

Agenda:

→ BERT - code

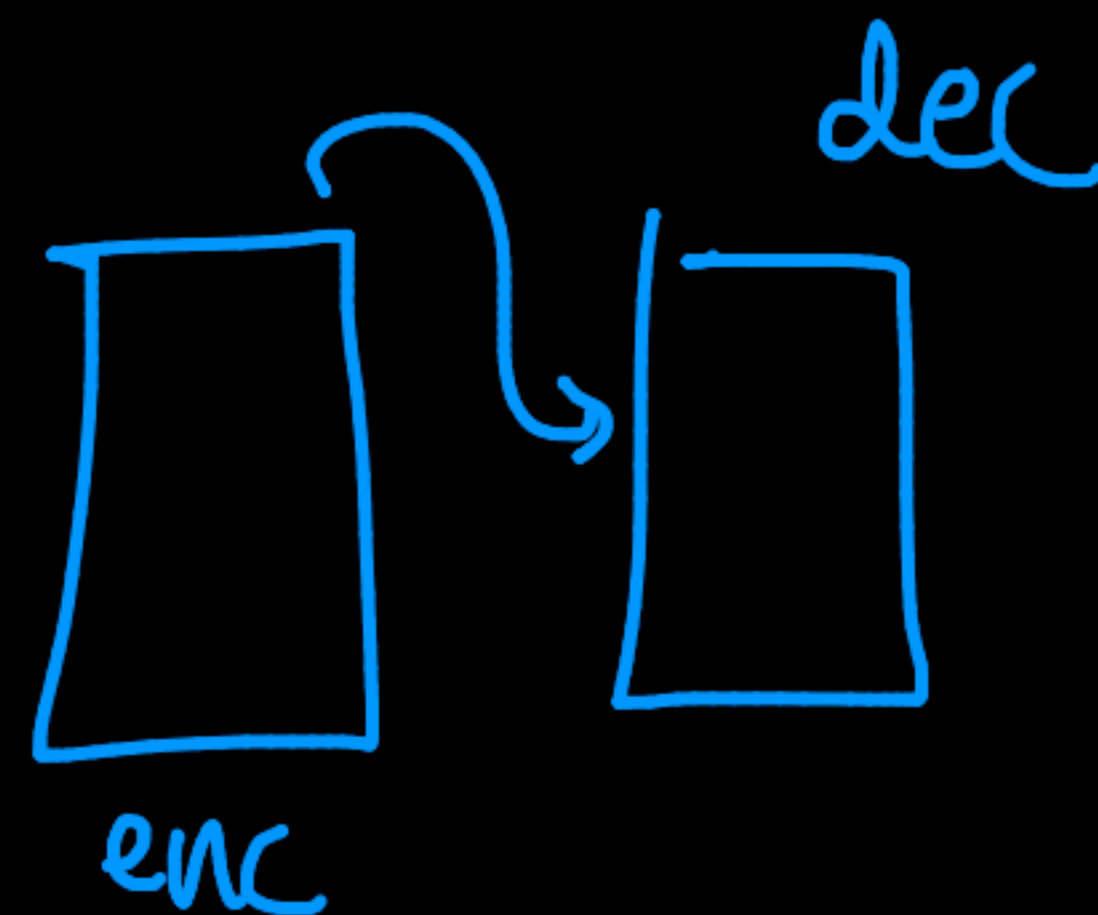
→ Two more problems + code (NLP)

(Q)

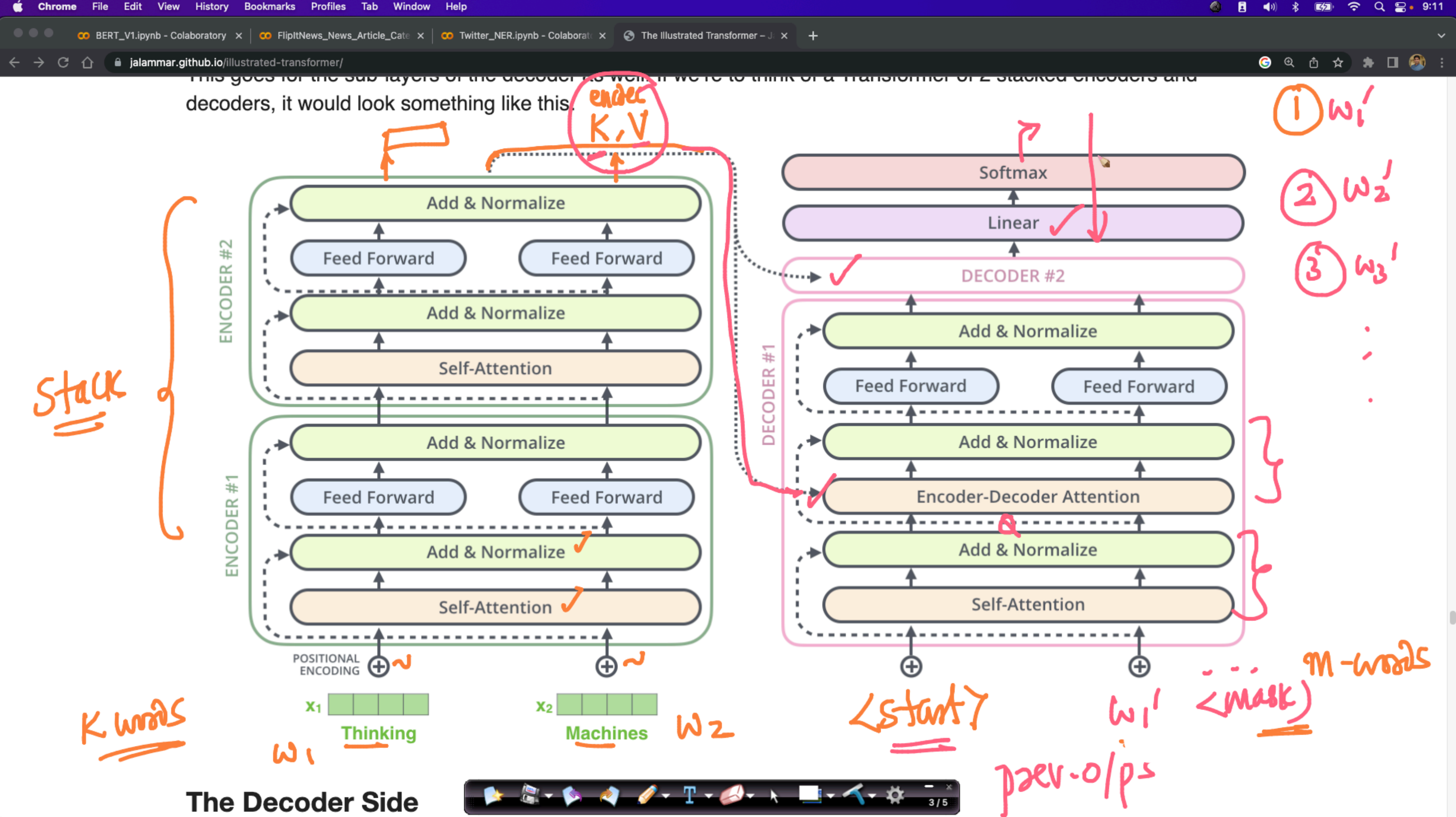
encoder-decoder

→ LSTM

→ Transformers ✓



(Recap)

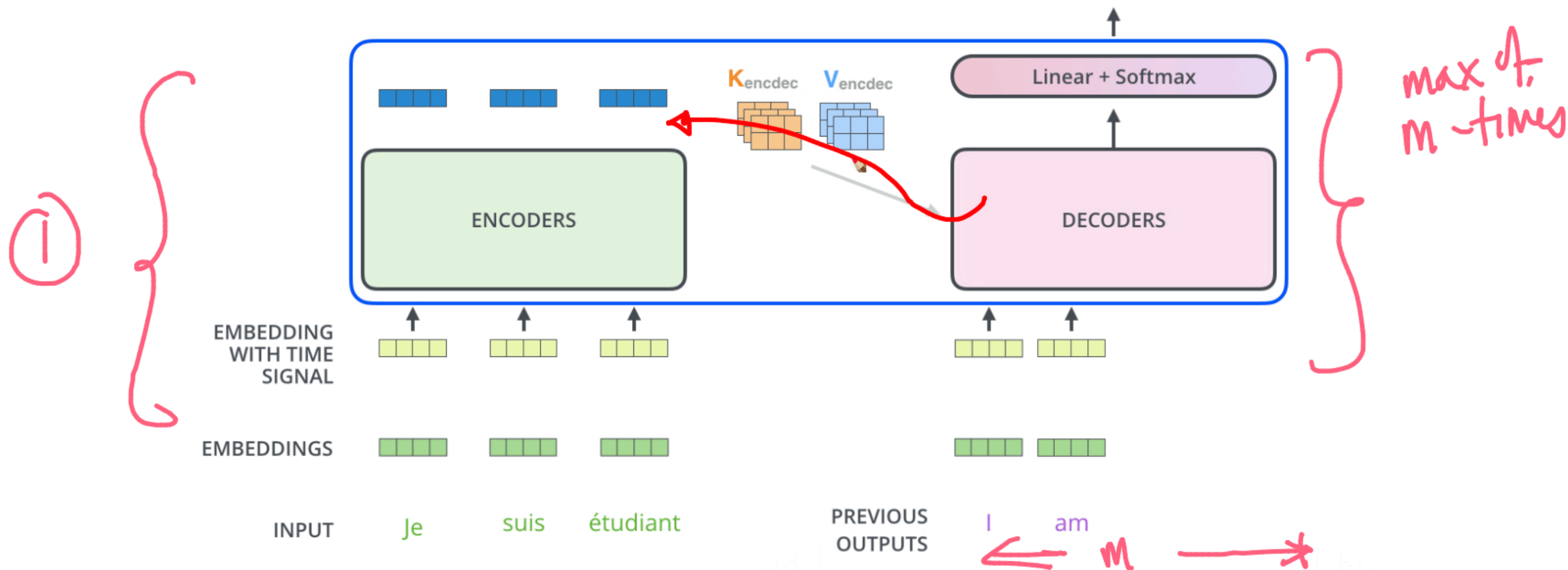


completed its output. The output of each step is fed to the bottom decoder in the next time step, and the decoders bubble up their decoding results just like the encoders did. And just like we did with the encoder inputs, we embed and add positional encoding to those decoder inputs to indicate the position of each word.

Decoding time step: 1 2 3 4 5 6

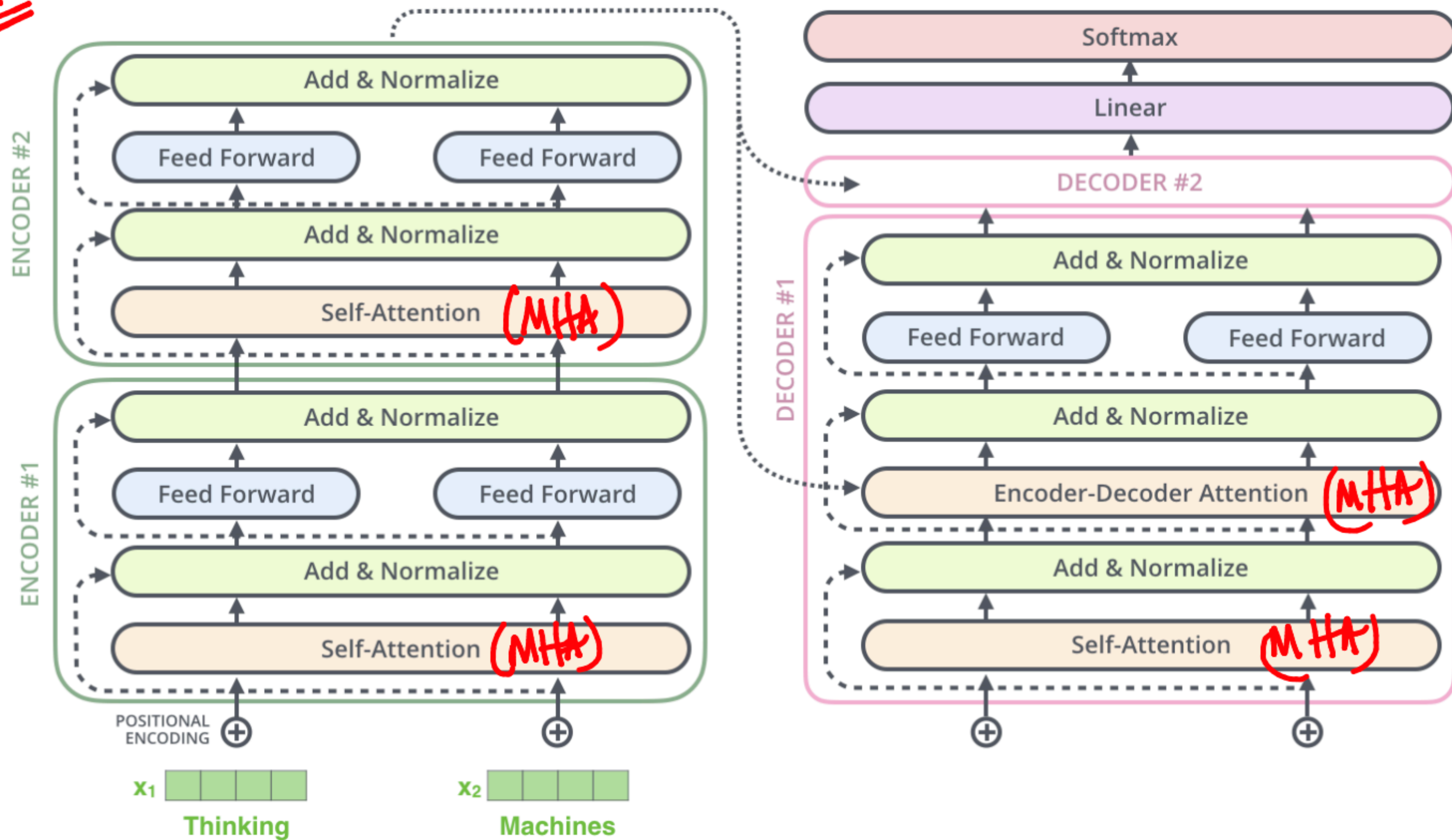
OUTPUT

I am a



The self attention layers in the

SHA - LSTM

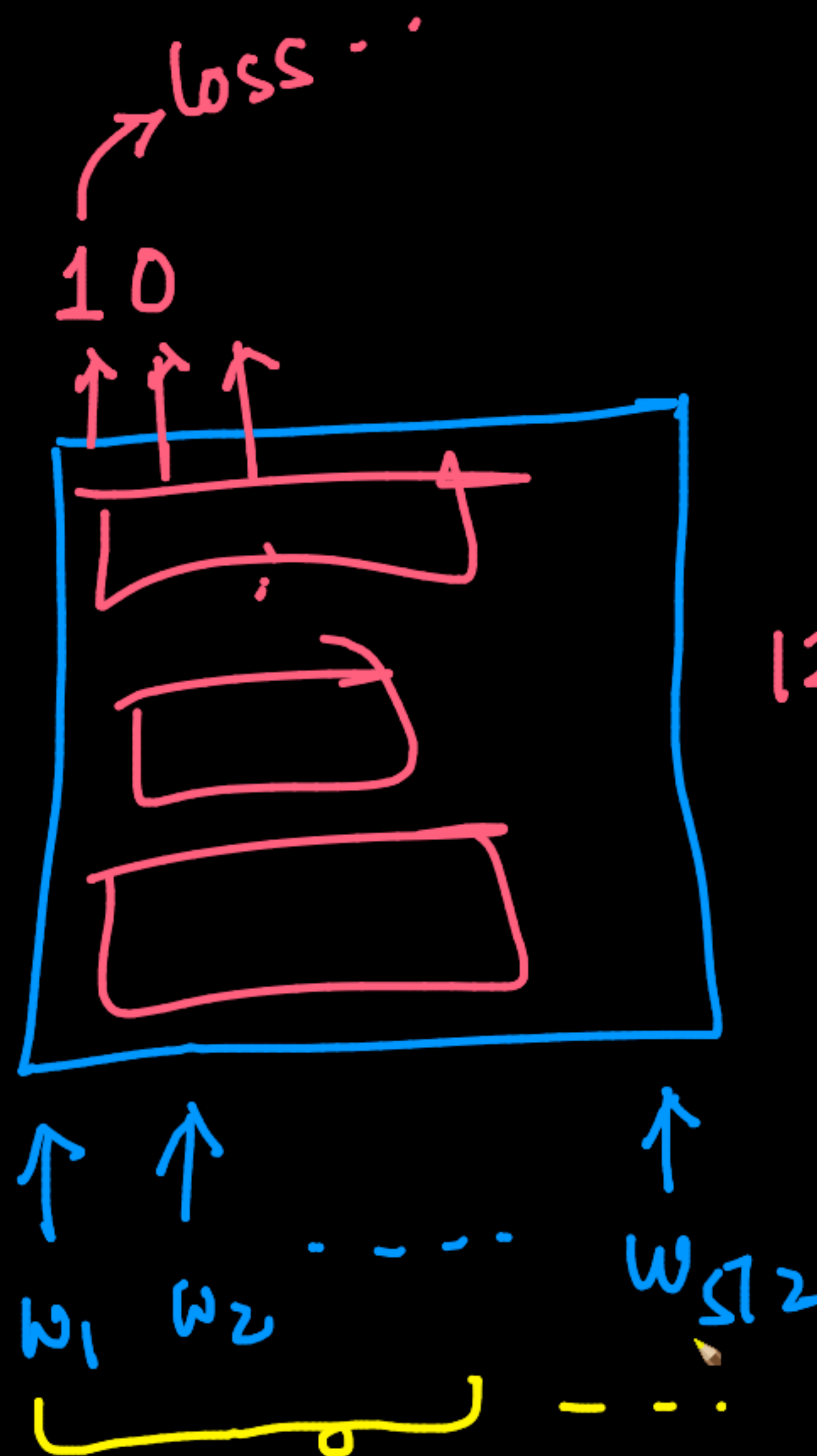


The Decoder Side

Now that we've covered most of the components on the encoder side, we primarily know how the components of



encoder
stack



12 encoders

$\begin{cases} 1: \text{disease name} \\ 0: \text{non disease} \end{cases}$

$\begin{cases} 0: \text{non-dis} \\ 1: \text{dis} \\ 2: \text{padding} \end{cases}$

Diagram illustrating a BERT-based neural network architecture for text classification:

- Input tokens: $\langle \text{CLS} \rangle, w_1, \dots, w_n$
- Embedding layer (implied by arrows pointing into the BERT box)
- BERT** (Pretrained model)
- Dense layer
- Softmax layer

The entire architecture is labeled as **{pretrained} [+ fine tune]**.

<>

> _

Simplest

(Let)

NB → 98% acc

BERT → 98.5% acc

110M

< >

Chrome

File

Edit

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History

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Profiles

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Window

Help

BERT_V1.ipynb - Colaboratory

FlitNews_News_Article_Cate

Twitter_NER.ipynb - Colaborat

The Illustrated Transformer - J

colab.research.google.com/drive/1_cSrODbBnhydyoaXm1Vs6puvaNrdBKLr#scrollTo=at3FQVEi0F-w

+ Code

+ Text

Last edited on 22 November

Connect

Problem statement

Context: Twitter is a microblogging and social networking service on which users post and interact with messages known as "tweets". Every second, on average, around 6,000 tweets are tweeted on Twitter, corresponding to over 350,000 tweets sent per minute, 500 million tweets per day. Twitter wants to automatically tag and analyze tweets for better understanding of the trends and topics without being dependent on the hashtags that the users use. Many users do not use hashtags or sometimes use wrong or mis-spelled tags, so they want to completely remove this problem and create a system of recognizing important content of the tweets.

Objective: You need to train a model that will be able to identify the various named entities.

Downloading data


[] !gdown 14_VHffl1qBUEnZ1IWFHnh6B9M5_A-Wf8
!gdown 1cnrGjppPOU_NtHNpGu0RJGg1CUNNsse_

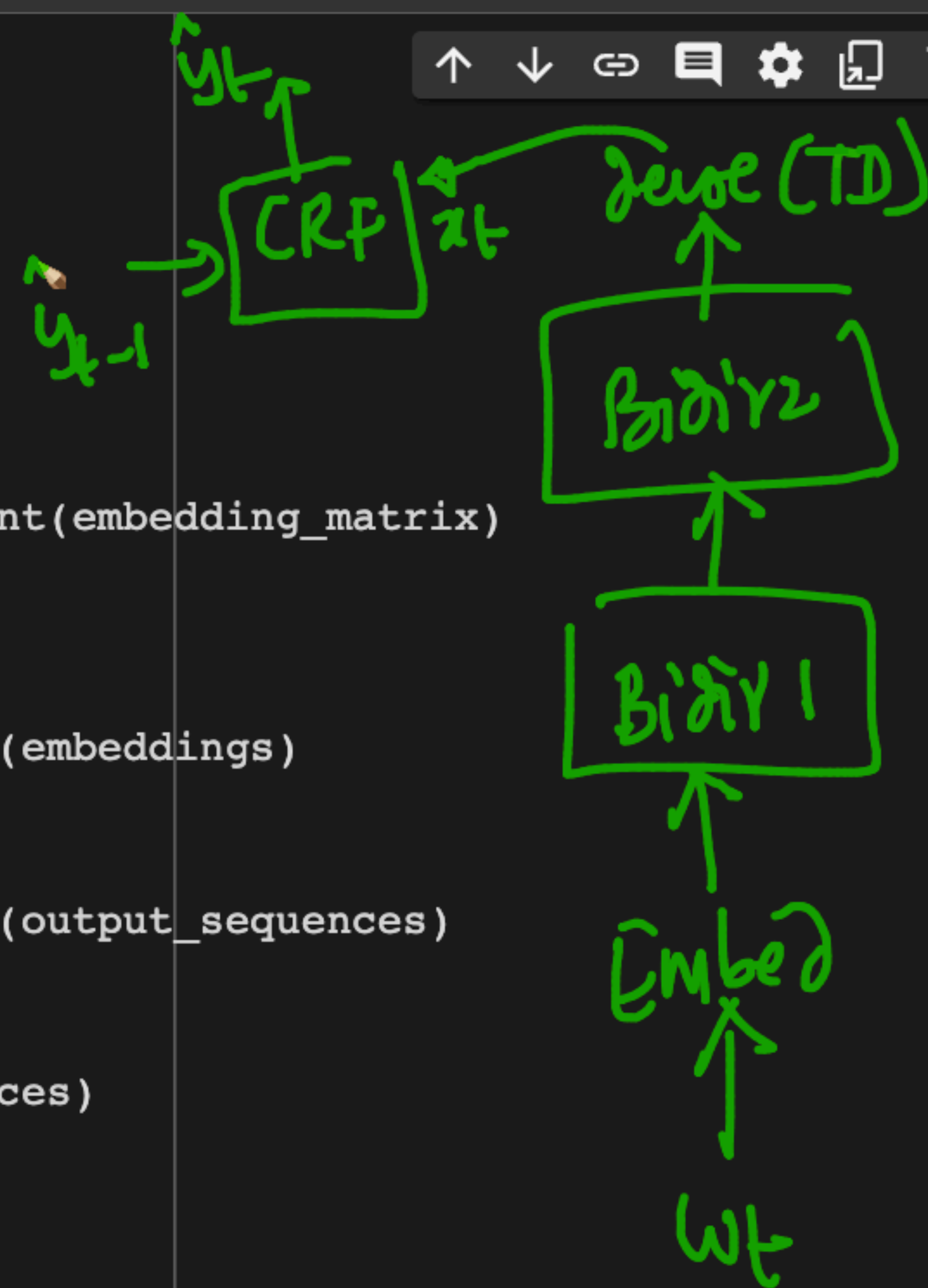
Downloading...
From: https://drive.google.com/uc?id=14_VHffl1qBUEnZ1IWFHnh6B9M5_A-Wf8
To: /content/wnut 16.txt.conll
100% 403k/403k [00:00<00:00, 118MB/s]
Downloading...
From: https://drive.google.com/uc?id=1cnrGjppPOU_NtHNpGu0RJGg1CUNNsse_
To: /content/wnut 16test.txt

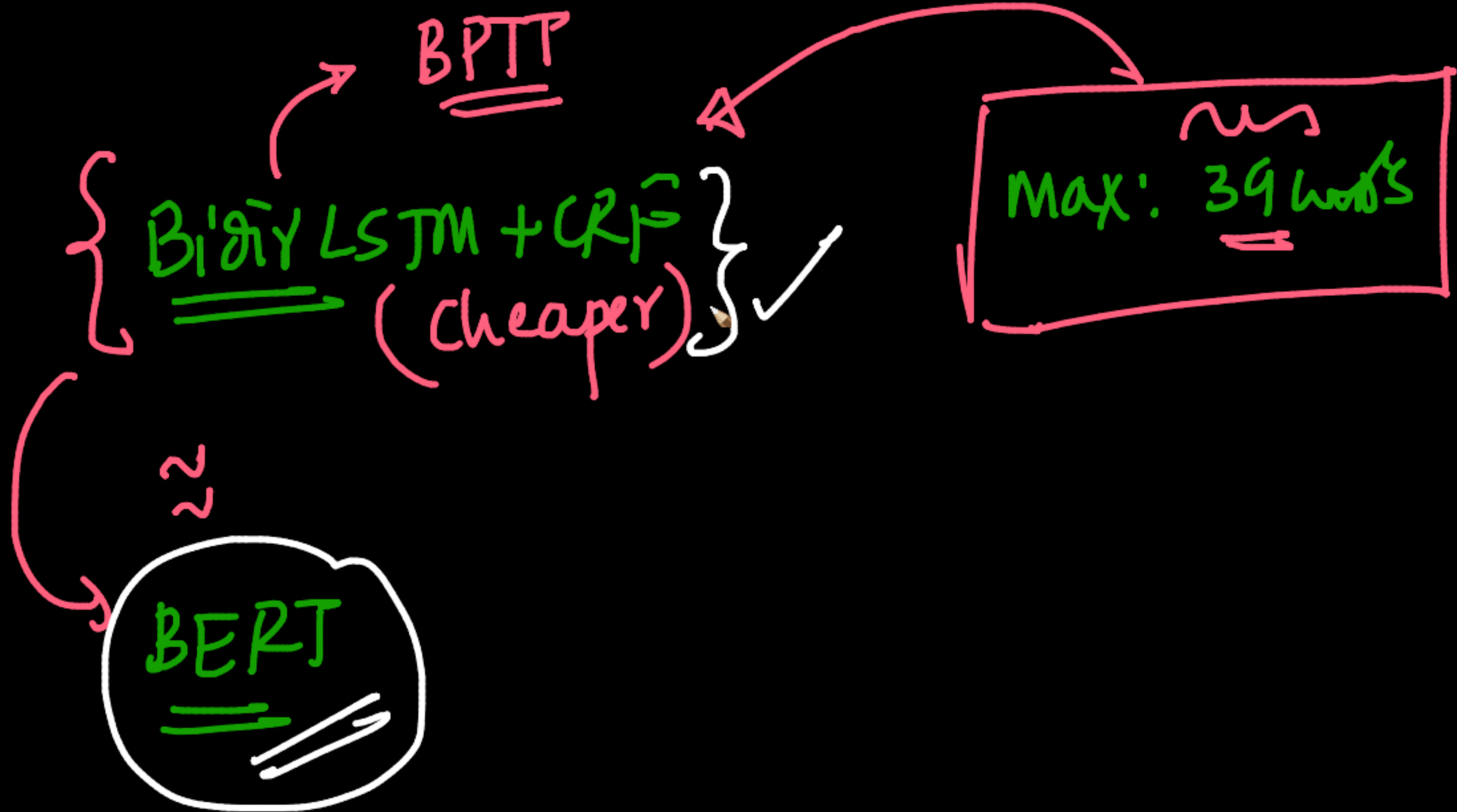
NER on short-text

① BiLSTM+CRF

② BERT

Connect    





1.13.0+cu117

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QUICKSTART

This section runs through the API for common tasks in machine learning. Refer to the links in each section to dive deeper.

Working with data

PyTorch has two primitives to work with data: torch.utils.data.DataLoader and torch.utils.data.Dataset. Dataset stores the samples and their corresponding labels, and DataLoader wraps an iterable around the Dataset.

```
import torch
from torch import nn
from torch.utils.data import DataLoader
from torchvision import datasets
from torchvision.transforms import ToTensor
```

PyTorch offers domain-specific libraries such as TorchText, TorchVision, and TorchAudio, all of which include datasets. For this tutorial, we will be using a TorchVision dataset.

The torchvision.datasets module contains Dataset objects for many real-world vision data like CIFAR, COCO (full list here). In this tutorial, we use the FashionMNIST dataset. Every TorchVision Dataset includes two arguments: transform and target_transform to modify the samples and labels respectively.

```
# Download training data from open datasets.
training_data = datasets.FashionMNIST(
    root="data",
    train=True,
```

Quickstart

Working with data

Creating Models

Optimizing the Model Parameters

Saving Models

Loading Models

10:16