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Pricing and Regression

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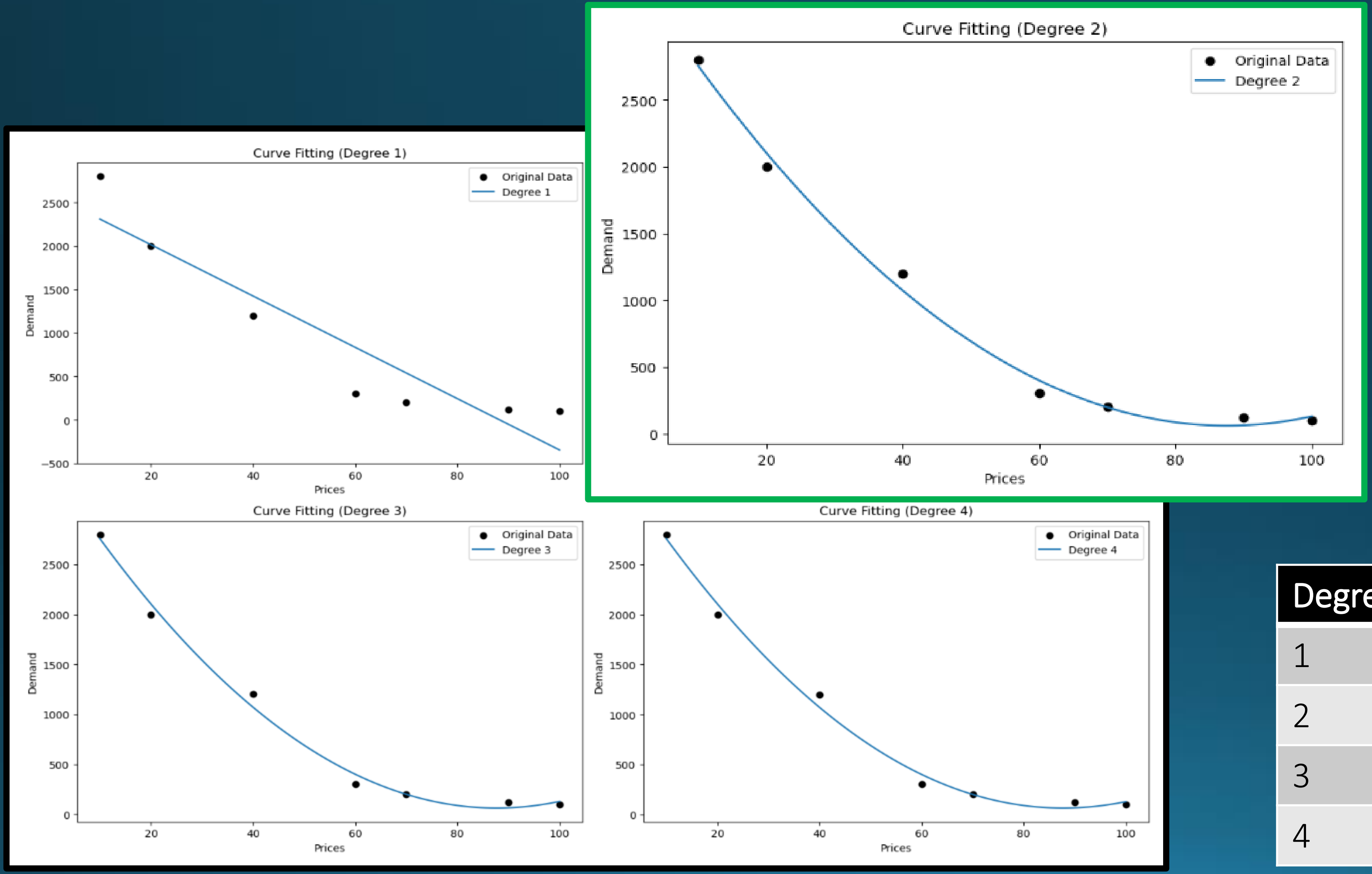
Optimal Pricing for Revenue Maximization

- Objective:
  - Drive revenue growth through an optimal pricing strategy.
- Approach:
  - Explore two distinct methodologies, dynamic programming and polynomial curve fitting, to pinpoint the price that maximizes revenue.
    - Dynamic Programming: Navigate through different prices to find the one that maximizes revenue.
    - Curve Fitting: Apply polynomial regression to fit a smooth curve to the demand data, enabling better-informed pricing decisions by capturing nuanced customer demand trends.
- Assumption:
  - Assume the provided demand-price data reflects the real-world scenario accurately.
  - Consider the validity of the revenue-maximizing price falling within the range of 10 to 100.
- Outcome:
  - Dynamic Programming resulted in a revenue-maximizing price of 40.
  - Polynomial Curve Fitting highlighted a maximum revenue at a price of 30 ✓

Demand Trends through Polynomial Regression

- Data Input
  - The demand quantities, i.e. the number of people willing to buy, at various price levels.
- Methodology:
  - Curve Fitting:
    - Applied polynomial regression to model the demand as a function of pricing.
    - Investigated degrees 1 to 4 to capture varying complexities in the demand-price relationship.
  - Optimal Price Identification:
    - Utilized the minimize_scalar function to find the price that maximizes revenue.
    - Constrained the search within the 10 to 100 price range.
  - Visualization:
    - Plotted original demand-price data and fitted curves for each polynomial degree.
- Key Findings:
  - Optimal Price & Revenue:
    - Degree 2 polynomial yielded an optimal price of 30, resulting in a maximum revenue of 46309.
  - Model Effectiveness:
    - Higher-degree polynomials did not contribute substantially to the model's predictive power.

Visualization



Degree	Price	Revenue
1	44	57441
2	30	46309
3	30	46229
4	30	46255

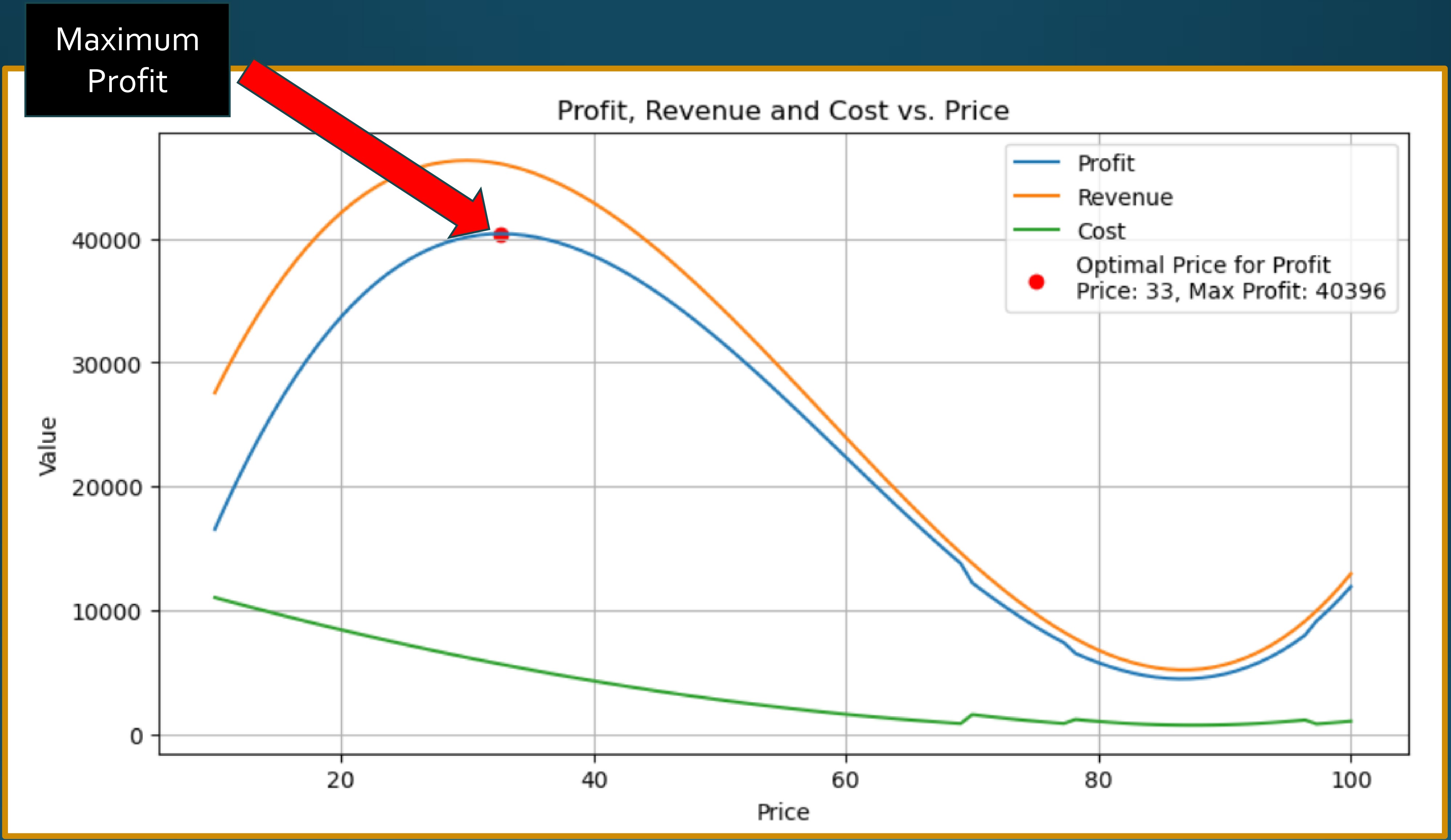
Optimal Pricing for Profit Maximization

- Objective:
  - Optimize pricing considering supplier pricing and maximize profits.
- Approach:
  - Develop a profit-maximizing model by integrating demand data and progressive supplier pricing.
  - Identify the price yielding maximum profits utilizing a combination of demand modeling and supplier pricing information.
- Assumption:
  - Assume the provided demand-price data reflects the real-world scenario accurately.
  - Consider the validity of the revenue-maximizing price falling within the range of 10 to 100.
  - The supplier pricing table reflects the cost structure accurately.
  - The only costs we have are the cost of the goods we sell.
- Outcome:
  - The model unveils the pricing strategy that optimally balances demand and supplier costs, ensuring maximal profitability.

Profit Patterns via Polynomial Regression

- Data Input:
  - The demand quantities, i.e. the number of people willing to buy, at various price levels.
  - Supplier pricing with progressive discounts
- Methodology:
  - Curve Fitting:
    - Utilized a polynomial of degree 2 to capture the curvature in the demand-price relationship.
  - Optimal Price Identification for Profit Maximization:
    - Formulated the profit function, considering cost and revenue based on the polynomial fit.
    - Applied the minimize_scalar function to find the price that maximizes profits within a realistic price range of 10 to 100.
  - Visualization:
    - Plotted the profit, revenue and cost curves against different pricing levels.
- Key Findings:
  - Optimal Price for Profit Maximization::
    - The analysis identified an optimal price of approximately 33 for profit maximization.
    - The maximum profit achievable at the optimal price was found to be around 40396.

Visualization

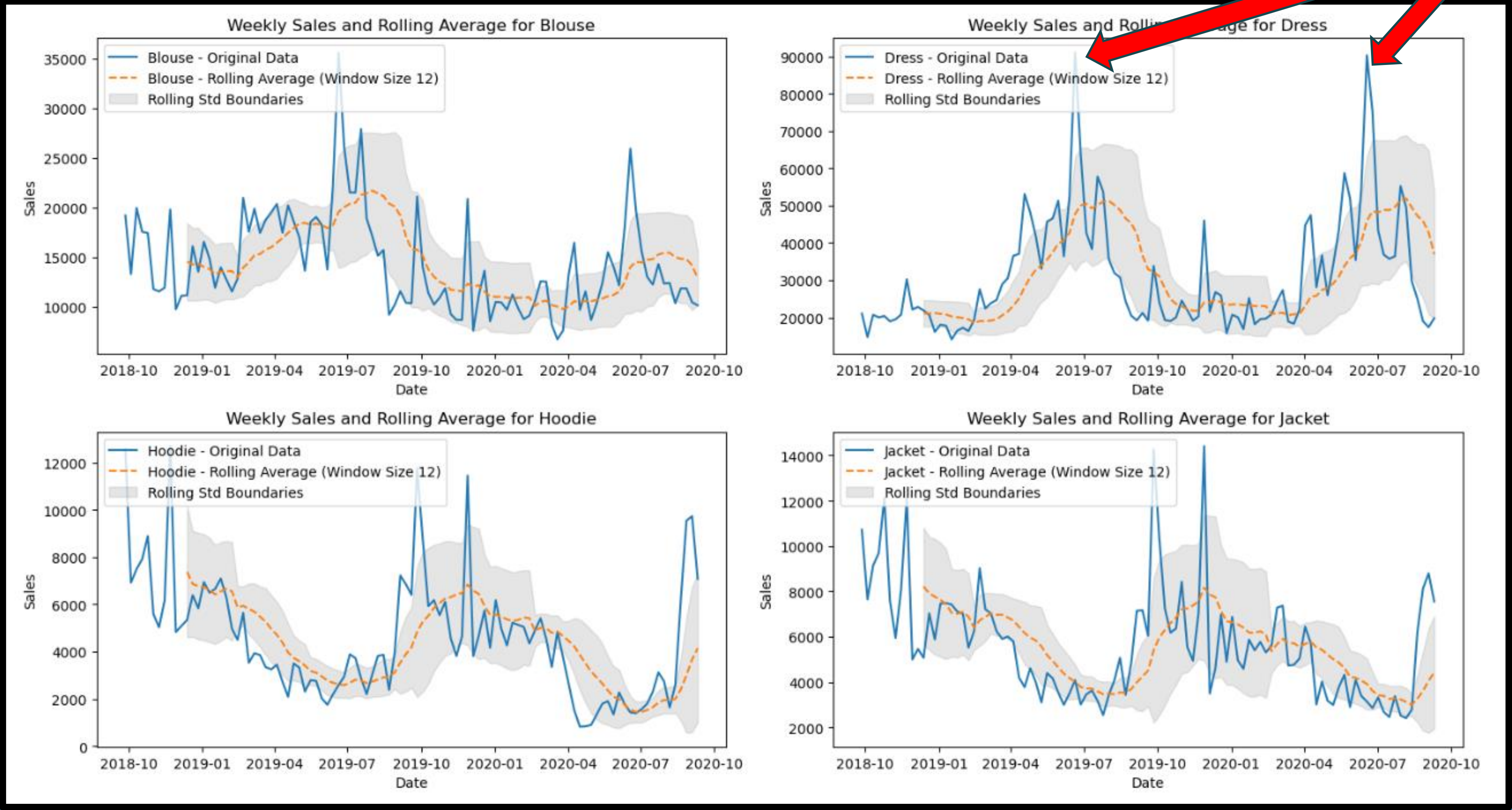


Regression

- Objective:
  - To gain insights into the demand dynamics of different product types through regression analysis.
  - Identify trends, seasonality and correlations within the sales data.
  - Develop a model to forecast for future sales, including confidence intervals.
- Approach:
  - Conducted exploratory data analysis to uncover patterns, trends and seasonality in the sales data.
  - Applied Seasonal-Trend decomposition to separate trend, seasonality and residual components.
  - Explored correlations between sales of different product types.
  - Utilized ARIMA model for forecasting a selected product type.
- Assumption:
  - Assumed that historical sales patterns would continue to influence future sales.
  - Expected ARIMA to effectively capture and forecast the underlying patterns in the time series data.
- Outcome:
  - Identified overall trends and seasonal patterns in the weekly sales data in different product types.
  - Investigated correlations to understand relationships between product types.
  - Developed accurate forecasts for a specific product type using ARIMA.

Data Visualization

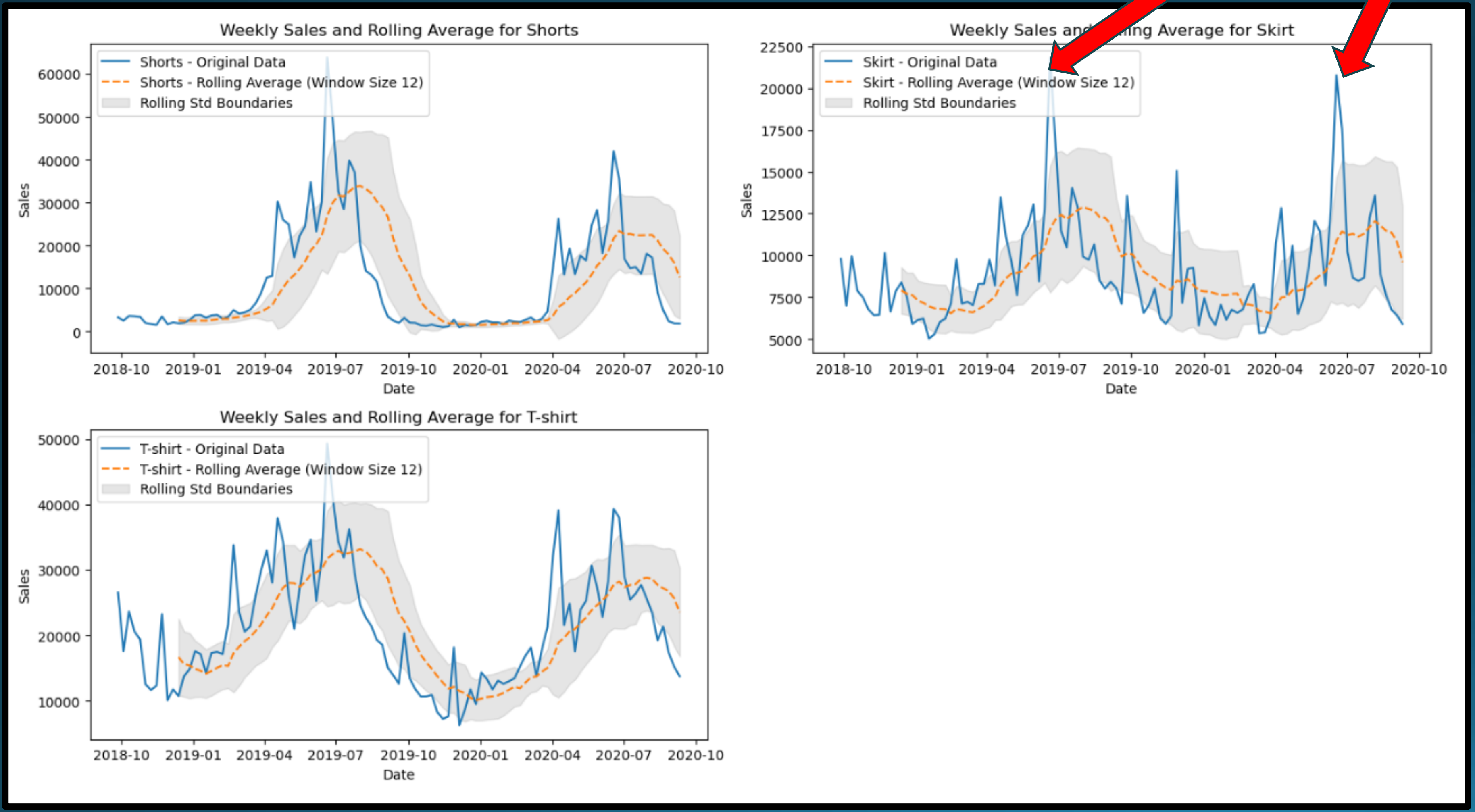
Seasonal Peaks



Product Types	Average Sales	Seasonal Peak (Max)
Blouse	14372	2.48x
Dress	31115	2.93x
Hoodie	4555	2.79x
Jacket	5675	2.54x

Data Visualization

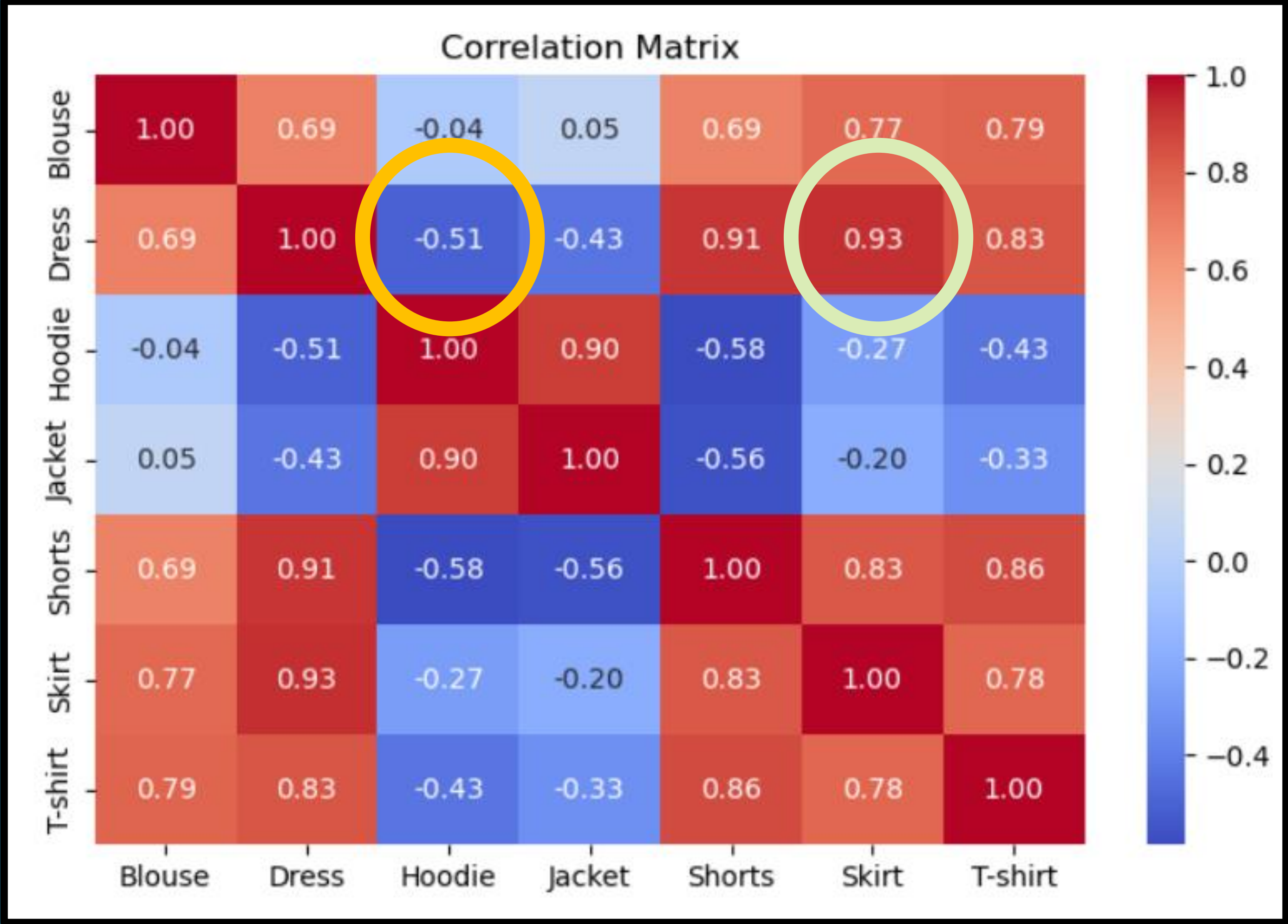
Seasonal Peaks



Product Types	Average Sales	Seasonal Peak (Max)
Shorts	11146	5.72
Skirt	8951	2.44
T-Shirt	21097	2.34

Correlations Between Sales of Different Product types

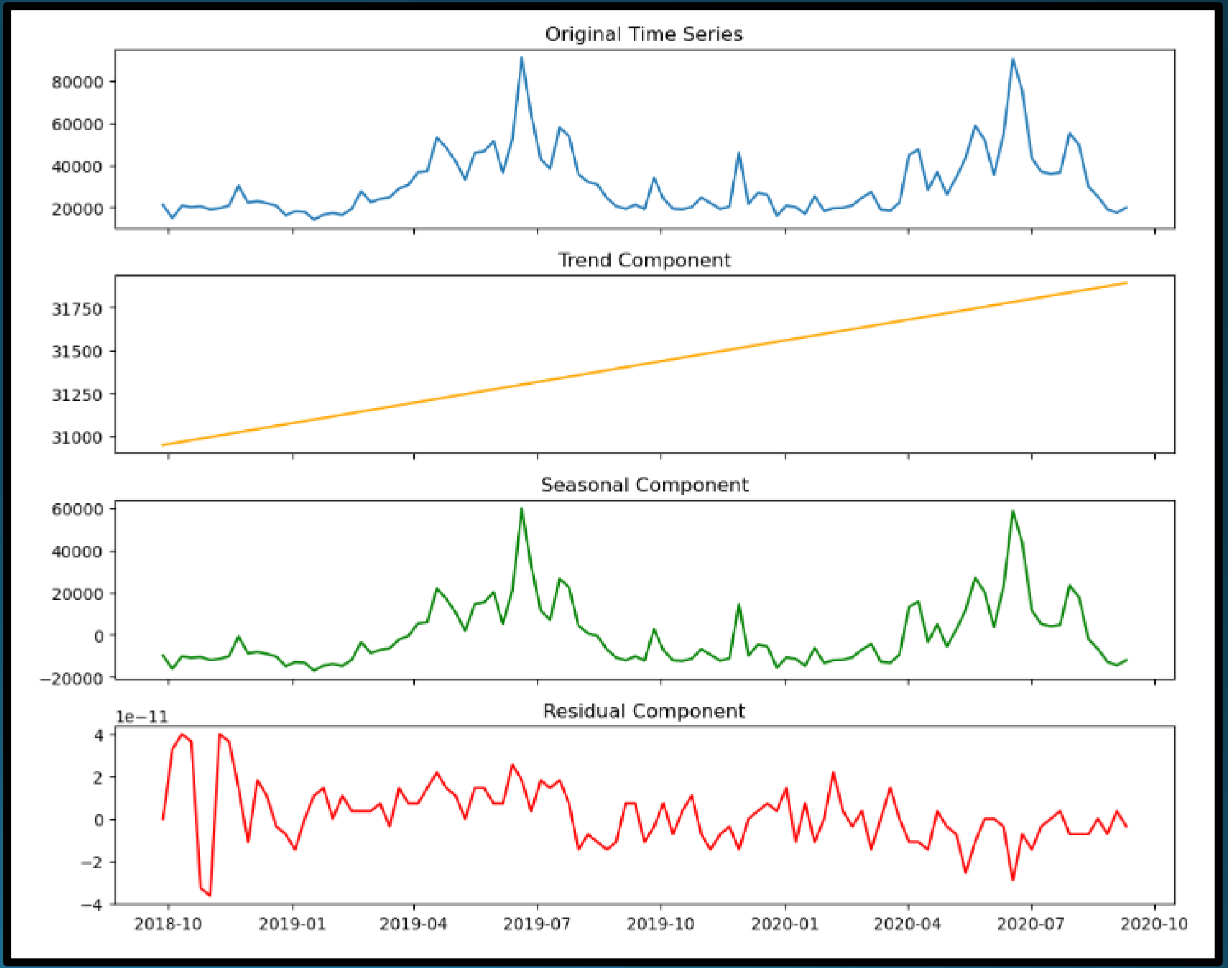
- Identified statistically significant correlations using Pearson's correlation coefficient.
- Dress and Hoodie: Moderate negative correlation of -0.51, suggesting potential substitution effects between these items.
- Dress and Skirt: Strong positive correlation of 0.93, indicating a potential trend in coordinating dress and skirt purchases.



“Dress” Sales - Trend and Seasonal Patterns

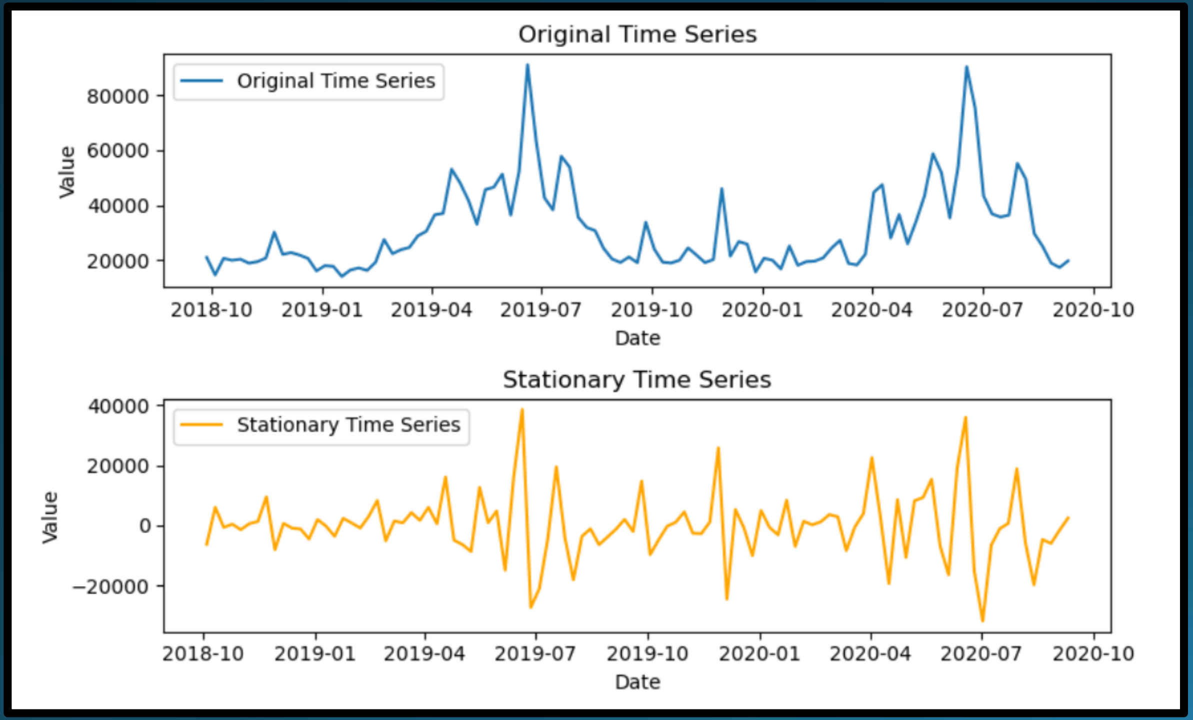
Trend Component: The long-term direction or tendency in the sales data. There is an upward trend in sales we can observe from the chart.

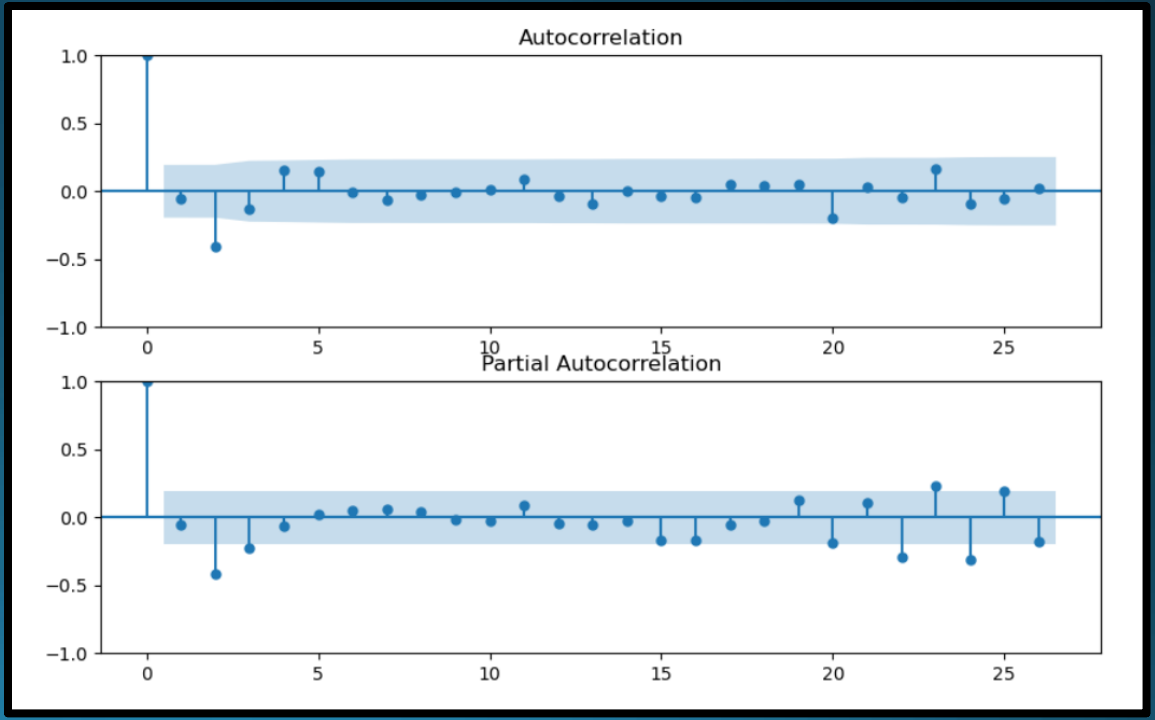
Seasonal Component: Recurrent patterns occurring at fixed intervals. Detected patterns that repeat on a yearly basis as we can see from the chart



“Dress” Sales - Stationarity and SARIMA parameters

- Performed the ADF test to evaluate the stationarity of the dress sales time series, revealing non-stationarity as the p-value (0.22) exceeds the significance level ($\alpha = 0.05$).
- Applied a first-order difference(d=1) to remove trends and seasonality from the original time series.
- ACF Analysis: Prominent spike at lag 2 implies a potential value of MA(q)=2.
- PACF Analysis: Spikes at lags 2 and 3 suggest potential values for AR(p) as {2,3}.
- The seasonal order (m) for the time series is set to 52, representing the weekly frequency. Considering yearly seasonality, a spike at lag 52 is anticipated, leading to a value of Q as 1.





ARIMA Model Performance

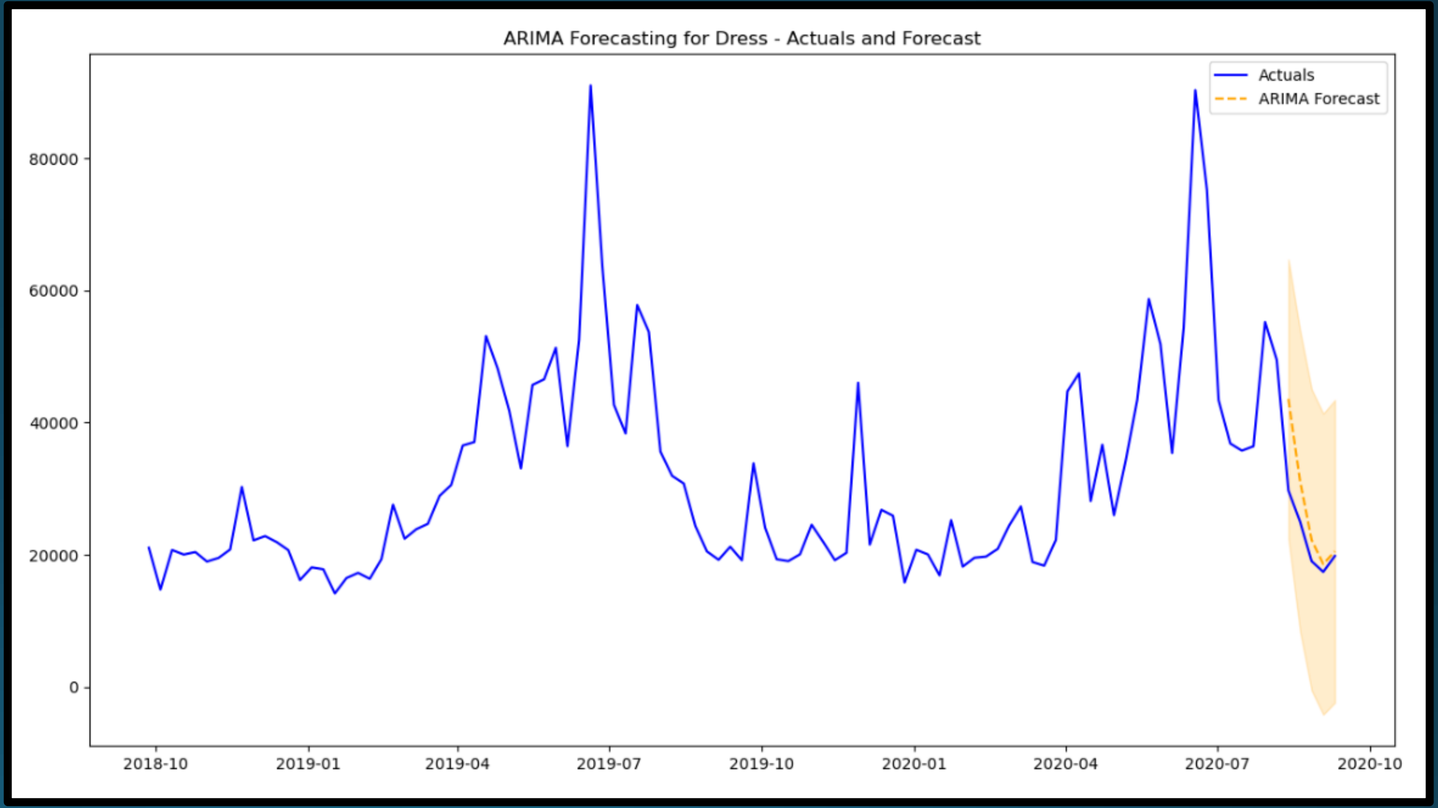
Data Input: "Dress" sales data for the last 2 years

Approach:
Split the data into training and validation sets to assess the forecasting model's performance accurately.

Employed a SARIMAX model with predefined parameters (order=(2, 1, 2), seasonal_order=(0, 1, 1, 52)).

Generated SARIMA forecasts for the validation period (last 5 weeks in the history), providing a predictive outlook for the future.

Accuracy = 84.81%

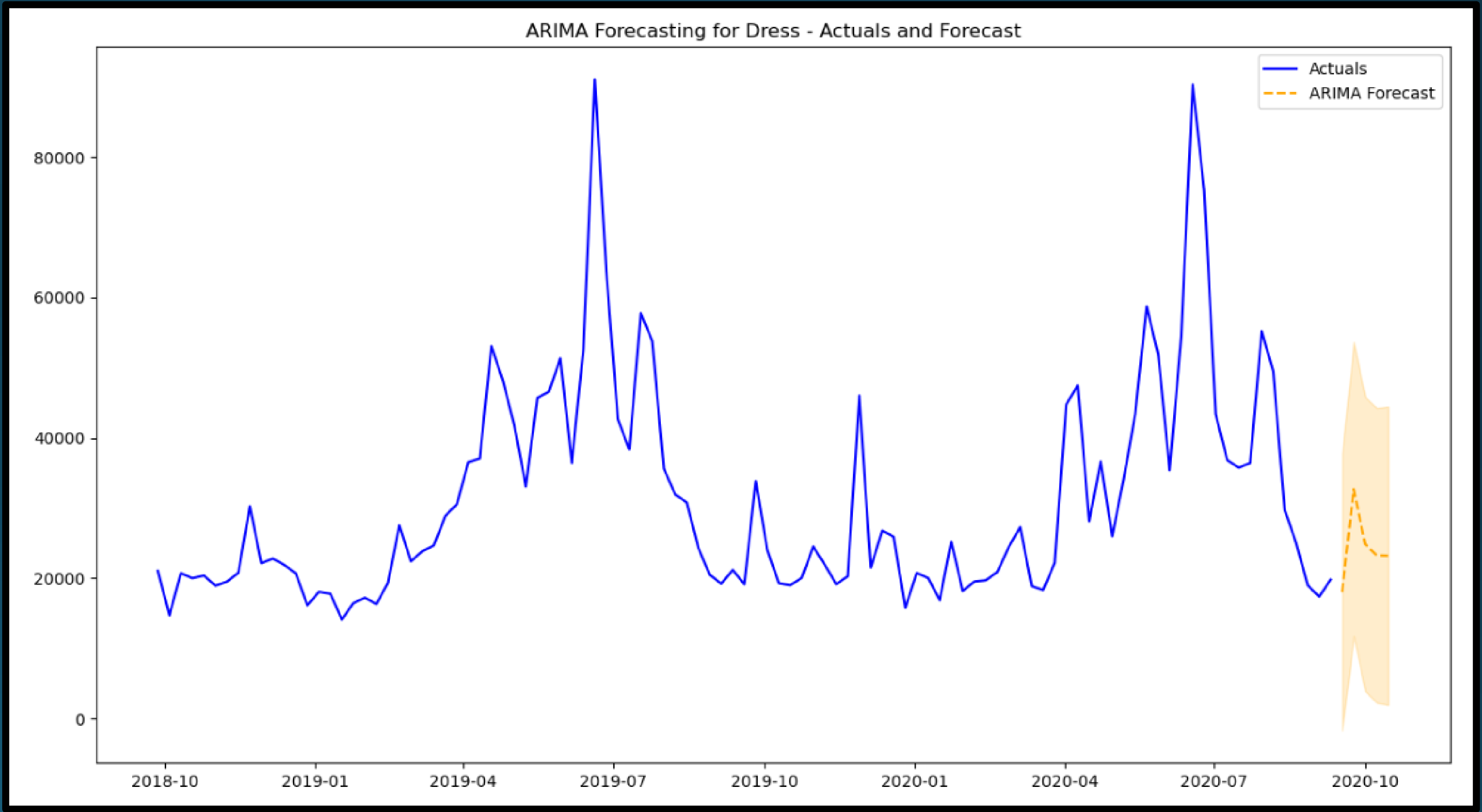


ARIMA Model Forecast for Future Period

Data Input: “Dress” sales data for the last 2 years

Dotted line represents future forecasts for the next 5 days.

Shaded area represents the confidence interval.



Next Steps

- Refinement of Forecasting Models:
  - Continuously refine and optimize forecasting models.
  - Explore alternative time series models and methodologies for improved accuracy.
- Incorporate External Factors:
  - Consider external factors influencing demand such as seasonality, holidays and marketing events, promotions
  - Evaluate the impact of economic indicators on sales patterns.
- Dynamic Inventory Management:
  - Implement dynamic inventory management strategies based on refined forecasts.
  - Adjust stock levels in response to changing demand patterns.
- Advanced Analytics and Machine Learning:
  - Explore advanced analytics techniques and machine learning algorithms.
- Continuous Monitoring and Evaluation:
  - Establish a continuous monitoring system for model performance.