TruChain

An Engineering Project in Community Service

Phase – II Report

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in partial fulfillment of the requirements for the degree of

Bachelor of Engineering and Technology

VIT Bhopal University
Bhopal
Madhya Pradesh

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Bonafide Certificate

Certified that this project report titled **"TruChain"** is the bonafide work of "20BCE10015 Akhil, 20BCE10082 Harsh Soni, 20BCE10227 Shivam Saurabh, 20BCE11104 Shivansh Rastogi, 20BCE10128 Gandhi Monil, 20BOE10072 Yashi Goswami, 20MEI10039 Narendra Kumar, 20MIM10100 Harshvardhan Saxena" who carried out the project work under my supervision.

This project report (Phase II - Final) is submitted for the Project Viva-Voce examination held on 19-05-2023.

Supervisor

Dr. Soumya Sankar Ghosh

1. INTRODUCTION -

Supply chain management is a complex process that involves the coordination of various activities, including procurement, production, transportation, and distribution, to deliver products or services to customers. The success of a supply chain depends on the ability to accurately forecast demand, manage inventory, and quickly detect and respond to anomalies or disruptions in the system. With the increasing availability of data and advances in machine learning techniques, there is a growing interest in using these tools to improve supply chain performance.

This review paper aims to provide an overview of the current state of research on machine learning techniques for supply chain forecasting and anomaly detection. We begin by discussing the challenges and issues in supply chain management, such as the bullwhip effect, demand uncertainty, and the impact of anomalies on the system. We then review the existing literature on machine learning techniques for supply chain forecasting, including traditional methods like time series analysis and newer approaches like deep learning and neural networks. Next, we examine the use of machine learning techniques for anomaly detection in supply chain data. We discuss the diverse types of anomalies that can occur in a supply chain, such as sudden changes in demand, disruptions in transportation, and inventory stockouts. We review the various machine learning algorithms that have been used for anomaly detection, including clustering, classification, and regression techniques.

Finally, we present the implementation of our web application, TruChain, designed to forecast the demand for bike rental data. TruChain leverages advanced forecasting techniques and machine learning algorithms to provide accurate predictions of bike rental demand. By analyzing historical data, market trends, and other relevant factors. The web application offers user-friendly interfaces and intuitive visualizations, empowering users to make informed decisions based on the forecasted demand. We highlight the importance of data quality, model interpretability, and the need for human expertise in the decision-making process.

1.1 Motivation

During the VIT Bhopal experiential learning industrial visit we came across various problem statements related to supply chain forecasting. Correct forecasting is important from a business perspective. From cutting costs to keeping consumers happy, forecasting is a vital component of supply chain management, helping companies fill orders on time, avoid unnecessary inventory expenses and plan for price fluctuations. If our forecast assumed fewer products sold than the actual demand then we lose profit. On the other hand, if our forecast was overestimated, so we actually sell fewer products, we also lose, we incur the cost of product stock, or worse, our products expire. One bad forecast has business, production, and logistical consequences.

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1.2 Objective

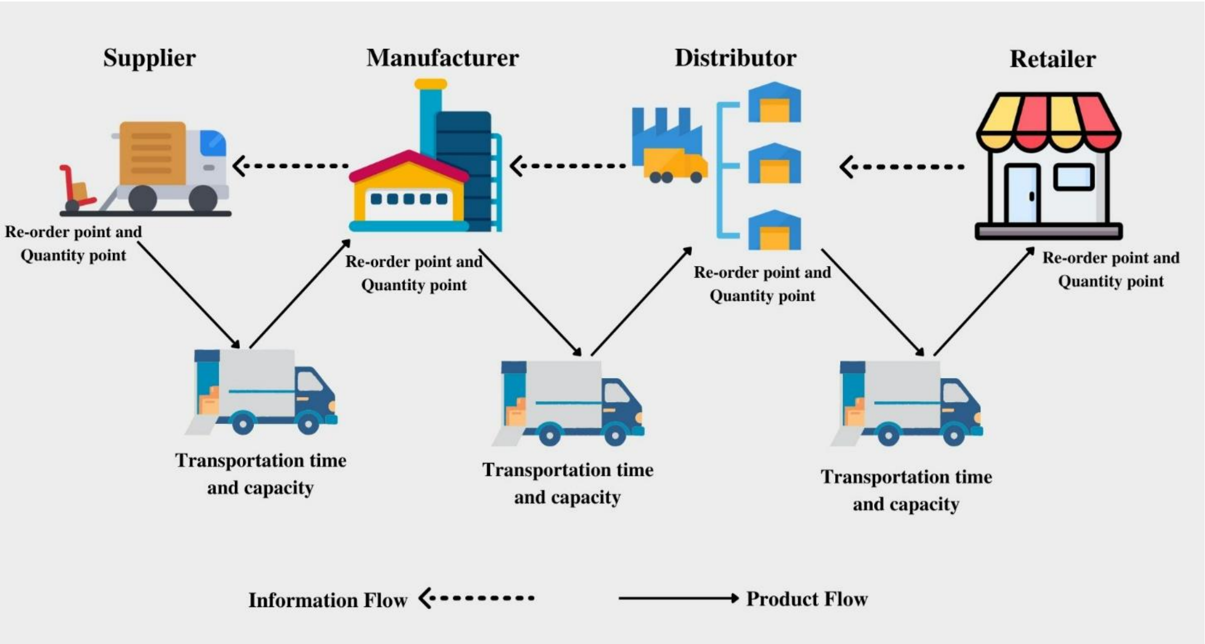
- Create new features based on the existing ones that enable machine learning algorithms to work. Getting the data right increases the quality of the data a lot because we transform the raw data into information that the model will transform into knowledge. Then the model can understand the pattern better and make better predictions.

- The user will be able to get both monthly and annual predictions regarding supply and demand.

- The objective of this project is to perform a comparative analysis of forecasting the distorted demand signals in the extended supply chain using non-linear machine learning techniques. More specifically, the work focuses on forecasting the demand at the upstream end of the supply chain to avoid the bullwhip effect.

2. Existing Work / Literature Review

We have studied the research papers and understood the steps involved in the supply chain (SC) management process, as shown below:



Here we can see the information and material flow between distinct phases. We will predict the product demand between retailer-distributor or distributor-producer or producer-supplier.

[2] Demand signals play a crucial role in the efficient functioning of supply chains and are essential pieces of information for demand planners within businesses. These signals serve as messages that are issued within business operations or supply chains to notify suppliers about the requirement for goods. By accurately capturing and analyzing demand signals, organizations can make informed decisions

regarding production, inventory management, and distribution, improving overall supply chain performance.

One important aspect of demand signals is their relevance in predicting product demand at various stages of the supply chain. Let us consider the three main phases: retailer-distributor, distributor-producer, and producer-supplier.

Retailer-Distributor: In this phase, demand signals originate from the retailers, indicating the expected consumer demand for specific products. These signals are based on numerous factors, including historical sales data, customer behavior analysis, market trends, and promotional activities. Retailers communicate the demand signals to the distributors, enabling them to plan their inventory levels and delivery schedules accordingly.

Distributor-Producer: The demand signals from the distributors serve as important feedback for the producers or manufacturers. These signals provide insights into the demand patterns at the distribution level, helping producers understand the quantities and types of products needed. By incorporating distributor demand signals into their forecasting models, producers can optimize their production plans, raw material procurement, and overall manufacturing processes.

Producer-Supplier: The demand signals generated by the producers are crucial for the suppliers of raw materials and components. These signals communicate the anticipated production requirements based on demand forecasts and production plans. By receiving accurate demand signals from the producers, suppliers can align their production and delivery schedules, ensuring the availability of materials at the right time and in the right quantities.

It is worth noting that demand signals can be influenced by numerous factors, such as seasonality, market trends, pricing strategies, and external events. Therefore, demand planners need to continuously monitor and analyze these signals, using advanced forecasting techniques and machine learning algorithms, to improve the accuracy of their predictions.

In the literature, several studies have explored the use of machine learning and time series forecasting methods to predict and leverage demand signals effectively. These studies have focused on developing models that can capture and analyze demand signals at various stages of the supply chain, enabling more accurate demand forecasting, better inventory management, and enhanced decision-making capabilities.

By incorporating demand signals into their forecasting and planning processes, businesses can reduce inventory holding costs, minimize stock-outs, improve customer satisfaction, and optimize overall supply chain performance.

Remember to cite relevant literature and studies in this section to support your discussion on demand signals and their importance in supply chain operations and forecasting.

This review paper explores the key factors that impact the performance of supply chains. By analyzing various elements such as supply chain structure, inventory control policy, information sharing, customer demand, forecasting methods, lead time, and the Sell-In/Sell-Out model, this paper aims to provide insights into the challenges and opportunities for improving supply chain efficiency. Understanding these factors and their interplay is crucial for businesses seeking to optimize their supply chain operations and enhance overall performance.

Introduction The efficient management of supply chains is essential for businesses to meet customer demands, reduce costs, and maintain competitive advantages. This section introduces the importance of supply chain performance and sets the stage for discussing the factors that influence it.

Supply Chain Structure The structure of a supply chain, including the number of facilities, stages, and the flow of material and information, plays a vital role in its complexity. This section examines how supply chain structure affects operational efficiency and identifies strategies for optimizing structure to improve performance.

Inventory Control Policy Effective inventory control ensures the availability of goods while minimizing costs associated with stock-outs and excess inventory. This section discusses the economic balance between holding inventory and cost savings, as well as decision-making processes regarding when and how much to order.

Information Sharing Information sharing among supply chain partners enables coordination and collaboration. This section emphasizes the importance of information flow in daily operations and highlights the role of information systems in facilitating customization, rapid product delivery, and understanding customer preferences.

Customer Demand Customer demand patterns significantly influence supply chain performance. This section explores the challenges posed by uncertain and difficult-to-forecast demand, including the bullwhip effect caused by order variance amplification. It also discusses the impact of demand volatility on capacity and inventory costs.

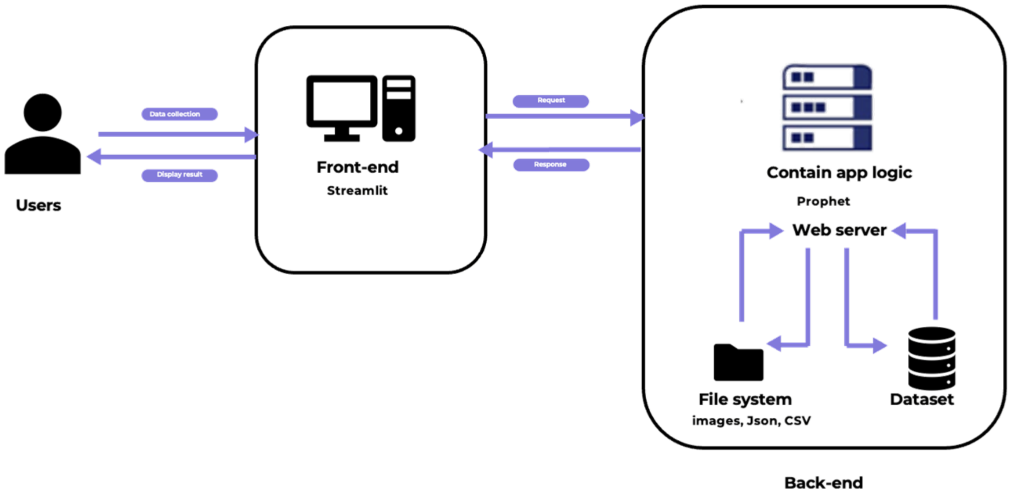
Forecasting Method Accurate demand forecasting is essential for supply chain members. This section examines the influence of forecasting methods on inventory costs, backorder costs, lost sales costs, and customer goodwill. It highlights the implications of inaccurate forecasts on factory capacity utilization and identifies demand forecasting as a contributor to the bullwhip effect.

Lead Time Lead time, the duration between order receipt and product delivery, significantly impacts supply chain performance. This section discusses how long lead times can lead to order fluctuations and contribute to the bullwhip effect.

Sell-In/Sell-Out Model This section introduces the Sell-In/Sell-Out model, which distinguishes between products sold by the manufacturer to the retailer (Sell In) and products sold by the retailer to end customers (Sell Out). It explores the relationship between supplier orders and retailer sales and highlights the impact of supply on retailer demand.

By comprehending and addressing the factors discussed in this review, businesses can optimize their supply chain performance, achieve operational efficiency, and improve customer satisfaction.

A) System Design / Architecture



The system architecture of the web app involves the utilization of the Prophet model for forecasting the demand for bike rentals. The app's user interface is built and hosted using Streamlit. The backend code performs various tasks, starting with loading the bike rental dataset from a CSV file. It then preprocesses the data by converting timestamps to DateTime format, resampling the data to a daily frequency, handling missing values, and renaming columns. The Prophet model is initialized with specific configurations for seasonality, including yearly and weekly patterns, and custom seasonal regressors. The model is trained on the preprocessed dataset using the fit function. To make future predictions, a future data frame is created using the make_future_dataframe function, and relevant features such as temperature, holiday indicators, and season information are added. The model's prediction function is then used to generate demand forecasts. The trained model is serialized to JSON format and saved in a file named model.json under the model directory.

On the frontend side, the Streamlit app creates an interactive user interface. The header section includes the app title, a description, and an image. The app loads assets such as Lottie animations and CSS stylesheets for customization. The sidebar provides navigation options, and users can choose the "Forecasting Model" option. The app loads the forecast data from the forecast.csv file. Users can select a specific date using the date input widget to view the predicted demand for that date. The front-end code retrieves the forecast information for the selected date from the forecast.csv file and displays it to the user. Additionally, a Prophet model plot is generated using the loaded forecast data and displayed using Plotly. Other sections in the app include "What We Do," "Our Approach," "Our Vision," and "Get in Touch with Us," providing information about the project and a contact form for users to send messages.

B) Working Principle

This section outlines the working principle of the machine learning model used for examining future statistics and predicting supply chain requirements. By leveraging previous datasets, the model aims to calculate and forecast the approximate demand to enable proactive ordering and minimize demand variability. Various machine learning models, including LSTM and Prophet, are employed and trained on a supply chain dataset to identify the most accurate forecasting approach.

1. Introduction The working principle of the machine learning model centers around leveraging historical supply chain data to predict future statistics and forecast demand. This section introduces the objective of implementing a machine learning model for supply chain forecasting, highlighting the importance of proactive ordering, and minimizing demand variability.
2. Dataset Acquisition To develop an accurate forecasting model, a comprehensive data set of the target supply chain is required. This dataset should include relevant historical data such as sales records, inventory levels, order patterns, and any other pertinent information. The availability and quality of the dataset play a crucial role in the accuracy of the predictions.
3. Model Training Once the dataset is acquired, it is used to train different machine learning models. Two commonly employed models, LSTM (Long Short-Term Memory) and Prophet, are mentioned as examples. LSTM is a recurrent neural network architecture known for its ability to capture dependencies and patterns in sequential data, making it suitable for time series forecasting tasks. Prophet is a forecasting model developed by Facebook's Core Data Science team, designed to handle time series data with multiple seasonality components.
4. Feature engineering During the model training process, relevant features are extracted or engineered from the dataset. These features may include variables such as historical sales, seasonality indicators, promotional activities, or other external factors that can impact supply chain demand. Feature engineering plays a crucial role in capturing the underlying patterns and improving the model's forecasting accuracy.
5. Model Evaluation and Selection Once the machine learning models are trained, they are evaluated using appropriate evaluation metrics such as mean squared error (MSE), root mean squared error (RMSE), or mean absolute error (MAE). The model that demonstrates the highest accuracy in predicting future statistics, such as demand requirements, is selected for further analysis and implementation.
6. Forecasting Demand Using the selected machine learning model, the supply chain demand is forecasted based on historical patterns and relevant features. The model considers factors such as previous demand records, peak demand seasons (e.g., festivals or sales), and any other relevant parameters. The goal is to provide an approximate requirement estimation that the supplier (upstream) can use to place orders in advance, minimizing demand variability and ensuring timely product availability.
7. Implementation and Application Once the forecasting model is developed and validated, it can be implemented within the supply chain operations. The model's predictions can inform decision-making processes related to inventory management, production planning, and procurement. The model's outputs enable proactive ordering, reducing the risk of stockouts and improving overall supply chain efficiency.

Approach

To address the performance bottleneck in the supply chain on the manufacturer's side, our approach focuses on two key aspects: supply chain forecasting and anomaly detection in sales and demand data. These approaches aim to enhance economic efficiency, optimize business operations, and provide insights into operating and marketing strategies.

1. Supply Chain Forecasting: In this part, we propose to work on both traditional and machine learning-based forecasting techniques. We begin by exploring various traditional forecasting methods commonly used in supply chain management. We then extend our analysis to incorporate state-of-the-art machine learning methodologies for forecasting. This comprehensive approach allows us to evaluate the strengths and limitations of different techniques and provide a comparative analysis.

   To conduct the analysis, we utilize historical data from a manufacturing company that produces a diverse range of products and distributes them to four warehouses located worldwide. The global distribution network results in significant lead times, with products taking months to reach the warehouses. Leveraging this dataset, we aim to develop forecasting models that can accurately predict future demand signals well in advance, providing valuable insights for the manufacturer.

   A precise forecast of the demand signal for the upcoming months would benefit the manufacturer, enabling them to plan production, inventory management, and distribution more effectively. The correlation between the demand signal sent to the warehouses and the average lead time, which spans several months, underscores the importance of accurately predicting future demand to mitigate the effects of the bullwhip effect and other factors impacting supply chain performance.

2. Anomaly Detection in Sales and Demand Data: In addition to supply chain forecasting, we propose the use of machine learning techniques to build an anomaly detection system for sales and demand data within the supply chain. Accurately identifying anomalies in sales provides valuable insights into the effectiveness of operating and marketing strategies employed by the company.

   Detecting negative anomalies in sales can indicate potential issues with marketing strategies, leading to a decline in sales. This signals the need to review and adjust the strategies accordingly. Conversely, detecting positive anomalies can provide opportunities for further investigation to understand the underlying reasons, leading to increased sales and the formulation of appropriate strategies for the future.

   By leveraging machine learning algorithms, we aim to develop an anomaly detection system that can analyze and identify patterns and deviations in the sales and demand data. This system will enable the company to gain insights into its operating and marketing strategies, optimize decision-making processes, and improve overall supply chain performance.

Analysis of the Dataset

- The first dataset will be collected from various archives which will be analyzed as Time-series data for forecasting and the second one will be the generated datasets for detecting an anomaly

- The training data and validation data will be prepared and data from the training set will be fed to train the models. In the training process, the number of cells, dropouts, and the learning rate of the model will be optimized.

- Comparative analysis will be performed on various models from traditional techniques like the LSTM model to the Prophet model of Forecasting and Anomaly Detection. This will help the client make decisions by providing historical trends in the company's sales data.

- Prophet provides several tools and techniques for detecting anomalies in time series data. By combining these techniques, we will develop a robust anomaly detection system that can identify and alert you to potential issues in our data.

C) Results and discussion

Exploratory data analysis-
https://colab.research.google.com/drive/1DLIqA4lQkUL_URUbZFMHqi0p4ULOBDM0?usp=sharing

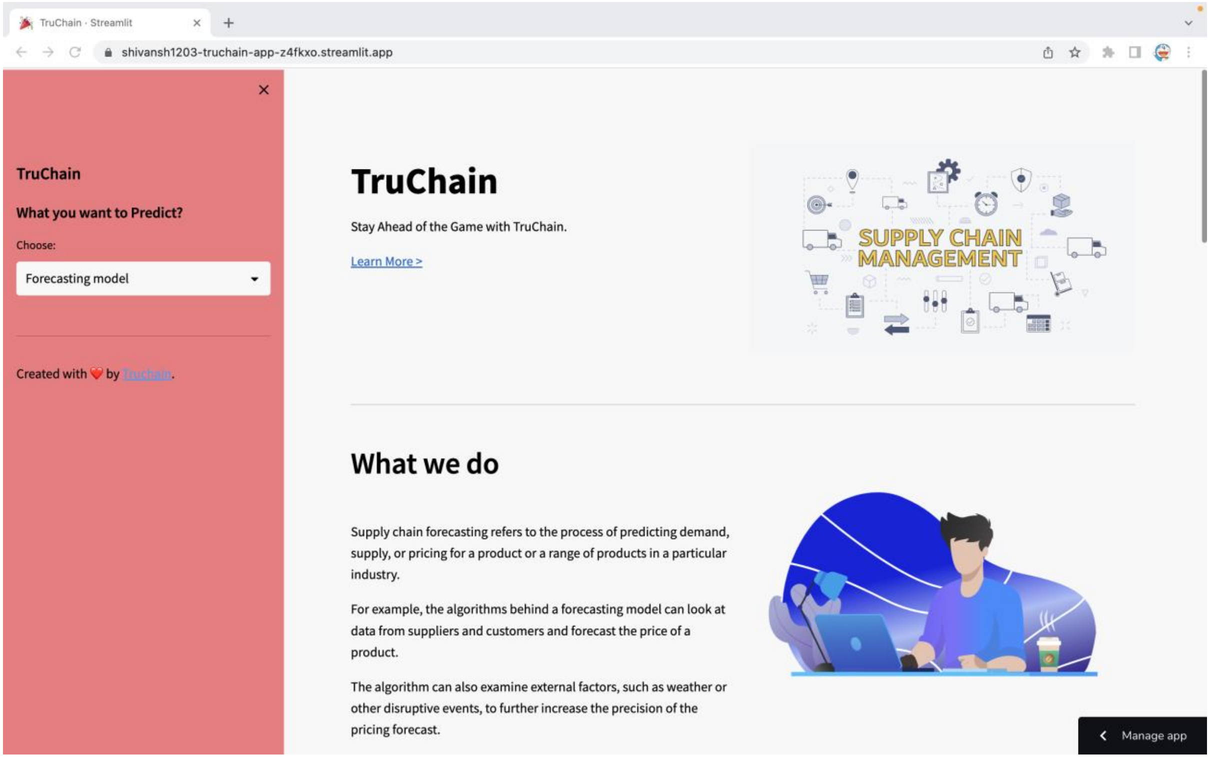
- There are a total of 4 categorical features, namely Season, is_holiday, is_weekend, and weather_code, and 7 numerical/continuous features along with 1 DateTime object, resulting in a total of 12 independent features with 10,886 rows. No missing data or duplicated rows are present in the dataset.
- The data covers a time period of almost 2 years, ranging from 1st January 2011 to 19th December 2012. During the months of September and October, the maximum number of bikes are rented. However, the bike rental count is less during the cold seasons of winter (November, December, January, and February) when people prefer not to ride bikes due to the cold.
- The month-wise bar plot shows that the demand for bikes at the beginning of the dataset is quite low compared to the months from March 2012 onwards. There's a drop in the middle of the dataset due to the cold and winter season. Outliers are present in windspeed and casual users, indicating that windspeed is not uniform, while the count of casual users varies as they are not registered and not serious about riding bikes.
- The exponential decay curve for the count (registered and non-registered users combined) indicates that as the number of users renting bikes increases, the frequency decreases. For weather_code, in the fourth category, i.e., Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog, the number of users renting bikes is much lower. Hence it's better to drop this feature while conducting further tests.
- The count of bikes rented on working days is much higher than on non-working days. During holidays, people do not prefer to ride bikes. However, when the weather_code is Clear with Few clouds, people tend to rent more bikes for their commute.

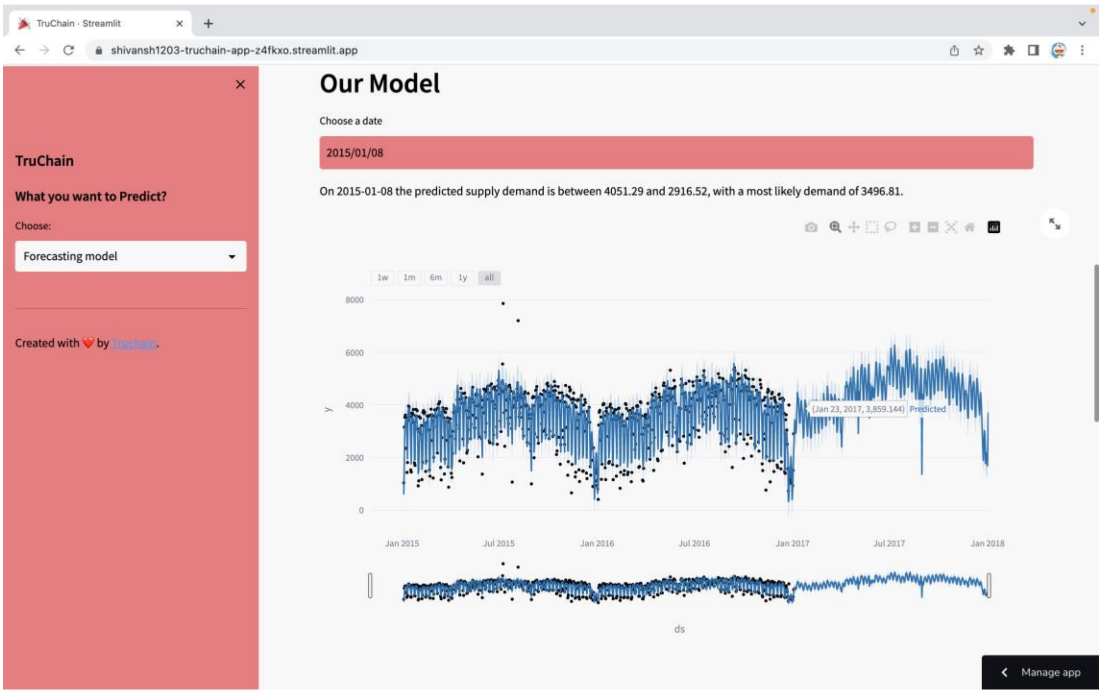
- During spring, summer, fall, and winter, the count is more or less equal for the users renting bikes. The registered user count has a higher correlation with the count as compared to the casual user count. The windspeed and season have a very low (near zero) positive correlation with the count, indicating that windspeed and season do not have a significant effect on the demand for rented bikes.
- The temperature and user-specific feeling of heat/cold have a moderate correlation (0.3) with the count. People tend to go out on bright sunny days when the temperature is normal. However, during harsh conditions such as too hot or too cold, the demand for bikes has seen a considerable dip. Casual users who rent bikes prefer to ride when the temperature is suitable.
- During holidays, the user count has seen a considerable dip, whereas, on working days, the count is normal.

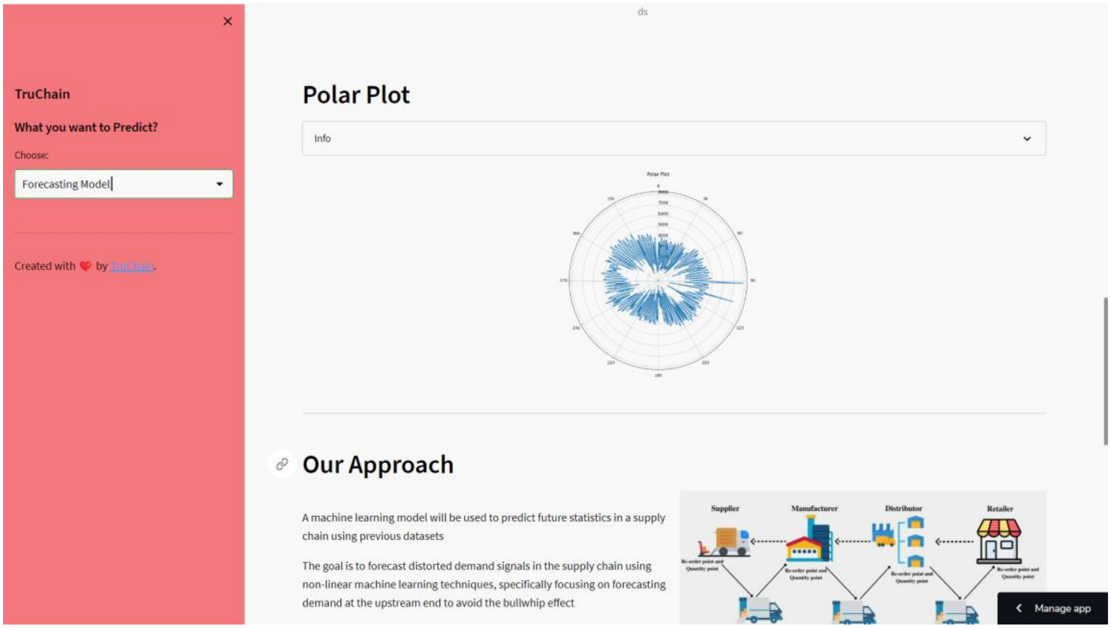
Our Model-

- Based on the EDA analysis, it can be concluded that the demand for bike rentals varies significantly based on seasonal factors such as weather, holidays, and time of year. The data contains 12 independent features and 10,886 rows, with no missing data, null values, or duplicated rows. Outliers were observed in the windspeed and casual user features, indicating that these factors do not have a uniform effect on bike rental demand.
- Prophet, a time series forecasting model, is a suitable choice for predicting bike rental demand due to its ability to capture seasonality and holidays. It also allows for the inclusion of external regressors such as weather codes and temperature. The model is based on an additive regression model with four main components: trend, seasonality, holidays, and regressors.
- Compared to a neural model like LSTM, Prophet has several advantages. First, Prophet is much easier to implement and requires minimal tuning, whereas LSTM requires complex hyperparameter tuning and model selection. Second, Prophet is faster to train and provides better interpretability of results, whereas LSTM requires a lot of computational power and can be challenging to interpret. Finally, Prophet's built-in feature selection and handling of missing values make it more suitable for time series forecasting tasks like bike rental demand prediction.
- In summary, based on the EDA analysis, the use of Prophet with seasonal regressors is justified for predicting bike rental demand. Prophet's ability to capture seasonality and holidays and handle external regressors makes it a superior choice over neural models like LSTM for this particular task.
- We have also added an Anomaly Detection feature in our dashboard to give the user a prior warning regarding sudden hikes in supply-demand needs.

UI/UX (tentative)-

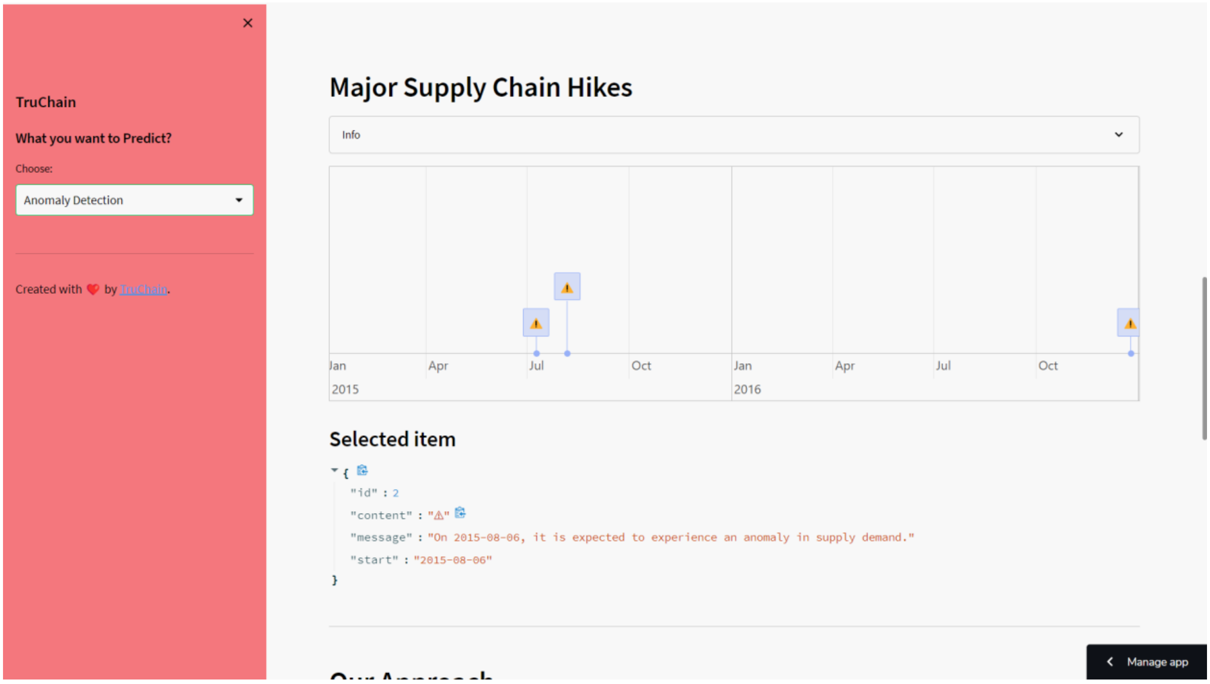






TruChain
What you want to Predict?
Choose:
Forecasting Model
Created with by TruChain.
Polar Plot
Info
Our Approach
A machine learning model will be used to predict future statistics in a supply chain using previous datasets
The goal is to forecast distorted demand signals in the supply chain using non-linear machine learning techniques, specifically focusing on forecasting demand at the upstream end to avoid the bullwhip effect
Supplier
Manufacturer
Distributor
Retailer
Manage app

TruChain
What you want to Predict?
Choose:
Anomaly Detection
Created with by TruChain.
Our Repository >
Anomaly Detection
Anomaly's
anomaly
No
Yes
Jan 2015
Jul 2015
Jan 2016
Jul 2016
Jan 2017
ds
Major Supply Chain Hikes
Info
Manage app


TruChain
What you want to Predict?
Choose:
Anomaly Detection
Created with ❤️ by TruChain.
Major Supply Chain Hikes
Info
Jan
Apr
Jul
Oct
Jan
Apr
Jul
Oct
2015
2016
Selected item
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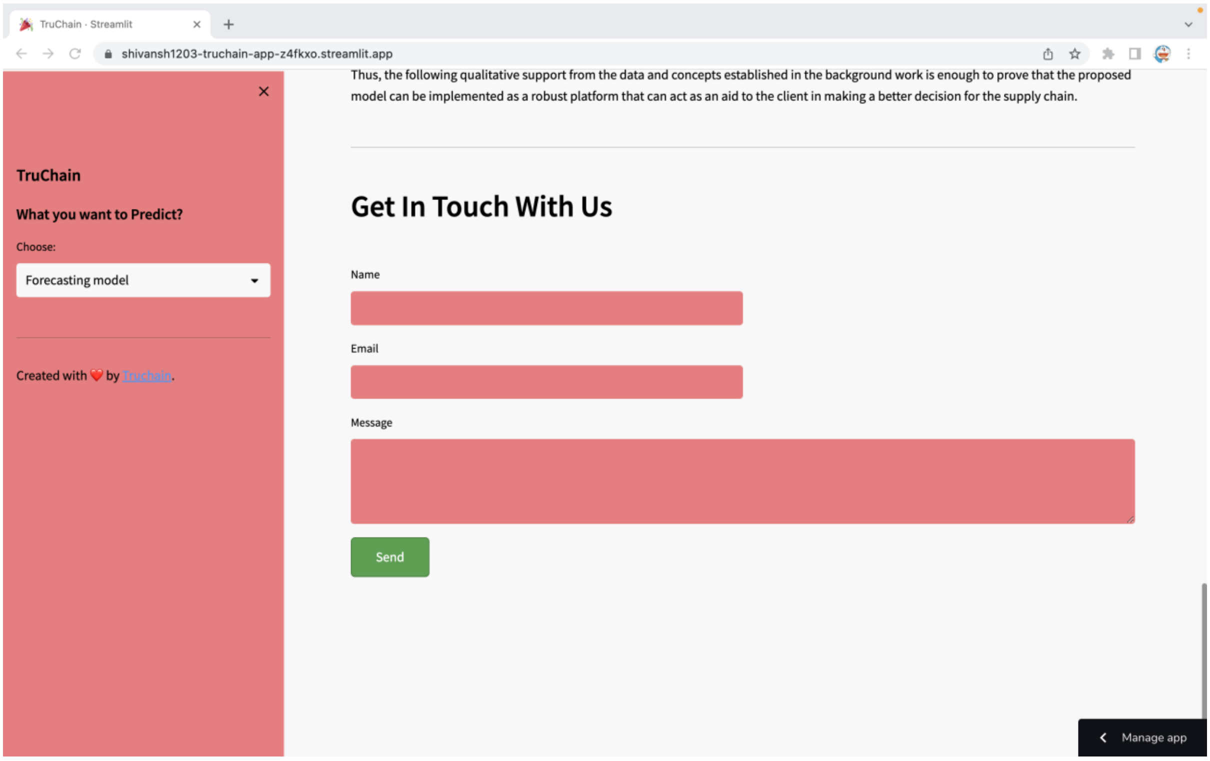
"content" : "⚠"
"message" : "On 2015-08-06, it is expected to experience an anomaly in supply demand."
"start" : "2015-08-06"
Manage app


TruChain · Streamlit
shivansh1203-truchain-app-z4fkxo.streamlit.app
Thus, the following qualitative support from the data and concepts established in the background work is enough to prove that the proposed model can be implemented as a robust platform that can act as an aid to the client in making a better decision for the supply chain.
TruChain
What you want to Predict?
Choose:
Forecasting model
Created with ❤️ by Truchain.
Get In Touch With Us
Name
Email
Message
Send
Manage app

Previous Phase Reviews

- During our previous project review with our esteemed faculty, valuable feedback was provided to enhance the overall quality and effectiveness of our project. In this section, we address the areas of improvement highlighted during the review, which include the following:

- 1- Addition of More Features: One of the key suggestions put forth by our faculty was to incorporate additional features into our project. We have taken this recommendation into careful consideration and have successfully implemented several new features like anomaly detection, polar plot, and prior warning timeline to further enhance the functionality and user experience. These additions aim to provide a wider range of capabilities, making the project more comprehensive and versatile.

- 2- Increased Research Paper References: To strengthen the academic foundation of our project, our faculty advised us to include more references to research papers. We recognize the importance of supporting our work with relevant studies and up-to-date research. In response, we have conducted an extensive literature review and have identified several scholarly articles that significantly contribute to the understanding and development of our project. By referencing these papers, we demonstrate a thorough understanding of the subject matter and acknowledge the broader scientific community's insights.

- 3- User Testing: Another crucial aspect highlighted during the project review was the need for thorough user testing. Our faculty emphasized the significance of incorporating user feedback to validate and refine our project's functionality and usability. We have taken this recommendation seriously and have conducted comprehensive user testing sessions. Through this process, we have gathered valuable insights, identified areas for improvement, and refined our project based on user preferences and requirements.

CONCLUSION

- During the course of this project, we will perform a comparative analysis of various models of forecasting, from traditional techniques like LSTM model to Prophet model, to improve accuracy and efficiency using the dataset provided by the manager based on our research for this project, which will be displayed on the web platform and android platform (Hybrid application). We will implement anomaly detection for quickly determining anomalies or unexpected patterns in sales, which will help the company gain insight into its operating and marketing strategies to make more effective decisions.

- As mentioned in the first phase of our approach, we proposed to provide a comprehensive analysis using a variety of ML techniques to highlight the importance of the featured parameters and how they can prove to be beneficial as information to the client.

- The parameters are collected from various datasets and analyzed for their feasibility in supporting the hidden trends of the data.
    - Seasonality patterns
    - Sell in / sell out

    - Bullwhip
    - The effects of an anomaly in the data.

- We have outlined the issues in the problem statement and have matched them to the concepts introduced in the various existing types of research that are mentioned in the background work section.

- Further better SC visibility can be achieved by establishing contracts between manufacturers and clients to share their sales data which will increase the quality of the data fed to the proposed model and ultimately increase the accuracy of the predictions.

- Thus, the following qualitative support from the data and concepts established in the background work is enough to prove that the proposed model can be implemented as a robust platform that can act as an aid to the client in making a better decision for the supply chain.

Team Contribution-

Akhil (20BCE10015)

- **Exploratory Data Analysis-** collaborated to perform in-depth exploratory data analysis. thoroughly examined the dataset, identified patterns, and gained insights into the underlying characteristics of the time series data..
- **Model Training-** worked to train machine learning models for time series forecasting. Employed various algorithms and techniques, fine-tuned model parameters, and evaluated model performance to achieve accurate predictions.
- **UI/UX-** focused on creating an intuitive user interface and ensuring a seamless user experience.
- Considered user requirements, designed interactive visualizations, and implemented an appealing interface for users to interact with the time series forecasting system.
- **Study of research paper-** conducted an extensive study of relevant research papers on time series forecasting.
- **System Architecture-** collaborated to design the overall system architecture

Shivansh Rastogi (20BCE11104)

- **Exploratory Data Analysis-** collaborated to perform in-depth exploratory data analysis. thoroughly examined the dataset, identifying patterns, and gained insights into the underlying characteristics of the time series data.
- Model Training- worked to train machine learning models for time series forecasting. Employed various algorithms and techniques, fine-tuned model parameters, and evaluated model performance to achieve accurate predictions.
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- Reviewed state-of-the-art techniques, identified best practices, and incorporated the latest advancements into the project.
- **System Architecture-** collaborated to design the overall system architecture.
- Defined the components, established data flow mechanisms, and ensured the system's scalability and reliability.
- **Analysis of dataset-** took the lead in analyzing the dataset.
- Performed statistical analysis, evaluated data quality, handled missing values or outliers, and prepared the dataset for training the machine learning models.

Harsh Soni (20BCE10082)

- **Exploratory Data Analysis-** collaborated to perform in-depth exploratory data analysis. thoroughly examined the dataset, identifying patterns, and gained insights into the underlying characteristics of the time series data.
- Model Training- worked to train machine learning models for time series forecasting. Employed various algorithms and techniques, fine-tuned model parameters, and evaluated model performance to achieve accurate predictions.
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Shivam Saurabh (20BCE10227)

- **Study of research paper-** conducted an extensive study of relevant research papers on time series forecasting.
- Reviewed state-of-the-art techniques, identified best practices, and incorporated the latest advancements into the project.
- **System Architecture-** collaborated to design the overall system architecture.
- Defined the components, established data flow mechanisms, and ensured the system's scalability and reliability.
- Analyzed the predictions generated by the models, assessed their accuracy, and provided an insightful discussion on the project's expected outcomes.

Gandhi Monil (20BCE10128)

- **UI/UX-** focused on creating an intuitive user interface and ensuring a seamless user experience.
- Considered user requirements, designed interactive visualizations, and implemented an appealing interface for users to interact with the time series forecasting system.
- Reviewed state-of-the-art techniques, identified best practices, and incorporated the latest advancements into the project.
- **System Architecture-** collaborated to design the overall system architecture.
- Analyzed the predictions generated by the models, assessed their accuracy, and provided an insightful discussion on the project's expected outcomes.
- **Study of research paper-** conducted an extensive study of relevant research papers on time series forecasting.

Yashi Goswami (20BOE10072)

- **Study of research paper-** conducted an extensive study of relevant research papers on time series forecasting.
- Reviewed state-of-the-art techniques, identified best practices, and incorporated the latest advancements into the project.
- Expected result and Conclusion- collaborated to draw meaningful conclusions from the project results.
- Analyzed the predictions generated by the models, assessed their accuracy, and provided an insightful discussion on the project's expected outcomes.

Narendra Kumar (20MEI10039)

- **Study of research paper-** conducted an extensive study of relevant research papers on time series forecasting.
- Reviewed state-of-the-art techniques, identified best practices, and incorporated the latest advancements into the project.
- Expected result and Conclusion- collaborated to draw meaningful conclusions from the project results.
- Analyzed the predictions generated by the models, assessed their accuracy, and provided an insightful discussion on the project's expected outcomes.

Harshvardhan Saxena (20MIM10100)

- **Study of research paper-** conducted an extensive study of relevant research papers on time series forecasting.
- Reviewed state-of-the-art techniques, identified best practices, and incorporated the latest advancements into the project.
- Expected result and Conclusion- collaborated to draw meaningful conclusions from the project results.
- Analyzed the predictions generated by the models, assessed their accuracy, and provided an insightful discussion on the project's expected outcomes.

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