Natural Language Processing

Class 3: Neural Networks & Introduction to Deep Learning Architectures

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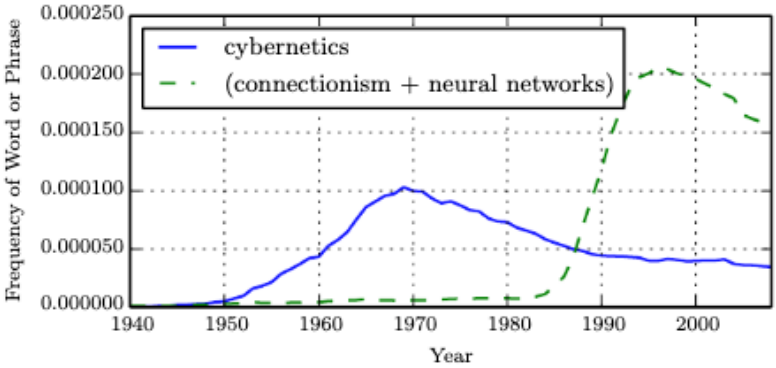
The Rise of Neural Networks

- How did a single ML algorithm, the Neural Network, come to dominate AI?
- 1940s - 1960s
  Perceptrons. Development of theories of biological learning and implementations of models such as the perceptron, enabling the training of a single neuron
- 1980 - 1995
  Connectionism. Connectionism with back-propagation makes possible the training of a neural network with one or two hidden layers.
- 2006 - present
  Deep Learning. RNNs, LSTMs, Small Language Models (SLMs), Large Language Models (LLMs)

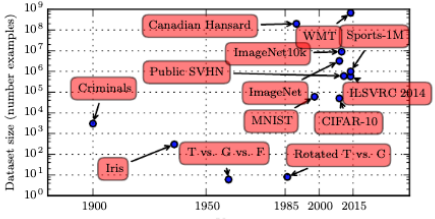
The Rise of Neural Networks

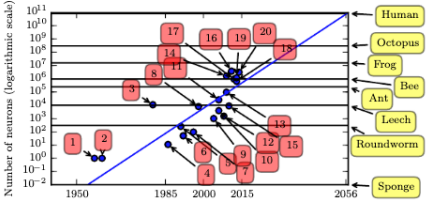
The changing fortunes of NNs over the years



The Rise of Neural Networks

The advent of faster compute (via the GPU), distributed computing, and access to larger datasets (via the internet) made NNs' contemporary resurgence possible



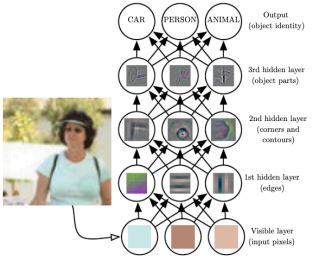


Why do DL networks work so well?

- A common explanation for Deep Learning's success is that a DL network's many hidden layers automatically discover abstract features which are then used to build representations in other layers
- These layers are called "hidden" because their values are not given in the data; instead the model must determine which concepts are useful for explaining the relationships in the observed data.

Why do DL networks work so well? Images

- Let's take an example from the world of image classification as an example of how DL models build their representations layer by layer
- The **first layer** identifies edges
- The **first hidden layer**s representation of of the edges is passed to the **second hidden layer** which uses them to find corners and contours
- The **second hidden layer**s representation o of corners and contours is passed to the **third hidden layer**, which uses the info to detect entire parts of objects

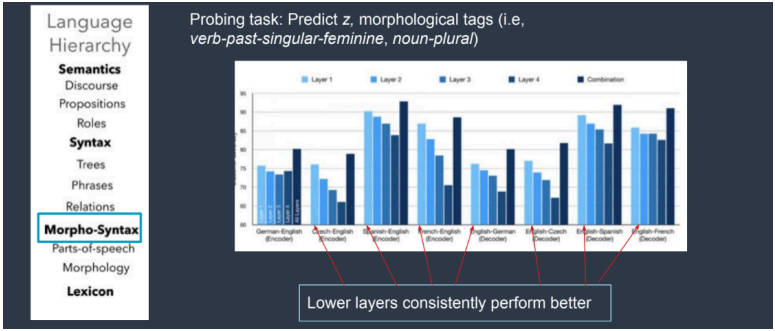


Why do DL networks work so well? NLP

- Are DL representations of language also built, layer by layer in hierarchical fashion?
- In the field, *probing tasks* as used to identify which layer of a NN is responsible for which aspect of language
- Basic idea: Given a NN trained on a task (sentiment analysis, machine translation), select one of the layers from the model and use that layer to train another classifier to predict some linguistic property of interest (syntactic parsing, semantic role labelling, part-of-speech tagging). Success on the secondary classification task is evidence that that particular layer has learned that linguistic property.

Why do DL networks work so well? NLP

- There is some evidence from probing tasks that network layer hierarchies in machine translation models mirror linguistic hierarchies

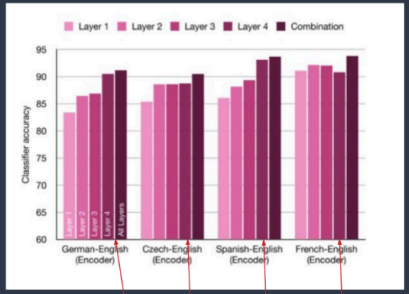


Why do DL networks work so well? NLP

Language Hierarchy

Semantics
Discourse
Propositions
Roles
Syntax
Trees
Phrases
Relations
Morpho-Syntax
Parts-of-speech
Morphology
Lexicon

Probing task: Predict z, a dependency label (subject, object, etc.) between words x_i and x_j



HIgher layers consistently perform better

Basic NN unit

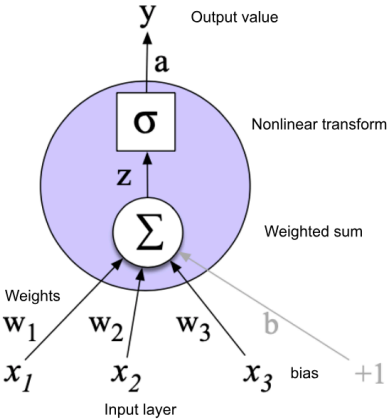


Figure 1: Basic NN unit

Basic NN unit

- Given a set of inputs $x_1 \dots x_n$, corresponding weights $w_1 \dots w_n$,and a bias b, the weighted sum z can be written as

$$z = b + \sum_i w_i x_i \tag{1}$$

- But it's more convenient to express this weighted sum using vector notation —recall that a vector is, at heart, just a list or array of numbers

$$z = wx + b \tag{2}$$

- Instead of simply passing z as the output value y we next apply a non-linear transformation f to z – this is our activation function. Since we are just modeling a single unit, the activation for the node is the final output of the network, y

$$y = a = f(z) \tag{3}$$

The Sigmoid function

- We'll discuss three popular non-linear functions f: the sigmoid, the tanh, and the rectified linear unit or ReLU
- The sigmoid has a number of advantages; it maps the output into the range (0,1), which is useful in squashing outliers toward 0 or 1. The sigmoid is also differentiable, which, as we'll discover later, is required for gradient descent-based learning

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

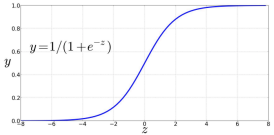


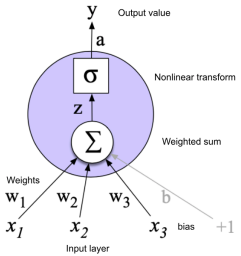
Figure 2: The Sigmoid function

The Sigmoid function

- Passing $z = wx + b$ into our sigmoid function gives us the output y of a single neural unit

$$y = \sigma(\mathbf{wx} + b) = \frac{1}{1 + e^{-(\mathbf{wx}+b)}}$$

which can be visualized as our original NN unit diagram



Problems with the Sigmoid function

There are a number of issues with the sigmoid function that make it generally dis-preferred as an activation function

- **Nonzero-centered outputs.** The outputs of the sigmoid function are not "zero-centered" and this has implications for the dynamics during gradient descent. If the data coming into a neuron is always positive, then the gradient on the weights become either all be positive or all negative, creating zigzag effects during training.
- **High computational complexity**. The exponential function e^z used by the sigmoid requires potentially thousands of addition, subtraction, multiplication, and division instructions on a general-purpose CPU

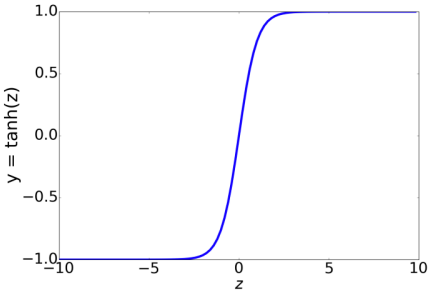
Problems with the Sigmoid function

- **Saturation problem.** Recall the squashed "S" in the previous slide. The left and right sides of the sigmoid function curve are nearly flat. When the input value x is a large positive or a small negative number, the gradient of the sigmoid function is close to 0, thus slowing down parameter updates. This phenomenon is called the *sigmoid saturation problem*.
- **Vanishing gradients.** Also, the derivative of the sigmoid function is in the range of $(0, 0.25]$ If the neural network has many layers (as occurs in Deep Learning), the partial derivative calculated with the chain rule is equal to the multiplication of many numbers less than 0.25. Again, this affects training, leading to a *vanishing gradient problem*, where the gradients approach 0 and learning stops.

The *tanh* function

- The hyperbolic tangent funciton(*tanh*) is a variant of the sigmoid that ranges from -1 to +1

$$y = tanh(z) = \frac{e_z - e_{-z}}{e_z + e_{-z}}$$



The *tanh* function

Advantages

- **Zero-centered** Output is symmetric around zero, which can make the learning dynamics more robust.
- **Stronger gradients** Has steeper gradients than the sigmoid function, which can help mitigate the vanishing gradient problem.

The *tanh* function

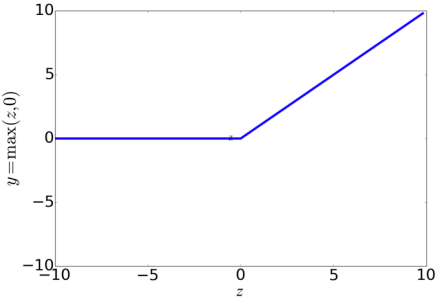
Disadvantages

- **Vanishing gradients.** The vanishing gradient problem isn't completely mitigated. *tanh*'s derivative can become very small, which can slow down learning.
- **Saturated output** For very large or small input values, *tanh*'s output can saturate, meaning it gets close to -1 or 1. This can lead to slower learning and decreased sensitivity to changes in the input.
- **High computational complexity**. As with the sigmoid, *tanh* calculates exponentials, which could involve thousands of computations per NN unit.

The *ReLU* function

The most popular activation function for NNs continues to be the Rectified Linear Unit, ReLU. This hockey-stick shaped function is simply z when z is positive, else 0

$$y = ReLU(z) = \max(z, 0)$$



The *ReLU* function

Advantages

- **Computational simplicity**. The *max()* function is computationally simple
- **Vanishing gradient mitigation**. Mitigates vanishing gradient problem since the gradient is simply 1 for $x > 0$ and 0 for $x < 0$.

The *ReLU* function

Disadvantages

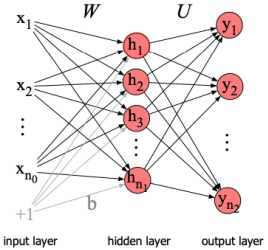
- **The "dying ReLU" problem** During training, neurons utilizing ReLU become inactive or dead. ReLU maps all negative values to zero. This means that the weighted sum of inputs to these neurons consistently results in a negative value, causing the ReLU activation to output zero. Once a neuron becomes inactive, it effectively stops learning, as the gradient during back-propagation is zero for negative inputs. (*Leaky ReLU* addresses the dying ReLU problem by introducing a small negative slope for the negative input values).

Fully connected FFNs

- **Feedforward network**: A network in which the units are connected with no cycles; the outputs from units in each layer are passed to units in the next higher layer, and no outputs are passed back to lower layers. (We'll touch on networks with cycles when we discuss RNNs later.)

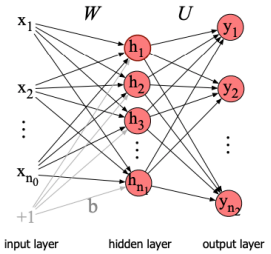
Fully connected FFNs

- FFNs have three kinds of nodes: input units, hidden units, and output units.



- The input layer x is a vector of simple scalar values
- The hidden layer h formed of hidden units h_i each of which is a neural unit as described in the previous section, taking a weighted sum of its inputs and then applying a non-linear transform.

Fully connected FFNs



- Each layer is *fully-connected*, meaning that each unit in each layer takes as input the outputs from all the units in the previous layer, and there is a link between every pair of units from two adjacent layers.

Fully connected FFNs

- **The weight matrix W.** A compact way of representing the parameters for the hidden layer is to combine the weight vector and bias for each neural unit i into a weight matrix W.
- Each element W_{ji} of the weight matrix W represents the weight of the connection from the ith input unit x_i to the jth hidden unit h_j
- This allows us to perform simple matrix operations when calculating the hidden layer computation:

$$h = \sigma(Wx + b) \tag{4}$$

Classification using FFNs

Recall our sentiment analysis task from Class 1:

Sentiment Analysis of movie reviews

- A binary classification problem *positive* or *negative* (assume no neutral reviews)
- "unbelievably disappointing" -> *positive*
- "Full of zany characters and richly applied satire, and some great plot twists" -> *positive*
- "It was pathetic. The worst part about it was the boxing scenes." -> *negative*

Classification using FFNs

We could also be dealing with a multiclass sentiment analysis task with three, rather than two, possible values: *positive, negative,* and *neutral.*

Sentiment Analysis of restaurant reviews

- "great service and great prices" -> *positive*
- "overpriced, slow service" -> *negative*
- "it was okay, no strong feelings one way or the other" -> *neutral*

Classification using FFNs

- For our binary, movie reviews classification task, we might have a single output node, and its scalar value y is the probability of positive versus negative sentiment.
- But for our multiclass, restaurant reviews classification task, we might have one output node for each class, where the output value is the probability of that class, and the values of all the output nodes must sum to one. The output layer is thus a vector y that gives a probability distribution across the output nodes

Using *softmax* to normalize z

- Problem: z is just vector of real-valued numbers and doesn't sum to *1*, e.g., for our thre-class restaurant review classification task the output might be

$$z = [0.6, 1.1, 1.5]$$

- We need a way to normalize this vector to get the required probability distribution. We do this via the *softmax* function

$$softmax(\mathbf{z}_i) = \frac{exp(\mathbf{z}_i)}{\sum_{j=1}^{d} exp(\mathbf{z}_j)}$$

which will return, e.g,

$$z = [0.10, 0.85, 0.05]$$

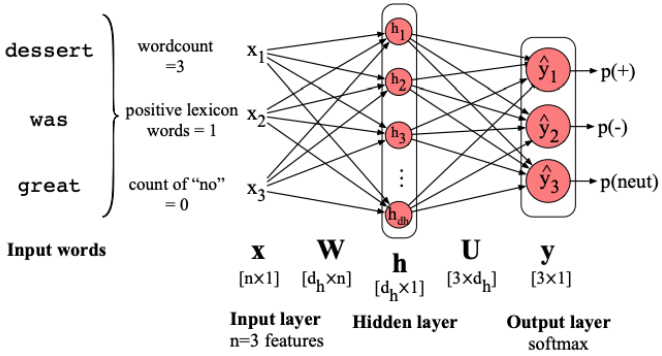
FFNs with traditional feature engineering

With softmax applied to final output layer, our restaurant review classifier has the following components:

$$\begin{aligned}\mathbf{x} &= [\mathbf{x}_1, \mathbf{x}_2, \ldots \mathbf{x}_N] \\ \mathbf{h} &= (\mathbf{W}\mathbf{x} + \mathbf{b}) \\ \mathbf{z} &= \mathbf{U}\mathbf{h} \\ \hat{y} &= softmax(\mathbf{z})\end{aligned} \tag{5}$$

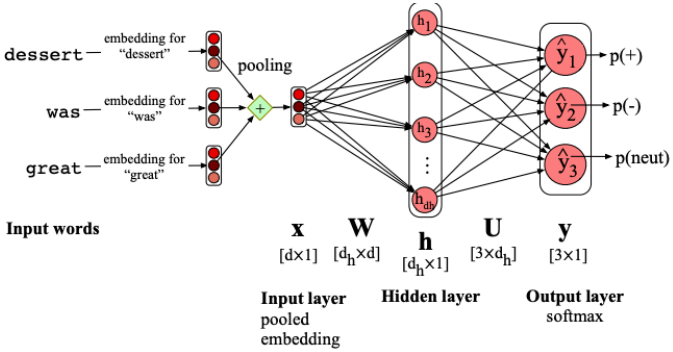
where each x_i is a hand-designed feature (e.g., x_1 = count(words $\in$ review), x_2 = count(positive lexicon words $\in$ review), x_3 = 1 if "no" $\in$ review, etc.) and the output layer $\hat{y}$ has three nodes, one for each class

FFNs with traditional feature engineering



FFNs with contemporary, embedding-based features

Pretrained embeddings, which we learned about last week, are a simple way to boost performance. Let's take a look at the notebook to see an example.



Recurrent Neural Networks (RNNs)

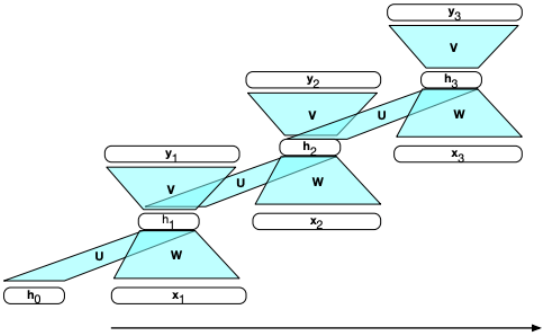
- The fact that the computation at time *t* requires the value of the hidden layer from time *t - 1* mandates an incremental inference algorithm that proceeds from the start of the sequence to the end:

function FORWARDRNN(**x**, *network*) **returns** output sequence **y**

$\mathbf{h}_0 \leftarrow 0$
for $i \leftarrow 1$ **to** LENGTH(**x**) **do**
  $\mathbf{h}_i \leftarrow g(\mathbf{U}\mathbf{h}_{i-1} + \mathbf{W}\mathbf{x}_i)$
  $\mathbf{y}_i \leftarrow f(\mathbf{V}\mathbf{h}_i)$
return *y*

Recurrent Neural Networks (RNNs)

- It's also standard to represent RNNs in their "unrolled"state.
- The various layers of units are copied for each time step to illustrate that they will have differing values over time. However, the various weight matrices are shared across time.



RNNs for Language Modelling

- Earlier, we motivated RNNs by noting their ability to model sequential data such as language
- Learning a probability distribution over text is the task of *language models*.
- This involves predicting the next word given some n previous words or *context*
- If the preceding context is “Thanks for all the“ and we want to know how likely the next word “fish“ is we would compute:

$$P(fish|Thanks\ for\ all\ the)$$

RNNs for Language Modelling

- Language models give us the ability to assign such a conditional probability to every possible next word, giving us a distribution over the entire vocabulary.
- We can also assign probabilities to entire sequences by combining these conditional probabilities using the chain rule of probability:

$$P(w_{1:n}) = \prod_{i=1}^{n} P(w_i | w < i)$$

Training an RNN-based Language Model

- All language modelling (include more sophisticated LMs such as ChatGPT) relies on the concept of *self-training*
- Given a massive *corpus* (collection of text) as training material, the model is asked to predict the next word at each time-step.
- “Self-trained“, or “self-supervised“ because we dont have to add any special gold labels to the data; the natural sequence of words is its own supervision

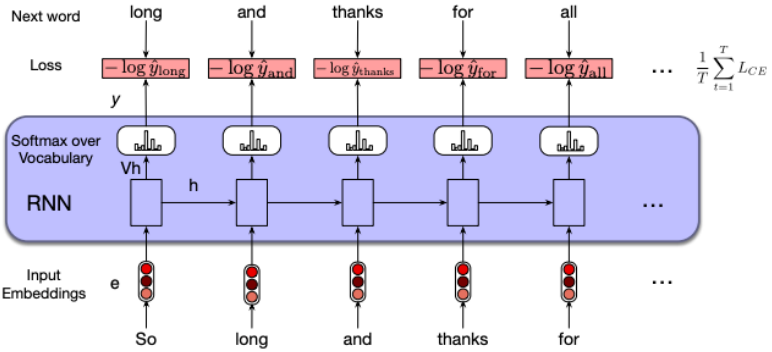
Training an RNN-based Language Model

- During self-training, the task is to minimize the error in predicting the true next word in the training sequence, using cross-entropy as the loss function
- Cross-entropy loss can be used to measure the difference between a predicted probability distribution and the correct distribution

$$L_{CE} = -\sum_{w \in V} y_t[w] \log \hat{y}_t[w]$$

- In the case of language modeling, the correct distribution y_t comes from knowing the next word.

Training an RNN-based Language Model

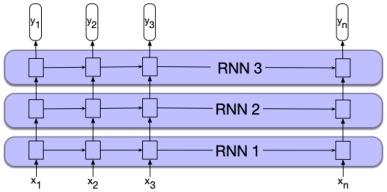


Teacher Forcing

- At each word position t of the input, the model takes as input the the correct word w_t together with $h_t - 1$, encoding information from the preceding $w_1 : t-1$, and uses them to compute a probability distribution over possible next words so as to compute the models loss for the next token $w_t + 1$.
- *But*, when predicting the next word after that, rather than using the model's prediction for the next word, we use the correct word $w_t + 1$ along with the prior history encoded to estimate the probability of token $w_t + 2$
- This is called *teacher forcing*

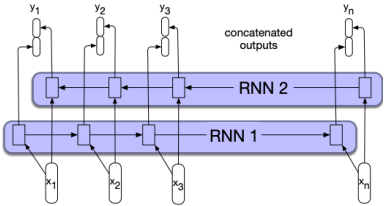
Stacked RNNs

- Stacked RNNs consist of multiple networks where the output of one layer serves as the input to a subsequent layer
- Stacked RNNs tend to outperform single RNNs. This is often explained as the result of the network learning different abstractions regarding language (parts-of-speech, syntax, etc.) at earlier layers which are then utilized by later layers.
- We'll revisit the benefits of stacked layers when we discuss Transformers



Bidirectional RNNs

- In bidirectional RNNs two independent bidirectional RNNs are combined, one where the input is processed from the start to the end, and the other from the end to the start
- The two representations computed by the networks are then concatenated into a single vector that captures both the left and right contexts of an input
- We'll revisit this use of bidirectionality in our discussion of *BERT*, one of the first and most powerful Transformer-based LMs



Long-distance dependencies

- A key feature of English is the so-called *long-distance* dependency. This can take many forms but a basic example is

  The man with the hat that I saw yesterday after lunch went fishing

  where *The man* takes *went fishing* as a verb. In this case *went fishing* is a long-distance dependency of *The man*
- Despite having access to the entire preceding sequence, the information encoded in the hidden states of RNNs tends to be fairly local, more relevant to the most recent parts of the input sequence
- Thus, if the RNN just sees the context *after lunch*, it might predict a comma and a subject pronoun as the next tokens, as in *after lunch, I*—it has lost the information contained in the initial tokens *The man*, etc.

Vanishing Gradients in RNNs

- Also, when RNNs attempt to model lengthy contexts, the hidden layers are subject to repeated multiplications, as determined by the length of the sequence
- A frequent result of this process is that the gradients are eventually driven to zero —the vanishing gradients problem

Next class: Feb 10

Gated Architectures: RNNs and LSTMs

- RNNs continued
- LSTMs

Reading

- Jurafsky & Martin Chapter 13: RNNs and LSTMs