

GANs

GENERATIVE ADVERSARIAL NETWORKS

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WiFi : SG-Guest

Problems with Installation? **ASK!**

PLAN OF ACTION

TODAY

- SGInnovate : Careers
- GANs ++
- Personal Project work

PLAN OF ACTION

WEDNESDAY

- Mobile
- Personal Project work

PLAN OF ACTION

27-NOV

- Finalize Projects

PERSONAL PROJECTS

- Form to fill in
- Plan to finish : **27**-Nov (last session)
- WSG DEADLINE : 30-Nov, including write-ups :
 - "Punchy Headline"
 - Minimum : README.md on GitHub page
 - Hosted slides / demo
 - Lightning Talk

GPU REQUIREMENTS

- Show of hands :
 - I have GPU(s), need more
 - I have got enough GPU lined up
 - I have no GPU and training v. painful
 - I have no GPU and it should be fine

SGINNOVATE



Looking for opportunities?
We find and match you to jobs based on
your skills and interests.

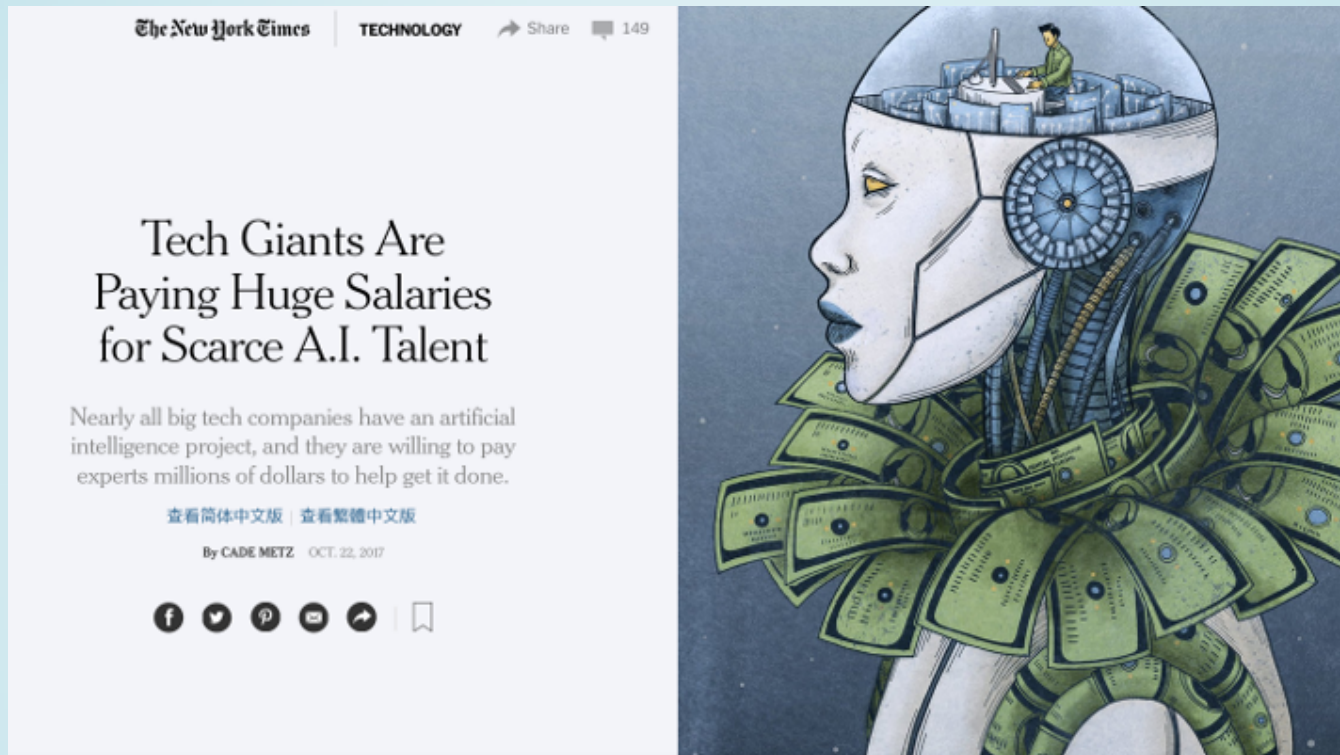
+65

PHONE NUMBER

APPLY

<http://bit.ly/2ialg60>
nicolette @ sginnovate.com

NEW YORK TIMES



[Article Link](#)

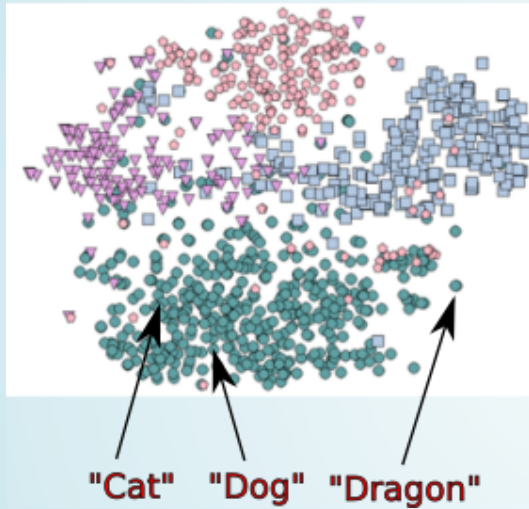
LEARNING TO TRANSLATE

WORD DICTIONARY

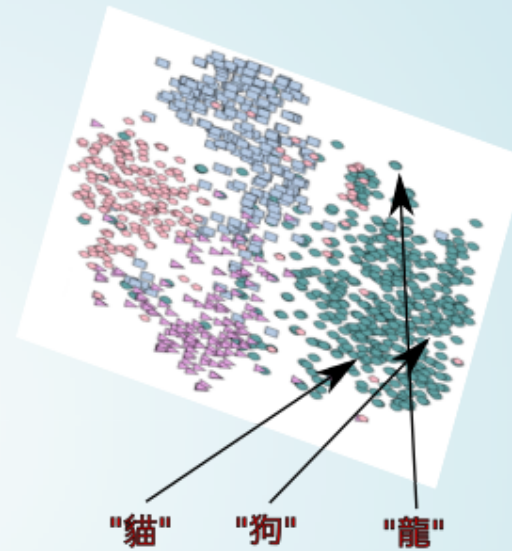
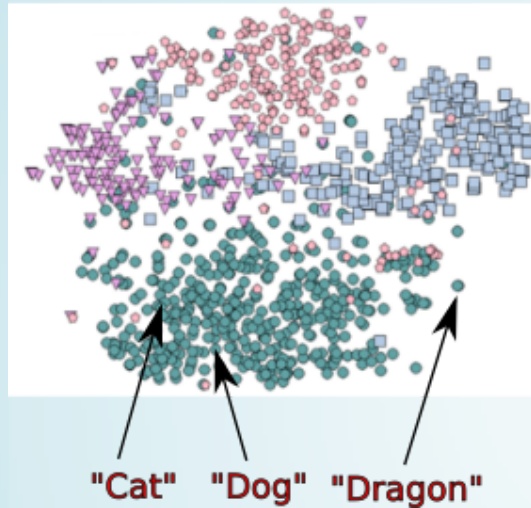
- Word Embedding picture
- Two Word Embeddings
- 5000 sample translations

WORD EMBEDDING

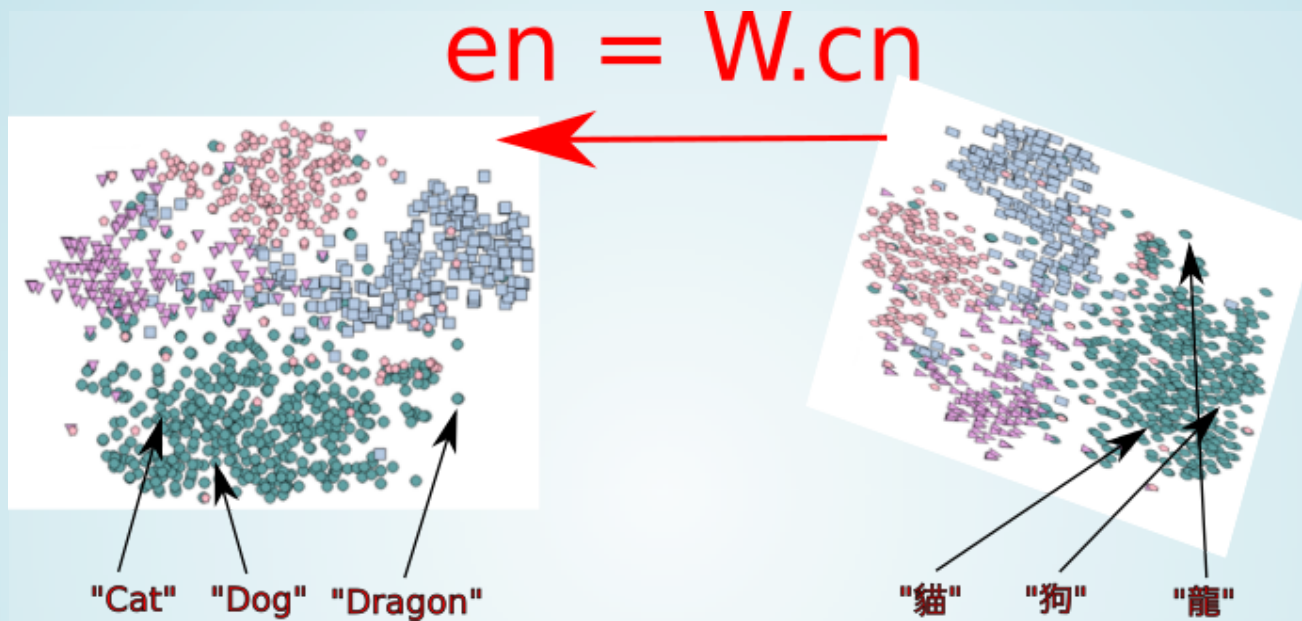
EG: 300D GLOVE



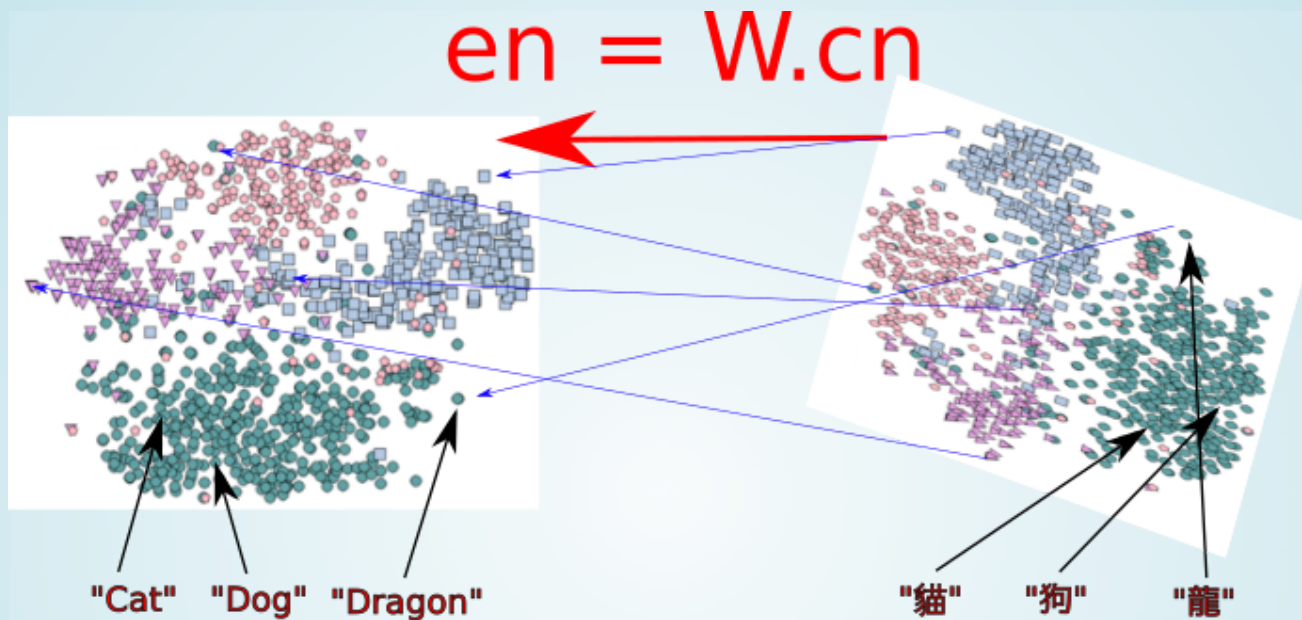
WORD EMBEDDINGS



EMBEDDING TRANSFORM?



EMBEDDING MATCHES



Exploiting Similarities among
Languages for Machine Translation

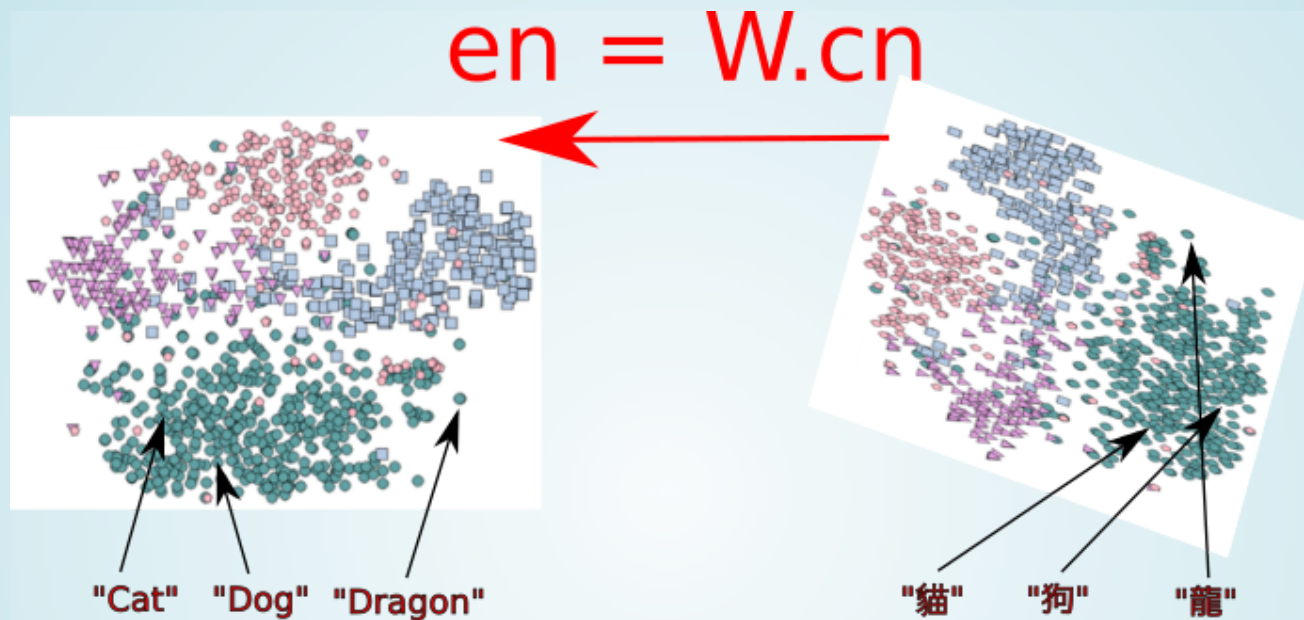
Need ~ 5000 translation pairs to make it work

LEARNING TO TRANSLATE

WORD DICTIONARY FROM ZERO

- 0 sample translations :
 - Initial random mapping
 - Change mapping until 'similar enough'
 - Find 5000 corresponding words
 - Potentially redo a few times
- Now have 5000 word sample 'translations'

GUESS THE TRANSFORM



Word Translation Without Parallel Data (Oct 2017)

SPOT THE DIFFERENCE

TRICK : DISTRIBUTION

- Train **a network** to tell apart :
 - random english words; from
 - random chinese words transformed by W
- Train both the network and the W parameters :
 - Optimise network to categorise well
 - Optimise elements of W to fool the detector

SPOT THE DIFFERENCE

TRICK: CONNECTIVITY

- Find examples of en and W. cn words :
 - That have the same 'local' similarity
 - How close are they to nearest neighbours ... in other language?
 - Good 'local similarity' ~ similar 'role'
- Pick 5000 of the 'good' matches
- Use them in the previous method

DICTIONARY FROM ZERO

RESULTS

	English to Italian			Italian to English		
	P@1	P@5	P@10	P@1	P@5	P@10
<i>Methods with cross-lingual supervision</i>						
Mikolov et al. (2013b) [†]	33.8	48.3	53.9	24.9	41.0	47.4
Dinu et al. (2015) [†]	38.5	56.4	63.9	24.6	45.4	54.1
CCA [†]	36.1	52.7	58.1	31.0	49.9	57.0
Artetxe et al. (2017)	39.7	54.7	60.5	33.8	52.4	59.1
Smith et al. (2017) [†]	43.1	60.7	66.4	38.0	58.5	63.6
Procrustes - CSLS	44.9	61.8	66.6	38.5	57.2	63.0
<i>Methods with cross-lingual supervision (Wiki)</i>						
Procrustes - CSLS	63.7	78.6	81.1	56.3	76.2	80.6
<i>Methods without cross-lingual supervision (Wiki)</i>						
Adv - Refine - CSLS	66.2	80.4	83.4	58.7	76.5	80.9

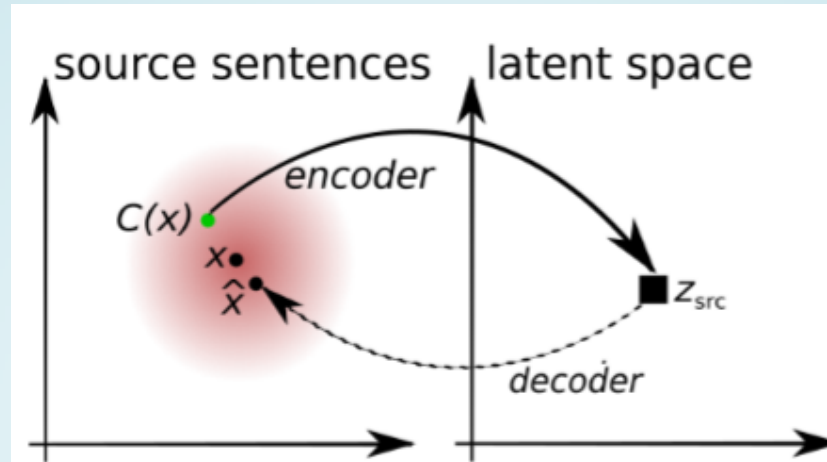
Word Translation Without Parallel Data (Oct 2017)

LEARNING TO TRANSLATE

SENTENCES FROM ZERO

- Unsupervised Machine Translation Using Monolingual Corpora Only (Nov 2017)
- Basic approach :
 - Learn to fix sentences in each language
 - First translation : word-by-word using dictionary
 - Iteratively fix-up the result
- No translations required

FIX UP SENTENCES

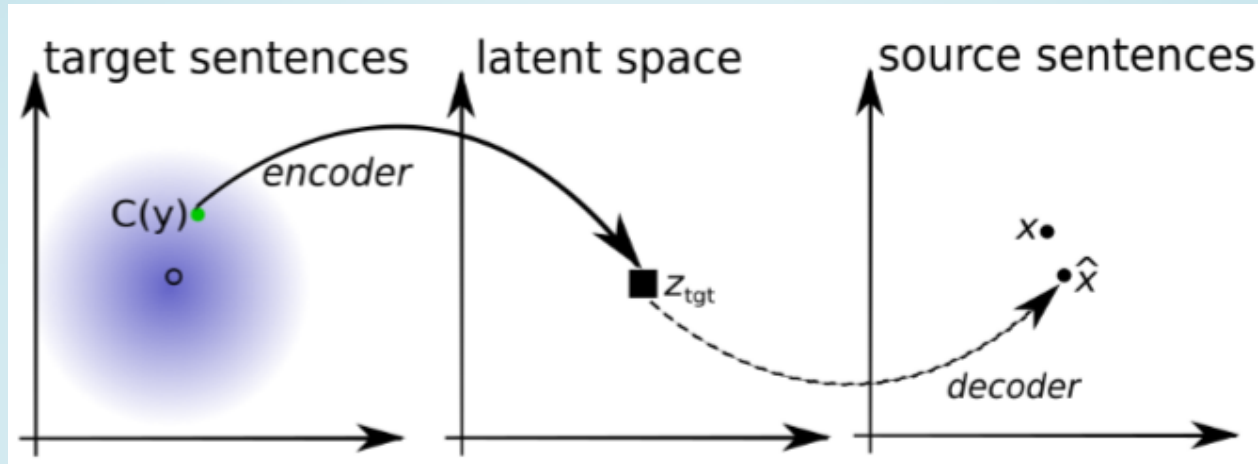


Corrupt sentences by dropping or switching words
Do this in both languages with same 'latent' space

LANGAUGE MODELS

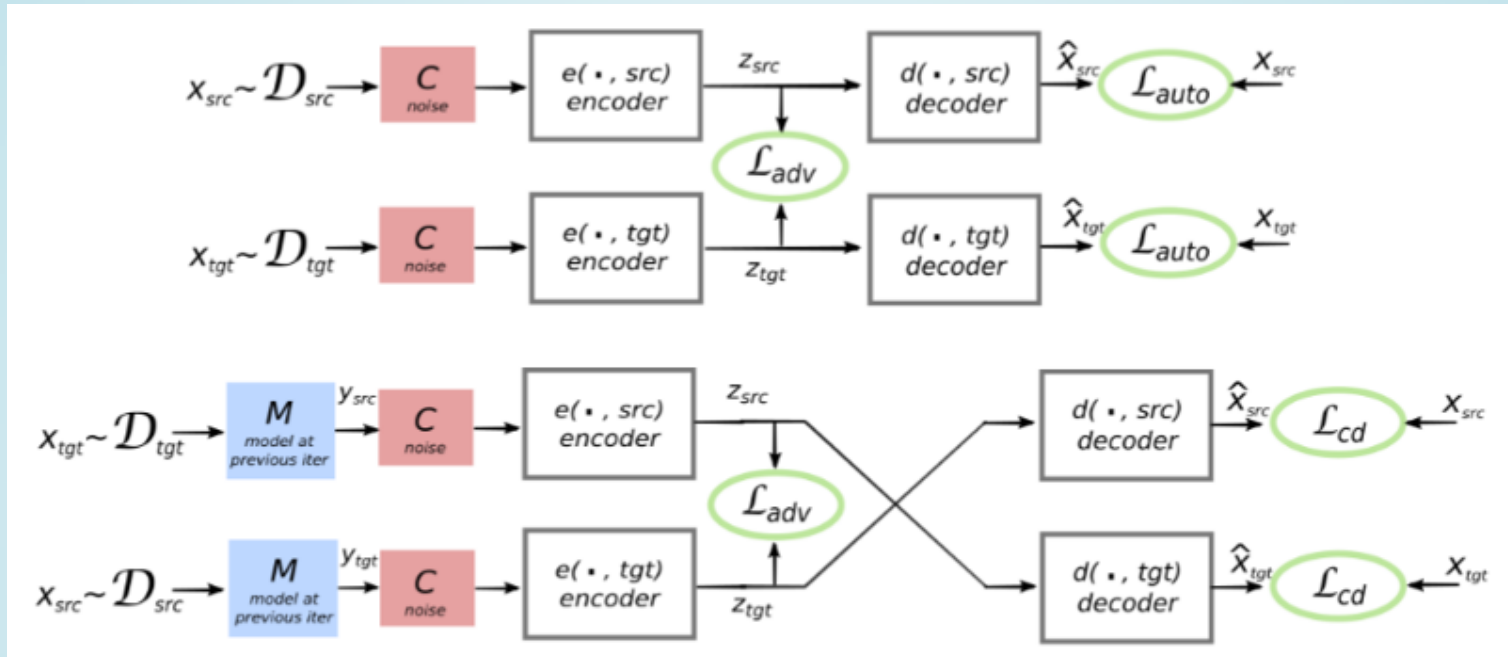
- Translation model :
 - Encoder : LSTM (to latent space vectors)
 - Decoder : LSTM with attention over latent
- Same model used in both directions with different embedding dictionaries

FIX UP TRANSLATION



Take a bad translation and fix it up

MATCH DISTRIBUTIONS



Three different Losses to fix at same time
This changes Encoder & Decoder

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

Similar to system with 100k sample translations...

SAMPLES

Source	un homme est debout près d' une série de jeux vidéo dans un bar .
Iteration 0	a man is seated near a series of games video in a bar .
Iteration 1	a man is standing near a closeup of other games in a bar .
Iteration 2	a man is standing near a bunch of video video game in a bar .
Iteration 3	a man is standing near a bunch of video games in a bar .
Reference	a man is standing by a group of video games in a bar .
Source	une femme aux cheveux roses habillée en noir parle à un homme .
Iteration 0	a woman at hair roses dressed in black speaks to a man .
Iteration 1	a woman at glasses dressed in black talking to a man .
Iteration 2	a woman at pink hair dressed in black speaks to a man .
Iteration 3	a woman with pink hair dressed in black is talking to a man .
Reference	a woman with pink hair dressed in black talks to a man .
Source	une photo d' une rue bondée en ville .
Iteration 0	a photo a street crowded in city .
Iteration 1	a picture of a street crowded in a city .
Iteration 2	a picture of a crowded city street .
Iteration 3	a picture of a crowded street in a city .
Reference	a view of a crowded city street .

Table 2: **Unsupervised translations.** Examples of translations on the French-English pair of the Multi30k-Task1 dataset. Iteration 0 corresponds to word-by-word translation. After 3 iterations, the model generates very good translations.

- QUESTIONS -

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My blog : <http://mdda.net/>

GitHub : [mdda](#)