PRINCETON
School of Engineering and Applied Science

Prompt as Parameter-Efficient Fine-Tuning

Chris Pan and Hongjie Wang

Agenda

Background (~5 minutes)

Prefix Tuning (~25 minutes)

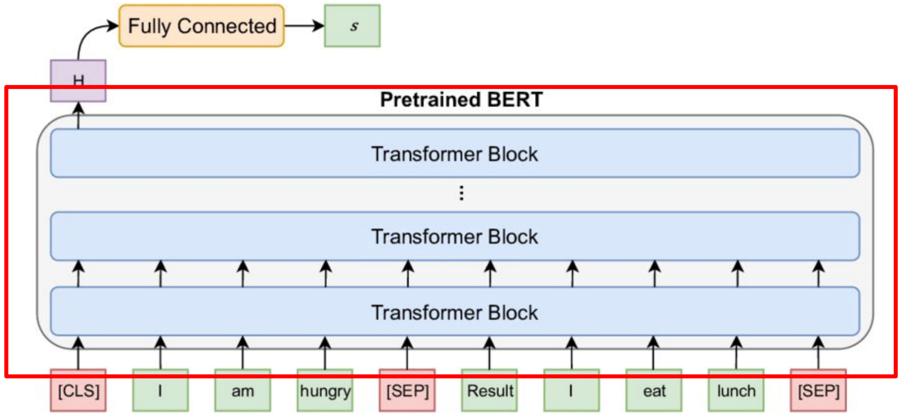
- Motivation
- Methodology
- Results
- Additional Experiments
- Discussion

Prompt Tuning (~30 minutes)

- Introduction
- Prompt tuning
- Design Decisions
- Compare with previous methods
- Resilience
- Prompt ensembling
- Interpretability

Background: Fine Tuning

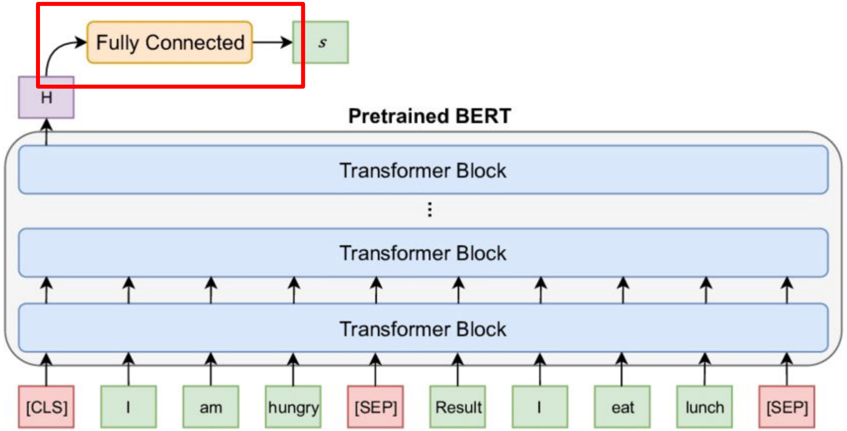
- **Pretrain a language model on task**



Devlin et al. 2019

Background: Fine Tuning

- Pretrain a language model on task
- **Attach a small task specific layer**



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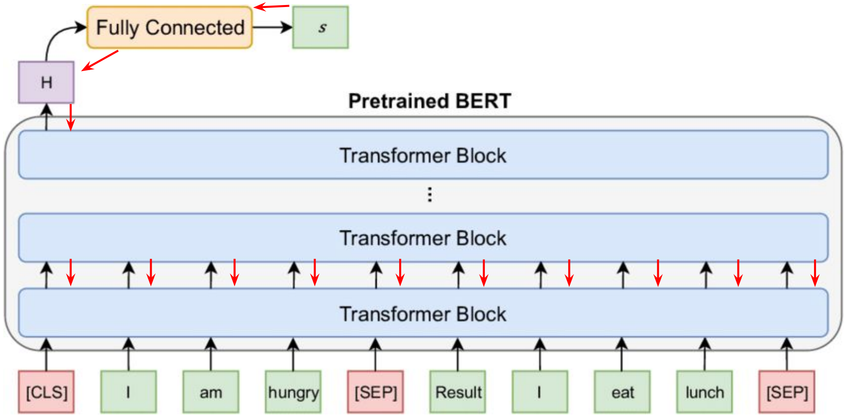
Background: Fine Tuning

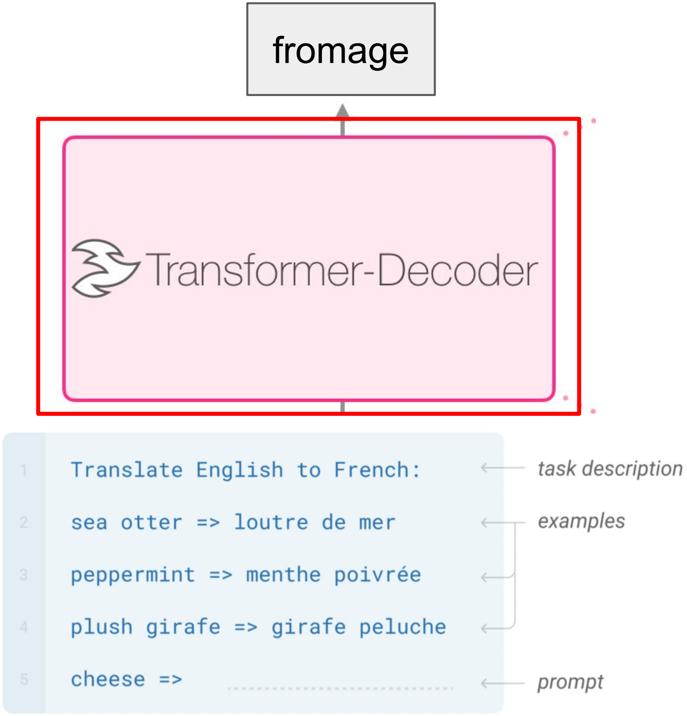
- Pretrain a language model on task
- Attach a small task specific layer
- **Fine-tune the weights of full NN by propagating gradients on a downstream task**



Devlin et al. 2019

Background: In-context Learning

- **Pretrain a language model on task (LM)**



```
Translate English to French:
sea otter => loutre de mer
peppermint => menthe poivrée
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Brown et al. 2020

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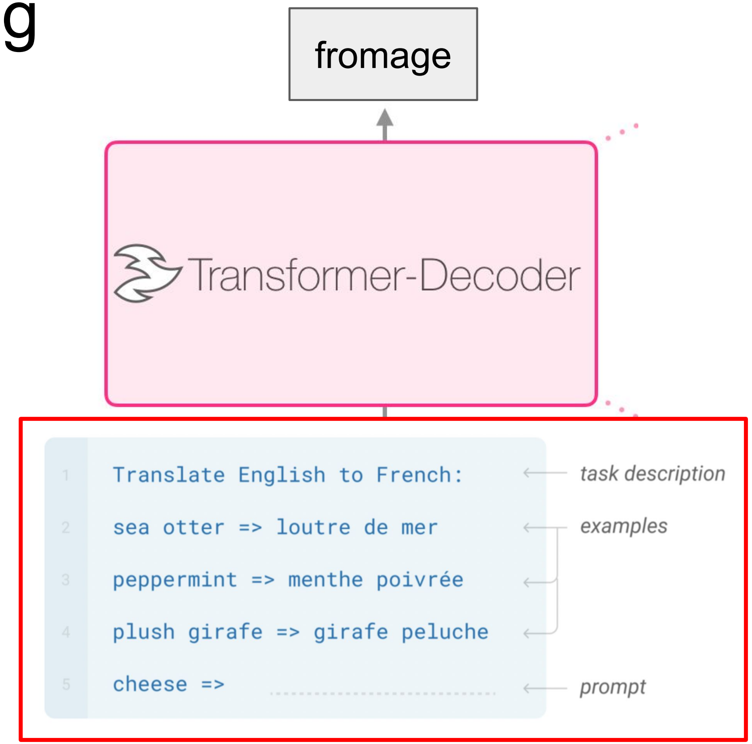
- **Manually design a “prompt” that demonstrates how to formulate a task as a generation task.**



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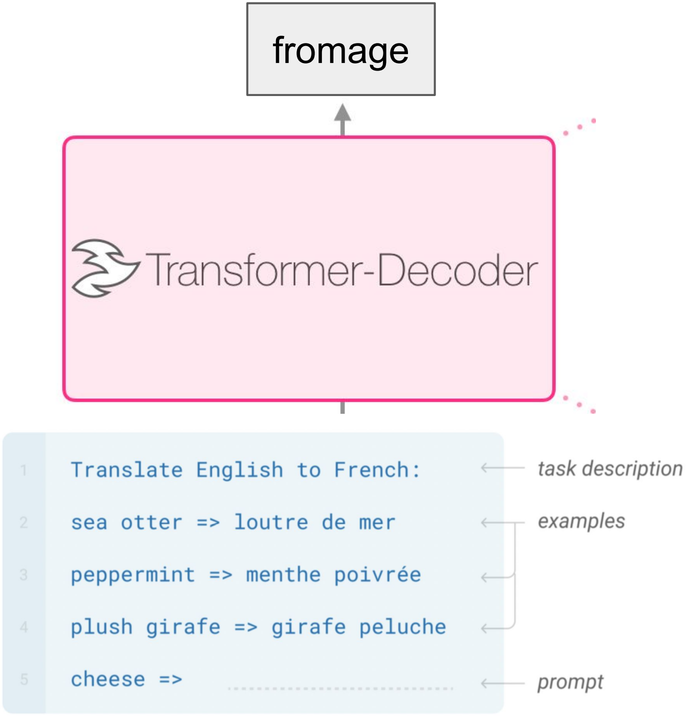
Background: In-context Learning

- Pretrain a language model on task (LM)
- Manually design a "prompt" that demonstrates how to formulate a task as a generation task.
- **No need to update the model weights at all!**



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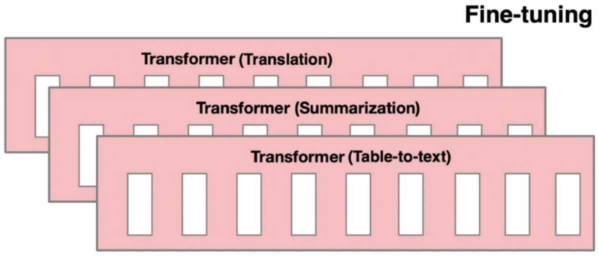
- With standard fine-tuning, we need to make a **new copy** of the model for each task.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Transformer (Translation)
Transformer (Summarization)
Transformer (Table-to-text)

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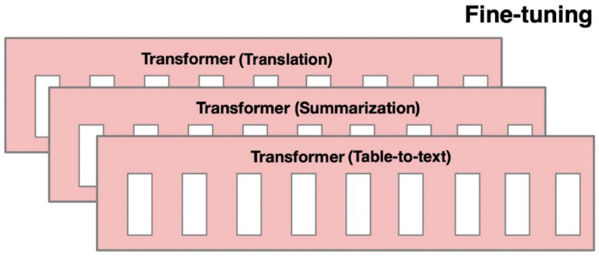
- In the extreme case of a different model per user, we could never store 1000 different full models.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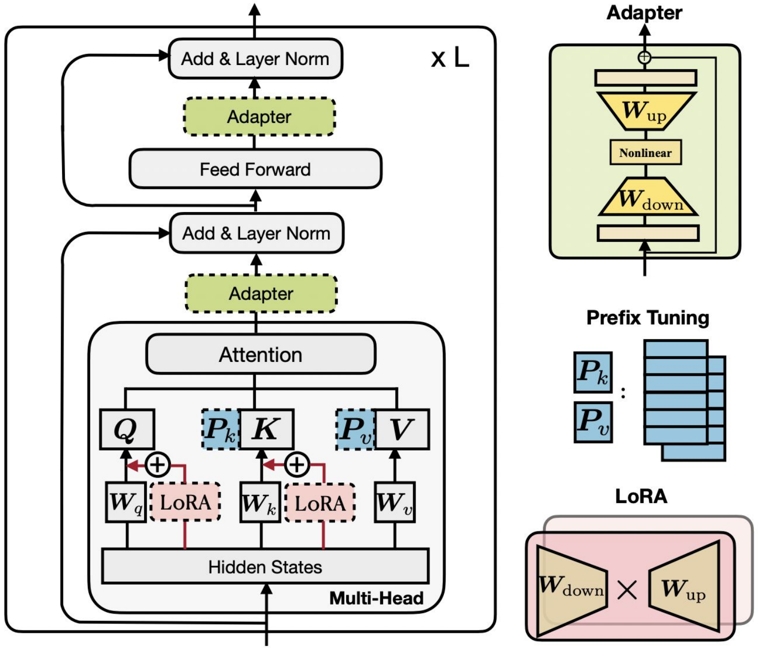

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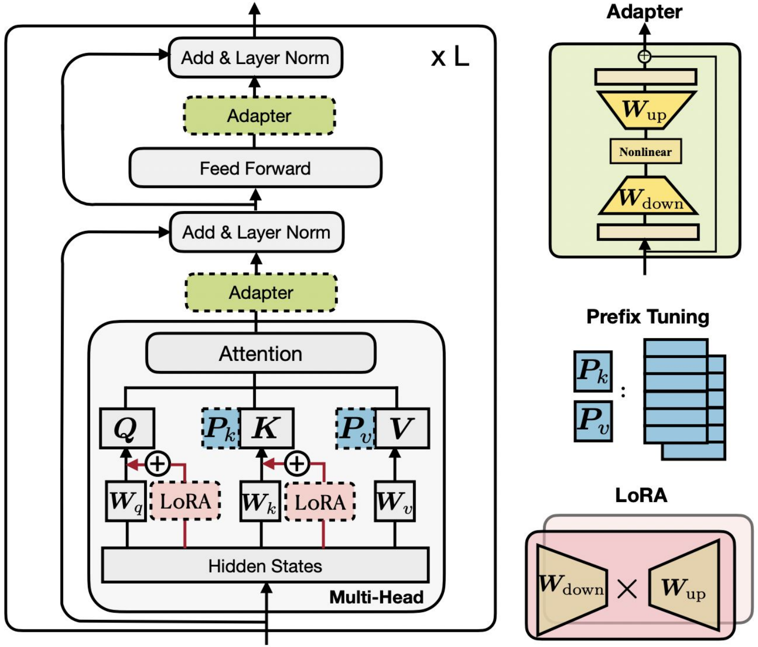

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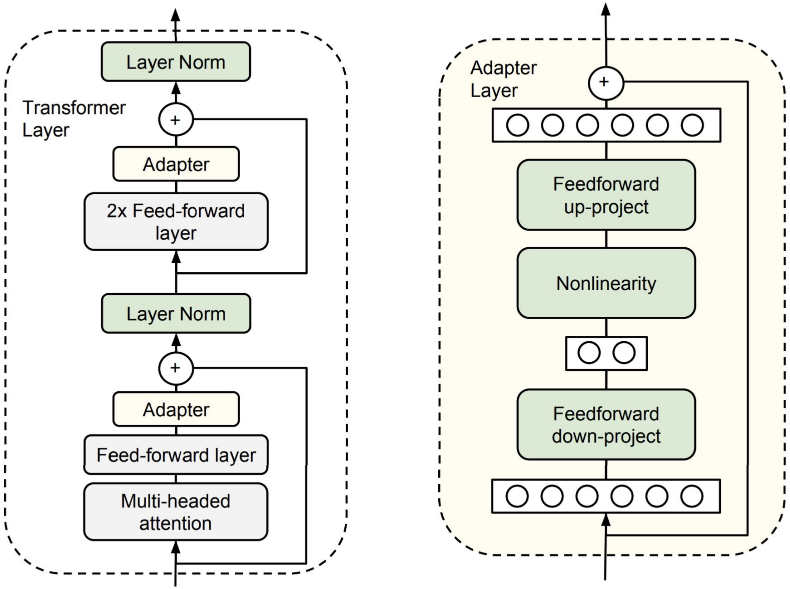

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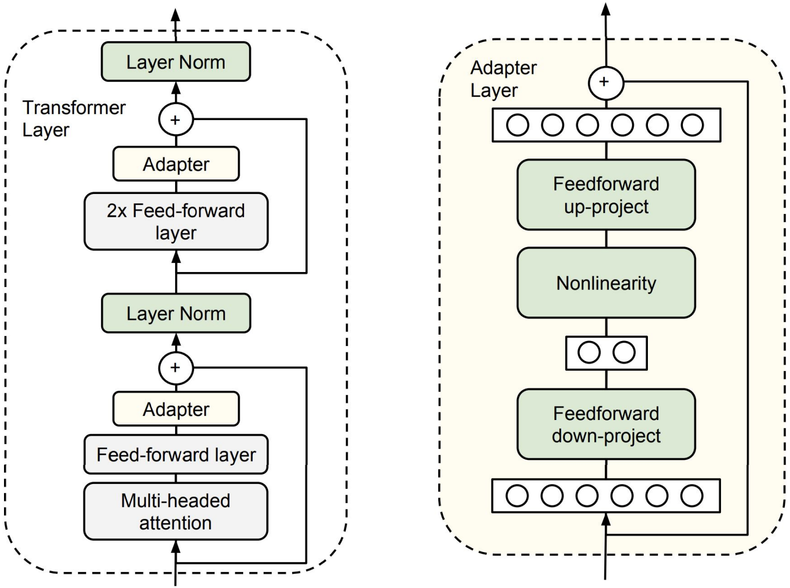

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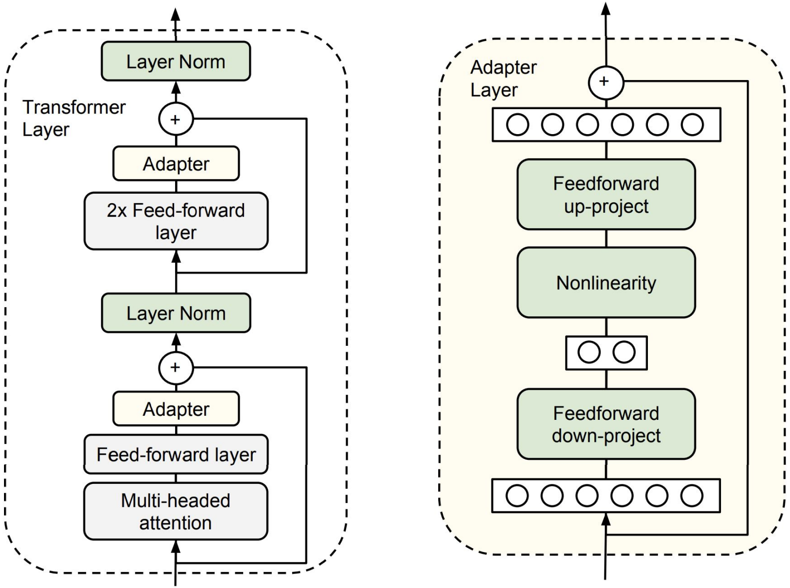

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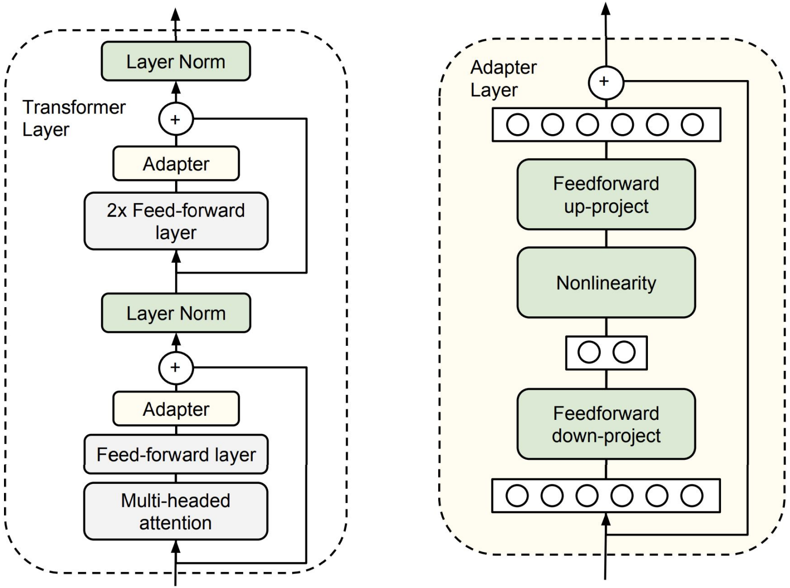
- **3.6%** of parameters needed!



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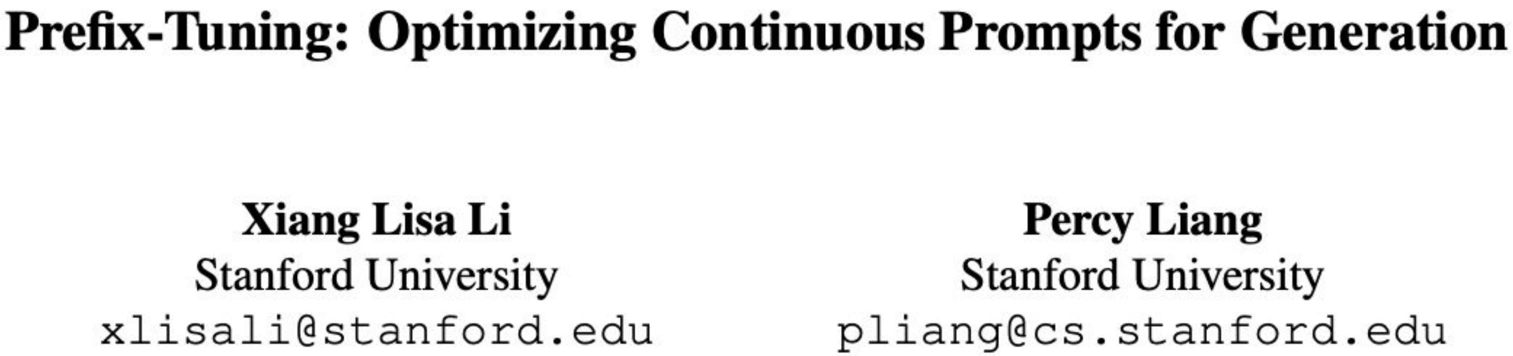

Prefix-Tuning: Optimizing Continuous Prompts for Generation

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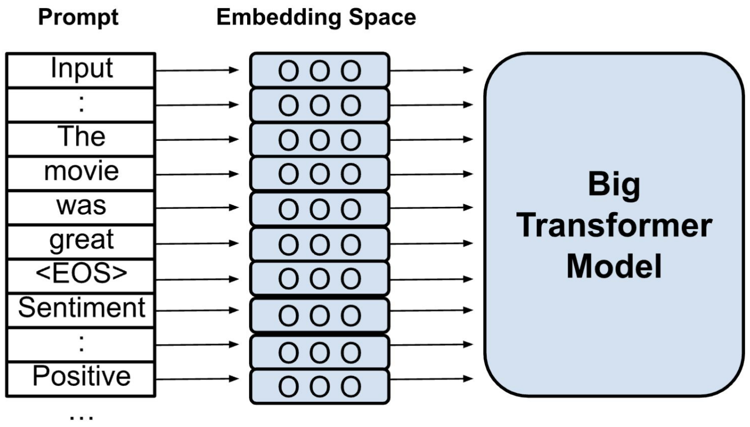
Published in ACL 2021

Motivation

- For prompt design (Brown et al. 2020), the **discrete prompt** is optimized manually.



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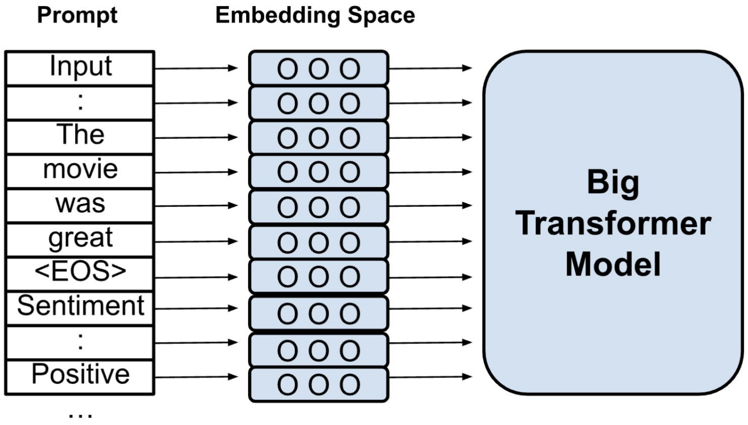

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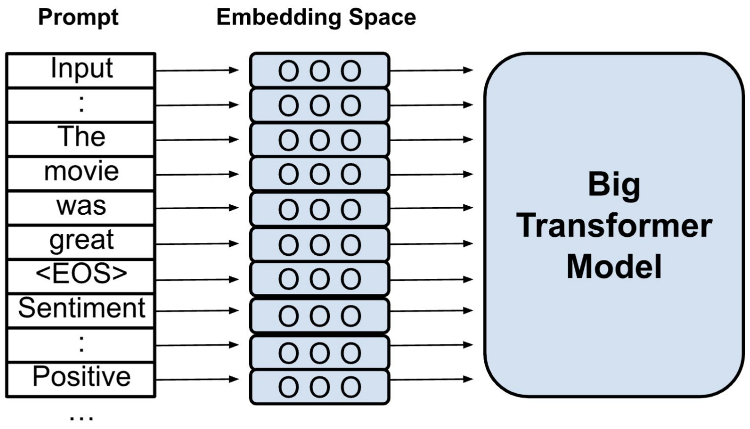

Motivation

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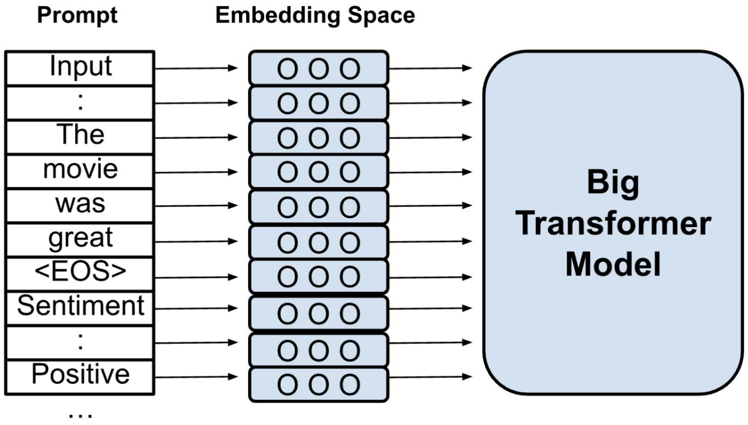
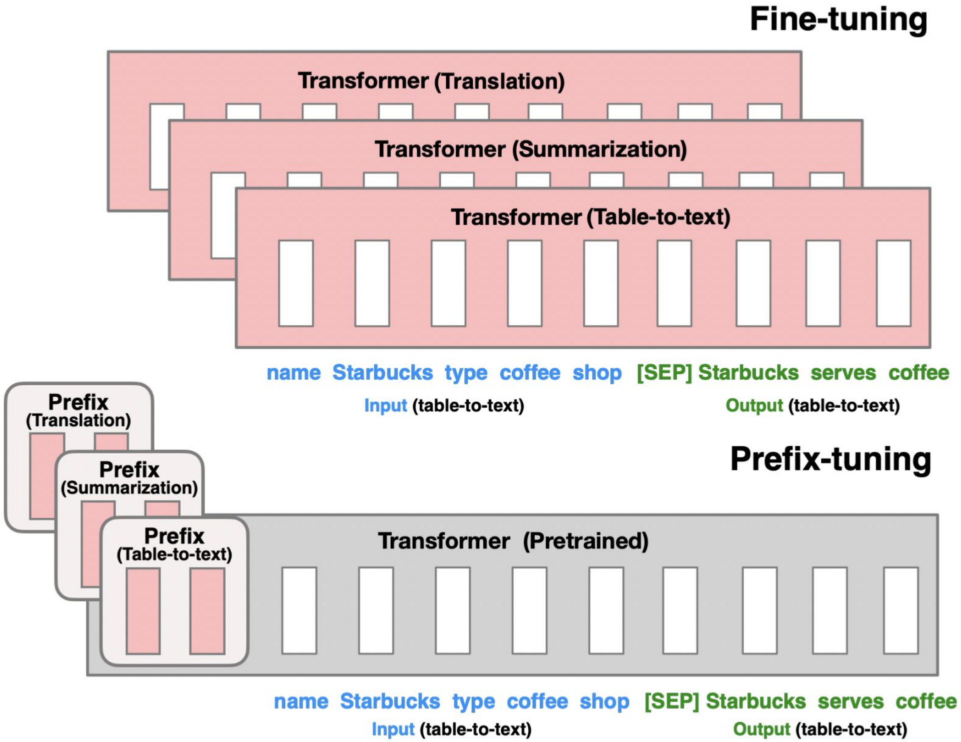
- What if we can optimize the prompt in the **continuous embedding space**?
- This would sacrifice interpretability but would be **easier to optimize.**



Methodology

- Rather than designing a prompt manually, we can **learn** an optimal prefix for each task.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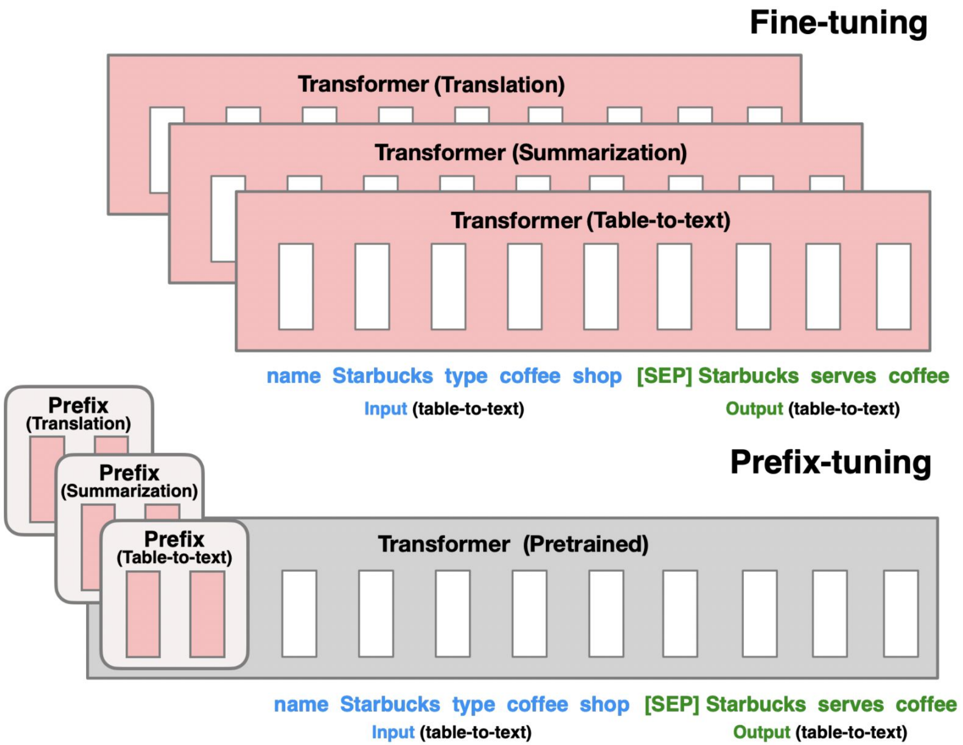
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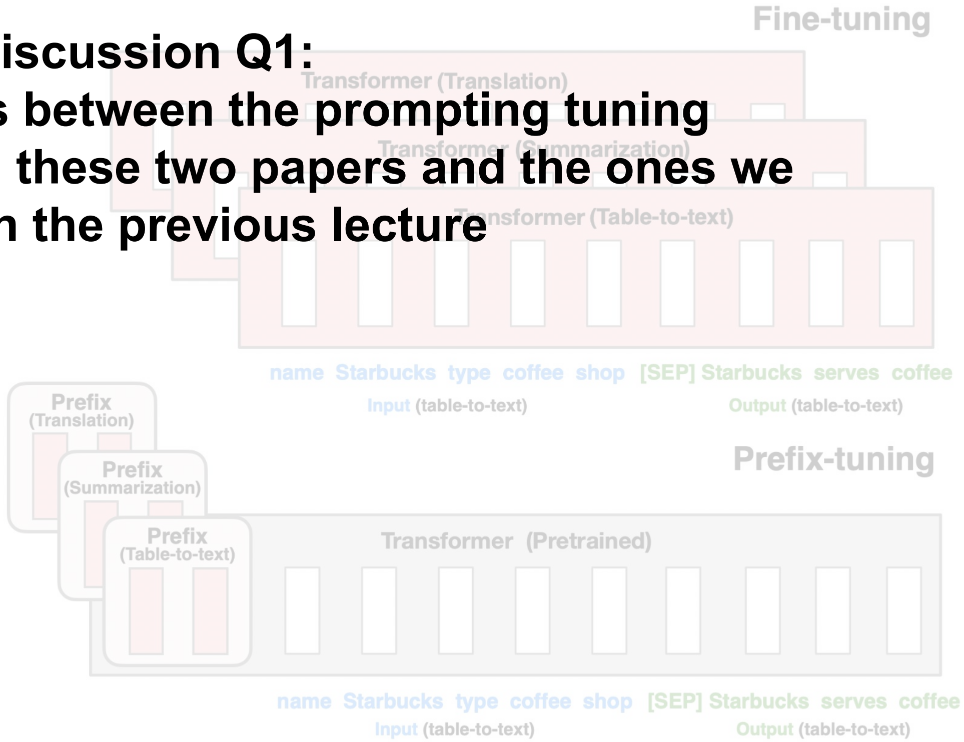
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Discussion Q1:
List the differences between the prompting tuning methods introduced in these two papers and the ones we learned in the previous lecture

Methodology

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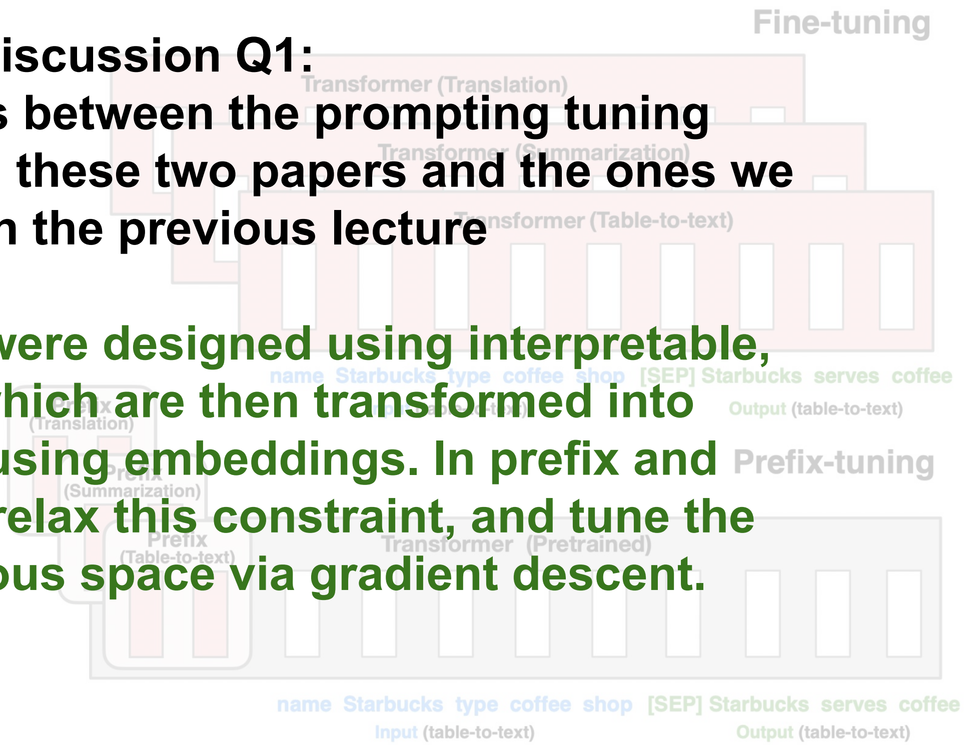
Discussion Q1:
List the differences between the prompting tuning methods introduced in these two papers and the ones we learned in the previous lecture

Previously, prompts were designed using interpretable, discrete tokens, which are then transformed into continuous space using embeddings. In prefix and prompt tuning, they relax this constraint, and tune the prompt in continuous space via gradient descent.



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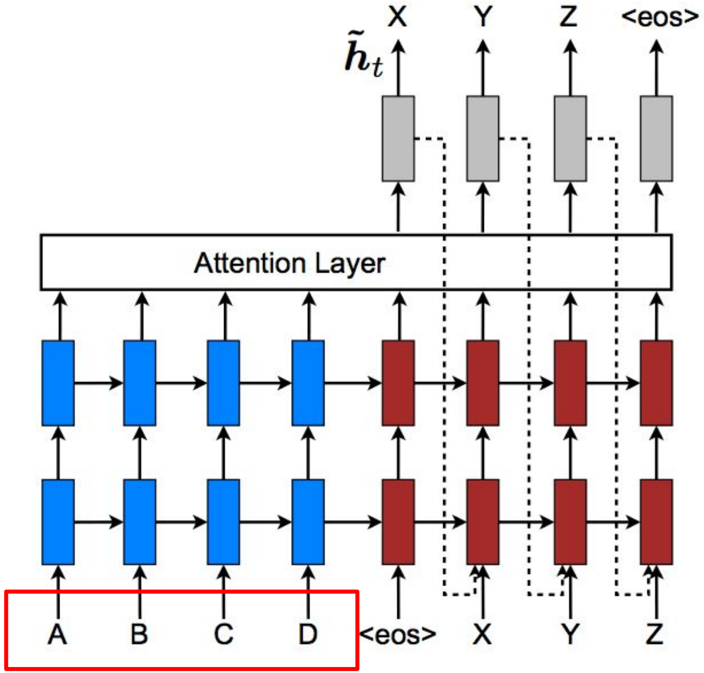
Methodology: Hidden State Tuning

- Can this be viewed as a continuous relaxation of discrete prompts?

Yay! We just get to tune these now →



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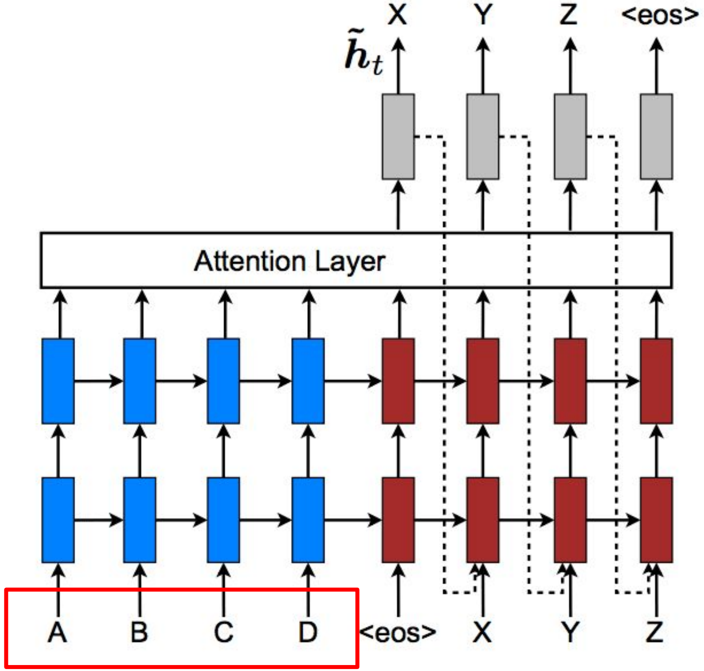

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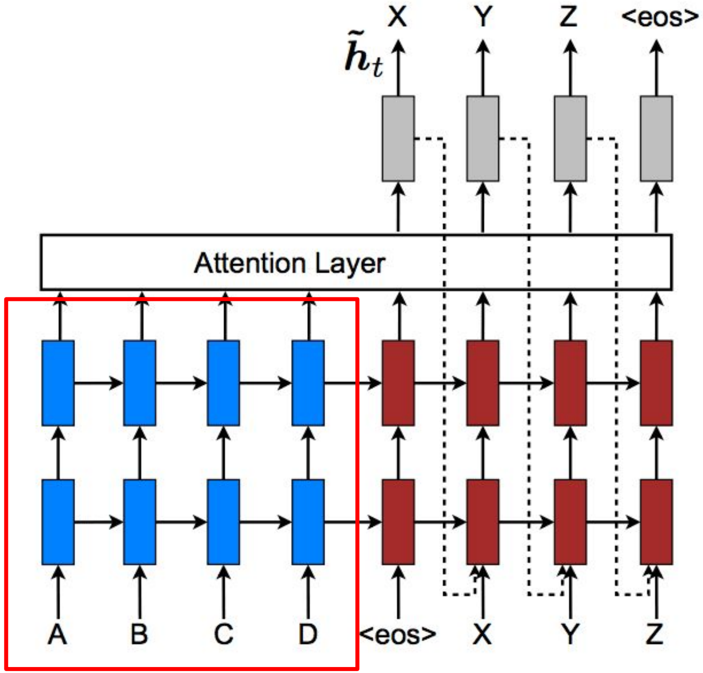
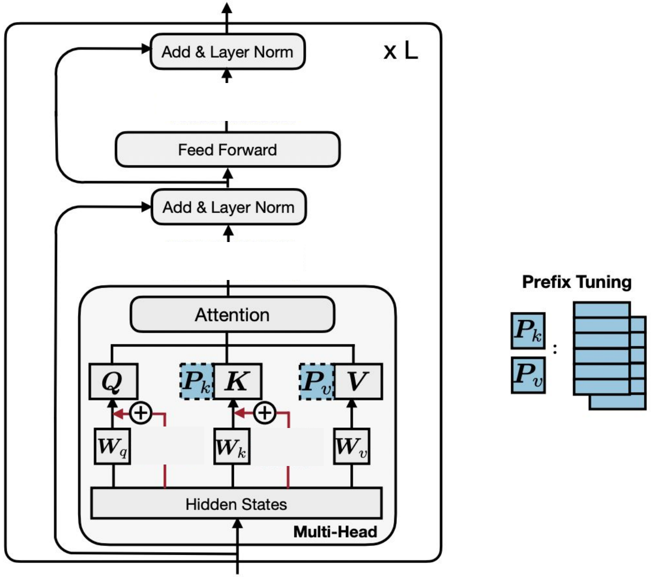
We actually get to tune ALL of these →



Methodology: Hidden State Tuning

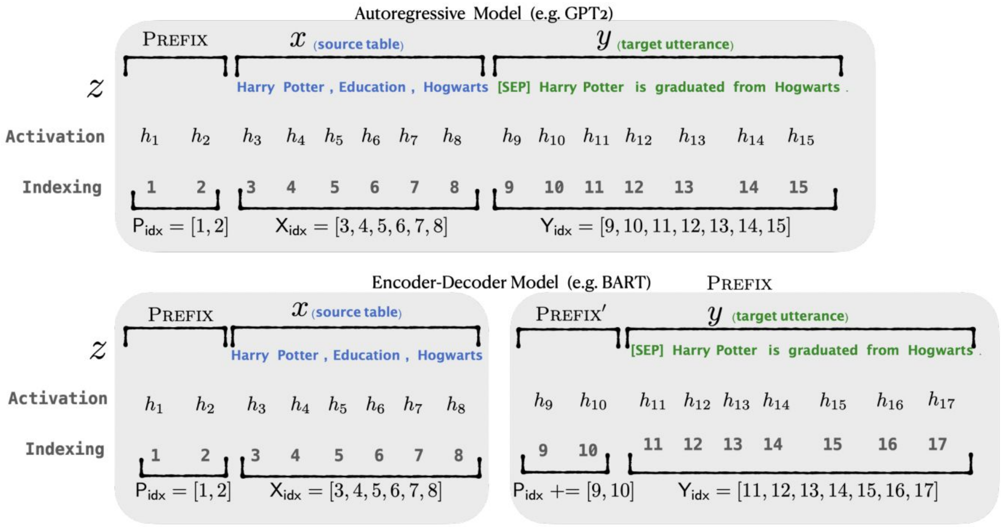
- Can this be viewed as a continuous relaxation of discrete prompts?
- **It’s not just the prompts in the prefix that get tuned, it is also the hidden representations of later layer.**

Image: (He et al. 2022)



Methodology: Encoder-decoder Models

- Encoder-decoder models get two trainable prefixes, one for encoder and one for decoder



Autoregressive Model (e.g. GPT2)
PREFIX
x (source table)
y (target utterance)
z
Harry Potter , Education , Hogwarts [SEP] Harry Potter is graduated from Hogwarts .
Activation
h_1 h_2 h_3 h_4 h_5 h_6 h_7 h_8 h_9 h_{10} h_{11} h_{12} h_{13} h_{14} h_{15}
Indexing
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
$P_{idx} = [1, 2]$
$X_{idx} = [3, 4, 5, 6, 7, 8]$
$Y_{idx} = [9, 10, 11, 12, 13, 14, 15]$
Encoder-Decoder Model (e.g. BART)
PREFIX
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x (source table)
PREFIX′
y (target utterance)
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Evaluation (Table-to-Text)

- Given a table, generate the information that the table contains in natural language.

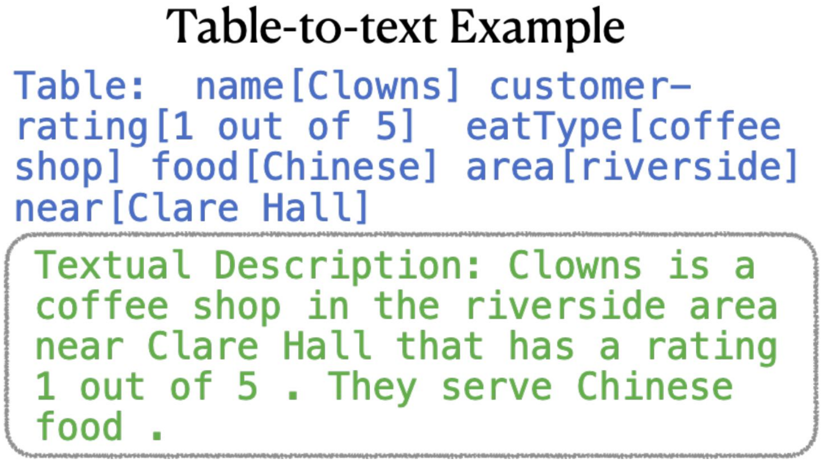


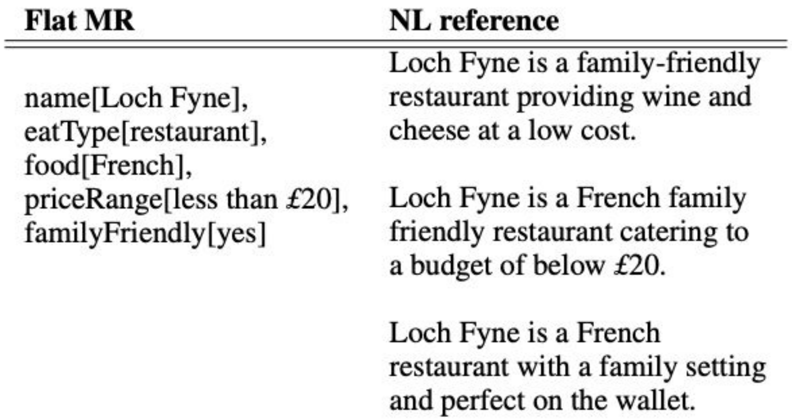
Table-to-text Example

```
Table:  name[Clowns] customer–
rating[1 out of 5]  eatType[coffee
shop] food[Chinese] area[riverside]
near[Clare Hall]
```

```
Textual Description: Clowns is a
coffee shop in the riverside area
near Clare Hall that has a rating
1 out of 5 . They serve Chinese
food .
```

Evaluation (Table-to-Text)

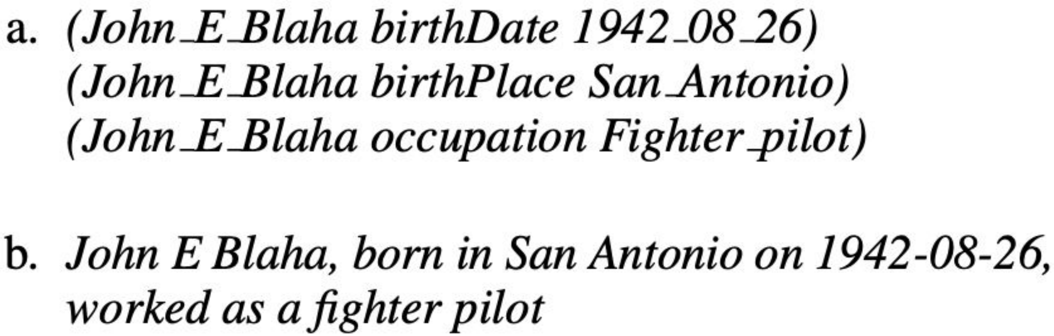
- Given a table, generate the information that the table contains in natural language.
- 3 Datasets
  - E2E: Restaurant Data
  - **(1 domain)**
  - [(Novikova et al. 2017)]



Flat MR	NL reference
name[Loch Fyne], eatType[restaurant], food[French], priceRange[less than £20], familyFriendly[yes]	Loch Fyne is a family-friendly restaurant providing wine and cheese at a low cost.
	Loch Fyne is a French family friendly restaurant catering to a budget of below £20.
	Loch Fyne is a French restaurant with a family setting and perfect on the wallet.

Evaluation (Table-to-Text)

- Given a table, generate the information that the table contains in natural language.
- 3 Datasets
  - WebNLG: <subject, property, object> triplets to text **(14 domains)**
  - (Gardent et al. 2017)

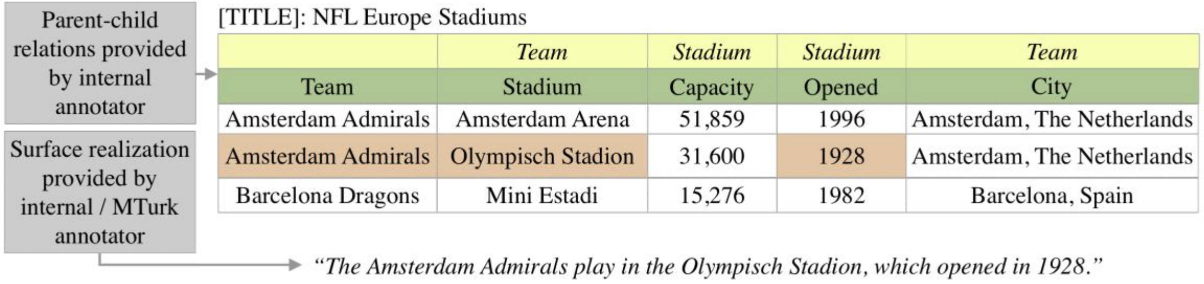


a. *(John_E_Blaha birthDate 1942_08_26)*
(John_E_Blaha birthPlace San_Antonio)
(John_E_Blaha occupation Fighter_pilot)

b. *John E Blaha, born in San Antonio on 1942-08-26, worked as a fighter pilot*

Evaluation (Table-to-Text)

- Given a table, generate the information that the table contains in natural language.
- 3 Datasets
  - DART: Triplets similar to WebNLG, but bigger and on all Wikipedia tables. **(Open domain)**
  - [(Nan et al. 2021)]()



Parent-child relations provided by internal annotator

Surface realization provided by internal / MTurk annotator

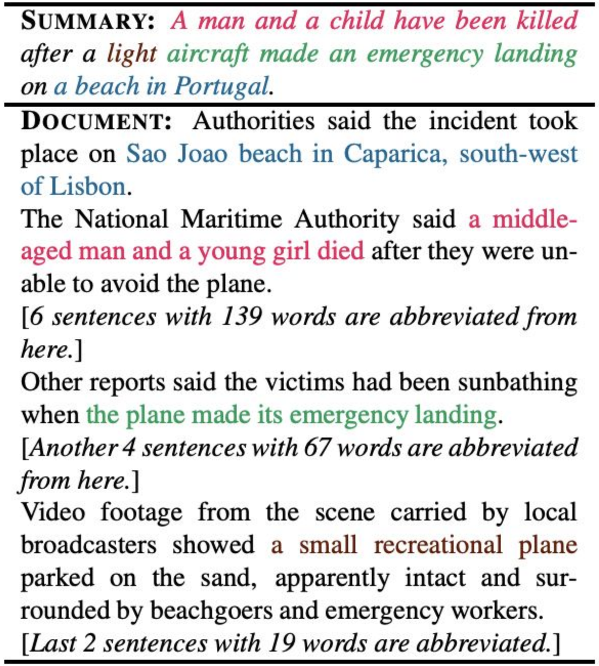
[TITLE]: NFL Europe Stadiums

	Team	*Stadium*	*Stadium*	*Team*
Team	Stadium	Capacity	Opened	City
Amsterdam Admirals	Amsterdam Arena	51,859	1996	Amsterdam, The Netherlands
Amsterdam Admirals	Olympisch Stadion	31,600	1928	Amsterdam, The Netherlands
Barcelona Dragons	Mini Estadi	15,276	1982	Barcelona, Spain

"The Amsterdam Admirals play in the Olympisch Stadion, which opened in 1928."

Evaluation (Summarization)

- Given a longer passage, generate a few summary sentences.
- XSUM dataset.
  - BBC News Articles
  - Summarization requires pulling information from **various parts** of the document, not just one.
  - Designed to **encourage abstraction** of high level concepts.
  - [(Narayan et al. 2018)](#)



SUMMARY: *A man and a child have been killed after a light aircraft made an emergency landing on a beach in Portugal.*

DOCUMENT: Authorities said the incident took place on Sao Joao beach in Caparica, south-west of Lisbon.

The National Maritime Authority said a middle-aged man and a young girl died after they were unable to avoid the plane.

[*6 sentences with 139 words are abbreviated from here.*]

Other reports said the victims had been sunbathing when the plane made its emergency landing.

[*Another 4 sentences with 67 words are abbreviated from here.*]

Video footage from the scene carried by local broadcasters showed a small recreational plane parked on the sand, apparently intact and surrounded by beachgoers and emergency workers.

[*Last 2 sentences with 19 words are abbreviated.*]

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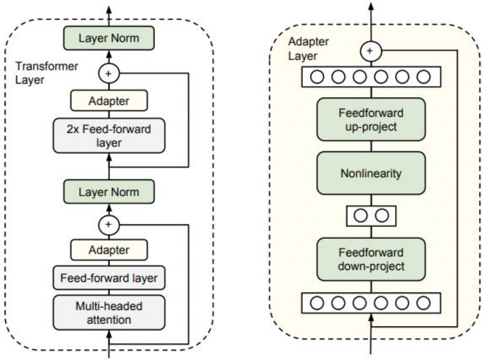

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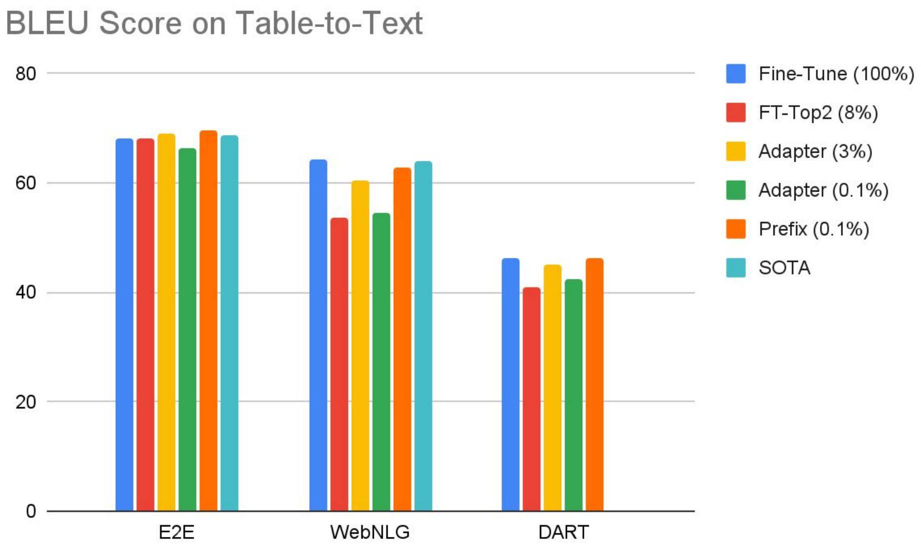
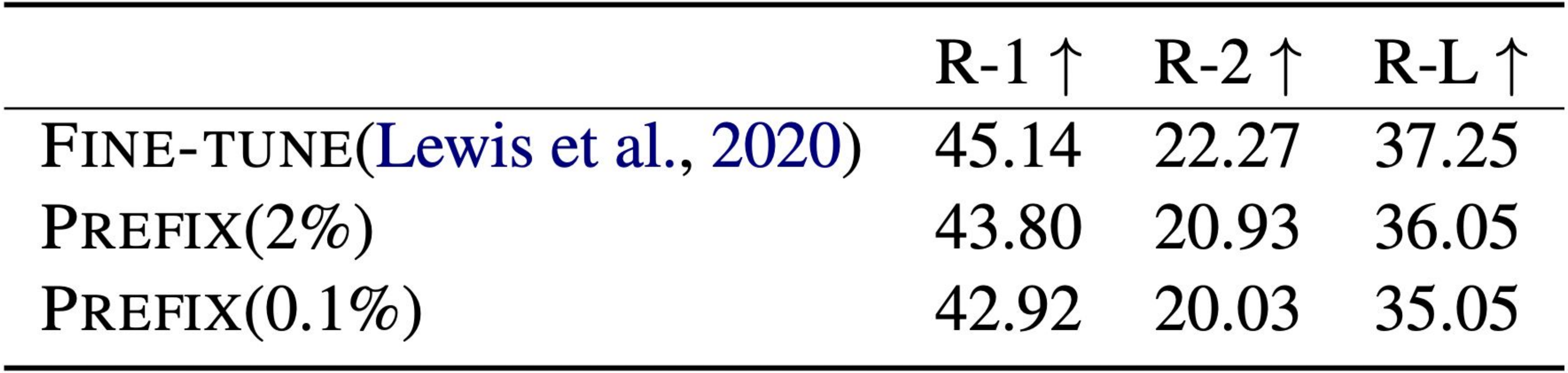
- State of the art on that task
- **If there is ever a percent sign after a method, it represents a variant of the method that uses that percent of the model's parameters.**
  - Ex: (Adapter 0.1%)

Results (Table to Text)

- Prefix tuning outperforms other lightweight tuning baselines. (with less params!)
- Comes close to fine tuning!



Results (Summarization)



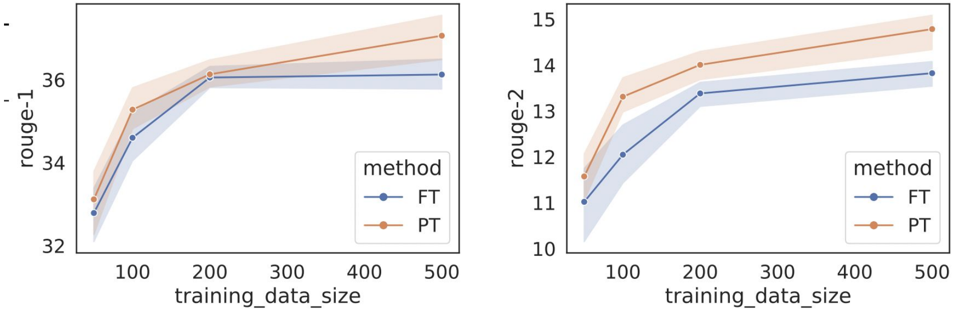
	R-1 ↑	R-2 ↑	R-L ↑
FINE-TUNE(Lewis et al., 2020)	45.14	22.27	37.25
PREFIX(2%)	43.80	20.93	36.05
PREFIX(0.1%)	42.92	20.03	35.05

- Prefix tuning underperforms fine-tuning. (Performance gets better when you increase the number of parameters)

Results (Low-data regimes)

- Prefix tuning outperforms fine-tuning when training data size is low.
- Trend seems unclear though.

Summarization



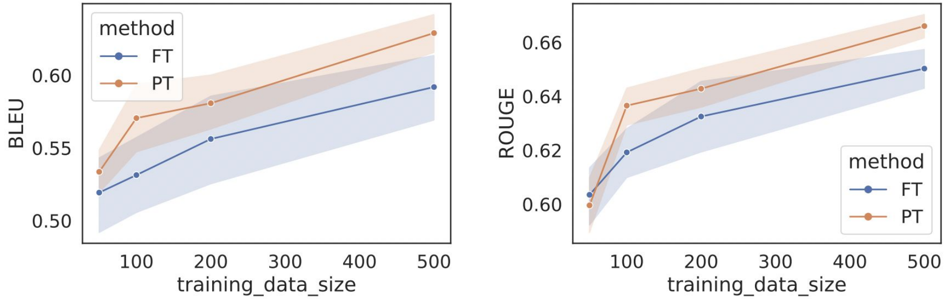
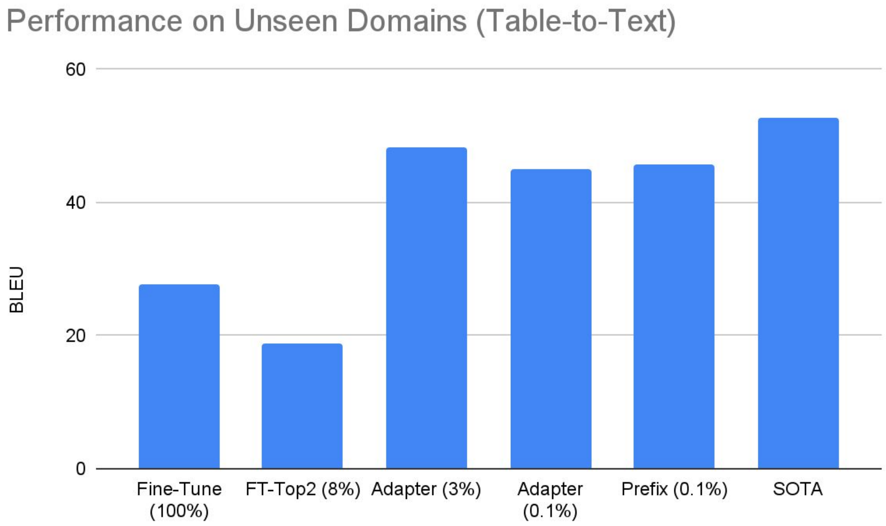


Table to text

Results (Generalization to Unseen Domains)

- Prefix tuning (and also Adapter) outperform fine-tuning on generalization to different domains!
- This holds for Table-to-Text and Summarization.
- Does not seem unique to prefix-tuning though.



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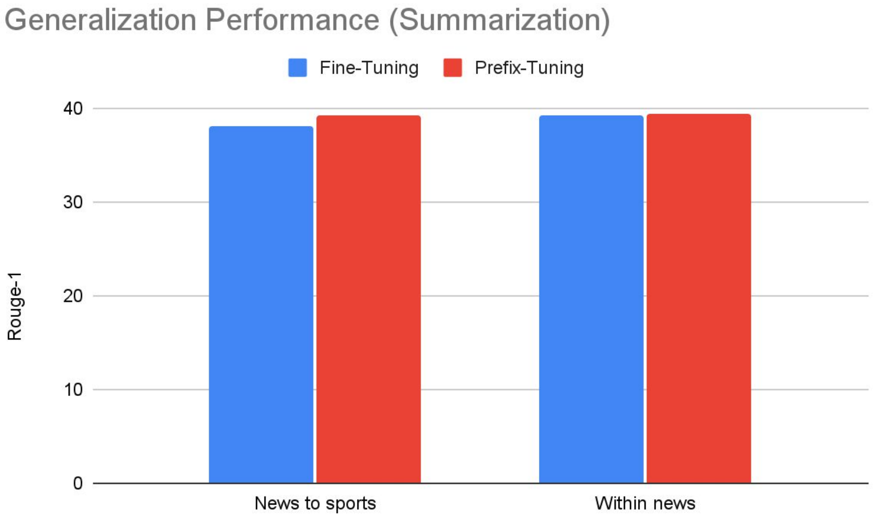
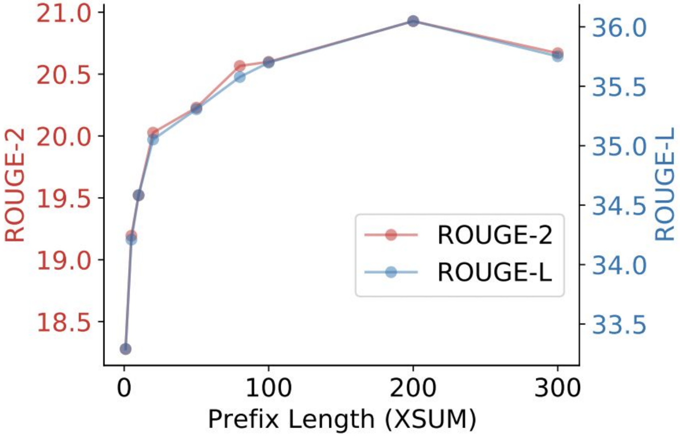
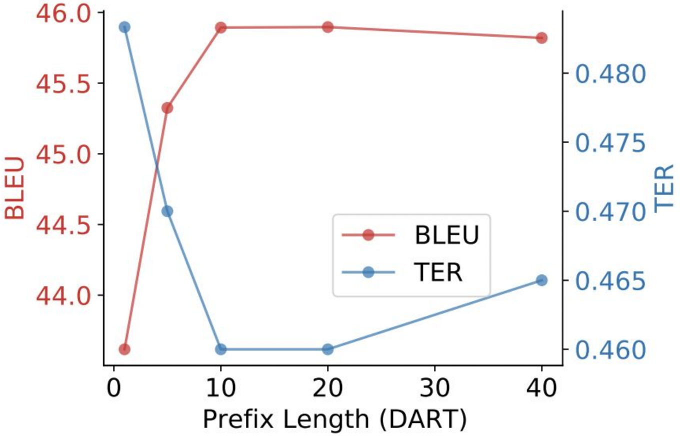


Ablations (Prefix-length)

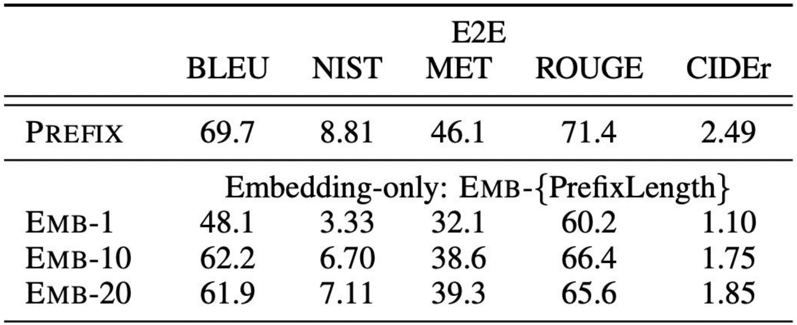
- As the tunable prefix-length increases, performance increases, with diminishing returns.
- Optimal length for table to text is 10 tokens, for summarization it seems closer to 200 tokens.



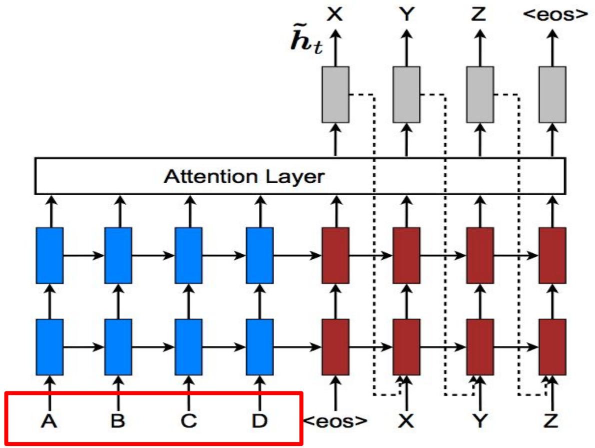


Ablations (Embedding-Only Tuning)

- Tuning only the embedding layer is not enough expressivity to match prefix-tuning performance.
- (Don't get too attached to this finding)

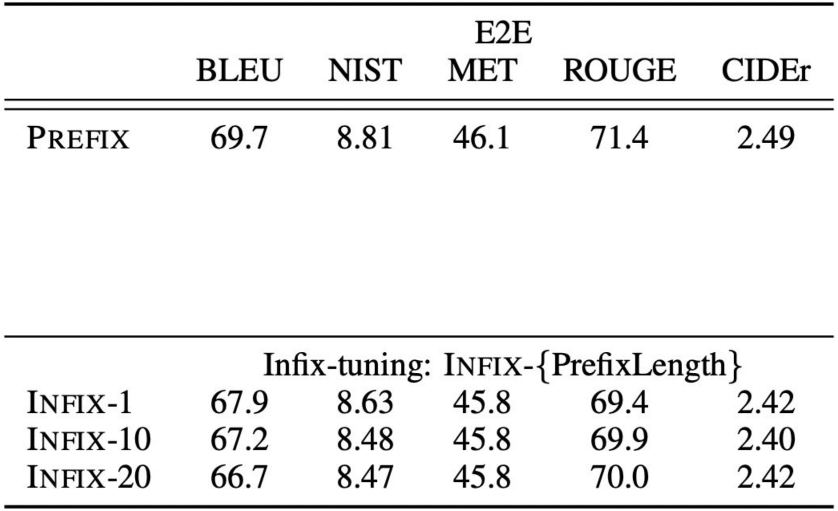


	E2E				
	BLEU	NIST	MET	ROUGE	CIDEr
PREFIX	69.7	8.81	46.1	71.4	2.49
	Embedding-only: EMB-{PrefixLength}				
EMB-1	48.1	3.33	32.1	60.2	1.10
EMB-10	62.2	6.70	38.6	66.4	1.75
EMB-20	61.9	7.11	39.3	65.6	1.85



Ablations (Prefix vs Infix)

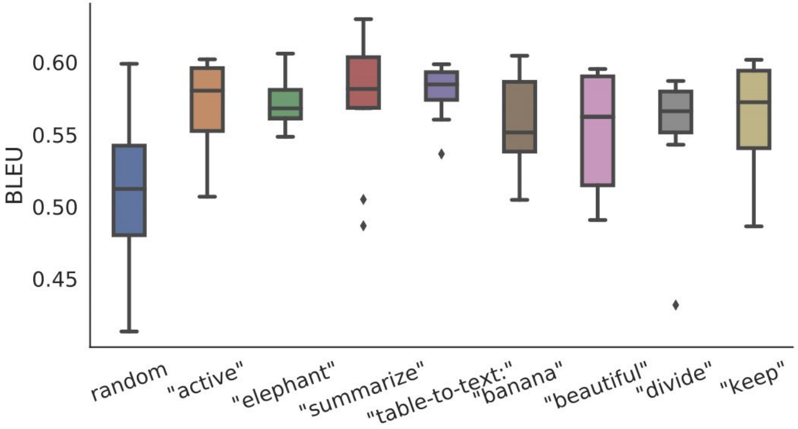
- Instead of tuning the prefix, tune a portion at the end of the input and before the output.
- In other words, now we do [Tunable, X_inp, Y_out], but we could instead do [X_inp, Tunable, Y_out]
- Infix tuning is worse than prefix tuning, since input embeddings cannot attend to infix.



			E2E		
	BLEU	NIST	MET	ROUGE	CIDEr
PREFIX	69.7	8.81	46.1	71.4	2.49
		Infix-tuning: INFIX-{PrefixLength}			
INFIX-1	67.9	8.63	45.8	69.4	2.42
INFIX-10	67.2	8.48	45.8	69.9	2.40
INFIX-20	66.7	8.47	45.8	70.0	2.42

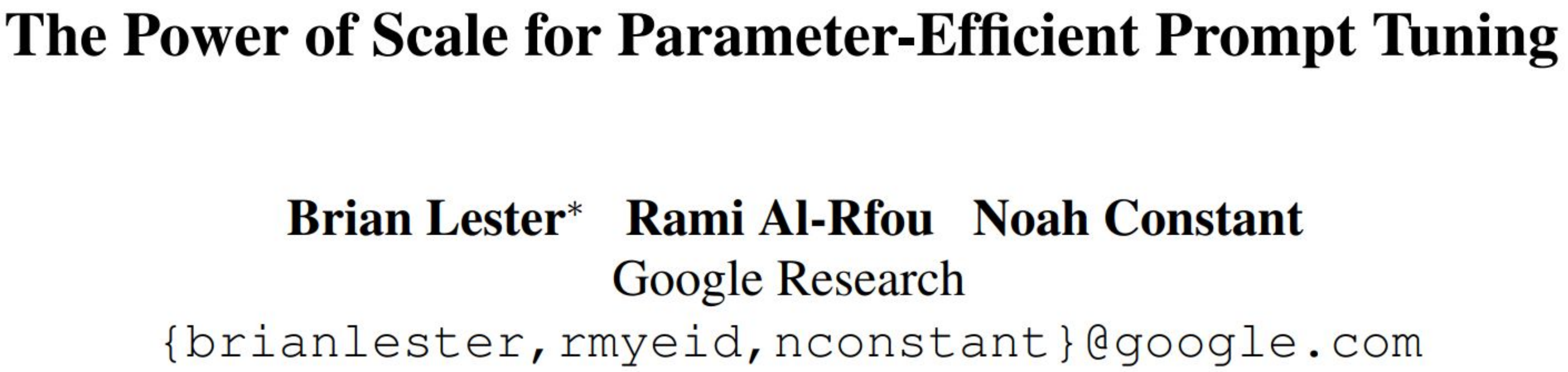
Ablation (Initialization)

- Initializing randomly performs poorly and has high variance.
- It’s better to initialize with words in the LM’s vocabulary.
- It’s even better to initialize with task specific words (summarize / table-to-text)



Key Findings

- Prefix-Tuning can come close to the performance of full model fine-tuning with **much less parameters.**
- Tuning less parameters leads to **better generalization performance**.



The Power of Scale for Parameter-Efficient Prompt Tuning

Brian Lester* Rami Al-Rfou Noah Constant
Google Research
{brianlester,rmyeid,nconstant}@google.com

Published in EMNLP 2021

Motivation

- Why do we need **prompt-tuning** if we already have **prefix-tuning**?
    - Prefix-tuning learns a sequence of prefixes that are prepended at **every transformer layer**
    - Prompt-tuning uses a **single** prompt representation that is prepended to the **embedded input**

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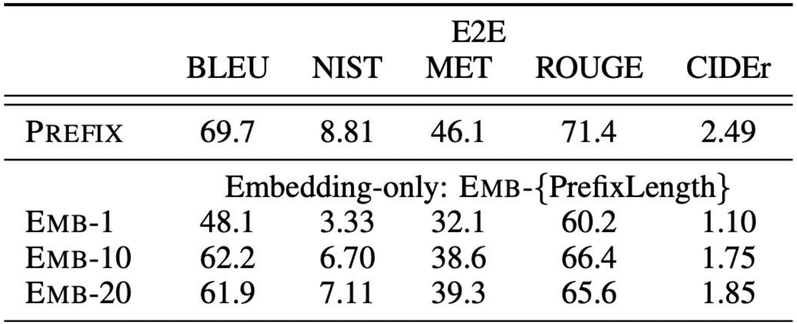
The “prefix-tuning” paper: *Tuning only the embedding layer is not expressive enough*

- Model scale?
- Prompt length?
- Prompt initialization?
- Pre-training settings?



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Methodology: Prompt-tuning

- Prepend **virtual tokens** to input
- Prompt and input representations flow through model like normal
- Learn embeddings of **only these special tokens** via backprop. Keep the rest **fixed**.

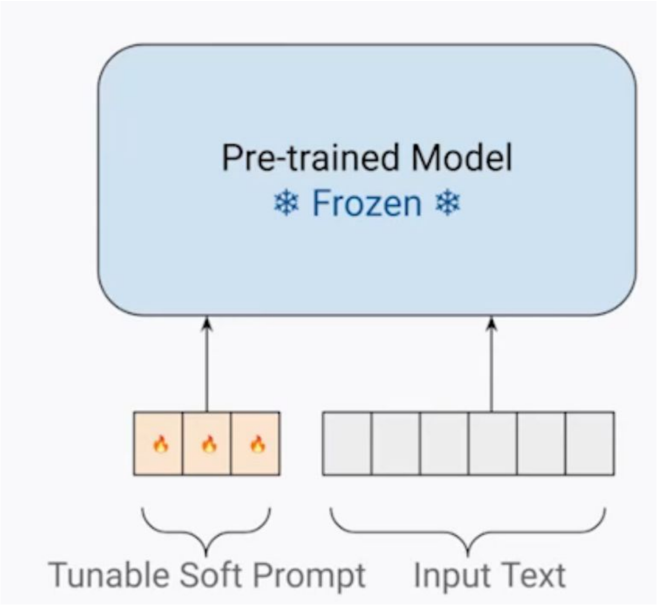

Image Credit: Brian Lester

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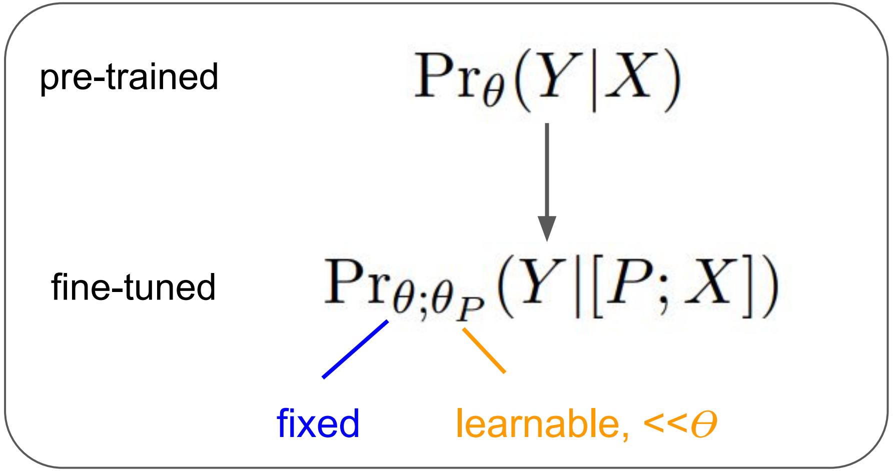

pre-trained $\Pr_{\theta}(Y|X)$

fine-tuned $\Pr_{\theta;\theta_P}(Y|[P;X])$

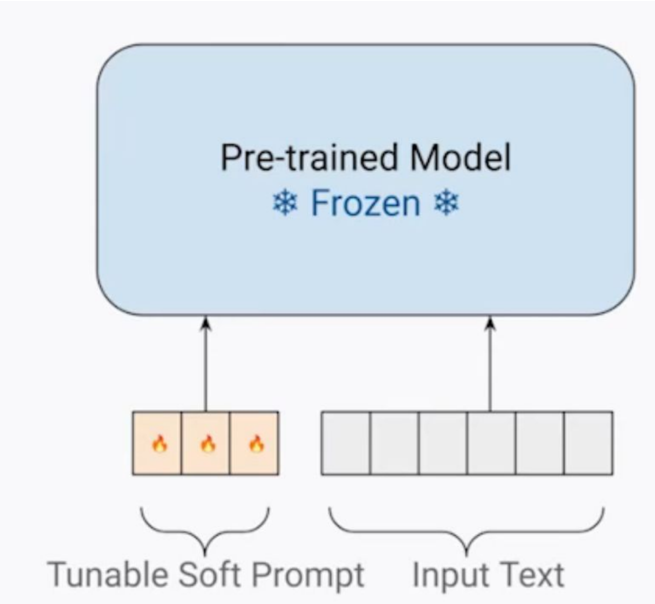

Image Credit: Brian Lester

Experiment Setup

- Model backbone: pre-trained T5 models (Small, Base, Large, XL, XXL)
- Design decisions to explore
  - Prompt initialization method
  - Prompt length
  - Pre-training method
  - LM adaptation steps (if use “LM adaptation” as the pre-training method)
- Benchmark: SuperGLUE (a collection of eight challenging English language understanding tasks)
  - Each prompt trains on a single task
  - Each dataset is translated into a text-to-text format
  - Task names prepended to inputs are omitted

Design Decision: Prompt Initialization

1. **Random initialization**: train the prompt representations from scratch
2. **Sampled vocabulary**: initialize each prompt token to an embedding drawn from the model’s vocabulary
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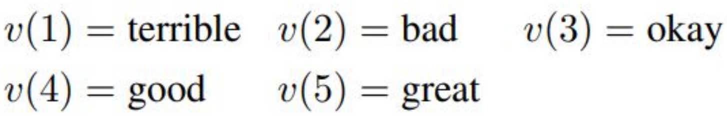
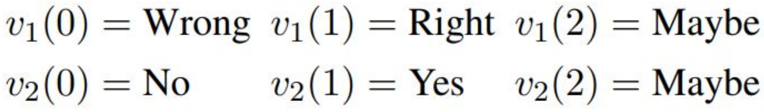


$$v(1) = \text{terrible} \quad v(2) = \text{bad} \quad v(3) = \text{okay}$$
$$v(4) = \text{good} \quad v(5) = \text{great}$$

Yelp dataset
(Zhang et al.,2015)

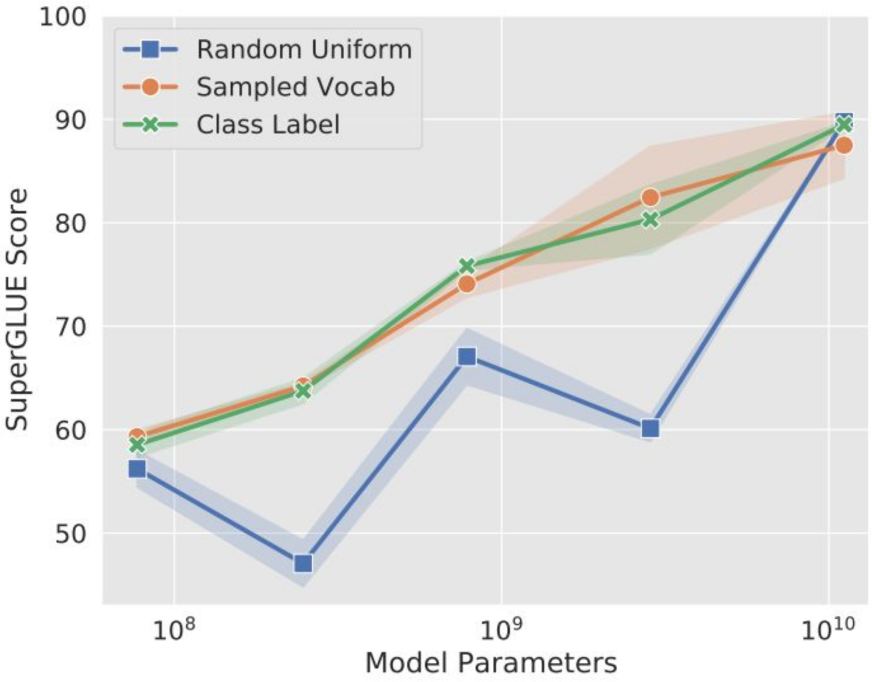


$$v_1(0) = \text{Wrong} \quad v_1(1) = \text{Right} \quad v_1(2) = \text{Maybe}$$
$$v_2(0) = \text{No} \quad v_2(1) = \text{Yes} \quad v_2(2) = \text{Maybe}$$

MNLI dataset
(Williams et al., 2018)

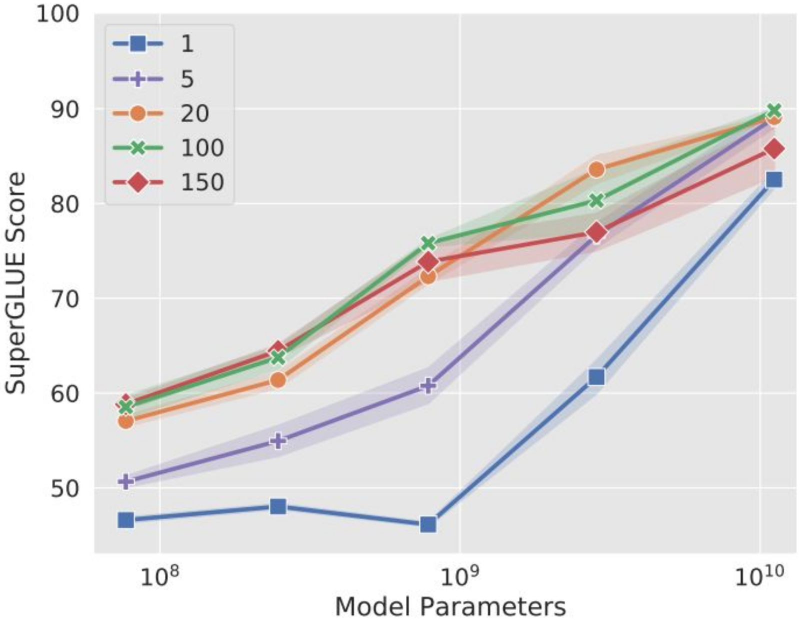
Design Decision: Prompt Initialization

- **Class label** based initialization performs best
- The gaps between different initializations **disappear** when the model is **scaled to XXL size**



Design Decision: Prompt Length

- The shorter the prompt, the fewer new parameters must be tuned

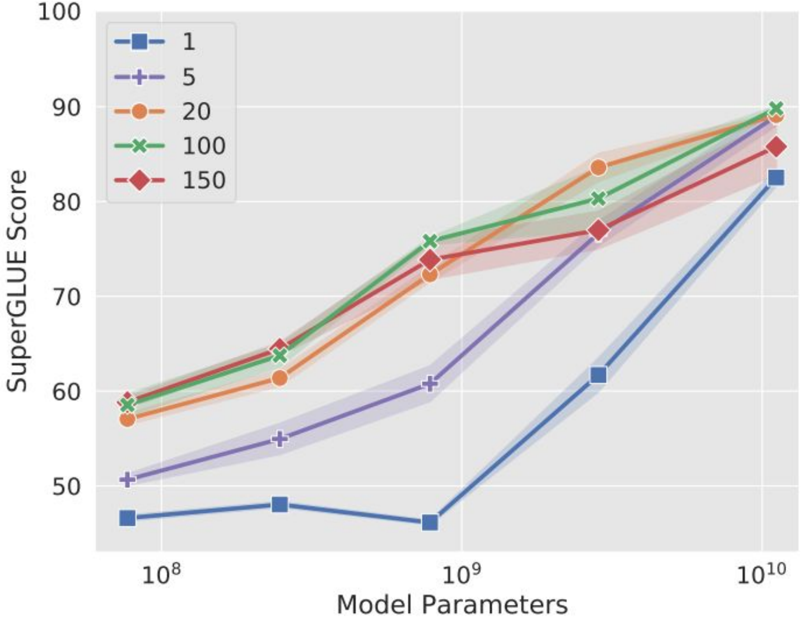


Design Decision: Prompt Length

- The shorter the prompt, the fewer new parameters must be tuned

Observations

- **Increasing prompt** length is **critical** to achieve good performance
- The **largest** model still gives strong results with a **single-token** prompt
- Increasing beyond 20 tokens only yields marginal gains



Design Decision: Pre-training Method

- **Span Corruption**: The model is tasked with “reconstructing” masked spans in the input text, which are marked with unique sentinel tokens.

sentinel

Pre-training

Input: Thank you <X> me to your party <Y> week
Output: <X> for inviting <Y> last <Z>

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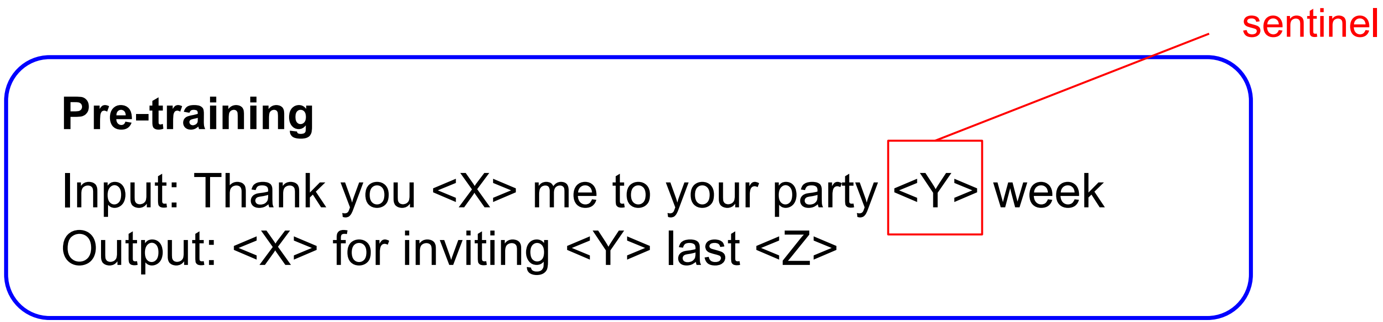
- **Span Corruption**: The model is tasked with “reconstructing” masked spans in the input text, which are marked with unique sentinel tokens.
- **Span Corruption + Sentinel**: prepend all downstream targets with a sentinel



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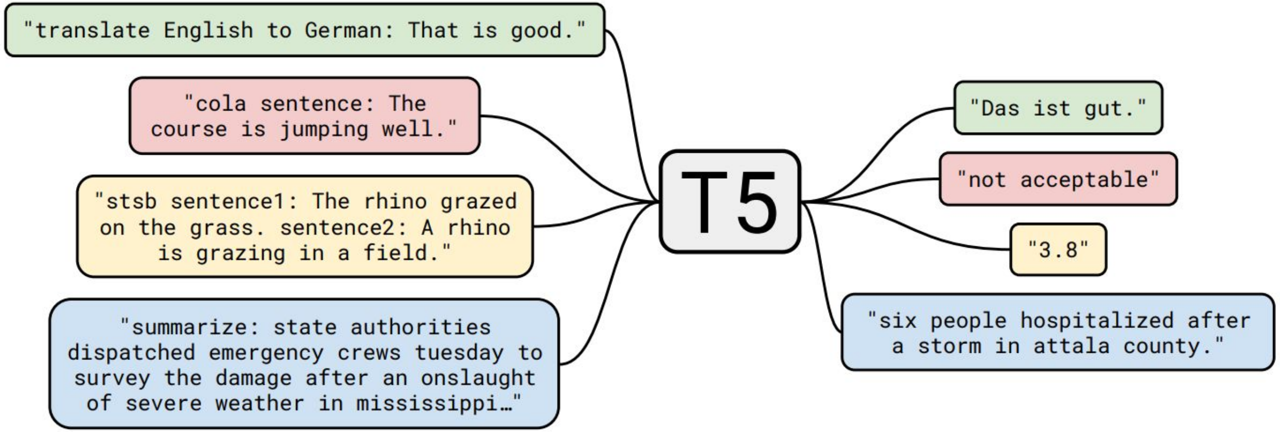
Design Decision: Pre-training Method

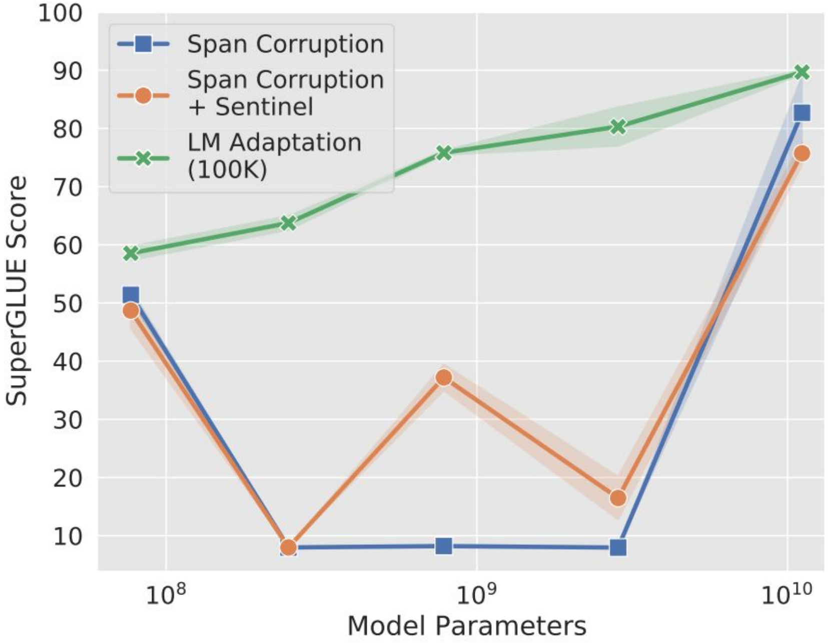
- **Span Corruption**: The model is tasked with “reconstructing” masked spans in the input text, which are marked with unique sentinel tokens.
- **Span Corruption + Sentinel**: prepend all downstream targets with a sentinel
- **“LM Adaptation”**: given a natural text prefix as input, the model must produce the natural text continuation as output


"translate English to German: That is good."
"cola sentence: The course is jumping well."
"stsb sentence1: The rhino grazed on the grass. sentence2: A rhino is grazing in a field."
"summarize: state authorities dispatched emergency crews tuesday to survey the damage after an onslaught of severe weather in mississippi…"
T5
"Das ist gut."
"not acceptable"
"3.8"
"six people hospitalized after a storm in attala county."

Raffel et al. (2020)

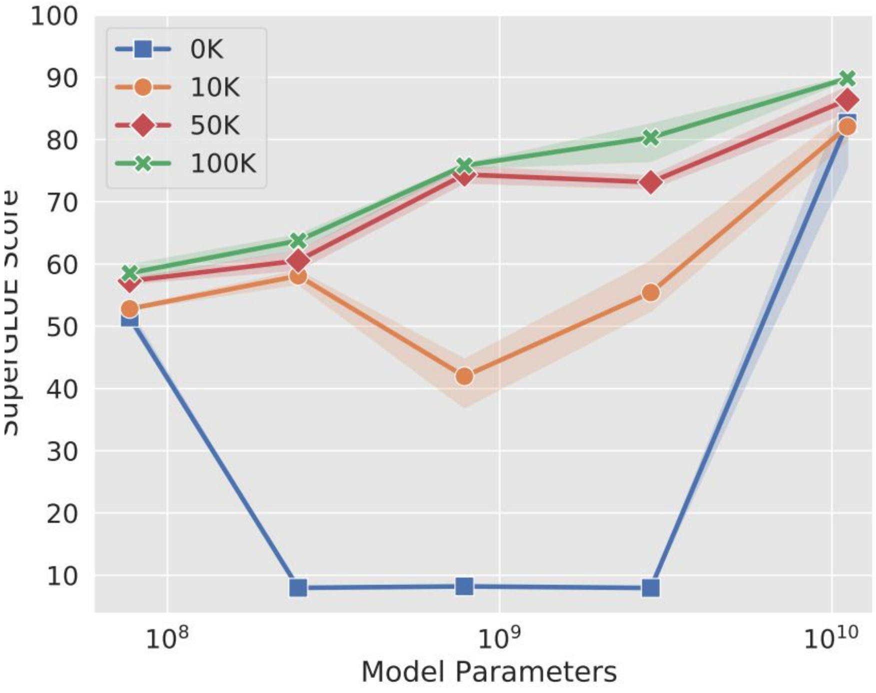
Design Decision: Pre-training Method

- "Span corruption" objective is **not well-suited** for pre-training frozen models
- Adding a sentinel to the downstream targets has **little benefit**
- **"LM Adaptation"** performs best for all sizes of models
- The **largest** model is the **most forgiving** one



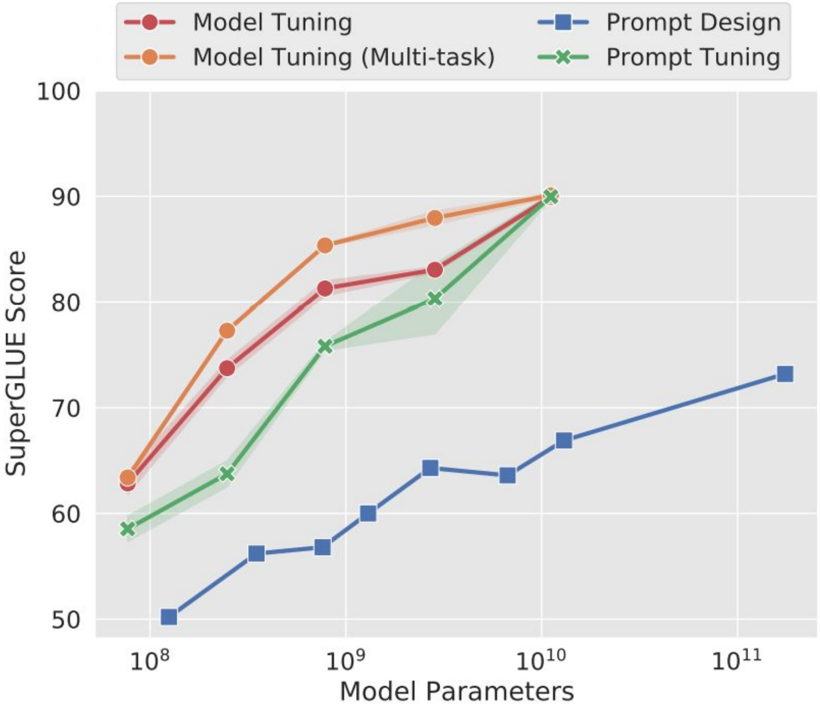
Design Decision: LM Adaptation Steps

- Longer adaptation provides additional gains, up to 100K steps
- At the **largest** model size, the gains from adaptation are quite modest



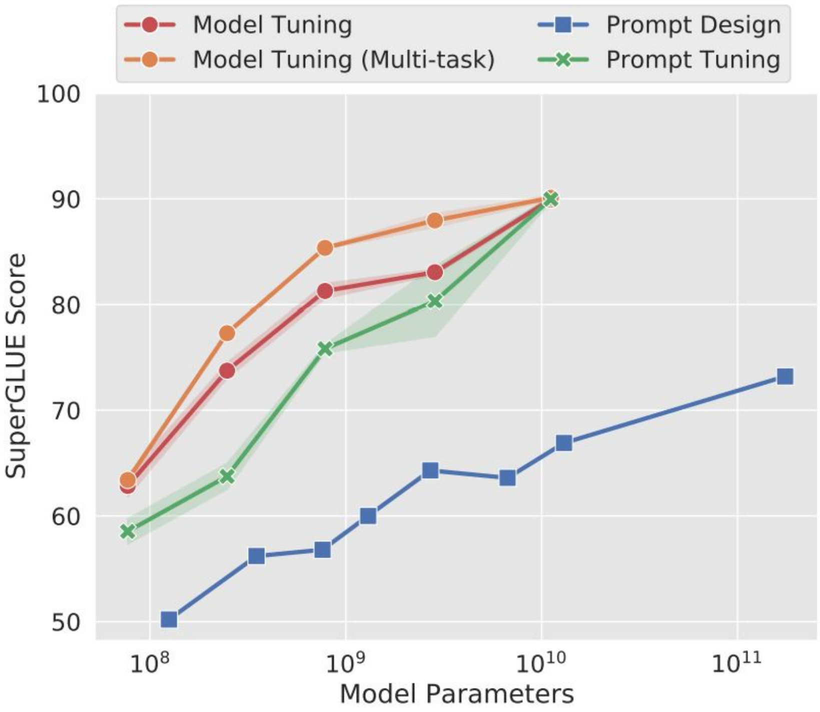
Closing the Gap

- Design configuration
  - Prompt initialization: class label
  - Prompt length: 100
  - Pre-training method: LM adaptation
  - LM adaptation steps: 100K



Closing the Gap

- Design configuration
  - Prompt initialization: class label
  - Prompt length: 100
  - Pre-training method: LM adaptation
  - LM adaptation steps: 100K
- Prompt tuning becomes **more competitive** with model tuning as scale increases
- Prompt tuning beats GPT-3 prompt design **by a large margin**



Closing the Gap

Q2. Comparing "model tuning", "prompt tuning" and "prompt design" in Lester et al., 2021, how do their task performances scale with model sizes? Why do you think it is the case?

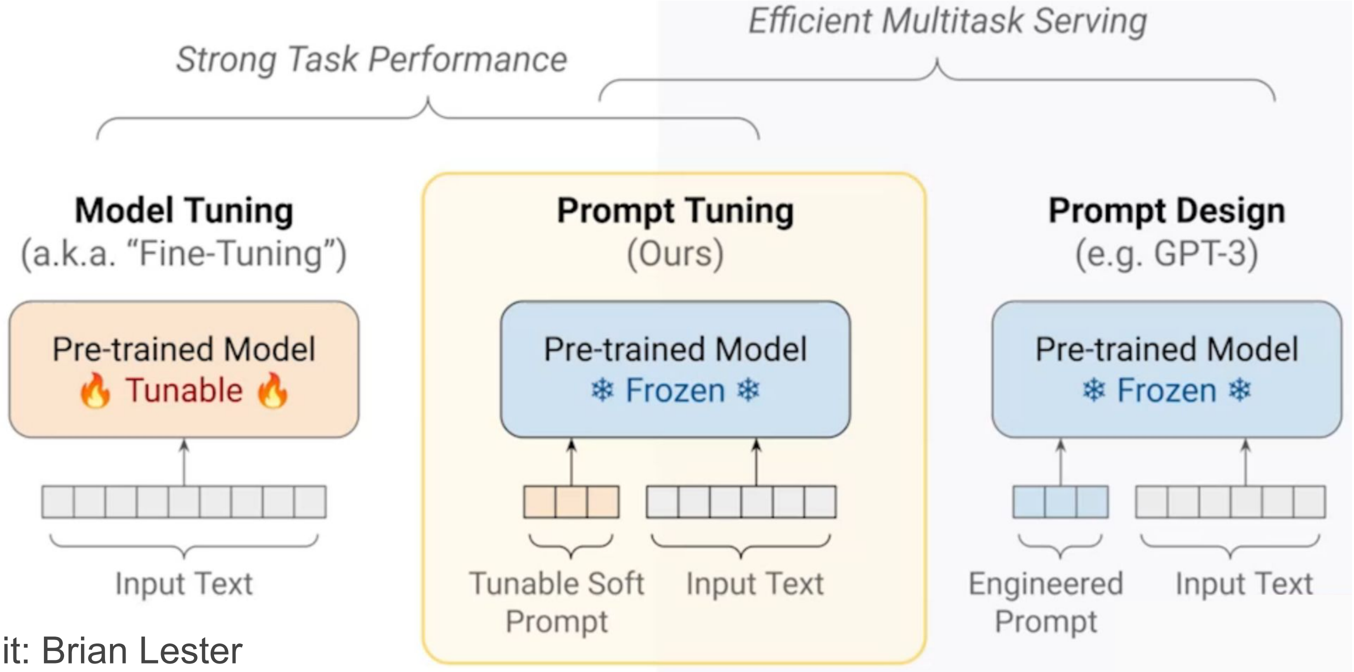


Image Credit: Brian Lester

Closing the Gap

Q2. Comparing "model tuning", "prompt tuning" and "prompt design" in Lester et al., 2021, how do their task performances scale with model sizes? Why do you think it is the case?

- Scalability
  - Model tuning: fairly good → poor
  - Prompt tuning: very good
  - Prompt design: poor
- Reason
  - Model tuning: possibly over-parameterized when model size is large
  - Prompt tuning: reserving general understanding and including tunable parameters
  - Prompt design: not fitting downstream tasks well

Closing the Gap

Q2. Comparing "model tuning", "prompt tuning" and "prompt design" in Lester et al., 2021, how do their task performances scale with model sizes? Why do you think it is the case?

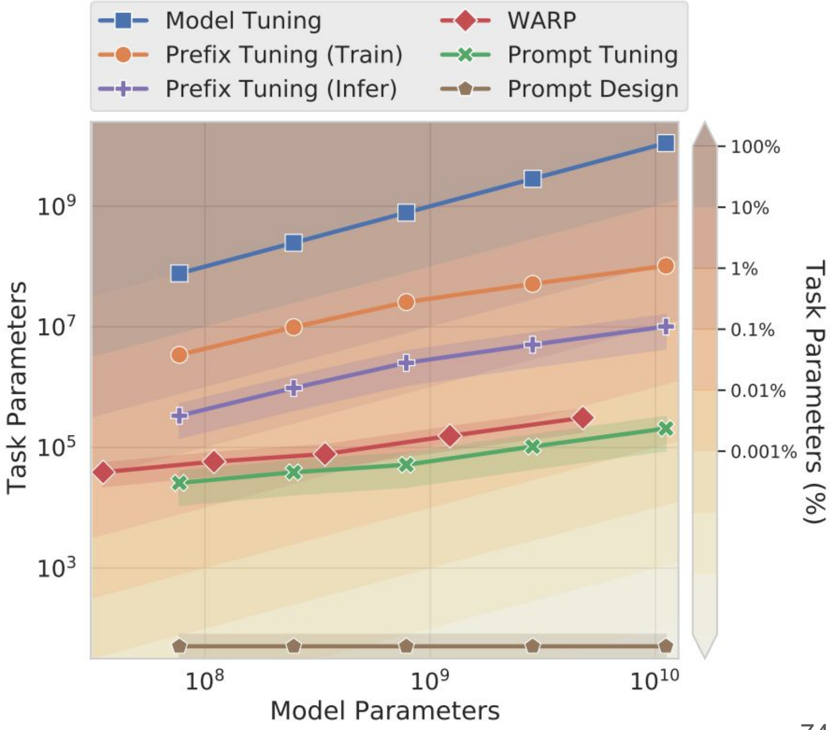
When the model size is relatively small, “model tuning” outperforms “prompt tuning” by a small margin. However, “prompt tuning” becomes more competitive with “model tuning” as scale increases. “Prompt tuning” beats “prompt design” by a large margin with all sizes of models.

In “prompt design”, prompts are chosen manually and there is no tunable task-specific parameters. Thus, the model can’t fit the downstream task well. When the model size is large, “model tuning” may be over-parameterized and more prone to overfit the training task. “Prompt tuning” prevents the model from modifying its general understanding of language and also includes tunable task-specific prompt representations.

Comparison to Similar Approaches

- Compared with prefix-tuning
  - Tuning only the embedding layer
  - No need for prefix reparameterization

- Compared with WARP
  - Less extra parameters
  - WARP can only work on classification



Resilience to Domain Shift

- Tasks: question answering (QA) and paraphrase detection
- Question answering
  - MRQA 2019 (Fisch et al., 2019) shared task on generalization
  - It collects extractive QA datasets in a unified format
  - Train on “in-domain” datasets and evaluate on “out-of-domain” datasets

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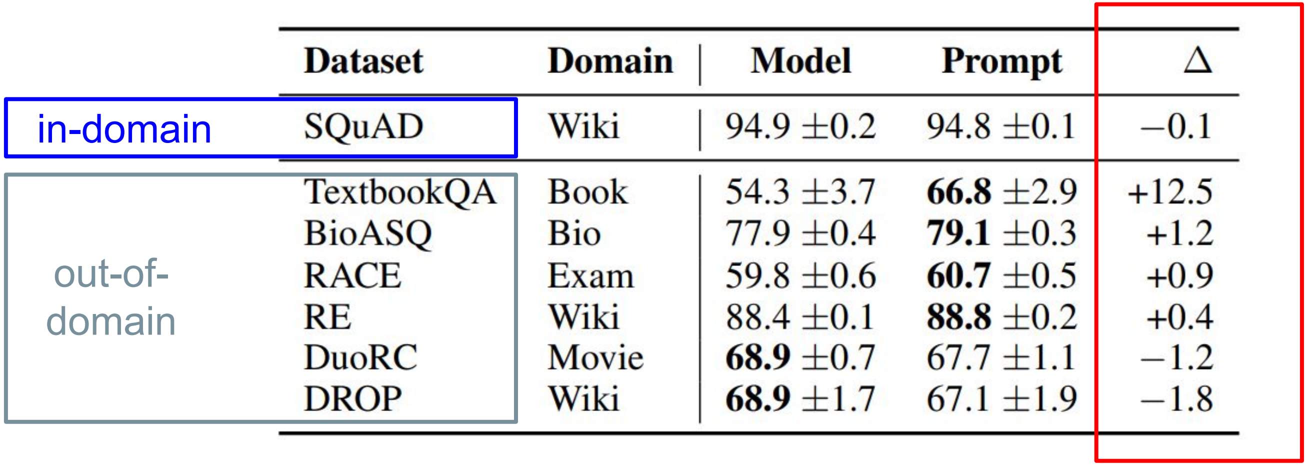

	Dataset	Domain	Model	Prompt	Δ
in-domain	SQuAD	Wiki	94.9 ±0.2	94.8 ±0.1	−0.1
out-of-domain	TextbookQA	Book	54.3 ±3.7	**66.8** ±2.9	+12.5
	BioASQ	Bio	77.9 ±0.4	**79.1** ±0.3	+1.2
	RACE	Exam	59.8 ±0.6	**60.7** ±0.5	+0.9
	RE	Wiki	88.4 ±0.1	**88.8** ±0.2	+0.4
	DuoRC	Movie	**68.9** ±0.7	67.7 ±1.1	−1.2
	DROP	Wiki	**68.9** ±1.7	67.1 ±1.9	−1.8

Resilience to Domain Shift

- Tasks: question answering (QA) and paraphrase detection
- Question answering
- Paraphrase detection
  - Transfer between two paraphrase tasks from GLUE (Wang et al., 2019b)
  - QQP (Iyer et al., 2017): ask if two questions from Quora are “duplicates”.
  - MRPC (Dolan and Brockett, 2005): asks if two sentences drawn from news articles are paraphrases

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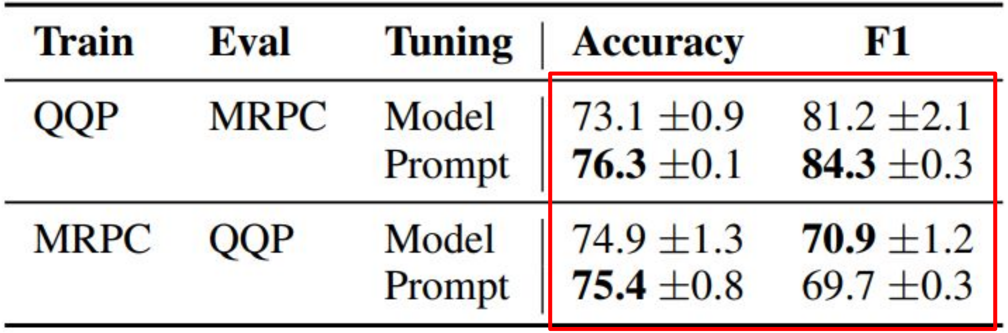

Train	**Eval**	**Tuning**	**Accuracy**	**F1**
QQP	MRPC	Model	73.1 ±0.9	81.2 ±2.1
		Prompt	**76.3** ±0.1	**84.3** ±0.3
MRPC	QQP	Model	74.9 ±1.3	**70.9** ±1.2
		Prompt	**75.4** ±0.8	69.7 ±0.3

Resilience to Domain Shift

- Tasks: question answering (QA) and paraphrase detection
- Question answering
- Paraphrase detection
- Conclusions
  - Prompt tuning prevents the model from modifying its **general understanding** of language
  - Model tuning may be **over-parameterized** and more prone to overfit the training task, to the detriment of similar tasks in different domains

Prompt Ensembling

- Train **N prompts** on the same task → create **N separate “models”**
- One example is **replicated** across the batch and is processed varying the prompt

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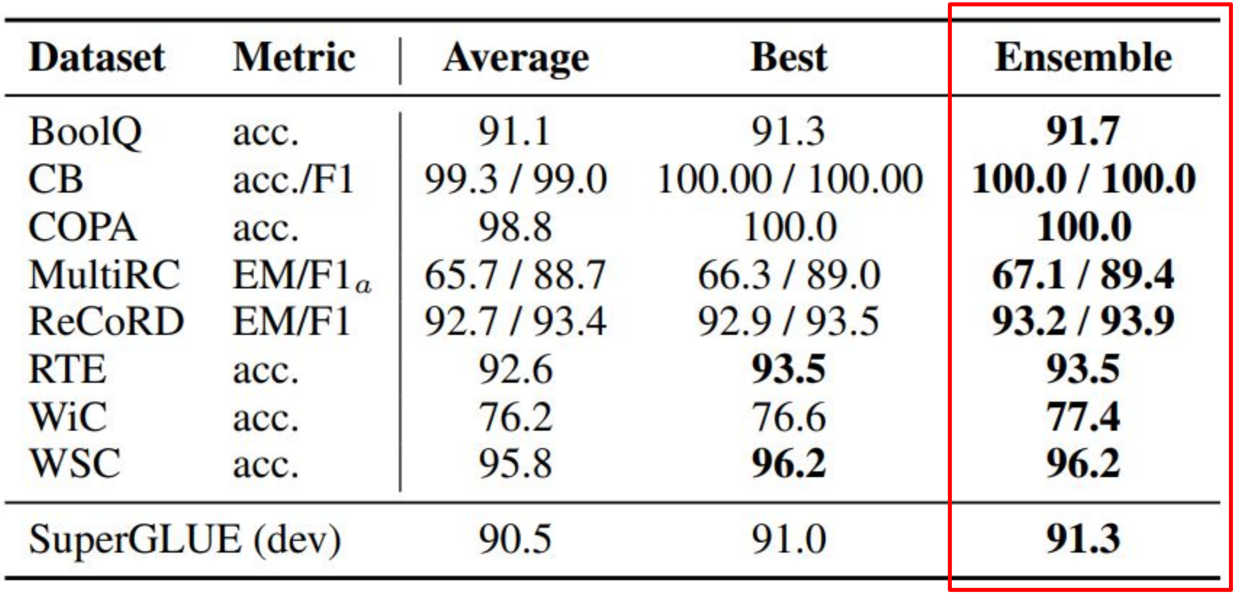

Dataset	Metric	Average	Best	Ensemble
BoolQ	acc.	91.1	91.3	**91.7**
CB	acc./F1	99.3 / 99.0	100.00 / 100.00	**100.0 / 100.0**
COPA	acc.	98.8	100.0	**100.0**
MultiRC	EM/F1$_a$	65.7 / 88.7	66.3 / 89.0	**67.1 / 89.4**
ReCoRD	EM/F1	92.7 / 93.4	92.9 / 93.5	**93.2 / 93.9**
RTE	acc.	92.6	**93.5**	**93.5**
WiC	acc.	76.2	76.6	**77.4**
WSC	acc.	95.8	**96.2**	**96.2**
SuperGLUE (dev)		90.5	91.0	**91.3**

Interpretability

- discrete token → continuous embedding: **difficult to interpret**
- Find the nearest neighbors to the learned prompts from the vocabulary
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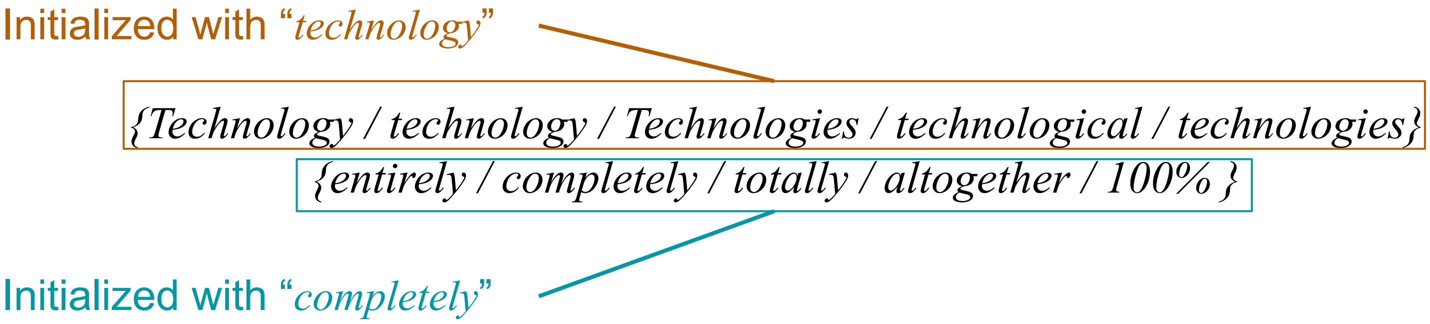
{Technology / technology / Technologies / technological / technologies}
{entirely / completely / totally / altogether / 100% }

Interpretability

- discrete token → continuous embedding: **difficult to interpret**
- Find the nearest neighbors to the learned prompts from the vocabulary
  - The top-5 nearest neighbors form **tight** semantic clusters: learning **“word-like”** representations
  - The class labels **persist** through training: learning to **store** the expected output



Initialized with “*technology*”

{Technology / technology / Technologies / technological / technologies}

{entirely / completely / totally / altogether / 100% }

Initialized with “*completely*”

Interpretability

- discrete token → continuous embedding: **difficult to interpret**
- Find the nearest neighbors to the learned prompts from the vocabulary
  - The top-5 nearest neighbors form **tight** semantic clusters: learning **“word-like”** representations
  - The class labels **persist** through training: learning to **store** the expected output
  - Several prompt tokens have the **same** nearest neighbors if the prompt is **long**: difficult to localize information to a specific position

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Don’t get too attached to the findings here!
A **“wayward”** behavior is observed:
https://arxiv.org/pdf/2112.08348.pdf

Key Findings

- **Prompt tuning** is a competitive technique due to
  - Better performance **scalability** as model size increases
  - **More forgiving** for bad design decisions (when model is large)
  - Improved **generalization** ability
  - Enabling efficient high-performing **prompt ensembling**

Discussion

Q3: You have collected a dataset for a downstream task of your interest and you are asked to design a prompting tuning method to solve it, which design choices do you need to consider? Can you think of other parameter-efficient methods besides what we have seen in these two papers?