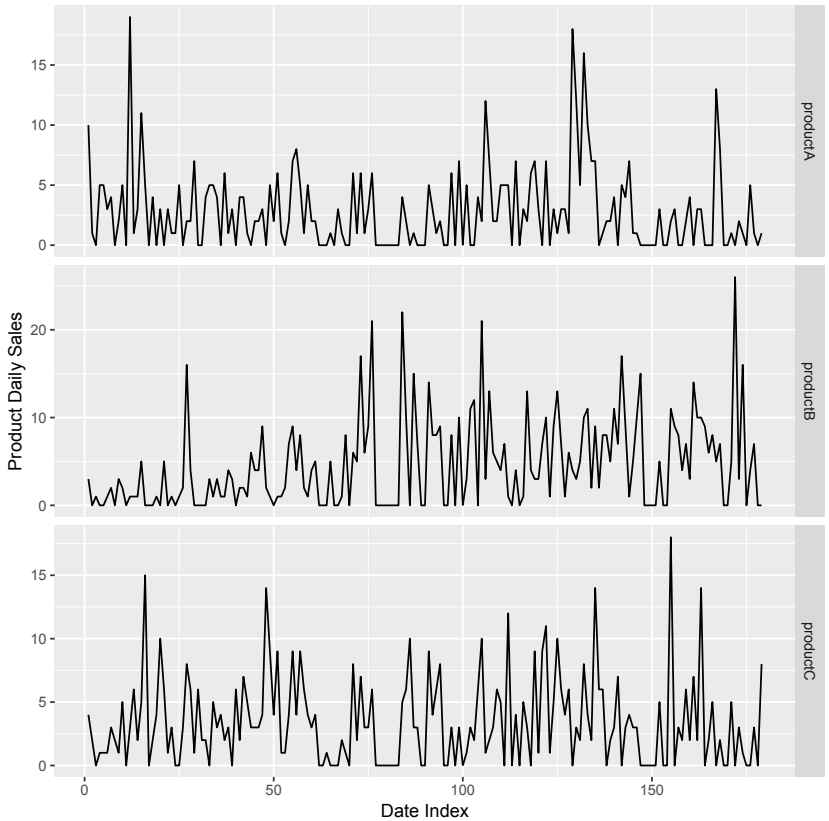


Figure: Daily sales demand of three different products over a four months period, extracted from *Walmart.com* [Bandara et al., 2019].

Vastness of related time series

- Large quantities of related, similar time series are available.
  - The sales demand in retail of thousands of different products.
  - The emergency medical services demand in multiple local government areas.
  - The multiple server performance measures in computer centers.
- State-of-the-art traditional forecasting techniques are mostly univariate methods.
  - Treat each time series separately and forecast them in isolation.
  - ETS, BaggedETS, Theta, ARIMA.
  - Unable to incorporate any key patterns and structures that may be shared by a group of time series
  - Single series may be too short to be forecast at all.

Outline

Substandard performance in forecasting competitions

- Sophisticated methods do not necessarily produce better forecasts than simpler ones [Makridakis and Hibon, 2000].
  - AutomatANN method in the M3 Competition.
- Did not perform well in the subsequent competitions.
  - NN3 and NN5 [Crone et al., 2011, Crone, 2008].
  - Held specifically for Computational Intelligent(CI) methods.
- Couldn't outperform simple standard methods in time series forecasting.
  - Theta method, simple exponential smoothing with drift [Hyndman and Billah, 2003].

Reasons for the under-performance

- Individual series are too short to be modelled effectively.
  - Amount of information that can be extracted is limited.
  - Higher probability of model over-fitting.
- Distant past is usually not very useful for forecasting.
- Neural networks do not perform well.
  - Not having enough data for learning [Zhang et al., 1998].
  - Not handle non-stationarity in the data adequately [Hyndman, 2016].
  - Large number of hyper-parameters to be determined [Yan, 2012].

Improving NNs for forecasting

- Preprocessing techniques.
  - Supplements the NN's learning process.
  - deseasonalizing and detrending data prior to modelling [Nelson et al., 1999, Ben Taieb et al., 2011, Zhang and Qi, 2005].
- Adapting NN architectures for forecasting
  - Ensemble architectures [Rahman et al., 2016, Barrow and Crone, 2016].
  - Generalized regression neural networks (GRNNs) [Yan, 2012].
  - Echo-state networks [Ilies et al., 2007].
  - Recurrent Neural Networks (RNNs) [Zimmermann et al., 2012, Fei and Yeung, 2015].

Global Forecast Models (GFMs)

- Methods that estimate model parameters jointly from all available time series [Januschowski et al., 2020].
- A unified forecasting model that is built using all a collection of time series.
  - Borrow similar behaviours and structures from other related time series.
  - Improves model generalizability.
  - Adequate data for model fitting.
  - Ability to exploit the cross-series information.
- Forecasting a large quantities of related time series: "Related" in terms of similarity of their DGP (not necessarily mere correlations)

Scalability of GFMs

- Enough data, due to more series, thus ML can be more competitive [Bergmeir, 2020]
  - Local model: typically fitting a model with few (<10) parameters to a single series.
  - If you have 10k series and fit 5 parameters, you end up with 50k parameters.
  - Fit a global model with 5k parameters instead.
- Overall complexity of set of local models grows when dataset grows; complexity of global model stays the same.

Complexity of GFMs

- Global models can afford to be more complex.
- Complexity can be added as:
  - Longer memory (longer input windows, more lags)
  - Non-linear/non-parametric models (NN variants, GBT, . . .)
  - Data partitioning (Time series clustering)
- GFMs can be designed with a much higher complexity, yet still achieve better generalisation error than the univariate models for larger datasets [Montero-Manso and Hyndman, 2021]

GFMs are not multivariate models

- Global models learn across series but predict every series in isolation.
- They can work on datasets where series have different lengths and/or are not aligned, like the M3, M4 datasets.
- They do not take into account interactions between series.

Evolution of GFMs

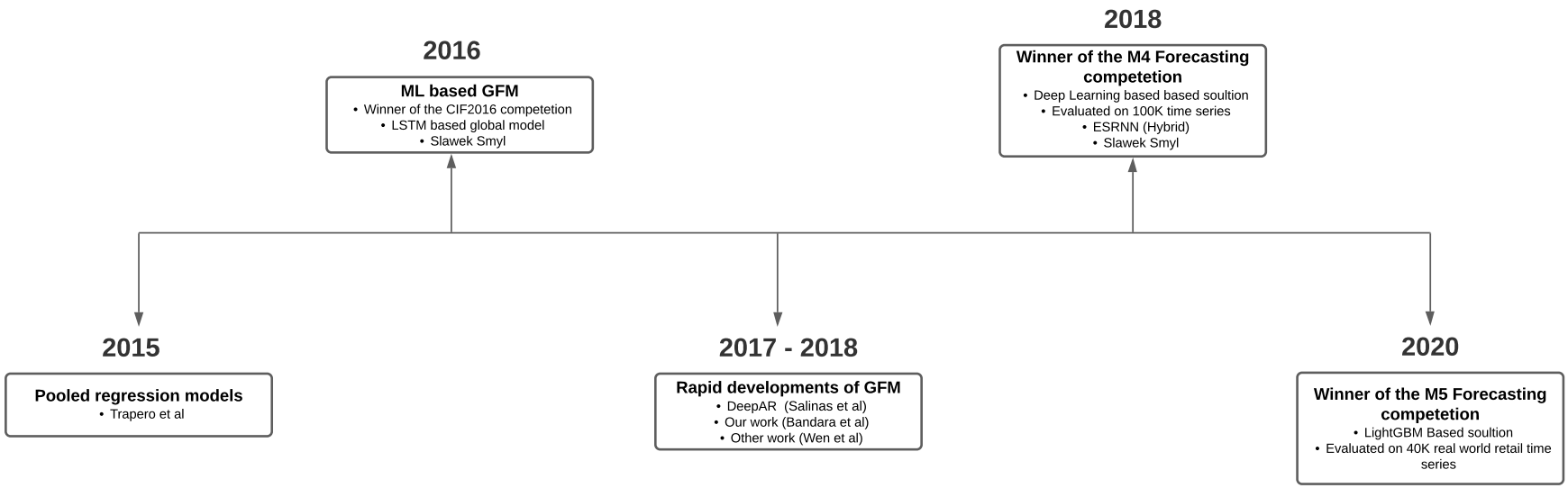


Figure: A brief overview of GFM developments

Moving window approach

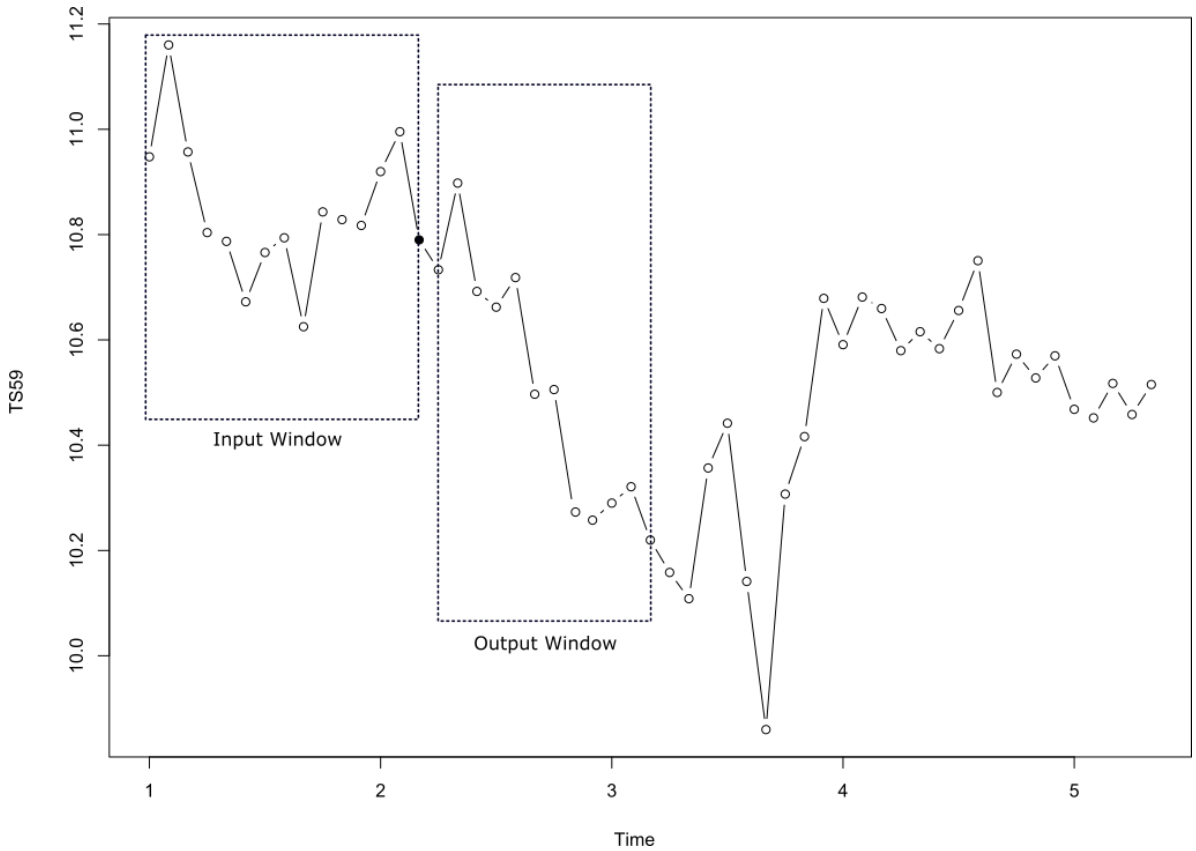


Figure: Applying the moving window approach over a time series . This is also known as the Multi-Input Multi-Output strategy (MIMO)

Dominance in the competitions

- CIF2016 Forecasting Competition (IEEE CIS)
  - LSTM based GFM solution [Smyl, 2016]
- Wikipedia Web Traffic Forecasting (Google, 2017)
  - RNN based Encoder-Decoder architecture [Suilin, 2018]
- M4 Competition (Makridakis, 2018)
  - ES-RNN: A hybrid architecture of RNNs and exponential smoothing [Smyl, 2019]
- M5 Competition (Makridakis, 2020)
  - LightGBM basedn GFM solution [Makridakis and Spiliotis, 2021]

Deep Learning based GFMs

- The recent NLP research (LSTM, attention, transformers) is adapted to the time series use case
  - most recent observations are the most important ones
  - long-term dependencies are relatively simple and stable (only seasonalities)
- Recurrent Neural Network based variants
  - Overview by [Hewamalage et al., 2021]
  - Stacking, Encoder-Decoder architectures
  - Have an internal state which allows them to memorize.
- Convolutional neural networks
  - Competitive as RNNs, but are a lot faster to train [Borovykh et al., 2017]
  - WaveNet architecture (causal convolutions, dilations) [Sen et al., 2019]

Specialised architectures

- DeepAR: Generative RNN model [Salinas et al., 2020]
- Deep state space models: Parametrizes a linear state-space model with an RNN [Rangapuram et al., 2018]
- NBEATS [Oreshkin et al., 2019]: Decomposes series into basis functions, residual stacking
  - State-of-the-art accuracy on M4 dataset.
  - 2nd place in M5 (as part of an ensemble)
- Transformers for forecasting [Li et al., 2019]
- Fusion Transformers [Lim et al., 2021]

GFMs for Forecast combination

- Ensembling works in forecasting just as well as in any other area.
- Local models to capture unique behaviours, Global models to capture common patterns.
- Ensembles of local and global models
  - Energy Demand Forecasting (IEEE CIS Competition)
  - Weekly time series forecasting [Godahewa et al., 2020]

Outline

Research Project 1

Research Question

Does building a notion of similarity between the time series assist the GFMs to distinguish the variations exist among a group of time series.

- Learning across these disparate set of time series may degenerate the overall accuracy of GFM models.
- A notion of similarity between the time series needs to be built into the global methods.
- Identify and account for the time series with homogeneous characteristics.

Research Project 1: Approach

- Building GFMs on subgroups of similar time series.
  - The Long Short-Term Memory Neural Networks (LSTMs) used as the primary GFM.
  - The similarity is captured through clustering the time series into subgroups.
  - Feature based clustering approach using kMeans, DBScan, Partition Around Medoids (PAM), and Snob.
- A prior time series clustering can supplement the GFM training procedure by improving the homogeneousness of the trainable time series.
  - Achieves competitive results on benchmarking datasets under competition evaluation procedures.

Research Project 1: Overall Architecture

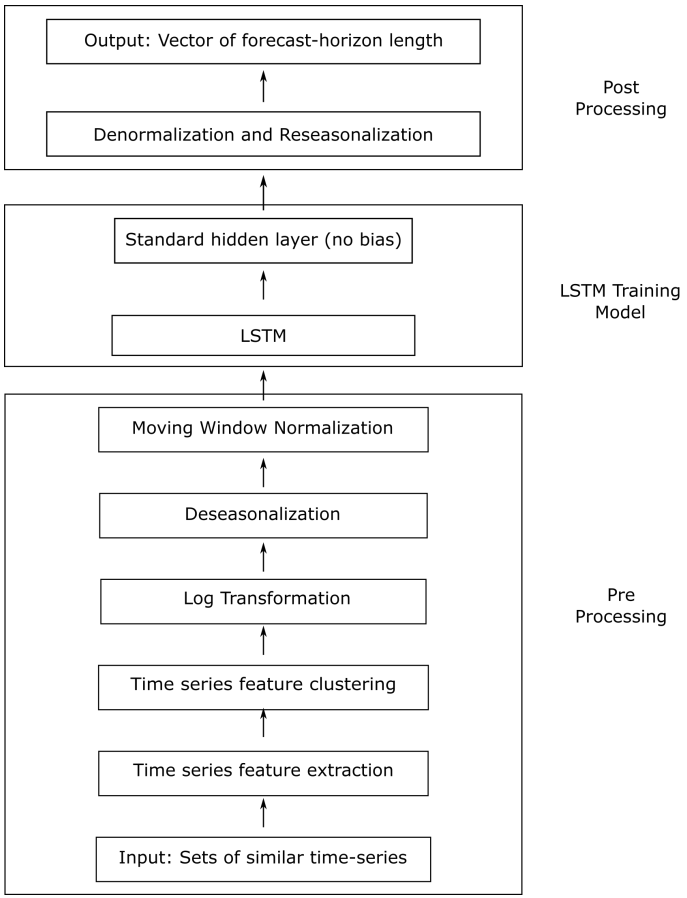


Figure: Pre-processing layer, LSTM training layer and a Post-processing layer.

Research Project 2

- Applying the clustering based GFM framework to forecast the demand in a E-commerce product assortment hierarchy
  - A product grouping strategy introduced to supplement the GFM learning schemes, in situations where sales patterns in a product portfolio are disparate.
- Empirically evaluated using real-world retail sales data from Walmart.com
  - A combination of static and dynamic features to model time series characteristics.
  - Product class, Product category, Calendar information (holidays, season etc.)
  - Evaluated on 20,000 items in the portfolio.
  - Outperforms the current forecasting pipeline at Walmart and many standard benchmarks.

Research Project 2: Overall Architecture

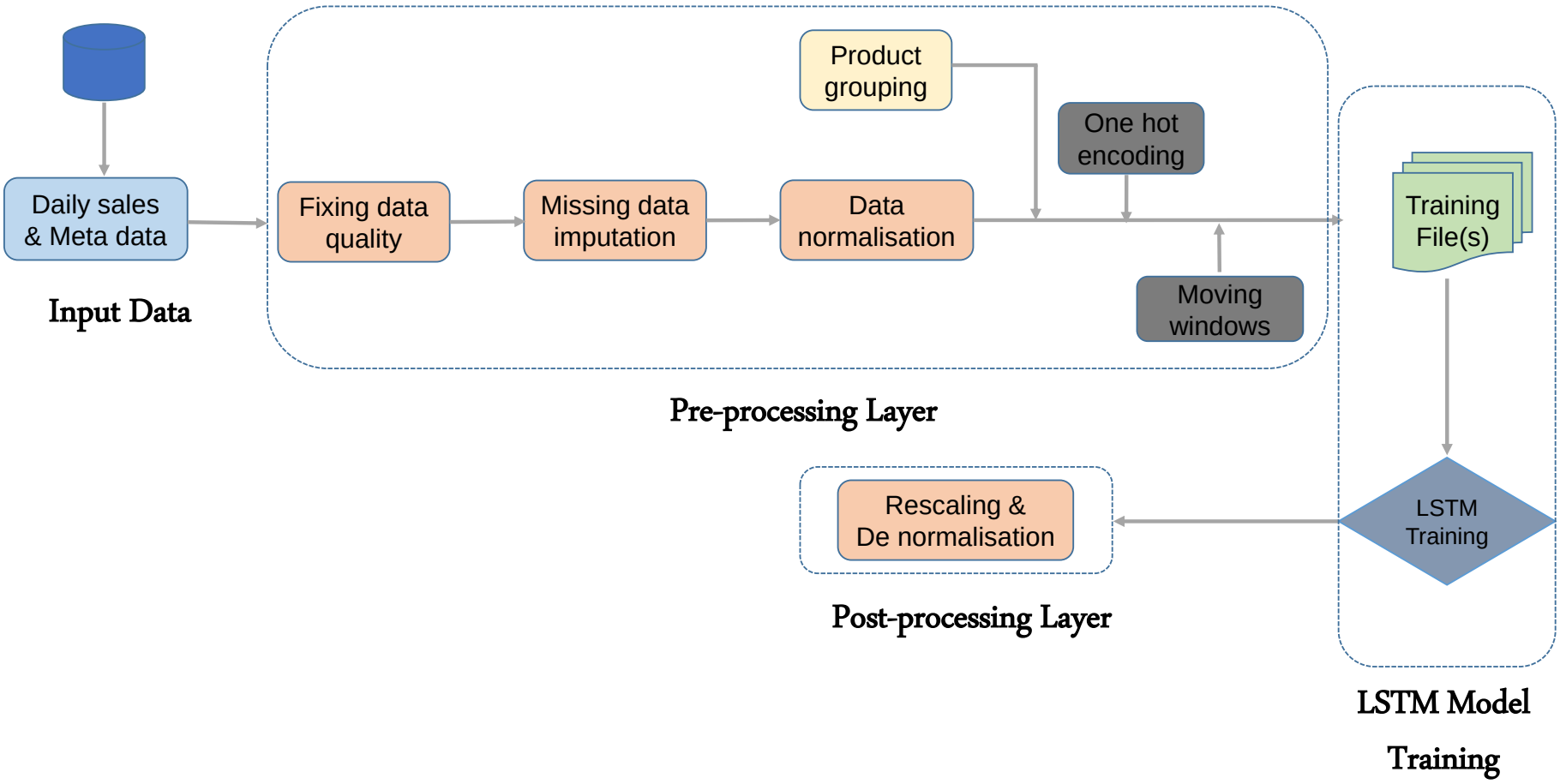


Figure: An overview of the proposed sales demand forecasting framework, which consists of a pre-processing, an LSTM training, and a post-processing part

Research Project 3

Research Question

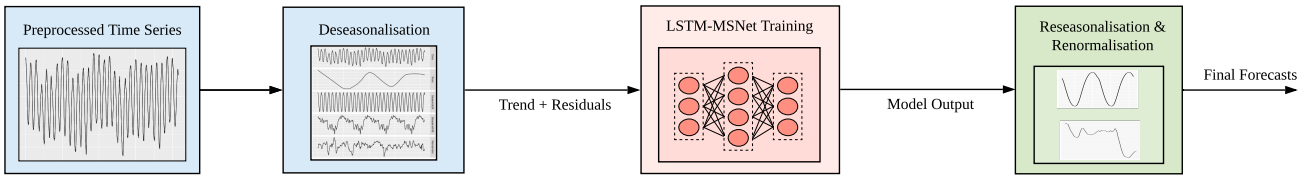
How various forms of multi-seasonal decomposition techniques can supplement the learning process of GFMs, when forecasting a group of time series with multiple seasonal cycles.

- Time series may exhibit complex behaviours.
  - Non-integer seasonality, Calendar effects, **Multiple seasonal patterns**.
- Time series with higher sampling rates (sub-hourly, hourly, daily) are becoming more common in many industries.
  - Utility demand industry (electricity and water usage).
  - Transportation, Tourist, and Health care industries.

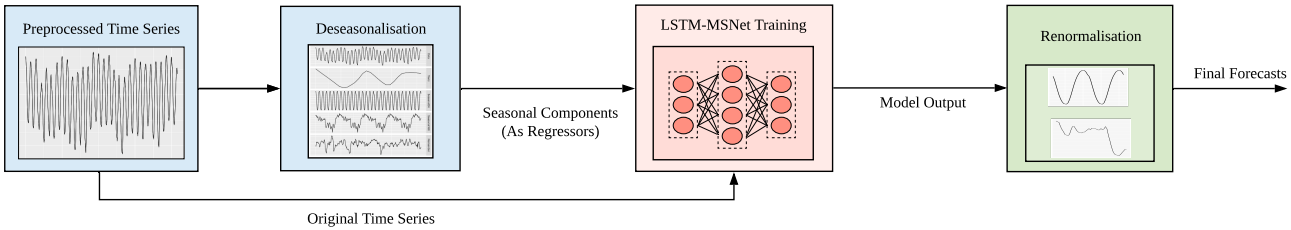
Research Project 3: Approach

- A decomposition based, GFM based prediction framework to forecast time series with multiple seasonal patterns.
- Using state-of-the-art multiseasonal decomposition techniques to supplement the RNN based GFM learning procedure.
  - Seasonal decomposition is advocated by many studies [Ben Taieb et al., 2011, Zhang and Qi, 2005].
  - Supplements the RNN's learning process.
  - Deseasonalized Approach: Seasonally adjusted time series
  - Seasonal Exogenous Approach: Seasonal components as external regressors.

Research Project 3: Overall Architecture



(a) The proposed DS training paradigm used to train the LSTM-MSNet



(b) The proposed SE training paradigm used to train the LSTM-MSNet

Figure: An overview of the proposed LSTM-MSNet training paradigms. In the DS approach, deseasonalised time series are used to train the LSTM-MSNet. Whereas in the SE approach, the seasonal values extracted from the deseasonalisation phase are employed as exogenous variables, along with the original time series to train the LSTM-MSNet.

Research Project 3: Major Findings

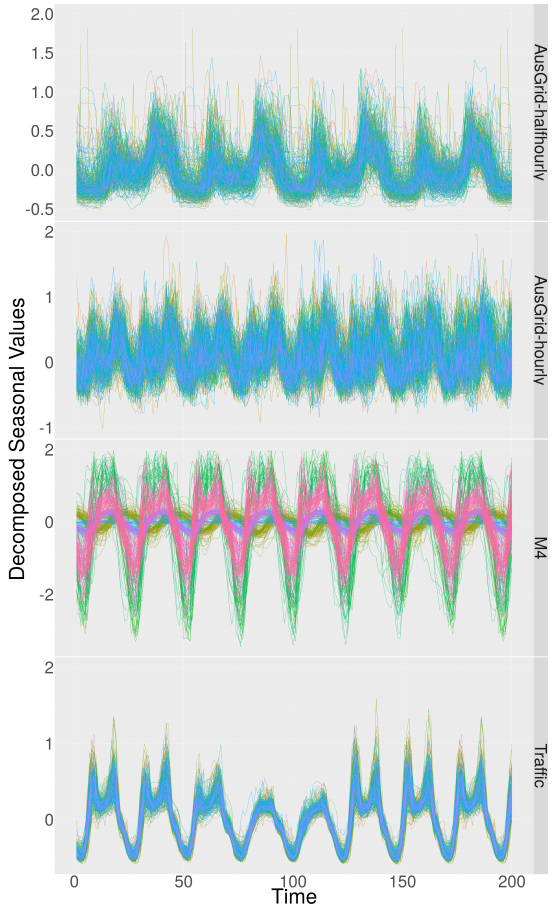


Figure: The seasonal components' distributions of the sum of multiple seasonalities extracted from the AusGrid-Energy (half hourly), AusGrid-Energy (hourly), M4 and the Traffic datasets, by applying the MSTL decomposition technique to the initial 200 data points of each time series.

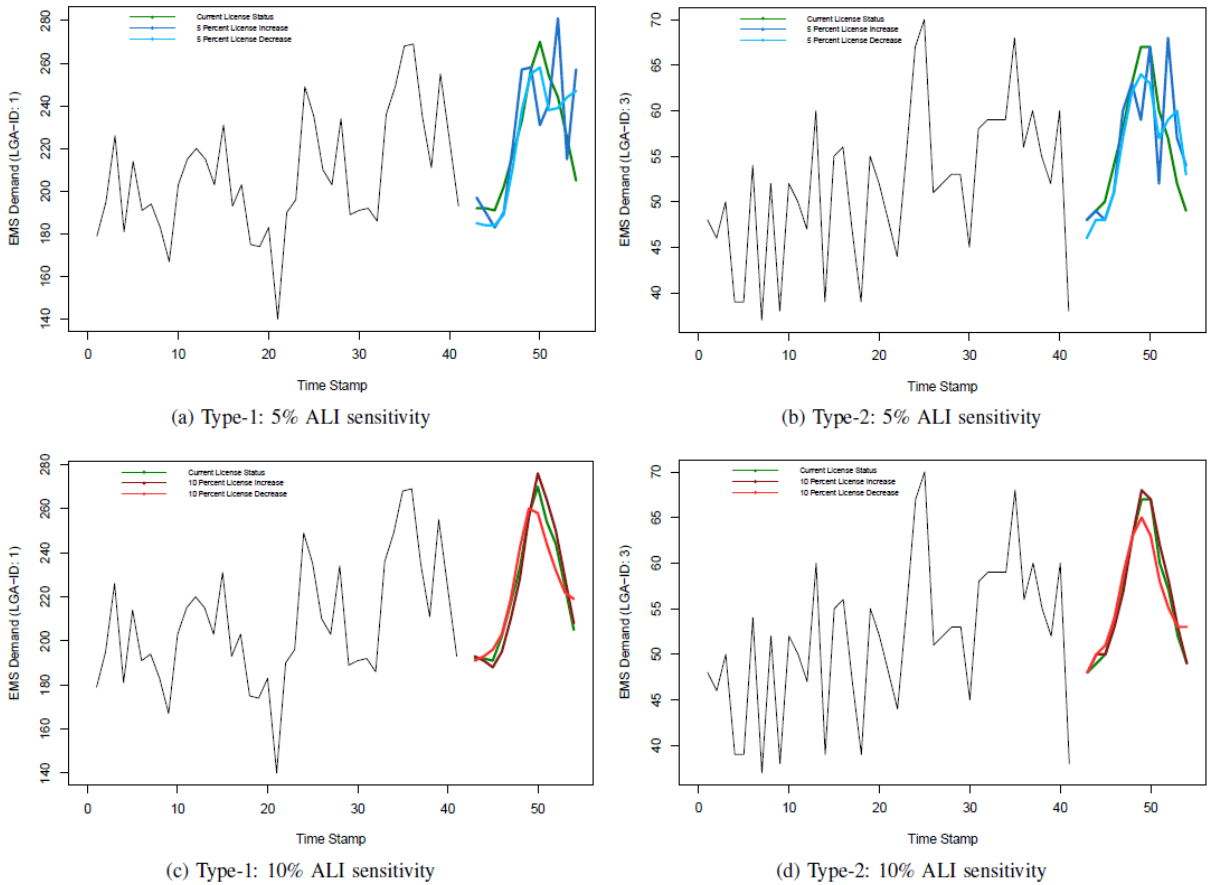
Research Project 4: DeepPPMNet

- GFM allows to train across all the available EMS demand time series to exploit the potential cross-series information available in multiple local governing areas (LGAs).
- Capable of exploring the causal relationships using the notion of Granger Causality, where the GFM enables to perform 'what-if' analyses.
  - Using potential external regressors to evaluate whether the base accuracies are improved.
  - Sensitivity analysis to assess their impact towards EMS.
  - GFMs make the 'what-if' analysis feasible even for relatively constant features.
  - Allows government decision makers to assess the factors that could drive the EMS demand.

Research Project 4: Evaluation

- The DeepPPMNet was evaluated using a realworld EMS demand dataset
  - National dataset of coded ambulance clinical records held by Turning Point, an Australian addiction research and education centre.
  - Related to alcohol overdose, suicide attempts, and other drug related harms.
  - 8 years worth of EMS related data for each LGA.
  - Our methods outperform state-of-the-art univariate time series models.
- A case study to investiage the use of DeepPPMNet
  - How the number of alcohol licenses issued (ALI) for a certain period of time can affect the alcohol related EMS demand patterns.

Research Project 4: DeepPPMNet Case Study



(a) Type-1: 5% ALI sensitivity

(b) Type-2: 5% ALI sensitivity

(c) Type-1: 10% ALI sensitivity

(d) Type-2: 10% ALI sensitivity

Figure: The application of 'what-if' scenario analysis, using the number of ALI (as a percentage of change) against the AO related EMS demand.

Research Project 5

Research Question

The effectiveness of using global models for causal Inference through Counterfactual Prediction

- Global model based Recurrent neural networks (RNN) to predict policy interventions' causal effects on an outcome over time through the counterfactual approach.
  - Traditional methods hold strong linearity and convexity assumptions in covariates, leading us to an non realistic fitting
  - Synthetic Control Method, Google Causal Impact
  - Limitations of equivalence assumption between the control and treated units distribution in the pre-treatment period.

Causal inference

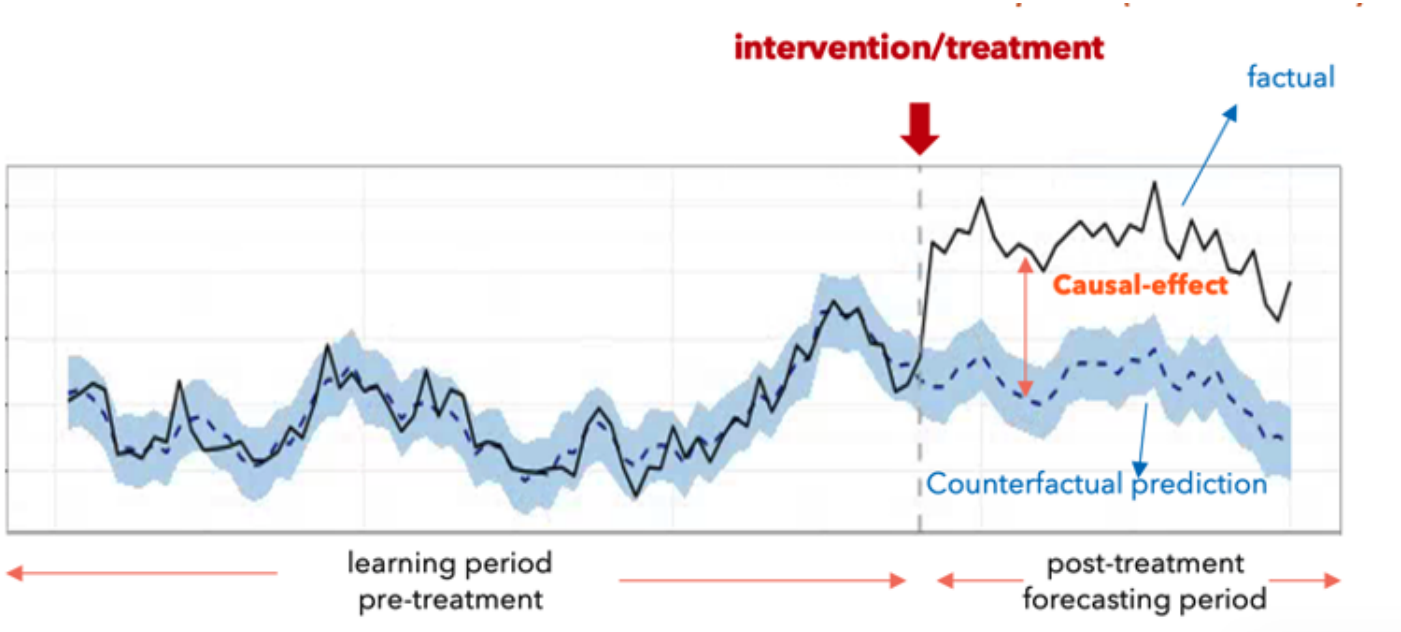


Figure: Generating counterfactual predictions for the units affected by intervention (treated units) based on a large-dimensional panel of observed time-series from a pool of untreated peers (control units)

Generating counterfactuals from DeepCPNet

- GFM is trained across all the panel of treated and control times series, before the intervention.
- Predicts the counterfactual trajectory for the treated unit simulating its behaviour in the absence of the intervention, after the intervention.
- Placebo tests to evaluate the counterfactual predictions
  - Null Effect of the treatment for the control units: performance of the model only over the forecasting of the control group.
  - The significance of the differences between the effects: the difference between the errors from treated and control units must be statistically significant (non-parametric paired Wilcoxon signed-rank)

Effect of COVID19 lockdown measures

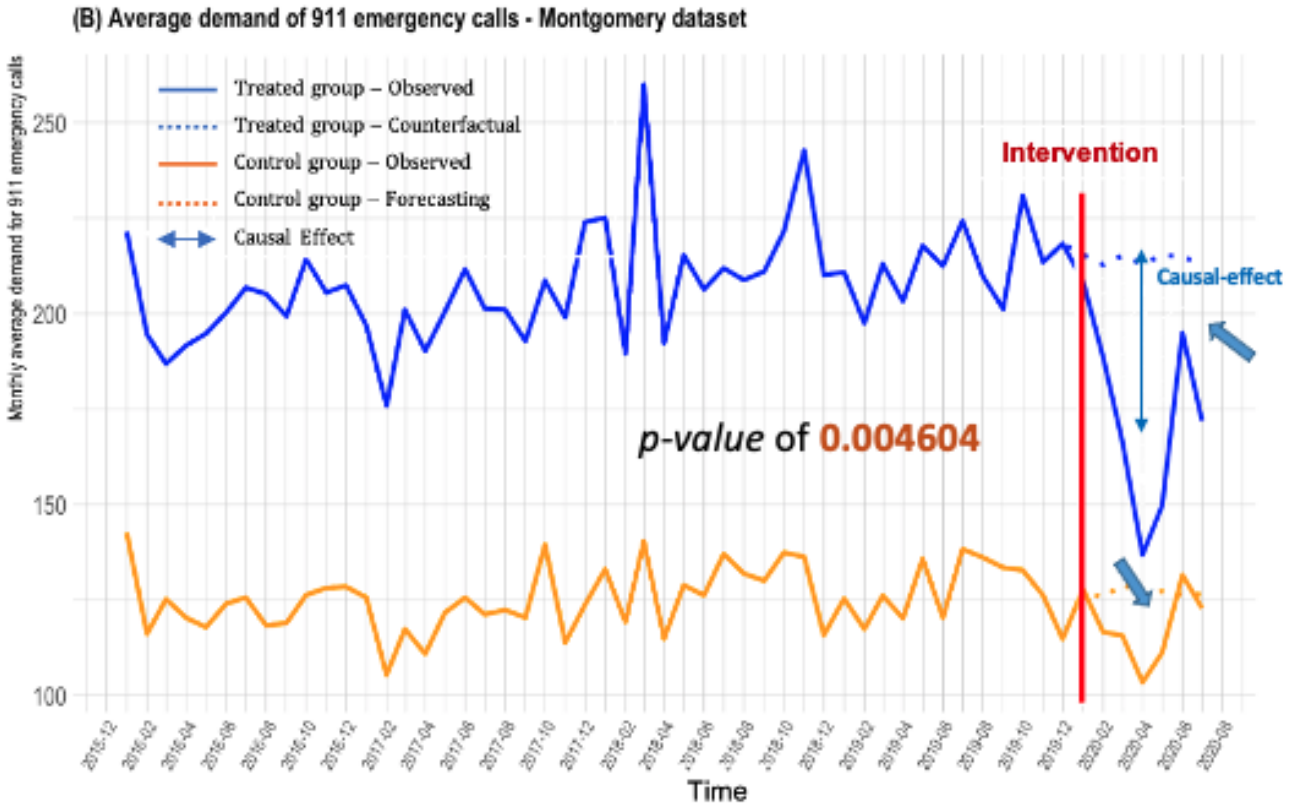


Figure: The causal effect of the COVID19 lockdown measures over the 911 emergency callouts

Research Project 6

Research Question

Can transfer learning approaches uplift the forecast accuracy of GFMs, in situations where the availability of time series is limited.

- RNN based GFMs are inherently data ravenous and require significant amount of training data.
  - Time series databases are often sparse, and may not hold adequate data.
  - The GFMs outshine univariate forecasting models, in situations where large quantities of related time series are available.

Research Project 6: Approach

- A host of transfer learning (TL) schemes to leverage the capabilities of GFMs to generate accurate forecast, in situations with less time series data
  - Adding residual connections to the RNN architecture.
  - Inspired by the ResNet architecture used for image classification tasks [He et al., 2016].
  - Allows to introduce substantially deeper GFM architectures.
- When TL methodology is constrained by the unavailability of a source dataset (D_s) to pre-train a model
  - Using a statistical generative model to artificially generate new copies of time series.
  - GRATIS package introduced by [Kang et al., 2019].
  - Employs a mixture autoregressive (MAR) models together with genetic algorithms to generate time series.

Research Contribution 6: Residual RNN Architecture

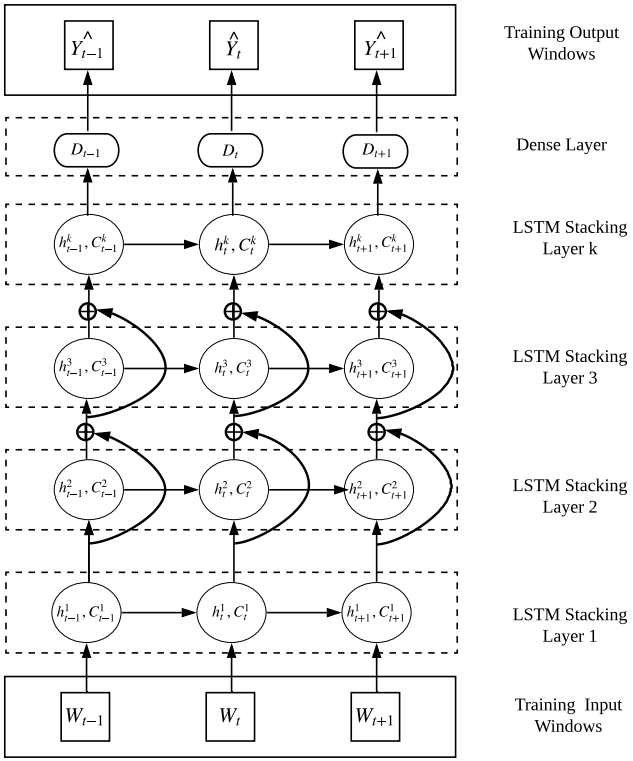


Figure: The unrolled representation of a residual recurrent network architecture with k number of stacking layers. Here, the residual connections are represented by curved arrows. Accordingly to [He et al., 2016], these residual connections allow the stacking layers to fit a residual mapping between W_t and $\hat{Y}_t$, while avoiding the network degradation with network depth increasing

Research Contribution 6: Overall Architecture

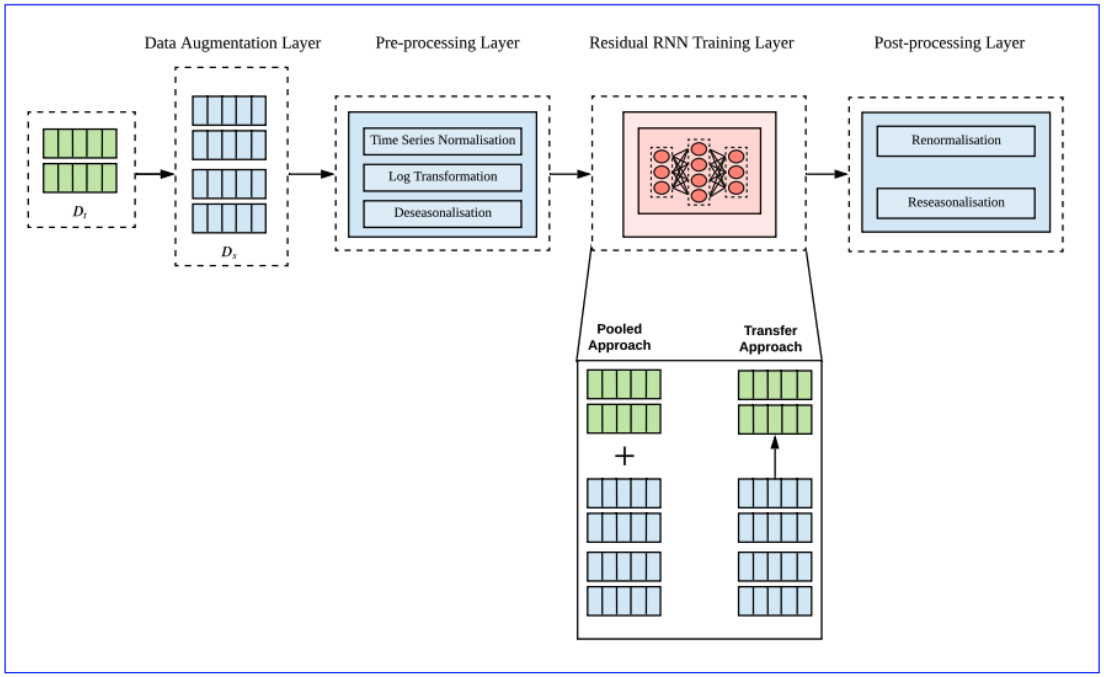
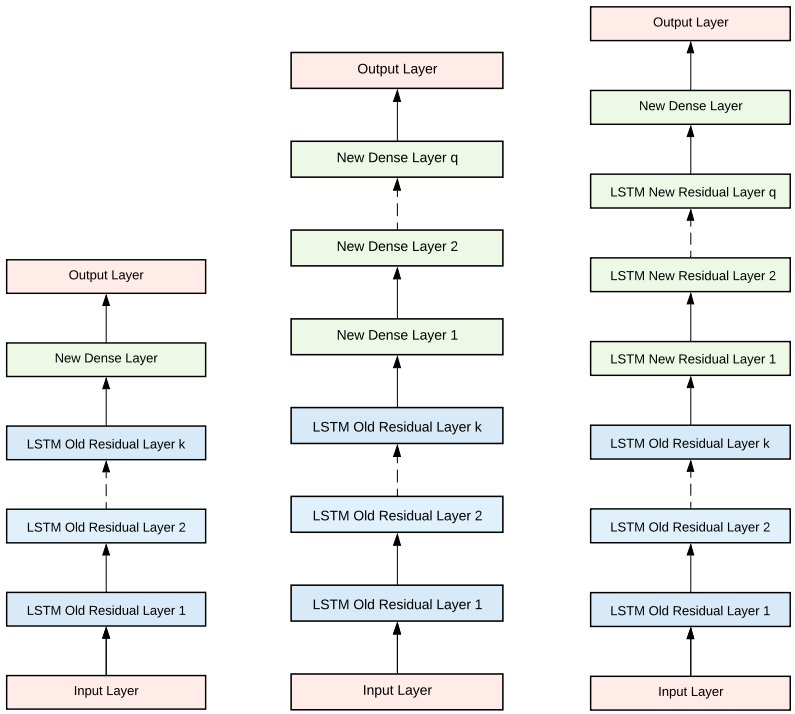


Figure: An overview of the proposed framework, which includes a data augmentation layer, pre-processing layer, residual RNN training layer, and a post-processing layer

Research Contribution 6: Transfer Learning Architectures



(a) TL-1 (b) TL-2 (c) TL-3

Figure: The layers used to build the base model using the D_s, are represented in blue colour, while the additional layers introduced, when building the target model using the D_t, are represented in green colour.

Outline

Recent research in GFMs

- Global models for hierarchical time series forecasting
- Local interpretable forecasting models using global models.
- Global models robust to concept drift.
- Global models for scenario-forecasting.

Thank you

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Slides available: `github.com/kasungayan/GoogleTalk`

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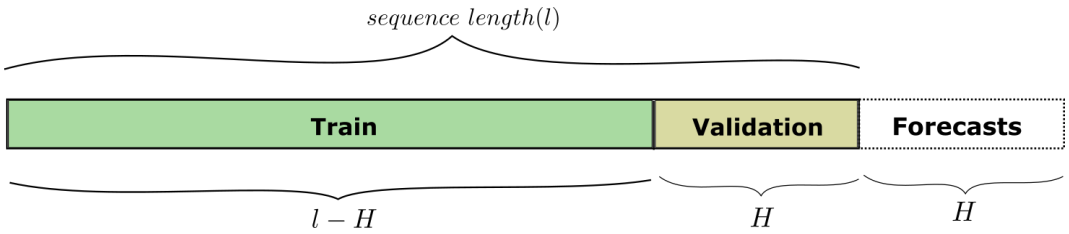
Appendix



Figure