## 2 Machine Learning for MT Preliminaries

First, before talking about any specific models, this chapter describes the overall framework of models that use data to *learn* how to perform MT. There are a number of (non-mutually-exclusive) concepts that fall under this overall umbrella, including **example-based machine translation** (EBMT; [3]), **statistical machine translation** (SMT; [2]), and **neural machine translation** (NMT; [1]) more formally.

First, we define our task of machine translation as translating a source sentence  $F = f_1, \ldots, f_J = f_1^{|F|}$  into a target sentence  $E = e_1, \ldots, e_I = e_1^{|E|}$ . Thus, any type of translation system can be defined as a function

$$\hat{E} = \operatorname{mt}(F), \tag{1}$$

which returns a translation hypothesis  $\hat{E}$  given a source sentence F as input.

Statistical machine translation systems are systems that perform translation by creating a probabilistic model for the probability of E given F,  $P(E \mid F; \theta)$ , and finding the target sentence that maximizes this probability:

$$\hat{E} = \underset{E}{\operatorname{argmax}} P(E \mid F; \theta), \tag{2}$$

where  $\theta$  are the parameters of the model specifying the probability distribution. The parameters  $\theta$  are learned from data consisting of aligned sentences in the source and target languages, which are called **parallel corpora** in technical terminology.<sup>2</sup> Within this framework, there are three major problems that we need to handle appropriately in order to create a good translation system:

**Modeling:** First, we need to decide what our model  $P(E \mid F; \theta)$  will look like. What parameters will it have, and how will the parameters specify a probability distribution?

**Learning:** Next, we need a method to learn appropriate values for parameters  $\theta$  from training data.

Search: Finally, we need to solve the problem of finding the most probable sentence (solving "argmax"). This process of searching for the best hypothesis and is often called decoding.<sup>3</sup>

The remainder of the material here will focus on solving these problems.

## References

[1] Robert B Allen. Several studies on natural language and back-propagation. In *Proceedings of the IEEE First International Conference on Neural Networks*, volume 2, page 341. IEEE Piscataway, NJ, 1987.

<sup>&</sup>lt;sup>1</sup>Note for the time being, we are assuming that we translate each sentence independently, although we will discuss document-level translation in Section 24.

<sup>&</sup>lt;sup>2</sup>Details about data can be found in Section 10.

<sup>&</sup>lt;sup>3</sup>This is based on the famous quote from Warren Weaver, likening the process of machine translation to decoding an encoded cipher.

- [2] Peter F. Brown, Vincent J.Della Pietra, Stephen A. Della Pietra, and Robert L. Mercer. The mathematics of statistical machine translation: Parameter estimation. *Computational Linguistics*, 19:263–312, 1993.
- [3] Makoto Nagao. A framework of a mechanical translation between Japanese and English by analogy principle. In *Proc. International NATO Symposium on Artificial and Human Intelligence*, pages 173–180, 1984.