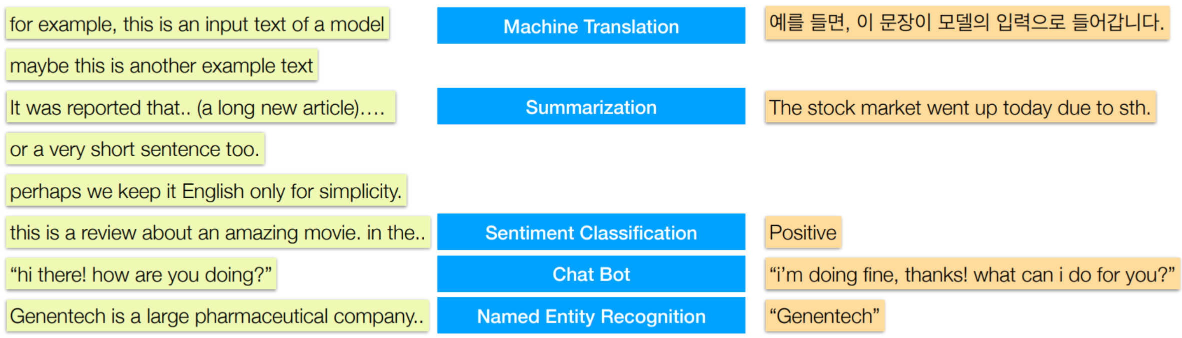
Lecture7 Transformer and Language Model

> Intro to Large Language Models by Andrej Karpathy https://www.youtube.com/watch?si=SSCVcFyY9FduwHbW&v=zjkBMFhNj_g&feature=youtu.be

1. Introduction

Traditional Language models



LMs take text as input and does something useful such as

- classification
- named entity recognition
- translation
- completion
- summarization
- Q&A
- chat

Large Language Models

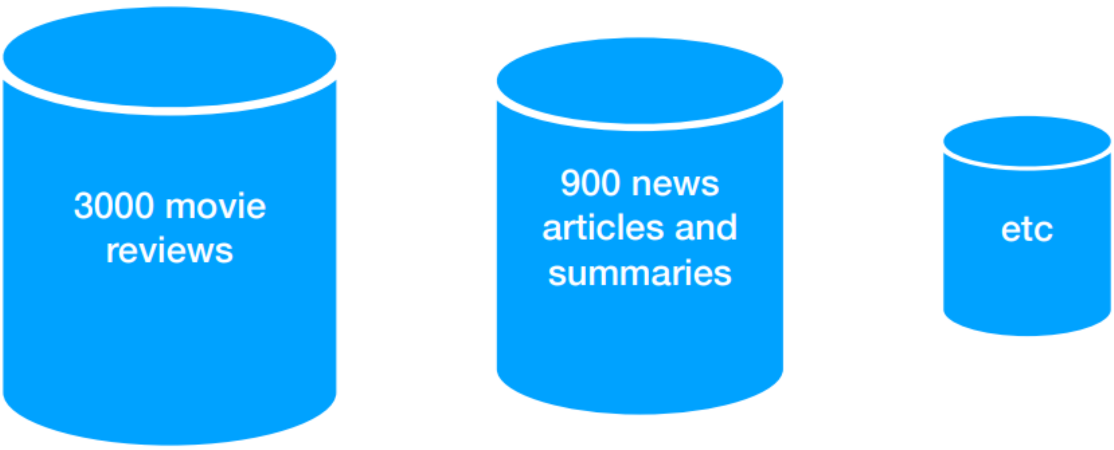
Large language models (e.g., GPT, llama, Gemini) are so powerful that then can various natural language tasks very well

Old <-> New Language Models

Model	Period	Text Data Handling	Features
E.g., Bag-of-word Classifier	2000s	Lots of text preprocessing (all sentences → counter of words)	Handwritten features (e.g., TF-IDF)
E.g., Machine Translation (deep learning models)	2015	Some text preprocessing (Punctuation removal, text normalization)	End-to-end training using bilingual text pairs
Large Language Models	2021+	Use text (almost) as-it-is	Any text

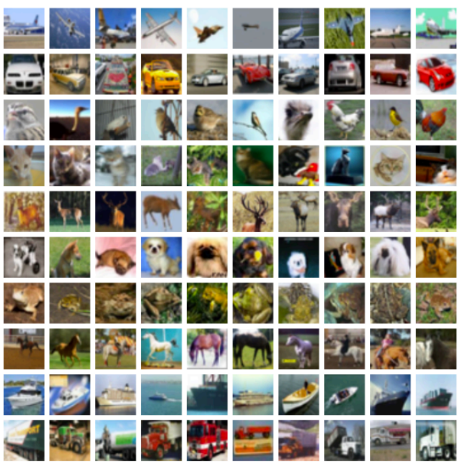
- bag-of-word: collect a bunch of positive or negative words

Traditional Models are Small Models



- With relatively limited resources (HW and data), we could handle **smaller** models only
- Each model was trained for a **specific task** e.g. summarization, sentient analysis, etc

2. Language As Data



Vs.

for example, this is an input text of a model. as you can imagine, text is a sequence of characters (or words), which is quite different from image data. images have two axes, which often have some physical implication and local correlation. that's why it makes sense to use convolutional neural networks to handle images, although there are other methods.

text is, by nature, a sequence. that is how we write, speak, and listen. a text snippet, or a document, is a sequence of characters or words. but more importantly, text is a sequence of symbols each of which means something.

- **image**: (row, col, channel), pixel with colors
- **text**: a sequence of characters

Neural Networks for Sequences

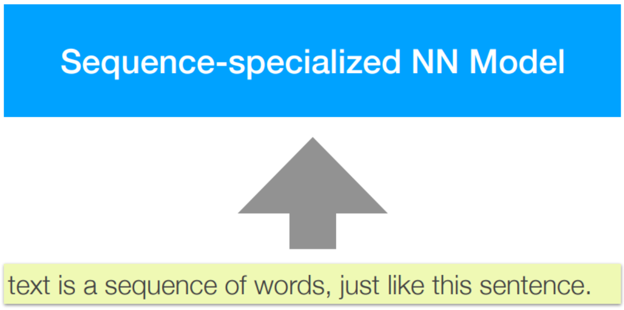
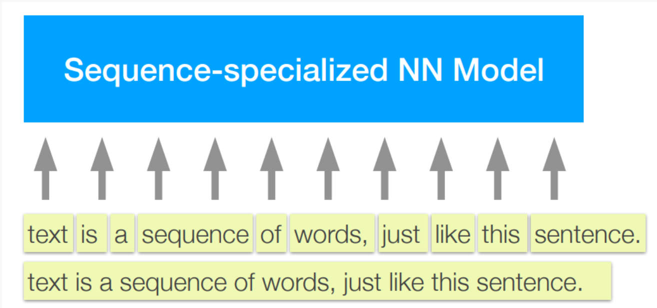
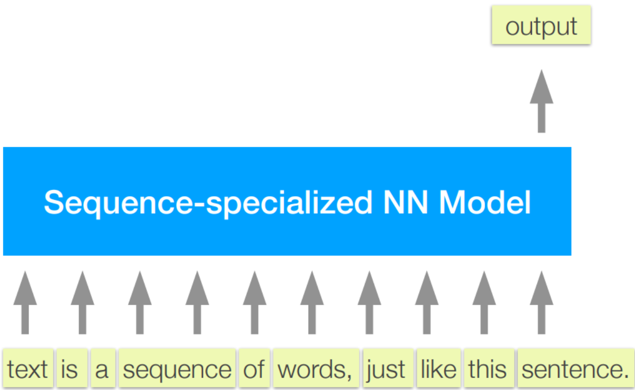
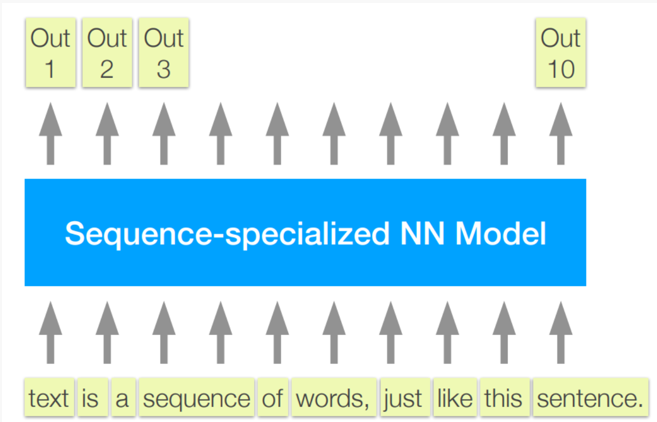
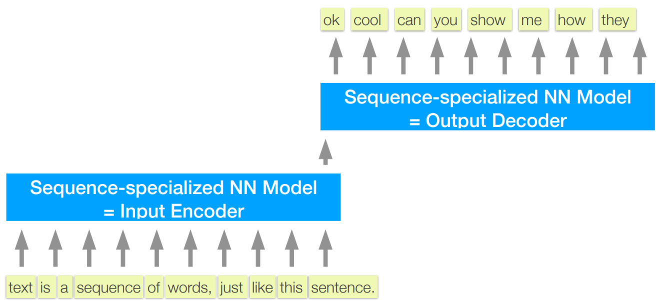
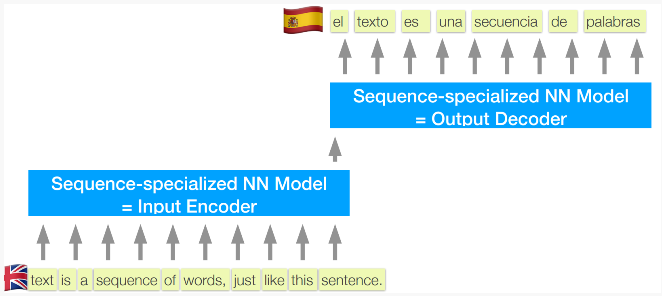
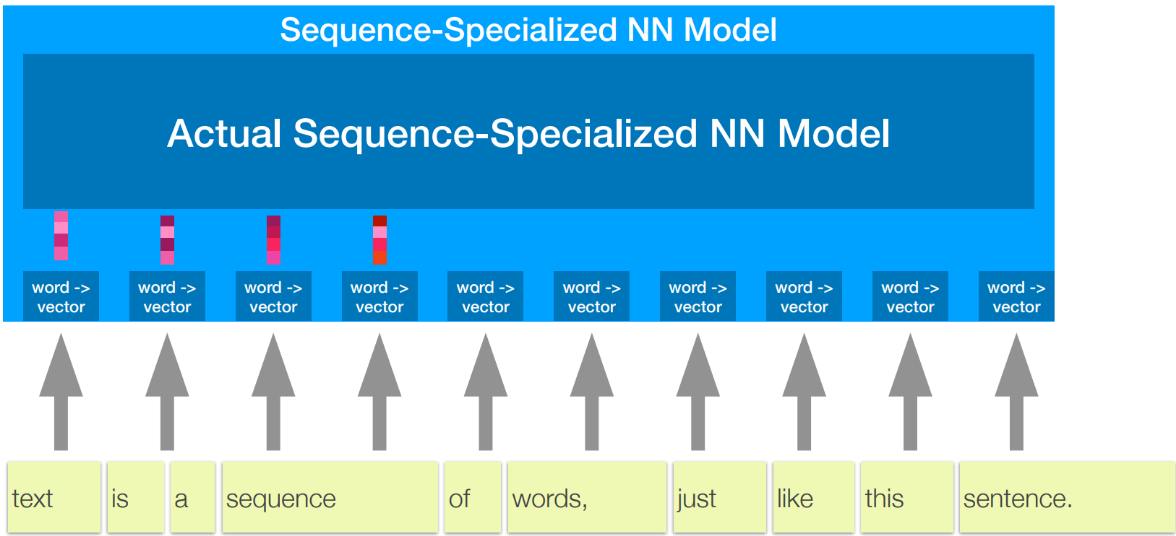
<table>
<tr><th>Illustration</th><th>Description</th></tr>
<tr><td>
</td><td></td></tr>
<tr><td>
</td><td>Split the sentence into sequence of words</td></tr>
<tr><td>
</td><td>Sequences with Single output
If sentient analysis: positive or negative? [0 or 1]</td></tr>
<tr><td>
</td><td>Sequences with Sequence output
If embedding learning: Each “Out n” is a vector that represents n-th word
Limit of this approach What if we want a chat bot? or translation? I.e., The output is not 1:1 to input words but about the whole input sequence.</td></tr>
</table>

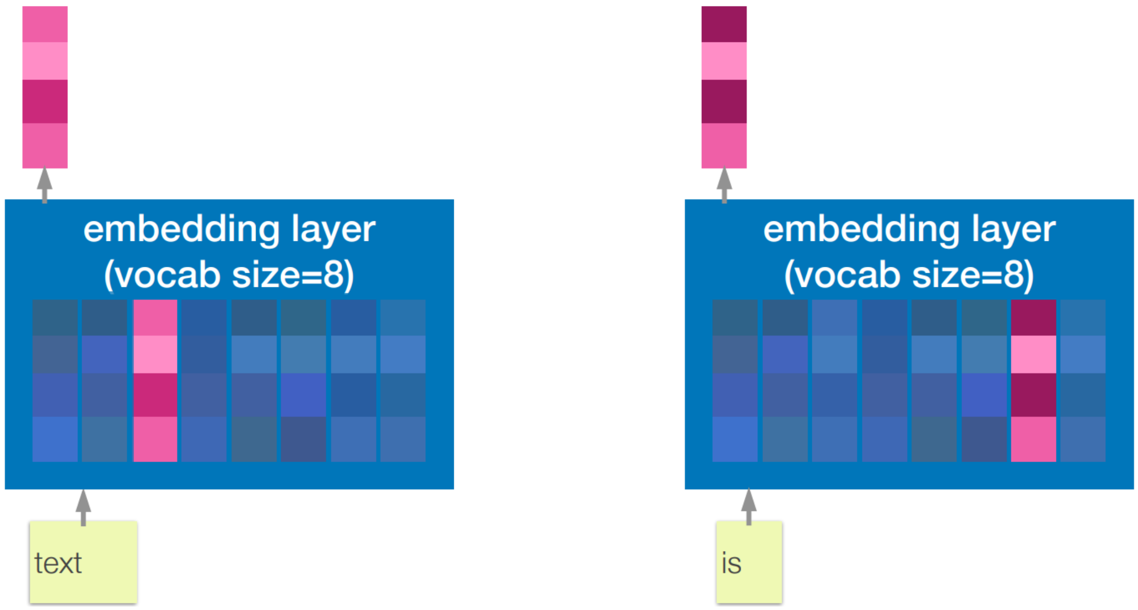
Illustration	Description
	Sequence-to-sequence Eg. Conversation
	Sequence-to-sequence Eg. Machine Translation

Word to vector (embedding)



Embedding layers

Embedding layer is a (trainable) Dense layer that maps each word to a vector



- vocabulary size = 8 in this cases
- each vector using a one-hot? representation

Advanced: It's not always "word"-based

There are **too many words** (like, millions of them) to handle. Words are not always completely independent to each other. e.g., "Speak" "Speaker" "Speaking", "Speakers", ..

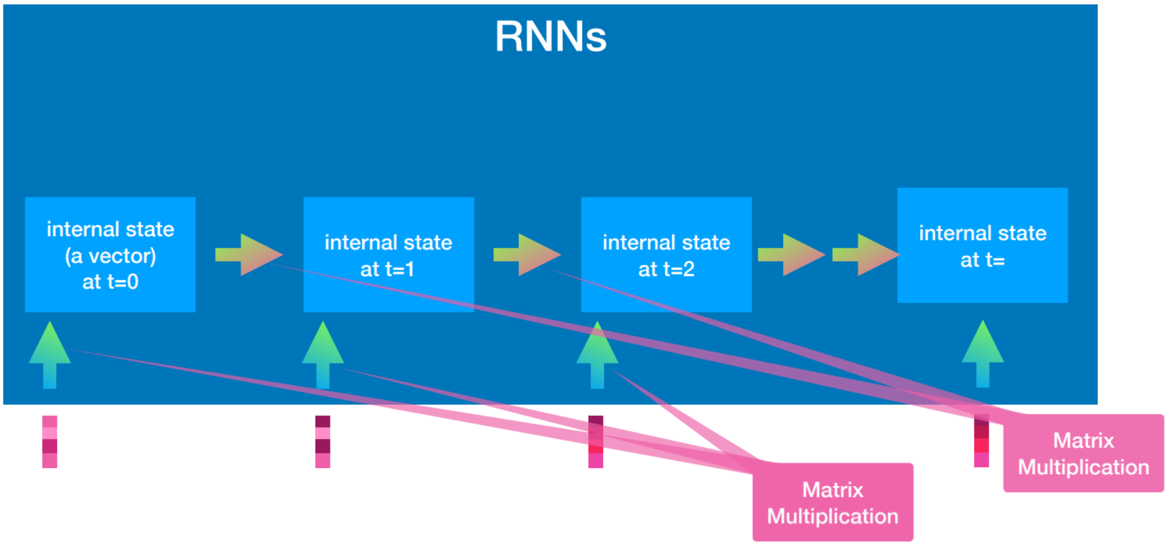
1. **Words**: used to be a choice: `speakers`
    - **Length**: A document can have few thousands words
    - **Vocab size**: even 50k is not enough; so out-of-vocab becomes an issue
2. **Characters**: `s`, `p`, `e`, `a`, `k`, `e`, `r`, `s`
    - **Length**: A document can have a hundred of thousands words (kinda too long)
    - **Vocab size**: English only has 26 alphabets: so it's good, but kinda too small
3. **Sub-word tokens**: `speak` - `er` - `s` (split the word into smaller units that somehow meaningful)
    - Can be optimal in both length and vocab size

3. Sequence-specialized Models

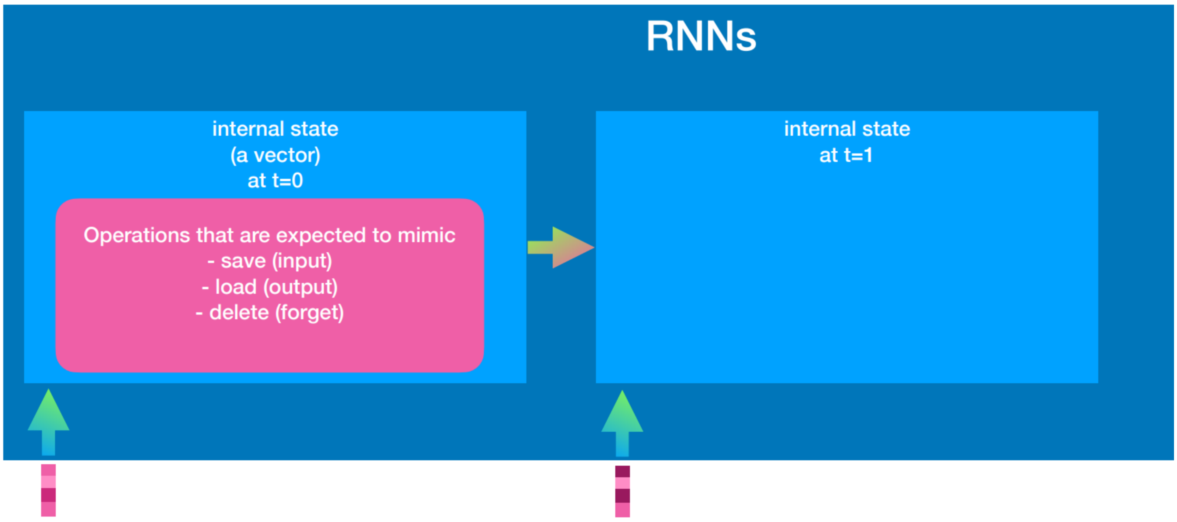
What do we want from such a model?

- Can handle a long sequence
- Can **remember** the sequence of input vectors, **process** them, and perform tasks **based on** the inputs.

RNNs: Recurrent Neural Networks

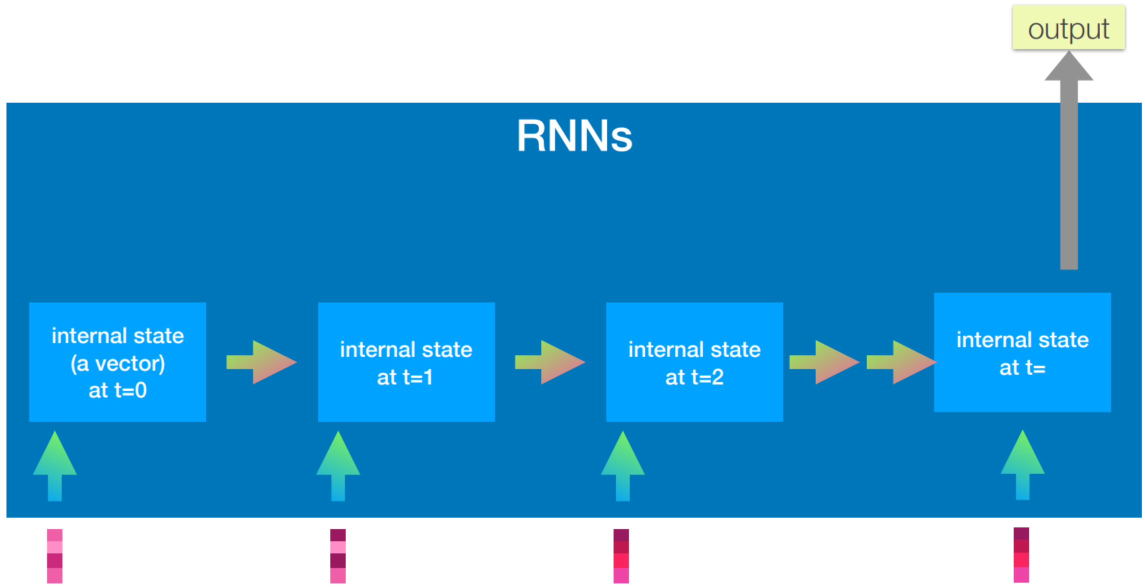


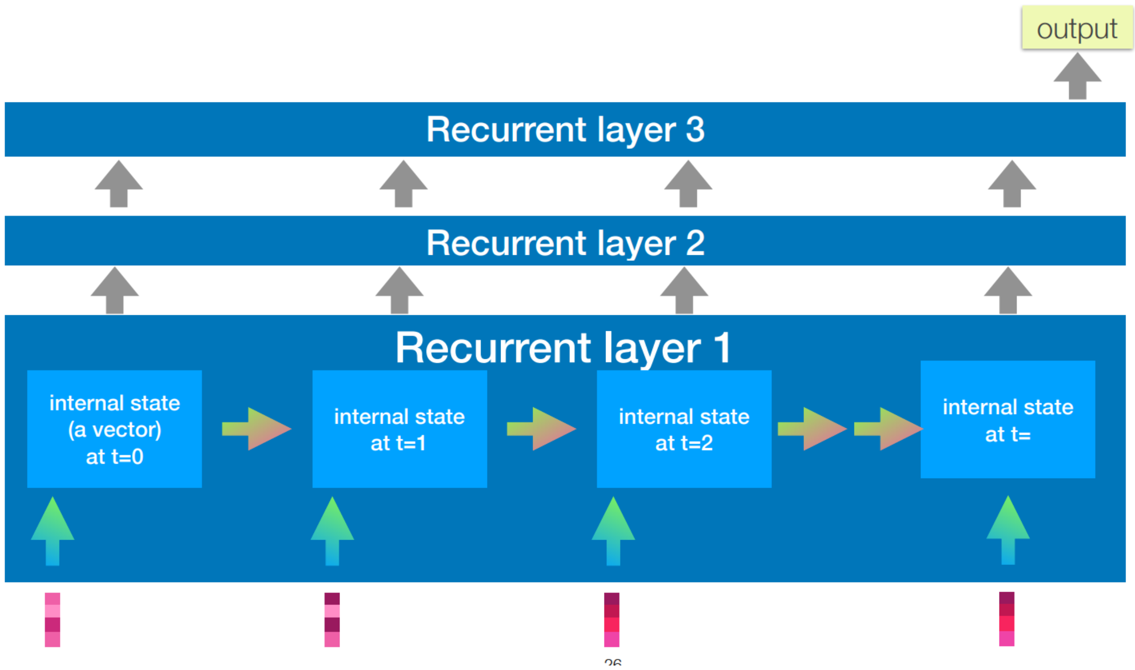
Inside a recurrent unit



- Operations that are expected to mimic
  - save (input)
  - load (output)
  - delete (forget)
- .. as long as they were trained to do so, implicitly, because perhaps they would be helpful to do the task,
- i.e., lower the loss and perform the training task

Output of RNN

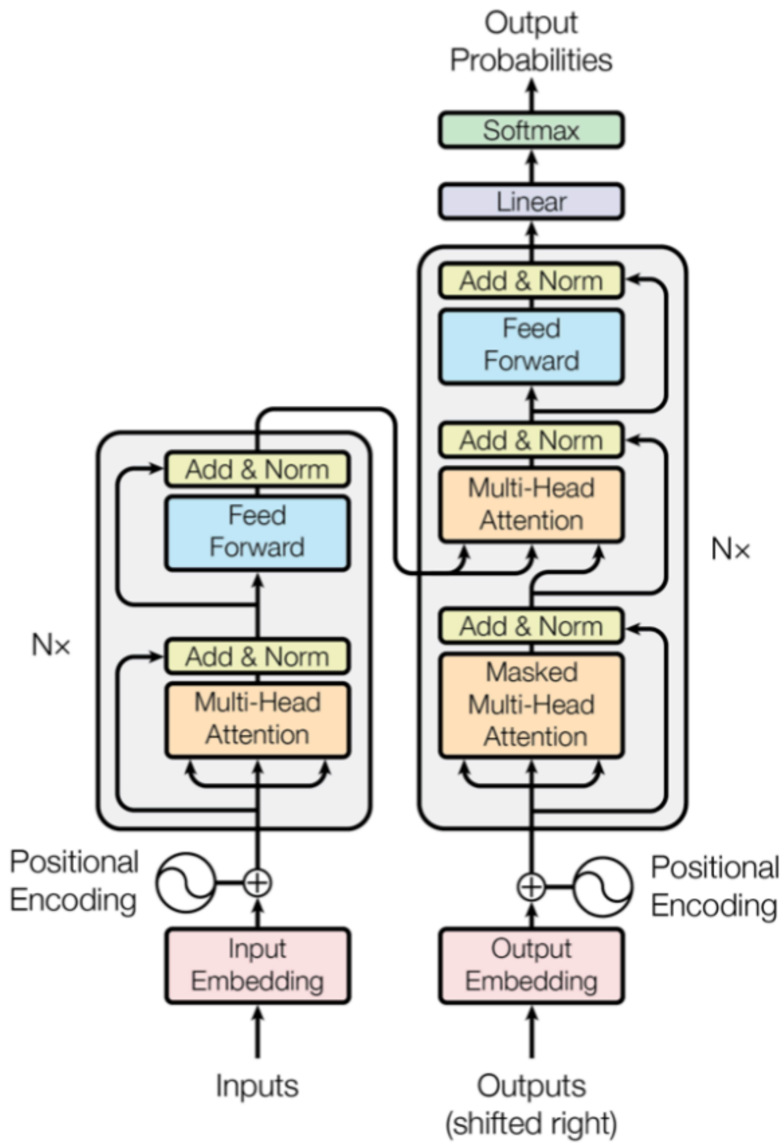


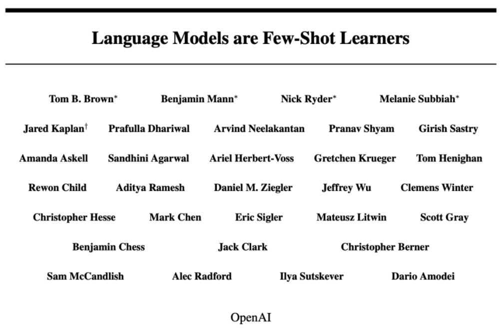


Pros and Cons of RNNs

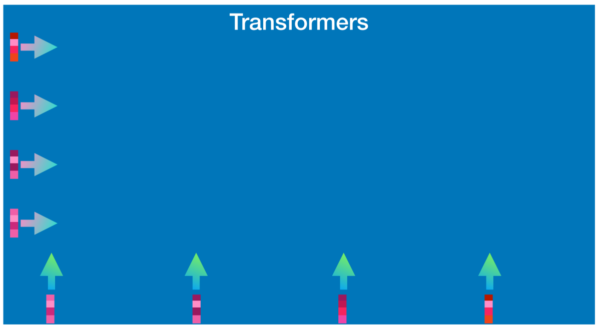
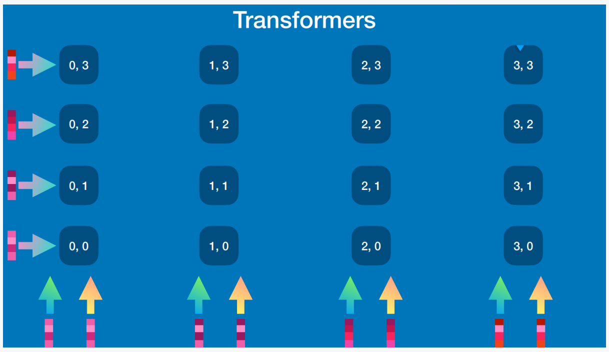
- **Pros**
  - It can handle sequences with arbitrary length.. in theory
  - With some modifications (e.g., LSTMs), it simply performs really well
  - Memory-efficient as the input sequence gets longer
- **Cons**
  - Long sequence == A very **deep** network → Difficult to train
  - N-length sequence → N-times matrix multiplication → Large latency
  - The final internal state is supposed to remember everything in the past → Is it even possible

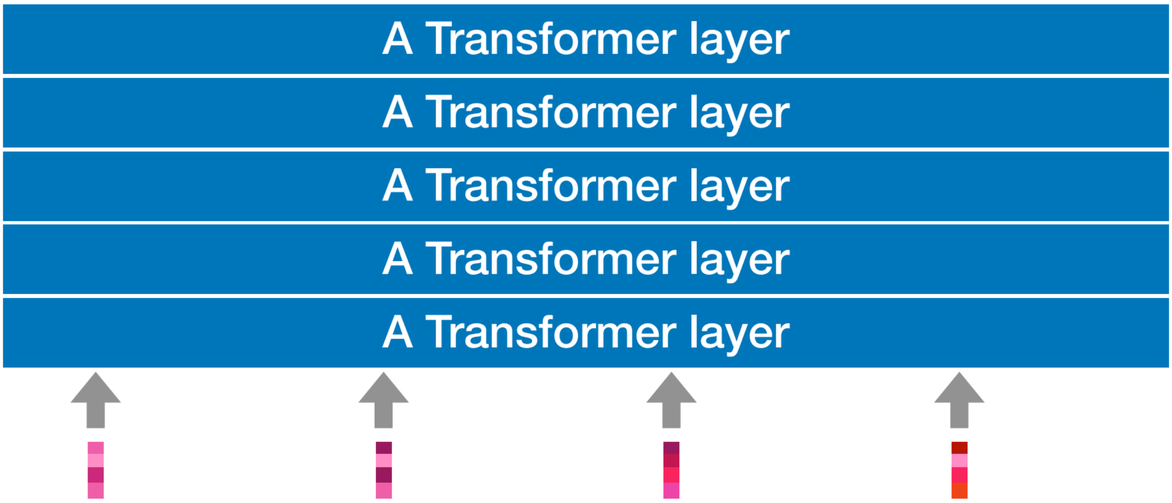
Transformers



First Paper about Transformers	GPT-3
 **Attention Is All You Need** **Ashish Vaswani*** Google Brain avaswani@google.com **Noam Shazeer*** Google Brain noam@google.com **Niki Parmar*** Google Research nikip@google.com **Jakob Uszkoreit*** Google Research usz@google.com **Llion Jones*** Google Research llion@google.com **Aidan N. Gomez*** † University of Toronto aidan@cs.toronto.edu **Łukasz Kaiser*** Google Brain lukaszkaiser@google.com **Illia Polosukhin*** ‡ illia.polosukhin@gmail.com	 **Language Models are Few-Shot Learners** **Tom B. Brown*** **Benjamin Mann*** **Nick Ryder*** **Melanie Subbiah*** **Jared Kaplan†** **Prafulla Dhariwal** **Arvind Neelakantan** **Pranav Shyam** **Girish Sastry** **Amanda Askell** **Sandhini Agarwal** **Ariel Herbert-Voss** **Gretchen Krueger** **Tom Henighan** **Rewon Child** **Aditya Ramesh** **Daniel M. Ziegler** **Jeffrey Wu** **Clemens Winter** **Christopher Hesse** **Mark Chen** **Eric Sigler** **Mateusz Litwin** **Scott Gray** **Benjamin Chess** **Jack Clark** **Christopher Berner** **Sam McCandlish** **Alec Radford** **Ilya Sutskever** **Dario Amodei** OpenAI

Everything connects to everything

Illustration	Description
	Input word vector, forming a 2d dimensional channel input
	Mutual "Relatedness" is computed by computing & comparing all the 4 x 4 = 16pairs, when input length is 4.



Pros and Cons for Transformers

- **Pros**
  - It outperforms RNNs and easy to train
  - It take all the mutual relationship between words
- **Cons**
  - n words $\rightarrow n^2$ relationships to compute and store $\rightarrow$ expensive!
  - It doesn't work with arbitrary length

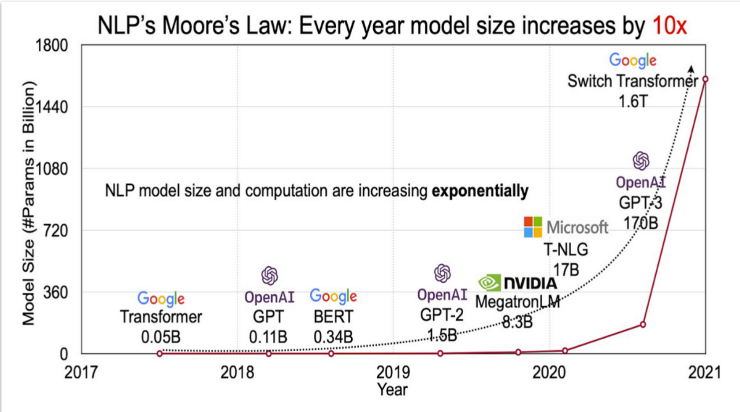
To Learn More

Search for these

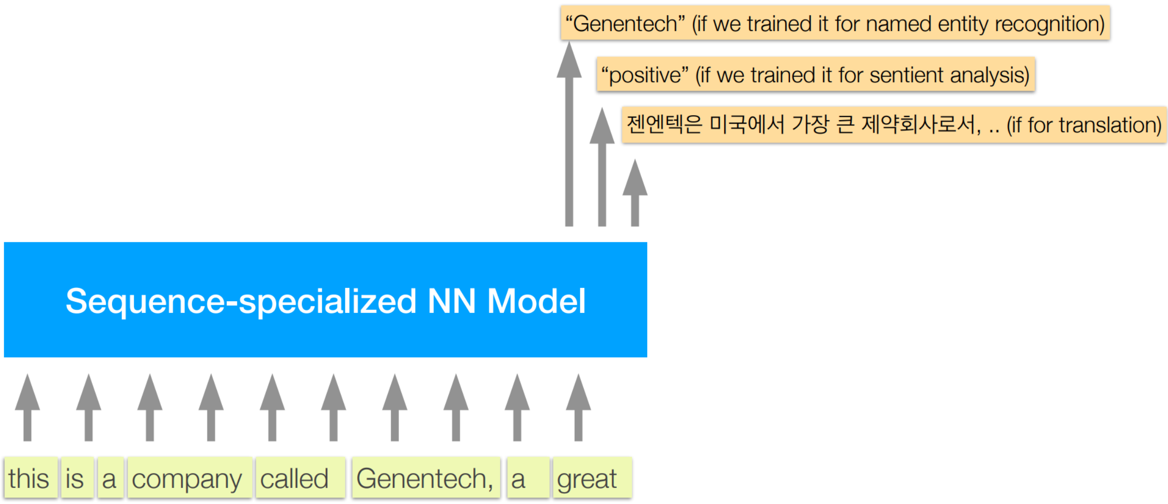
- Illustrated Transformers
- Annotated Transformers

4. Large Language Model

LLM = A lot of transformer layers



Coming back to Tasks

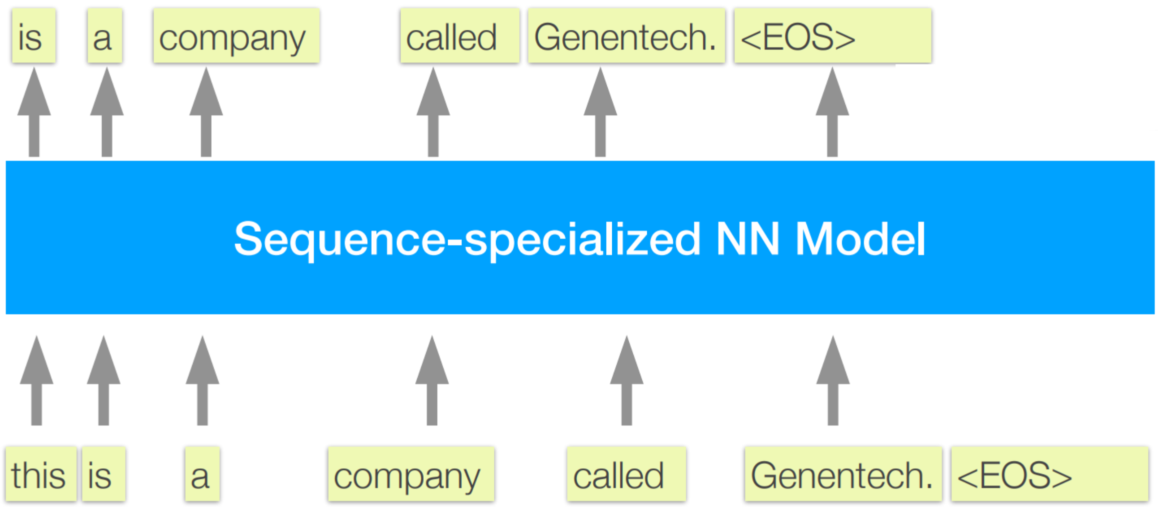


- Not ideal that we have to train N models for N tasks.

Autoregressive training for Pre-training

> Autoregressive models are a type of statistical model used in time series forecasting and **sequence prediction**.
>
> The core idea is that the **future state of a sequence depends solely on its previous states**. This is particularly powerful in fields like language modeling, where the sequence of words is predicted based on the preceding context.

As known as "next-token prediction"



- At one step, the model performs and learns from 6 token predictions. → Efficient!
- OpenAI and others trained LLMs with this objective; using A LOT of data. We call it **LLM pre-training**.
- After pre-training, the model becomes excellent at text completion; called "**foundational model**"

Next token prediction as pretraining task

- Used in all the modern LLMs (GPT, GPT2, GPT3, LLaMA, etc)
- Universally useful for some specific task.
- Effectiveness, relevance: That's how we speak and how we think to speak
- Efficiency: If 2048 token length, we make 2048 predictions, get 2048 losses (information about how the model is doing), make update related to 2048 of them!

Autoregressive training for finetuning

- Once the model is good at text completion, we can further train the model to **steer the direction of the answer**.
- A specific application is "instruction finetuning" i.e., **tune** the model to perform a given task.
- This makes GPT → ChatGPT.

Summary

- Language Models have advanced a lot, and these days they're really strong.
- The modern language models consists of deep learning models that can handle sequential data.
- Data processing is still a part of the work, although it's becoming less and less important.
- Language Models are not perfect!

What do they learn?

- Originally: to predict the next tokens
- Now: Perfect grammar and writing + Questionable logical thinking

Why is it so amazing?

- Text data
    - A LOT on internet
    - Very cheap to get and handle (unlike images, audio, music)
    - Language is a crucial and complex representation of our knowledge; arguably the most important invention of human species