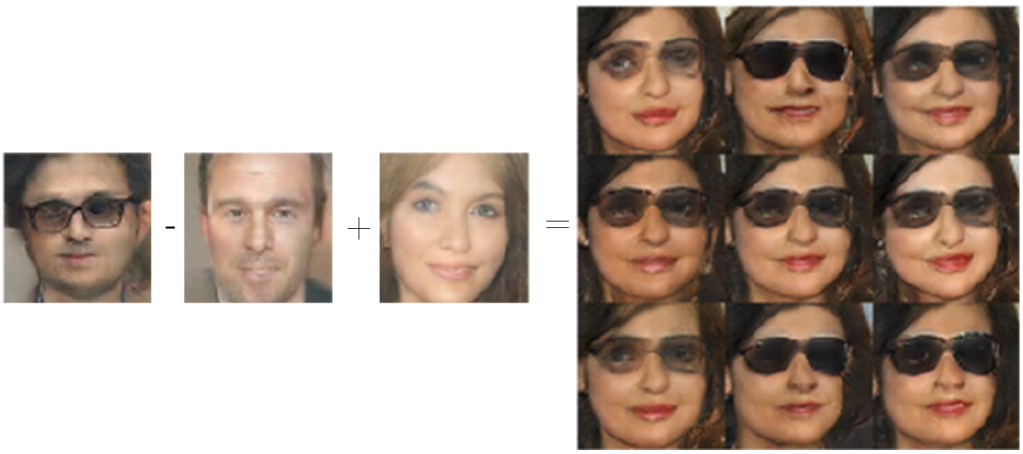

Figure 15.9: A generative model has learned a distributed representation that disentangles the concept of gender from the concept of wearing glasses. If we begin with the representation of the concept of a man with glasses, then subtract the vector representing the concept of a man without glasses, and finally add the vector representing the concept of a woman without glasses, we obtain the vector representing the concept of a woman with glasses. The generative model correctly decodes all of these representation vectors to images that may be recognized as belonging to the correct class. Images reproduced with permission from Radford *et al.* (2015).

common is that one could imagine *learning about each of them without having to see all the configurations of all the others*. Radford *et al.* (2015) demonstrated that a generative model can learn a representation of images of faces, with separate directions in representation space capturing different underlying factors of variation. Figure 15.9 demonstrates that one direction in representation space corresponds to whether the person is male or female, while another corresponds to whether the person is wearing glasses. These features were discovered automatically, not fixed a priori. There is no need to have labels for the hidden unit classifiers: gradient descent on an objective function of interest naturally learns semantically interesting features, so long as the task requires such features. We can learn about the distinction between male and female, or about the presence or absence of glasses, without having to characterize all of the configurations of the $n - 1$ other features by examples covering all of these combinations of values. This form of statistical separability is what allows one to generalize to new configurations of a person's features that have never been seen during training.