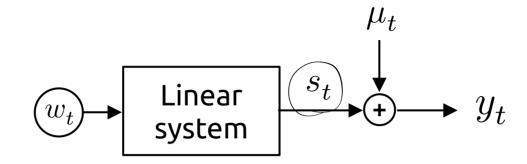


# Statistics and Data Science for Engineers E178 / ME276DS

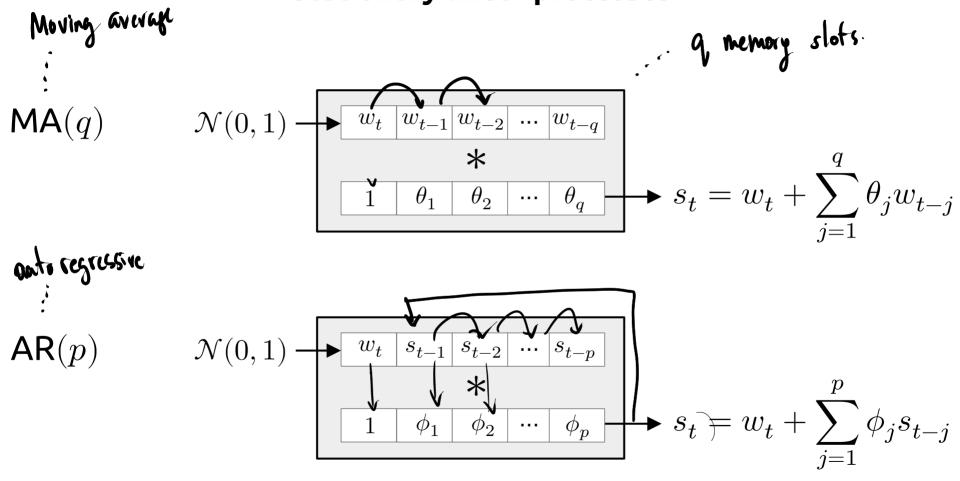
Time series analysis Part 2

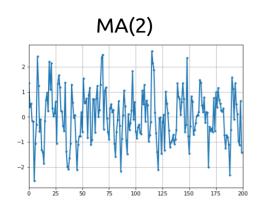
#### Recall

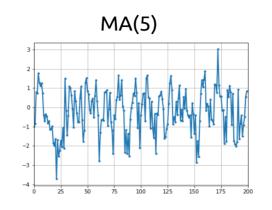


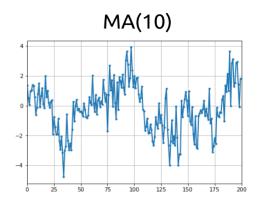
- $\mu_t$  ... deterministic signal
- ullet  $s_t$  ... zero-mean stochastic signal

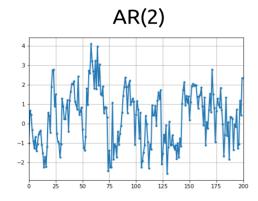
# Stationary linear processes

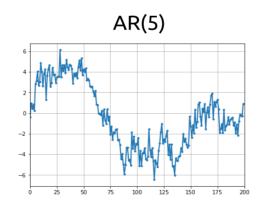


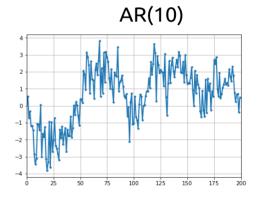










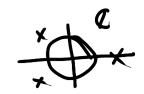


## Polynomial representation

Backward shift operator B:  $Bs_t = s_{t-1}$ 

$$\begin{array}{c|c} \mathbf{MA}(q) & \mathbf{AR}(p) \\ \hline \\ s_t = w_t + \sum_{j=1}^q \theta_j w_{t-j} \\ = \underbrace{w_t + \sum_{j=1}^q \theta_j B^j w_t} \\ = \underbrace{\left(1 + \sum_{j=1}^q \theta_j B^j\right) w_t} \\ = \theta(B) w_t & \underbrace{\left(1 - \sum_{j=1}^p \phi_j B^j\right) s_t = w_t} \\ \hline \\ \phi(B) s_t = w_t \end{array}$$

$$\% = \beta(e) \cdot \phi(e) \cdot \%$$



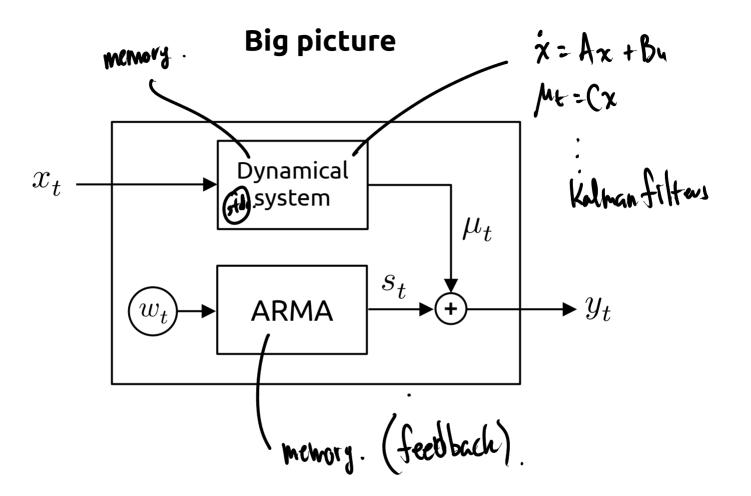
		MA(q)	AR(p)
	Polynomial	$s_t = \theta(B)  w_t$	$(B) s_t = w_t$
	Relationship	$\widehat{\theta(B)\phi(B)} = 1$	
	-) Stationary	Always	roots $(\phi(B))$ have magnitude > 1
*	Causal	roots $(\theta(B))$ have magnitude > 1	Always

# $\mathsf{ARMA}(p,q)$

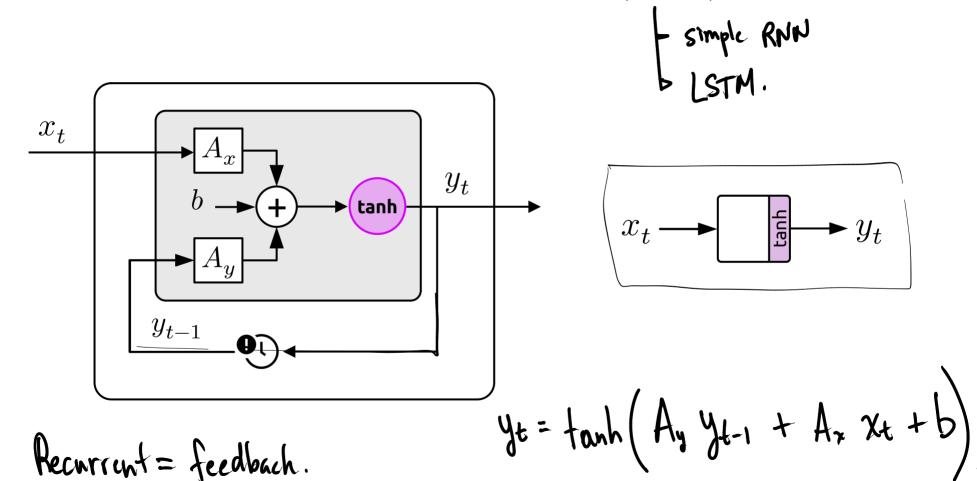
$$S_{\mathbf{k}} = w_t + \sum_{j=1}^q \theta_j w_{t-j} + \sum_{j=1}^p \phi_j s_{t-j}$$
 
$$S_{\mathbf{k}} = \frac{\theta(B)}{\phi(B)} w_t$$

- Hyper-parameters: q and p. ... orders of  $\theta(B)$ ,  $\phi(B)$ .
- Tunable parameters:  $\theta_j$ 's and  $\phi_j$ 's.

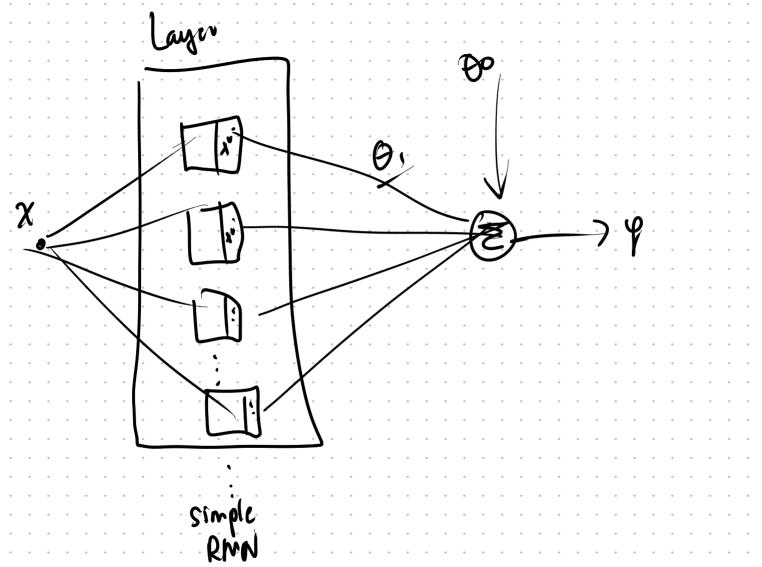
... complicated.



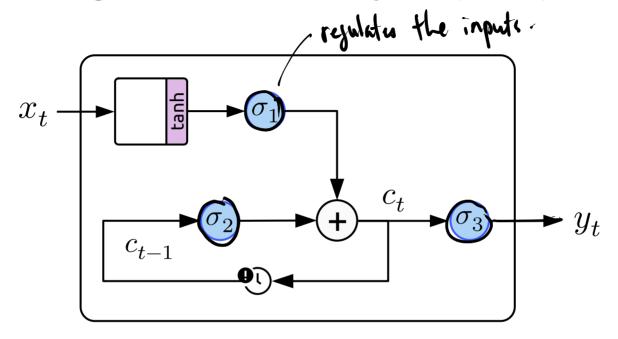
# Recurrent neural networks (RNNs)



Activation functions: Sigmoid hard saturation



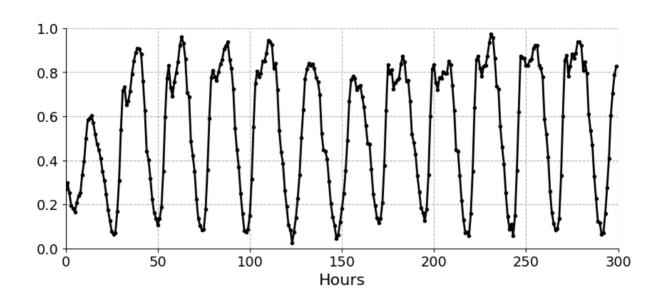
### Long-short term memory cell (LSTM)



Sigmoid.

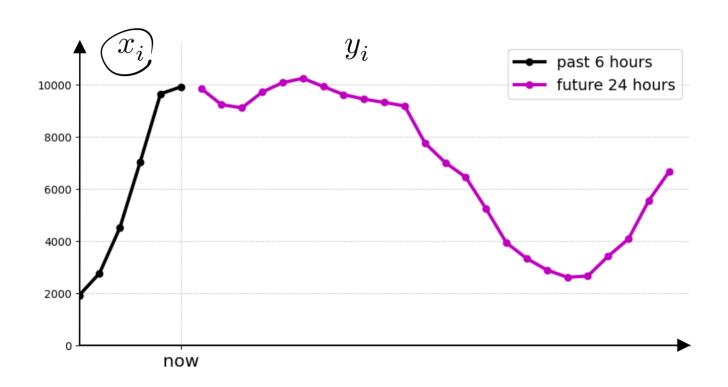
- Each  $\sigma_i$  is a sigmoid gate:  $\sigma_i = \sigma(A_{x,i}x_t + A_{y,i}\ y_{t-1} + b_i)$
- $c_t$  is a memory vector.

### **Example: Freeway traffic flow prediction**



- $y_t$  is hourly flows on a freeway.
- <u>Problem</u>: Predict the next 24 hours from the previous 6 hours.

Training data 
$$\mathcal{D}_{\text{train}} = \{(x_i, y_i)\}_N$$



#### Perceptron

```
model_dense = Sequential([
    Flatten(),
    Dense(5, activation="relu"),
    Dense(24)
])
```

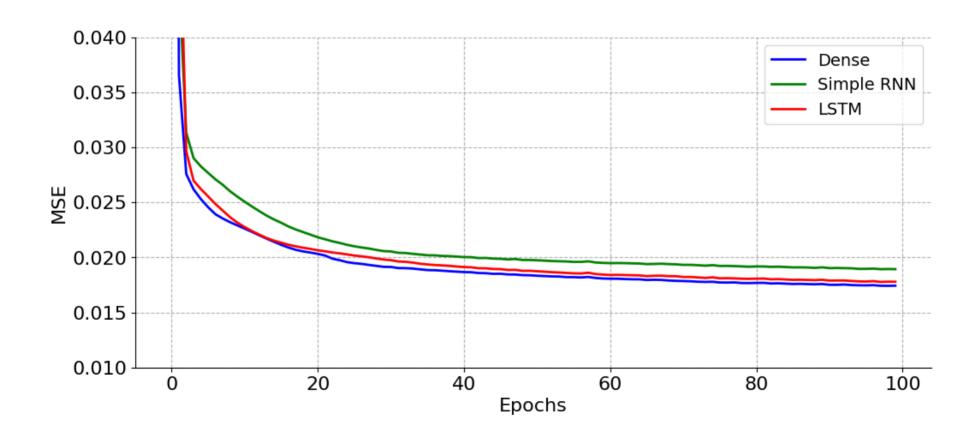
#### Simple RNN

```
model_simprnn = Sequential([
    SimpleRNN(5,input_shape=(1,6)),
    Dense(24)
])
```

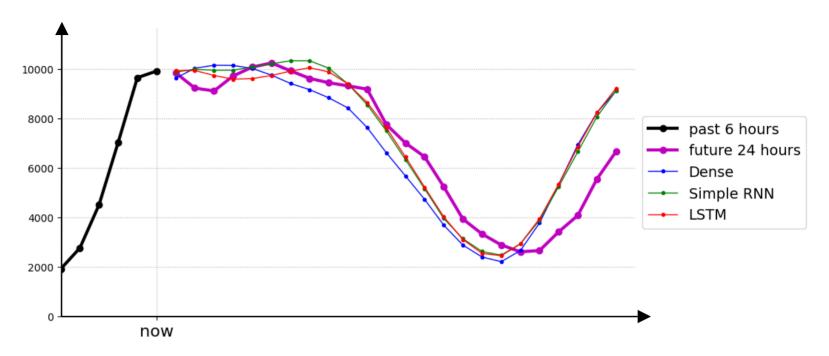
#### **LSTM**

```
model_lstm = Sequential([
    LSTM(5, input_shape=(1, 6)),
    Dense(24)
])
```

# Training MSE:



#### Prediction:



MAE on test data: Dense: 21.7%

Simple RNN: 19.0%

LSTM: 17.7%