On Transferability of Prompt Tuning for Natural Language Processing

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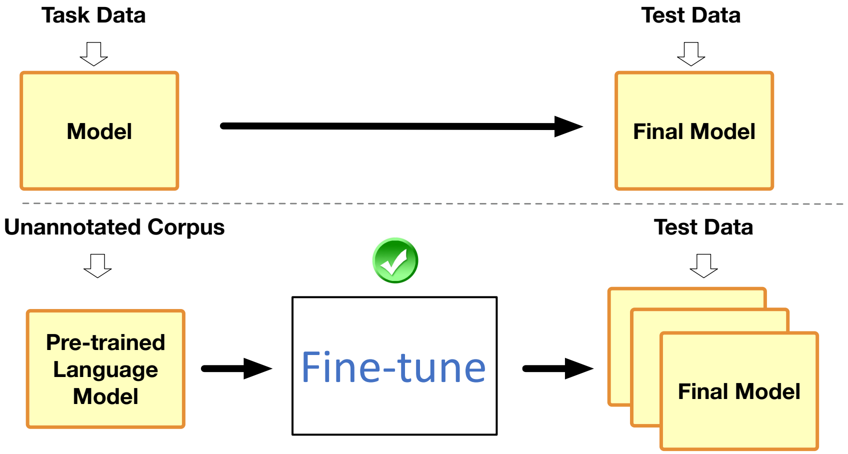
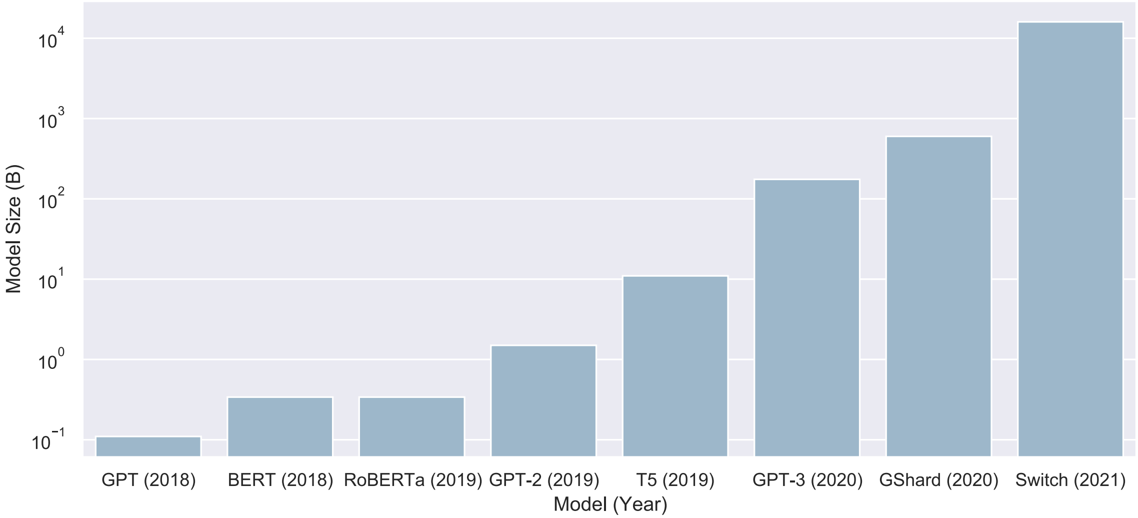
Background

Development of PLM



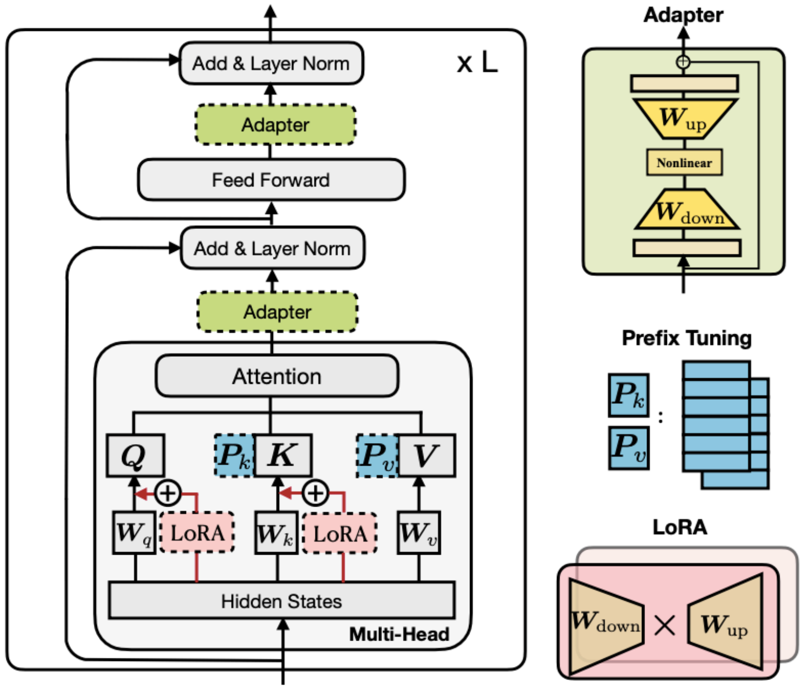
Fine-tuning paradigm becomes de-facto standard

Challenge in Fine-tuning



Background

- **Parameter-Efficient Tuning (PET) Methods**
  - PET methods only optimize a small part of parameters for downstream tasks while freezing the rest of the parameters of the PLM. [6]
  - Methods: Adapter [1], Prefix [2], LoRA [3], BitFit [4], Prompt [5], etc.

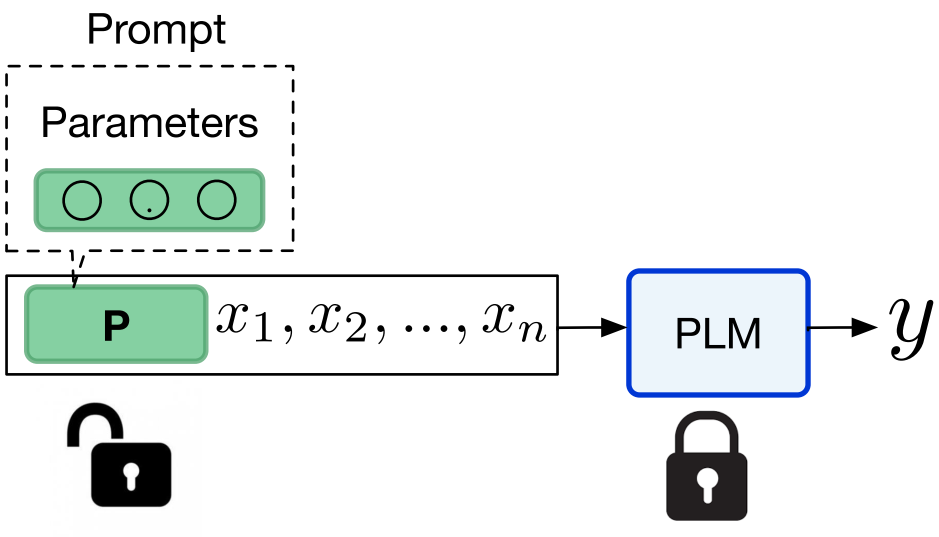


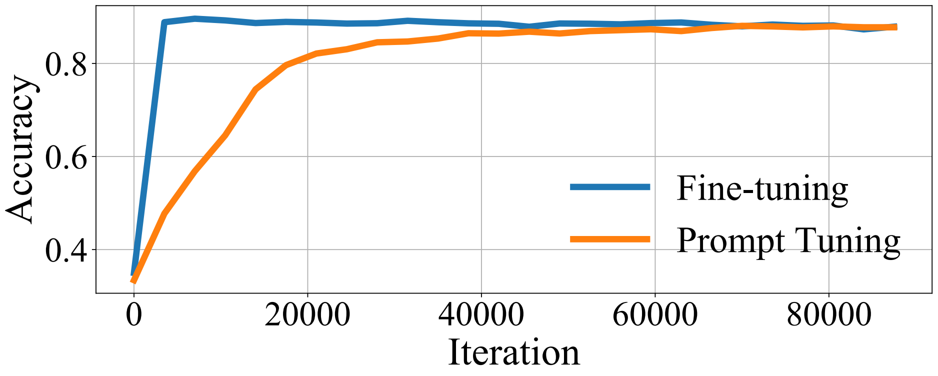
[6]

[1] Neil, 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, ICLR, 2022.
[4] Zaken, et al., BitFit: Simple Parameter-efficient Fine-tuning for Transformer-based Masked Language-models, ACL, 2022.
[5] Lester et al., The Power of Scale for Parameter-Efficient Prompt Tuning, EMNLP, 2021.
[6] He et al., Towards a Unified View of Parameter-Efficient Transfer Learning, ICLR, 2022.

Background

- **Prompt Tuning (PT)**
  - Advantage: Lowest computation costs
  - Challenge: Slow Convergence



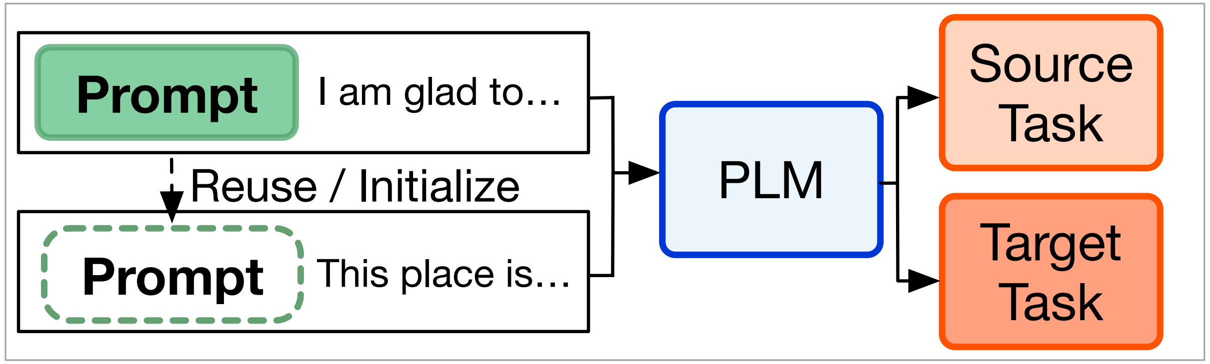


$$L = p(y|\boldsymbol{P}, x_1, \ldots, x_n)$$

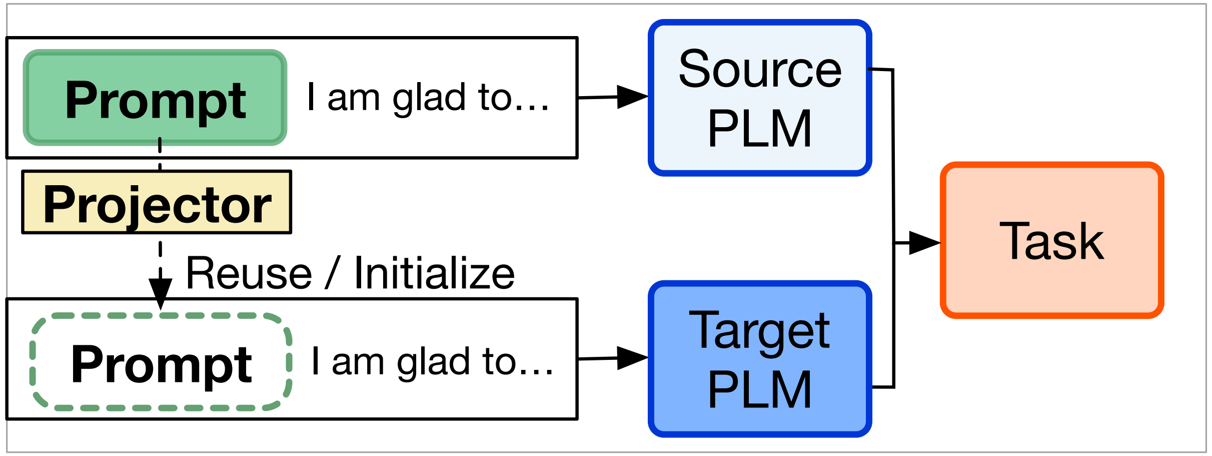
On Transferability of Prompt Tuning for NLP

- **Prompt Tuning (PT)**
  - Solution: Transferring the trained prompts
    - Cross-Task Transfer
    - Cross-Model Transfer

Cross-Task Transfer

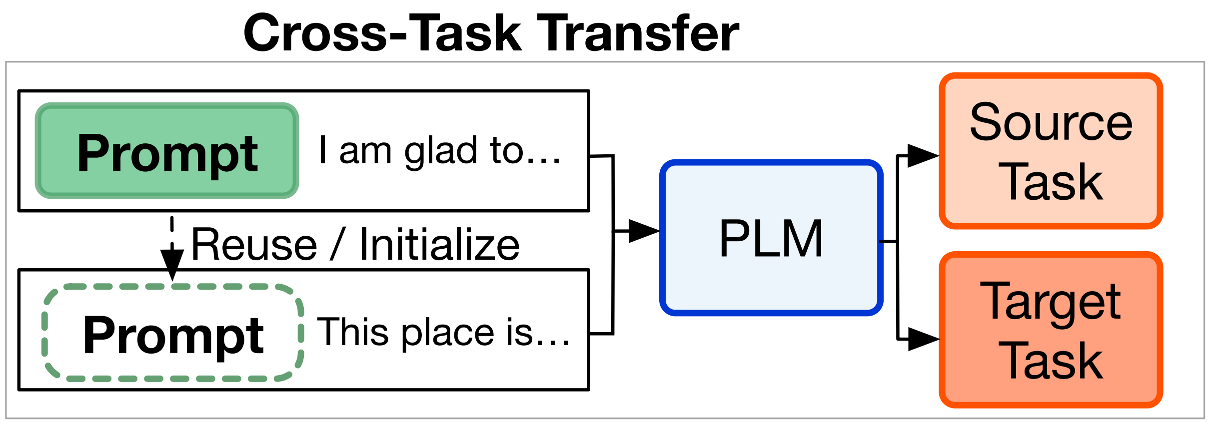


Cross-Model Transfer

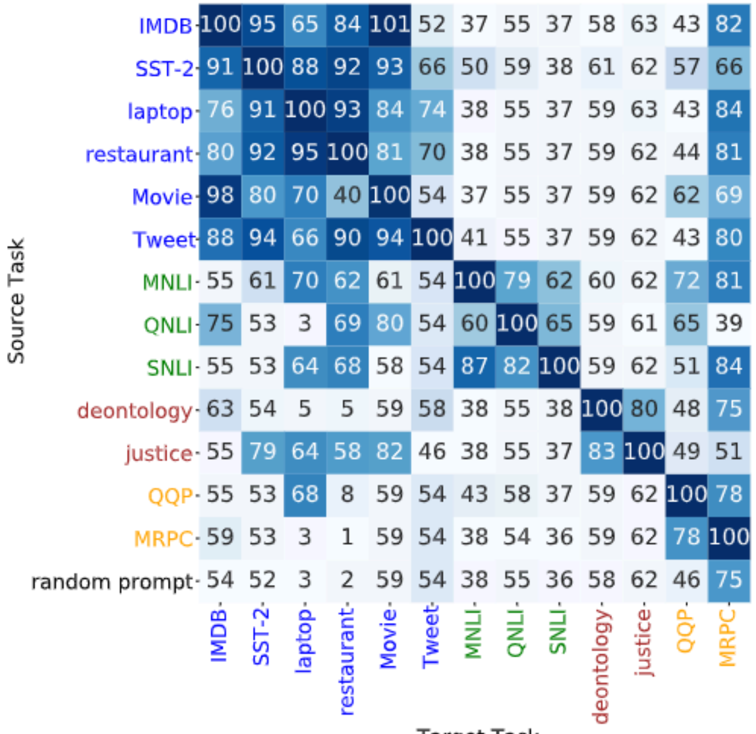


On Transferability of Prompt Tuning for NLP

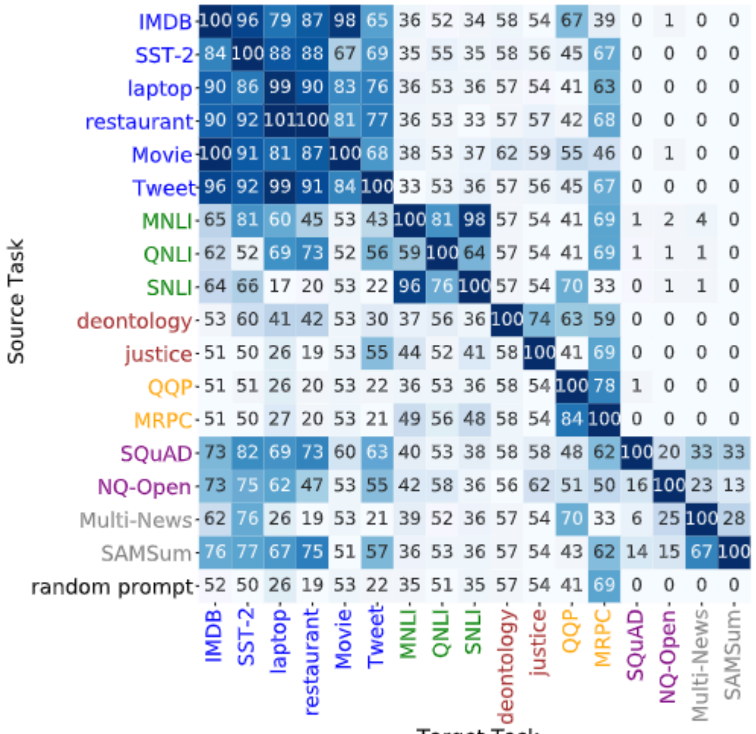
- **Prompt Tuning (PT)**
  - Solution: Transferring the trained prompts
    - **Cross-Task Transfer**
      - Motivation: Similar tasks may require similar skills



- **Cross-Task Transfer**
  - Zero-shot Transferability
    - For the tasks within the same type, transferring prompts between them can generally perform well



(a) RoBERTa$_{\text{LARGE}}$



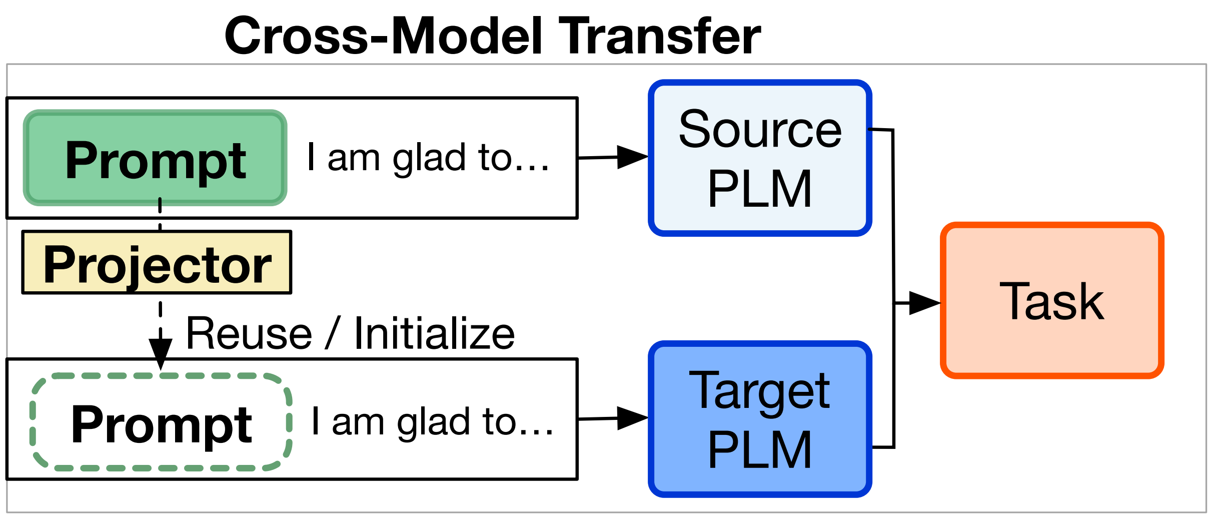
(b) T5$_{\text{XXL}}$

(Relative Performance)

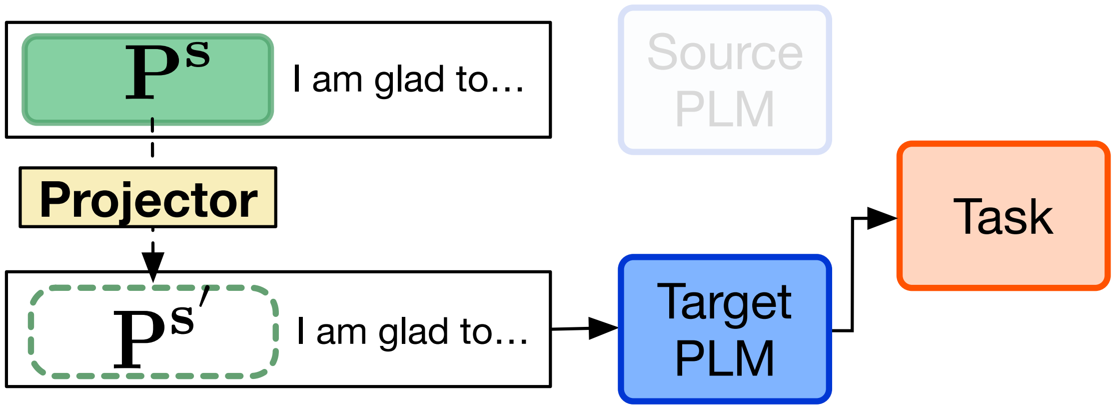
- **Cross-Task Transfer**
  - Transfer with Initialization (TPT_{TASK})
    - Initializing soft prompts with well-trained prompts of the most similar task and then starts PT can speed up training and achieve better performance

Task Type	SA						NLI			EJ		PI		QA		SUM	
Task	IMDB	SST-2	laptop	restaurant	Movie	Tweet	MNLI	QNLI	SNLI	deontology	justice	QQP	MRPC	SQuAD	NQ-Open	Multi-News	SAMSum
Metric	Acc.	Acc.	Acc.	Acc.	Acc.	Acc.	Acc.	Acc.	Acc.	Acc.	Acc.	Acc.	Acc.	F1	F1	ROUGE-L	ROUGE-L
RoBERTa$_{LARGE}$																	
Performance (PT) (%)	92.2	96.1	76.4	83.7	84.9	**76.1**	87.3	92.4	**91.9**	**85.6**	**81.0**	**88.9**	**81.2**	N/A	N/A	N/A	N/A
Performance (TPT_{TASK}) (%)	**92.4**	**96.3**	**79.1**	**85.8**	**85.1**	**76.1**	**87.9**	**93.1**	**91.9**	**85.6**	78.2	86.1	79.2	N/A	N/A	N/A	N/A
Convergence Speedup	1.7	1.1	1.0	1.9	1.2	0.9	1.2	1.2	1.3	0.9	0.7	0.8	0.9	N/A	N/A	N/A	N/A
Comparable-result Speedup	2.5	2.4	1.0	3.8	1.5	1.3	1.1	2.3	1.0	0.9	N/A	N/A	N/A	N/A	N/A	N/A	N/A
T5$_{XXL}$																	
Performance (PT) (%)	96.5	97.4	76.6	**90.1**	**97.9**	76.2	90.5	95.2	93.4	87.0	**92.5**	90.0	86.3	**86.3**	20.8	29.2	45.8
Performance (TPT_{TASK}) (%)	**96.6**	**97.8**	**84.2**	88.6	97.5	**77.0**	**92.0**	**96.2**	**94.0**	**95.3**	90.7	**90.9**	**89.0**	85.9	**21.3**	**29.3**	**46.8**
Convergence Speedup	1.2	49.7	2.2	1.1	3.9	1.4	12.5	24.9	49.9	29.8	1.5	1.0	3.3	1.1	1.0	2.0	2.0
Comparable-result Speedup	1.2	48.9	219.8	N/A	N/A	1.5	12.5	29.9	49.9	29.9	N/A	1.0	5.0	N/A	1.0	2.0	2.5

- **Prompt Tuning (PT)**
  - Solution: Transferring the trained prompts
    - Cross-Task Transfer
    - **Cross-Model Transfer**
      - Motivation: Train prompts on a small and computationally efficient PLM and use them on a massive and computationally expensive PLM



- **Cross-Model Transfer**
  - Cross-Model Prompt Projection
    - Distance Minimizing
    - Task Tuning



Source prompt: $\mathbf{P}^{\mathrm{s}}$; Target prompt: $\mathbf{P}^{\mathrm{t}}$;

$\mathbf{P}^{\mathrm{s}'} = Proj(\mathbf{P}^{\mathrm{s}})$;

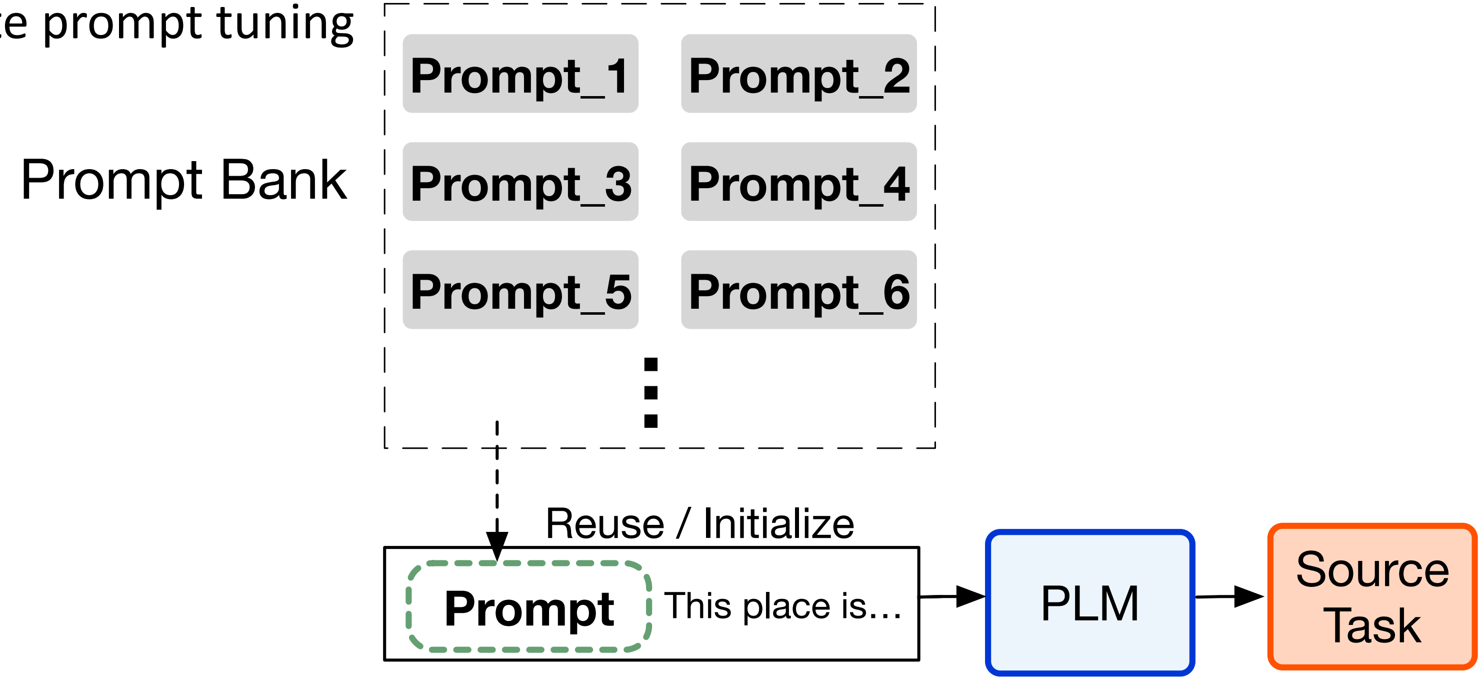
Distance Minimizing: $L_D = \min||Proj(\mathbf{P}^{\mathrm{s}}) - \mathbf{P}^{\mathrm{t}}||_2$

Task Tuning: $L_T = p(y|\mathbf{P}^{\mathrm{s}'}, x_1, \ldots, x_n)$

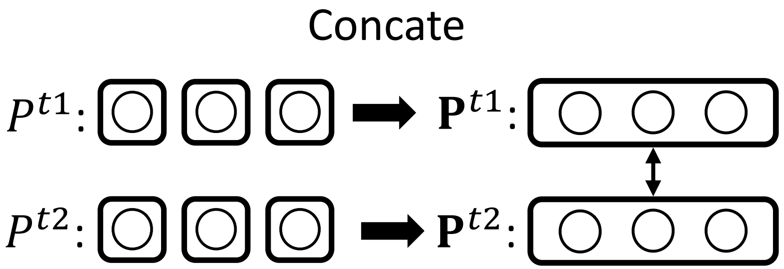
- **Cross-Model Transfer**
  - Zero-shot Transfer Performance
    - **Task Tuning** (projector) generalizes to same-type unseen tasks of the training tasks
  - Transfer with trained prompt Initialization (TPT_{TASK})
    - Accelerate convergence, improve performance

Method		SA						NLI			EJ		PI	
		IMDB	SST-2	laptop	restaurant	Movie	Tweet	MNLI	QNLI	SNLI	deontology	justice	QQP	MRPC
PT on $T5_{XXL}$		96.5	97.4	76.6	88.1	97.9	72.5	90.5	95.2	93.4	87.0	92.5	90.0	86.3
Random Prompt		49.7	49.0	19.8	17.0	51.6	15.5	31.8	49.3	31.9	51.3	50.0	36.4	67.0
(a) Zero-shot Transfer Performance (%)														
laptop	Prompt Mapping	49.6	49.0	76.6	17.5	51.5	14.4	31.8	48.1	32.8	53.3	49.9	36.8	66.6
	Task Tuning	**82.9**	**89.3**	**80.3**	**85.7**	**78.6**	**58.4**	32.4	50.7	33.6	54.9	51.6	33.9	63.7
MNLI	Prompt Mapping	49.6	50.1	19.8	18.3	51.2	15.0	**90.5**	49.0	32.9	50.3	49.0	36.8	65.6
	Task Tuning	49.7	48.8	19.8	17.0	51.6	16.0	89.8	**82.7**	**88.2**	49.7	50.0	36.8	67.7
(b) Transfer with Initialization (TPT_{MODEL})														
laptop	Performance (%)	96.5	97.4	82.9	90.3	97.4	74.4	91.0	95.4	93.4	92.5	92.5	90.0	87.9
	Convergence Speedup	1.1	1.7	1.9	1.3	0.6	1.3	0.9	0.9	1.0	1.0	0.7	1.1	1.1
	Comparable-result Speedup	1.0	19.0	16.0	6.0	N/A	2.2	3.6	1.1	6.0	6.0	0.9	1.8	3.4
MNLI	Performance (%)	96.5	97.4	82.7	88.5	95.8	74.7	91.2	95.9	93.5	94.6	92.5	90.0	87.7
	Convergence Speedup	1.0	1.6	1.8	0.9	0.4	1.3	1.0	1.1	1.4	2.0	1.7	0.9	0.9
	Comparable-result Speedup	1.0	18.0	15.0	1.6	N/A	1.5	18.0	20.0	30.0	7.5	5.0	1.5	1.9

- **Exploring Transferability Indicator**
  - Motivation
    - Explore why the soft prompts can transfer across tasks and what decides the transferability between them
    - Find suitable prompts for performing transfer to achieve better performance or accelerate prompt tuning



- **Exploring Transferability Indicator**
  - Embedding Similarity
    - Euclidean similarity
    - Cosine similarity
  - Model Stimulation Similarity



$$\mathrm{E}_{\mathrm{concat}}(P^{t_1}, P^{t_2}) = \frac{1}{1 + \|\mathbf{P}^{t_1} - \mathbf{P}^{t_2}\|}$$

$$\mathrm{C}_{\mathrm{concat}}(P^{t_1}, P^{t_2}) = \frac{\mathbf{P}^{t_1} \cdot \mathbf{P}^{t_2}}{\|\mathbf{P}^{t_1}\|\|\mathbf{P}^{t_2}\|}$$

[1] Geva, et al., Transformer Feed-Forward Layers Are Key-Value Memories, EMNLP, 2021.

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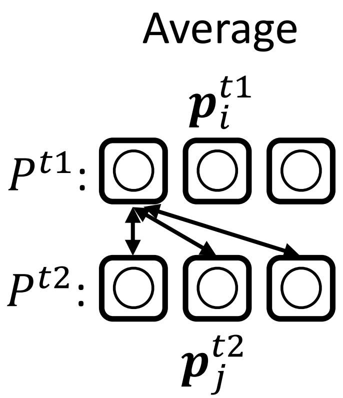

$$\mathrm{E}_{\mathrm{average}}(P^{t_1}, P^{t_2}) = \frac{1}{1 + \frac{1}{l^2}\sum_{i=1}^{l}\sum_{j=1}^{l}\|\mathbf{p}_i^{t_1} - \mathbf{p}_j^{t_2}\|}$$

$$\mathrm{C}_{\mathrm{average}}(P^{t_1}, P^{t_2}) = \frac{1}{l^2}\sum_{i=1}^{l}\sum_{j=1}^{l}\frac{\mathbf{p}_i^{t_1} \cdot \mathbf{p}_j^{t_2}}{\|\mathbf{p}_i^{t_1}\|\|\mathbf{p}_j^{t_2}\|}$$

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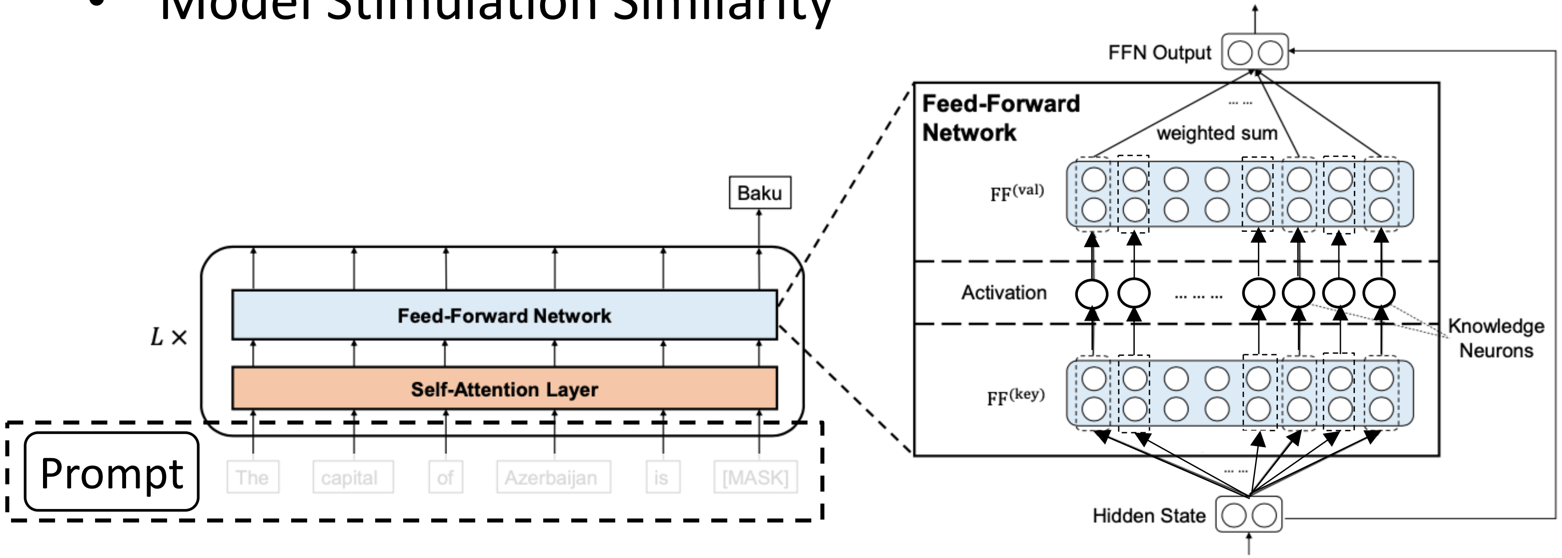

$$\mathrm{FFN}(\mathbf{x}) = \boxed{\max(\mathbf{x}W_1^\top + \mathbf{b_1}, \mathbf{0})}W_2 + \mathbf{b_2},$$

[1] Geva, et al., Transformer Feed-Forward Layers Are Key-Value Memories, EMNLP, 2021.

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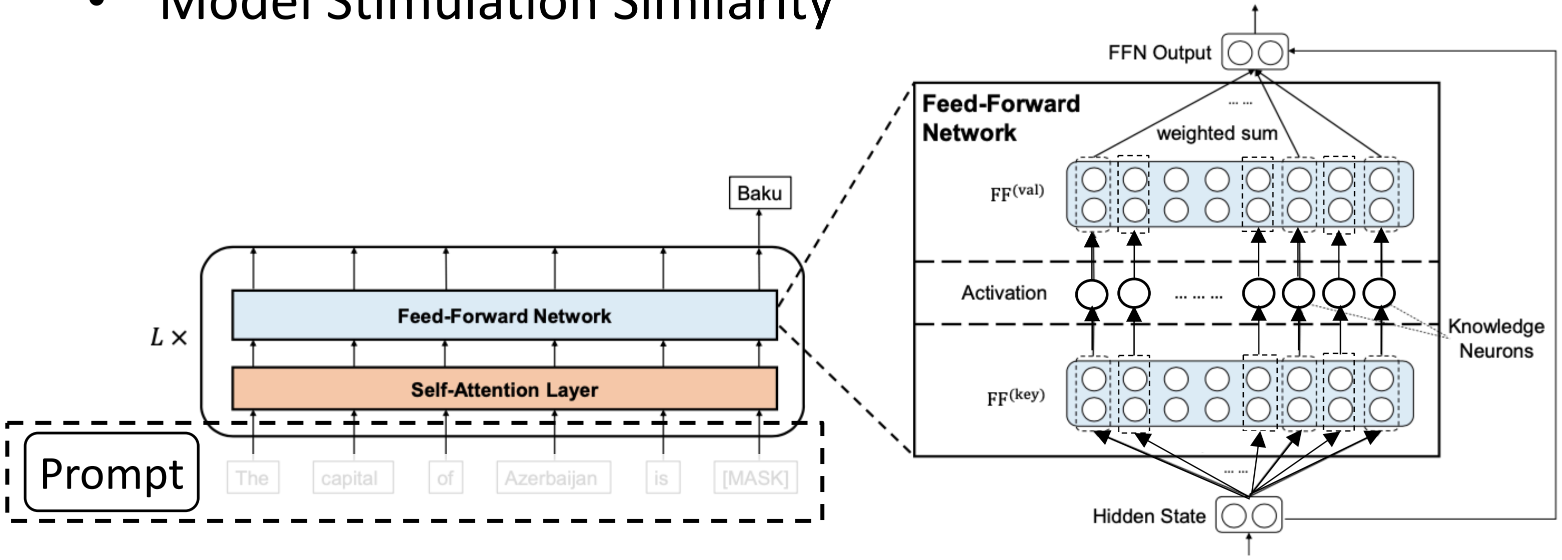

$$\mathrm{FFN}(\mathbf{x}) = \max(\mathbf{x}W_1^\top + \mathbf{b_1}, \mathbf{0})W_2 + \mathbf{b_2},$$

$$\mathrm{AS}(P) = [\mathbf{s}_1; \mathbf{s}_2; ...; \mathbf{s}_L]$$

[1] Geva, et al., Transformer Feed-Forward Layers Are Key-Value Memories, EMNLP, 2021.

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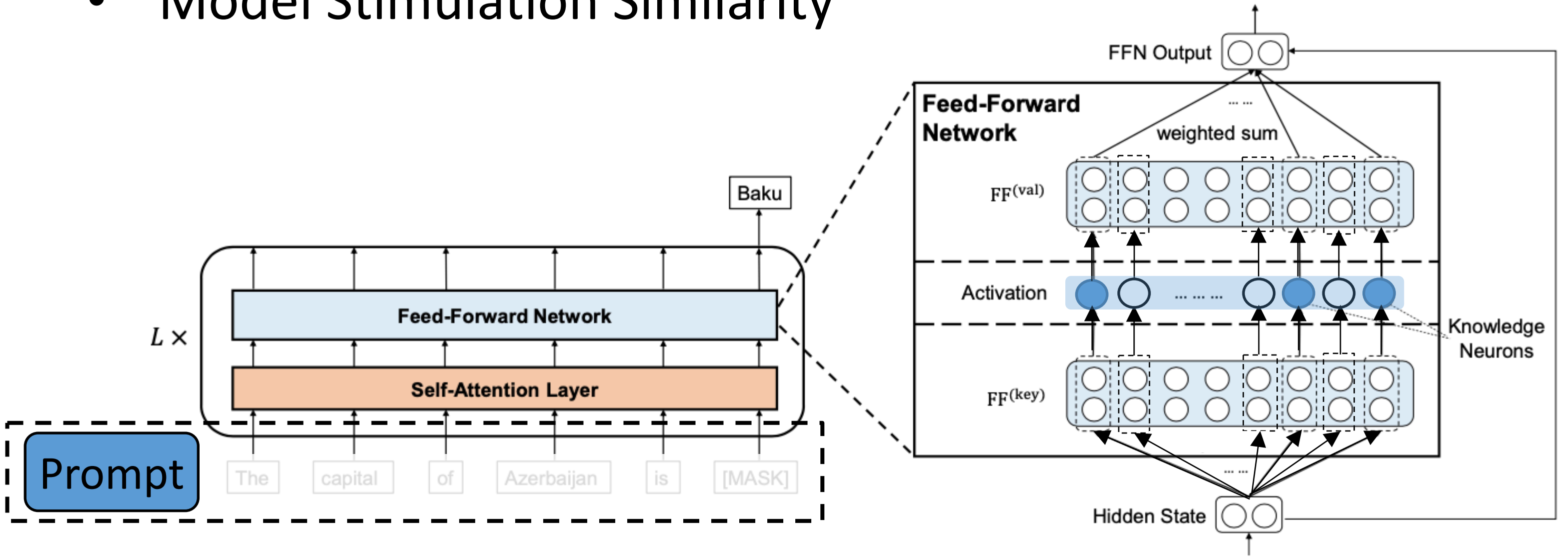

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[1] Geva, et al., Transformer Feed-Forward Layers Are Key-Value Memories, EMNLP, 2021.

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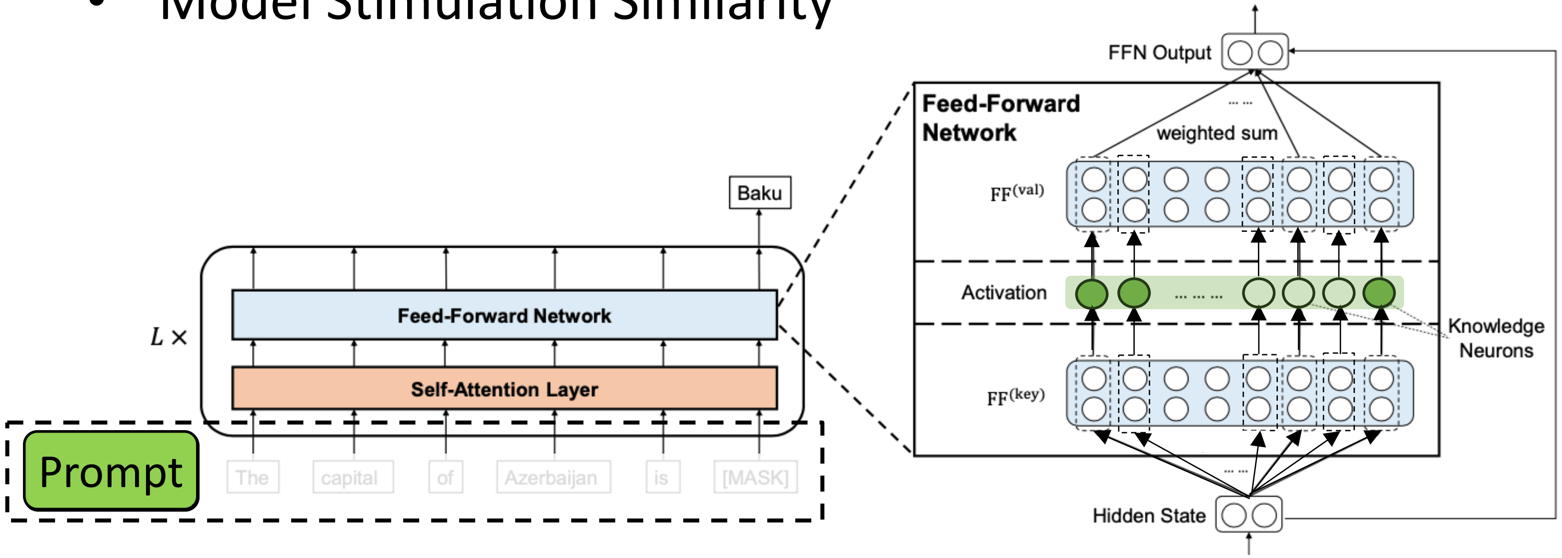

$$\mathrm{FFN}(\mathbf{x}) = \boxed{\max(\mathbf{x}W_1^\top + \mathbf{b_1}, \mathbf{0})} W_2 + \mathbf{b_2},$$

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[1] Geva, et al., Transformer Feed-Forward Layers Are Key-Value Memories, EMNLP, 2021.

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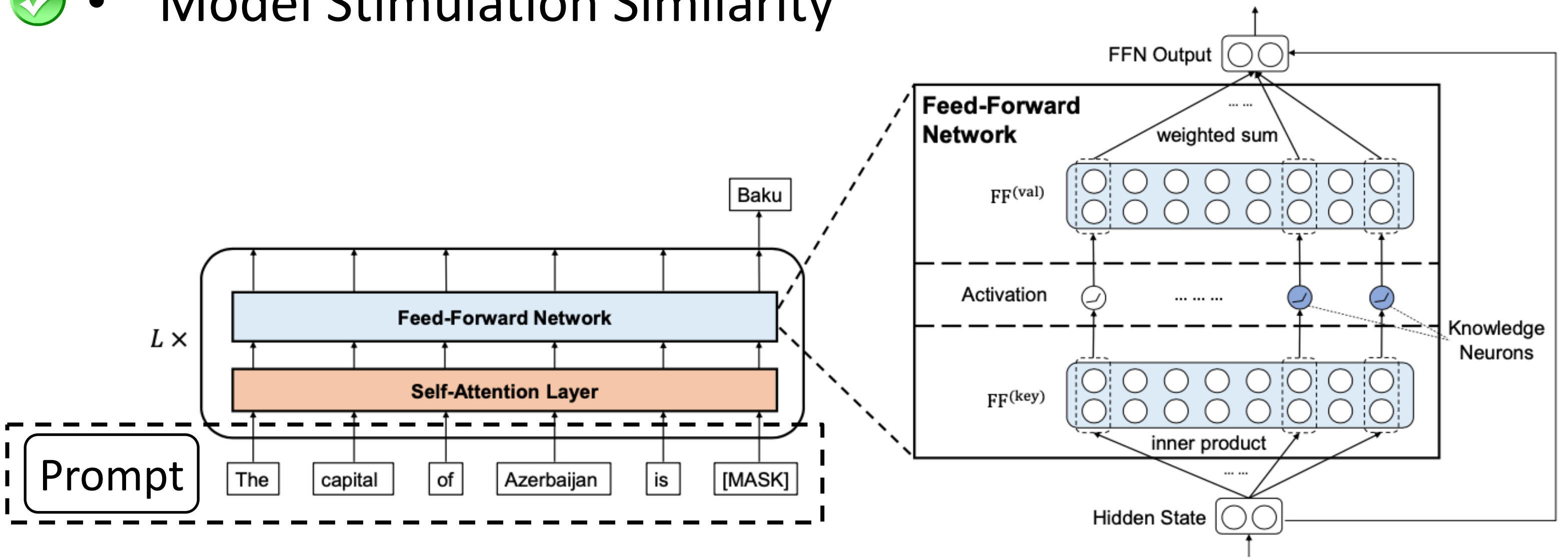
  - Embedding Similarity
    - Euclidean similarity:
    - Cosine similarity:
  - Model Stimulation Similarity



$$\mathrm{FFN}(\mathbf{x}) = \boxed{\max(\mathbf{x}W_1^\top + \mathbf{b_1}, \mathbf{0})} W_2 + \mathbf{b_2},$$

$$\mathrm{AS}(P) = [\mathbf{s}_1; \mathbf{s}_2; \ldots; \mathbf{s}_L]$$

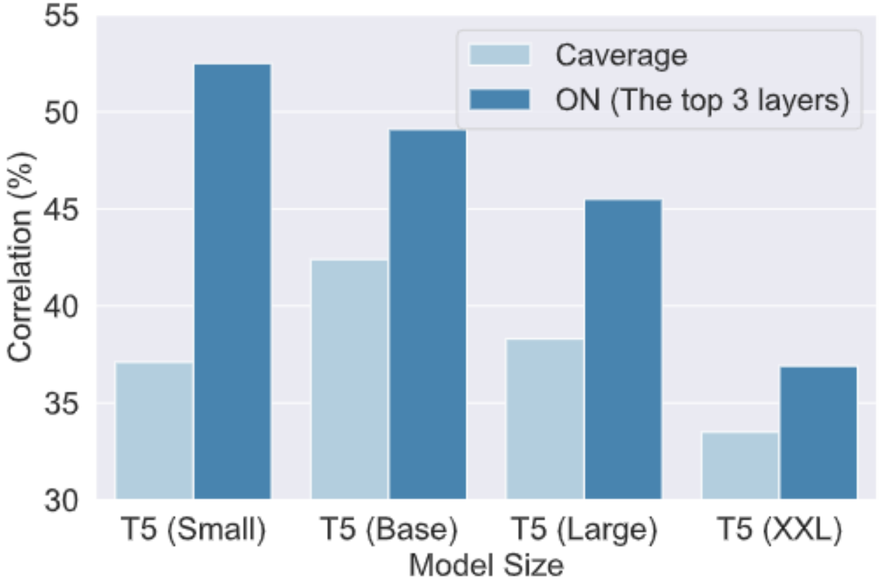
$$\mathrm{ON}(P^{t_1}, P^{t_2}) = \frac{\mathrm{AS}(P^{t_1}) \cdot \mathrm{AS}(P^{t_2})}{\|\mathrm{AS}(P^{t_1})\| \|\mathrm{AS}(P^{t_2})\|}$$

[1] Geva, et al., Transformer Feed-Forward Layers Are Key-Value Memories, EMNLP, 2021.

- **Exploring Transferability Indicator**
  - Model Stimulation Similarity (ON)
    - ON has the higher Spearman's correlation with the transferability
    - ON works worse on the larger PLMs because of the higher redundancy [1]

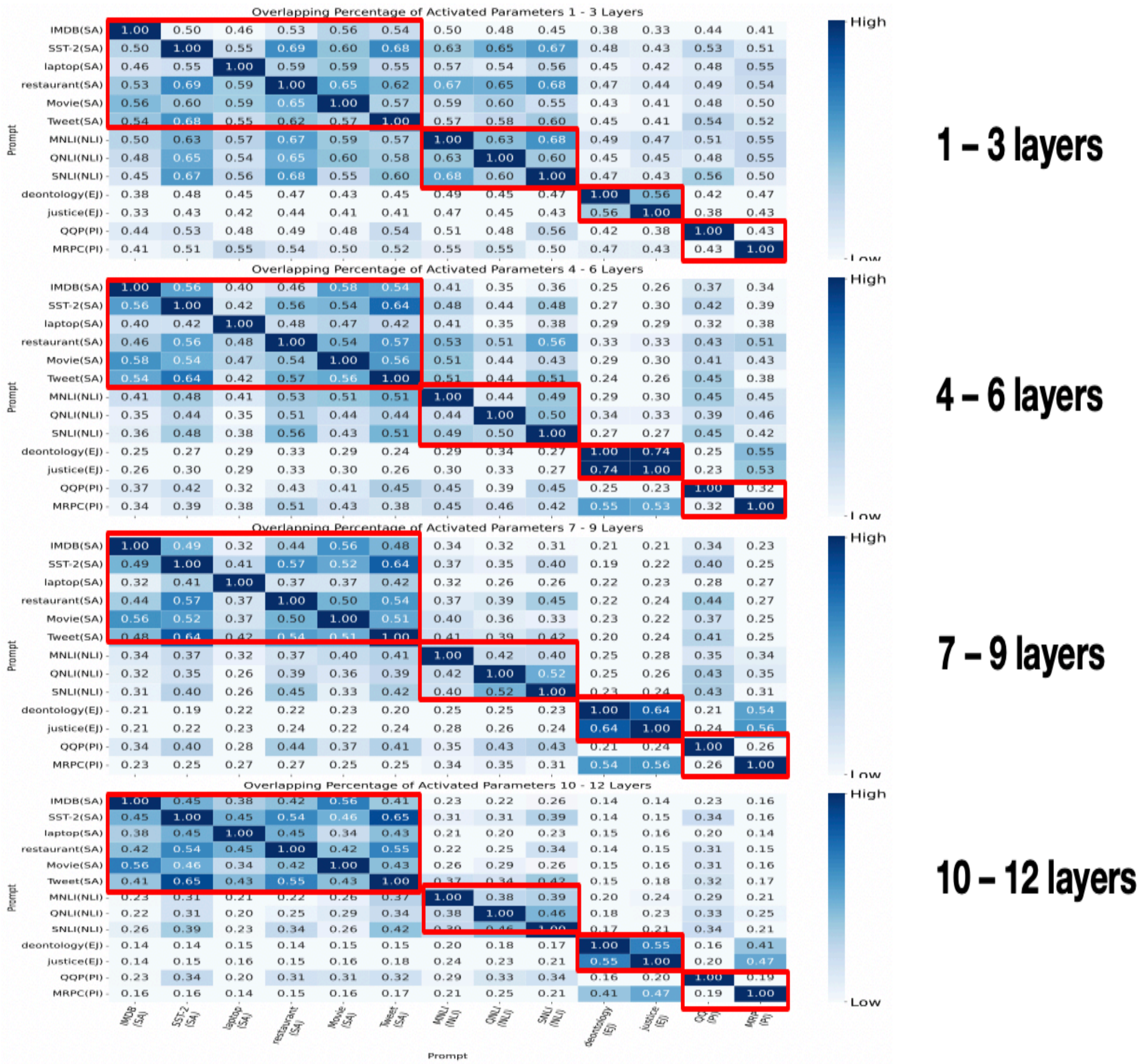
Metric	Model	
	$\text{RoBERTa}_{\text{LARGE}}$	T5_{XXL}
E_{concat}	22.6	12.9
$E_{average}$	2.8	-2.5
C_{concat}	24.8	31.6
$C_{average}$	44.7	33.5
ON	**49.7**	**36.9**

Spearman's correlation



[1] Aghajanyan, et al., Intrinsic Dimensionality Explains the Effectiveness of Language Model Fine-Tuning, ACL, 2021.

- **Exploring Transferability Indicator**
  - Distribution of Activated Neuron
    - The activated neurons are comm-on in the bottom layers but more task-specific in top layers



Conclusion

- **Transferability of Prompts**
  - In the cross-task setting
    - Soft prompts can transfer to similar tasks to accelerate prompt tuning and achieve better performance
  - In the cross-model setting
    - Soft prompts can transfer to different PLMs with a projector trained on similar tasks
  - Transferability Indicator
    - We can utilize activated neurons of soft prompts to well indicate transferability between tasks

Q&A

THUNLP

[paper]

[code]