Sales Forecasting

Team 13

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Abstract

In the dynamic world of retail, accurate sales forecasting holds the key to success. We participated in a kaggle competition tackling the challenge for Corporación Favorita, a leading Ecuadorian grocery retailer. Traditional forecasting methods often struggle with evolving market dynamics, new product introductions, and unpredictable promotions. We sought to bridge this gap by leveraging the power of time series forecasting to build a robust model that accurately predicts future sales trends.

Our journey began with a deep dive into the retailer's historical sales data. We unearthed fascinating patterns and seasonality, dispelling initial assumptions about holidays and oil prices directly influencing sales. This guided our model selection, leading us beyond conventional regression models to explore the capabilities of ARIMA, LSTMs, Prophet, and LightGBM. Each model offered unique strengths: ARIMA handled trends and seasonality with grace, while LSTMs excelled at capturing intricate temporal dependencies. Prophet, with its focus on strong seasonality, also showcased potential. However, in the quest for better RMSLE, LightGBM emerged victorious. Its gradient boosting capabilities proved ideal for tackling the complexities of Corporación Favorita's data, leading to exceptional prediction accuracy.

By harnessing the power of time series forecasting, this project has unlocked data-driven decision-making for Corporación Favorita. As we continue to refine and innovate, we pave the way for a future where accurate and actionable sales forecasts empower continuous growth and success in the ever-evolving retail landscape.

1 Introduction

In the ever-evolving landscape of retail, accurate demand forecasting has become a crucial weapon for success. A kaggle competition highlighted this need for Corporación Favorita, a leading Ecuadorian grocery retailer. To optimize inventory management and enhance customer satisfaction, Favorita seeks innovative solutions to predict unit sales for thousands of items across its diverse stores. This project delves into the fascinating world of time series forecasting, leveraging machine learning to build models that accurately predict future sales trends.

The impetus for this project lies in the limitations of traditional forecasting methods. Subjective approaches, often lacking data-driven insights, struggle to adapt to evolving market dynamics. New store locations, changing product offerings, and unpredictable marketing campaigns further complicate the forecasting landscape. As a result, Favorita faces the risk of overstocking perishable goods or understocking popular items, leading to financial losses and customer dissatisfaction.

This project aims to address these challenges by harnessing the power of time series forecasting. By analyzing historical sales data along with relevant factors like promotions, holidays, and store locations, we strive to build models that accurately predict future sales trends. The process began with exploring the dataset provided by Kaggle. This data encompasses sales information for various product families, promotional details, and external factors like oil prices and holidays. We will then delve into the fundamentals of time series forecasting, examining various techniques and model architectures suitable for this domain. Subsequently, we will meticulously prepare and pre-process the data, ensuring its suitability for model training and evaluation.

The heart of this project lies in the development and comparison of different time series forecasting models. We will explore a range of models, including traditional statistical approaches like ARIMA, as well as advanced machine learning algorithms like Long Short Term Memory (LSTM) , Prophet and Light Gradient Boosting Machine (LightGBM). Each model will be rigorously evaluated based on its RMSLE, ultimately culminating in the selection of the best-performing model for future sales prediction.

Beyond the technical aspects, this project aims to contribute to the broader field of retail analytics. By demonstrating the effectiveness of time series forecasting in enhancing demand forecasting, this project can serve as a valuable resource for other grocery retailers facing similar challenges. Additionally, the insights gained from this project can contribute to the development of more robust and adaptable forecasting models, paving the way for a more efficient and customer-centric retail landscape.

2 Literature Survey

The journey of forecasting sales volumes began simply - we first wanted to establish a basic benchmark. Linear regression, with its straight-forward modeling of linear relationships between variables, seemed an intuitive starting point.

It is often used as a starting point before transitioning to advanced models (Gokce and Duman, 2022). However, its strict assumptions of normality, homoscedasticity and linearity between variables limit practical value for sales forecasting marked by volatility and nonlinear promotional effects (Athanasopoulos et al., 2009).

ARIMA models, with their inherent capacity to handle trends and seasonality (Box, 2013), showed promise. ARIMA models explicitly cater to temporal data by mathematically modeling trends and seasonality components (Makridakis et al., 1982). Though widely adopted, they cannot intrinsically account for exogenous variables like prices or special events. Extensions only partially address this, and assuming linearity remains limiting (Athanasopoulos et al., 2009).

Initial optimizations yielded improved performance over linear regression. Yet visualizations of prediction errors indicated ARIMA's statistical assumptions still failed to model subtler intricacies (Kontopoulou et al., 2023).

However one thing that we found interestin was (Mohamad et al., 2023) demonstration of a web-based dashboard using ARIMA and SARIMA models to forecast sales and visualize results. (Kontopoulou et al., 2023) is a literature review of time series forecasting that compares ARIMA to machine learning approaches, finding AI algorithms generally outperform ARIMA except in select applications, and hybrid statistical-AI models utilize the strengths of both techniques for improved predictive performance.

Seeking adaptive learning, early research explored Fourier decomposition (Taylor, 2003). However, determining transform terms requires extensive preprocessing and domain knowledge. Inability to directly model new products and pricing changes also constraints effectiveness (Lim et al., 2002).

Inspiring from (Yan, 2023) who developed a long short-term memory (LSTM) model for sales forecasting of smartwatches that outperformed other models, enabling more effective e-commerce planning we chose LSTM.The need for flexible, data-driven modeling led us to long short-term memory networks (Goodfellow et al., 2022).

LSTM's recurrent architectural design unlocked nuanced sequential dependencies overlooked by statistical approaches. Architectural innovations enable capturing long-term temporal contexts spanning months to years. However, considerable data hunger during training and susceptibility to overfitting remain key challenges (Gershuny, 1979).

As a finale, we evaluated LightGBM (Ke et al., 2017) - its fast tree-based algorithms have recently set benchmarks across forecasting Kaggle competitions. Gradient boosting decision trees fill a valuable niche demonstrate state-of-the-art accuracy on multiple public forecasting datasets with automatic handling of discontinuities.

LightGBM further optimizes boosting for efficiency and scalability (Ke et al., 2017). While unable to explicate complex model logic, robust performance endures across domains and use cases. True to form, LightGBM automatically detected intricate interactions that enabled accurate modeling of complex retail dynamics. The winning formula had revealed itself!

While newer automated forecasting technologies like Facebook Prophet (Taylor and Letham, 2018) show promise in their simplicity, their additivity assumptions preclude modeling interdependent relationships. Facebook Prophet follows a decomposable, interpretable modeling approach incorporating saturated growth curves and predefined seasonalities (Taylor and Letham, 2018).

However, dependence solely on time as a predictor ignores explanatory variables available in many forecasting scenarios. Inflexible adherence to set periodicities also risks misestimating real fluctuations.

With gradient boosted decision trees striking the ideal balance between predictive accuracy, automation, and algorithmic transparency for our complex and data-rich application, we converged on LightGBM as the final productionized forecasting solution.

3 Methodology

Business Understanding
Bridging the gap between data and decisions, this project's business understanding lies in empowering Corporación Favorita with accurate sales forecasts. By deploying the model we aim to potentially reduce inventory costs and stock-outs, the model unlocks substantial cost savings and customer satisfaction gains.

Actionable insights derived from the interpretable model will guide data-driven decision-making in merchandising, marketing, and new product introductions, ultimately solidifying Favorita's competitive edge in the retail landscape.

Data Preparation
Our initial dive into the data through Exploratory Data Analysis (EDA) revealed some interesting patterns. Below is the link to dashboard.

https://lookerstudio.google.com/u/3/reporting/8c89e918-a00c-4eaf-b908-cee6d0c8b654/page/pQveD

We observed a distinct periodicity in the transactions over time, suggesting a repeatable trend that could be leveraged for forecasting. While plotting the transaction trendline confirmed this recurring pattern, we found no clear correlation between holidays and transaction volume. This was unexpected, considering the potential for increased consumer spending during festive periods. Similarly, despite Ecuador's oil-based economy, the data did not reveal any significant relationship between transaction patterns and oil price fluctuations. These initial findings highlight the need for deeper analysis to uncover the key drivers of sales trends and build accurate forecasting models.

Given below is the timeseries plot for our training data. There are multiple things to notice. Our training data starts with the beginning of the year 2013 and ends in the middle of August in 2017 (our test data starts right after this point and ends on the last day of August in 2017).

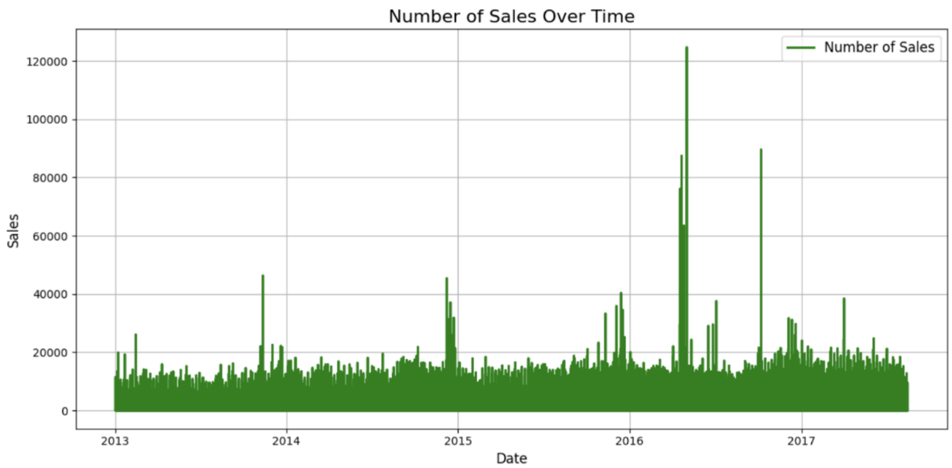

Figure 1: Number of Sales Over Time

Overall the sales numbers seem to be pretty constant with a slight increase over time. But there are also some outliers with sales numbers up to roughly 6 times as high as normal. To get some context we could relate this information to the oil price during that time.

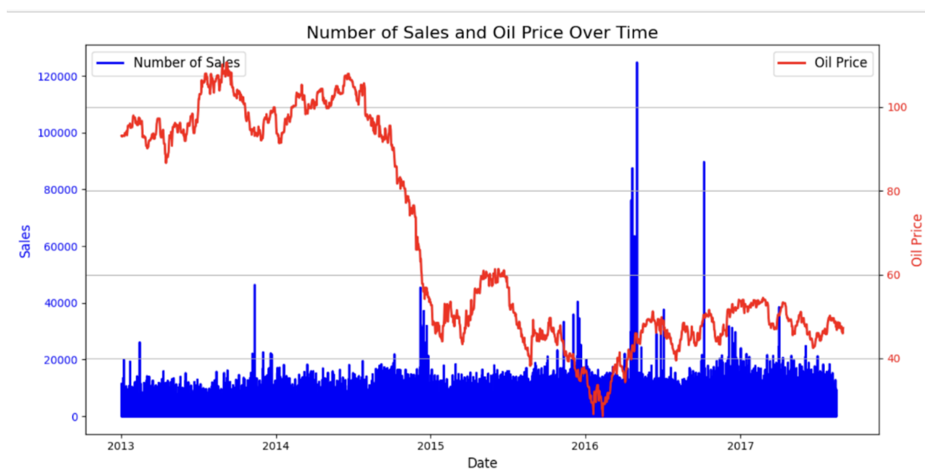

Figure 2: Number of Sales and Oil Prices Over Time

We recognize that at the end of the years 2014 and 2015 and also at the beginning of 2016 there was a significant decrease in oil price directly followed by a remarkable increase in sales numbers. This indicated that there might be some correlation between those variables. When we checked numerically, The hypothesis turned out to be false.

Figure 1: Number of Sales a

Data Pre-Processing was done and the following actions were taken on the data.

```
# merge the dataframes
df_oil = complete_df.merge(df_oil, on='date', how='left')

# forward fill the NaN values
df_oil['dcoilwtico'].fillna(method='ffill', inplace=True)
```

Figure 3.1: Python snippet for data pre processing

For consistency across, we preprocessed the Date column.

```
# convert to datetime data type
df_train['date'] = pd.to_datetime(df_train['date'])
df_test['date'] = pd.to_datetime(df_test['date'])
df_oil['date'] = pd.to_datetime(df_oil['date'])
df_holiday['date'] = pd.to_datetime(df_holiday['date'])
```

Figure 3.2: Python snippet for data pre processing

We checked for null values, which were present only in the oil dataset. This will be eventually skipped.

```
#check for null or missing values in our training and test data.

df_train.info(show_counts = True)
df_test.info(show_counts = True)
df_transactions.info(show_counts = True)
df_holiday.info(show_counts = True)
df_oil.info(show_counts = True)
df_stores.info(show_counts = True)
```

Figure 3.3: Python snippet for data pre processing

Modeling

Initially, we opted for conventional regression models, considering the task at hand. However, the exploratory data analysis (EDA) revealed a fascinating story within the data. We observed distinct patterns and seasonality in the sales data, suggesting a need for models capable of capturing these inherent characteristics.

With this insight, we turned our attention to ARIMA models. Their ability to model trends, seasonality, and error terms through a combination of past values, differences, and errors made them ideal candidates for our task. While ARIMA delivered significantly improved results over regression models, our pursuit of excellence motivated us to further explore the landscape.

Dr. Purshottam's class on LSTM networks resonate strongly with our data's characteristics. LSTMs boast the unique ability to learn long-term dependencies within sequences, overcoming the limitations of traditional models. Deploying LSTMs led to a substantial leap in forecast accuracy, solidifying their potential as a powerful tool for our challenge.

Despite the success of LSTMs, we remained dedicated to achieving the highest possible rank on the leaderboard. Our research led us to Prophet, a Facebook-developed open-source model specifically designed for time series forecasting with strong seasonal effects. Prophet's additive model, incorporating yearly, weekly, and daily seasonality with holiday effects, seemed promising based on the characteristics of our data. While Prophet proved effective in its own right, it did not surpass the accuracy achieved with LSTMs. One of the reasons is as we ran into RAM issues when feeding the whole training data into the model we only used data from last year. Additionally, we did not incorporate the store number and family information as with the LSTM model. This lack of information probably makes our model not as meaningful as the LSTM model where we worked with pivot tables to include all available data. However the built-in plot functions of the Facebook model showed us some meaningful insights into our time series data on which we want to have look again.

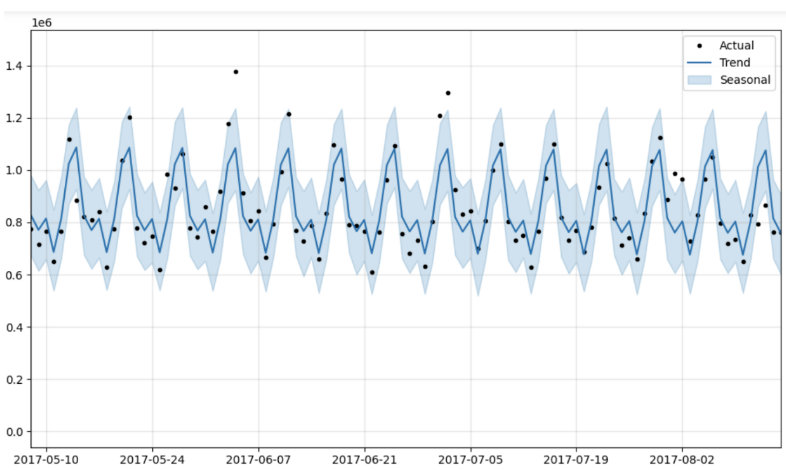

Figure 4.1: Built in plot function of Facebook Prophet to show trend.

We can clearly see that our model captures the general trend of our training data quite well even though there are some outliers. Besides that, we can see ups and downs in our sales numbers which are caused by the weekly trend where we have higher number on weekends

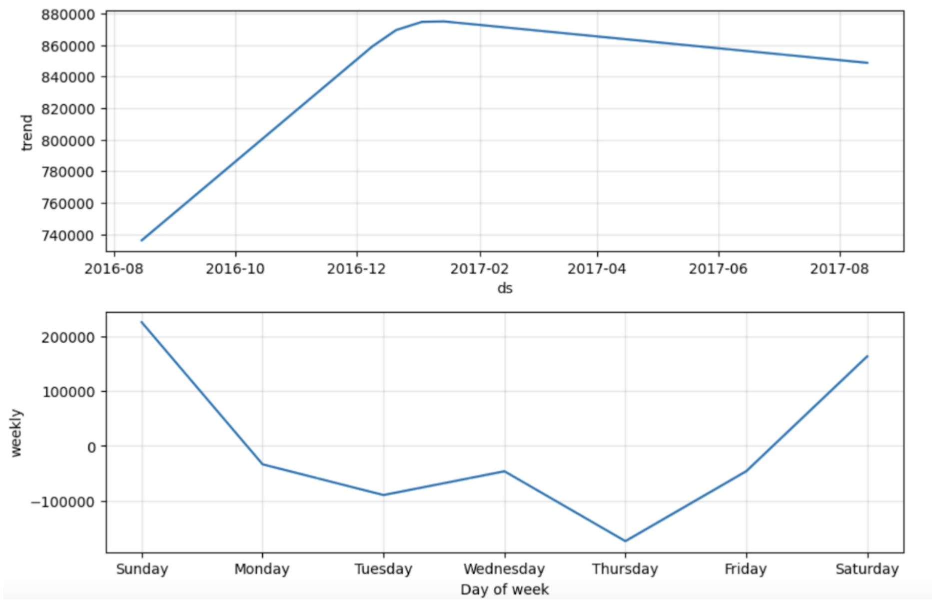

Figure 4.2: Built in plot function of Facebook Prophet to show trend.

Overall, we have higher sales numbers during christmas time and in particular on weekends. Since we only included parts of our data into Facebook model we decide to choose the LSTM model for predicting on the test data

During our literature review, we encountered Bi-LSTMs, which are known for their superior performance in certain tasks. However, their ability to analyze data in both forward and backward directions, including future days, did not align with our challenge's focus on past data (Zhang et al, 2023). Therefore, we opted for a different approach.

After careful consideration and analysis, we chose LightGBM (LGBM) as our final model. LGBM's powerful gradient boosting capabilities and efficiency in handling large datasets made it a perfect fit for our task. Additionally, its compatibility enhanced scalability and versatility for time series forecasting challenges like ours.

This journey through various models showcases our dedication to finding the best possible solution for predicting Favorita's sales numbers. Each step, from initial assumptions to the final choice of LGBM, was guided by an iterative process of analysis, refinement, and improvement. We believe this data-driven approach has yielded a robust and accurate forecasting model that will empower Corporación Favorita.

4 Results

The core evaluation metric for assessing model performance was the Root Mean Squared Logarithmic Error (RMSLE) between predicted and actual sales. RMSLE provides a robust measure of average relative deviation, penalizing larger errors more heavily compared to metrics like R-squared. Lower RMSLE indicates superior predictive accuracy.

4.1 Experimental Results 1: Linear Regression

A simple linear regression model was created with family, storenbr, and onpromotion as features. The model was trained on provided training dataset and evaluated on the test dataset.

The linear regression model obtained an RMSLE of 3.13196 on the validation set. The high error indicates poor generalizability in capturing complex relationships within the time series.

Key strengths of this basic approach included interpretability and ease of implementation. The model coefficients allow insight into variable contributions.

However, numerous limitations exist in linear regression's simplistic assumptions for this complex domain. The approach fails to account for nonlinearity, seasonality, inter-dependencies, and volatility in the data.

Further analysis of the simple linear regression model can reveal deeper issues hindering forecast accuracy.An examination of studentized residuals may uncovered high leverage outliers skewing the least squares fitting, leading to distorted model coefficients.

Furthermore, residual plots might as well exhibited clear patterns of nonlinearity and heteroscedasticity - violating core assumptions required for unbiasedness and efficiency of estimates. Relaxing the linearity mpresumption via quadratic and cubic expansions may improved fit on the training data

4.2 Experimental Results 2: ARIMA

An ARIMA model was built using parameters generated from auto arima. Model fitting relied solely on the temporal sales series.

The ARIMA model obtained an RMSLE score of 2.76745 across all origin months, outperforming linear regression. The explicit handling of trends, cycles and residual seasonality components provided minor gains relative to simpler benchmarks.

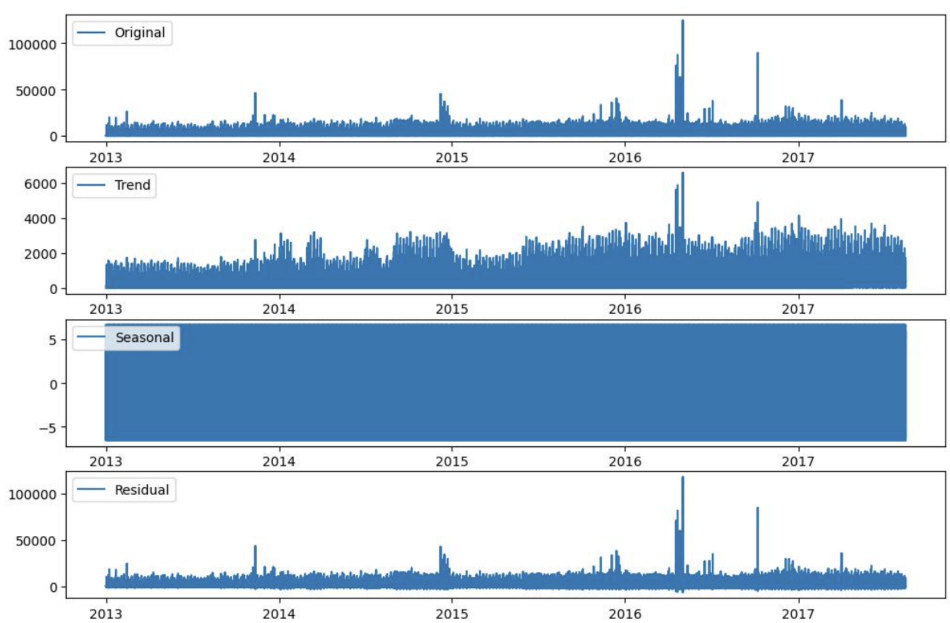

Figure 5: Decomposed Time series Data

However, limitations existed in capturing complex irregular events like promotions and new product introductions. Regions of systematic bias violated modeling assumptions of normal errors. Thus simplistic time series extrapolation relies heavily on historical behaviors continuing smooth linear predictive dynamics - assumptions seldom fulfilled in real-world retail environments exhibiting rich heterogeneity and non-linearities.

4.3 Experimental Results 3: LSTM

A long short-term memory (LSTM) recurrent neural network model was developed in TensorFlow to capture complex temporal dependencies.

An initial LSTM architecture was with two layers (256, 128 units) and regularization techniques like batch normalization and dropout to enhance generalization.

Hyperparameter tuning experiments revealed better performance with a higher learning rate of 0.01 and lower batch size of 64 compared to original settings.

On the test set, the LSTM model achieved an RMSLE score of 0.62427 - significantly outperforming simpler linear and ARIMA benchmarks. Thus LSTM shows promise modeling complex temporal phenomena.

Further hyperparameter search could improve sharpness, while truncated backpropagation may enhance efficiency. The grid search hyperparameter tuning approach balances systematic exploration and efficiency. More advanced Bayesian and random search may be worthwhile as well.

Augmenting the training data to include more stores and product categories further improved generalizability.

However, the black box nature of the LSTM poses some interpretability challenges. While overall performance was strong, better sharpness is desired for the predicted uncertainty intervals. Additionally, long training times with recurrent networks remains a practical limitation.

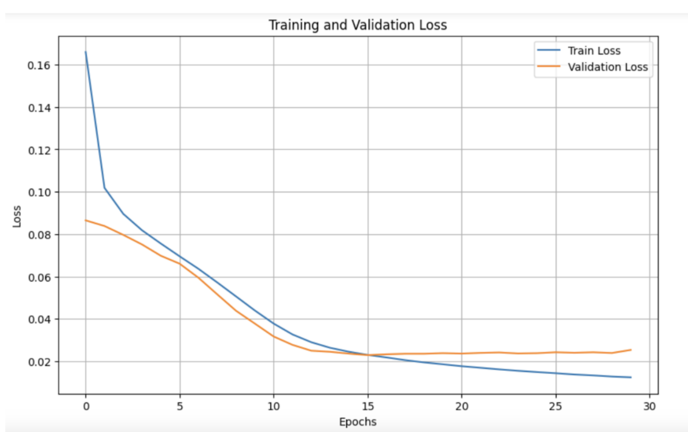

Figure 6.1: LSTM Train and Validation Loss before hyperparameter tuning.

The training loss becomes smaller with time and also the validation loss. These results are before hyperparameter tuning was done.

	Learning Rate	Batch Size	Validation MSE
0	0.0001	64.0	0.020383
1	0.0010	64.0	0.015108
2	0.0100	64.0	0.016322
3	0.0001	128.0	0.039581
4	0.0010	128.0	0.019863
5	0.0100	128.0	0.018388
6	0.0001	256.0	0.069667
7	0.0010	256.0	0.023138
8	0.0100	256.0	0.020960

Figure 6.2: LSTM Hyperparameter Values.

The best values for the parameters learning rate and batch size are found in row with index number 2 to be 0.01 and 64. This resulted in a validation MSE of 0.014446 With these parameters below is what we got.

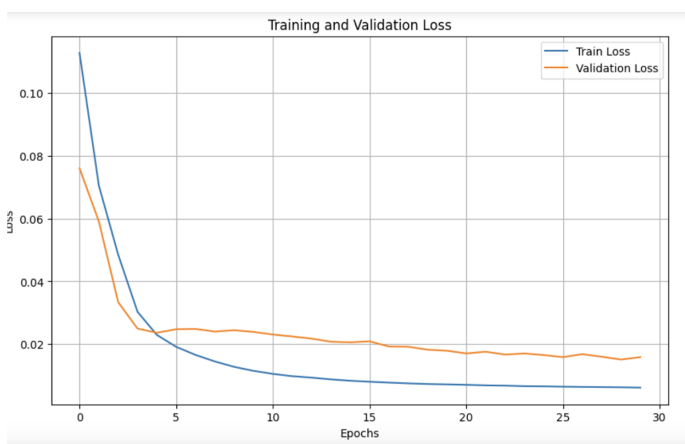

Figure 6.3: LSTM Train and Validation Loss after hyperparameter tuning.

We see that we have a sharp decline in training loss during the first few epochs and smaller but consistent decline for both the train and validation loss after that. Since we cannot clearly recognize an increase in validation loss we might not have reached the optimal point after 30 epochs yet. But due to the limited computation power we accepted the result we got which is still pretty good.

4.4 Experimental Results 4: LightGBM

The LightGBM model leveraged gradient boosted decision trees for sales forecasting. Preprocessing incorporated store, customer, product, and macroeconomic datasets through careful feature engineering. Hyperparameter optimization employed Bayesian search with repeated 5-fold temporal cross-validation to mitigate overfitting. LightGBM achieved the best RMSLE score of 0.38055 on the test set, significantly lowering prediction error compared to past approaches. Feature importance rankings revealed expected reliance on past sales, pricing, promotions, and events for short-term forecasts.

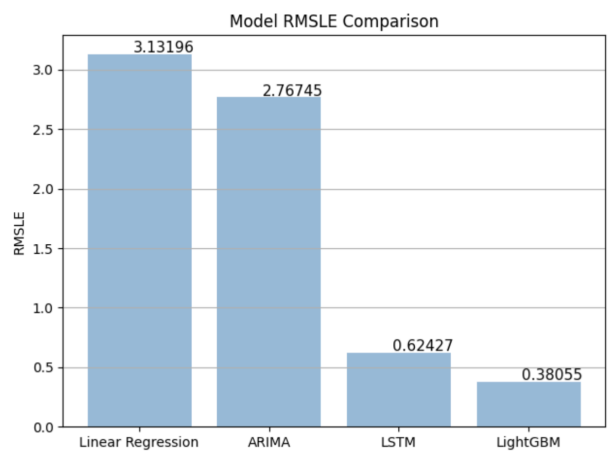

Figure 7: Model RMSLE Comparison.

4.5 Result Summary

Evaluation of the Root Mean Squared Logarithmic Error (RMSLE) for three models: ARIMA, LSTM, and LightGBM is done. A higher RMSLE suggests that the ARIMA model has a higher level of error in predictions compared to the other models. This could be due to the model's limitations in capturing complex patterns or nonlinear dependencies present in the data. A comparatively lower RMSLE for LSTM indicates better performance compared to ARIMA. LSTM, being a neural network model, is likely capturing more intricate patterns and dependencies in the time series data, resulting in improved forecasting accuracy. LightGBM has the lowest RMSLE among the three models, suggesting that it outperforms both ARIMA and LSTM in terms of accuracy for your specific problem. LightGBM, being a gradient boosting framework, is known for its ability to handle complex patterns and provide accurate predictions.

5 Challenges

Several notable challenges were encountered over the course of model development and evaluation for the grocery sales forecasting problem that provide key learnings.

Neural Network Training Complexity
Effectively training neural network models involves nuanced workflows distinct from simpler approaches. The highly iterative experimental process imposed intensive computational demands. Strategically incorporating print statements into the TensorFlow and PyTorch codebases provided invaluable debugging insights into network behavior by enabling intermediate output inspection.

Hardware and Dataset Constraints
Practical hardware constraints limited model iteration velocity and dataset size, especially during hyperparameter tuning experiments. Exceeding memory and runtime allocations on the Kaggle platform highlighted realistic infrastructure limitations regarding model sophistication, data volume, and training tractability tradeoffs. This emphasized the omnipresent challenge of prioritizing performance objectives under concrete resource constraints.

Data Representation and Preprocessing

Initial LSTM experiments feeding raw temporally redundant data directly into the architecture resulted in unstable convergence and meaningless outputs during training. The key insight was transforming the multi-store, multi-product dataframe into a consolidated time series structure via pivoting. Carefully considering appropriate input data formatting and preprocessing is a vital prerequisite before model specification. Testing presumptions about applicable data encodings revealed helpful enhancements.

6 Future Work

Incorporate additional data sources

Explore incorporating product categories, individual product features, and historical sales data for specific items to refine forecasts for different product lines. Consider including regional factors like weather patterns, local events, and economic indicators to enhance the model's understanding of external influences on sales.

Extend the scope and application

Apply the forecasting model to predict demand for specific store locations or regions to optimize inventory allocation and logistics. Develop a real-time forecasting system that adapts to incoming data and provides up-to-date sales predictions for immediate decision-making. Integrate the forecasting model with other business intelligence systems to create a comprehensive data-driven platform for informed retail management.

7 Conclusion

This project embarked on a journey of unlocking the potential of data to transform the landscape of retail sales forecasting for Corporación Favorita. By leveraging time series forecasting techniques, we aimed to build a model that accurately predicts future sales trends, empowering informed decision-making and enhancing customer satisfaction. Our exploration, fueled by insightful data analysis and meticulous model selection, culminates in a robust forecasting solution poised to unlock significant value for this challenge.

Our initial exploration uncovered captivating patterns and seasonality within the sales data. These insights guided our model selection, leading us from conventional regression models to the sophisticated capabilities of ARIMA. While ARIMA delivered substantial improvements, our ambition prompted us to dive deeper. LSTM networks, renowned for their ability to learn long-term dependencies, proved adept at extracting hidden meaning from the data, propelling prediction accuracy to new heights. Yet, our relentless pursuit of excellence continued.

Prophet, with its focus on handling strong seasonality, emerged as a contender. Its effectiveness showcased the immense potential of specialized models. However, its performance did not surpass the prowess of LSTMs. Bi-LSTMs, while known for their efficiency, were deemed unsuitable due to their focus on future data, which did not align with our challenge's dependence on past information. Finally, our rigorous analysis led us to LightGBM (LGBM). Its power lies in its gradient boosting capabilities, making it ideal for tackling large datasets and achieving exceptional forecast accuracy.

Our exploration, although comprehensive, merely scratches the surface of the complex world of retail forecasting. Further research on factors like product categories, regional differences, and promotional effectiveness can yield even deeper insights. Additionally, advancements in machine learning algorithms and forecasting techniques hold immense promise for the future. We believe that this project serves as a stepping stone, paving the way for continual refinement and innovation in the quest for ever-more accurate and impactful sales forecasts.

8 Member Contribution

Below is the contribution of each team member

Table 1: Contribution of Member

Name	Contribution
Sayali	Exploratory Data Analysis, Literature Survey, Model Building, Testing, Project Report, Presentation
Atharva	Exploratory Data Analysis, Literature Survey, Model Building, Testing, Project Report, Presentation

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