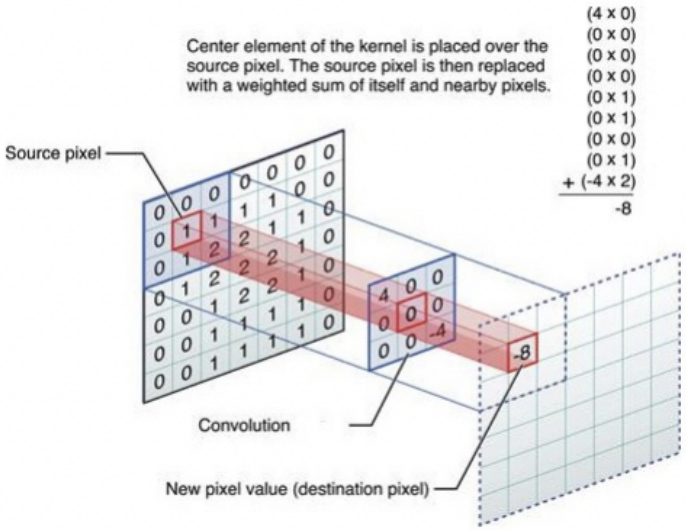
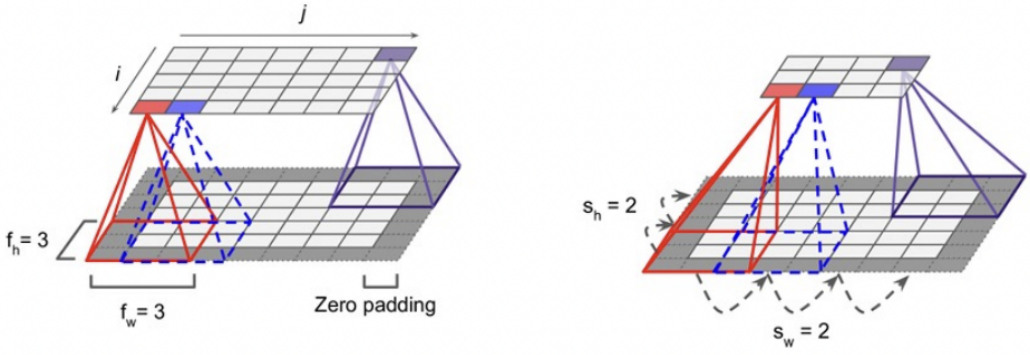
CAS CS 505
Lec 16

Neural Network Tuning and Advanced Features, Part 2

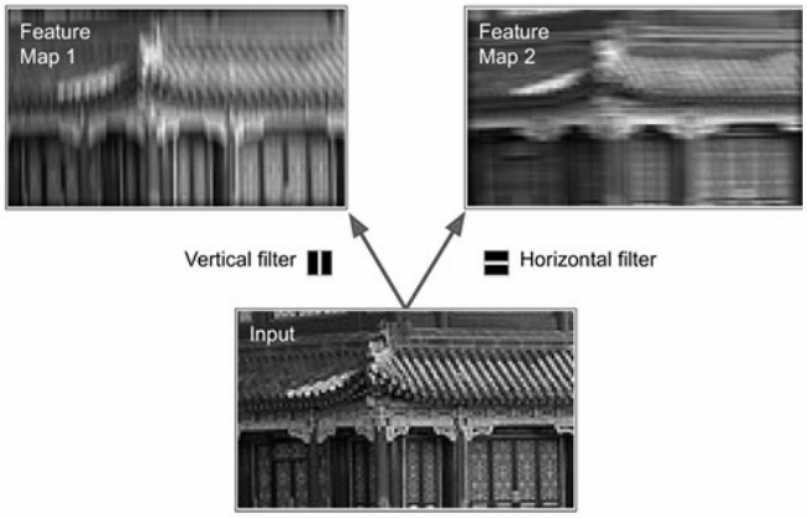
1. Convolutional Neural Networks
    a. Convolutional neural networks have had great success in image processing, and to a more limited degree, in NLP.
    b. CNNs add convolution and pooling layers to focus on small regions of the data (here, images). Each input to the next layer is calculated as the dot product of the convolution kernel with a small region of the image.



    c. (kernels are weighted sum of pixel values and are multiplied by the source pixel)
    d. Can be weighted sum or weighted average → the convolution weights summarize parts of the image (to detect edges, blur the image, and etc.)
    e. It reduces the image size by one pixel from all directions
    f. The convolution kernels are moved around the image, perhaps by some skip....
    g. The kernel values are started randomly and are learned (some hyperparameters → skip, move one by one, have extra layer as zero padding, etc.)

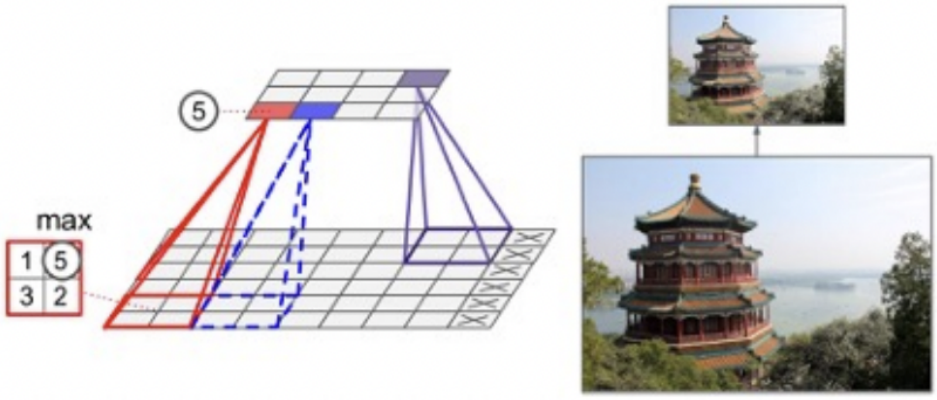


h. Since data is shared in the region covered by the kernel, various “features” of the image can be recognized in multiple places around the image:

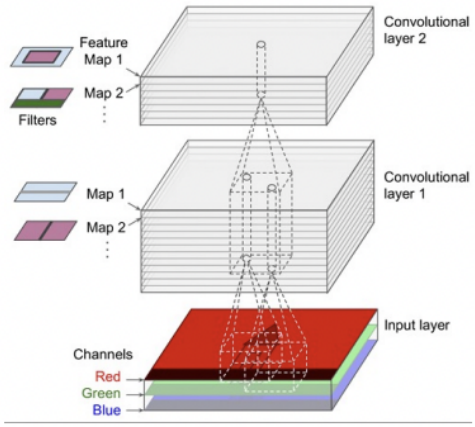


   i. The vertical filters are [[0,1,0],[0,1,0],[0,1,0]]
   ii. The horizontal filters are [[0,0,0],[1,1,1],[0,0,0]]

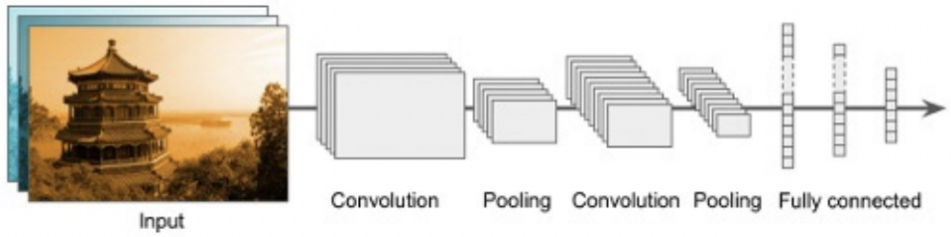
i. A pooling layer performs dimensionality reduction by averaging (or taking the maximum) of small regions in the previous layer:



j. And layers can have multiple “maps”(convolution and pooling) and be stacked:



k. It is typical to alternate convolution and pooling layers and end with fully connected layers before output: (played more role in images)



   i. Backpropagate the error and learn the hyperparameters

l. So… if this is an NLP class, why are we discussing CNNs for images??

m. Three reasons:

   i. One: Language is not just represented by linear sequences of Unicode symbols, it also exists in handwritten form!

   ii. In fact, the very first big success in NNs was achieved by Yann LeCunn and colleagues at Bell Labs in the 1990s, solving the problem of handwritten digit and letter recognition using CNNs:

iii.

Gradient-Based Learning Applied to Document Recognition

YANN LECUN, MEMBER, IEEE, LÉON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

Invited Paper

Table 14-1. LeNet-5 architecture

Layer	Type	Maps	Size	Kernel size	Stride	Activation
Out	Fully Connected	–	10	–	–	RBF
F6	Fully Connected	–	84	–	–	tanh
C5	Convolution	120	1 × 1	5 × 5	1	tanh
S4	Avg Pooling	16	5 × 5	2 × 2	2	tanh
C3	Convolution	16	10 × 10	5 × 5	1	tanh
S2	Avg Pooling	6	14 × 14	2 × 2	2	tanh
C1	Convolution	6	28 × 28	5 × 5	1	tanh
In	Input	1	32 × 32	–	–	–

iv.

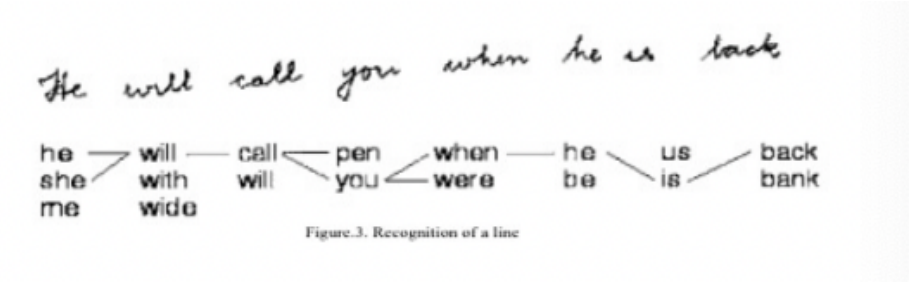
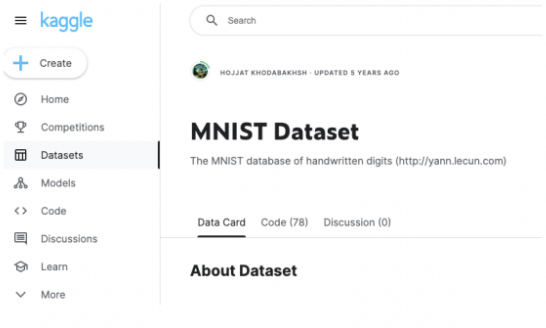
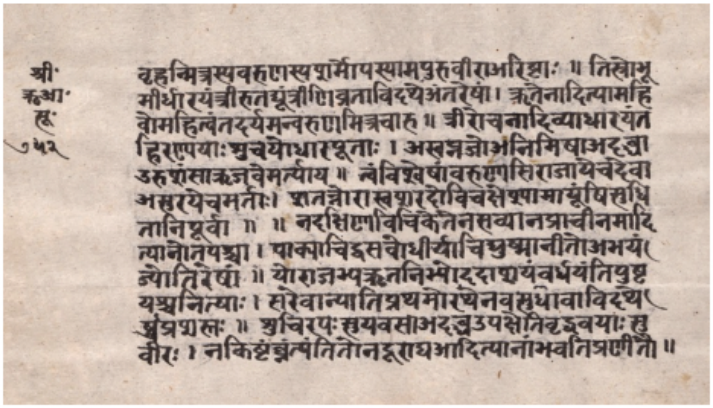


Figure.3. Recognition of a line

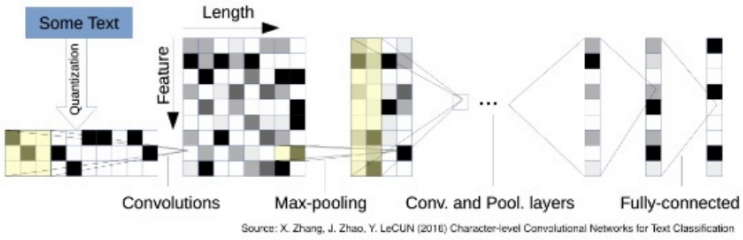
n. The dataset from that classic paper is now the “Hello World” of neural network programming!

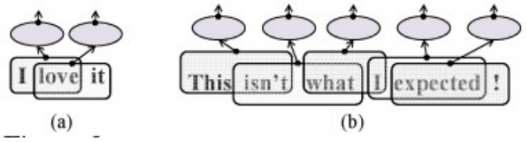


o. Similar techniques are used in decoding and transcribing historical manuscripts (handwritten many centuries before Unicode!):

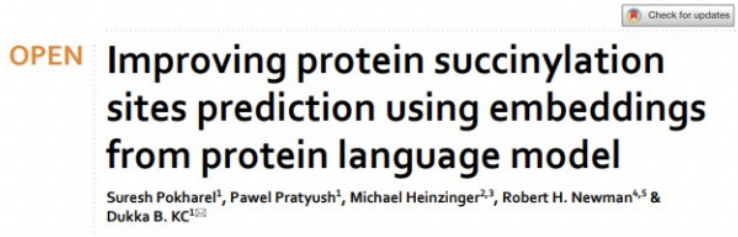


p. Second: 2D CNNs turned out to not be that useful (say in matrices of embedding sequences), but 1D CNNs (which essentially recognize Ngrams) have proved useful in sentiment analysis – essentially the convolution recognizes N-grams!
   i. Each word in the text is a column and each row can be embeddings in 2D → didn't work that well
   ii. The kernel is now 1 by n and has the weighted average of the sequence (can send convolutional kernel of different threads → which is n-gram)





q. Third: NLP techniques based on CNNs are used in many non-linguistic contexts, particularly in analyzing DNA and other linear molecules:



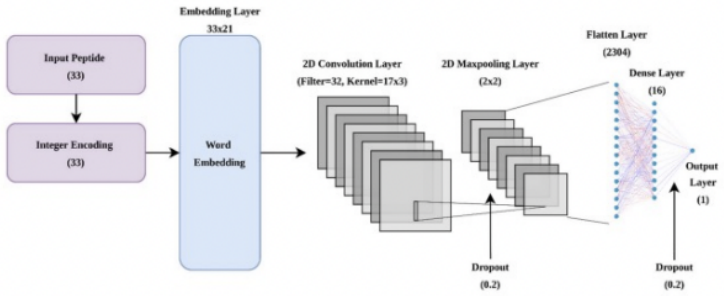


Figure 1. Architecture of supervised word embedding based model using a convolutional neural network.

r. CNNs in Pytorch:

```
class CNN_Net1(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 32, kernel_size=3)
        self.conv2 = nn.Conv2d(32, 64, kernel_size=3)
        self.conv2_drop = nn.Dropout2d(0.4)
        self.fc2 = nn.Linear(500, 100)
        self.fc3 = nn.Linear(100, 10)

    def forward(self, x):
        x = self.conv1(x)
        x = F.relu(F.max_pool2d(x, 2))
        x = self.conv2(x)
        x = self.conv2_drop(x)
        x = F.relu(F.max_pool2d(x, 2))
        x = x.view(-1, 1600)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        x = self.fc3(x)
        return x
```

2. Embedding Layers
    a. Current NLP systems all use word embeddings as inputs:

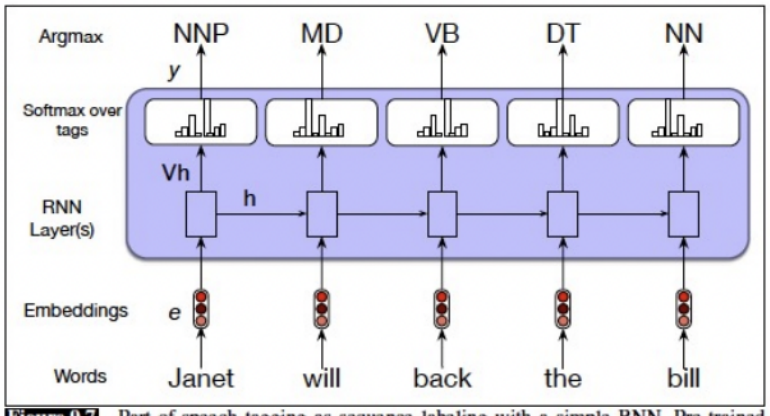


Figure 9.7 Part-of-speech tagging as sequence labeling with a simple RNN. Pre-trained word embeddings serve as inputs and a softmax layer provides a probability distribution over the part-of-speech tags as output at each time step.

    b. Therefore, Pytorch and other NN platforms provide built-in embedding layers….
    c. An embedding layer is a simple lookup table which maps indices to embedding vectors (an array of D floats for some dimension D).
    d. By default, the embedding layer is untrained, so the vectors are random floats:

In [19]:
```
class EmbeddingExample(nn.Module):

        def __init__(self):
            super().__init__()
            self.embedding_layer = nn.Embedding(10,50)

        def forward(self,x):
            x = self.embedding_layer(x)
            return x

embedding_model = EmbeddingExample()

embedding_model( torch.tensor(0) )
```

Out[19]:
```
tensor([-1.5466, -0.7189, -1.3827, -0.1787,  1.0937,  1.8469,  0.3557,  1.8965,
         1.1616, -1.3141, -0.7681,  0.1190, -0.5923, -0.2816,  0.9321,  1.2912,
        -1.0337, -0.4085,  0.8838,  0.4950, -0.4681,  1.2889, -1.0458,  1.2371,
        -0.7286, -1.3844, -0.5985, -0.8621, -1.8770, -3.3333, -0.2535, -0.0394,
        -0.5554, -0.1743,  0.7165,  0.3712,  1.1531,  0.9583,  1.9512,  0.3636,
         0.9459, -2.3356,  0.6509,  1.3928, -1.9889,  0.0838,  0.2376,  0.0719,
        -1.6311, -0.0457], grad_fn=<EmbeddingBackward0>)
```

        i. You give 0 and it spits out length 50 embedding
        ii. You give it an integer → all it does is look it up from the 10 by 50 matrix (which needs to be trained)

e. The vocabulary is represented by (tensor) indices from into the vocabulary array

```
In [20]:
1  sentence = "This is a sentence of words for the embedding example"
2
3  words = sentence.lower().split()
4
5  vocab = sorted(set(words))
6
7  vocab_idx = { w : torch.tensor(i) for (i,w) in list(enumerate(vocab)) }
8
9  vocab_idx

Out[20]: {'a': tensor(0),
          'embedding': tensor(1),
          'example': tensor(2),
          'for': tensor(3),
          'is': tensor(4),
          'of': tensor(5),
          'sentence': tensor(6),
          'the': tensor(7),
          'this': tensor(8),
          'words': tensor(9)}
```

```
In [21]:
1  embedding_model( vocab_idx['sentence'] )

Out[21]: tensor([-1.0522, -1.5031, -0.8273, -0.2849, -0.6338,  0.9456, -0.1177,  0.4843,
                 -1.0190,  0.4294, -0.6801, -0.7463,  2.4668, -2.3485,  0.1480,  0.5330,
                  0.3156, -1.5070, -0.2272,  1.5661, -1.4879, -0.0688,  0.4833,  0.7480,
                 -1.4878, -0.4362,  0.4736, -0.5361, -0.0888, -0.4081, -0.4166,  0.2677,
                 -0.4611, -1.4399, -0.4965,  0.4376,  2.4829, -0.4196,  1.4912,  0.2124,
                  0.1241,  0.4749, -0.3347, -0.2382,  0.2249,  0.5873,  1.4045,  0.9617,
                 -0.6000, -0.4867], grad_fn=<EmbeddingBackward0>)
```

   i. Index for a number like the one hot position and then translates into embeddings

f. Embedding Layers can be used in two (overlapping) ways:
   i. You can create randomly-initialized embeddings, and train them via backprop as you process sequences of words in your task.
      1. Train on the sequences of the words (it will keep track of the where they are and train them)
   ii. You can load pretrained embeddings such a GloVe and use them as is; or
   iii. You can do both: import pretrained embeddings and further train them to specialize to your corpus.
      1. Word not in corpus and start from random to train

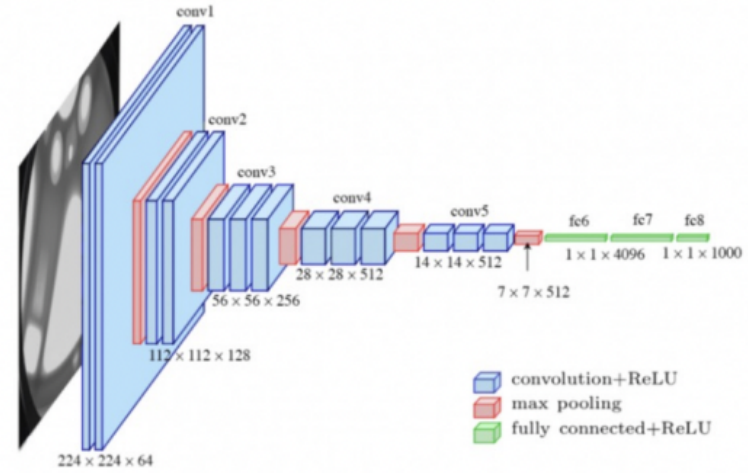
g. In Pytorch using torchtext:
   i. The only complication is that for each word in our vocabulary, we have to replace the initial random weights with the GloVe embedding if it is available, else initialize randomly.

ii.

```
# Load pre-trained GloVe embeddings
def load_glove_embeddings(path):
    ….
embeddings = load_glove_embeddings('glove.6B.100d.txt')

TEXT = Field(tokenize='spacy', tokenizer_language='en_core_web_sm', lower=True)

TEXT.build_vocab(train_dataset, vectors=GloVe(name='6B', dim=100))

weight_matrix = torch.zeros((len(TEXT.vocab), 100))

for word, index in vocab.stoi.items():
    weight_matrix[index] = embeddings.get(word, torch.randn(embedding_dim))

class EmbeddingLayer(nn.Module):

    def __init__(self, weights_matrix):
        super().__init__()
        num_embeddings, embedding_dim = weights_matrix.size()
        self.embeddings = nn.Embedding.from_pretrained(weights_matrix, freeze=False)

    def forward(self, input):
        return self.embeddings(input)


embedding_model = EmbeddingLayer(weight_matrix)
```

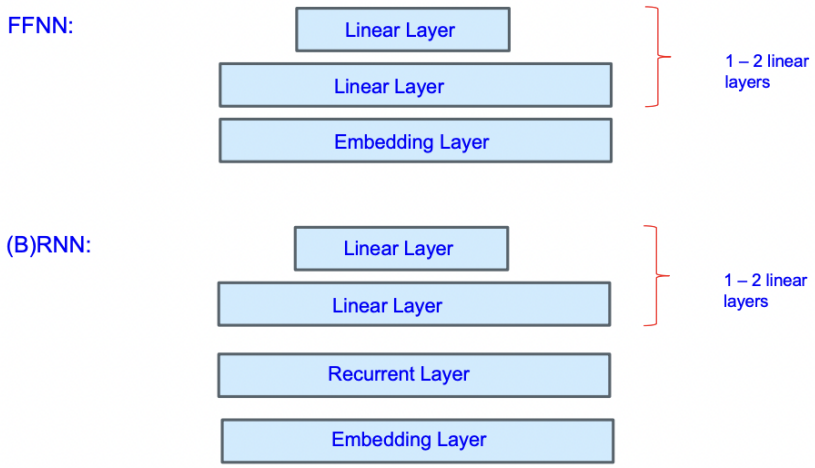
1. When you use pre-trained embeddings, we have to use Embedding.from_pretrained and give (weights_matrix → weight matrix from glove for example)
2. If the word is in dictionary, it returns it
3. If not, it returns a random one → train using the data
4. Weight matrix is therefore the embeddings for the layer
5. Freeze = true means do not update it (use the original from glove)

3. Network Geometries
    a. The biggest remaining question is then:
    b. How many layers, how wide, and what type?
    c. As usual, “it depends,” but some general principles have emerged:
        i. 1. Deep networks are necessary for image processing, where the information is found in hierarchical groupings of image features:



ii. 2. Information in text is sequential (linear), with dependencies among words, but FFNNs and (B)RNNs have a limited ability to deal with long-range dependencies.

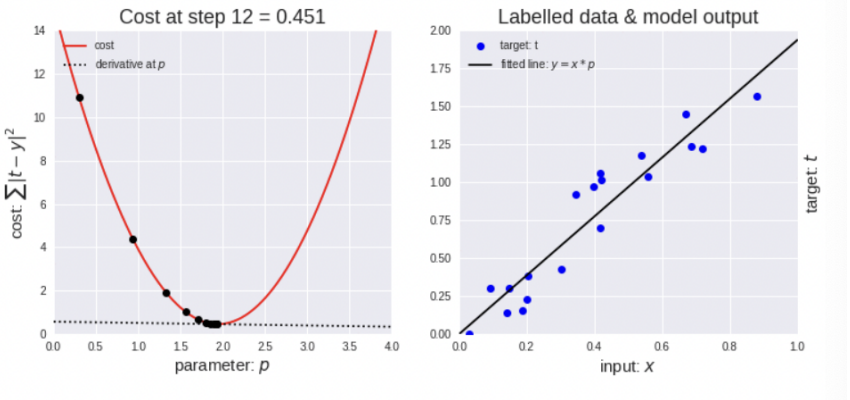
1. Hence, deep networks are not as useful – until we introduce transformers!



2.

a. One to two recurrent layers tend not to go deeper

iii. 3. Each neuron has essentially a linear discrimination power. You can (very roughly) consider each neuron having the ability to draw a line (or hyperplane) distinguishing two regions of your data.

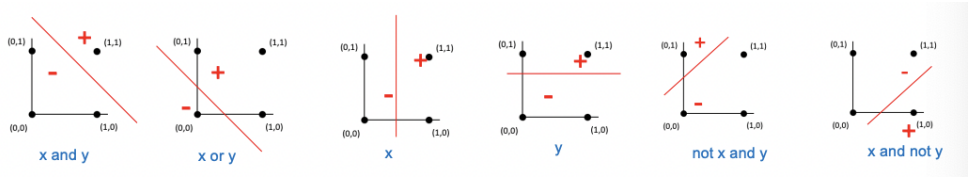


1. Each neuron is a regression machine with a non-linear activation function and the training finds a hyperplane or a line

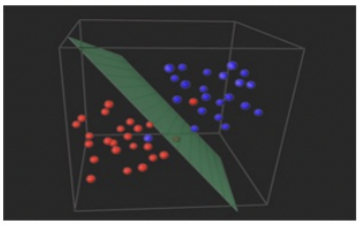
4. Network Geometries: How wide and deep?

a. Bumper Sticker Version: Each NN unit can draw a single line and hence can calculate Boolean functions of inputs.

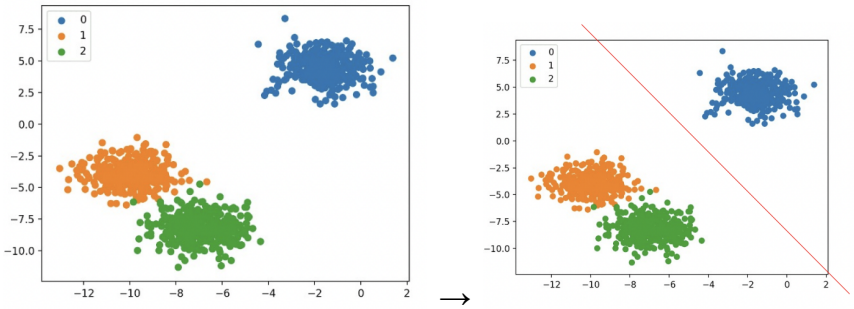
b. Example: A single unit can perform binary classification on 4 points:



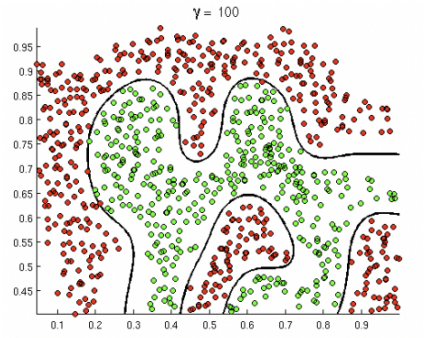
c. NOTE: This is happening in multiple dimensions, so we are really trying to draw hyperplanes!



d. Adding neurons allows us to draw multiple hyperplanes (or lines)



e. Complex data sets involve lots of combinations of lines!



f. Conclusions:
   i. For a given NLP data set, there is a particular width of layer that will have enough discriminatory power to do the task, and
      1. There is a certain number that will do the job
   ii. Adding more neurons will (it will memorize)
      1. Not necessarily improve its accuracy,
      2. Lead to excessive training time,
      3. More overfitting, and

    4. Less ability to generalize.

iii. You are better off experimenting with different types of layers and not just increasing the depth and width.
    1. There is a sweet spot that is somewhere middle

iv. Recurrent networks are best for simpler NLP tasks (such as classification)

v. Transformers are best for tasks involving sequence-to-sequence tasks such as machine translation, summarization, and conversation agents.