

If your task is similar to another task that has been studied extensively, you will probably do well by first copying the model and algorithm that is already known to perform best on the previously studied task. You may even want to copy a trained model from that task. For example, it is common to use the features from a convolutional network trained on ImageNet to solve other computer vision tasks ([Girshick *et al.*, 2015](#)).

A common question is whether to begin by using unsupervised learning, described further in part [III](#). This is somewhat domain specific. Some domains, such as natural language processing, are known to benefit tremendously from unsupervised learning techniques such as learning unsupervised word embeddings. In other domains, such as computer vision, current unsupervised learning techniques do not bring a benefit, except in the semi-supervised setting, when the number of labeled examples is very small ([Kingma *et al.*, 2014](#); [Rasmus *et al.*, 2015](#)). If your application is in a context where unsupervised learning is known to be important, then include it in your first end-to-end baseline. Otherwise, only use unsupervised learning in your first attempt if the task you want to solve is unsupervised. You can always try adding unsupervised learning later if you observe that your initial baseline overfits.

11.3 Determining Whether to Gather More Data

After the first end-to-end system is established, it is time to measure the performance of the algorithm and determine how to improve it. Many machine learning novices are tempted to make improvements by trying out many different algorithms. However, it is often much better to gather more data than to improve the learning algorithm.

How does one decide whether to gather more data? First, determine whether the performance on the training set is acceptable. If performance on the training set is poor, the learning algorithm is not using the training data that is already available, so there is no reason to gather more data. Instead, try increasing the size of the model by adding more layers or adding more hidden units to each layer. Also, try improving the learning algorithm, for example by tuning the learning rate hyperparameter. If large models and carefully tuned optimization algorithms do not work well, then the problem might be the *quality* of the training data. The data may be too noisy or may not include the right inputs needed to predict the desired outputs. This suggests starting over, collecting cleaner data or collecting a richer set of features.

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