Forecasting Monthly Time Series Using the M4 Dataset

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Date: [28-07-2025]

Executive Summary

The goal of this project is to forecast monthly time series data from the **M4 competition dataset** and compare different forecasting methods.

Three models were evaluated:

- **Naive Forecast**
- **ETS (Exponential Smoothing)**
- **Auto ARIMA (automated ARIMA model selection)**

The evaluation metric used is **sMAPE (Symmetric Mean Absolute Percentage Error)**.

The best-performing model was **Auto ARIMA with an average sMAPE of 9.42%**, outperforming Naive and ETS models.

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1. Dataset Description

- **Source:** M4 Competition Dataset (GitHub link)
- **Subset Used:** 50 Monthly series (Frequency = 12)
- **Files Used:**
    - **Monthly-train.csv** – Historical data for training
    - **Monthly-test.csv** – Actual future values for evaluation
    - **M4-info.csv** – Metadata with series category and start date

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2. Methodology

2.1 Models Implemented

1. Naive Forecast
Uses the last observed value for all future points.

2. ETS (Exponential Smoothing)
Captures trend patterns using additive method.

3. Auto ARIMA
Automatically selects the best ARIMA parameters (p,d,q) using stepwise search.

2.2 Evaluation Metric

- **sMAPE (Symmetric Mean Absolute Percentage Error)**
  Formula:

  sMAPE = (200/n) * Σ |Forecast - Actual| / (|Forecast| + |Actual|)

  Lower sMAPE indicates better accuracy.

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3. Results

3.1 Average sMAPE by Model

Model	Avg sMAPE (%)
Auto ARIMA	**9.42**
Naive	10.72
ETS	11.31

✅ Auto ARIMA performed best overall.

3.2 Performance by Category

Models perform differently across domains (Macro, Finance, Industry, etc.).
A heatmap was generated to visualize category-wise performance.

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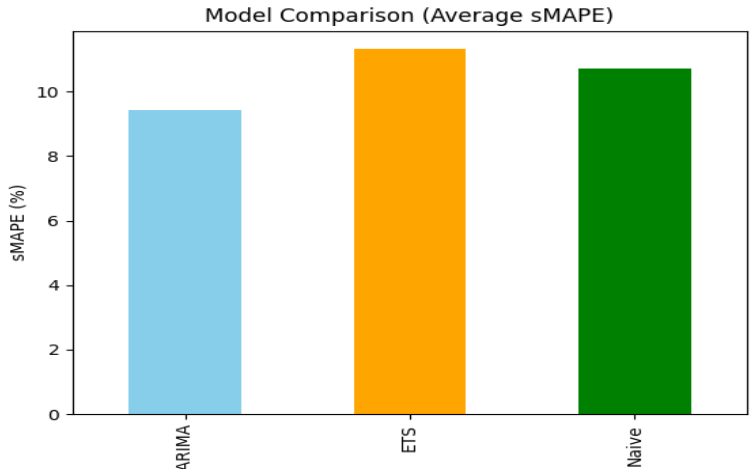
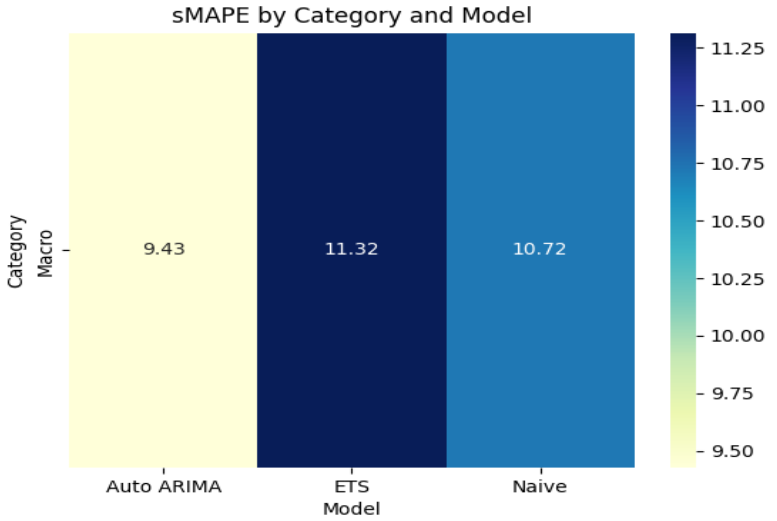
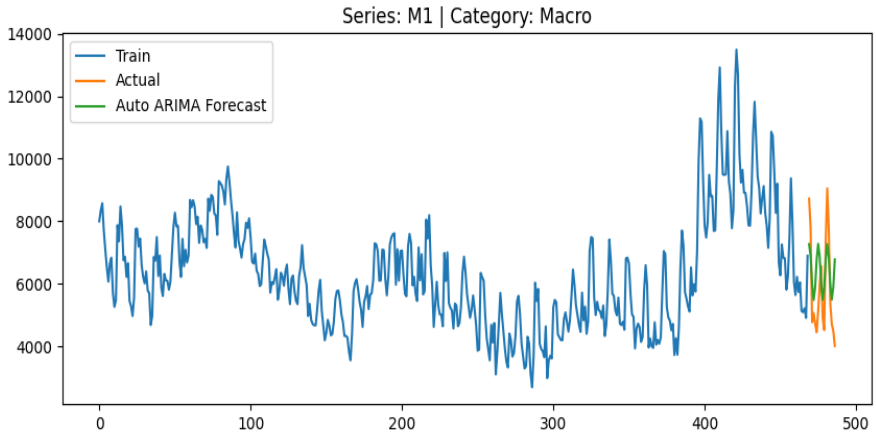
4. Visualizations







- **Model Comparison Bar Chart**
- **Heatmap by Category and Model**
- **Example Forecast Plot (Auto ARIMA)**

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5. Insights

- **Auto ARIMA** consistently outperformed Naive and ETS across most categories.
- Naive is still competitive for stable time series.
- ETS underperformed, likely due to ignoring seasonality.

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6. Future Work

- Add **Seasonal ARIMA (SARIMA)** for seasonal series.
- Test **Facebook Prophet** for trend and seasonality modeling.
- Explore **LSTM / Deep Learning models** for complex series.
- Scale analysis to the **entire M4 Monthly dataset**.

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7. Technologies Used

- Python
- Pandas, NumPy
- Statsmodels
- pmdarima
- Matplotlib, Seaborn