Time Series Forecasting of Monthly Gold Prices

# Objective

The primary objective of this project is to forecast future gold prices using historical monthly data. By analyzing the time series characteristics of gold price trends, we aim to build a statistical model that can generate reasonably accurate predictions, which are valuable for investment planning and financial analysis.

# Duration

May 2025 – June 2025

# Tools & Technologies Used

- Programming Language: Python  
- Libraries: Pandas, NumPy, Matplotlib, Seaborn, Statsmodels, scikit-learn  
- IDE: Jupyter Notebook  
- Model: ARIMA (AutoRegressive Integrated Moving Average)

# Dataset Overview

- Name: gold\_monthly\_csv.csv  
- Records: Monthly gold prices  
- Attributes:  
 - Date – Month and Year  
 - Price – Average price of gold for that month  
- Source: (Specify data source if available, e.g., Kaggle, World Bank, etc.)

# Methodology

1. Data Preprocessing:  
 - Parsed the Date column and converted it to datetime format.  
 - Sorted the dataset chronologically.  
 - Checked for missing or null values and handled them.

2. Exploratory Data Analysis:  
 - Line plots used to visualize trends.  
 - Decomposition into Trend, Seasonality, and Residuals.  
 - Conducted ADF (Augmented Dickey-Fuller) test for stationarity.

3. Modeling:  
 - Differencing used to make the data stationary.  
 - Analyzed ACF and PACF plots to determine suitable ARIMA parameters (p, d, q).  
 - Built the ARIMA model and trained it on historical data.

4. Forecasting:  
 - Forecasted prices for future months.  
 - Visualized both actual and predicted prices on a line plot.

5. Model Evaluation:  
 - Evaluated predictions using Root Mean Squared Error (RMSE).  
 - Lower RMSE indicated better model performance.

# Results

- The ARIMA model was able to forecast future gold prices with acceptable accuracy.  
- Visualization showed smooth continuation from past price trends.  
- The model captured both short-term fluctuations and long-term trends.

Evaluation Metric:  
- RMSE: [Add calculated RMSE here]  
- Forecast Period: [Mention forecast range if available]

# Key Takeaways

- Learned the importance of making a time series stationary before modeling.  
- Understood model tuning using ACF and PACF plots.  
- Gained practical experience in ARIMA modeling.  
- Realized the limitations and opportunities in financial time series forecasting.

# Future Work

- Implement other models like Facebook Prophet or LSTM for performance comparison.  
- Incorporate macroeconomic indicators like inflation, interest rates, etc., to build a multivariate model.  
- Build a real-time dashboard using Streamlit or Power BI.

# Author & Contact

Name: Vikas Kumar  
Role: Data Analyst & Aspiring Financial Data Scientist  
Location: Kanpur, Uttar Pradesh  
Email: your.email@example.com  
LinkedIn: https://linkedin.com/in/vikas-kumar-yourlink  
GitHub: https://github.com/yourusername