Neural Machine Translation

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About the lecturer

D.Sc. (Tech.), 2012
Post-doc 2013–2018

Research Scientist
2013–2016

University Researcher
2019–

Lead Data Scientist
2017–

Goals of the lecture

Neural machine translation

- Why NMT is the mainstream approach?
- What path led to the current state-of-the-art NMT?
- How are the current state-of-the-art NMT systems built?
- What are the challenges and limitations for the systems?

Outline

Motivation

Model architectures

Data, preprocessing, and learning techniques

State-of-the-art and future

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Why neural machine translation?

Ability to generalize

Model similarity of related words and phrases

- Semantically related: synomyms, paraphrases, ...
- Morphologically related: inflections, derivations, compounds

Avoid sparsity problems encountered in phrase-based MT.

Flexibility

Different context vectors are easy to include as input.

Enables paragraph and document-level modeling.

Integration

Easier to combine with other sources of information:
Text in other languages, speech, images, videos, ...

Multitask learning

Paradigm shift to NMT

Dominant paradigm since the latter half of the 2010's.

Reasons for the paradigm shift

Increased computation power (GPUs).

Matured deep learning software frameworks and libraries: TensorFlow, (Py)Torch, Chainer, etc.

Improvements in training algoritms for neural networks:

- Adam (Kingma and Ba 2014),
- Layer normalization (Ba, Kiros, and Hinton 2016),
- Dropout (Srivastava et al. 2014).

Cross-pollination between fields of research

Success of deep learning in computer vision and speech recognition inspired NMT.

Later, NMT architectures such as Attention and Transformers spread to other fields.

Some NMT toolkits

- Fairseq
- Joey NMT
- Marian
- OpenNMT
- Sockeye
- Trax
- ...
- (Hugging Face)

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Reminder: The autoregressive language model

$$P(X) = \sum_i P(x_i \mid x_0, \ldots, x_{(i-1)})$$

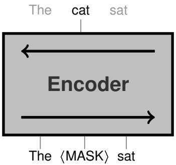
Here is a fragment of text. Tell me how this fragment might go on.

According to this model of the statistics of human language, what words are likely to come next?

Types of language models

Masked LM

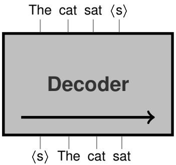
a.k.a. encoder-only



E.g. BERT

Autoregressive

a.k.a. decoder-only, causal



E.g. GPT

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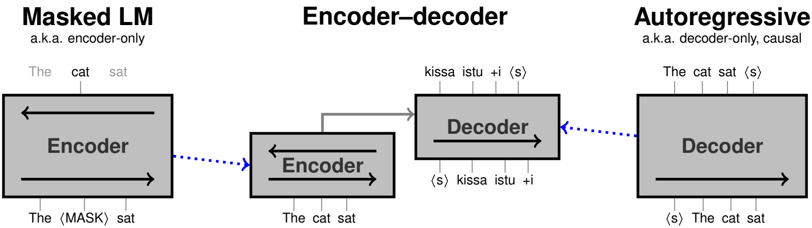


E.g. BERT

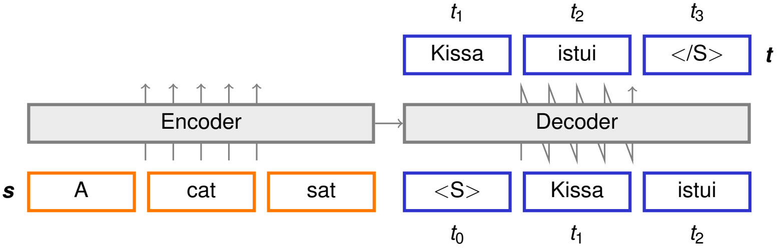
NMT models, but also e.g. T5

E.g. GPT

MT systems are conditional language models

$$P(\; t_j \mid t_0, \ldots, t_{(j-1)}, \; \boldsymbol{s})$$

$$P(\; \text{“istui”} \mid \text{“<S>”, “Kissa”}, \; \boldsymbol{s})$$



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Predicts the target conditioned on the source.

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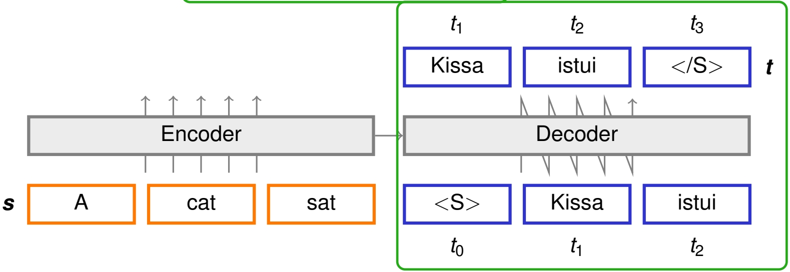

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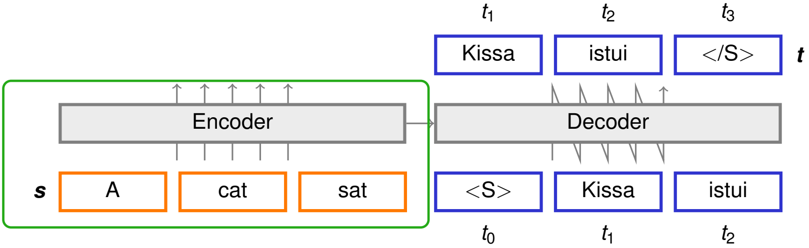

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History lesson

Let's look at some of the breakthroughs leading towards current SOTA architectures, and the challenges that inspired these breakthroughs.

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How to encode sequences (words, phrases, sentences) $x_1, x_2, \ldots, x_n$ of variable length $n \geq 1$ to fixed length representations?

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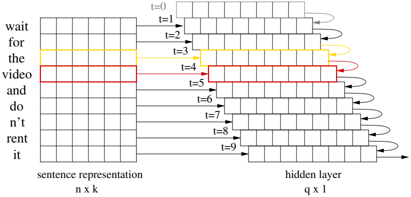
But how to combine them? Summing or averaging discards the sequence order.

Remember from LM Lecture: Neural network language models are able to store information over long contexts.

History: Sequence encoding with RNN and CNN

Recurrent neural networks: Take the last hidden state as sentence embedding. (Elman 1990; Mikolov et al. 2010)



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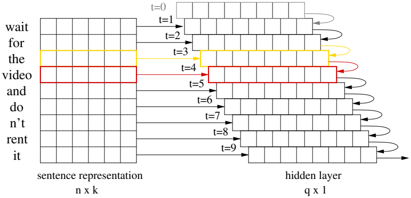
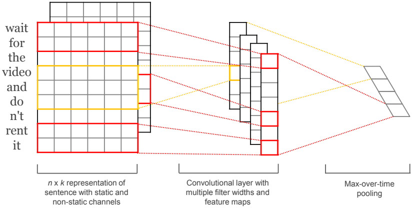
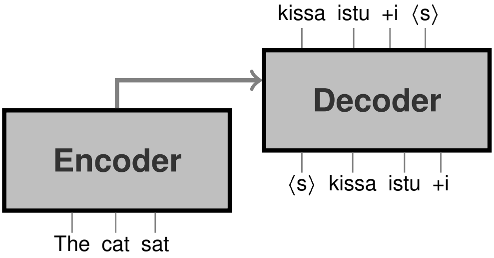


Alternative: Convolutional neural networks (Fukushima 1980; Kim 2014)



History: Encoder-decoder model



History: Sequence decoding

How to implement the decoder?

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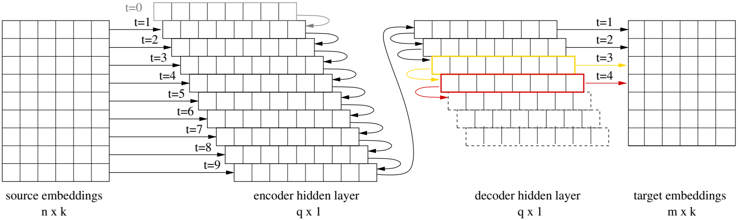
How to implement the decoder?

Again, we can use an RNN language model
— just initialize the hidden state with the sentence representation from encoder!

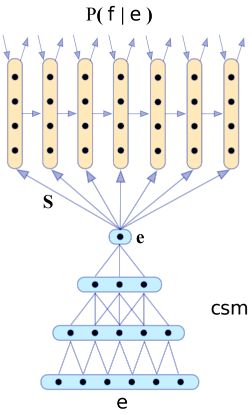


History: First complete NMT systems

Kalchbrenner and Blunsom 2013: Encode with convolutional neural networks (CNN), decode with recurrent neural network (RNN) language model

Sutskever, Vinyals, and Le 2014: Encode and decoder with RNN with long short-term memory (LSTM) units

Cho et al. 2014b: Encode with RNN with gated recursive units (GRU) or gated recursive CNN, decoder with RNN with GRUs

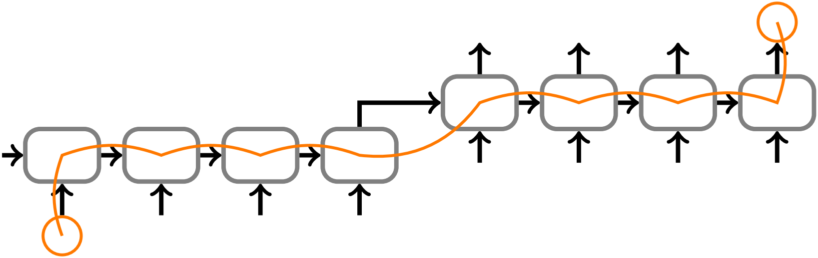


RCTM I

History: Vanishing gradient problem

The error signal decreases exponentially with the number of layers in backpropagation and gradient-based learning.

The RNN encoder must process entire sentence before sentence encoding is ready: The long path makes it hard to learn relevant information from first time steps (beginning of sentence).



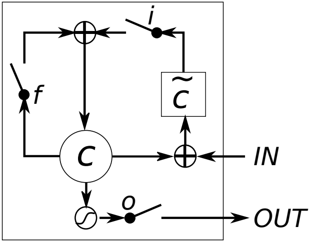
History: Gated units in recurrent neural networks

Solution:

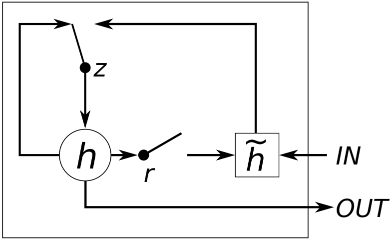
- Predict what information to keep and what to forget from the state representation.
- Gates: sigmoid activation (0–1) followed by pointwise multiplication with the target signal.

History: Gated units in recurrent neural networks

LSTM and GRU are two gate architectures with similar performance (Chung et al. 2014)



Long short-term memory
(Hochreiter and Schmidhuber 1997)



Gated recurrent unit
(Cho et al. 2014a)

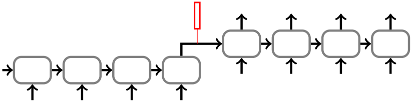
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

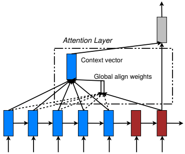
History: Attention model

Even with gated units, it is hard to decode a sensible target sentence from a single embedded source vector.

Encoder provides embeddings for each input unit — allow decoder to look at them.

Attention model: At each decoder time step, predict which parts of the source encoding are relevant for next output.

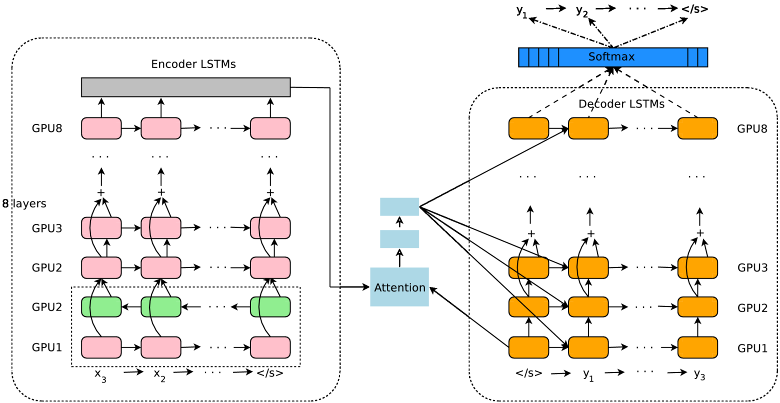




(Luong, Pham, and Manning 2015)
(Bahdanau, Cho, and Bengio 2015)

http://distill.pub/2016/augmented-rnns/#attentional-interfaces

History: Adding layers



Google NMT (Wu et al. 2016)

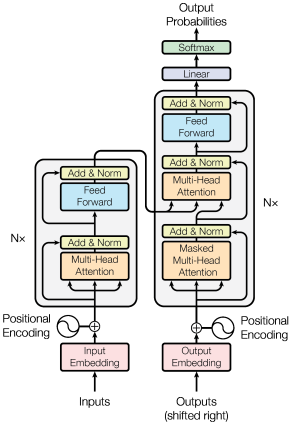
History: Transformer architecture

Recurrent networks require sequential computation ($O(n)$ for n units in sentence)

Can we cope without them?

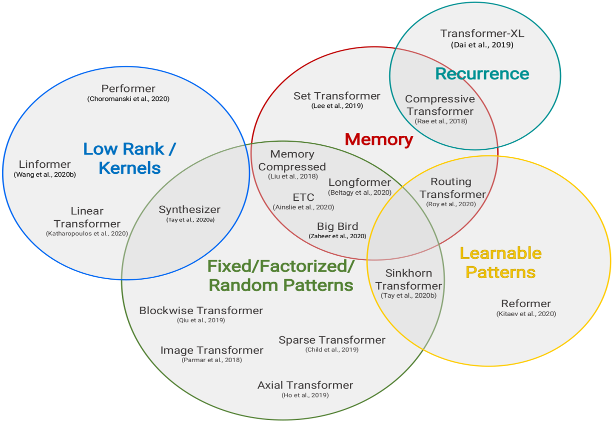
"Attention is all you need" — Google's Transformer architecture (Vaswani et al. 2017)

Multiple layers of attention networks in both encoder and decoder



https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

Transformers: the sequels



Taxonomy of efficient Transformer architectures (Tay et al. 2020).

Mixture of Experts

In Mixture of Experts (MoE), a gating network selects which subnetworks to use for the example.

- A sparse network: not all parameters are used each time.
- Can be combined with the Transformer architecture.

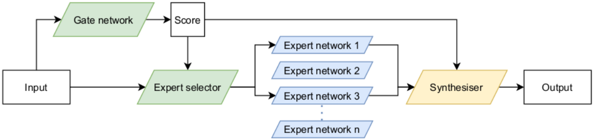


Figure 1: An illustrative example of an MoE layer. In this example, expert 1 and expert 3 are selected by the gate for computation.

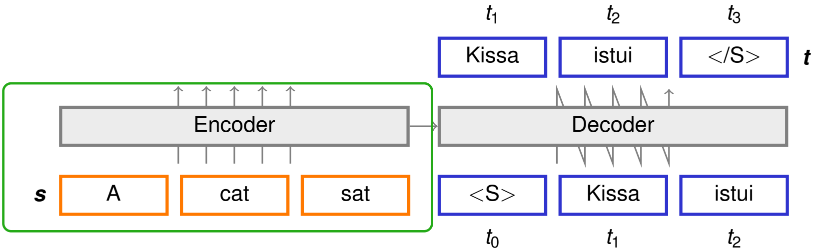
- Figure from (He et al. 2021)

Discuss in groups (a few minutes)

What happens if the conditioning on the source fails to be learned?

$$P(\quad t_j \quad | \quad t_0, \ldots, t_{(j-1)}, \quad \boxed{\boldsymbol{s}})$$

$$P(\quad \text{“istui”} \quad | \quad \text{“<S>”, “Kissa”}, \quad \boxed{\boldsymbol{s}})$$



Examples

EN source: Stealing food is a common crime in student halls.

ET source: Laktoosi puhul see nii ju ongi!
(That's the case with lactose!)

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EN source: Stealing food is a common crime in student halls.
FI: Lapsenteko on yhteistä rikollisuutta.
(Making children is shared crime.)

ET source: Laktoosi puhul see nii ju ongi!
(That's the case with lactose!)

EN: I've been thinking about it.

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Data, preprocessing, and learning techniques

State-of-the-art and future

Is Transformer all you need?

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But the model architecture is not everything!

Especially for low-resource language pairs and morphologically rich languages, we need methods for:

1. Learning from bilingual data in other languages
2. Using monolingual corpora in source or target language
3. Selecting input and output units

Transfer learning

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- Labeled data for other tasks.
- Unlabeled data.

Labeled and unlabeled in the context of MT

Let's say the goal is a English-to-Finnish system.

Labeled data for this task: English-Finnish sentence pairs

- Input English sentence
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Unlabeled data:

- Monolingual English,
- or monolingual Finnish.

Transfer learning techniques

Transfer learning: Use knowledge gained from solving one task in a related task.

How are the different learning tasks timed?

- Sequential transfer
- Parallel transfer
- Mix: Scheduled multi-task learning

Transfer learning techniques

Sequential transfer

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Transfer learning techniques

Sequential transfer

- Often called just "transfer learning"

1. Train a system on one task (“pretraining”),
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- e.g. multi-task pretraining + multi-task fine-tuning

Cross-lingual transfer: Settings

Given training data between languages A and B, can it help translating from language C to D?

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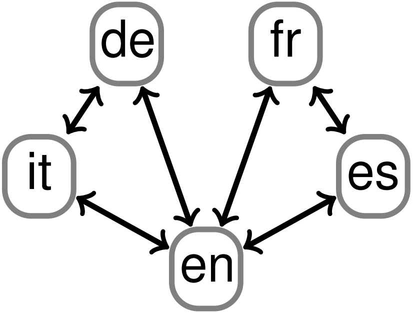
Training a multilingual MT system is a multi-task training scenario:

- Each language pair is one task.
- Multilingual settings:
  - one-to-many
  - many-to-one
  - many-to-many
- Can also combine with monolingual tasks.

Cross-lingual transfer: Zero-shot and universal translation

Many-to-many translation enables new language pairs without training data ("zero-shot") or explicit pivot language.



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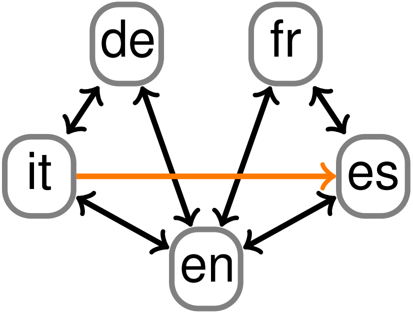

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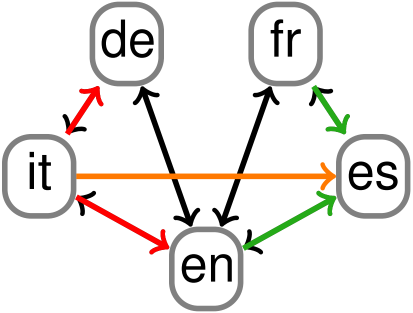

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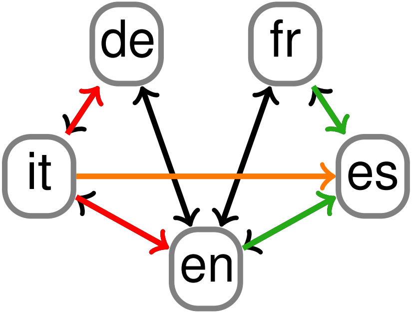

Universal translation: Extension of many-to-many translation to cover all languages.

How effective is cross-lingual transfer?

When model capacity is insufficient and tasks are too different, you get interference (negative transfer).

The accepted wisdom used to be that cross-lingual transfer

- is good for medium and low-resource languages,
- but for high-resource pairs bilingual was better.

Recently this was put in question

- Facebook AI's WMT 2021 News task submission (Tran et al. 2021)
- Large enough multilingual models outperform single-pair models even for high-resource language pairs like En$\leftrightarrow$Cs, En$\leftrightarrow$De, En$\leftrightarrow$Ru.

Massively multilingual machine translation

No Language Left Behind: Scaling Human-Centered Machine Translation (Costa-jussà et al. 2022)

- Massively multilingual model from Meta AI.
- Supports 200 languages,
  including both high- and low-resource languages.
- Transformer Mixture-of-Experts (MoE),
  54.5B parameters in total.

Using monolingual corpora

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Approaches:

- Pretraining
- Autoencoding
- Back-translation

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4. Language model fusion

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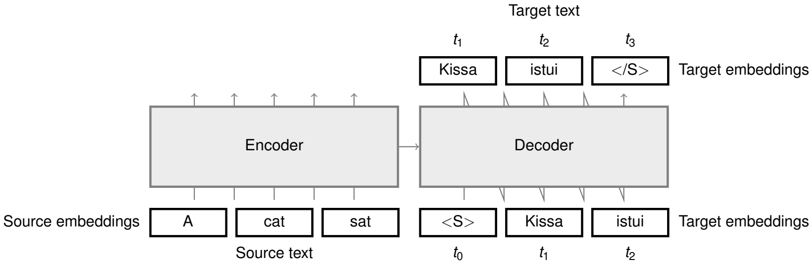

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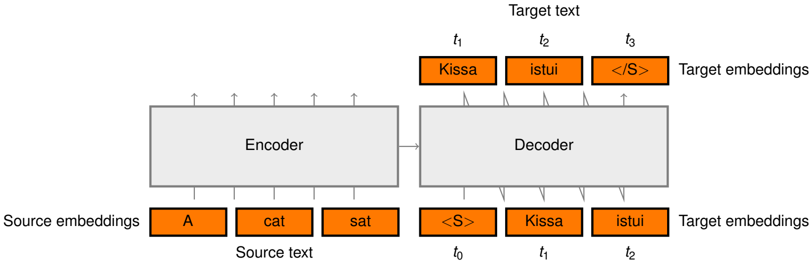
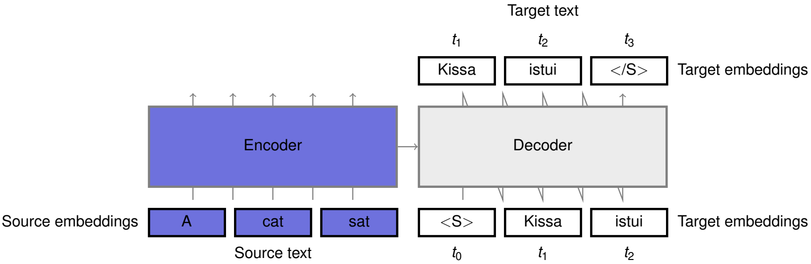


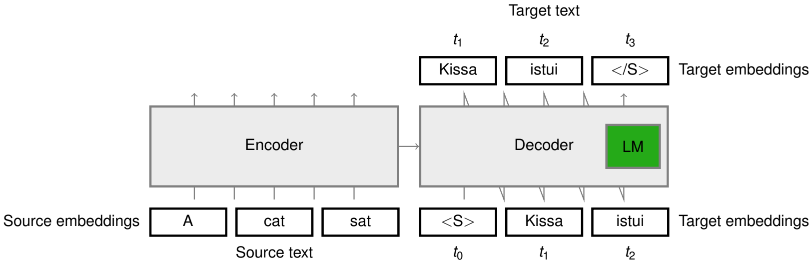
Pretrained embeddings

Parameter sharing in NMT transfer learning



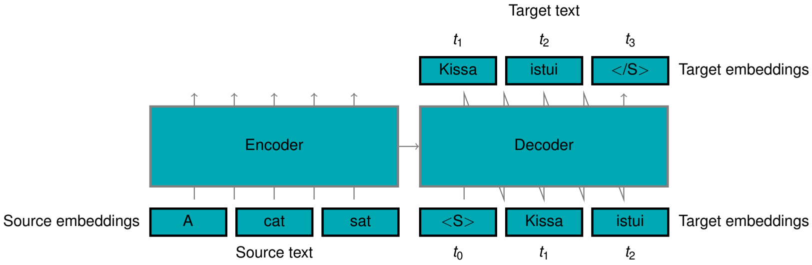
Pretrained encoder

Parameter sharing in NMT transfer learning



Language model fusion

Parameter sharing in NMT transfer learning



Full parameter sharing

Monolingual corpora: Autoencoding

Parallel transfer: Use multi-task learning with source-to-source or target-to-target autoencoding as an additional task.

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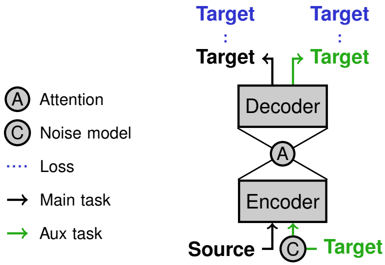

Denoising autoencoder
for target language

Monolingual corpora: Autoencoding

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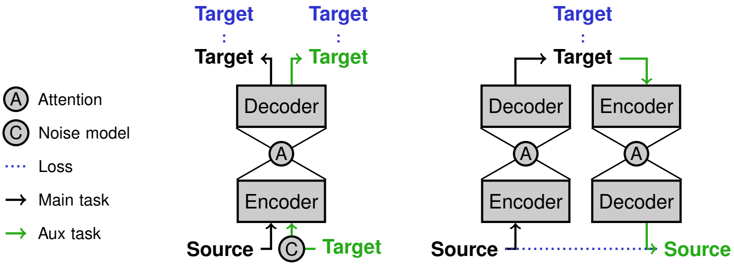

Denoising autoencoder for target language

Dual learning (Xia et al. 2016)

Monolingual corpora: Back-translation

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Large gains, but double work in training.

Lexical units in NMT

Limiting issues in phrase-based MT:

- Many tokens per sentence makes decoding more difficult.
- Different number of tokens in source and target sentence makes word alignment more difficult.

No such restrictions in NMT!

Units for encoder and decoder

Encoder input symbols

Words: large vocabulary, rare words, OOVs.

- But factors (e.g. morphological analysis) easy to integrate.

Using characters may slow down attention too much.

- Softmax operation on input tokens.

Decoder output symbols

Computational complexity increases with vocabulary size due to softmax in output layer.

Conclusion

Subword units are a good compromise.

- Morphological segmentation (if available)
- Statistical subwords (strong encoders compensate for non-sensible segmentations)

Multilingual units

Current standard practice in segmentation:

- SentencePiece (Kudo 2018)

Still popular:

- Byte-pair encoding (BPE) (Sennrich, Haddow, and Birch 2016b)

Joint segmentation: The source and target language corpora — or more languages in a multilingual system — can be combined as a single training corpus for SentencePiece / BPE.

- Very practical for massively multilingual models: no need for language-specific preprocessing.

Outline

Motivation

Model architectures

Data, preprocessing, and learning techniques

State-of-the-art and future

Challenges

Training SOTA-size models is computationally expensive.

- Increasing the number of layers improves results but requires more GPU/TPU resources.
- Distributed training over enormous number of GPUs.

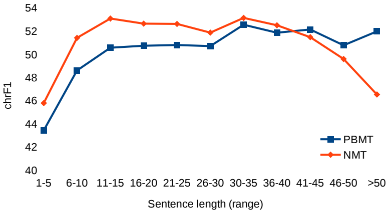
NMT is a "black box" system.

- No "phrase table" to observe or modify.
- Inconvinient especially for translation industry, where correct terminology is very important.

Challenges (cont.)

Translation quality issues

- Problems with long texts.
  - Long sentences used to be problematic (Toral and Sánchez-Cartagena 2017)



  - Now the challenge is in document-level translation.
- Good fluency, but sometimes very misleading translations — can be less predictable than PBMT

NMT quality on par with human translators?

Sometimes human evaluation has indicated that NMT would be on the level of human translation.

E.g. paper by Microsoft Research:
"Achieving Human Parity on Automatic Chinese to English News Translation" (Hassan Awadalla et al. 2018)

- Direct assessment (score 0-100) by bilingual humans.
- No statistically significant difference between NMT output and reference translations by humans!

NMT quality on par with human translators?

Caveats:

- Are the human translators professionals? Are they translating to their native language?
- How about the human evaluators?
  - Do they understand what to judge (e.g. fluency vs. adequacy)? Even bad NMT is fluent.
  - Skill and time spent: ability to notice subtle differences.
  - Bilingual vs evaluators only speaking target language (use source, or only reference?)
  - Is the document context available?

Toral et al. 2018, Läubli et al. 2020

https://www.linkedin.com/pulse/
microsoft-mt-reaches-parity-bad-human-translation-tommi-nieminen

Large language models as translators

LLMs are often trained on multilingual data.

- Zero-shot translation

LLMs fine-tuned for conversational usage (e.g. ChatGPT) can be asked to do various tasks, including translation.

- Prompt engineering

How good they are in translation compared to NMT models?

ChatGPT vs commercial translation services

Table 8: Performance of GPT-4 (Date: 2023.03.15) for multilingual translation.

System	De⇒En	En⇒De	Zh⇒En	En⇒Zh	De⇒Zh	Ro⇒Zh
Google	45.04	41.16	31.66	43.58	38.71	39.05
DeepL	49.23	41.46	31.22	44.31	40.46	38.95
Tencent	n/a	n/a	29.69	46.06	40.66	n/a
ChatGPT (Direct)	43.71	38.87	24.73	38.27	34.46	30.84
ChatGPT (Direct$_{new}$)	n/a	n/a	n/a	n/a	30.76	27.51
ChatGPT (Pivot$_{new}$)	n/a	n/a	n/a	n/a	34.68	34.19
GPT-4	46.00	45.73	28.50	42.50	38.16	37.84

Jiao et al. 2023

- Direct prompt: "Please provide the [TGT] translation for these sentences:"
- Pivot prompt: "Please provide the [PIV] translation first and then the [TGT] translation for these sentences one by one:"

Future of NMT

If LLMs are already so good translators, do we need separate NMT models?

- Multiple questions: Architecture, size, training.

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- Multiple questions: Architecture, size, training.

Architecture: Is encoder-decoder redundant?

- Translation Language Models of similar size perform equally well (Gao et al. 2022).

Future of NMT (cont.)

Size: "GPT-scale" LLMs have NMT challenges multiplied: computation, memory, ...

- Only large corporations have resources for training.
- Not possible to run the models locally.
- Environmental impact.

Future of NMT (cont.)

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- Not possible to run the models locally.
- Environmental impact.

Training: Adapting conversational LLMs to specific tasks and domains is not simple (prompt engineering).

Future of NMT (cont.)

How to create accessible and efficient translation models?

- Re-usable models and modular architectures
- Efficient fine-tuning (e.g. low-rank adaptation)
- Knowledge distillation (small model trained on large model's output)
- Related on-going projects at University of Helsinki: FoTran, HPLT, GreenNLP

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