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Github link for files and code: https://github.com/DevonARP/DeepLearning_A3

Problem 1: Part A

CNN's are better at identifying images as each layer in it's architecture helps extract prominent features to figure out what the object in the image is, this is also helped by the feed-forward model it follows.

They are also really good at reducing the dimensions of the data, this is also caused by the layers filtering the image but it significantly reduces the computations and time needed to classify an image.

Problem 1: Part B

RNN's are typically better at dealing with temporal or sequential data, in this regard if we're dealing with text or speech, which is just sequential words at different points of time, an RNN would be preferred.

They are also great at getting context from the data, as it includes loops in it's architecture, this keeps it iterating through data sequences in order to grab the meaning of the data in regards to how it is used and what type of data is around it at that point in time.

Problem 2

Hidden state: $H_t = x_t - h_{t-1}$

Number of inputs: n

So lets start 2n inputs, this keeps the amount of the inputs even:

$h_{2n} = x_{2n} - h_{2n-1}$

$h_{2n} = x_{2n} - x_{2n-1} + h_{2n-2}$

$h_{2n} = x_{2n} - x_{2n-1} + x_{2n-2} - h_{2n-3}$

Following the alternating sign pattern:

$h_{2n} = x_{2n} - x_{2n-1} + x_{2n-2} \ldots - x_3 + x_2 - x_1 + h_0$

I'm attaching the work I manually did below this question. I used an example with 4 inputs of consecutive numbers. I also did the example above as well.

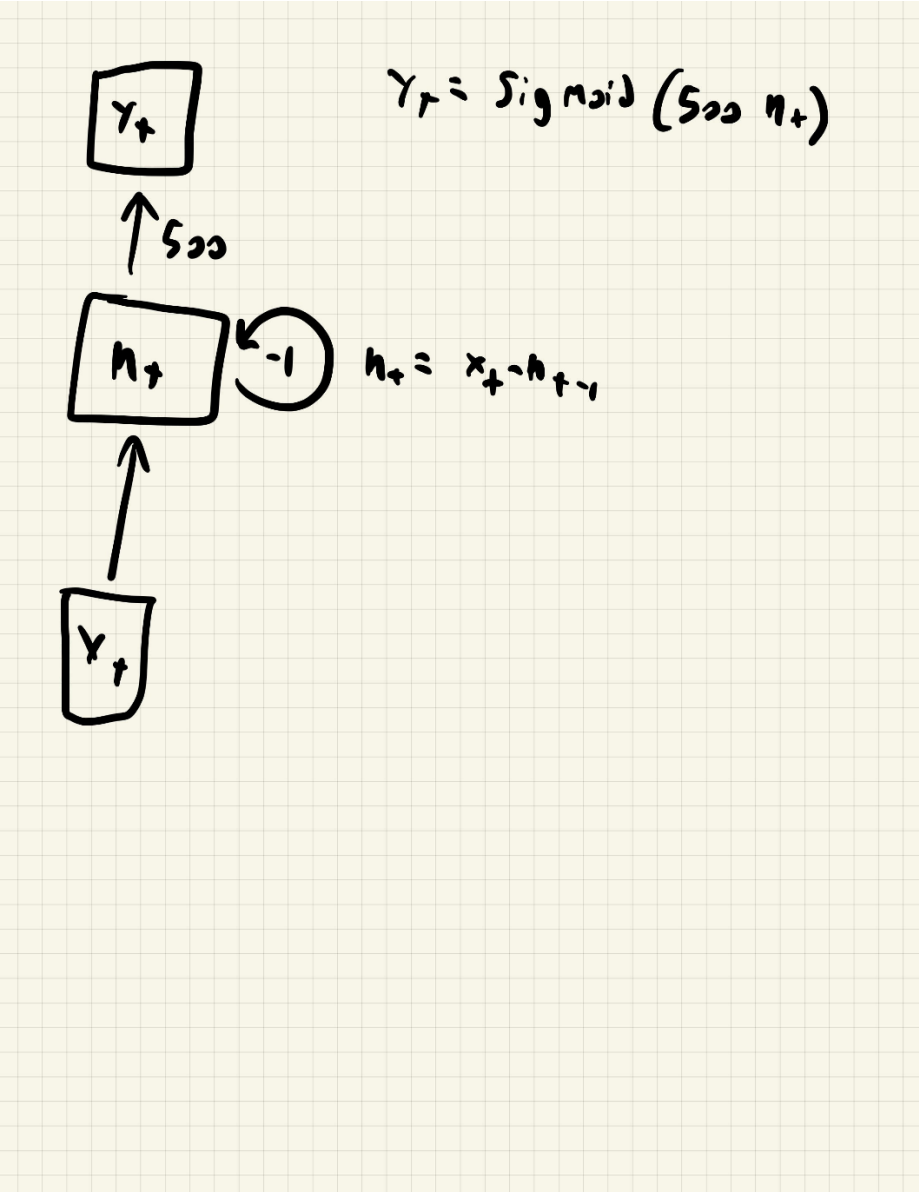
Pattern noticed:

- If the input order number is odd, the input value will end up being a negative value in the equation
- If the input order number is even, the input value will end up being a positive value in the equation

- If the values of the inputs are consecutive and the total inputs is still an even length, then the final value would be $n/2 + h_0$

Output: $y_t = \text{sigmoid}(500*h_{2n})$

$y_t = \text{sigmoid}(500*(x_{2n} - x_{2n-1} + x_{2n-2} \ldots - x_3 + x_2 - x_1 + h_0))$

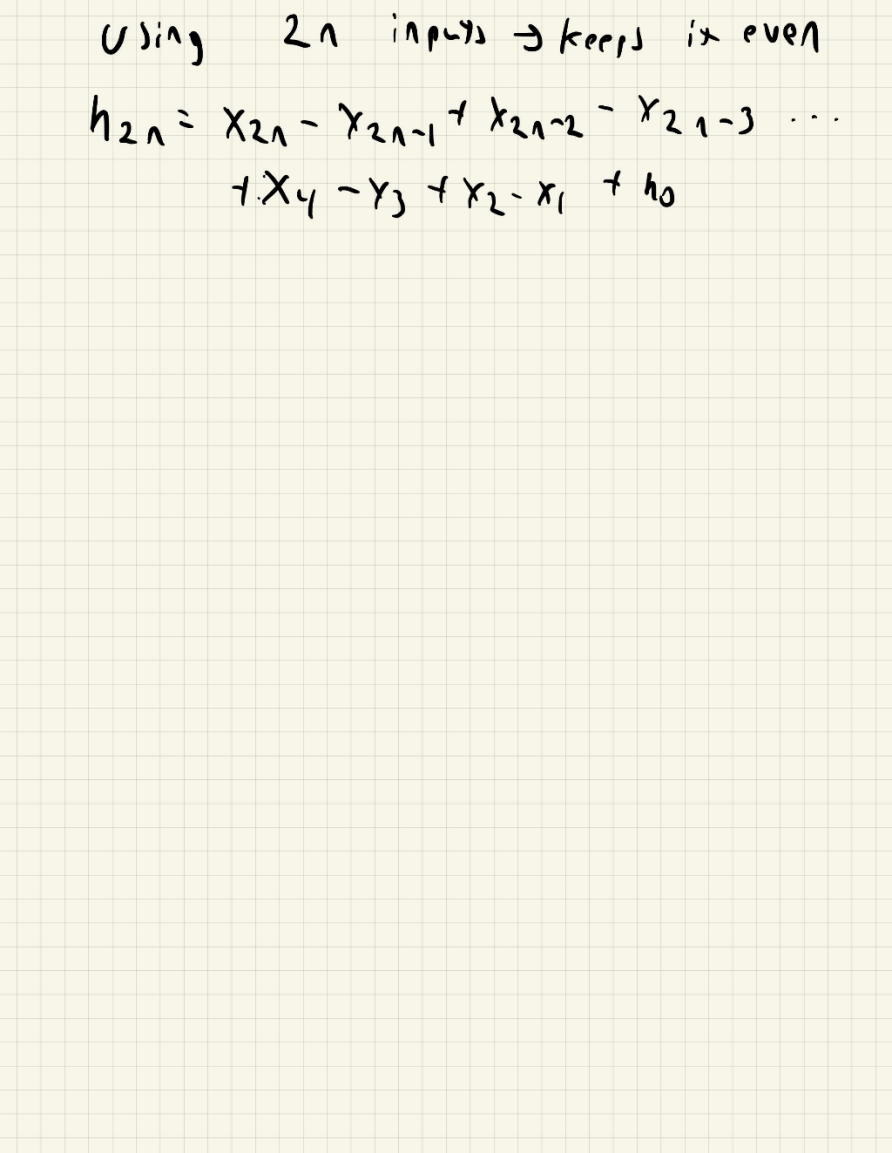


Example with 4 inputs [1,2,3,4]

$$h_4 = x_4 - h_3$$
$$= x_4 - (x_3 - h_2)$$
$$= x_4 + h_2 - x_3$$
$$= x_4 + (x_2 - h_1) - x_3$$
$$= x_4 + x_2 - (x_1 - h_0) - x_3$$
$$= x_4 + x_2 + h_0 - x_1 - x_3$$
$$= 4 + 2 + h_0 - 1 - 3$$
$$= 2 + h_0$$

- if inputs are consecutive $h_1 = \frac{1}{2} + h_0$
- all odd input orders will be subtracted & all even ones will be added

$$y_t = \text{sigmoid}\left(f_{20}\left(x_4 + x_2 + h_0 - x_1 - x_3\right)\right)$$



Problem 3

These are both in O(n) time.

We can use Longformer, which is a sparse attention, it scales linearly with the sequence length instead of quadratically, making it take up substantially less time. It uses a dilated sliding window, which lets us cover more variety of tokens but it still can lead to a loss of information. Another con is that a custom CUDA kernel is needed to make it effective as this is a sparce matrix multiplication instead of a dense one.

We can also use a matrix factorization method such as a Linformer, which makes it a linear scaling as well, it can factorize matrices into lower rank ones without losing much information. This is a great option but it does have a downside in that data is lost here, with every factorization, some data is being lost.

References:

https://towardsdatascience.com/demystifying-efficient-self-attention-b3de61b9b0fb

https://huggingface.co/docs/transformers/model_doc/longformer

https://shubhamg.in/nlp/transformer/review/longformer/2020/05/11/longformer.html

https://appliedsingularity.com/2022/05/31/nlp-tutorials-part-21-linformer-self-attention-with-linear-complexity/

https://arxiv.org/pdf/2111.14556.pdf

https://www.researchgate.net/publication/347999026_A_Transformer_Self-Attention_Model_for_Time_Series_Forecasting

https://stackoverflow.com/questions/65703260/computational-complexity-of-self-attention-in-the-transformer-model

https://www.youtube.com/watch?v=fjJOgb-E41w

Problem 4 Part A

Code is attached

Problem 4 Part B

Code is attached

Problem 4 Part C

I notice the conditional GAN seems to be a bit better at generating the images, a GAN seems to have much more noise as shown by the MNIST Gan vs the MNIST Conditional GAN at step 5000 image.

Problem 4 Part D

I did 4 different examples, 2 are on the Fashion dataset and 2 are on MNIST. They each have one Conditional GAN and one GAN being used on the data. The key difference I found is the randomness of what's generated, the Conditional GAN would be consistent and specify what type of object or number it would generate while the regular GAN would not.