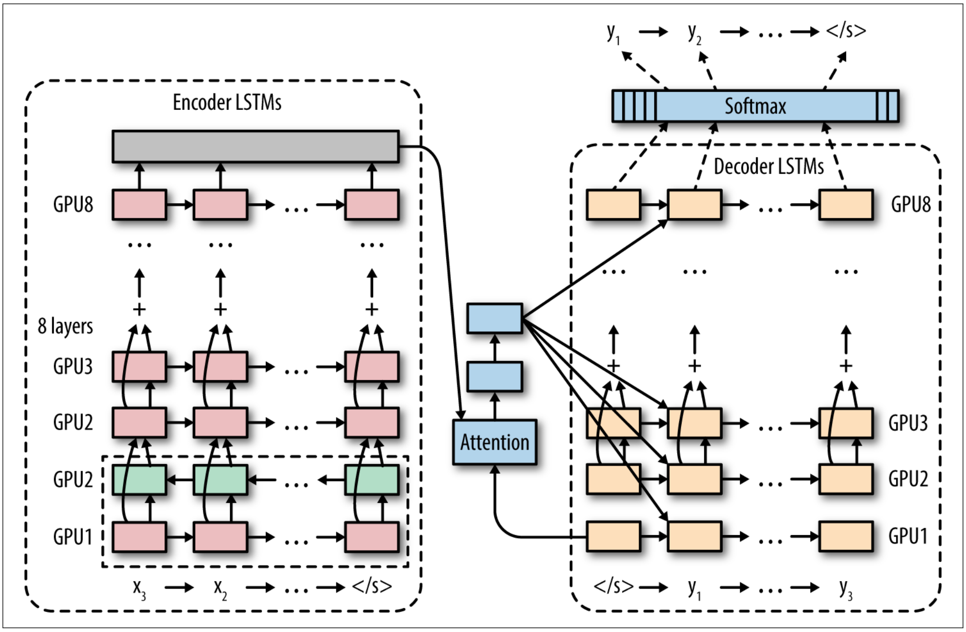

Figure 1-9. The Google neural machine translation system uses a deep recurrent architecture to process the input sentence and a second deep recurrent architecture to generate the translated output sentence.

One-Shot Models

One-shot learning is perhaps the most interesting new idea in machine/deep learning. Most deep learning techniques typically require very large amounts of data to learn meaningful behavior. The AlexNet architecture, for example, made use of the large ILSVRC dataset to learn a visual object detector. However, much work in cognitive science has indicated that humans can learn complex concepts from just a few examples. Take the example of baby learning about giraffes for the first time. A baby shown a single giraffe at the zoo might be capable of learning to recognize all giraffes she sees from then on.

Recent progress in deep learning has started to invent architectures capable of similar learning feats. Given only a few examples of a concept (but given ample sources of side information), such systems can learn to make meaningful predictions with very few datapoints. One recent paper (by an author of this book) used this idea to demonstrate that one-shot architectures can learn even in contexts babies can't, such as in medical drug discovery. A one-shot architecture for drug discovery is illustrated in Figure 1-10.

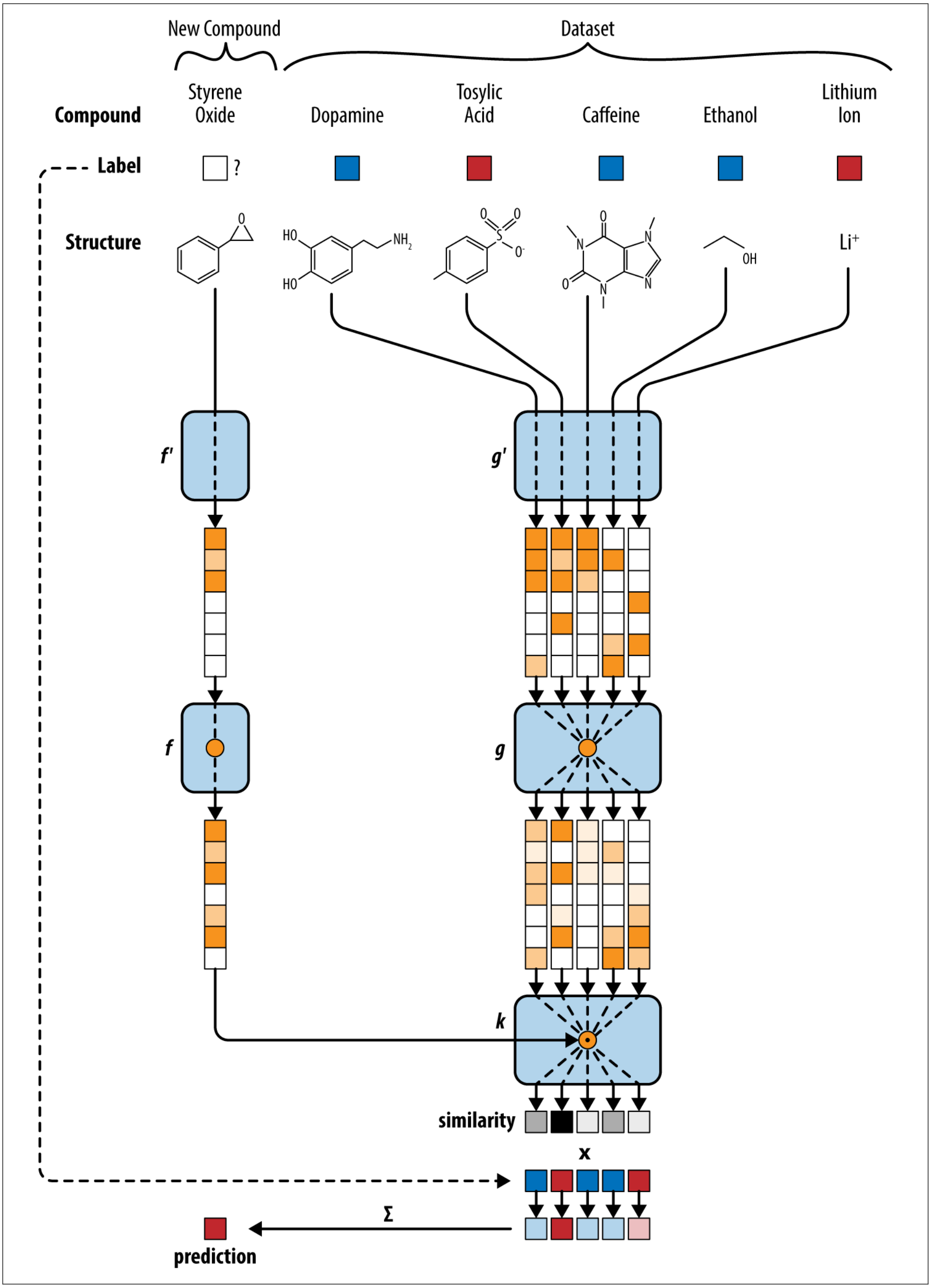

Figure 1-10. The one-shot architecture uses a type of convolutional network to transform each molecule into a vector. The vector for styrene oxide is compared with vectors from the experimental dataset. The label for the most similar datapoint (tosylic acid) is imputed for the query.

AlphaGo

Go is an ancient board game, widely influential in Asia. Computer Go has been a major challenge for computer science since the late 1960s. Techniques that enabled the computer chess system Deep Blue to beat chess grandmaster Garry Kasparov in 1997 don't scale to Go. Part of the issue is that Go has a much bigger board than chess; Go boards are of size 19 × 19 as opposed to 8 × 8 for chess. Since far more moves are possible per step, the game tree of possible Go moves expands much more quickly, rendering brute force search with contemporary computer hardware insufficient for adequate Go gameplay. Figure 1-11 illustrates a Go board.

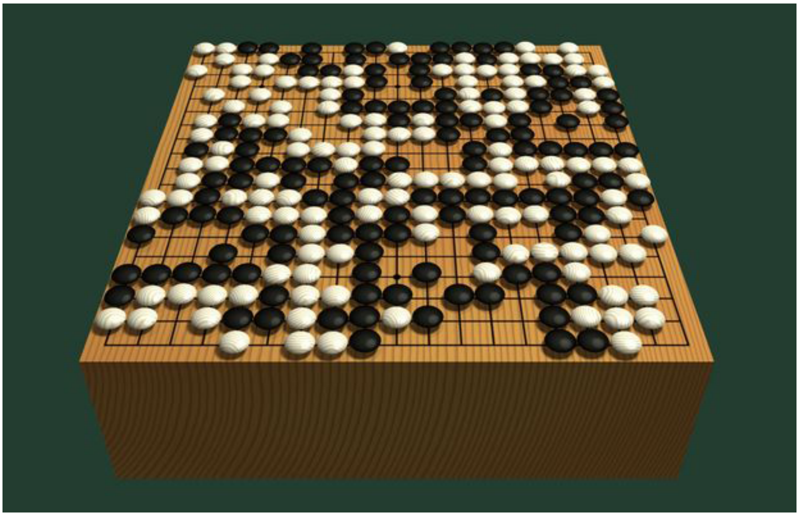

Figure 1-11. An illustration of a Go board. Players alternately place white and black pieces on a 19 × 19 grid.

Master level computer Go was finally achieved by AlphaGo from Google DeepMind. AlphaGo proved capable of defeating one of the world's strongest Go champions, Lee Sedol, in a five-game match. Some of the key ideas from AlphaGo include the use of a deep value network and deep policy network. The value network provides an estimate of the value of a board position. Unlike chess, it's very difficult to guess whether white or black is winning in Go from the board state. The value network solves this problem by learning to make this prediction from game outcomes. The policy network, on the other hand, helps estimate the best move to take given a current board state. The combination of these two techniques with Monte Carlo Tree search (a classical search method) helped overcome the large branching factor in Go games. The basic AlphaGo architecture is illustrated in Figure 1-12.