

# Attention models

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One of the most impactful of the family of Transformers is BERT

*Bidirectional Encoder Representations from Transformers*

From Google, trained on 2 500M words

# Attention models

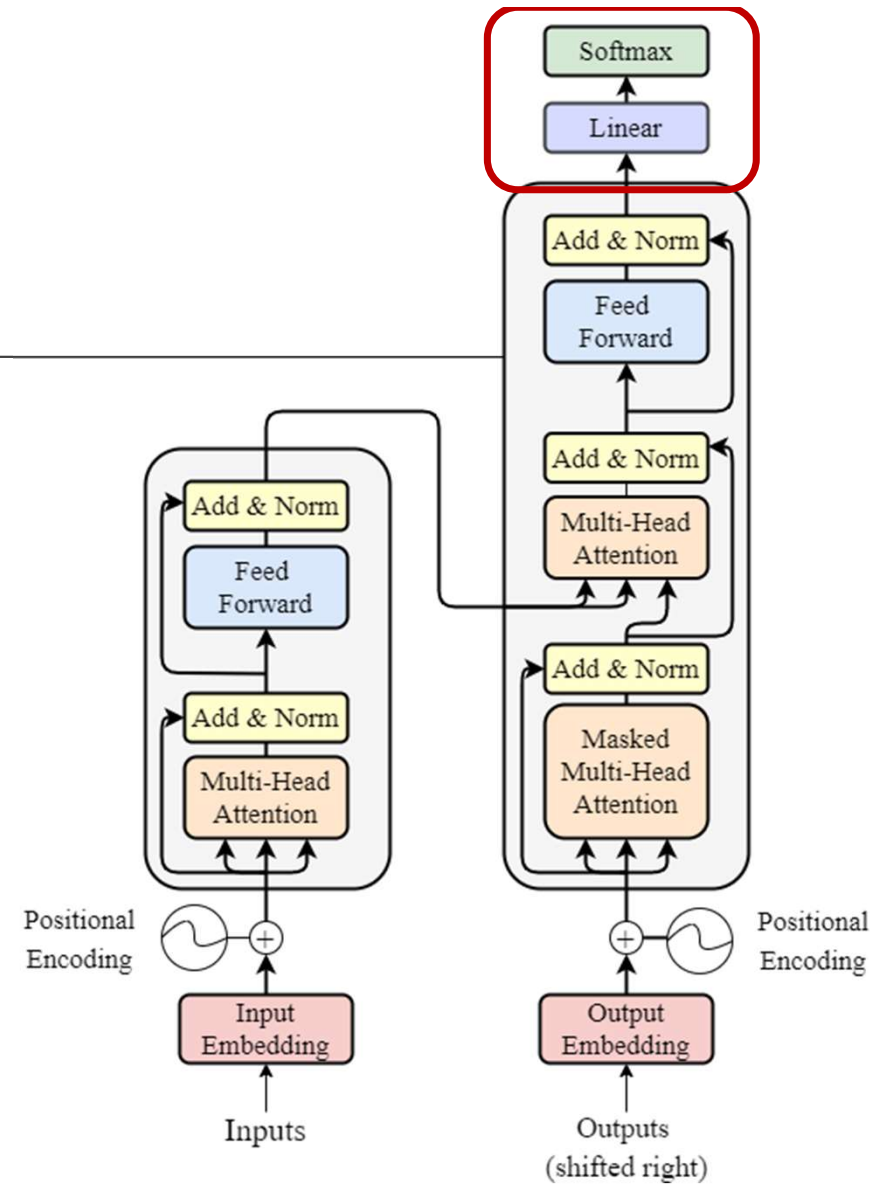
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Because what do we do with Transformers?

Well... we take these pretrained models and finetune them!

# Attention models

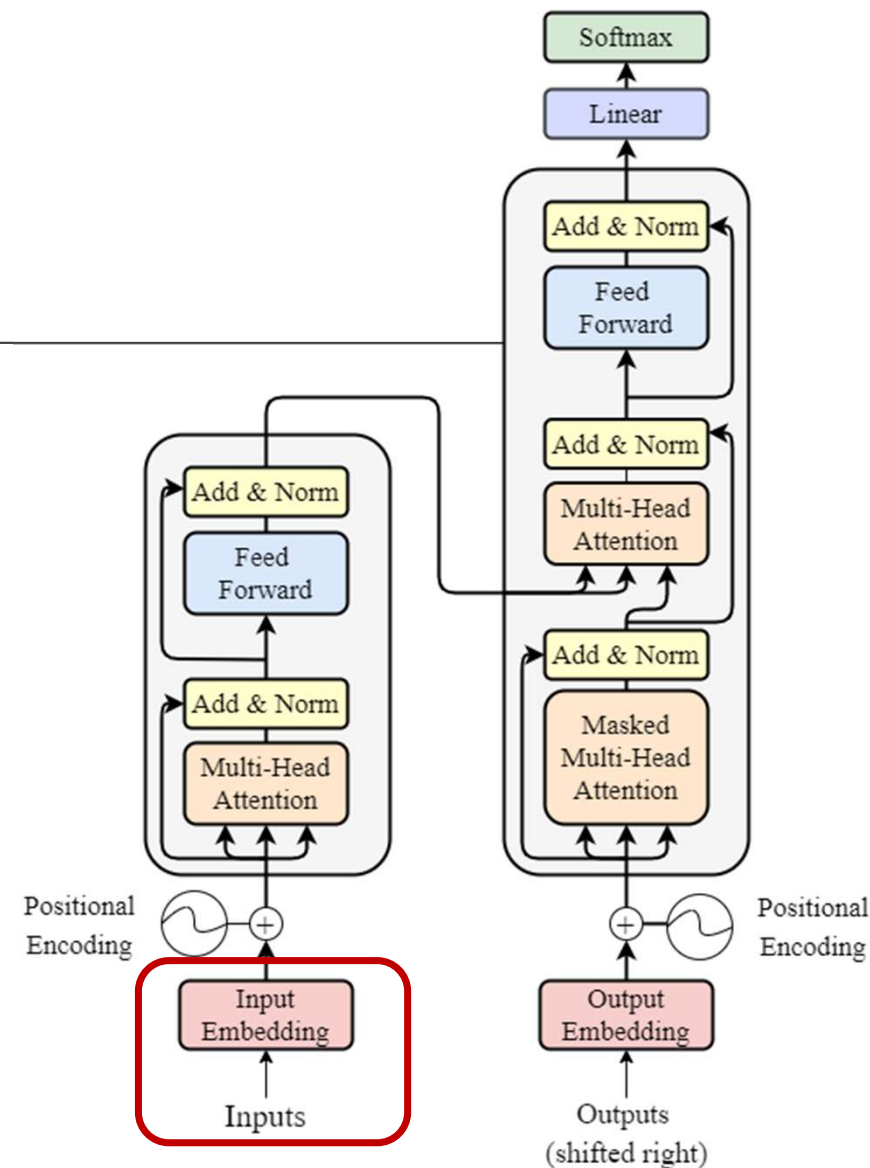
So mostly this bit...



# Attention models

So mostly this bit...

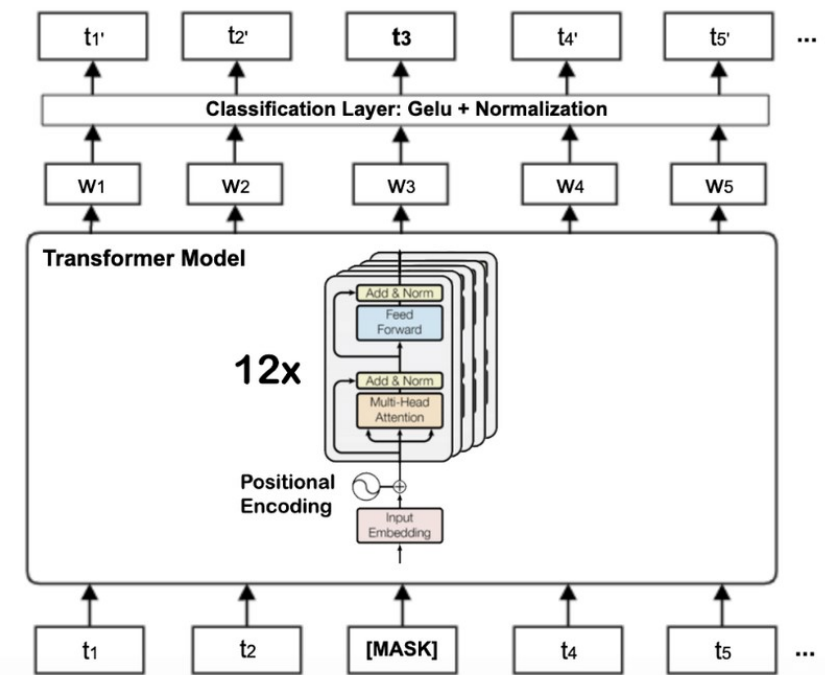
With its backprop influence, all the way to this bit



# Attention models

Although BERT uses a different architecture because it does

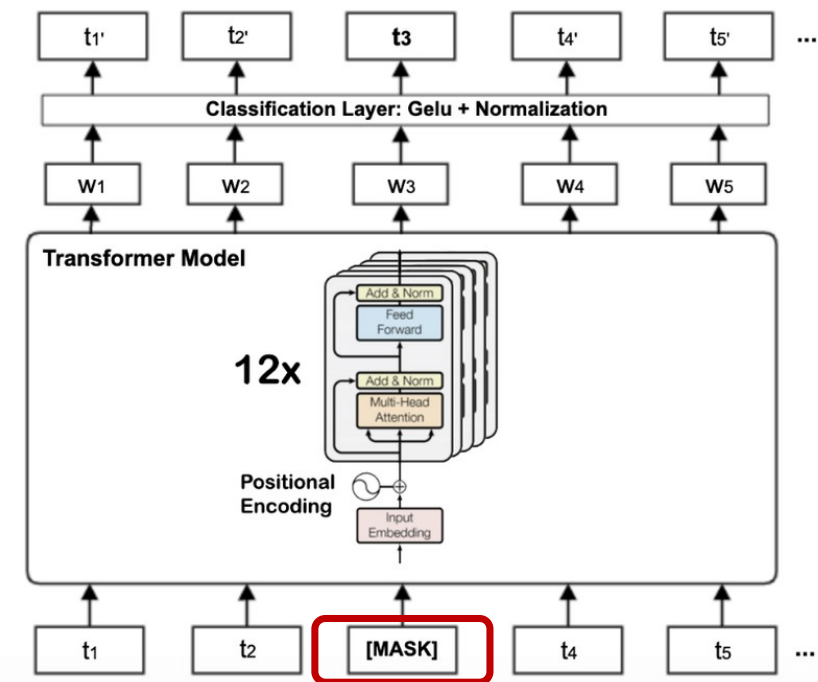
- Masked language modeling
- Next sentence prediction



# Attention models

Although BERT uses a different architecture because it does

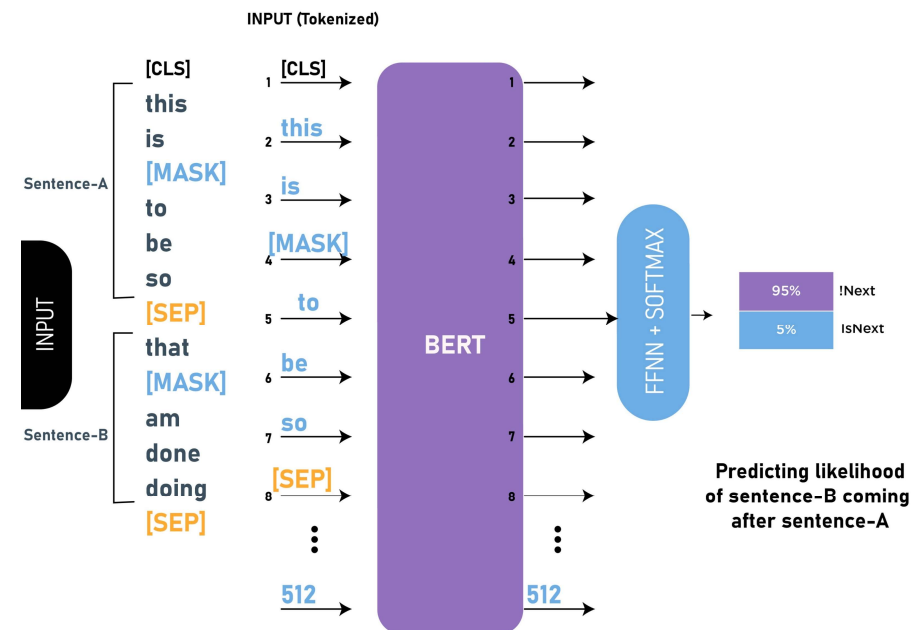
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# Attention models

Although BERT uses a different architecture because it does

- Masked language modeling
- Next sentence prediction



# Attention models

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BERT is an encoder only, so what do Q, K and V mean here?

- ❑ MLM – Query is [MASK], Key and Value are all other tokens in the input ([MASK] too)
  - ❑ Attention is used to explain (unveil) [MASK] by the other words
- ❑ NSP – Works the same but Q is from first sentence and K and V are from **both** to capture relationships
  - ❑ Attention is used to explain dependencies between first sentence and next sentence, capturing information from both



# Attention models

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Wait – what is this [MASK]?

# Attention models

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What does BERT's input look like?

- A special token, [SEP], to mark the end of a sentence
- A special token, [CLS], to mark start of text. This token is used for classification tasks, but BERT expects it no matter what your application is.
- Tokens that conform with the fixed vocabulary used in BERT
- The Token IDs for the tokens, from BERT's tokenizer
- Mask IDs to indicate which elements in the sequence are tokens and which are padding elements
- Segment IDs used to distinguish different sentences
- Positional Embeddings used to show token position within the sequence

# Attention models

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Note that BERT's vocabulary does not just consist of words!

- Whole words
- Characters
- Subword information from the start of the word (superceded with some special token, mostly ##)
- Special subword information not at the start (preceded with some special token, mostly ##)

This is called WordPiece tokenization

# Attention models

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Note – getting a word vector from BERT is not trivial

# Attention models

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Note – getting a word vector from BERT is not trivial

Because a word will have different vectors based on its context

# Attention models

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Note – getting a word vector from BERT is not trivial

There are multiple approaches and each library chooses its own...

They all use some pooling mechanism though

# Attention models

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Note: a sentence vector is simply the (contextualized) word-vector for [CLS] !

Isn't that cool?



# Attention models

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So what can we use these Transformers for?



# Attention models

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What not?!

# Attention models

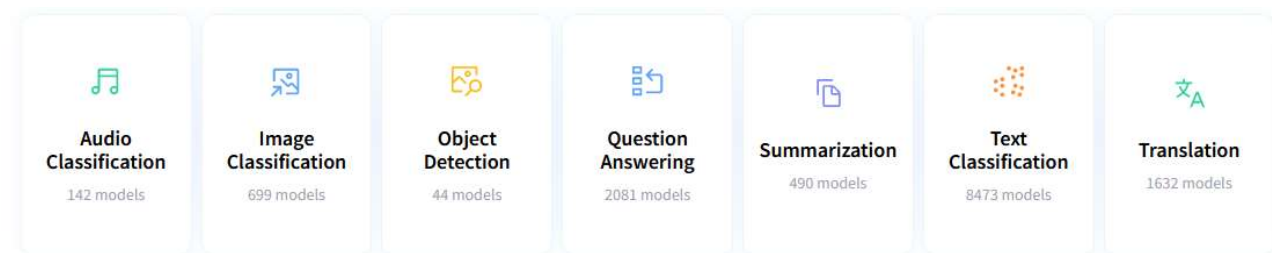
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- ☐ Vectors models
- ☐ Text classifiers
- ☐ Sequence to sequence (machine translation)
- ☐ Other fields like image recognition
- ☐ Multi-modal learning (NLP + Image in one go)
- ☐ Text generation

# Attention models

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# Attention models

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Notably, BERT (& co, there are many derivatives) is used for (contextualized) embeddings and hence classification

# Attention models

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Notably, BERT (& co, there are many derivatives) is used for (contextualized) embeddings and hence classification

BERT, RoBERTa, CamemBERT, DistilBERT, etc. etc.

# Attention models

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There is a competitor named XLM (cross lingual model)

# Attention models

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Then we have machine translation, mostly done using BART or NLLB

# Attention models

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Then there are a bunch focused on non-NLP tasks



# Attention models

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And then there is text generation!



# Attention models

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- ☐ GPT1
- ☐ GPT2
- ☐ GPT3
- ☐ WuDAO
- ☐ BLOOM
- ☐ ChatGPT / GPT 4

# Attention models

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□ GPT1

□ This was fun, promising

□ GPT2

□ GPT3

□ WuDAO

□ BLOOM

□ ChatGPT / GPT 4

# Attention models

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❑ GPT1

❑ GPT2

❑ This made reasonably well-written documents when used well

❑ GPT3

❑ WuDAO

❑ BLOOM

❑ ChatGPT / GPT 4

# Attention models

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❑ GPT1

❑ GPT2

❑ GPT3

❑ This stuff scared the world!

❑ WuDAO

❑ BLOOM

❑ ChatGPT / GPT 4

# Attention models

---

❑ GPT1

❑ GPT2

❑ GPT3

❑ This stuff scared the world!

❑ WuDAO

❑ BLOOM

## A college student used GPT-3 to write fake blog posts and ended up at the top of Hacker News

*He says he wanted to prove the AI could pass as a human writer*

By Kim Lyons | @SocialKimLy | Aug 16, 2020, 1:55pm EDT

# Attention models

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- ❑ GPT1

- ❑ GPT2

- ❑ GPT3

- ❑ WuDAO

  - ❑ Uses “GPT3-like” architecture to reason and “communicate” – and not just English!

- ❑ BLOOM

- ❑ ChatGPT / GPT 4

# Attention models

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- ❑ GPT1
- ❑ GPT2
- ❑ GPT3
- ❑ WuDAO
- ❑ BLOOM
  - ❑ 46 languages(!), collaboration of many researchers
- ❑ ChatGPT / GPT 4



# Attention models

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- ❑ GPT1
- ❑ GPT2
- ❑ GPT3
- ❑ WuDAO
- ❑ BLOOM
  - ❑ 46 languages(!), collaboration of many researchers  
And 13 programming languages 😊
- ❑ ChatGPT / GPT 4

# Attention models

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~~☐ GPT1~~

~~☐ GPT2~~

~~☐ GPT3~~

~~☐ WU DAO~~

~~☐ BLOOM~~

ChatGPT



# Attention models

---

 ~~GPT1~~

 ~~GPT2~~

 ~~GPT3~~

 ~~WuDAO~~

 ~~BLOOM~~

ChatGPT

(Well, LLMs like ChatGPT: LLaMa, Claude,  
Vicuna, etc.)



# ChatGPT

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So what is this thing?

# ChatGPT

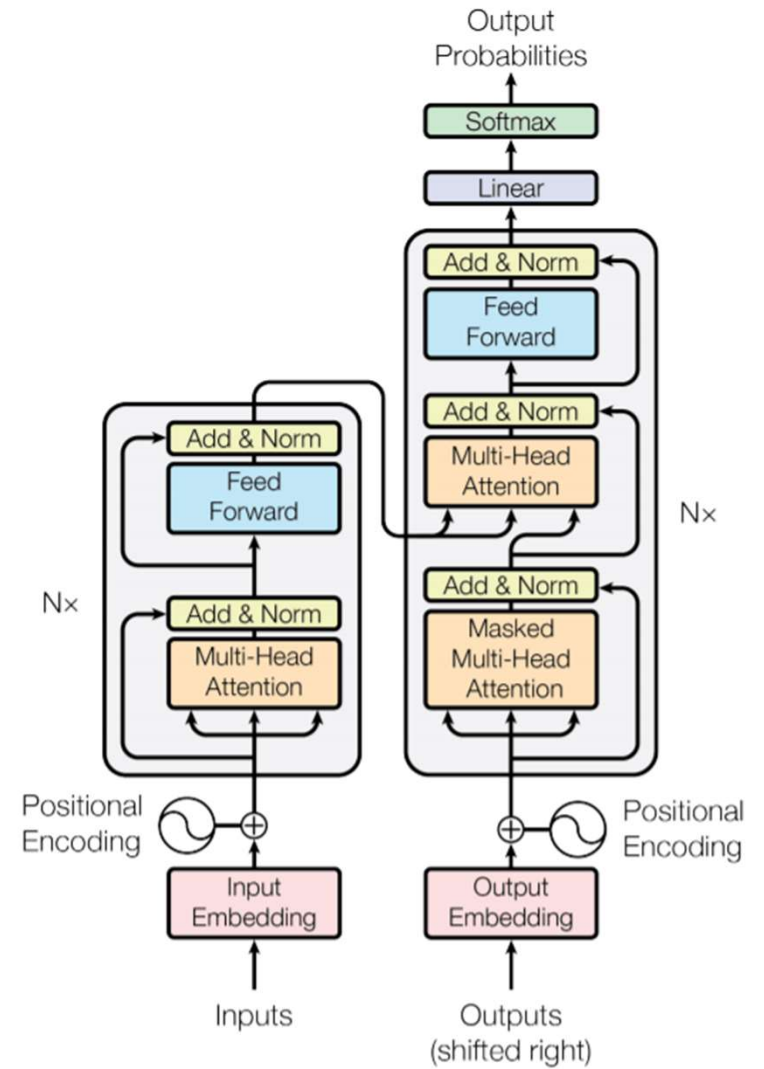


Figure 1: The Transformer - model architecture.

# ChatGPT

This is the same base fundament as BERT

Encoder-only

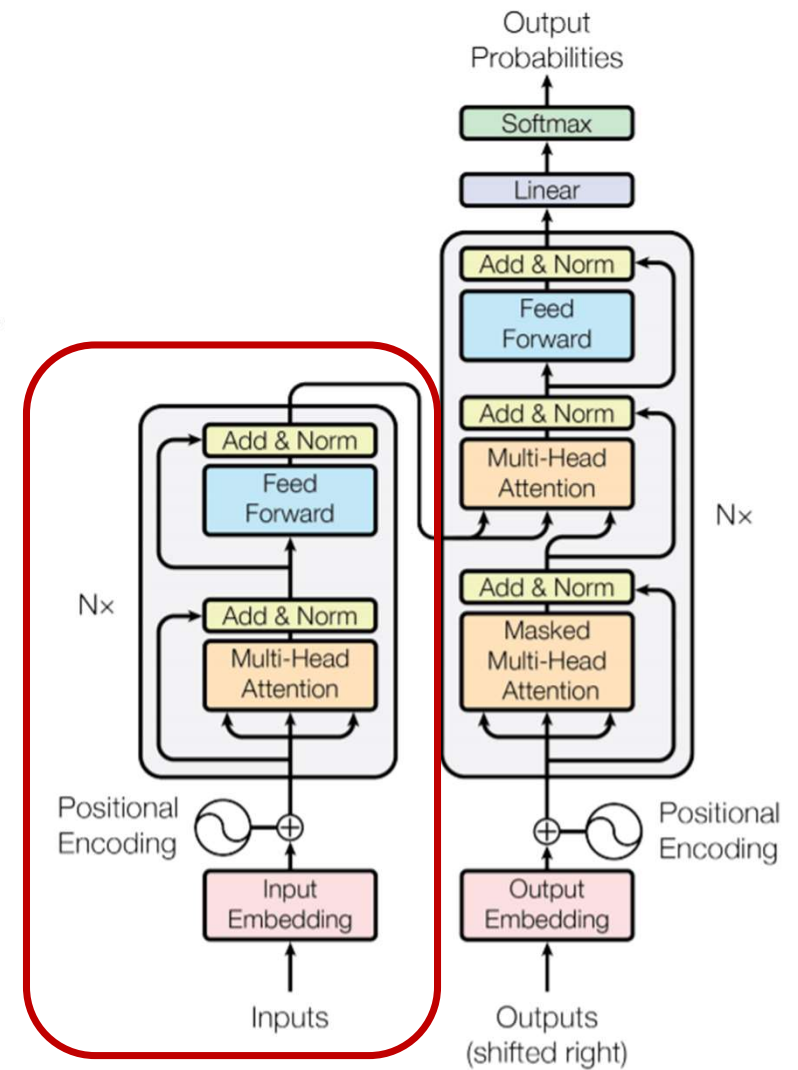


Figure 1: The Transformer - model architecture.

# ChatGPT

And this is GPT

Decoder-only

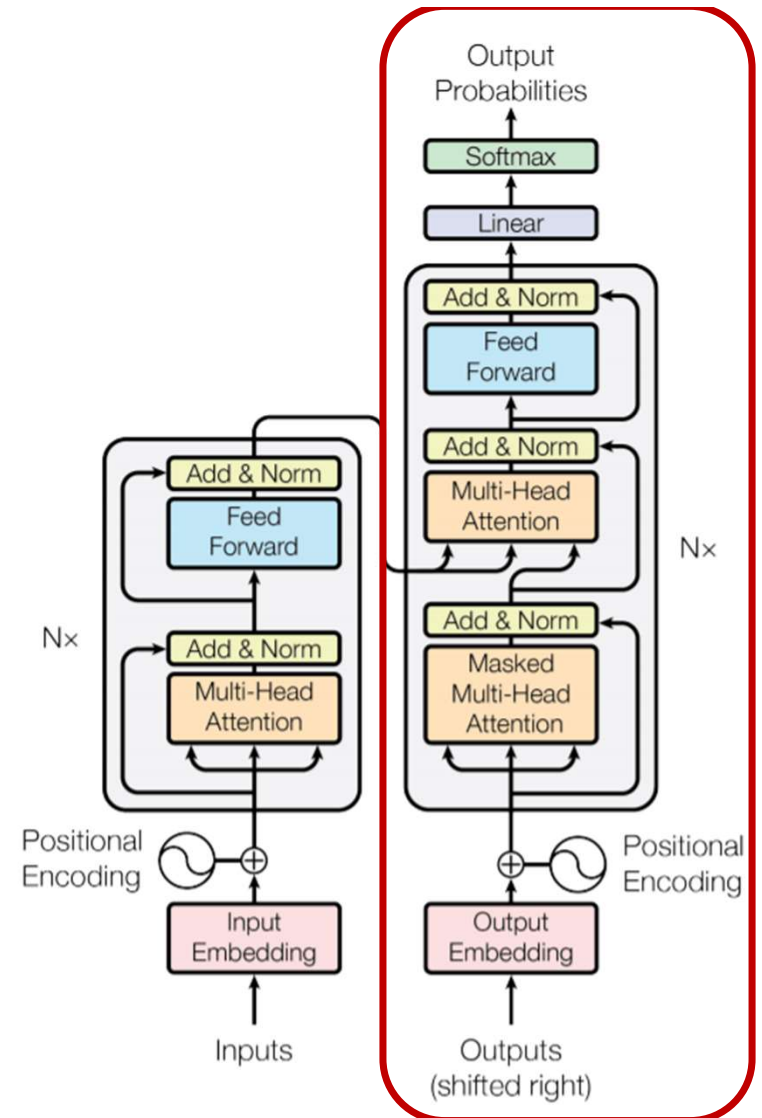


Figure 1: The Transformer - model architecture.

# ChatGPT

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Where BERT does masked-language-modeling

GPT does autoregressive language modeling: predict the next token/word  
(based on input + already predicted words)



# ChatGPT

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Query – The token being generated

Key – Previously generated (or input) tokens

Value – The attention vectors associated with the Keys

So for the current token (Q) we pay attention to the previously generated tokens (K) and how much information (attention, V) they bear towards the current token

# ChatGPT

---

Query – The token being generated

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So for the current token (Q) we pay attention to the previously generated tokens (K) and how much information (attention, V) they bear towards the current token

For training: compute self-attention, for generation: sample from probability distribution and select most probable one

# ChatGPT

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## Next-token-prediction

The model is given a sequence of words with the goal of predicting the next word.

Example:  
Hannah is a \_\_\_\_

Hannah is a *sister*  
Hannah is a *friend*  
Hannah is a *marketer*  
Hannah is a *comedian*

## Masked-language-modeling

The model is given a sequence of words with the goal of predicting a 'masked' word in the middle.

Example  
Jacob [mask] reading

Jacob *fears* reading  
Jacob *loves* reading  
Jacob *enjoys* reading  
Jacob *hates* reading

# ChatGPT

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So that is GPT, what is ChatGPT?

# ChatGPT

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InstructGPT with RLHF



# ChatGPT

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RLHF (Reinforcement Learning from Human Feedback)

1. Supervised fine-tuning from human inputs – basically let GPT generate responses and pick a good option (or suggest a new one)
2. Humans rank responses for quality and train model to favor higher quality responses

# ChatGPT

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## InstructGPT

1. Build on the principles of GPT and RLHF but input queries are now instructions
2. Humans label data to generate answers that best “follow” the instructions

# ChatGPT

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ChatGPT tries to disambiguate **questions** from **instructions**





# ChatGPT

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ChatGPT tries to disambiguate **questions** from **instructions**

And RLHF + InstructGPT make sure the answers are contextually relevant

# ChatGPT

## Step 1

**Collect demonstration data, and train a supervised policy.**

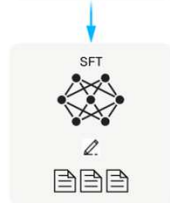
A prompt is sampled from our prompt dataset.



A labeler demonstrates the desired output behavior.



This data is used to fine-tune GPT-3 with supervised learning.



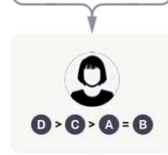
## Step 2

**Collect comparison data, and train a reward model.**

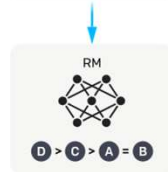
A prompt and several model outputs are sampled.



A labeler ranks the outputs from best to worst.



This data is used to train our reward model.



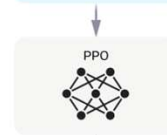
## Step 3

**Optimize a policy against the reward model using reinforcement learning.**

A new prompt is sampled from the dataset.

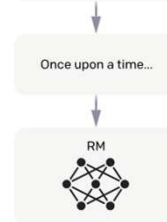


The policy generates an output.

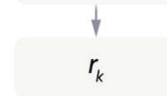


Once upon a time...

The reward model calculates a reward for the output.



The reward is used to update the policy using PPO.



# ChatGPT

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See also

<https://openai.com/research/instruction-following>

# Attention models

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So is ChatGPT (or LLMs) the answer to everything?

# Attention models

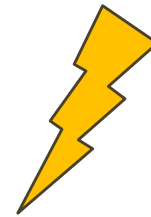
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What about text classification?

# Attention models

---

What about text classification?



Well maybe with some prompt engineering

# Attention models

---

What about text classification?



Well maybe with some prompt engineering

Speaking of which...

# Attention models

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Back to Transformers

So how do we use this in practice?



# Attention models

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One option

Go to [chat.openai.com](https://chat.openai.com) and voila 😊

# Attention models

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Or, go over to <https://huggingface.co/> and start coding!

# Attention models

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Example for classification

# Attention models

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```

from transformers import AutoTokenizer, AutoModelForSequenceClassification,
    TrainingArguments, Trainer, DataCollatorWithPadding
tokenizer = AutoTokenizer.from_pretrained("distilbert-base-uncased")

def preprocess_function(examples):
    return tokenizer(examples["text"], truncation=True)

tokenized_imdb = imdb.map(preprocess_function, batched=True)
data_collator = DataCollatorWithPadding(tokenizer=tokenizer)
model = AutoModelForSequenceClassification.from_pretrained("distilbert-base
-uncased", num_labels=2)

training_args = TrainingArguments(
    output_dir="./results",
    learning_rate=2e-5,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    num_train_epochs=5,
    weight_decay=0.01,
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=tokenized_imdb["train"],
    eval_dataset=tokenized_imdb["test"],
    tokenizer=tokenizer,
    data_collator=data_collator,
)

trainer.train()

```

# Attention models

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Example for generation

# Attention models

```
from transformers import (GPT2LMHeadModel, GPT2Tokenizer)
MAX_LENGTH = int(10000)
args = obj({
    'model_type': 'gpt2',
    'model_name_or_path': 'gpt2',
    'length': 50,
    'temperature': 1.0,
    'repetition_penalty': 1.0,
    'k': 50,
    'p': 0.95,
    'seed': 1337,
    'num_return_sequences': 1,
    'device': None,
    'n_gpu': None
})
model_class = GPT2LMHeadModel
tokenizer_class = GPT2Tokenizer
tokenizer = tokenizer_class.from_pretrained(args.model_name_or_path)
model = model_class.from_pretrained(args.model_name_or_path)
model.to(args.device)
```

```
args.length = adjust_length_to_model(args.length,
    max_sequence_length=model.config.max_position_embeddings)
encoded_prompt = tokenizer.encode(input_text, add_special_tokens=False,
    return_tensors="pt")
encoded_prompt = encoded_prompt.to(args.device)
if encoded_prompt.size()[-1] == 0:
    input_ids = None
else:
    input_ids = encoded_prompt
output_sequences = model.generate(
    input_ids=input_ids,
    max_length=args.length + len(encoded_prompt[0]),
    temperature=args.temperature,
    top_k=args.k,
    top_p=args.p,
    repetition_penalty=args.repetition_penalty,
    do_sample=True,
    num_return_sequences=args.num_return_sequences,
)
```

# Attention models

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Example for topic modelling

# Attention models

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There is KeyBERT and BERTopic

<https://github.com/MaartenGr/KeyBERT>

<https://maartengr.github.io/BERTopic/index.html>



# Attention models

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But, really, just check the docs, they are quite good.

<https://huggingface.co/docs/transformers/index>

# Program

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- ~~Basics of Deep Learning (for NLP)~~
- ~~Vectorization models~~
- ~~Auto-encoders~~
- ~~Recurrent neural nets~~
- ~~Recursive neural nets~~
- ~~LSTMs~~
- ~~Attention models~~
- Deep learning for NLP in practice
- t-SNE
- Google Colab

# DL NLP in practice

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So this is all cool stuff!

Let's go ahead and train some models ourselves 😊

Or not?

# DL NLP in practice

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There are many challenges with DL NLP in practice!

We'll check out a couple and how to remedy them.

# DL NLP in practice

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- ☐ Cost
- ☐ Language support
- ☐ Knowledge on usage
- ☐ Explainability (ethical AI)

# DL NLP in practice

---

## Cost

### Speeds, Sizes, Times

Training logs: [Tensorboard link](#)

- Dates:
  - Started 11th March, 2022 11:42am PST
  - Estimated end: 5th July, 2022
- Checkpoint size:
  - Bf16 weights: 329GB
  - Full checkpoint with optimizer states: 2.3TB
- Training throughput: About 150 TFLOP per GPU per second
- Number of epochs: 1
- Estimated cost of training: Equivalent of \$2-5M in cloud computing (including preliminary experiments)
- Server training location: Île-de-France, France

### Environmental Impact

The training supercomputer, Jean Zay ([website](#)), uses mostly nuclear energy. The heat generated by it is reused for heating campus housing.

**Estimated carbon emissions:** *(Forthcoming.)*

**Estimated electricity usage:** *(Forthcoming.)*

# DL NLP in practice

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# DL NLP in practice

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## Cost

OpenAI recently published GPT-3, the largest language model ever trained. GPT-3 has 175 billion parameters and would require 355 years and \$4,600,000 to train - even with the **lowest priced GPU cloud on the market**.<sup>[1]</sup>



# DL NLP in practice

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# DL NLP in practice

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GPU RAM required (for inference!)

□ LLaMA 65B	<b>260GB</b>
□ Falcon 40B	<b>160GB</b>
□ LLaMA 33B	<b>132GB</b>
□ Falcon 7B	<b>28GB</b>
□ LLaMa 7B	<b>14GB</b> (with some tricks)

# DL NLP in practice

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But the bigger the context window, the more vRAM you need.

# DL NLP in practice

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But the bigger the context window, the more vRAM you need.

Claude 2.1 has a 200k window!

# DL NLP in practice

---

But the bigger the context window, the more vRAM you need.

Claude 2.1 has a 200k window!

# DL NLP in practice

---

Note that all these LLMs (Large Language Models) are highly subsidized and sponsored by governments, industry and NVIDIA

# DL NLP in practice

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Solution?

# DL NLP in practice

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Solution?

Don't train these yourself. Use pre-trained models off the bat or finetune only!



# DL NLP in practice

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- ☐ Cost
- ☐ Language support
- ☐ Knowledge on usage
- ☐ Explainability (ethical AI)

# DL NLP in practice

---

So now you want to use this stuff for Dutch! Great, go ahead.



# DL NLP in practice

---

So now you want to use this stuff for Dutch! Great, go ahead.

But wait a minute...

# DL NLP in practice

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No Dutch in BLOOM ☹️

No Dutch for GPT3 ☹️

No Dutch for GPT2 ☹️

No Dutch in LLaMa2 ☹️

# DL NLP in practice

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Or even worse: real-life use-case – Kirundi, main language in Burundi.

There isn't even a wikipedia in Kirundi

# DL NLP in practice

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Why is this?

# DL NLP in practice

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These are the most widely used datasets to train (unsupervised) on

Dataset	# Tokens (Billions)
Total	499
Common Crawl (filtered by quality)	410
WebText2	19
Books1	12
Books2	55
Wikipedia	3

# DL NLP in practice

---

These are the most widely used datasets to train (unsupervised) on

This is skewed to world languages!

English

Spanish

Chinese

Arabic

Dataset	# Tokens (Billions)
Total	499
Common Crawl (filtered by quality)	410
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Books2	55
Wikipedia	3



# DL NLP in practice

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Reality check

Dutch is not a world language ☹️

# DL NLP in practice

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Solution?

- ☐ Don't model small languages?
- ☐ Join a tech giant?
- ☐ Pray someone trains your language?
- ☐ Use transfer learning
  - ☐ Take pre-trained mixed language models and apply them to your language
  - ☐ Use machine translation (there's a model for that) to your language

# DL NLP in practice

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- ☐ Cost
- ☐ ~~Language support~~
- ☐ Knowledge on usage
- ☐ Explainability (ethical AI)

# DL NLP in practice

---

Knowledge on usage – que es eso?

# DL NLP in practice

---

Question

Do you have a GPU?

Which one?

Does it run CUDA?

Tensorflow, cuDNN, torch, cuBLAS?

# DL NLP in practice

---

Will you install all of this?

Maintain it?

# DL NLP in practice

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What about all these parameters?

Epochs, mini-batch size, sliding window, vectorization

# DL NLP in practice

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What layers would you use when?

When to use dropout, with which thresholds?



# DL NLP in practice

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Bottom line: deep learning is pretty complex

And this is not just about understanding what a neural network does!

# DL NLP in practice

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Fun anecdote

Geoff Hinton and his crew started winning a lot of Kaggle competitions

Without being specialized in niches like NLP, Image, Sensor data

# DL NLP in practice

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Fun anecdote

That means that

1. Deep learning can help tackle problems without deep domain knowledge
2. Doing it, is somewhat of a black art (tho we are democratizing it)

# DL NLP in practice

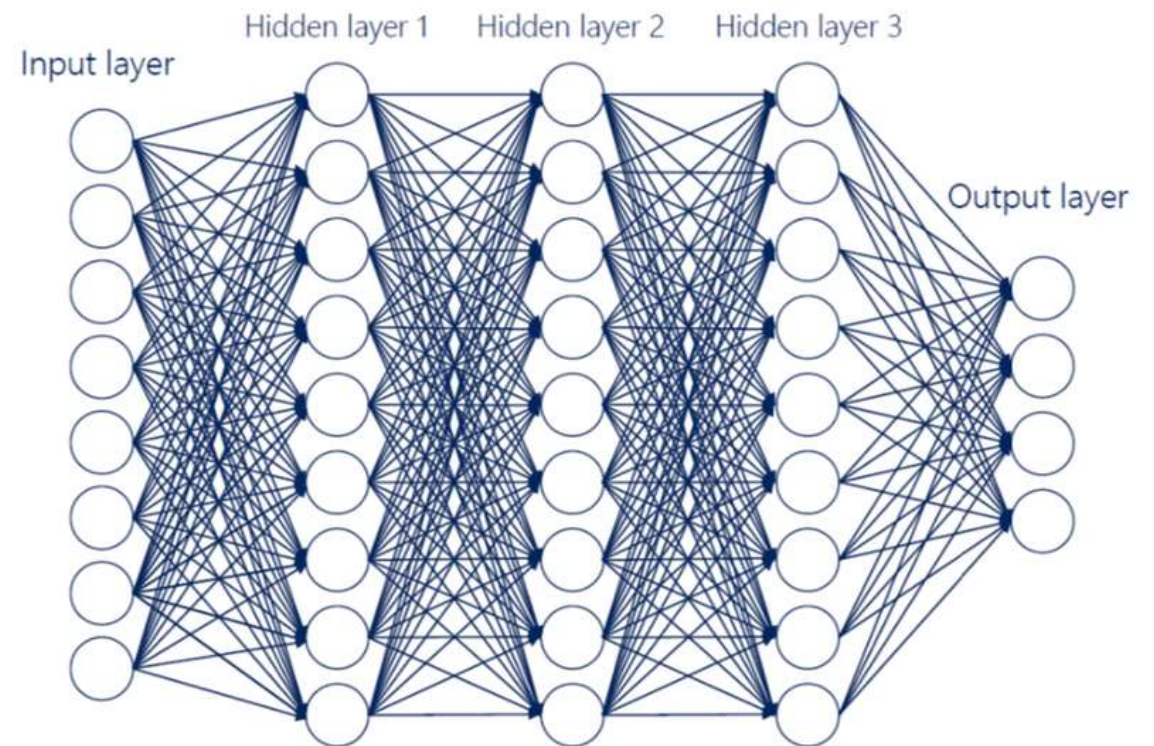
---

- ☐ Cost
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# DL NLP in practice

---

Question – here's a neural net

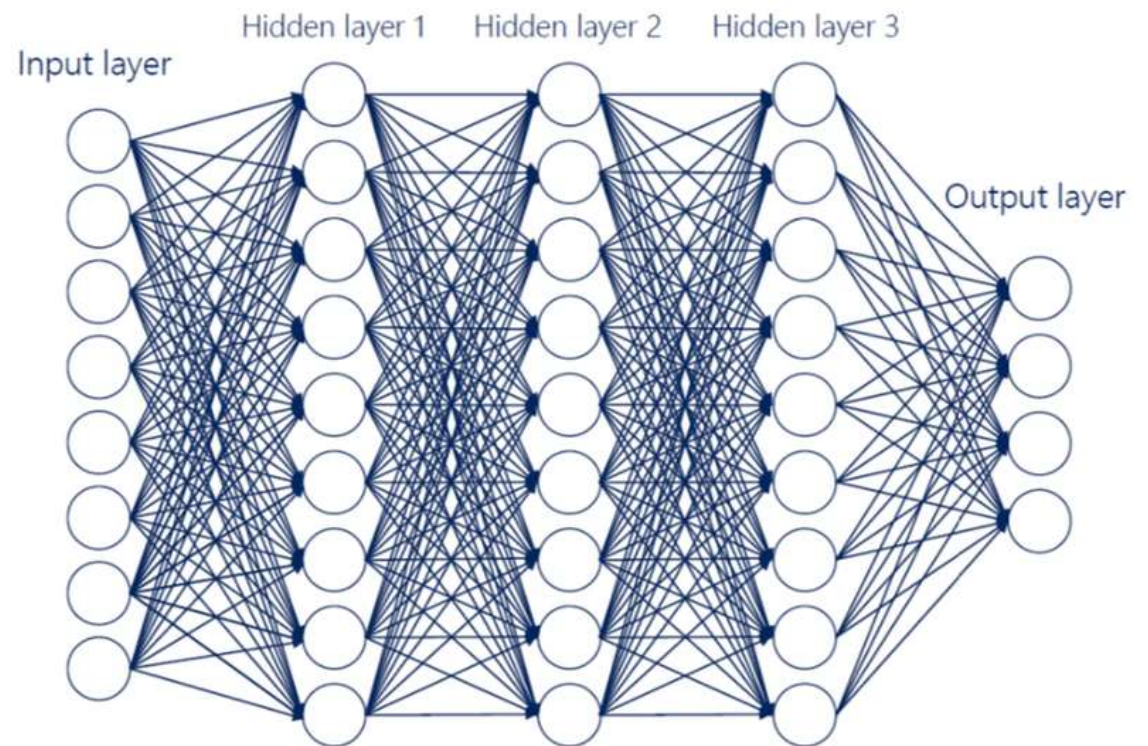


# DL NLP in practice

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Question – here's a neural net

Why do I get  $[0.2, 0.8, -0.2, 1.0]$   
out for my input which is a sentence?



# DL NLP in practice

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Or better said: how do we explain what a neural net does?

# DL NLP in practice

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Or better said: how do we explain what a neural net does?

And more importantly: the bias it contains



# DL NLP in practice

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True story

Amazon built a model that predicted if a candidate was a good match to become a software engineer within Amazon

# DL NLP in practice

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True story

But because the model was trained on existing software engineers, being predominantly male, the model just learned “*if you are male, you are hired*”

# DL NLP in practice

---

Result

*Big scandal*



World Business Markets Breakingviews Video More

RETAIL · OCTOBER 11, 2018 / 1:04 AM / UPDATED 4 YEARS AGO

**Amazon scraps secret AI recruiting tool that showed bias against women**

<https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G>

# DL NLP in practice

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In this case even, the outcome was tangible – we can see it hired men only

But what if we have complex, autonomous, automated outcomes that are not curated?

# DL NLP in practice

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GPT3, BLOOM, etc. can create human-like texts

DALL-E, MidJourney, Stable Duffision can create human-like art, images

Deepfake methods can create human-like videos

# DL NLP in practice

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GPT3, BLOOM, etc. can create human-like texts

DALL-E, MidJourney, Stable Duffision can create human-like art, images

Deepfake methods can create human-like videos



# DL NLP in practice

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Ethical AI tries to advocate against all these practices

But developments outpace what we can monitor and manage...

# DL NLP in practice

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- ☐ Cost
- ☐ Language support
- ☐ Knowledge on usage
- ☐ Explainability (ethical AI)



# Program

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- ~~Basics of Deep Learning (for NLP)~~
- ~~Vectorization models~~
- ~~Auto-encoders~~
- ~~Recurrent neural nets~~
- ~~Recursive neural nets~~
- ~~LSTMs~~
- ~~Attention models~~
- ~~Deep learning for NLP in practice~~
- t-SNE
- Google Colab

# t-SNE

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You: Hey Erik, I got a really cool vectorization model that captures semantics, syntax, irony and sarcasm in one go!



# t-SNE

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Me: prove it

# t-SNE

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Meet: t-SNE

(t-Distributed Stochastic Neighbor Embedding)

A dimension reduction method developed at TU Delft



# t-SNE

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What does it do?

Compress your vectors into less dimensions – normally 2

Capturing as much information as possible in those 2 dimensions



# t-SNE

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Compress your vectors into less dimensions – normally 2

Capturing as much information as possible in those 2 dimensions

Which means we can plot it (our word vectors!)





# t-SNE

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```

from gensim.models import word2vec
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

model = word2vec.Word2Vec(corpus, size=100, window=20, min_count=200, workers=4)

labels = []
tokens = []
for word in model.wv.vocab:
    tokens.append(model[word])
    labels.append(word)

tsne_model = TSNE(perplexity=40, n_components=2, init='pca', n_iter=2500, random_state=23)
new_values = tsne_model.fit_transform(tokens)

x = []
y = []
for value in new_values:
    x.append(value[0])
    y.append(value[1])

plt.figure(figsize=(16, 16))
for i in range(len(x)):
    plt.scatter(x[i], y[i])
    plt.annotate(labels[i], xy=(x[i], y[i]), xytext=(5, 2), textcoords='offset points', ha='right', va='bottom')

plt.show()

```

<https://www.kaggle.com/code/jeffd23/visualizing-word-vectors-with-t-sne/notebook>



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# Google Colab

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Remember our points about DL being hard?



# Google Colab

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Remember our points about DL being hard?

GPU, CUDA, Tensorflow, Huggingface, compiling libraries...

# Google Colab

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Well, meet Google Colab!

It does all the hard for you – and you don't need to buy an expensive GPU

# Google Colab

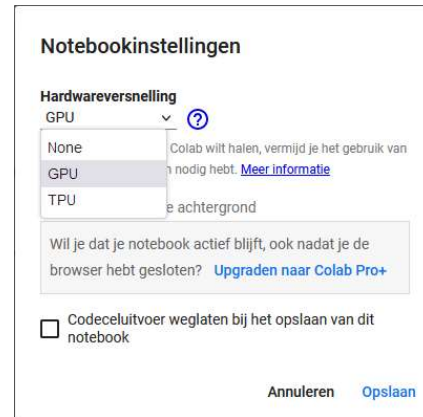
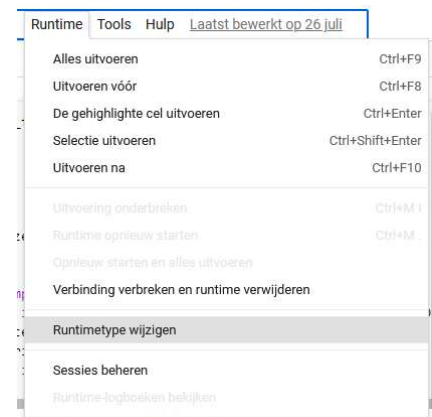
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Create a Google account with your JADS e-mail address

Go to <https://colab.research.google.com/>

# Google Colab

Create a notebook, make sure you use a GPU runtime when working with DL libraries such as Keras, Tensorflow, Huggingface



# Google Colab

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You will get a 12GB capable GPU that you can use for 12 hours in one go

# Google Colab

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You will get a 12GB capable GPU that you can use for 12 hours in one go

Tip: checkpoint your epochs in between to continue across 12h sessions!



# Google Colab

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You can also connect Google Drive to Colab

# Google Colab

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You can also connect Google Drive to Colab

Including the datasets

# Google Colab

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```
from google.colab import drive
drive.mount('/content/drive')

import pandas as pd
df = pd.read_json("/content/drive/MyDrive/dataset.json", encoding='utf8', lines=True)
df.head
```

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# Questions?

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Thanks for this DL ride

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<https://www.futureclub.nl/>

<https://github.com/AI-Commandos/LLaMa2lang>

<https://github.com/AI-Commandos/RAGMeUp>

<https://www.linkedin.com/in/eriktromp/>

<https://www.udemy.com/course/the-definitive-intro-to-big-data-science/?referralCode=47E37006CFC5B5599874>

<https://www.udemy.com/course/every-data-architecture-is-the-same/?referralCode=CD1F8BF2562089D63617>

