CSC411/2515 Fall 2015

Neural Networks Tutorial

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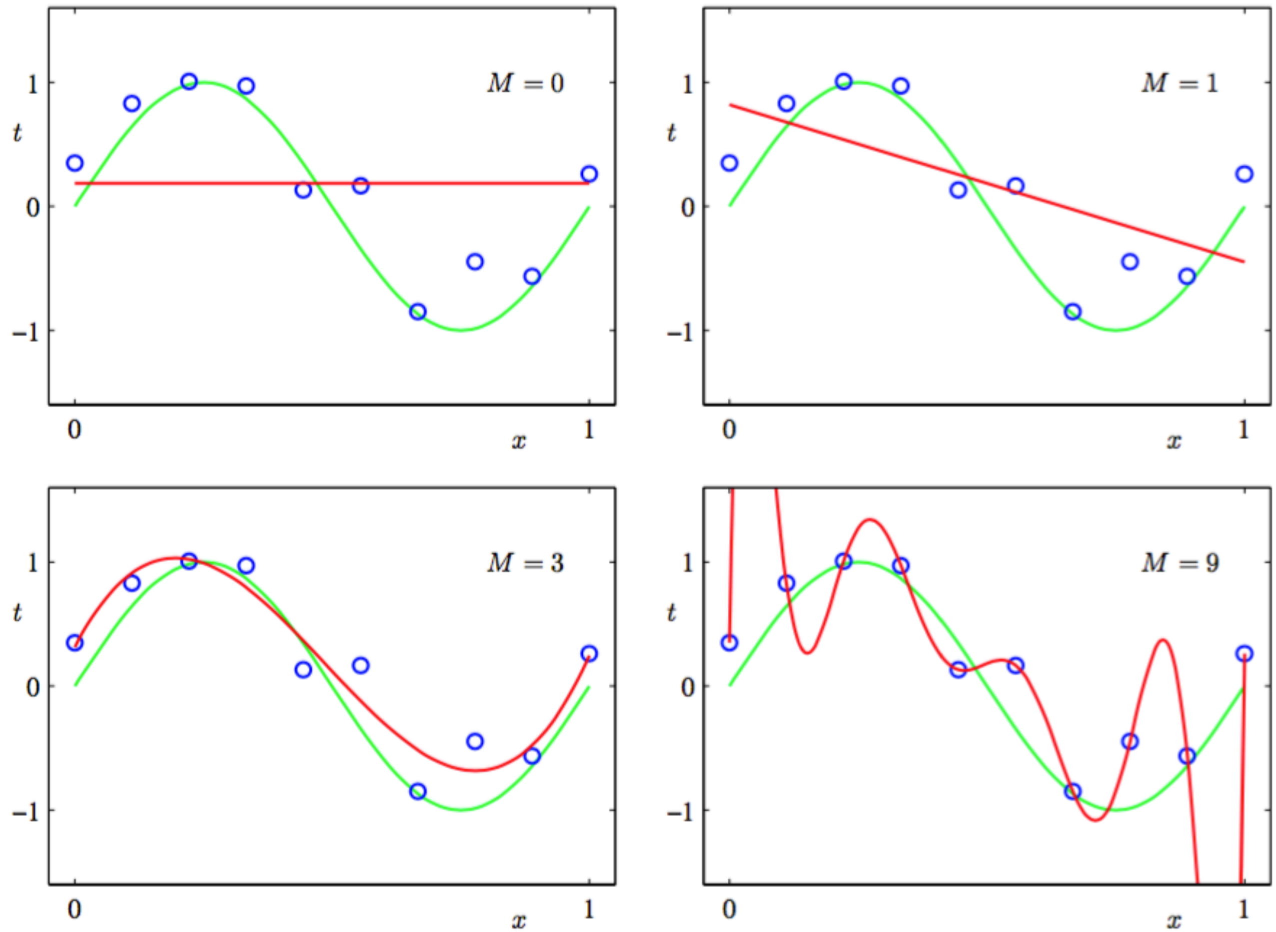
Slides adapted from Prof. Zemel's lecture notes.

Overfitting

- The training data contains information about the regularities in the mapping from input to output. But it also contains noise
  - The target values may be unreliable.
  - There is sampling error. There will be accidental regularities just because of the particular training cases that were chosen

- When we fit the model, it cannot tell which regularities are real and which are caused by sampling error.
  - So it fits both kinds of regularity.
  - If the model is very flexible it can model the sampling error really well. This is a disaster.

Overfitting



Picture credit: Chris Bishop. Pattern Recognition and Machine Learning. Ch.1.1.

Preventing overfitting

- Use a model that has the right capacity:
  - enough to model the true regularities
  - not enough to also model the spurious regularities (assuming they are weaker)

- Standard ways to limit the capacity of a neural net:
  - Limit the number of hidden units.
  - Limit the size of the weights.
  - Stop the learning before it has time to overfit.

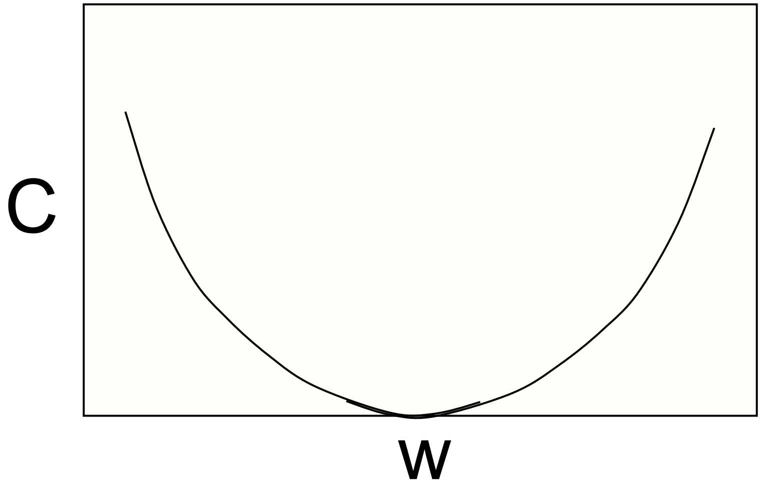
Limiting the size of the weights

Weight-decay involves adding an extra term to the cost function that penalizes the squared weights.

- Keeps weights small unless they have big error derivatives.

$$C = E + \frac{\lambda}{2}\sum_i w_i^2$$

$$\frac{\partial C}{\partial w_i} = \frac{\partial E}{\partial w_i} + \lambda w_i$$

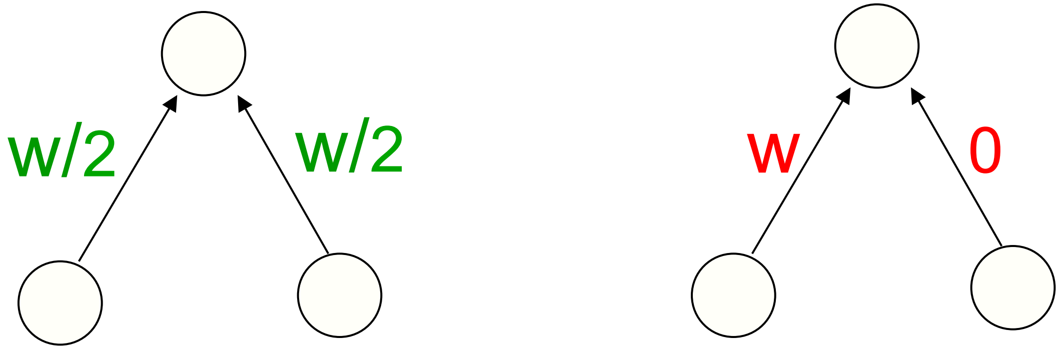


$$when \quad \frac{\partial C}{\partial w_i} = 0, \quad w_i = -\frac{1}{\lambda}\frac{\partial E}{\partial w_i}$$

The effect of weight-decay

- It prevents the network from using weights that it does not need
  - This can often improve generalization a lot.
  - It helps to stop it from fitting the sampling error.
  - It makes a smoother model in which the output changes more slowly as the input changes.

- But, if the network has two very similar inputs it prefers to put half the weight on each rather than all the weight on one → other form of weight decay?



Deciding how much to restrict the capacity

- How do we decide which limit to use and how strong to make the limit?
  - If we use the test data we get an unfair prediction of the error rate we would get on new test data.
  - Suppose we compared a set of models that gave random results, the best one on a particular dataset would do better than chance. But it won't do better than chance on another test set.

- So use a separate validation set to do model selection.

Using a validation set

- Divide the total dataset into three subsets:
  - Training data is used for learning the parameters of the model.
  - Validation data is not used of learning but is used for deciding what type of model and what amount of regularization works best
  - Test data is used to get a final, unbiased estimate of how well the network works. We expect this estimate to be worse than on the validation data

- We could then re-divide the total dataset to get another unbiased estimate of the true error rate.

Preventing overfitting by early stopping

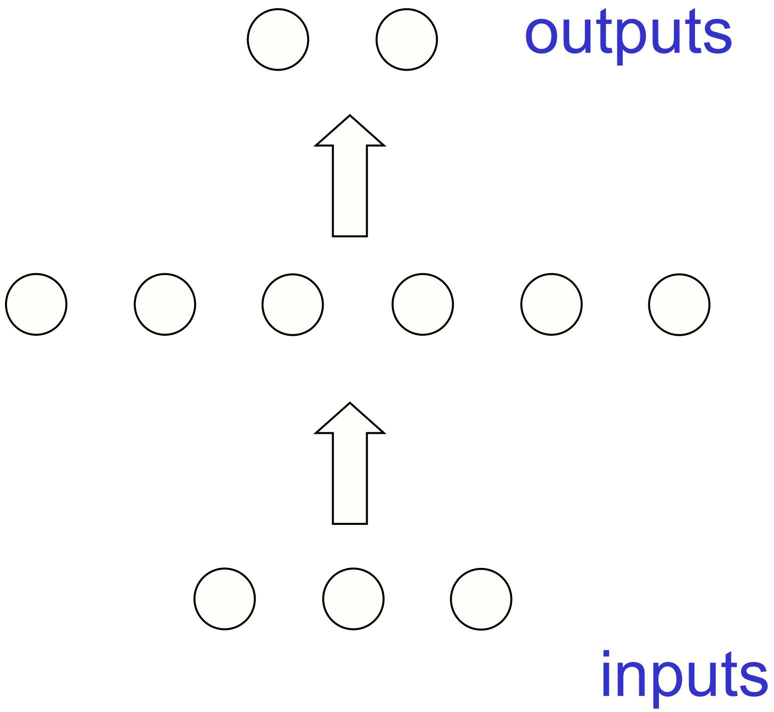
- If we have lots of data and a big model, its very expensive to keep re-training it with different amounts of weight decay

- It is much cheaper to start with very small weights and let them grow until the performance on the validation set starts getting worse

- The capacity of the model is limited because the weights have not had time to grow big.

Why early stopping works

- When the weights are very small, every hidden unit is in its linear range.
  - So a net with a large layer of hidden units is linear.
  - It has no more capacity than a linear net in which the inputs are directly connected to the outputs!
- As the weights grow, the hidden units start using their non-linear ranges so the capacity grows.



Le Net

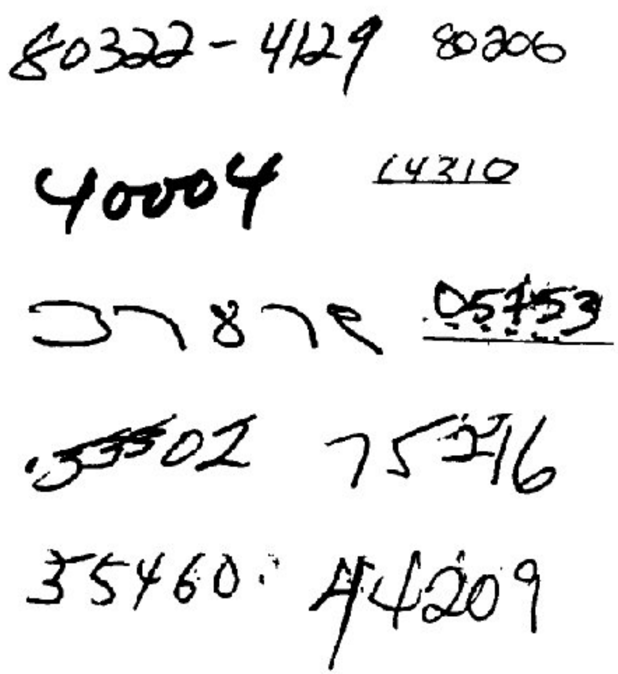
- Yann LeCun and others developed a really good recognizer for handwritten digits by using backpropagation in a feedforward net with:
  - Many hidden layers
  - Many pools of replicated units in each layer.
  - Averaging the outputs of nearby replicated units.
  - A wide net that can cope with several characters at once even if they overlap.

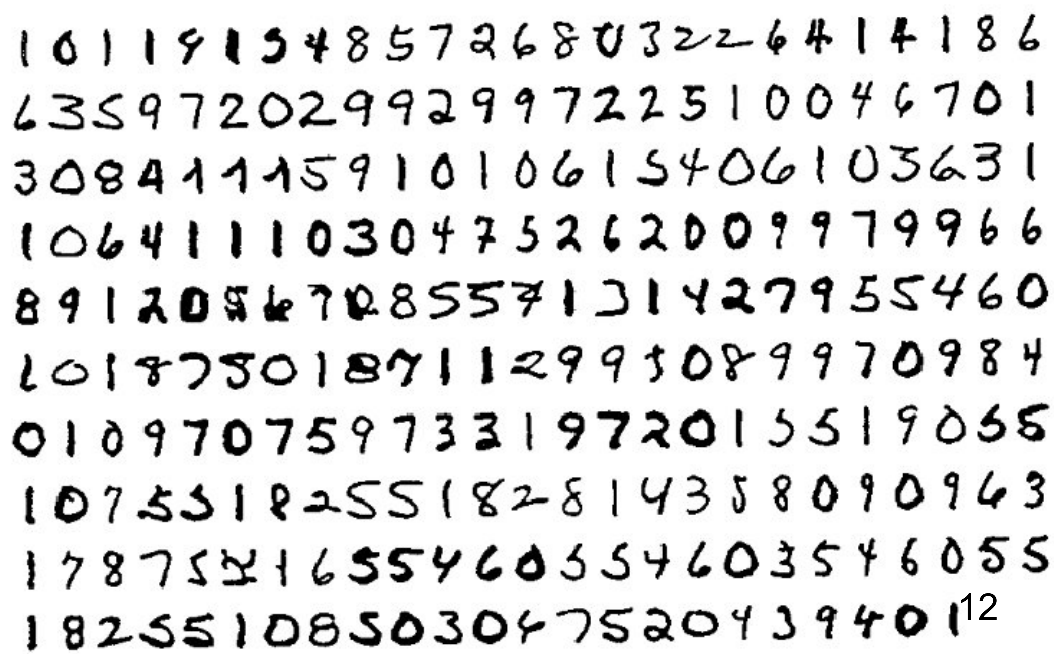
- Demos of LENET at http://yann.lecun.com

Recognizing Digits

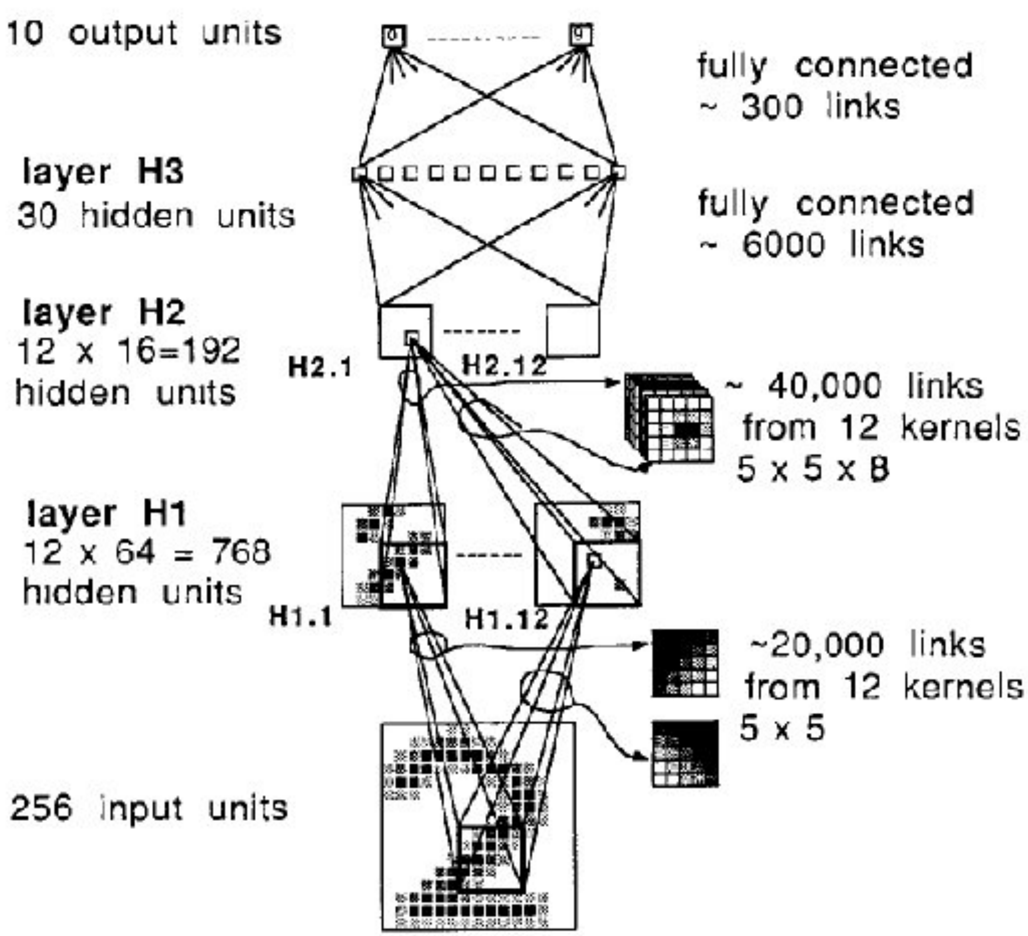
Hand-written digit recognition network

- 7291 training examples, 2007 test examples
- Both contain ambiguous and misclassified examples
- Input pre-processed (segmented, normalized)
  - 16x16 gray level [-1,1], 10 outputs





LeNet: Summary



Main ideas:

- Local → global processing
- Retain coarse posn info

Main technique: weight sharing – units arranged in feature maps

Connections: 1256 units, 64,660 cxns, 9760 free parameters

Results: 0.14% (train), 5.0% (test)

vs. 3-layer net w/ 40 hidden units: 1.6% (train), 8.1% (test)

The 82 errors made by LeNet5

Notice that most of the errors are cases that people find quite easy.

The human error rate is probably 20 to 30 errors

A brute force approach

- LeNet uses knowledge about the invariances to design:
  - the network architecture
  - or the weight constraints
  - or the types of feature

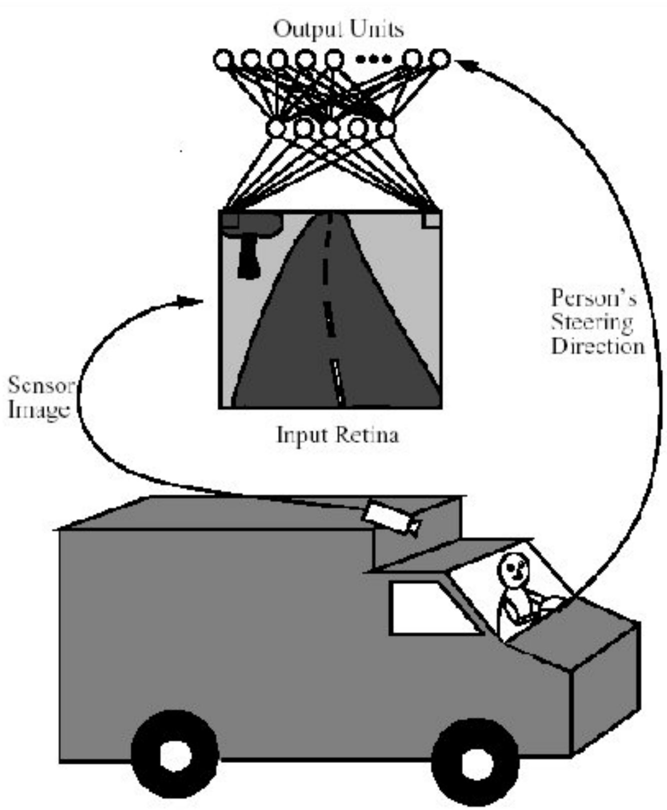
- But its much simpler to incorporate knowledge of invariances by just creating extra training data:
  - for each training image, produce new training data by applying all of the transformations we want to be insensitive to
  - Then train a large, dumb net on a fast computer.
  - This works surprisingly well

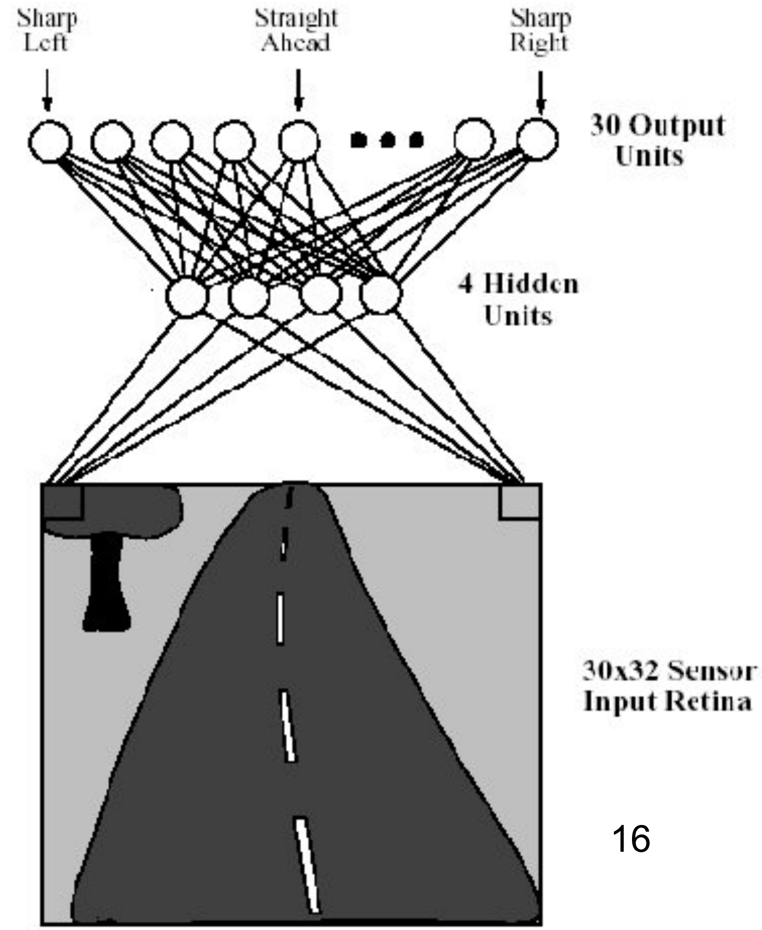
Fabricating training data

Good generalization requires lots of training data, including examples from all relevant input regions

Improve solution if good data can be constructed

Example: ALVINN



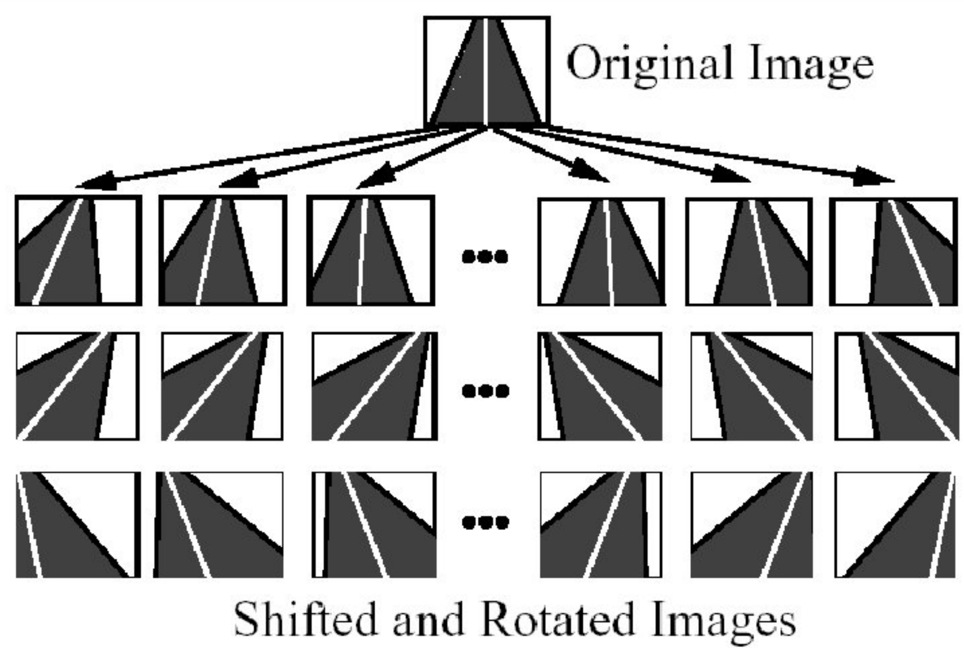


ALVINN: simulating training examples

On-the-fly training: current video camera image as input, current steering direction as target

But: over-train on same inputs; no experience going off-road

Method: generate new examples by shifting images



Replace 10 low-error & 5 random training examples with 15 new

Key: relation between input and output known!

Making backpropagation work for recognizing digits

- Using the standard viewing transformations, and local deformation fields to get lots of data.

- Use many, globally connected hidden layers and learn for a very long time
  - This requires a GPU board or a large cluster

- Use the appropriate error measure for multi-class categorization
  - Cross-entropy, with softmax activation

- This approach can get 35 errors on MNIST!

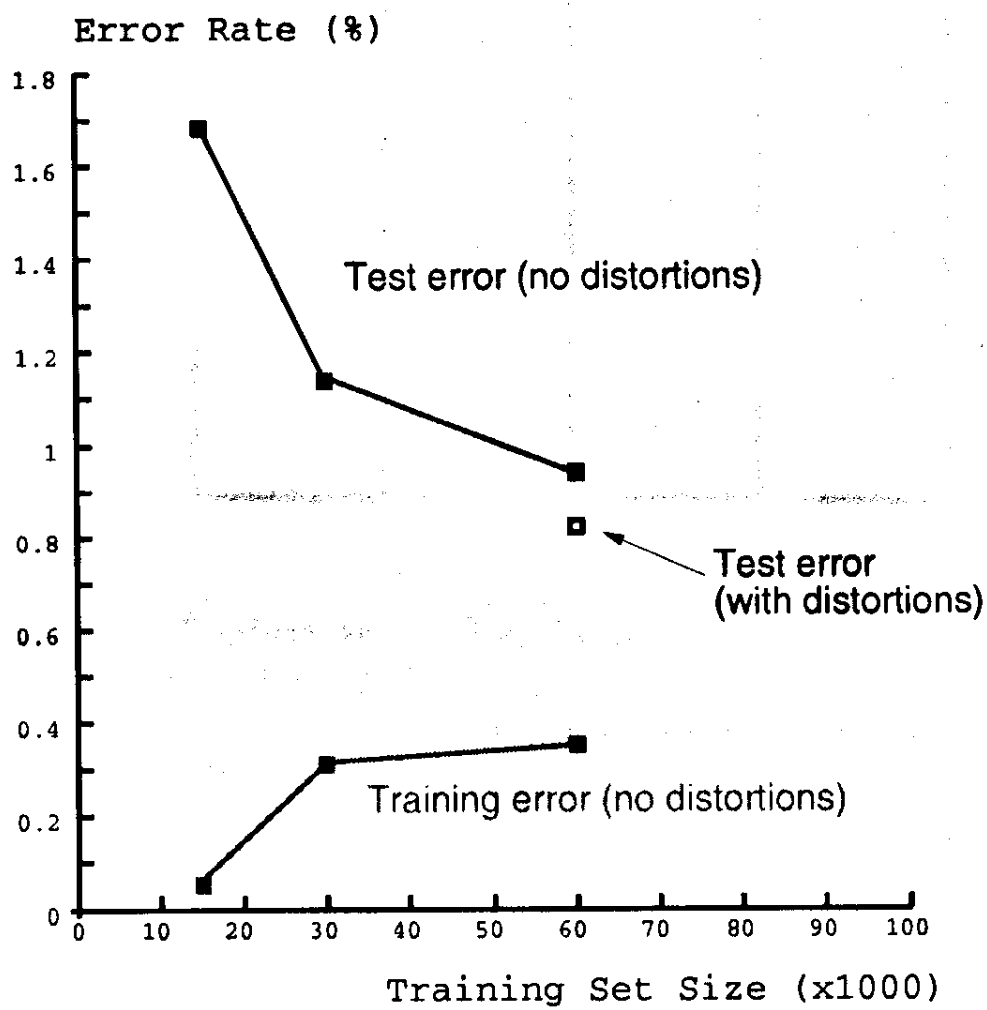


Fig. 6. Training and test errors of LeNet-5 achieved using training sets of various sizes. This graph suggests that a larger training set could improve the performance of LeNet-5. The hollow square show the test error when more training patterns are artificially generated using random distortions. The test patterns are not distorted.

Neural Net Demos