Natural Language Processing (CS-472) Spring-2023

Muhammad Naseer Bajwa

Assistant Professor,
Department of Computing, SEECS
Co-Principal Investigator,
Deep Learning Lab, NCAI
NUST, Islamabad
naseer.bajwa@seecs.edu.pk

Overview of this week's lecture

Pretraining Transformers

- Subword Modelling
- Model pretraining from word embeddings
- GPT: Pretrained decoder
- BERT: Pretrained encoder
- T5: Pretrained encoder-decoder

Why subword models are required?

- So far we have assumed a fixed vocabulary from the training set.
  - All *novel* words seen at test time are mapped to a single UNK token.

	Word	**Vocab Mapping**
Common words	Hat	Hat (Index)
	Learn	Learn (Index)
Variations	Goooood	UNK (Index)
Misspellings	Laern	UNK (Index)
Novel Items	Transformerify	UNK (Index)

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- Finite vocabulary assumptions make even less sense in languages other than English.
- Many languages exhibit complex morphology, or word structure.
  - The effect is more word types, each occurring fewer times.

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- Subword modelling encompasses methods for reasoning about structure below the word level.
  - Parts of words, characters, bytes, etc.
- The dominant modern paradigm is to learn a vocabulary of parts of words (subword tokens).
  - At training and testing time, each word is split into a sequence of known subwords.
- Byte-pair encoding is a simple yet effective strategy for defining a subword vocabulary.
  - Start with a vocabulary containing only characters and an 'end-of-word' symbol.
  - Using a corpus of text, find the most common adjacent characters 'a, b'; add 'ab' as a Subword.
  - Replace instances of the character pair with the new subword; repeat until desired vocab size.
  - Example: Starting characters $\{a, b, \dots, z\}$. Ending vocab: $\{a, \dots, z, apple, app\#, \#ly, \dots\}$

https://www.youtube.com/watch?v=HEikzVL-lZU

Subword models take advantage of lexical morphology

- Common words end up being a part of the Subword vocabulary, while rarer words are split into (sometimes intuitive, sometimes not) components.
  - In the worst case, words are split into as many subwords as they have characters.

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- Recall the adage in the early lectures,

You shall know a word by the company it keeps

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- This quote is a summary of distributional semantics and motivated $word2vec$.

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- Consider the sentence,

'I record the record.'

  - The two instances of the word 'record' mean differently.

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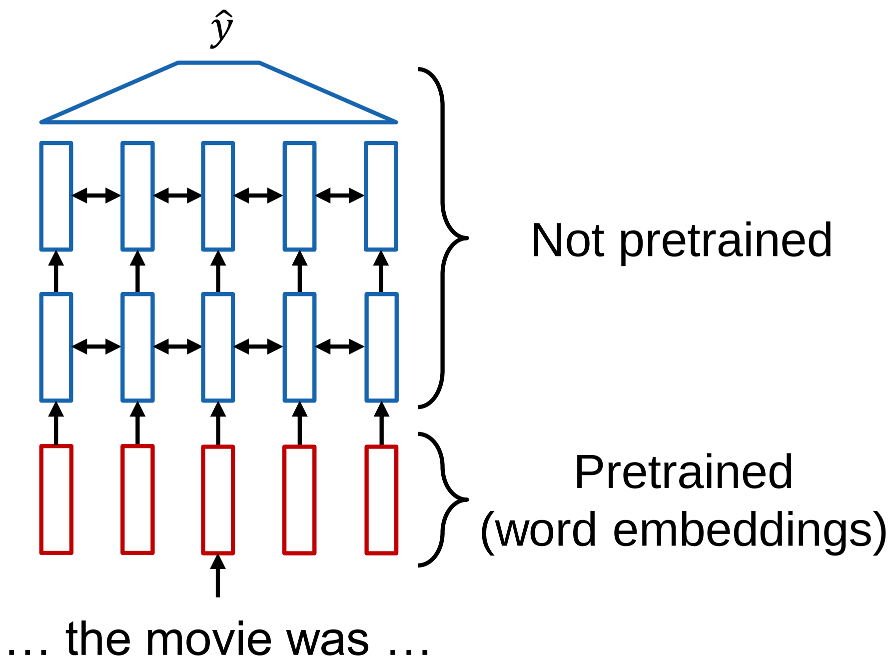
  - Learn how to incorporate context in an LSTM or Transformer while training on the upstream task (using supervision).



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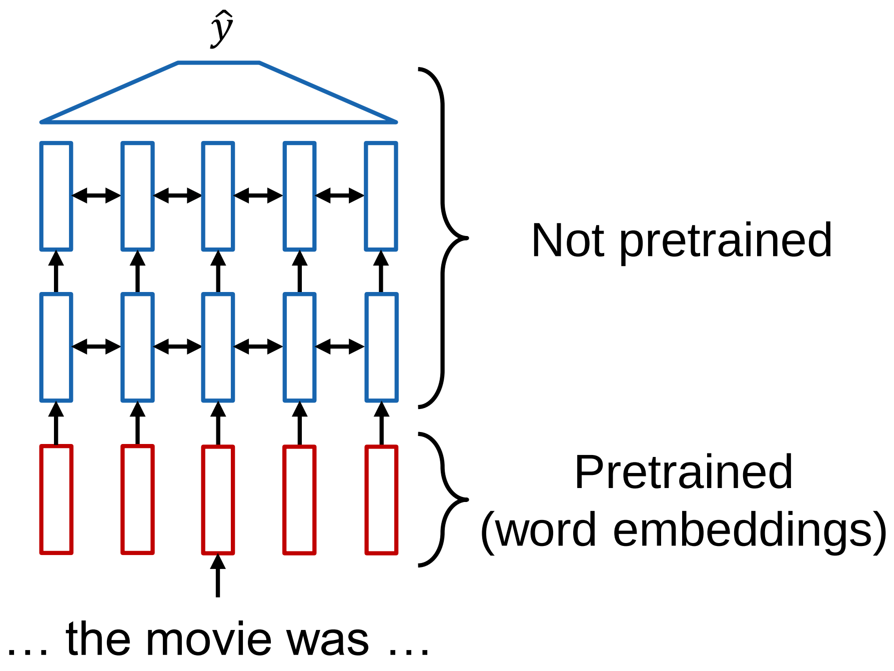

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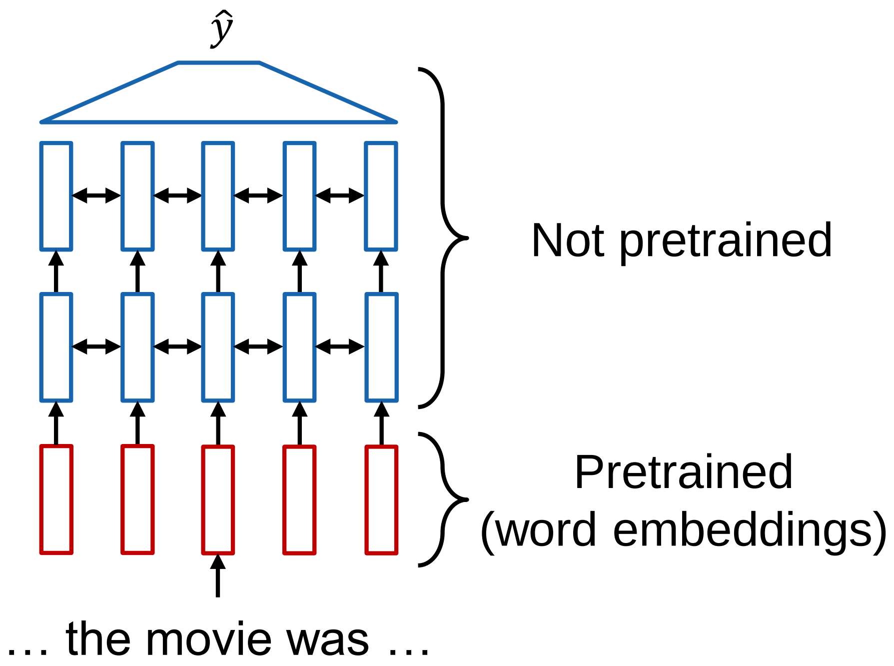
- What's wrong with this approach?
  - The training data we have for our downstream task (like question answering) must be sufficient to teach all contextual aspects of language.
  - Most of the parameters in our network are randomly initialized!



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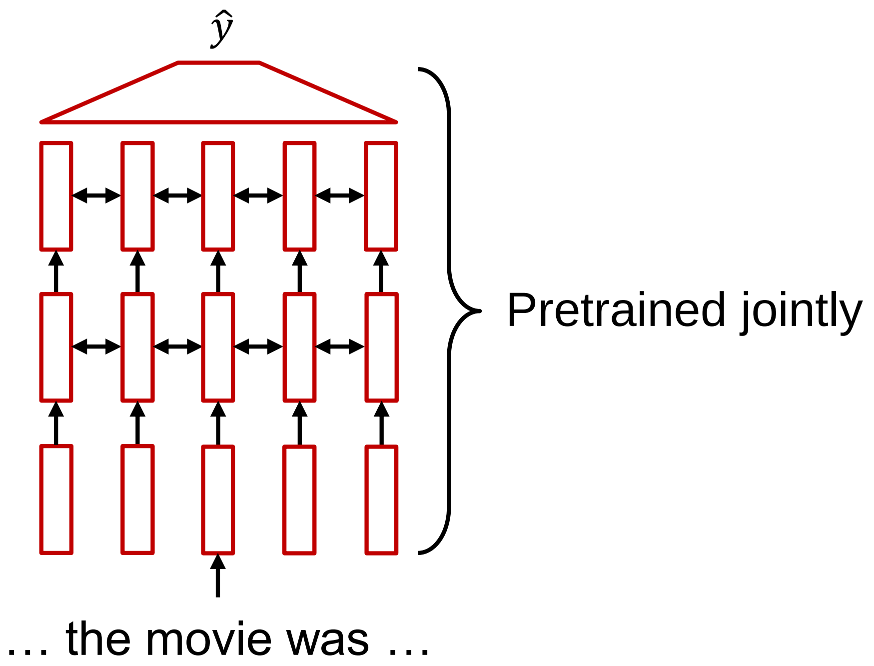
- All (or almost all) parameters in NLP networks are initialised via pretraining.



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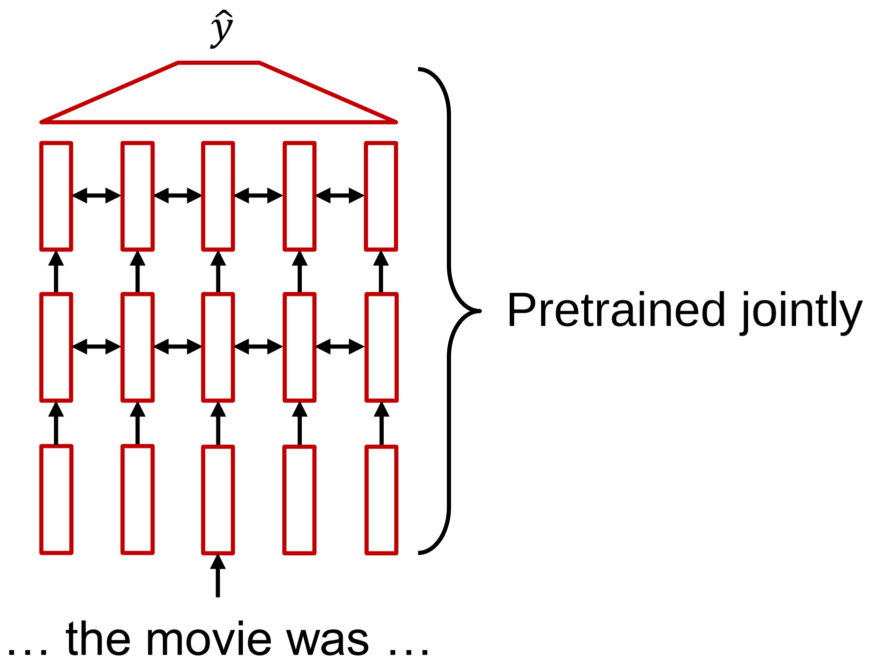

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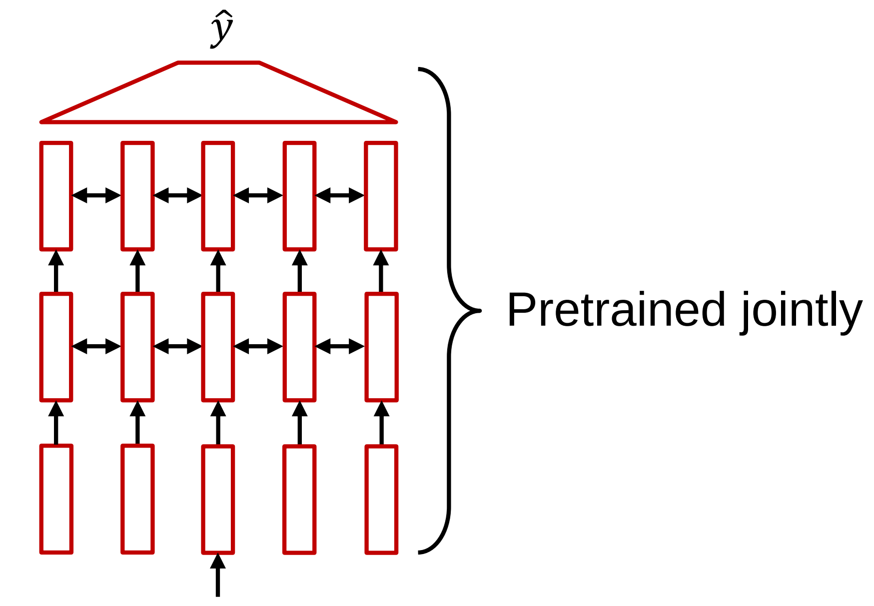
- This has been exceptionally effective at building strong:
    - Representations of language
    - Parameter initialisations for strong NLP models.
    - Probability distributions over language that we can sample from.



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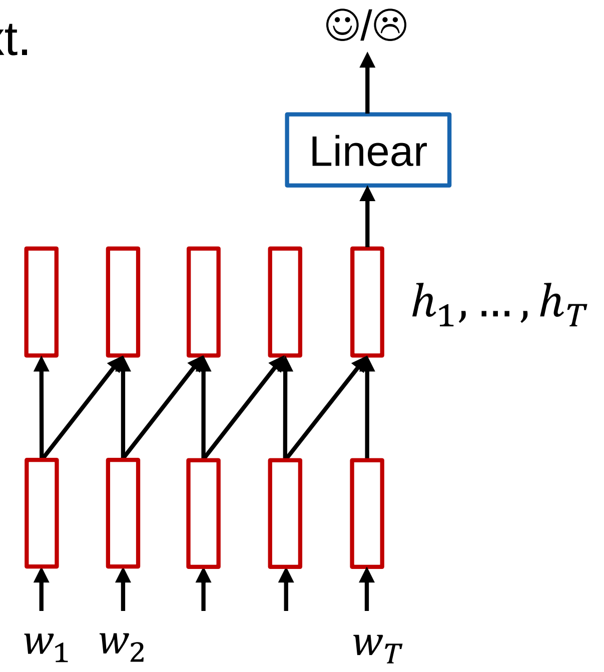
- I was thinking about the sequence that goes, 1, 1, 2, 3, 5, 8, 13, _____(algorithm)

Pretraining decoders can be used for classification tasks

- Train a neural network to perform language modelling on a large amount of text.
    - Learn $p(w_t|w_{1:t-1})$.
    - Save the network parameters.



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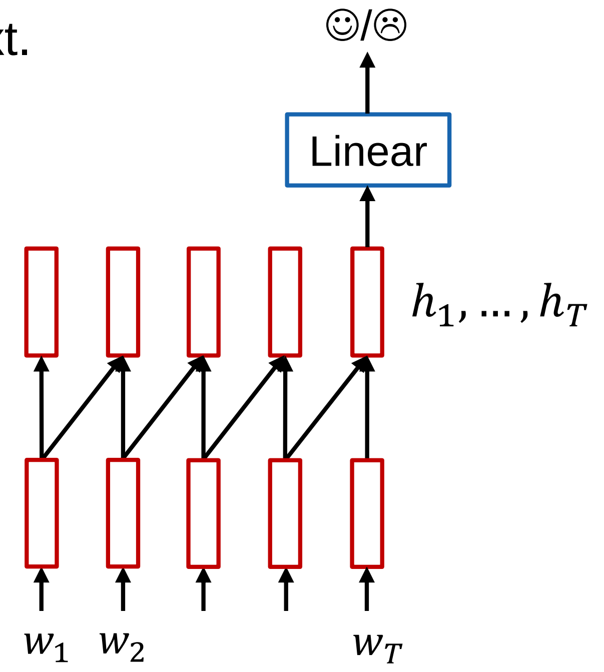

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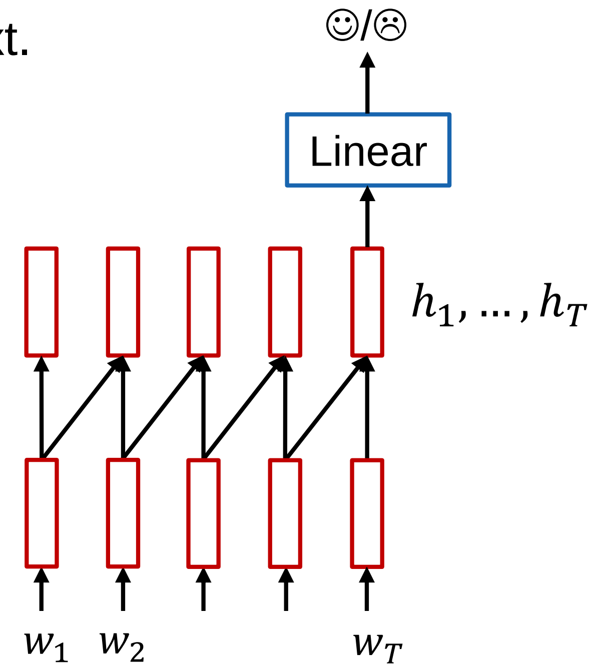
- When using decoders pretrained as language model, ignore that they were trained to model language.
- Finetune them by training a classifier on the last word's hidden state.

$$h_1, \ldots, h_T = Decoder\,(w_1, \ldots, w_T)$$

$$y \sim Ah_t + b$$

    - Where A and b are randomly initialised and specified by the downstream task.
    - Gradients backpropagate through the whole network.



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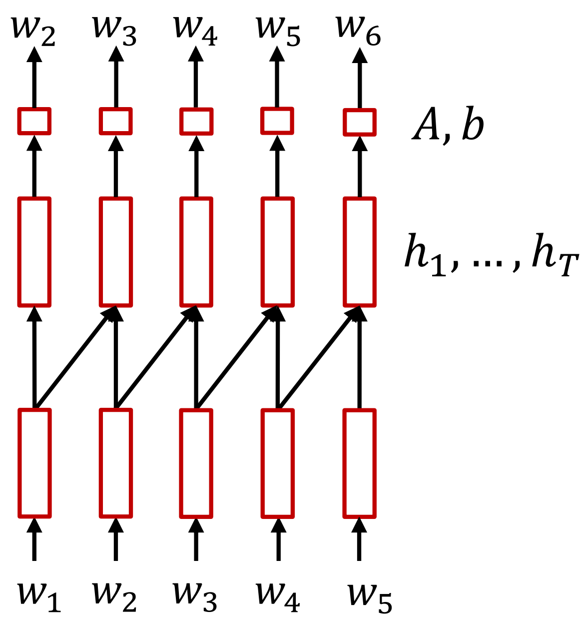

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- Train a language model on lots of text to learn general things.

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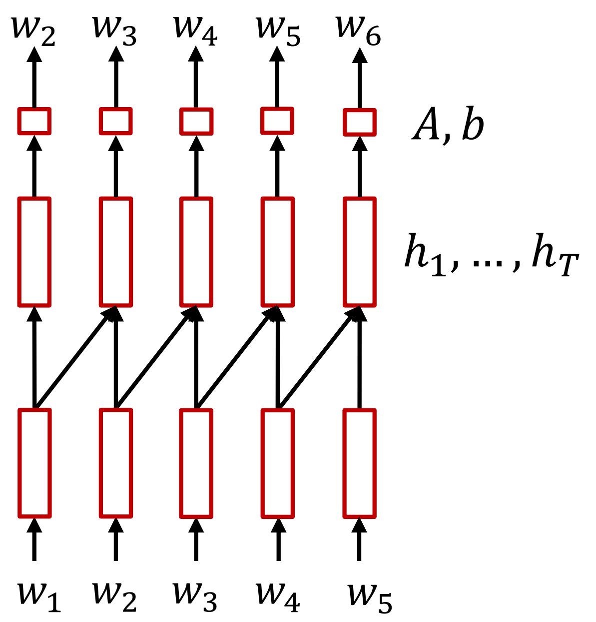

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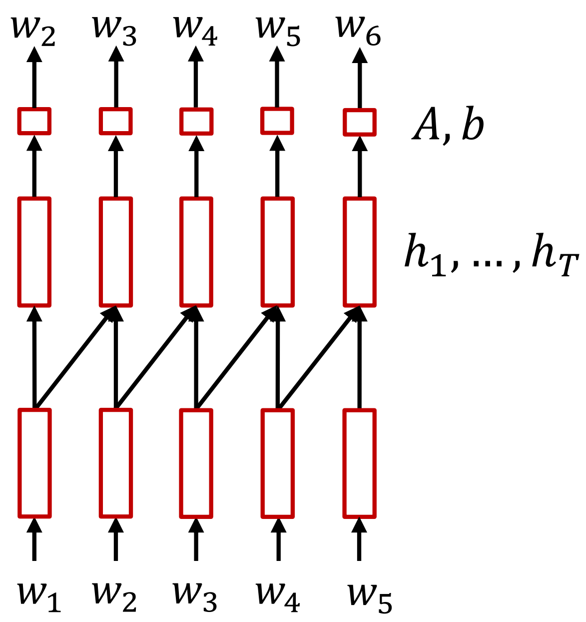
- This is helpful in tasks where the output is a sequence with a vocabulary like that at pretraining time like dialogue generation or summarisation.

$$h_1, \dots, h_T = Decoder\ (w_1, \dots, w_T)$$

$$w_t \sim Ah_t + b$$

    - Where A and b were pretrained in the language model.



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GPT was a big success in pretraining a decoder

- GPT consisted of
  - A transformer decoder with 12 layers.
  - 768-dimensional hidden states, 3072-dimensional feedforward hidden layers.

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  - Contains long spans of contiguous text, for learning long-distance dependencies.
- The acronym GPT never showed up in the original paper. It could stand for ‘Generative PreTraining’ or ‘Generative Pretrained Transformer’.

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How input is formatted for finetuning tasks in GPT?

- Natural Language Inference is a sentence classification task with three labels as *entailing/contradictory/neutral*.

    - Premise: He drives daily to work.

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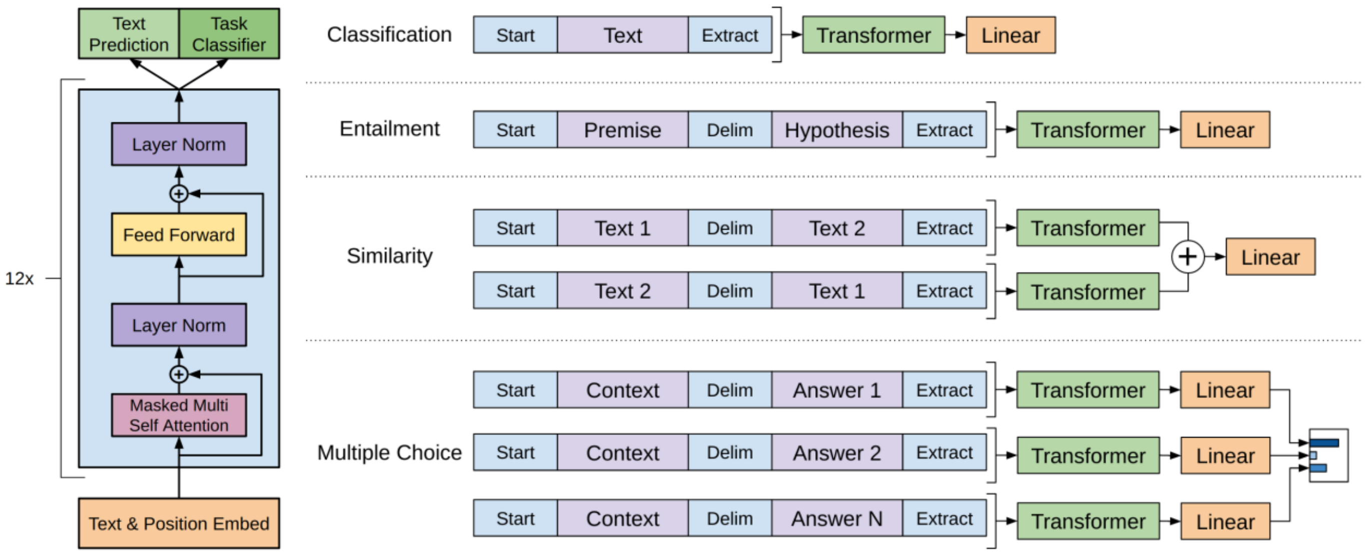

Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

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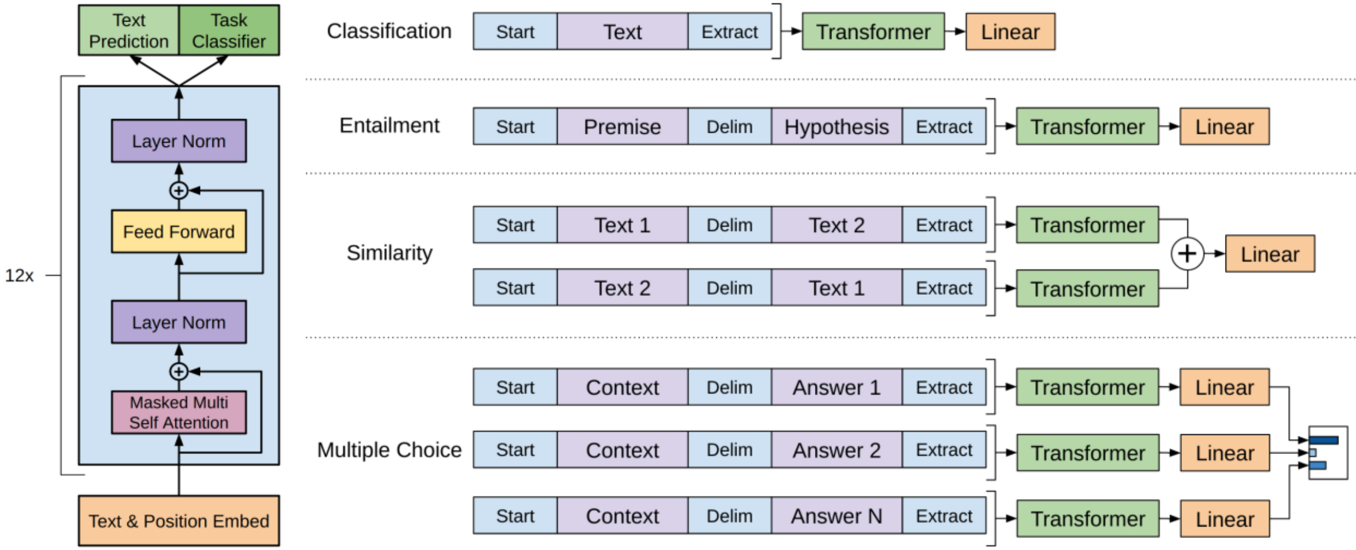
- The linear classifier is applied to the representation of the [EXTRACT] token.



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GPT set new state-of-the-art on many NLP tasks

Table 2: Experimental results on natural language inference tasks, comparing our model with current state-of-the-art methods. 5x indicates an ensemble of 5 models. All datasets use accuracy as the evaluation metric.

Method	MNLI-m	MNLI-mm	SNLI	SciTail	QNLI	RTE
ESIM + ELMo [44] (5x)	-	-	89.3	-	-	-
CAFE [58] (5x)	80.2	79.0	89.3	-	-	-
Stochastic Answer Network [35] (3x)	80.6	80.1	-	-	-	-
CAFE [58]	78.7	77.9	88.5	83.3		
GenSen [64]	71.4	71.3	-	-	82.3	59.2
Multi-task BiLSTM + Attn [64]	72.2	72.1	-	-	82.1	**61.7**
Finetuned Transformer LM (ours)	**82.1**	**81.4**	**89.9**	**88.3**	**88.1**	56.0

Table 3: Results on question answering and commonsense reasoning, comparing our model with current state-of-the-art methods.. 9x means an ensemble of 9 models.

Method	Story Cloze	RACE-m	RACE-h	RACE
val-LS-skip [55]	76.5	-	-	-
Hidden Coherence Model [7]	77.6	-	-	-
Dynamic Fusion Net [67] (9x)	-	55.6	49.4	51.2
BiAttention MRU [59] (9x)	-	60.2	50.3	53.3
Finetuned Transformer LM (ours)	**86.5**	**62.9**	**57.4**	**59.0**

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GPT-2 generated increasingly convincing text

- GPT-2 is just bigger GPT trained on larger dataset.

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- It is used as a generative model that can produce reasonably good text.

Context (human-written): In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

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GPT-2: The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them – they were so close they could touch their horns.

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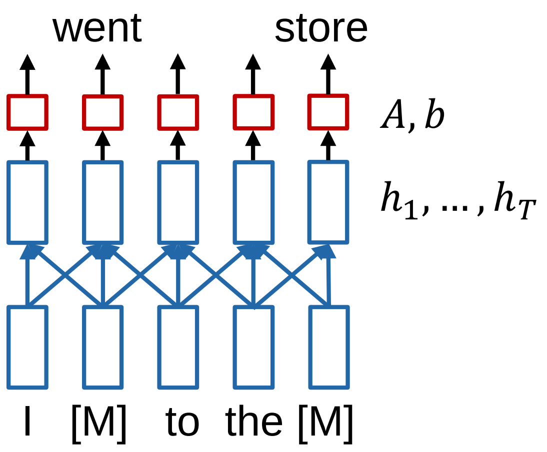
  - Since encoders have bidirectional context, they cannot be trained as language models.
- Transformer encoders are pretrained on the task of Masked Language Modelling.
  - Replace some fraction of words in the input with a special [MASK] token
  - Predict the masked words using bidirectional context.

$$h_1, \ldots, h_T = Encoder\,(w_1, \ldots, w_T)$$

$$y_i \sim Aw_i + b$$



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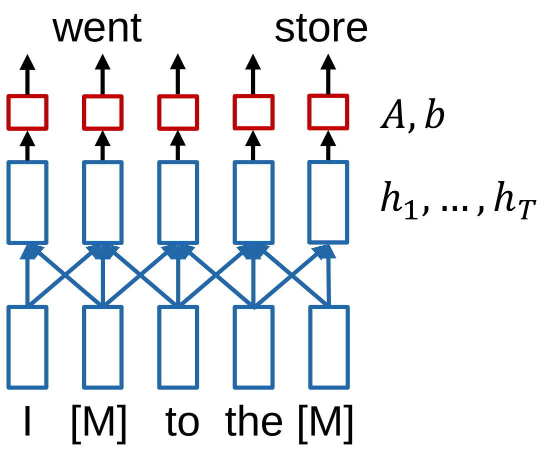

- Only add loss terms from words that are masked out.
  - Let $\tilde{x}$ be the masked version of x, learn $p_\theta(x|\tilde{x})$

BERT is the most famous pretrained encoder model.

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- Why replace token with random words or leave them unchanged but still predict?
  - It doesn’t let the model complacent and encourage building strong representations of non-masked words also.
  - No masks are provided at fine-tuning time.

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BERT pretraining input is a two separate contiguous chunks of text

- The models is trained to predict whether one chunk follows the other or is it randomly sampled.
  - Later works showed this was not necessary.

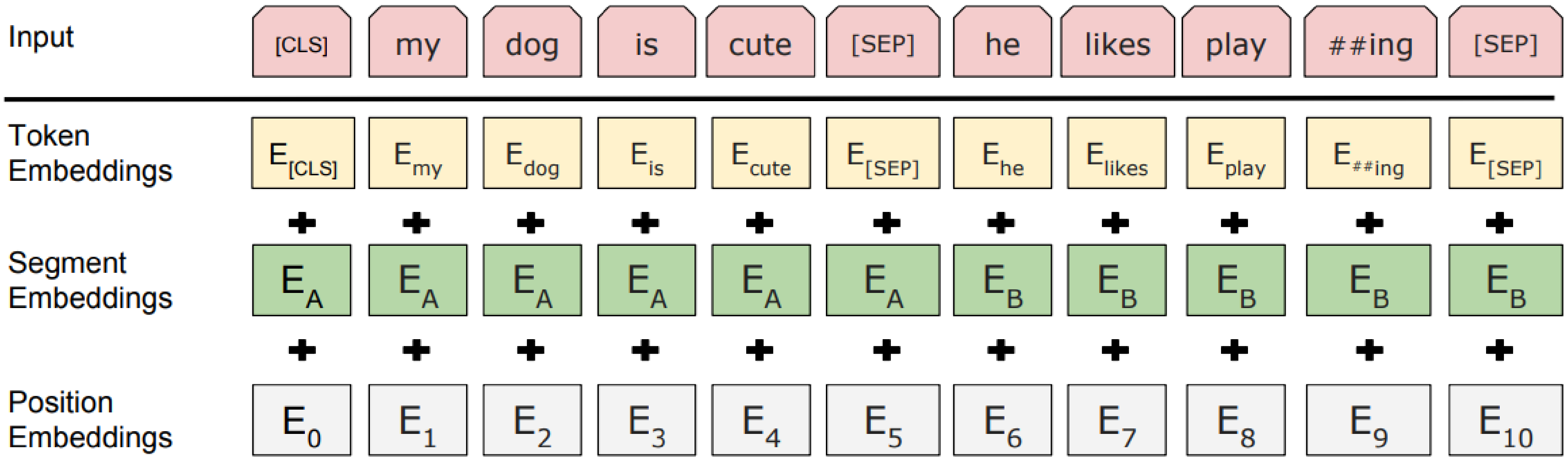

Figure 2: BERT input representation. The input embeddings are the sum of the token embeddings, the segmentation embeddings and the position embeddings.

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BERT is a large and computation heavy model

- BERT-base: 12 layers, 768-dim hidden states, 12 attention heads, 110 million parameters.
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- Pretrained with 64 TPUs for four days.

    - Finetuning can be done on single GPU on smaller datasets.

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BERT is massively popular and hugely versatile

- Finetuning BERT led to new state-of-the-art on a range of NLP tasks.

QQP: Quora Question Pairs

QNLI: Natutal Language Inference over Question Answering

SST-2: Stanford Sentiment Treebank

CoLA: Corpus of Linguistic Acceptability

STS-B: Semantic Textual Similarity

MRPC: Microsoft Paraphrase Corpus

RTE: A small NLI corpus.

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Table 1: GLUE Test results, scored by the evaluation server (https://gluebenchmark.com/leaderboard). The number below each task denotes the number of training examples. The "Average" column is slightly different than the official GLUE score, since we exclude the problematic WNLI set.[8] BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.

There are many variants of BERT

- RoBERTa: Just trained BERT for longer and removed next sentence prediction.

Model	data	bsz	steps	SQuAD (v1.1/2.0)	MNLI-m	SST-2
RoBERTa						
with Books + Wiki	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	**94.6/89.4**	**90.2**	**96.4**
$\text{BERT}_{\text{LARGE}}$						
with Books + Wiki	13GB	256	1M	90.9/81.8	86.6	93.7
$\text{XLNet}_{\text{LARGE}}$						
with Books + Wiki	13GB	256	1M	94.0/87.8	88.4	94.4
+ additional data	126GB	2K	500K	94.5/88.8	89.8	95.6

Liu, Yinhan, et al. "RoBERTa: A robustly optimized bert pretraining approach." arXiv preprint arXiv:1907.11692 (2019).

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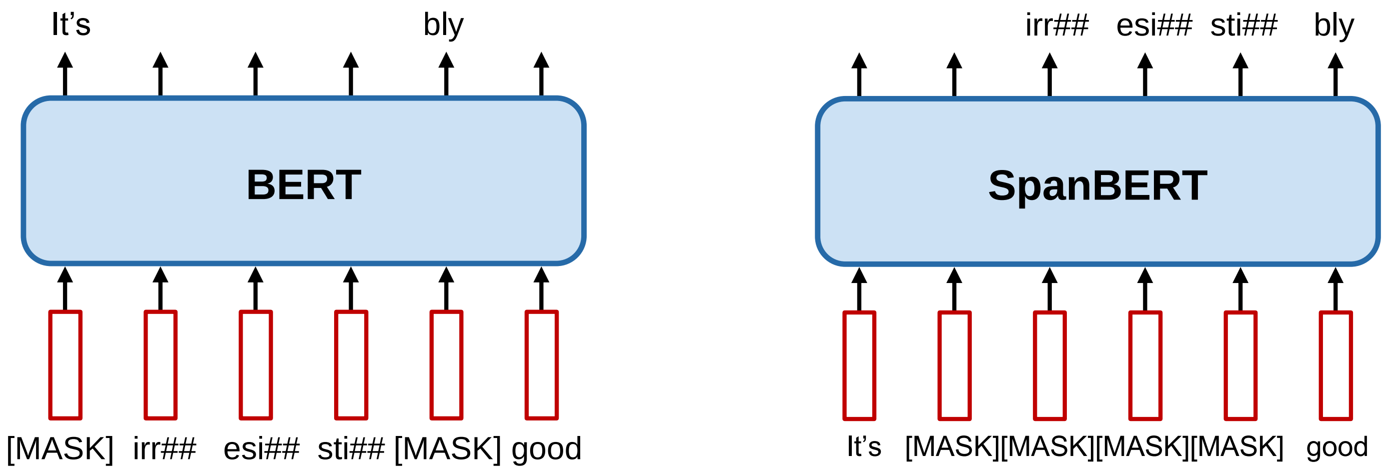

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- FinBERT: BERT trained on financial data for sentiment analysis.

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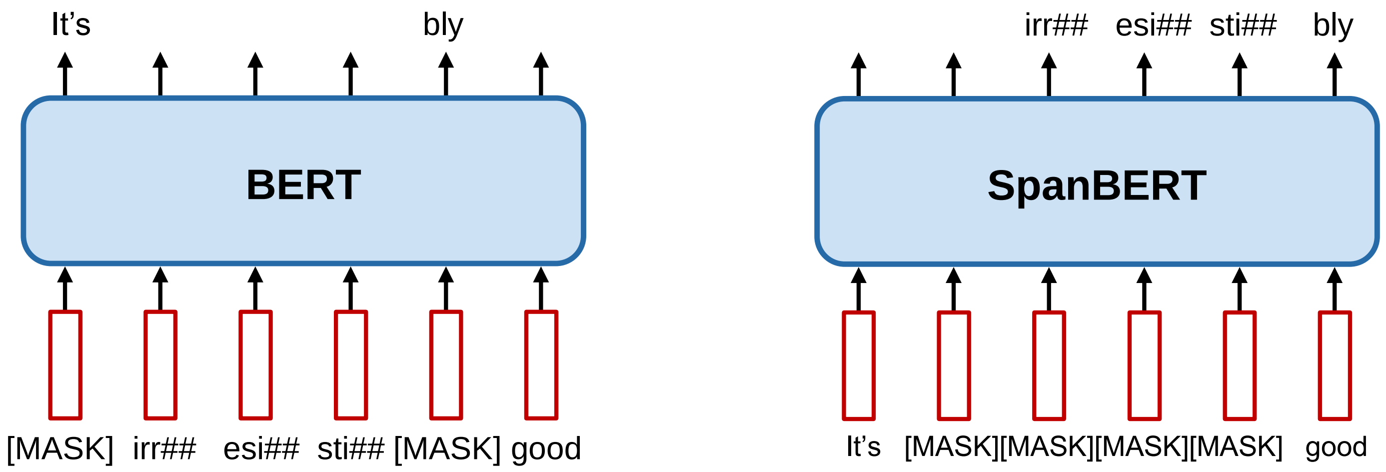

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Pretraining encoders has some limitations

- BERT gave excellent results and is versatile but we can’t use it for everything.

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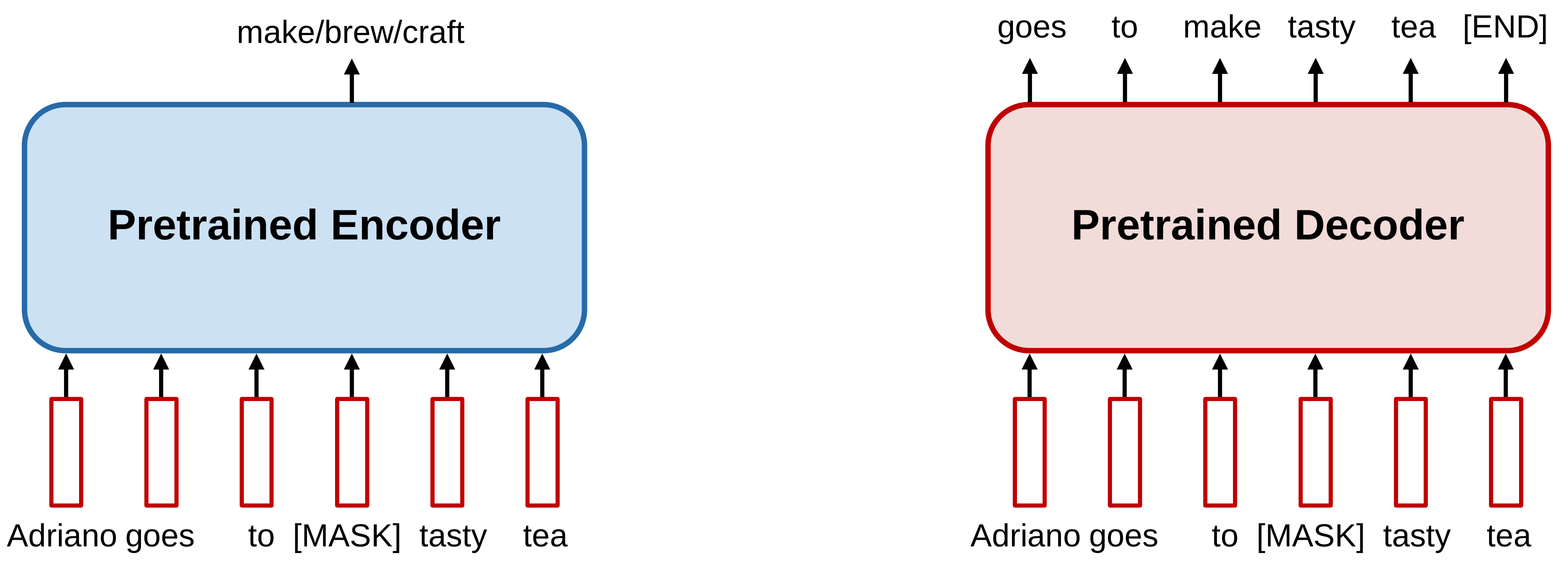
- For generative tasks, pretrained decoders are still better choice.

  - BERT and other pretrained encoders don’t naturally lead to nice autoregressive generation methods.



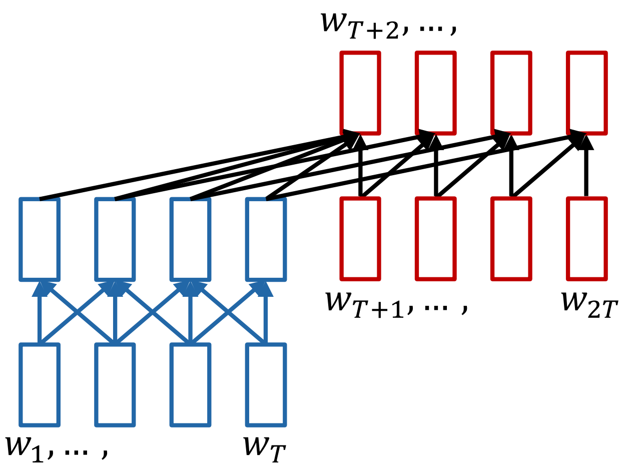
How can we pretrain an encoder-decoder model?

- Train encoder-decoder model like language modelling.

$$h_1, \dots, h_T = Encoder\ (w_1, \dots, w_T)$$

$$h_{T+1}, \dots, h_{2T} = Decoder\ (w_1, \dots, w_T, h_1, \dots, h_T)$$

$$y_i \sim Aw_i + b, i > T$$



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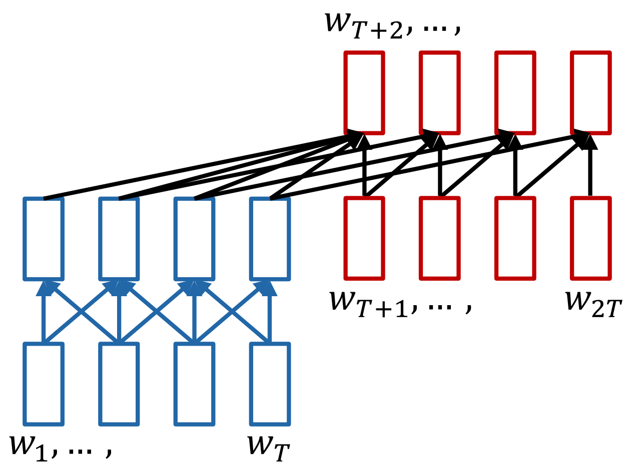

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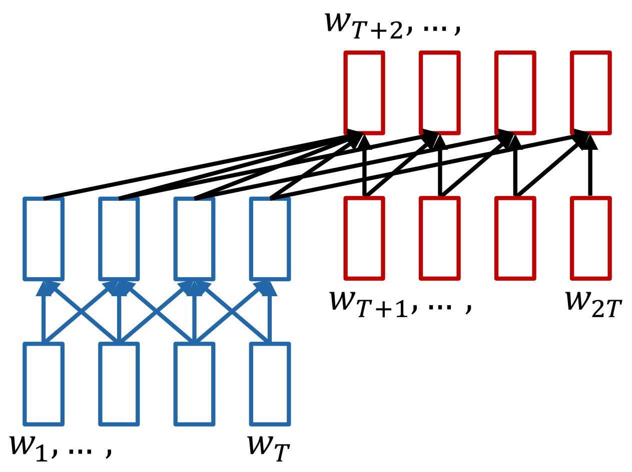

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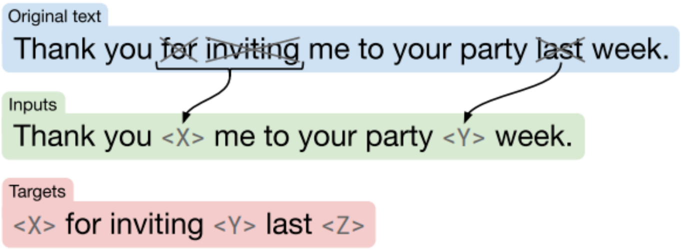
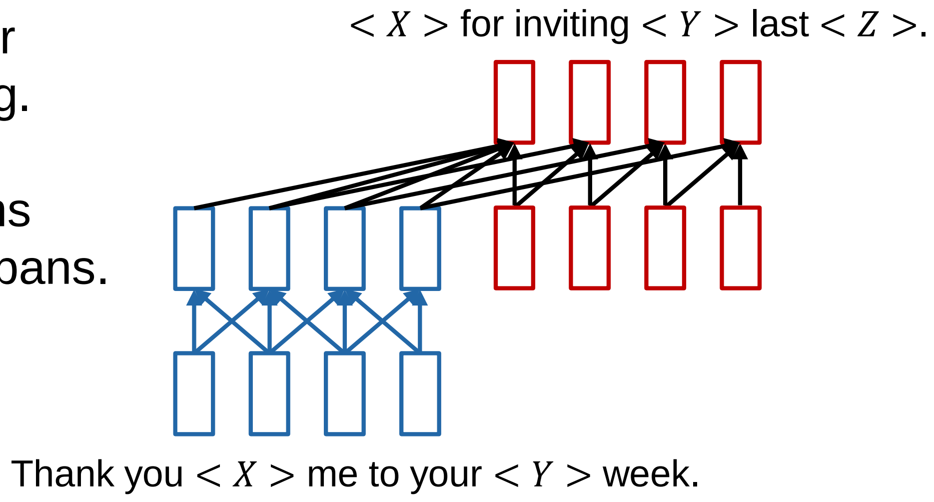
- T5 used Span Corruption for training. Replace different-length spans from the input with unique placeholders and decode the replaced spans.





Raffel, Colin, et al. "Exploring the limits of transfer learning with a unified text-to-text transformer." The Journal of Machine Learning Research 21.1 (2020): 5485-5551.

Pretraining encoder-decoder worked better than decoders for some tasks

- Training T5 model using span corruption was found to work better than language modelling.

Architecture	Objective	Params	Cost	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Encoder-decoder	Denoising	$2P$	M	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
Enc-dec, shared	Denoising	P	M	82.81	18.78	**80.63**	**70.73**	26.72	39.03	**27.46**
Enc-dec, 6 layers	Denoising	P	$M/2$	80.88	18.97	77.59	68.42	26.38	38.40	26.95
Language model	Denoising	P	M	74.70	17.93	61.14	55.02	25.09	35.28	25.86
Prefix LM	Denoising	P	M	81.82	18.61	78.94	68.11	26.43	37.98	27.39
Encoder-decoder	LM	$2P$	M	79.56	18.59	76.02	64.29	26.27	39.17	26.86
Enc-dec, shared	LM	P	M	79.60	18.13	76.35	63.50	26.62	39.17	27.05
Enc-dec, 6 layers	LM	P	$M/2$	78.67	18.26	75.32	64.06	26.13	38.42	26.89
Language model	LM	P	M	73.78	17.54	53.81	56.51	25.23	34.31	25.38
Prefix LM	LM	P	M	79.68	17.84	76.87	64.86	26.28	37.51	26.76

In-context learning and very large models

- So far the pretrained models we learnt are used in two ways
  - Sample from the distribution they define (maybe providing a prompt).
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    - Thanks -> Danke
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  Hello -> Hallo
  Excuse me -> Entschuldegung
- **GPT-3** is the canonical example of this. The largest T5 model had 11 billion parameters. GPT-3 has 175 billion parameters.

Exact mechanism of in-context learning is not well understood

Learning via SGD during unsupervised pre-training

5 + 8 = 13	*gaot* → *goat*	*thanks* → *danke*
7 + 2 = 9	*sakne* → *snake*	*hello* → *hallo*
1 + 0 = 1	*brid* → *bird*	*bread* → *brot*
3 + 4 = 7	*fsih* → *fish*	*wall* → *wand*
5 + 9 = 14	*dcuk* → *duck*	*mint* → *minze*
9 + 8 = 17	*cmihp* → *chimp*	*othter* → *andere*
In-context learning	In-context learning	In-context learning

Do you have any problem?

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