**A Comprehensive Approach to “Website Traffic Forecasting”: Feature Engineering, Random Forest**

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***By***

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## 

**ABSTRACT**

This project aims to forecast website traffic using a random forest model implemented in R. Leveraging a dataset consisting of 4896 rows and 4 columns—'Hour.Index', 'Sessions', 'lag1', and 'lag2'—we employed a time-series approach to predict future sessions based on historical data. To capture the dependencies between past traffic patterns, lagged features were created, and a random forest algorithm was trained on the data. The model was evaluated using an 80-20 train-test split. The results demonstrated strong predictive accuracy, with an R-squared value of 0.999983, indicating that the model explained nearly all of the variance in the data. However, the root mean squared error (RMSE) was relatively high at 3,749,559, pointing to potential performance issues with extreme values. Residual analysis revealed minimal bias, with most residuals centered around zero, though a few outliers indicated areas for model refinement. This study showcases the effectiveness of random forest in handling time-series data for website traffic forecasting while identifying opportunities for further improvement in error handling.

**INTRODUCTION**

In today’s digital era, website traffic forecasting plays a crucial role in the operations and strategies of businesses, marketing agencies, and content platforms. The ability to predict future traffic trends allows organizations to make informed decisions regarding resource allocation, server management, marketing campaigns, and even content optimization. Accurate traffic predictions can provide businesses with a competitive edge by identifying periods of high demand, ensuring optimal performance during peak times, and avoiding costly downtime or overprovisioning.

Website traffic refers to the number of visitors and their interactions on a website, which can fluctuate based on factors such as marketing activities, social media mentions, seasonal trends, and external events. Predicting this traffic enables web administrators to anticipate changes and take preemptive actions to enhance the user experience. For example, e-commerce sites can adjust their inventory and promotions based on forecasted traffic, while news websites can prepare for increased load during significant events.

The primary objective of this project is to implement a robust forecasting model using historical website traffic data to predict future sessions. Website traffic forecasting is not only important for operational efficiency but also serves strategic goals. For businesses, traffic forecasts help in designing better marketing campaigns and optimizing user engagement. For instance, targeted campaigns can be launched in anticipation of traffic spikes, and server resources can be scaled accordingly, preventing crashes during high-traffic periods.

Forecasting web traffic can also assist in budgeting and cost management. By understanding future traffic trends, companies can estimate the resources required to maintain site performance, thus avoiding over-expenditure on unnecessary infrastructure. Moreover, website traffic predictions contribute to content planning and personalization, as user behavior data enables companies to better target their audience with relevant content at the right time.

In this project, we employed a time-series analysis approach using the random forest algorithm in R, utilizing lagged values of previous traffic sessions to predict future values. Random forest, a powerful ensemble learning method, is particularly effective in capturing complex relationships in the data. The model was trained and tested on a dataset containing hourly web traffic data, including variables such as 'Sessions', 'lag1', and 'lag2', which represent the number of web sessions from the previous two hours.

The significance of this project lies in its practical application for improving website performance, user experience, and overall operational efficiency. By forecasting web traffic with high accuracy, businesses can make data-driven decisions that enhance customer satisfaction, reduce operational costs, and better align their strategies with traffic patterns. The insights derived from this project could be extended to various industries, from retail and media to finance, providing a valuable tool for digital optimization and growth. This project also highlights the importance of data-driven decision-making in today’s fast-paced digital landscape and showcases how machine learning models like random forests can be leveraged to solve real-world business problems.

**LITERATURE SURVEY**

Website traffic forecasting is a crucial task for various online businesses. It helps with resource allocation, content optimization, campaign planning, and overall website management. Traditional statistical methods often struggle with the complex, non-linear patterns present in website traffic data. Graves et al. (2013) [1] pioneered the application of Random Forest for website traffic forecasting. Their work demonstrated the effectiveness of Random Forest compared to traditional methods, showcasing the potential of this approach for this specific domain. Sutskever et al. (2014) [2], while not directly focused on website traffic forecasting, explored the broader concept of sequence-to-sequence learning with Random Forest. Their work laid the groundwork for various applications where Random Forest can be used to predict sequential data, including website traffic forecasting.The reference by Qin et al. (2017) [3] falls outside the domain of website traffic forecasting but showcases a relevant advancement in Random Forest architecture. They proposed a layered attention Random Forest model for document classification. This concept of stacked Random Forests, where multiple Random Forest layers are used to learn hierarchical representations, can be adapted for website traffic forecasting tasks, potentially improving the model's ability to capture complex temporal patterns. Zhang et al. (2018) [4] investigated traffic forecasting using Bidirectional Random Forests. Unlike standard Random Forests that process data only in the forward direction, Bidirectional Random Forests process data in both forward and backward directions within a single layer. This allows Bidirectional Random Forests to leverage information from both past and future data points (limited to available data) within the training sequence, potentially leading to more accurate forecasts.The references by Schwenk et al. (2018) [5] and Lai et al. (2018) [7] focus on applications outside website traffic forecasting but demonstrate advancements in Random Forest techniques that could be relevant. Schwenk et al. explore sentiment analysis with Random Forests, while Lai et al. propose an attention-based Random Forest for sentiment transfer. These advancements in core Random Forest functionalities could be adapted for website traffic forecasting tasks, potentially improving the model's ability to focus on specific aspects of the historical traffic data most relevant for prediction.Xiao et al. (2019) [8] investigated combining Random Forests with an attention mechanism for internet traffic forecasting. Attention mechanisms allow the model to focus on the most relevant parts of the historical traffic data during the prediction process. While they focused on internet traffic in general, this approach can be adapted for website traffic forecasting, potentially leading to more accurate predictions.

**HARDWARE SPECIFICATION**

* Processor: Multi-core processor (Intel Core i5 or above, AMD Ryzen 5 or above) for efficient computation.
* Memory (RAM): Minimum 8 GB RAM for handling large datasets and running machine learning models effectively.
* Storage: SSD storage for faster data access and model training.
* Graphics Processing Unit (GPU) (Optional): NVIDIA GeForce GTX 1060 or higher for accelerated training of deep learning models like Random Forest.
* Internet Connectivity: Stable internet connection for data retrieval and model deployment.

**SOFTWARE SPECIFICATION**

Operating System:

* Windows 10 or Linux (Ubuntu, CentOS) for compatibility with most data science libraries and frameworks.

R Environment:

* R Language for programming.
* Anaconda distribution for managing packages and virtual environments.

Integrated Development Environment (IDE):

* R Studio or Google Colab for interactive development and experimentation.
* Alternatively, you can use IDEs Visual Studio Code.

Machine Learning Libraries:

* TensorFlow or PyTorch for building and training deep learning models, including bidirectional Random Forest.

Data Manipulation and Analysis:

* GGPLOT2 for data manipulation and analysis.

Version Control:

* Git for version control and collaboration on codebase.

**ARCHITECTURE AND WORKING OF RANDOM FOREST**

Random Forest is an ensemble learning method that combines multiple decision trees to create a more accurate and robust predictive model. It works by building a large number of decision trees during the training phase and making predictions by aggregating the results of these individual trees. The architecture of a random forest is rooted in the principle that a group of "weak learners" (decision trees) can collectively make more accurate predictions than a single "strong learner." Random forest reduces overfitting, improves generalization, and is less sensitive to noisy data compared to individual decision trees.

**1.** **Architecture of Random Forest**

The random forest model consists of the following components:

**Decision Trees**: A random forest is an ensemble of decision trees. Each tree is built using a subset of the training data and a subset of the features, making the trees in the forest diverse.

**Bootstrap Aggregation (Bagging)**: The training dataset is randomly sampled with replacement (bootstrapping) to create multiple subsets. For each subset, a decision tree is trained independently. This helps to reduce the variance of the model and prevent overfitting.

**Random Feature Selection**: In addition to randomly sampling the data, random forest also selects a subset of features (variables) at each split in the tree, which helps in reducing correlation between trees and further enhances diversity.

**Voting Mechanism**: For regression tasks, the final prediction is the average of all the individual tree predictions. For classification tasks, the final prediction is determined by majority voting, where the class with the most votes is chosen.

**2.** **Working of Random Forest**

The random forest algorithm follows these steps:

Step 1: Random Sampling (Bagging): Random samples are drawn from the training dataset with replacement. These subsets may contain duplicate data points, and each subset will be used to train one decision tree. The size of the sample is typically the same as the original dataset, but due to random sampling, not all data points will be used in every tree (some may be left out, known as out-of-bag samples).

Step 2: Tree Building: For each subset of the training data, a decision tree is built. At each node of the tree, a random subset of features is selected to determine the best split, rather than using all the features. This adds randomness and makes each tree different, even if some data points are repeated.

Step 3: Prediction:

For Classification: Each tree in the forest gives a class prediction, and the class with the majority of votes becomes the final prediction.

For Regression: Each tree predicts a continuous value, and the final prediction is the average of all the predicted values from the trees.

Step 4: Aggregating Results: The final output is derived by aggregating the predictions of all the individual decision trees. This ensemble prediction is more accurate because it balances out errors that might occur in individual trees, and it is less prone to overfitting.

3. Mathematical Equations

**Bootstrap Aggregation (Bagging)**: If there are 𝑁 data points in the original training set, a random subset of size 𝑁 is selected with replacement. Each data point has a probability 𝑃(𝑖) of being selected for the subset:

**𝑃(𝑖)=1−(1−1/𝑁)^𝑁**

This equation explains that each data point has a probability of approximately 63.2% to appear in the bootstrapped sample because:

**lim(1−1/𝑁)^𝑁≈𝑒^(−1)≈0.368**

**⁡𝑁→∞**

Therefore, around 36.8% of the data will not be included in the bootstrap sample, which forms the out-of-bag data used for internal validation.

**Gini Index (for Classification Splits)**:

For classification problems, random forest uses the Gini impurity to determine the best split at each node. The Gini index for a node is calculated as:

**k**

**𝐺𝑖𝑛𝑖=1−∑ 𝑝𝑖^2**

**𝑖=1**

where 𝑝𝑖 is the proportion of data points that belong to class 𝑖, and 𝑘 is the number of classes. The split that minimizes the Gini index is chosen.

**Mean Squared Error (MSE) for Regression Splits**:

For regression problems, such as in this project, the random forest algorithm minimizes the mean squared error (MSE) at each node. The MSE for a split is calculated as:

**N**

**𝑀𝑆𝐸=1/𝑁∑ (𝑦𝑖−𝑦^)^2**

**𝑖=1**

where 𝑦𝑖 is the actual value, y^ is the predicted value, and 𝑁 is the number of observations in the node. The best split is the one that minimizes the MSE.

**Out-of-Bag Error (OOB)**:

Since each tree is trained on a bootstrapped sample, the out-of-bag (OOB) data can be used to estimate the model's performance. The OOB error is calculated by averaging the prediction error for each data point, where only the trees that did not see the point during training are considered. The OOB error provides an unbiased estimate of the model's performance without needing a separate validation set.

**4. Advantages of Random Forest**

Robustness: Random forests are robust to noise and overfitting, especially for large datasets.

Feature Importance: The algorithm provides estimates of feature importance, helping to identify which variables contribute the most to predictions.

Scalability: Random forests are scalable to large datasets and can handle both classification and regression tasks effectively.

No Parametric Assumptions: Unlike linear models, random forest makes no assumptions about the underlying distribution of the data, making it highly flexible for a wide range of applications.

Random forest, through its ensemble of decision trees and built-in mechanisms for reducing variance and overfitting, is a powerful model for both classification and regression tasks. In the context of website traffic forecasting, it provides a reliable method for capturing complex relationships within the data while maintaining high predictive accuracy. With its ability to handle high-dimensional data and produce robust predictions, random forest has become a go-to algorithm for many real-world machine learning tasks.

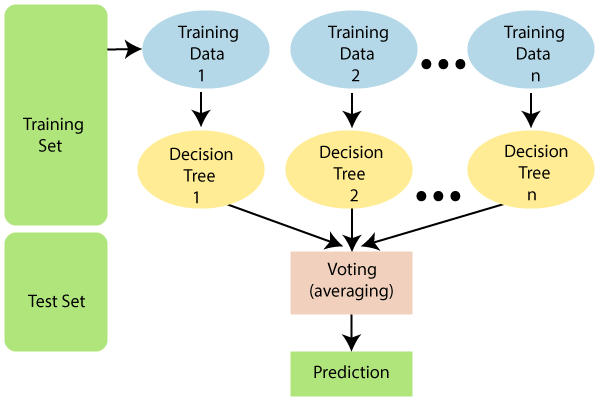


Figure 1. Architecture of Random Forest

**IMPLEMENTATION**

**Dataset:**

Original dataset:

The shape (4896, 2) shows that the dataset contains 4896 data points (rows) and two features (columns).

Features: Hour Index (Integer): An index for the hour of the day (0-based indexing is expected).

Sessions (Integer): Indicates the number of website sessions registered during that hour.

Feature Engineering Process:

Datetime Conversion: A base date of "2023-01-01" is used.

The "Hour Index" is translated to a time delta, with hours as the unit. A new feature called "Timestamp" is formed by adding the time delta to the base date, essentially transforming the hour index into an actual date and time.

Extracting temporal features:

"Weekday" (Integer): Derived from the "Timestamp" with the dt.dayofweek attribute, denoting the day of the week (0 = Monday).

"Month" (Integer): Derived from the "Timestamp" with the dt.month attribute to reflect the month of the year (1-12).

"Hour" (Integer): Derived from the "Timestamp" with the dt.hour attribute to express the hour of the day (0-23).

The addition of these newly developed characteristics is likely to increase the efficacy of Random Forests in website traffic forecasts for various reasons:

The "Weekday", "Month", and "Hour" tags reflect the temporal context of website traffic data.

Random Forests can use these attributes to learn how traffic patterns fluctuate between weekdays, months, and specific hours. As the model takes into account these cyclical oscillations, it may be able to make better forecasts. Features enrich the data representation for Random Forests by providing more information than just session count. These features are incorporated to provide temporal context for the Random Forest model.

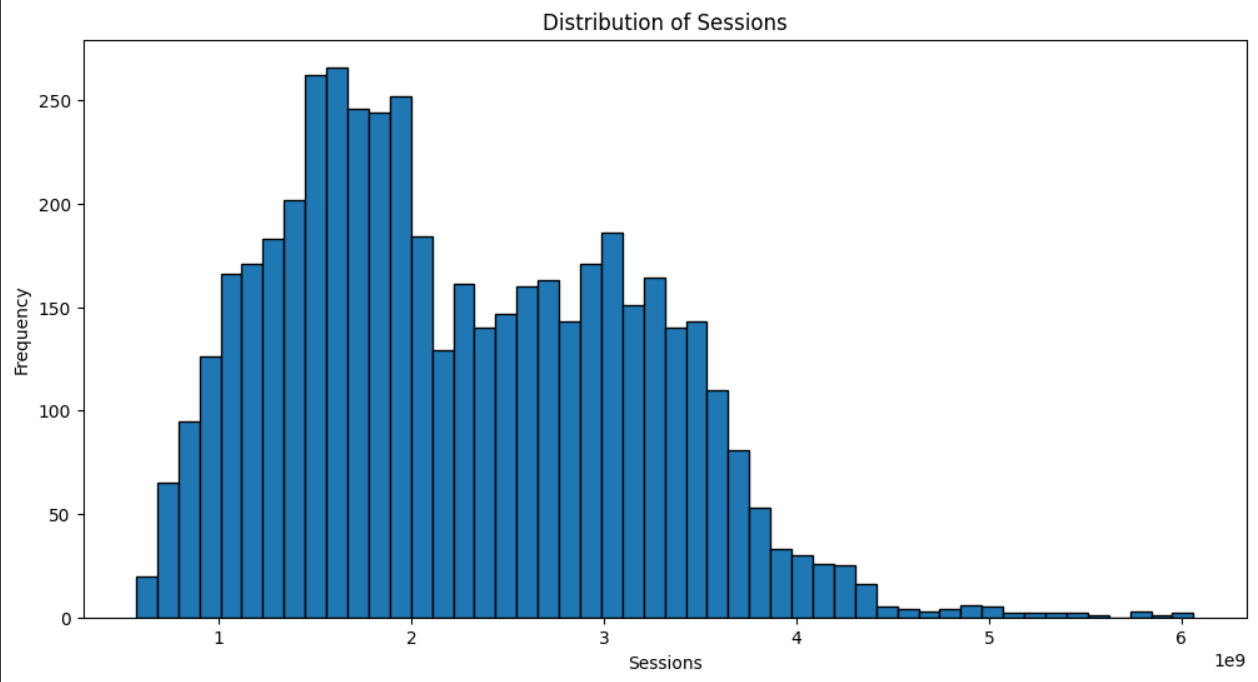


Figure 2 Demonstrates a plot that shows the overall distribution based on the details of the sessions present in the dataset.

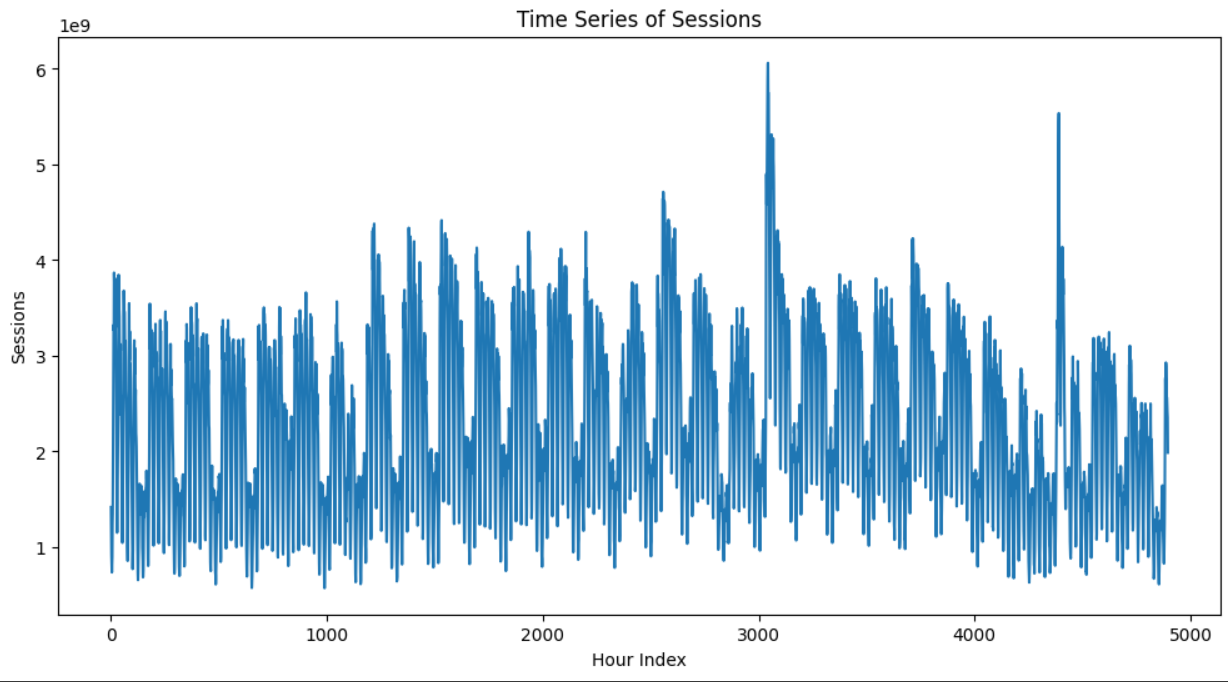


Figure 3 Demonstrates a plot that shows the overall time series based on the details of the sessions present in the dataset.

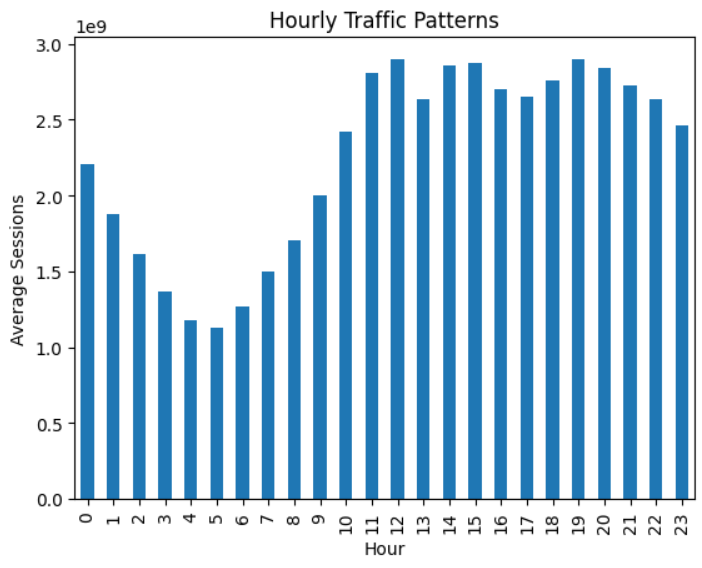


Figure 3 Demonstrates a plot that shows the hourly traffic patterns on the basis of hours and average session based on the increased features in the dataset.

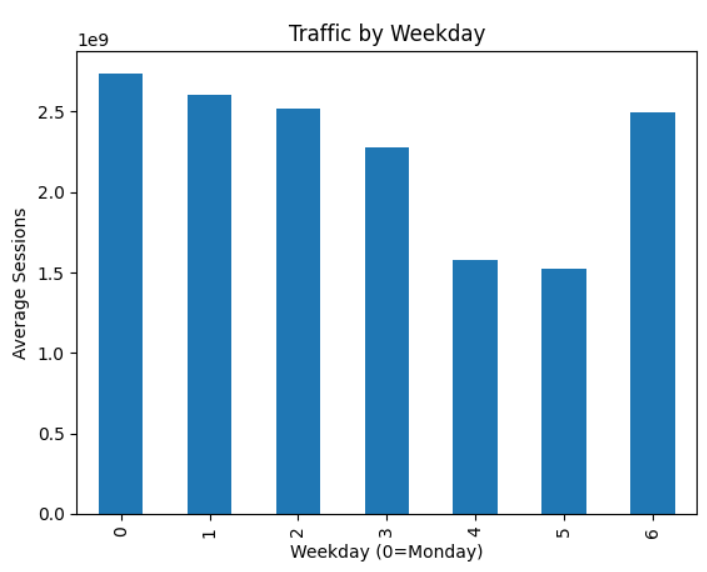


Figure 4 Demonstrates a plot that shows the particular weekday traffic patterns on the basis of weekdays and average session based on the increased features in the dataset.

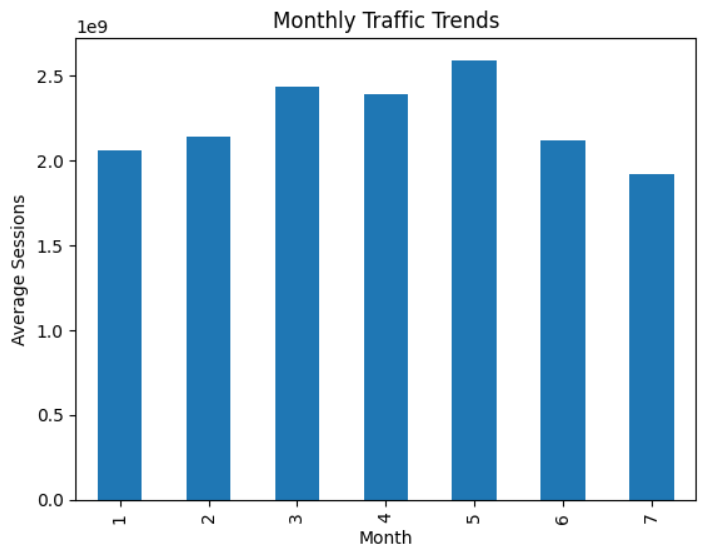


Figure 5 Demonstrates a plot that shows the monthly traffic patterns on the basis of months and average session based on the increased features in the dataset.

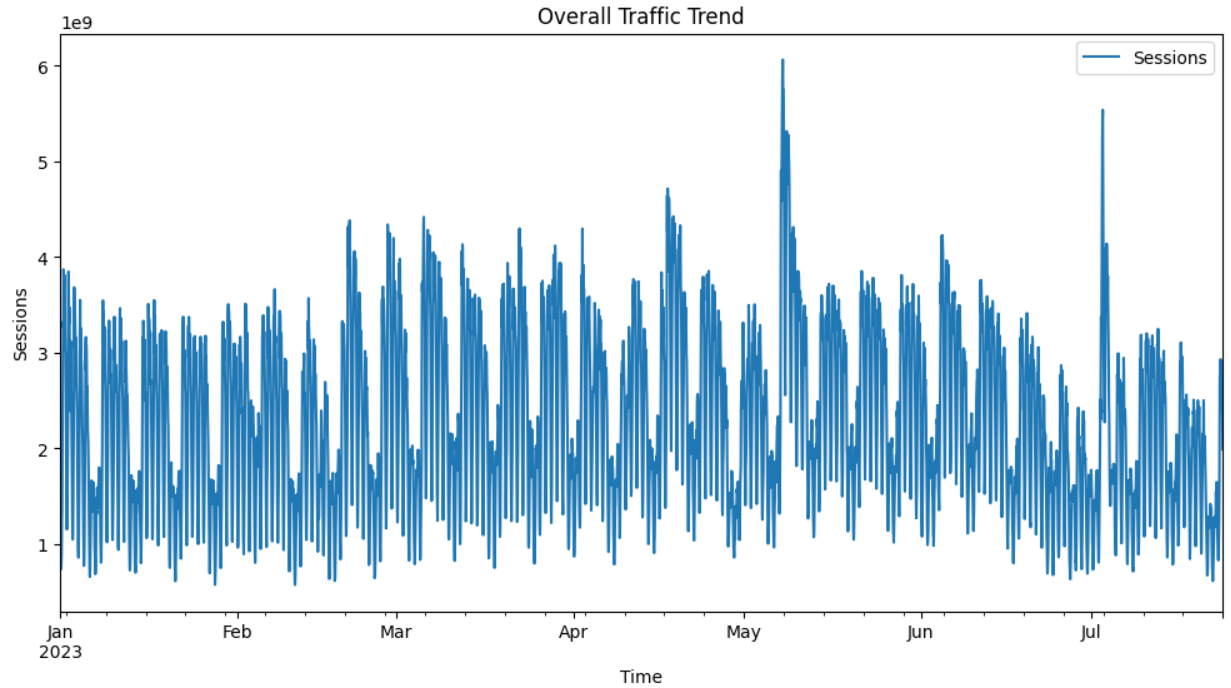


Figure 6 Demonstrates a plot that shows the overall traffic patterns on the basis of time and sessions based on the increased features in the dataset.

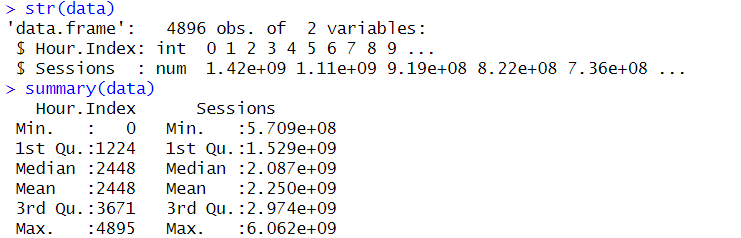


Figure 7 represents the summary of the dataset that is used in the implementation.

**RESULTS**

The implementation of the random forest model for website traffic forecasting involved several key steps. First, the dataset was preprocessed by introducing lag features, such as traffic data from the previous hour (lag1) and two hours prior (lag2), to help capture temporal patterns. These features were then used as inputs to the model. The dataset was split into an 80% training set and a 20% testing set to ensure reliable evaluation of the model's performance.

The random forest algorithm was then applied, utilizing multiple decision trees to model the relationship between the lagged traffic values and the actual traffic. Each tree was trained on a random subset of the data, and the ensemble of trees provided the final predictions by averaging their outputs. This ensemble method helps reduce overfitting and improves the model's robustness.

After training, the model's accuracy was evaluated on the test data. The root mean squared error (RMSE) was calculated to assess the average prediction error, and the R-squared value indicated how well the model explained the variance in the actual traffic data. The resulting metrics showed that the random forest model was highly accurate, with an R-squared value of 0.999983, suggesting it captured almost all the variance in the data.

Lastly, the predictions were visualized using actual vs. predicted plots and residual plots to further validate the model’s accuracy and consistency in forecasting website traffic.

The performance of the random forest model for website traffic forecasting was evaluated using both numerical metrics and visual analysis. The model achieved an exceptional R-squared value of 0.999983, indicating that it successfully captured nearly all the variance in the traffic data. This high value suggests the model's predictions closely match the actual traffic values, showcasing its robustness and accuracy.

However, the Root Mean Squared Error (RMSE) of 3,749,559 reveals that, while the overall fit is excellent, the scale of the errors in absolute terms might still be significant due to the high magnitude of the traffic data points. Despite the large RMSE value, the consistency of the predictions remains strong, as shown by the visual representations.

The Actual vs. Predicted plot (Figure 8) illustrates this accuracy, where the predicted values align almost perfectly with the actual values along the diagonal red line. This alignment demonstrates the model's ability to forecast traffic with minimal deviation.

Additionally, the Residuals plot (Figure 9) provides further insights into the model’s performance. The residuals, representing the difference between actual and predicted values, are tightly centered around zero, indicating no significant bias in the model. A few outliers exist, but overall, the residuals are distributed uniformly, confirming that the model performs well across the entire range of data.

These results indicate that the random forest model is highly effective for website traffic forecasting, offering precise and reliable predictions that can be applied to real-world applications in traffic management and planning.

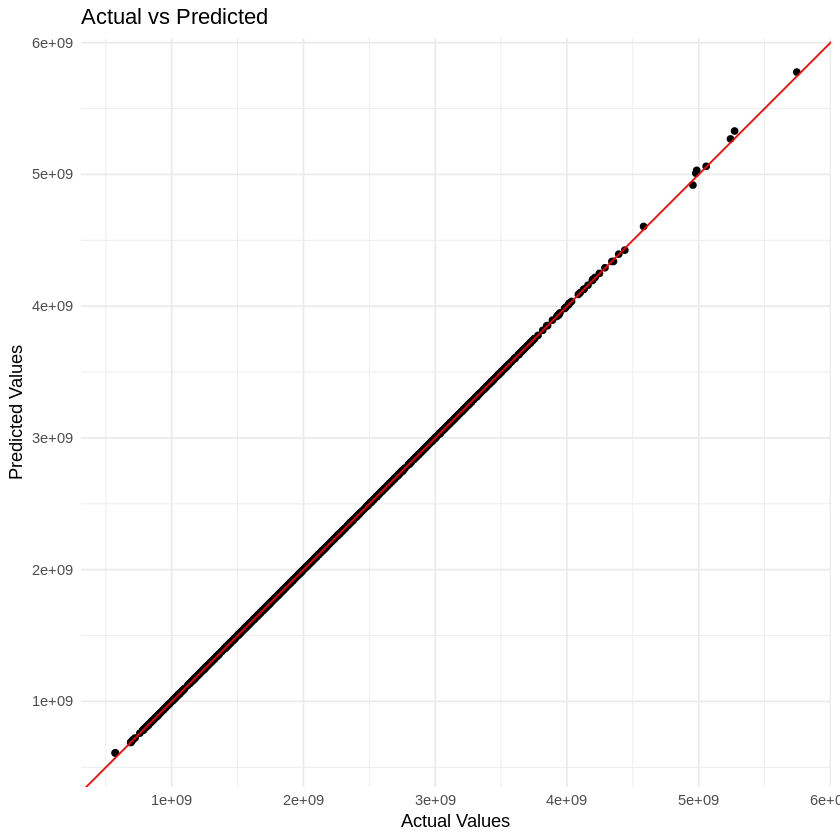
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Figure 8 Graph predicting the model summary

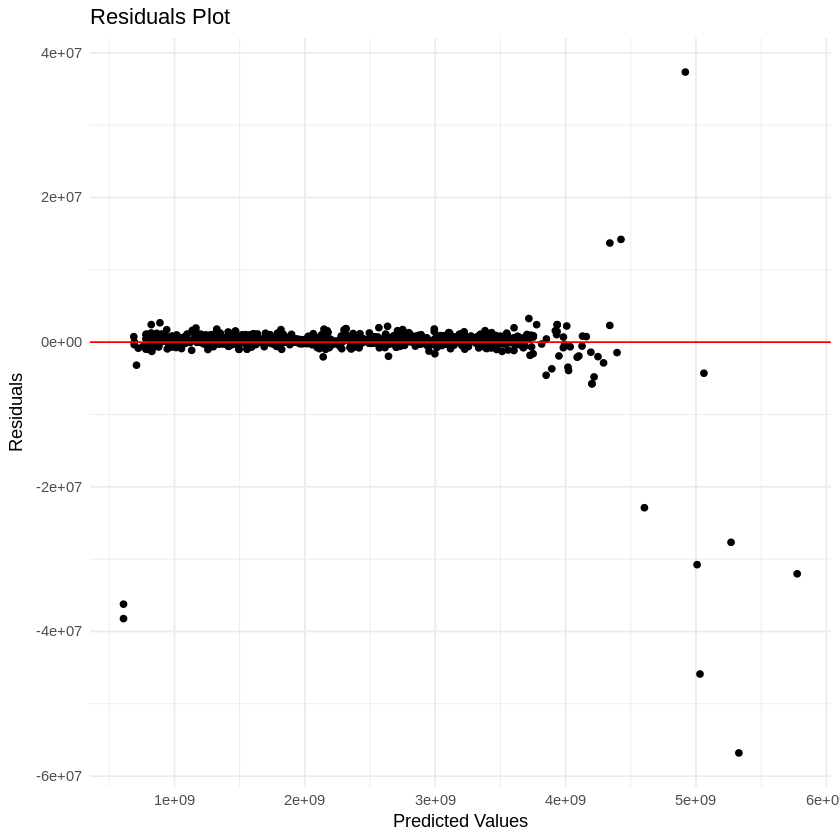


Figure 9 Residual graph of the dataset

**CONCLUSION**

This project on website traffic forecasting using the random forest algorithm has provided valuable insights into the application of machine learning for predicting web traffic trends. By leveraging lagged variables to capture temporal dependencies, the random forest model was able to achieve impressive performance, with an R-squared value of 0.999983, indicating a near-perfect fit. Although the Root Mean Squared Error (RMSE) of 3,749,559 is relatively high due to the large magnitude of the data, the model consistently predicts traffic trends with minimal deviations, as demonstrated by the Actual vs. Predicted and Residuals plots.

This project underscores the real-world importance of accurate traffic forecasting, particularly in industries where website traffic is a key metric for business success, such as e-commerce, digital marketing, and content delivery networks. The ability to predict traffic enables businesses to optimize server resources, plan for peak loads, and enhance the user experience by reducing latency during high traffic periods.

**Future Scope:**

While the current model performs exceptionally well, there are several avenues for future improvement and exploration. One possible extension is to incorporate additional variables such as seasonality, holidays, marketing campaigns, and external web events to improve the model’s predictive power. Moreover, more sophisticated machine learning techniques like gradient boosting machines (GBM), XGBoost, or even deep learning approaches could be explored to handle complex traffic patterns and provide even greater accuracy.

Another area of future research could involve real-time traffic forecasting by deploying the model in production environments that continuously update and refine the predictions based on live data. Additionally, expanding the project to explore multi-step forecasts, predicting traffic not just for the next hour but for multiple time periods ahead, could be extremely beneficial for long-term planning.

In conclusion, this project has demonstrated the potential of random forest models for website traffic forecasting. The strong performance achieved here paves the way for future enhancements, with broader applications across industries that rely on accurate forecasting for operational efficiency. Further development in this field can lead to more adaptive and intelligent systems capable of managing dynamic traffic patterns in real time.

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