The Ottawa Hospital RESEARCH INSTITUTE | L'Hôpital d'Ottawa INSTITUT DE RECHERCHE

uOttawa | Institut de recherche sur le cerveau | Brain and Mind Research Institute

Workshop on Applied Deep Learning in Intracranial Neurophysiology

Part 6 –Recurrent Neural Networks

September 17, 2019

Presented by Chadwick Boulay, MSc, PhD
Sachs Lab

Superior arm-movement decoding from cortex with a new, unsupervised-learning algorithm

Joseph G Makin[1], Joseph E O'Doherty, Mariana M B Cardoso and Philip N Sabes

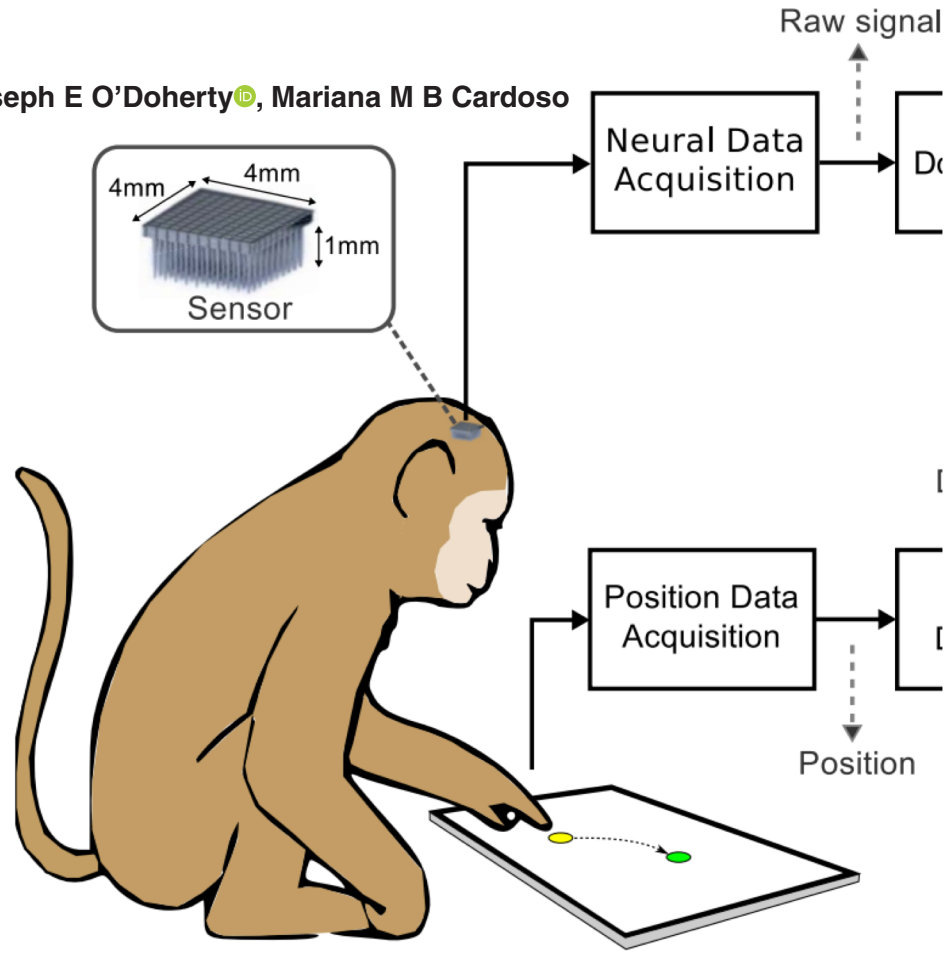
Dataset

2 96-ch Utah arrays: M1 and S1

- 24.4 kHz
- BP filt 500-5000 Hz
- Thresholded at 3.5-4.0 STDs

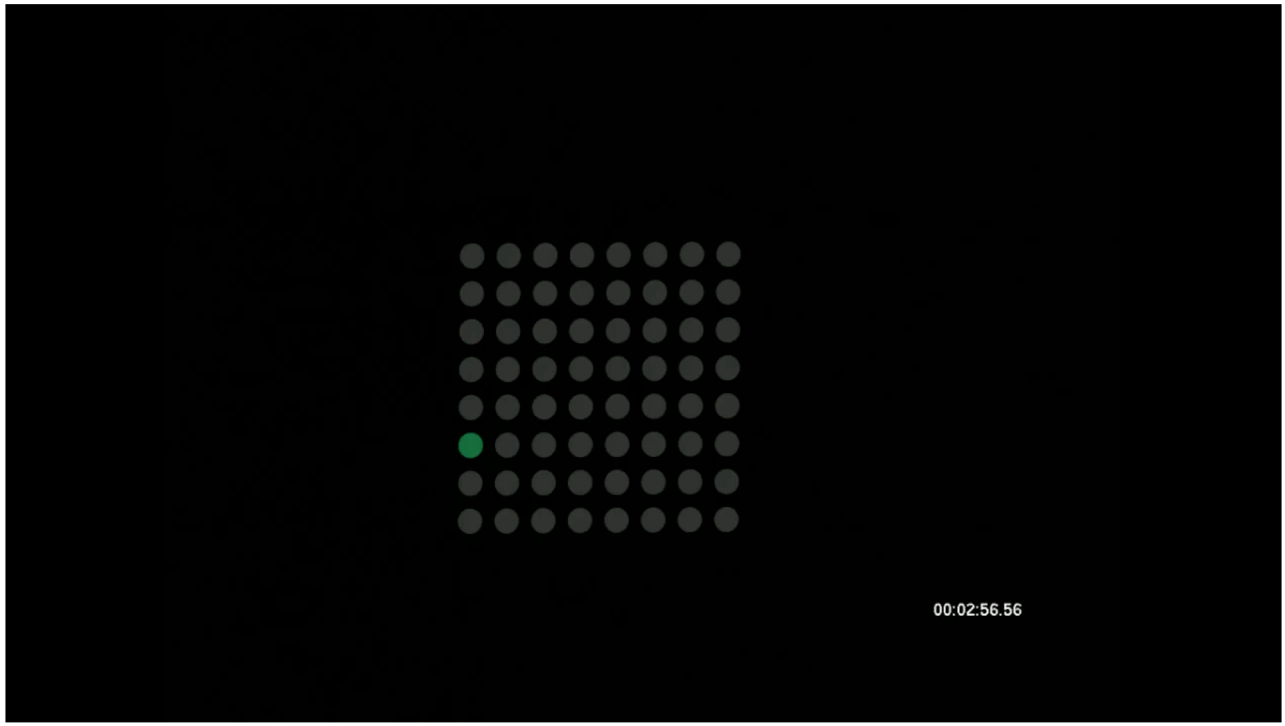
XYZ finger position recorded with Polhemus (magnetic) at 250 Hz

[Available online]

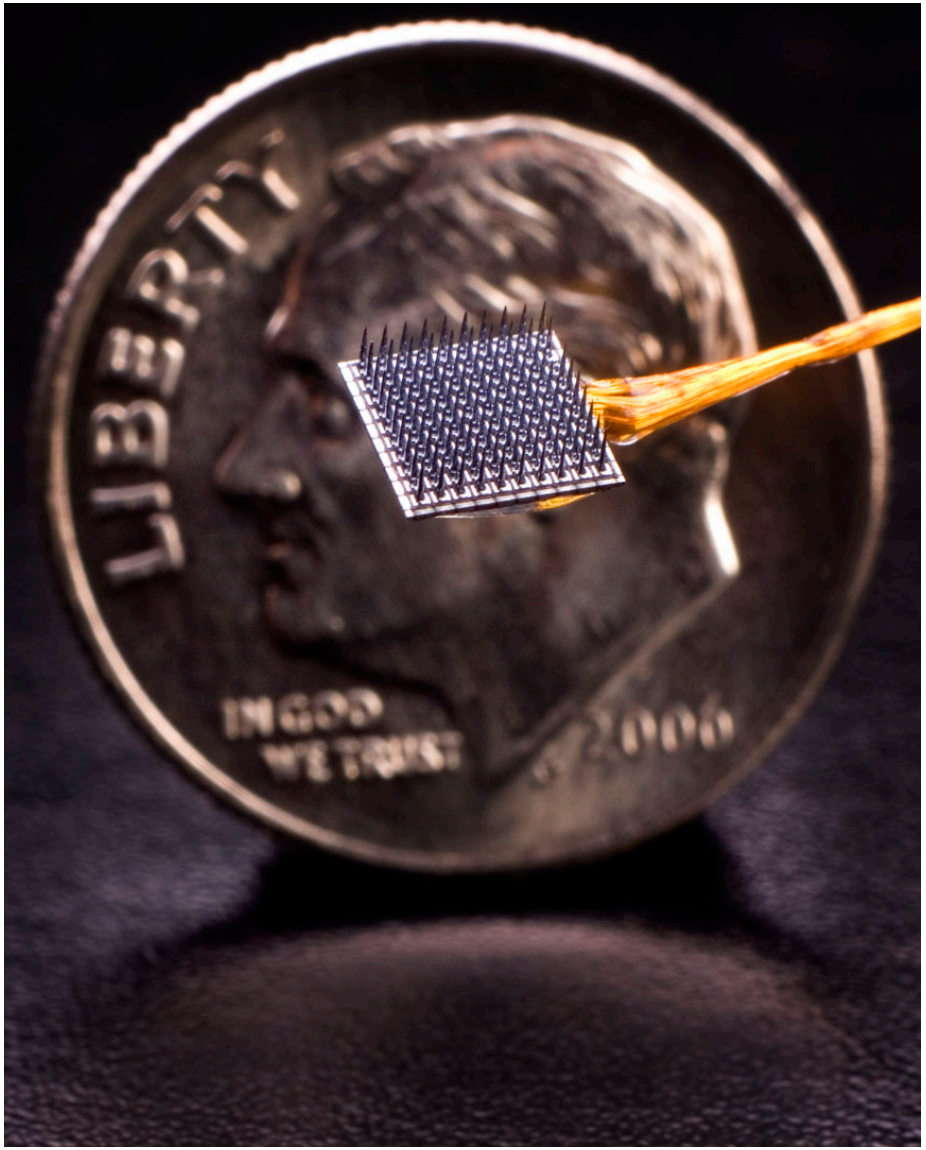


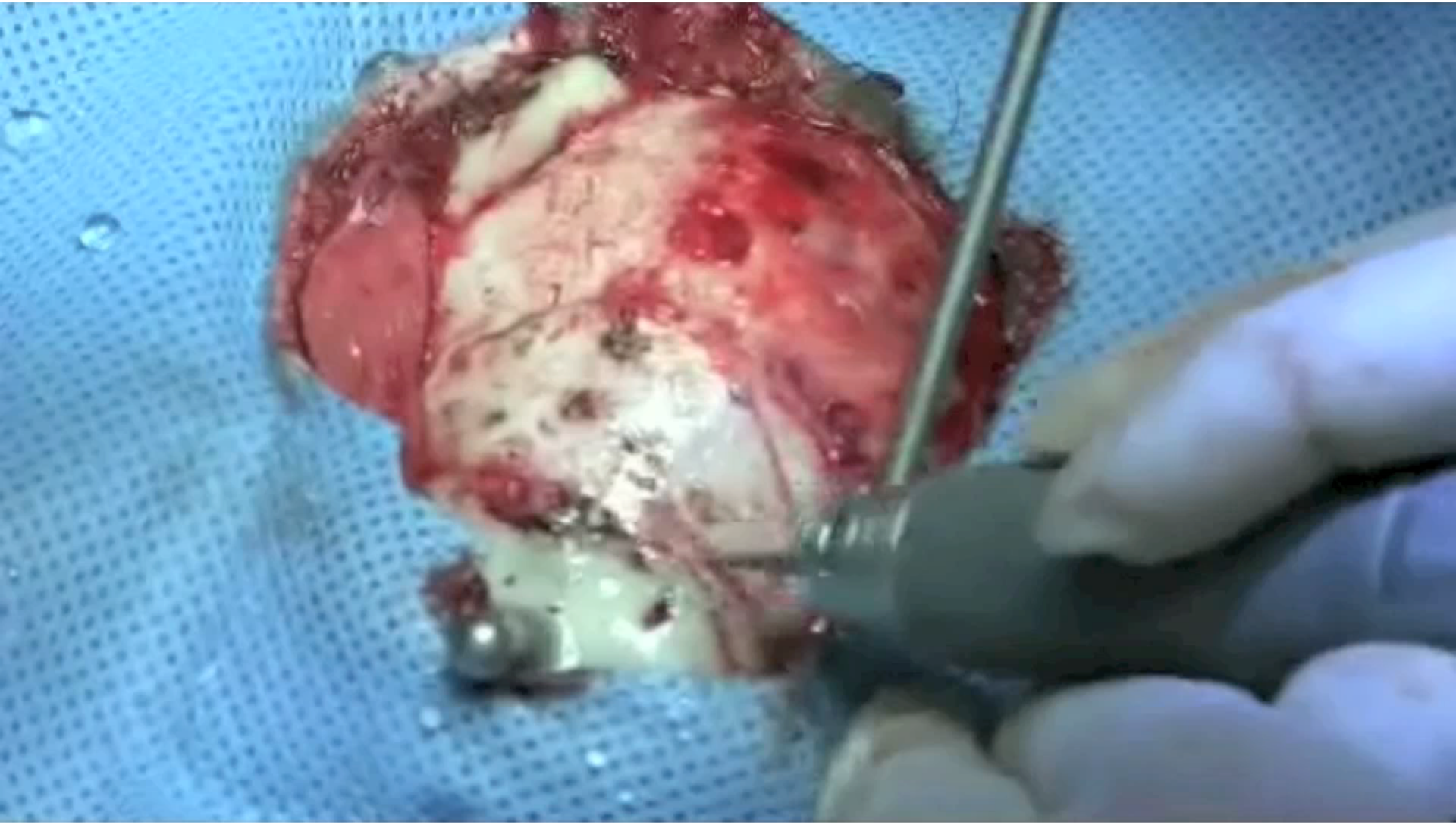
3D finger position projected onto 2D plane

$$\begin{pmatrix} 0 & 0 \\ -10 & 0 \\ 0 & -10 \end{pmatrix}$$



Utah Array



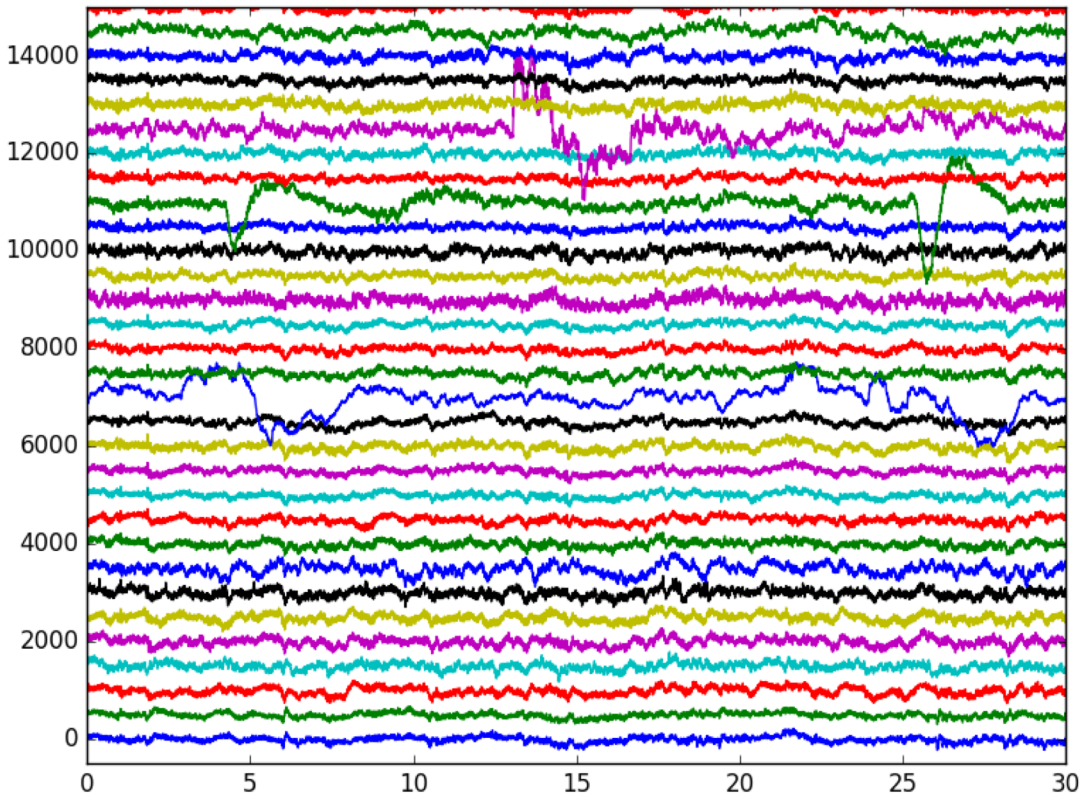


• Data contents:

- Events

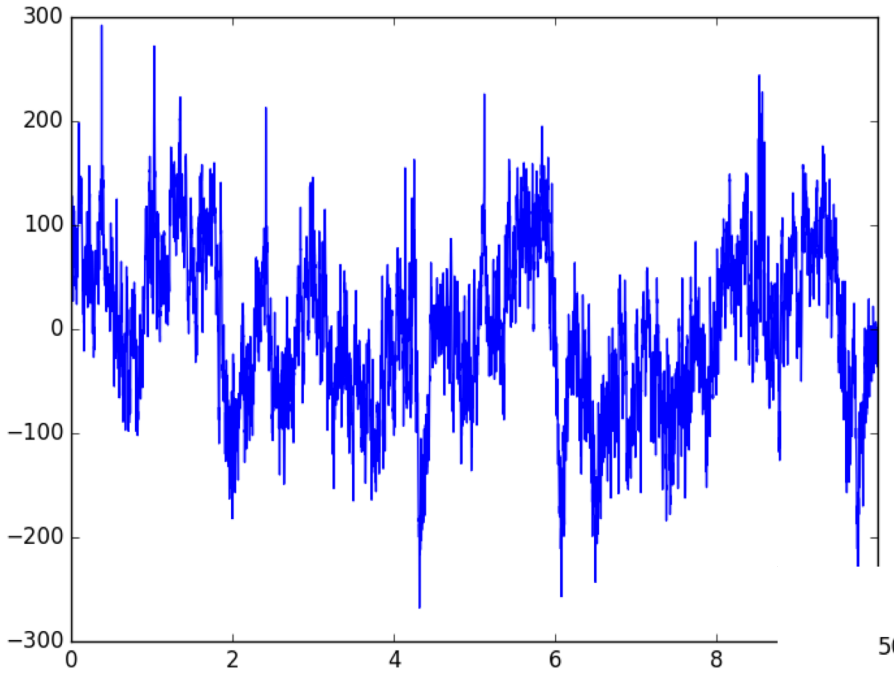
```
events = [(timestamp, event_string), ...]
```

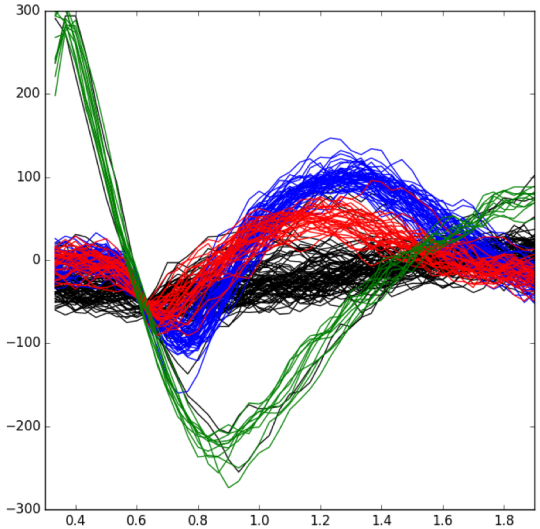
- Broadband Field Potentials
  - Low-pass filter
    - Downsample (decimate) to get LFP
  - High-pass filter
    - Get threshold crossing
    - Get spike waveforms



Preprocess

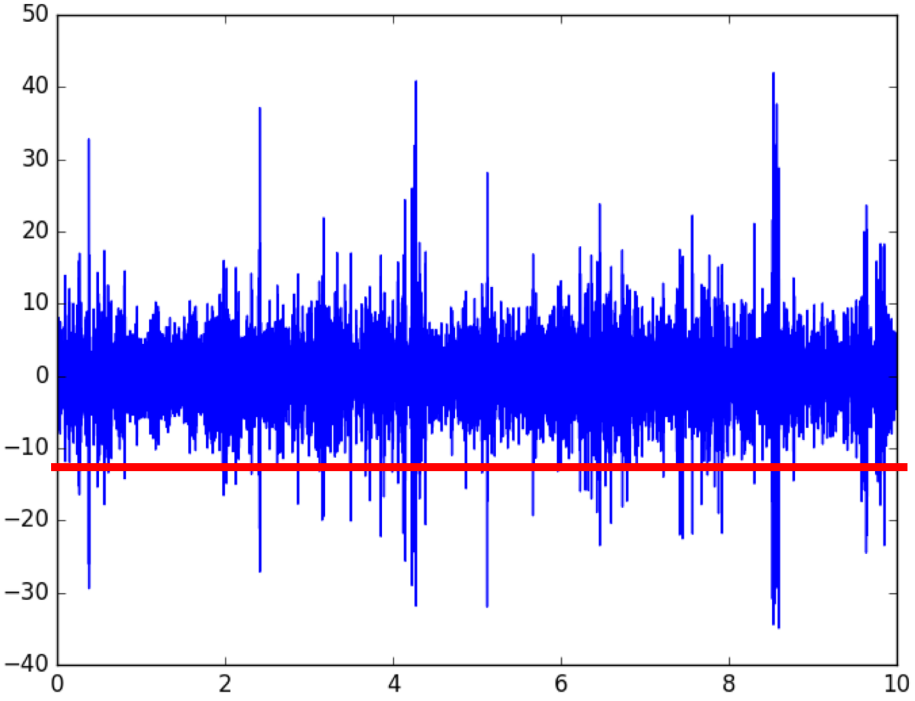
Raw

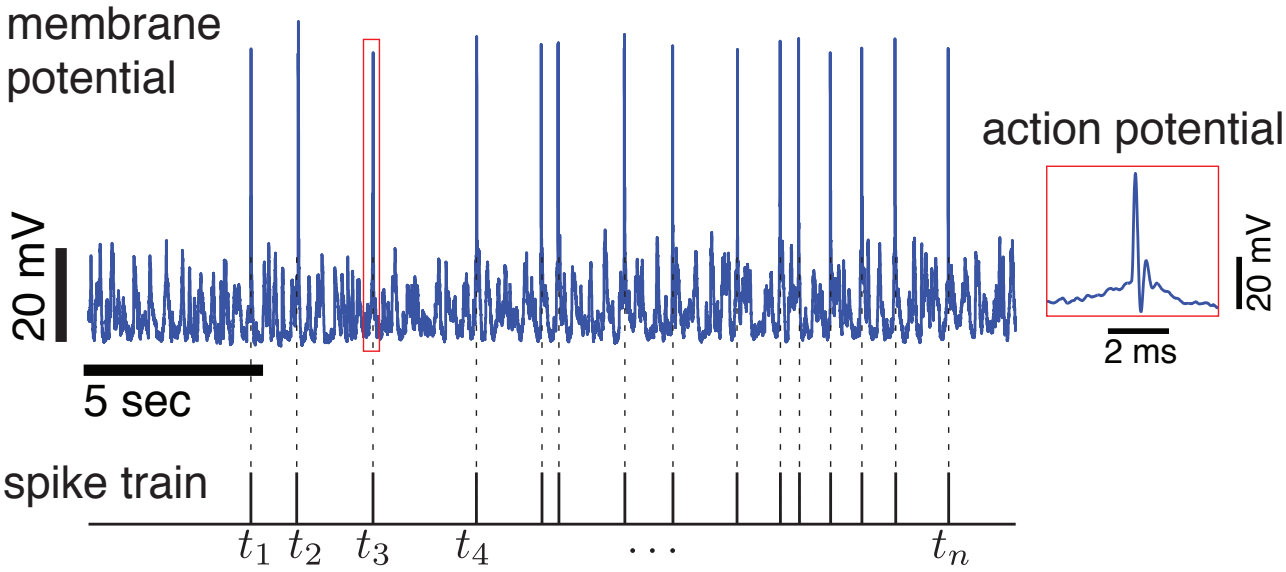




~ -3.5 – -4 SD

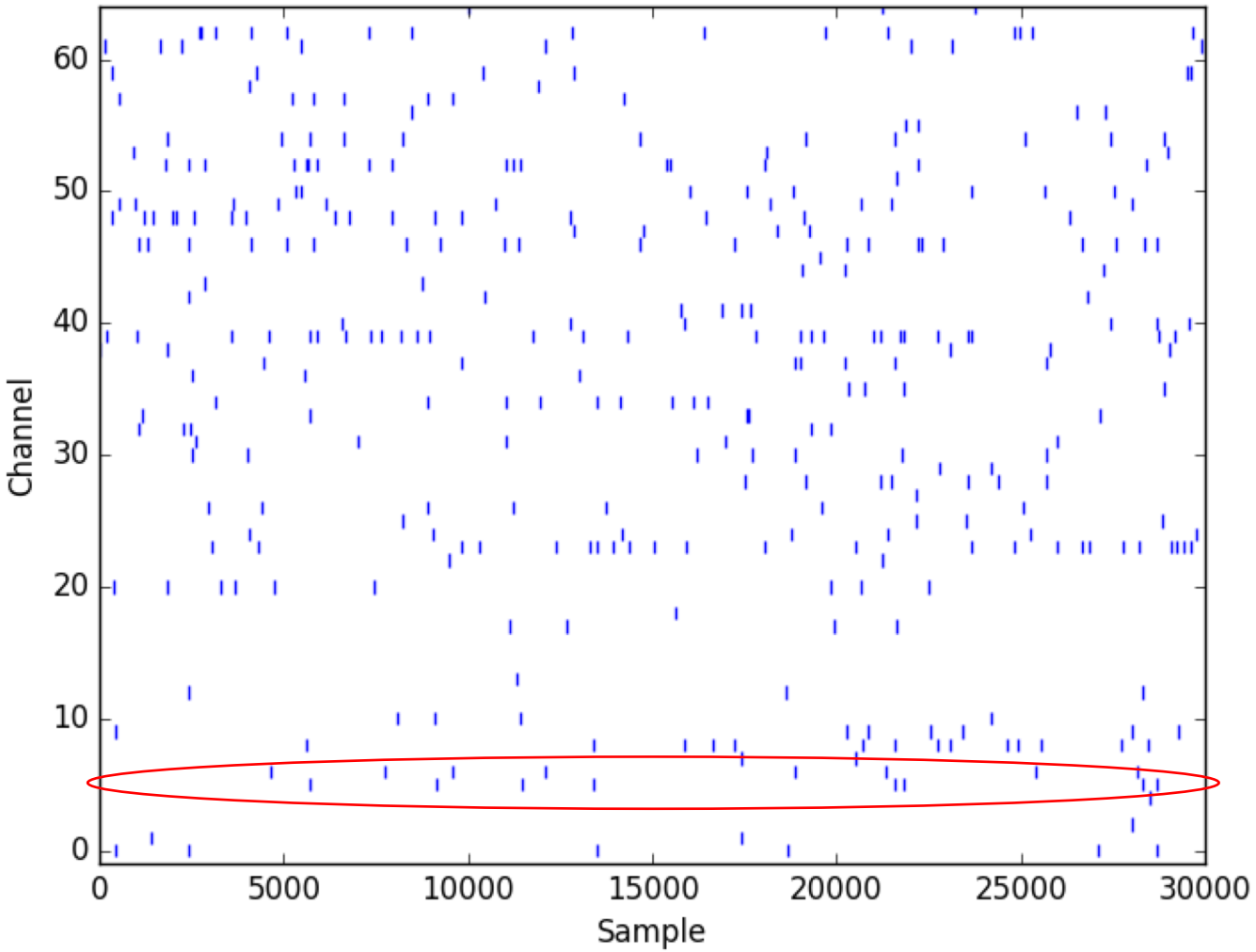
Highpass Filtered



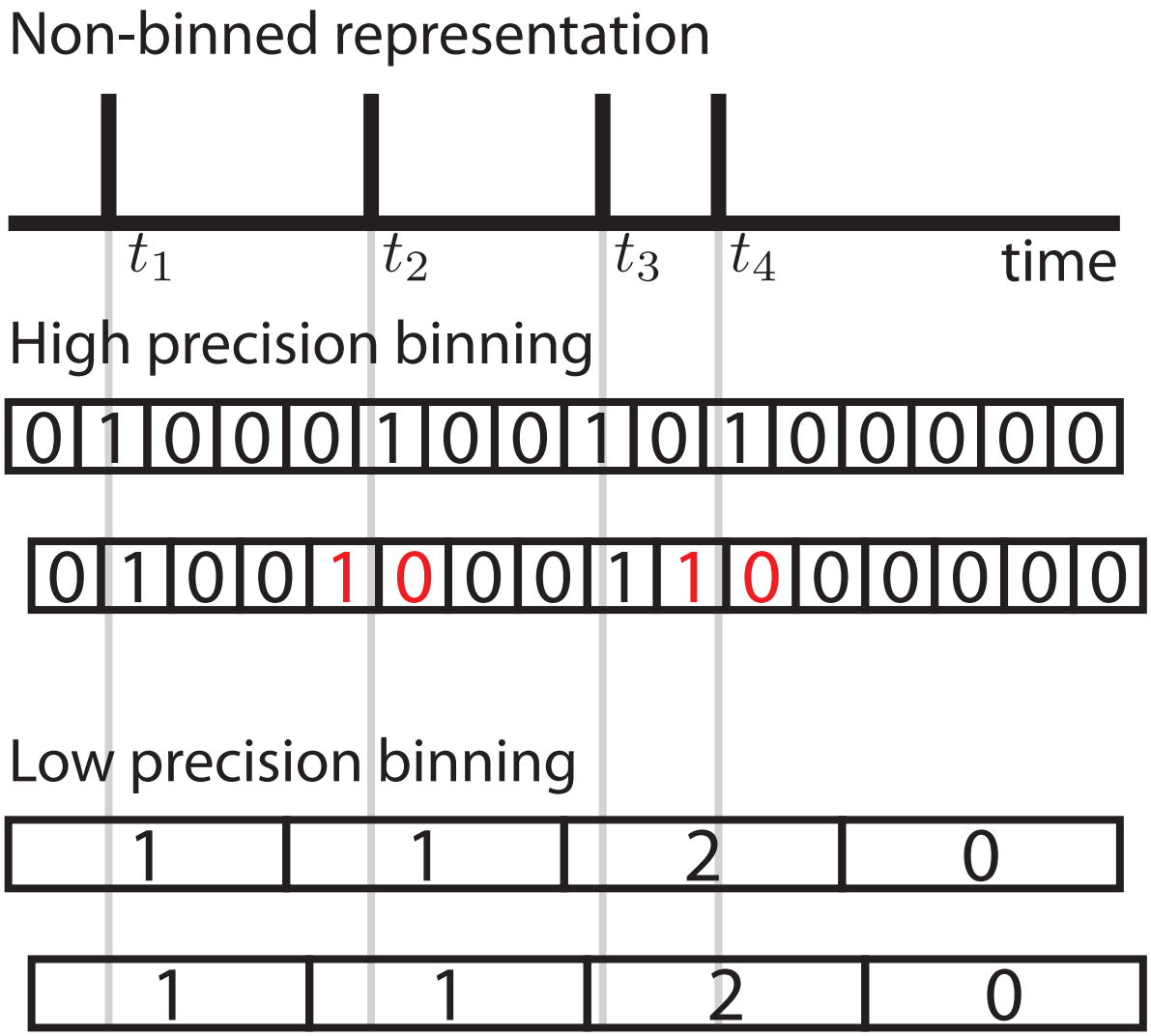


Park et al., IEEE Sig. Proc. Mag. 2013

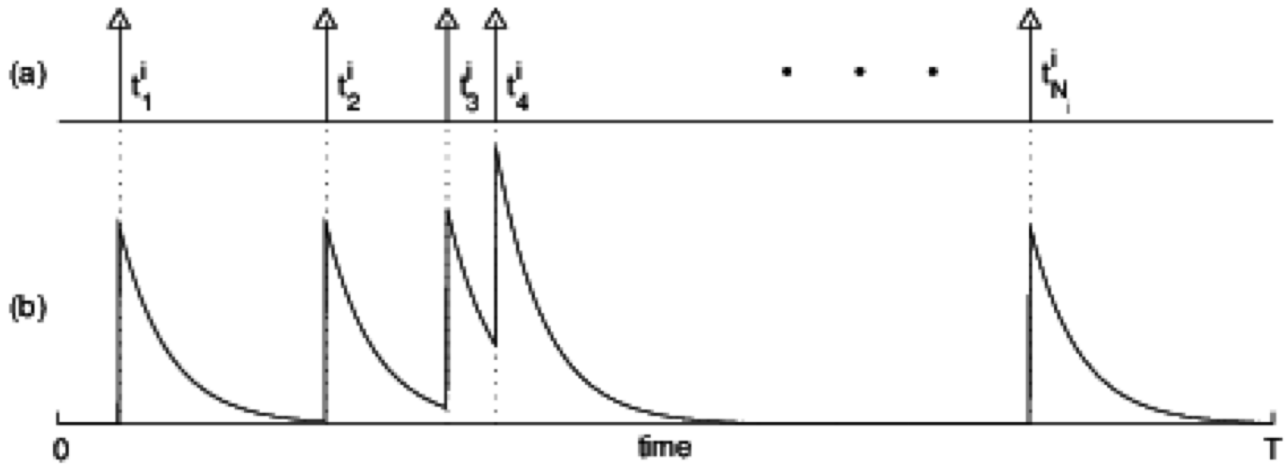
Spike Trains



Rate coding – Binned spike counts



Rate coding – Kernel convolution

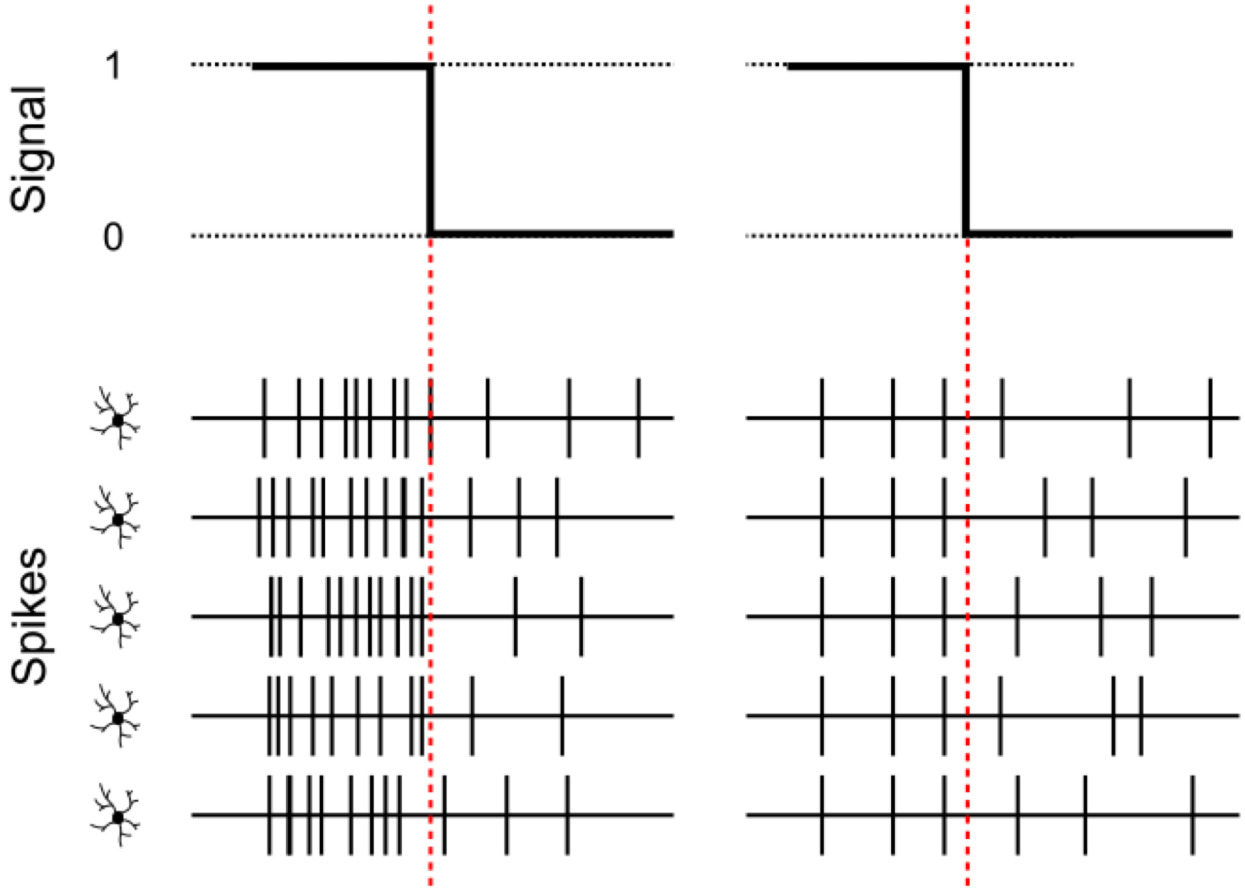


Paiva et al., Neural Computing and Applications, 2010

Kernels:
'auto', **'rectangular'**, **'gaussian'**, **'exponential'**, **'alpha'**

Auto: Gaussian with optimized standard deviation
H. Shimazaki and S. Shinomoto, "Kernel Bandwidth Optimization in Spike Rate Estimation," in Journal of Computational Neuroscience 29(1-2): 171–182, 2010

Rate-coding is not the whole story



Increase response in neuron types

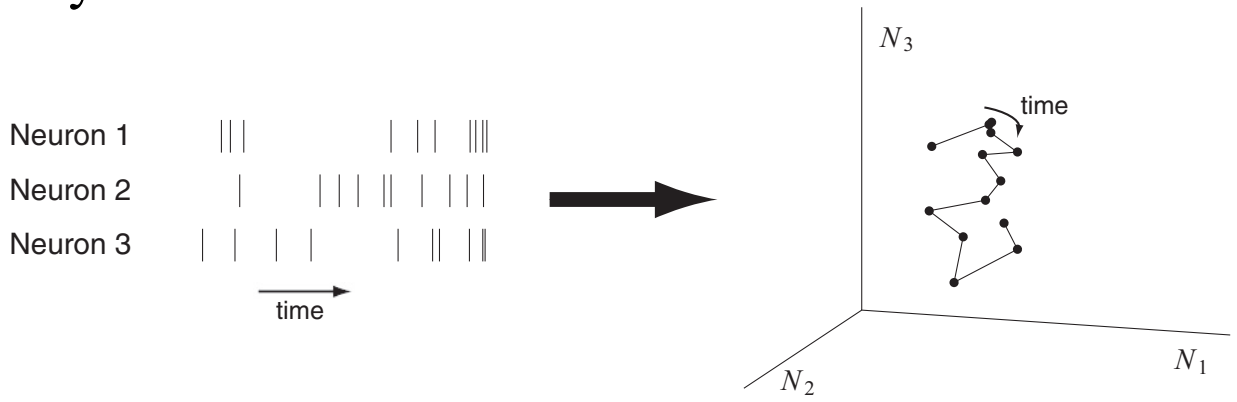
SST+

PV+

@tyrell_turing

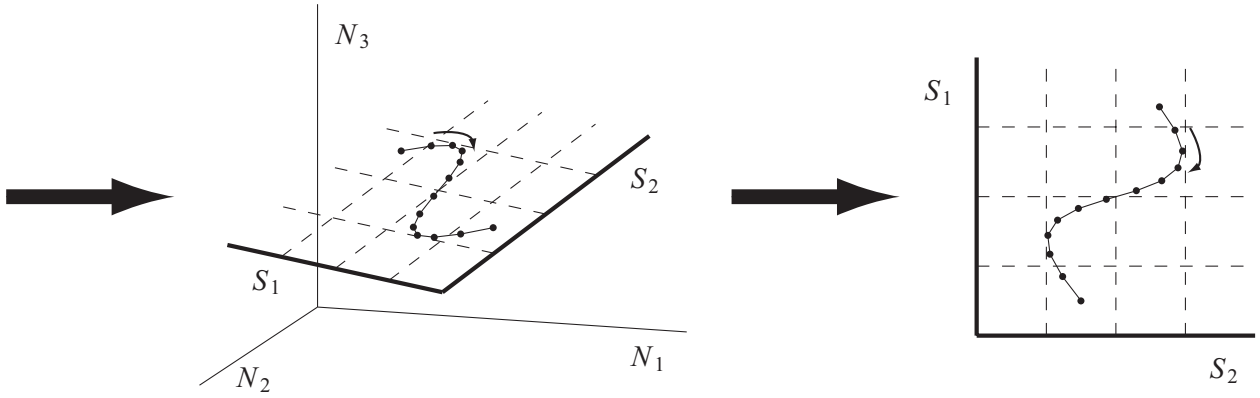
bioRrxiv

Standard Approach:
Dimensionality reduction



Spike trains

Noisy time series



Denoised time series

Low-dimensional time series

Yu et al., J Neurophysiol. 2009

Standard Approach:

- State Estimation (Kalman Filter)
  - Uncertain Information → Educated Guess about What System Will do Next
  - Example:
    - Robot moving in one direction with **fairly** constant speed
    - It has a GPS which tells us the exact position with 10 meters **uncertainty**
    - We define its state as $\overrightarrow{x_k} = (\vec{p}, \vec{v})$
    - Kinematics **OR** GPS ?
    - Using all available information would give us a better answer than either estimation

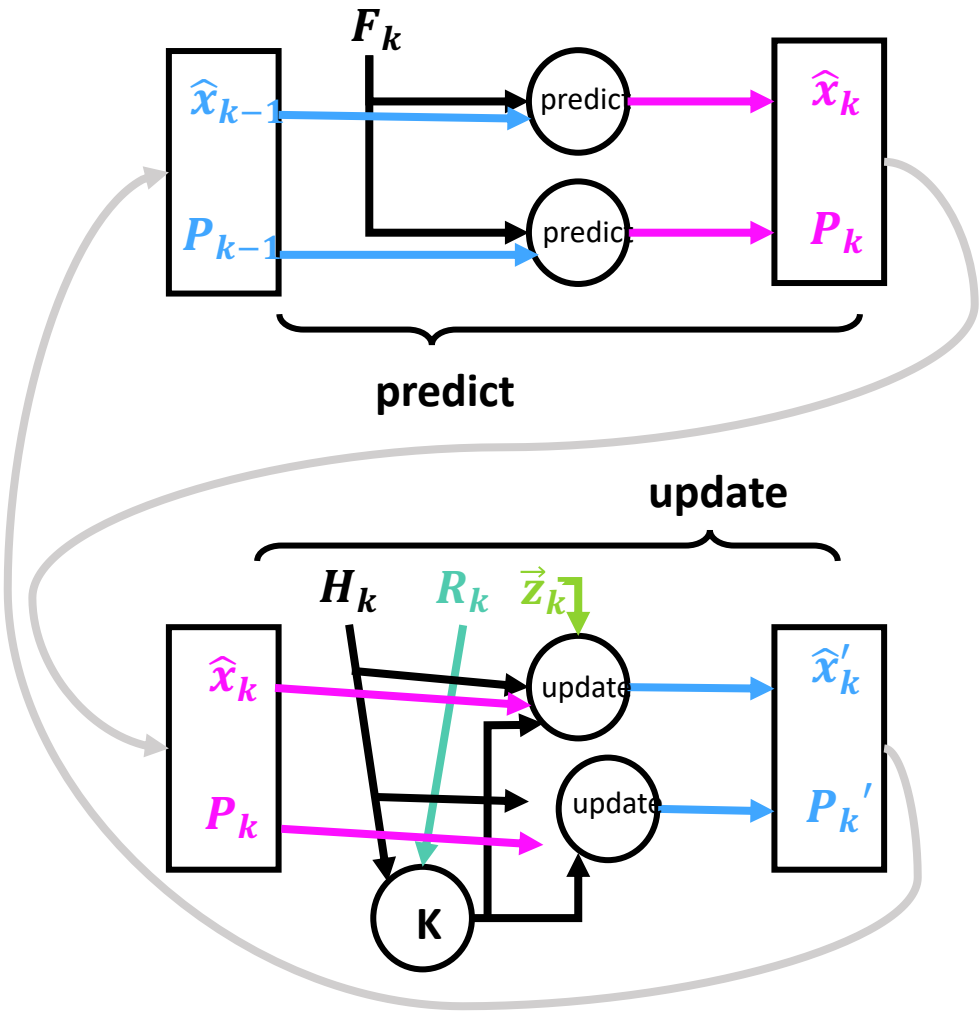
State Vector (x) comprises

- Position
- Velocity
- Acceleration

Predict next step (position = velocity * time_delta)

Update with neural input (z)

Optional: z can include history with previous time bins (taps)

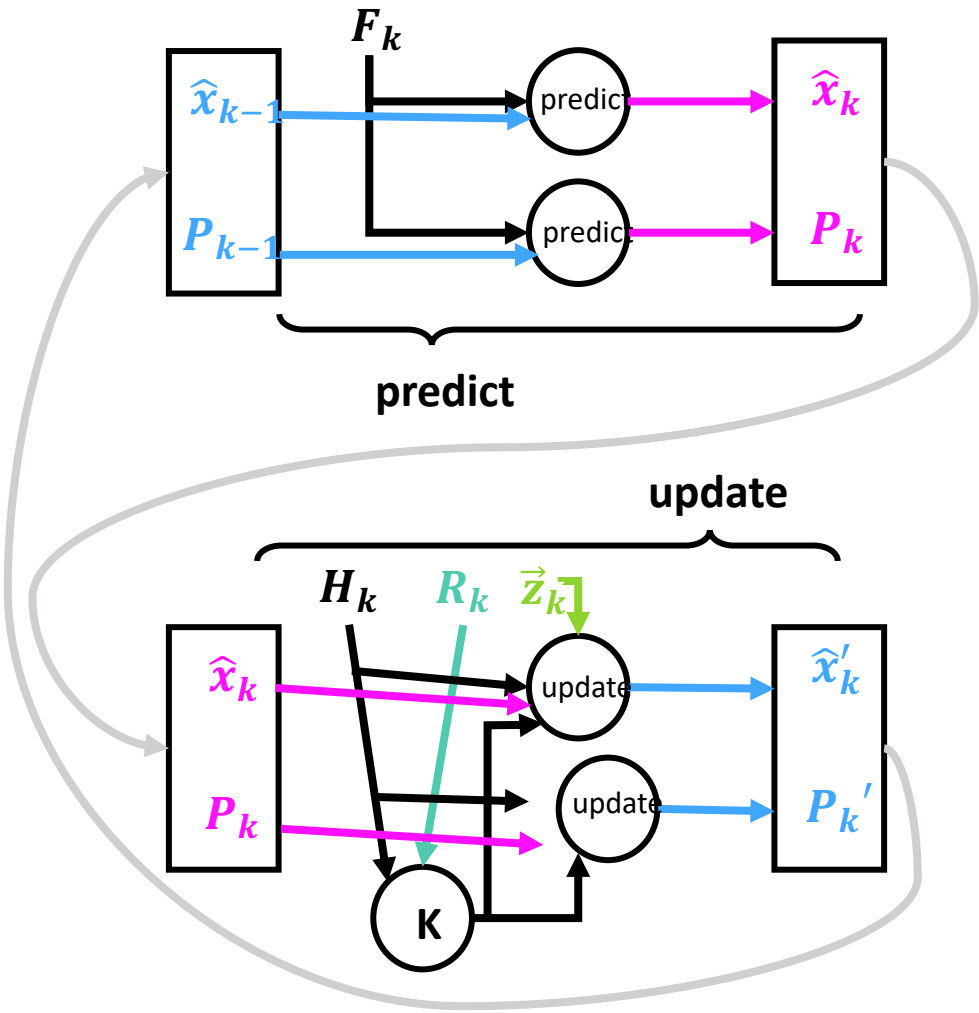


Source: bzarg.com

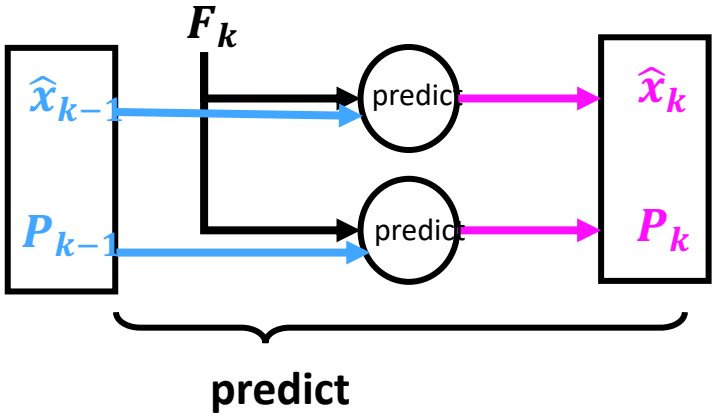
- State Estimation (Kalman Filter)

  - **Predict**
  - $\hat{x}_k = F_k \hat{x}_{k-1}$
  - $P_k = F_k P_{k-1} {F_k}^T$

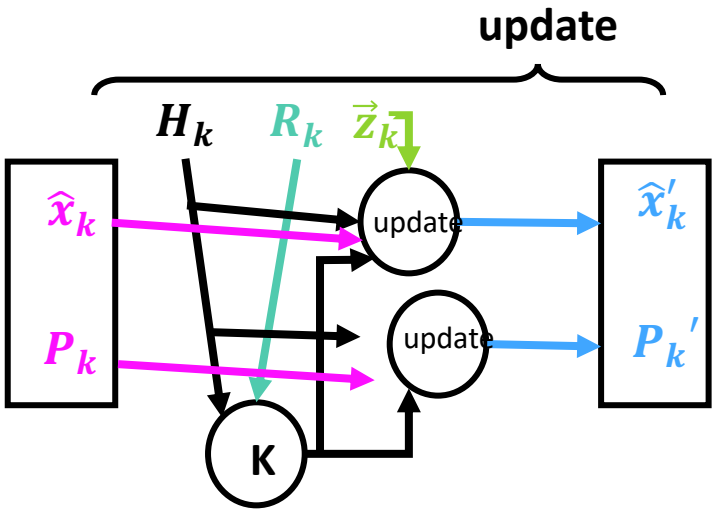
  - **Update**
  - $\hat{x}'_k = \hat{x}_k + K'(\vec{z}_k - H_k \hat{x}_k)$
  - ${P_k}' = P_k - K' H_k P_k$
  - $K' = P_k {H_k}^T (H_k P_k {H_k}^T + R_k)^{-1}$



- State Estimation (Kalman Filter)
  - **Predict**
  - New estimate is predicted from previous best estimate
  - New uncertainty is predicted from old uncertainty



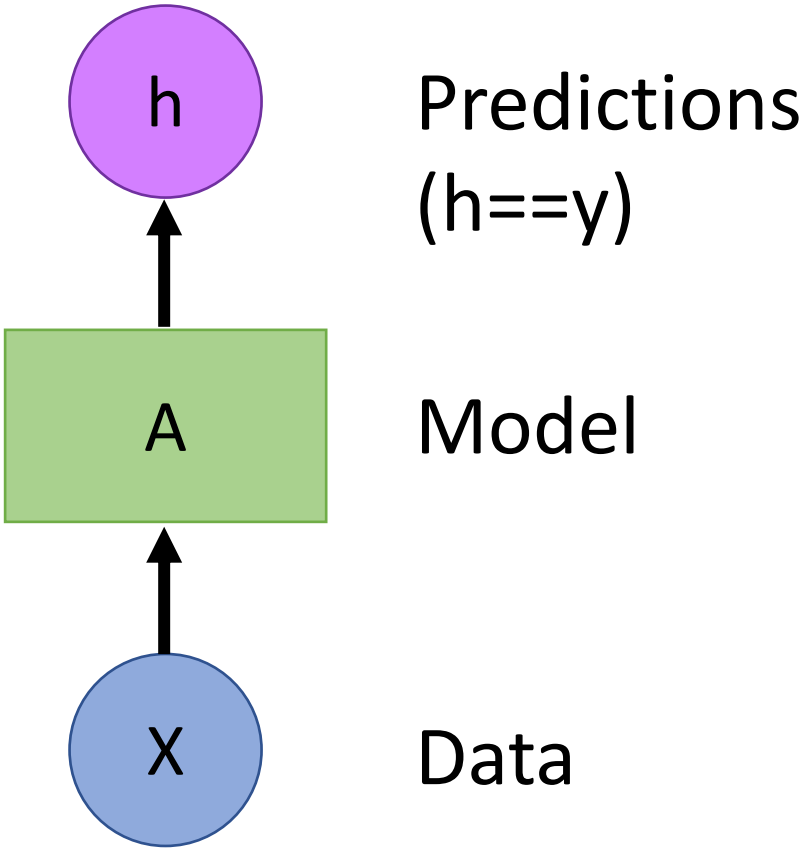
  - **Update**
  - New best estimate is predicted from new estimate and sensor input
  - Overall new uncertainty is predicted from new uncertainty and sensor noise



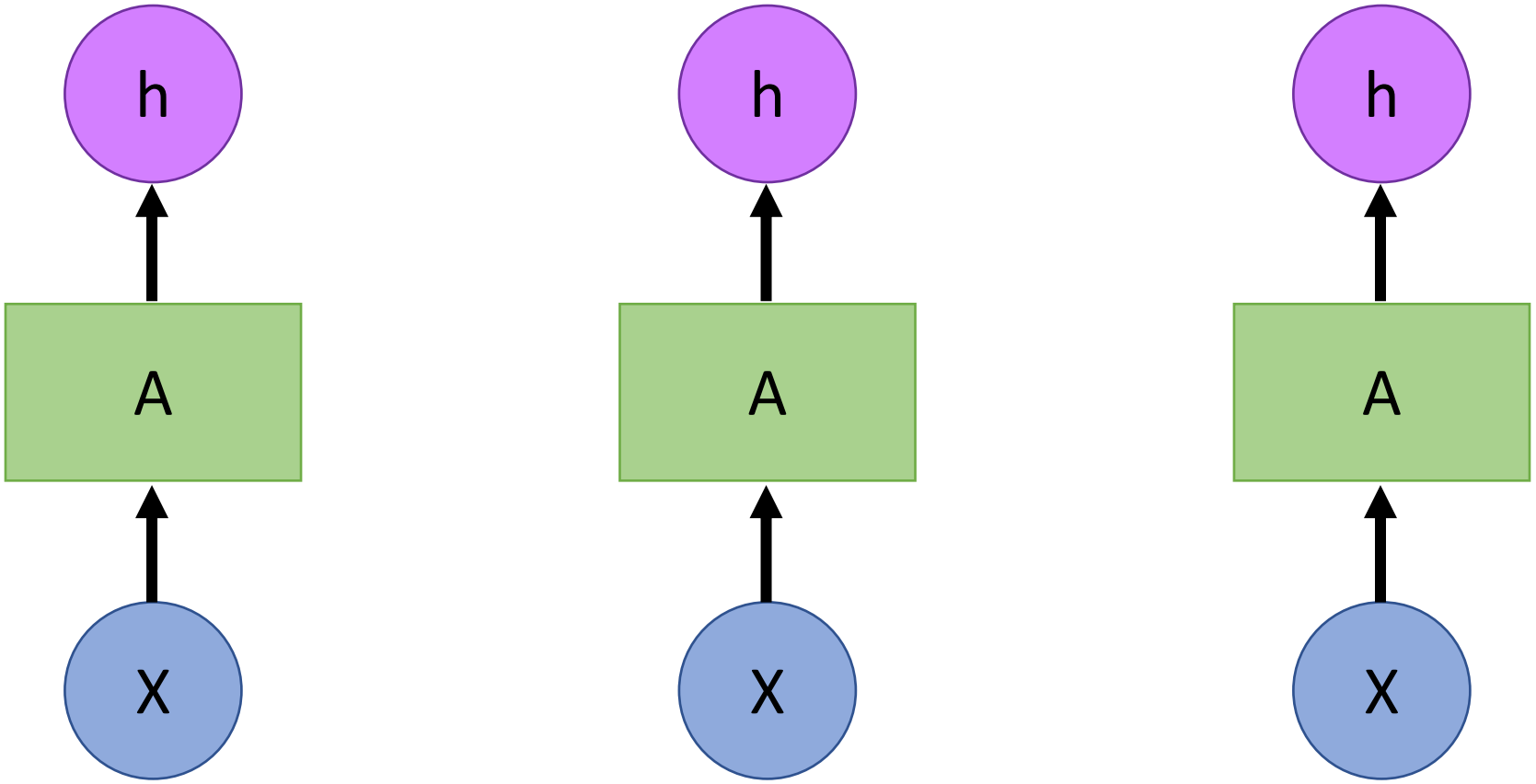
❖ F_k is how new prediction is related to previous (i.e. Kinematics)

❖ H_k is how we measure our state from sensor inputs

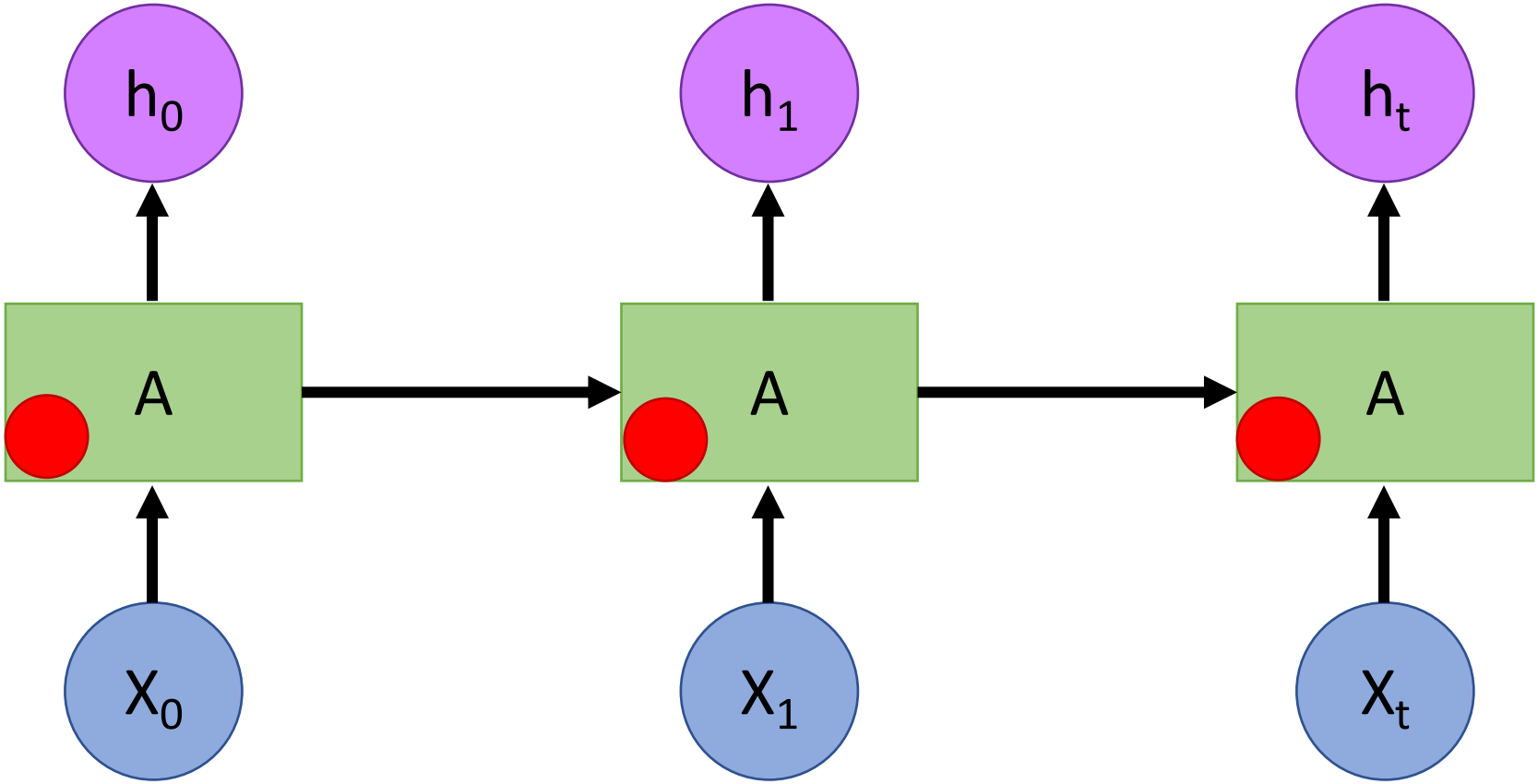
Vanilla CNN is stateless: no memory



Vanilla CNN is stateless: no memory



A model that remembers its (recent) data history is desirable.



Recurrent neural networks (RNNs) can use past information to make the current prediction

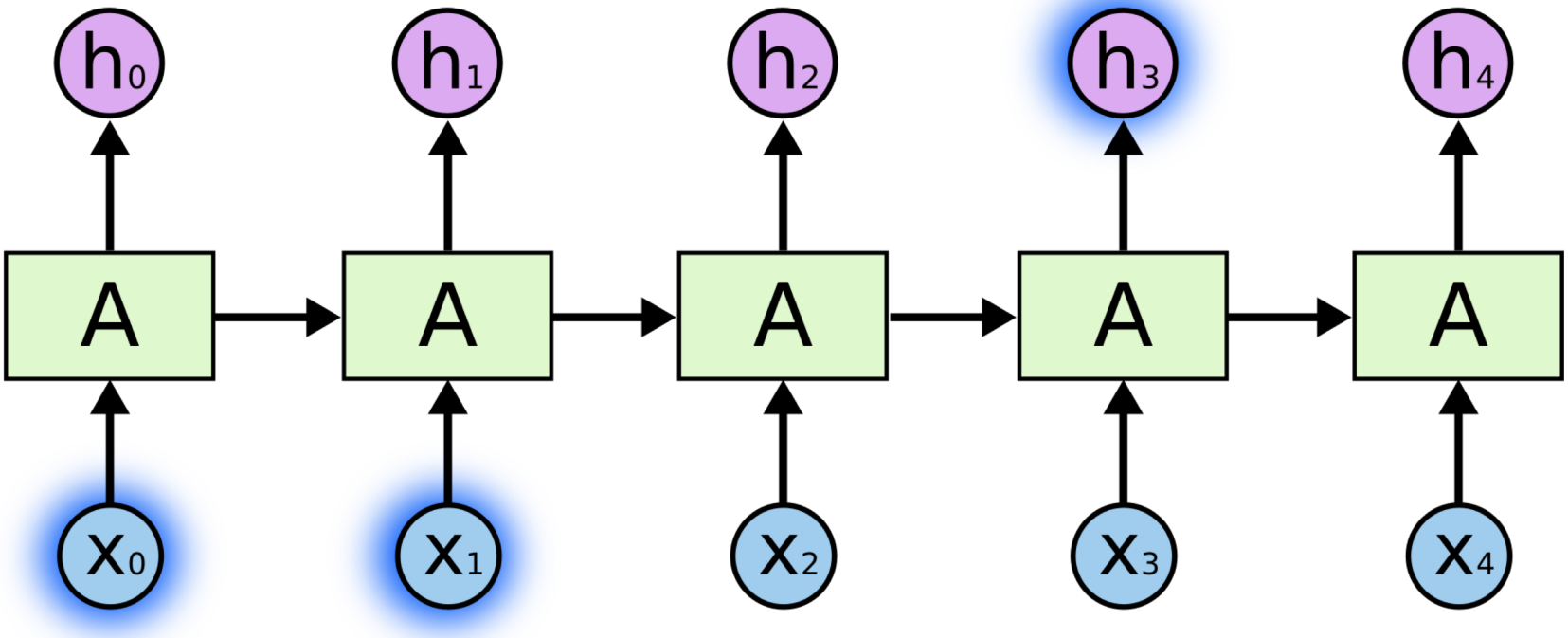
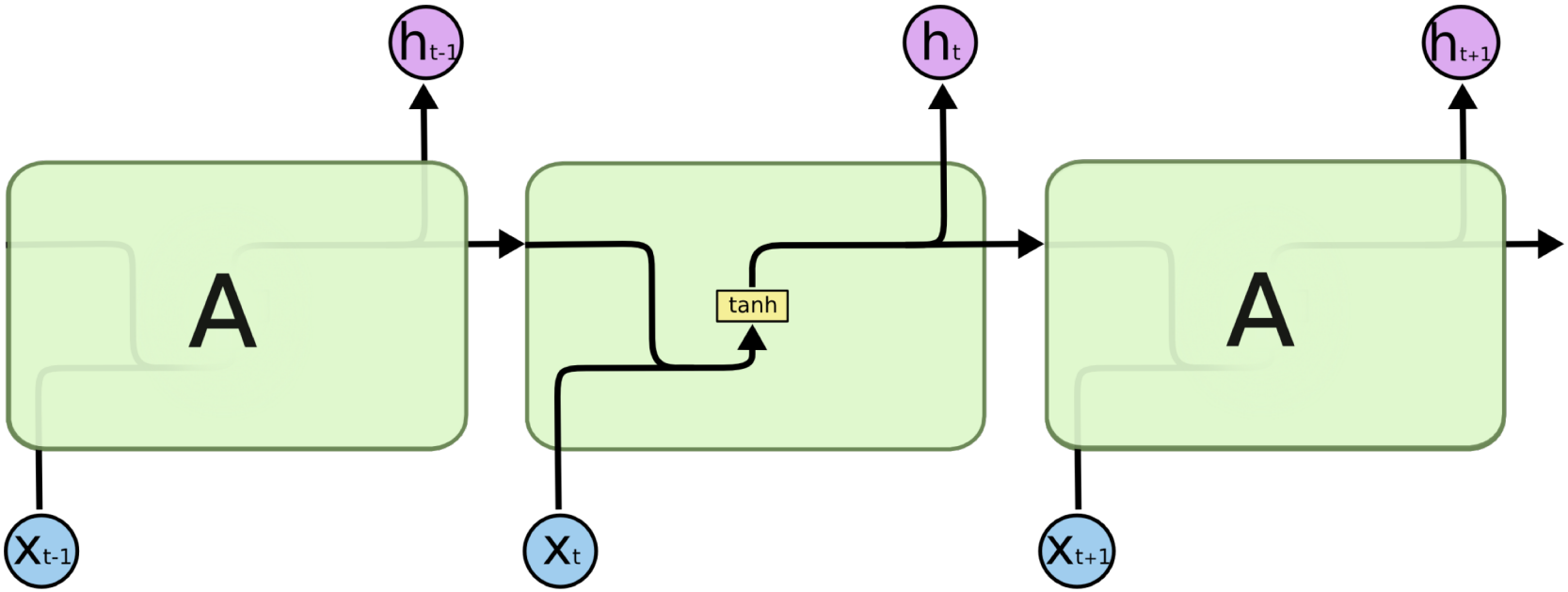
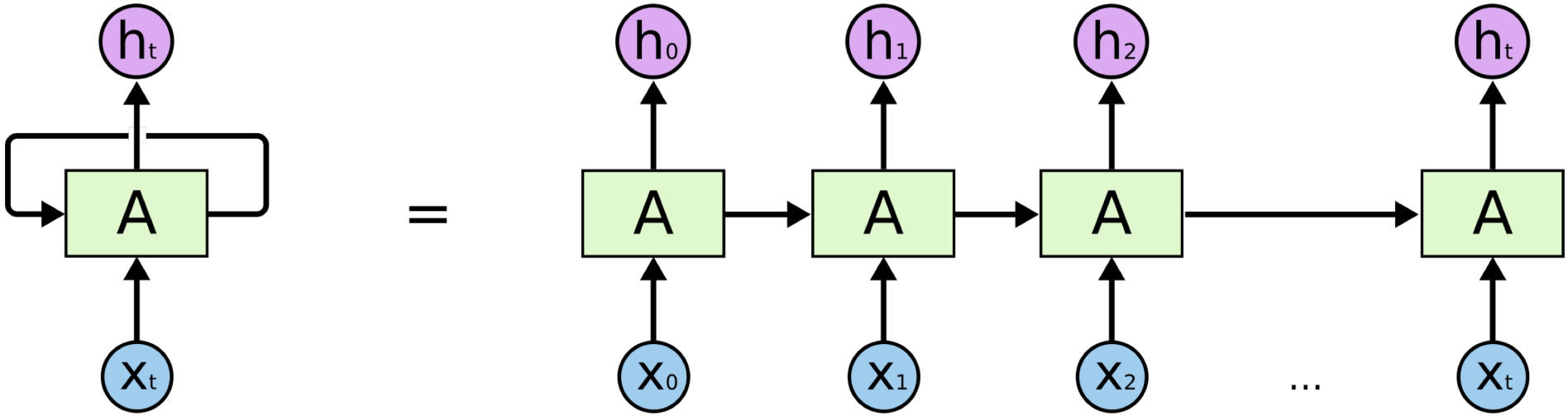


Figure source


h_{t-1}
h_t
h_{t+1}
A
tanh
A
X_{t-1}
X_t
X_{t+1}

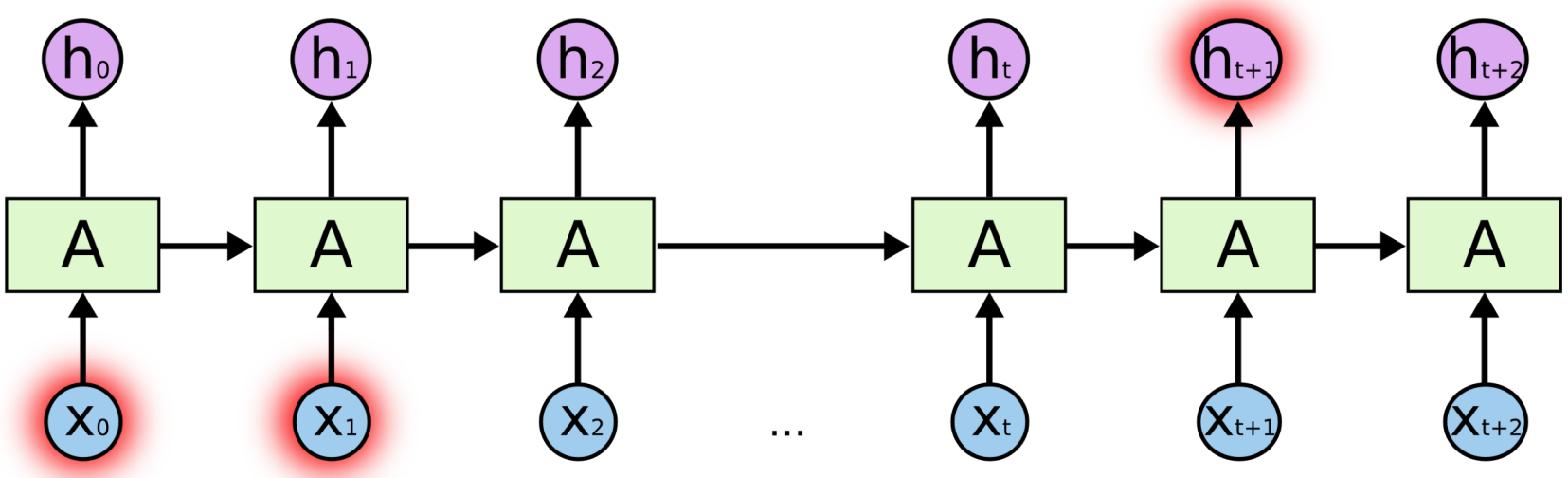
A model that maintains state and loops over its input is represented with a single looping model



- 06_01_intro_to_RNNs.ipynb
- When that's done, open 06_02 and start downloading data, then resume here.

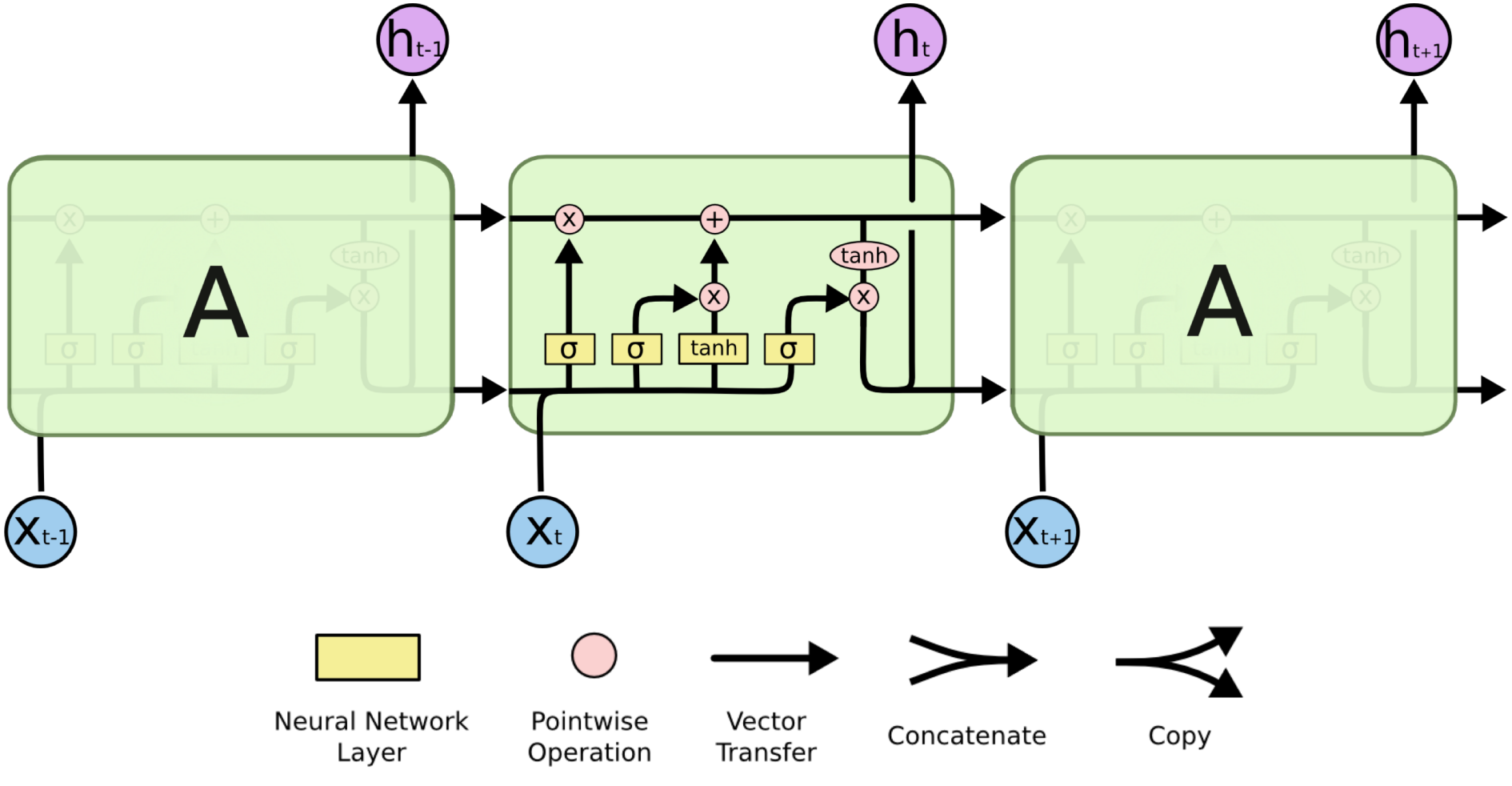
Learning Long-Term Dependencies with Gradient Descent is Difficult

Bengio et al., 1994

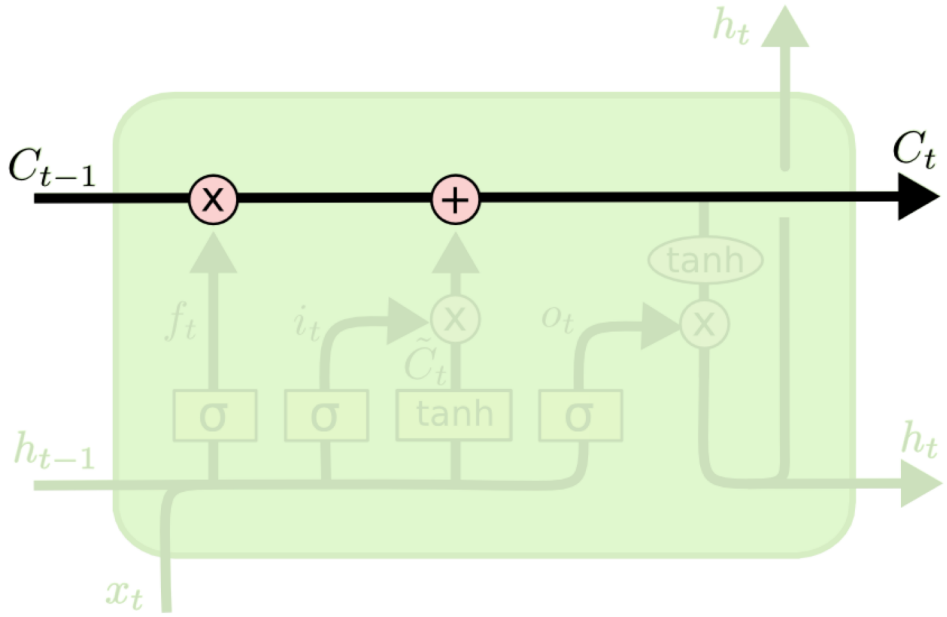


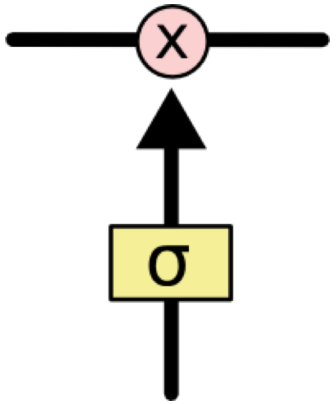
- In practice, simple RNNs cannot maintain information for more than a few steps
  - Exploding/Vanishing gradient

Long-Short Term Memory (LSTM) are a special kind of RNN capable of learning long(er)-term dependencies



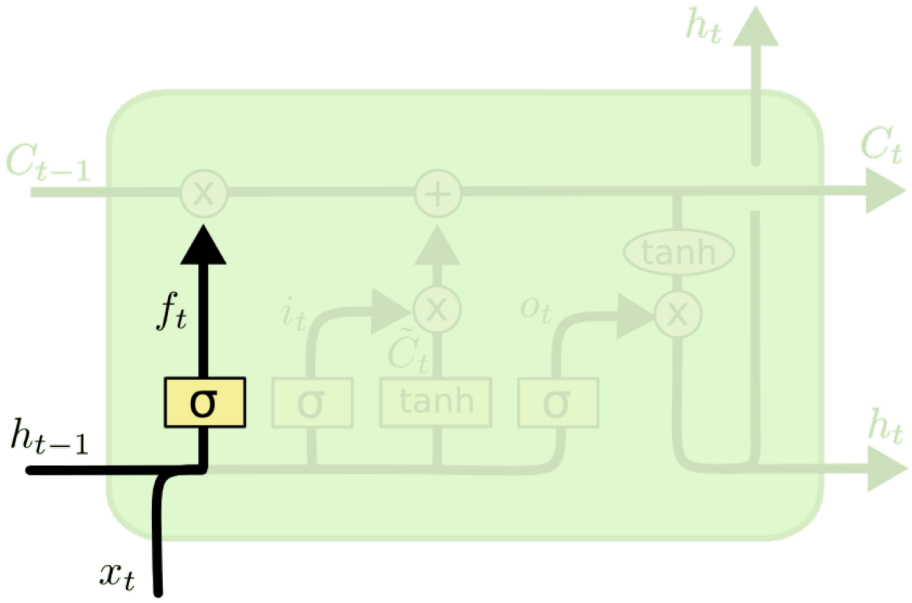
The cell state C persists across iterations. Its contents may be modified, determined by gates.





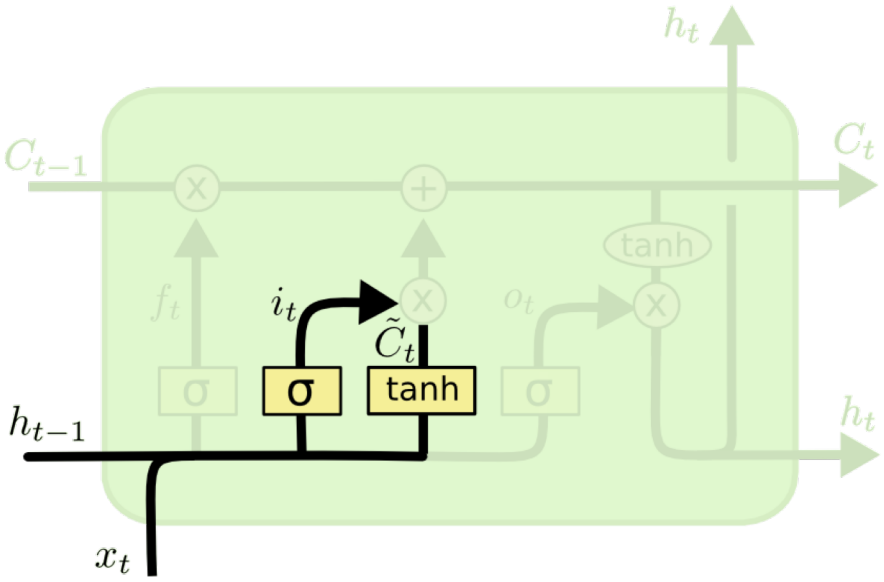
Sigmoid gating mechanism

LSTM Step 1: Forget Gate



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

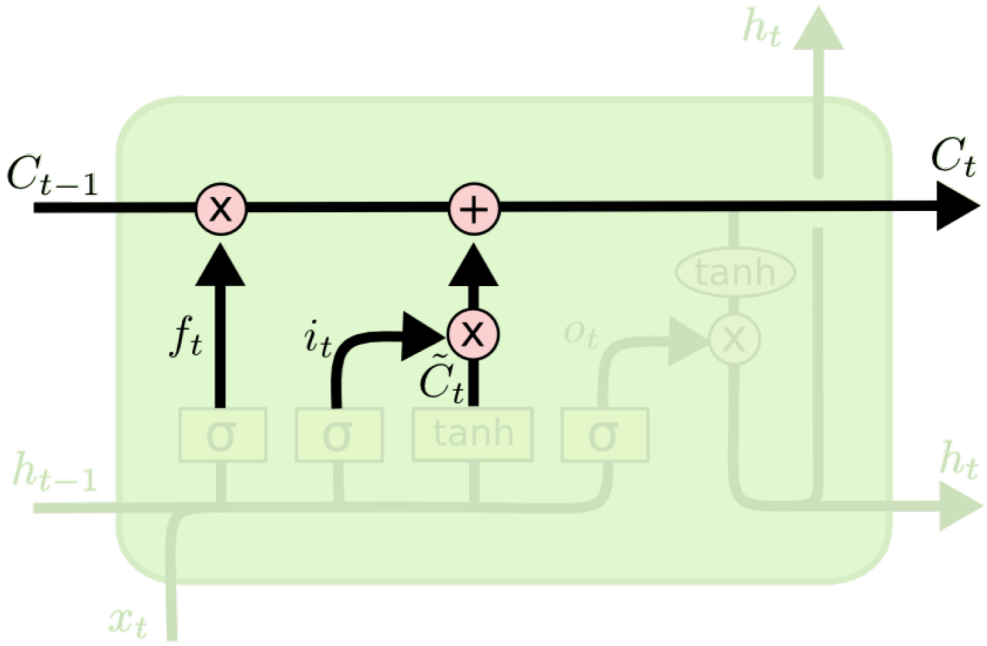
LSTM Step 2: Input Gate



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

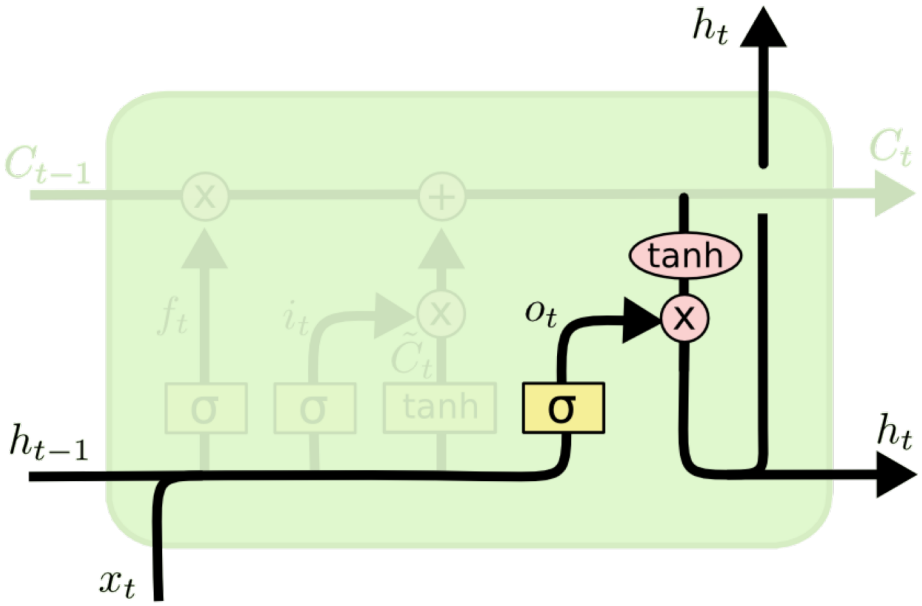
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

LSTM Step 3: Modify State



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

LSTM Step 4: Combine (new) state and input to produce output



$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Gated Recurrent Unit (GRU)

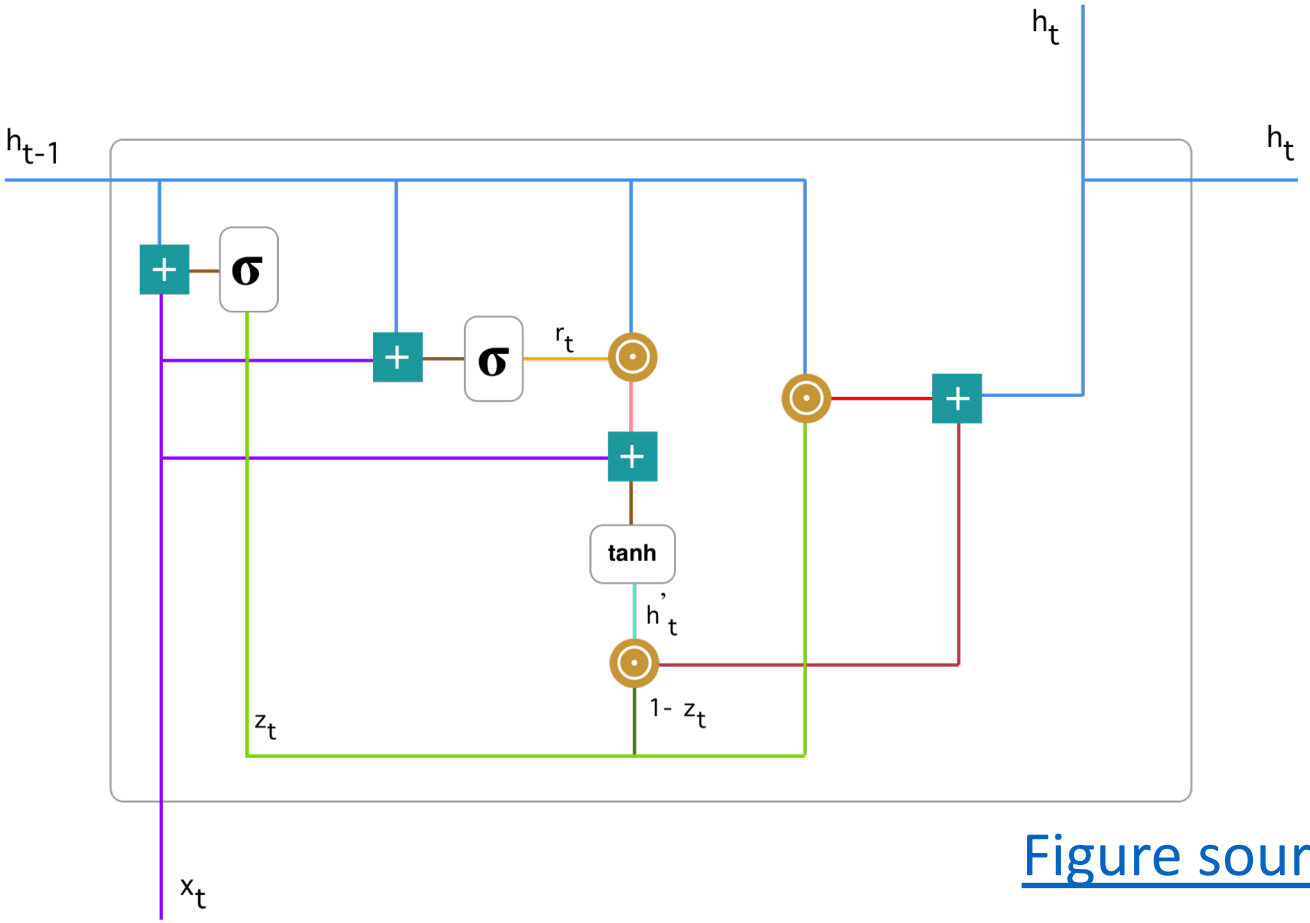
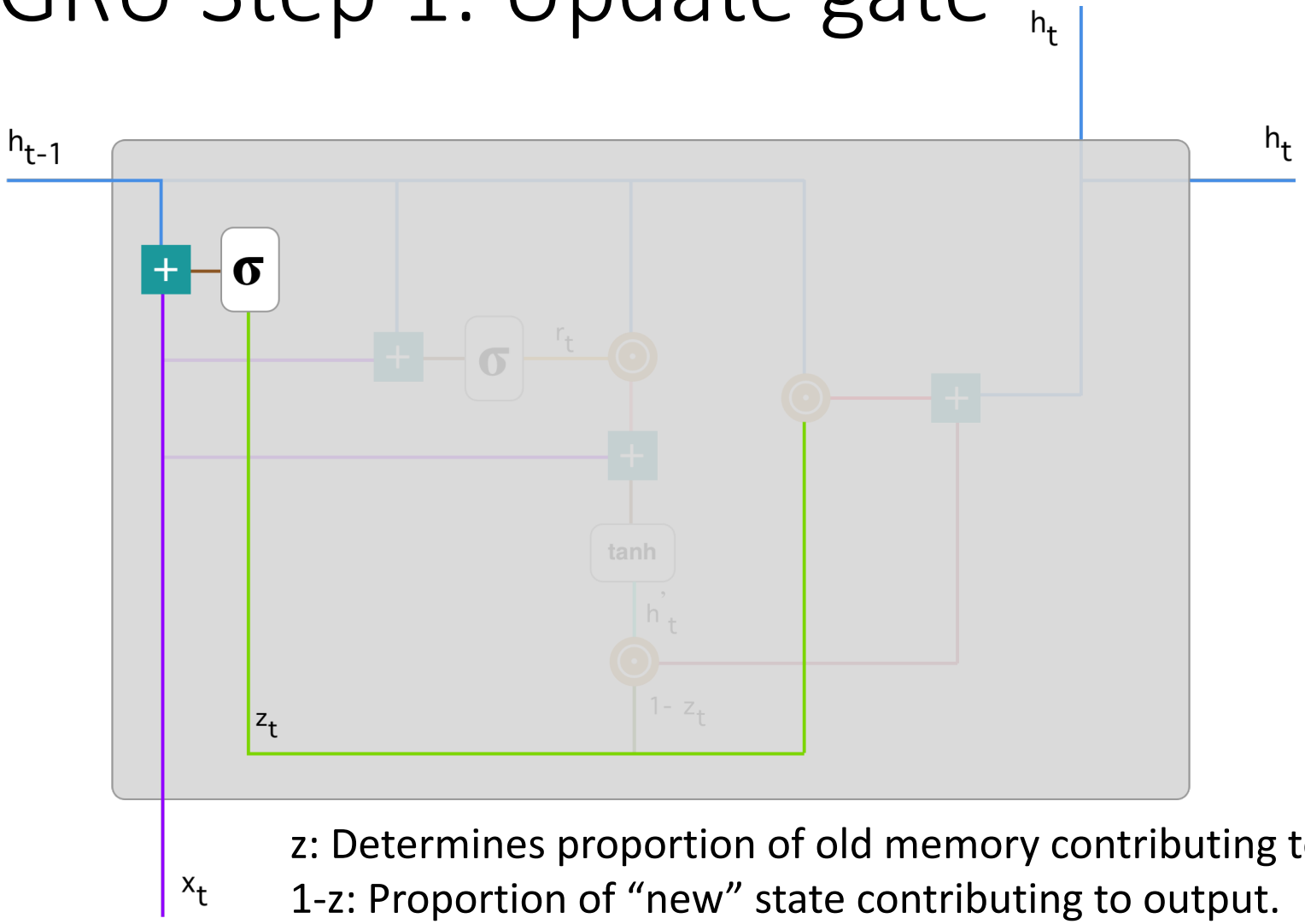


Figure source

GRU Step 1: Update gate

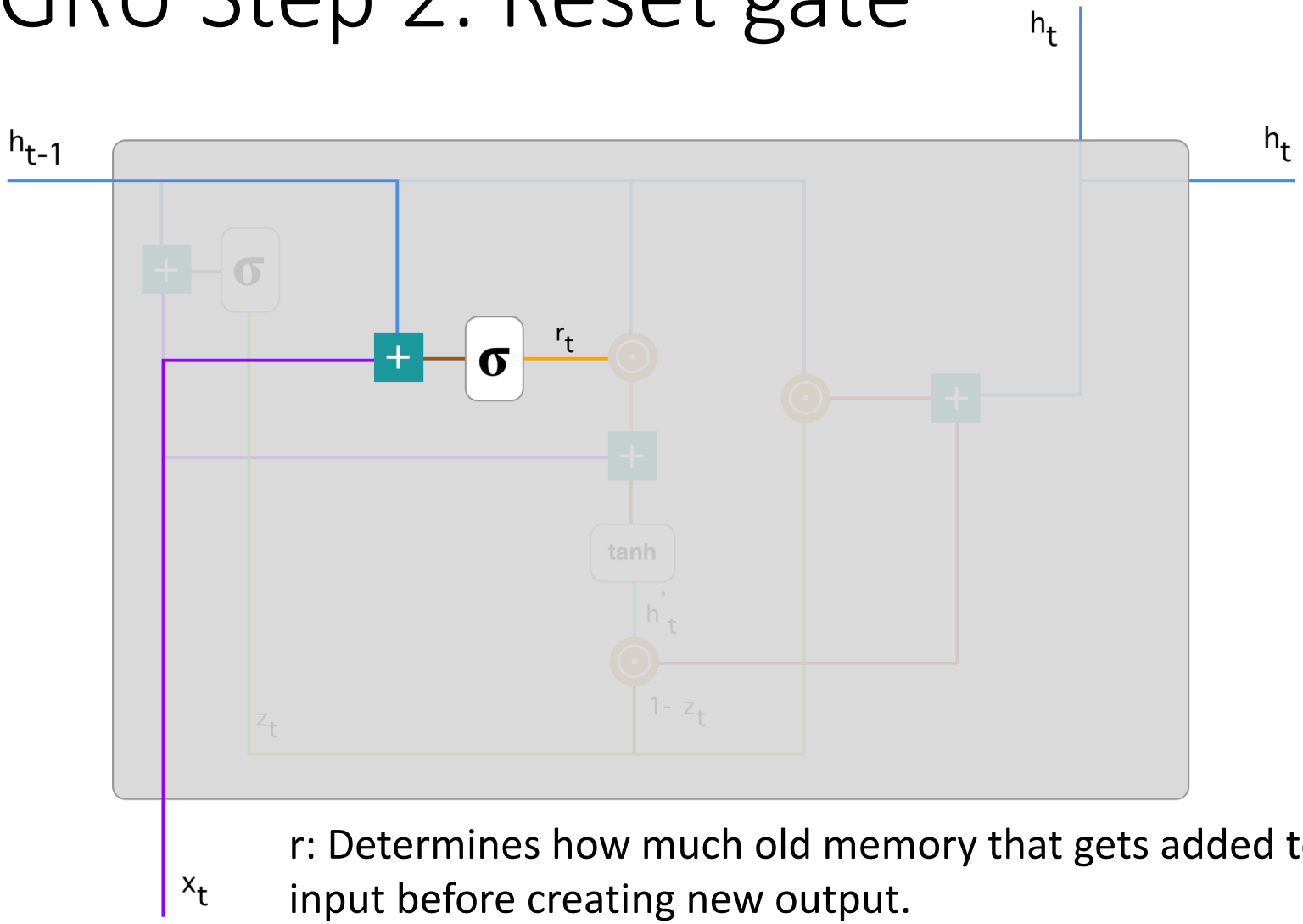


z: Determines proportion of old memory contributing to output.

1-z: Proportion of "new" state contributing to output.

$$z_t = \sigma(W^{(z)}x_t + U^{(z)}h_{t-1})$$

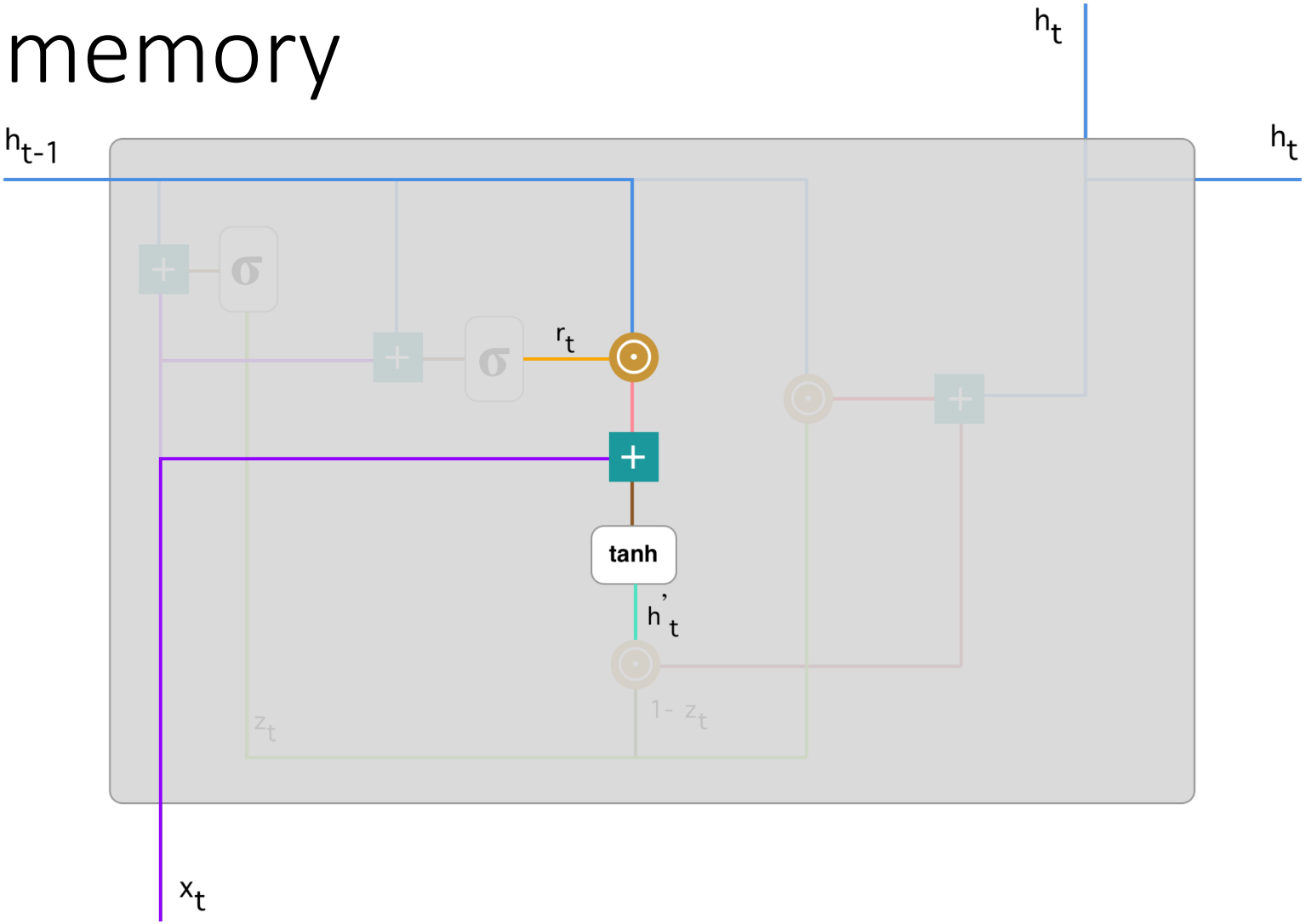
GRU Step 2: Reset gate



r: Determines how much old memory that gets added to new input before creating new output.

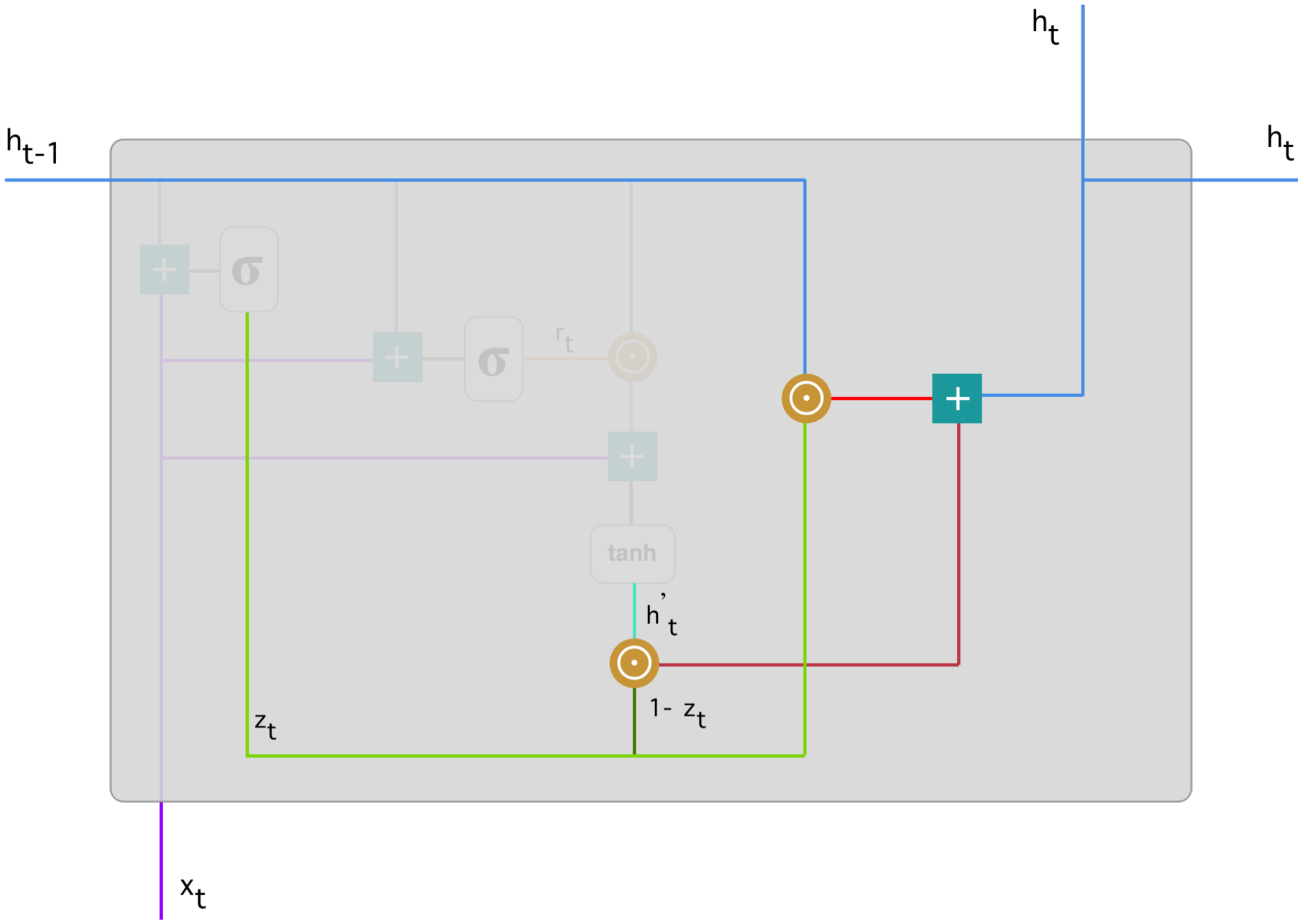
$$r_t = \sigma(W^{(r)}x_t + U^{(r)}h_{t-1})$$

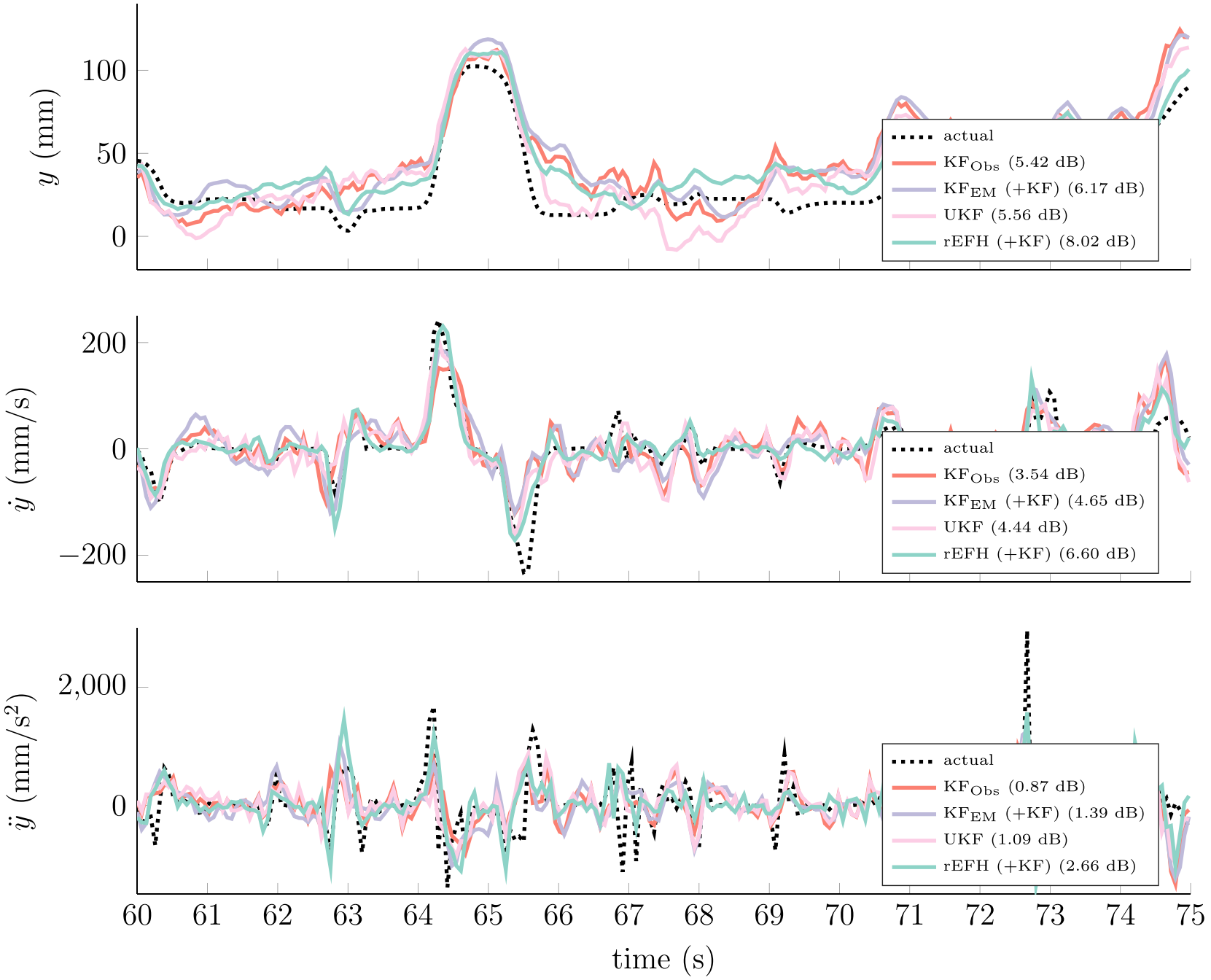
GRU Step 3: Combine input and memory



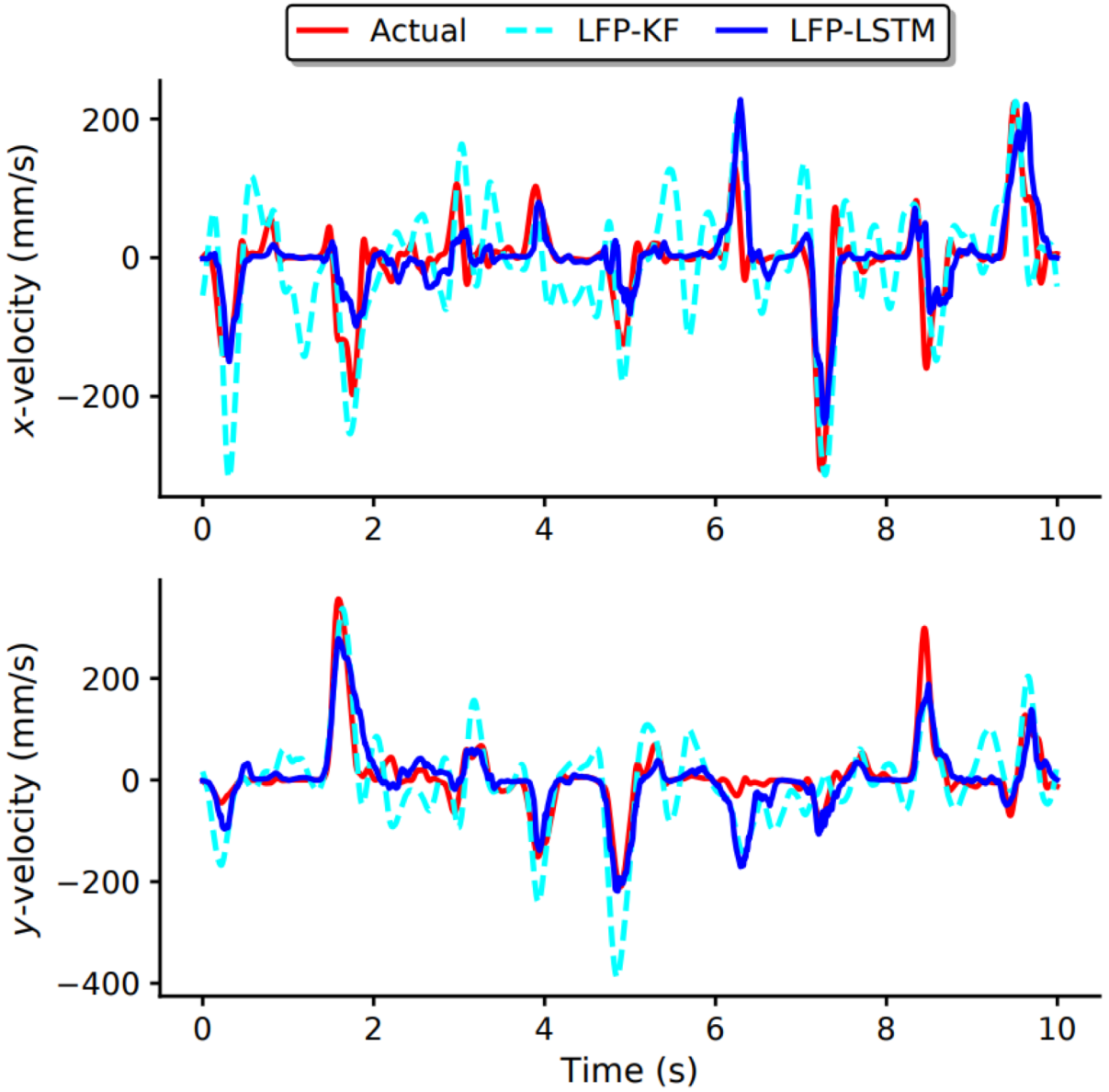
$$h_t' = \tanh(Wx_t + r_t \odot Uh_{t-1})$$

GRU Step 4: Update memory



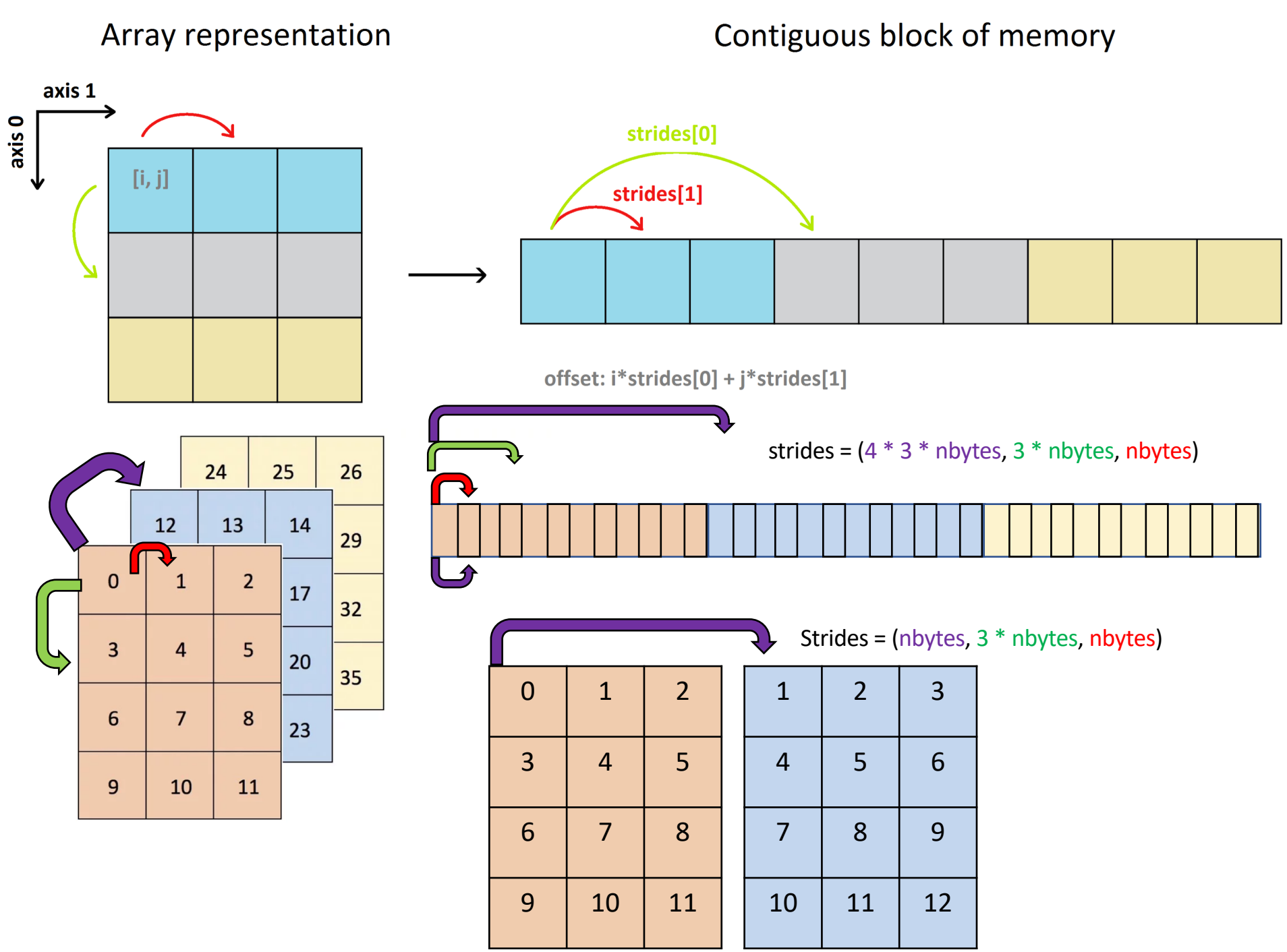


Result from Makin et al using same dataset



Result from Ahmadi et al., arXiv 2019

- 06_02_LSTM_and_GRU


Array representation
Contiguous block of memory
axis 1
axis 0
[i, j]
strides[0]
strides[1]
offset: i*strides[0] + j*strides[1]
strides = (4 * 3 * nbytes, 3 * nbytes, nbytes)
Strides = (nbytes, 3 * nbytes, nbytes)
24 25 26
12 13 14
29
0 1 2
17
3 4 5
32
20
6 7 8
35
23
9 10 11
0 1 2
3 4 5
6 7 8
9 10 11
1 2 3
4 5 6
7 8 9
10 11 12

Decoding Movements from Cortical Ensemble Activity Using a Long Short-Term Memory Recurrent Network

Po-He Tseng, Núria Armengol Urpi, Mikhail Lebedev and Miguel Nicolelis

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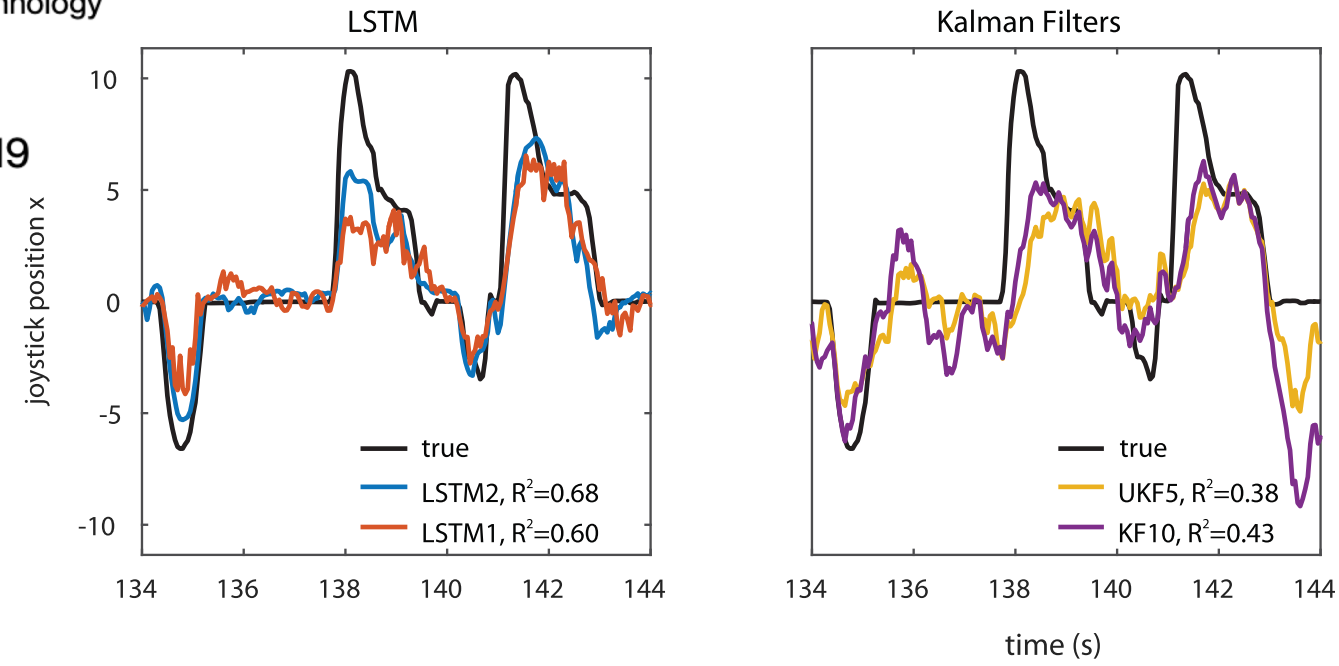


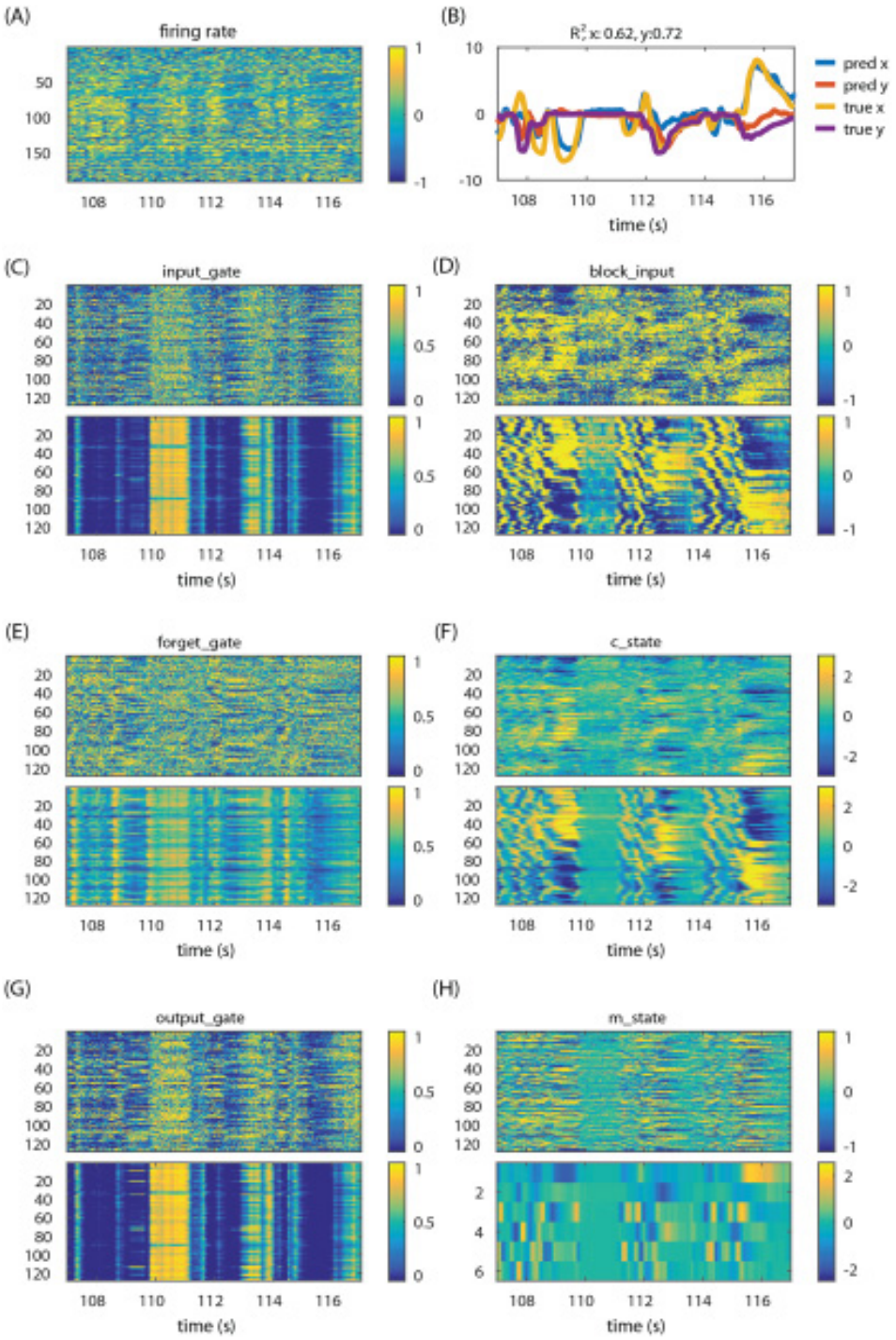
Model internal values in LSTM layers 1 and 2

Layers presented in pairs, with layer 1 on top.

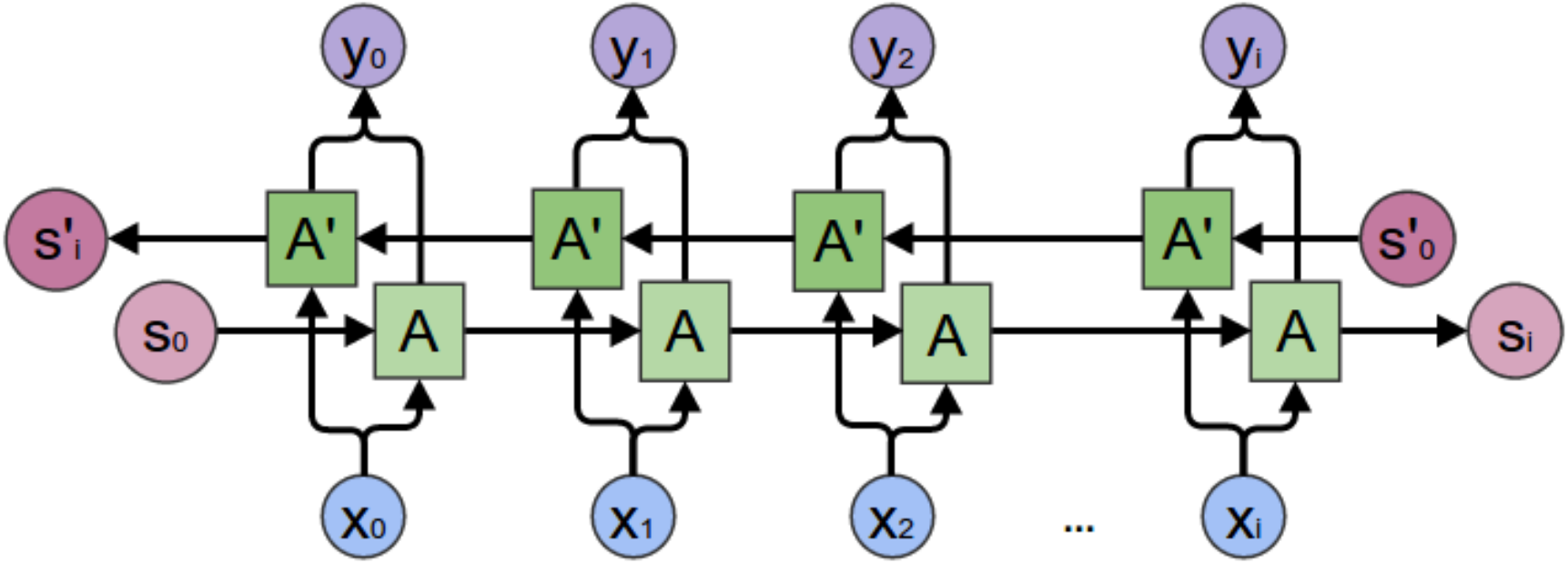
Layer 2 activations had higher contrast than layer 1, primarily because layer 2 gates were more fully closed.

(Not shown) layer 2 units were directionally tuned.

Does this tell us anything about how the brain works?



Bidirectional RNN



Loop forward over the sequence.
Loop backward over the sequence.
Combine output(s).