Machine Translation BDRP

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What is Machine Translation?

Machine Translation is a sub-field of computational linguistics that aims to automatically translate text from one language to another.

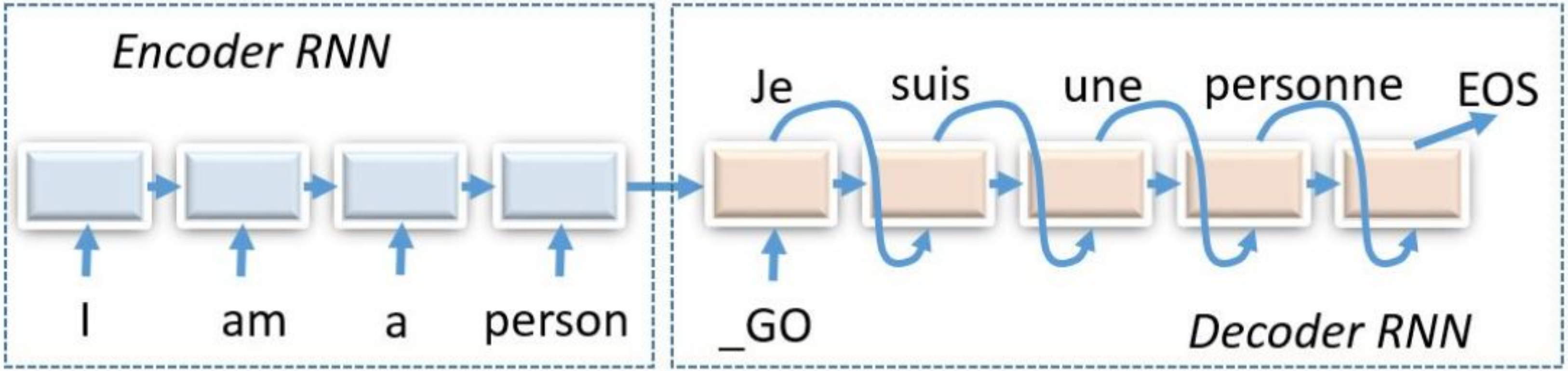
Demand of MT has grown exponentially over past couple of years, considering the enormous exchange of information between different regions with different regional languages

What are the challenges in Machine Translation?

Many challenges, among which:

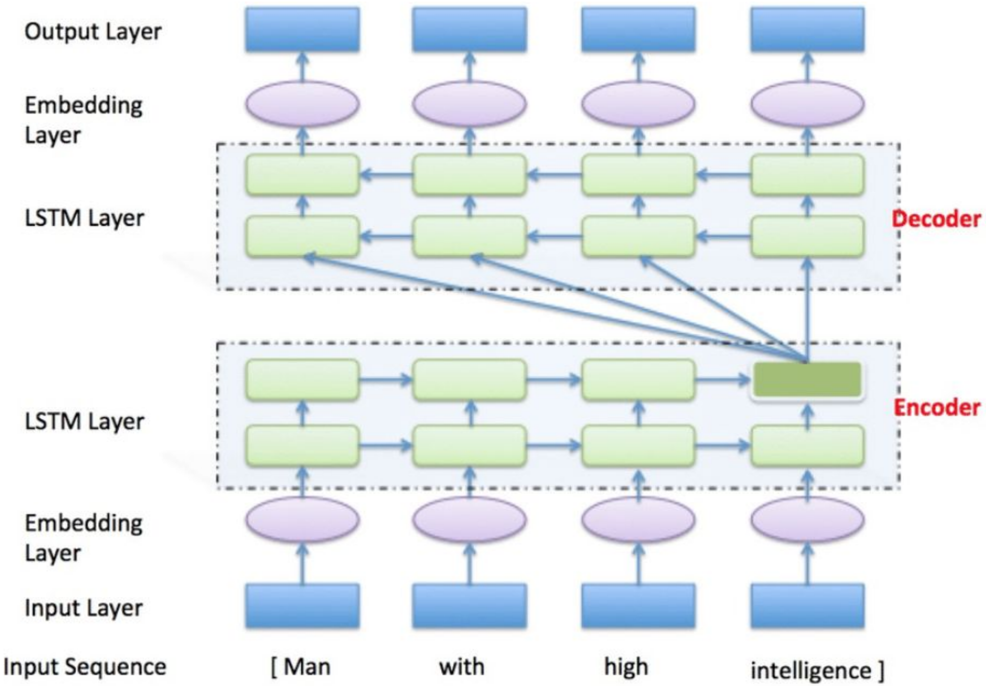
a) Not all words in one language has equivalent word in another language
b) Two given languages may have completely different structures
c) Words can have more than one meaning
d)There is no unique way for a word, sentence to be translated

Related Work



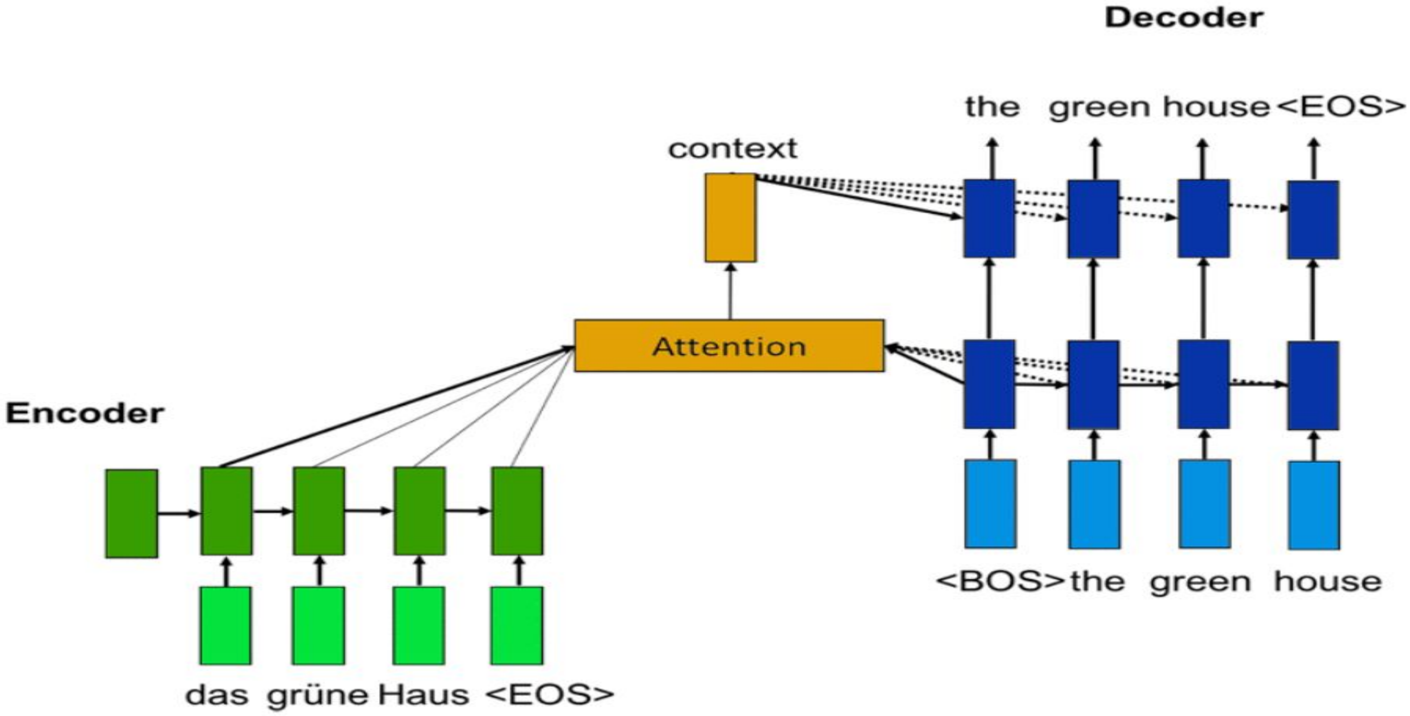
Learning phrase representations using RNN encoder-decoder for statistical machine translation, Cho, 2014

Related Work



Sequence to sequence learning with neural networks, Sutskever 2014

Related Work



Neural machine translation by jointly learning to align and translate, Bahdanau 2014

Related Work

- Google’s neural machine translation system: Bridging the gap between human and machine translation, Wu 2016: used in Google Translate

- Convolutional sequence to sequence learning, Gehring 2017: by Facebook, outperformed GMT

- Attention is all you need, Vaswani 2017: currently best results

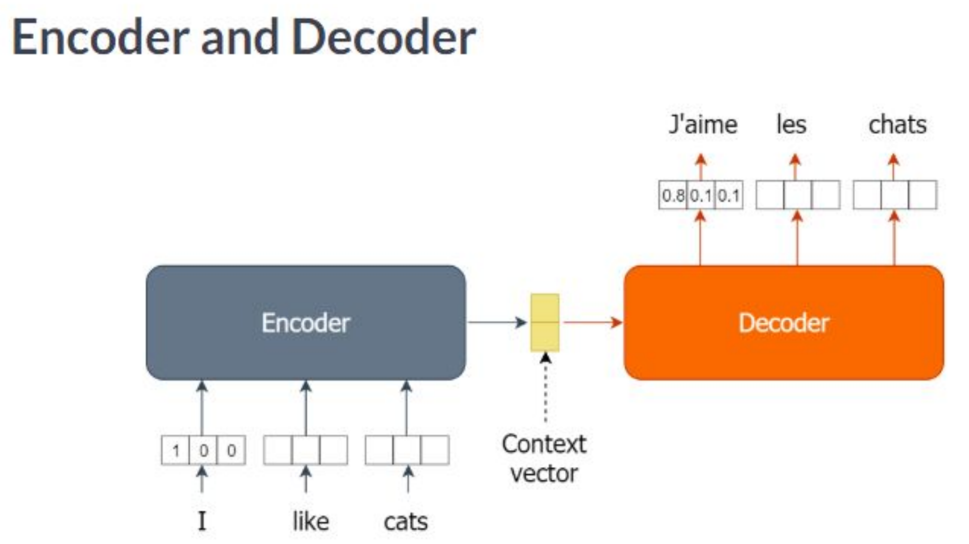
Problem definition

Analysing the impact of different configurations/strategies on the results of machine translation accuracy, considering the constraint of low computational resources.

Strategies:

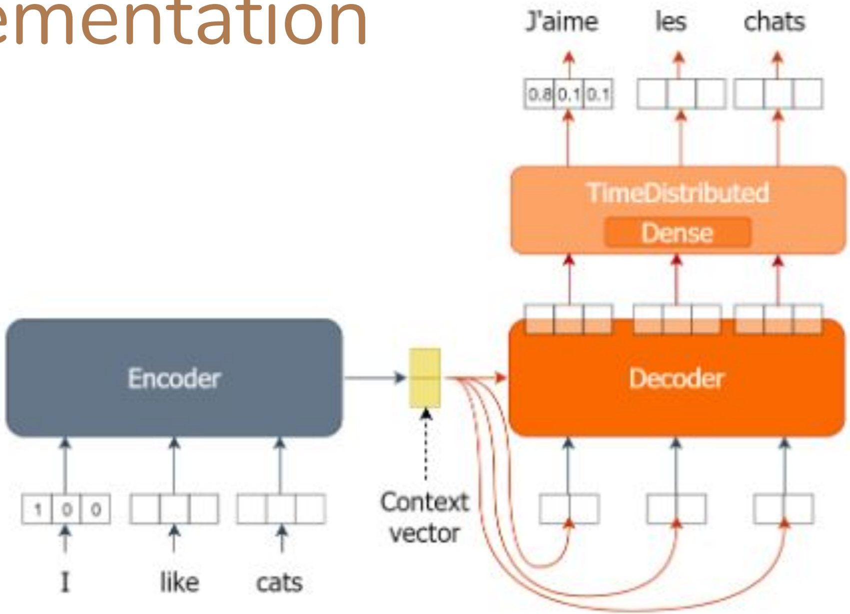
- Using more data for training and testing
- Unidirectional vs Bidirectional layer in the encoder
- Shallow vs Deep 2-layer network
- Using different numbers of nodes within a LSTM unit
- Word embeddings

Base Model for Machine Translation



- Word embeddings
- 1-layer Encoder with LSTM units
- 1-layer Decoder with LSTM units
- Adam optimizer
- Categorical cross-entropy loss function

Keras Implementation




```python
def create_model(vocab_size_src, vocab_size_trg, seq_size_src, seq_size_trg, n_nodes):
    nn = Sequential()
    nn.add(Embedding(vocab_size_src, n_nodes, input_length=seq_size_src, mask_zero=True))
    nn.add(LSTM(n_nodes))
    nn.add(RepeatVector(seq_size_trg))
    nn.add(LSTM(n_nodes, return_sequences=True))
    nn.add(TimeDistributed(Dense(vocab_size_trg, activation='softmax')))
    return nn
```

Environments/Libraries

jupyter

python

NLTK

A Tool Kit for Natural Language Processing

gensim

topic modelling for humans

K Keras

Data

Tatoeba project - Tab delimited Bilingual Sentence Pairs: https://tatoeba.org/eng

- Afrikaans - English afr-eng.zip (749)
- Albanian - English sqi-eng.zip (408)
- Algerian Arabic - English arq-eng.zip (155)
- Arabic - English ara-eng.zip (11175)
- Azerbaijani - English aze-eng.zip (2072)
- Basque - English eus-eng.zip (666)
- Belarusian - English bel-eng.zip (3698)

4	Run!	Courez !
5	Who?	Qui ?
6	Wow!	Ça alors !
7	Fire!	Au feu !
8	Help!	À l'aide !

- Train and test on French to English sentence corpus
- Total data available: 170K+ sentences
- Initially working with 10K sentences
- For the model we require the size of the vocabulary and maximum length of a sentence for either language

Data preprocessing

Text pre-processing:

- Lowercase all the words
- Normalising language-specific characters (e.g. é to e)
- Remove punctuation
- Remove non-alphabetic characters

Input and output pre-processing:

- Input: word embeddings
- Output: one hot vectors

Model Evaluation

Bilingual Evaluation Understudy, BLEU

- An algorithm for evaluating the quality of text which has been machine-translated from one language to another.
- The metric is that "the closer a machine translation is to a professional human translation, the better it is".
- A metric which is highly correlated with human judgments of quality

Experiments

Experiment 1: Impact of data set size

	1 LSTM layer of encoder, 1 LSTM layer of decoder	
Metric	10000 phrases	20000 phrases
BLEU-1	0.451	0.576
BLEU-2	0.326	0.462
BLEU-3	0.265	0.402
BLEU-4	0.135	0.238

Experiment 2: Impact of bidirectional layer

Metric	Base model (10K)	Bidirectional encoder (10K)
BLEU-1	0.54732	0.56076
BLEU-2	0.44148	0.44965
BLEU-3	0.35848	0.38341
BLEU-4	0.15688	0.18903

Experiments

Experiment 3: Shallow vs Deep network

Metric	Base model (10K)	Base model (20K)	Deep network (10 K)	Deep network (20K)	Deep network (30K)
BLEU-1	0.54732	0.5766	0.41228	0.53371	0.55356
BLEU-2	0.44148	0.46271	0.27795	0.4151	0.43459
BLEU-3	0.35848	0.40283	0.19157	0.34934	0.37877
BLEU-4	0.15688	0.2384	0.0629	0.18943	0.23749

Experiment 4: Different number of units within LSTM

	1 LSTM layer of encoder, 1 LSTM layer of decoder		
	10000 phrases; 9000 for training, 1000 for testing		
Metric	128 units	256 units	512 units
BLEU-1	0.369	0.451	0.563
BLEU-2	0.228	0.326	0.463
BLEU-3	0.145	0.265	0.394
BLEU-4	0.041	0.135	0.201

Experiments

Experiment 5: Impact of word embeddings

	1 LSTM layer of encoder, 1 LSTM layer of decoder	
Metric	Word2Vec	pre-trained Word2Vec
BLEU-1	0.55	0.561
BLEU-2	0.428	0.438
BLEU-3	0.364	0.371
BLEU-4	0.205	0.216

Experiment 6: Different language pair DE - EN

Metric	Base model (10K) for FR-EN	Base model (10K) for DE-EN
BLEU-1	0.54732	0.53537
BLEU-2	0.44148	0.40294
BLEU-3	0.35848	0.31645
BLEU-4	0.15688	0.14515

Conclusions

- Crucial to have a good amount of high-quality training data
- Important to have a sufficiently complex architecture
  - Bidirectional LSTM layer
  - Having deep network depending on the amount of data
  - Having sufficient number of units within a layer

- Differences on the translation quality depending on the different pair of languages

Future Work

- Deeper networks such as 4 layers
  - requires higher computing power and millions of sentences
- Training with more data
- Attention mechanism
- Pre-trained word embeddings on huge corpuses

References

Slide 4, https://rickyhan.com/jekyll/update/2017/09/14/autoencoders.html
Slide 5, https://www.researchgate.net/figure/LSTM-Encoder-Decoder-Model_fig1_308072447
Slide 6, https://aws.amazon.com/blogs/machine-learning/train-neural-machine-translation-models-with-sockeye/
Slides 9,10, https://www.datacamp.com/home
Slide 11, https://abstract-technology.fr/media/technology/python-logo.png/image_view_fullscreen
Slide 12, http://www.manythings.org/anki/

Overleaf

https://www.overleaf.com/project/5dc3f746ca27c80001d30f2a