Chapter 15

Representation Learning

In this chapter, we first discuss what it means to learn representations and how the notion of representation can be useful to design deep architectures. We discuss how learning algorithms share statistical strength across different tasks, including using information from unsupervised tasks to perform supervised tasks. Shared representations are useful to handle multiple modalities or domains, or to transfer learned knowledge to tasks for which few or no examples are given but a task representation exists. Finally, we step back and argue about the reasons for the success of representation learning, starting with the theoretical advantages of distributed representations (Hinton *et al.*, 1986) and deep representations and ending with the more general idea of underlying assumptions about the data generating process, in particular about underlying causes of the observed data.

Many information processing tasks can be very easy or very difficult depending on how the information is represented. This is a general principle applicable to daily life, computer science in general, and to machine learning. For example, it is straightforward for a person to divide 210 by 6 using long division. The task becomes considerably less straightforward if it is instead posed using the Roman numeral representation of the numbers. Most modern people asked to divide CCX by VI would begin by converting the numbers to the Arabic numeral representation, permitting long division procedures that make use of the place value system. More concretely, we can quantify the asymptotic runtime of various operations using appropriate or inappropriate representations. For example, inserting a number into the correct position in a sorted list of numbers is an $O(n)$ operation if the list is represented as a linked list, but only $O(\log n)$ if the list is represented as a red-black tree.

In the context of machine learning, what makes one representation better than