A Comprehensive Study of Deep Learning Techniques for Supply Chain Demand Forecasting

IPE 4000

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Significance Overview

- Demand forecast has always been a vital part of supply chain.
- Accurate forecasts = More Response, Failure Resiliency, Profit
- Forecasting error = Costs to the organization
- Traditional methods have low accuracy.
- Today's supply chain demand is more complex incorporating more variables, seasonal components, special days, e-commerce etc..
- Deep Learning have the potential to address these problems.

Objectives

To study different deep learning techniques for supply chain demand forecasting.

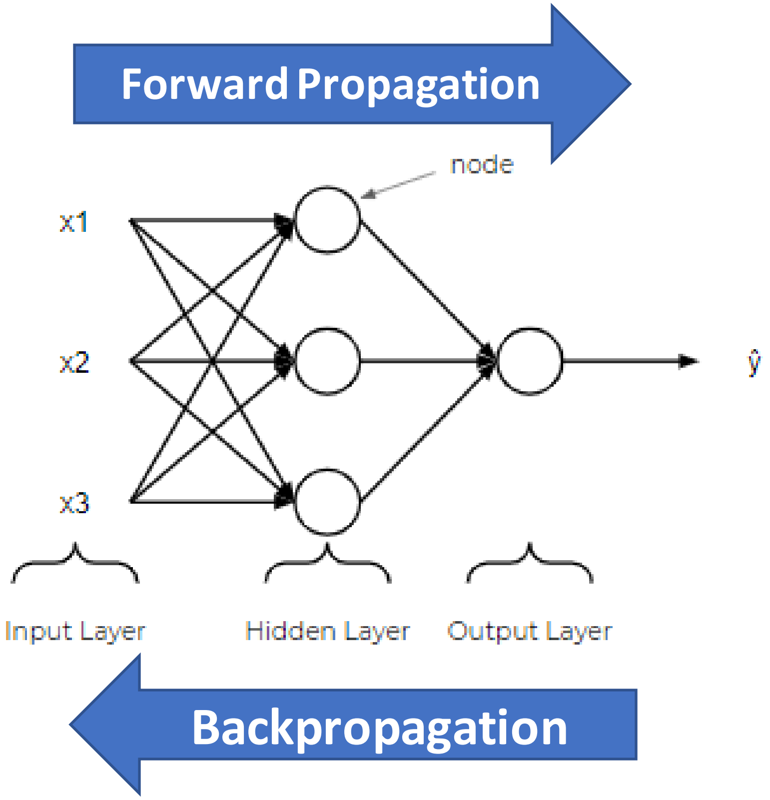
To evaluate the performance of advanced deep learning techniques in forecasting demand with high variability and seasonal components.

Methodology

Forecasting problem can be modeled as a supervised learning problem:

$$\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{x})$$

Where, $\boldsymbol{x}$ is previous demand data and $\boldsymbol{y}$ is the forecast output.



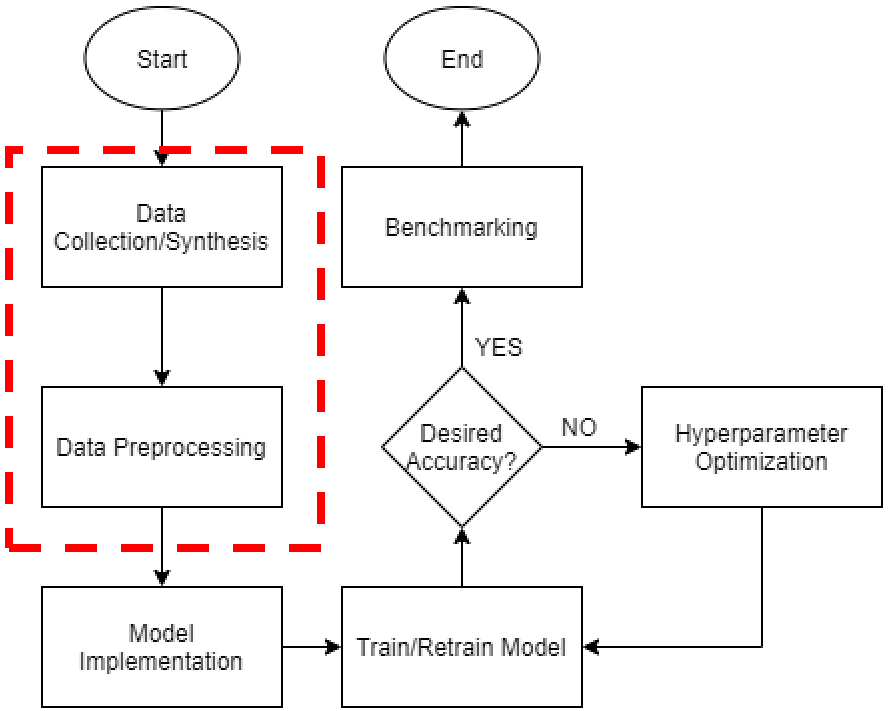
Linear function:

$$z^{[l]} = w^T x + b$$

Activation function:

$$a^{[l]} = \sigma\left(z^{[l]}\right)$$

Cost Function



Methodology-Data

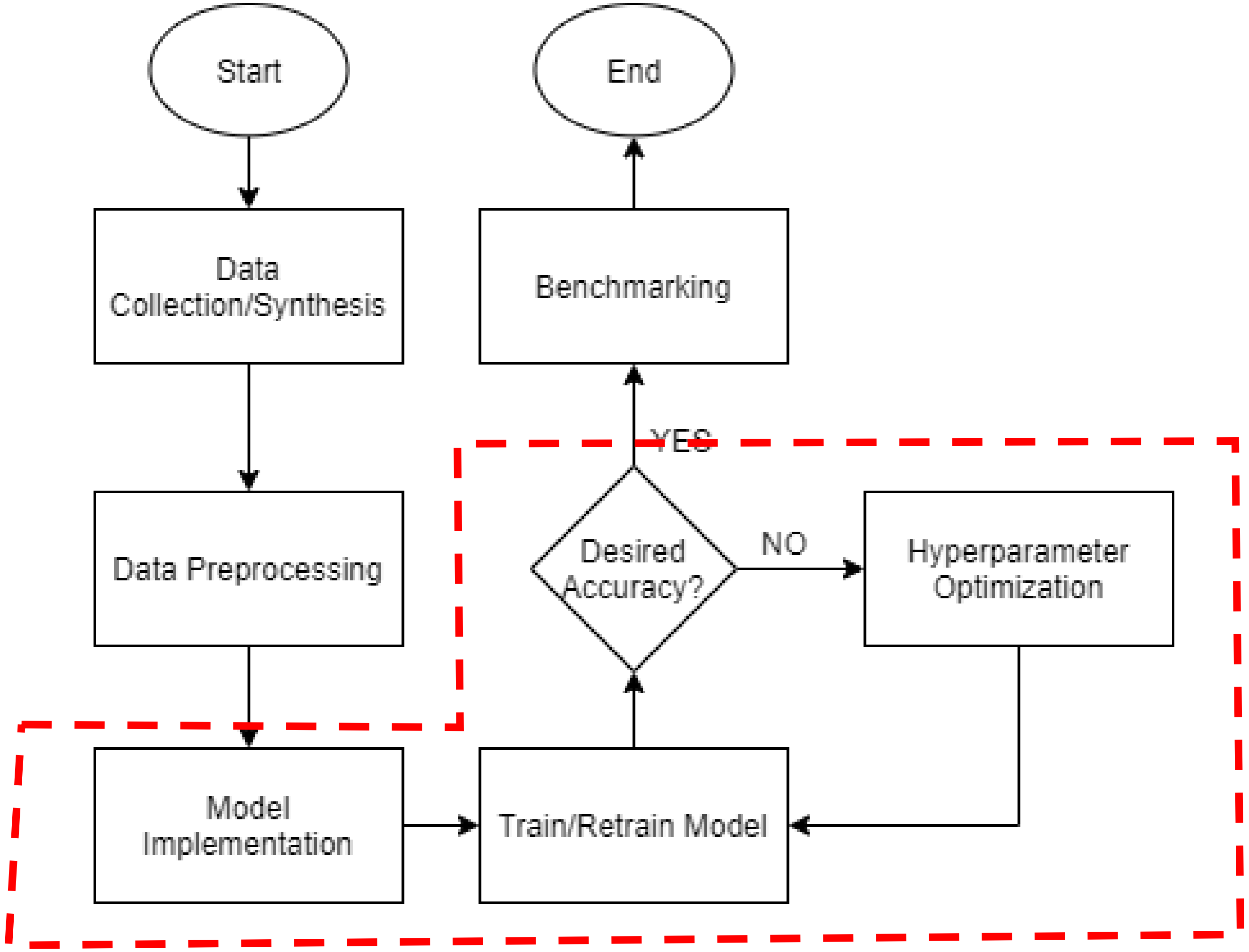
- Two datasets:
  - Simulated Supply Chain
  - Real-world
- Windowing

20
30
45
60
70
52
40
?

x	y
[20, 30, 45, 60]	70
[30, 45, 60, 70]	52
[45, 60, 70, 52]	40
[60, 70, 52, 40]	?

Window size

Methodology



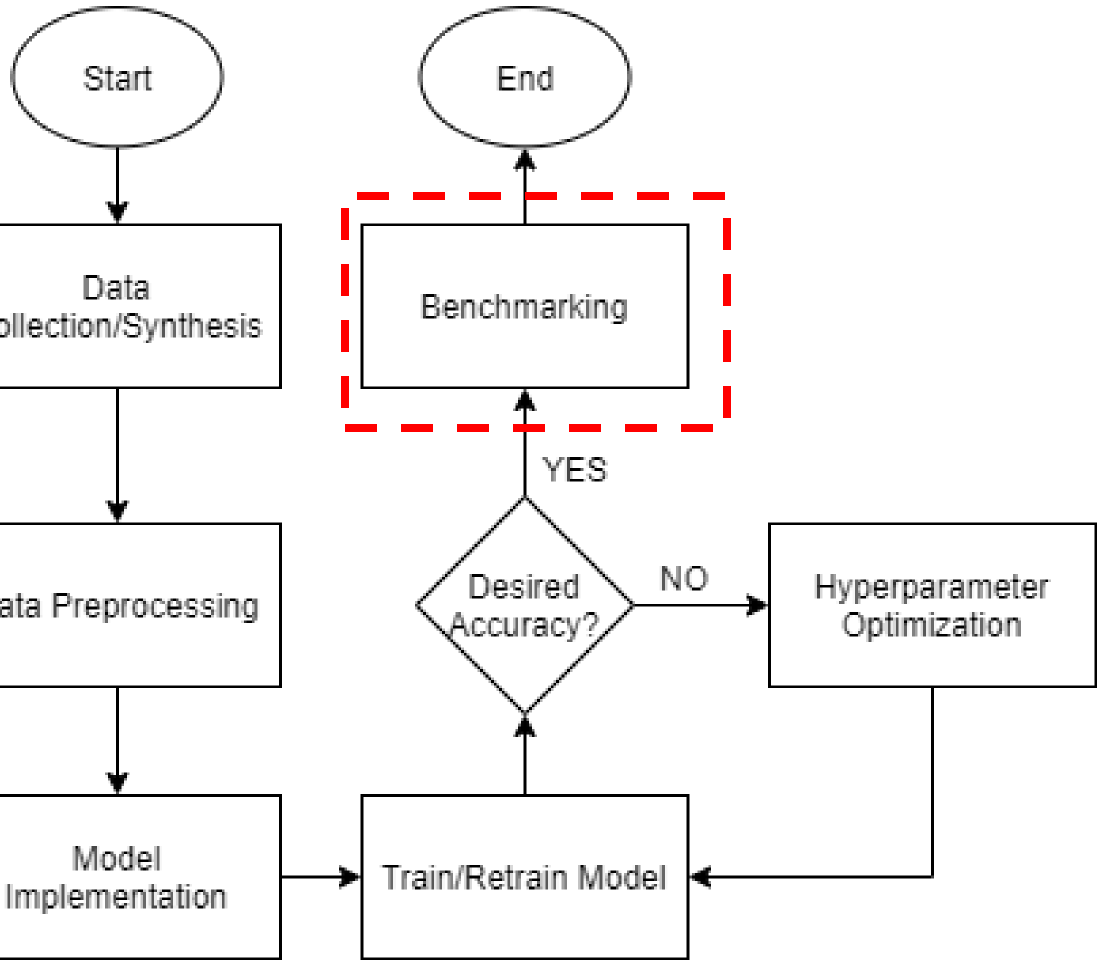
Methodology- Models

Model optimization

- Number of hidden layers
- Learning rate
- Choice of activation function
- Window size

State-of – the-art techniques	Hybrid-models	Other approaches
• ANN • CNN • RNN • LSTM	• CNN-RNN • CNN-LSTM	• Decomposition-based model • Auxiliary variable addition • Transfer Learning

Methodology



Methodology-Benchmarking

Three metrics:

- $RMSE = \sqrt{\frac{\sum_1^n (\hat{y}-y)^2}{n}}$
- $MAPE = \frac{1}{n}\sum_1^n \left|\frac{y-\hat{y}}{y}\right|$
- Data costs

Expected Results

Reduced **RMSE** and **MAPE**.

Low data and development costs.

Model feasibility considering costs and other challenges.

Timeframe

Literature Study – Already completed

Data Collection – by February 2020

Model Implementation and Benchmarking - by March 2020

Results and Discussion – by April 2020

Thank you!