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Original Article

Data Gush – Trend Analysis & Capacity Forecasting Web Traffic via Web UI Interface Using Machine Learning Platform

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Abstract *- This research investigates how Machine Learning (ML) estimating strategies can be utilized for capacity planning, particularly utilizing Prophet. The ponder investigates the challenges and openings in applying ML strategies to complex operations. We prepare and test a few AI/ML and conventional measurable models utilizing broad information. Based on this, this approach viably progresses in estimating exactness, underscoring the importance of fitting ML models for determining requests. This investigation presents an AI/ML-driven approach that rises above simple estimating, advertising a down-to-earth pathway to oversee capacity considering imperatives. This paper presents a system planned to precisely estimate future exchange activity in the budgetary segment and classify the item portfolio based on the anticipated level of determining unwavering quality. The system, useful for any company in the budgetary industry, leverages Facebook's Prophet calculation. Real-world determining benchmark information obtained tentatively in a generation environment at one of the biggest money-related companies was utilized to assess the system and highlight its adequacy in a real-world scenario.*

Keywords *- Capacity Planning & Forecasting, Machine Learning Platform, Stream lit, Automation, Prophit*.

1. Introduction

Currently, capacity forecasting is manual spreadsheet driven; with this product, it will be fully automated. Estimating server infrastructure for transaction processing is complex due to fluctuating demand and system changes. An AI/ML forecast model is proposed to address this. Problem complexity: estimating the required server infrastructure for transaction processing is challenging due to fluctuating demand, response time of third-party components, and frequent changes in application code and system architecture. The proposed solution involves developing an AI/ML forecast model that learns transaction volume trends during promotions and holidays using historical data and concurrency calculations based on third-party latency.

Generating product-level estimates is significant in the monetary industry due to the critical part stock control and generation arranging play in a company's competitiveness. Precise figures result in reserve funds, and fetch decreases by upgrading generation and stock arranging, competitive estimating, and opportune advancement arranging. Then again, destitute estimations can be expensive and lead to client dissatisfaction. The monetary industry commerce environment is profoundly energetic and unstable, driven by occasional impacts. Unlike scholastic datasets for benchmarking different time-series estimating strategies, real-world volume information in money-related industries shows challenges such as profoundly exchange preparing chronicled information, unpredictable designs, and exceedingly irregular exchange handling data. A module competent in sensibly precise estimating, combined with a module for solid classification of the item portfolio based on figure capacity, would be advantageous to any money-related company. This work centers on creating a module for solid classification of the item portfolio concurring with the anticipated level of estimating unwavering quality. The results are based on a dataset tentatively obtained in a generation environment at one of the biggest fund companies. Whereas deal figures can run from every day to yearly skylines, the center is on month-to-month and quarterly estimates, as these periods are the most noteworthy intrigue for generation and stock planning.

The structure of this paper is as follows: area Writing survey offers a common depiction of past ponders relating to the utilization of the diverse approaches and calculations in related monetary determining issues and strategies for understanding. Area Almost Capacity Arranging & Determining gives an outline of the system by briefly clarifying the structure of the input dataset, information sifting and preprocessing steps, the preparation of item portfolio

choice, the Prophet device, execution measurements and estimate capacity investigation utilizing backtesting tests, and rules for classifying the item portfolio, while area Comes about appears the capabilities of the proposed estimating system in a real-world utilize case situation. The conclusions drawn from the conclusions in terms of the proposed objective are given in segment Conclusions, with a brief portrayal of headings for future work to assist in the improvement and application of the proposed system.

2. About Capacity Planning and Forecasting

The process of estimating application capacity requires significant effort and resources when numerous applications need management with limited staff. Multiple elements add to the task's complexity, encompassing unpredictable transaction processing requirements, third-party service dependencies and regular updates to application codes or system architecture. MLP Forecasting focuses on estimating future Transaction Per Second (TPS), Daily Volumes and Infrastructure Demand, along with additional metrics, for different applications. The system implements a sophisticated machine-learning methodology that integrates multiple libraries and frameworks, including Prophet and Streamlit, among others. Managing application capacity predictions becomes highly demanding when organizations must work with multiple applications yet face restricted staff resources. These key considerations and strategies will help you handle the outlined challenges.

2.1. Automate Forecasting

Utilize Automated Tools: like Prophet, Deep AR, and Temporal Fusion Transformer can automate much of the forecasting process. Batch Processing: Implement batch processing to generate forecasts for multiple applications simultaneously.

2.1.1. Consider Transaction Variability

Fourth Seasonality and Trends: Use models that can manage seasonality (e.g., SARIMA, Prophet) to account for country-specific holidays and promotions. Exogenous Variables: Include exogenous variables (e.g., holiday calendars, sales events) in your models to improve accuracy.

2.1.2. Incorporate Response Time Variability

Dynamic Models that can dynamically adjust to changes in transaction processing capacity, such as LSTM or SARIMAX. Real-Time Data Integration integrates real-time data from third-party services to continuously update forecasts.

2.1.3. Adapt to Frequent Changes

Continuous Learning employs machine learning models that can adapt to changes in application code or system architecture (e.g., N-BEATS, Temporal Fusion Transformer). Version Control: Maintain version control of forecasting models to update and revert changes as needed easily.

2.1.4. Scalability

Cloud Infrastructure uses scalable cloud infrastructure to oversee the computational load and forecast many applications. Parallel Processing: Implement parallel processing to speed up forecast generation.

2.1.5. Staff Efficiency

User-Friendly Interfaces: develop or use user-friendly interfaces for non-technical staff to interact with the forecasting system. Training: Provide training for staff on how to interpret and use forecasts effectively.

2.2. Application Capacity Forecasting

The integration of automated forecasting tools with historical and real-time data allows you to generate precise, actionable insights that effectively resolve common questions.

- Application Operations: Can we go single DC for ‘Application X’ on October 15th, 2024? Response: Use capacity forecasts to evaluate the load on the data center and simulate a single data center scenario. Ensure the forecast accounts for peak loads and redundancy requirements.
- Release Management: Can we do an urgent release/deployment tomorrow at 3:00 PM? Response: Analyze historical data and current capacity forecasts to assess the impact of the release on system performance. Ensure there is sufficient buffer to manage any potential spike in load.
- PRE (Platform Reliability Engineering): How many servers can we take out for maintenance on October 4th, 2024? Response: Use capacity forecasts to determine the minimum number of servers required to maintain optimal performance. Determine the off-peak times that allow maintenance to take place without causing significant disruptions.
- Product Development & Business Operations: A merchant announced a promotion this weekend. Do we have sufficient capacity for headroom? Response: Forecast the expected increase in load due to the promotion using historical data from similar events. Ensure there is sufficient capacity headroom to manage the anticipated spike in transactions.
- PSO Team: We are onboarding a new load for ‘Merchant A’ next month for 60 M transactions. Do we have sufficient headroom? Response: Integrate the projected load into the capacity forecast and evaluate if the current infrastructure can oversee the additional transactions. Plan for any necessary scaling.
- Management: When should we put a hard freeze or control period? Response: Analyze capacity trends and identify periods of high activity or critical operations. Control periods during peak load times or major events are recommended to ensure system stability.
- Capacity: How much infrastructure do we need by next year? Response: Use long-term capacity forecasting

models to predict future infrastructure needs based on growth trends, upcoming projects, and expected increases in load. Submit your comprehensive infrastructure roadmap for the upcoming year.

2.3. Literature Review

A process of transaction forecasting is used to estimate future traffic. Those accurate processes help companies to prognosticate all kinds of performances and to make important business decisions. Company vaticinations can be grounded on trends in frugality, once deals data, and comparisons in assiduity. Formerly established companies can fluently prognosticate unborn deals grounded on one business data. New companies must produce their vaticinations on information, not being vindicated enough, similar to competitive intelligence and request exploration.

Deals soothsaying enables an approach into the company's pool, coffers, and cash inflow. Prophetic deals data is pivotal for businesses to get investment capital. Fiscal businesses must use their coffers in an effective way and make strategic opinions to increase their earnings and stabilize them, especially when conditions become more competitive.

2.3.1. Problem

Estimating the server infrastructure needed to sustain growth in sales processing is a homemade and innately complex task. The demand for sale processing fluctuates based on country-specific leaves, deals, and elevations offered by merchandisers specific to each country. Also, sales processing capacity is determined by the response time or quiescence of third-party factors. Likewise, staying up to date with changes in vaticinations becomes gruelling due to the frequent variations in operation law and system armature.

2.3.2. Existing Alternatives

Manual forecasting using spreadsheets.

2.3.3. Solution

To develop an AI/ML forecast model that can effectively learn trends and patterns in transaction volumes during merchant promotions and holidays, we can utilize various techniques. By leveraging historical data, the model can identify and understand the relationships between transaction volumes and specific events. Additionally, the model can incorporate concurrency calculations based on latency from third-party application components to provide more accurate forecasts for upcoming peak seasons.

To achieve this, we can use the processing capacity of each application and the server configuration, considering factors such as CPU and RAM, as input for the forecast model. This information will help the model understand the system's capabilities and constraints. By analyzing past data and considering the inputs, the model can generate forecasts for transaction volumes during peak periods.

The model output will provide insights into the required server infrastructure to support the expected growth in transaction volumes. With this information, estimating the necessary budget for purchasing the hardware becomes more straightforward and accurate.

By enforcing this AI/ML forecast model, we can optimize resource allocation, ensure scalability during peak times, and make informed decisions regarding server infrastructure, thereby effectively supporting growth in transaction volumes.

2.3.4. Uniq Value Proposition

The Unique Value Proposition of this AI/ML forecast model lies in its ability to provide accurate predictions of transaction volumes during merchant promotions and holidays, considering numerous factors such as historical data, concurrency calculations, and server configuration. Here are some key elements that make this model unique:

Accurate forecast: The model leverages advanced AI/ ML ways to dissect literal sale data, identify trends, and learn patterns. This enables it to induce largely accurate vaticinations for sale volumes during peak seasons, considering specific events similar to trafficker elevations and leaves.

Consideration of Concurrency and Quiescence: Unlike traditional soothsaying styles, this model incorporates concurrency computations grounded on quiescence from third-party operation factors. By considering the impact of concurrency on sale volumes, the vaticinations become more precise and reflective of real-world scenarios.

Optimization of server infrastructure: The model considers the processing capacity of each operation and the garçon configuration, including factors similar to CPU and RAM. Assaying these inputs and soothsaying sale volumes provides perceptivity to the needed garçon structure demanded to support the anticipated growth in deals. This optimization helps efficiently allocate coffers and ensure icing scalability during peak ages.

Cost Estimation: The model not only forecasts. The needed garçon structure also facilitates estimating the budget for copping the necessary tackle. This capability enables businesses to make informed opinions regarding tackle investments, icing that they have the right coffers to manage sales volumes during peak seasons while optimizing costs.

Overall, the Unique Value Proposition of this AI/ ML cast model lies in its capability to give accurate, data-driven prognostications for sale volumes, consider concurrency and quiescence factors, optimize garçon structure, and grease cost estimation. By using these capabilities, businesses can effectively plan and allocate coffers to support growth and meet client demands during peak ages.

2.3.5. High-Level Concept

The High-Level Concept of this AI/ML forecast model is to leverage advanced machine learning ways to directly prognosticate sale volumes during trafficker elevations and leaves. The model considers several factors similar to literal data, concurrency computations, and garçon configuration to induce precise vaticinations.

By assaying patterns and trends in sale volumes, the model can give perceptivity to the needed garçon structure and estimate the budget for the copping tackle. The overarching thing is to optimize resource allocation, ensure scalability during peak ages, and make informed opinions regarding garçon structure to support sales growth.

2.3.6. Unfair Advantage

The "Unfair Advantage" represents a particular capability or asset that allows a business or product to stand out from competitors while providing substantial market superiority. The AI/ML forecast model achieves its Unfair Advantage through unique features that create a superior product that competitors find hard to copy. Here are some examples:

Advanced Algorithm and Data Analysis: The model implements specialized proprietary or cutting-edge algorithms developed uniquely to forecast transaction volume accurately. The model's advanced algorithms deliver better insights and predictions than typical forecasting methods competitors use. Rich and Diverse Data Sources: The model has access to a wide variety of data sources, which encompass historical transaction data, merchant promotions with holiday schedules, metrics from third-party applications and server configuration details. The comprehensive dataset gives a competitive edge because it allows the model to detect intricate patterns and associations.

Integration and Scalability: The model provides easy integration with current systems and infrastructure, facilitating smooth deployment and scalable application across various business settings. Businesses experience minimal operational disruption while they rapidly implement and gain advantages from the forecast model.

Continuous Learning and Improvement: The model incorporates an internal system that enables ongoing learning and development, which allows it to update its forecasting skills using live data and feedback. The model remains current with evolving market conditions, and this capability boosts its accuracy and reliability.

Industry Expertise and Insights: The organization that developed the model holds extensive domain knowledge and understands transaction processing, merchant promotions, and holiday patterns. Their deep industry knowledge enables them to build systems that capture industry-specific details to create precise and relevant forecasts.

A range of unfair advantages enables this AI/ML forecast model to stand out from its competitors while offering businesses improved performance and value for their server infrastructure and transaction processing optimization needs.

2.3.7. Revenue Structure

Minimizing inventory cost with more accurate planning Infrastructure expenses decrease through better allocation of server resources.

The Prophet algorithm proves to be an essential forecasting tool in the financial sector because of multiple strong advantages.

- Accurate and Fast: Prophet achieves precise forecasting results while maintaining speed, which makes it ideal for real-time use in dynamic scenarios.
- Open Source: Open-source software guarantees transparency while benefiting from community support and ongoing enhancements. Users benefit from zero licensing charges when using the Prophet algorithm.
- Fully Automatic: Prophet requires minimal input from users to operate effectively, which makes it accessible to individuals who lack specialized time-series analysis knowledge.
- Tunable Forecasts: Prophet functions perfectly in its default state but provides extensive customization options that help users adjust the model according to their data needs and requirements.
- Availability in R and Python: Data scientists can easily incorporate Prophet into their systems since it exists in both R and Python, which are two dominant languages in the field. The features of Prophet establish it as the ideal tool for producing reliable and prompt forecasts in financial applications.

3. Solution for Transaction Forecasting

ML Model can learn trends and patterns from time series data and identify patterns of load fluctuations. Analyze “what if” scenarios such as the increase in Fraud transactions from the current 16% to 40% Or the increase in response time from “Transaction B” from the current average of 700 MS to 900 MS. Forecast of infrastructure demand(servers/VMs). Determine available capacity headroom for any day. Derive new control Periods or hard freeze windows. Produce forecast for a substantial number of applications.

3.1. Solution Approach for Machine Learning Forecasting

- Prophet is a procedure for soothsaying time series data grounded on a cumulative model where non-linear trends fit with monthly,
- weekly, and diurnal seasonality, plus vacation goods
- Works best with time series with strong seasonal goods and several seasons of literal data.
- Prophet is robust in terms of missing data and shifts in trends and generally manages outliers well.
- Customizable with “model tunable” parameters

3.2. Model Summary

- Attributes – Historical Transaction Volume of Application X– last 3 years
- Source of data – Grafana, Hadoop
- Modeling Technique – Time Series Forecasting
- Algorithm Used – Prophet Algorithm (Forecasting Algo)
- Programming Language – Python 3
- Environment – Jupiter (Installed in ddcls05 cluster, POC Environment)

3.3. Benefits of Using Machine Learning for Capacity Forecasting

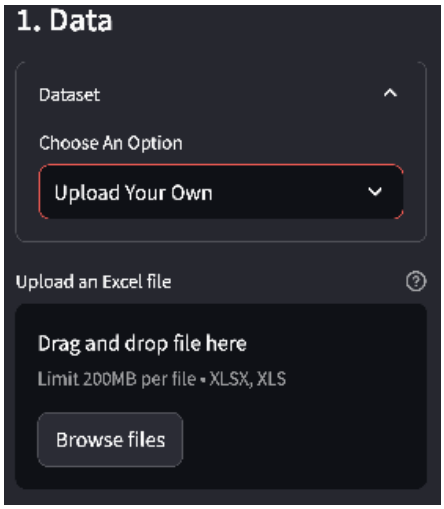
- Automation: Enables quick and efficient capacity forecasts without manual intervention.
- Pattern Recognition: Learns trends and patterns associated with holidays, weekdays, and weekends, providing accurate predictions.
- Dynamic Analysis: Capable of performing rapid analysis of processing capacity changes with varying transaction response times and workload distributions.
- Infrastructure Demand Forecasting: Predicts future infrastructure needs, such as servers or VMs.
- Capacity Headroom: Provides insights into available capacity headroom for any specific day.
- Traffic Pattern Insights: Helps determine control periods or hard freeze periods based on observed traffic patterns during promotions or holidays.

4. Producing Forecast

The application is called “Data Gush,” where “Data” refers to the information that the application is handling, processing and visualizing, and “Gush,” which means a sudden and copious flow, symbolizes how our application can handle large amounts of data quickly, and further how it can provide many insights from the data.
In the sidebar, there are several sections:

4.1. Data

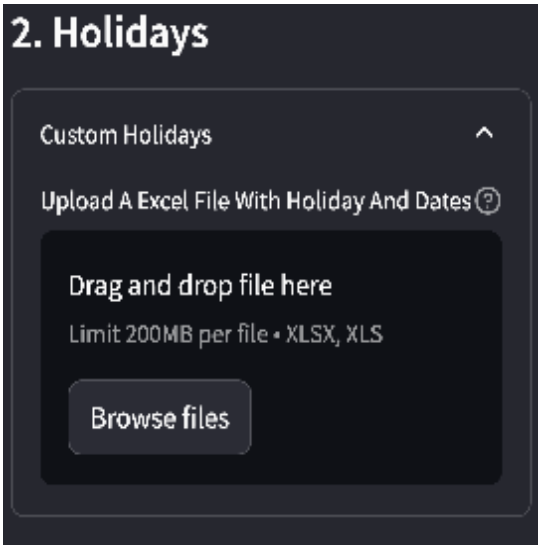
- You can choose to forecast from preloaded data or upload your data by choosing the corresponding option from the "Dataset" dropdown.
- If you choose “Upload Your Own,” you will be prompted to select a file of type xlsx or xls from your computer. After uploading, in the "Columns" section of the sidebar, you will be asked to specify which column name in your spreadsheet corresponds to certain values. With this option, you must ensure your file has the following 2 columns:
- ds: date, given as timestamps. For ex.: “year/month/day hr:min:sec” (2020/01/01 00:00:00).
- y: the data for which you are forecasting. For example, this might be max transactions per second per hour.
- If you choose “Use Preloaded Data,” select an application to generate the forecast from the “Select an Option” dropdown.



4.2. Holidays

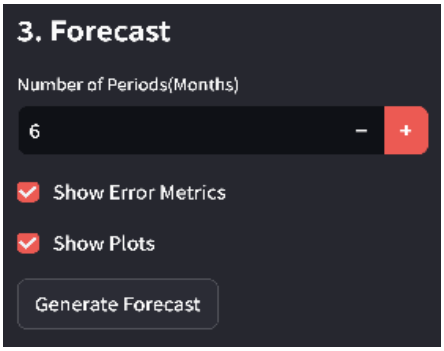
We use holidays to specify which dates may be especially significant in capturing trends. If you do not upload your own holiday data, default holidays will be used. Otherwise, under “Custom Holidays,” select an xlsx or xls file from your computer, which includes the following four columns:

- Holiday: the name of the holiday.
- ds: The date of the holiday is given as a timestamp. For ex.: “year/month/day hr: min:sec” (2019/11/29 00:00:00).
- Optional: lower window: extend the holiday back into the past. Ex. To include Christmas Eve in addition to Christmas, the lower window for that row would be -1.
- Optional: upper window: extend the holiday into the future. Ex. To include Black Friday in addition to Thanksgiving, the upper window for that row would be one.
- Note that you must include all occurrences of the holiday, both back into the past (until the earliest date your data includes) and into the future (until the latest date you want to forecast



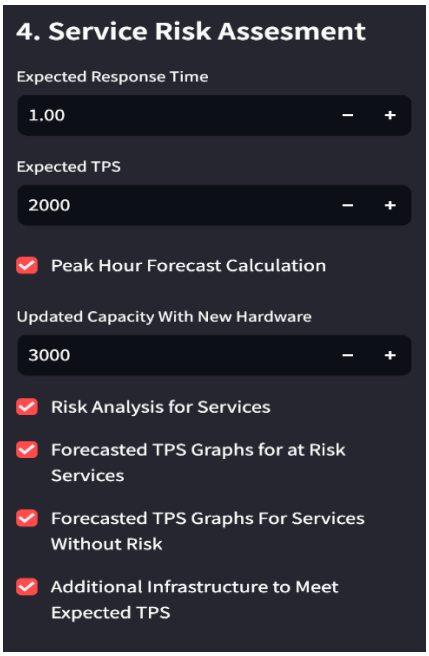
4.3. Forecast

- The number of Periods (Months) determines how far into the future you want the forecast to go. For example, if you want to see the prediction for 6 months into the future, you will increment this value to 6.
- The "Show Error Metrics" checkbox will report the accuracy of the forecast if selected.
- Hit the "Generate Forecast" button to see the results.
- If you select "Upload Your Own," it will take around 45 minutes to an hour to produce a forecast, depending on how much data you are forecasting. However, it takes a few seconds if you choose "Use Preloaded Data".
- After the forecast is produced, you will first see the forecasted values in spreadsheet format in the main area. The column "yhat" shows the forecasted value for each timestamp, and there are also columns for components and uncertainty intervals. You can download the data as a .csv file by hovering over the data and clicking the download icon from above the top right corner of the box.
- Below that is an interactive graph of the data and the forecast. You can full screen it, zoom in on certain sections, and more using the controls in the top right corner, as well as hovering your mouse over the graph.
- Next, the forecast is broken down into components and visualized in terms of the trend: holidays, weekly, yearly, and daily.
- After that is an Hourly Volume Forecast graph, which also includes the upper bound of the forecast. This is an interactive graph as well.



4.4. Service Risk Assessment

- If you choose "Use Preloaded Data" in step (1), the sidebar will show this section after generating a forecast.
- Here, you can modify the expected response time and expected Transactions-Per-Second (TPS).
- The "Updated Capacity with New Hardware" box determines if/how many breaches will occur with a new, hypothetical capacity that you input.
- The remaining checkboxes allow you to customize which aspects of the risk assessment you would like to see. They start out automatically checked.
- The graphs displayed in this section are also interactive.



5. Conclusion

Multi-Layer Perceptron (MLP) Forecasting delivers precise predictions about application Transactions Per Second (TPS) through its advanced methodology. The ability to predict resource requirements plays a critical role in optimizing how resources are allocated while improving total system performance. Organizations that anticipate future demand can actively manage their infrastructure resources and prevent the problems caused by both resource over-provisioning and under-provisioning. Advanced tools like Prophet and Streamlit enhance the functionality of MLP when integrated together.

The forecasting tool Prophet, developed by Facebook, offers exceptional performance for time series data analysis when dealing with strong seasonal patterns and incomplete datasets. The forecasting system gains enhanced robustness and reliability in complex scenarios through the integration of Prophet with the MLP framework. The system benefits from Streamlit by delivering an intuitive platform that enables effective visualization and user interaction. The interface enables users to effortlessly analyze forecast data, which leads to actionable insights and better decision-making. Streamlit's interactive dashboards and real-time visualizations give stakeholders fast access to precise forecasting results that support prompt strategic decisions.

The integration of these tools produces a more detailed and effective strategy for Capacity Planning. IT departments can forecast future workloads and modify their capacity plans based on precise TPS forecasts. This maintains application performance at its best and ensures user satisfaction by making sure all necessary computational resources are ready to manage incoming traffic. The combined use of MLP

Forecasting with Prophet and Streamlit creates a strong system for predicting the application of TPS. Efficient resource allocation benefits from this system, while system performance improves because applications prepare adequately for future demands. The forecasting system generates essential insights that support Capacity Planning by enabling organizations to preempt potential performance bottlenecks, which helps maintain uninterrupted operations. Data-driven business strategies make it essential to maintain precise forecasting capabilities alongside efficient resource management. The integration of predictive analytics with resource optimization marks a major development in IT infrastructure adaptability and resilience.

Author Literature

- https://arxiv.org/ftp/arxiv/papers/2TOOLS005/2005.07575.pdf
- https://digitalsc.mit.edu/wp-content/uploads/2024/02/Americold-ColdChain-S_OP.pdf
- https://www.researchgate.net/publication/341071241_Application_of_Facebook's_Prophet_Algorithm_for_Successful_Sales_Forecasting_Based_on_Real-world_Data
- https://www.researchgate.net/publication/376596105_Time-series_Forecasting_of_Web_Traffic_Using_Prophet_Machine_Learning_Model

References

[1] Emir Zunic et al., "Application of Facebook's Prophet Algorithm for Successful Sales Forecasting Based on Real-world Data," *International Journal of Computer Science and Information Technology*, vol. 12, no. 2, pp. 23-36, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] Ilya Jackson et al., "Revolutionize Cold Chain: An AI/ML Driven Approach to Overcome Capacity Shortages," *International Journal of Production Research*, vol. 63, no. 6, pp. 2190-2212, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[3] Rejwan Bin Sulaiman et al., "Time-Series Forecasting of Web Traffic Using Prophet Machine Learning Model," *FMDB Transactions on Sustainable Computer Letters*, vol. 1, no. 3, pp. 161-177, 2023. [Google Scholar] [Publisher Link]

[4] Emily Barnes, and James Hutson, "Developing Empathetic AI: Exploring the Potential of Artificial Intelligence to Understand and Simulate Family Dynamics and Cultural Identity," *DS Journal of Artificial Intelligence and Robotics*, vol. 2, no. 3, pp. 1-24, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] P. Rajadurai, "Machine Learning-based Secure Cloud-IoT Monitoring System for Wireless Communications," *DS Journal of Artificial Intelligence and Robotics*, vol. 1, no. 1, pp. 37-43, 2023. [CrossRef] [Google Scholar] [Publisher Link]