ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
CAMPUS DI FORLÌ

91258 / B0385
Natural Language Processing

Lesson 20. Beyond

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Transformers[1]

[1] Partially based on https://neptune.ai/blog/bert-and-the-transformer-architecture-reshaping-the-ai-landscape

Attention (Vaswani et al., 2017)

- RNNs are [were] at the core of NLU tasks —language modeling, machine translation and question answering

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- Comparison against recurrent and convolutional models:
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- By reading one word at a time, RNNs have a hard time modelling distant word interactions
- CNN’s get all the info at once, but combining distant relationships comes late

https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

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Transformer (Devlin et al., 2019)

- A small/constant number of steps (chosen empirically)

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Example:

I arrived at the bank after crossing the river
I arrive at the bank after crossing the road

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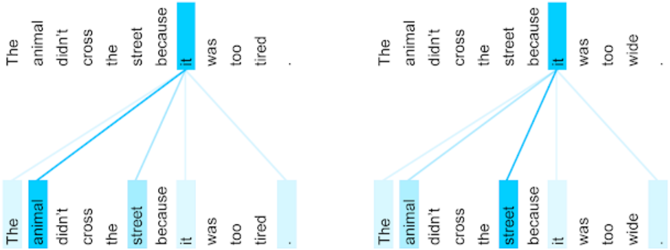
Let us look at an animated example for MT: transform20fps.gif

1. Initial embedding representations (empty circles)
2. new representation (filled circles) ← aggregating info (attention) from all other words (context)[3]

[3] In parallel for all words, multiple times

Transformer (Devlin et al., 2019)

The attention can be *observed*, here within two contexts:

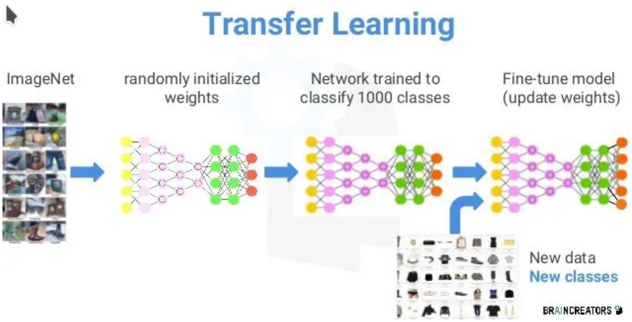


How to translate it in these cases?

https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

Pre-trained models

Transfer learning (image recognition, again)



1. Train a model on a (large) [open,out-of]-domain corpus
2. Fine-tune it with new data to your task of interest

Picture from `https://madhuramiah.medium.com/deep-learning-using-resnets-for-transfer-learning-d7f4799fa863`

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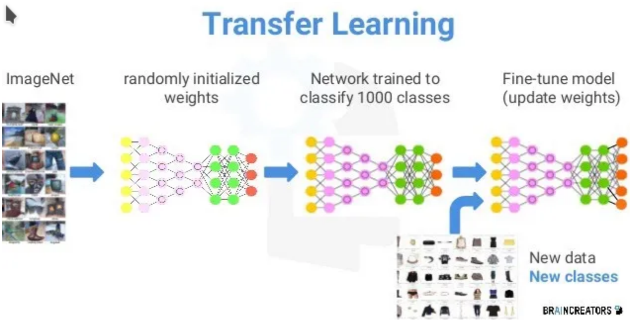

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* Change of paradigm wrt, for instance, word2vec

Picture from `https://madhuramiah.medium.com/deep-learning-using-resnets-for-transfer-learning-d7f4799fa863`

Pre-trained models

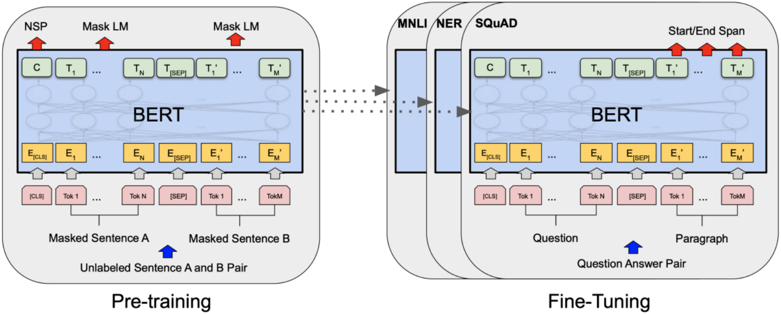
Typical current setting

1. An organisation with large computing capabilities trains a large language model[4]
2. Download and fine-tune the model with a few thousand instances[5]

[4] GPT-3 is trained on 45TB of data; it has 175B parameters

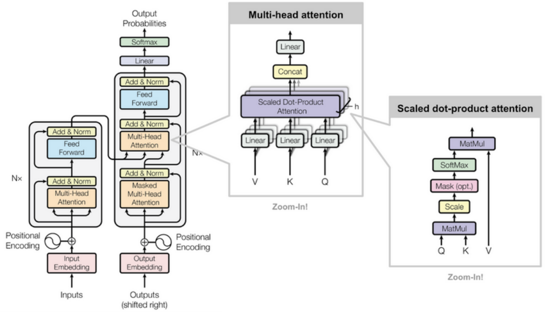
[5] Or even less: zero-shot and few-shot learning; e.g., Muti and Barrón-Cedeño (2022)

Fine-Tuning



Picture from Devlin et al. (2019)

Transformer architecture[6]



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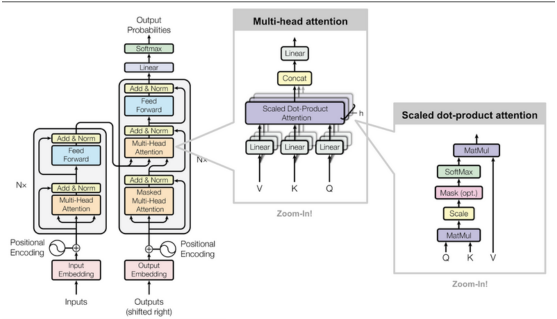

- Scaled dot-product attention multiple times, in parallel
- Similar to looping over an RNN, without vanishing gradient descent

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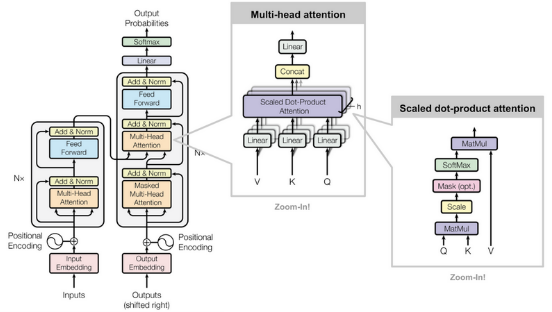

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Multiple times?

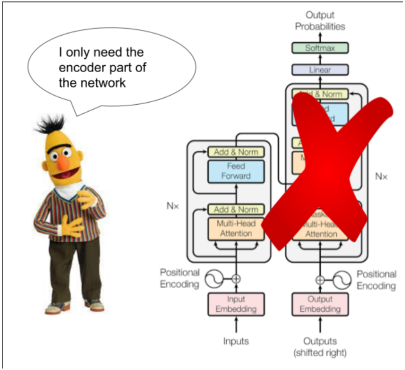
BERT : 24 attention layers
GPT-2 : 12 attention layers
GPT-3 : 96 attention layers

[6] Don't panic!

Bert

BERT

Bi-directional encoder representations from transformers



BERT

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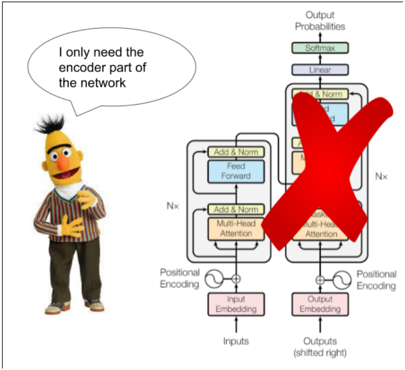

- Encodes the semantic and syntactic information in the embedding[a]

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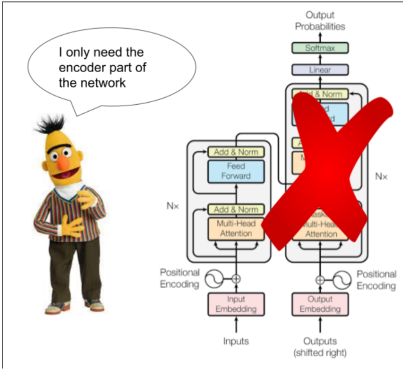

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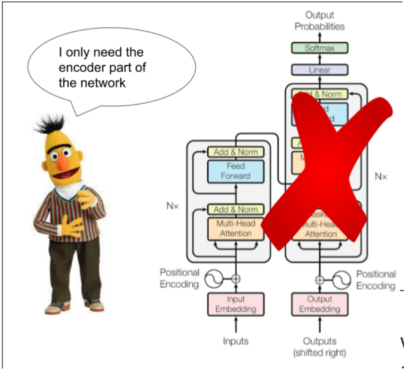

- Encodes the semantic and syntactic information in the embedding[a]
- No decoding: it's output is an embedding, not text or a class (e.g., to compute similarities; bertscore)
- Extra training layer: predicts hidden or masked words to force the encoder to learn more about the context

[a] Not for text generation (it can generate words),
allows for multiple languages

BERT
Masking (cloze test)

- When training to predict the next word, BERT might cheat and just copy it from the right-to-left component

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  - 15% of the input tokens are masked (picked randomly):

%	masked with	Sentence
	(original)	BERT can see all the words in this sentence

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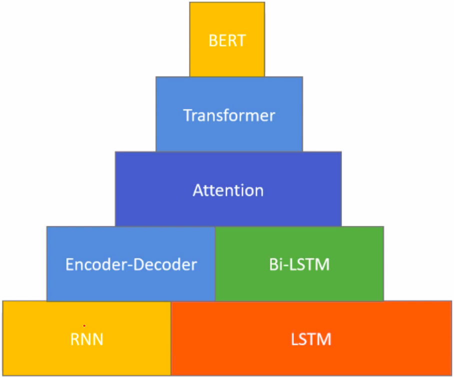
BERT

Learning Pyramid



Picture from https://iq.opengenus.org/introduction-to-bert/

BERT in other Languages

For instance:

- Spanish (Cañete et al., 2020)
- Italian (AlBERTo) (Polignano et al., 2019)

(Muti and Barrón-Cedeño, 2020)

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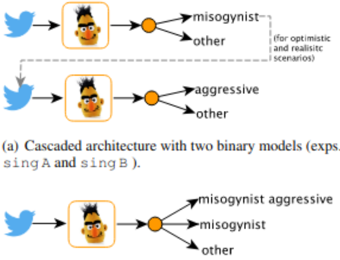
Use case: misogyny identification in Italian



(a) Cascaded architecture with two binary models (exps. `singA` and `singB`).

(b) Multi-class architecture model (exp. `multi`).

Figure 1: The two alternative system architectures for misogyny and aggressiveness identification.

(Muti and Barrón-Cedeño, 2020)

Multilingual models

What makes multilingual BERT multilingual? (Liu et al., 2020)

(Muti and Barrón-Cedeño, 2022)

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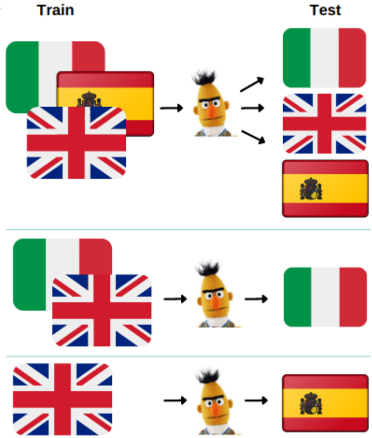

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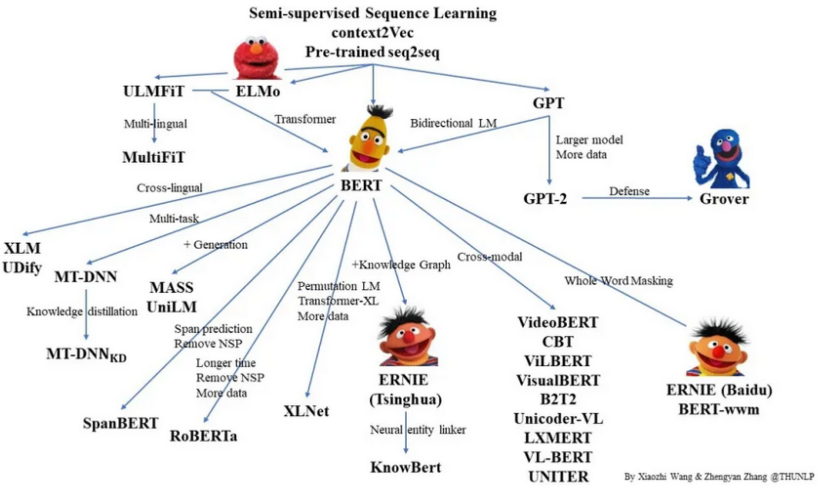
BERTology



Picture from https://github.com/thunlp/

(Other) Reference Libraries

- Spacy
  Industrial-Strength Natural Language Processing
  https://spacy.io/
- Stanza
  A Python NLP Package for Many Human Languages
  https://stanfordnlp.github.io/stanza/
- Hugging Face
  The AI community building the future
  https://huggingface.co/

Conferences (non-exhaustive)

NLP-ish	IR-ish	MT-ish
Top		
ACL	SIGIR	WMT
EMNLP	CIKM	EAMT
NAACL	WSDOM	
EACL	ECIR	
Nice		
SemEval	CLEF	
CICLing[7]	TREC	
LREC		
National		
CLIC-it	IIR	
Evalita		

[7] Apparently gone

Recap

Recap: The path

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13. Using a better memory: LSTM
14. LSTM to produce text
15. Intro to transformers

Recap: The future path

- We covered Parts 1 and 2 of Lane et al. (2019) (up to Section 9)
- That's 9 out of 13 chapters of Natural Language Processing in Action

Now go and celebrate the end of the course

...and worry about your project from Jan 2nd!

- I'm available during January for 1-to-1 discussion on your project upon request!

References I

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