Recurrent Attention Network

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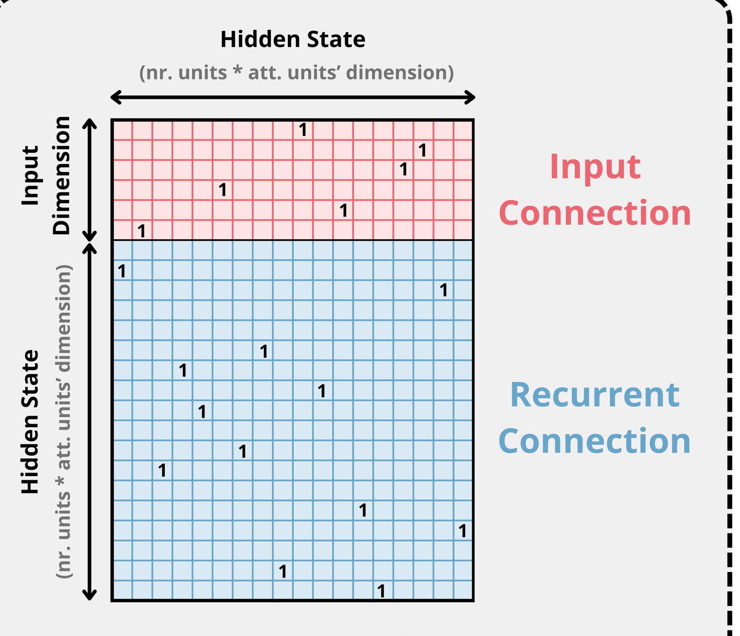
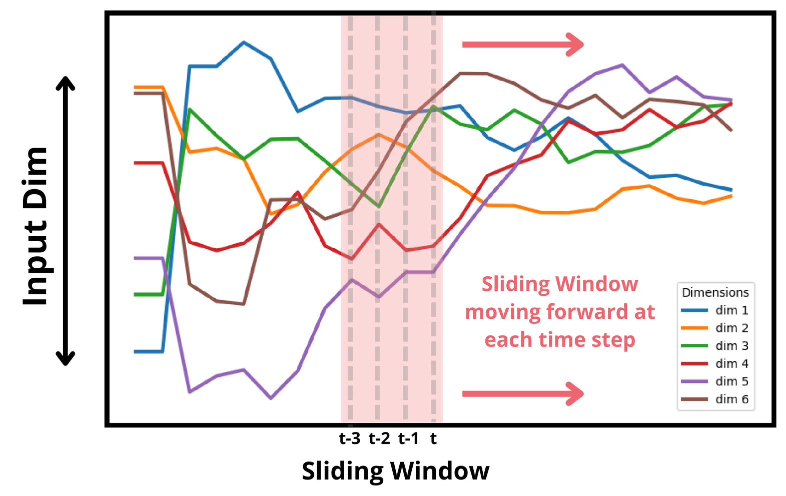
Inspired by Transformers, we're trying to make Reservoir Computing scalable, by using more complex units.

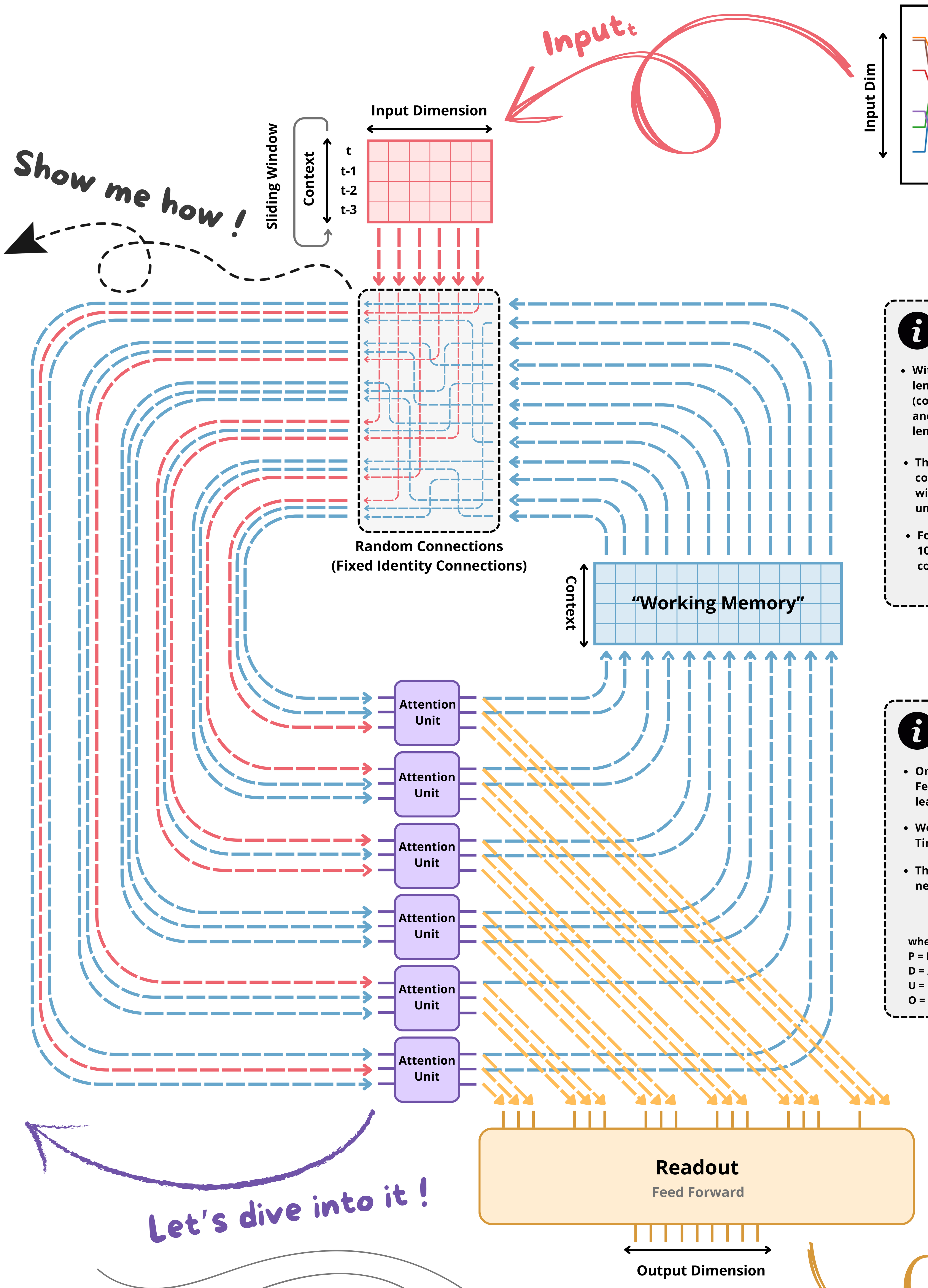
Random Connections (Fixed Identity Connections)



- Each input and recurrent dimensions are mapped to only one input dimension of only one unit.
- Every connections are sparse and topographic / identity connections.

Show me how !





Working Memory and Context Length

- With a "Working Memory" and a fixed context length, we can compute each step in O(1) (constant time) instead of O(n²) (quadratic time) and still access information beyond context length thanks to recurrent connections.
- The shorter the context length is, the faster the computations. It's better to have a lot of units with a very small context length, than a few units with a very large context length.
- For example, one unit of with context length of 100 takes more time than 20 units of with context length of 5 :
  $100^2 > 20*5^2$

Trainable Parameters and Learning

- Only Attention Weight (W_q, W_k, W_v), Unit's Feed-Forward (FF_{in}, FF_{out}) and the Readout are learned.
- We use Truncated BackPropagaton Throught Time with the length of the context.
- The number of parameters trained in the network follows that formula :

$$P = 11D^2U + UDO + 8DU + O$$

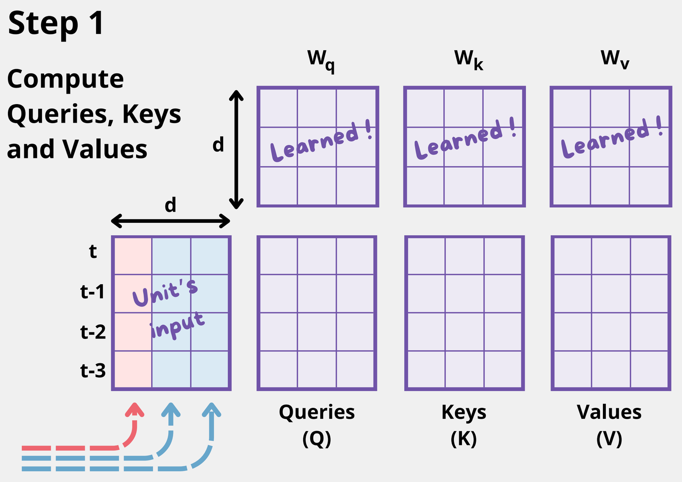
where
P = Number of Trained Parameters
D = Attention Units' Dimension
U = Number of Attention Units
O = Output Dimensions

Inside an Attention Unit

Attention Unit are inspired from Attention Head in [1].

Step 1

Compute Queries, Keys and Values

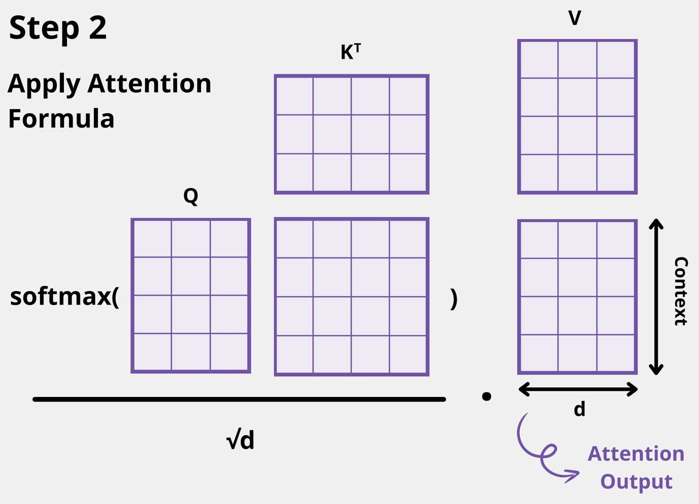


- We could use fixed and random W_q and W_k to compute our Queries and Keys.
- It might extract some diverse patterns and learn to work with it in the same way Reservoir Computing [4] does.
- As we observe in some experiences [3], in doing so, training could converge faster.

PERSPECTIVES

Step 2

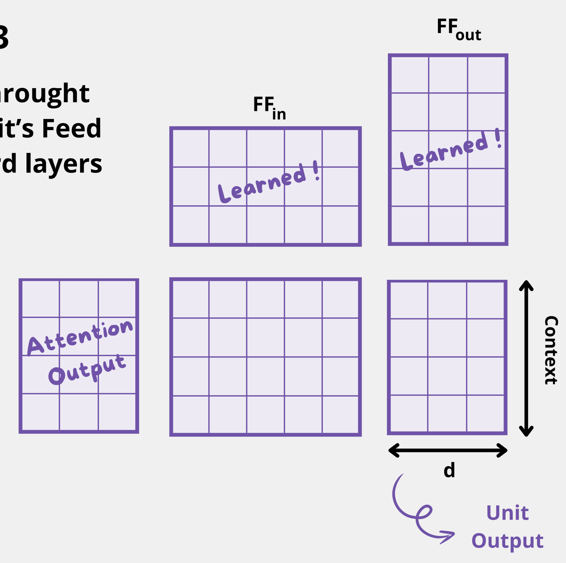
Apply Attention Formula



- Input connections brings new and fresh information of time t, while Recurrent connections brings a mix of old informations computed some steps before.
- Thus, we can apply attention on spatial & temporal informations.

Step 3

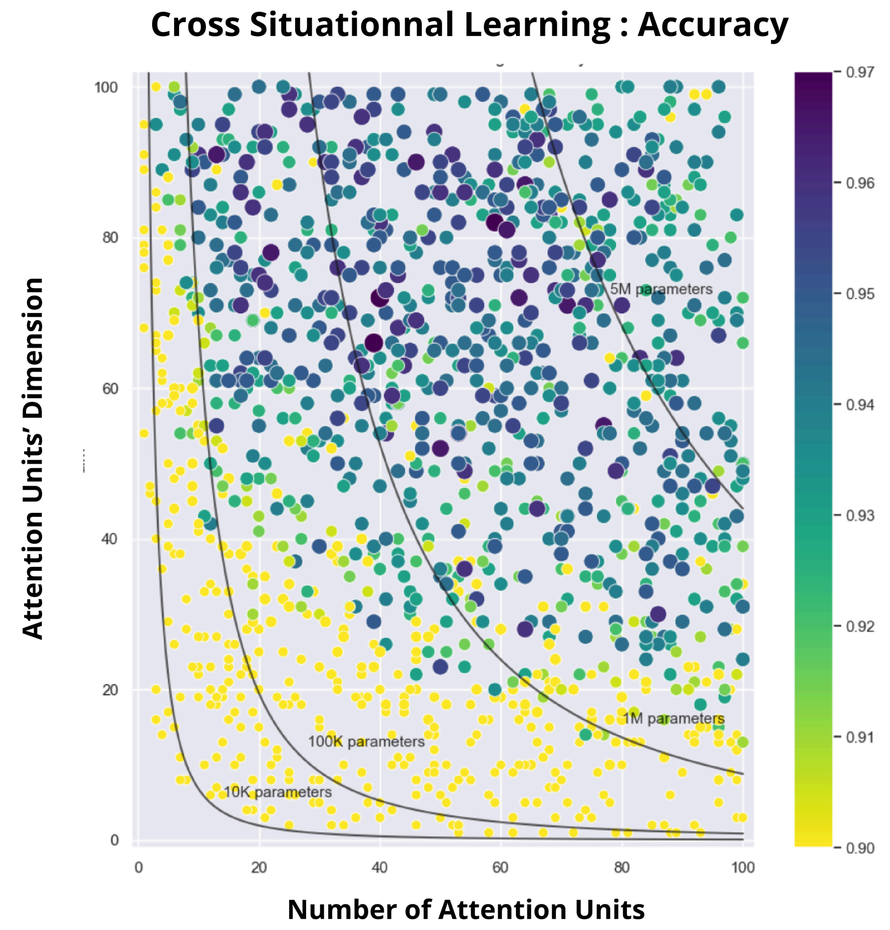
Pass throught the Unit's Feed Forward layers

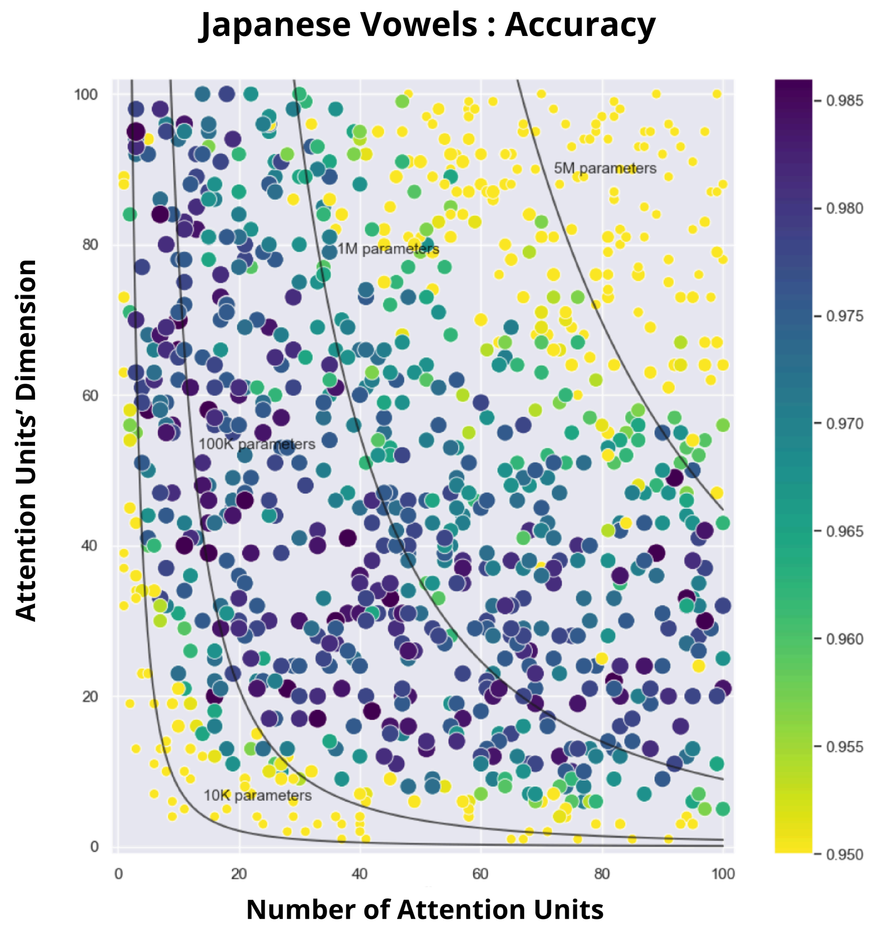


- According to [2], this step retrieves and combines memories.
- We could decompose those Units into two different ones :
  - Attention Only (step 1-2)
  - Memory Only (step 3)
- Thus, some memories could be shared between different Units of Attention Only.
- And, we will be able to tune the model in function of the task's needs : more or less attention or memory units.

PERSPECTIVES

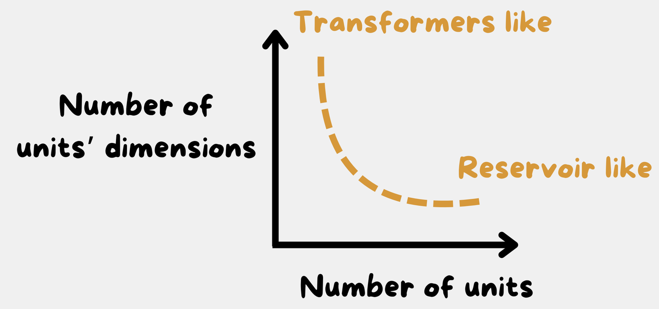
What about the results ?





How to understand the results ?

- This model is a middle ground between Transformers and Reservoir Computing.
- We get closer to Transformers when the number of units is low compared to units' dimension.
- We get closer to Reservoir Computing when number of units is high compared to units' dimension.



References

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