# Personalization for BERT-based Discriminative Speech Recognition Rescoring

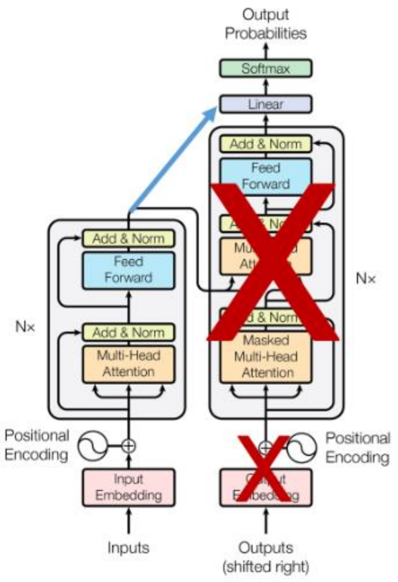
Amazon Alexa(Jari et al)

surim-lab

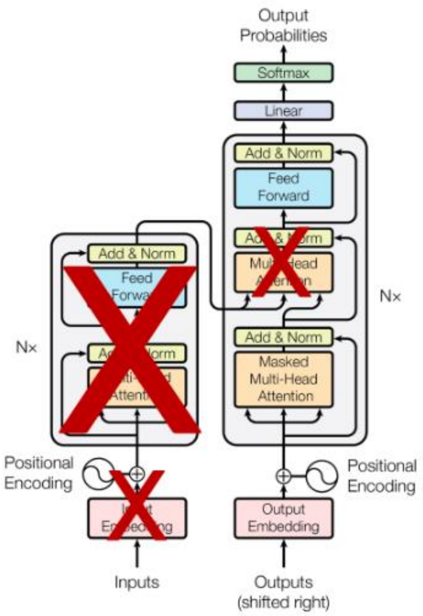
# I. RescoreBERT

(1) BERT VS GPT, RescoreBERT

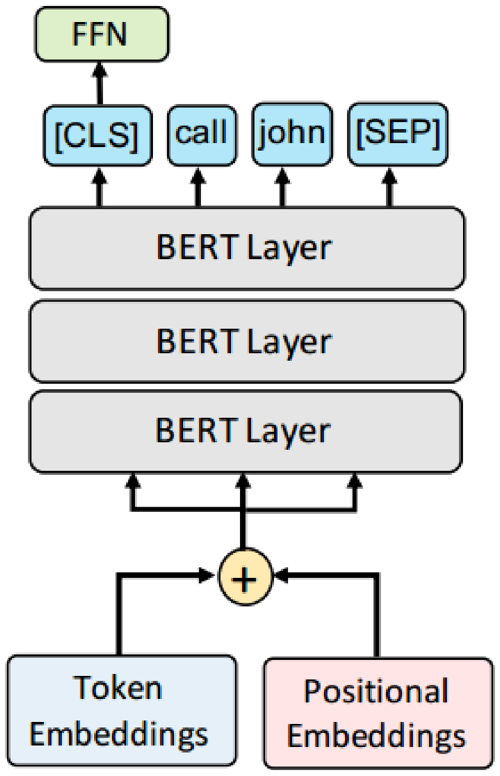
$$\mathrm{Attention}(\mathbf{Q},\mathbf{K},\mathbf{V}) = \mathrm{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^{\top}}{\sqrt{d_K}}\right)\mathbf{V}$$




**BERT**
(Bidirectional Encoder Representations from **Transformer,** masked LM)




**GPT**
(Generative Pretrained **Transformer,** unidirectional)




**RescoreBERT**

## Transformer

- Encoder: 소스 시퀀스 압축 및 전송
- Decoder: 타깃 시퀀스 생성
- Self Attention: Q, K, V 로 문맥적 관계성 학습

  -> Multi-head attention

## Rescoring

- 1st pass in ASR: 음성 정보로 예측값 리스트 생성
- $2^{nd}$ : 가능한 표기 확인하여 재집계
- 최종 점수: $20*1^{st} + 2^{nd}$ $v_i = \alpha u_i + \beta s_i$

## RescoreBERT

- Bidirectional Transformer Rescoring Model
- ASR loss로 학습하여 WER 최소화 위해 예측값으로부터 단일 점수 예측
- FFN + CLS token

# II. ER in ASR

(1)CSID, Edit Distance, WER, CER, PER,  WERR

- **CSID: Correct(일치), Substitution(대체), Insertion(삽입), Deletion(삭제)**
- **ER = Edit Distance / N(정답지 단어 수) = min(S + D + I) / (S + D + C)**

**= {WER(Word), CER(Character), PER(Phoneme), TER(Token), SER(Sentence)… }**

*** WERR: WER Reduction (+ : WER ↑ ←→ - : WER ↓ (성능↑) )**

| Model | Personalized | General |
|---|---|---|
| Oracle | -57% | -58% |
| Tiny RescoreBERT | +3.9% | -5.3% |
| Big RescoreBERT | +4.8% | -7.1% |
| Tiny RescoreBERT (fine-tuned) | +2.5% | -5.3% |
| Big RescoreBERT (fine-tuned) | +1.7% | -6.8% |

# II. ER in ASR

(2) CSID(Levenshtein) Algorithm, (1) snow VS sunny

- **방향**

(1)↓+1 : Deletion
(2)→+1 : Insertion
(3)↘+0 : Correct
(3)↘+1 : Substitution

편집 거리 계산

- **알고리즘 일부**

```
arr[i][j] = min(
        arr[i-1][j]+1, # D(1) ↓
        arr[i][j 1]+1, # I(2) →
        arr[i-1][j-1] + cost)
        # S(cost=1)|C(0)(3) ↘
```

| | | S | U | N | N | Y |
|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 |
| S | 1 | | | | | |
| N | 2 | | | | | |
| O | 3 | | | | | |
| W | 4 | | | | | |

(2,2): min(1+1(D), 1+1(I), 0+0(C)) =0

| | | S | U | N | N | Y |
|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 |
| S | 1 | 0 | 1 | 2 | 3 | 4 |
| N | 2 | | | | | |
| O | 3 | | | | | |
| W | 4 | | | | | |

C I

(2,6): min(5+1(D), 3+1(I), 4+1(S)) =4

| | | S | U | N | N | Y |
|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 |
| S | 1 | 0 | 1 | 2 | 3 | 4 |
| N | 2 | 1 | 1 | 1 | 2 | 3 |
| O | 3 | | | | | |
| W | 4 | | | | | |

C I C

| | | S | U | N | N | Y |
|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 |
| S | 1 | 0 | 1 | 2 | 3 | 4 |
| N | 2 | 1 | 1 | 1 | 2 | 3 |
| O | 3 | 2 | 2 | 2 | 2 | 3 |
| W | 4 | | | | | |

C I C S

| | | S | U | N | N | Y |
|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 |
| S | 1 | 0 | 1 | 2 | 3 | 4 |
| N | 2 | 1 | 1 | 1 | 2 | 3 |
| O | 3 | 2 | 2 | 2 | 2 | 3 |
| W | 4 | 3 | 3 | 3 | 3 | 3 |

CICSS → 3(not C)

# II. ER in ASR

(2) kitten VS sitting

| | | S | I | T | T | I | N | G |
|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| K | 1 | | | | | | | |
| I | 2 | | | | | | | |
| T | 3 | | | | | | | |
| T | 4 | | | | | | | |
| E | 5 | | | | | | | |
| N | 6 | | | | | | | |

| | | S | I | T | T | I | N | G |
|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| K | 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| I | 2 | | | | | | | |
| T | 3 | | | | | | | |
| T | 4 | | | | | | | |
| E | 5 | | | | | | | |
| N | 6 | | | | | | | |

S

| | | S | I | T | T | I | N | G |
|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| K | 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| I | 2 | 2 | 1 | 2 | 3 | 4 | 5 | 6 |
| T | 3 | | | | | | | |
| T | 4 | | | | | | | |
| E | 5 | | | | | | | |
| N | 6 | | | | | | | |

S C

| | | S | I | T | T | I | N | G |
|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| K | 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| I | 2 | 2 | 1 | 2 | 3 | 4 | 5 | 6 |
| T | 3 | 3 | 2 | 1 | 2 | 3 | 4 | 5 |
| T | 4 | | | | | | | |
| E | 5 | | | | | | | |
| N | 6 | | | | | | | |

S C C

| | | S | I | T | T | I | N | G |
|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| K | 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| I | 2 | 2 | 1 | 2 | 3 | 4 | 5 | 6 |
| T | 3 | 3 | 2 | 1 | 2 | 3 | 4 | 5 |
| T | 4 | 4 | 3 | 2 | 1 | 2 | 3 | 4 |
| E | 5 | | | | | | | |
| N | 6 | | | | | | | |

S C C C

| | | S | I | T | T | I | N | G |
|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| K | 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| I | 2 | 2 | 1 | 2 | 3 | 4 | 5 | 6 |
| T | 3 | 3 | 2 | 1 | 2 | 3 | 4 | 5 |
| T | 4 | 4 | 3 | 2 | 1 | 2 | 3 | 4 |
| E | 5 | 5 | 4 | 3 | 2 | 2 | 3 | 4 |
| N | 6 | | | | | | | |

S C C C S

| | | S | I | T | T | I | N | G |
|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| K | 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| I | 2 | 2 | 1 | 2 | 3 | 4 | 5 | 6 |
| T | 3 | 3 | 2 | 1 | 2 | 3 | 4 | 5 |
| T | 4 | 4 | 3 | 2 | 1 | 2 | 3 | 4 |
| E | 5 | 5 | 4 | 3 | 2 | 2 | 3 | 4 |
| N | 6 | 6 | 5 | 4 | 3 | 3 | 2 | 3 |

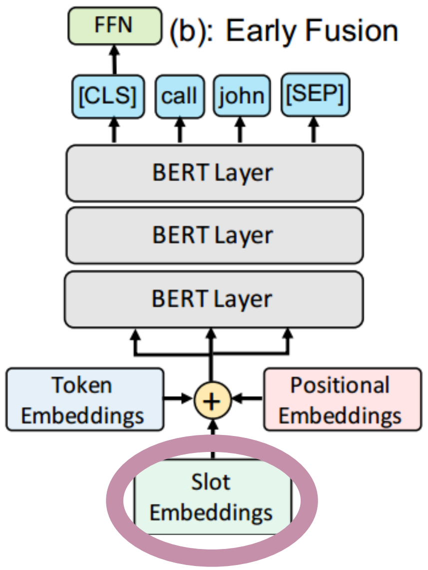
S C C C S C

| | | S | I | T | T | I | N | G |
|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| K | 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| I | 2 | 2 | 1 | 2 | 3 | 4 | 5 | 6 |
| T | 3 | 3 | 2 | 1 | 2 | 3 | 4 | 5 |
| T | 4 | 4 | 3 | 2 | 1 | 2 | 3 | 4 |
| E | 5 | 5 | 4 | 3 | 2 | 2 | 3 | 4 |
| N | 6 | 6 | 5 | 4 | 3 | 3 | 2 | 3 |

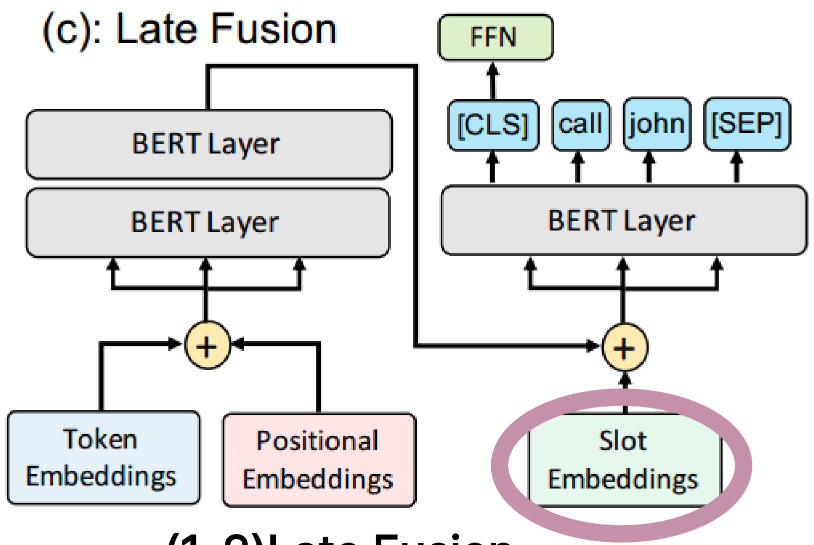
S C C C S C I → 3(not C)

# III. Personalized Approaches

## (1) Gazetteers 적용 2가지 방식; early fusion & late fusion




(1-1)Early Fusion




(1-2)Late Fusion

- Original: $s_i = f \circ g(E_t(x_i) + E_p).$

  ➔ f(FFN), g(BERT layer), $x_i$ = hypothesis token, $E_t(x_i)$=TE, $E_p$=PE

* Ex of slot: 영화 제목, 노래 제목

- Gazetteers: 토큰 임베딩 + 위치 임베딩 + 슬롯 임베딩
  - Early: $s_i = f \circ g(E_t(x_i) + E_p + E_s(y_i)),$
  - Late : $s_i = f \circ g_n\left(E_s + g_{n-1} \circ \cdots \circ g_1(E_t + E_p)\right).$

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# III. Personalized Approaches

(2) Natural Language prompting

## (2) **Natural Language Prompting**

**Match Condition:** 문장 일부 ⊂ 집합 D{ = 토큰화된 문자열, …}

Ex) I want you to call Felix(call [entity])

**Prompt:** 원문+ 구(증강 프롬프트)

Ex) I want you call to Felix as I need to contact Felix

(as I need to contact [Entity])

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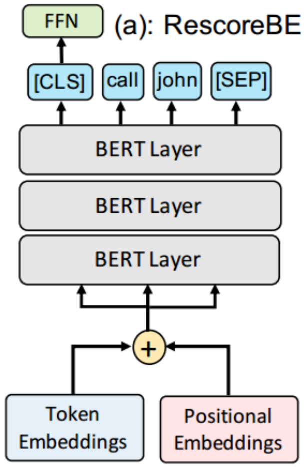
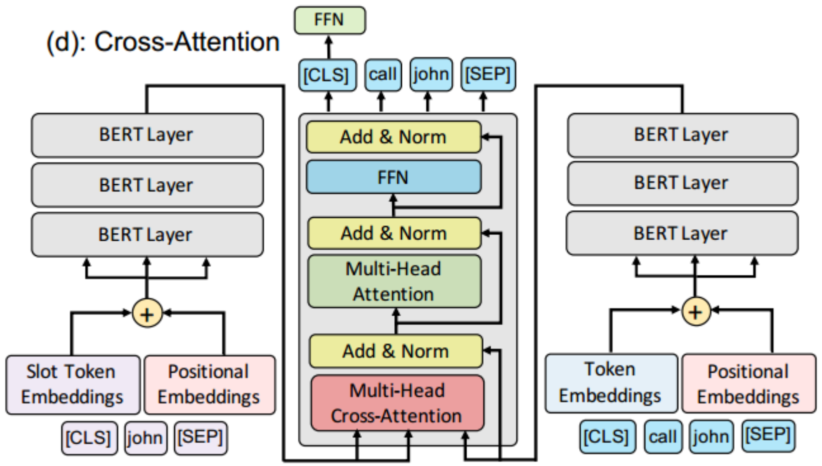
# III. Personalized Approaches

(3)Cross Attention based encoder-decoder model




(0)RescoreBERT(baseline)




(3)Cross Attention based encoder-decoder model

(3) **Cross Attention based encoder-decoder model**

$Z_i$: 슬롯 토큰 시퀀스

ex) [CLS] [entity #1] [SEP] [entity #2] [SEP] $\cdots$ [SEP].

$$X_i = g(E_t(x_i) + E_p)$$
$$Z_i = g(E_t(z_i) + E_p)$$
$$s_i = f \circ m(Z_i, X_i),$$

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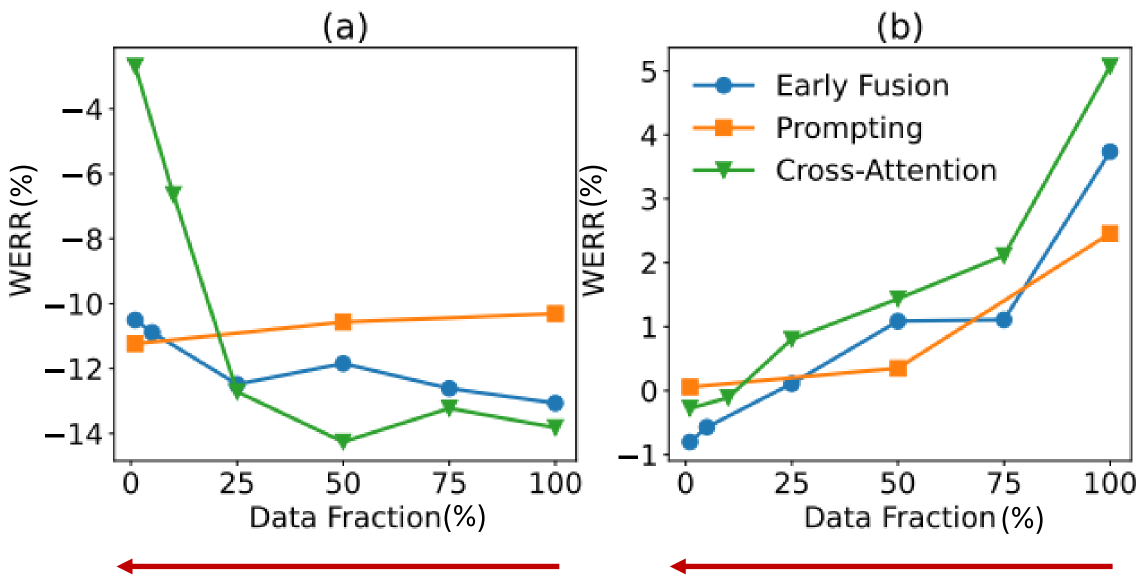
# IV. Result of Experiments




## Explanation

- 데이터: 개인화된 개체명 포함하는 Alexa 데이터
- 목적: 개인화 내용에서의 WER ↓
- X축: 개인화된 개체 데이터 비율
- 실험진행방향: 일반화 데이터 추가되는 방향(반대)
- L/R: 개인화 / 일반화 테스트 집합

## (1) NL Prompting

- (2) & (3) 성능의 중간
- 無학습 WERR -7% & 일반화데이터 성능 매우 약간↓ (학습 데이터↓시 유용)

## (2) Cross Attention

- 데이터 비율에 민감(L 왼쪽방향 급격한 상승)
- 일반화에서 성능↓

## (3) Gazetteers(Early Fusion)

- L: <= -10 % WERR
- R: WER 유일 감소( < 0 )

# Thank you

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2024.01.26