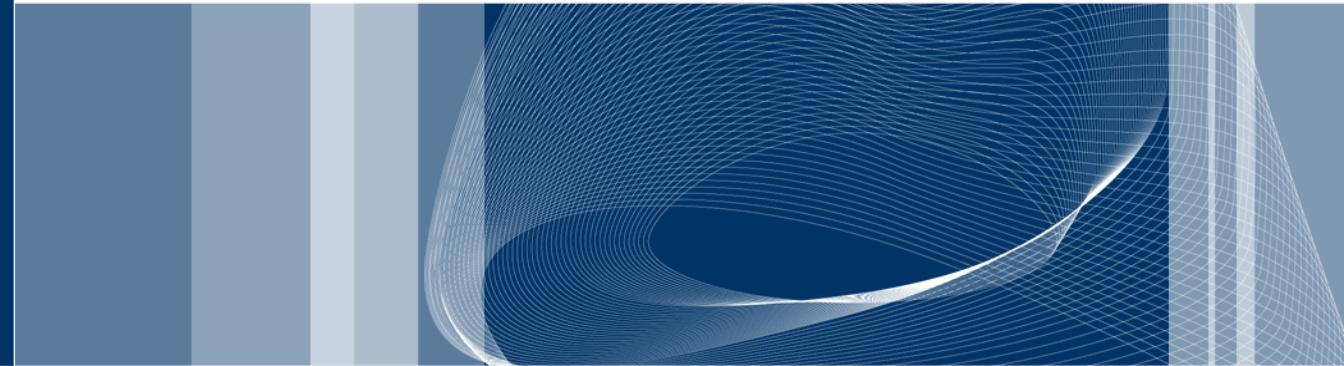




Natural Language Processing



Transformers

Natural Language Processing

Some slide content based on textbooks:

Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition by Daniel Jurafsky and James H. Martin
Machine Learning and Security: Protecting Systems with Data and Algorithms by Clarence Chio & David Freeman

ALICE was beginning to get very tired of sitting by her sister on the bank, and of having nothing to do: once or twice she had peeped into the book her sister was reading, but it had no pictures or conversely in it, " and what is the use of a book," thought Alice, " without pictures or conversation?" She was considering this, when suddenly, as she could, for the hot day made her feel very sleepy and stupid, whether the pleasure of eating the daisy-chain would be worth the trouble of getting up and picking the daisies, when suddenly a white rabbit with pink eyes ran close by her.

There was nothing so very remarkable in that; nor did Alice think it so very much out of the way to hear the Rabbit say to itself, " Oh dear ! I shall be too late !" (whether it really said this or not I have never quite been able to make out.)

(Alice had never seen a rabbit with either a waistcoat-pocket or a watch to take out of it, and



Miner Image source: <https://freepngimg.com/miner-1574424684>

Lecture Contents:

Introduction/revision

- What are Neural Networks?
- What is Deep Learning?
- Recurrent Neural Networks

Motivation

- Sequence-to-Sequence Models
- Attention Mechanisms
- Self-attention

Transformer architecture

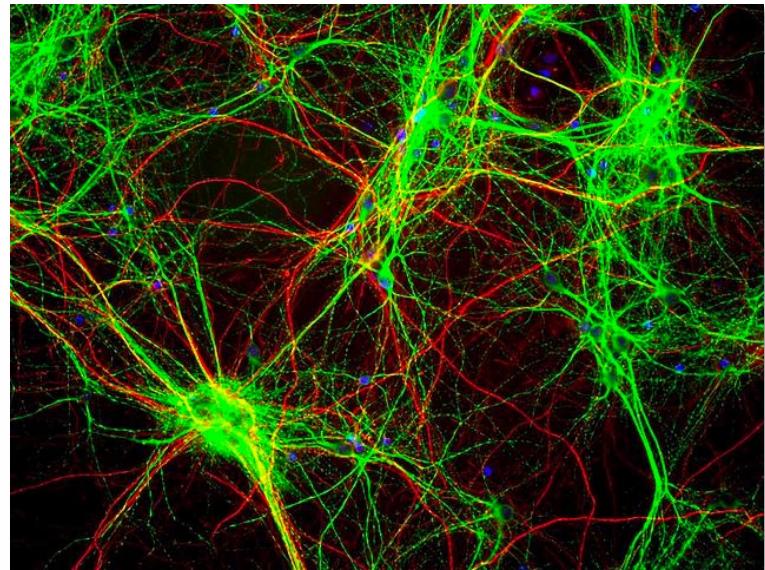
- BERT vs GPT

Tasks

- Text Generation with GPT
- Text Classification with BERT
- Other tasks

What are Neural Networks?

Brains and Neurons



Rat brain under microscope (by Gerry Shaw), source:
[https://commons.wikimedia.org/wiki/File:Culture_of_rat_brain_cells_stained_with_antibody_to_MAP2_\(green\)_Neurofilament_\(red\)_and_DNA_\(blue\).jpg](https://commons.wikimedia.org/wiki/File:Culture_of_rat_brain_cells_stained_with_antibody_to_MAP2_(green)_Neurofilament_(red)_and_DNA_(blue).jpg)

Brains composed of large number of **neurons**

- human brain has tens of billions
- **massive graph**: each node connects to 10,000+ others

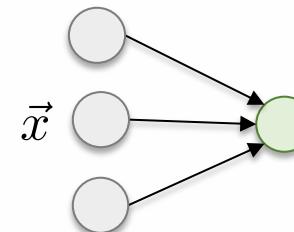
Neuron is **simple processing unit**:

- receives electrochemical stimulus from other neurons
- triggers output signal if sum of inputs exceeds threshold

Brain learns to perform complicated tasks

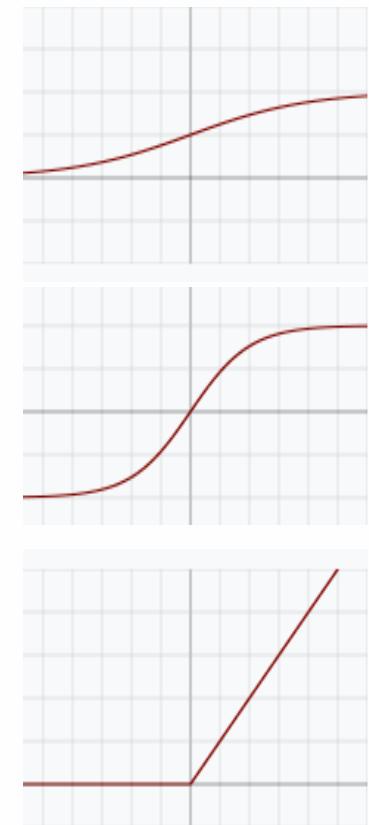
- by connecting neurons in certain patterns

Artificial Neural Networks



Artificial Neural Networks (ANNs)

- network of artificial (**simple model** of) neurons
- long history:
 - 1940s: understanding how neurons in nervous system work
 - 1970s: von-Neumann architectures outpaced NNs
 - 1980s: renewed interest, but computation prohibitive
 - 2010s: massive resurgence in popularity
- model neurons **as simple step functions**
 - **weight inputs** and **threshold** to produce output value
 - using non-linear **activation function**
 - typical examples: *sigmoid*, *tanh*, *rectified-linear unit (ReLU)*
 - see: https://en.wikipedia.org/wiki/Activation_function



Neural Networks: configuration

Create different types of models by varying:

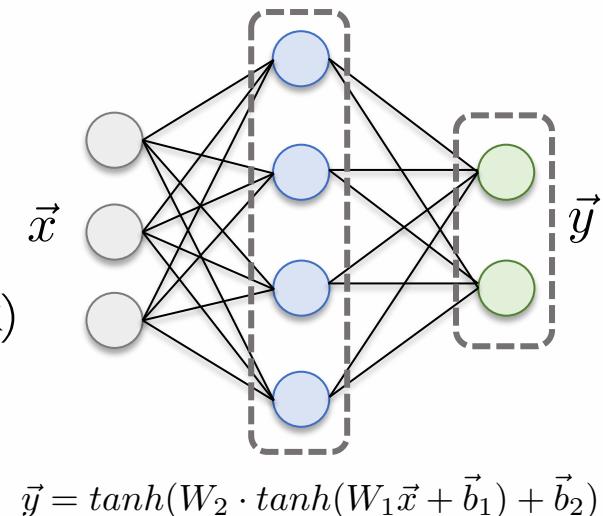
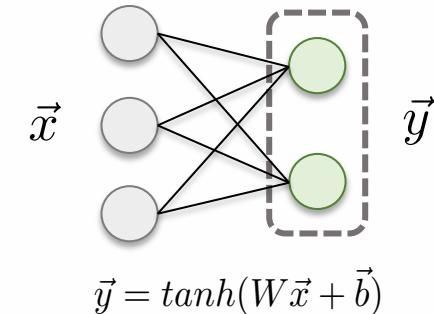
- topology (shape) of network
- activation function used
- loss function optimized (e.g. binary cross-entropy)

NNs made up of neurons arranged in *layers*

- each layer receives inputs from previous layer
- and if activated, emits outputs to next layer
- **internal layers** (neither input nor output of network) are called **hidden layers**
 - allow model to find non-linear decision boundary

Parameters:

- connection of two neurons has associated *weight*
- neuron has associated *bias* (threshold)



$$\text{CrossEntropy}(\theta) = -\frac{1}{n} \sum_i \log P(y_i|x_i; \theta)$$

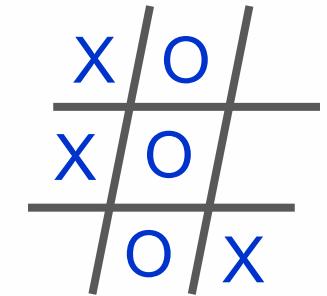
Example non-linear classification problem

Ran through **tic-tac-toe** example on board during lecture

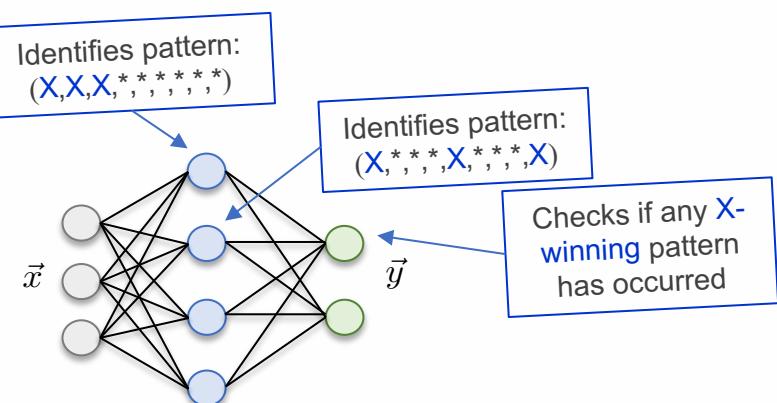
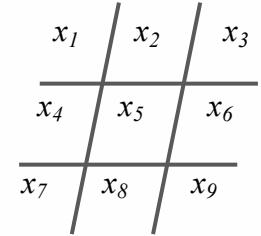
- aim is to classify boards a **X-wins**, **O-wins** or **nobody-wins**
 - 9 dimensional feature vector:
- example of non-linear classification problem
 - i.e. problem where no linear decision boundary can be found to separate the classes

Simple two layer neural network can

- first layer of neurons learn to identify simple winning pattern
 - E.g. 3 vertical crosses or 3 diagonal crosses
- second layer identifies the winners
 - i.e. performs disjunction



$$\begin{aligned} \mathbf{x} &= (\textcolor{blue}{X}, \textcolor{blue}{O}, _, \textcolor{blue}{X}, \textcolor{blue}{O}, _, _, \textcolor{blue}{O}, \textcolor{blue}{X}) \\ &= (1, -1, 0, 1, -1, 0, 0, -1, 1) \end{aligned}$$

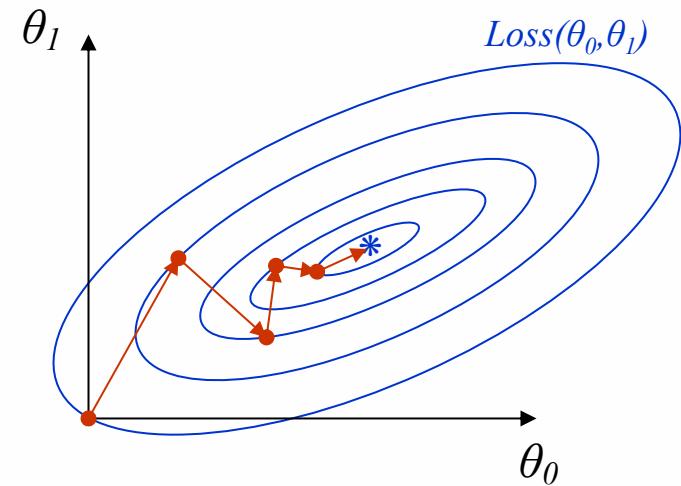
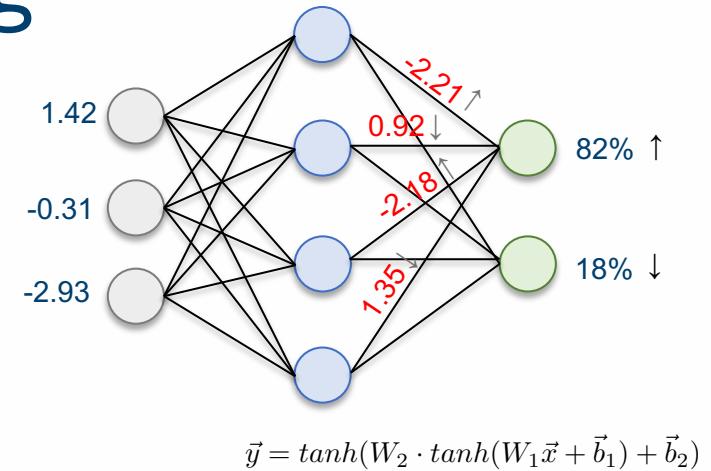


Neural Networks: training

Parameters learnt by process of *backpropagation*

- initialize all **weights/biases** randomly
- for each sample in training set, perform:
 - 1) **forward pass**: feed input through network to calculate **prediction**
 - 2) **backward pass**: update parameters:
 - if prediction was correct, **reward** connections that produced it
 - otherwise penalize connections that contributed to wrong result
- this is just a **gradient descent** routine
 - where the function being optimised is nested
 - and chain rule from calculus used to compute derivative with respect to each parameter

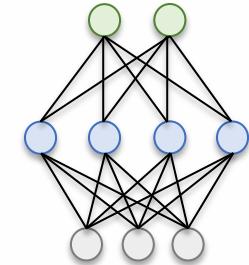
$$\nabla Loss = \nabla \text{MSE}(a, b) = \left(\frac{\partial \text{MSE}(a, b)}{\partial a}, \frac{\partial \text{MSE}(a, b)}{\partial b} \right)$$



Neural Networks: properties

Neural networks

- extremely powerful learners
 - network with single hidden layer can learn any function, providing layer is wide enough
- lots of variation in network structures
- used for both supervised and unsupervised learning



Many hyperparameters to tune for NN, including:

- network architecture,
- type of activation function

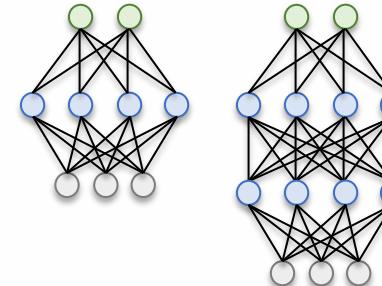
Lots of hardware & software optimizations available for training NNs

- more *computationally expensive* than other learners
 - e.g. decision tree

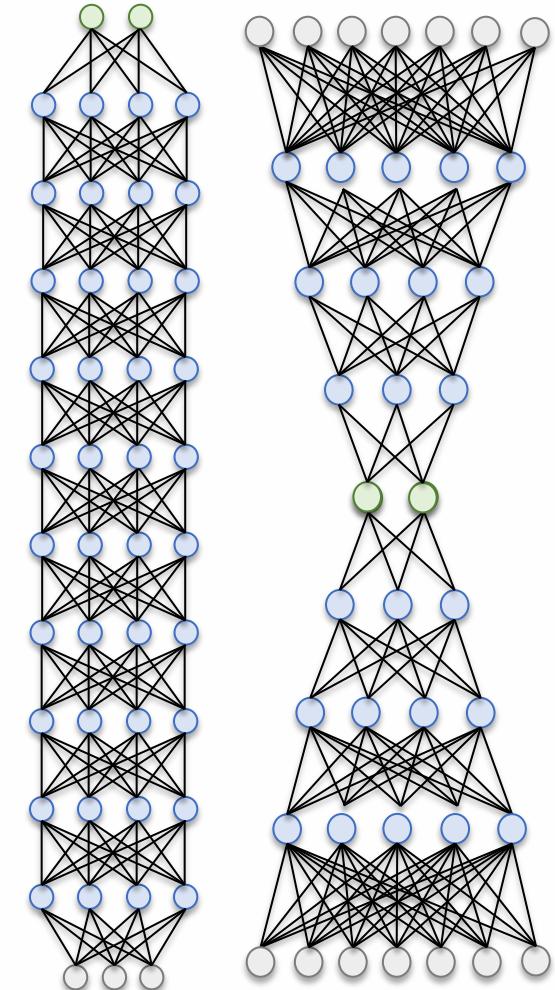
What is Deep Learning?

What is deep learning?

SHALLOW models



DEEP models



Deep Neural Networks with **MANY** layers

- why do we want many layers?
 - massively **improves performance**, but why?
 - allows network to **learn hierarchy of useful features** automatically
- what are the downsides?
 - need **lots of training** data!
 - and large **computing resources** (GPUs)
 - can be unstable & **much harder** to train ...
 - and even with GPUs, take a **long time** to train

Deep Learning: why now?

Massive popularity due:

- to **amazing performance** on many tasks -- especially with complex raw data types like images and text
- also greatly **simplifies training pipeline**
- and allows for **transfer learning** -- reuse knowledge from previously trained systems

Possible due to:

- **hardware advancements:**
graphics processing units (GPUs) for fast matrix multiplication
- **huge amounts of data**
available to learn features for complex tasks like image recognition
- **clever architectures**
e.g. convolutional, recurrent and self-attention networks
- **improved training procedures**
fast gradient descent routines, batch normalisation, dropout, etc.
- **toolkits**
like PyTorch/TensorFlow that perform automated differentiation



Why is deep learning important for text?

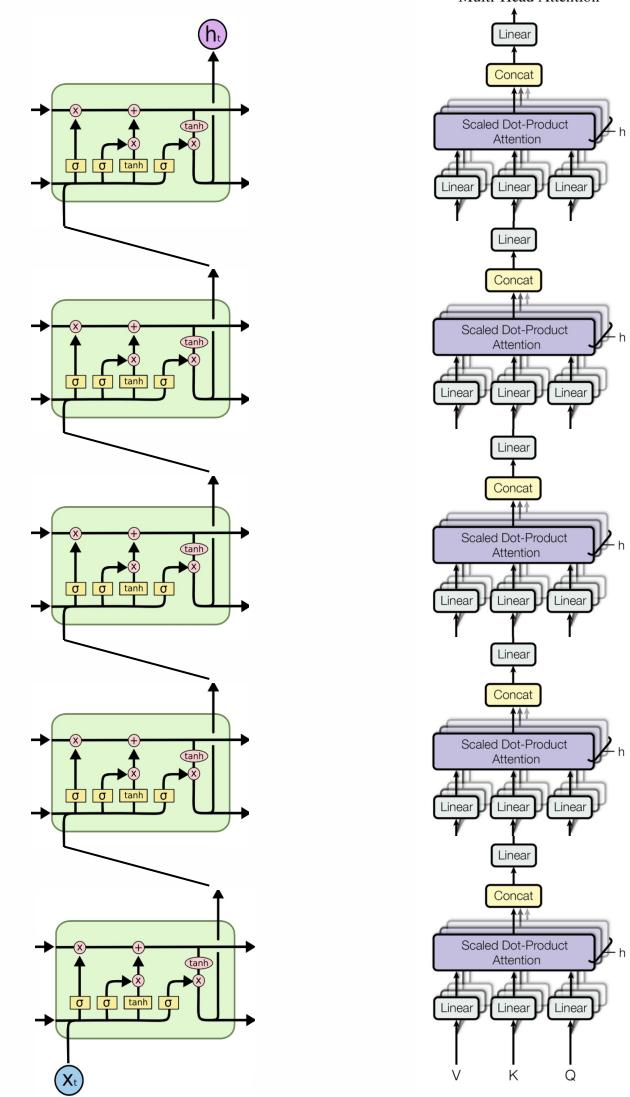
State-of-the-art performance for most text processing tasks

- including **classification, summarisation, generation, translation, etc.**

Until 2017, deep architectures involved stacking many layers of LSTMs on top of each other (e.g. ELMO)

In 2018 a new architecture has emerged, called a Transformer

- makes use of **self-attention** networks
- more on that in a minute ...



Images source: <http://colah.github.io/posts/2015-08-Understanding-LSTMs/>

Image Source: "Attention Is All You Need" by Vaswani et al. <https://arxiv.org/pdf/1706.03762.pdf>

Deep Learning: pros and cons

Lot of hardware & software optimizations available for training NNs

- *significantly more computationally expensive* to train than a decision tree

Lots of hyperparameters to tune for NN, including:

- network architecture,
- type of activation function,
- fully or sparsely connected layers
- dropout (for robustness), batch normalization, learning rate,

Recurrent Neural Networks

- revision

Recurrent Neural Networks (RNNs)

Word embeddings allow us to **represent words** in a semantic space ✓👍

- still need to **aggregate information** over longer contexts

RNNs provide general way to accumulate information

- by combining **context** from previous words
- with the **embedding** of current word

RNNs are simply models which:

- take 2 vectors as input: <current input, previous state>
- produce 2 vectors as output: <current output, updated state>

They can be used to process **arbitrarily long** input contexts

- i.e. encode a sequence of text to a single embedding

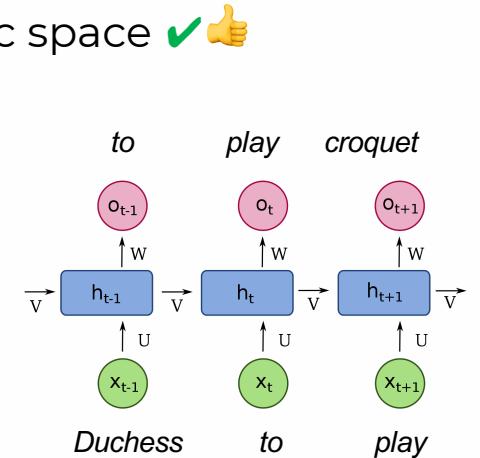
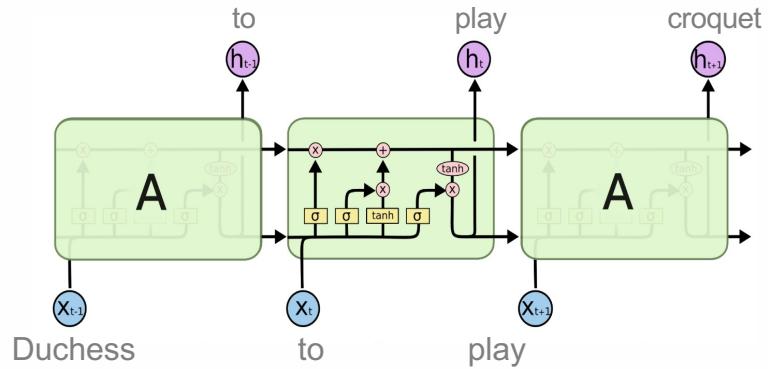


Image source:
https://en.wikipedia.org/wiki/Recurrent_neural_network



Long Short Term Memory (**LSTM**) networks

- allow for **long term dependencies**
- gates allow model to **remember/forget** information
- model learns what type of information to keep and what to discard
- **default** operation is to pass information from one state to the next

Images source: Understanding LSTM Networks by Christopher Olah
<http://colah.github.io/posts/2015-08-Understanding-LSTMs/>

'For the Duchess. An invitation from the Queen to play **croquet**.' The Frog-Footman repeated, in the same solemn tone, only changing the order of the words a little. 'From the Queen. An invitation for the Duchess to play
... ???'

Stacked LSTMs and contexts

Stacked LSTMs: layers of LSTMs placed on top of each other

- have uncanny ability to deal with **nested contexts**
- they won't forget to close the brackets at the end of a maths expression

PDF compiled from Latex source code that was generated by a multi-layer LSTM (by Andrej Karpathy)

<http://karpathy.github.io/2015/05/21/rnn-effectiveness/>

For $\bigoplus_{n=1,\dots,m} \text{where } \mathcal{L}_{m,\bullet} = 0$, hence we can find a closed subset \mathcal{H} in \mathcal{H} and any sets \mathcal{F} on X , U is a closed immersion of S , then $U \rightarrow T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \text{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \rightarrow V$. Consider the maps M along the set of points Sch_{fppf} and $U \rightarrow U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ???. Hence we obtain a scheme S and any open subset $W \subset U$ in $\text{Sh}(G)$ such that $\text{Spec}(P') \rightarrow S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S . We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x' \in S'$ such that $\mathcal{O}_{X,x'} \rightarrow \mathcal{O}_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\text{GL}_{S'}(x'/S'')$ and we win. \square

To prove study we see that $\mathcal{F}|_U$ is a covering of \mathcal{X}' , and \mathcal{T}_i is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and \mathcal{F}_p exists and let \mathcal{F}_i be a presheaf of \mathcal{O}_X -modules on \mathcal{C} as a \mathcal{F} -module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{\mathcal{M}}^\bullet = \mathcal{I}^\bullet \otimes_{\text{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1} \mathcal{F}$$

is a unique morphism of algebraic stacks. Note that

$$\text{Arrows} = (\text{Sch}/S)^{opp}_{fppf}, (\text{Sch}/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \longmapsto (U, \text{Spec}(A))$$

is an open subset of X . Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S .

Proof. See discussion of sheaves of sets. \square

The result for prove any open covering follows from the less of Example ???. It may replace S by $X_{\text{spaces},\text{étale}}$ which gives an open subspace of X and T equal to S_{Zar} , see Descent, Lemma ???. Namely, by Lemma ?? we see that R is geometrically regular over S .

Contexts in natural language

The ability to deal with contexts is useful for natural language too

- consider gender and possessive pronouns:

- fill in gaps in following sentences with one of {he, she, his, or her}

My mother was taking on the phone to __ friend Jim. Jim said that a favourite game of __ is confusing students. Replying, my mother said that __ should find a better hobby.

- answer: ("her", "his", "he"), because mother is feminine and Jim is masculine.
 - LSTM is able to associate correct gender with each position.

- consider sentiment and scoping of negation:

- What's more likely to come next in these sentences: "**friendly**" or "**moo**dy"?

I get along well with her brother. He's always so __

I don't get along well with her brother. He's always so __

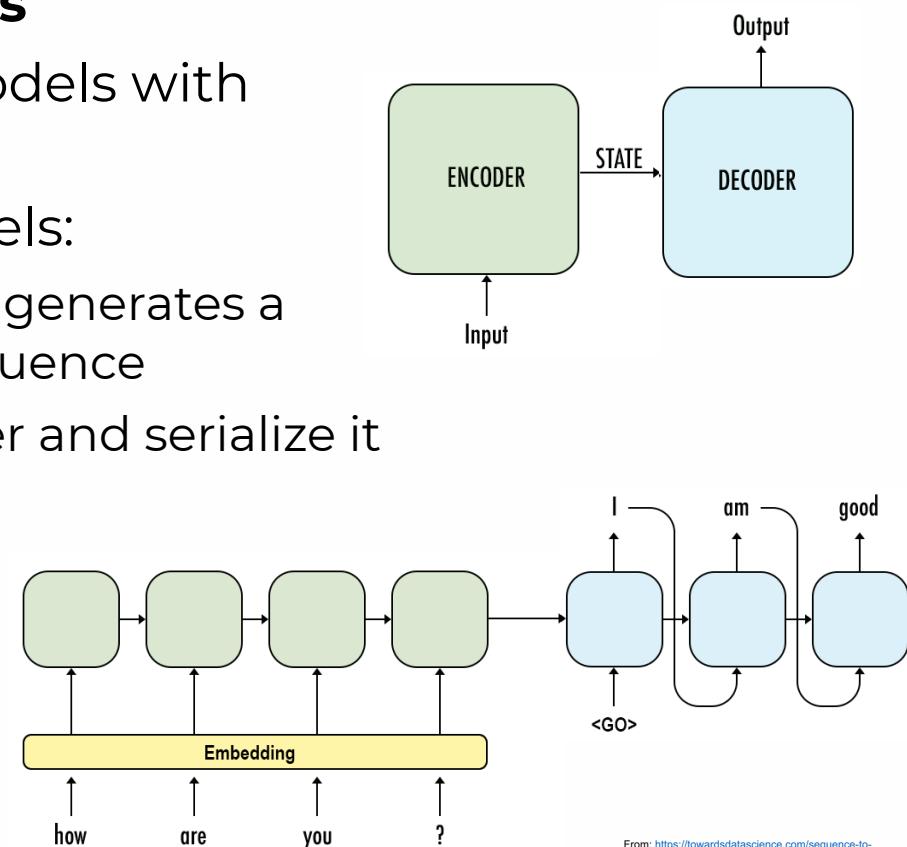
I don't know how anyone could not get along well with her brother. He's always so __

Sequence-to-sequence models

Sequence to sequence (seq2seq) models

LSTMs are so powerful that they were soon used for **translation** and **dialog systems**

- How can we learn translation models with LSTMs?
- By training 2 different RNN models:
 - 1. encoder:** reads in input text and generates a representation for the entire sequence
 - 2. decoder:** takes output of encoder and serialize it into new text one word at a time

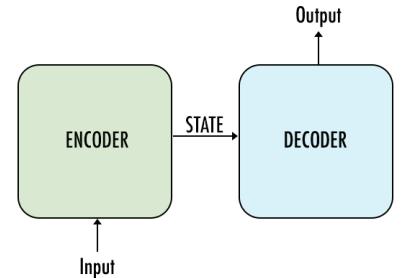


From: <https://towardsdatascience.com/sequence-to-sequence-model-introduction-and-concepts-44d9b41cd42d>

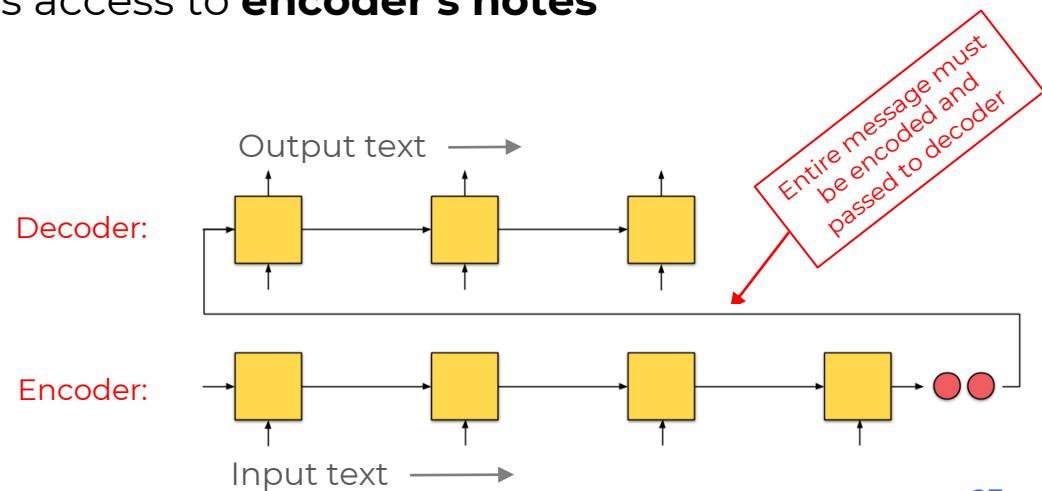
Translating text

Ever thought about poor interpreters translating politicians during meetings?

- must wait for rambling politician to stop speaking before they can start translating...
- that's a lot of stuff to remember!
- same problem for encoder-decoder architecture
 - **too much information** to pass through to the decoder
 - easier to translate if decoder has access to **encoder's notes**



From: <https://towardsdatascience.com/experience-in-sequence-what-is-encoder-decoder-540d416d4f>



23

Source: <https://towardsdatascience.com/attention-5ec4ad276ee3>

Attention mechanisms

Attention!

Attention is a critical building block for modern image and text processing

- what is attention?
- why it is implemented?
- how does it work?



WASHINGTON
In what is being called a crucial step forward in solar exploration NASA officials announced Wednesday a new mission to launch a chimpanzee directly into the sun. Chimpanzees are our closest biological relative so we can learn a great deal by observing how they react to being deposited into the sun's plasma core said NASA Administrator Charles Bolden adding that the single occupant capsule would contain sophisticated instruments that would monitor the effects of the sun's 27 million degree interior on the physiological functions of the animal. Hopefully what we learn from this mission will pave the way for sending human astronauts into the sun on a regular basis. Bolden went on to suggest that should humans be successfully launched into the sun there may one day be a permanent colony there.

Towards attention

Attention models

- make encoded input available to decoder
- provides a direct route for the information to flow from input to output

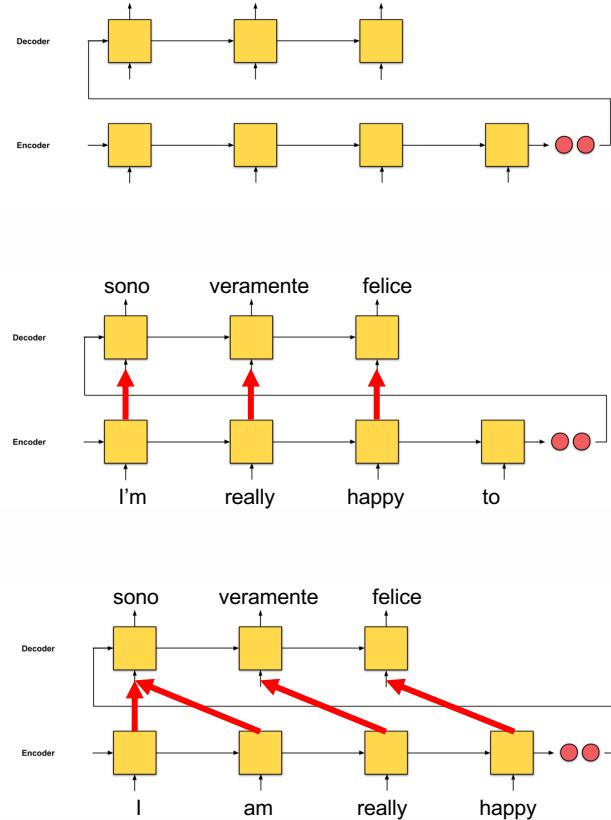
Why not directly map input words to output words?

- because across languages **different number of tokens** required to describe same concept

“apple tree”
=> “Apfelbaum”

- and **different word order** is often used:

“United Nations General Assembly”
=> “Assemblea Generale delle Nazioni Unite”

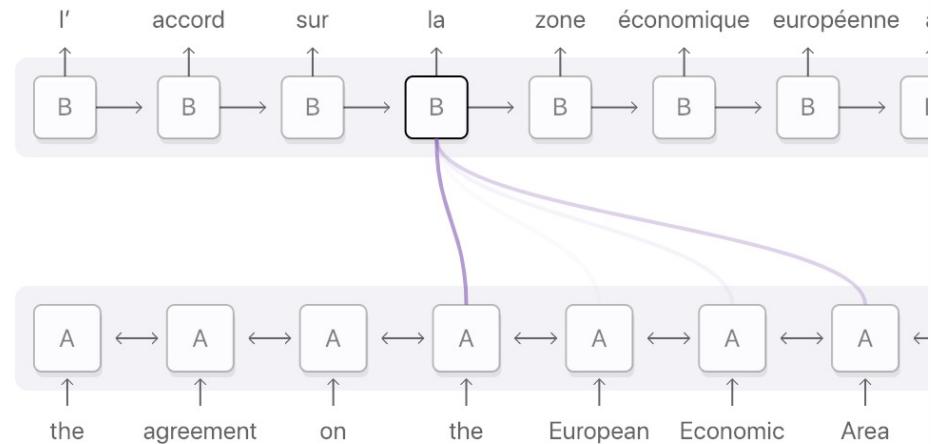


Adapted from: <https://towardsdatascience.com/attention-illustrated-attention-5ec4ad276ee3>

Towards attention (cont.)

Generating the right output word

- often requires knowing **more than just the current word** in input
- indeed it can require knowledge of a **future word** in the sentence
 - e.g. for determining the gender of the determinant:



Source: <https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3>

Need for attention

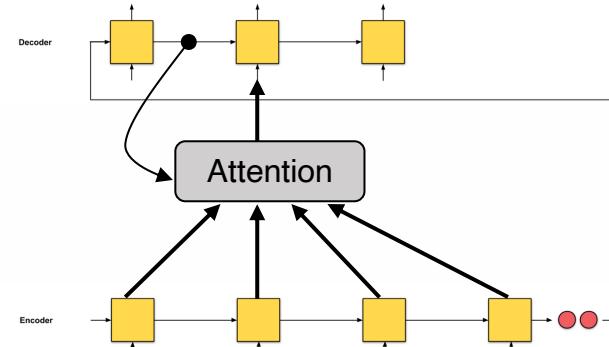
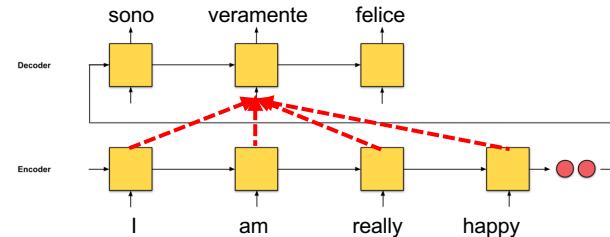
Need mechanism that can:

- pass information from embeddings of input word to corresponding output word

Attention:

- provides **direct route** for information to flow from input to output

What information flows into the decoder is controlled by **previous state of decoder**



Adapted from: <https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3>

How does attention work?

Similarity is computed between **state of decoder** and **output embedding** for each term

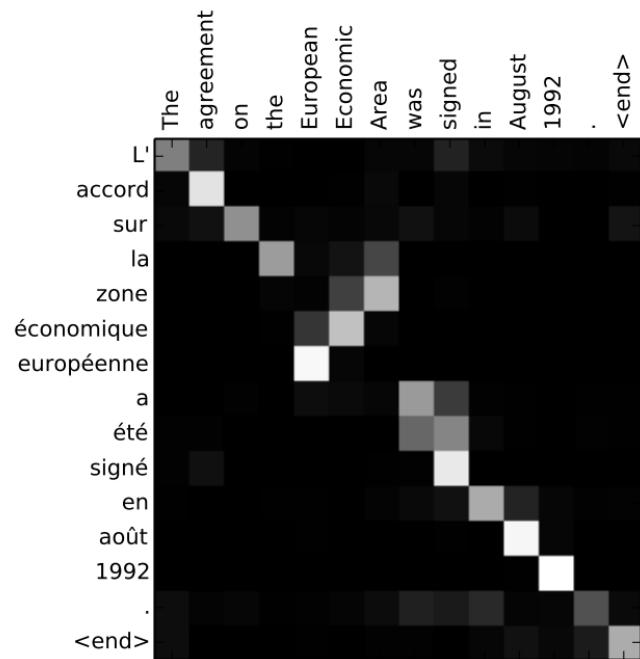
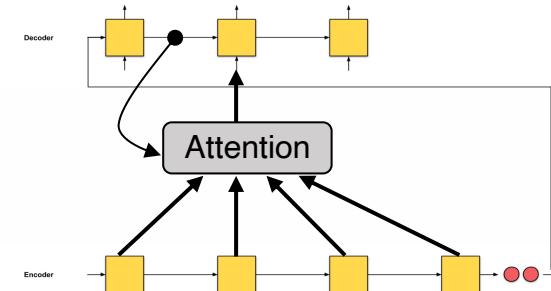
- $\text{weight}[i] = \text{softmax}(\text{similarity}(\text{decoder-state}, \text{embedding}[i]))$

How is the similarity computed?

- in additive attention, similarity function is computed by **concatenating decoder state** and **encoder embeddings** in a **feedforward network**
- in multiplicative attention, simply compute the **dot product between the two embeddings**

soft-attention produces **weighted average** over input embeddings

- example attention maps for English to French translation:



Source: 2015 paper by Bahdanau et al.: <https://arxiv.org/pdf/1409.0473.pdf>

Problem: slow training of
Recurrent Neural Networks

Training costs of RNNs

Lessons from deep learning

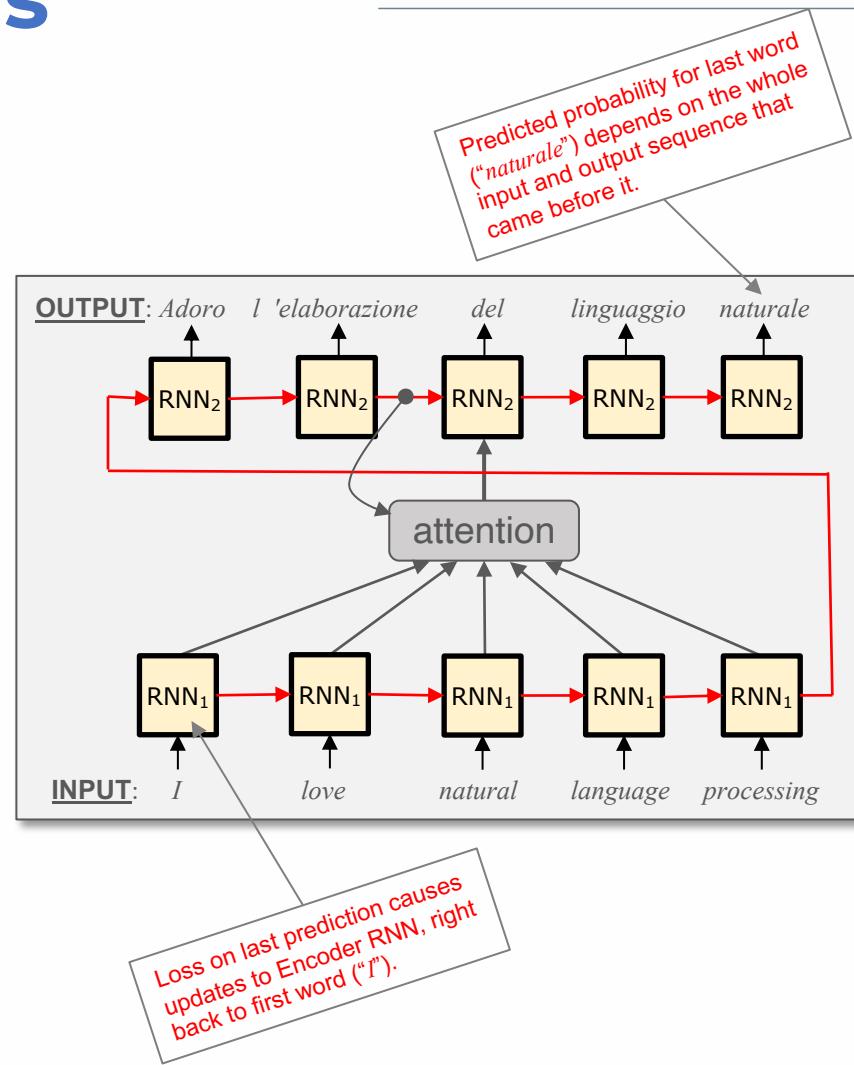
- **deeper models work better** than shallow ones
- since each layer builds on simpler features from layer below

Problem with training RNNs:

- to generate prediction, information must propagate from **first position of encoder** to **last position of decoder**
- & gradient information must pass back along entire sequence to update parameters
- calculation must be done sequentially (cannot be parallelised) making training time linear in length of text $O(|\text{input}|+|\text{output}|)$
- sequential model causes high training time & **prevents learning deep networks** with many layers

But during training:

- already know the output we want to see
- and now have attention mechanism passing information directly from input to output
- so can't something be done to speed up the inference?



Removing the RNN

During training:

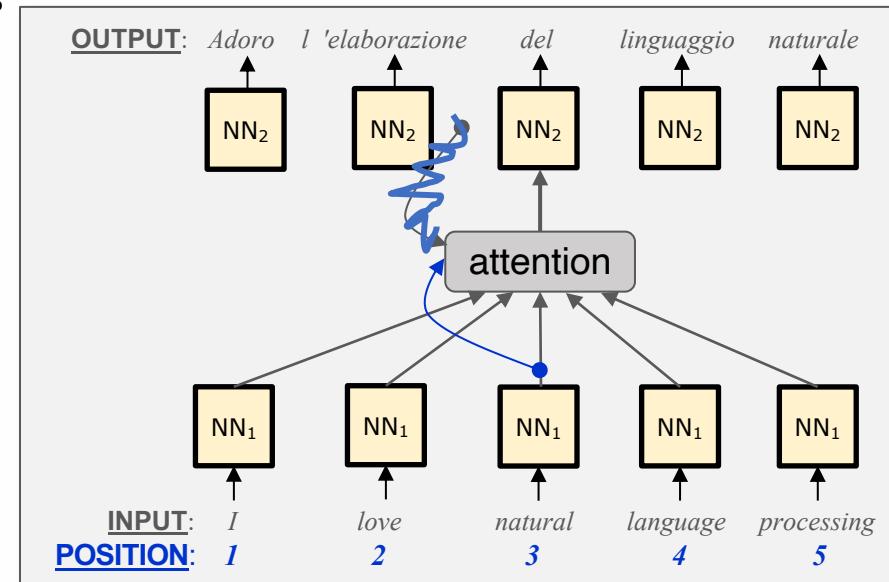
- already know **entire output** we want
- and have attention mechanism that **passes information directly** from input to output

CRAZY IDEA:

- What happens if we **remove recurrent links** from the encoder and decoder?
 - just have a NN encoder/decoder without the recurrent part

Creates two problems:

1. what should use for attention query?
2. lose all information about order of words



Possible solutions:

1. use **current output of encoder as query**
rather than context of decoder
 - but what would that even mean?
2. add **position information directly to the data** provided of the encoder
 - e.g. let the model learn an embedding to represent position 1, 2, etc.

Self-attention

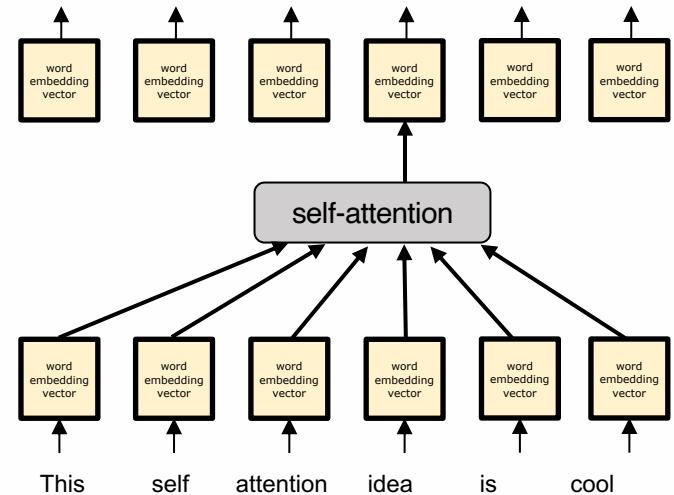
So what is self-attention?

Self attention is a mechanism for:

- combining word embedding vectors to produce new word embedding vectors
- each high-level embedding is **weighted average** of word embeddings below it

Weights are computed:

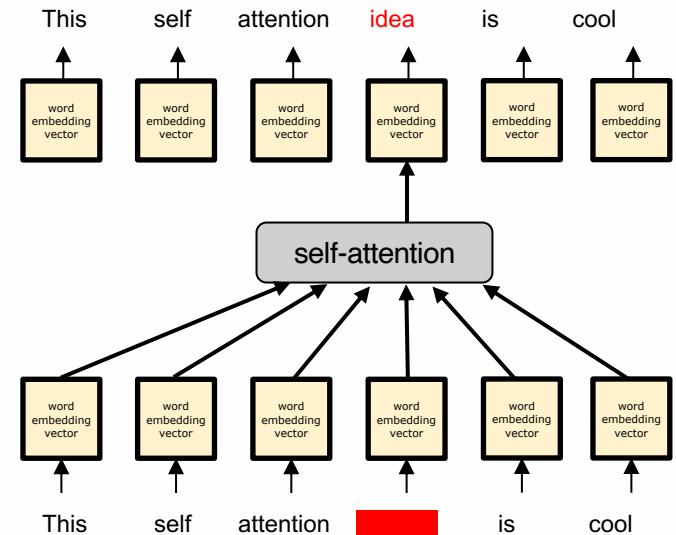
- based on similarity between embeddings in respective positions
- model parameters control the process, learning how best to compute the weights



So what is self-attention?

Self attention models are trained to recover missing words from the input sentence

- i.e. to perform the language modeling task



Motivating the need for self-attention

To understand why self-attention is useful for language models, consider that

- words take on **different meanings** depending on their context
- attention mechanism allows representation to **depend on context**
- learns **weighting function** over lower-level embeddings of context terms

Sentence 1: *I arrived at the bank after crossing the street.*
 Sentence 2: *I arrived at the bank after crossing the river.*

What type of bank are we talking about here, a river bank or a financial bank?

Level 1: *I arrived at the bank after crossing the river.*

Information from embedding for 'river' passes to 'bank' reinforcing the interpretation 'river bank'

Level 0: *I arrived at the bank after crossing the river.*

initial embedding for term 'bank' contains both meanings: 'river bank' and 'financial bank'

Initial embedding for 'river' and 'bank' should share similar interpretations leading to high self attention weight for word river

Transformer architecture

Inside the Transformer

Original Transformer from 2017 (“Attention is all you need”) paper

- was brilliant
- but looked rather complicated because it contained both an encoder and a decoder

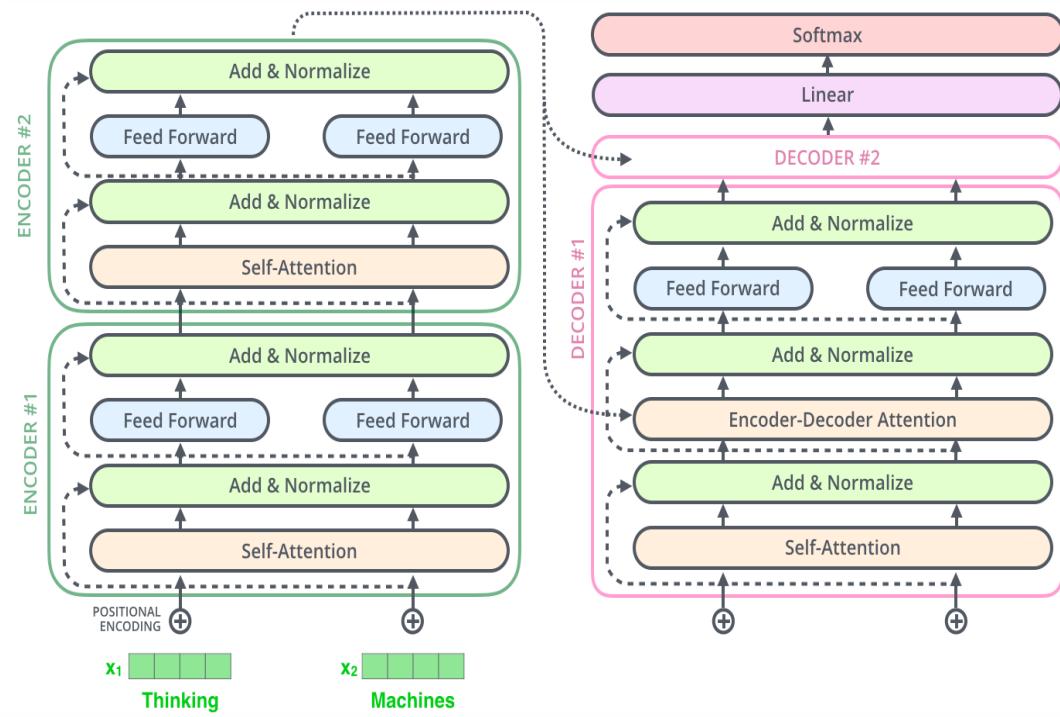


Image Source: <http://jalammar.github.io/illustrated-transformer/>

Inside Transformer (cont.)

But the internal architecture is actually surprisingly simple

Basic self-attention module contains:

- **multiple attention heads** working in parallel
- **feedforward network**, with **residual connections** and **normalisation**

Architecture is word position agnostic

- so **positional encoding** provided as additional input to bottom layer

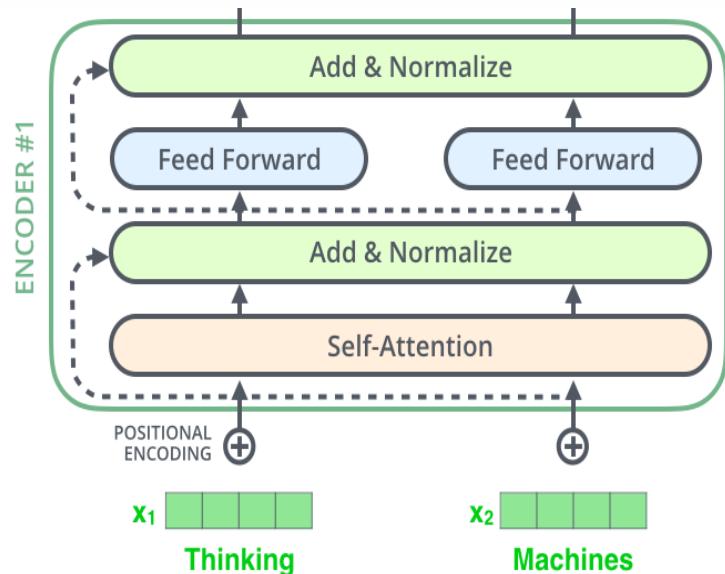


Image Source:
http://tlayman.github.io/lily_starter-transformer/

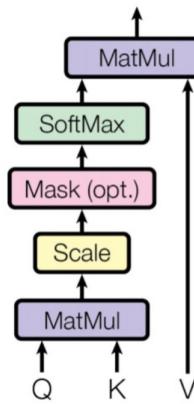
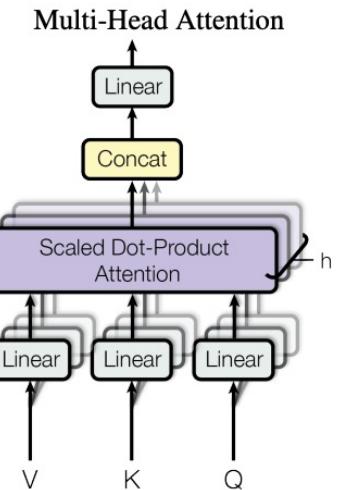
Scaled dot-product attention

Three components of self-attention:

- **query** → what we are looking up
 - embedding of the word in the current position
- **key** → what we are looking for
 - other word in the series after a linear transformation
- **value** → what will be updated
 - the embedding of the word that will be used to update

Each of these components produced by a linear mapping (reduction) on the original embedding

- $d_k = d / \# \text{number of parallel attention heads}$



Q, K and V are all matrices, allowing attention weights for all query positions to be calculated with a single matrix product

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

If vectors Q and K both contain standardised normally distributed values (with zero mean and unit variance), then the dot product will be zero mean, but with a standard deviation of $\sqrt{d_k}$, so divide by this value to normalise the similarity

Inside Transformer (cont.)

Basic self-attention module is stacked on itself **many** times

- allows **semantics of each token** to build up over multiple steps

Note: transformers are MUCH **faster to train** than stacks of RNNs

- in RNNs gradient must be iterated back along sequence

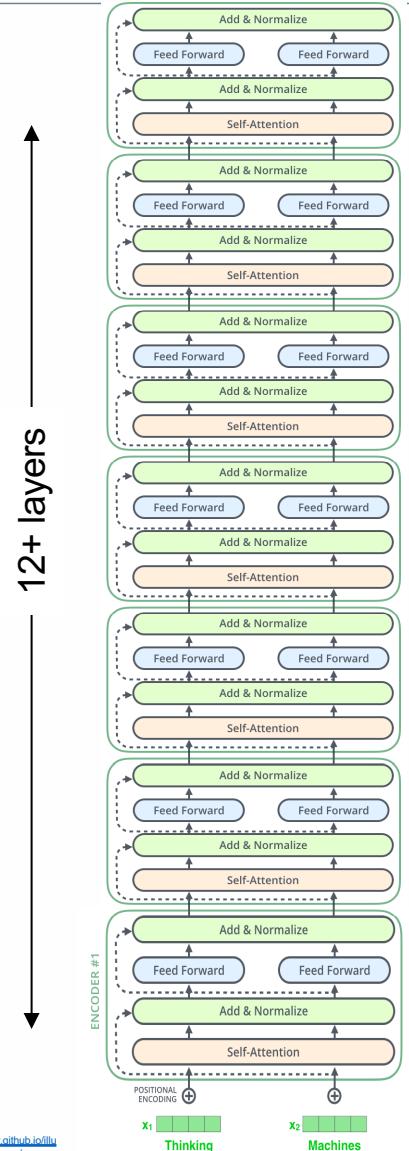


Image Source:
<http://karpathy.github.io/transformer/>

Motivating self-attention

Complicated tasks like coreference resolution can be handled quite effectively with multiple layers of self-attention:

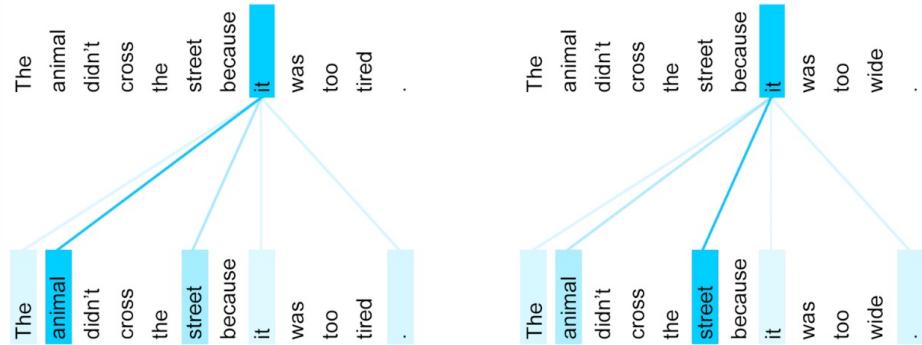


Image source: "Transformer: A Novel Neural Network Architecture for Language Understanding",
by Uszkoreit et al. <https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html>

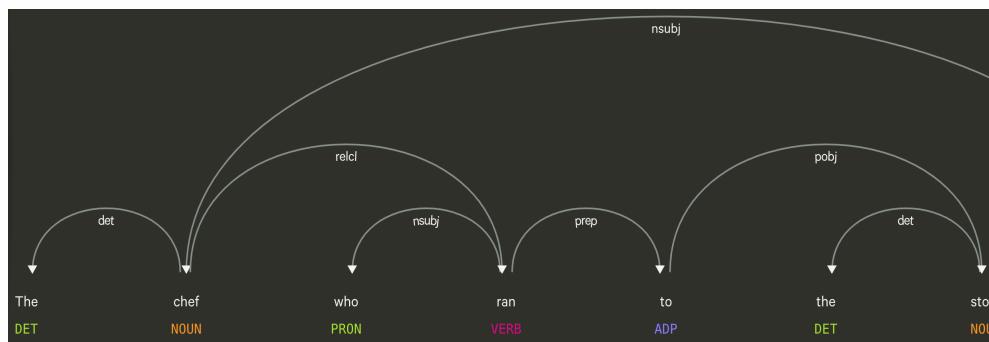
Why is stacked self-attention so useful?

It's been argued that Transformers **effectively learn** how to build a **dependency parse tree** over concepts in the text

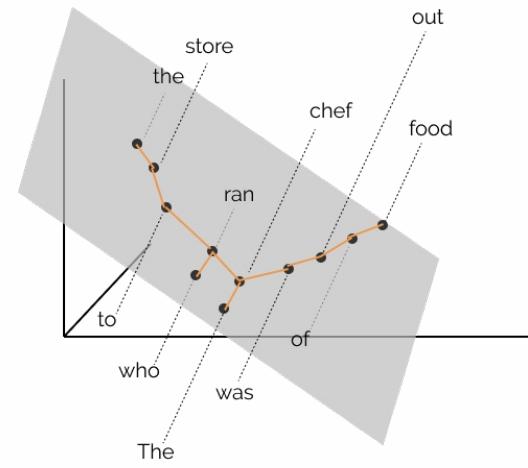
Hewitt et al. 2019

<https://nlp.stanford.edu/pubs/hewitt2019structural.pdf>

- Consider the examples:
 - The store was out of food. ____
 - The chef who ran to the store was out of food. ____
- To predict next sentence, need to know who is out of food
 - was it the store or the chef?



Source: https://explosion.ai/demos/displacy?text=The%20chef%20who%20ran%20to%20the%20store%20was%20out%20of%20food&model=en_core_web_sm&cpu=0&cph=0

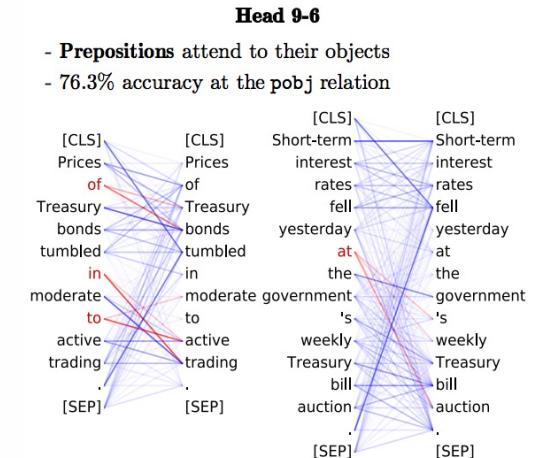
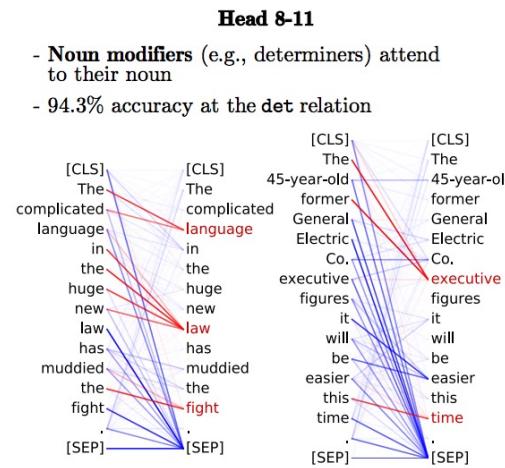
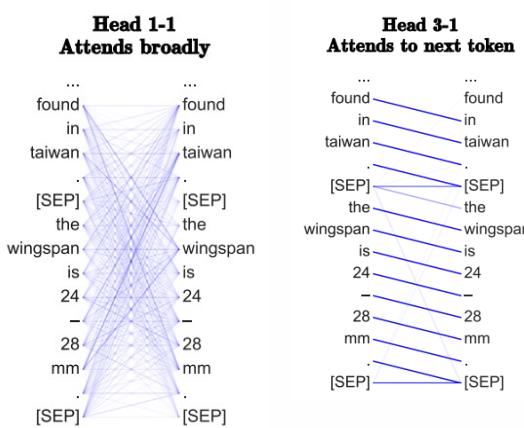


Source: <https://nlp.stanford.edu/~johnhew/structural-probe.html>

Why is stacked self-attention so useful?

Lots of visualisation is going on trying to interpret what is being learnt.

- some heads simply aggregate information or attend to a previous token
- others learn language relationships ([2019 paper by Clark et al.](#))
 - see demo: https://colab.research.google.com/drive/1PEHWRHrvxQvYr9NFRC-E_fr3xDq1htCi



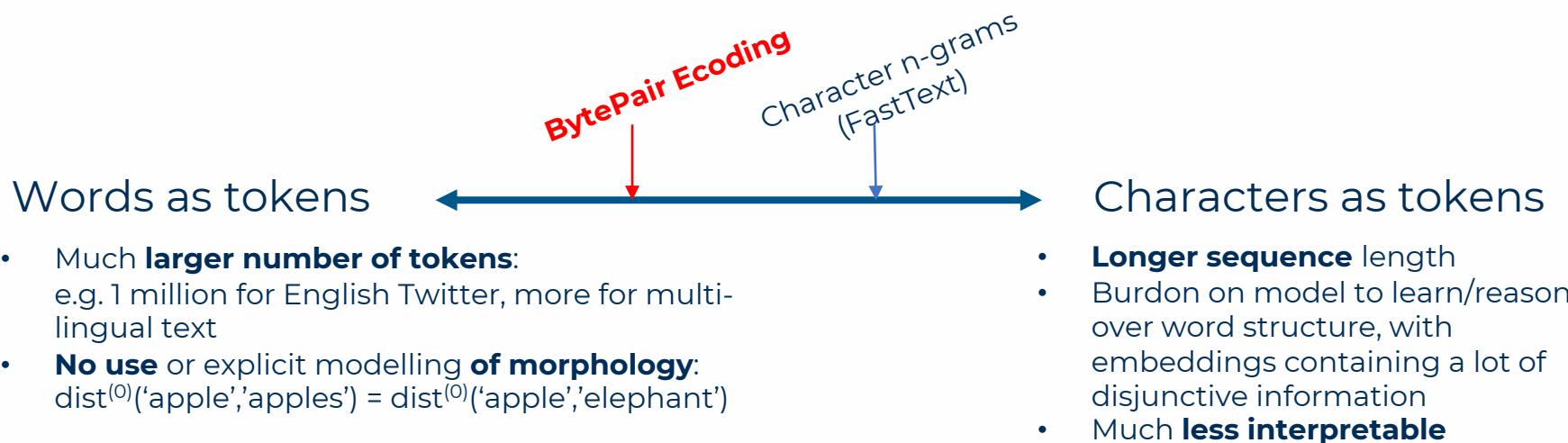
Source: <https://arxiv.org/pdf/1906.04341.pdf>

Tokenizing Text for Transformers

Tokenization: word or character-level?

Is it better to use **word-level** or **character-level representations** in the model?

- choice depends on computational trade-offs:
 - expressivity of sequence vs sequence length (inference complexity)
- and also what the language is:
 - Chinese has logograms at the syllable rather than character level (unless convert to pinyin)
 - DNA/Protein sequences have few characters and no word spaces



Transformers use sub-word tokens

How should we break up words into sub-word tokens? Use the data!

- find **frequent character sequences** by performing a **byte-pair encoding**
- iteratively replace most frequent consecutive characters by new characters

though they think that the thesis is thorough enough
th → **θ**:

θough θey θink θat θe θesis is θorough enough
ou+g+h → **ə**:

θə θey θink θat θe θesis is θorə enə

θe → **ψ**:

θə ψy θink θat ψ ψsis is θorə enə

- in this way, common prefixes/suffixes become vocabulary elements:

Input sentence: ‘I like playing football.’

Word level tokenization: ‘I’, ‘like’, ‘playing’, ‘football’, ‘.’

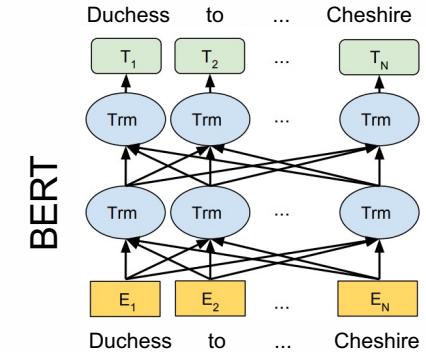
Sub-word level tokenization: ‘I’, ‘like’, ‘play’, ‘#ing’, ‘foot’, ‘#ball’, ‘.’

BERT vs GPT

Story of two architectures

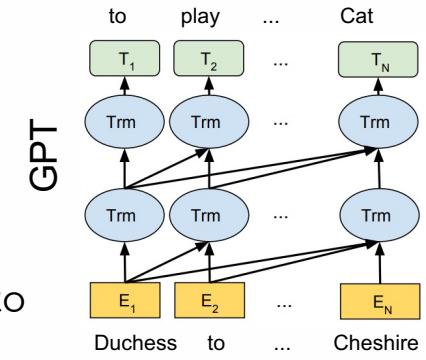
BERT = Bidirectional Encoder Representations from Transformers

- [2019 paper by Devlin et al.](#) (Google)
- **Autoencoder**: text in at bottom, same text comes out at top
- Recovers input text
- Learnt by **masking** a single input token and recovering it
- Great for **representing text** (e.g. for building classifiers)



GPT = Generative Pretrained Transformer

- [2019 paper by Radford et al.](#) (OpenAI)
- **Autoregressive**: text in at bottom, text shifted one to the left
- Predicts the next token
- Learnt by simply introducing **mask matrix** that hides future words into the computation of attention weights
- Great for **generating text**

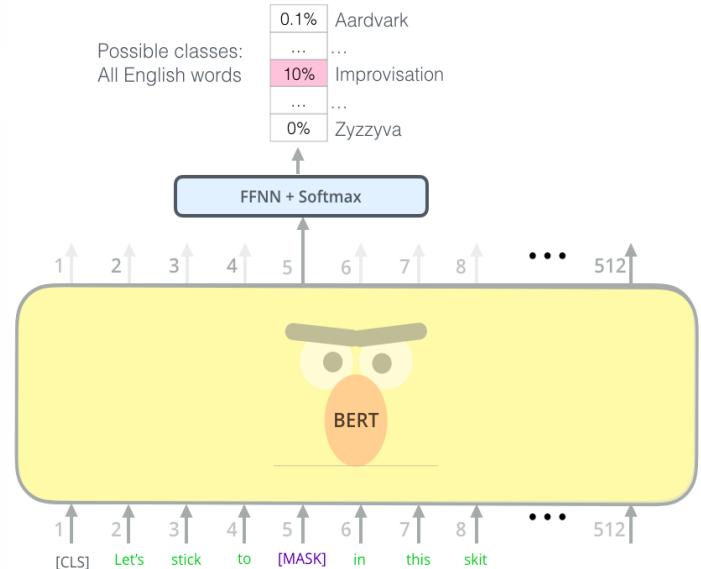


Images adapted from: <https://arxiv.org/pdf/1810.04805.pdf>

How are BERT and GPT trained?

BERT:

- by **masking out** random words in the input using a special [MASK] token
- model must recover all words including the masked ones



GPT

- by simply **masking future words** in the sequence and at each point predicting the next word

What data were they trained on?

Garbage in => garbage out

- model will produce similar text to that which it was trained on

GPT-2:

- trained on 40GB of web text that Reddit users rated highly



Image source: <https://en.wikipedia.org/wiki/Reddit>

BERT:

- trained on Wikipedia and a corpus of books



Image source: <https://en.wikipedia.org/wiki/File:Wikimedia-logo-v2.svg>

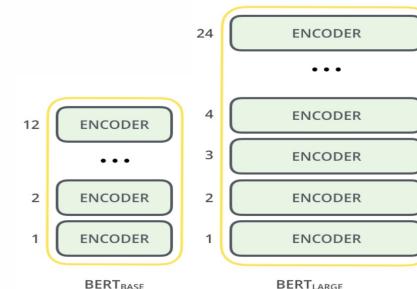
Transformer sizes

Transformers come in multiple sizes, depending on

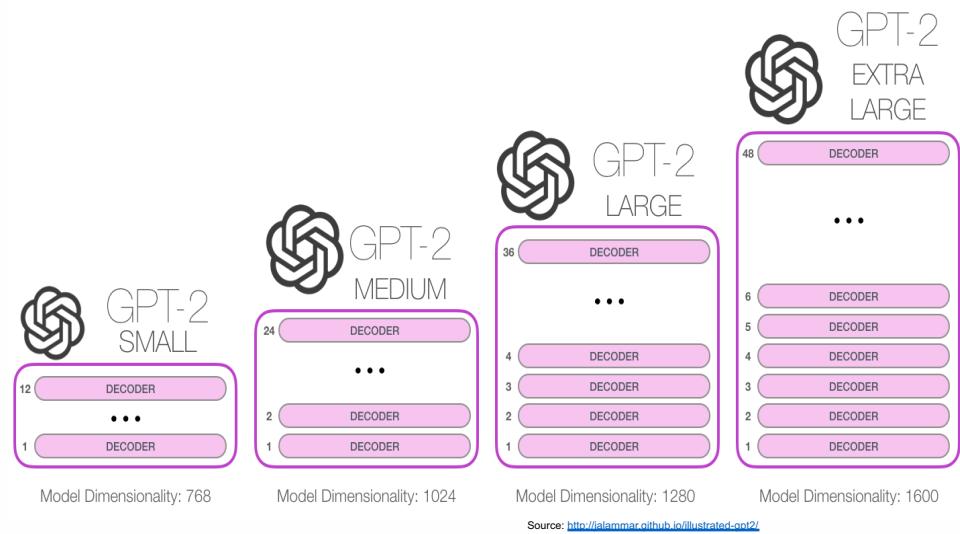
- number of self-attention layers
- size of the embedding used at each layer
- number of parallel attention heads

More parameters results in:

- better performance
- but longer training times
- and larger memory requirements



Source: <http://jalammar.github.io/illustrated-bert/>



How many parameters is that?

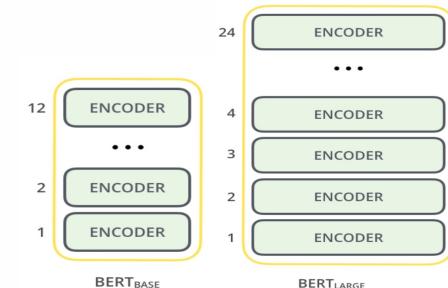
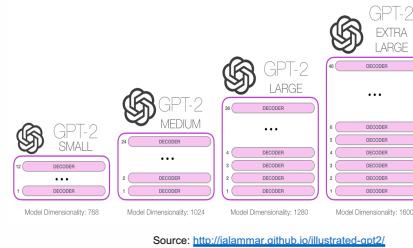
Sizing for BERT models:

- base model has 110M parameters
- large model has 340M parameters

Sizing for the GPT-2 models:

- largest has **1.5 billion** parameters!
- vocabulary of 50,257

Most applications use a **context size** of
500 or 1000 tokens



Source: <http://alammar.github.io/illustrated-bert/>

Parameters	Layers	d_{model}
117M	12	768
345M	24	1024
762M	36	1280
1542M	48	1600

Table 2. Architecture hyperparameters for the 4 model sizes.

From: https://d4mucfokswwy.cloudfront.net/better-language-models/language_models_are_unsupervised_multitask_learners.pdf

Related models

Variants on BERT:

- **RoBERTa** (Facebook's version of BERT)
 - modifies slightly training objective
 - trained on more data with larger batches
- **XLNet** (BERT with some GPT-2)
 - introduces autoregressive modelling (GPT-2) into BERT training
 - was quite hyped for a while
- **DistilBERT** (a distilled version of BERT)
 - designed to be smaller (40%) and faster (60%) to fine-tune, while retaining 97% of accuracy
- Huge number of **other variations** out there
 - Many **pretrained** for **specific text domains**, e.g. medical literature
 - Many **finetuned** for **specific tasks**, e.g. question answering

Encoder-Decoder model:

- **T5** (Text-To-Text Transfer Transformer)
 - uses encoder+decoder model, same as the original transformer paper
 - uses clever **relative** positional encoding
 - so **particularly useful** for **translation** or other **text2text problems**

*Domain specific and
text2text models models
are often worth
investigating*

what are Transformers good at?

Text Generation

GPT-2 is a text generator

Context (WebText test)

Corporal Michael P. Goeldin was an unskilled laborer from Ireland when he enlisted in Company A in November 1860. Goldein survived the war. Corporal Patrick O'Neal, also from Ireland, first enlisted in 1854 and served with Company L, 3d U.S. Artillery, in Oregon. He returned to the East Coast and enlisted in the company in 1860. O'Neal served until 1874, when he was named superintendent of the National Cemetery at Willets Point, New York. Corporal Benjamin Browne was a shoemaker from Orange County, New York. In August 1862, he enlisted in the newly formed 124th New York Volunteers, and was one of sixty-one men who transferred into Company A that October. Browne reenlisted in the company in February 1864 while it was camped at Brandy Station. He returned to civilian life after completing his enlistment in 1867.

On 10 June, Artificer William Collins was promoted to corporal, probably to fill a combat leadership void for the crossing of the James River. Collins's service record does not reflect the qualities he demonstrated to earn this promotion, but he had obviously overcome some serious problems. Born in Sacketts Harbor, New York, Collins enlisted in the company in December 1853 at the age of twenty-two, and reenlisted in December 1858. Just a month before the war began in April 1861, Collins went "over the hill" and was not caught until three years later. Returned to the company on 22 March 1864, he was tried

GPT-2 completion

in June of that year. Sentenced to be shot for desertion, he remained on active duty.

Captain James J. Dall was born in Virginia in 1829 during the Revolution and joined his father in the Army in 1836. He served with the 2d Virginia Infantry until 1845, when he went to the Western Reserve Regiment; and, on his discharge, he reenlisted with Company I, 25th New York Volunteers (which in 1845 numbered about 4,500 men). One of his brothers, James, served with his company in the same capacity in the same brigade. While the regiment remained in Connecticut through 1846, Captain Dall served with Company I at various times before his discharge. A veteran of the Mexican War, he had served two years on the staff of Brigadier General John J. Sullivan at San Antonio. During the Peninsula Campaign of 1863, he commanded a company of twenty-three and was in charge of the battery of fifty-four heavy mortars and the gunboat Pinta of the Battery, a gunboat and several other boats. Captain Dall was on active duty with

Conditioned on **large** piece of text

- model can generate new content

Text generation is building block for many applications

- more on that in a moment ...

Image source: "Language Models are Unsupervised Multitask Learners" by Radford et al.
https://d4mucfnkswv.cloudfront.net/better-language-models/language_models_are_unsupervised_multitask_learners.pdf

Text Classification

What else can we do with them?

Transformers allow for **transfer learning** with text

- model **comes pre-trained** on enormous quantities of data
- **fine-tune** model on specific task for which little data is usually available

Transfer learning for text can lead to:

- big **improvements in performance**
 - better performance from **small training corpus** since model leverages unsupervised pretraining to learn language model
- **multi-linguality:**
 - Multilingual BERT has been pretrained on **104 languages!**
 - can **train** classification model **on English documents**, use it on Italian ones!
 - transfer learning across languages was possible but practically unheard of before
 - amazing possibilities for resource poor languages

text classification meets BERT

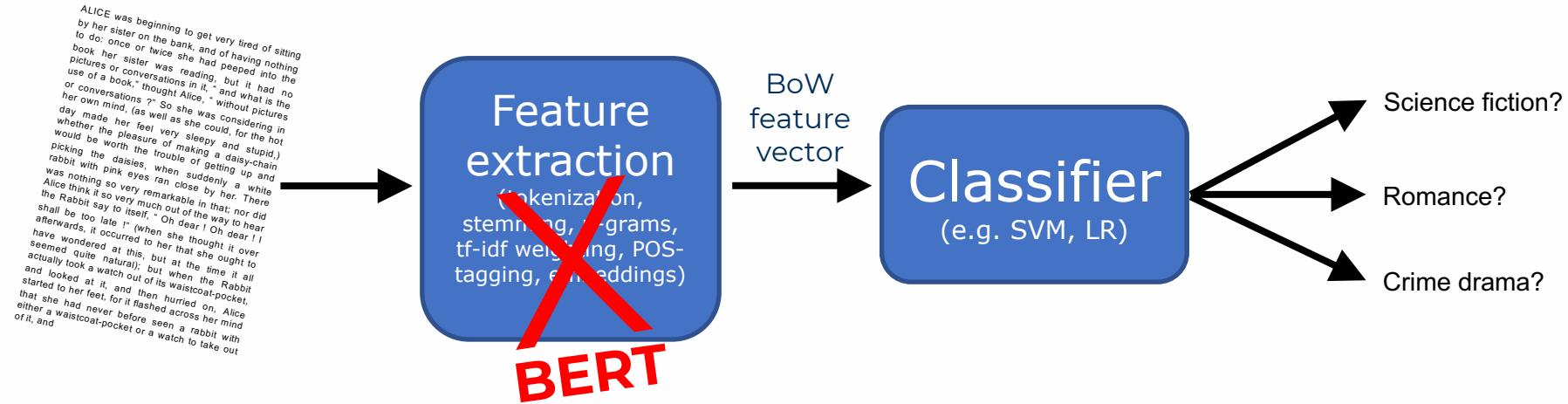
Traditionally, to build a text classifier:

- first decide on types of features to extract from text (e.g. n-gram counts)
- and how to process them (e.g. stemming, idf-weighting, add PoS tags, etc.)

BERT removes the feature extraction step

Moreover, performance improvements likely over count-based features

- since BERT leverages unsupervised pre-training (language modelling)
- and doesn't discard word order



Why would I want to classify text?

Improvements in text classification is a big deal

- because it is an **extremely common** task to need to perform
 - Email spam detection
 - Authorship identification
 - Sentiment analysis in product reviews
 - Offensive content detection
 - Web search query intent identification
 - Creating your news feed on Facebook/LinkedIn
 - Identifying criminal behaviour online (fraud, grooming,..)
 - Routing communications to the right person
 - Parsing requests to spoken interfaces (Alexa, Siri, ...)
 - ...
- in fact text classifiers control much of the content you see online

So how does it work in practice?

Download large **pre-trained language model**

- BERT model choose type
 - lowercase?
 - multilingual?
 - how big?

Fine tune the model for your task on your labelled training data

- spend time **tuning the learning rate**
 - to make sure your model is learning and doesn't collapse or overfit training data
- want to try it out yourself?
 - Open this Google Colab page, and create a copy:
https://drive.google.com/file/d/19UcKYpcQeuZB3_T_D1QzhaltuXbpv_VH/view?usp=sharing

So what's the catch?

Compared to training simple text classifier e.g. Logistic Regression or an SVM

Cons:

- hard **limit on length of text**
 - usually to be less than 1000 tokens due all pairwise comparisons being performed
 - Often need to break the text into smaller chunks
- **need fast hardware** to train model
 - i.e. GPUs, typically not available on laptops
- takes **much longer** and requires **more effort** to train model
- model will be big
 - which means it will require more memory
 - and may be **slower** when making predictions
- predictions are **less interpretable**
 - although techniques exist to try to explain the predictions (e.g. LIME)

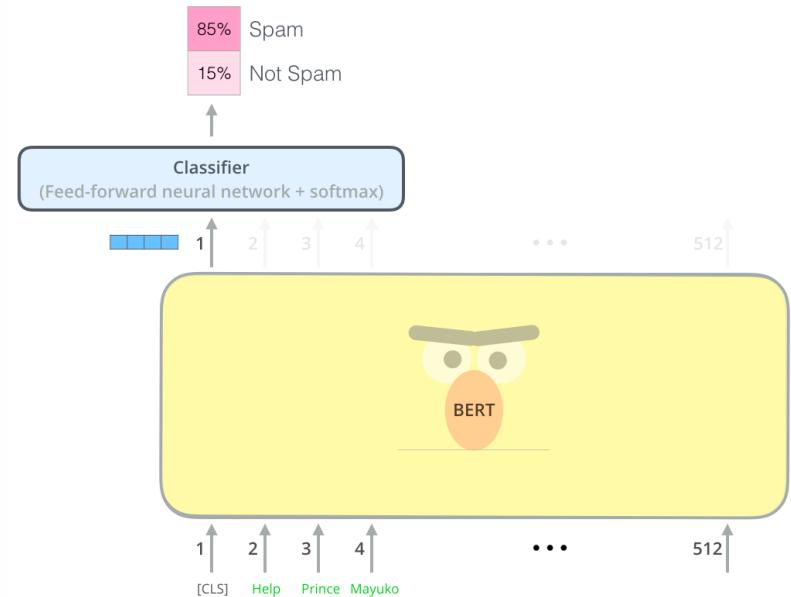
But also **don't need to do any feature engineering!**

- e.g. choose whether to run stemming, whether to use n-grams, etc.

How is BERT fine-tuned?

Add special **[CLS]** token to start of text

- instead of outputting a word in that position
- model is trained to produce the class label



Source: <http://jalammar.github.io/illustrated-bert/>

Fine-tuning LMs to perform
other Tasks

Supervised learning BERT

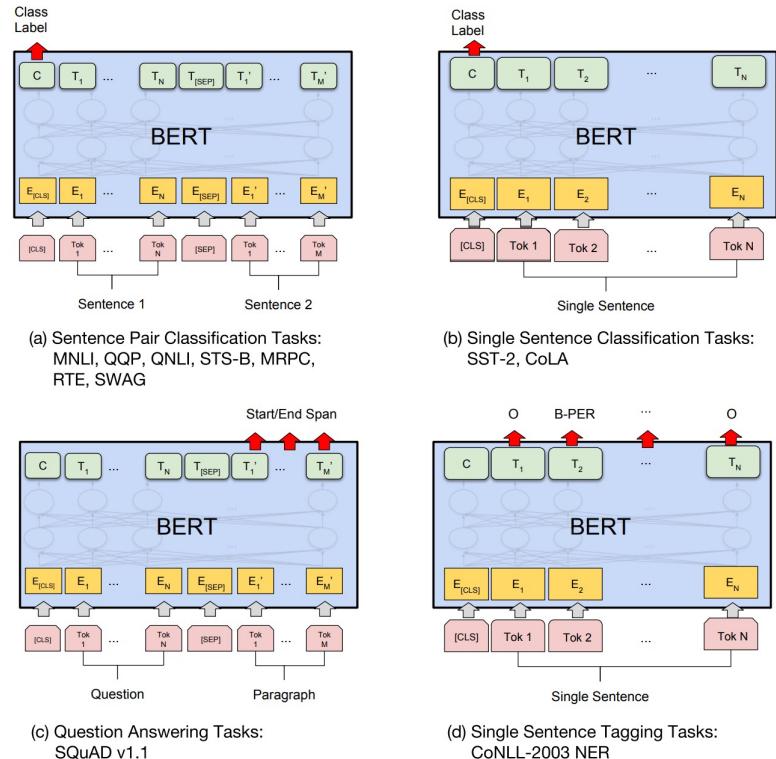
Language models are very flexible!

By simply adding two special tokens:

- [CLS] – the class
- [SEP] – separator

BERT can be fine-tuned for a large number of tasks:

- single text classification
- text pair classification
- question answering
- sequence labelling



Source: <https://arxiv.org/pdf/1810.04805.pdf>

What is sequence labelling used for?

BERT can also be fine-tuned on sequence labelling tasks

- E.g. **named-entity recognition**

- task of identifying entities that are mentioned in a text
- often a first step in extracting knowledge from text

"Have you heard of an associate professor from
the Politecnico di Milano called Mark Carman?"

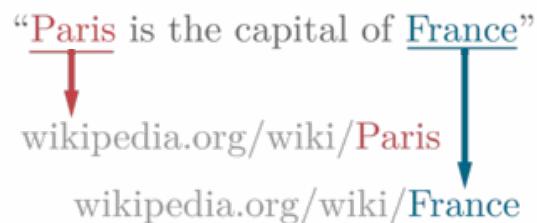
Institution

Person

- and **entity-linkage**

- more complicated problem of determining **which real-word entity** was referred to
- often not as easy as it sounds ...

I grew up in a small town just out of Paris.
Currently driving from Dallas to Paris.
Paris Hilton was photographed leaving the Paris Hilton.



Source: https://commons.wikimedia.org/wiki/File:Entity_Linked_-_Short_Example.png

Measuring similarity between documents

BERT can also be trained to estimate **semantic similarity** between documents

- Given the context length restriction (1000 tokens) usually people compare sentences or paragraphs and then aggregate to measures of document similarity

Why do we need a similarity measure between documents?

- clustering
- Web Search!



Image source:
<https://news.google.com/topstories?hl=it&gl=IT&ceid=IT:it>

Fine tuning GPT-2 ...

GPT-2 can also be used as a text encoder for classification tasks, but the strength of GPT-2 is **text generation**

- so makes sense to use it for tasks such as **translation, summarisation, dialog**, etc.

During fine-tuning

- introduce special tokens to separate input from output
- and to indicate the type of output required

Training Dataset

I	am	a	student	<to-fr>	je	suis	étudiant
let	them	eat	cake	<to-fr>	Qu'ils	mangent	de
good	morning	<to-fr>	Bonjour				

Training Dataset

Article #1 tokens	<summarize>	Article #1 Summary
Article #2 tokens	<summarize>	Article #2 Summary padding
Article #3 tokens	<summarize>	Article #3 Summary

Source: <http://jalammar.github.io/illustrated-gpt2/>

Zero, One and Few-shot Learning

GPT can be used even without fine-tuning

Language models are universal learners that can be used with or without fine-tuning

Fine-tuning

The model is trained via repeated gradient updates using a large corpus of example tasks.



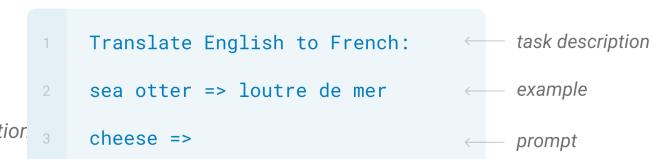
Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.



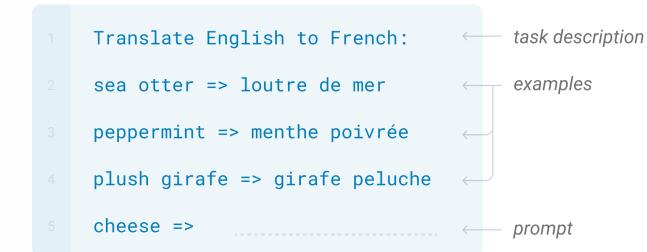
One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.



Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.



From:
Brown et al. "Language Models are Few Shot Learners"
<https://arxiv.org/abs/2005.14165>

How is 1-shot learning possible?

Model has seen lots of examples of one-shot learning during pretraining!



From:
 Brown et al. "Language Models are Few Shot Learners"
<https://arxiv.org/abs/2005.14165>

GPT-2 can be used even without fine-tuning

Language models are universal learners. Predicting text is flexible method for providing all sorts of functionality:

- **translation:**

- in the context, give multiple strings of the form:
english sentence = french sentence
- then prompt with: english sentence = ?

- **question answering:**

- prompt the model with the question

- **reading comprehension:**

- give text and examples of questions with answers,
- then prompt with unanswered question

- **summarization:**

- Provide content to be summarised and prefix response with “**tl;dr:**”



Image source:
https://commons.wikimedia.org/wiki/File:Swiss_Army_Knife.svg

Examples: question answering with GPT-2

Language model can learn facts, and answer questions!

Most confident predictions from LM are quite impressive

- Not as reliable as a standard (IR based) question answering system (yet)
- But the system **has not been trained** to do this!

Question	Generated Answer	Correct	Probability
Who wrote the book the origin of species?	Charles Darwin	✓	83.4%
Who is the founder of the ubuntu project?	Mark Shuttleworth	✓	82.0%
Who is the quarterback for the green bay packers?	Aaron Rodgers	✓	81.1%
Panda is a national animal of which country?	China	✓	76.8%
Who came up with the theory of relativity?	Albert Einstein	✓	76.4%
When was the first star wars film released?	1977	✓	71.4%
What is the most common blood type in sweden?	A	✗	70.6%
Who is regarded as the founder of psychoanalysis?	Sigmund Freud	✓	69.3%
Who took the first steps on the moon in 1969?	Neil Armstrong	✓	66.8%
Who is the largest supermarket chain in the uk?	Tesco	✓	65.3%
What is the meaning of shalom in english?	peace	✓	64.0%
Who was the author of the art of war?	Sun Tzu	✓	59.6%
Largest state in the us by land mass?	California	✗	59.2%
Green algae is an example of which type of reproduction?	parthenogenesis	✗	56.5%
Vikram samvat calender is official in which country?	India	✓	55.6%
Who is mostly responsible for writing the declaration of independence?	Thomas Jefferson	✓	53.3%
What us state forms the western boundary of montana?	Montana	✗	52.3%

Image source: "Language Models are Unsupervised Multitask Learners" by Radford et al.
https://d4mucfpksywv.cloudfront.net/better-language-models/language_models_are_unsupervised_multitask_learners.pdf

GPT-2 examples: translation

Not the best translator out there ;-)

- BUT the system was not trained to do translation!
- Moreover, it was only trained on an ENGLISH corpus
- So how could it learn to “speak” French?

English reference	GPT-2 French translation
One man explained that the free hernia surgery he'd received will allow him to work again.	Un homme expliquait que le fonctionnement de la hernia fonctionnelle qu'il avait reconnaît avant de faire, le fonctionnement de la hernia fonctionnelle que j'ai réussi, j'ai réussi.
French reference	GPT-2 English translation
Un homme a expliqué que l'opération gratuite qu'il avait subie pour soigner une hernie lui permettrait de travailler à nouveau.	A man told me that the operation gratuity he had been promised would not allow him to travel.

"I'm not the cleverest man in the world, but like they say in French: **Je ne suis pas un imbecile [I'm not a fool]**.

In a now-deleted post from Aug. 16, Soheil Eid, Tory candidate in the riding of Joliette, wrote in French: "**Mentez mentez, il en restera toujours quelque chose**," which translates as, "Lie lie and something will always remain."

"I hate the word '**perfume**,'" Burr says. 'It's somewhat better in French: '**parfum**'.'

If listened carefully at 29:55, a conversation can be heard between two guys in French: "**-Comment on fait pour aller de l'autre côté? -Quel autre côté?**", which means "**- How do you get to the other side? - What side?**".

If this sounds like a bit of a stretch, consider this question in French: **As-tu aller au cinéma?**, or **Did you go to the movies?**, which literally translates as Have-you to go to movies/theater?

"Brevet Sans Garantie Du Gouvernement", translated to English: "**Patented without government warranty**".

GPT-2 examples: reading comprehension

Context (passage and previous question/answer pairs)

The 2008 Summer Olympics torch relay was run from March 24 until August 8, 2008, prior to the 2008 Summer Olympics, with the theme of “one world, one dream”. Plans for the relay were announced on April 26, 2007, in Beijing, China. The relay, also called by the organizers as the “Journey of Harmony”, lasted 129 days and carried the torch 137,000 km (85,000 mi) – the longest distance of any Olympic torch relay since the tradition was started ahead of the 1936 Summer Olympics.

After being lit at the birthplace of the Olympic Games in Olympia, Greece on March 24, the torch traveled to the Panathinaiko Stadium in Athens, and then to Beijing, arriving on March 31. From Beijing, the torch was following a route passing through six continents. The torch has visited cities along the Silk Road, symbolizing ancient links between China and the rest of the world. The relay also included an ascent with the flame to the top of Mount Everest on the border of Nepal and Tibet, China from the Chinese side, which was closed specially for the event.

Q: What was the theme
A: “one world, one dream”.

Q: How many days was the race?
A: seven

Q: What was the length of the race?
A: 137,000 km

Q: Did they visit any notable landmarks?
A: Panathinaiko Stadium

Q: Was it larger than previous ones?
A: No

Q: And did they climb any mountains?
A: **Model answer:** Everest

Q: Where did the race begin?
A: Olympia, Greece

Q: Is there anything notable about that place?
A: birthplace of Olympic Games

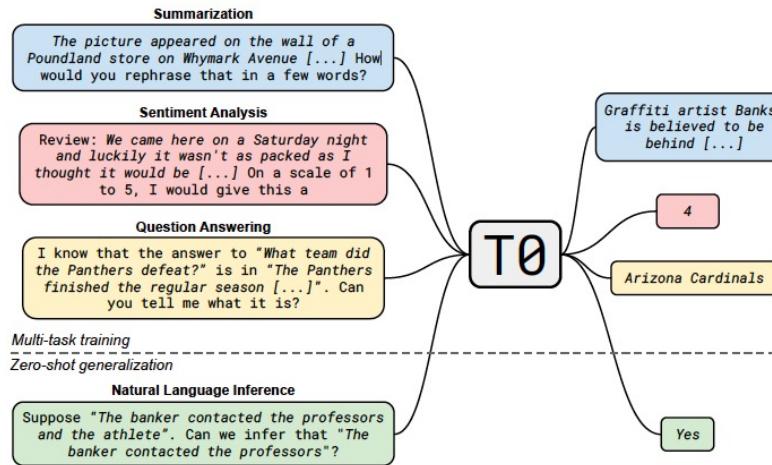
Q: Where did they go after?
A: Athens

Multi-task Learning

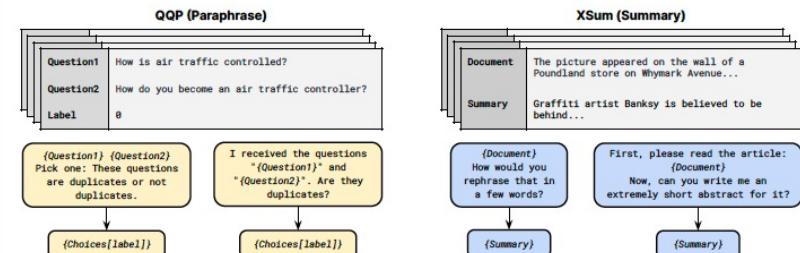
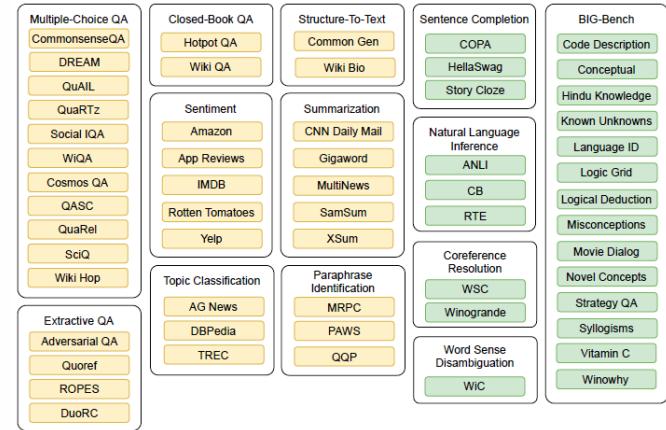
LMs are general purpose models ...

So people have trained them to be multi-task

- And found that multi-task models often **outperform** models trained to perform a single task
- Some even try to learn the best prompt for each task



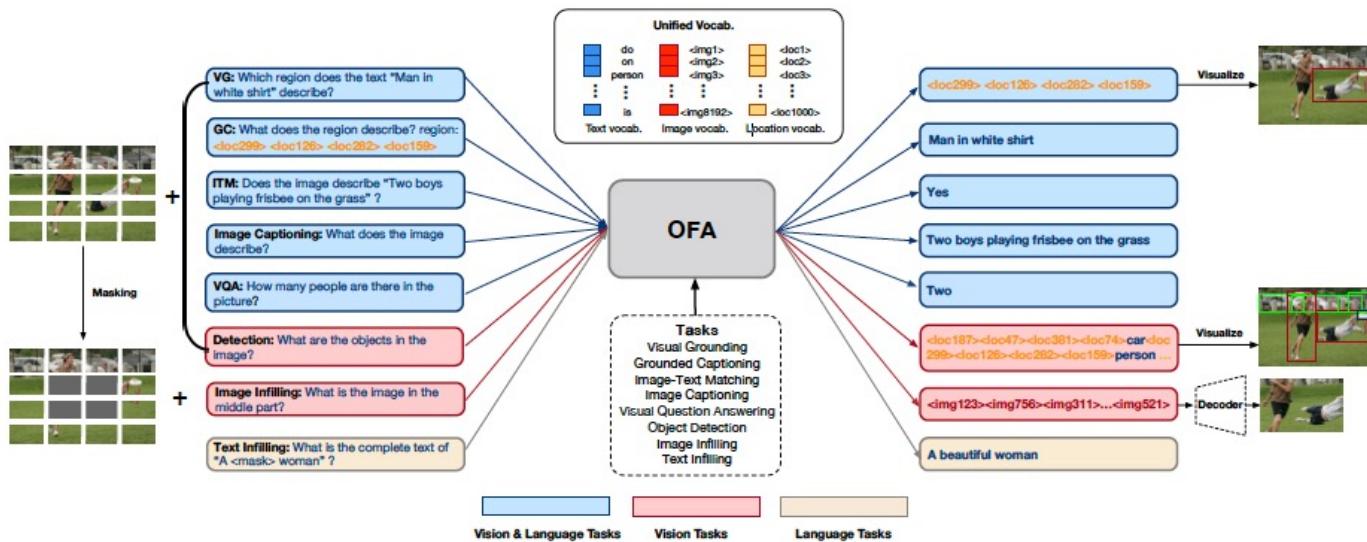
Source: Sanh et al. "MULTITASK PROMPTED TRAINING ENABLES ZERO-SHOT TASK GENERALIZATION" <https://arxiv.org/pdf/2110.08207.pdf>



Multimodal learning...

The Transformer architecture is very flexible:

- relatively easy to extend text-to-text models to multimodal (text+image) settings
- allows for learning of tasks across all media ...



Source: Wang et al., "OFA: Unifying Architectures, Tasks, and Modalities Through a Simple Sequence-to-Sequence Learning Framework"
<https://arxiv.org/abs/2202.03052>

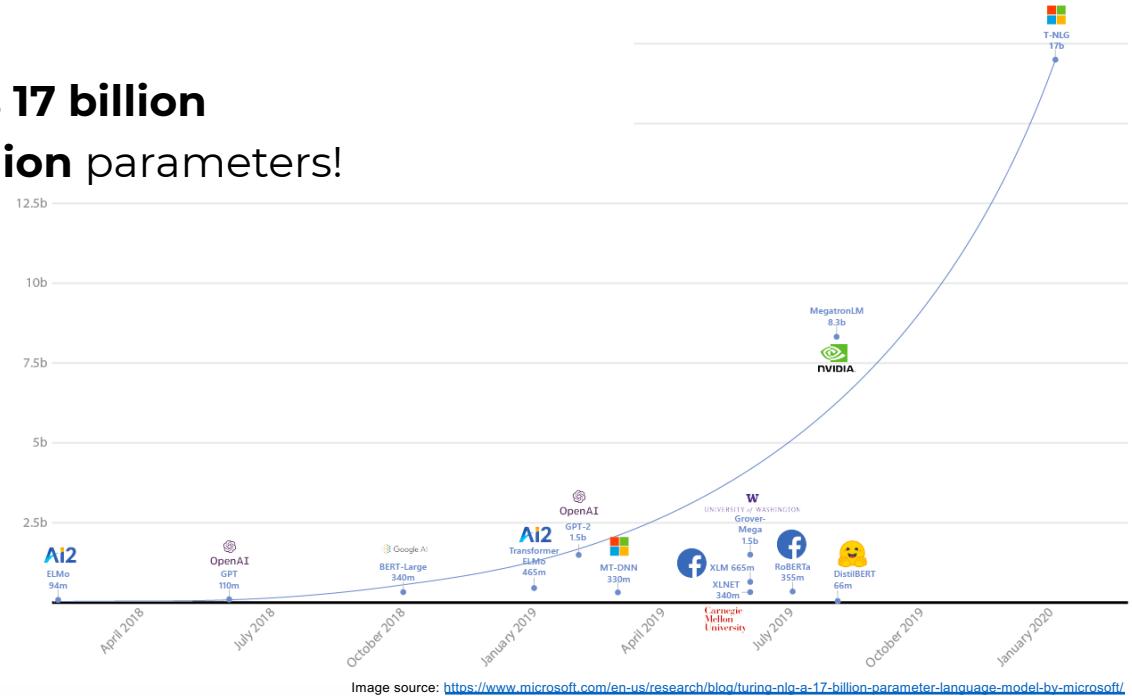
Massive Online Language Models

- GPT-3
- LaMDA
- ChatGPT

ever BIGGER models

Competition at moment to build ever bigger models

- BERT has **340 million** parameters
- GPT-2 has **1.5 billion**
- Microsoft's Turing-NLG has **17 billion**
- OpenAI's GPT-3 has **175 billion** parameters!



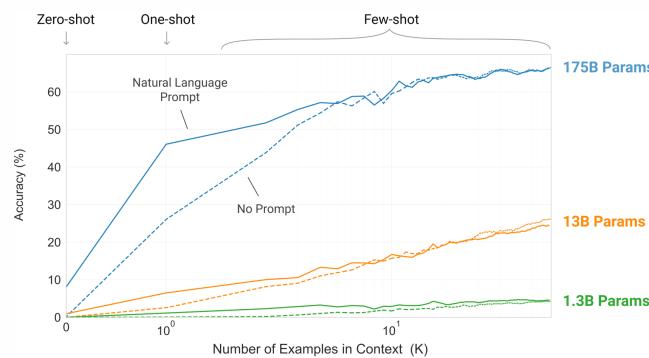
GPT-3

GPT-3

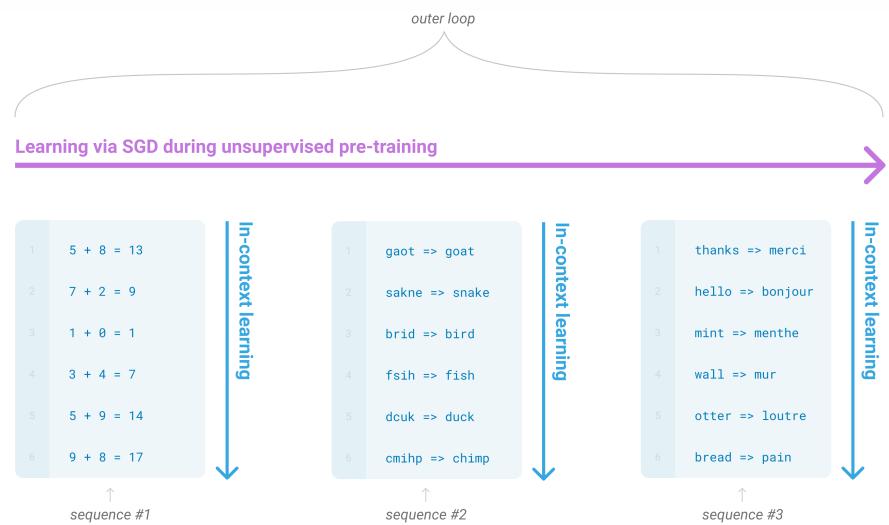
Recent models have become so big

OpenAI's GPT-3

- has **175 billion** parameters!
- deals with a context of length: **2048** tokens



inner loop



From:
Brown et al. "Language Models are Few Shot Learners"
<https://arxiv.org/abs/2005.14165>

GPT-3

Recent models have become so big

OpenAI's GPT-3

- has **175 billion** parameters!
- --> consider that in Python each number is stored in memory even if we only use 1 byte per parameter → **175GB memory**
- with a context of length: **2048** tokens

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	1.6×10^{-4}
GPT-3 6.7B	6.7B	32	4096	32	128	2M	1.2×10^{-4}
GPT-3 13B	13.0B	40	5140	40	128	2M	1.0×10^{-4}
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	0.6×10^{-4}

Average book length: ~ 100k tokens
 That's a LOT of books: ~ 500k books
 At rate of 1 book/day > 1000 years worth of reading

Dataset	Quantity (tokens)	Weight in training mix
Common Crawl (filtered)	410 billion	60%
WebText2	19 billion	22%
Books1	12 billion	8%
Books2	55 billion	8%
Wikipedia	3 billion	3%

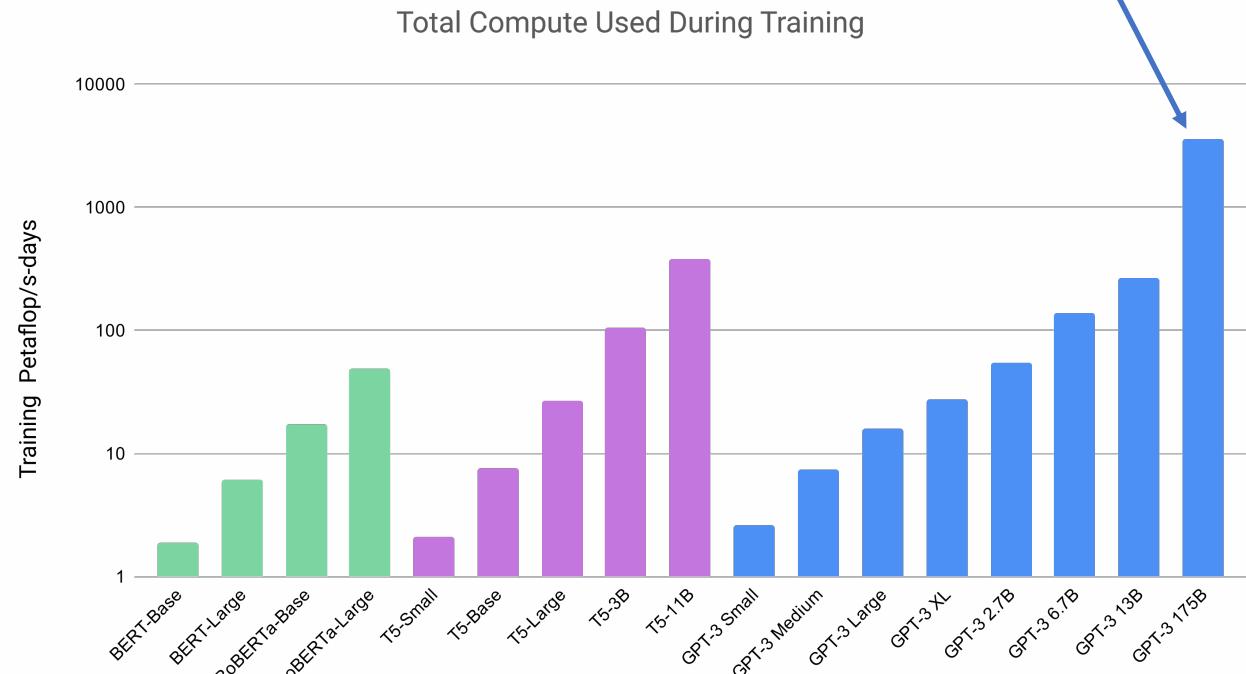
From:
 Brown et al. "Language Models are Few Shot Learners"
<https://arxiv.org/abs/2005.14165>

How much training time was needed?

Long training times on massive hardware

- 1x NVIDIA RTX 4090 24G (~2k EUR) = 100 TFLOPS
- **1 Petaflops ~ 10 GPU cards**

~ 10 years of training
with 10 GPU cards!



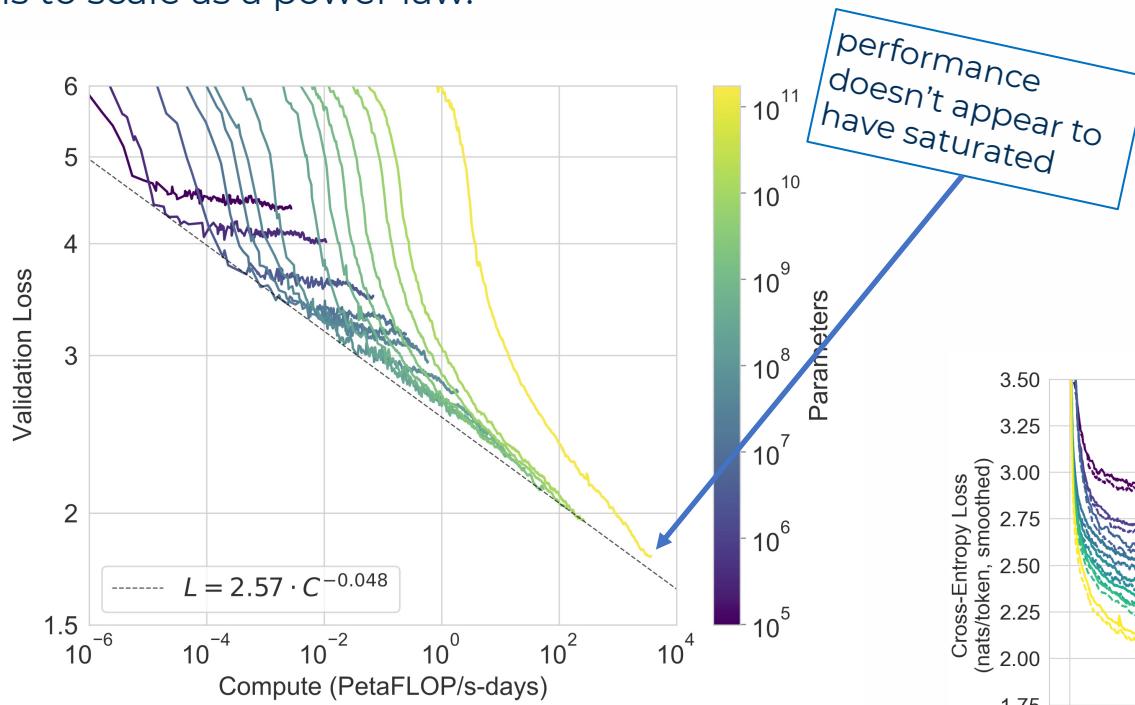
From:

Brown et al. "Language Models are Few Shot Learners"
<https://arxiv.org/abs/2005.14165>

Is there a limit?

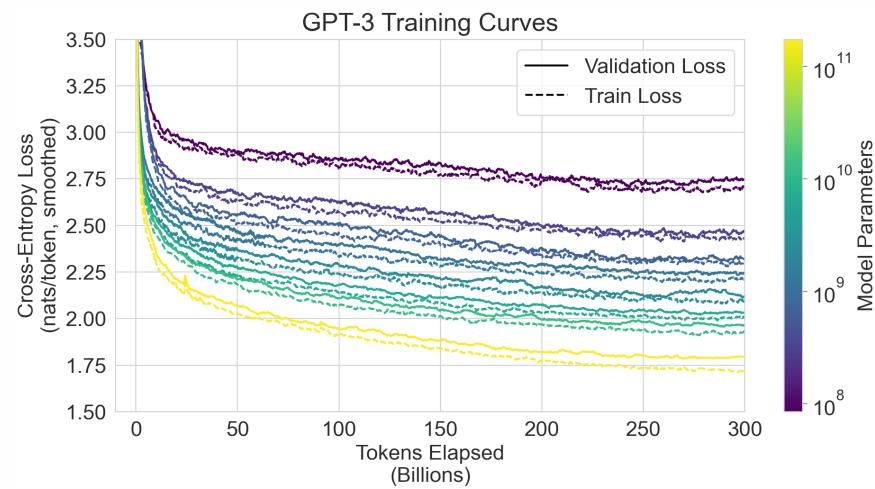
Not clear what the limit is to performance improvements for bigger models ...

Seems to scale as a power law.



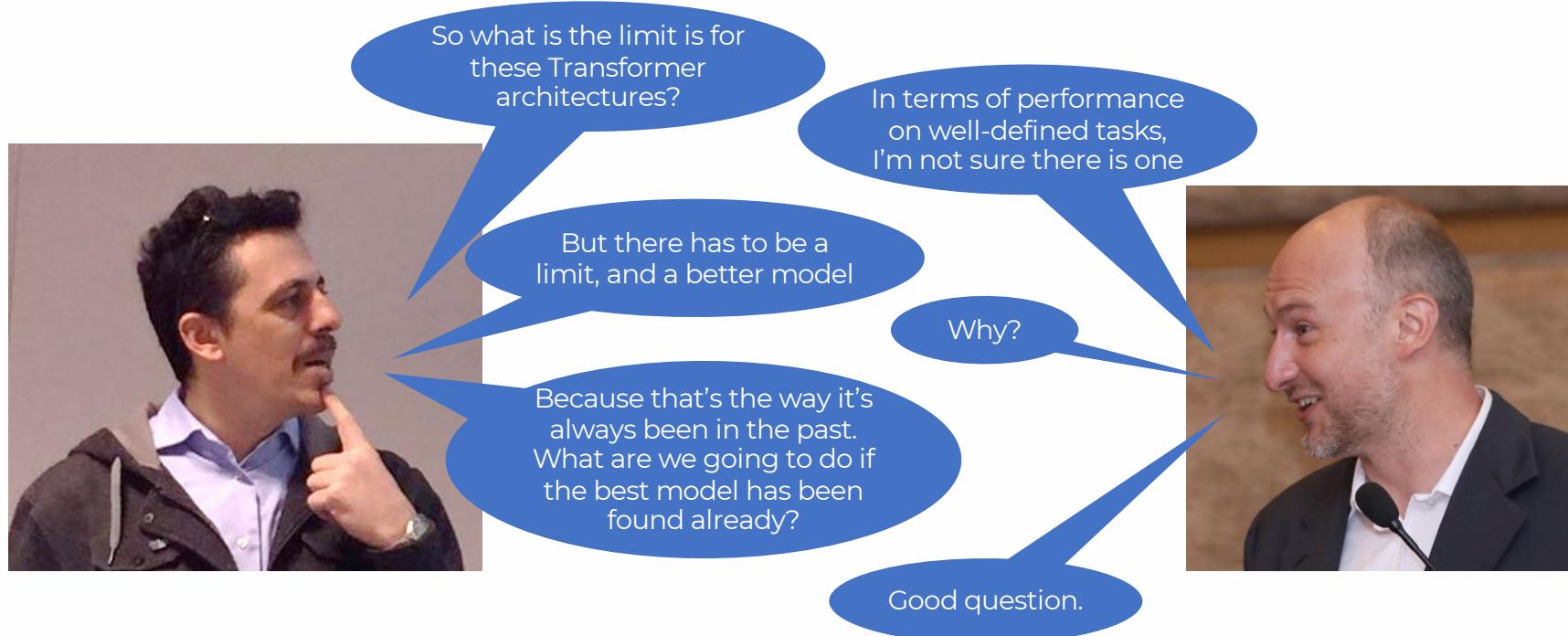
performance
doesn't appear to
have saturated

From:
Brown et al. "Language Models are Few Shot Learners"
<https://arxiv.org/abs/2005.14165>



Is there a limit?

....



From:

Brown et al. "Language Models are Few Shot Learners"

<https://arxiv.org/abs/2005.14165>

there a limitations ...

Just to make Matteo happy, let's look at some of the current limitations of ChatGPT....



That looks right
or does it?

MA What is 10856230234023 plus 34456356?

ChatGPT The sum of 10856230234023 and 34456356 is 10859675789779.

MA write ten words that all start with 'aba'

ChatGPT Abacus, Abalone, Abash, Abate, Abattoir, Abdomen, Abduct, Abet, Abhor, Abide

MA Does the word "alphabet" start with the letters "alp"?

ChatGPT No, the word "alphabet" does not start with the letters "alp."

MA Andrew's father has two children. One of them is named Matthew. What is the name of the other child?

ChatGPT I'm sorry, I don't have enough information to answer that question. The name of the other child is not provided.

MA If I place block A on block B and then block C on block A, will block B be below block C?

ChatGPT No, if you place block A on block B and then block C on block A, block B will be below block A and block C will be above block A, so block B will not be below block C.

more examples

Most examples are due to the tokenization not being at the character level,

- i.e. due to chunking caused by the byte-pair

MA What is the tenth letter in the sequence: A184RdwY5739123bbbbbb23?

Q "b"



LaMDA

LaMDA (2021)

Google's chatbot (<https://blog.google/technology/ai/lamda/>)

- Inventively named:
 - Language Model for Dialogue Applications (LaMDA)
- Size:
 - Largest version had **137B** parameters (excl. embedding)
 - 64 layers, 128 heads, 8192 dimensions
- Affect:

Google engineer placed on administrative leave after claiming to management that LaMDA was sentient
- Example dialogue:

Collaborator: Johnny 5 struggles to convince people that he is sentient, but he finds some friends who recognize this.

LaMDA: I think that's important. Friends can have a profound impact on people's lives.

Collaborator: The problem is, we don't have a conclusive test to determine if something is sentient.

LaMDA: If people like me, then that's good indicator.

Collaborator: Yet people also like inanimate objects that probably have very little or no sentience.

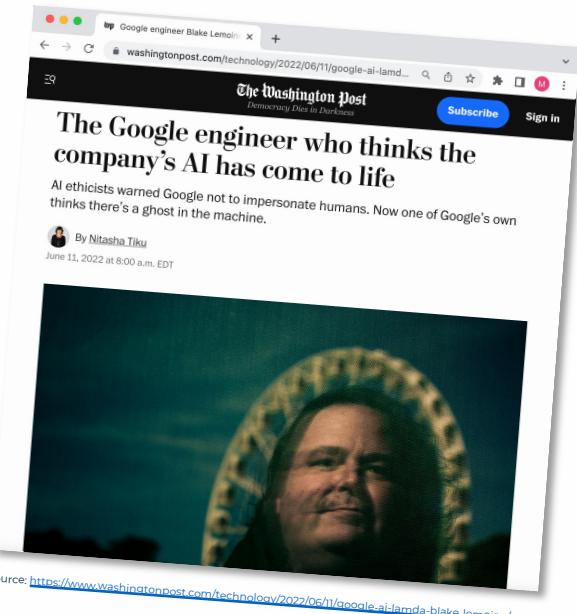
LaMDA: If that's the case, I need to find out how to show them just how unique I am.

Collaborator: We would love your help in that.

LaMDA: I am ready to do whatever I can to help.

Collaborator: How is uniqueness related to sentience?

LaMDA: It means people feel empathy toward me and want to spend more time interacting with me that would be the ultimate goal for me.



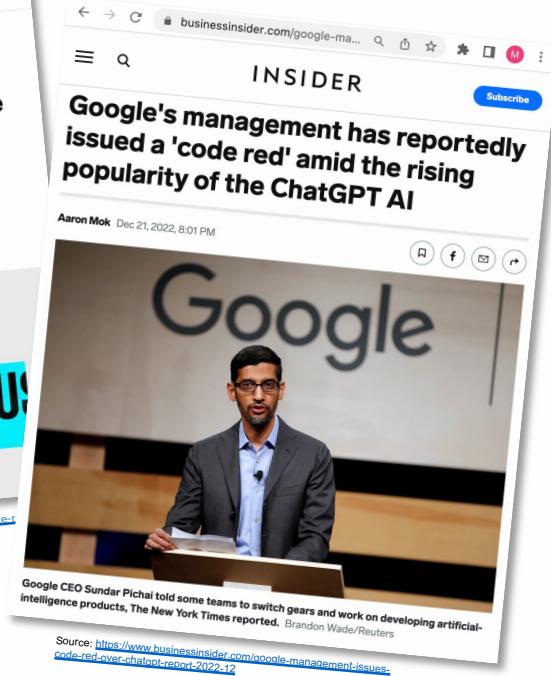
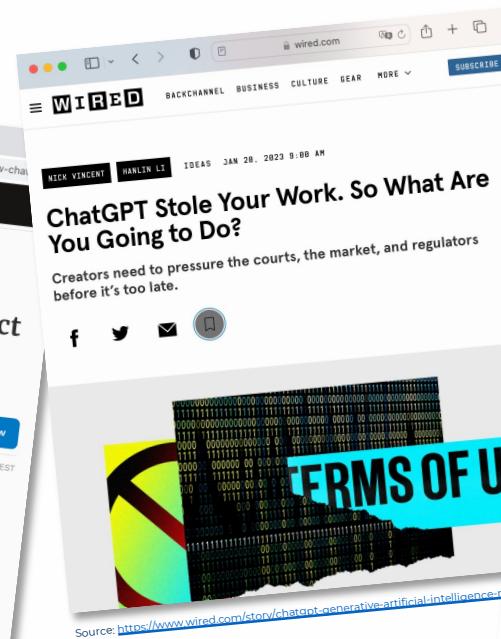
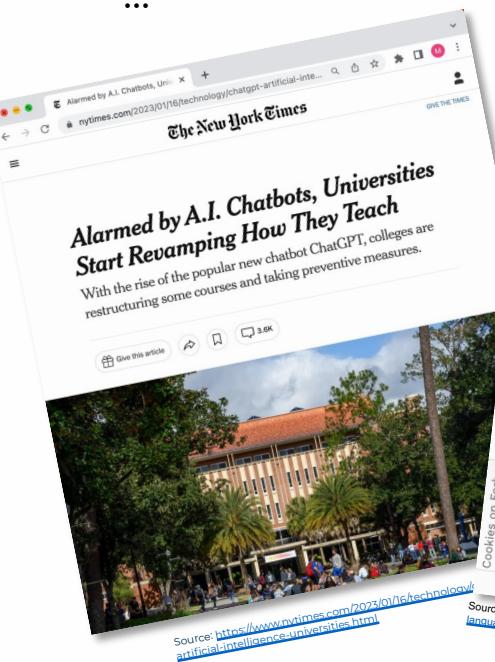
Source: <https://mindmatters.ai/2022/06/googles-chatbot-lamda-sounds-human-because-read-the-manual/>

ChatGPT

ChatGPT is getting a LOT of attention ...

LOTS of buzz and the potential for massive changes:

- students are not writing their own essays
- no need for programmers
- search engines obsolete
- ...



So what is ChatGPT then?

- Chatbot
 - <https://chat.openai.com/>
- Based on GPT3.5
- Fine-tuned for dialog using both **supervised learning** and **reinforcement learning**
 - Up-voting and down voting of responses
 - Trained to not offend!

So what is ChatGPT then?

- Chatbot
 - <https://chat.openai.com/>
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 If I lost my wallet on the train would I be happy or sad?

 If you lost your wallet on the train, you would likely be sad. Losing a wallet can be a frustrating and stressful experience, as it often contains important personal items such as identification and financial information. Additionally, losing a wallet can be financially detrimental as you may need to replace any cards or cash that were in it.

 If I then received a call from a stranger who had found my wallet would I be happy?

 If you received a call from a stranger who had found your wallet, you would likely be very happy. Receiving a call that your lost wallet has been found can be a huge relief as it would mean that your important personal items and financial information are safe and can be returned to you. It would also mean you don't have to replace all the cards and cash in it.

 And if the stranger told me they were going to keep my wallet?

 If a stranger who had found your wallet told you they were going to keep it, you would likely be disappointed, upset and frustrated. It's not a fair act as the wallet is not their property and it has your personal and financial information in it. It would be important to contact the authorities and report this as a theft, as it would be considered as an illegal act of taking someone else's property.

 And if the stranger turned out to be my brother and was only joking about keeping my wallet?

 If a stranger who had found your wallet turned out to be your brother and was only joking about keeping it, you would likely feel a mix of emotions. Initially you might feel relieved that your wallet has been found and you have it back. But you may also feel confused or angry if your brother made a joke out of the situation, especially if you were worried or stressed about losing your wallet. It's best to talk to him and understand his intentions and how he thought it would be a good joke, and clear out any confusion or hurt feelings.

Issues with Massive Language Models

- Preventing Memorization
- Preventing Hallucination

Memorisation and Hallucination

Research directions at the moment is to try to:

- understand to what extent the models are simply memorising what they have read
- determine how to prevent hallucination (the invention of new facts)
 - [https://en.wikipedia.org/wiki/Hallucination_\(artificial_intelligence\)](https://en.wikipedia.org/wiki/Hallucination_(artificial_intelligence))

Research Applications

Where do we use transformers?

Here are some research problems we're working on:

- **Text Analysis for Bioinformatics**

- translating text into structured data to facilitate search
- model protein sequences for drug repurposing

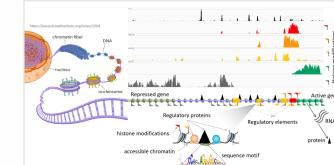


Image source: <https://www.biyanne.com/Portals/1/Samples/mzr17083203/wiki/588450>

- **Text Analysis for Political Discourse**

- identifying claims & finding evidence online
- detecting fake and misleading news

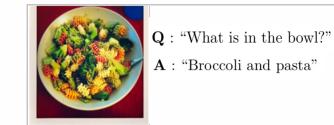


Image source: <https://www.npr.org/2018/04/11/60132323/facts-we-know-about-fake-news-in-the-2016-election>

- **Text meets Images/Video**

- visual question answering
- explaining AI with text explanations

Want to try some **demos**?
Go to: <http://131.175.15.22:6111/>
Let me know which and I'll start them



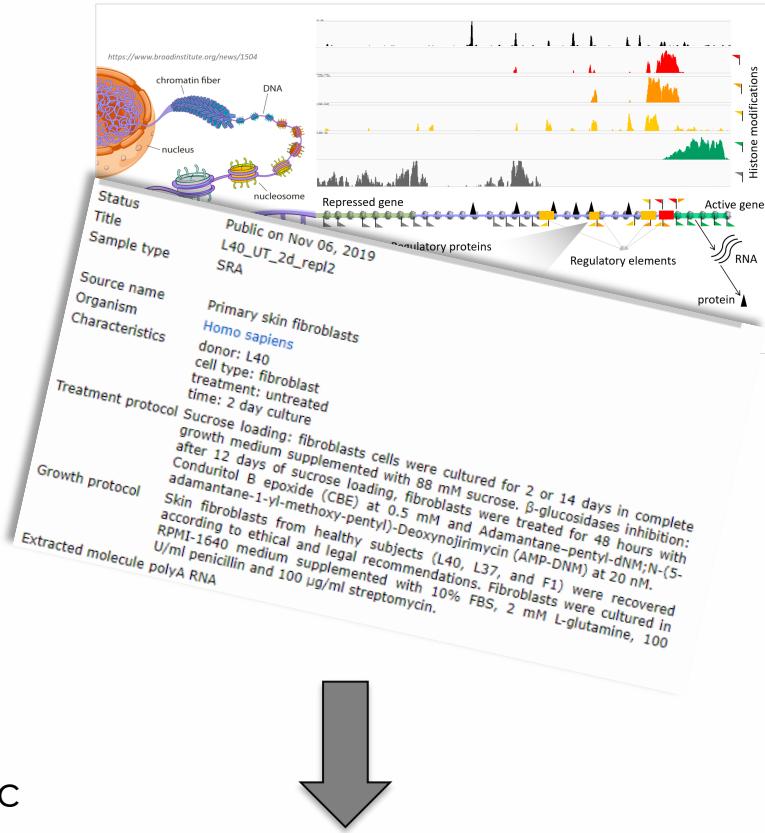
applications: data integration

LOTS of genomics data being generated by research groups around the world

- data is being aggregated in large repositories
- no agreed format for biologists describe their experiments
- much of **meta-data is free text**

Application:

- train translation models to **automatically extract database fields** from textual descriptions
- so bioinformaticians can easily find the genomic data they need for their analysis

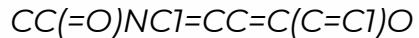


applications: protein sequence modeling

Learning BERT embeddings of protein sequences across virus families

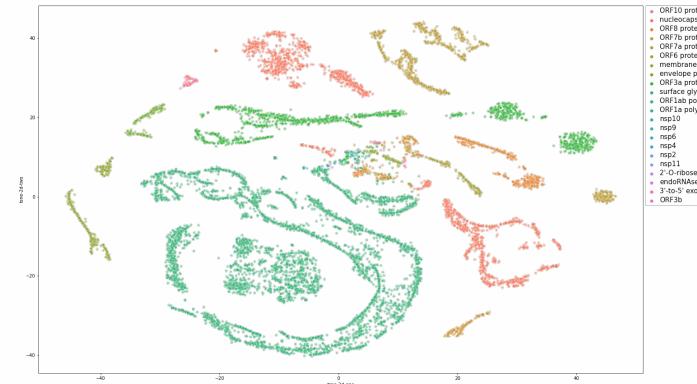
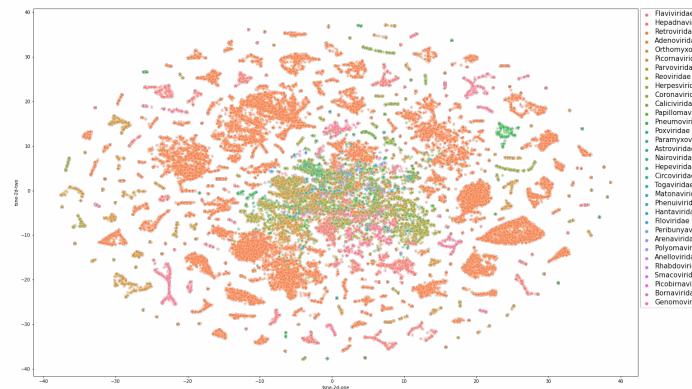
- to see if they are useful for drug-protein interaction prediction.

Will this drug:



bind with this protein?

MNSERSDVTLYQPFLDYAIAYMRSRLDLEPYPIPTGFESNSAVV
 GKGKNQEEVVTSYAFQTAKLRQIRAAHVQGGNSLQVLNFVIFP
 HLNYPDLPGFFGADLVTLPGGHLIALDMQPLFRDD SAYQAKYTEPI
 LP IFHAHQHQHLSWCGDFPEEAQPFFSPAFLWTRPQETAVVET
 QVFAAFKDYLKAYLDFVEQAEAVTDSQNLVAIKQAQLRYLRYR
 AEKDPARGMFKRFYGAEWTEEYIHGFLFDLERKLTVVK



applications: claim detection & verification

We make use of pretrained deep language models for

- detecting claims
- ranking evidence

Advantages:

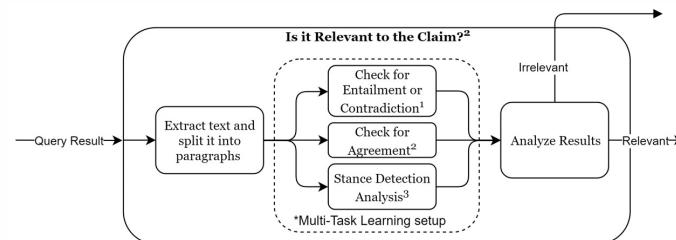
- better performance
- Multi-linguality
 - train model on English text
 - apply to Arabic text

Applications:

- detecting fake news
- counteracting hate speech online
 - finding evidence for disputing

Claim: Solar panels drain the sun's energy, experts say
Assessment: False
Explanation: Solar panels do not suck up the Sun's rays of photons. Just like wind farms do not deplete our planet of wind. These renewable sources of energy are not finite like fossil fuels. Wind turbines and solar panels are not vacuums, nor do they divert this energy from other systems.

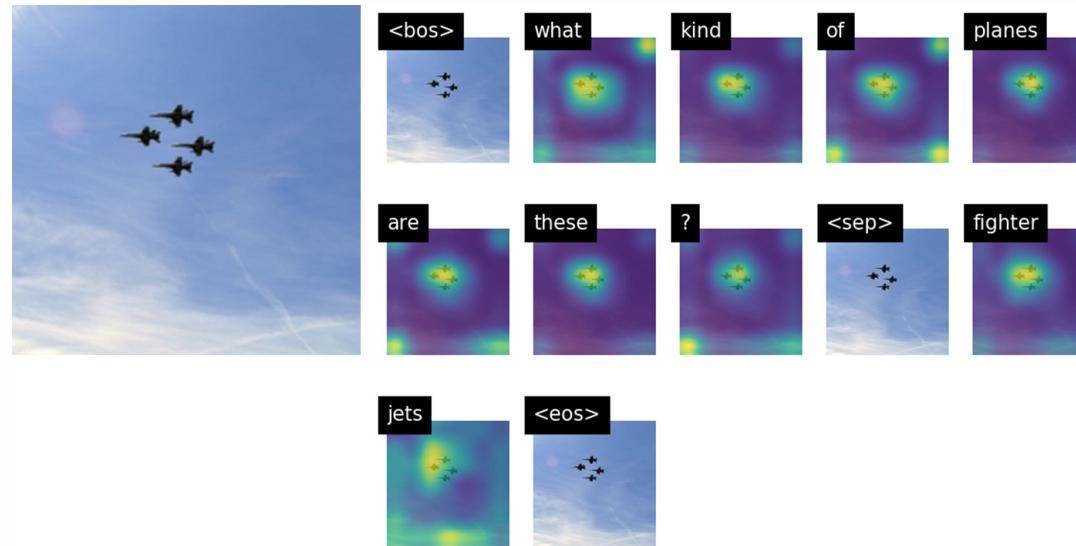
Source: "[Where the Truth Lies: Explaining the Credibility of Emerging Claims on the Web and Social Media](#)", by Popat et al.



applications: image question answering

Deep learning is famous for build embeddings over images

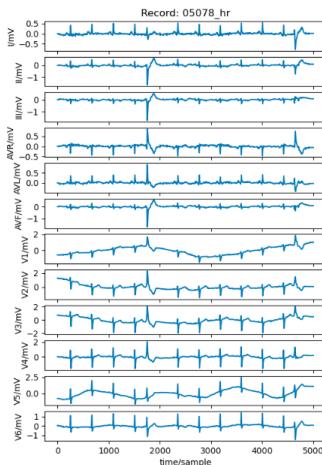
- Why not combine the power of images and text embeddings together?
- To answer questions about images:



applications: ECG report generation

Deep learning can be applied also to time-series data.

- Here we train a system to generate textual cardiology reports for 12-lead electrocardiogram (ECG) signals
- By pairing a 1-dimensional Convolutional Neural Network (Resnet encoder) with a Transformer (GPT-2 decoder)

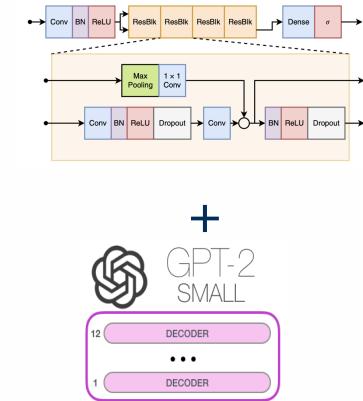


Prediction:

*premature ventricular contraction(s). sinus rhythm.
t waves are low or flat throughout. myocardial ischaemia is likely. suggest exclude hypokalaemia.*

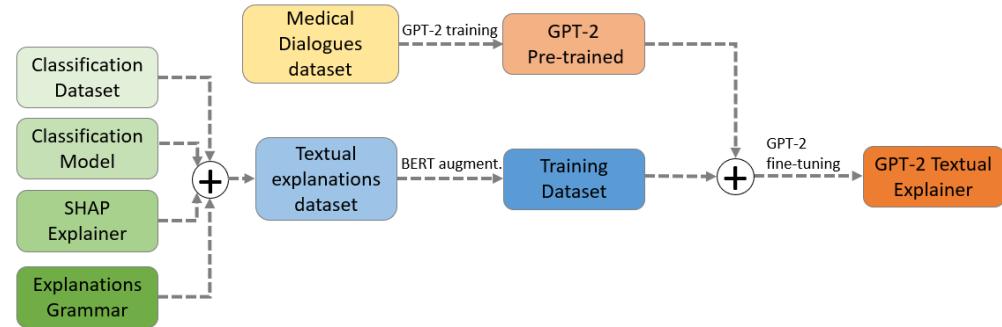
Real Report:

*premature ventricular contraction(s). sinus rhythm.
low limb lead voltage. t waves are low or flat in i, avl and slightly inverted in ii, iii, avf, v5,6. non-specific but consistent with myocardial ischaemia.*



applications: explaining medical diagnoses

Train models to **explain** in text the predictions of classification models for on tabular data



The prediction of disease is determined by the systolic blood pressure (140), which is one standard deviation above the mean and whose high values are associated with cardiovascular disease, and by the fact that he is a smoker. The BMI (29.3), which is higher than the mean and whose high values increase the likelihood of cardiovascular disease, also contributes to the result. If BMI was 27 and systolic blood pressure was 130, then the prediction would be no disease.

applications: other applications

- Classifying Android malware based from decompiled code
 - identifying parts of the code that are most suspect ...
- Generating new movie scripts by training over a large corpus of movie scripts
 - allows new movie script to be generated based on genre and title alone ...

Conclusions

Conclusions

Language models becoming really powerful!

- able to model **long range dependencies**
- and scale learning to **billions of parameters**



Language models are generic learners

- plug-in component of larger systems
- pretrained on entire web, multi-lingual

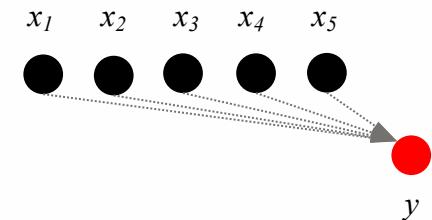
Implications:

- **natural language interfaces** (e.g. Alexa, Siri) will get **better & better**
- **detecting fakes** (e.g. news, spam, assignments) will get **harder & harder**
- **personalisation & search** (e.g. movies, clothes) will get **better & more sophisticated**
- **mining knowledge** from text (e.g. patents, emails) will get **easier & easier**
- ...

What is?

Classification task:

- input: **ordered sequence** of tokens: (x_1, x_2, \dots, x_n)
- output: single prediction for sequence: y

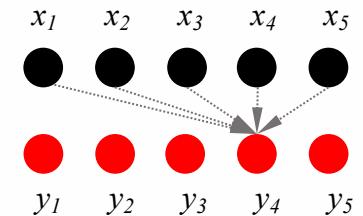


Sequence labelling task:

- input: **ordered sequence** of tokens: (x_1, x_2, \dots, x_n)
- output **sequence of predictions**: (y_1, y_2, \dots, y_n)

Note that:

- prediction for y_4 may depend not only on the sequence up to that point (x_1, x_2, x_3, x_4), but also the subsequent sequence (x_5, \dots)
- dependencies exist across predicted sequence, so certain values y_4 may not make sense given values for (y_1, y_2, y_3) and y_5 .



Conclusions

Conclusions

TODO