Notes on Neural Machine Translation

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# Introduction to Statistical Machine Translation (SMT)

## A Little Bit of History with IBM Models for SMT

The IBM translation models go back to late 1980s and early 1990s. These models still form the basis for many SMT now in use today.

Let us assume that the task is to translate from *French* (the *source* language) into *English* (the *target* language).

//TODO: mainly [16] and [17]

## Alignment in Neural Machine Translation (NMT)

In NMT, *alignment* is the process of identifying word or phrase correspondence between source and target sentences. While early NMT models did not explicitly model alignment, modern approaches, particularly those using attention mechanisms, have incorporated ways to learn these relationships implicitly or explicitly.

Soft Implicit Alignment achieved with the Attention Mechanism

NMT especially those based on the Transformer architecture, utilize attention mechanisms to weight the importance of different parts of the source sentence when generating each word of the target sentence.

These attention weights effectively create a *soft alignment*, indicating the degree to which each source word influences the target word. Higher attention weights suggest stronger alignment. The soft alignment through Attention represents a model of *implicit alignment*.

For example in translating *“The cat sat on the mat”* to French, the attention mechanism may assign higher weights to *“cat”* when generating the French word *“chat”*, and to “mat” when generating *“tapis”*.

Explicit Alignment Models

While Attention provides implicit alignment, some research explores explicit alignment for better interpretability, constant imposition, and handling of specific translation phenomena. Explicit Alignment Models coexist with the main NMT model.

# Sequence Transduction (ST)

Sequence Transduction is the transformation of input sequences into output sequences.

Examples of sequence transduction:

Speech recognition

Machine translation

Protein secondary structure prediction

Challenge in sequence transduction:

Learning to represent both the input and output sequences in a way that is invariant to sequential distortions such as *shrinking*, *stretching*, and *translating*.

RNNs are powerful sequence learning architecture that has proven

//TODO: Finish this section (mainly [1])

## Continuous Translation Models (CTM)

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## Recurrent Continuous Translation Models (RCTM)

RCTM are a class of probabilistic

//TODO: Finish this section (mainly using [5])

# References

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