# Neural Machine Translation (Tutorial)

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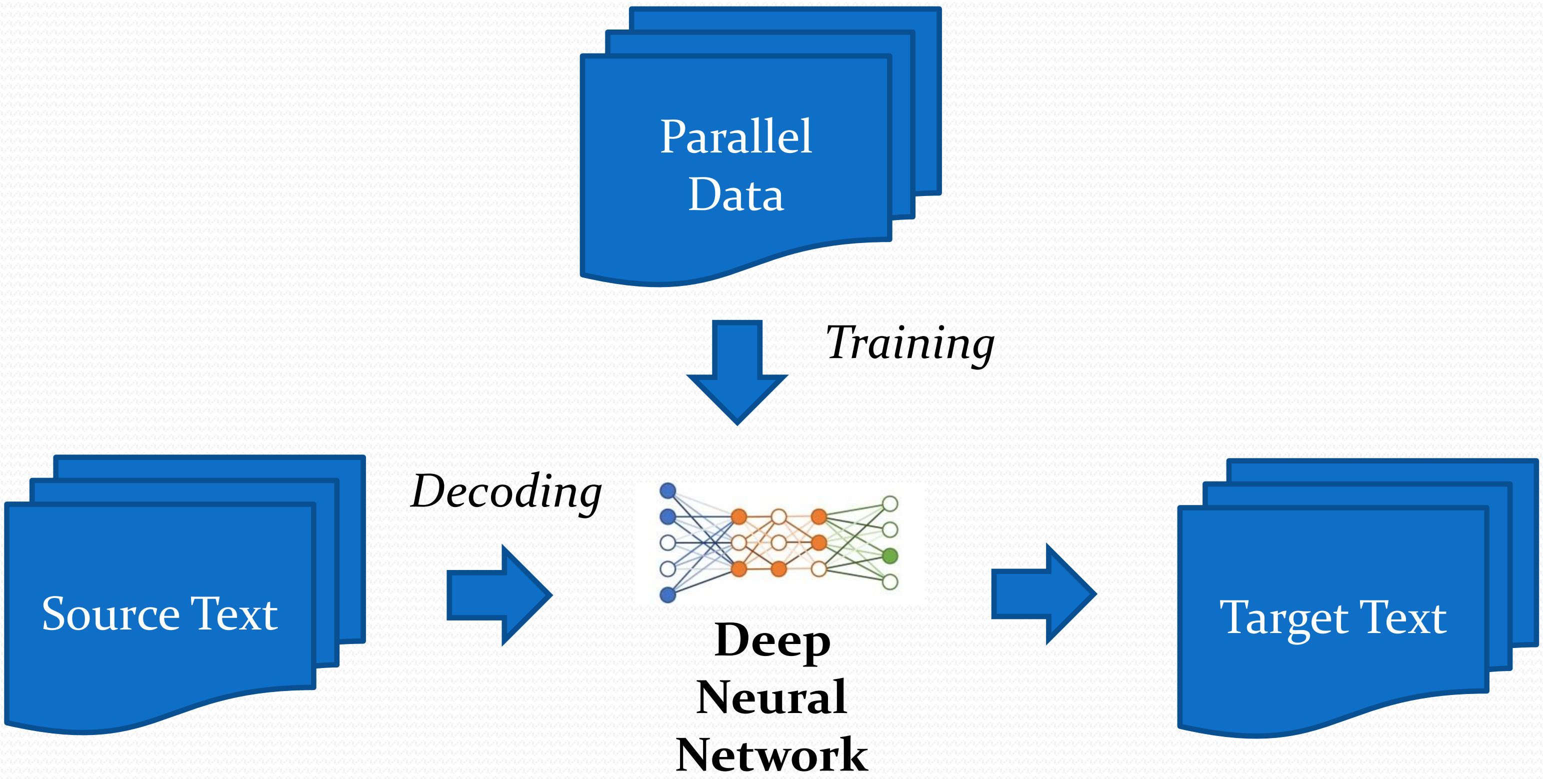
# Machine Translation

- Automatically translate a sentence from one human language (English) to another human language (German)

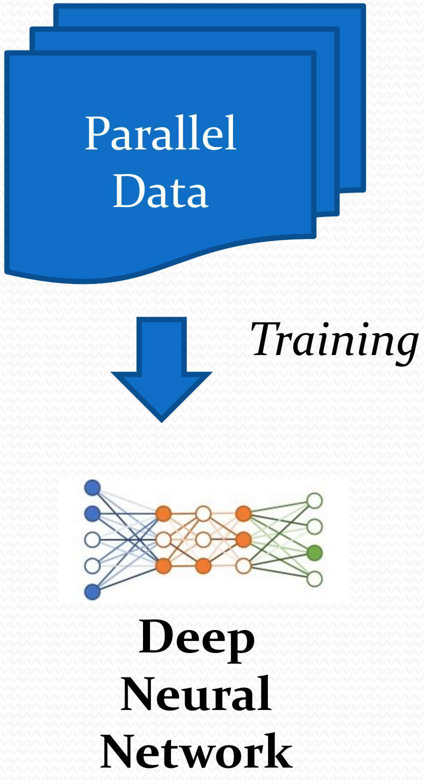
# Neural Machine Translation

- Use neural networks to train the translation system



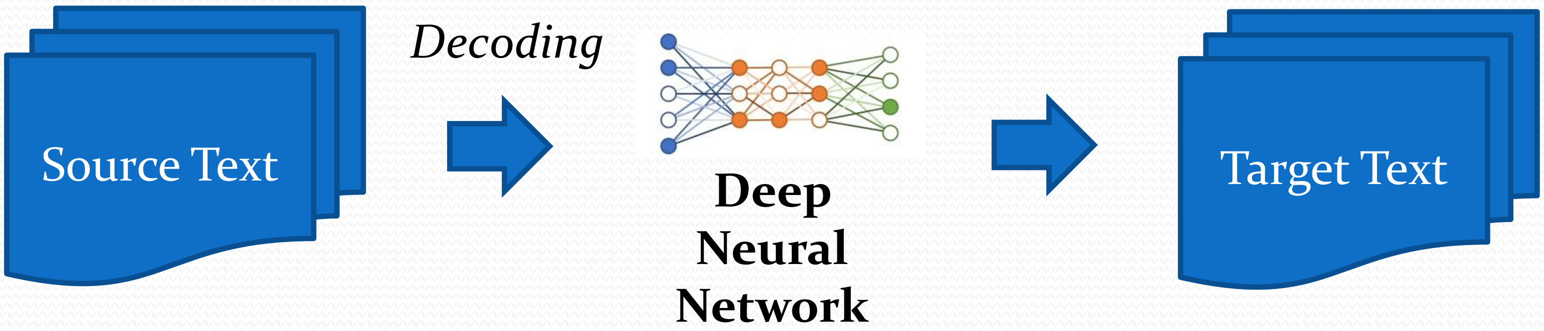
# Training the Model

- Train model on:
  - Training data
  - Validation data



# Decoding the Model

- Test model on:
  - Test data
- No overlap between test and training/validation data



# (1) Download Parallel Data

- Aligned sentences
- Also called Bilingual data

| **English (source) Data** | | **German (target) Data** |
|---|---|---|
| This was reported by broadcaster SABC. | → | Dies berichtete der Sender SABC. |
| The crime had caused nationwide horror. | → | Die Tat hatte landesweit Entsetzen ausgelöst. |
| We've got to remember who we are.' | → | Wir müssen uns daran erinnern, wer wir sind. |
| I'm reading a terribly sad book these days. | → | Ich lese derzeit ein furchtbar trauriges Buch. |

# (2) Extract Raw Data

```
<srcset setid="newstest2014" srclang="any">
<doc docid="007c7b2cf0eaeb1b05efd7ef4871b255" genre="news" origlang="xx">
<seg id="1">This was reported by broadcaster SABC.</seg>
<seg id="2">The crime had caused nationwide horror.</seg>
<seg id="3">We've got to remember who we are.'</seg>
<seg id="4">I'm reading a terribly sad book these days.</seg>
</doc>
```

↓

```
This was reported by broadcaster SABC.
The crime had caused nationwide horror.
We've got to remember who we are.'
I'm reading a terribly sad book these days.
```

# (3) Tokenize Data

```
We've got to remember who we are.'
```

```
We &apos;ve got to remember who we are . &apos;
```

# (4) Truecase & Clean Data

- Case changes meaning

```
Later, newcomer Nick Jonas decided to google the answer.
```

```
In 2007, Google researchers estimated there
were one hundred trillion words on the Internet.
```

- Learn a truecase model on train data

- Remove very long sentences
  - Ratio of source sentence length vs target sentence length

# (5) Byte Pair Encoding

- No 100% overlap in train and target vocabulary
- A lot of unknown words in test data
- BPE reduces the number of unknown words
- Convert words to sub-words (delimiter for separation)

| | | | |
|---|---|---|---|
| **Training Vocabulary** | `unknown` | -> | `un@@ known` |
| | `fortunate` | -> | `fortunate` |
| | `slowly` | -> | `slow@@ ly` |
| **Unknown word in test** | `unfortunately` | -> | `un@@ fortunate@@ ly` |

# (5) Word to Integer Sequence

- Create vocabulary
- Convert words to indices and sentences to sequence of indices
- Easy to use during NMT training

# (5) Word to Integer Sequence

**(i) Create Vocabulary**

| | |
|---|---|
| we | 0 |
| , | 1 |
| was | 2 |
| an | 3 |
| er | 4 |
| ed | 5 |
| as | 6 |
| . | 7 |
| train@@ | 8 |
| surface | 9 |
| so | 10 |
| histori@@ | 11 |
| scann@@ | 12 |
| finally | 13 |
| 3d | 14 |
| i | 15 |
| a | 16 |
| used | 17 |

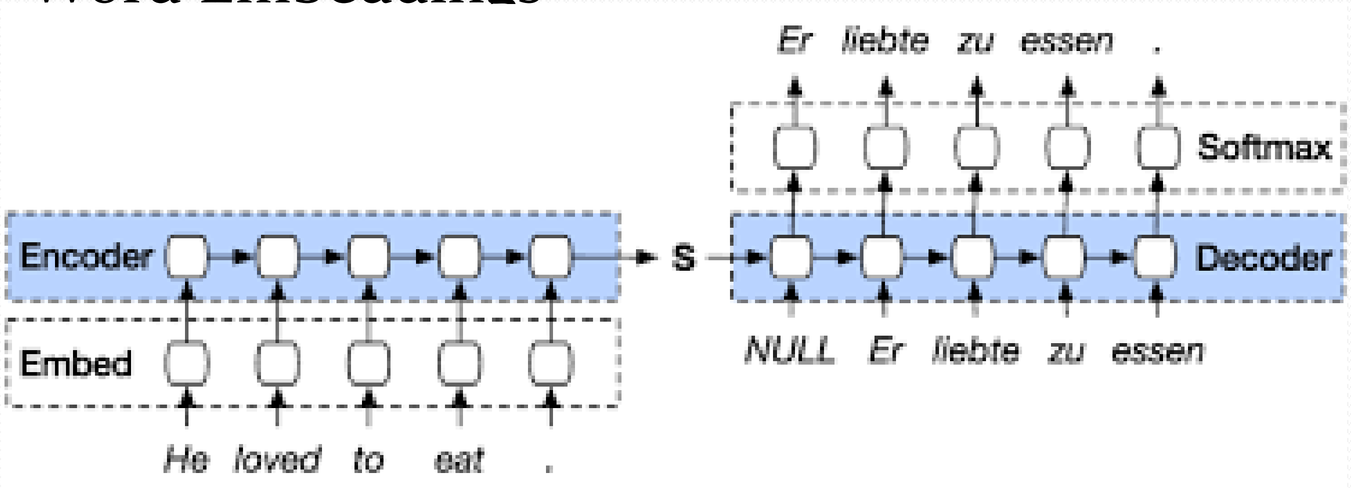
```
so finally , we used a 3d surface scann@@ er .
so i was train@@ ed as a histori@@ an .
```

**(ii) Convert to Indices**

```
10 13 1 0 17 16 14 9 12 4 7
10 15 2 8 5 6 16 11 3 7
```

# (6) Train NMT Model

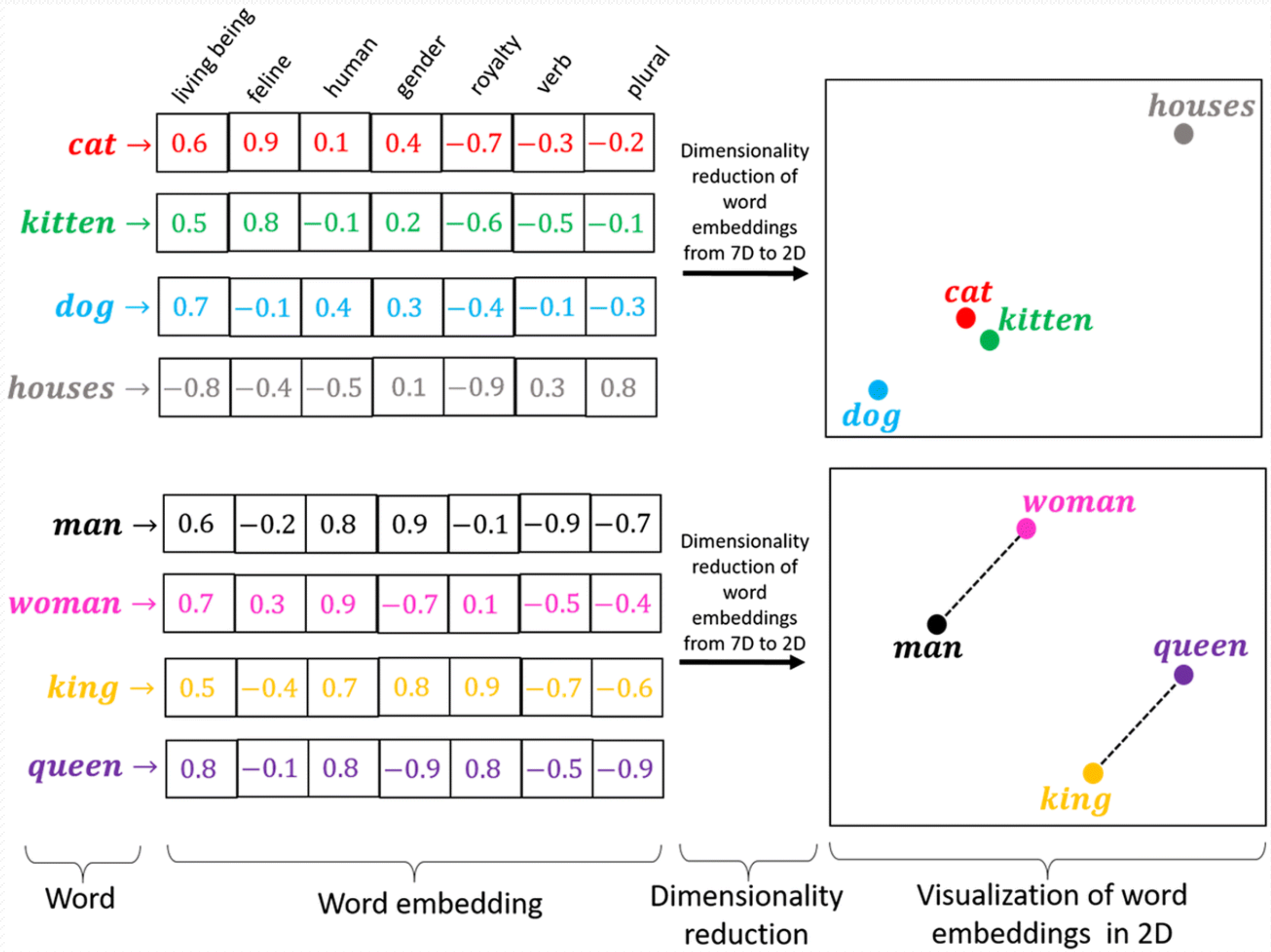
- Recurrent Neural Network
  - Basic Sequence-to-Sequence (Seq2Seq) Model
  - Encoder/Decoder framework
  - Word Embeddings



# Word Embeddings

- Neural Networks use vectors as inputs
- Convert a word to a fixed-length vector
- Semantic meaning of words is preserved

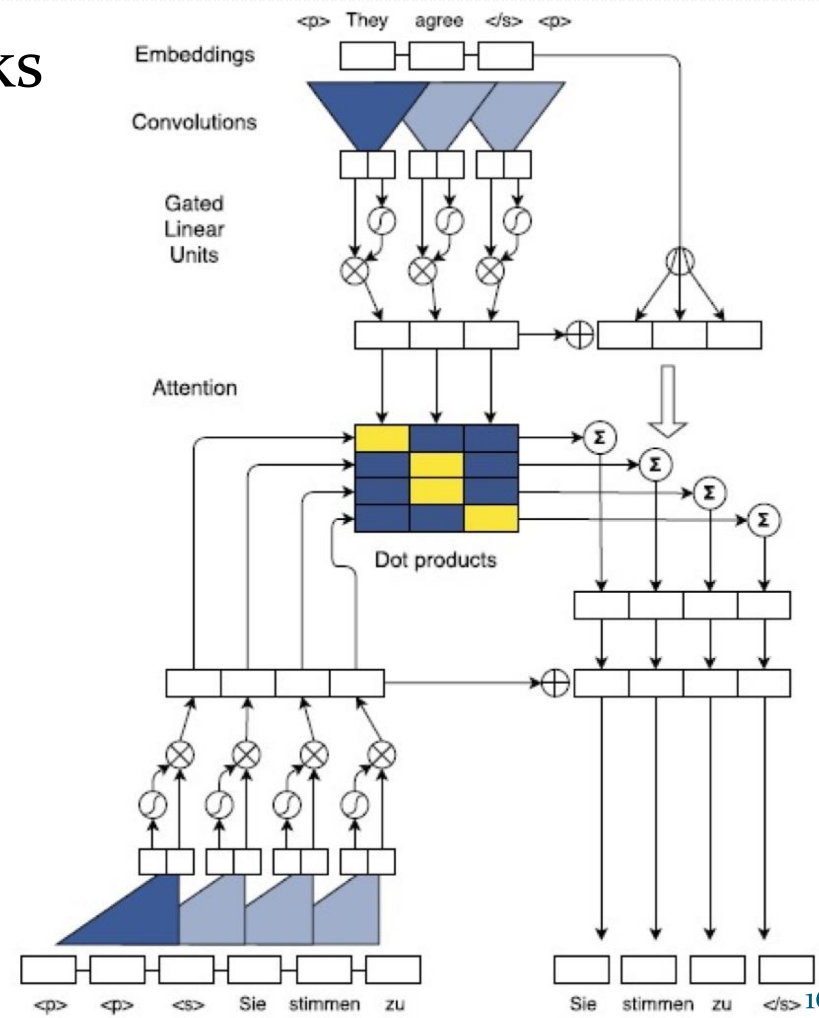
# Word Embeddings




| | living being | feline | human | gender | royalty | verb | plural |
|---|---|---|---|---|---|---|---|
| *cat* → | 0.6 | 0.9 | 0.1 | 0.4 | −0.7 | −0.3 | −0.2 |
| *kitten* → | 0.5 | 0.8 | −0.1 | 0.2 | −0.6 | −0.5 | −0.1 |
| *dog* → | 0.7 | −0.1 | 0.4 | 0.3 | −0.4 | −0.1 | −0.3 |
| *houses* → | −0.8 | −0.4 | −0.5 | 0.1 | −0.9 | 0.3 | 0.8 |
| *man* → | 0.6 | −0.2 | 0.8 | 0.9 | −0.1 | −0.9 | −0.7 |
| *woman* → | 0.7 | 0.3 | 0.9 | −0.7 | 0.1 | −0.5 | −0.4 |
| *king* → | 0.5 | −0.4 | 0.7 | 0.8 | 0.9 | −0.7 | −0.6 |
| *queen* → | 0.8 | −0.1 | 0.8 | −0.9 | 0.8 | −0.5 | −0.9 |

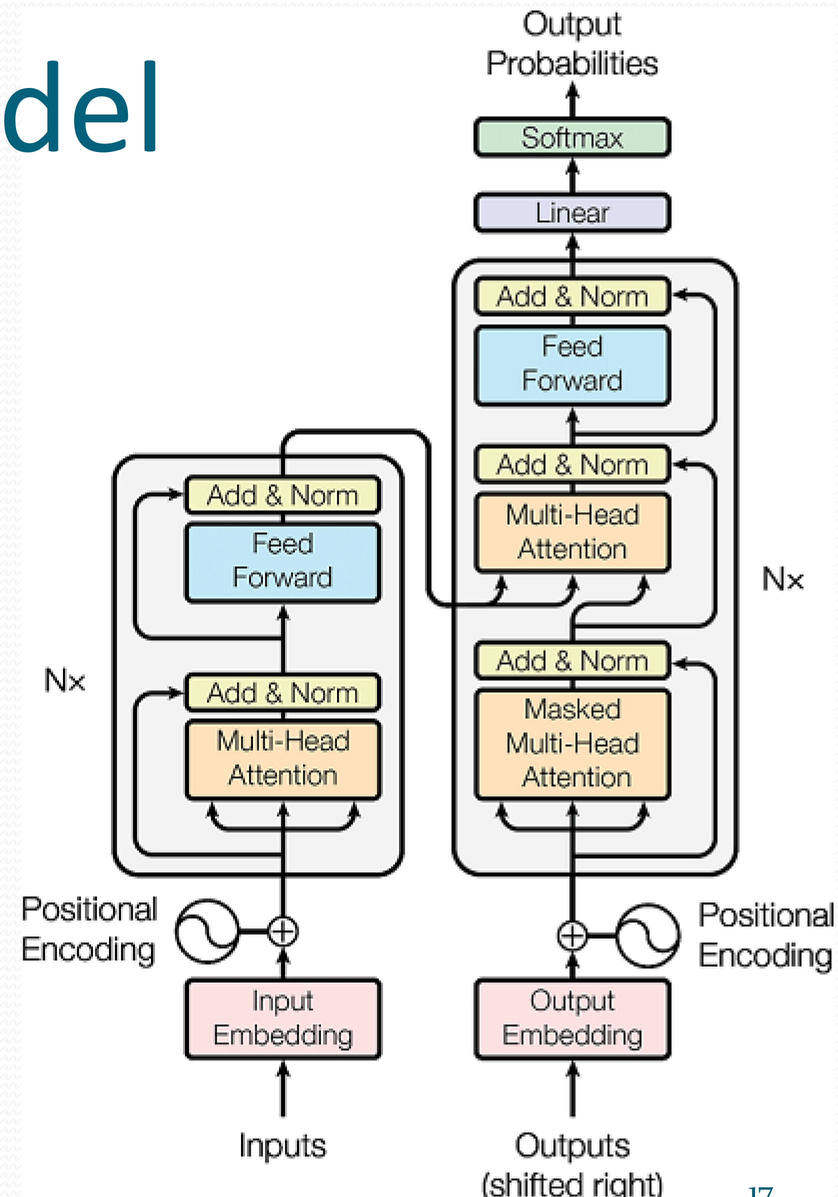
# (6) Train NMT Model

- More sophisticated networks
- Convolutional Seq2Seq
  - Convolutions
  - Position Embeddings
  - Attention



# (6) Train NMT Model

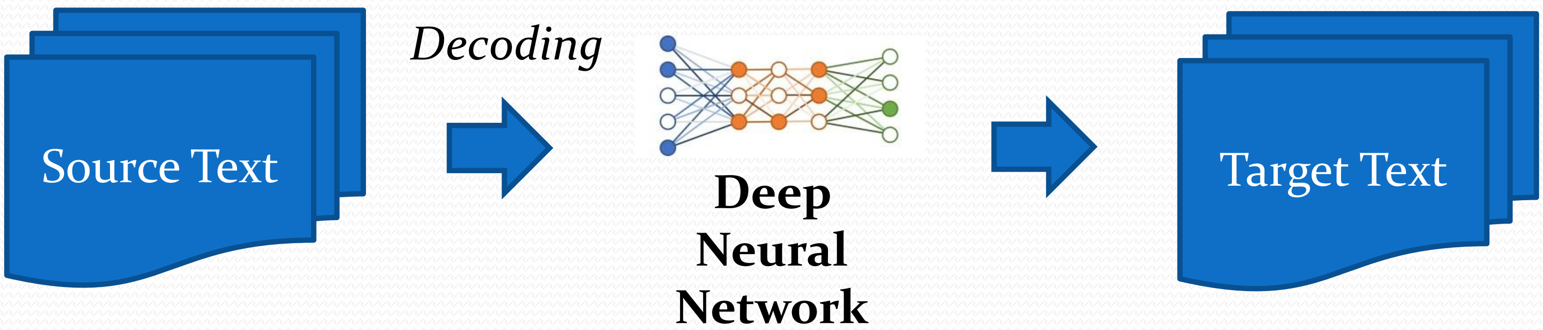
- More sophisticated networks
- Transformer
  - Self-Attention
  - Multi-Head Attention



# (6) Train NMT Model

- A number of model parameters (hyperparameters) can be tuned
- GPU Memory
  - Size of word embeddings (encoder/decoder dimensions)
  - Number of sentences to learn simultaneously (batch size)
- Training Time
  - Maximum number of runs (epochs)
  - When to stop training? (patience)

# (7) Decoding NMT Model



# (8) Post-processing

- Convert BPE sub-words into words
- Remove truecasing
- Remove tokenization

# (9) Automatic Evaluation

- Compare translation outputs (hypothesis) with the original translations (reference)
- **B**i**L**ingual **E**valuation **U**nderstudy (BLEU)
- From 0 to 1
  - 1 for identical hypothesis and reference
- Usually represented in percentage (0-100%)
- Higher than 30% considered a good BLEU score
- Sacrebleu
- Mteval

# (9) Automatic Evaluation

- **BLEU** Cased & Un-cased
- **W**ord **E**rror **R**ate (WER)
  - Similar to Edit distance
- **M**etric for **E**valuation of **T**ranslation with **E**xplicit **Or**dering (METEOR)
- Round-trip Translation
  - Translate the translation to source language and compare original source
  - Comparing not 1 but 2 systems
  - Used mostly in unsupervised translation (no parallel data)

# (10) Manual Evaluation

- By human translators
  - Adequacy
  - Fluency

| | Fluency | Adequacy |
|---|---|---|
| 1 | incomprehensible | none |
| 2 | disfluent English | little meaning |
| 3 | non-native English | much meaning |
| 4 | good English | most meaning |
| 5 | flawless English | all meaning |

# References

- Byte Pair Encoding
  - "*Neural Machine Translation of Rare Words with Subword Units*" Sennrich et al. 2015
- Word Embeddings
  - "*Distributed Word Representation of Words and Phrases and their Compositionality*" Mikolov et al. 2013
- Recurrent Neural Network
  - "*Sequence to Sequence Learning with Neural Networks*" Sutskever et al. 2014
  - "*Learning Phrase representation using RNN Encoder-Decoder for Statistical Machine Translation*" Cho et al. 2014
  - "*Neural Machine Translation by Jointly Learning to Align and Translate*" Bahdanau et al. 2014
- Convolutional Neural Network
  - "*Convolutional Sequence to Sequence Learning*" Gehring et al. 2017
- Transformer
  - "*Attention is all you need*" Vaswani et al. 2017

# Thank You!