Time Series Models – Study Guide

# 1. Naive Models

Naive Forecast:  
Assumes that the future value is equal to the last observed value.  
Formula: ŷₜ₊₁ = yₜ  
Best used as a baseline or for slow-changing series.

# 2. Moving Average Models

a. Simple Moving Average (SMA):  
Takes the average of the last n observations to smooth out short-term noise.  
Formula: SMAₜ = (1/n) ∑ (from i=0 to n-1) yₜ₋ᵢ  
  
b. Weighted Moving Average (WMA):  
Recent observations are given more importance by assigning weights.

# 3. Exponential Smoothing Models

a. Simple Exponential Smoothing (SES):  
Applies to data with no trend or seasonality.  
Formula: ŷₜ₊₁ = αyₜ + (1 - α)ŷₜ  
  
b. Holt’s Linear Trend Model:  
Extends SES to account for trend.  
  
c. Holt-Winters Model:  
Accounts for both trend and seasonality.

# 4. ARIMA (AutoRegressive Integrated Moving Average)

Combines AR (p), I (d), and MA (q) components.  
Used for univariate, stationary time series.  
Example: ARIMA(1,1,1) – One autoregressive, one differencing, one moving average term.

# 5. SARIMA (Seasonal ARIMA)

Extends ARIMA to handle seasonality.  
Format: SARIMA(p,d,q)(P,D,Q)[m], where m = seasonal period (e.g., 12 for monthly data).

# 6. Machine Learning-Based Models

a. Random Forest / XGBoost:  
Work with engineered features such as lags and rolling stats.  
  
b. LSTM (Long Short-Term Memory):  
Deep learning model ideal for capturing long-term dependencies in sequential data.

# 7. Prophet (by Facebook)

Designed for business forecasting with trend, seasonality, and holiday effects.  
Easy to use, handles outliers and missing data well.  
Formula: Forecast = Trend + Seasonality + Holiday Effects

# Summary Comparison Table

Model Trend Seasonality Complexity Suitable For  
Naive ❌ ❌ Very Low Baseline  
SMA/WMA ❌ ❌ Low Smoothing  
SES ❌ ❌ Low No Trend/Seasonality  
Holt ✅ ❌ Medium Trend Only  
Holt-Winters ✅ ✅ Medium Trend + Seasonality  
ARIMA ✅ ❌ High Stationary Series  
SARIMA ✅ ✅ Higher Seasonal Series  
Prophet ✅ ✅ Medium Business/Marketing  
LSTM/XGBoost ✅ ✅ Very High Complex Patterns