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Dropout: A Simple Way to Prevent Neural Networks from Overfitting

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Abstract

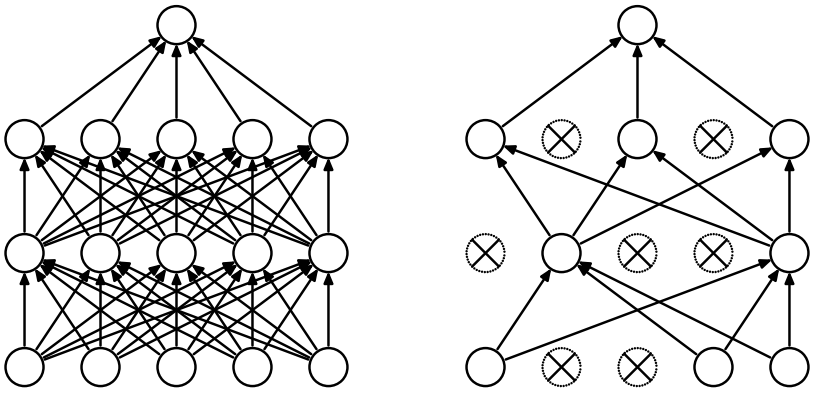
Deep neural nets with a large number of parameters are very powerful machine learning systems. However, overfitting is a serious problem in such networks. Large networks are also slow to use, making it difficult to deal with overfitting by combining the predictions of many different large neural nets at test time. Dropout is a technique for addressing this problem. The key idea is to randomly drop units (along with their connections) from the neural network during training. This prevents units from co-adapting too much. During training, dropout samples from an exponential number of different "thinned" networks. At test time, it is easy to approximate the effect of averaging the predictions of all these thinned networks by simply using a single unthinned network that has smaller weights. This significantly reduces overfitting and gives major improvements over other regularization methods. We show that dropout improves the performance of neural networks on supervised learning tasks in vision, speech recognition, document classification and computational biology, obtaining state-of-the-art results on many benchmark data sets.

Keywords: neural networks, regularization, model combination, deep learning

1. Introduction

Deep neural networks contain multiple non-linear hidden layers and this makes them very expressive models that can learn very complicated relationships between their inputs and outputs. With limited training data, however, many of these complicated relationships will be the result of sampling noise, so they will exist in the training set but not in real test data even if it is drawn from the same distribution. This leads to overfitting and many methods have been developed for reducing it. These include stopping the training as soon as performance on a validation set starts to get worse, introducing weight penalties of various kinds such as L1 and L2 regularization and soft weight sharing (Nowlan and Hinton, 1992).

With unlimited computation, the best way to "regularize" a fixed-sized model is to average the predictions of all possible settings of the parameters, weighting each setting by



(a) Standard Neural Net (b) After applying dropout.

Figure 1: Dropout Neural Net Model. **Left**: A standard neural net with 2 hidden layers. **Right**: An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped.

its posterior probability given the training data. This can sometimes be approximated quite well for simple or small models (Xiong et al., 2011; Salakhutdinov and Mnih, 2008), but we would like to approach the performance of the Bayesian gold standard using considerably less computation. We propose to do this by approximating an equally weighted geometric mean of the predictions of an exponential number of learned models that share parameters.

Model combination nearly always improves the performance of machine learning methods. With large neural networks, however, the obvious idea of averaging the outputs of many separately trained nets is prohibitively expensive. Combining several models is most helpful when the individual models are different from each other and in order to make neural net models different, they should either have different architectures or be trained on different data. Training many different architectures is hard because finding optimal hyperparameters for each architecture is a daunting task and training each large network requires a lot of computation. Moreover, large networks normally require large amounts of training data and there may not be enough data available to train different networks on different subsets of the data. Even if one was able to train many different large networks, using them all at test time is infeasible in applications where it is important to respond quickly.

Dropout is a technique that addresses both these issues. It prevents overfitting and provides a way of approximately combining exponentially many different neural network architectures efficiently. The term "dropout" refers to dropping out units (hidden and visible) in a neural network. By dropping a unit out, we mean temporarily removing it from the network, along with all its incoming and outgoing connections, as shown in Figure 1. The choice of which units to drop is random. In the simplest case, each unit is retained with a fixed probability p independent of other units, where p can be chosen using a validation set or can simply be set at 0.5, which seems to be close to optimal for a wide range of networks and tasks. For the input units, however, the optimal probability of retention is usually closer to 1 than to 0.5.