Day83_Time_Series_Forecasting_Theory

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Time Series — Theory Notes

1 What is a Time Series?

- A time series is a sequence of data points recorded at successive intervals of time.
- **Examples**: daily stock prices, monthly rainfall, hourly temperature, yearly GDP.
- The key difference from other data: **order matters** (yesterday influences today).

2 Components of a Time Series

- **Trend** → Long-term upward or downward movement (e.g., rising housing prices).
- **Seasonality** → Regular repeating pattern over fixed periods (e.g., ice cream sales higher in summer).
- **Cyclic patterns** → Fluctuations without fixed periods, often related to business/economic cycles.
- **Noise (Residual)** → Random variation that cannot be explained.

3 Stationarity

- A **stationary time series** has constant mean, variance, and autocovariance over time.
- Why important? Many models (ARIMA, SARIMAX) assume stationarity.
- Non-stationary → Apply transformations (log, differencing) to stabilize.

4 Autocorrelation

- Measures how observations relate to their past values.
- **ACF (Autocorrelation Function)** → correlation of a series with its past lags.
- **PACF (Partial Autocorrelation Function)** → correlation of a series with past lags after removing effects of shorter lags.
- Helps in deciding AR (autoregressive) and MA (moving average) terms in ARIMA.

5 Decomposition

Breaking a series into:

1. Trend
2. Seasonality

3. Residuals

Two methods:

- **Classical decomposition** (simple, additive/multiplicative).
- **STL (Seasonal-Trend decomposition using Loess)** (robust and modern).

6 Forecasting Methods

6.1 Naive Forecast

- Assumes tomorrow's value = today's value.
- Simple baseline to compare with advanced models.

6.2 Moving Average

- Forecast = average of recent values (smooths short-term fluctuations).

6.3 Exponential Smoothing

- Weights recent observations more heavily.
- Holt-Winters method handles trend + seasonality.

7 ARIMA Models

- **ARIMA(p,d,q)**
  - **p** = autoregressive part (dependence on past values).
  - **d** = differencing (to make data stationary).
  - **q** = moving average part (dependence on past forecast errors).
- **SARIMA/SARIMAX** adds seasonal components and exogenous variables (e.g., holidays, marketing campaigns).

8 Modern Approaches

- **Auto-ARIMA** → automatically selects the best p, d, q.
- **Prophet (by Meta)** → easy-to-use, handles multiple seasonalities and trend shifts.
- **Machine Learning (LSTM, GRU, Transformers)** → capture long-term dependencies in sequential data.

9 Model Evaluation

- Metrics:
  - **MAE (Mean Absolute Error)** → average absolute errors.
  - **RMSE (Root Mean Squared Error)** → penalizes large errors.
  - **MAPE (Mean Absolute Percentage Error)** → percentage-based error.
- **Cross-validation for time series** → rolling window or expanding window approach (can't shuffle like normal ML).

10 Practical Applications

- Stock price prediction
- Weather forecasting
- Industrial demand forecasting
- Sales & supply chain management
- Autonomous driving (sensor data)

11 Key Insights

- Always check for **stationarity** before applying models.
- Start simple (Naive, Moving Average), then move to advanced (ARIMA, SARIMAX).
- Use decomposition to understand patterns before forecasting.
- Always validate using appropriate metrics and cross-validation.
- Deep learning is powerful but needs large data and compute

12 Summary & Key Takeaways

- Time series analysis helps in **understanding patterns** and **predicting the future**.
- Common models used:
  - **Moving Average** → Simple smoothing method
  - **Exponential Smoothing (Holt-Winters)** → Captures trend & seasonality
  - **ARIMA** → Handles trend, autocorrelation, differencing
  - **Prophet** → Flexible, easy to use, especially for business forecasting
- Model performance can be compared using **MAE** and **RMSE**.

13 Next Steps:

- Try different hyperparameters for ARIMA `(p,d,q)`

- Explore SARIMA (Seasonal ARIMA) for strong seasonality

- Use real datasets (sales, weather, finance) instead of dummy data

- Experiment with Prophet for holiday effects and business applications