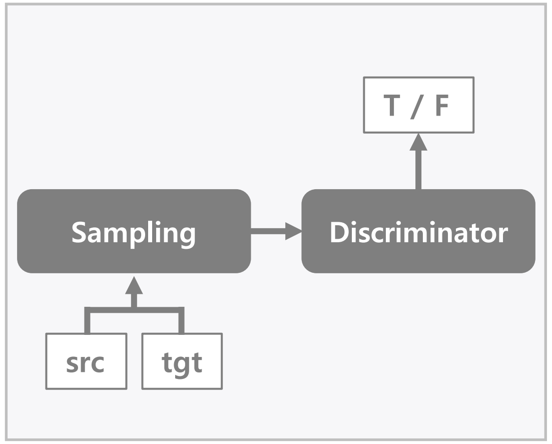
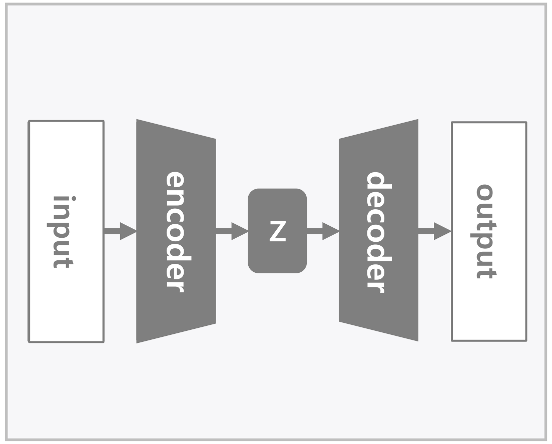
Unsupervised Machine Translation Using Monolingual Corpora Only

집현전 중급 14조 이원호 김택현 양수영

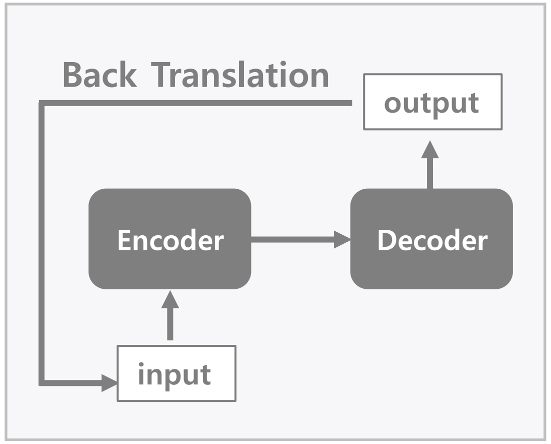
Before we start



Adversarial Learning

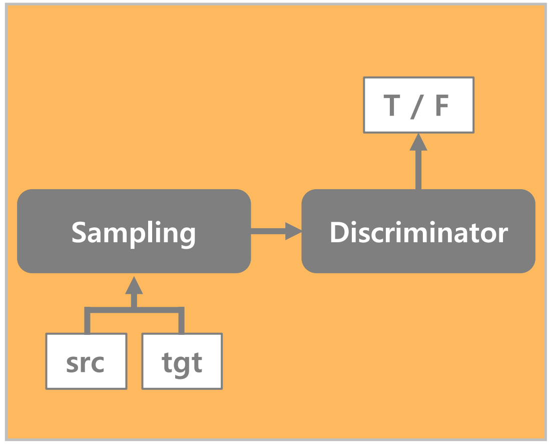


Auto Encoding



Back Translation

Before we start



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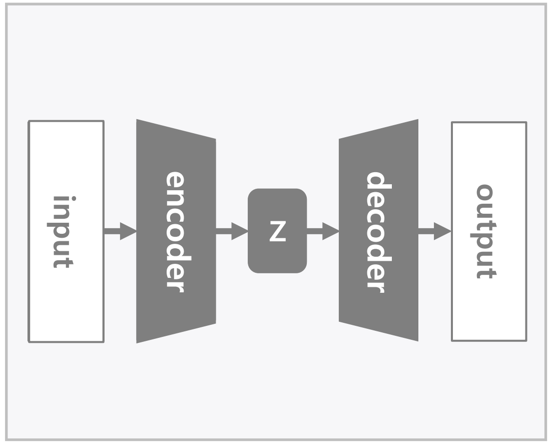

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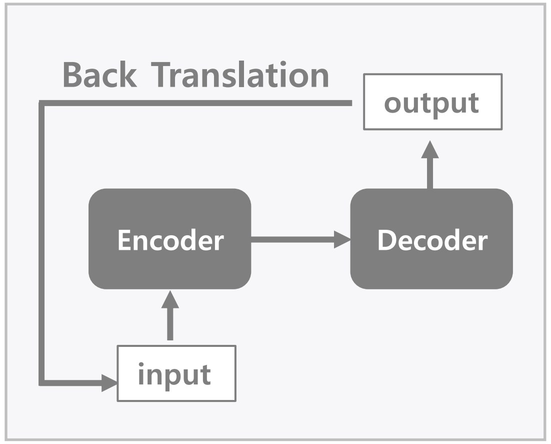


Back Translation

Before we start

Adversarial Attack

이미 훈련된 모델에 대해 입력 데이터를 조작해 잘못 예측하도록 함

방어책

- Adversarial Training

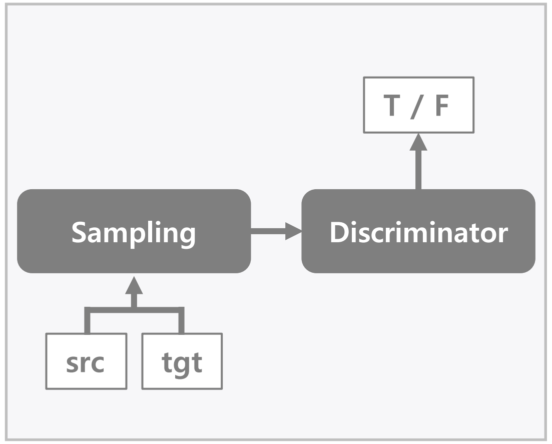
  입력 데이터와 조작된 데이터 간의 구분을 위한 새로운 신경망을 학습시켜

  모델이 임의로 조작된 데이터를 받지 않아도 이를 학습할 수 있는 방식

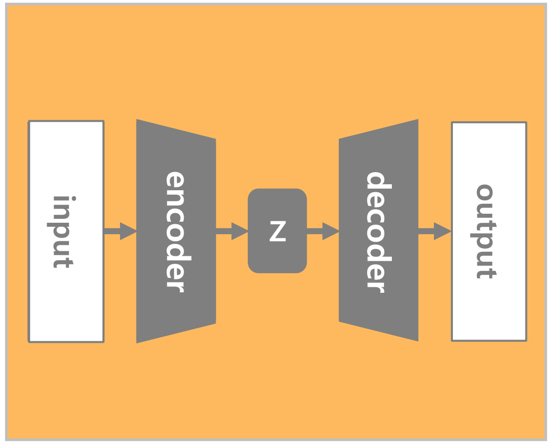
- Defensive Distillation

  조작된 데이터까지 모델에 학습시키는 방식

Before we start



Adversarial Learning



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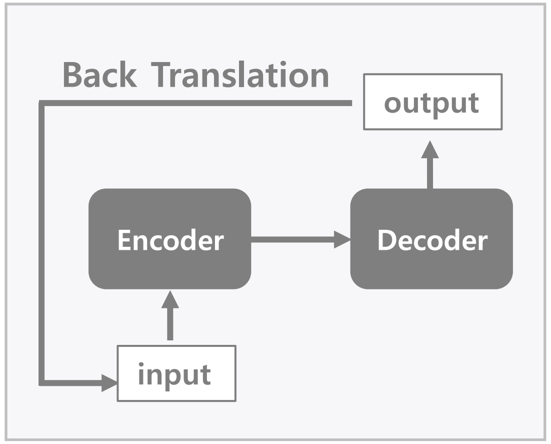
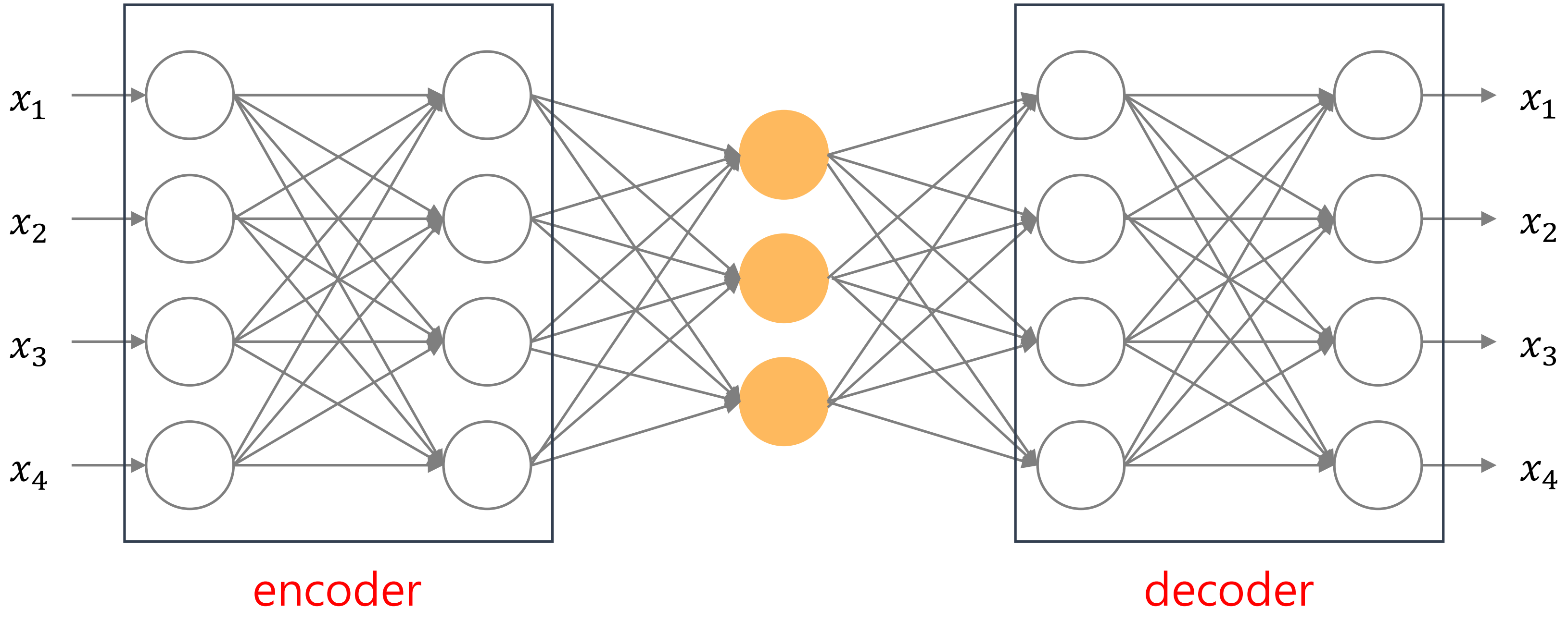


Back Translation

Before we start

Auto Encoder

- 출력이 입력 데이터와 같아지도록 학습한 네트워크
- 차원 축소, noise 제거, 이상 데이터 검출, pre-train 등에 활용



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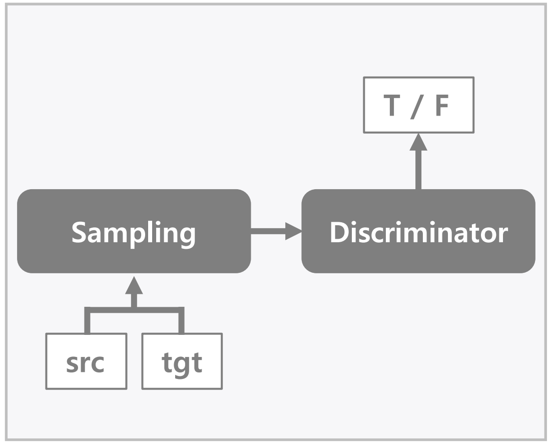
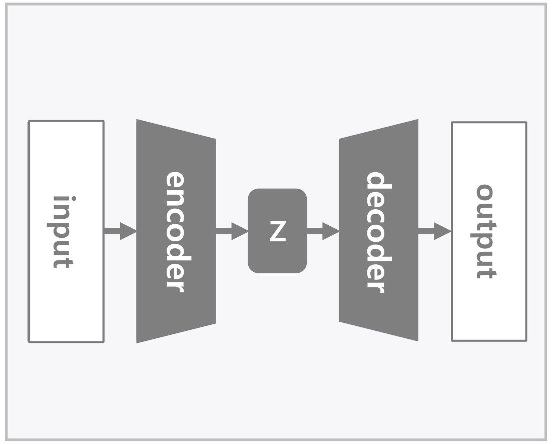


Adversarial Learning



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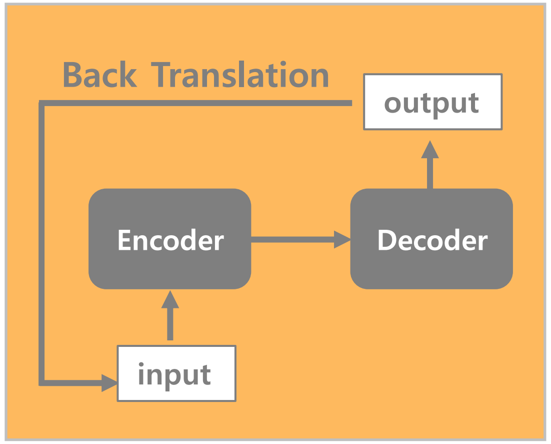

Back Translation

Before we start

Improving Neural Machine Translation Models with Monolingual Data

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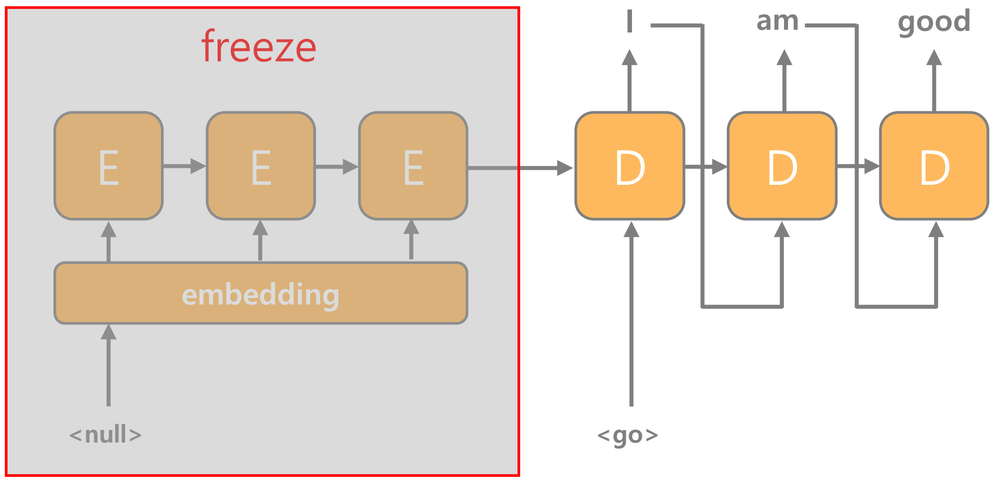
{rico.sennrich,a.birch}@ed.ac.uk,bhaddow@inf.ed.ac.uk

기존 Machine Translation Model과 달리 Monolingual Data로 학습이 가능한 방법을 제안

- Dummy Source Sentence
- Synthetic Source Sentence → **Back Translation**

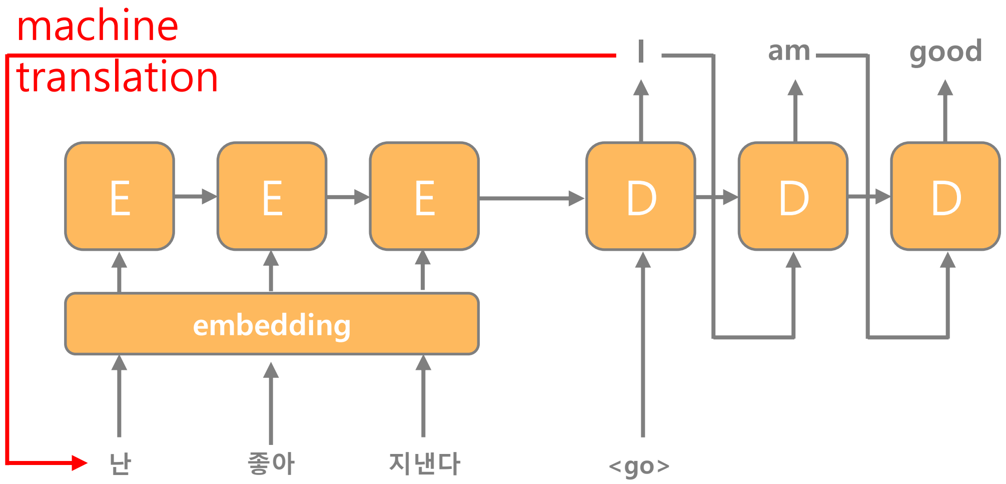
Before we start

Dummy Source Sentence



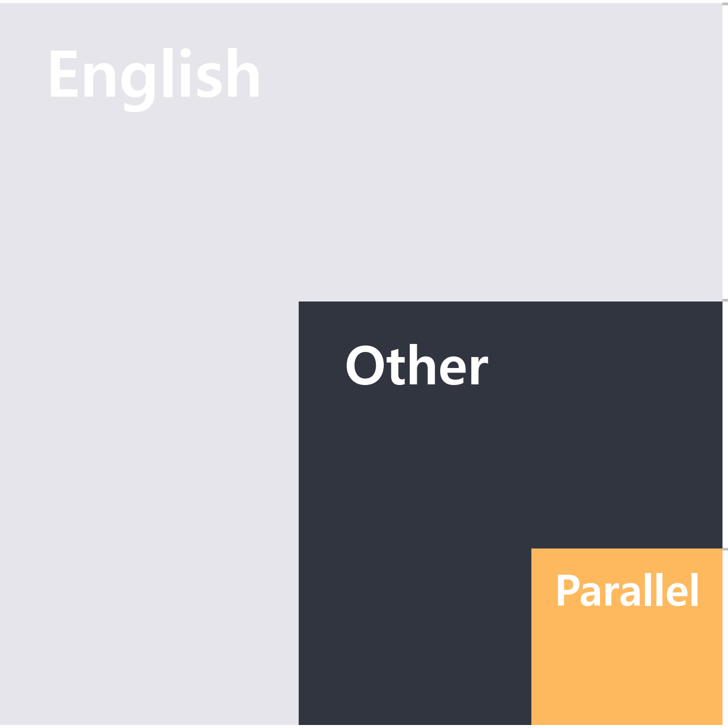
Encoder - dummy값, Decoder - target sentence가 되도록
한 뒤 Encoder의 parameter를 갱신되지 않도록 하며 학습

Synthetic Source Sentenece



Encoder에 인공적으로 만든 source sentence를 넣어 학습
인공데이터 생성 과정 = Back translation

Unsupervised Translation



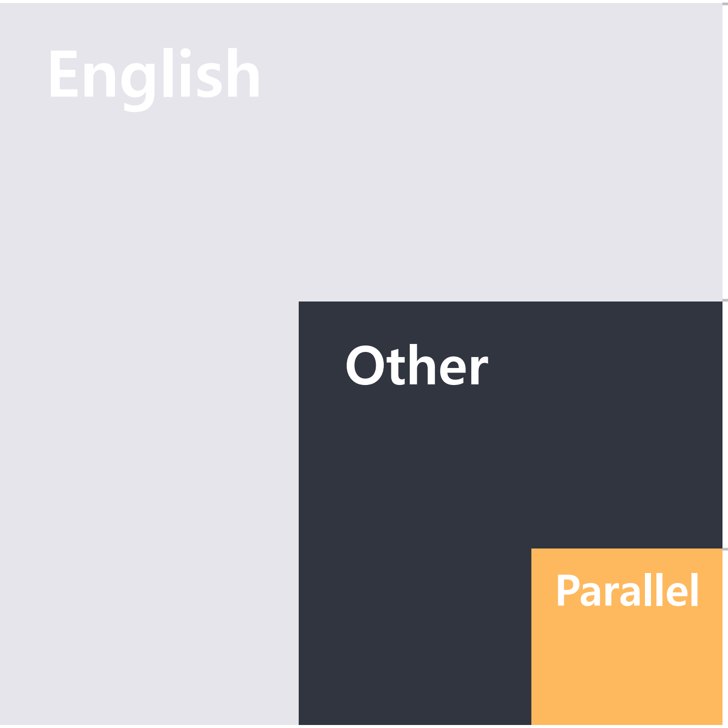
ENGLISH CORPUS

OTHER CORPUS

PARALLEL SENTENCE

- 구축에 전문 지식 필요
- 구축에 많은 비용 소요

Unsupervised Translation



ENGLISH CORPUS

OTHER CORPUS

- low resource 언어는 parallel corpus가 없음
- 단일 언어로 이루어진 corpus는 있음

PARALLEL SENTENCE

Method - Overview

- D_{src} : a dataset of sentences in the source domain
- D_{tgt} : another dataset in the target domain

- Naïve한 unsupervised translation model M
  → word-by-word translation

- 문장을 drop, swap하여 noise를 만듦
- D_{src}, D_{tgt}의 latent distribution을 align하기 위해 adversarial setting사용

- Noise가 있는 문장을 encoder, decoder로 번역
- Reconstruct 와 translation을 측정하는 object function이 최소화되도록 학습

- 이렇게 학습된 encoder와 decoder를 다음 iteration에서 사용

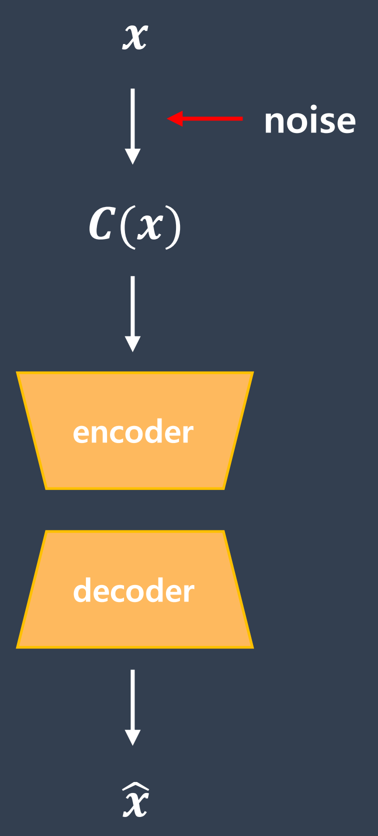
Method - Detail

Denoising Auto-Encoding

- D_{src}, D_{tgt} 간에 latent space를 만들기 위한 단계
- Source sentence x 에 noise를 주어 $C(x)$로 만듦
- $C(x)$를 encoder, decoder 통과 시켜 $\hat{x}$으로 만듦
- x와 $\hat{x}$을 latent space에 투영하여 거리를 가깝게 만듦

Object function

$$L_{auto}(\theta_{enc}, \theta_{dec}, Z, l) = E_{x\sim D_l, \hat{x}\sim d(e(C(x),l,l)}[\Delta(\hat{x}, x)]$$



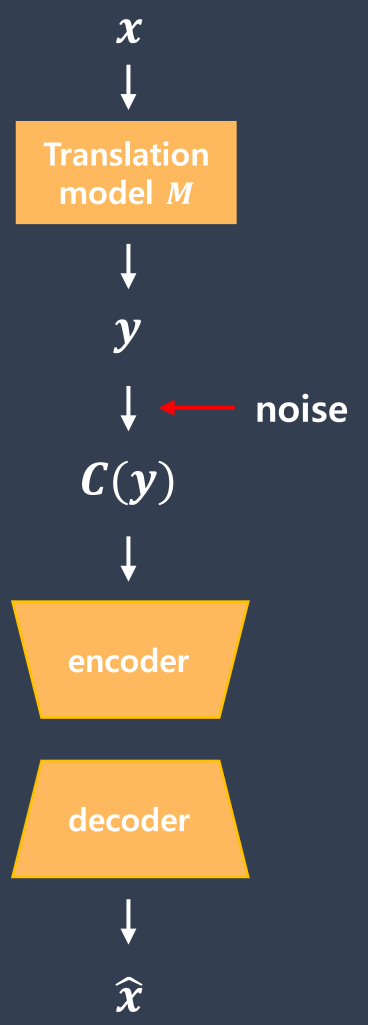
Method - Detail

Cross Domain Training

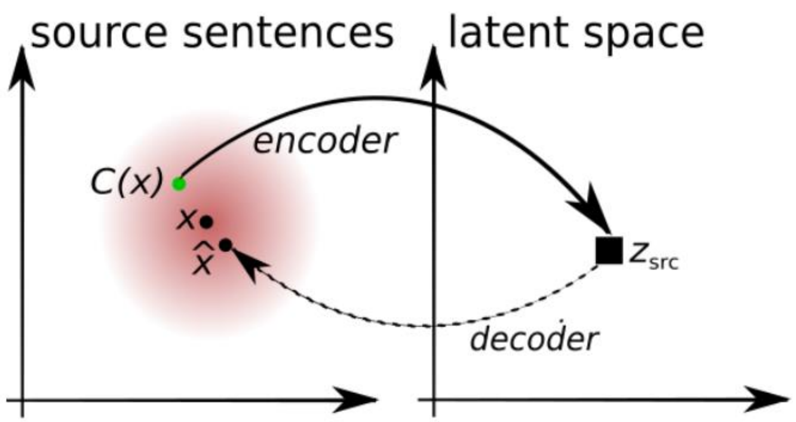
- D_{l_1}의 sentence를 D_{l_2}로 mapping하는 단계

Loss

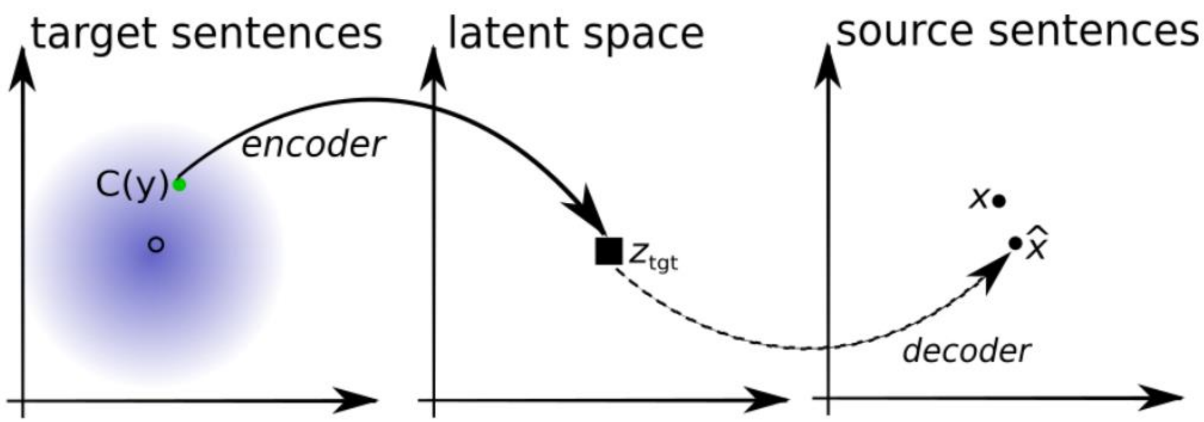
$$L_{cd}(\theta_{enc},\theta_{dec},Z,l_1,l_2) = E_{x\sim D_{l_1},\hat{x}\sim d(e(C(M(x)),l_1,)l_2)}[\Delta(\hat{x},x)]$$



Method - Detail



Denoising Auto Encoding



Cross Domain Training

Method - Detail

Adversarial Training

- Decoder에 encoder의 output과 비슷한 값을 input으로 줌
- Discriminator가 input문장이 D_{src}, D_{tgt} 중 어디에 속하는지 예측
- Encoder는 discriminator를 속이도록 학습

Objective Function

$$L(\theta_{enc}, \theta_{dec}, Z) = \lambda_{auto}[L_{auto}(\theta_{enc}, \theta_{dec}, Z, src) + L_{auto}(\theta_{enc}, \theta_{dec}, Z, tgt)] +$$

$$\lambda_{cd}[L_{cd}(\theta_{enc}, \theta_{dec}, Z, src, tgt) + L_{cd}(\theta_{enc}, \theta_{dec}, Z, tgt, src)] +$$

$$\lambda_{adv} L_{adv}(\theta_{enc}, Z | \theta_D)$$

Training Strategy

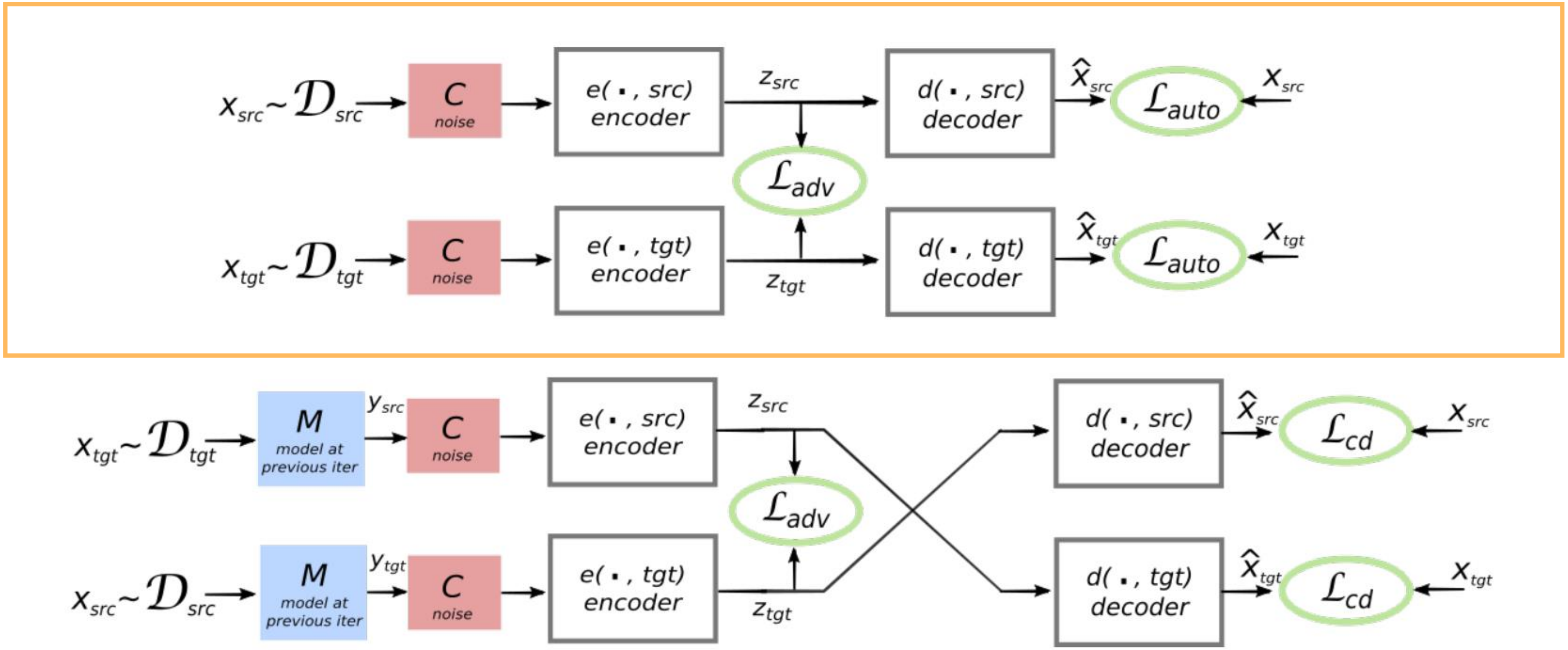
Interative Training

- Parallel word dictionary를 활용한 M의 번역이 input의 최소한의 정보를 담고 있다고 가정
- Noisy한 input이지만 denoising auto encoder이기에 latent feature space에 잘 mapping
- 이에 따라 decoder도 noiseless한 번역을 생성
- 같은 과정을 반복

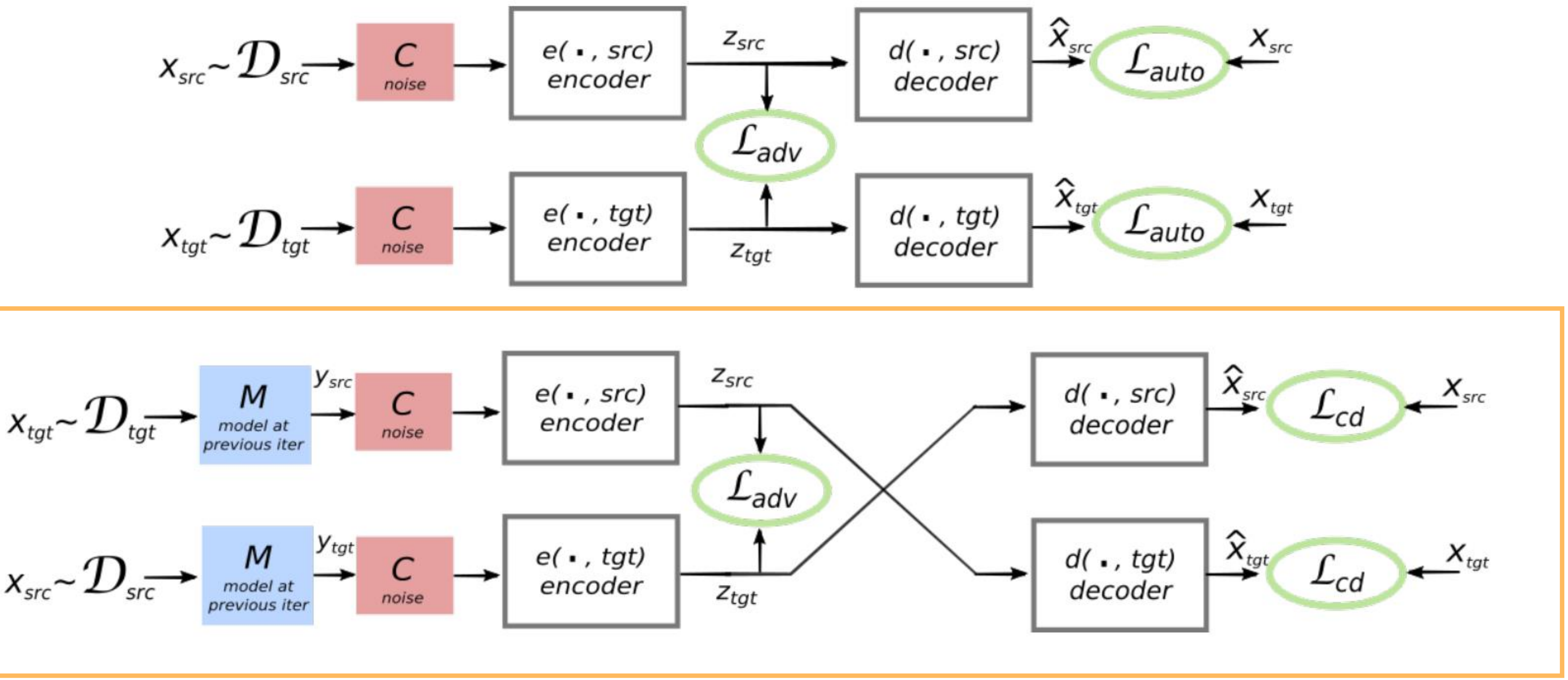
Algorithm 1 Unsupervised Training for Machine Translation

procedure TRAINING($\mathcal{D}_{src}, \mathcal{D}_{tgt}, T$)
  Infer bilingual dictionary using monolingual data (Conneau et al., 2017)
  $M^{(1)} \leftarrow$ unsupervised word-by-word translation model using the inferred dictionary
  for $t = 1, T$ **do**
    using $M^{(t)}$, translate each monolingual dataset
    // discriminator training & model training as in eq. 4
    $\theta_{\text{discr}} \leftarrow \arg\min \mathcal{L}_D, \quad \theta_{\text{enc}}, \theta_{\text{dec}}, \mathcal{Z} \leftarrow \arg\min \mathcal{L}$
    $M^{(t+1)} \leftarrow e^{(t)} \circ d^{(t)}$ // update MT model
  end for
  return $M^{(T+1)}$
end procedure

Training Strategy



Training Strategy



Training Strategy

Criterion

- Parallel dataset이 아니기 때문에 번역의 품질 평가 어려움
- 따라서 input을 2step 번역을 통해 재구성하여 재구성한 문장과 input을 비교
- D_{src}, D_{tgt} 을 각각 비교하여 평균점수가 가장 높은 model 선택

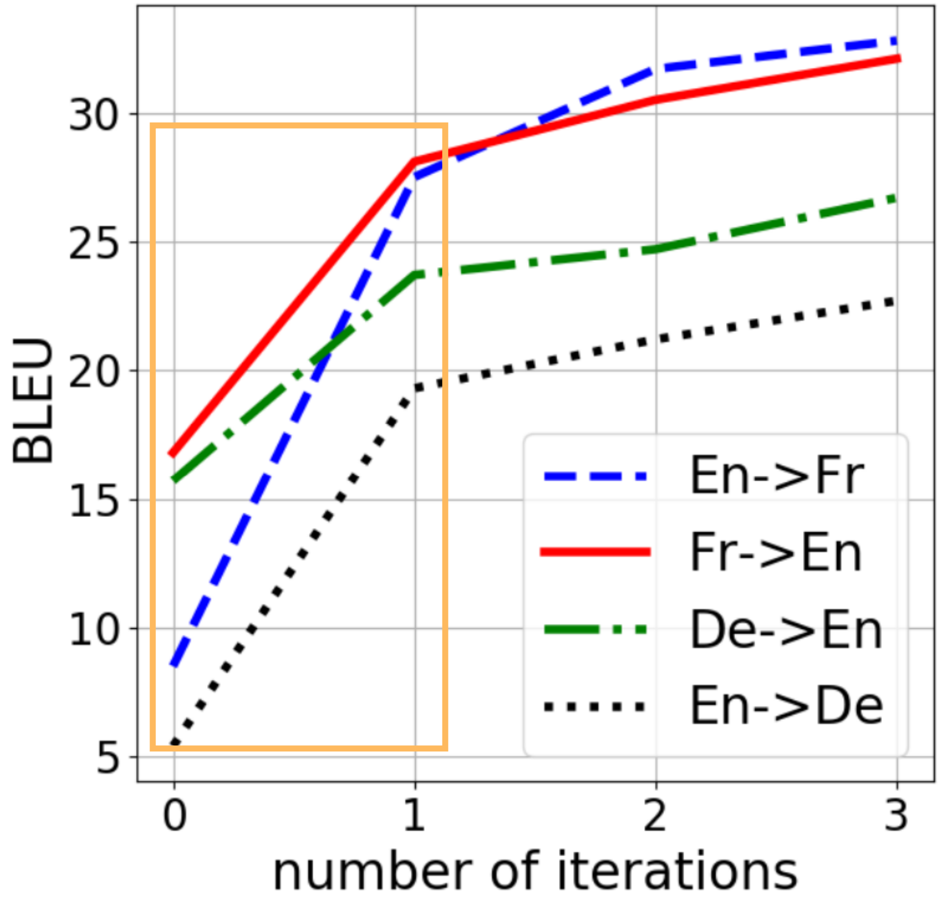
$$
\begin{aligned}
MS(e, d, \mathcal{D}_{src}, \mathcal{D}_{tgt}) \quad = \quad & \frac{1}{2}\mathbb{E}_{x\sim\mathcal{D}_{src}}\left[\mathrm{BLEU}(x, M_{src\to tgt}\circ M_{tgt\to src}(x))\right] + \\
& \frac{1}{2}\mathbb{E}_{x\sim\mathcal{D}_{tgt}}\left[\mathrm{BLEU}(x, M_{tgt\to src}\circ M_{src\to tgt}(x))\right]
\end{aligned}
$$

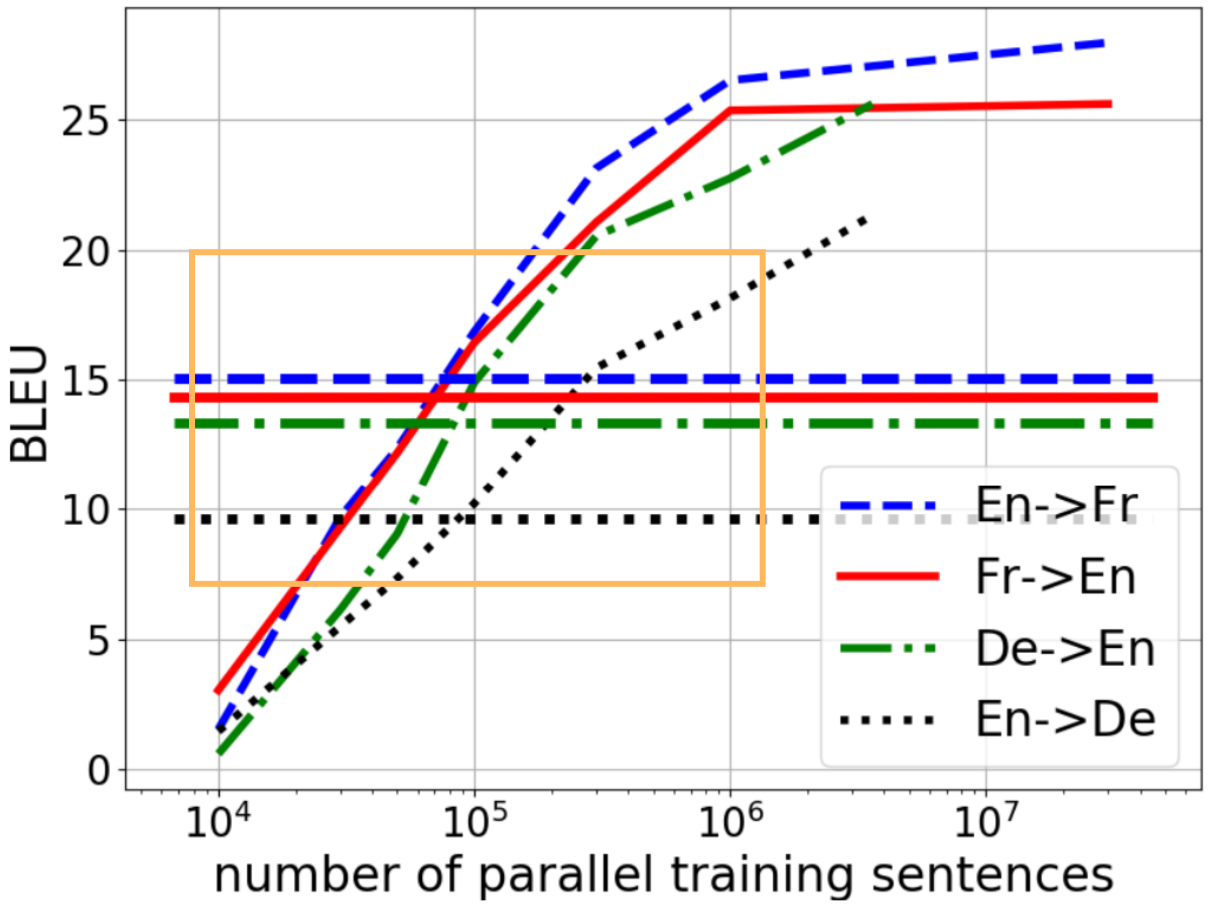
Experiment Results

	Multi30k-Task1				WMT			
	en-fr	fr-en	de-en	en-de	en-fr	fr-en	de-en	en-de
Supervised	56.83	50.77	38.38	35.16	27.97	26.13	25.61	21.33
word-by-word	8.54	16.77	15.72	5.39	6.28	10.09	10.77	7.06
word reordering	-	-	-	-	6.68	11.69	10.84	6.70
oracle word reordering	11.62	24.88	18.27	6.79	10.12	20.64	19.42	11.57
Our model: 1st iteration	27.48	28.07	23.69	19.32	12.10	11.79	11.10	8.86
Our model: 2nd iteration	31.72	30.49	24.73	21.16	14.42	13.49	13.25	9.75
Our model: 3rd iteration	32.76	32.07	26.26	22.74	15.05	14.31	13.33	9.64

Table 2: **BLEU score on the Multi30k-Task1 and WMT datasets** using greedy decoding.

Experiment Results





Ablation

- Word를 alignment하는 것
- Latent sentence representation의 분포(adversarial component)
- Input에 corruption을 주는 것

	en-fr	fr-en	de-en	en-de
$\lambda_{cd} = 0$	25.44	27.14	20.56	14.42
Without pretraining	25.29	26.10	21.44	17.23
Without pretraining, $\lambda_{cd} = 0$	8.78	9.15	7.52	6.24
Without noise, $C(x) = x$	16.76	16.85	16.85	14.61
$\lambda_{auto} = 0$	24.32	20.02	19.10	14.74
$\lambda_{adv} = 0$	24.12	22.74	19.87	15.13
Full	**27.48**	**28.07**	**23.69**	**19.32**

Table 4: **Ablation study on the Multi30k-Task1 dataset.**

Question and Answer

Thank You ☺