How does it work? Google Translate

CSE 705

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Background and Motivation

Why do we need it?

- You’re at a foreign country, and you need help with directions - locals don't know the languages you speak
- Friends talking smack behind your back in a different language
- Talking about numbers, about 50% of information on the web is in English, but only 20% know English
- Human only translation approach is too expensive or too slow to translate for personal work i.e. you can’t always have a human translator
- A lot of times, a completely accurate translation isn’t necessary

Non-ML based approach

- Word-Phrase translation
- Also known as PBMT (Phrase Based Machine Translation)
- Involves usage of a look-up table (LUT)
- Word/Phrase in a language is mapped to another word/phrase in the resulting language
- That seems pretty easy, right?

English Greetings in French	
good morning	bonjour
good evening	bonsoir
good night	bonne nuit
goodbye	au revoir
hi / bye	salut
thank you	merci
thank you very much	merci beaucoup

Problems with Non-ML approach

- Any language has two components
  - **Tokens**
  - **Grammar**
- Grammar defines the arrangement of tokens such that a given sequence of tokens makes sense
- Word-Word and Phrase Translations do not incorporate grammar and are very naive approaches

Sentence:

"It is a beautiful day"

Word-Phase Translation (French):

"Ce-est-un-belle-le jour"

(It) (is) (a) (beautiful) (day)

Translation:

"C'est une belle journée"

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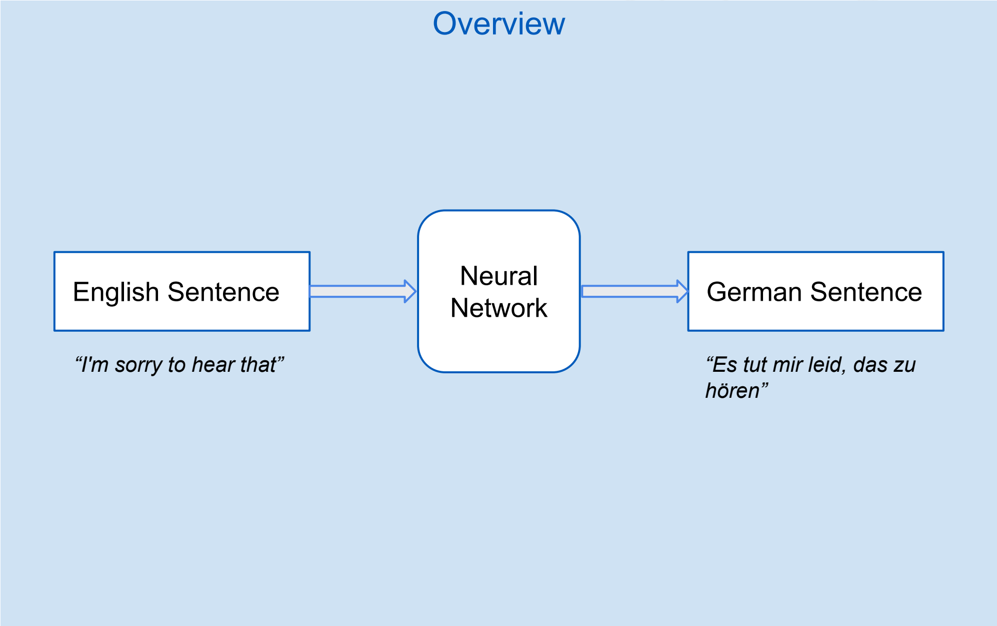
Neural Machine translation

Modeling the problem

- Sentence to Sentence translation over word-word/phrase
- Model sequences to another sequence
  - English sentence to German sentence
  - Input sequence → Translator → Output Sequence
- Input and output shapes might be different
  - Depends on language
- *Syntax* is important - correct grammatical structure
- *Semantics* i.e. the resultant sentence has some contextual meaning

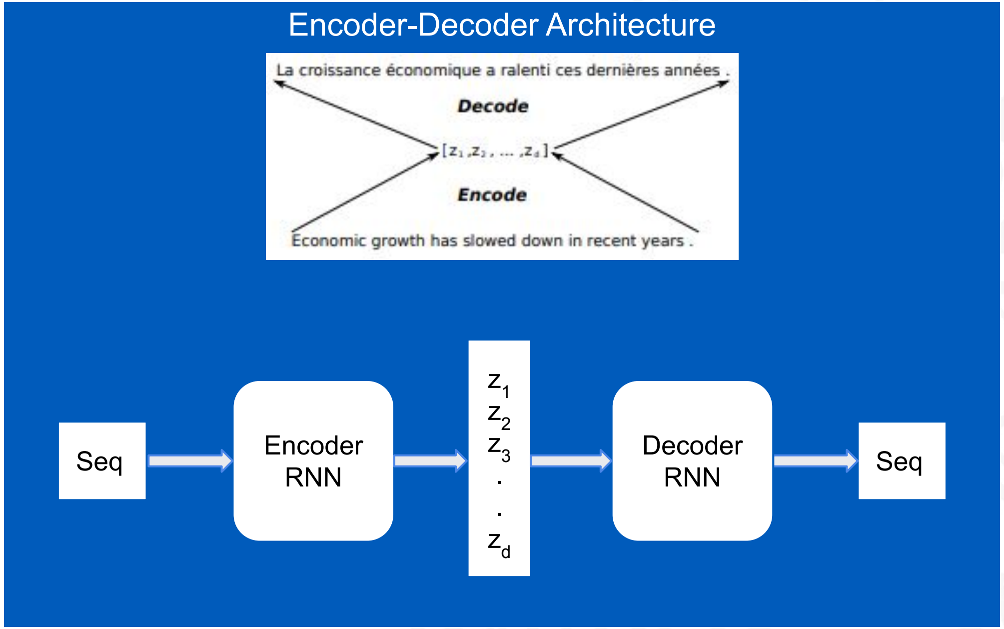
Using a Neural Network

- The advancements in Deep Learning has allowed us to model sequences from sequences with help of sequence modeling
- Seq2Seq model architecture which involves Encoder and Decoder Recurrent Neural Network (RNN) cells
- Can model different sized inputs to different sized outputs as well



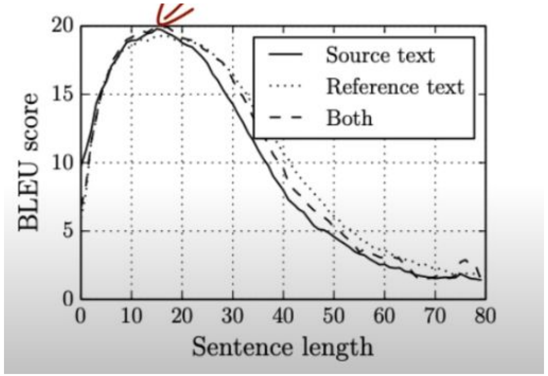
Encoder-Decoder Architecture (Seq2Seq)

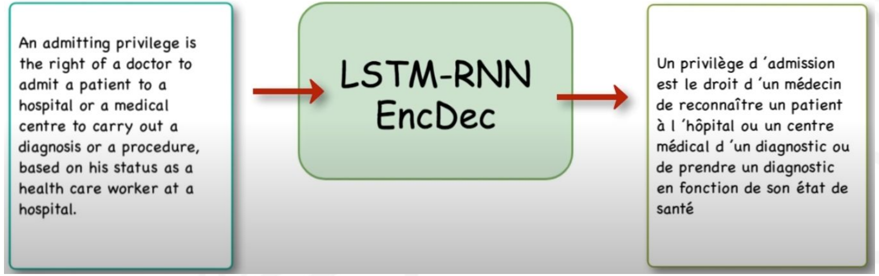
- Encoder inputs a sequence and outputs a vector
- Decoder takes the vector and converts it into a sequence
- Encoder+Decoder inputs a sequence and outputs a sequence, hence Seq2Seq
- Also used in time-series prediction

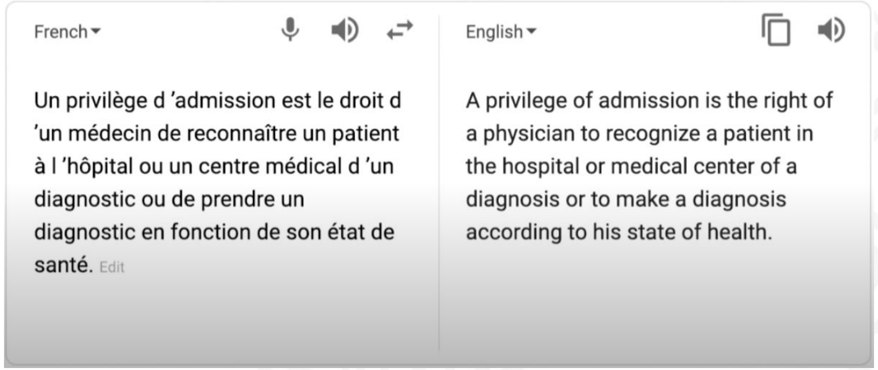


Problems with Vanilla Seq2Seq

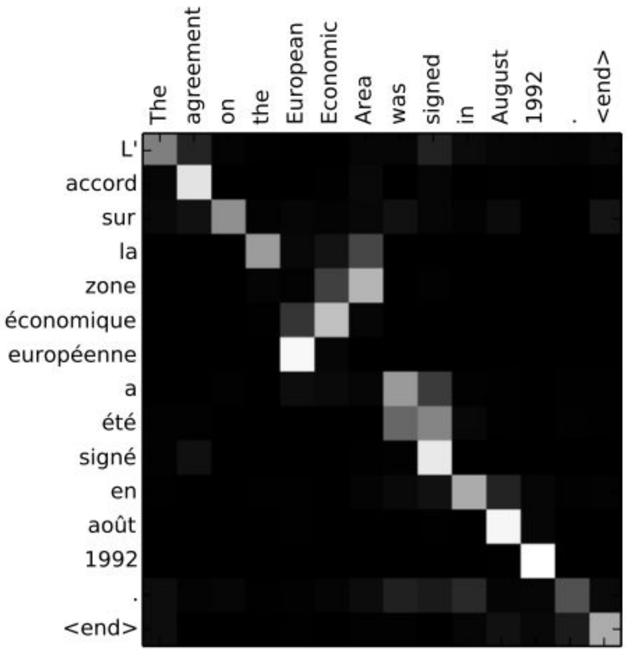
- Bad performance on longer sentences
- Even with LSTM cells, the best performance achieved is around 15 words



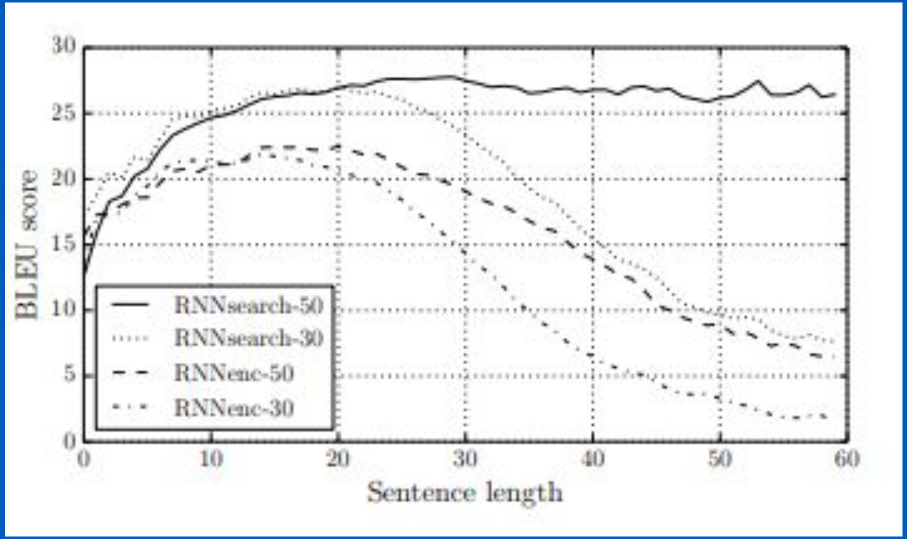




What if we try to learn to align and translate?



Results

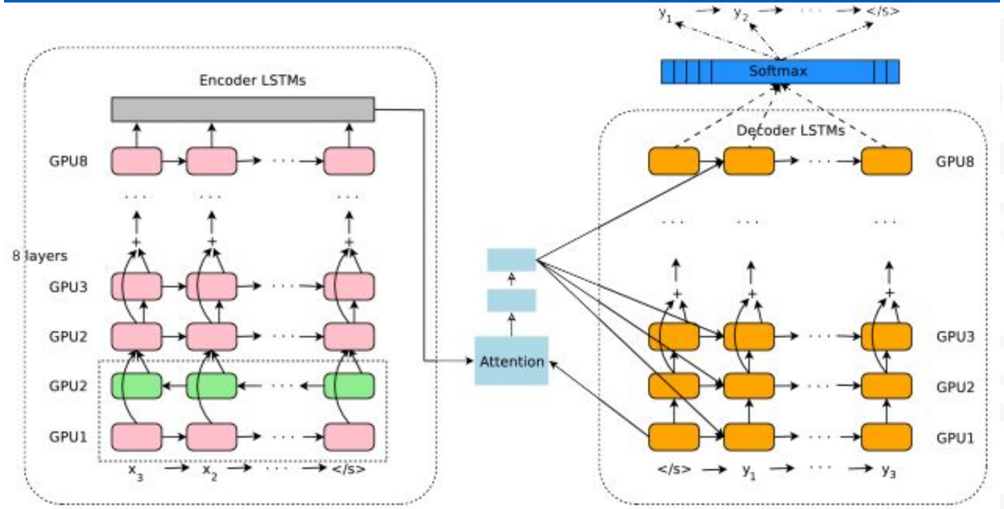


- Also known as the attention mechanism

Google's Neural Translation Model

- LSTM cells over vanilla RNN cells
- Use of residual connections for better gradient flow
- Attention function is a simple 1-layered MLP
- First layer of the encoder is bi-directional
- Uses a modified beam search on decoder outputs to get resultant sequence
- Coverage penalty and length normalization

Google NMT architecture (2016)



Training Criteria

- Maximum log-Likelihood objective - maximizing the sum of log probabilities of the ground-truth outputs given the corresponding inputs
  - does not reflect the task reward function as measured by BLEU score
  - does not explicitly encourage a ranking among *incorrect* output sequences
- In comes Reinforcement Learning
  - model refinement using the expected reward objective
  - Use GLEU score for sentence pairs
- First train model using the maximum likelihood objective until convergence
- Refine this model using a mixed maximum likelihood and expected reward objective, until BLEU score on a development set is no longer improving

$$\mathcal{O}_{\mathrm{ML}}(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log P_{\theta}(Y^{*(i)} \mid X^{(i)})$$

Max log-likelihood objective

$$\mathcal{O}_{\mathrm{RL}}(\boldsymbol{\theta}) = \sum_{i=1}^{N} \sum_{Y \in \mathcal{Y}} P_{\theta}(Y \mid X^{(i)}) \; r(Y, Y^{*(i)}).$$

Expected Reward Objective

$$\mathcal{O}_{\mathrm{Mixed}}(\boldsymbol{\theta}) = \alpha * \mathcal{O}_{\mathrm{ML}}(\boldsymbol{\theta}) + \mathcal{O}_{\mathrm{RL}}(\boldsymbol{\theta})$$

Fine-tuning Objective Function

Experimental Results

Without RL training

Table 4: Single model results on WMT En→Fr (newstest2014)

Model	BLEU	CPU decoding time per sentence (s)
Word	37.90	0.2226
Character	38.01	1.0530
WPM-8K	38.27	0.1919
WPM-16K	37.60	0.1874
WPM-32K	38.95	0.2118
Mixed Word/Character	38.39	0.2774
PBMT [15]	37.0	
LSTM (6 layers) [31]	31.5	
LSTM (6 layers + PosUnk) [31]	33.1	
Deep-Att [45]	37.7	
Deep-Att + PosUnk [45]	39.2	

Table 5: Single model results on WMT En→De (newstest2014)

Model	BLEU	CPU decoding time per sentence (s)
Word	23.12	0.2972
Character (512 nodes)	22.62	0.8011
WPM-8K	23.50	0.2079
WPM-16K	24.36	0.1931
WPM-32K	24.61	0.1882
Mixed Word/Character	24.17	0.3268
PBMT [6]	20.7	
RNNSearch [37]	16.5	
RNNSearch-LV [37]	16.9	
RNNSearch-LV [37]	16.9	
Deep-Att [45]	20.6	

Model Ensemble and RL training

Table 7: Model ensemble results on WMT En→Fr (newstest2014)

Model	BLEU
WPM-32K (8 models)	40.35
RL-refined WPM-32K (8 models)	41.16
LSTM (6 layers) [31]	35.6
LSTM (6 layers + PosUnk) [31]	37.5
Deep-Att + PosUnk (8 models) [45]	40.4

Table 8: Model ensemble results on WMT En→De (newstest2014). See Table 5 for a comparison against non-ensemble models.

Model	BLEU
WPM-32K (8 models)	26.20
RL-refined WPM-32K (8 models)	26.30

Table 9: Human side-by-side evaluation scores of WMT En→Fr models.

Model	BLEU	Side-by-side averaged score
PBMT [15]	37.0	3.87
NMT before RL	40.35	4.46
NMT after RL	41.16	4.44
Human		4.82

Table 10: Mean of side-by-side scores on production data

	PBMT	GNMT	Human	Relative Improvement
English → Spanish	4.885	5.428	5.504	87%
English → French	4.932	5.295	5.496	64%
English → Chinese	4.035	4.594	4.987	58%
Spanish → English	4.872	5.187	5.372	63%
French → English	5.046	5.343	5.404	83%
Chinese → English	3.694	4.263	4.636	60%

Further developments

Transformer Architecture

- Completely replaces usage of recurrent neural network cells which are slow in computations
- Based solely on attention mechanisms
- Only drawback is longer training time
- Achieves 28.4 BLEU on the WMT 2014 English-to-German and BLEU score of 41.8 on the WMT 2014 English-to-French translation task, establishing a new single-model state-of-the-art BLEU score of 41.8
- Generalizes well to other tasks

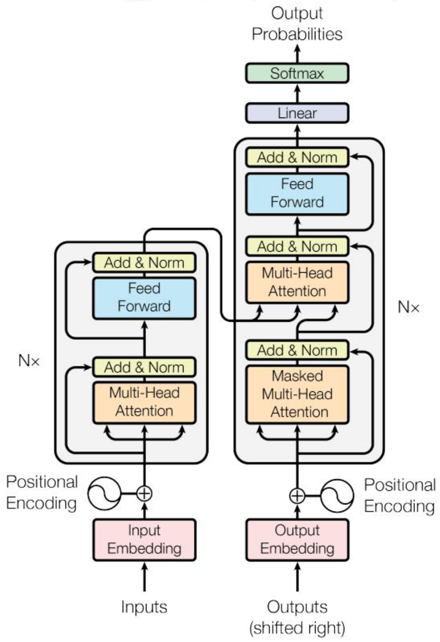


Figure 1: The Transformer - model architecture.

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Thank you!