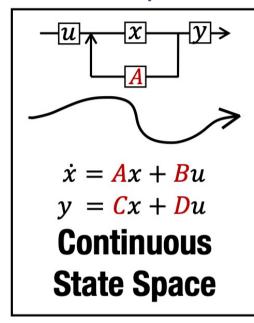
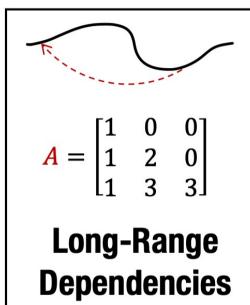


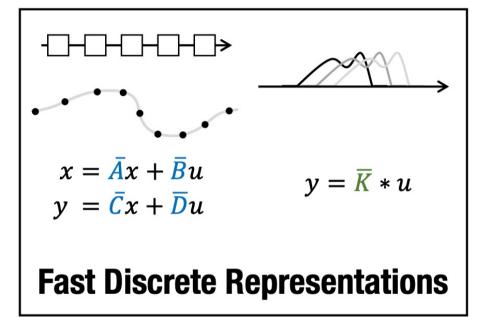
Mamba: Linear-Time Sequence Modeling with Selective State Spaces

S4 (easy mode)

Why S4? Not a basic SSM?







- (1) SSM can model long sequence
- (2) However, a basic SSM has prohibitive computation and memory requirements!
- (3) S4 computes efficiently and require less memory (30x faster + 400x less usage than conventional SSM)

S4 introduces a novel parameterization that efficiently swaps between these representations, allowing it to handle a wide range of tasks, be efficient at both training and inference, and excel at long sequences.

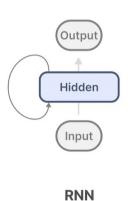
Three representations: Recurrent

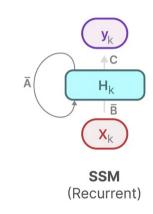
$$x = \bar{A}x + \bar{B}u$$
$$y = \bar{C}x + \bar{D}u$$

Recurrent Representation

Bilinear method:

$$\bar{A} = \left(I - \frac{\Delta}{2} * A\right)^{-1} \left(I + \frac{\Delta}{2} * A\right)$$
$$\bar{B} = \left(I - \frac{\Delta}{2} * A\right)^{-1} \Delta B$$
$$\bar{C} = C$$





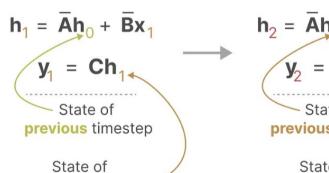
Timestep 0

$$h_0 = \overline{B}x_0$$

$$y_0 = Ch_0$$

Timestep -1 does not exist so

Ah₋₁ can be ignored **Timestep 1**

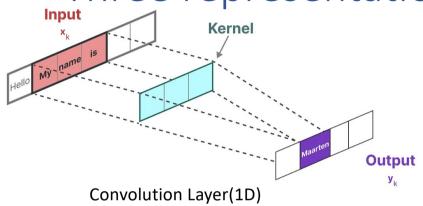


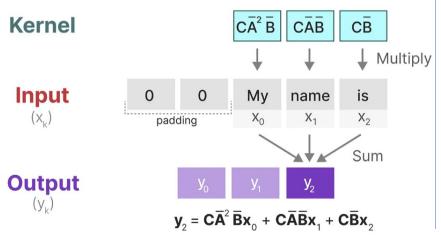
current timestep

Timestep 2

State of current timestep

Three representations: Convolutional





$$y = \overline{K} * u$$

Convolutional Representation

time	hidden	prediction
0	$\bar{B}x_0$	$C\overline{B}x_0$
1	$\bar{A}h_0 + \bar{B}x_1$	$C\bar{A}\bar{B}x_0 + C\bar{B}x_1$
2	$\bar{A}(\bar{A}h_0 + \bar{B}x_1) + \bar{B}x_2$	$C\bar{A}^2\bar{B}x_0 + C\bar{A}\bar{B}x_1 + C\bar{B}x_2$

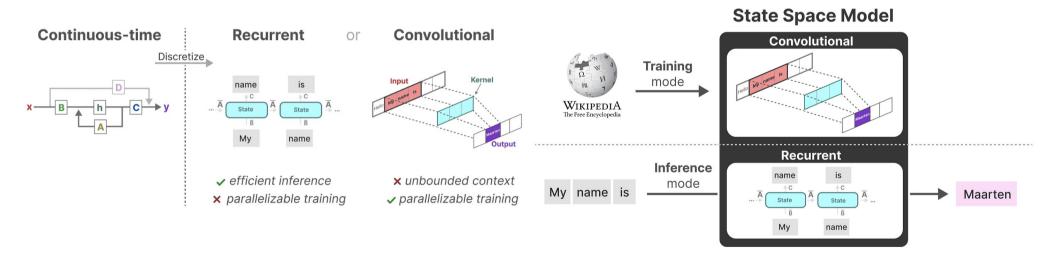
If conv size is fixed, like conv size = 3, Conv kernel should be: $\overline{K} = (C\bar{A}^{L-1}B,...,C\bar{A}^2\bar{B},C\bar{A}\bar{B},C\bar{B})$

Difficulties: L times for computing $y = \overline{K} * x$

Solve: truncated generating function (convert the power of matrix to the inverse of matrix, like

$$y = fun_1(A) * fun_2(A^{-1}) * x$$

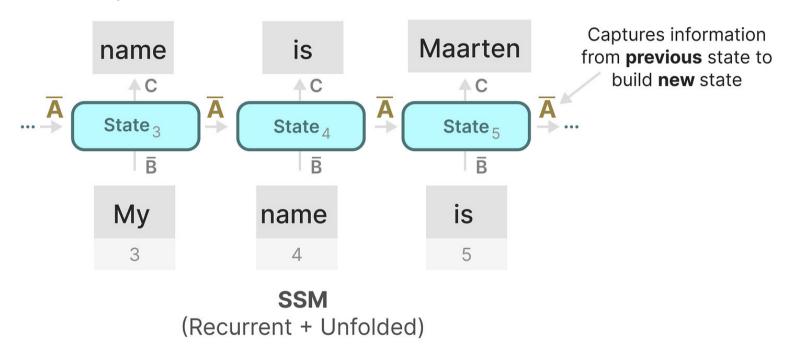
Summary of three representations



LSSL(Linear State-Space Layer)

Property: Linear Time Invariance(LTI)

The importance of Matrix A

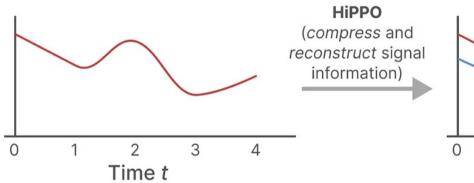


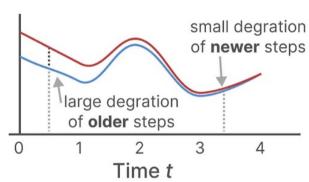
How can we get a Matrix A to retain the large memory (since it only look at previous states)

HIPPO Matrix

Input Signal

Reconstructed Signal





(**HiPPO Matrix**)
$$m{A}_{nk} = -egin{cases} (2n+1)^{1/2}(2k+1)^{1/2} & ext{if } n > k \ n+1 & ext{if } n = k \ 0 & ext{if } n < k \end{cases}$$

Mathematically, it does so by tracking the coefficients of a Legendre polynomial which allows it to approximate all of the previous history.

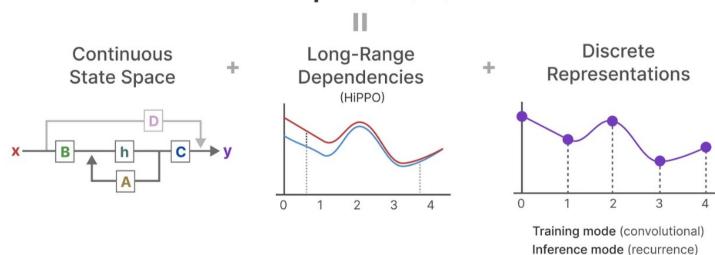
https://hazyresearch.stanford.edu/blog/2020-12-05-hippo

https://proceedings.neurips.cc/paper/2019/hash/952285b9b7 e7a1be5aa7849f32ffff05-Abstract.html

Summary of S4

- State Space Model
- HiPPO for handling long-range dependencies
- Discretization for creating recurrent and convolution representations

Structured State Spaces for Sequences (S4)



Differ from basic SSMs:

- (1) Modeling challenge for LRD: using a special formula for the A matrix (HiPPO).
- (2) Computational Challenge: introducing a special representation and algorithm to be able to work with this matrix (truncated generating function)