Compute correlation between the residuals from (1) & (2)

$$x_t = \phi x_{t-1} + \varepsilon_t$$

High ACF values for small lags → strong short-term dependency

Gradual decay → autoregressive AR Process

Sharp cutoff → moving average process (MA)

oscillating (or) repeating spikes → seasonality (or) cycle.

Simple Moving Average

Cumulative moving Average

Exponential weight moving Average

Moving Average

rolling function()   window size = 5

SMA: (Simple moving average):
is a technique used in time series analysis to smooth out short term fluctuations fluctuations and highlight the long-term trend.

It calculates the average of the last N points. where N is chosen window.

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$$SMA_t = \frac{X_t + X_{t-1} + X_{t-2} + \cdots X_{t-(N-1)}}{N}$$

N= window Size.

* SMA helps in Smoothing the noisy data:

⇒ So we can find trend direction
does the Series going upward (or) downward

⇒ Reduces randomness
As daily / hourly variations may distract from true pattern

→ Less Sensitive to Extreme outliers.
As the Each point has equal weights.

⇒ Good for Stable & Slow moving data.
works well when data does not change rapidly.

Disadvantages:

⇒ Giving equal weights to old & new data points
Some times recent data matter more.

⇒ Requires enough historical data.
A 30 day SMA needs 30 past points & loses initial data.

→ Not good for highly Volatile data
SMA Smooths to much and hides important changes.

→ Breaks at missing values.

Cummulative moving Average :- (CMA)

Average of all ~~main~~ data points from the beginning upto the currant time.

In the SMA the window size is fixed. In CMA all the Previous values.

$$CMA_t = \frac{x_1 + x_2 + \cdots x_t}{t}$$

* understand long term overall trend
  ⇒ Since it averages all the data, it Smooths noise extremely well.

* Stabilizes as more data Comes in
* Early values matter less over time.

Disadvantages:

* Very Slow to react to new changes Because it includes all data from the Start.

* Early values affect the average forever, if the Early data was noisy CMA becomes biased

* cannot adjust to seasonality Because ~~some~~ every Point has the equal weight from the start.

Mostly used very Stable, slow MA, realtime data averaging.

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EMA (Exponential Moving Average):

Is a type of MA that gives more weight to recent data points and less to older data points.

It reacts faster to new information compared to SMA

Smoothing factor (α) $= 2/N+1$ N is window size

$$EMA_t = \alpha x_t + (1-\alpha) EMA_{t-1}$$

to calculate the 1st EMA we EMA_{t-1} we take the SMA value of N

If the price suddenly jump up the EMA also jump up Not as much as the price but faster than SMA.

Momentum indicators / oscillators.

In time series analysis the momentum means how fast the price is moving and in which direction.

An oscillator is a formula for the indicators that oscillate between fixed upper and lower values (0-100)
these can identify conditions like

over bought
over sold
Reversals.

Rate of change (ROC) $= \frac{Price_t - Price_{t-n}}{Price_{t-n}} \times 100$

ROC > 0 ↑ Momentum & < 0 ↓ momentum
Trend strengthening   trend weakening

Momentum indicators (MI) = $Price_t - Price_{t-n}$

+ indicats ↑ Pressure & (-) indicates ↓'es pressure

Relative Strength index (RSI)

$$RSI = 100 - \frac{100}{1+RS}$$

$$RS = \frac{\text{Avg gain}}{\text{Avg Loss}}$$

RSI > 70 overbought → sell

RSI < 30 over sold → Buy.

usually the n=14 periods.

gain/Loss = $Close_t - Close_{t-1}$ > 0 ⇒ Loss = 0
< 0 ⇒ Gain = 0

once we calculate for the first 14 values then we Exponential like smoothing, for next steps.

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Autoregressive Model (AR)

AR(P) ⇒ Auto regressive model of order P

A future value depends on its past P-values.

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + + \cdots \phi_p y_{t-p} + \epsilon_t$$

c = constant y_t = value at current time

ϕ_i = AR coefficients. ϵ_t = white noise (Error)

AR parameters are computed by yule-walker Equations.
* Maximum Likelihood Estimation
* Least Squares.

Moving Average Model (MA): MA(q)

The future values depends on past shocks/errors not past values.

$$y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots \theta_q \epsilon_{t-q}$$

ϵ_t = current random shock
ϵ_{t-1} ⇒ Previous shock
θ_i = MA Coefficients

And the coefficients are calculated by MLE

ARMA Model.

AR = Long term Correlations
MA = Short term Shocks

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_t + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}$$

ARIMA where we add 'I' Indexing to store the No. of times the data is been differencing.

RNN: Is a neural network that processes sequential data by keeping a hidden state that carries information across time.

h_t = tanh(W_xh * x_t + W_hh * h_{t-1} + b_h)

y_t = w_hy * h_t + b_y

Matrix shapes

w_xh = [H x D]

w_hh = [H x H]

w_hy = [O x H]

h_t = [H x 1]

x_t = [D x 1]

y_t = [O x 1]

Initial State

$w_{xt} * x_t$ works?

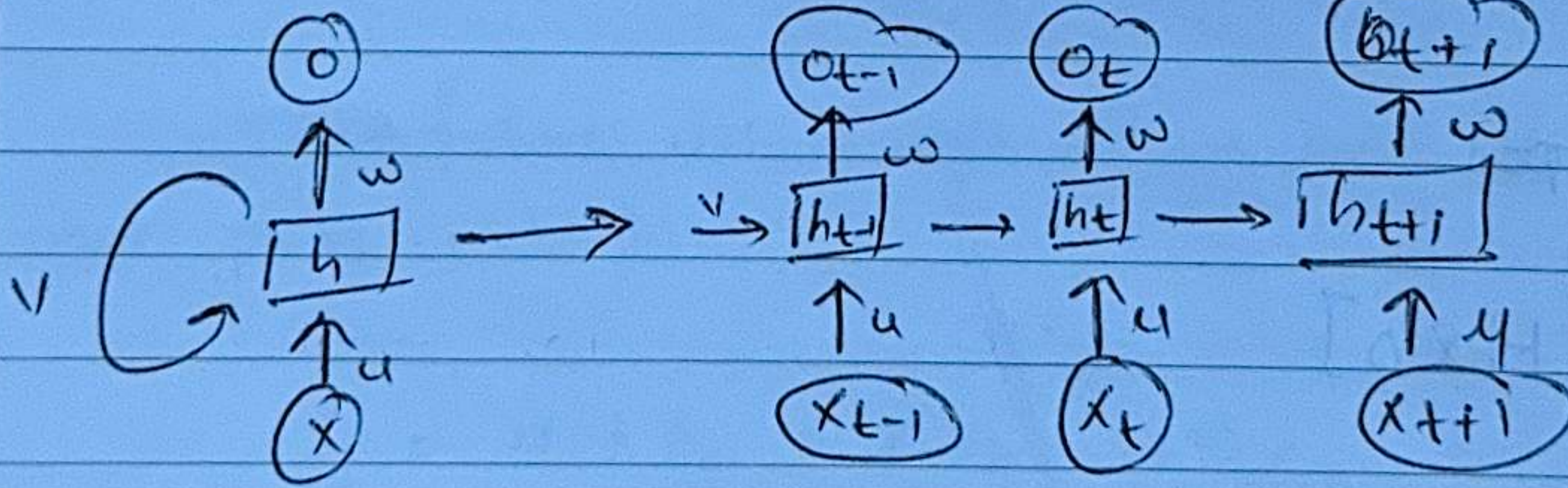
w_{xt} has H rows each row is a filter picking important parts of input.

types of RNN networks.

Standard RNN:

$(x_t, h_t) \rightarrow (y_t + h_{t+1})$

x_t: input vector
h_t: hidden vector
y_t: output vector
θ: neural network parameters.



Its a neural network that maps an input x_t into an output y_t with hidden vector h_t playing role of memory. Partial record of all previous input output pairs. At each step it transforms input to an output and modifies its memory to help it to better perform future processing.