# Prefix-Tuning: Optimizing Continuous Prompts for Generation

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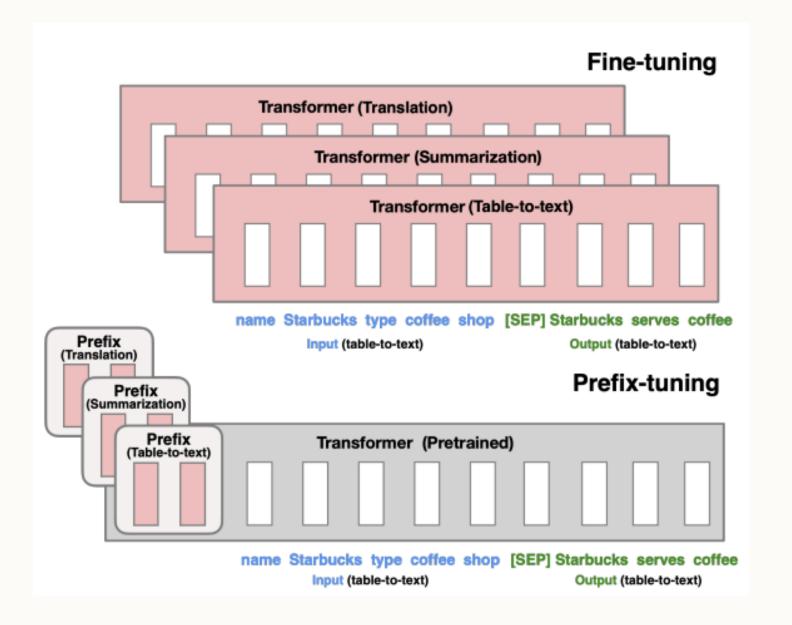
## 1. Introduction

Fine-tuning의 단점을 보완하고자 Preix-tuning을 제안

Prefix 이용시,

Fine-tuning 같이 모델 전체를 학습 시키지 않고

Prefix부분만 조정하면 된다.



# 2. Related Work

Fine-tuning

모델의 모든 매개변수를 특정 작업에 맞게 전체 조정

Lightweight fine-tuning

대부분의 사전 훈련 매개변수 고정 > 일부 조정 (adapter layer 추가 및 조정)

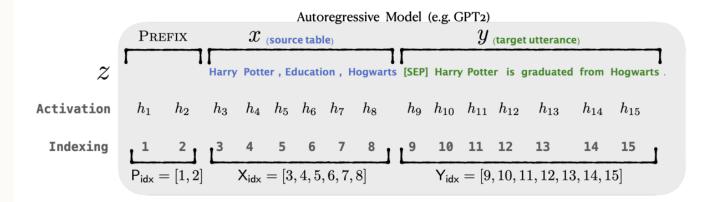
Controllable generation.

언어 모델의 출력을 특정 속성에 맞게 조정

Prompting

지시사항, 예제(특정 트리거 단어 시퀀스)를 작업 입력 > 원하는 결과 출력

# 3. Fine-tuning

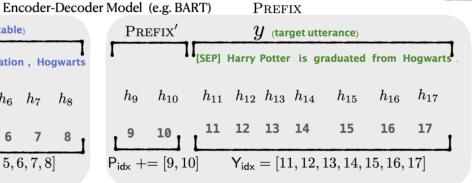


### Summarization Example

Article: Scientists at University College London discovered people tend to think that their hands are wider and their fingers are shorter than they truly are. They say the confusion may lie in the way the brain receives information from different parts of the body. Distorted perception may dominate in some people, leading to body image problems ... [ignoring 308 words] could be very motivating for people with eating disorders to know that there was a biological explanation for their experiences, rather than feeling it was their fault."

Summary: The brain naturally distorts body image — a finding which could explain eating disorders like anorexia, say experts.

### 



### Table-to-text Example

Table: name[Clowns] customerrating[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.

# 3. Fine-tuning

- pretrained parameters  $\phi$  > initialize
- $p\phi$  = trainable language model distribution
- gradient updates (log-likelihood objective)

$$\max_{\phi} \ \log p_{\phi}(y \mid x) = \sum_{i \in \mathsf{Y}_{\mathsf{idx}}} \log p_{\phi}(z_i \mid h_{< i}).$$

# 4. Prefix-Tuning

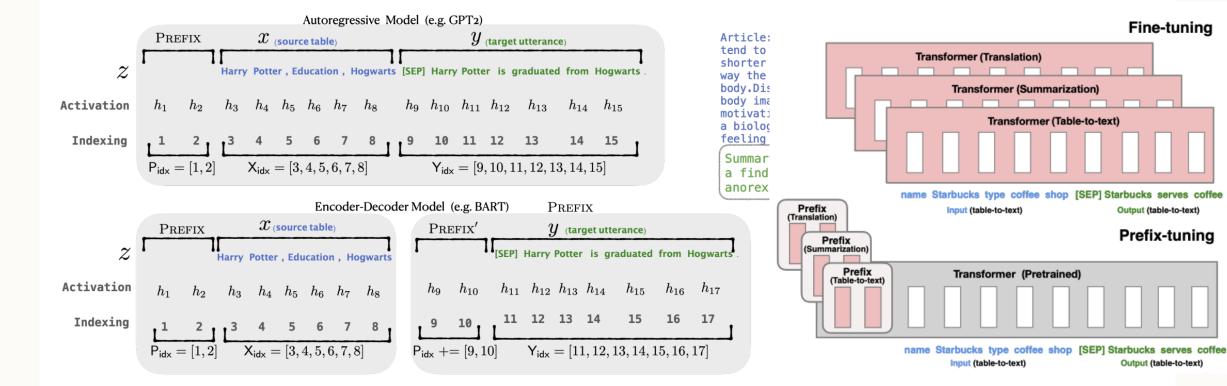
### collocation

Obama + Barack

Instead of discrete tokens, Sequential word embedding 최적화 가능

Pros and cons: expressive discrete tokens < Prefix-Tuning < all layers of the activations

# 4. Prefix-Tuning



Fine-tuning

Output (table-to-text)

Prefix-tuning

Output (table-to-text)

# 4. Prefix-tuning

- Parametrization of prefix parameters
- 문제점: directly updating > unstable optimization
- 해결책: Reparametrize

$$P_{\theta}[i,:] = \text{MLP}_{\theta}(P'_{\theta}[i,:])$$
 by a smaller matrix  $(P'_{\theta})$ 

- 차원을 줄이면서 매개변수 감소 > 최적화 과정 안정화
- Mlp 통과하면서 동일한 차원으로 확장 > 복잡한 패턴 특성 학습 + 안정성

# 5. Experimental Setup

### **Experiment:**

1. table-to-text : GPT-2 Medium, Large 모델

2. summarization : BART Large 모델

### Data set:

table-to-text: E2E, WebNLG, DART

summarization: XSUM

비교 방법:

Table-to-text Example

FINE-TUNE

FT-TOP2

ADAPTER(3%)

Adapter(0.1%)

PREFIX(0.1%)

Summarization Example

FINE-TUNE

PREFIX

### Summarization Example

Article: Scientists at University College London discovered people tend to think that their hands are wider and their fingers are shorter than they truly are. They say the confusion may lie in the way the brain receives information from different parts of the body. Distorted perception may dominate in some people, leading to body image problems ... [ignoring 308 words] could be very motivating for people with eating disorders to know that there was a biological explanation for their experiences, rather than feeling it was their fault."

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### 평가 메트릭스:

BLEU, NIST, METEOR, ROUGE-L, CIDEr

# 6. Main Results

SOTA

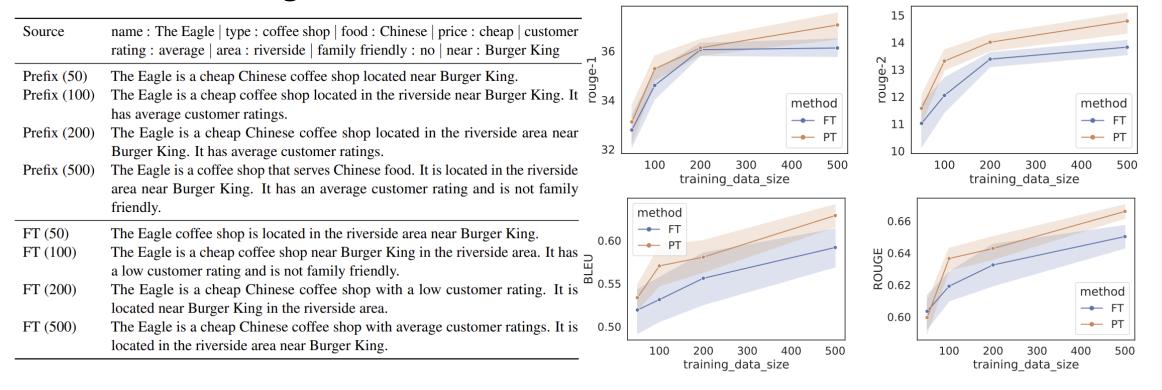
Table-1	to-text Ex	amn	le .																		
Table-to-text Example -		E2E WebNLG							DART												
		BLEU	NIST	MET	R-L	CIDEr		BLEU			MET			TER 🗸	-	BLEU	MET	$TER\downarrow$	Mover	BERT	BLEURT
							S	U	A	S	U	A	S	U	A						
											GP'	T-2 <sub>ME</sub>	DIUM								
	FINE-TUNE	68.2	8.62	46.2	71.0	2.47	64.2	27.7	46.5	0.45				0.76	0.53	46.2	0.39	0.46	0.50	0.94	0.39
	FT-TOP2	68.1	8.59	46.0	70.8	2.41	53.6	18.9	36.0	0.38	0.23	0.31	0.49	0.99	0.72	41.0	0.34	0.56	0.43	0.93	0.21
	ADAPTER(3%)	68.9	8.71	46.1	71.3	2.47	60.4	48.3	54.9	0.43	0.38	0.41	0.35	0.45	0.39	45.2	0.38	0.46	0.50	0.94	0.39
	Adapter $(0.1\%)$	66.3	8.41	45.0	69.8	2.40	54.5	45.1	50.2	0.39	0.36	0.38	0.40	0.46	0.43	42.4	0.36	0.48	0.47	0.94	0.33
	Prefix(0.1%)	<b>69.7</b>	8.81	46.1	71.4	2.49	62.9	45.6	55.1	0.44	0.38	0.41	0.35	0.49	0.41	46.4	0.38	0.46	0.50	0.94	0.39
											GI	PT-2 <sub>LA</sub>	RGE								
	FINE-TUNE	68.5	8.78	46.0	69.9	2.45	65.3	43.1	55.5	0.46	0.38	0.42	0.33	0.53	0.42	47.0	0.39	0.46	0.51	0.94	0.40
	Prefix	70.3	8.85	46.2	71.7	2.47	63.4	47.7	56.3	0.45	0.39	0.42	0.34	0.48	0.40	46.7	0.39	0.45	0.51	0.94	0.40

68.6 8.70 45.3 70.8 2.37 | 63.9 52.8 57.1 0.46 0.41 0.44 - - - | - -

Summarization Examp	<b>R-1</b> ↑	R-2 ↑	R-L↑	
I	FINE-TUNE(Lewis et al., 2020)	45.14	22.27	37.25
I	Prefix(2%)	43.80	20.93	36.05
I	Prefix(0.1%)	42.92	20.03	35.05

# 6. Main Results

### **Low-data Setting**



# 6. Main Results

# Extrapolation : 훈련데이터에 포함 되지 않은 데이터에 대한 예측

Table-to-text Example

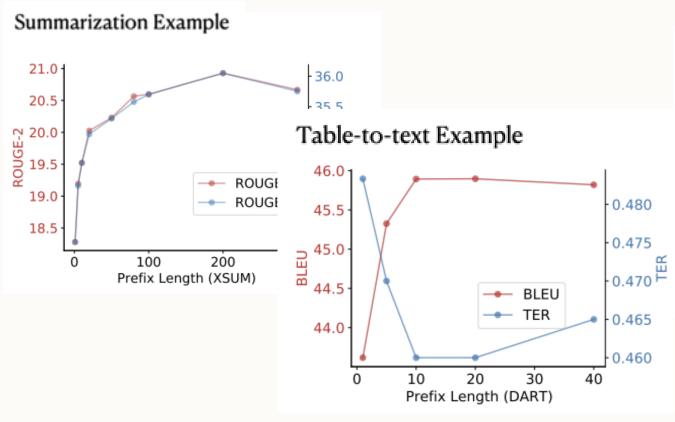
	,	BLEU	r	W		TER ↓			
	S	U	Α	S	MET U	A	S	U	Α
					GF	T-2 <sub>ME</sub>	DIUM		
FINE-TUNE	64.2	27.7	46.5	0.45	0.30	0.38	0.33	0.76	0.53
FT-TOP2	53.6	18.9	36.0	0.38	0.23	0.31	0.49	0.99	0.72
ADAPTER(3%)	60.4	48.3	54.9	0.43	0.38	0.41	0.35	0.45	0.39
ADAPTER $(0.1\%)$	54.5	45.1	50.2	0.39	0.36	0.38	0.40	0.46	0.43
Prefix(0.1%)	62.9	45.6	55.1	0.44	0.38	0.41	0.35	0.49	0.41
					G	PT-2 <sub>LA</sub>	RGE		
FINE-TUNE	65.3	43.1	55.5	0.46	0.38	0.42	0.33	0.53	0.42
Prefix	63.4	47.7	56.3	0.45	0.39	0.42	0.34	0.48	0.40
SOTA	63.9	52.8	57.1	0.46	0.41	0.44	-	-	-

### Summarization Example

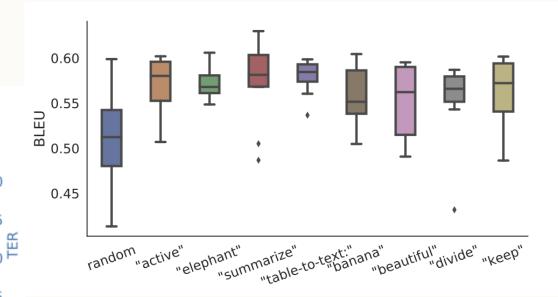
	news	-to-sp	orts	within-news				
	<b>R-1</b> ↑	<b>R-2</b> ↑	R-L↑	R-1 ↑	R-2 ↑	R-L↑		
FINE-TUNE								
PREFIX	39.23	16.74	31.51	39.41	16.87	31.47		

# 7. Intrinsic Evaluation

### 1. Prefix length



### 2. prefix 매개변수 초기화



# 8. Discussion & Conclusion

### Prefix-tuning 제안

- fine-tuning과 비슷하거나 더 높은 성능
- prefix 조정 모듈 및 공간 효율적

### 개인 정보 보호와 같은 실용적인 방안

• Personalization & Batching Across Users

### 일반화 능력 향상

• Inductive Bias of Prefix-tuning

# Thank you