# Neural Machine Translation Introduction

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## Neural Probabilistic Models

A statistical model of language can be represented by the conditional probability of the next word given all the previous ones since

(npm.1)

where is the -th word, and writing sub-sequence .

When building statistical models of natural language , one considerably reduces the difficulty of this modeling problem by taking advantage of word order, and the fact that temporally closer words in the word sequence are statistically more dependent. Thus, n-gram models construct tables of conditional probabilities for the next word, for each one of a large number of contexts, i.e. combinations of the last words:

(npm.2)

We only consider those combinations of successive words that actually occur in the training corpus, or that occur frequently enough. What happens when a new combination of n words appears that was not seen in the training corpus? We do not want to assign zero probability to such cases, because such new combinations are likely to occur, and they will occur even more frequently for larger context sizes. A simple answer is to look at the probability predicted using a smaller context size, as done in back-off trigram models or in smoothed (or interpolated) trigram models. So, in such models, how is generalization basically obtained from sequences of words seen in the training corpus to new sequences of words? A way to understand how this happens is to think about a generative model corresponding to these interpolated or backoff n-gram models. Essentially, a new sequence of words is generated by “gluing” very short and overlapping pieces of length words that have been seen frequently in the training data. The rules for obtaining the probability of the next piece are implicit in the particulars of the back-off or interpolated n-gram algorithm. Trigrams (n = 3) used to be popular in the beginning of 21st century and additional improvements were added.

//TODO: summarize the interesting points from Bengio’s article from 2003

## Statistical Machine Translation (SMT)

The goal of statistical machine translation (SMT) is to produce target string from source string where models are estimated from examples. Among the possible target strings the one with max probability is chosen. The Bayes relation is used to introduce a target language model:

(smt.1)

where is the *translation model* and is the *language model*. That is, the *translation model* is the probability that the source string is the translation of the target string while *language model* is the probability of seeing the target language string .

//TODO: finish this section (from

## Sequence to Sequence Network (Seq2Seq)

Drawback of Deep Neural Networks – can only be applied to problems whose inputs and targets can be sensibly encoded with vectors of fixed dimensionality. This is a significant limitation since many important problems are best expressed with sequences whose lengths are not known a-priori. For example, speech recognition and machine translation are sequential problems. Likewise, question answering can be seen as mapping a sequence of words representing the question to a sequence of words representing the answer.

## Continuous Space Language Models (CSLM) for Statistical Machine Translation

In most statistical approaches to machine translation the basic units of translation are phrases that are composed of one or more words. At the heart of the translation systems are models that estimate the translation probabilities for pairs of phrases, one phrase being from the source language and the other from the target language. Such models count phrase pairs and their occurrences as distinct if the surface forms of the phrases are distinct. Although distinct phrase pairs often share significant similarities, linguistic or otherwise, they do not share statistical weight in the models’ estimation of their translation probabilities. Besides ignoring the similarity of phrase pairs, this leads to general sparsity issues. The estimation is sparse or skewed for the large number of rare or unseen phrase pairs, which grows exponentially in the length of the phrases, and the generalization to other domains is often limited.

Continuous representations have shown promise at tackling these issues. Continuous representations for words are able to capture their morphological syntactic and semantic similarity.

//TODO: finish the section on Continuous Space Language Models

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