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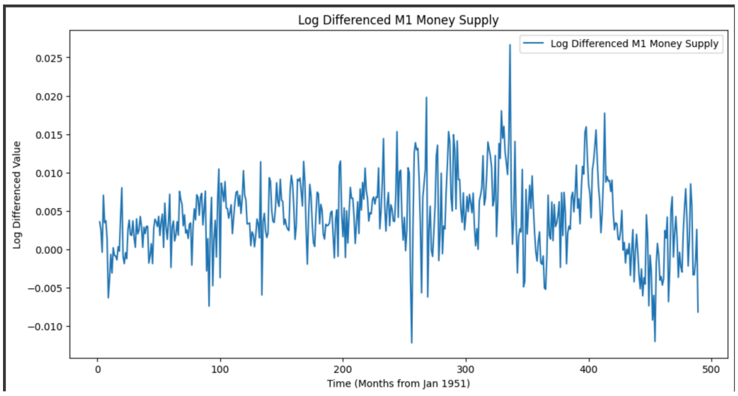

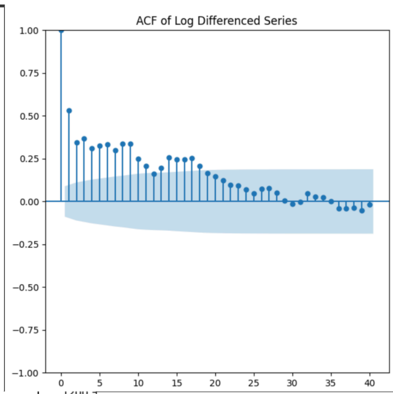

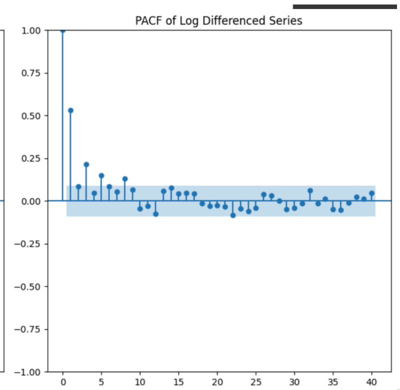

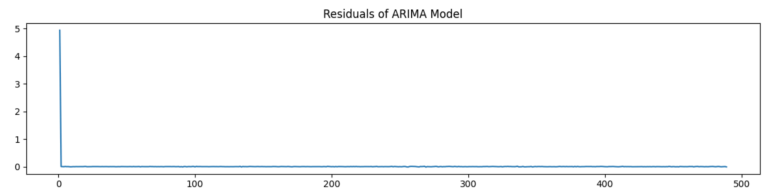

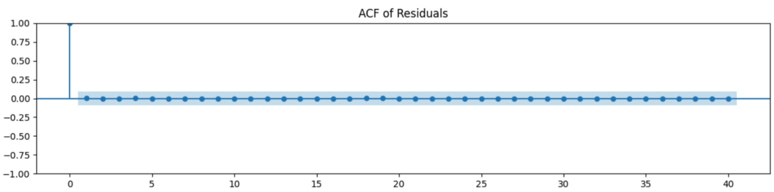

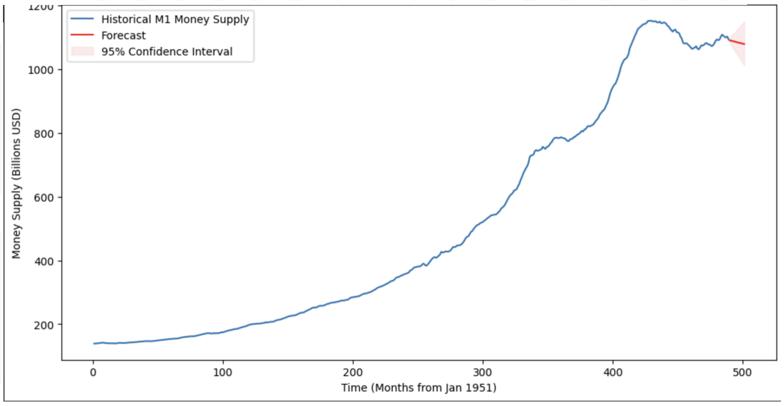

Interpretations:

Loading and Preparing the Dataset:

The M1 money supply data (in billions USD) from January 1951 to September 1991 is loaded into a DataFrame, with TIME set as the index. This step ensures the data is structured as a time series, with each row representing a monthly observation. Proper indexing is critical for time series analysis, as ARIMA models require sequential data to capture temporal dependencies.

Visualizing the Raw Time Series:

The raw M1 money supply data is plotted to inspect its behavior, revealing trends, seasonality, or non-stationarity. The plot typically shows an upward trend, suggesting non-stationarity, which informs the need for transformations (e.g., differencing or logging) to make the series suitable for ARIMA modeling. This visual inspection is a crucial first step in understanding the data's characteristics.

Testing for Stationarity with the ADF Test:

The Augmented Dickey-Fuller (ADF) test is applied to assess whether the series is stationary. A high p-value (> 0.05) indicates non-stationarity, as seen in the original M1 data due to its trend. Stationarity is a prerequisite for ARIMA modeling, as non-stationary series can lead to unreliable forecasts. This test guides the need for transformations to achieve stationarity.

Transforming the Series for Stationarity:
To achieve stationarity, a logarithmic transformation is applied to stabilize variance, followed by first differencing to remove the trend. The ADF test on the log-differenced series typically yields a low p-value (< 0.05), confirming stationarity. This step determines the differencing order (d=1) for the ARIMA model, ensuring the series meets the stationarity requirement.

Plotting the Transformed Series:
The log-differenced series is plotted to visually confirm stationarity. The absence of trends and fluctuations around a constant mean indicate that the series is ready for ARIMA modeling. This visualization validates the effectiveness of the transformations and provides confidence in proceeding with model identification.

Identifying ARIMA Parameters with ACF and PACF Plots:
Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the log-differenced series are generated to determine the AR (p) and MA (q) orders. Significant lags in the PACF suggest the number of AR terms (p), while significant lags in the ACF suggest the number of MA terms (q). For this data, significant lags at 1 and 2 often indicate p=2 and q=2, guiding manual parameter selection when automatic tools are unavailable.

Selecting the ARIMA Model:
If pmdarima is available, auto_arima is used to automatically select the optimal (p, d, q) parameters by minimizing the Akaike Information Criterion (AIC), with d=1 based on the differencing needed for stationarity. If pmdarima is unavailable, an ARIMA(2,1,2) model is chosen based on ACF/PACF analysis. This step ensures the model is appropriately specified to capture the series' autocorrelation structure.

Fitting the ARIMA Model:
The ARIMA model is fitted to the log-transformed M1 money supply data using the selected (p, d, q) parameters. The model estimates coefficients for the AR and MA terms, modeling the series' dynamics. A well-fitted model effectively captures the underlying patterns, preparing the data for residual analysis and forecasting.

Validating the Model with Residual Analysis:
Residuals from the fitted ARIMA model are analyzed to ensure the model is adequate. The residual plot should resemble white noise with no clear patterns, and the ACF of residuals should show no significant lags. This indicates that the model has captured most of the autocorrelation in the data. Significant residual patterns would suggest the need to revise the model parameters.

Forecasting Future Values:
The fitted ARIMA model is used to forecast the M1 money supply for the next 12 months. Since the model was fitted on log-transformed data, predictions and 95% confidence intervals are exponentiated to return to the original scale (billions USD). This step provides actionable predictions, with confidence intervals quantifying the uncertainty of the forecasts.

Visualizing the Forecast:
The historical M1 money supply is plotted alongside the 12-month forecast, with the forecast shown as a distinct line and the 95% confidence interval as a shaded area. This visualization illustrates how the forecast extends the historical trend and highlights increasing uncertainty (widening intervals) further into the future, aiding interpretation of the predictions.

Summarizing Forecast Results:
The forecast values are presented in a table, listing the predicted M1 money supply and the lower and upper bounds of the 95% confidence interval for each of the next 12 months. This numerical summary provides precise forecast estimates, facilitating detailed analysis or decision-making based on the model's predictions.