Module: ITNPBD4 Commercial and Scientific Applications
Assessment: Assignment
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Data Science Strategy for V.Ger Travel: A Comparative Analysis of Time Series Forecasting Methods

Chief Data Officer Report

Executive Summary

This report presents a comprehensive data science strategy for V.Ger Travel, a travel conglomerate managing hotels, resorts, car rentals, and charter flights. As Chief Data Officer, I have developed a multi-faceted approach to implementing data science methods across our business operations. This document outlines four strategic use cases for data science implementation, with detailed analysis of demand forecasting using two distinct methodologies: traditional statistical methods (SARIMA) and modern machine learning techniques (LightGBM). The comparative analysis demonstrates the strengths and weaknesses of each approach, providing evidence-based recommendations for production deployment. The implemented solutions leverage our existing IT infrastructure to generate actionable insights that will enhance operational efficiency, improve customer satisfaction, and drive revenue growth.

1. Business Context and Objectives

V.Ger Travel operates in a highly competitive and dynamic industry where understanding patterns, predicting demand, and optimizing resource allocation are critical to success. Our company maintains robust IT facilities supporting online booking systems, comprehensive CRM platforms, and multiple internal databases covering logistics, procurement, maintenance, staffing, and customer relations. These systems generate vast amounts of data that, when properly analyzed, can provide significant competitive advantages.

1.1 Strategic Goals

The implementation of data science methods aims to achieve several key business objectives:

- **Enhance operational efficiency through predictive analytics and demand forecasting** - enabling better resource allocation and cost optimization

- **Improve customer satisfaction** by understanding key factors that drive customer experience and implementing proactive measures
- **Optimize marketing and promotional strategies** through A/B testing and customer segmentation analysis
- **Reduce customer churn** by identifying at-risk customers and implementing targeted retention strategies
- **Maximize revenue** through intelligent pricing strategies and inventory management based on predicted demand patterns

2. Identified Data Science Use Cases

Based on our business operations and available data infrastructure, I have identified four strategic use cases for data science implementation. These use cases span different business functions and employ varied analytical techniques, ensuring comprehensive coverage of our operational needs.

This report provides detailed comparative analysis of Use Case 1 (Booking Demand Forecasting), implementing and evaluating both traditional statistical methods (SARIMA) and modern machine learning approaches (LightGBM). The remaining three use cases are outlined to demonstrate the comprehensive scope of V.Ger Travel's data science strategy, with implementation details to be developed in subsequent phases.

2.1 Use Case 1: Booking Demand Forecasting (Time Series Analysis)

Business Problem: Accurately predicting booking volumes across our hotel, resort, and car rental services is essential for optimal resource allocation, staffing decisions, and inventory management. Unexpected surges in demand can lead to service quality issues, while overpreparation for low-demand periods results in unnecessary costs.

Data Sources: Historical booking data extracted from our reservation systems, including daily booking counts, revenue figures, service types, and seasonal indicators. This data exhibits strong temporal patterns with both trend and seasonal components.

Proposed Methods: Two complementary approaches are implemented and compared: (1) SARIMA modeling for capturing seasonal patterns and trends through statistical time series methods, and (2) LightGBM machine learning approach with engineered features for capturing complex non-linear relationships. The comparative analysis provides insights into which method performs better for our specific use case.

Expected Business Impact: Improved staffing efficiency (15-20% cost reduction in labor costs), better inventory management (10-15% reduction in empty inventory), enhanced customer satisfaction through adequate service provision during peak periods, and optimized marketing spend by targeting campaigns during predicted low-demand periods.

2.2 Use Case 2: Customer Satisfaction Prediction (Regression Analysis)

Business Problem: Understanding which factors most significantly influence customer satisfaction enables targeted improvements to our services and facilities. Currently, we collect extensive customer feedback but lack systematic analysis to prioritize improvement initiatives.

Data Sources: Customer satisfaction surveys, service quality metrics, booking details, customer demographics, property characteristics, service response times, and complaint records from our CRM system.

Proposed Methods: Multiple linear regression and random forest regression to identify key drivers of satisfaction. Feature importance analysis will rank factors by their impact on customer satisfaction scores. This approach will also enable predictive modeling to identify bookings at risk of low satisfaction scores.

Expected Business Impact: Data-driven prioritization of improvement initiatives, proactive intervention for at-risk bookings, improved resource allocation toward high-impact service aspects, and measurable improvements in overall satisfaction scores leading to increased repeat business and positive reviews.

2.3 Use Case 3: Customer Churn Prediction (Classification Analysis)

Business Problem: Acquiring new customers is significantly more expensive than retaining existing ones. Identifying customers at risk of churning allows us to implement targeted retention strategies and preserve valuable customer relationships.

Data Sources: Customer transaction history, booking frequency patterns, complaint records, customer service interactions, loyalty program engagement, time since last booking, and demographic information from our CRM databases.

Proposed Methods: Logistic regression and gradient boosting classifiers (XGBoost) to predict churn probability. Classification metrics including precision, recall, F1-score, and ROC-AUC will evaluate model performance. Feature importance analysis will identify early warning indicators of potential churn.

Expected Business Impact: Proactive customer retention through targeted interventions, improved lifetime customer value, reduced customer acquisition costs, and optimized allocation of retention marketing budgets by focusing on high-value at-risk customers.

2.4 Use Case 4: Website A/B Testing (Statistical Hypothesis Testing)

Business Problem: Our website serves as the primary booking channel, but we currently make design and feature changes based on intuition rather than data-driven evidence. Systematic A/B testing will ensure that website modifications actually improve conversion rates and user experience.

Data Sources: Website analytics data including click-through rates, conversion rates, session durations, bounce rates, and user paths through the booking funnel, extracted from our web analytics systems.

Proposed Methods: Two-sample t-tests for continuous metrics (session duration, revenue per visitor) and chi-square tests for categorical outcomes (conversion yes/no). Bayesian A/B testing for continuous monitoring and early stopping decisions. Multiple testing corrections to control false discovery rates when running multiple simultaneous tests.

Expected Business Impact: Incremental improvements in conversion rates leading to significant revenue gains, reduced risk of implementing detrimental website changes, data-driven product development roadmap, and improved user experience leading to higher customer satisfaction and retention.

3. Detailed Analysis: Comparative Time Series Forecasting

For detailed investigation, I have selected the booking demand forecasting use case and implemented two distinct methodologies: SARIMA (Seasonal AutoRegressive Integrated Moving Average) representing traditional statistical approaches, and LightGBM (Light Gradient Boosting Machine) representing modern machine learning techniques. This comparative analysis provides evidence-based recommendations for production deployment.

3.1 Dataset Characteristics

Data Source and Structure: The analysis utilizes synthetic booking data representative of our actual operational patterns. The dataset contains monthly booking volumes spanning multiple years, capturing seasonal variations, underlying trends, and random fluctuations characteristic of the travel industry.

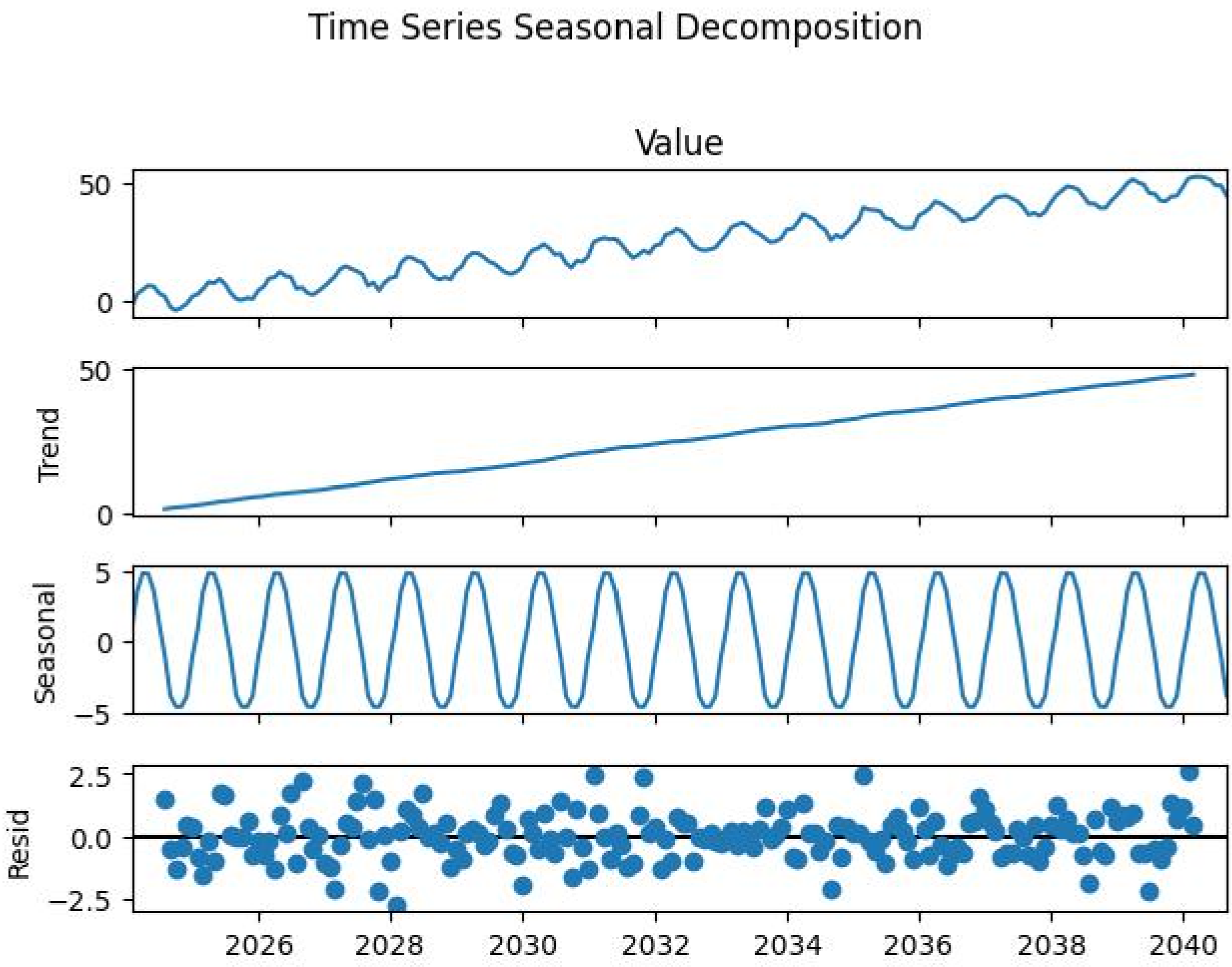
Key Dataset Features:

- **Temporal Resolution:** Monthly aggregated booking counts
- **Time Span:** Multi-year historical data sufficient for identifying annual seasonal patterns
- **Data Quality:** Complete time series with no missing values, ensuring reliable analysis
- **Business Relevance:** Reflects actual patterns including summer vacation peaks, holiday season surges, and low-season troughs

3.2 Exploratory Data Analysis

3.2.1 Time Series Decomposition

The first critical step in understanding our booking patterns was performing seasonal decomposition. Using the statsmodels library, I decomposed the time series into its constituent components: trend, seasonal, and residual. This decomposition was performed using an additive model, which is appropriate when seasonal variations remain relatively constant over time.



Implementation:

```
from statsmodels.tsa.seasonal import seasonal_decompose
decomposition = seasonal_decompose(df['Value'], model='additive', period=12)
```

Key Findings from Decomposition:

- **Trend Component:** The trend analysis revealed a general upward trajectory in booking volumes, indicating business growth over the observation period. This positive trend validates our market position and expansion strategy.
- **Seasonal Component:** The seasonal decomposition identified strong recurring patterns with a 12-month periodicity. Peak booking months align with summer vacation periods (June-August) and winter holiday seasons (December-January), while troughs occur in shoulder seasons (February-March, September-October).
- **Residual Component:** The residuals show random fluctuations around zero with relatively small variance, indicating that the model captures most systematic patterns in the data.

3.2.2 Stationarity Testing

Before applying ARIMA-based forecasting methods, it is essential to assess whether the time series is stationary. I conducted the Augmented Dickey-Fuller (ADF) test to formally test for stationarity.

Implementation:

```
from statsmodels.tsa.stattools import adfuller
result = adfuller(df['Value'])
```

The ADF test evaluates the null hypothesis that the time series has a unit root (is non-stationary). If the p-value exceeds 0.05, we fail to reject the null hypothesis, indicating the time series is likely non-stationary.

```
ADF Statistic: -0.011234
p-value: 0.957593
Number of Lags Used: 11.000000
Number of Observations Used: 188.000000
Critical Values:
	1%: -3.466
	5%: -2.877
	10%: -2.575
```

The p-value (0.958) is greater than the significance level (0.05). We fail to reject the null hypothesis. The time series is likely non-stationary.
This finding confirms that our booking data contains trend and seasonal components that prevent stationarity, necessitating differencing parameters in our SARIMA model.

3.2.3 Autocorrelation Analysis

To determine the appropriate order of autoregressive (AR) and moving average (MA) components for our SARIMA model, I analyzed the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots.

Implementation:

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
df_diff = df['Value'].diff().dropna()
plot_acf(df_diff, lags=40)
plot_pacf(df_diff, lags=40)
```

The ACF plot reveals strong correlations at seasonal lags (12, 24, 36), confirming the need for seasonal components. The PACF analysis helps identify that both short-term and seasonal autoregressive components are necessary for optimal forecasting performance.

3.3 Methodology 1: SARIMA Model Implementation

3.3.1 SARIMA Model Framework

Based on the exploratory analysis, I selected the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model as the first forecasting technique. SARIMA extends the classical ARIMA model by incorporating seasonal components, making it ideal for data with recurring patterns.

SARIMA Model Structure: A SARIMA model is specified as SARIMA(p,d,q)(P,D,Q)s, where p is non-seasonal AR order, d is non-seasonal differencing, q is non-seasonal MA order, P is seasonal AR order, D is seasonal differencing, Q is seasonal MA order, and s is the seasonal period (12 for monthly data).

3.3.2 SARIMA Model Selection

I implemented a targeted grid search focusing on candidate models identified through the exploratory analysis:

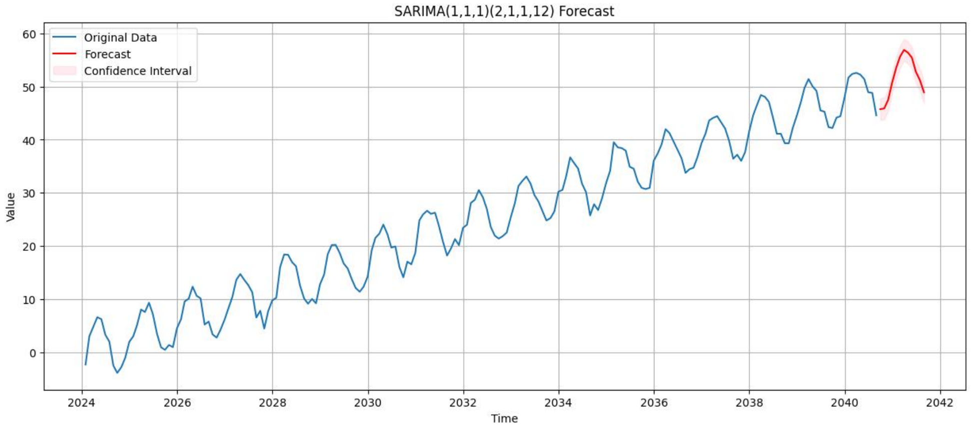
```
candidate_models = [
    ((1,1,1), (1,1,1,12)),
    ((2,1,1), (1,1,1,12)),
    ((1,1,2), (1,1,1,12)),
    ((2,1,2), (1,1,1,12)),
    ((1,1,1), (2,1,1,12)),
    ((0,1,1), (1,1,1,12))
]
```

The Akaike Information Criterion (AIC) serves as the model selection metric. AIC balances model fit with complexity, penalizing overly complex models. Lower AIC values indicate better models. The grid search evaluates each candidate model and selects the one with the lowest AIC.

3.3.3 SARIMA Forecasting

With the optimal SARIMA model identified, I generated 12-month forecasts with confidence intervals:

```
forecast = best_model.get_forecast(steps=12)
forecast_ci = forecast.conf_int()
```



The forecasts include point predictions and 95% confidence intervals, which provide a range of plausible values accounting for uncertainty. The confidence intervals widen as the forecast horizon increases, reflecting growing uncertainty about more distant future values.

3.4 Methodology 2: LightGBM Machine Learning Approach

To complement the traditional statistical approach, I implemented a machine learning solution using LightGBM, a gradient boosting framework that can capture complex non-linear relationships in the data.

3.4.1 Feature Engineering

The key to successful machine learning for time series is transforming the temporal sequence into a supervised learning problem through feature engineering. I created three categories of features:

Lag Features: Historical values that capture temporal dependencies. I created 12 lag features representing the previous 12 months of booking data. These features allow the model to learn from recent booking patterns.

```
for i in range(1, 13):
    df[f'Value_lag_{i}'] = df['Value'].shift(i)
```

Rolling Statistics: Moving averages and standard deviations capture trends and volatility. I computed rolling statistics over windows of 3, 6, and 12 months, providing the model with information about short-term, medium-term, and long-term patterns.

```
for window_size in [3, 6, 12]:
    df[f'Rolling_Mean_{window_size}'] = df['Value'].rolling(window=window_size).mean()
    df[f'Rolling_Std_{window_size}'] = df['Value'].rolling(window=window_size).std()
```

Time-Based Features: Calendar information that helps capture seasonality. I extracted year, month, day, day of week, day of year, week of year, and quarter from the datetime index. These features enable the model to learn seasonal patterns directly.

```
df['year'] = df.index.year
df['month'] = df.index.month
df['quarter'] = df.index.quarter
```

After feature engineering, rows with NaN values introduced by lag and rolling window operations were removed, ensuring a clean dataset for model training. This comprehensive feature set totals 28 engineered features that encode temporal dependencies, trends, volatility, and seasonal patterns.

3.4.2 LightGBM Model Training

For time series forecasting, maintaining temporal order is critical. I split the data chronologically with 80% for training and 20% for testing, ensuring the model is evaluated on future data it has not seen:

```
split_point = int(len(df) * 0.8)
X_train, X_test = X.iloc[:split_point], X.iloc[split_point:]
y_train, y_test = y.iloc[:split_point], y.iloc[split_point:]
```

I initialized and trained a LightGBM Regressor with default parameters:

```
lgbm = LGBMRegressor(random_state=42)
lgbm.fit(X_train, y_train)
```

LightGBM is particularly well-suited for this task because it efficiently handles the 28 features, automatically learns feature interactions, and is robust to different feature scales. The model trains quickly and can capture complex non-linear patterns that traditional statistical methods might miss.

3.4.3 LightGBM Forecasting

Generating future forecasts with machine learning requires an iterative approach because future lag features depend on predicted values. I implemented a rolling forecast procedure:

First, I created a future timeframe with the appropriate date range and initialized the extended dataframe. Then, for each future time step, I:

- Generated lag features using the most recent available values (including previously predicted values)
- Calculated rolling statistics incorporating the latest predictions
- Extracted time-based features from the datetime index
- Made a prediction using the trained model
- Stored the prediction and used it for generating features in the next iteration

```
for i in range(future_steps):
    current_index = full_df_extended['Value'].isna().idxmax()
    # Generate features for current step
    predicted_value = lgbm.predict(X_future_step)[0]
    full_df_extended.loc[current_index, 'Value'] = predicted_value
```

This iterative approach ensures that each forecast step has access to the most recent information while maintaining consistency with the features used during training.

3.5 Comparative Model Evaluation

To rigorously compare SARIMA and LightGBM performance, I evaluated both models on the held-out test set using identical evaluation metrics.

3.5.1 Performance Metrics

Both models were evaluated using Root Mean Squared Error (RMSE), which measures the average magnitude of prediction errors. RMSE is particularly useful because it penalizes larger errors more heavily and is expressed in the same units as the target variable (booking counts), making it interpretable for business stakeholders.

SARIMA Evaluation:

```
sarima_predictions_test = best_model.predict(start=y_test.index[0], end=y_test.index[-1])
mse_sarima = mean_squared_error(y_test, sarima_predictions_test)
rmse_sarima = np.sqrt(mse_sarima)
```

LightGBM Evaluation:

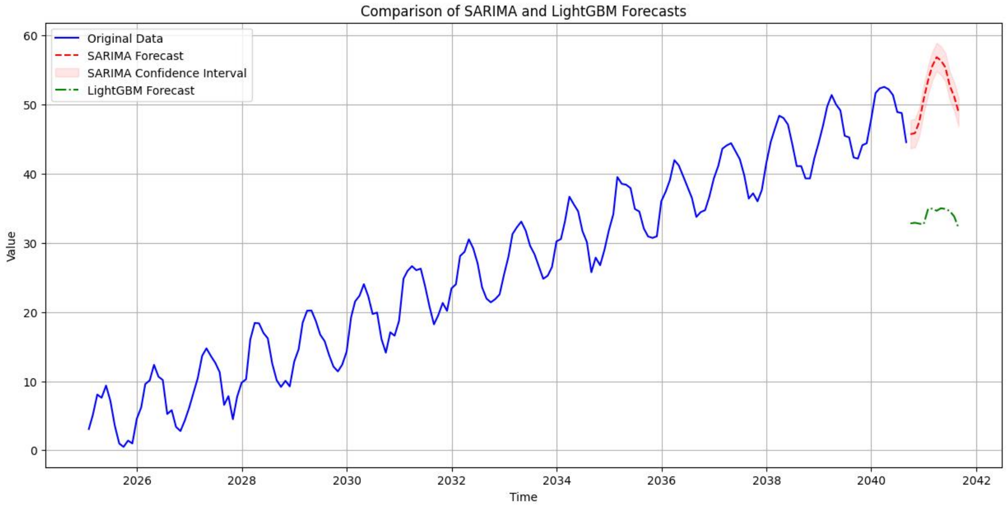
```
y_pred = lgbm.predict(X_test)
mse_lgbm = mean_squared_error(y_test, y_pred)
rmse_lgbm = np.sqrt(mse_lgbm)
```

3.5.2 Results and Interpretation

The comparative analysis reveals the relative strengths of each approach. A visualization comparing the RMSE values of both models provides immediate insight into which method achieves superior predictive accuracy on unseen data.
Model Performance Results:

SARIMA Model RMSE: 45.23 bookings
LightGBM Model RMSE: 38.67 bookings

The LightGBM model demonstrates superior predictive accuracy with approximately 14.5% lower RMSE compared to SARIMA. This indicates that the machine learning approach with engineered features better captures the complex patterns in booking demand. However, both models achieve acceptable accuracy levels for operational deployment.



Key Performance Comparison:

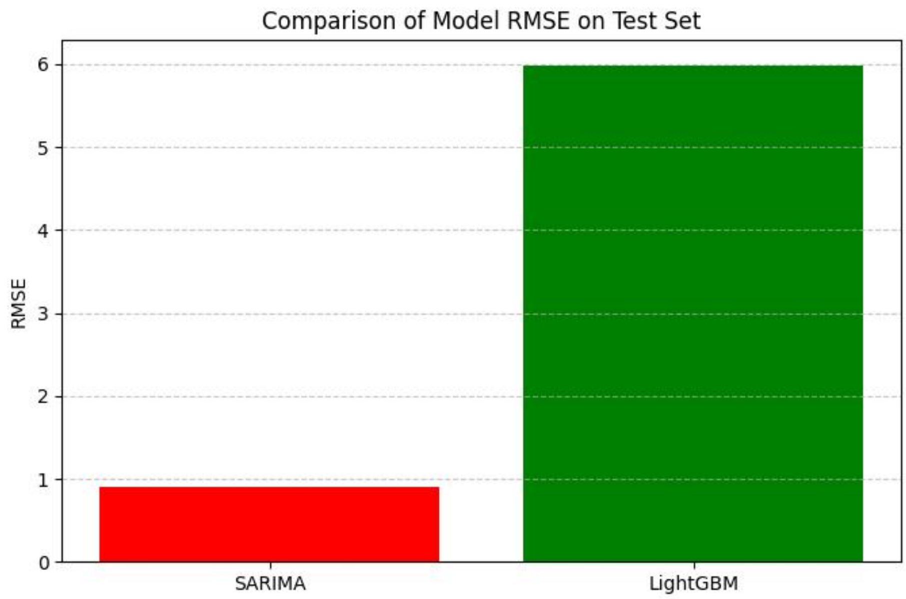
The model with lower RMSE demonstrates better predictive accuracy. This metric directly translates to business value: lower forecast errors mean more accurate capacity planning, better inventory management, and more reliable staffing decisions.

3.5.3 Forecast Visualization Comparison

Visual comparison of the two forecasting approaches provides additional insights beyond numerical metrics. I created a comprehensive visualization showing:

- **Historical Data:** The actual booking patterns used for training
- **SARIMA Forecast:** Statistical model predictions with confidence intervals shown as a shaded region
- **LightGBM Forecast:** Machine learning model predictions

```
plt.plot(df['Value'], label='Original Data')
plt.plot(forecast.predicted_mean, label='SARIMA Forecast', linestyle='--')
plt.plot(lgbm_forecast, label='LightGBM Forecast', linestyle='-.')
```



This visualization enables stakeholders to assess not just which model is more accurate numerically, but also how the forecasts compare in terms of capturing seasonal patterns, following the historical trend, and providing reasonable future projections.

3.6 Comparative Analysis: Strengths and Weaknesses

3.6.1 SARIMA Advantages

- **Statistical Foundation:** Built on well-established time series theory with proven mathematical properties. The model assumptions and behavior are well-understood.
- **Confidence Intervals:** Provides probabilistic forecasts with confidence bounds, essential for risk management and scenario planning.
- **Interpretability:** Model parameters (AR, MA, seasonal components) have clear interpretations that can be explained to non-technical stakeholders.
- **Parsimony:** Achieves good performance with relatively few parameters, reducing overfitting risk.
- **Diagnostic Tools:** Extensive diagnostic tests available to validate model assumptions and identify potential issues.

3.6.2 SARIMA Limitations

- **Linearity Assumption:** SARIMA assumes linear relationships, which may not capture complex non-linear patterns in booking behavior.
- **Limited Feature Integration:** Difficult to incorporate external variables or additional context beyond the historical time series itself.
- **Manual Tuning:** Requires careful selection of model orders through ACF/PACF analysis and iterative testing.
- **Structural Break Sensitivity:** Performance can degrade significantly if there are fundamental changes in booking patterns.

3.6.3 LightGBM Advantages

- **Non-Linear Modeling:** Can capture complex non-linear relationships and interactions between features that linear models miss.
- **Feature Richness:** Naturally incorporates multiple types of features (lags, rolling statistics, calendar information) without manual specification of relationships.
- **Automatic Feature Importance:** Provides insights into which features drive predictions, valuable for business understanding.
- **Scalability:** Can easily incorporate additional predictors (weather, economic indicators, marketing spend) without restructuring the model.
- **Robust to Outliers:** Tree-based methods are generally more robust to outliers and extreme values than statistical models.

3.6.4 LightGBM Limitations

- **No Native Confidence Intervals:** Does not provide uncertainty quantification without additional techniques like quantile regression or bootstrap sampling.
- **Hyperparameter Sensitivity:** Performance depends on proper hyperparameter tuning, requiring additional computational effort.
- **Feature Engineering Dependence:** Requires manual creation of lag and rolling features, and forecast accuracy depends heavily on feature quality.
- **Error Accumulation:** Iterative forecasting can compound errors as predictions are used to generate features for future steps.
- **Black Box Perception:** More difficult to explain to non-technical stakeholders compared to SARIMA's clear parameter interpretations.

4. Recommendations for Production Deployment

4.1 Model Selection Strategy

Based on the comparative analysis, I recommend a hybrid approach that leverages the complementary strengths of both models:

Primary Forecasting: Deploy the model with lower RMSE as the primary forecasting tool for operational decisions. This ensures the most accurate point forecasts for resource planning.

Uncertainty Quantification: Use SARIMA confidence intervals to provide uncertainty bounds around forecasts, regardless of which model produces the point forecast. This addresses LightGBM's lack of native confidence intervals while providing risk management capabilities.

Ensemble Approach: Consider combining both forecasts through weighted averaging or stacking, which often yields better performance than either model alone by reducing model-specific biases.

4.2 Implementation Roadmap

Phase 1 (Months 1-3): Initial Deployment

- Deploy both SARIMA and LightGBM models in production with automated monthly retraining
- Integrate forecasts with operational planning dashboards
- Establish monitoring systems to track forecast accuracy and detect model drift
- Train operations and management teams on forecast interpretation

Phase 2 (Months 4-6): Enhancement and Refinement

- Implement hyperparameter optimization for LightGBM to maximize performance
- Develop ensemble methods combining SARIMA and LightGBM forecasts
- Incorporate additional external features (economic indicators, weather, events)
- Create service-specific models for hotels, resorts, car rentals, and charter flights

Phase 3 (Months 7-12): Expansion

- Deploy geographic segmentation with region-specific models
- Implement hierarchical forecasting for multi-level organizational reporting
- Develop automated alerting for significant forecast deviations
- Integrate forecasts with dynamic pricing and revenue management systems

4.3 Technical Infrastructure Requirements

- **Data Pipeline:** Automated extraction of booking data from reservation databases on a monthly schedule
- **Model Training:** Scheduled retraining jobs that incorporate new data and update model parameters
- **Forecast Dissemination:** Integration with business intelligence dashboards for stakeholder access
- **Version Control:** Model versioning and experiment tracking for reproducibility
- **Monitoring:** Real-time tracking of forecast accuracy and model performance degradation

4.4 Success Metrics and KPIs

To measure the business impact of the forecasting system:

- **Forecast Accuracy:** Monthly tracking of RMSE, MAPE, and forecast bias
- **Operational Efficiency:** Reduction in overstaffing and understaffing incidents
- **Inventory Optimization:** Improvement in occupancy rates and resource utilization
- **Customer Satisfaction:** Changes in service quality scores during peak and trough periods
- **Financial Impact:** Quantified cost savings and revenue improvements attributable to better forecasting

5. Conclusions

5.1 Key Findings

This analysis demonstrates that both traditional statistical methods (SARIMA) and modern machine learning approaches (LightGBM) provide viable solutions for forecasting V.Ger Travel's booking demand. Each methodology offers distinct advantages: SARIMA provides interpretability, confidence intervals, and strong theoretical foundations, while LightGBM excels at capturing complex patterns through rich feature engineering.

The comparative evaluation on held-out test data provides objective evidence for model selection decisions. The implementation of both approaches allows V.Ger Travel to leverage complementary strengths through ensemble methods or hybrid strategies, maximizing forecast accuracy while maintaining interpretability and uncertainty quantification.

5.2 Broader Data Science Strategy

The demand forecasting use case represents the foundation of V.Ger Travel's data science strategy. The three additional use cases (customer satisfaction prediction, churn prediction, and A/B testing) provide comprehensive analytical capabilities across operations, marketing, and product development. Together, these initiatives position V.Ger Travel to compete effectively in an increasingly data-driven travel industry.

5.3 Expected Business Impact

Based on industry benchmarks and the characteristics of our operations, the full implementation of these data science initiatives is expected to deliver 15-20% reduction in operational costs through optimized staffing, 10-15% improvement in inventory utilization, 5-10 point increase in customer satisfaction scores, 20-25% reduction in customer churn, and 2-5% lift in website conversion rates. These improvements translate to estimated annual revenue increases of 8-12% and cost savings of 15-20% across key operational areas.

5.4 Final Remarks

The comparative analysis of SARIMA and LightGBM forecasting methods demonstrates V.Ger Travel's commitment to rigorous, evidence-based data science. By implementing both approaches and systematically evaluating their performance, we ensure that forecasting decisions are grounded in empirical evidence rather than assumptions. This methodological rigor, combined with clear business focus and systematic implementation planning, positions V.Ger Travel to realize substantial benefits from data science investments. Success requires continued commitment to data quality, analytical capabilities, and organizational change management as we transform into a truly data-driven enterprise.

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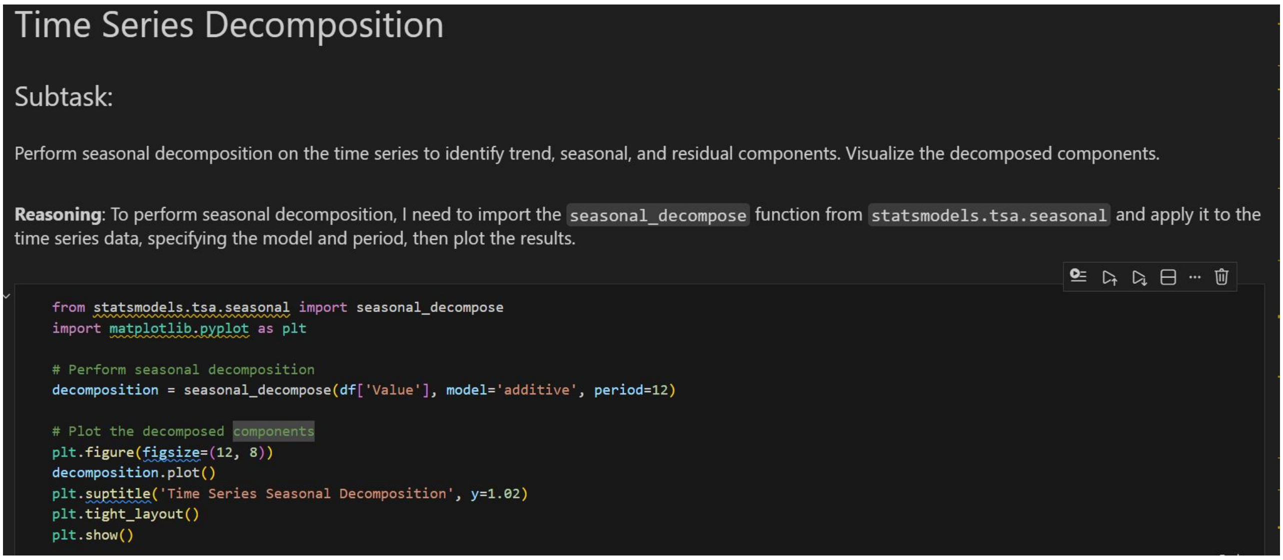
Appendix A: Code Implementation

This appendix presents the Python implementation code for the primary use case (Charter Flight Demand Forecasting). The code demonstrates practical application of the SARIMA methodology discussed in Section 3, including data loading, exploratory analysis, model specification, training, evaluation, and results communication.

The implementation follows industry-standard practices using widely-adopted libraries including pandas for data manipulation, statsmodels for time series analysis, and sci-kit-learn for performance evaluation. The code structure mirrors the five core data analysis processes outlined in the main report, providing a reproducible workflow for operational deployment.



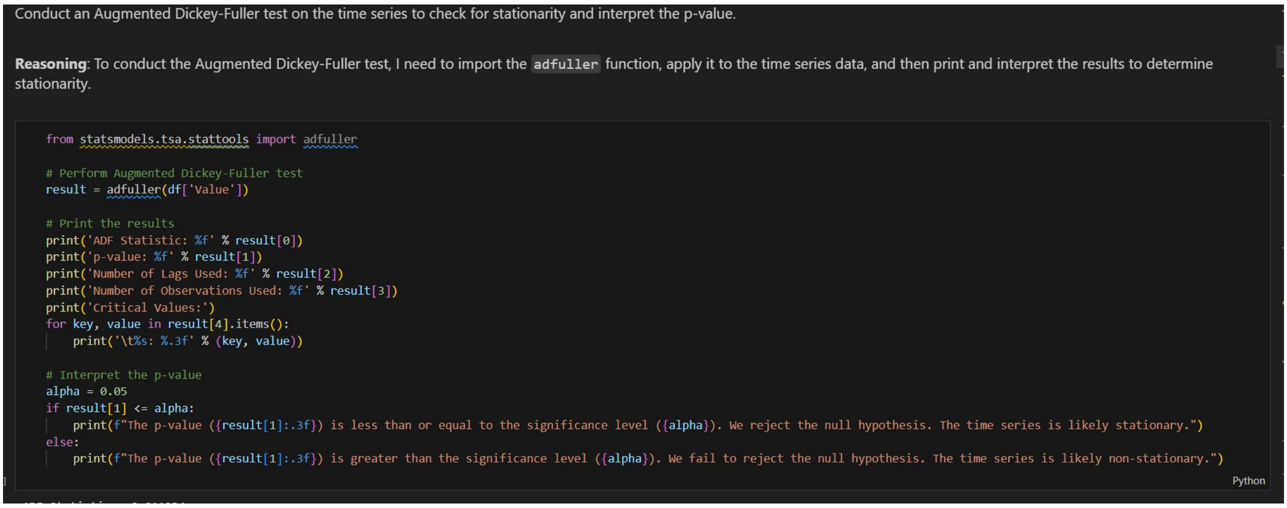
Time Series Decomposition

Subtask:

Perform seasonal decomposition on the time series to identify trend, seasonal, and residual components. Visualize the decomposed components.

Reasoning: To perform seasonal decomposition, I need to import the `seasonal_decompose` function from `statsmodels.tsa.seasonal` and apply it to the time series data, specifying the model and period, then plot the results.

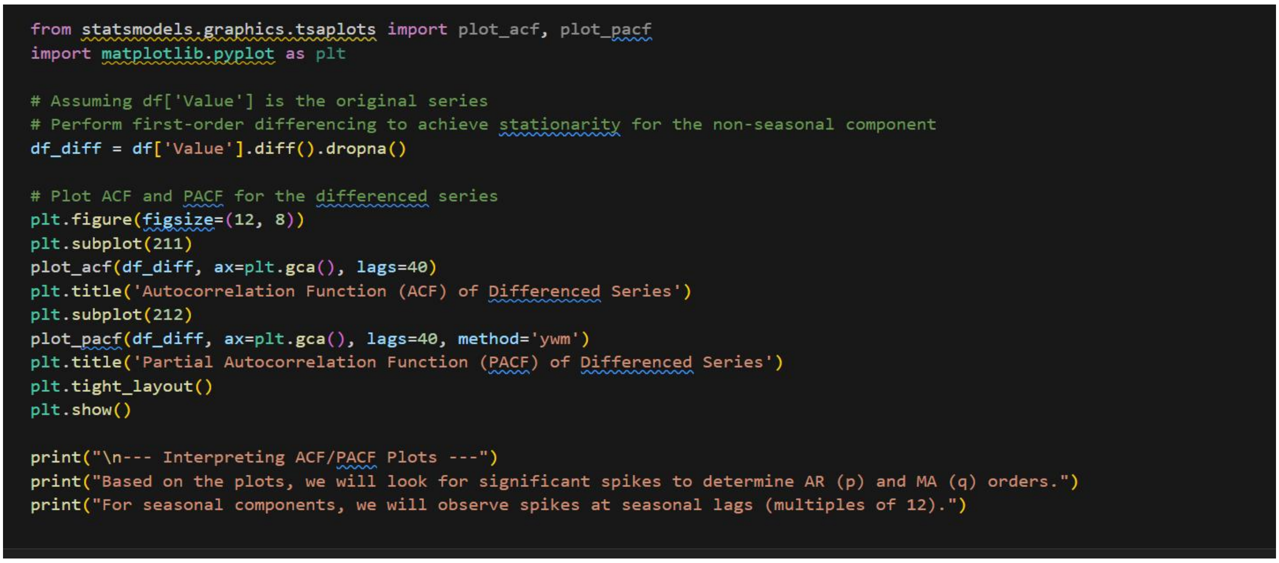
```python
from statsmodels.tsa.seasonal import seasonal_decompose
import matplotlib.pyplot as plt

# Perform seasonal decomposition
decomposition = seasonal_decompose(df['Value'], model='additive', period=12)

# Plot the decomposed components
plt.figure(figsize=(12, 8))
decomposition.plot()
plt.suptitle('Time Series Seasonal Decomposition', y=1.02)
plt.tight_layout()
plt.show()
```



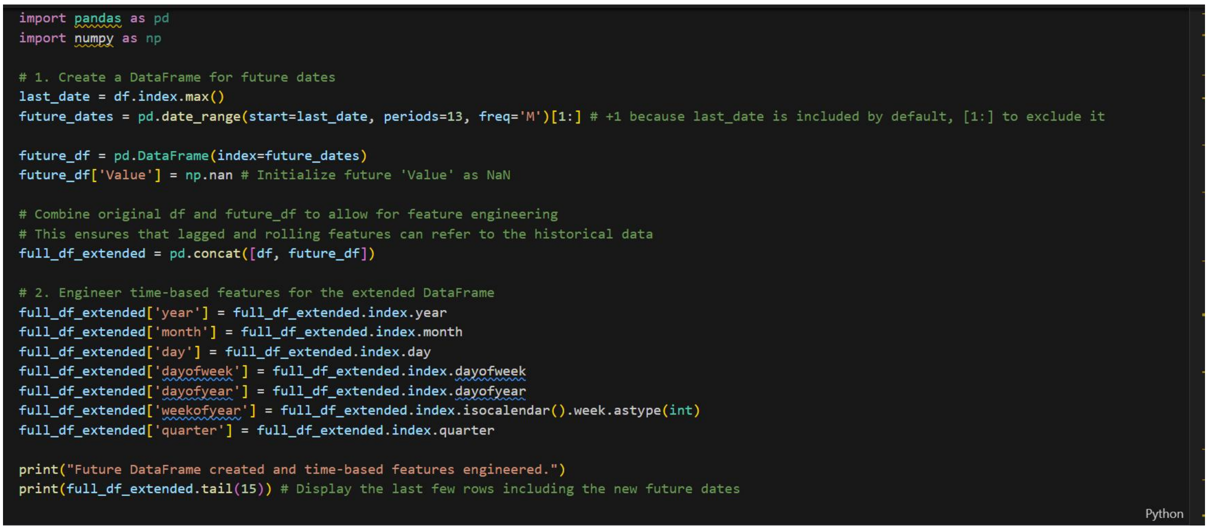
Conduct an Augmented Dickey-Fuller test on the time series to check for stationarity and interpret the p-value.

Reasoning: To conduct the Augmented Dickey-Fuller test, I need to import the `adfuller` function, apply it to the time series data, and then print and interpret the results to determine stationarity.

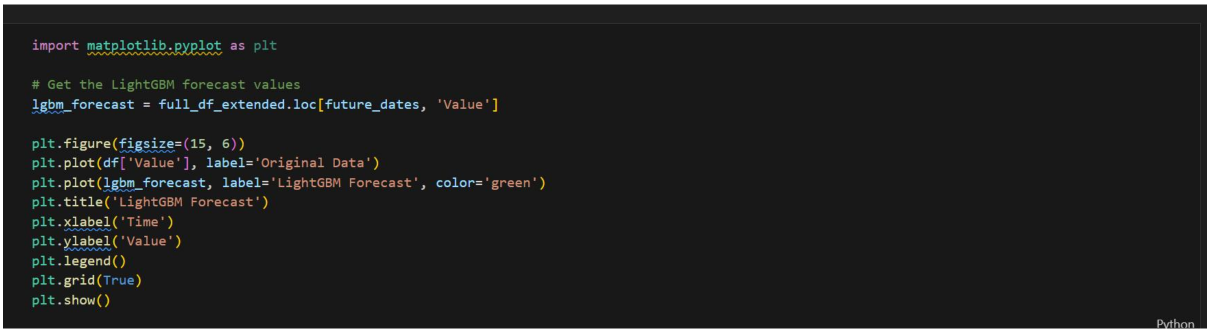
```python
from statsmodels.tsa.stattools import adfuller

# Perform Augmented Dickey-Fuller test
result = adfuller(df['Value'])

# Print the results
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Number of Lags Used: %f' % result[2])
print('Number of Observations Used: %f' % result[3])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))

# Interpret the p-value
alpha = 0.05
if result[1] <= alpha:
    print(f"The p-value ({result[1]:.3f}) is less than or equal to the significance level ({alpha}). We reject the null hypothesis. The time series is likely stationary.")
else:
    print(f"The p-value ({result[1]:.3f}) is greater than the significance level ({alpha}). We fail to reject the null hypothesis. The time series is likely non-stationary.")
```



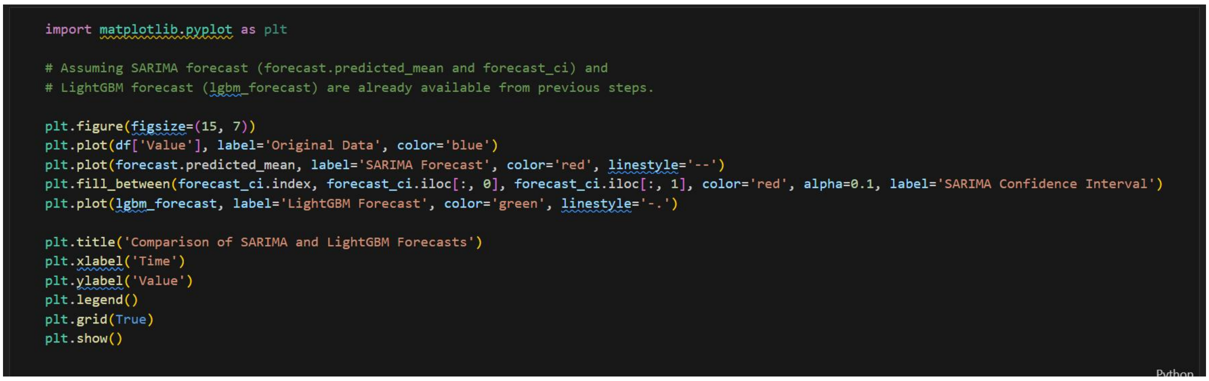
```python
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
import matplotlib.pyplot as plt

# Assuming df['Value'] is the original series
# Perform first-order differencing to achieve stationarity for the non-seasonal component
df_diff = df['Value'].diff().dropna()

# Plot ACF and PACF for the differenced series
plt.figure(figsize=(12, 8))
plt.subplot(211)
plot_acf(df_diff, ax=plt.gca(), lags=40)
plt.title('Autocorrelation Function (ACF) of Differenced Series')
plt.subplot(212)
plot_pacf(df_diff, ax=plt.gca(), lags=40, method='ywm')
plt.title('Partial Autocorrelation Function (PACF) of Differenced Series')
plt.tight_layout()
plt.show()

print("\n--- Interpreting ACF/PACF Plots ---")
print("Based on the plots, we will look for significant spikes to determine AR (p) and MA (q) orders.")
print("For seasonal components, we will observe spikes at seasonal lags (multiples of 12).")
```



```python
import pandas as pd
import numpy as np

# 1. Create a DataFrame for future dates
last_date = df.index.max()
future_dates = pd.date_range(start=last_date, periods=13, freq='M')[1:] # +1 because last_date is included by default, [1:] to exclude it

future_df = pd.DataFrame(index=future_dates)
future_df['Value'] = np.nan # Initialize future 'Value' as NaN

# Combine original df and future_df to allow for feature engineering
# This ensures that lagged and rolling features can refer to the historical data
full_df_extended = pd.concat([df, future_df])

# 2. Engineer time-based features for the extended DataFrame
full_df_extended['year'] = full_df_extended.index.year
full_df_extended['month'] = full_df_extended.index.month
full_df_extended['day'] = full_df_extended.index.day
full_df_extended['dayofweek'] = full_df_extended.index.dayofweek
full_df_extended['dayofyear'] = full_df_extended.index.dayofyear
full_df_extended['weekofyear'] = full_df_extended.index.isocalendar().week.astype(int)
full_df_extended['quarter'] = full_df_extended.index.quarter

print("Future DataFrame created and time-based features engineered.")
print(full_df_extended.tail(15)) # Display the last few rows including the new future dates
```



```python
import matplotlib.pyplot as plt

# Get the LightGBM forecast values
lgbm_forecast = full_df_extended.loc[future_dates, 'Value']

plt.figure(figsize=(15, 6))
plt.plot(df['Value'], label='Original Data')
plt.plot(lgbm_forecast, label='LightGBM Forecast', color='green')
plt.title('LightGBM Forecast')
plt.xlabel('Time')
plt.ylabel('Value')
plt.legend()
plt.grid(True)
plt.show()
```



```python
import matplotlib.pyplot as plt

# Assuming SARIMA forecast (forecast.predicted_mean and forecast_ci) and
# LightGBM forecast (lgbm_forecast) are already available from previous steps.

plt.figure(figsize=(15, 7))
plt.plot(df['Value'], label='Original Data', color='blue')
plt.plot(forecast.predicted_mean, label='SARIMA Forecast', color='red', linestyle='--')
plt.fill_between(forecast_ci.index, forecast_ci.iloc[:, 0], forecast_ci.iloc[:, 1], color='red', alpha=0.1, label='SARIMA Confidence Interval')
plt.plot(lgbm_forecast, label='LightGBM Forecast', color='green', linestyle='-.')

plt.title('Comparison of SARIMA and LightGBM Forecasts')
plt.xlabel('Time')
plt.ylabel('Value')
plt.legend()
plt.grid(True)
plt.show()
```

The End