Deep Learning Applications for collider physics Lecture 3

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Plan for this week

	Day1	Day2	Day3	Day4	Day5
Lecture	Introduction	ConvNN	RNNs	Graphs	Unsupervised Learning
Tutorial	Fully Connected Classifier	ConvNN Classifier	RNNs Classifier	Graphs Classifier	Anomaly Detection

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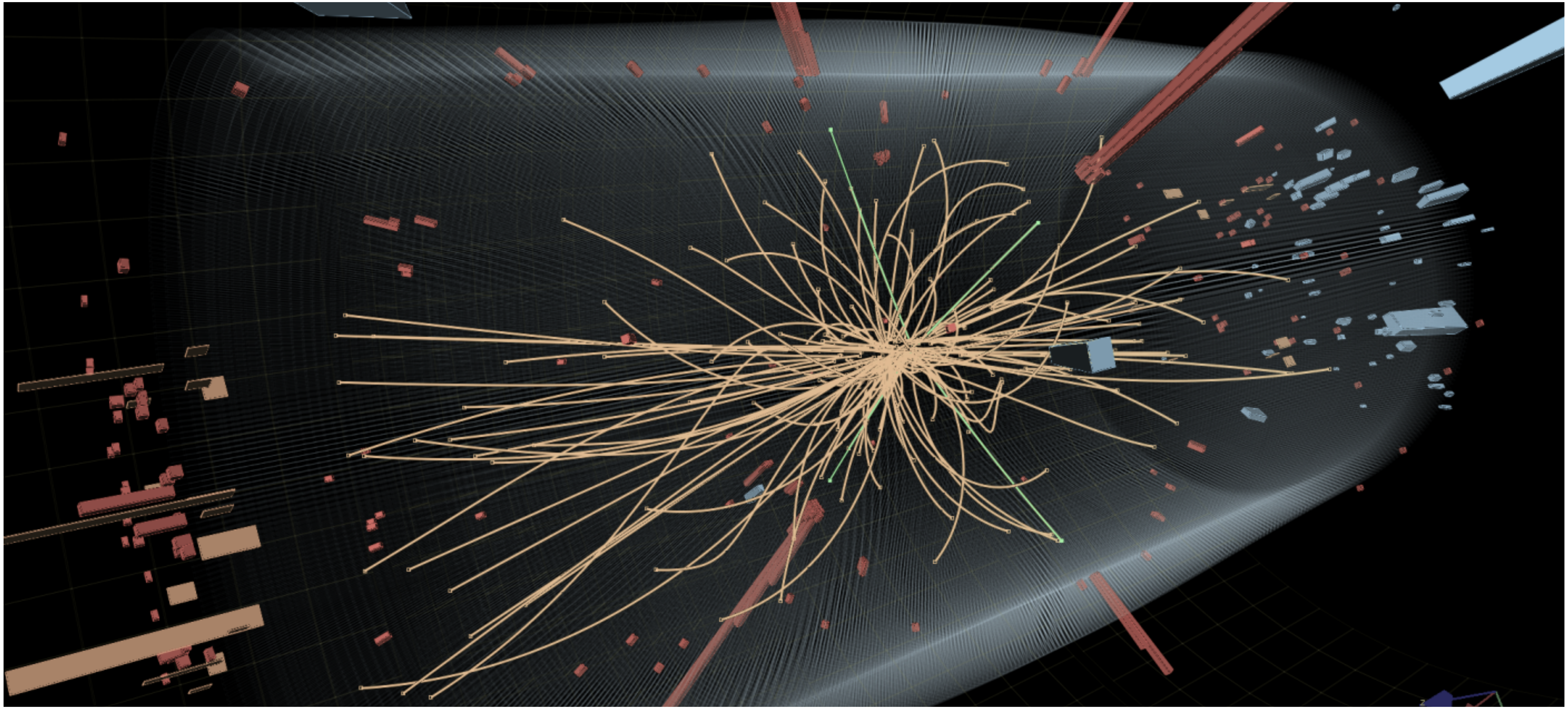
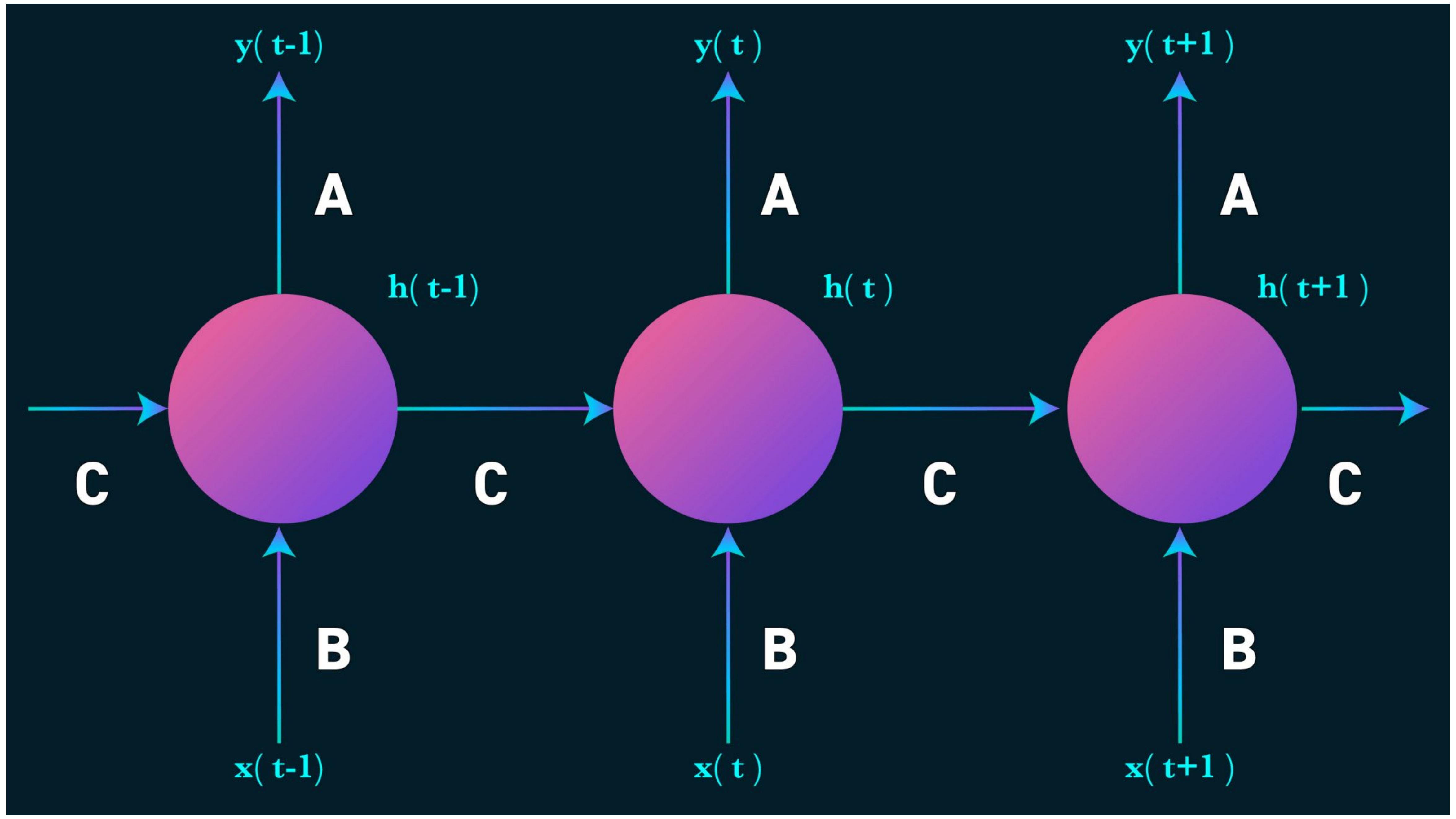


Language processing for particle physics

Recurrent networks

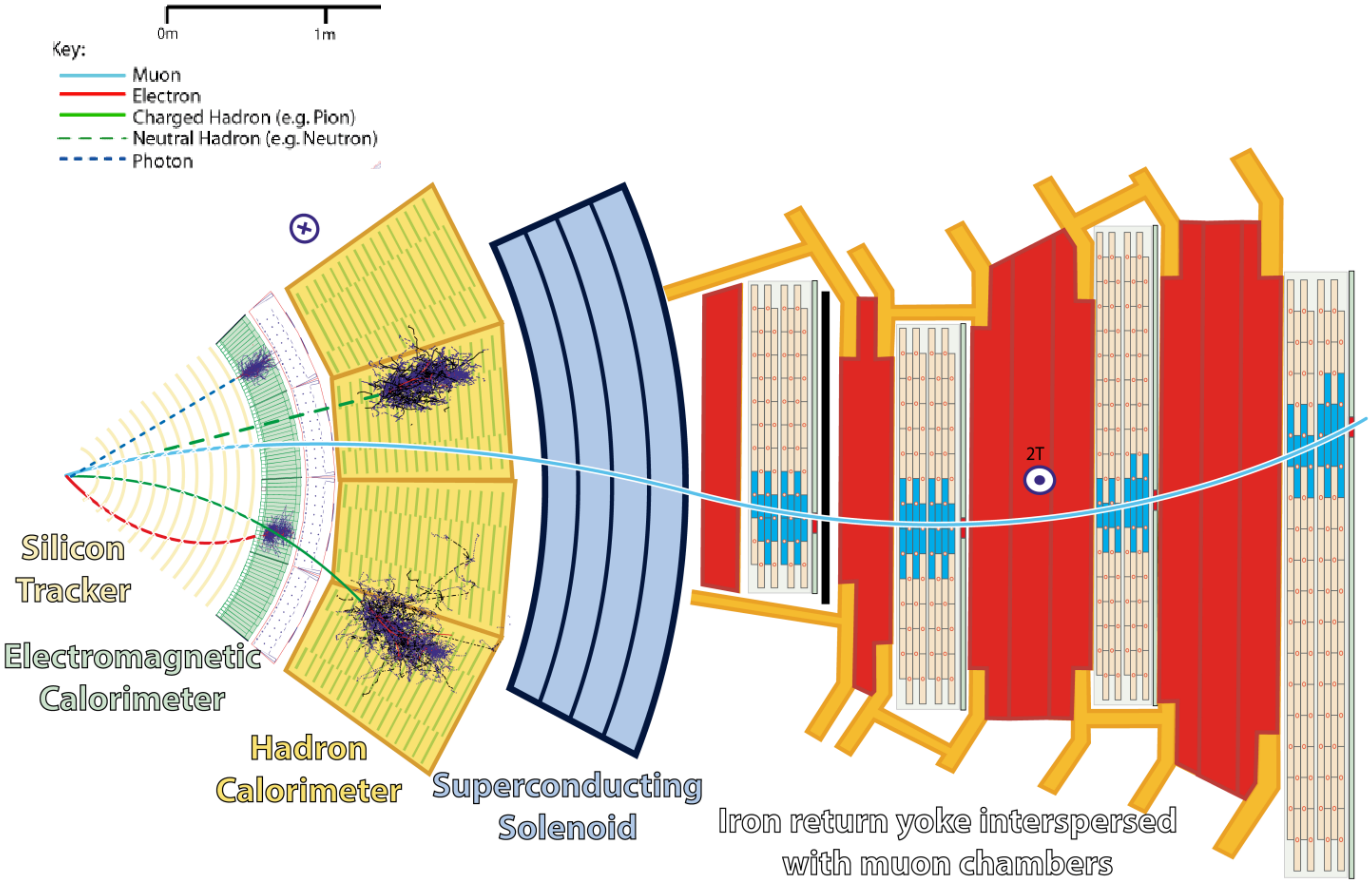
- Recurrent architectures are designed to process sequences of data
- Then idea is to have information flowing in the network while the sequence is sequentially processed
- Through this idea, recurrent networks mimic memory persistence
- Advantages
  - the input is not fixed-sized



https://towardsdatascience.com/understanding-rnn-and-lstm-f7cdf6dfc14e

RNNs for particle physics

- RNN can be used to deal with list of reconstructed particles
- Their architecture better fits our needs
  - No underlying assumption on the detector geometry
- This comes at two costs
  - Some ordering principle needs to be specified
  - Inference is sequential (not ideal for L1 real time)



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LHC events & language processing

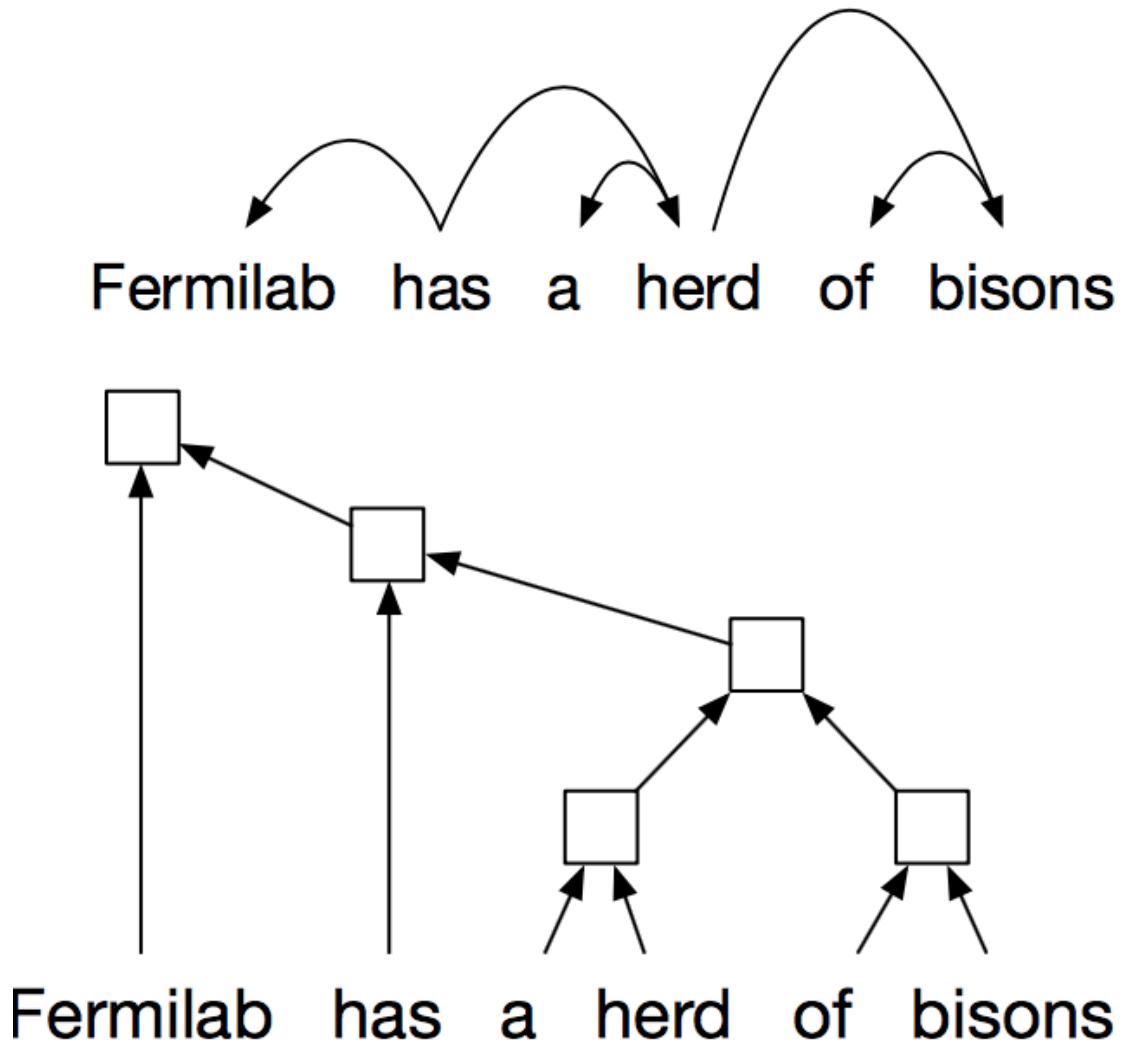
- *RNNs learn sentence meaning by order, which (for a given language) carries a lot of the information about the underlying grammar*

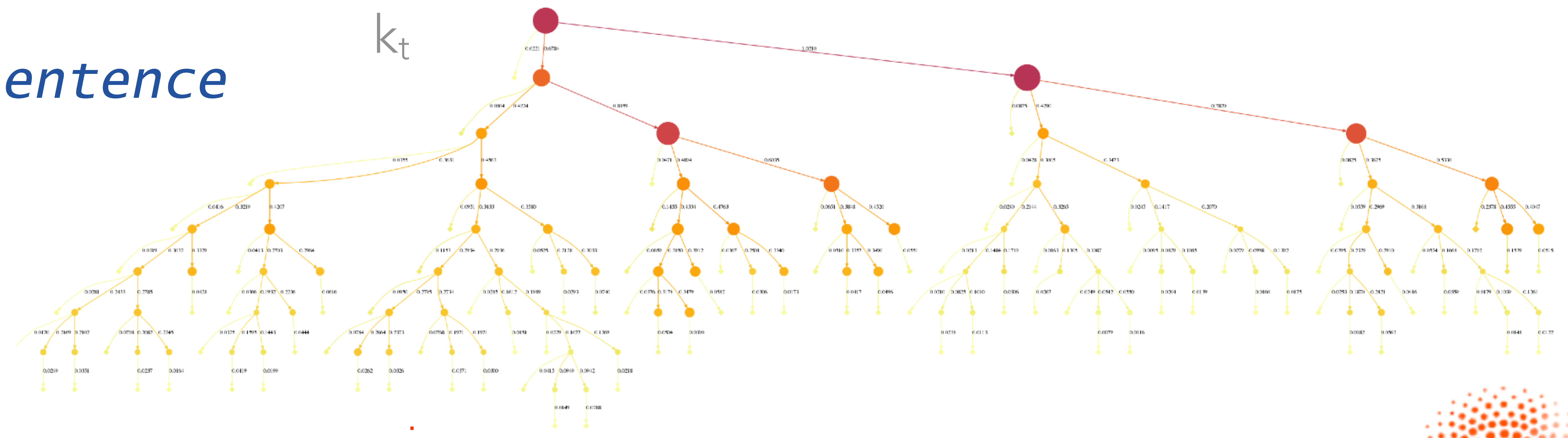
- *One could attempt something similar with physics, e.g., understanding the hadronization processes in jets from a sequence of jet constituents*

- *Which order: not a clear answer. One can use pT ordering, angular ordering, etc. as in parton-shower MC simulation (pythia, sherpa, …) and jet clustering algorithms (kT, anti-kT, etc.)*

  - *particles as words in a sentence*

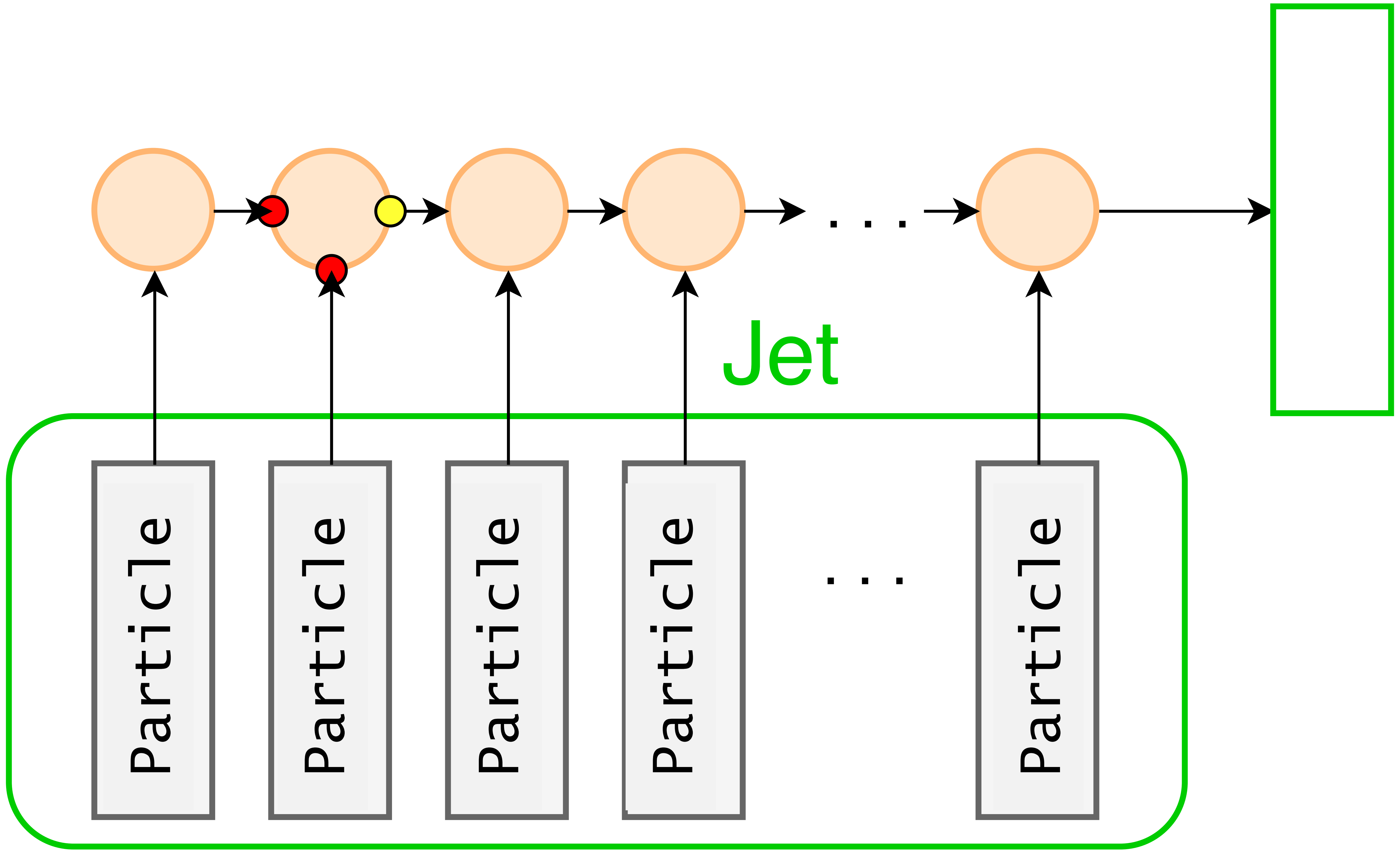
  - *QCD is the grammar*





Recurrent Neural Networks

- Given an ordered list of jet constituents, one could then learn jet features
  - Jet ID, as in our problem
  - Jet substructure quantities, jet kinematic, etc
- One could use the same approach on the whole event, w/o jet clustering (topology classifier)
- Not my best option as of today: graph networks emerged as a more suitable architecture for this (can process unordered sets)



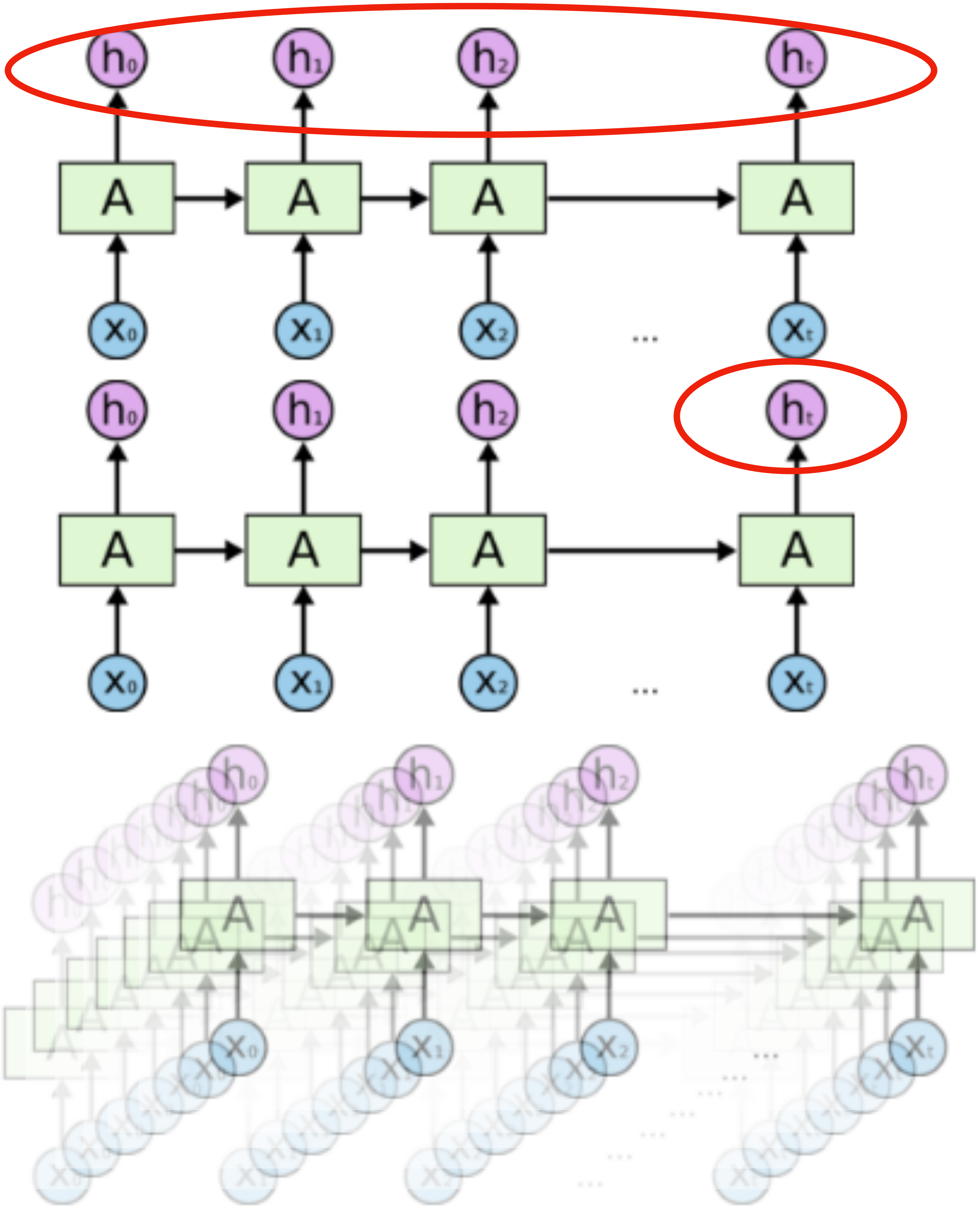
Recurrent networks

- *Recurrent networks can be operated in two ways*
  - *one can inject a sequence and received a sequence*
  - *one could just focus on the result of the last iteration, translating a sequence in a quantity (*)*

- **return_sequences**: Boolean. Whether to return the last output in the output sequence, or the full sequence. Default: `False`.

From Keras

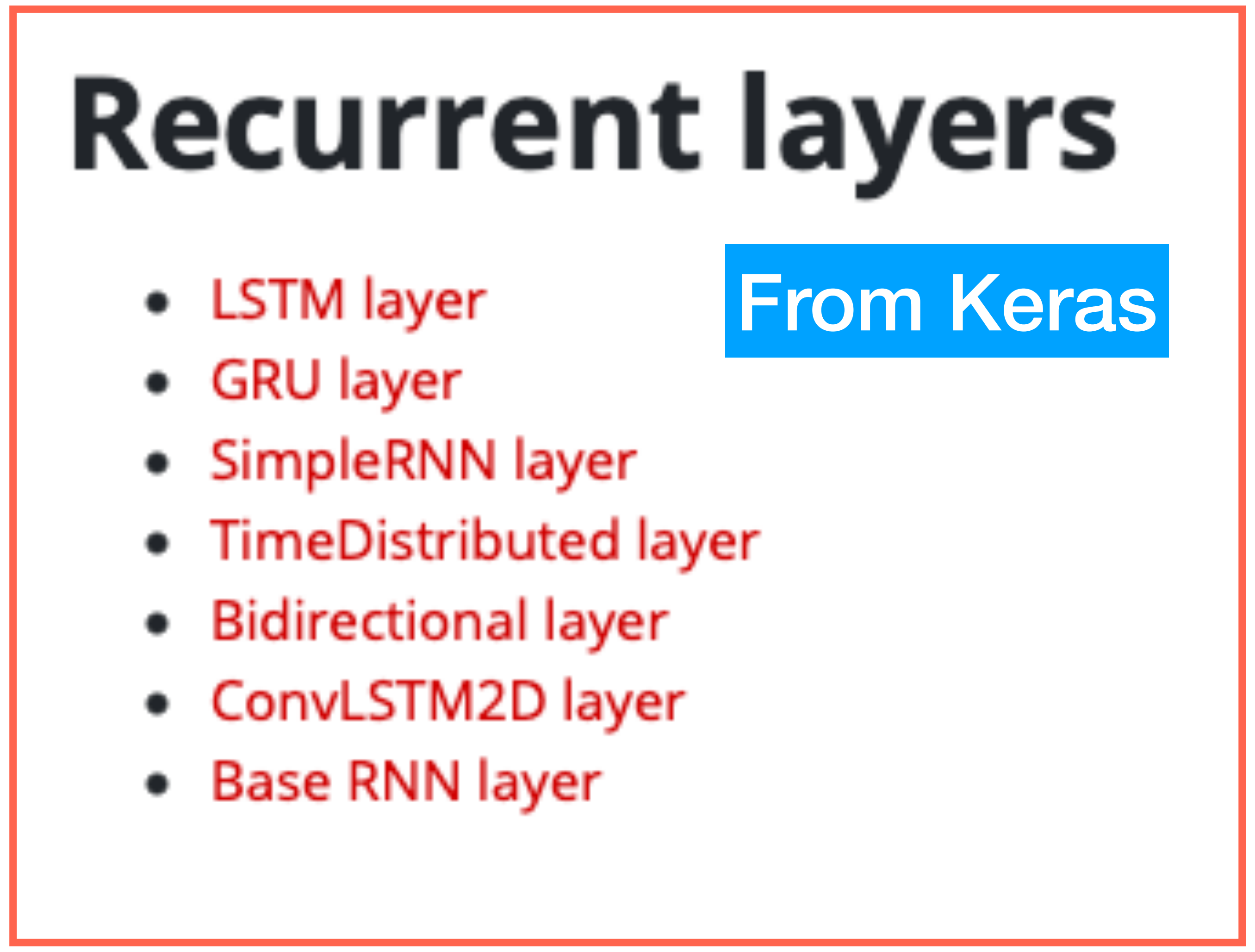
  - *One typically operates many recurrent units at once in a recurrent layer (like nodes in a dense layer, or kernels for CNN)*



(*) This is what we will be doing

Recurrent networks

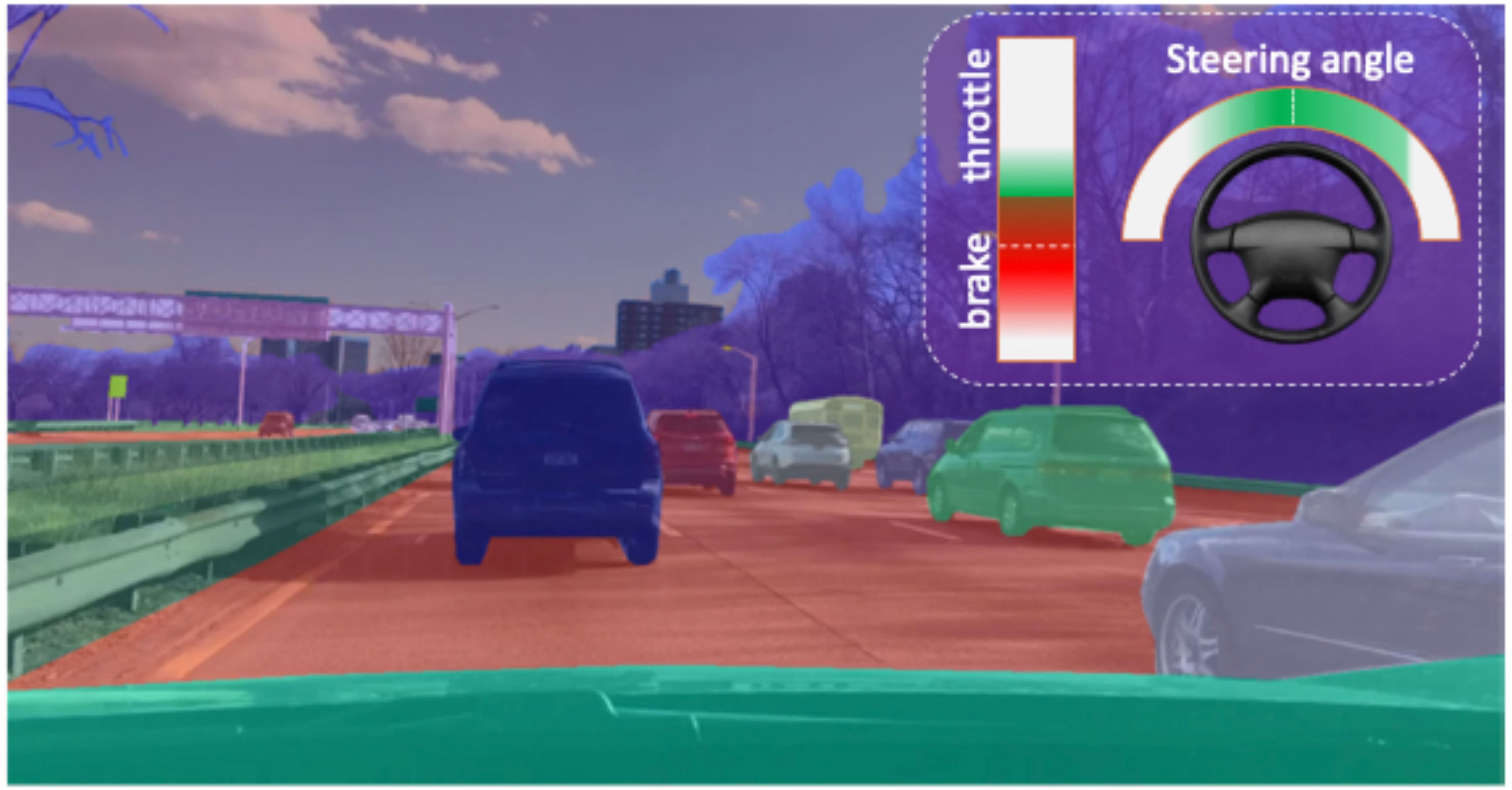
- Several architectures proposed
  - what changes is what happens in the A block
- We will focus on the first three
  - LSTMs (1995): the most popular (and performing) choice for serial-data processing
  - GRUs (2014): essentially an LSTM with a forget gate, with less parameters (and similar performance) as LSTM
  - SRNs, aka Elman (1990) and Jordan (1997) networks: simplest realisation of the idea



Recurrent layers

- LSTM layer
- GRU layer
- SimpleRNN layer
- TimeDistributed layer
- Bidirectional layer
- ConvLSTM2D layer
- Base RNN layer

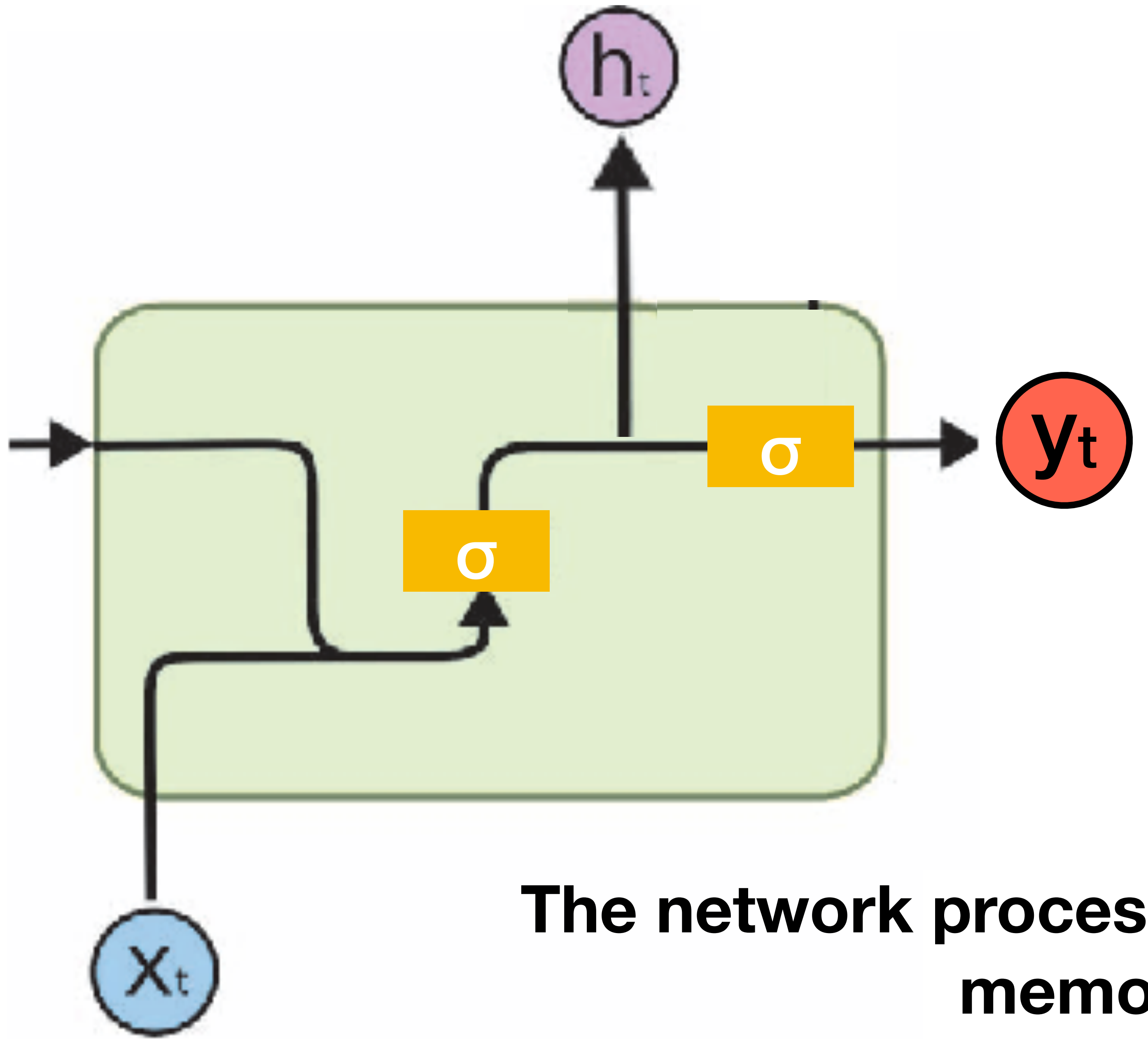
From Keras



(*) This is what we will be doing

SRN

- *The simplest recurrent architecture*
  - *The processing unit receives an input x and the output of the previous-particle processing h (the context)*
  - *The product of the two is activated by a tank function*
  - *the result can be used as it is and/or passed to the next processing*



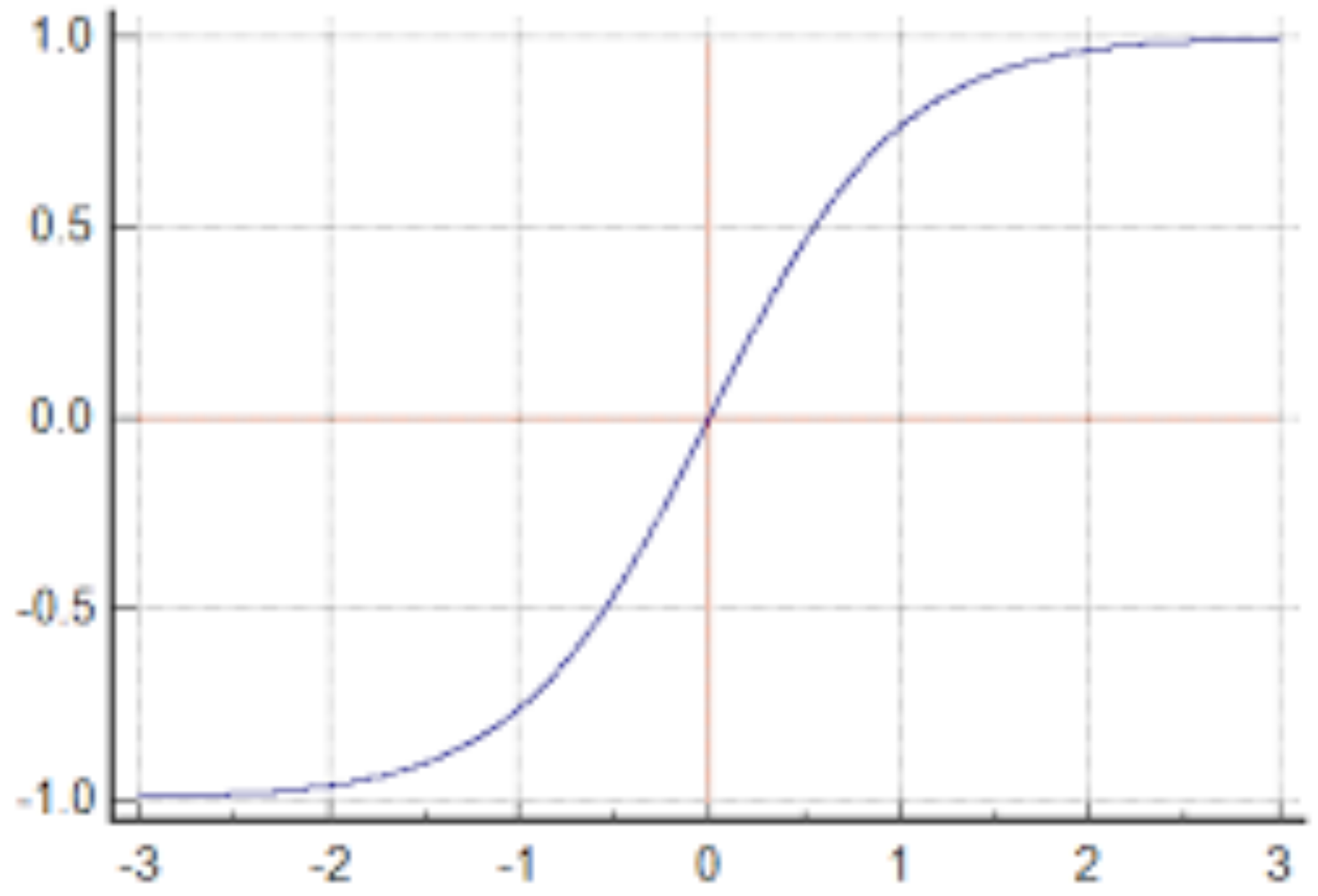
Elman network

$$h_t = \sigma_h(W_h x_t + U_h h_{t-1} + b_h)$$
$$y_t = \sigma_y(W_y h_t + b_y)$$

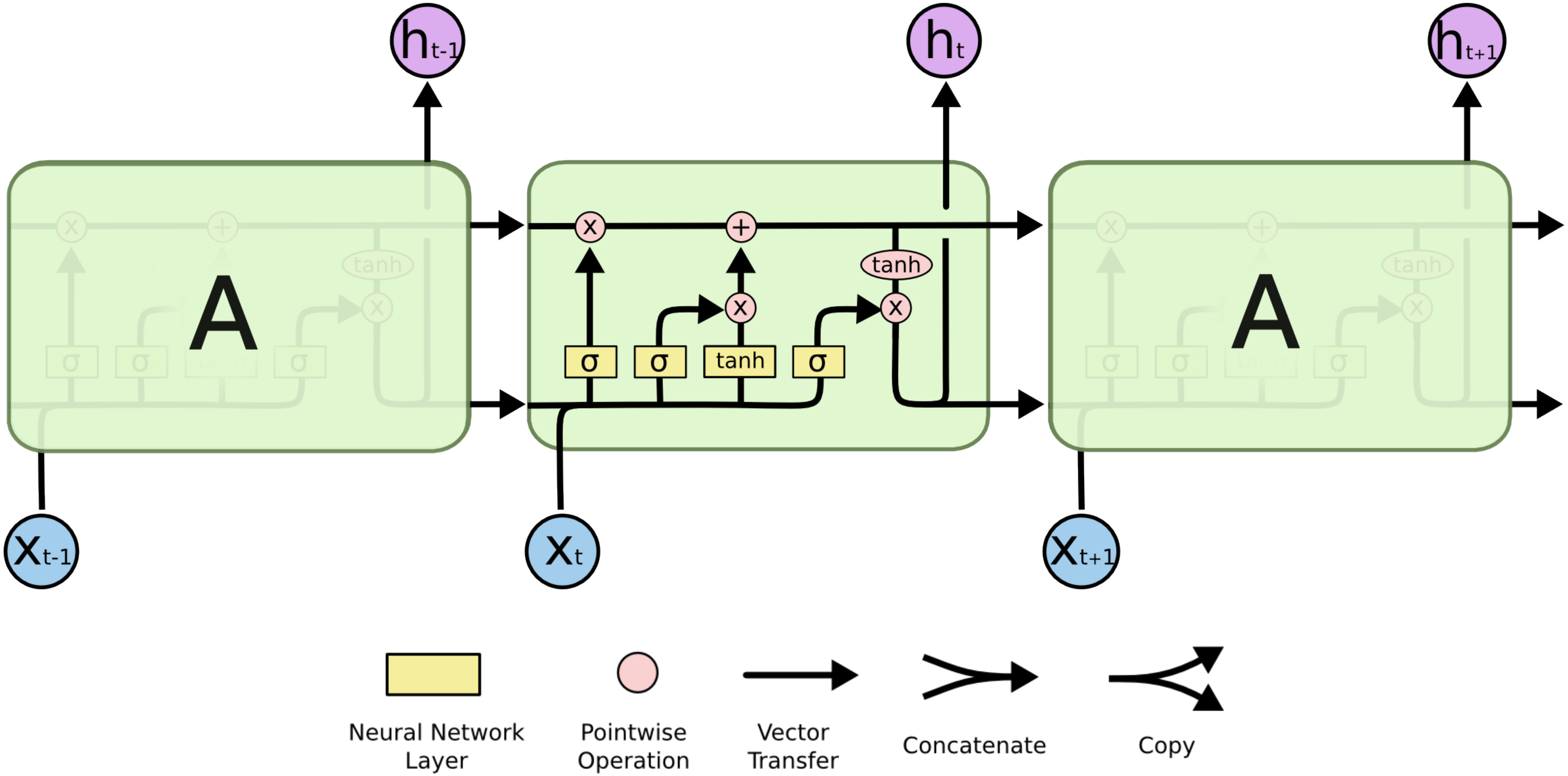
Jordan network

$$h_t = \sigma_h(W_h x_t + U_h y_{t-1} + b_h)$$
$$y_t = \sigma_y(W_y h_t + b_y)$$

The network processing essentially works as memory gates ->
One typically uses sigmoids or tanh as activation functions

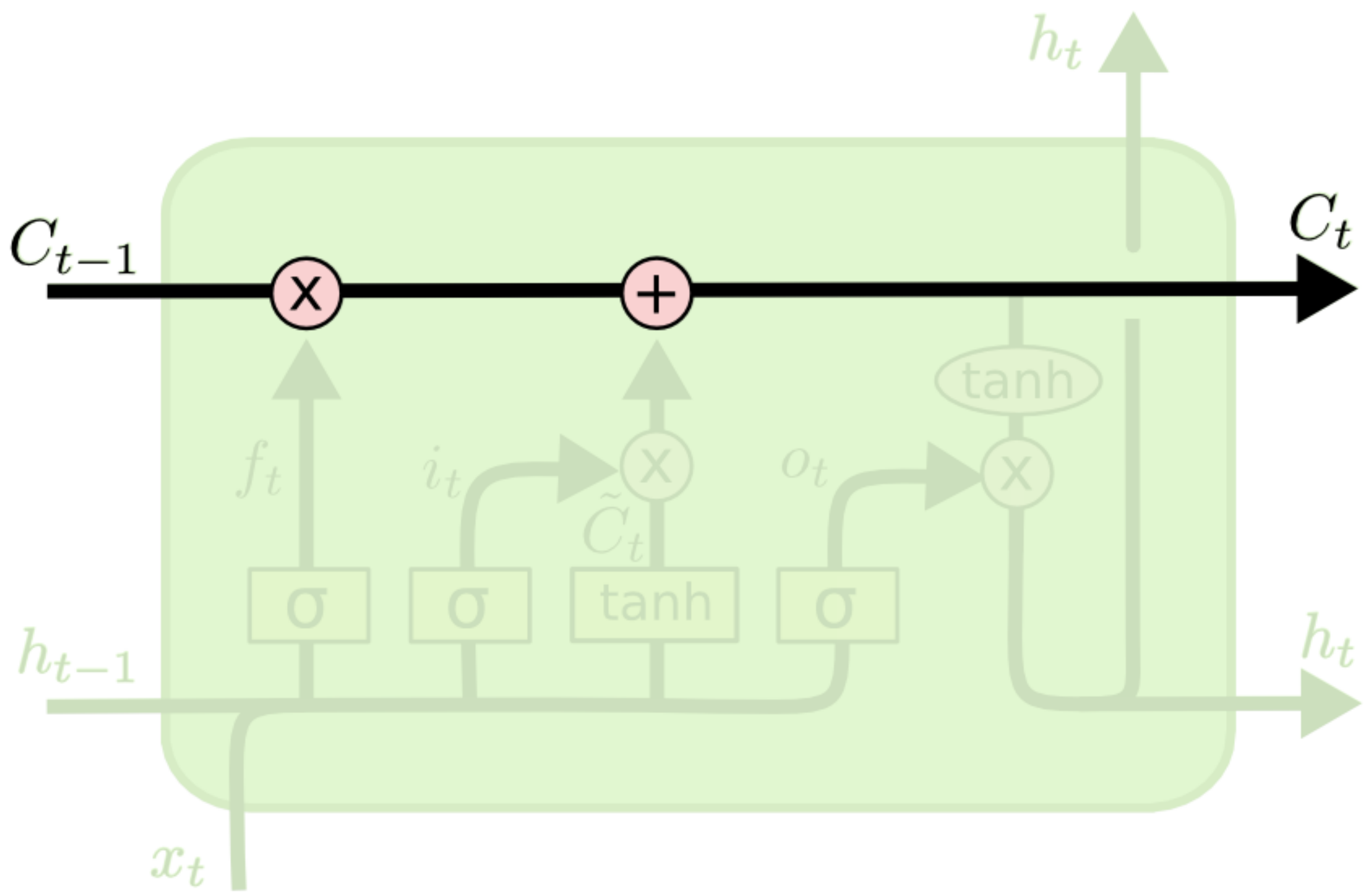


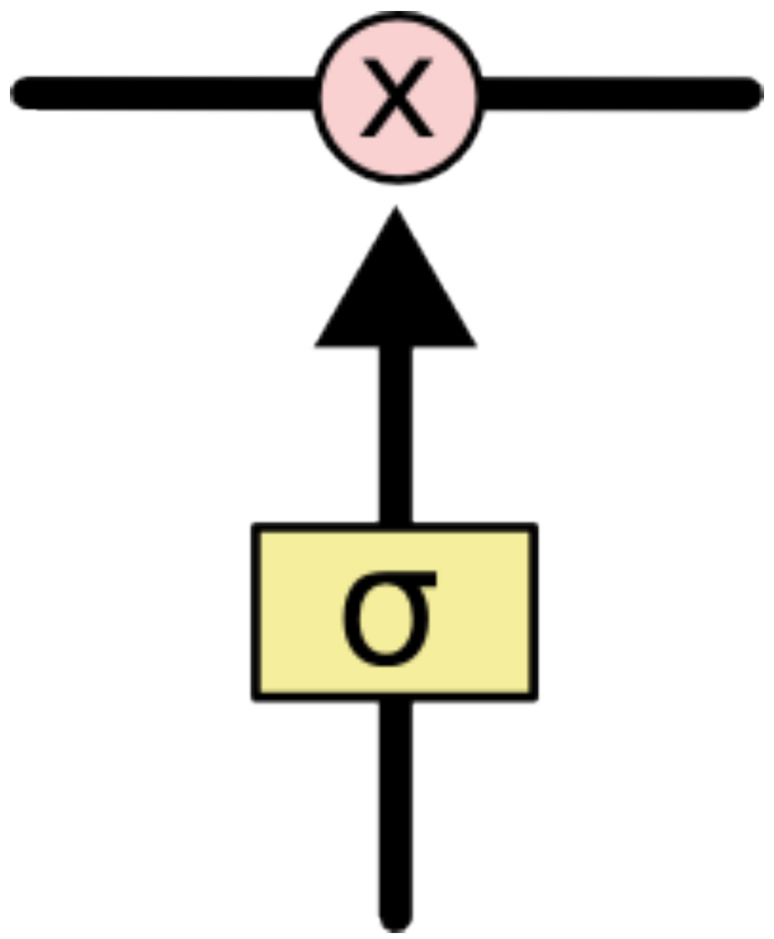
LSTM



h_{t-1}
h_t
h_{t+1}
A
σ
tanh
A
X_{t-1}
X_t
X_{t+1}
Neural Network Layer
Pointwise Operation
Vector Transfer
Concatenate
Copy

LSTM's memory cell

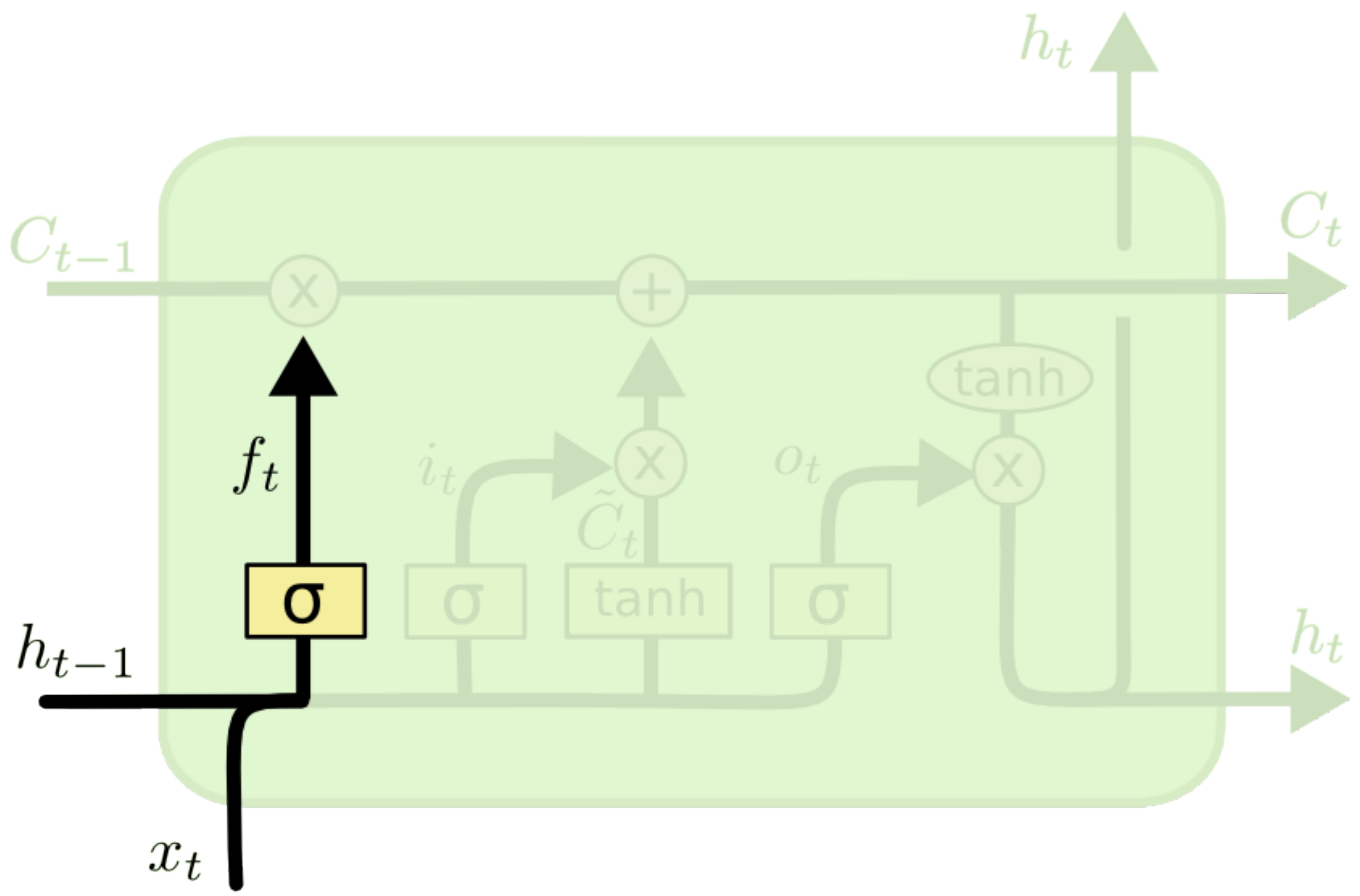




- *Information in the network flows through the memory cell*
  - *simple operations on it (to make the flow easy)*
  - *depending on gates (computed from next input), memory cell can be reset (yes/no decision taken by adequate activation function)*

LSTM processing

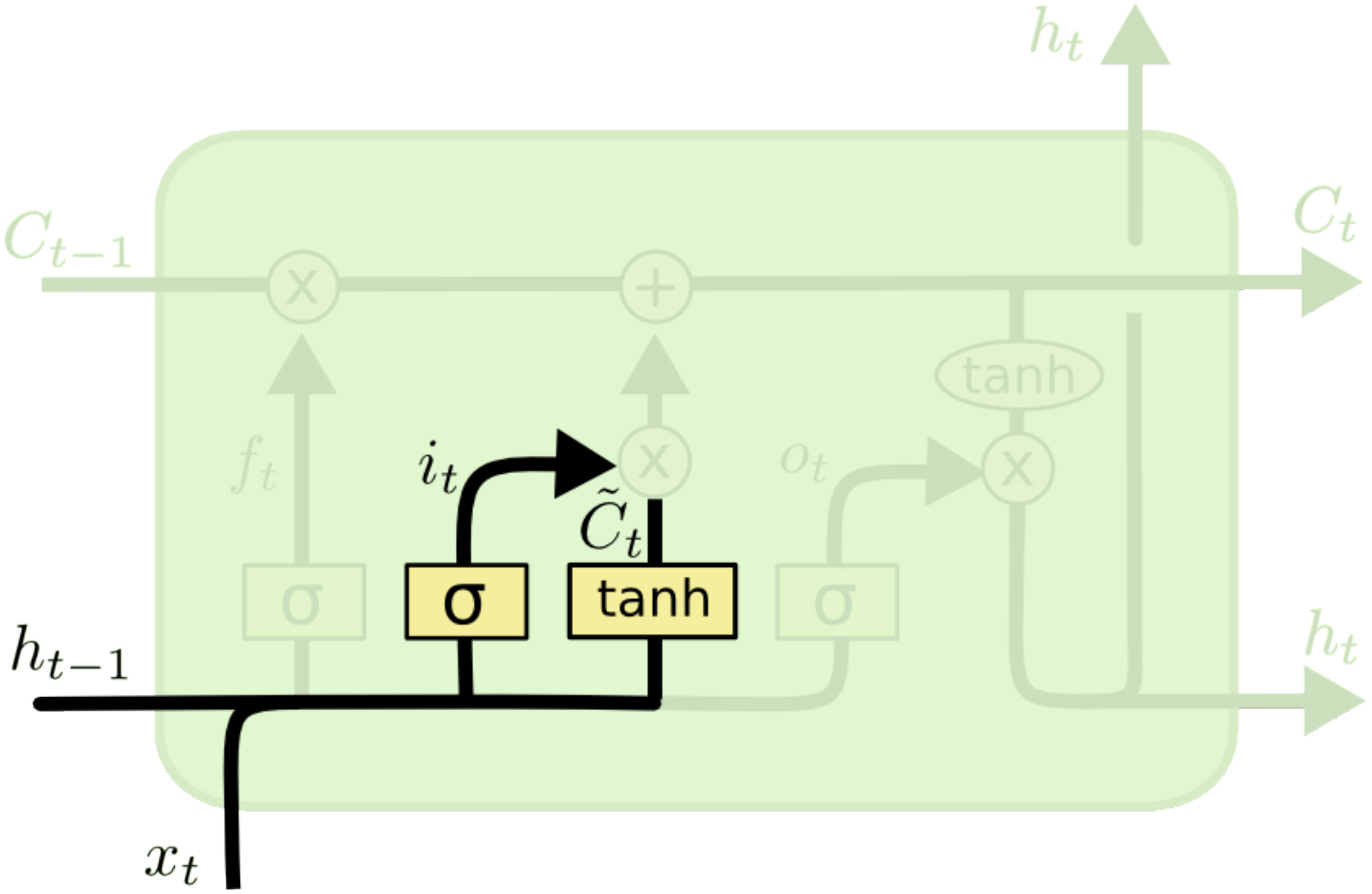
- ***Layer1:*** *decide if the context stored in the memory cell is to be forgotten or not*
  - *yes/no question -> sigmoid function*
  - *decision taken based on context and input*



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

LSTM processing

- ***Layer2:*** *two networks act to update the memory cell*
  - *a sigmoid (as in layer 1) decides which values in (0,1) to pass through*
  - *a tanh function assigns a weight in (-1,1) to it*

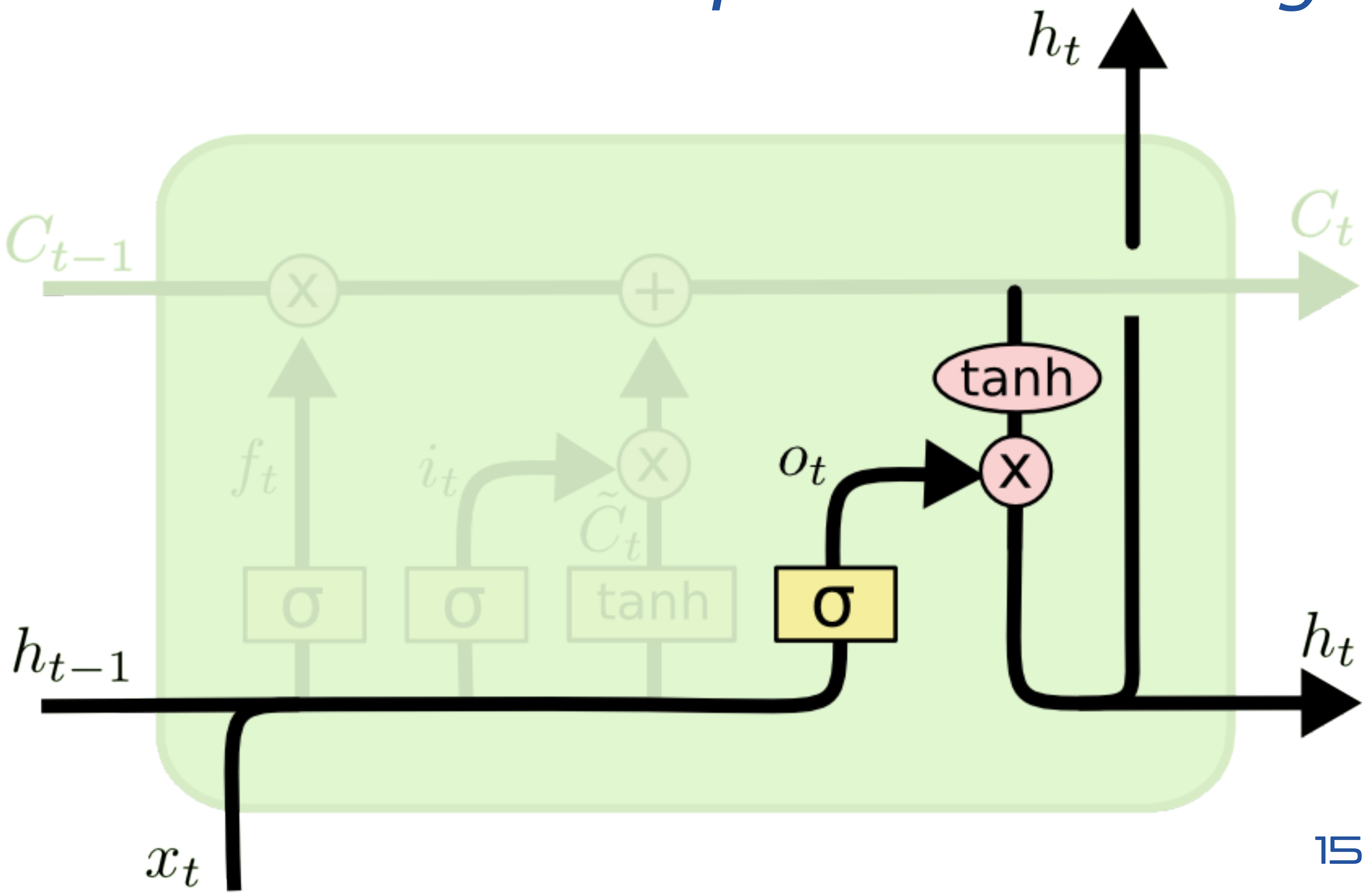


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

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

LSTM processing

- ***Layer3:*** *fixes the output value to be passed next*
  - *the cell content C_t is pushed in (-1,1) by a tanh*
  - *a gate function (sigmoid) sets which fraction of the cell content is passed through*



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

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

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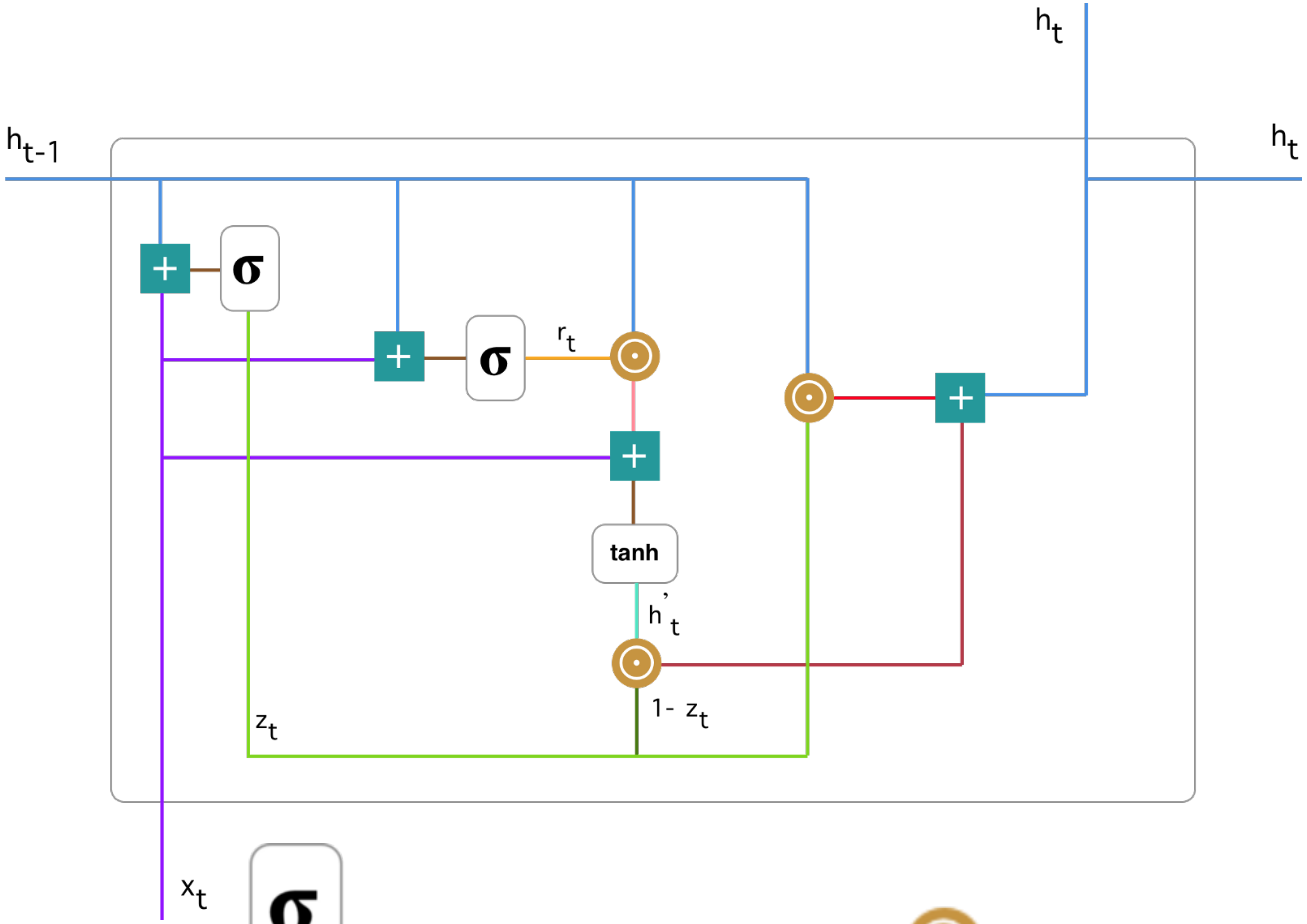
Gated Recurrent Unit



https://towardsdatascience.com/understanding-gru-networks-2ef37df6c9be

“plus” operation

σ

“sigmoid” function

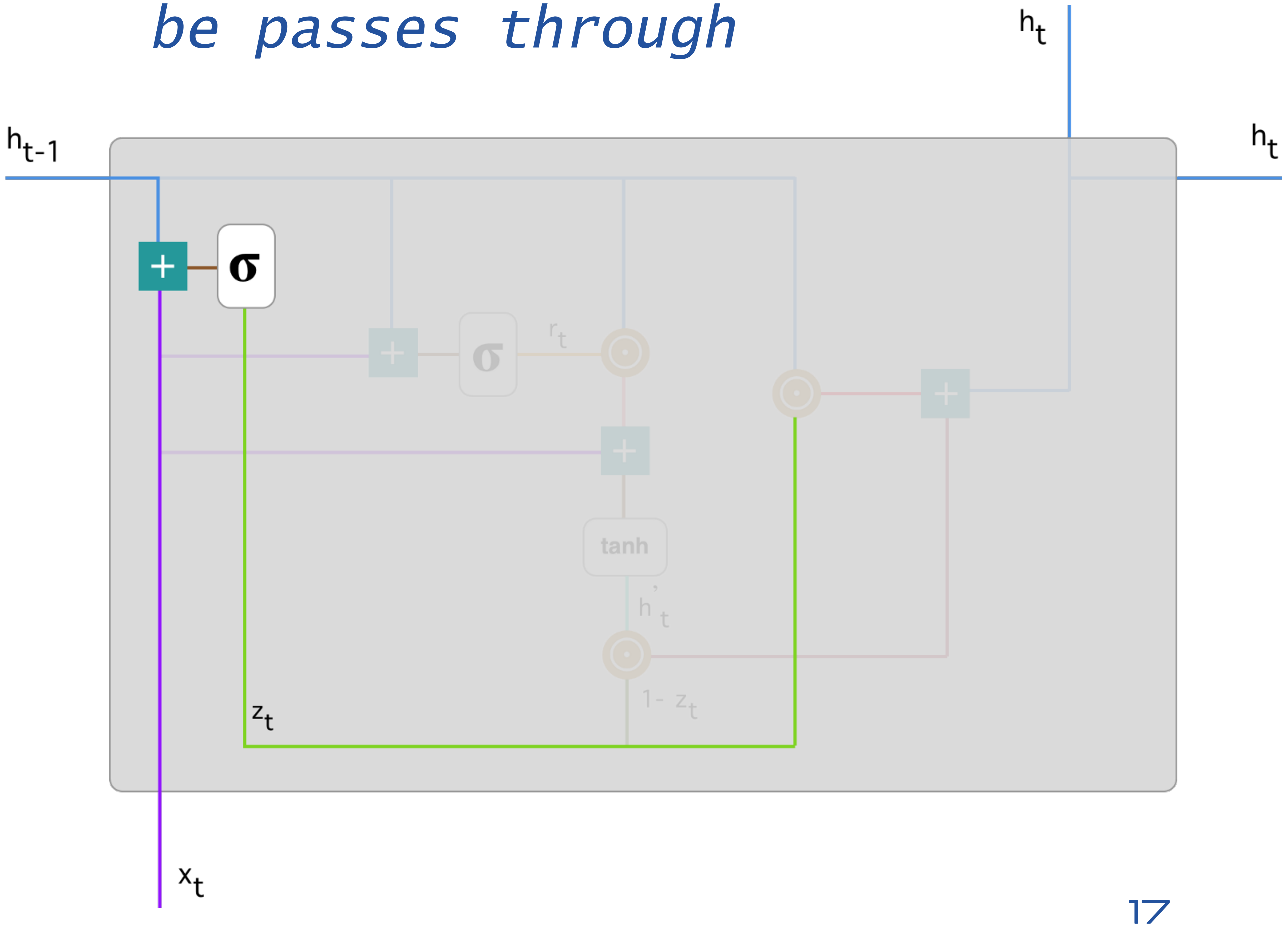
“Hadamard product” operation
(aka element-wise product)

tanh

“tanh” function

GRU processing

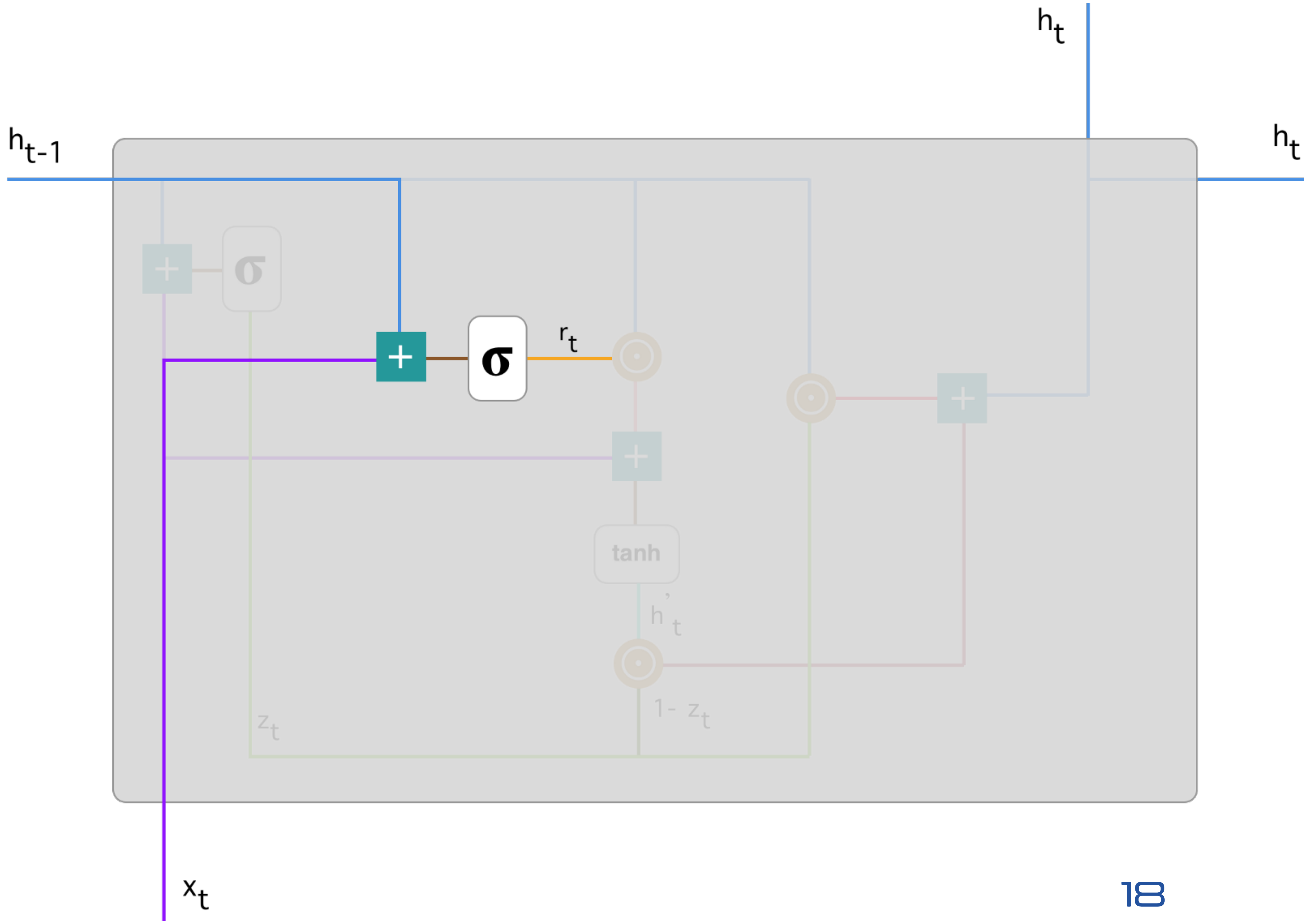
- ***Layer1:*** *update gate*
  - *multiply input and context by update weights*
  - *based on that, decide how much of the previous information should be passes through*



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

GRU processing

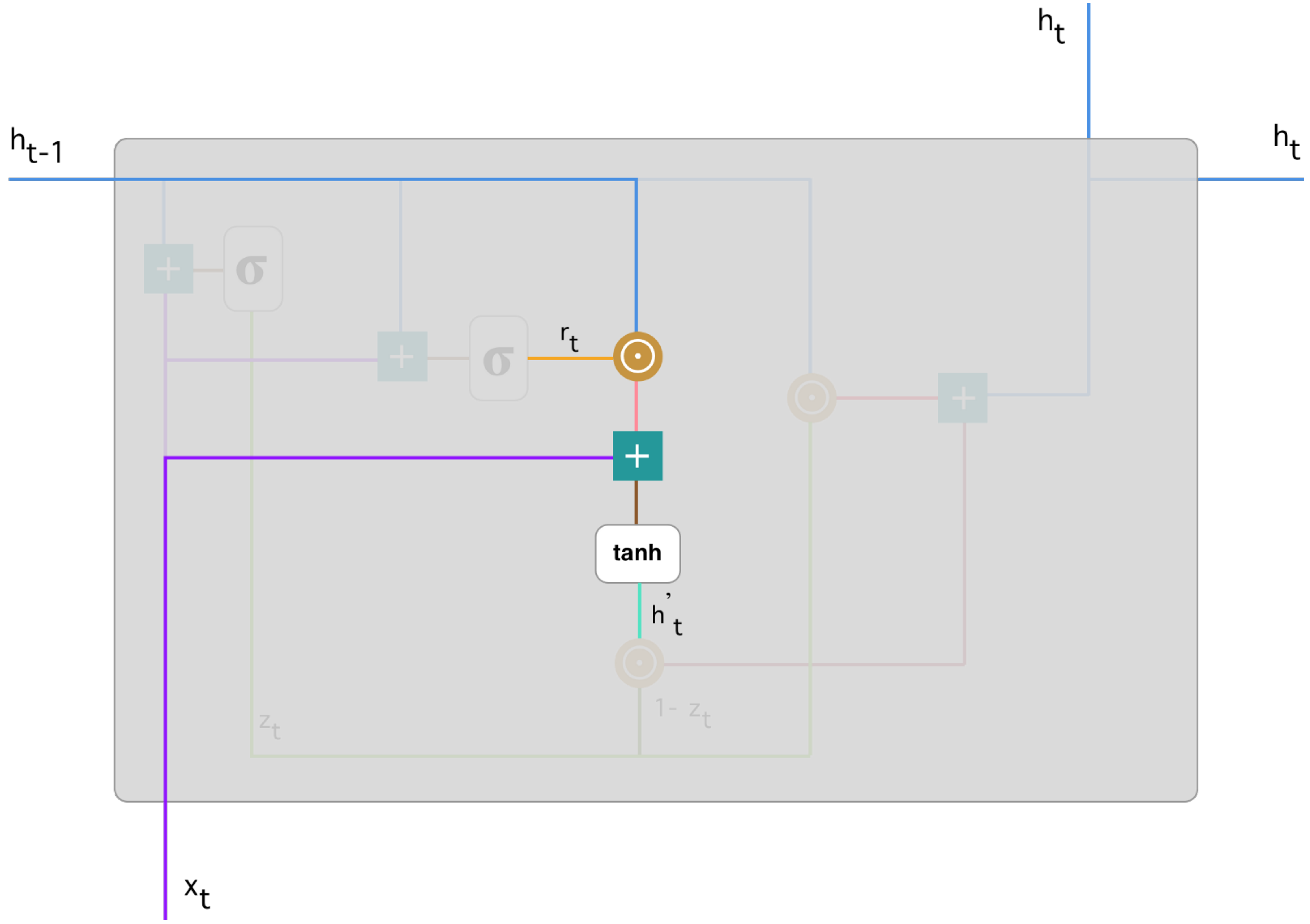
- ***Layer2:*** *reset gate*
  - *multiply input and context by reset weights*
  - *decide how much of the previous information is to be forgotten*



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

GRU processing

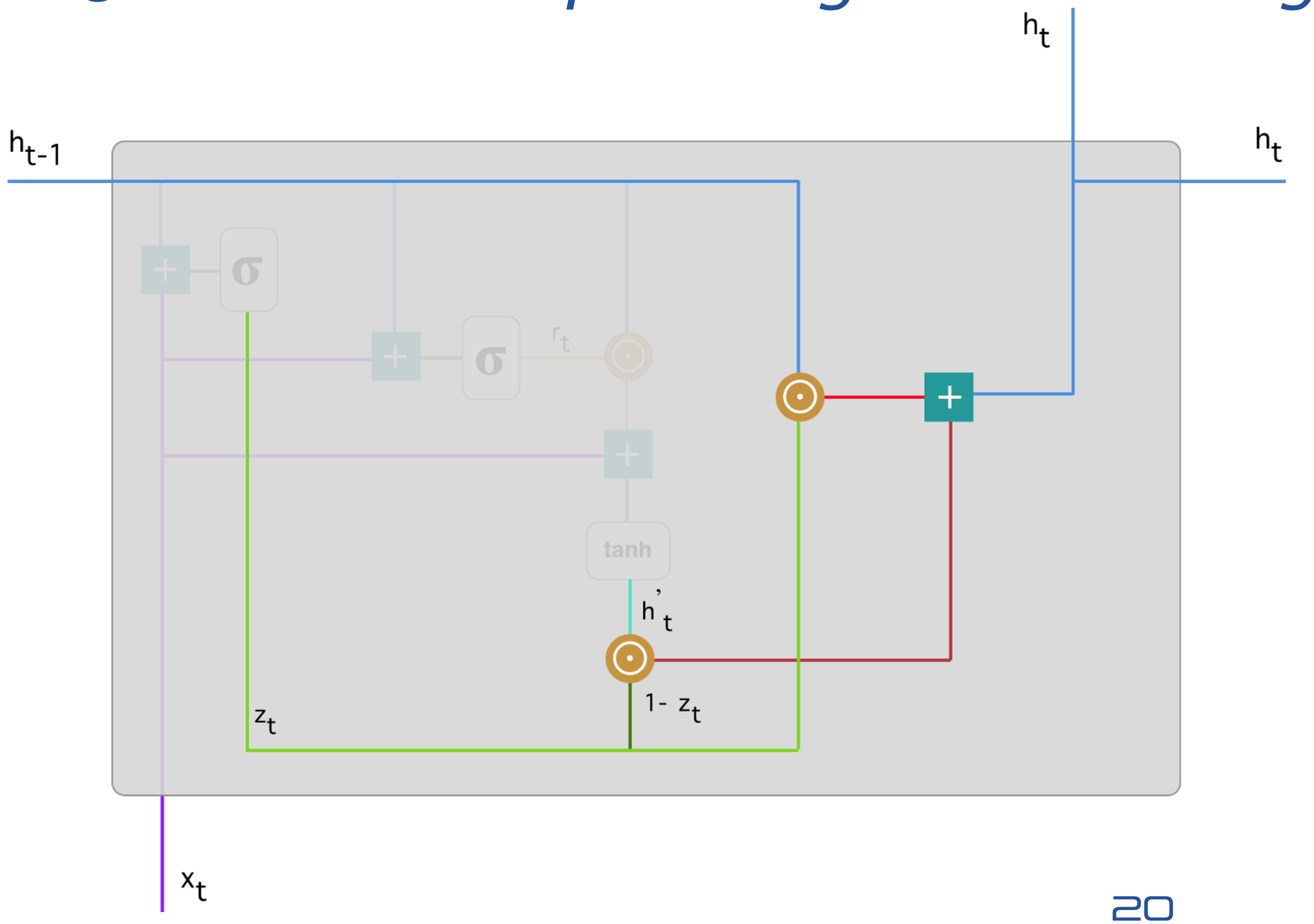
- ***Layer3:*** *determine the current memory content*
  - *the context information is partially removed to an element-by-element product with the reset gate*
  - *the result is summed to the (weighted) input and passed through a tank activation function*



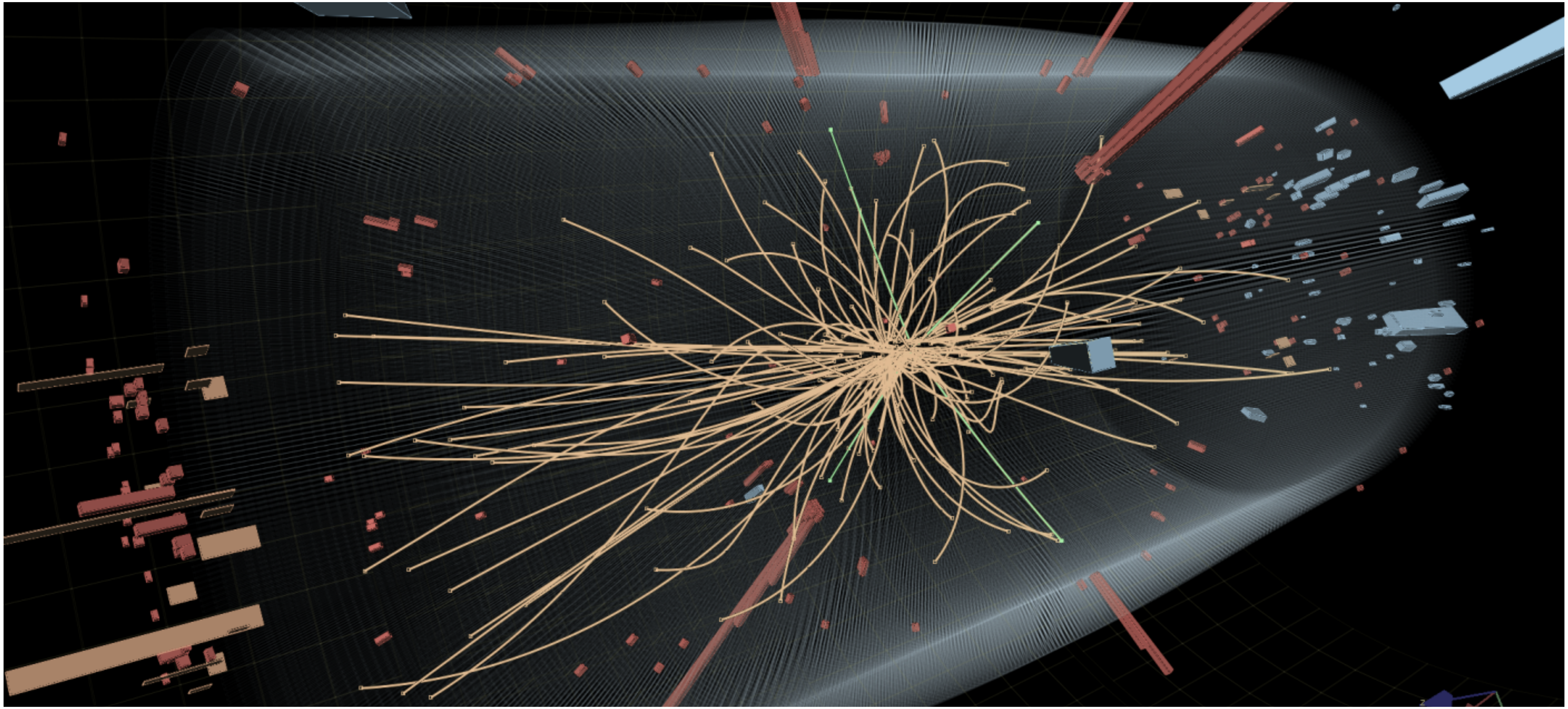
$$h_t^{'} = \tanh(Wx_t + r_t \odot Uh_{t-1})$$

GRU processing

- **Layer4:** *compute the new memory state, to pass through*
  - *mixes the current memory state with the input one*
  - *uses the update gate to weight the two contributions*



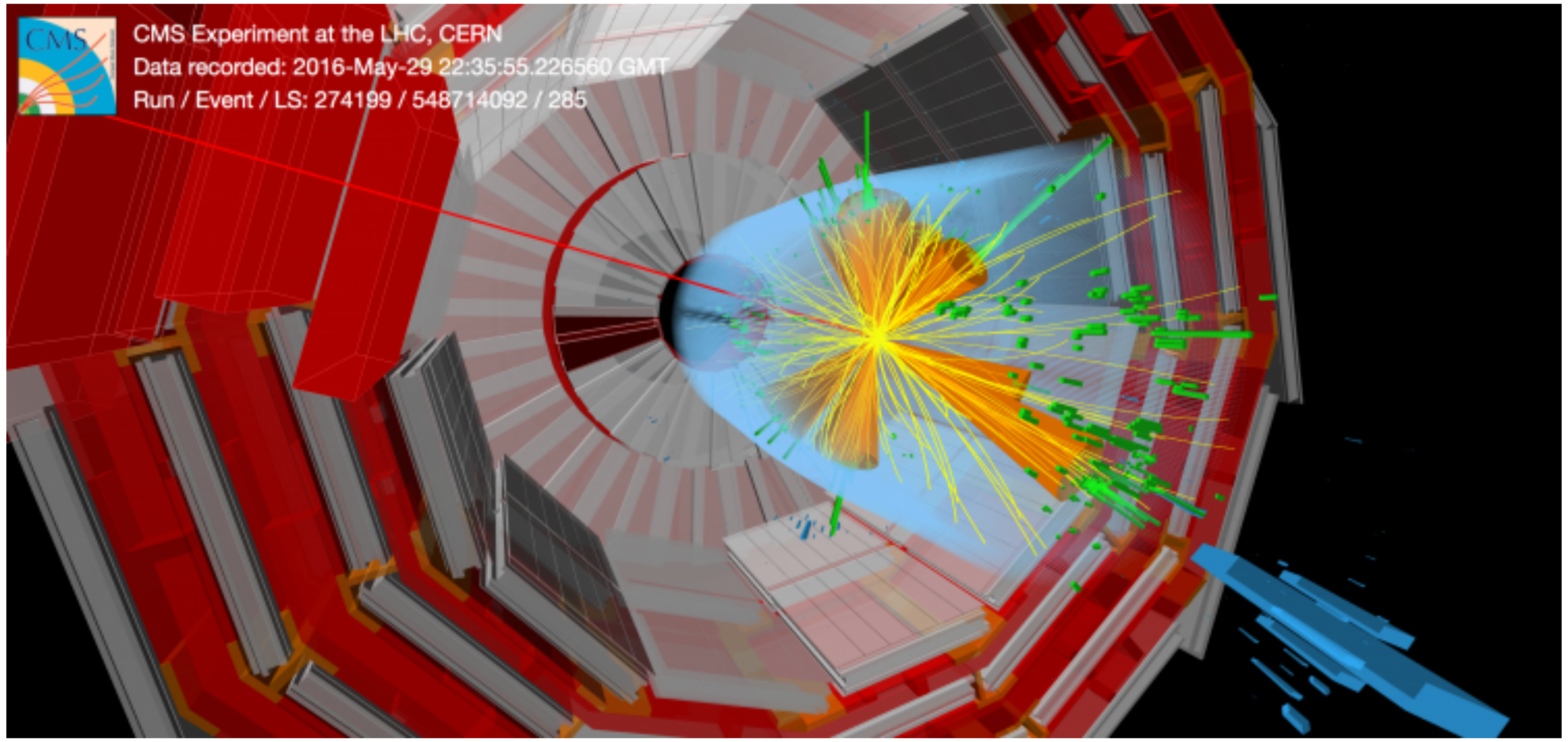
$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h_t'$$



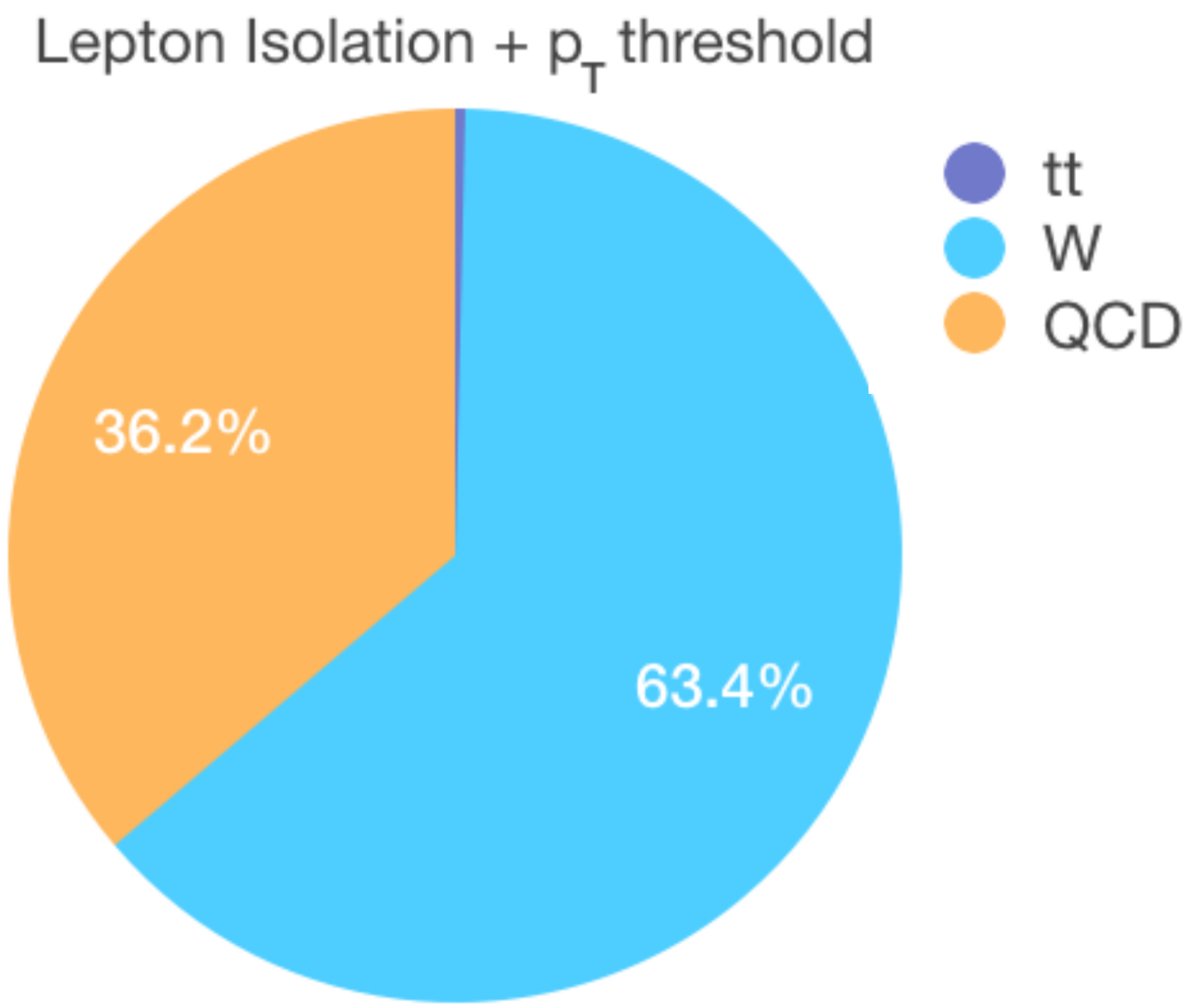
Application to HEP data

Example: topology classification @LHC

- *Finding which process generated an event is a typical task @LHC experiments*

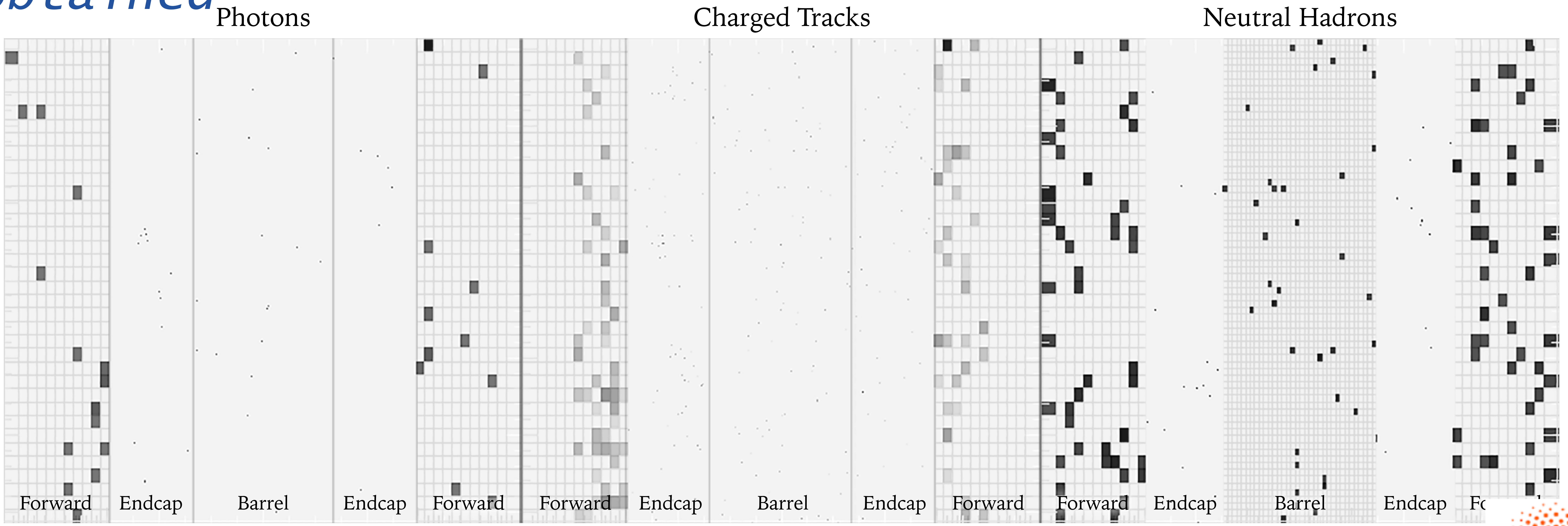


- *Let's take as input the events with one energetic electron or muon (lepton)*
  - *After some loose selection, mainly three processes left: jet production (QCD, the background) + W or tt productions (the signals)*
  - *We want to separate the three components*

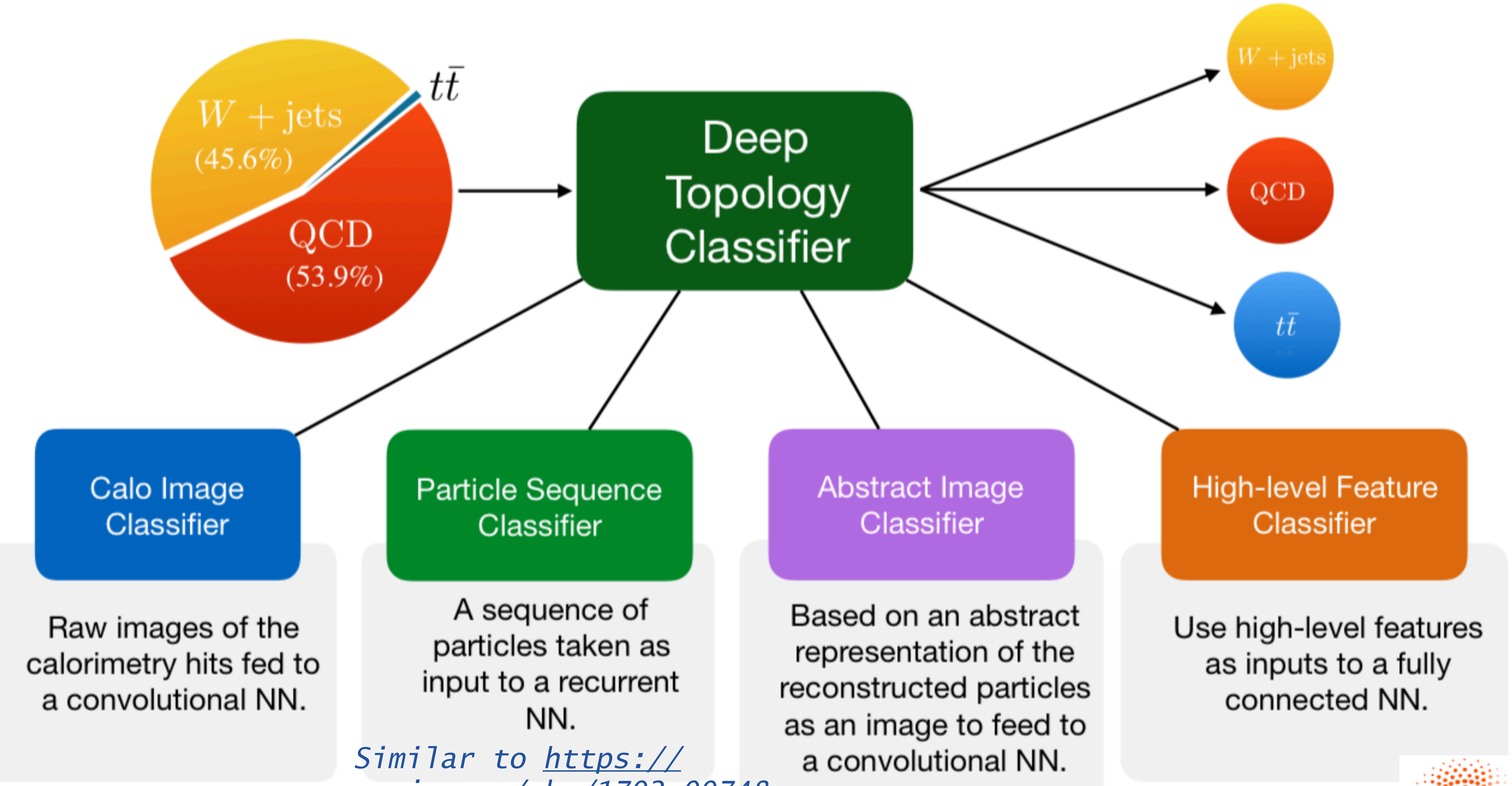


What the event looks like

- sparse image with many pixels
  - not the kind of image that CNNs usually deal with
  - still, reasonable performances (AUC~90%) can be obtained



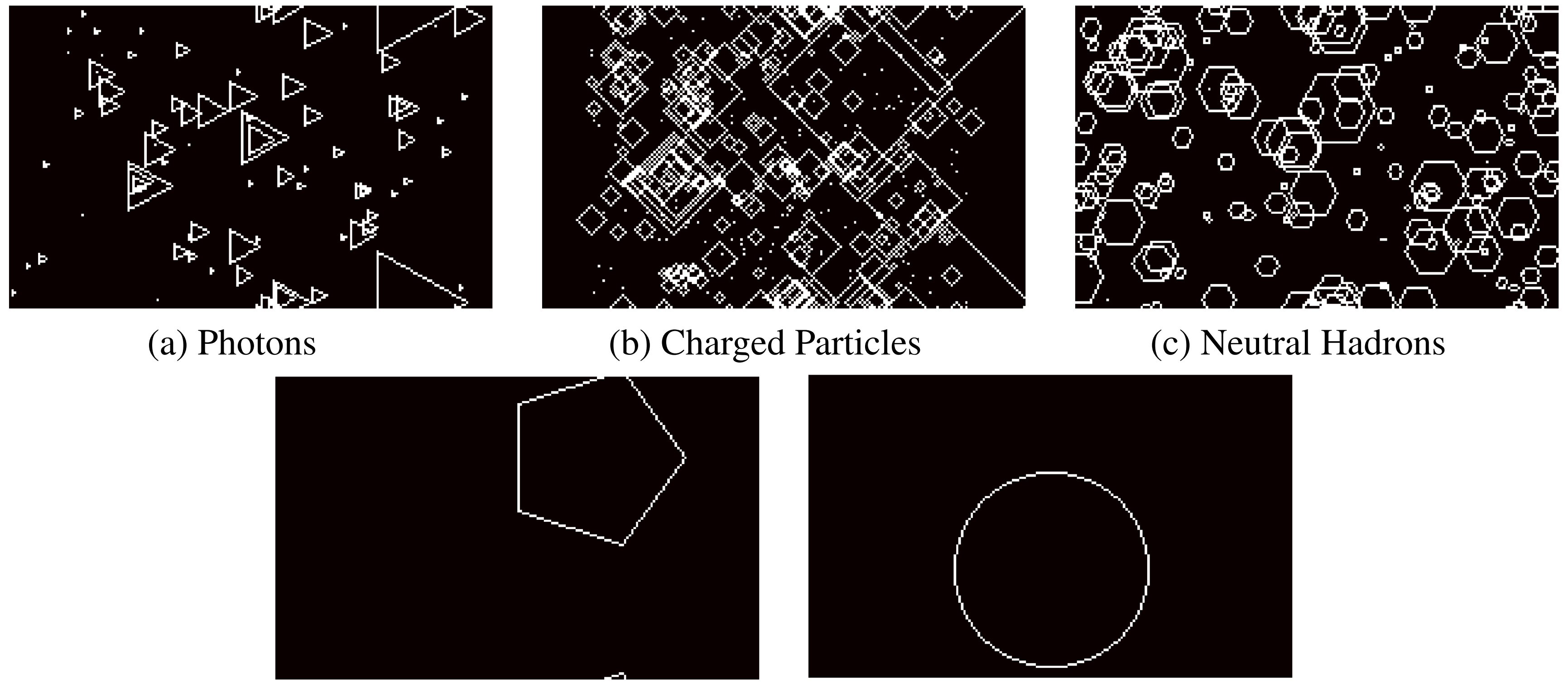
Event Representations



Similar to https://arxiv.org/abs/1702.00748

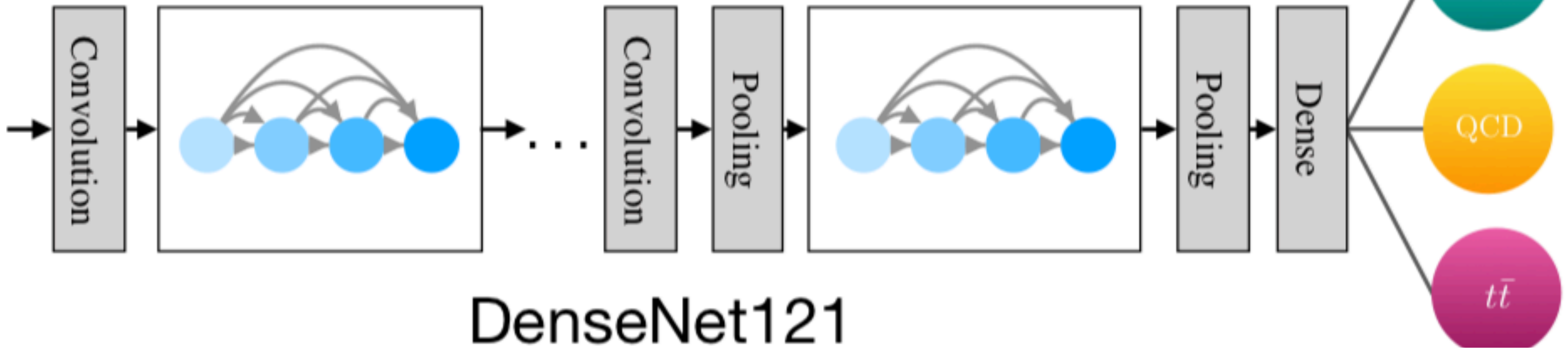
Inspired from https://arxiv.org/abs/1708.07034

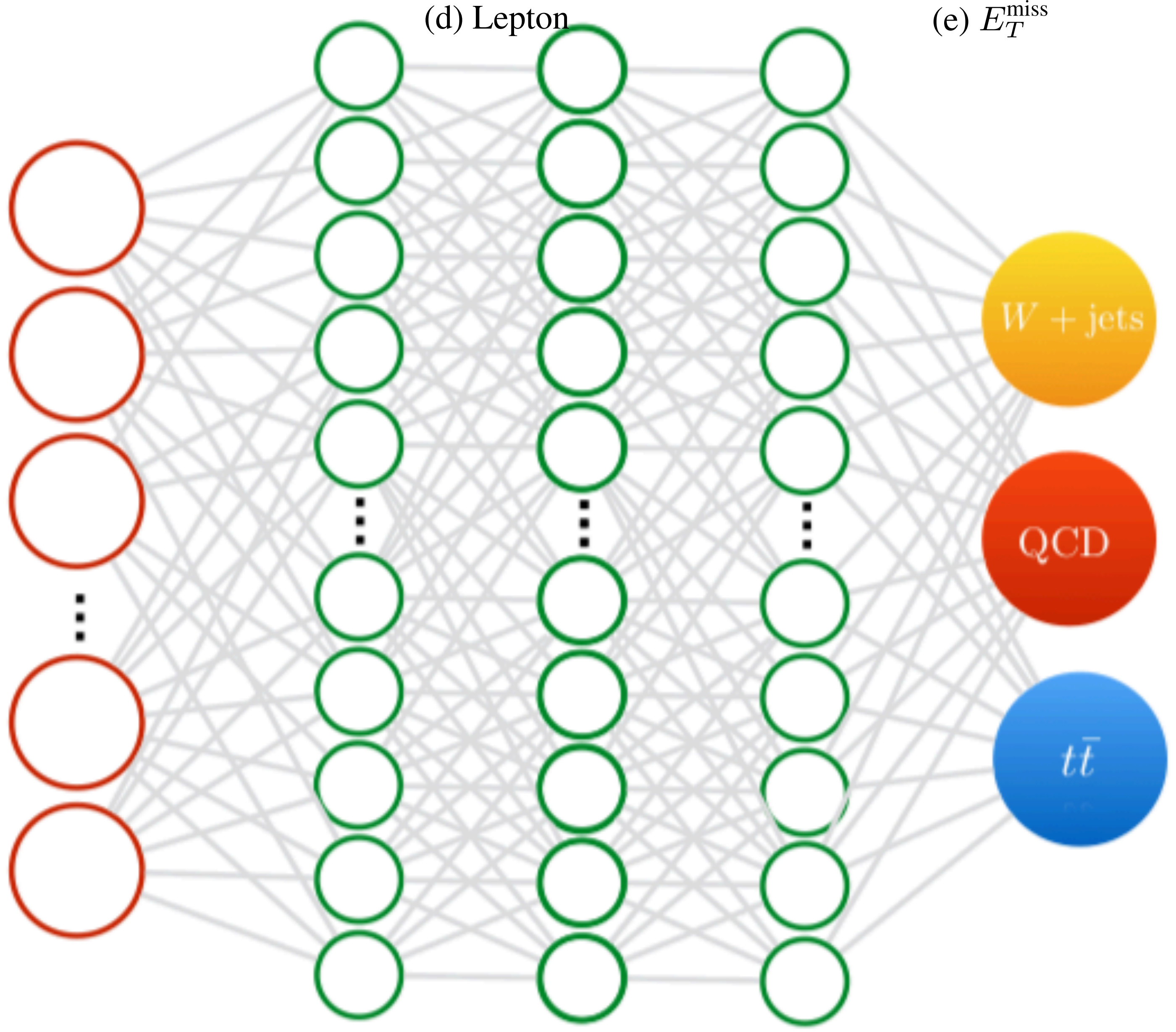
Event Representations



(a) Photons (b) Charged Particles (c) Neutral Hadrons (d) Lepton (e) E_T^{miss}

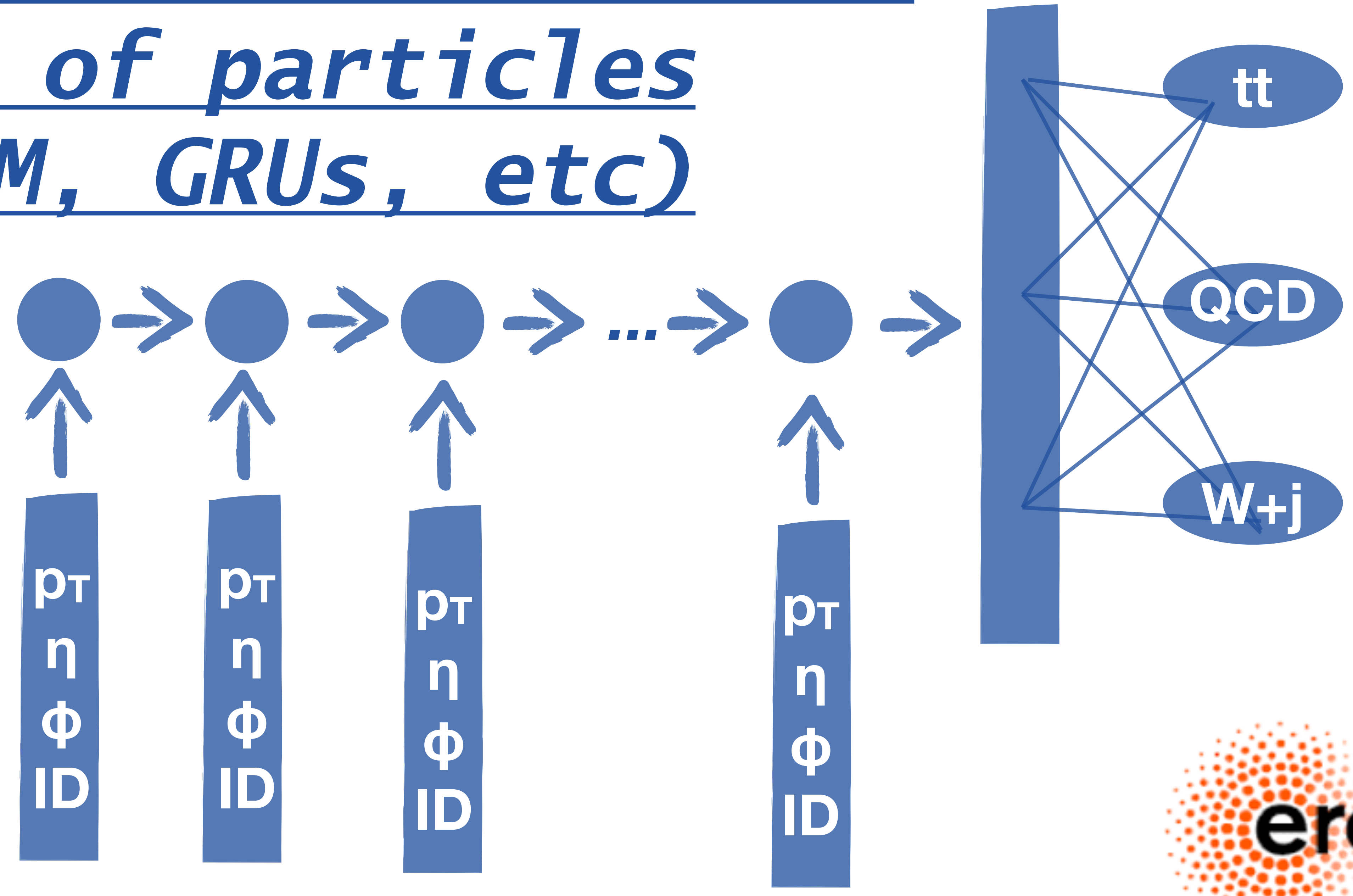
DenseNet on images





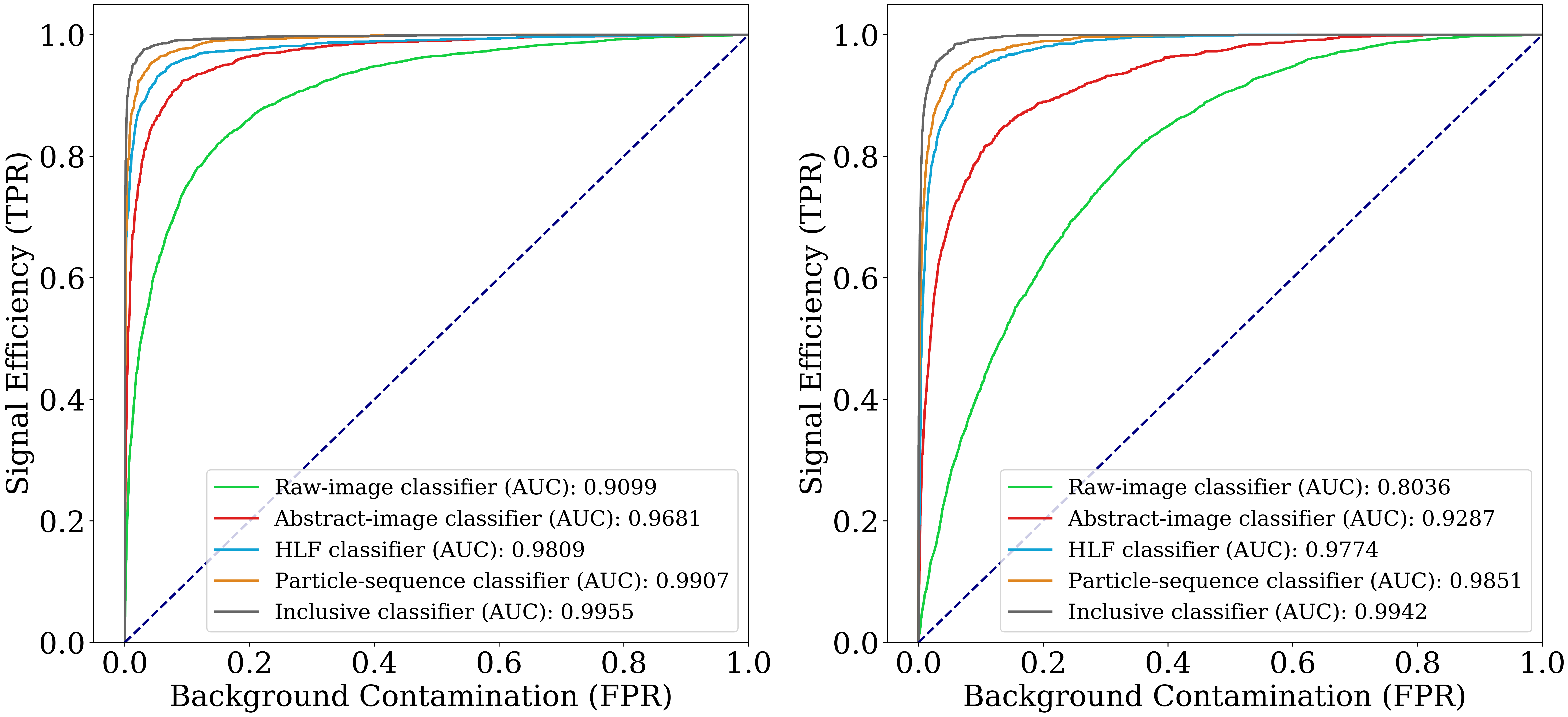
Fully-Connected classifier on physics-motivated features

Recurrent nets on the list of particles (LSTM, GRUs, etc)



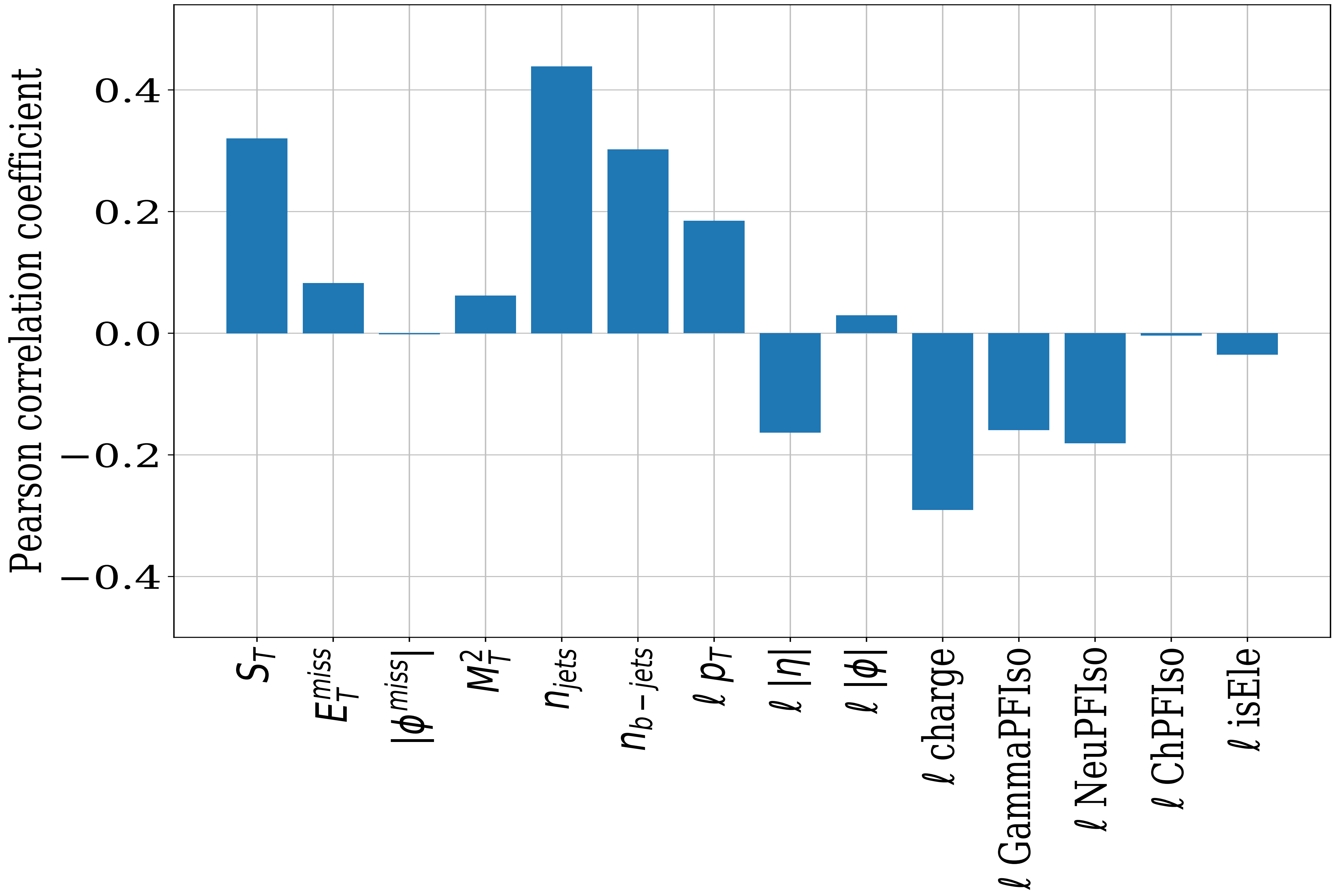
Performance

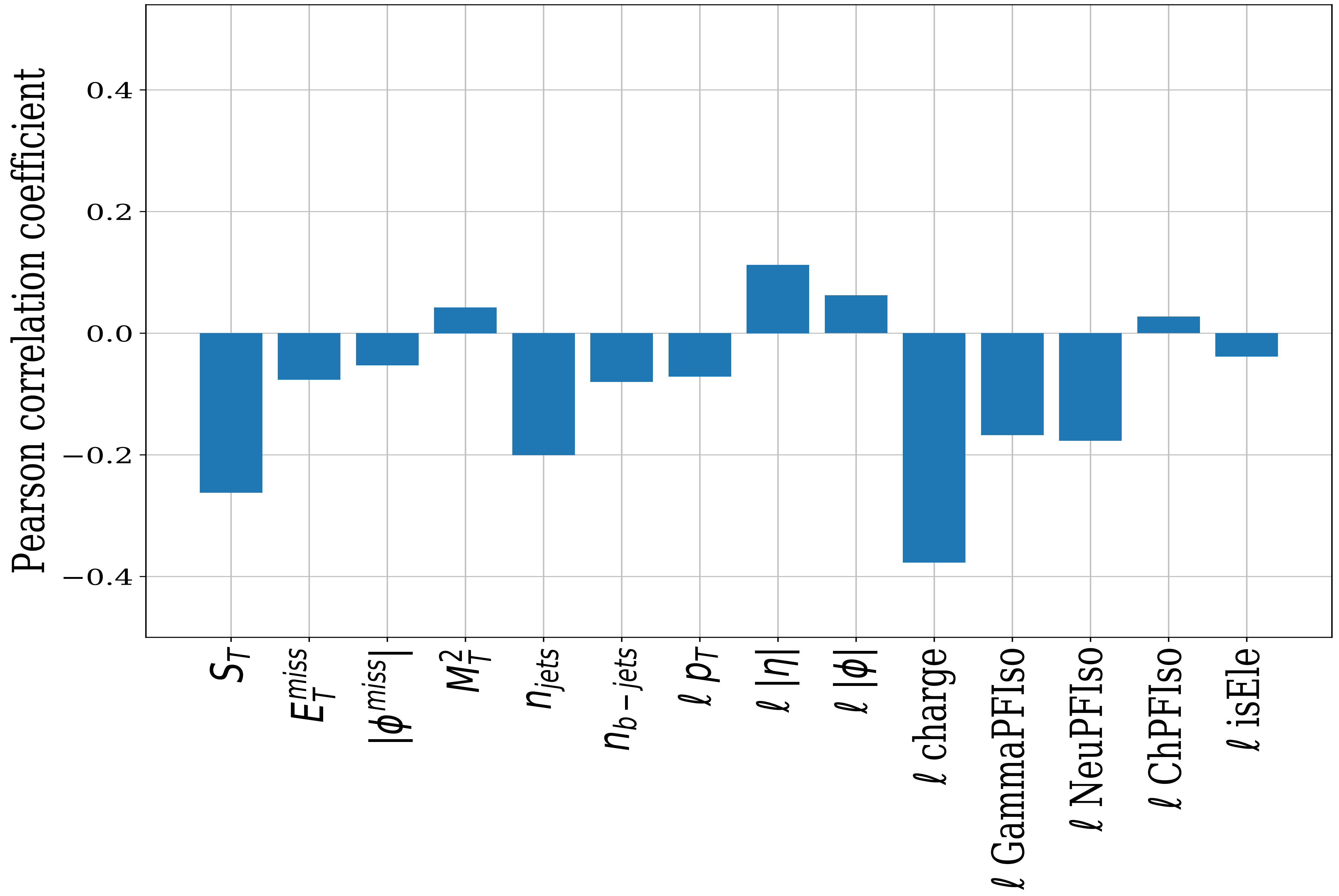
- The GRU provides the best discrimination power
- The HLFs come second
- The combination of the two further improve



(a) $t\bar{t}$ selector (b) W selector

Selection performances





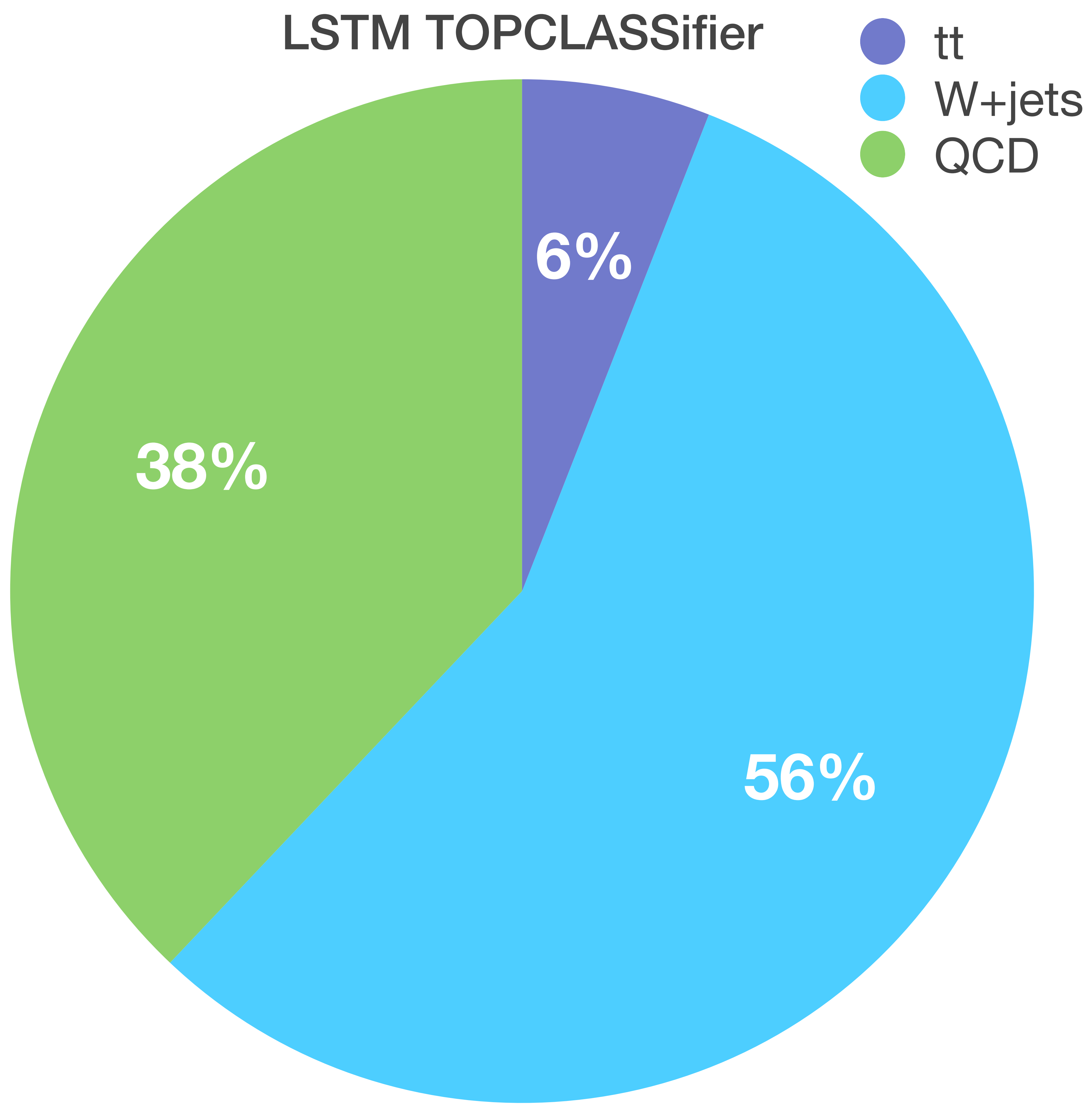
What is the network learning?

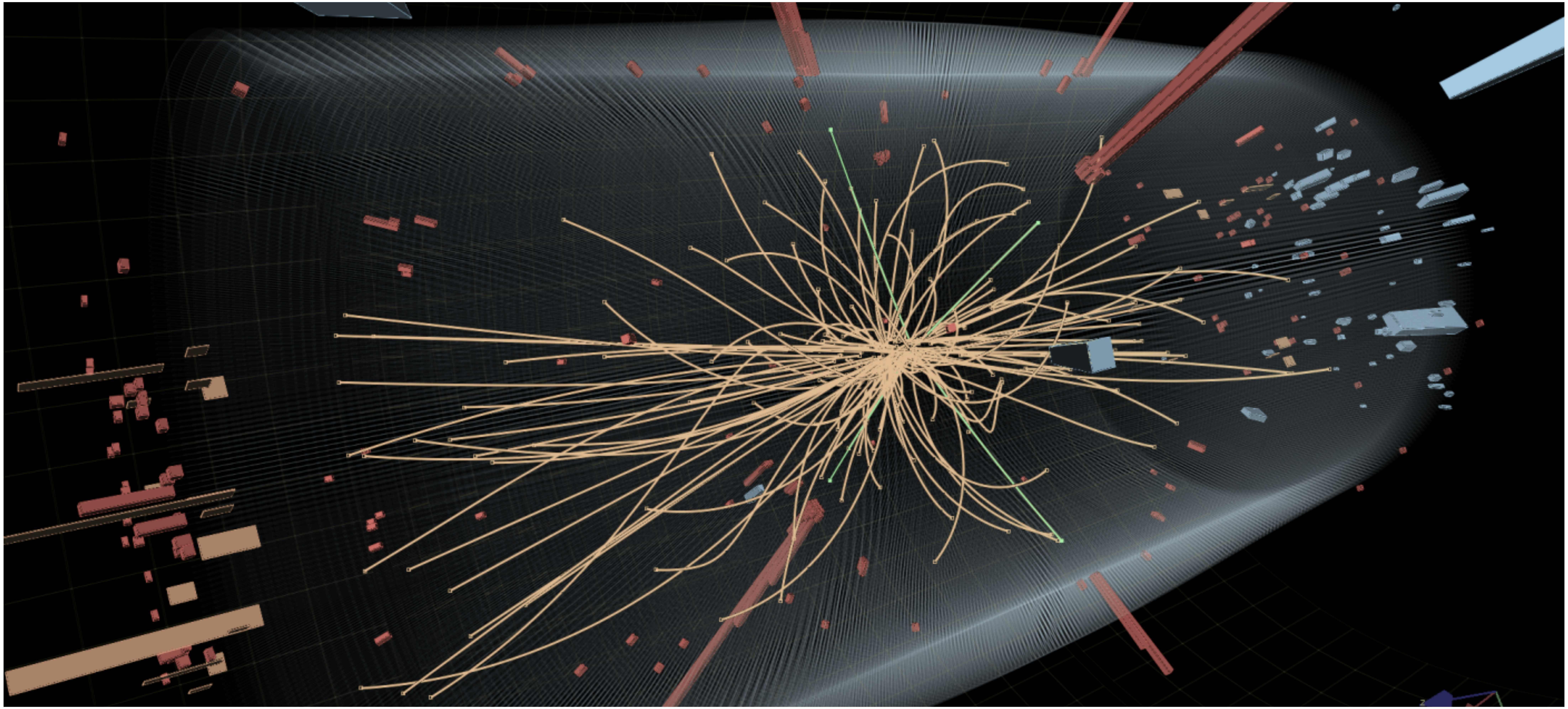
- tt events are more crowded that W events
- leptons in W and tt events are isolated from other particles

Cleaning up selected sample

A typical example: leptonic triggers

- *at the LHC, producing an isolated electron or muon is very rare. Typical smoking gun that something interesting happened (Z,W,top,H production)*
- *Triggers like those are very central to ATLAS/CMS physics*
- *The sample selected is enriched in interesting events, but still contaminated by non-interesting ones*
- *Contamination can be reduced with a DL classifier that rejects obvious false positives looking at the full event, not just at the lepton*

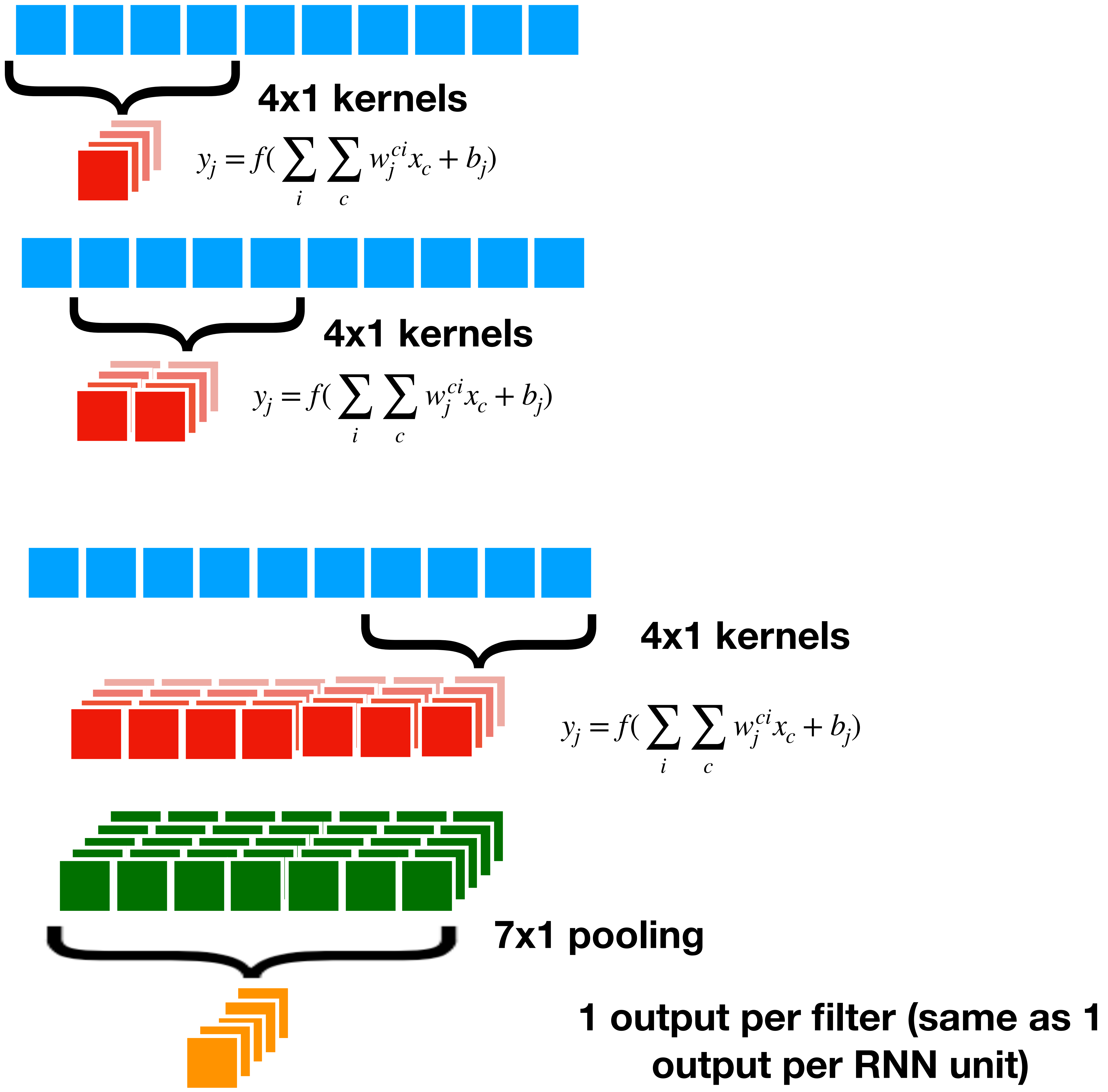




Alternative approach with 1D CNN

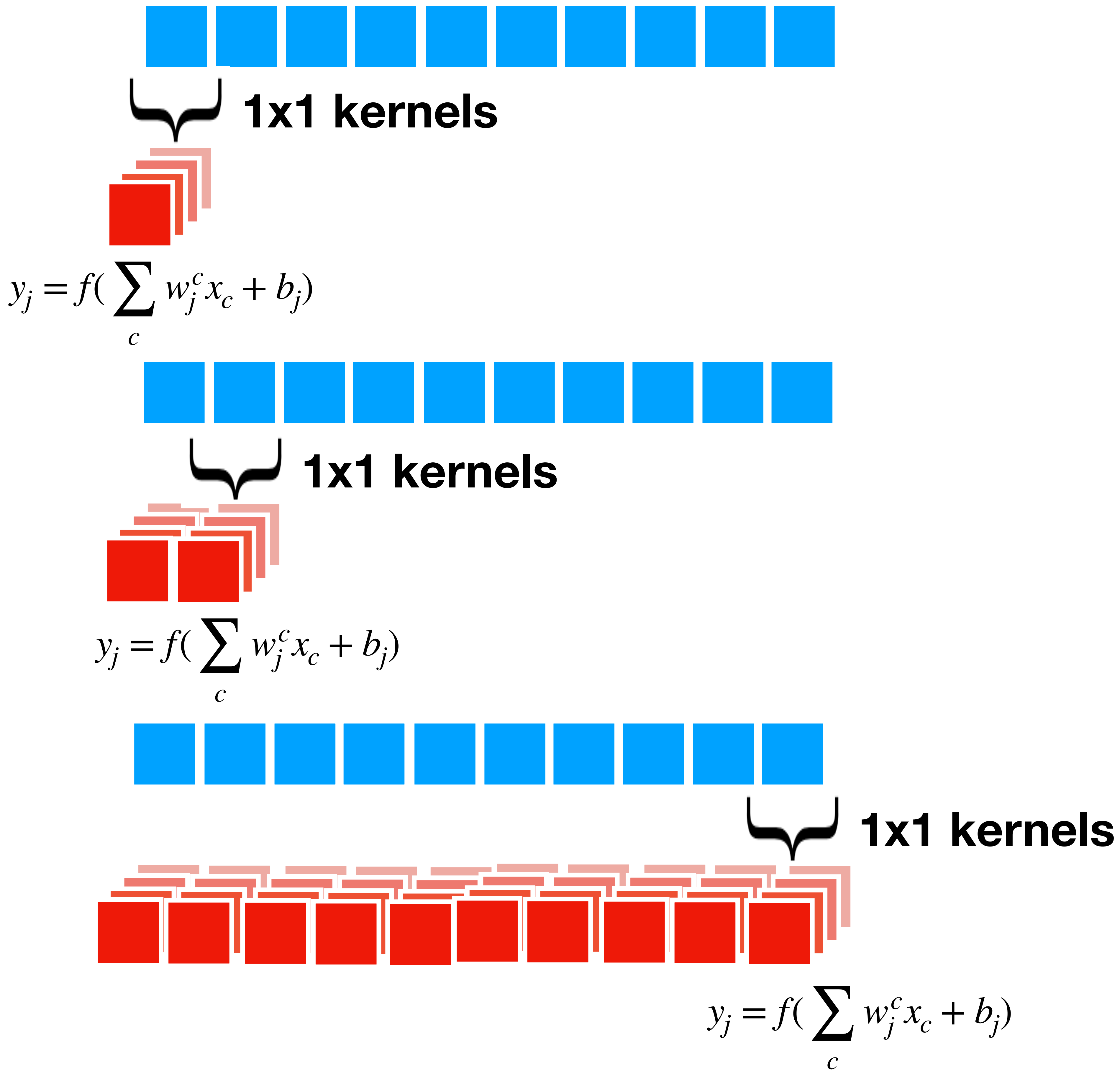
1D Convolution

- *Rather than a sequential processing, one could use a 1D kernel*
  - *Same as 2D conv, but acting on 1D sequence*
  - *The channels here are the features of the i-th element of the sequence (e.g., pT, η, φ of jet constituents)*
  - *Advantage comes from parallel processing (no memory cell) -> faster*
  - *Performance can be comparable, but usually LSTMs are better*



1x1 kernel for pre-processing

- *Sometimes, 1x1 kernels are used (in 1D, 2D, etc) as pre-processing networks*
- *If you look at the math, it's the same as running a DNN in parallel on the c features of each element*



Summary

- We discuss recurrent NNs and their potential usage to save processing resources @LHC
  - Learn underlying "particle physics grammar" by sequential processing of ordered lists of particles
  - Can be used in jets (our exercise of today)
  - Can be used on whole event
  - A step fwd wrt CNNs: don't require regular detector geometry
  - Not yet the ultimate solution: require ordering principle, not always uniquely defined
- We also saw 1D CNN as an alternative solution to the same problem
  - parallel process -> faster
  - no memory gate mechanism -> might not work that well