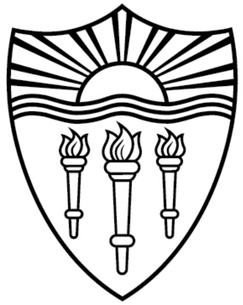
CSCI 544: Applied Natural Language Processing

Contextualized Embeddings & Large-scale Pre-training

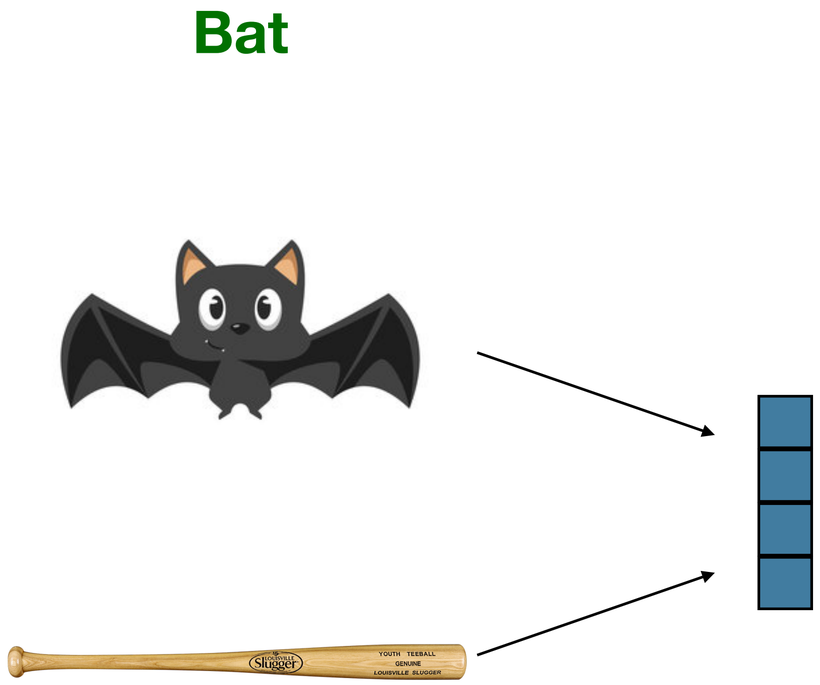
Xuezhe Ma (Max)



USC University of Southern California

What's Wrong with Word Embeddings?

- One vector for each word type
- Complex characteristics of word use: syntax and semantics
- Polysemous words



What's Wrong with Word Embeddings?

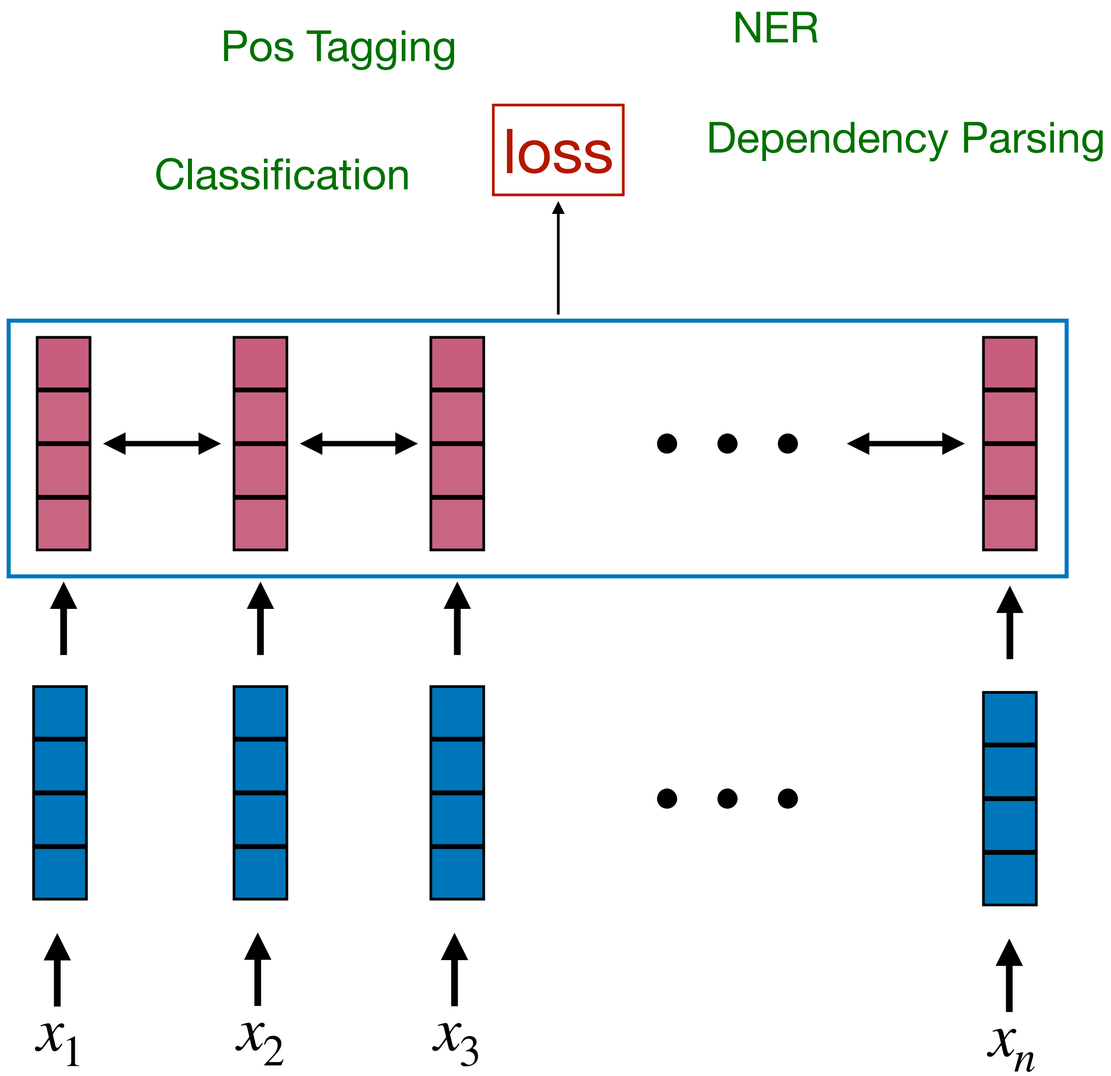
- The semantic meaning of a word depends on this context

hit with bat

hit the bat

What's Wrong with Task-Specific Learning?

- **We have contextualized models!**



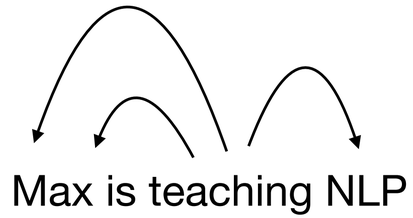
Contextualized Embeddings?

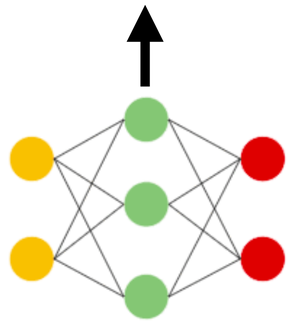
general contextualized embeddings!

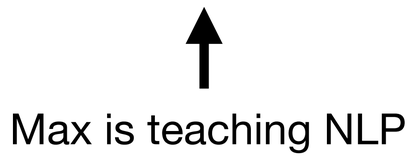
An Interesting Observation

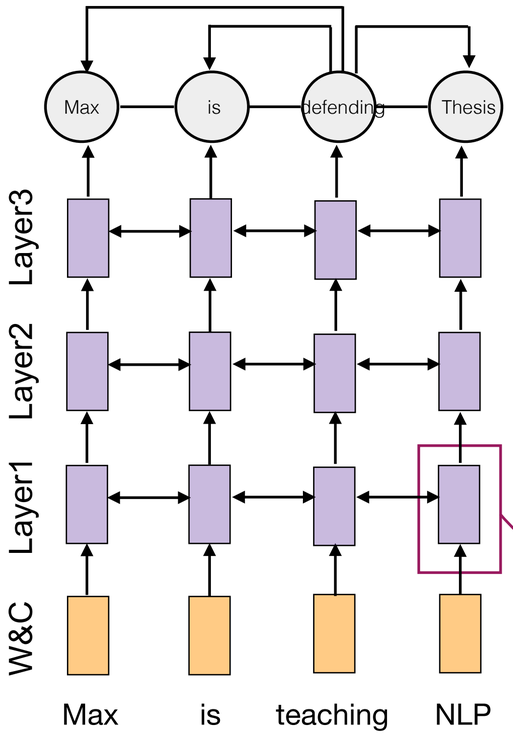
- **A Probing Experiment**

Main task: Dependency Parsing



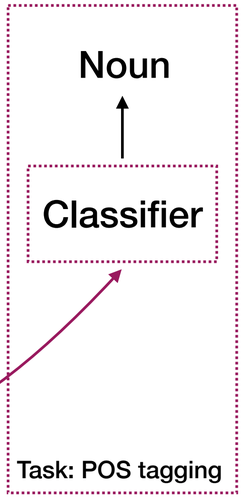






Probing task:

- POS tagging



An Interesting Observation

	POS Tagging
BLSTM-CNN-CRF	97.6%
LSTM1 + SVM	97.7%
LSTM2 + SVM	97.8%

Neural Representations learned from a more challenging tasks can be applied to down-stream tasks!

Objective for Pre-training

- **Easy to collect a large amount of data**
  - Requiring no labeled data
- **General and Semantic**
  - Learning almost full knowledge about data, not only for specific tasks

Outline

- **Large-scale Pre-training**
  - **Key Idea:** Training a large-scale model with a general semantic objective
  - **Encoder:** Contextualized Embeddings
  - **Encoder-Decoder:** Denoising Seq2seq Modeling
  - **Decoder:** Neural Language Modeling
- **Using Pre-trained Models**
  - Fully Fine-tuning
  - Parameter-Efficient Fine-tuning
  - Prompting/In-context Learning

Contextualized Embeddings: Pre-trained Encoders

Contextualized Embeddings: Pre-trained Encoders

- ELMo = **E**mbeddings from **L**anguage **Mo**dels
- BERT = **B**idirectional **E**ncoder **R**epresentations from **T**ransformers

Deep contextualized word representations [PDF] arxiv.org

ME Peters, M Neumann, M Iyyer, M Gardner… - arXiv preprint arXiv …, 2018 - arxiv.org

We introduce a new type of deep contextualized word representation that models both (1) complex characteristics of word use (eg, syntax and semantics), and (2) how these uses vary across linguistic contexts (ie, to model polysemy). Our word vectors are learned functions of …

☆ 99 Cited by 6367 Related articles All 20 versions »

Bert: Pre-training of **deep bidirectional transformers** for **language understanding** [PDF] arxiv.org

J Devlin, MW Chang, K Lee, K Toutanova - arXiv preprint arXiv …, 2018 - arxiv.org

We introduce a new **language** representation model called BERT, which stands for **Bidirectional** Encoder Representations from **Transformers**. Unlike recent **language** representation models, BERT is designed to pre-train **deep bidirectional** representations …

☆ 99 Cited by 17552 Related articles All 26 versions »

Contextualized Word Embeddings

	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM	Chico Ruiz made a spectacular play on Alusik 's grounder {...}	Kieffer , the only junior in the group , was commended for his ability to hit in the clutch , as well as his all-round excellent play .
	Olivia De Havilland signed to do a Broadway play for Garson {...}	{...} they were actors who had been handed fat roles in a successful play , and had talent enough to fill the roles competently , with nice understatement .

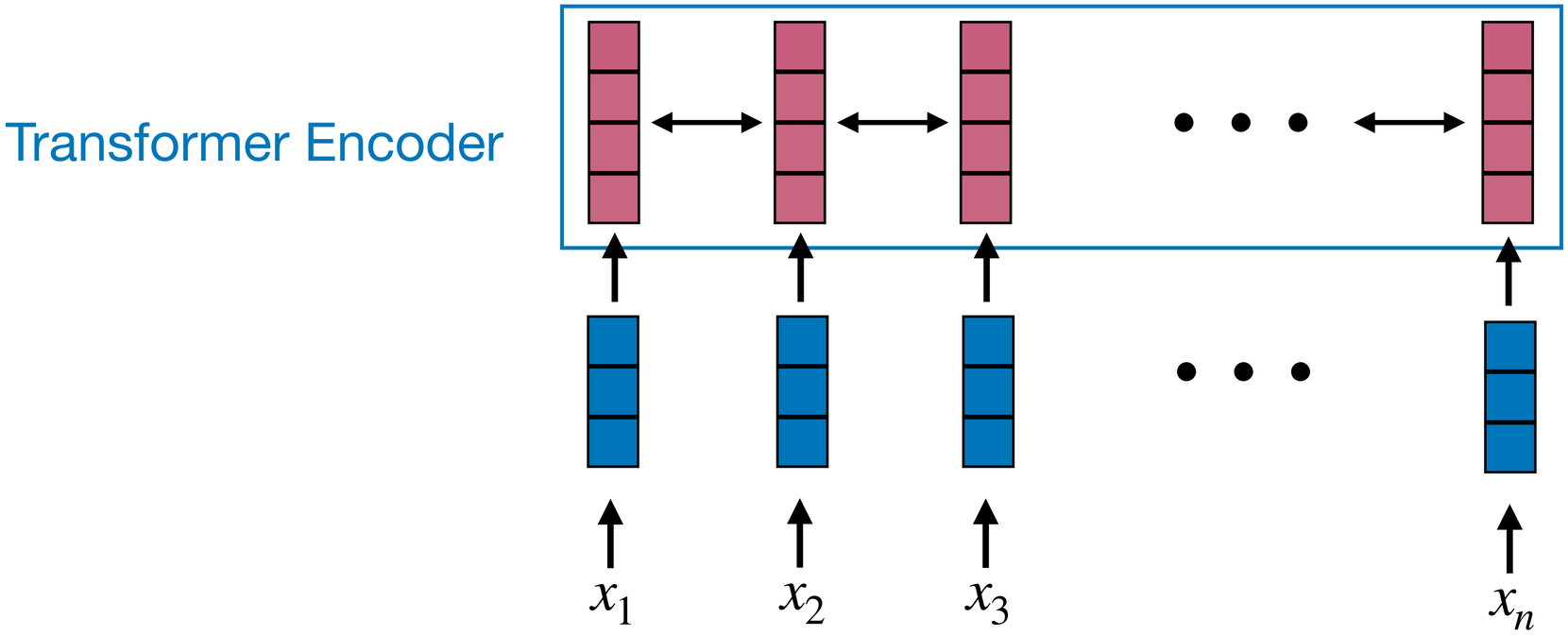
Deep contextualized word representations (Peters et al., 2018)

How can we get these contextualized embeddings?

- **The key idea of BERT:**
  - Objective: masked language modeling
  - Reconstructing masked words with surrounding tokens

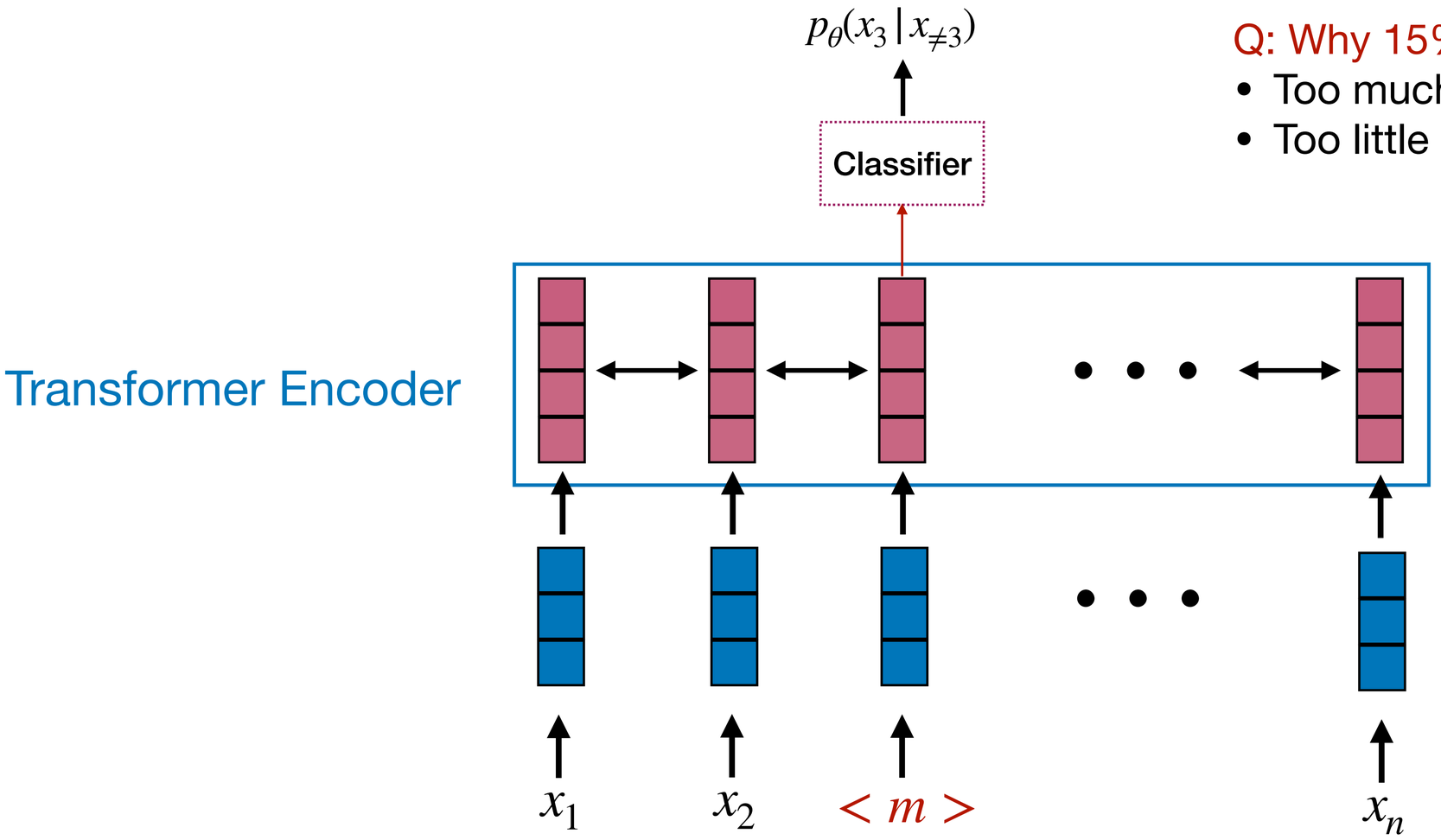
Masked Language Modeling

- **Mask out 15% of the input words, and then predict the masked words**



Masked Language Modeling

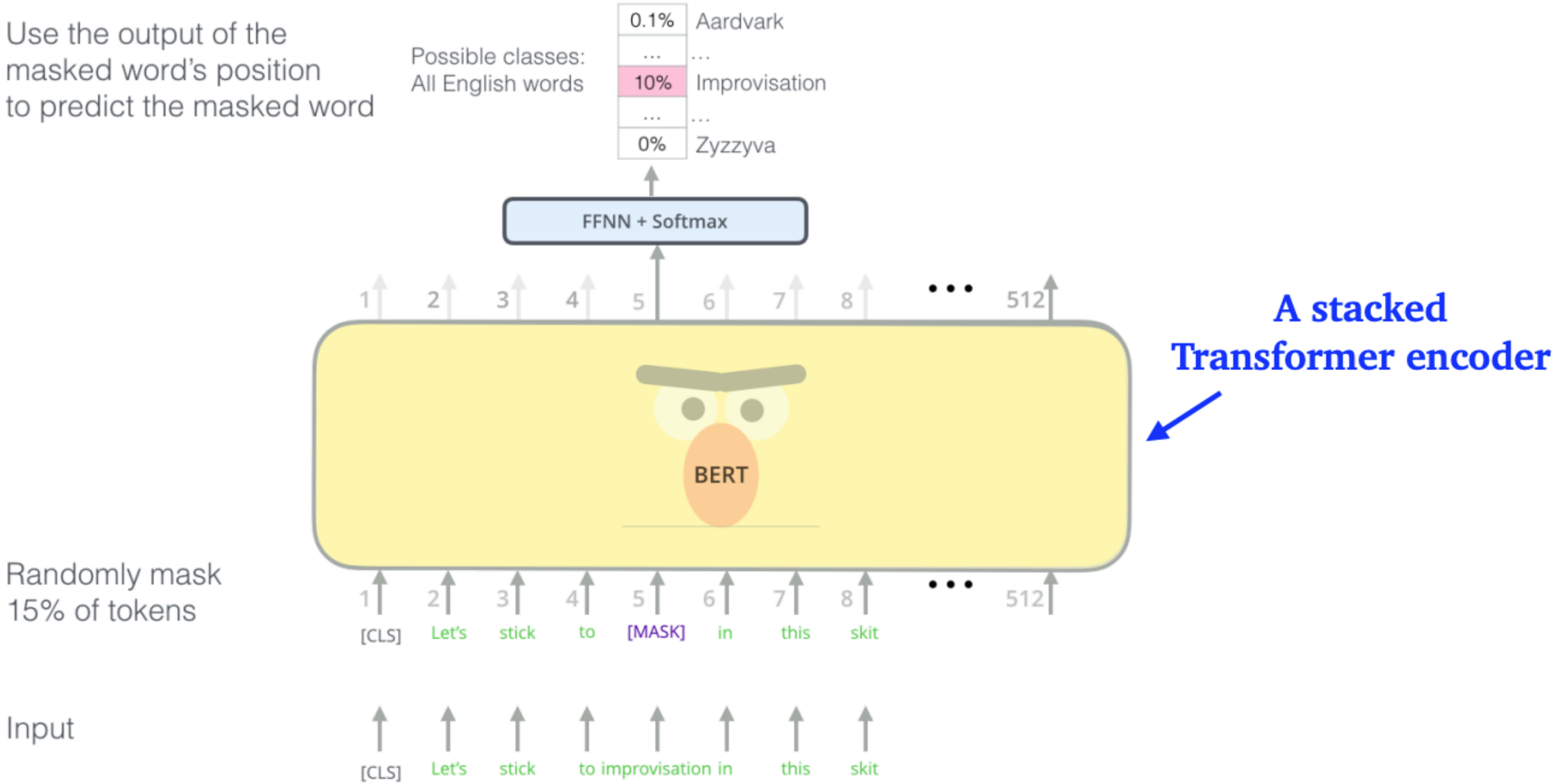
- **Mask out 15% of the input words, and then predict the masked words**



Q: Why 15%

- Too much masking: not enough context
- Too little masking: too inefficient to train

Masked Language Modeling (MLM)



Why Masked Language Modeling

- **An semantic-level task**
  - General contextualized embeddings

- **Able to access both left and right context**
  - Bidirectionality is VERY crucial in language classification tasks!

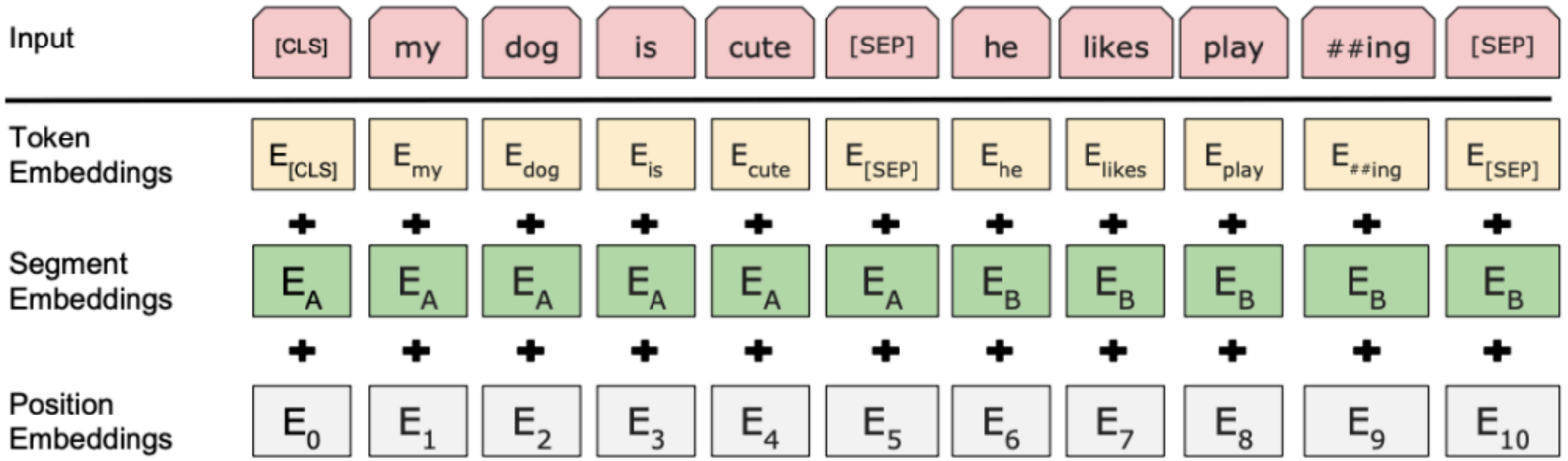
We will see some examples soon!

Training a BERT!

- **Training Data**
  - Wikipedia (2.5B words)
  - BooksCorpus (800M words)
- **Preprocessing**
  - BPE
  - Each segment: 512 BPE tokens
- **Transformer Encoder**
  - BERT-base: L=12, H=768, A=12, #parameters=110M
  - BERT-large: L=24, H=1024, A=16, #parameters=340M
- **Next sentence prediction (NSP)**
  - Later work shows that NSP hurts performance, so we omit it here

BERT: Pre-training

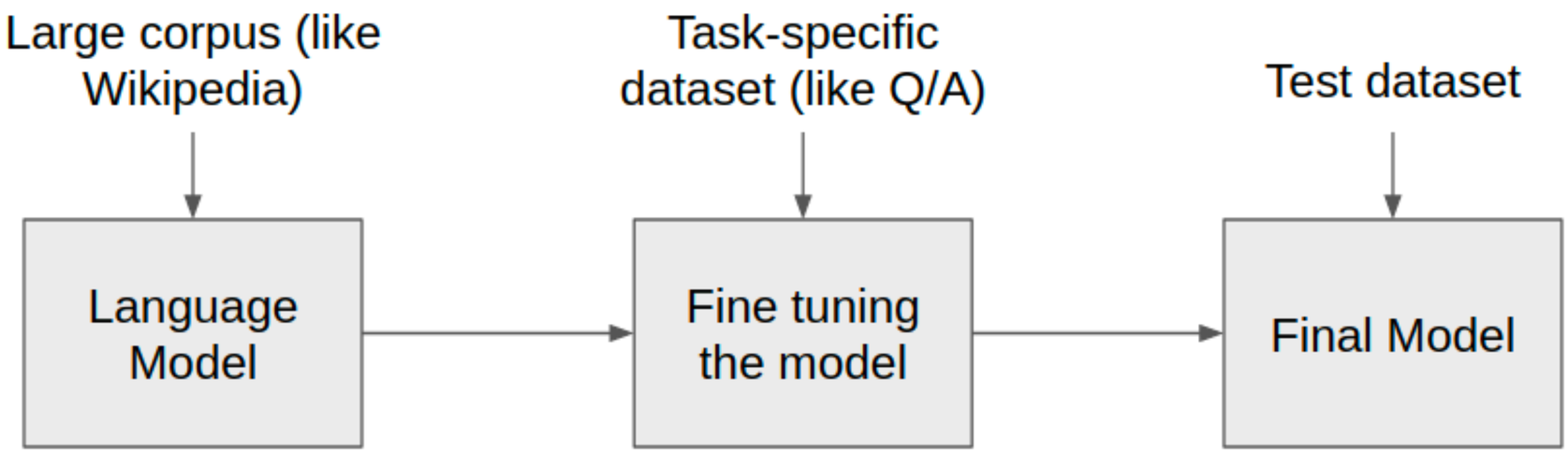
- Input representations



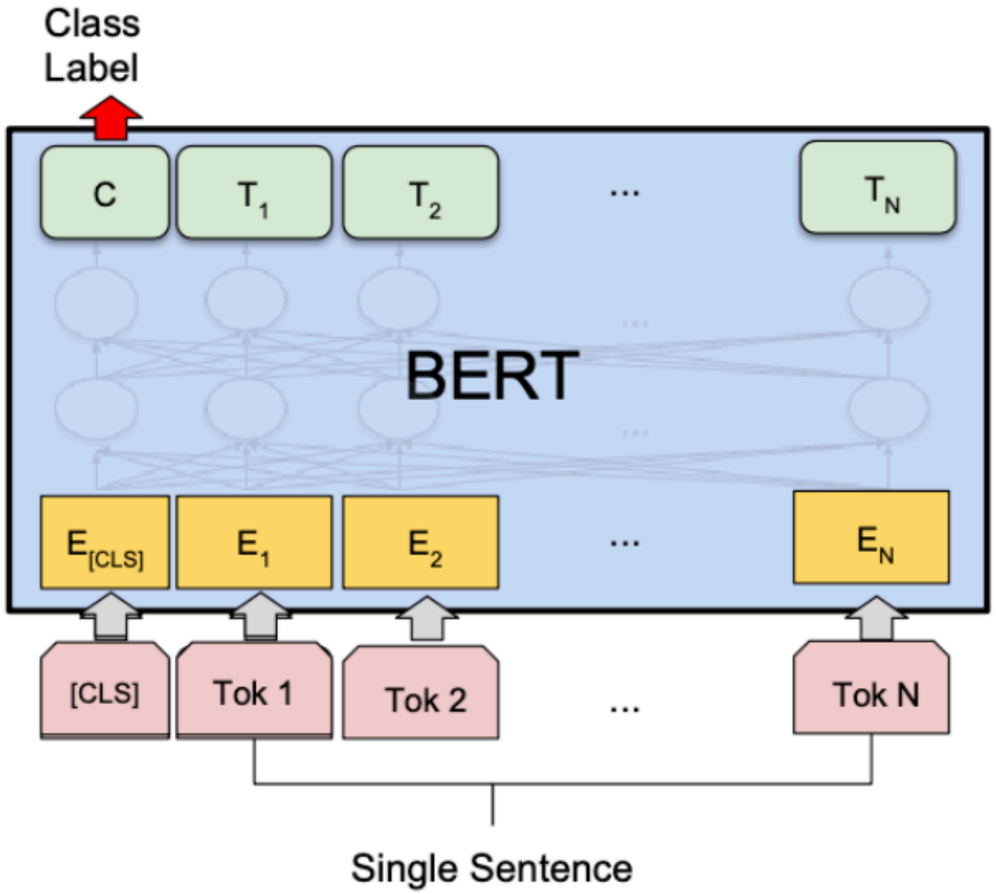
- Segment length: 512 BPE (=byte pair encoding) tokens
- Trained 40 epochs on Wikipedia (2.5B tokens) + BookCorpus (0.8B tokens)
- Released two model sizes: BERT_base, BERT_large

How to use BERT?

- **Fine-tuning BERT for downstream tasks!**



Fine-Tuning



Fine-tuning notes:

- Learning rate needs to be small
- Sufficient regularization to prevent overfitting

All the parameters will be learned together (original BERT parameters + new classifier parameters)

BERT: Results

BiLSTM: 63.9

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
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	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

BERT: Ablation Studies

Tasks	Dev Set MNLI-m (Acc)	QNLI (Acc)	MRPC (Acc)	SST-2 (Acc)	SQuAD (F1)
$\text{BERT}_{\text{BASE}}$	84.4	88.4	86.7	92.7	88.5
No NSP	83.9	84.9	86.5	92.6	87.9
LTR & No NSP	82.1	84.3	77.5	92.1	77.8
+ BiLSTM	82.1	84.1	75.7	91.6	84.9

Unidirectional LMs don't work!

Table 5: Ablation over the pre-training tasks using the $\text{BERT}_{\text{BASE}}$ architecture. "No NSP" is trained without the next sentence prediction task. "LTR & No NSP" is trained as a left-to-right LM without the next sentence prediction, like OpenAI GPT. "+ BiLSTM" adds a randomly initialized BiLSTM on top of the "LTR + No NSP" model during fine-tuning.

Hyperparams				Dev Set Accuracy		
#L	#H	#A	LM (ppl)	MNLI-m	MRPC	SST-2
3	768	12	5.84	77.9	79.8	88.4
6	768	3	5.24	80.6	82.2	90.7
6	768	12	4.68	81.9	84.8	91.3
12	768	12	3.99	84.4	86.7	92.9
12	1024	16	3.54	85.7	86.9	93.3
24	1024	16	3.23	86.6	87.8	93.7

Table 6: Ablation over BERT model size. #L = the number of layers; #H = hidden size; #A = number of attention heads. "LM (ppl)" is the masked LM perplexity of held-out training data.

The bigger, the better..

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding (Devlin et al., 2019)

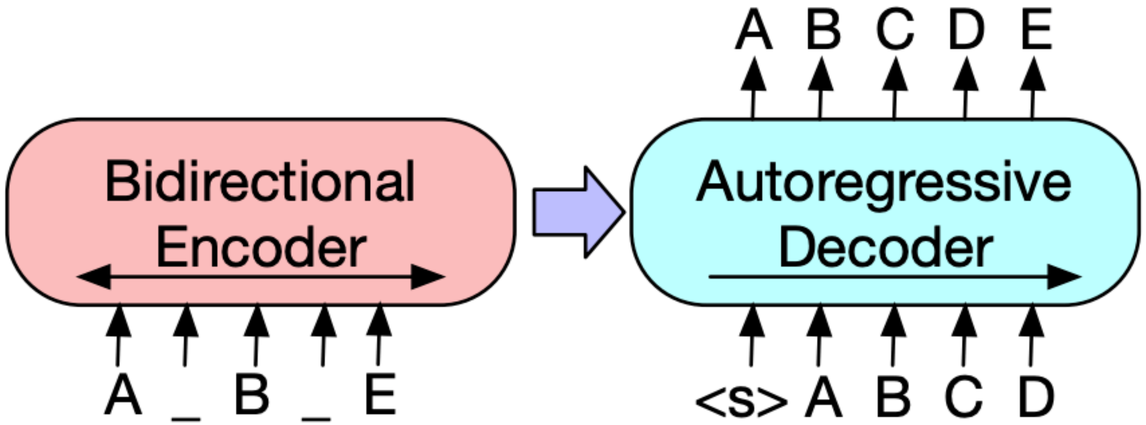
BERT: Summary

- **Masked Language Modeling**
  - Capturing both left and right contexts
- **Pre-training on large corpus**
  - Segment-level inputs (multiple sentences)
- **Large models**
  - BERT-base: 110M parameters
  - BERT-large: 340M parameters
- **Transformer Encoder**
  - Unable to generate sentences!

De-noising Seq2seq Modeling: Pre-trained Encoder-Decoders

BART: Denoising Seq2seq Pre-training

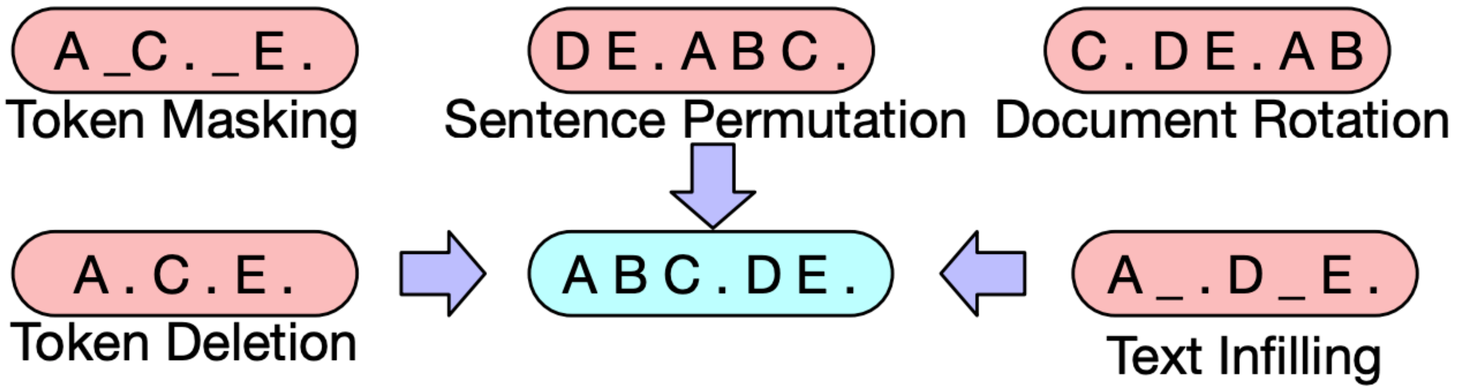
- **Key idea:** formulate pre-training as seq2seq generation
  - Encoder: input sentences with noisy transformations
  - Decoder: reconstruct the original input from the noisy one



Very useful for seq2seq tasks such as summarization!

BART: Denoising Seq2seq Pre-training

- **Token Masking:** similar to BERT
- **Token Deletion:** need to decide the positions of missing tokens
- **Text Infilling:** replacing a span of texts with a single <mask>
- **Sentence Permutation:** shuffling the order of sentences inside a document
- **Document Rotation:** Rotating a document/sentence such that the chosen token becomes the start token



BART on Summarization

	CNN/DailyMail			XSum		
	R1	R2	RL	R1	R2	RL
Lead-3	40.42	17.62	36.67	16.30	1.60	11.95
PTGEN (See et al., 2017)	36.44	15.66	33.42	29.70	9.21	23.24
PTGEN+COV (See et al., 2017)	39.53	17.28	36.38	28.10	8.02	21.72
UniLM	43.33	20.21	40.51	-	-	-
BERTSUMABS (Liu & Lapata, 2019)	41.72	19.39	38.76	38.76	16.33	31.15
BERTSUMEXTABS (Liu & Lapata, 2019)	42.13	19.60	39.18	38.81	16.50	31.27
BART	**44.16**	**21.28**	**40.90**	**45.14**	**22.27**	**37.25**

Multilingual BART

- **Training BART on monolingual corpus over 25/100 languages:**
  - Shared BPE vocabulary
  - Shared model parameters

Multilingual BART

- mBART-25

Languages	En-Gu		En-Kk		En-Vi		En-Tr		En-Ja		En-Ko	
Data Source	WMT19		WMT19		IWSLT15		WMT17		IWSLT17		IWSLT17	
Size	10K		91K		133K		207K		223K		230K	
Direction	←	→	←	→	←	→	←	→	←	→	←	→
Random	0.0	0.0	0.8	0.2	23.6	24.8	12.2	9.5	10.4	12.3	15.3	16.3
mBART25	**0.3**	**0.1**	**7.4**	**2.5**	**36.1**	**35.4**	**22.5**	**17.8**	**19.1**	**19.4**	**24.6**	**22.6**

Languages	En-Nl		En-Ar		En-It		En-My		En-Ne		En-Ro	
Data Source	IWSLT17		IWSLT17		IWSLT17		WAT19		FLoRes		WMT16	
Size	237K		250K		250K		259K		564K		608K	
Direction	←	→	←	→	←	→	←	→	←	→	←	→
Random	34.6	29.3	27.5	16.9	31.7	28.0	23.3	34.9	7.6	4.3	34.0	34.3
mBART25	**43.3**	**34.8**	**37.6**	**21.6**	**39.8**	**34.0**	**28.3**	**36.9**	**14.5**	**7.4**	**37.8**	**37.7**

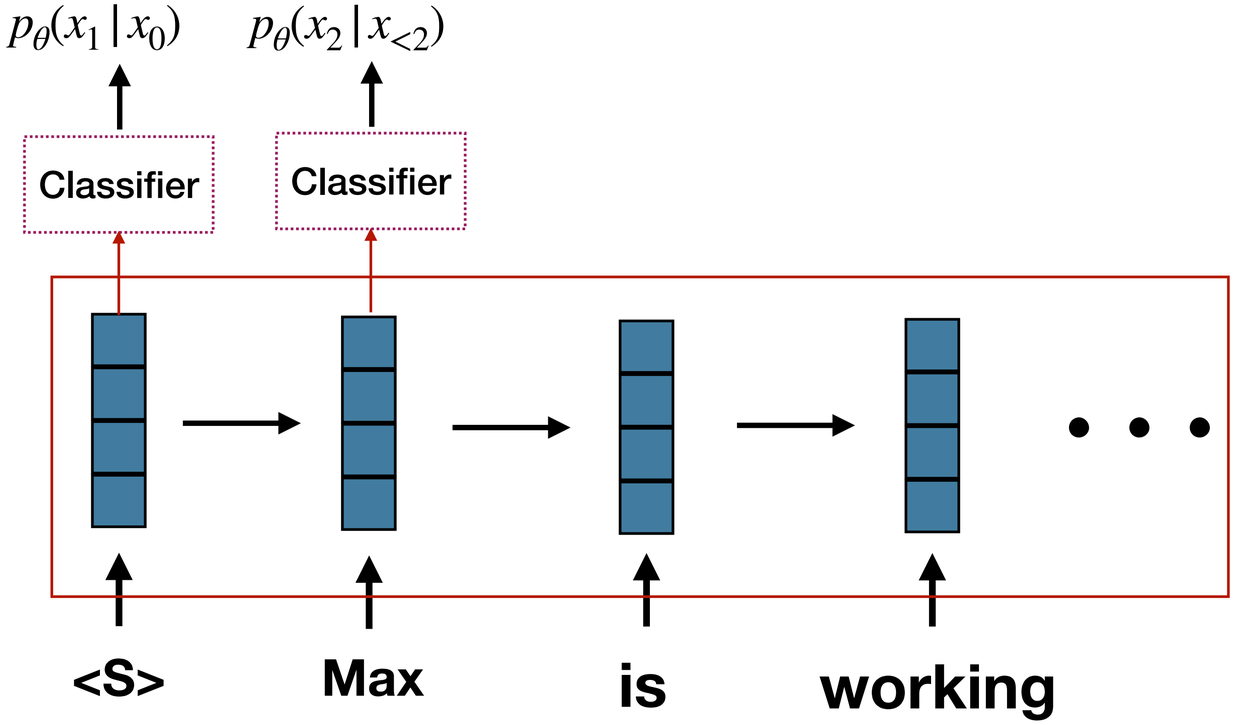
Languages	En-Si		En-Hi		En-Et		En-Lt		En-Fi		En-Lv	
Data Source	FLoRes		ITTB		WMT18		WMT19		WMT17		WMT17	
Size	647K		1.56M		1.94M		2.11M		2.66M		4.50M	
Direction	←	→	←	→	←	→	←	→	←	→	←	→
Random	7.2	1.2	10.9	14.2	22.6	17.9	18.1	12.1	21.8	20.2	15.6	12.9
mBART25	**13.7**	**3.3**	**23.5**	**20.8**	**27.8**	**21.4**	**22.4**	**15.3**	**28.5**	**22.4**	**19.3**	**15.9**

Neural Language Modeling: Pre-trained Decoders

Auto-regressive Generative Models

- **Auto-regressive Neural Language Models**

$$p_\theta(X) = \prod_{t=1}^{T} p_\theta(x_t \mid x_{<t})$$



Transformer Decoder
Basic Architecture for GPT-2&3

GPT-3

- **Training data**
  - Common Crawl (410B tokens)
  - WebText2 (19B tokens)
  - Books1 & Books2 (12B + 55B tokens)
  - Wikipedia (3B tokens)
- **Transformer Encoder**
  - Medium: 350M
  - Large: 760M
  - X-Large: 1.3B

Q: How to use GPT-3?

- Fine-tuning is too expensive
- Prompting!

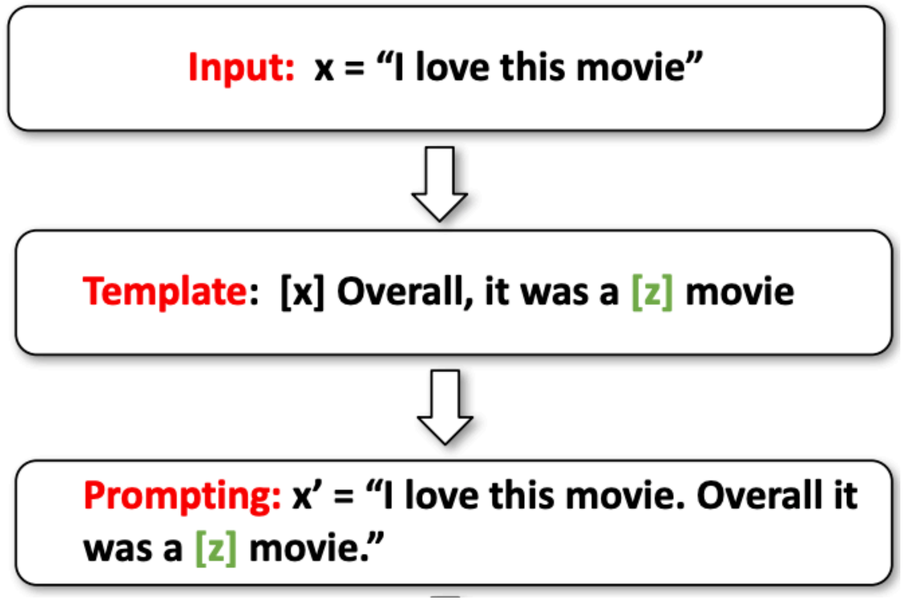
we will see some examples soon!

Prompting

- Prompt Addition
- Answer Prediction
- Answer-Label Mapping

Prompt Addition

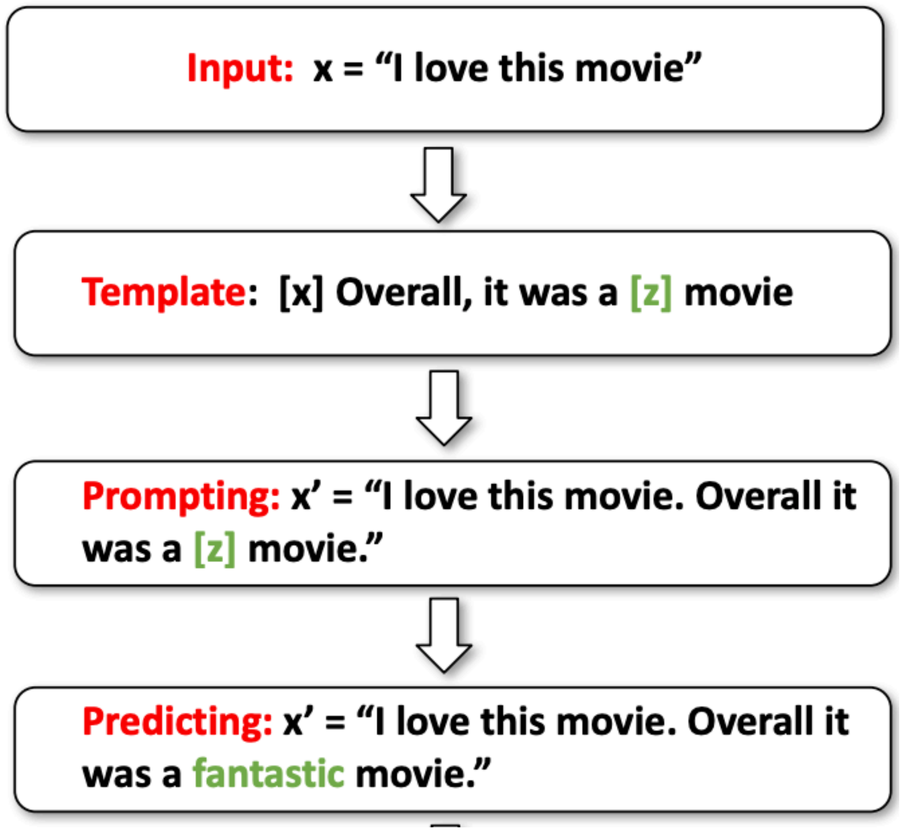
- **Given input x, we create a prompt with two steps:**
  - Define a template with two slots, one for input [x], and one for the answer [z]
  - Fill in the input with slot [x]



Example: sentiment classification

Answer Prediction

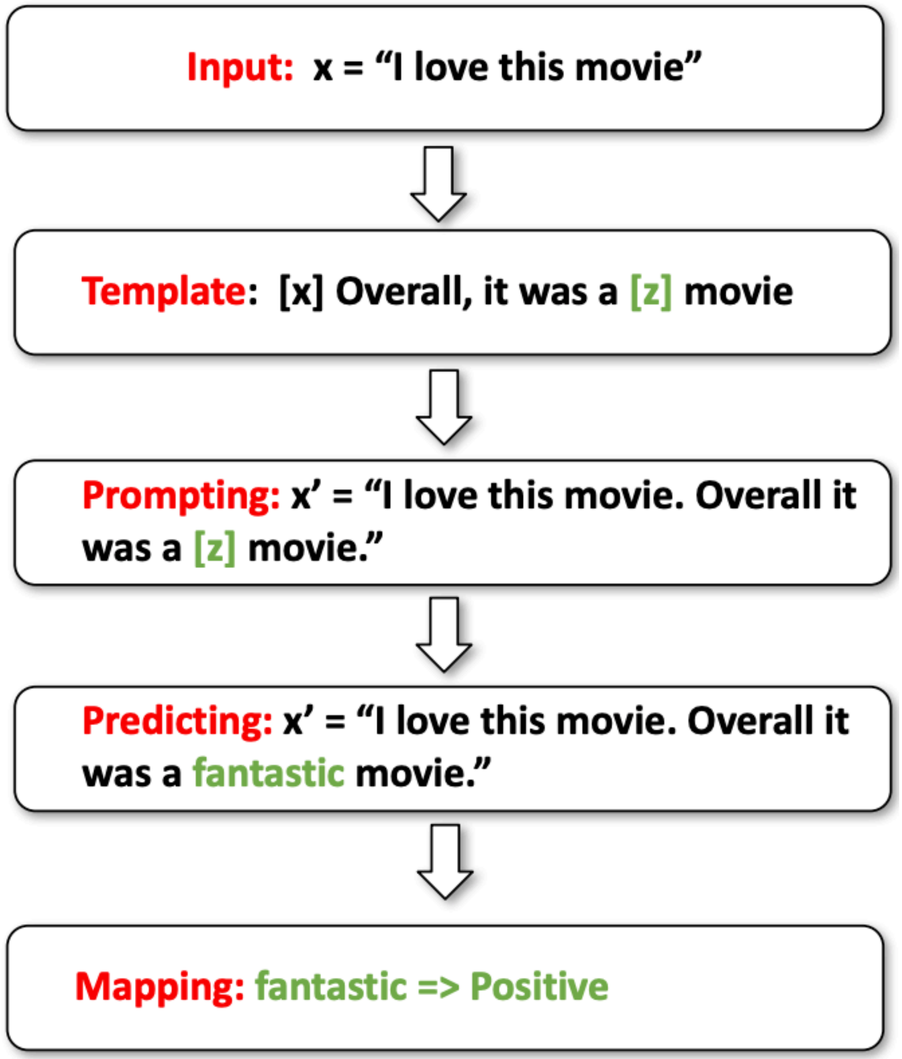
- **Given a prompt, predict the answer [z]**



Example: sentiment classification

Answer-Labeling Mapping

- Given an answer, map it into a class label



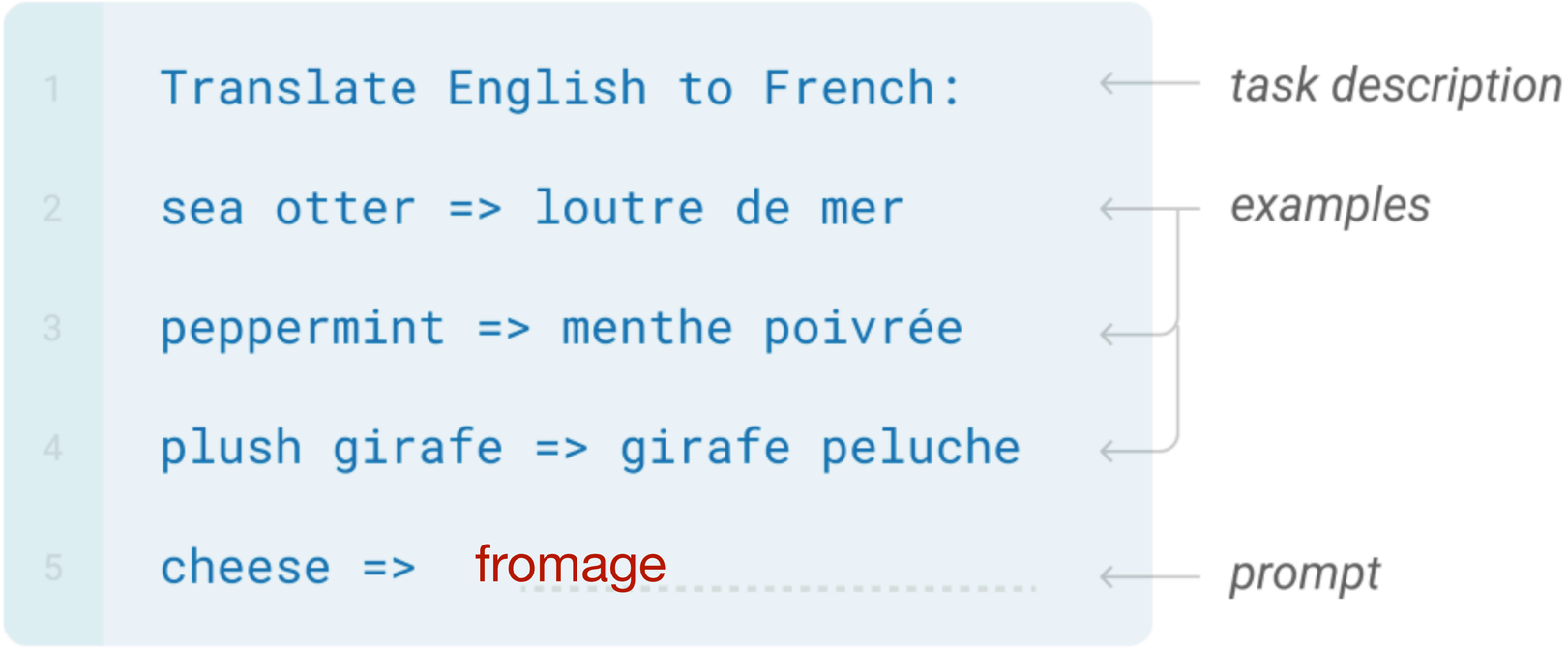
Example: sentiment classification

Types of Prompts

- **Cloze Prompt:**
  - I love this Movie. Overall, it was a [z] movie
  - Masked Language Modeling (BERT)
- **Prefix Prompt**
  - I love this Movie. Overall, this movie is [z]
  - Auto-regressive Language Modeling (GPT-3)

Prompting in Few-shot Learning

- **Suppose we have a few (less than 20) examples of the task**



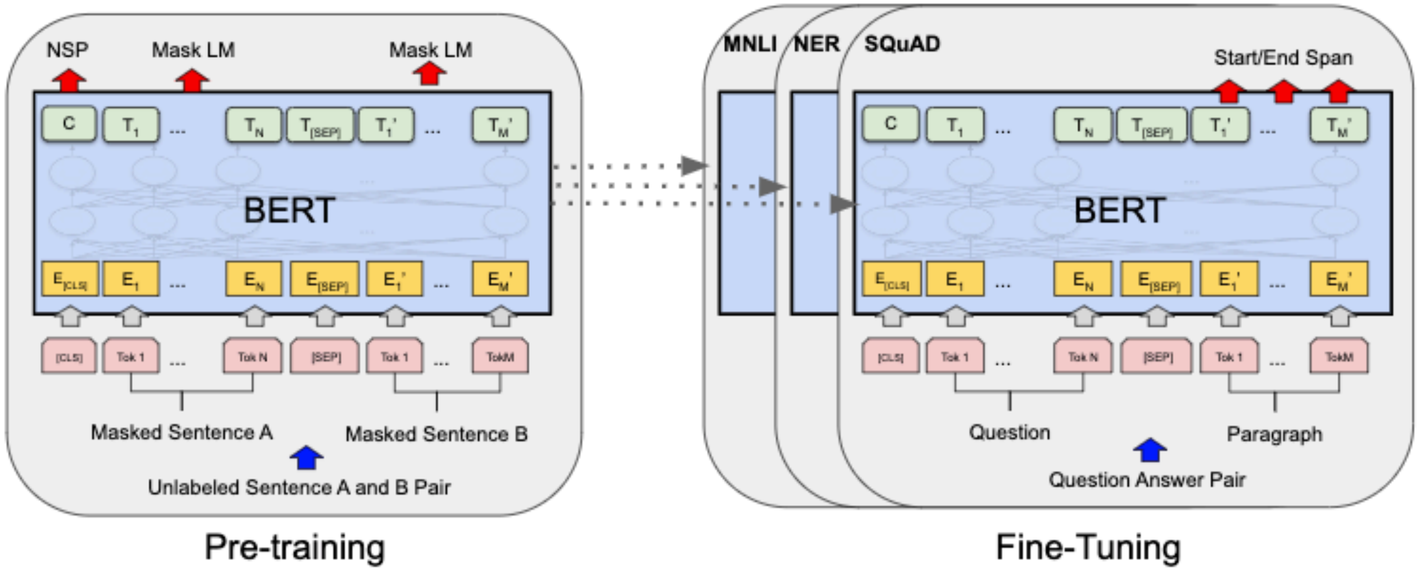
Prompting in GPT-3 for English to French Translation

Open Questions

- **Fine-tuning is expensive**
  - Parameter-efficient fine-tuning
- **Design of prompts is tricky**
  - Human Instruction Following
  - Reinforcement Learning with Human Feedback

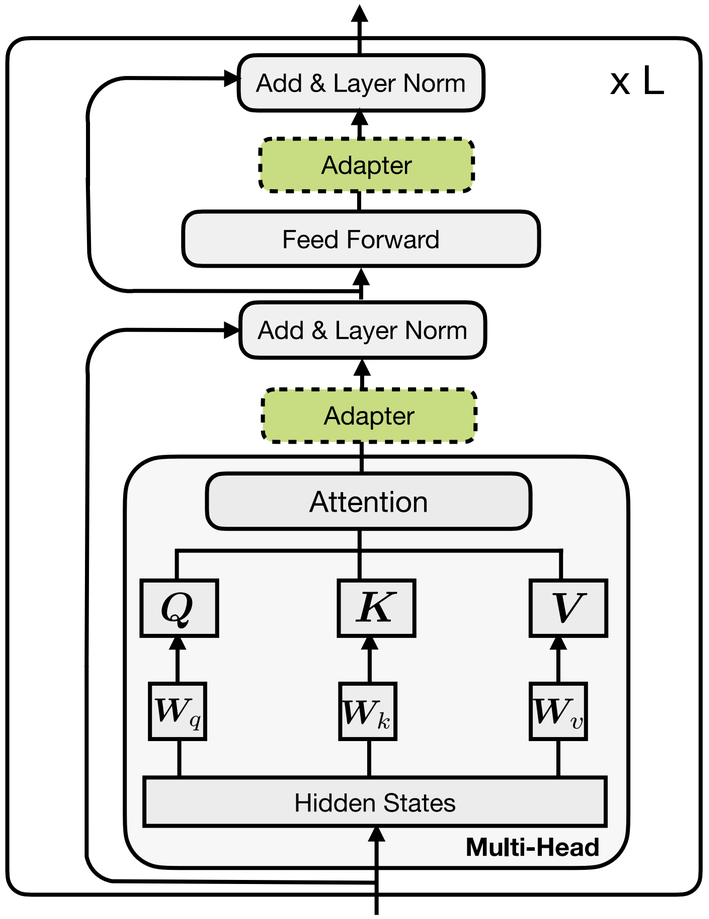
Parameter-Efficient Fine-tuning

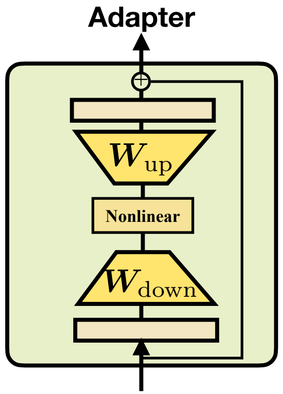
- **Fully Fine-tuning**



Each task needs a separate model copy
—> expensive as the number of tasks and model size grow

Parameter-Efficient Fine-tuning



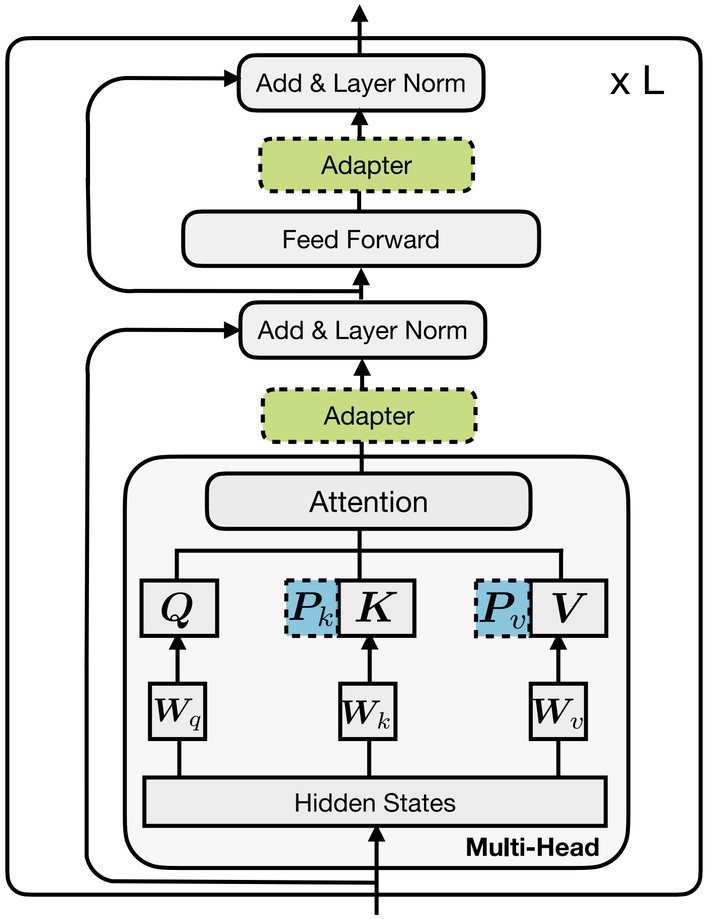


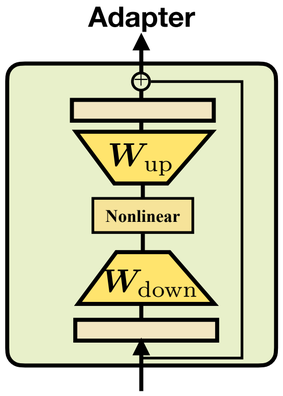
Adapters:

$$\boldsymbol{h} \leftarrow \boldsymbol{h} + f(\boldsymbol{h}\boldsymbol{W}_{\text{down}})\boldsymbol{W}_{\text{up}}$$

[1] Houlsby et al. Parameter-Efficient Transfer Learning for NLP. ICML 2019

Parameter-Efficient Fine-tuning





Adapters:

$$\boldsymbol{h} \leftarrow \boldsymbol{h} + f(\boldsymbol{h}\boldsymbol{W}_{\text{down}})\boldsymbol{W}_{\text{up}}$$

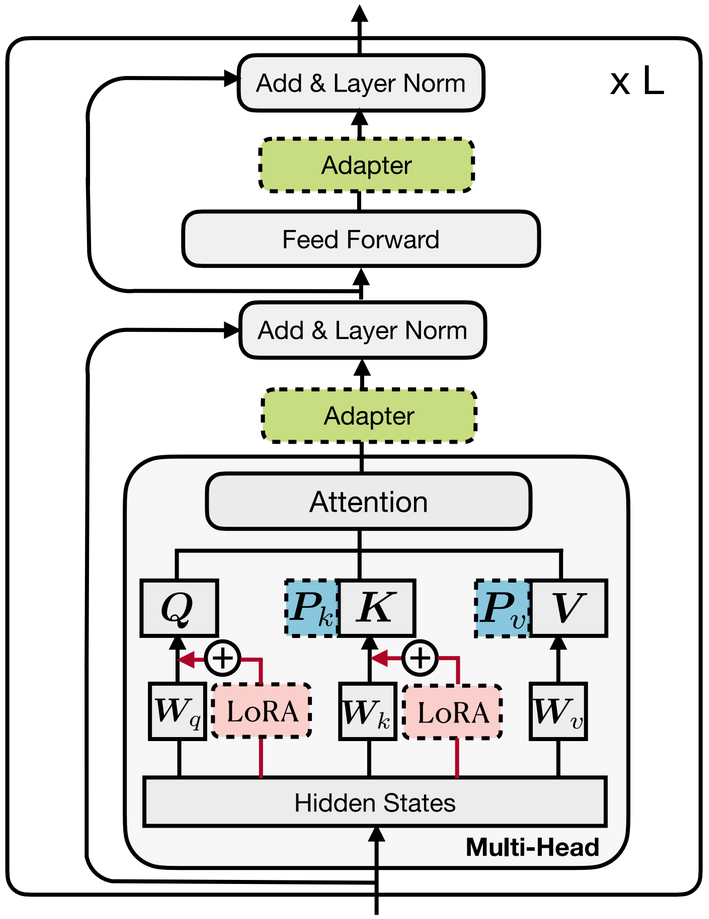
Prefix Tuning:

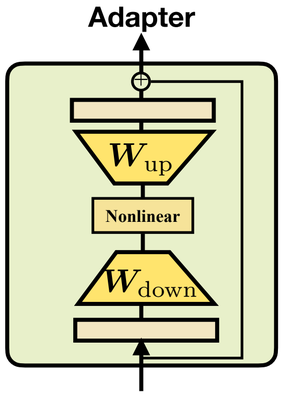
$$\text{head}_i = \text{Attn}(\boldsymbol{x}\boldsymbol{W}_q^{(i)}, \text{concat}(\boldsymbol{P}_k^{(i)}, \boldsymbol{C}\boldsymbol{W}_k^{(i)}), \text{concat}(\boldsymbol{P}_v^{(i)}, \boldsymbol{C}\boldsymbol{W}^{(i)}))$$

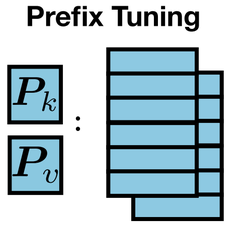
[1] Houlsby et al. Parameter-Efficient Transfer Learning for NLP. ICML 2019

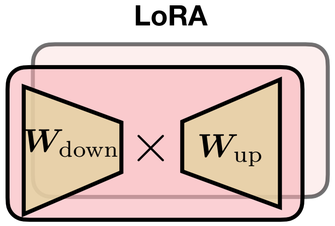
[2] Li et al. Prefix-Tuning: Optimizing Continuous Prompts for Generation. ACL 2021

Parameter-Efficient Fine-tuning









Adapters:

$$\boldsymbol{h} \leftarrow \boldsymbol{h} + f(\boldsymbol{h}\boldsymbol{W}_{\text{down}})\boldsymbol{W}_{\text{up}}$$

Prefix Tuning:

$$\text{head}_i = \text{Attn}(\boldsymbol{x}\boldsymbol{W}_q^{(i)}, \text{concat}(\boldsymbol{P}_k^{(i)}, \boldsymbol{C}\boldsymbol{W}_k^{(i)}), \text{concat}(\boldsymbol{P}_v^{(i)}, \boldsymbol{C}\boldsymbol{W}^{(i)}))$$

LoRA:

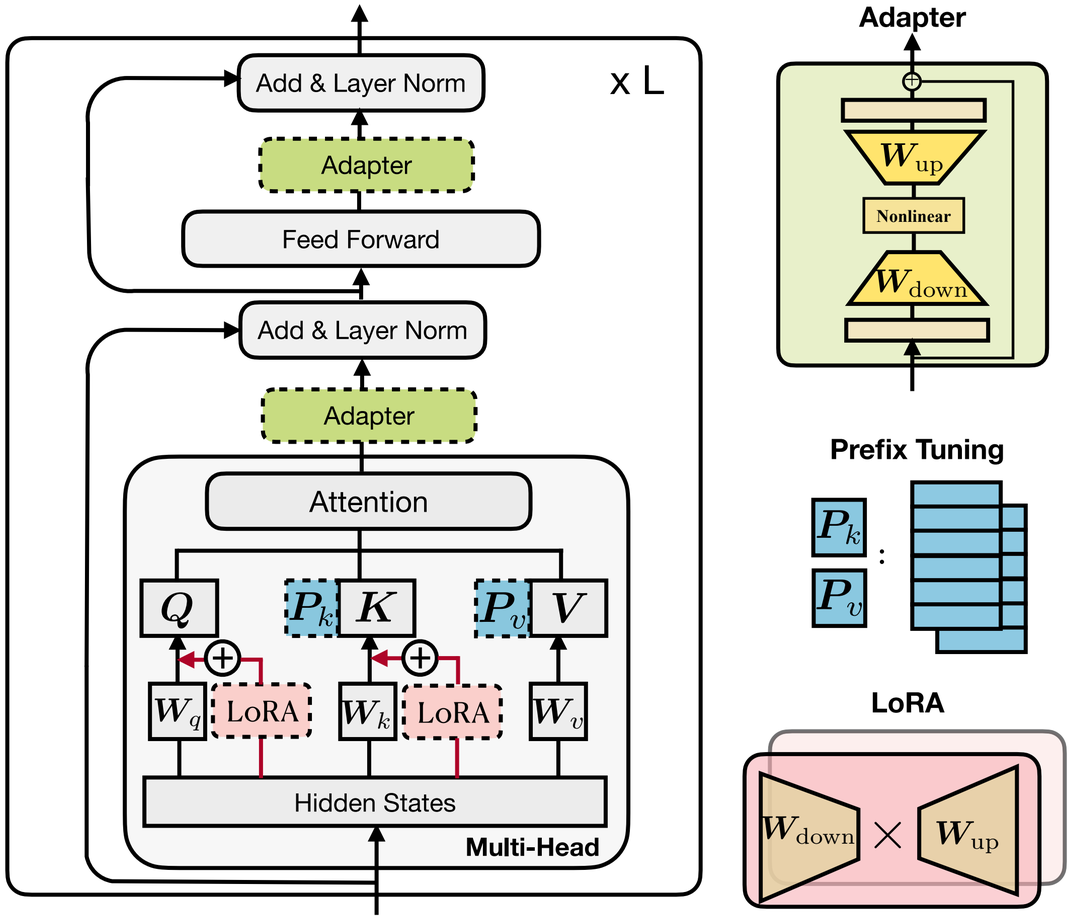
$$\boldsymbol{h} \leftarrow \boldsymbol{h} + s \cdot \boldsymbol{x}\boldsymbol{W}_{\text{down}}\boldsymbol{W}_{\text{up}}$$

[1] Houlsby et al. Parameter-Efficient Transfer Learning for NLP. ICML 2019

[2] Li et al. Prefix-Tuning: Optimizing Continuous Prompts for Generation. ACL 2021

[3] Hu et al. LoRA: Low-Rank Adaptation of Large Language Models. Preprint 2021

Existing Methods



He et al., 2022:

- A unified framework for all the three existing methods
- Enabling to design better adapters

[1] Houlsby et al. Parameter-Efficient Transfer Learning for NLP. ICML 2019

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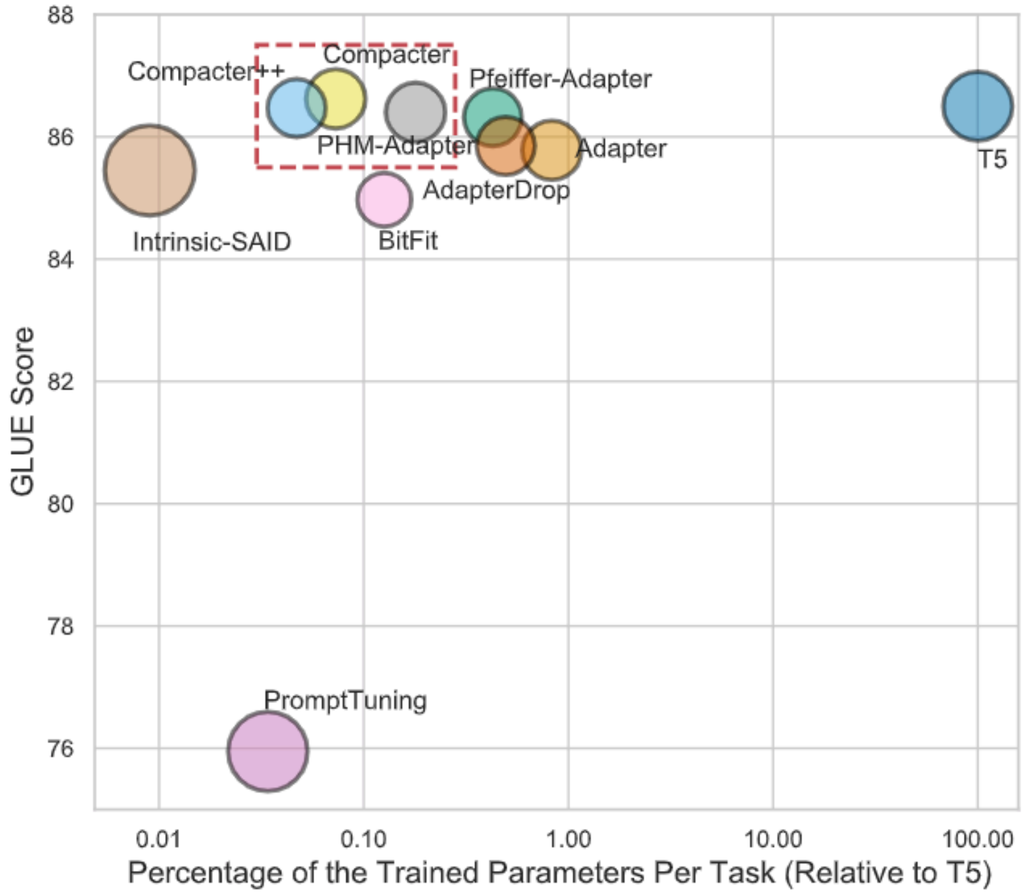
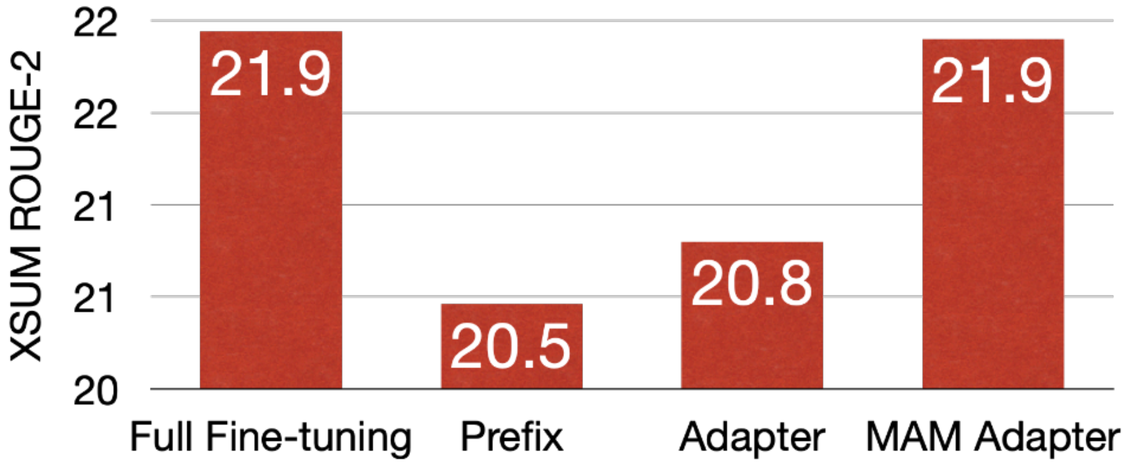
Parameter-Efficient Fine-tuning



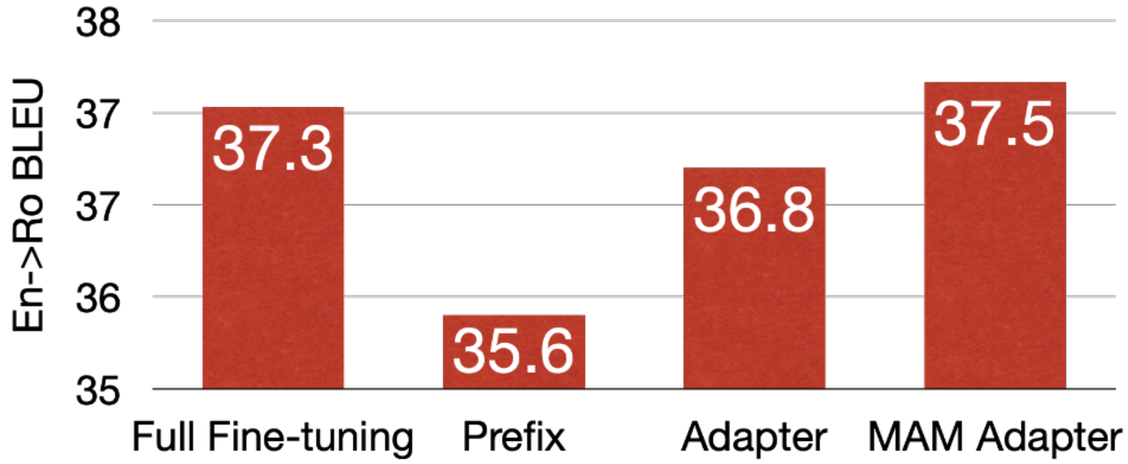
Less than 1% of parameters are tuned to achieve comparable performance to full fine-tuning (He et al., 2022)

Mix-and-Match (MAM) Adapter

XSum: Abstractive Summarization, BART-large



WMT16 En-Ro Translation, mBART-large



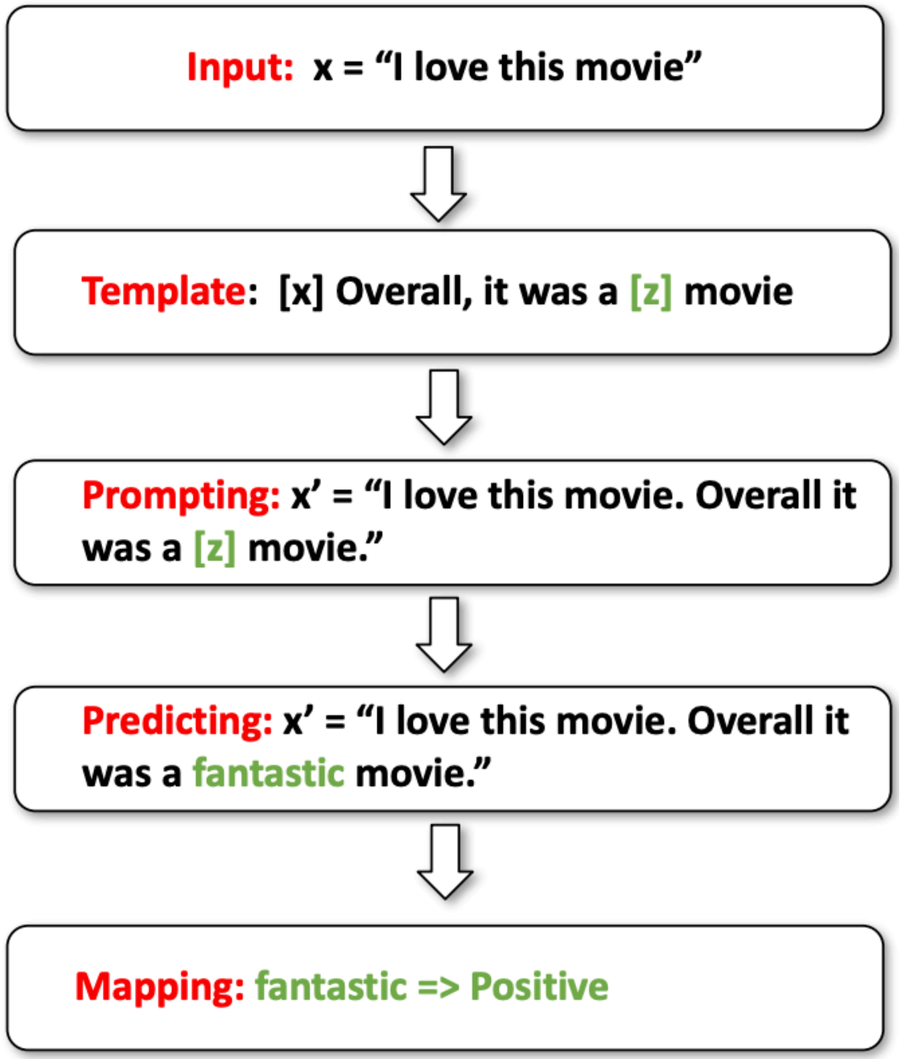
Comparable performance to full fine-tuning while tuning 6.7% relative size of parameters

Open Questions

- **Fine-tuning is expensive**
  - Parameter-efficient fine-tuning
- **Design of prompts is tricky**
  - Human Instruction Following
  - Reinforcement Learning with Human Feedback

Fine-tuning via Human Instructions

- **Prompting/In context Learning**



Example: sentiment classification

Fine-tuning via Human Instructions

- Can we directly communicate with LLMs via instructions in human languages

What is the sentiment of “I love this movie”

The sentiment of this sentence is positive, because …

Fine-tuning via Human Instructions

- **Collect a set of prompts/instructions**
  - Different categories
- **Create a dataset with demonstration data**
  - Demonstrating the desired output behavior
- **Fine-tune the model with the demonstration data**

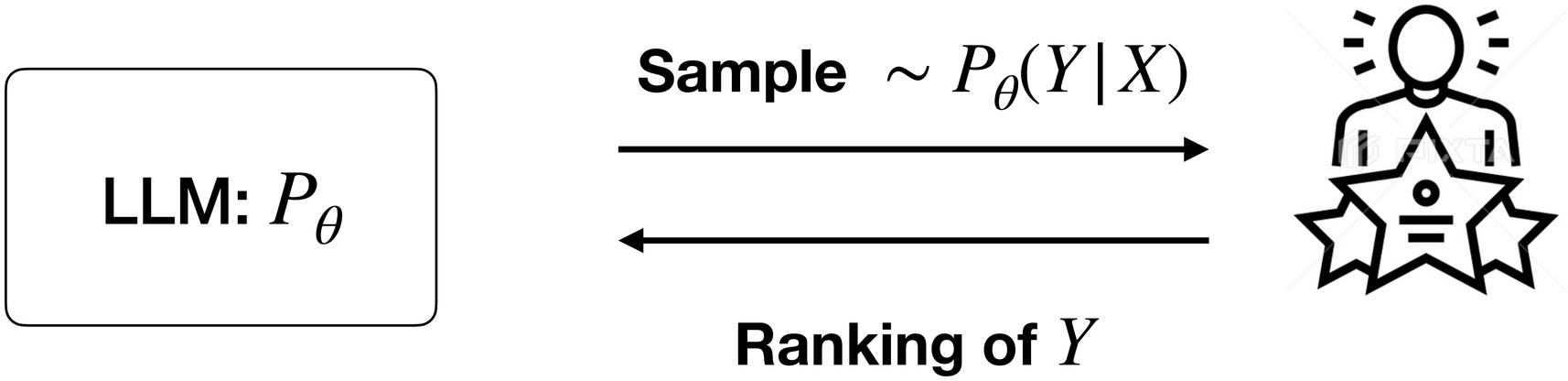
Demonstration Data

Use-case	(%)
Generation	45.6%
Open QA	12.4%
Brainstorming	11.2%
Chat	8.4%
Rewrite	6.6%
Summarization	4.2%
Classification	3.5%
Other	3.5%
Closed QA	2.6%
Extract	1.9%

Use-case	Prompt
Brainstorming	List five ideas for how to regain enthusiasm for my career
Generation	Write a short story where a bear goes to the beach, makes friends with a seal, and then returns home.
Rewrite	This is the summary of a Broadway play: """ {summary} """ This is the outline of the commercial for that play: """

The ability of following human-instruction is generalizable to general cases

Reinforcement Learning with Human Feedbacks



Guest lecture from Prof Jon May on 03/06

Reading Materials

- **Relavant Papers**
  - BERT
  - GPT-3
  - BART
  - Prompting
  - Parameter-Efficient Fine-tuning