Applied Deep Learning

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DATA SCIENCE

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What is deep learning?

Conventional machine learning algorithms often require careful engineering of features and even some expertise in the subject in order organize or represent the data in a way that an algorithm can digest it.

Deep learning, however, is considered a representation learning class of algorithms.

This means that instead of humans thinking really hard about how to organize and process the data to make it easiest for the algorithm to correctly function.

In deep learning however, the model is learning how to do this representation itself.

It still contains a conventional machine learning component but the ‘deep’ parts of these algorithms are actually only trying to learn how to represent the data for its conventional machine learning component which exists at the end.

http://www.cs.toronto.edu/~hinton/absps/NatureDeepReview.pdf

Why deep learning?

Deep learning is an extremely powerful machine learning technique that is well suited to things that could be called machine perception. This also makes it particularly fun because it allows you to do things with computers that used to be almost impossible.

We can design systems that can perceive the world and draw inferences on those perceptions.

A short list of examples include: image classification, facial recognition, speech recognition, machine translation, image caption generation, automatic text generation and game playing (AlphaGo).

Why deep learning?

Deep learning also has a philosophical difference to many other machine learning techniques.

It attempts to do it’s own feature engineering or representation end-to-end while training.

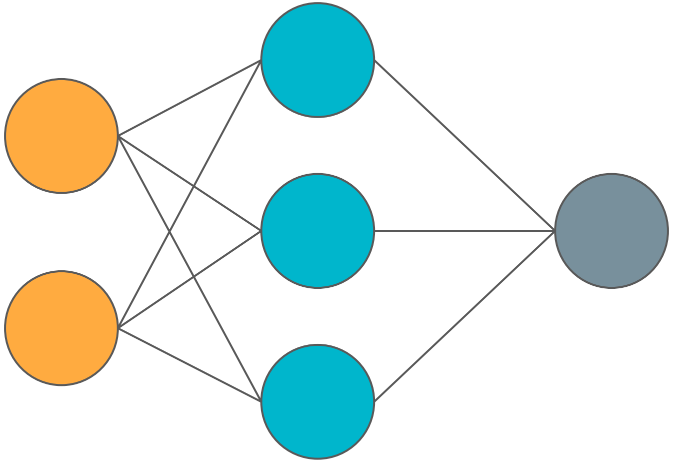
For example, something like a random forest will try and find the optimal splits within the features a deep learning model will attempt to ‘morph’ the features into something that easier for a linear classifier to deal with.

We will get into some of the geometric intuition behind this idea a little later.

What is deep learning?

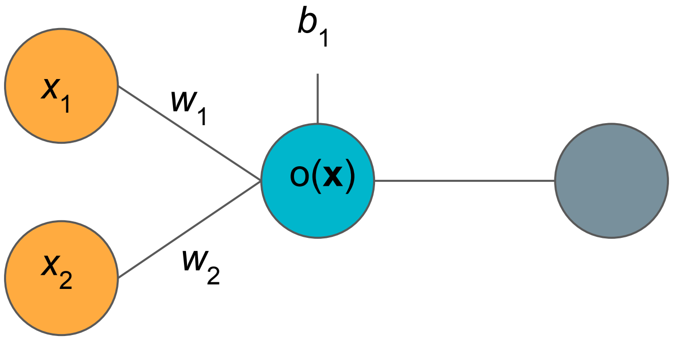
Basically, it’s a rebranding of neural networks.

The function of a neural network is to basically receive an input, perform a series of calculations on that input, and then provide an output.



Starting simple

The first neural network was basically a single mathematical function that was inspired by biological neurons.

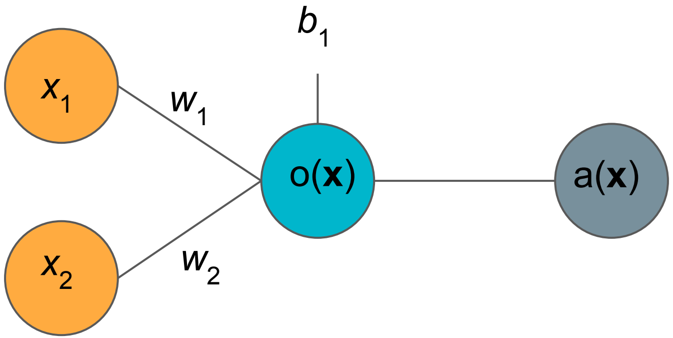


For a ‘preactivation’ *o* the network simply takes the input data then multiplies each data point by some weight value. Then it will sum up those multiplications with an optional bias term *b*.

$$o(x) = b + \sum_{i}^{n} x_i w_i$$

Starting simple

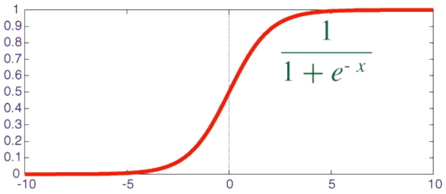
After we get the weighted sum of the input data there is typically one final function that we apply to get the final output of the network.



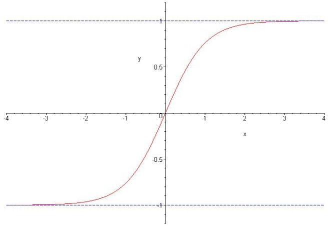
The function that we apply to the weighted sum is typically called the activation of the neuron. Hence the term ‘preactivation’ for o(**x**). This can really be any function but there are a few that have been found to be useful in practice.

$$a(x) = a(o(x)) = a(b + \sum_{i}^{n} x_i w_i)$$

Activation Functions

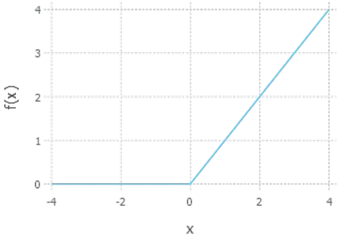


Sigmoid Function - popular in the past but has fallen out of favor



$$\frac{e^z - e^{-z}}{e^z + e^{-z}}$$

Tanh Function - similar to sigmoid except has the benefit of being centered on 0, still common in RNN



Rectified Linear Unit (ReLU) - Most common activation function now. It’s simply max(x, 0)

Is it useful?

This is basically the same as a simple linear or logistic regression (depending on output nonlinearity) model.

In order to create something that looks like what we call deep learning we compose a lot of these simple linear units together.

Is it useful?

Let’s say that we have three functions $f^{(1)}$,$f^{(2)}$, and $f^{(3)}$ all chained together.

$$f(x) = f^{(3)}(f^{(2)}(f^{(1)}(x)))$$

This chaining of functions is the foundation for deep learning. Where each function is a group of linear units that we looked at earlier.

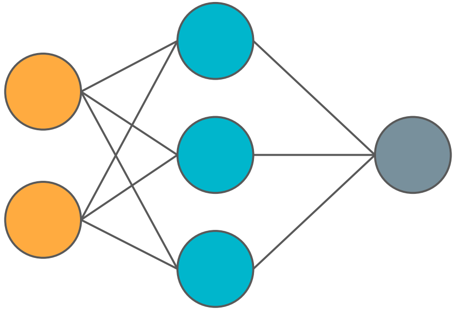
We can comprise an entire group of linear units as a weight matrix **W** instead of just a vector of weights like what we had before.

What is deep learning?

Deep learning is basically the combination of many of those small neurons.

Each one of those simple functions is useful on it’s own but have some serious limitations if we want to use them for the tasks that we listed at the beginning.

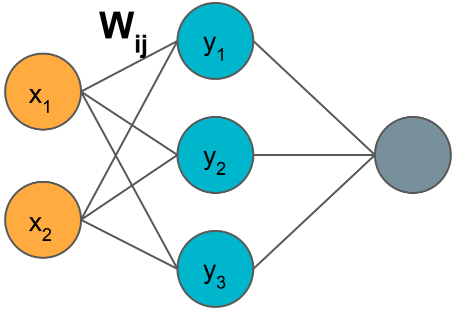
To get around this we combine many of them together into a chain of layers. Each function’s output will become the next functions input.



What is deep learning?

The chaining of these linear combinations turns out to be a very powerful idea. It allows the network to create meaningful abstractions and representations.

Each node performs a simple linear combination and applies an ‘activation’ function. For example the calculations resulting in y_1 would look like: $y_1 = f(x_1w_{11} + x_2w_{12} + b_1)$ where *f* is some function to apply to the output of the calculation.

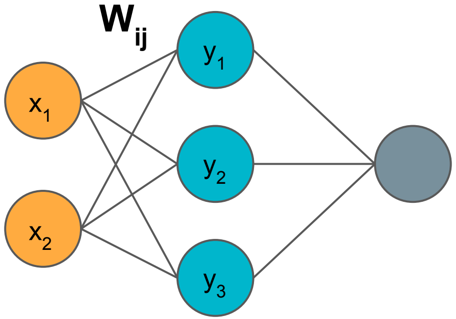


What is deep learning?

The same types of calculations are performed for y_2 and y_3.

The values y_1, y_2, and y_3 then become the input data for the final node of the network.

The same types of calculations are performed again, except with a new set of weights for the second layer.



How to train a network?

Almost every single deep learning model is trained by an algorithm called Stochastic Gradient Descent.

Typically a machine learning algorithm has some function that calculates how good (bad) the algorithm did at the given problem. We call this the cost function.

With small models and datasets we can usually solve this function analytically.

We can not do this with deep learning because the number of parameters in the model and the size of the data that we typically deal with make this prohibitive.

What is SGD?

Instead what we do is approximate the gradient with a small number of examples chosen randomly from the dataset. Hence the name, stochastic gradient

For each data pair *k*, we calculate the difference between target and given output then square that (squared error).

$$F(k) = (t(k) - a(k))^2$$

So then we use that error term and calculate the partial derivative of that error w.r.t. each weight.

Finally, we update each weight in the direction of the negative gradient. We want to move in the opposite direction of the gradient value.

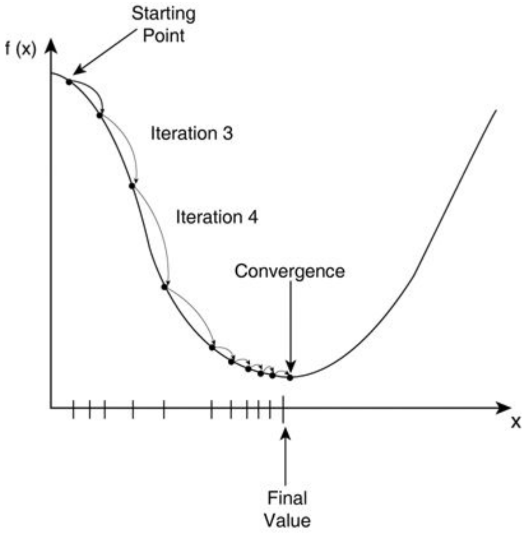
What is SGD?

We repeat that process until we get through all of the training dataset.

Then we repeat some more until we’ve looped through the dataset for the predetermined number of iterations.

SGD is interesting because we are applying it to a non-convex problem, there is no guarantee that it converge to a solution, or even that converging to a solution will happen within a reasonable amount of time. BUT! In practice it usually works really well if we have sufficiently large datasets.

SGD



We call this process gradient descent. We are basically trying to ride the gradient down to the minimum point which should correspond to the weight values that give us the best possible performance.

Source: http://www.yaldex.com/game-development/1592730043_ch18lev1sec4.html

Backpropagation

The process to updating the weights with each stochastic gradient calculation is called backpropagation.

We define neural networks as composed functions.

$$f(x) = f^{(3)}(f^{(2)}(f^{(1)}(x)))$$

When we make predictions or outputs from the network we feed the data forward through these functions.

To update the weights we just go backwards through each functions and take the derivatives along the way. It’s basically an exercise in the chain rule of calculus.

Backpropagation

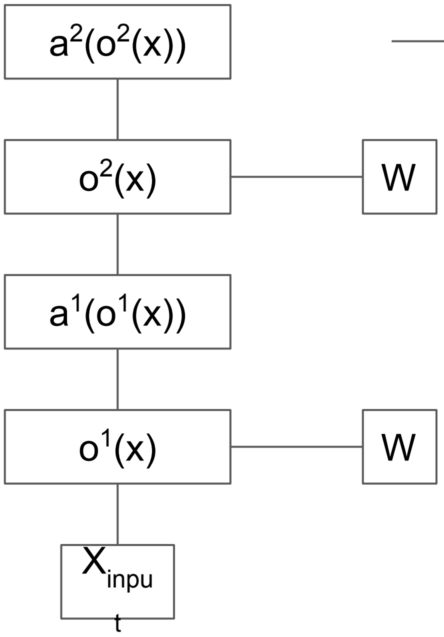
Let's say we have have functions *y* = *g*(x) and *z* = *f*(*g*(x)) = *f*(*y*). To find the derivative of *z* w.r.t. to *x* we have to move through the intermediate function *y*.

$$\frac{dz}{dx} = \frac{dz}{dy}\frac{dy}{dx}$$

If you are familiar with the chain rule for finding derivatives, then you can think of backpropagation as an application of the chain rule.

$$a(x) = a(o(x)) = a(b + \sum_{i}^{n} x_i w_i)$$

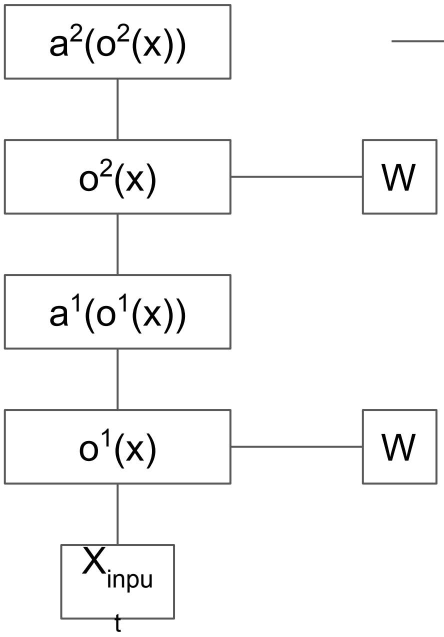
Backpropagation



$$F(x) = (t(x) - a^2(x))^2$$

$$a^2(x) = a^2(o^2(x))$$

Backpropagation



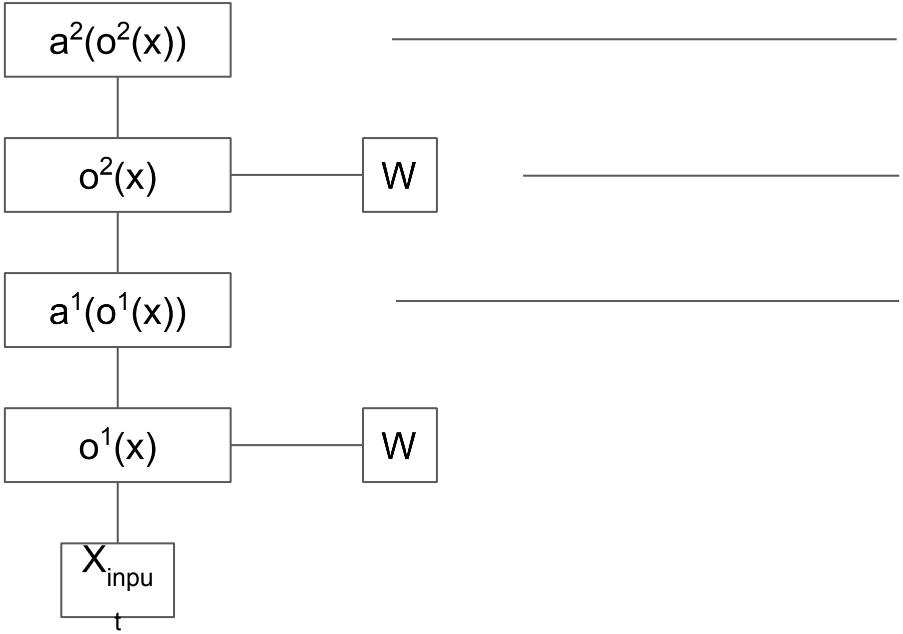
$$F(x) = (t(x) - a^2(x))^2$$

$$a^2(x) = a^2(o^2(x))$$

$$o^2(x) = b + \sum_i^n x_i w_i \qquad ; x_i = a^1(o^1(x))$$

Backpropagation

$$F(x) = (t(x) - a^2(x))^2$$



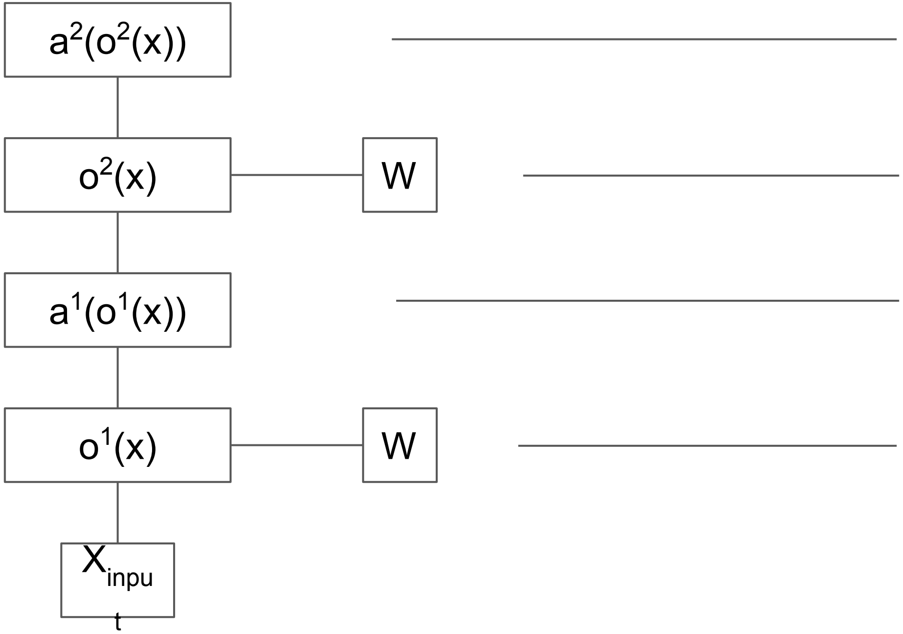
$$a^2(x) = a^2(o^2(x))$$

$$o^2(x) = b + \sum_{i}^{n} x_i w_i \qquad ; x_i = a^1(o^1(x))$$

$$x = a^1(o^1(x))$$

Backpropagation

$$F(x) = (t(x) - a^2(x))^2$$



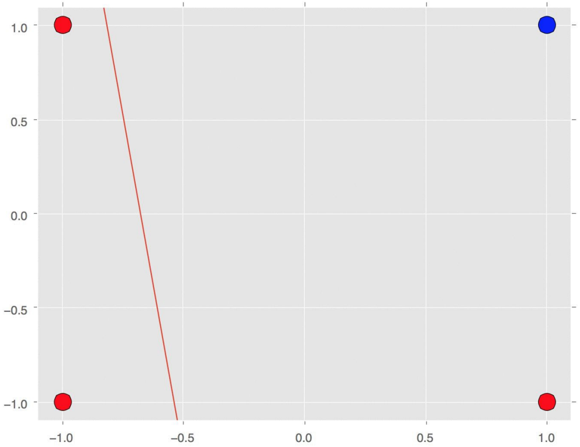
$$a^2(x) = a^2(o^2(x))$$

$$o^2(x) = b + \sum_{i}^{n} x_i w_i \qquad ; x_i = a^1(o^1(x))$$

$$x = a^1(o^1(x))$$

$$o^1(x) = b + \sum_{i}^{n} x_i w_i \qquad ; x_i = x_{input}$$

Iterative training

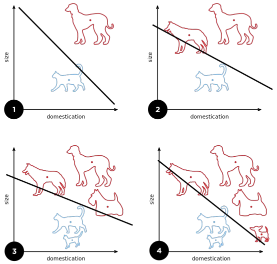


Here is an animation that I made showing a single linear unit finding a linear boundary to separate two classes. It updates with each input-desired output pair that it is shown. Starting from random weight initialization.

Why chain?

One of the first neural networks, called a perceptron, was simply just a single node. It was created in the 1950s as a model of how biological neurons were thought to have worked.

Critics were quick to point out that this perceptron could only correctly classify items that were linearly separable. Like this example from wikipedia.

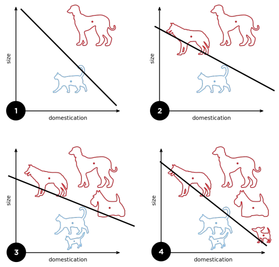


What is deep learning?

The answer to that criticism was just to add more ‘neurons’ to that first model.

Pretty reasonable response, if it doesn’t work just throw more resources at the problem.

The result of adding more neurons gave neural networks the ability to sort of tweak the input data and reshape the problem so that it was easier.

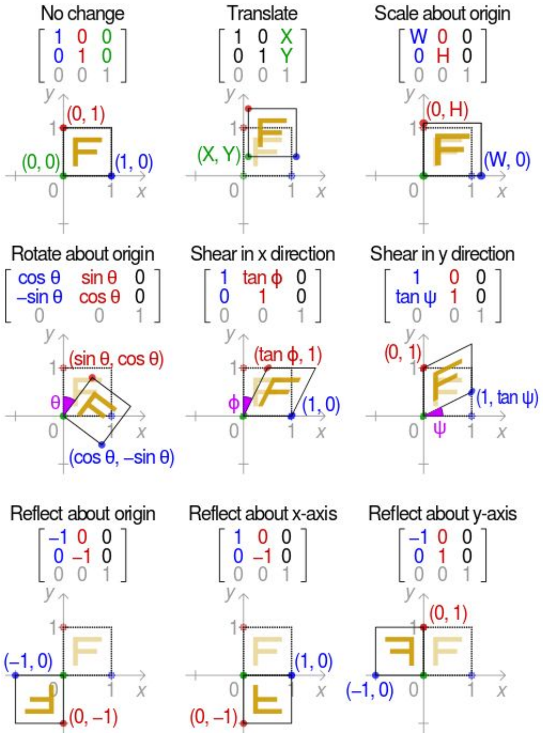


How does the representation happen?

If we think about input and output mappings in a geometric way we can think of each of those linear combinations as doing a simple affine transformation.

If we take our input vector **x** and apply our weight matrix **W** to it we can map our input data into new places in space.

$$x \mapsto Wx + b$$



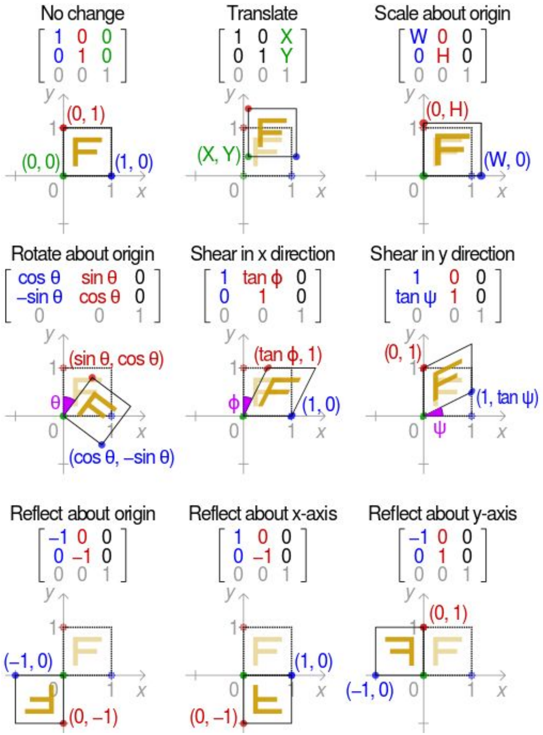
Source: https://en.wikipedia.org/wiki/Affine_transformation

How does the representation happen?

With gradient descent the weights in the matrix **W** will update on each iteration in a way that cause it to map the **x** data in the best possible way.

So you can image that if the final layer in a neural network wants to draw a straight line or hyperplane to separate the data then the weight matrices will update in a way that tries to ‘move’ the two classes away from each other.

$$x \mapsto Wx + b$$



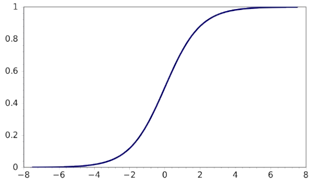
Source: https://en.wikipedia.org/wiki/Affine_transformation

How does the representation happen?

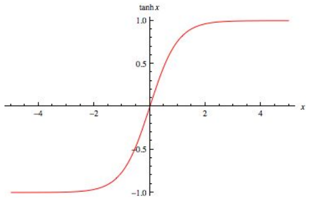
In addition to those rigid transformations, neural networks apply functions on top of those mappings.

Those functions are often called ‘activations’ for the activation of the neuron or ‘nonlinearities’ to allow the network to do more than just linear transformations.

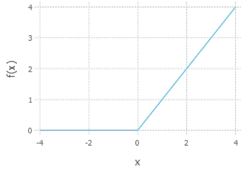
Without those the entire neural network would function just like a big linear transformation. This allows the network to make more sophisticated representations.



http://tikalon.com/blog/blog.php?article=2011/sigmoid

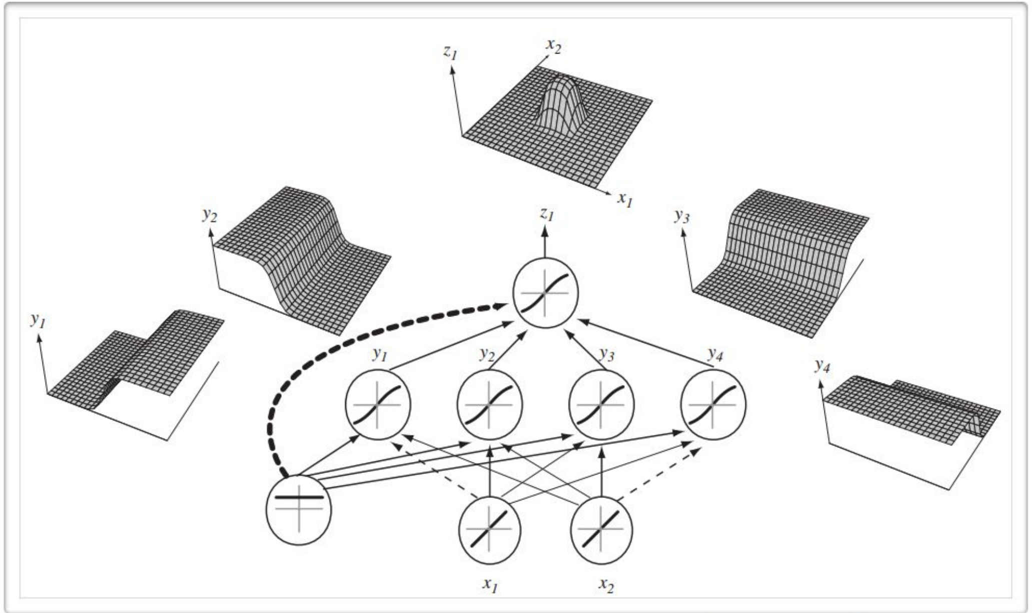


http://mathworld.wolfram.com/HyperbolicTangent.html



http://int8.io/neural-networks-in-julia-hyperbolic-tangent-and-relu/

How does the representation happen?

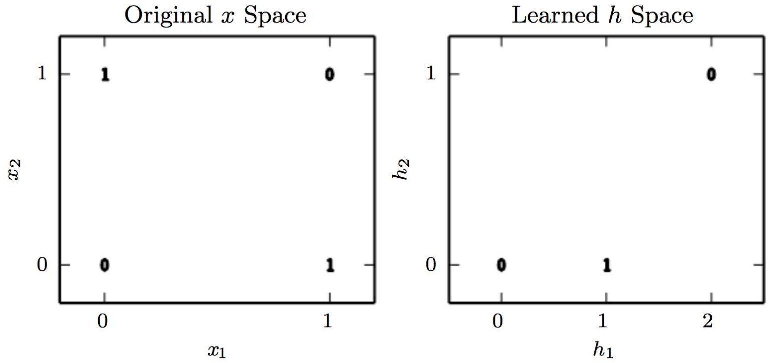


(from Pascal Vincent's slides)

http://www.cs.cmu.edu/~rsalakhu/10807_2016/Lectures/Lecture_NN_Part1.pdf
Who in turn took this slide from another presentation (Pascal Vincent)

What do these representations look like?

One of the simplest examples of what a neural network can solve that a linear model can't is the XOR problem.

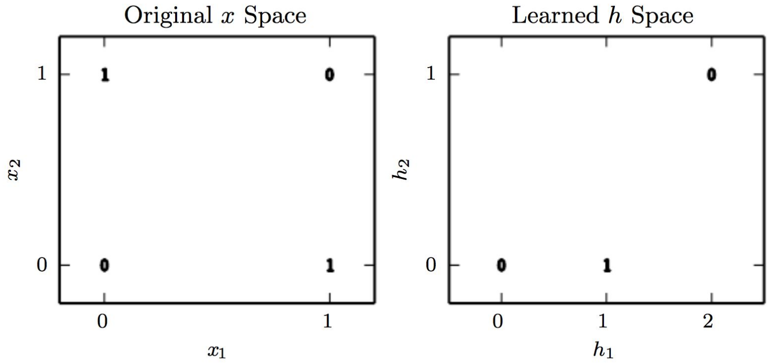


On the left we have the original dataset, on the right we have the learned feature representations that a multi-neuron network can learn.

Source deep learning book: http://www.deeplearningbook.org/

What do these representations look like?

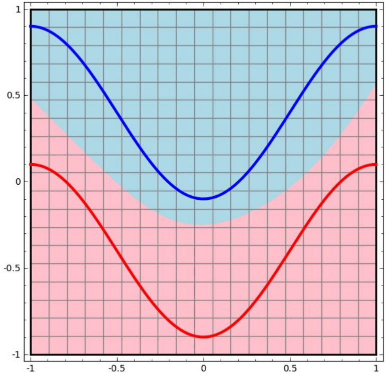
It’s desirable to morph the feature space to be linearly separable because the final neuron in the network is itself just a linear model.

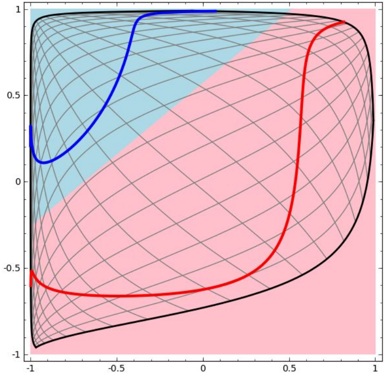


Source deep learning book: http://www.deeplearningbook.org/

What is deep learning?

What do I mean by best way to represent data to solve a problem? Let’s say we have the two lines on the left and we want to separate them by drawing a straight line. Well we can’t. So instead what if we warp the space so that we make the problem easy?



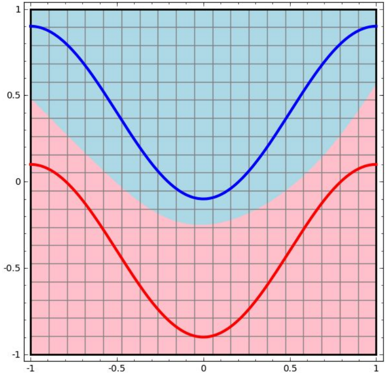


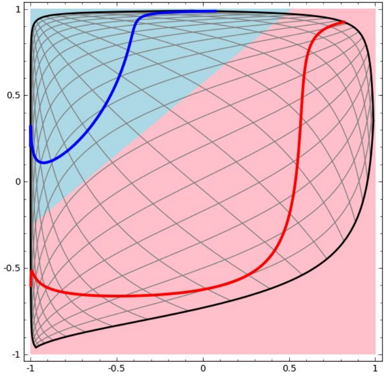
Source: Christopher Olah (Google Brain) http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

What is deep learning?

This sort of warping can be achieved by the same processes that were used to solve the XOR problem from a few slides ago.

However this type of warping can only be achieved by including that function *f* that we included in the beginning.

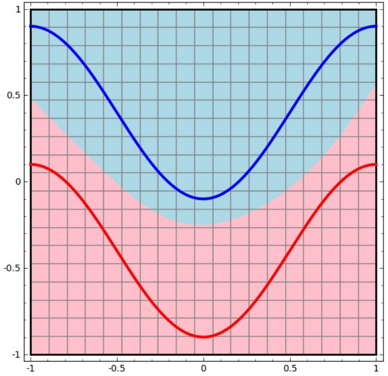


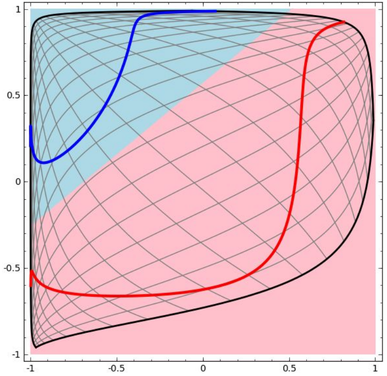


Source: Christopher Olah (Google Brain) http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

What is deep learning?

The reason is that a series of equations in the form $y_1 = x_1w_{11} + x_2w_{12} + b_1$ can only really perform affine transformations on the input data. Meaning that the grid lines on the plot on the left will always 'look' parallel to each other through each transformation. Introducing the 'nonlinearity' function *f* allows for the warping.

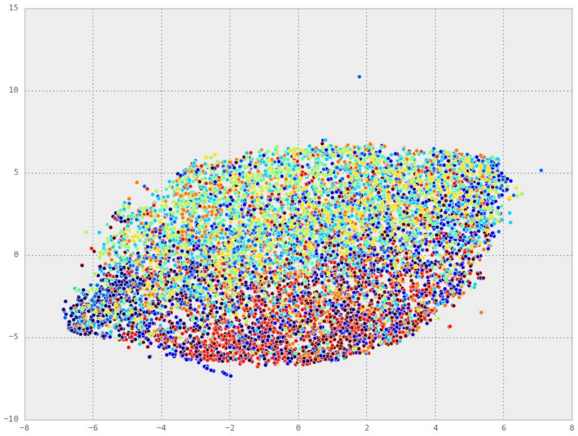


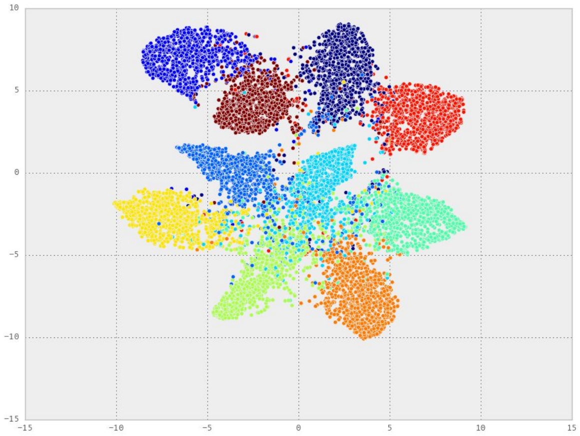


Source: Christopher Olah (Google Brain) http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

What do these representations look like?

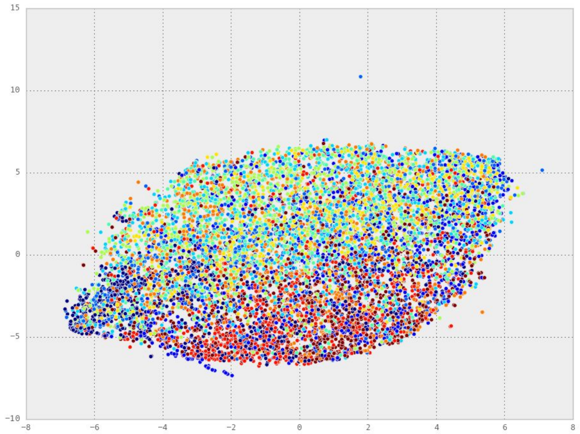
Here is a similar test that I did with some natural images. I did some unsupervised clustering on the raw images and then again on the features extracted from the final layer of a deep neural network.

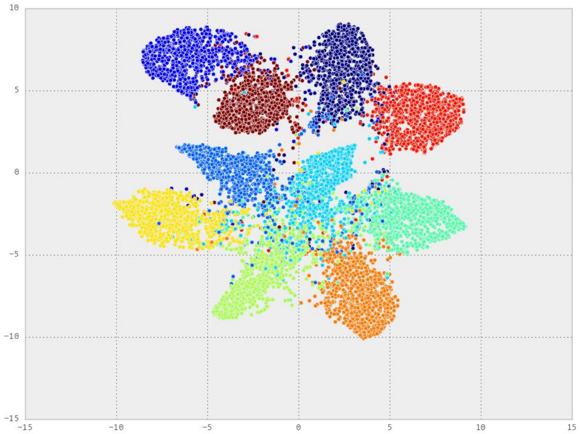




What do these representations look like?

The successive transformations on the input data made it possible to represent the images in a way that made it possible to easily cluster them into their respective classes.





References on vectorized representation of data

Decoding the Thought Vector

http://gabgoh.github.io/ThoughtVectors/

Christopher Olah: Neural Network Manifolds

http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

What do these representations look like?

That network that allowed for the images to be so easily categorized was 16 layers deep and had 133 million weight parameters.

This is why people sometimes refer to neural networks as black boxes. It’s easy to image what is happening in the tiny toy models but when we scale those up we can only generalize those insights.

a(x) = ¯_(ツ)_/¯(x)

What is deep learning?

Another useful interpretation is that a multilayer neural network is like a multi-step computer program. Each node or layer in the network has a specific function that acts on the input data.

The data flows from the input through all of the layers and ends up at the output. As the data passes through each layer a process is done on that data. Each successive layer will receive the processed data from the previous layer.

So as the data moves through the network it is changing with each layer.

A network with greater depth and do more things to the data as it’s flowing through.

Representation learning

Learning the best way to represent the input data is the real strength of deep learning.

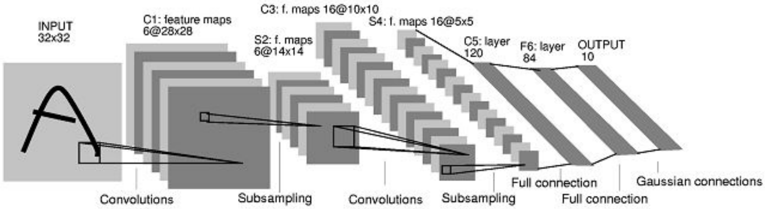
Typical machine learning applications involve feature engineering and all kinds of clever thinking.

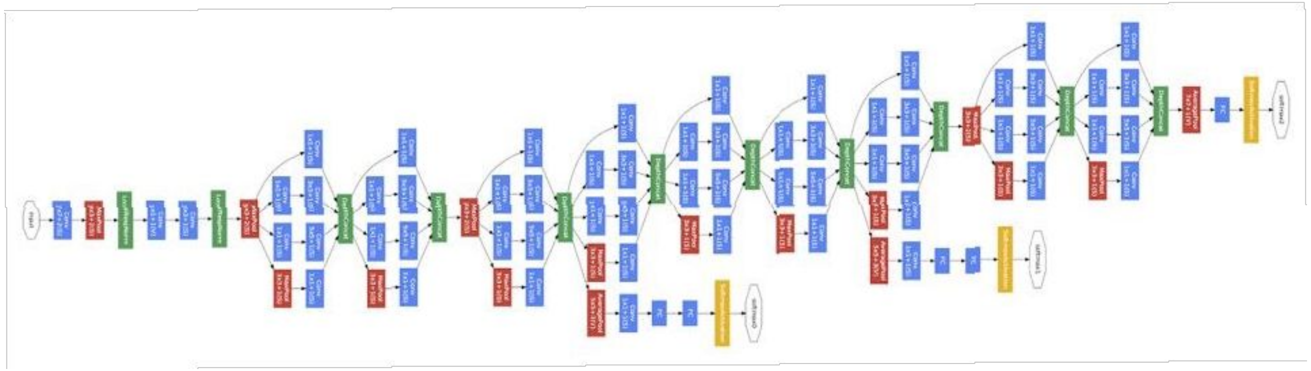
Deep learning promises to learn the features for you and to do it in a way that also trains the final classifier at the same time. All it takes is some time and calculus.

Convolutional Neural Networks

ConvNets

Convolutional Neural Networks (ConvNets) are a special type of feedforward neural network that are particularly well suited for data which contain some kind of spatial structure.





ConvNets

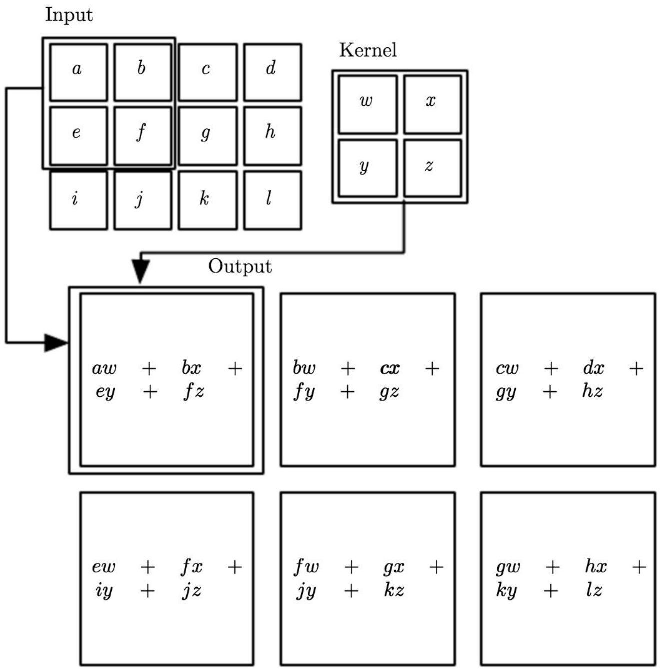
Very simple architecture that takes the representation learning idea and tweaks it so that the representations learned are more appropriate for certain data types.

Instead of using a simple linear model for each node a ConvNet will use kernels that are applied to data.

Each kernel has their own weights and biases just like the normal types of layers that we looked at earlier.

The major differences are in the way that the weights are applied.

ConvNets



Input

a	b	c	d
e	f	g	h
i	j	k	l

Kernel

w	x
y	z

Output

$aw + bx + ey + fz$	$bw + cx + fy + gz$	$cw + dx + gy + hz$
$ew + fx + iy + jz$	$fw + gx + jy + kz$	$gw + hx + ky + lz$

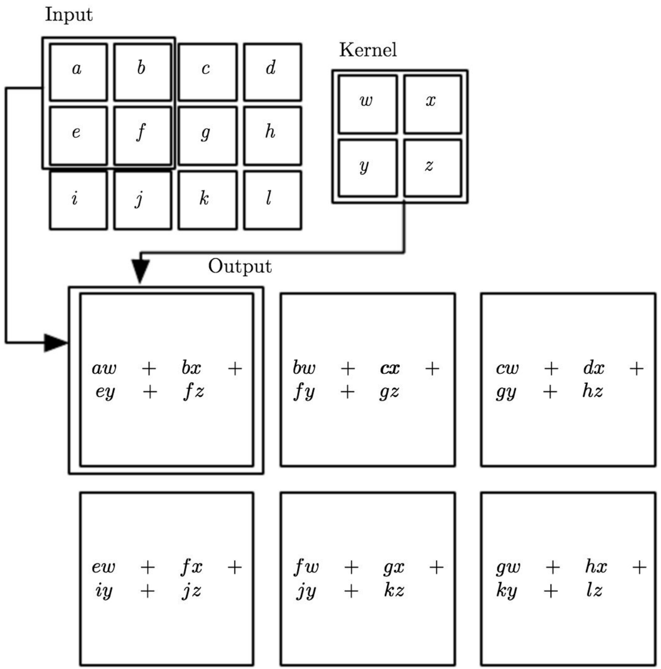
The kernels are applied like a sliding window along the input data.

In this example that data is 2D, like an image.

The weights in the kernel are multiplied to the data in the corresponding position.

The output of that operation will be the sum of each kernel weight multiplied by each corresponding input data point.

ConvNets

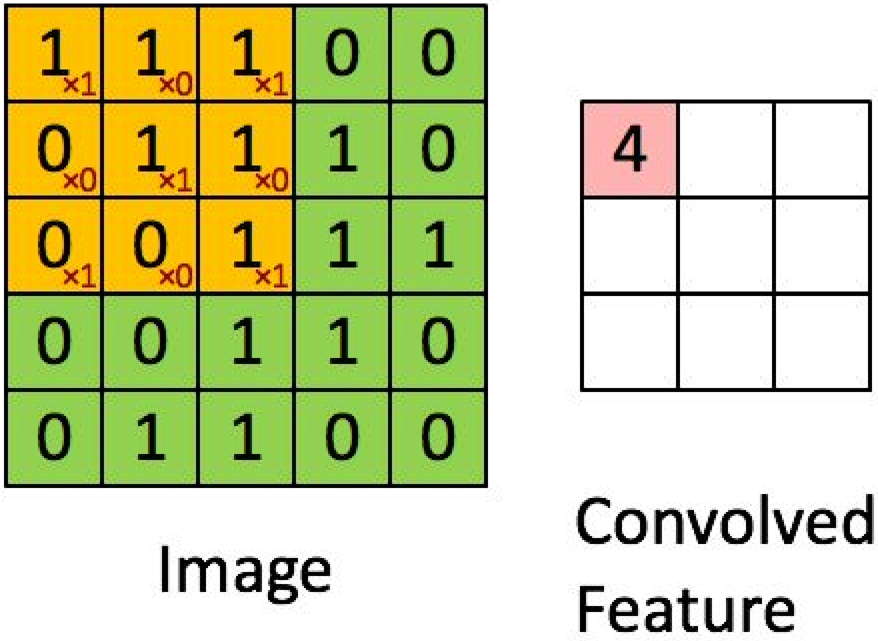


A single number is the output for each unique position that the kernel can occupy.

In this example, sliding a 2x2 kernel over a 3x4 matrix results in a new 2x3 matrix.

We call that new 2x3 matrix a feature map and it can then become the input to a following kernel.

ConvNets



$1_{\times1}$	$1_{\times0}$	$1_{\times1}$	0	0
$0_{\times0}$	$1_{\times1}$	$1_{\times0}$	1	0
$0_{\times1}$	$0_{\times0}$	$1_{\times1}$	1	1
0	0	1	1	0
0	1	1	0	0

4		

http://deeplearning.stanford.edu/tutorial/

ConvNets

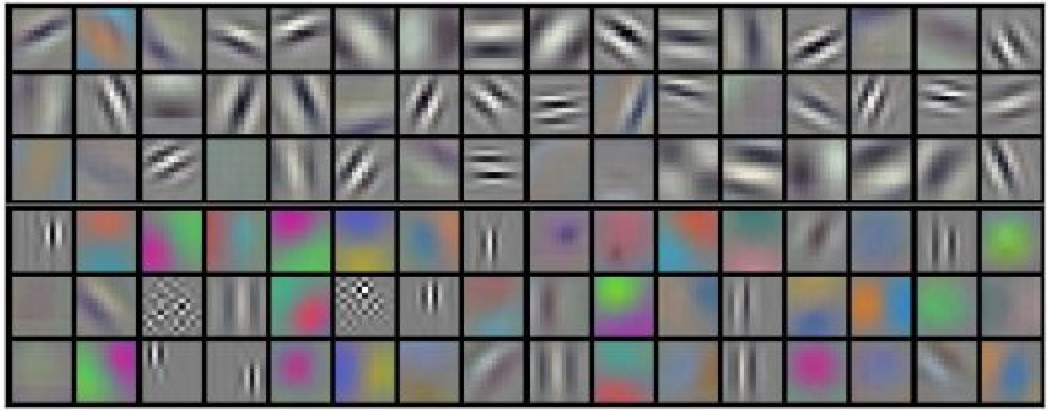
Just like with the neural networks that we looked at earlier these ConvNets are also processed in a feedfoward way. The data flows through the network in order from input through the layers and to the output.

It is common to use many kernels in each layer. Each kernel will learn to represent the data in a different way and produce it's own unique feature maps.

In a similar way that the basic neural networks started to warp the feature space, these ConvNets will also start to change the input data.

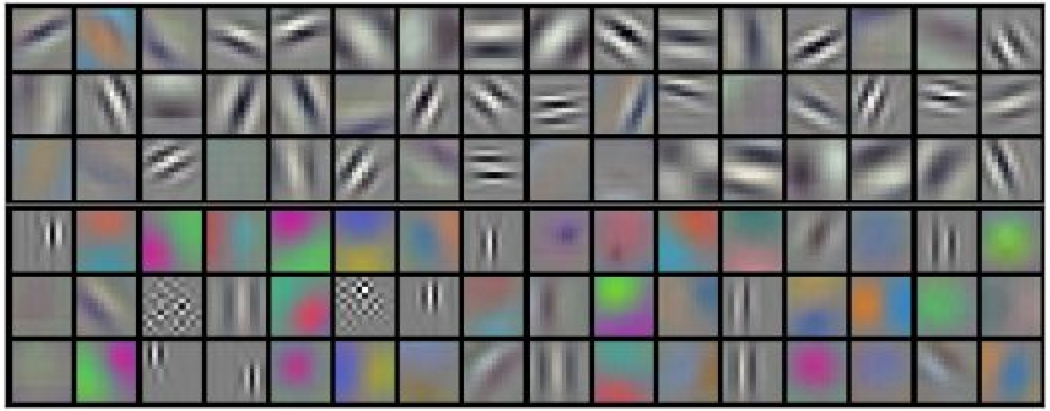
ConvNets

One of the most striking examples is to look at the kernels in the first layer of a well trained ConvNet. If we plot the kernels like they are images we'll see things very similar to the types of feature extractors that people have come up with for computer vision.



ConvNets

If we think about the types of feature maps that will be generated from these kernels we can start to envision how a ConvNet can take apart an image and find the most useful things inside of it to complete it's task.

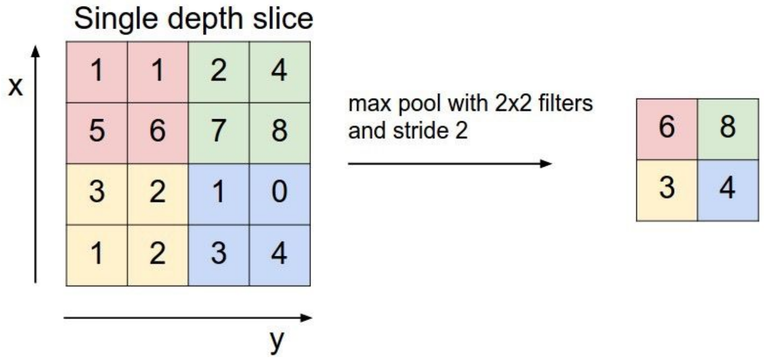


Pooling

Another useful tool for ConvNets are pooling layers.

The most common type of pooling is max pooling. We take the maximum value over a region and only return that value.

Typically pooling layers are put after every single/couple of convolution layers.



1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

6	8
3	4

http://cs231n.github.io/convolutional-networks/

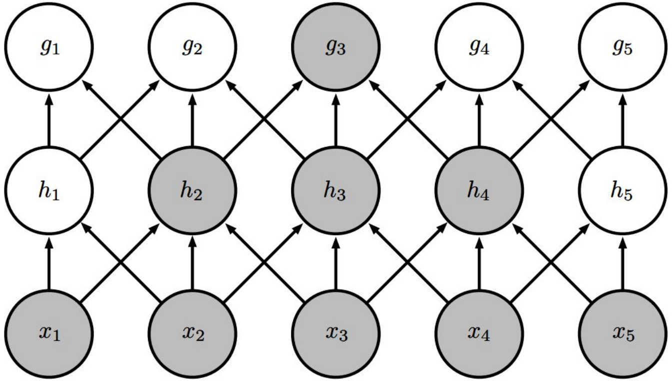
Pooling

One intuition about why pooling is important is that it forces a type of spatial invariance. It also scales the image down so that sub sequential convolution layers will be looking for bigger features in the image.

Once a useful feature has been identified (edges of certain orientations) we shouldn’t care exactly where they are. They are important at all positions. Other features might be important in terms of their locations relative to other features, not their exact locations.

If we do max pooling over a region of 4 activations we are essentially throwing away 75% of those activations. So they also force some sparsity, which could help with overfitting and generalization.

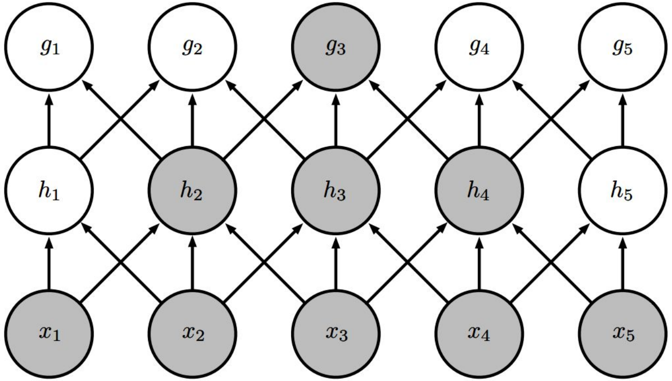
Pooling



A key benefit of the depth of ConvNets and the pooling layers is that it allows the receptive field over the input data to grow as the network gets deeper.

We can see that g_3 takes three neurons as it's input, but each of those three also take three. So g_3 receives information from a much wider area than just its immediate connections.

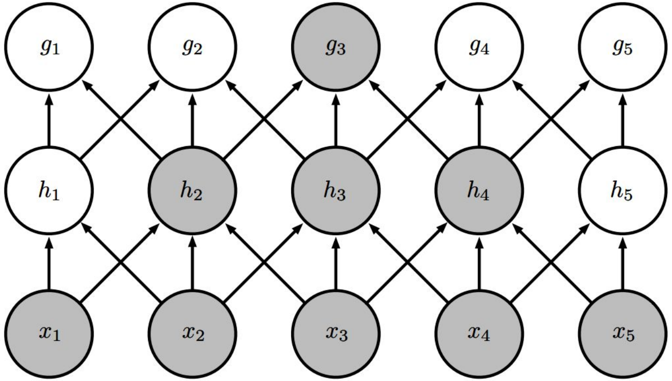
Pooling



If we assume that the h_n layers contain the types of edge and color filters that we saw a few slides ago we can imagine that the g_n layers are combining those edges into shapes.

Layers following the g_n group could then take those shapes and combine them into higher level features.

Pooling



If we assume that the h_n layers contain the types of edge and color filters that we saw a few slides ago we can imagine that the g_n layers are combining those edges into shapes.

Layers following the g_n group could then take those shapes and combine them into higher level features.

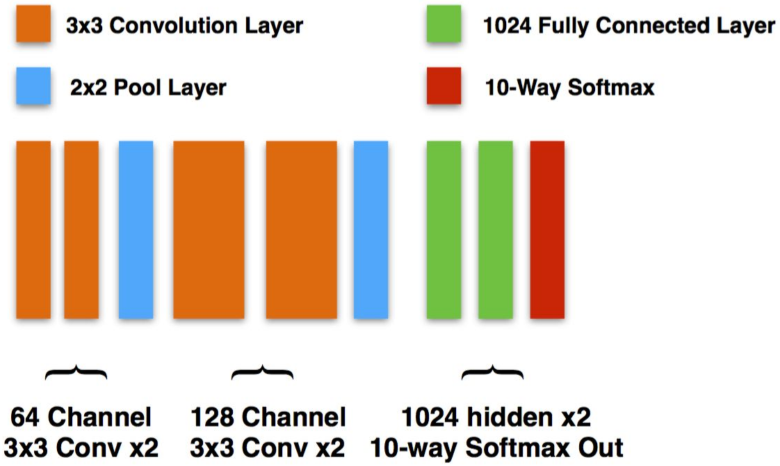
Putting the layers together

Since 2014 it has been popular to only use 3x3 convolutions (‘Very deep convolutional networks for large-scale image recognition’, Simonyan et al. 2014)

Typically people will stack a few convolution layers together then insert a pooling layer.

Since pooling layers down-sample your image size, we can go as far as possible then insert a fully-connected layer or two. Those fully-connected layers are the same as an MLP.

Finally we tack on a classifier or regression layer depending on the problem.



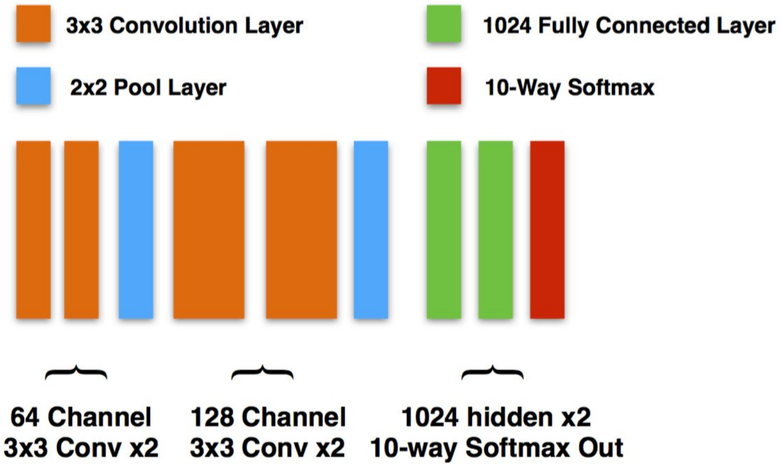
Putting the layers together

In this example we start with an image, say 32x32x3. 32x32 pixels and three channels for RGB.

The first layer contains 64 3x3 kernels. So that 32x32x3 image is expanded from three channels to 64.

The second layer also has 64 channels so the output shape is kept the same.

The third layer is a pool, so we down-sample the image to 16x16x64.



🟧 3x3 Convolution Layer

🟦 2x2 Pool Layer

🟩 1024 Fully Connected Layer

🟥 10-Way Softmax

64 Channel
3x3 Conv x2

128 Channel
3x3 Conv x2

1024 hidden x2
10-way Softmax Out

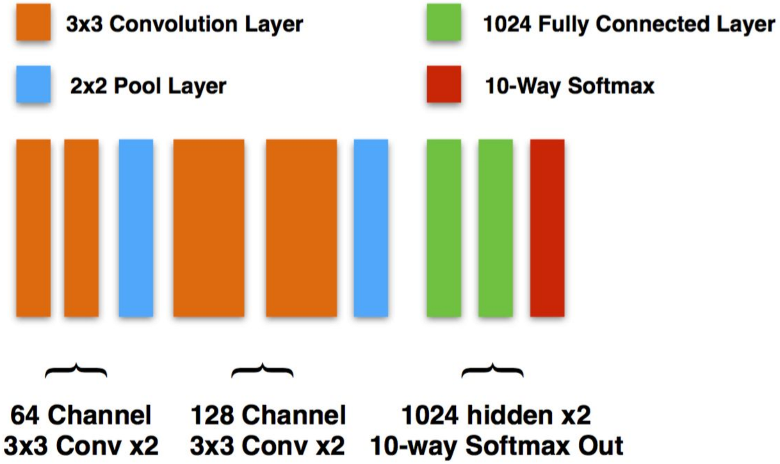
Putting the layers together

We repeat the same pattern with the next convolution layers except this time there are 128 channels.

These second set of kernels is now looking at a much larger portion of the image than the ones in the first layer. They will be trying to make some sense out of those low level feature maps.

We down-sample with another pooling layer. Now our data shape is 8x8x128.

We could keep going, but here we stick an MLP with a final classifier layer on the end.



Learning

We train ConvNets with stochastic gradient descent in pretty much the same way that we train other neural networks. There are some special special things that need to happen because of the kernels and pooling layers but that is beyond the scope of this quick intro and isn't necessary to know to put them in practice with neural network libraries.

It's still an iterative process where we show a series of inputs with their desired output.

ConvNet References

Stanford: Convolutional Neural Networks for Visual Recognition

http://cs231n.github.io/convolutional-networks/

Deep Learning Book: ConvNets Chapter

http://www.deeplearningbook.org/contents/convnets.html

Michael Nielsen's Neural Networks and Deep Learning ConvNet Chapter

http://neuralnetworksanddeeplearning.com/chap6.html

Convolutional Neural Networks Use Cases

What can we do with a ConvNet?

1) **Image Classification**: are these pictures of dogs, cars, people, …?
2) **Image Similarity**: Clustering, reverse image search
3) **Object Localization**: where is a specific object, where are certain landmarks, find every object of a certain type.
4) **Self Driving Car Lane Assist**: Predict steering angle.
5) **Audio Classification**: music genre classification, transcribing music, transcribing speech
6) **Text**: classification, sentiment analysis, translation

Image Classification

Applying convolutional neural networks to a novel image classification task typically follows a standard workflow.

1) We obtain a labeled dataset with examples for our problem.
    a) Can be things like a folder with a lot of cat pictures and another with a lot of dog pictures.
2) Find an appropriate pretrained model.
    a) The groups that are pushing deep learning performance are also very generous with their models. They typically release their highest performing models which turn out to be very good general feature extractors. All we have to do is slightly tweak them to be useful for our problems. This allows us to have state of the art performance with much less data.

Image Classification

3. Either fine tune the network on the new dataset or just use the pretrained network as a feature extractor to vectorize the images that we have.

a. The problems that researchers tend to solve are very general. You don’t want to evaluate a state of the art computer vision algorithm on only images of one type. You could never know if your algorithm was actually improving the state of the art in general or if it’s only good at one thing, like classifying cars or dogs.

b. This benefits us, as people trying to apply machine learning to real problems we are the ones that are looking to only do well at a specific task. So starting with a very general model we only need to do some small tweaks to get there.

c. We can take a state of the art model and repurpose it in just a few minutes

Image Clustering

Applying convolutional neural networks to find similar images is a great exercise in exploiting the central philosophy of deep learning.

As we saw earlier today, deep learning is really about finding good representations of our data.

We can exploit this property by extracting the internal representation of each of our images.

Image Clustering

This image from earlier is a perfect example of how successful clustering can be with the internal representations of ConvNets.

We just return the activation from the layer before the final classifier layer to get these representations.

Using a state of the art pretrained model the only thing that we have to do is pass each image through that model. No training needed!

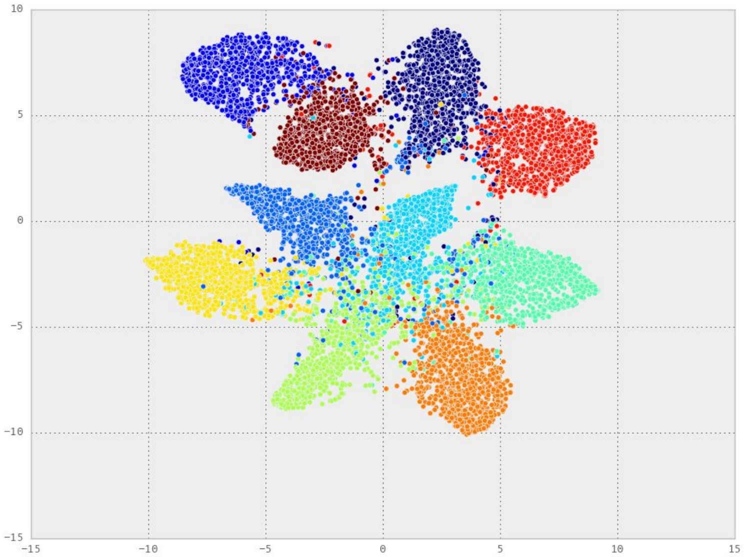
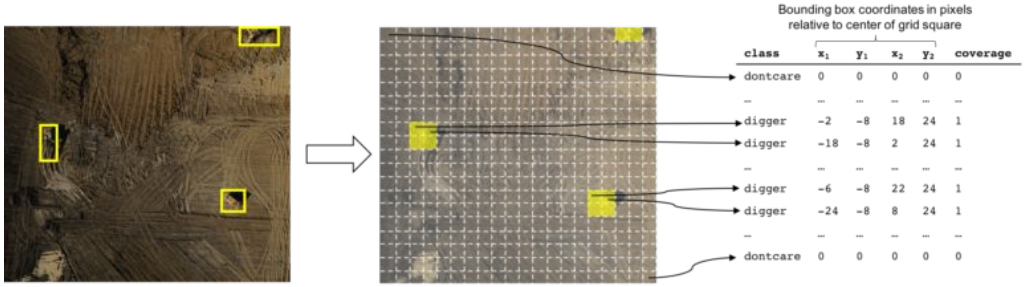


Image Localization

Convolutional neural networks are also great for localization.



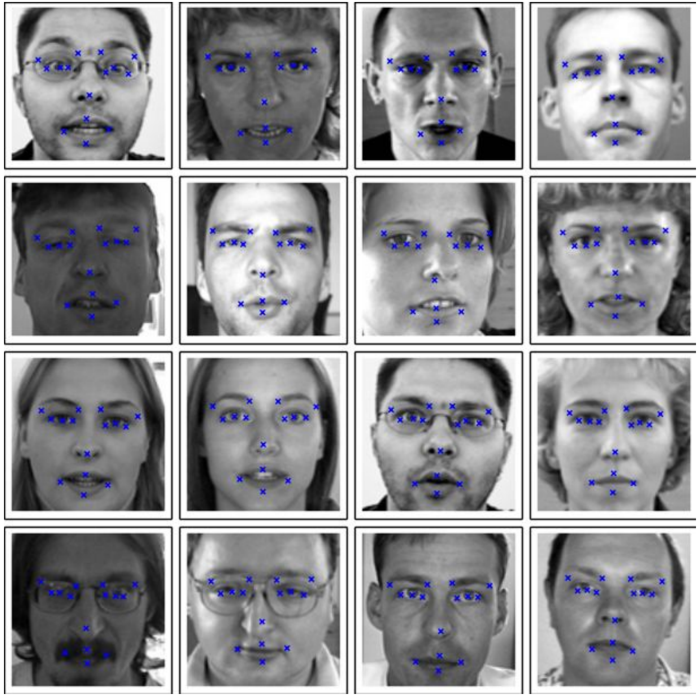
Training image with bounding box annotations

Bounding boxes mapped to grid squares

Bounding box coordinates in pixels relative to center of grid square

class	x_1	y_1	x_2	y_2	coverage
dontcare	0	0	0	0	0
...	...	...	...	...	...
digger	-2	-8	18	24	1
digger	-18	-8	2	24	1
...	...	...	...	...	...
digger	-6	-8	22	24	1
digger	-24	-8	8	24	1
...	...	...	...	...	...
dontcare	0	0	0	0	0

DetectNet input data representation



https://devblogs.nvidia.com/parallelforall/detectnet-deep-neural-network-object-detection-digits/

http://danielnouri.org/notes/2014/12/17/using-convolutional-neural-nets-to-detect-facial-keypoints-tutorial/

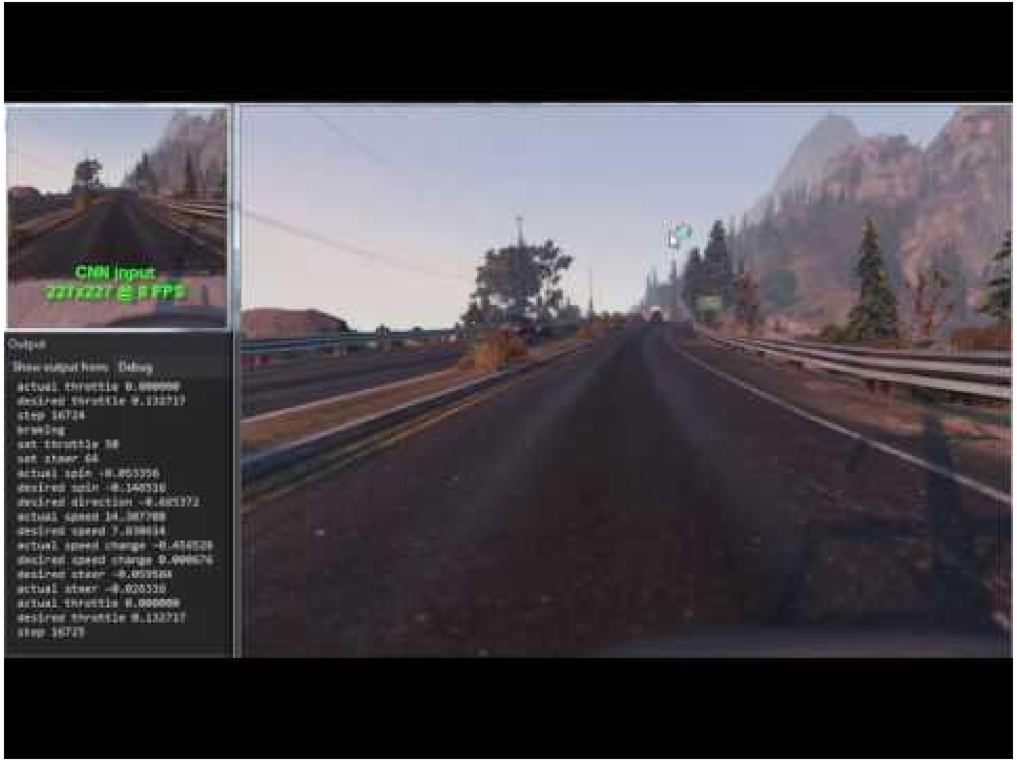
Image Localization

Instead of predicting labels for each image we are instead predicting points or regions.

We need to have annotated images to train the network with, could be coordinates of the key points or coordinates of the bounding boxes.

If we are doing regions, we convert the coordinates into those discrete objects and then train the network as if it were a classification problem. Predicting a yes/no for each region.

Self Driving Car

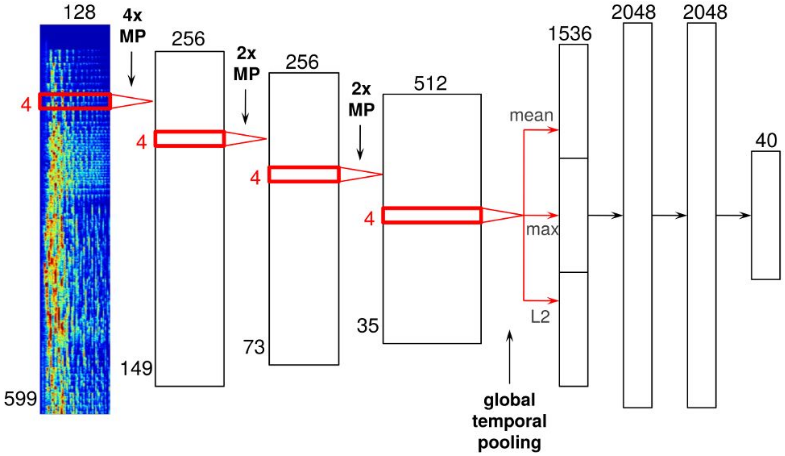


```
actual throttle 0.000000
desired throttle 0.132717
step 16724
braking
set throttle 50
set steer 64
actual spin -0.053356
desired spin -0.140318
desired direction -0.485372
actual speed 14.387708
desired speed 7.030614
actual speed change -0.454528
desired speed change 0.000676
desired steer -0.059584
actual steer -0.020338
actual throttle 0.000000
desired throttle 0.132717
step 16725
```

http://deepdrive.io/

Audio Classification

ConvNets are also great at dealing with audio classification.



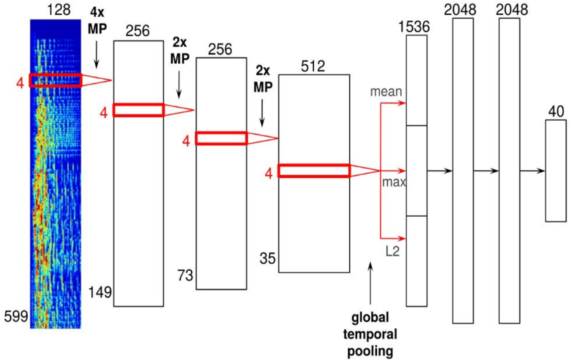
http://benanne.github.io/2014/08/05/spotify-cnns.html

Audio Classification

This ends up becoming a very similar workflow to image classification.

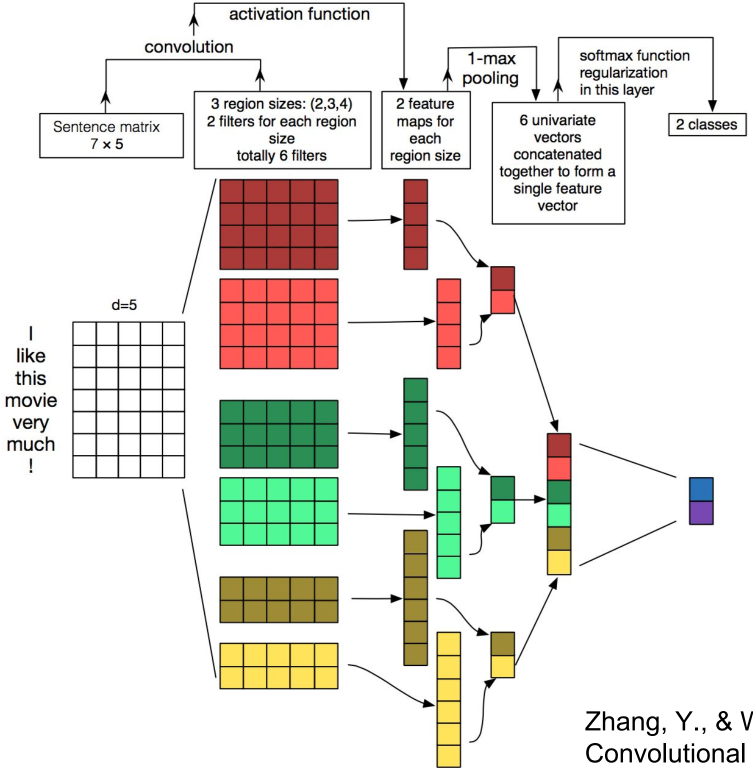
By working with the audio spectrogram the neural network will process it in almost exactly the same way that it does with an image.

The differences being that it's only a 2D matrix instead of 3D.



http://benanne.github.io/2014/08/05/spotify-cnns.html

Text Classification



Although it may seem a little counter intuitive, convolutional neural networks can be very successfully applied to natural language problems.

The intuition here is that a sentence can be represented as a structured matrix.

Zhang, Y., & Wallace, B. (2015). A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification.

Code Introduction

Keras

“Keras is a minimalist, highly modular neural networks library, written in Python and capable of running on top of either TensorFlow or Theano. It was developed with a focus on enabling fast experimentation. Being able to go from idea to result with the least possible delay is key to doing good research.

Use Keras if you need a deep learning library that:

Allows for easy and fast prototyping (through total modularity, minimalism, and extensibility).

Supports both convolutional networks and recurrent networks, as well as combinations of the two.

Supports arbitrary connectivity schemes (including multi-input and multi-output training).

Runs seamlessly on CPU and GPU.”

Source: https://keras.io/

Keras

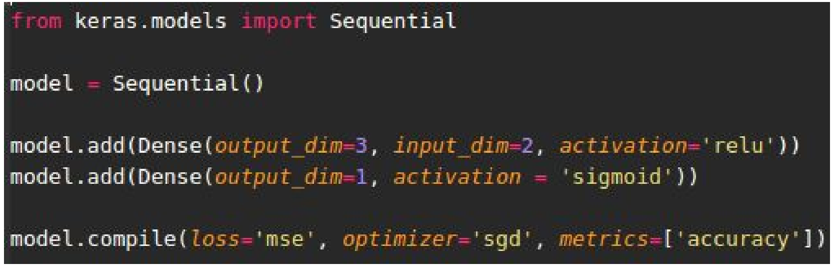
There are two ways to use Keras. Referred to as the sequential and functional apis.

You can do most things with either method but the functional api will be more flexible and useful for more advanced architectures.

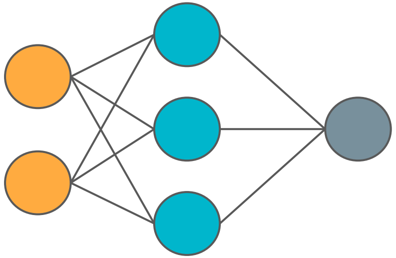
The sequential model is just how it sounds. You set up the layers to process the data in a sequential start to finish type of order. It’s similar to thinking about the models like the convolutional neural network diagrams that I showed three slides back.

The functional models will make it much easier to split, branch and get crazy with your networks. This is more similar to thinking about the models as a computational graph, like the node diagrams that we saw in the beginning.

Sequential Models



```
from keras.models import Sequential

model = Sequential()

model.add(Dense(output_dim=3, input_dim=2, activation='relu'))
model.add(Dense(output_dim=1, activation = 'sigmoid'))

model.compile(loss='mse', optimizer='sgd', metrics=['accuracy'])
```

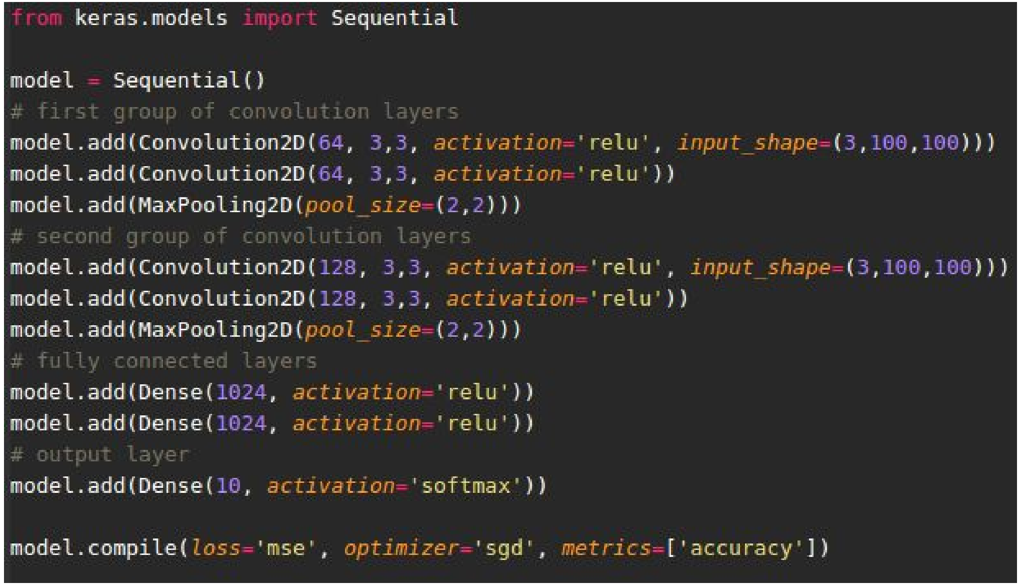


With the sequential model you start by declaring your model as a sequential. That gives you a blank canvas to start working.

From there you can add anything you want using model.add(). The data will flow through the model in the order that you declare each layer.

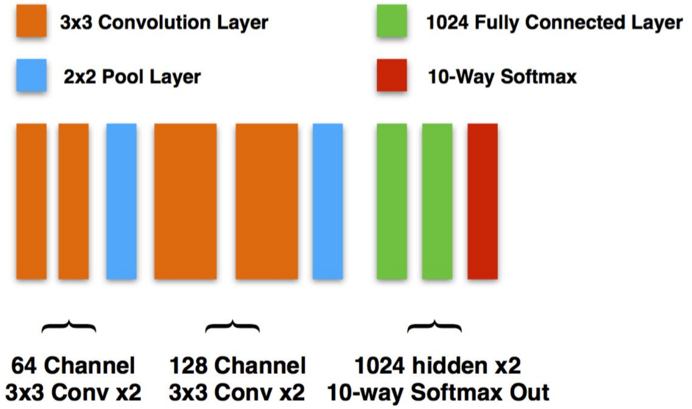
The example on the left builds the small neural network that we looked at the in the beginning.

Sequential Models



```python
from keras.models import Sequential

model = Sequential()
# first group of convolution layers
model.add(Convolution2D(64, 3,3, activation='relu', input_shape=(3,100,100)))
model.add(Convolution2D(64, 3,3, activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
# second group of convolution layers
model.add(Convolution2D(128, 3,3, activation='relu', input_shape=(3,100,100)))
model.add(Convolution2D(128, 3,3, activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
# fully connected layers
model.add(Dense(1024, activation='relu'))
model.add(Dense(1024, activation='relu'))
# output layer
model.add(Dense(10, activation='softmax'))

model.compile(loss='mse', optimizer='sgd', metrics=['accuracy'])
```

A slightly more complicated and modern looking ConvNet.



Sequential Models

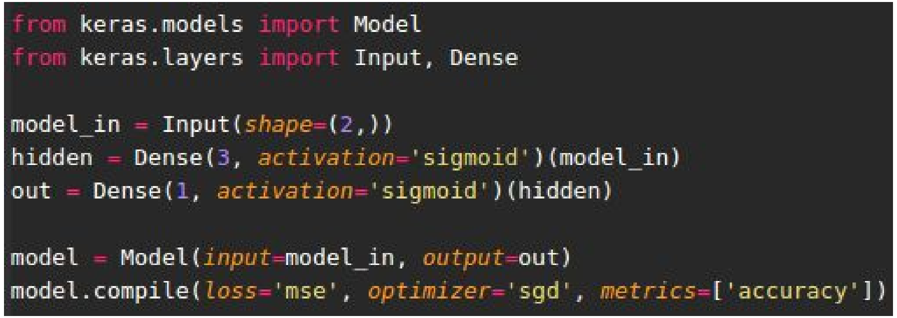
The sequential model in Keras makes it pretty painless and trivial to define big models.

Simply define your model in the same order that the data will flow through it. This has the added benefit of having your code look very similar to the tables that people sometimes use when reporting their network architectures. That way things are pretty intuitive.

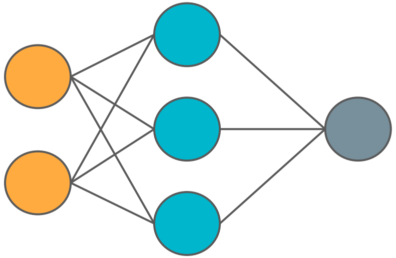
It’s possible to do more complicated things with the sequential model. But, for me it seems a little bit clunky and makes for some unnecessary typing.

It could very well be a matter of preference, but I believe that the functional method of creating models in Keras is much for flexible. I also like the way I think about the models when I use the functional methods. Instead of stacking layers I think more about the flow of information through the computational stages of the model.

Functional Models



```
from keras.models import Model
from keras.layers import Input, Dense

model_in = Input(shape=(2,))
hidden = Dense(3, activation='sigmoid')(model_in)
out = Dense(1, activation='sigmoid')(hidden)

model = Model(input=model_in, output=out)
model.compile(loss='mse', optimizer='sgd', metrics=['accuracy'])
```

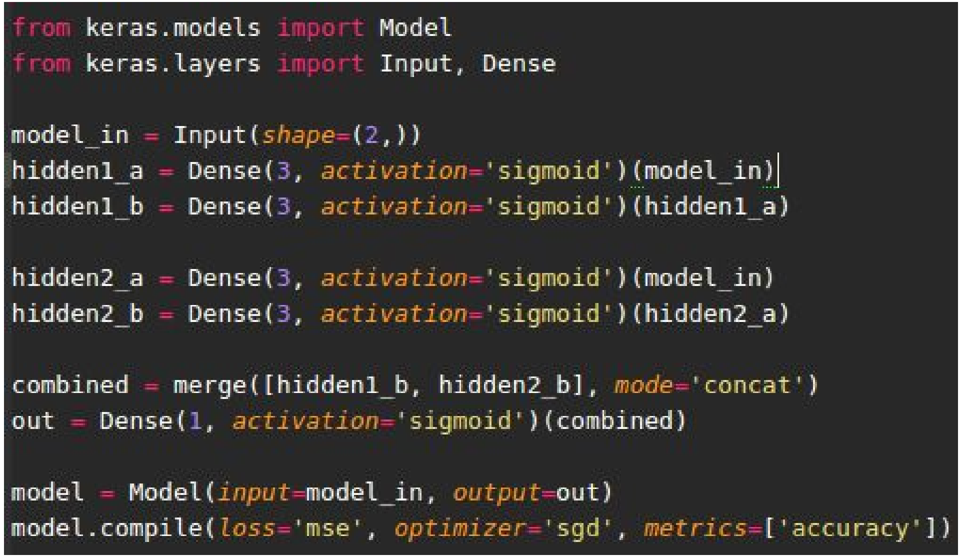


With the functional model you give each computational layer a name instead of just stacking them up with model.add().

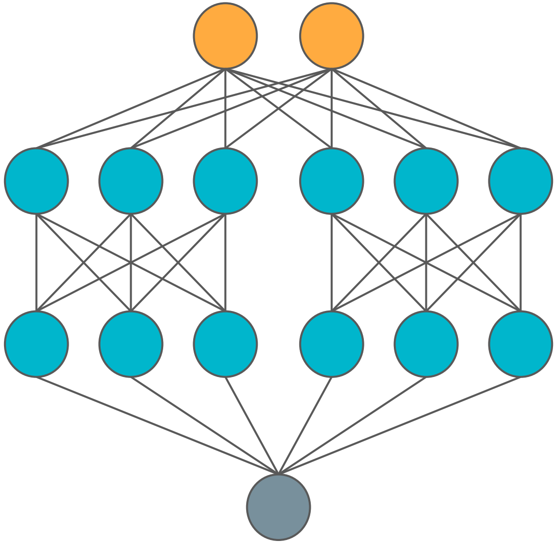
This is key, because you also explicitly provide the input to each layer. This allows you more freedom to try some different architectures with no extra effort to hack the sequential models.

For example some architectures could have multiple independent branches of neurons coming off of the input. This method makes setting that up a breeze.

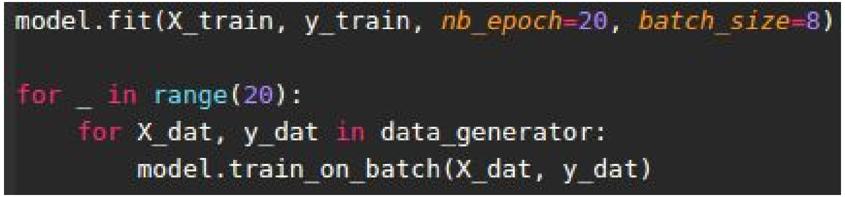
Functional Models



```
from keras.models import Model
from keras.layers import Input, Dense

model_in = Input(shape=(2,))
hidden1_a = Dense(3, activation='sigmoid')(model_in)
hidden1_b = Dense(3, activation='sigmoid')(hidden1_a)

hidden2_a = Dense(3, activation='sigmoid')(model_in)
hidden2_b = Dense(3, activation='sigmoid')(hidden2_a)

combined = merge([hidden1_b, hidden2_b], mode='concat')
out = Dense(1, activation='sigmoid')(combined)

model = Model(input=model_in, output=out)
model.compile(loss='mse', optimizer='sgd', metrics=['accuracy'])
```



Using Models



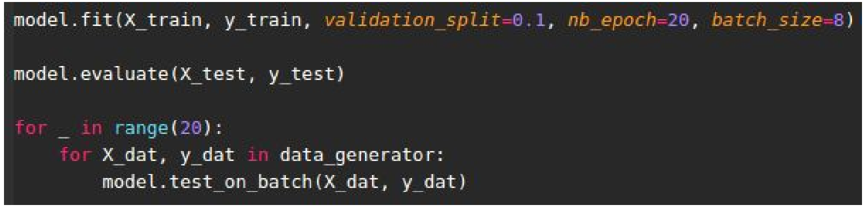
```python
model.fit(X_train, y_train, nb_epoch=20, batch_size=8)

for _ in range(20):
    for X_dat, y_dat in data_generator:
        model.train_on_batch(X_dat, y_dat)
```

Once you have defined and created your models it’s pretty straightforward to run them. Keras gives you a few different options.

Training a network is an iterative process, so basically we’ll be creating loops that stream the data into each model.

We can use Keras built in methods or create our own. The ‘data_generator’ would just be some function that would loop through the data and divide it up into batches to stream into the model.

Using Models



```
model.fit(X_train, y_train, validation_split=0.1, nb_epoch=20, batch_size=8)

model.evaluate(X_test, y_test)

for _ in range(20):
    for X_dat, y_dat in data_generator:
        model.test_on_batch(X_dat, y_dat)
```

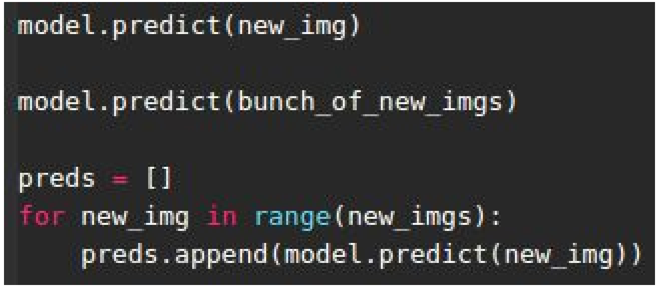
Evaluating the models on a hold out validation data set is just as easy.

With .fit() we don’t have to split the data into training and testing before using it. Just tell Keras what percentage of data we want to use to evaluate the model with.

With .evaluate() we split the data before training and use it the same way that we use .fit(). Except this time it won’t update parameters it will just return evaluation metrics.

Or we can create our own loops like we did with training.

Using Models



```
model.predict(new_img)

model.predict(bunch_of_new_imgs)

preds = []
for new_img in range(new_imgs):
    preds.append(model.predict(new_img))
```

Making predictions or putting the model to use is also pretty easy.

Each model has a .predict(), it can be used in a variety of ways. Similar to how training and evaluating had a variety of methods, except each one of these will be called with .predict().

You can pass a single new point of data, a numpy array of new data.

You could also loop through the data and make a prediction on each data point.

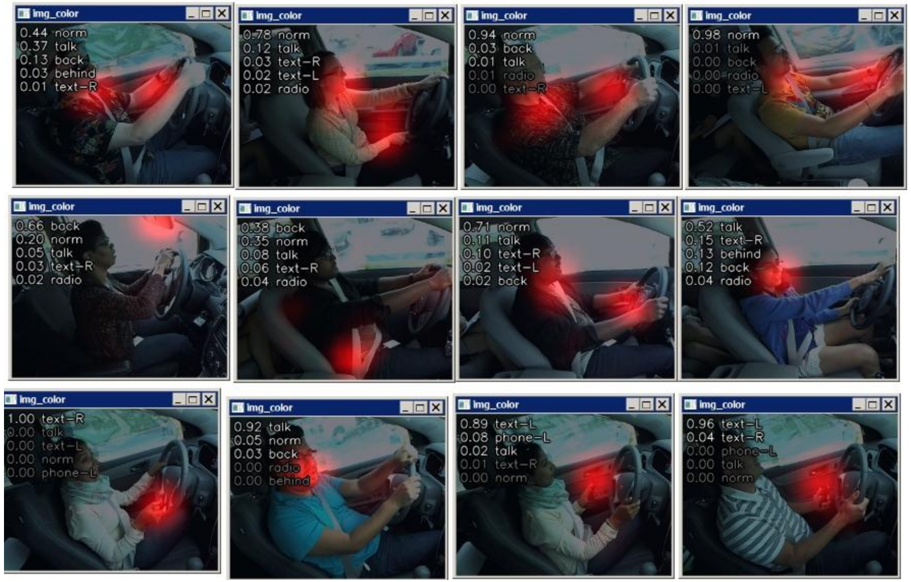
Hands on Practice

Classification Heatmaps

One technique that can be incredibly helpful when training a ConvNet for an image classification problem is to make heatmaps.

The basic idea here is to occlude parts of the image and record the effect on the output probabilities.

If you cover a part of an image and the confidence in a certain classification goes down then you can reasonably conclude that you have covered an important feature for classification.



```
0.44 norm
0.37 talk
0.13 back
0.03 behind
0.01 text-R
```

```
0.78 norm
0.12 talk
0.03 text-R
0.02 text-L
0.02 radio
```

```
0.94 norm
0.03 back
0.01 talk
0.01 radio
0.00 text-R
```

```
0.98 norm
0.01 talk
0.00 back
0.00 radio
0.00 text-L
```

```
0.66 back
0.20 norm
0.05 talk
0.03 text-R
0.02 radio
```

```
0.38 back
0.35 norm
0.08 talk
0.06 text-R
0.04 radio
```

```
0.71 norm
0.11 talk
0.10 text-R
0.02 text-L
0.02 back
```

```
0.52 talk
0.15 text-R
0.13 behind
0.12 back
0.04 radio
```

```
1.00 text-R
0.00 talk
0.00 text-L
0.00 norm
0.00 phone-L
```

```
0.92 talk
0.05 norm
0.03 back
0.00 radio
0.00 behind
```

```
0.89 text-L
0.08 phone-L
0.02 talk
0.01 text-R
0.00 norm
```

```
0.96 text-L
0.04 text-R
0.00 phone-L
0.00 talk
0.00 norm
```

From Kaggle user: Heng CherKeng
https://www.kaggle.com/c/state-farm-distracted-driver-detection/forums/t/21994/heat-map-of-cnn-output

Classification Heatmaps Examples

Visualizing and Understanding Convolutional Neural Networks, Matthew D Zeiler, Rob Fergus
https://arxiv.org/abs/1311.2901

Example Code from Daniel Nouri:
https://github.com/dnouri/nolearn/blob/master/nolearn/lasagne/visualize.py#L105

Example for Keras from Jacob Gildenblat: https://github.com/jacobgil/keras-cam

Recurrent Neural Networks

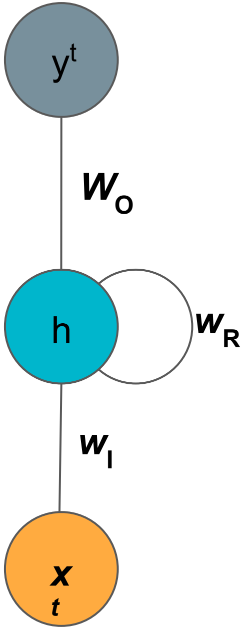
Recurrent Neural Networks

Useful when trying to apply deep learning to sequential types of data. Text, speech, and audio.

They also let us get around some problems where the input has to be a fixed size. For example with the images that we just worked with they always had to be scaled to the same exact size. But, if we wanted to train a deep learning model on sentences we can't guarantee that they are always the same size.

Not only do they let us vary the length of the input, but they are also sensitive to temporal dependencies. Back to the sentence example, different words in different positions could be dependent each other.

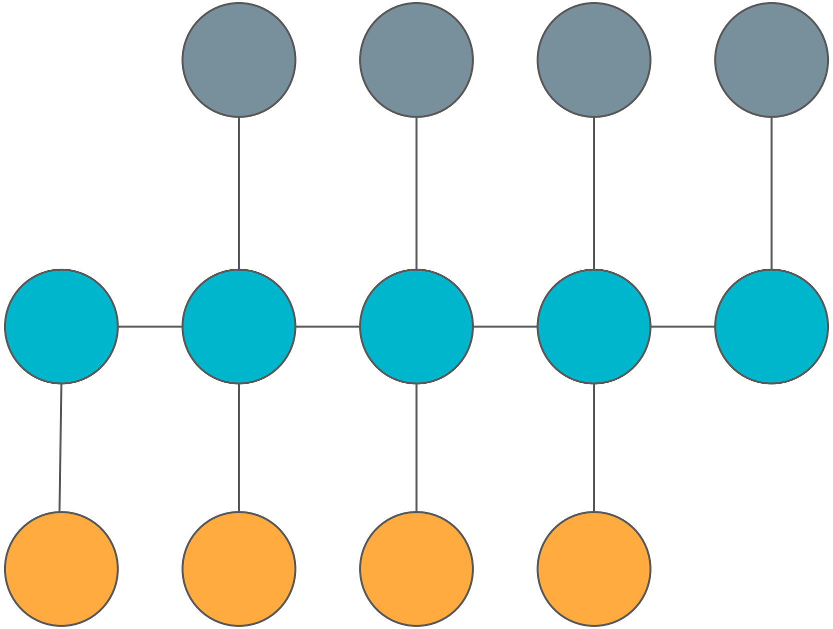
Recurrent Neural Networks



$$h^t = a_h(W_I x^t + W_R h^{t-1} + b_h)$$

$$y^t = a_y(W_o h^t + b_y)$$

Recurrent Neural Networks

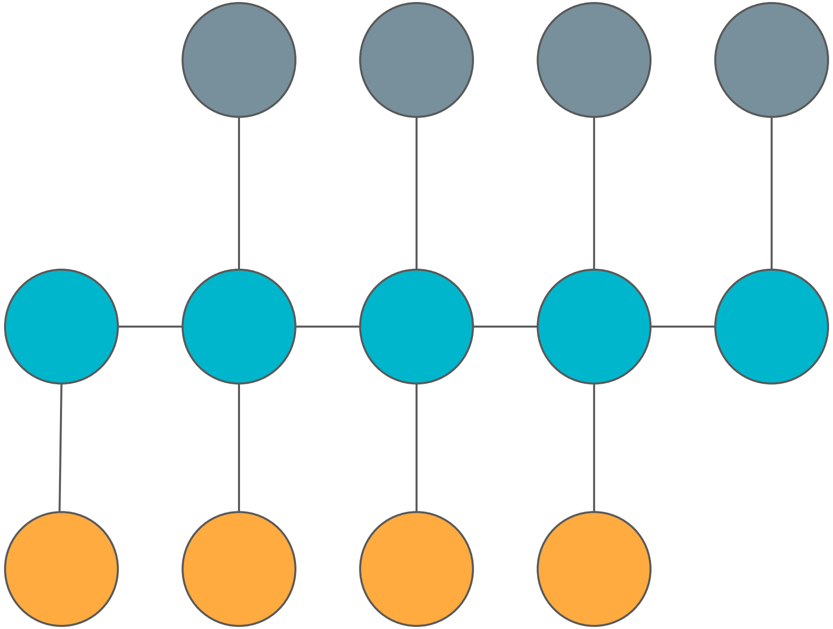


Recurrent Neural Networks

Unrolling the network like this is also helpful to gain some intuition about how they are trained.

For each output, we backpropagate the error all the way back to the first input.

It works exactly like the feed forward networks that we looked at before with the added headache of keeping track of all the connections.

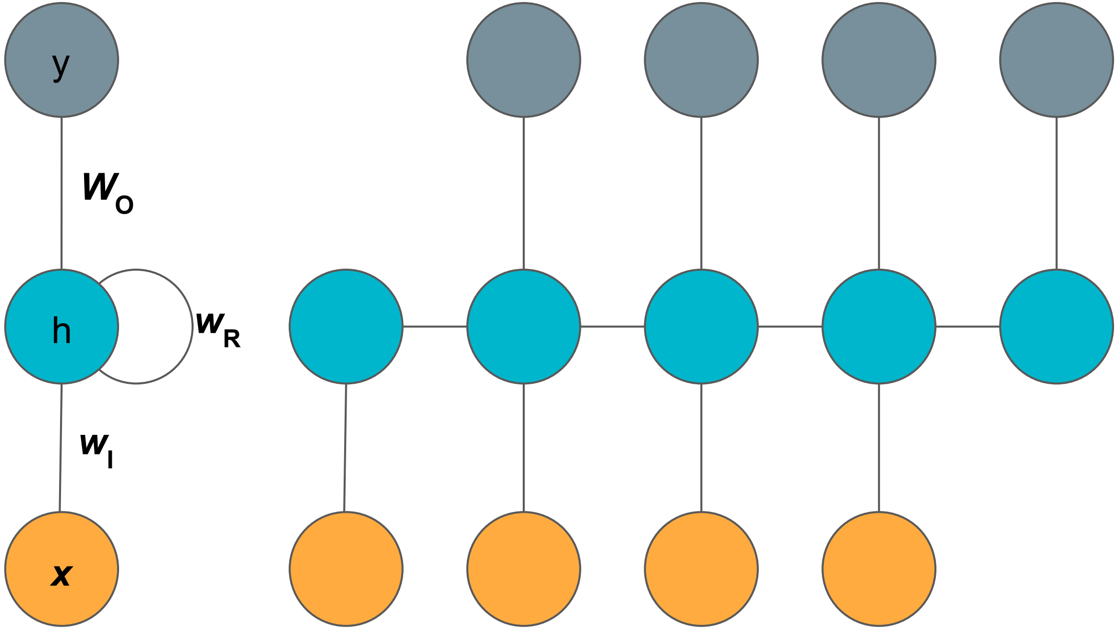


Vanishing and Exploding Gradients

One caveat here is that the weights that exist between all of the connects are shared in each time step.

So W_I, W_R, and W_O are used multiple times. So if you calculate the error at many time steps the magnitude of the update is scaled up.

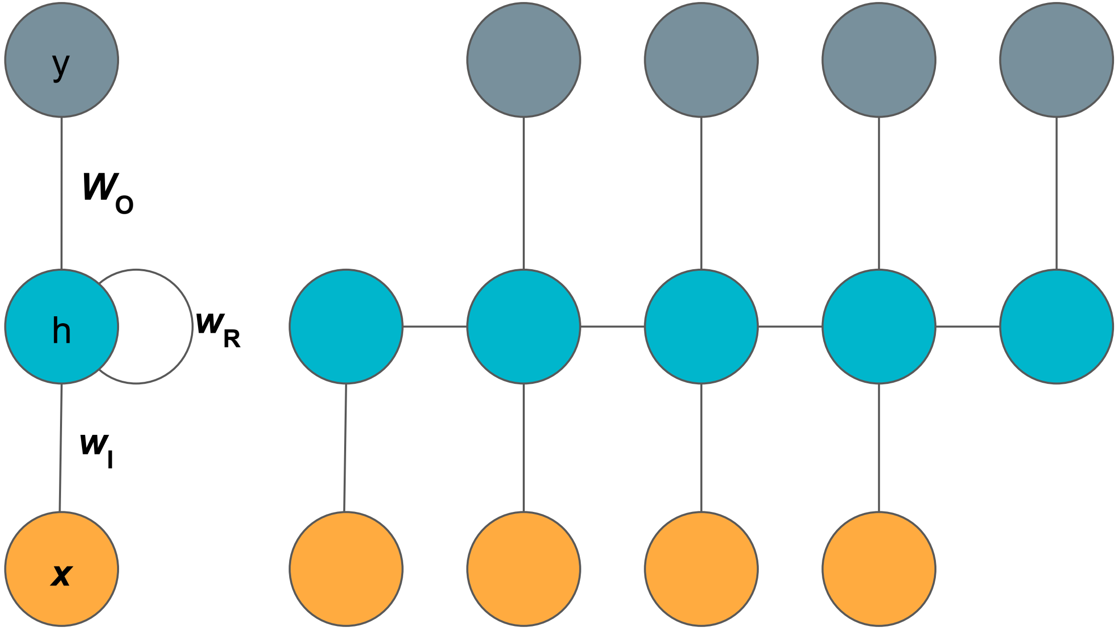
We could find ourselves in situations where the gradient signal either becomes 0 or incredibly large.



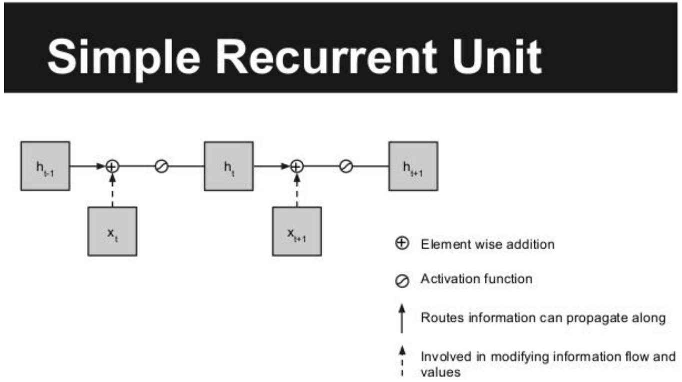
Vanishing and Exploding Gradients

The most effective way that people combat this is to clip the gradient so that they can only take on some maximum value.

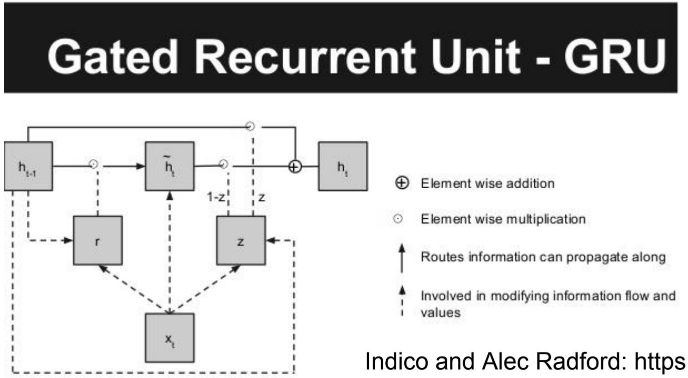
This seems kind of simple and hacky but in reality it works out pretty well.



Gated Recurrent Units



Simple Recurrent Unit
h t-1
h t
h t+1
x t
x t+1
⊕ Element wise addition
⊘ Activation function
Routes information can propagate along
Involved in modifying information flow and values



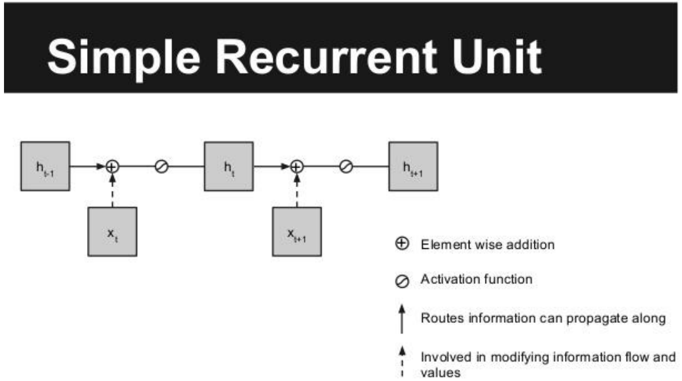
Gated Recurrent Unit - GRU
h t-1
h̃ t
h t
r
z
x t
1-z
z
⊕ Element wise addition
⊙ Element wise multiplication
Routes information can propagate along
Involved in modifying information flow and values

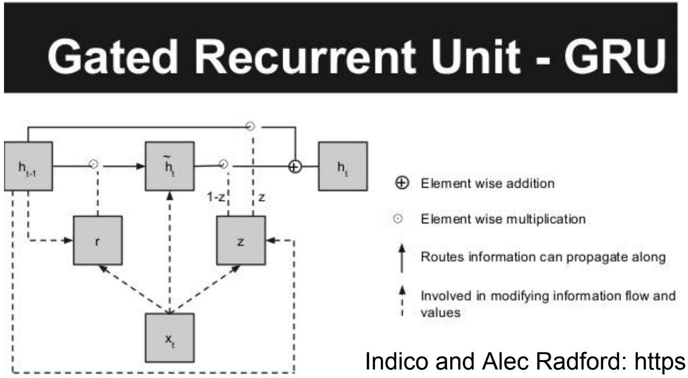
These recurrent neural networks that we just looked at turn out not to function as well in practice. They have a significant draw-back in that the recurrent weight matrix is continuously updated. This make it difficult for information to persist through many time steps.

If you wanted to train a recurrent network on a very large body of text the network will have trouble relating words at the end of a document to words at the beginning.

Indico and Alec Radford: https://www.youtube.com/watch?v=VINCQghQRuM

Gated Recurrent Units




Gated Recurrent Unit - GRU
h_{t-1}
$\tilde{h}_t$
h_t
r
z
1-z
z
x_t
⊕ Element wise addition
⊙ Element wise multiplication
Routes information can propagate along
Involved in modifying information flow and values

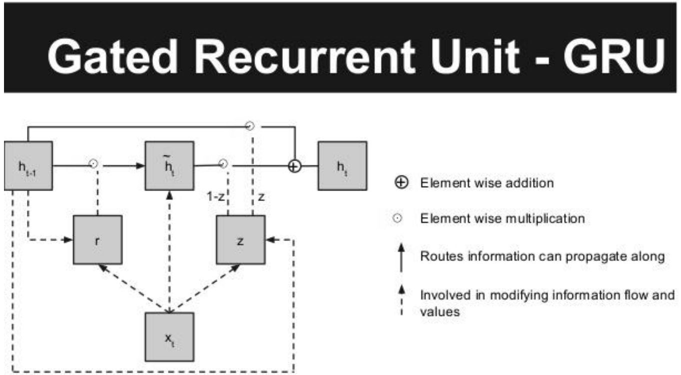
The GRU is like a simple RNN except that it has two matrices that function like gates. We typically call these gates *r* and *z.*

The reset gate, *r*, determines how much to combine the previous hidden state with the new input at time *t*. The update gate, *z*, determines how much the hidden state of the network should update with each example.

This is powerful because the network will have the ability to keep information within its hidden state for much longer.

Indico and Alec Radford: https://www.youtube.com/watch?v=VINCQghQRuM

Gated Recurrent Units



Gated Recurrent Unit - GRU

⊕ Element wise addition

⊙ Element wise multiplication

↑ Routes information can propagate along

⇡ Involved in modifying information flow and values

$$z_t = \sigma(W_z h_{t-1})$$

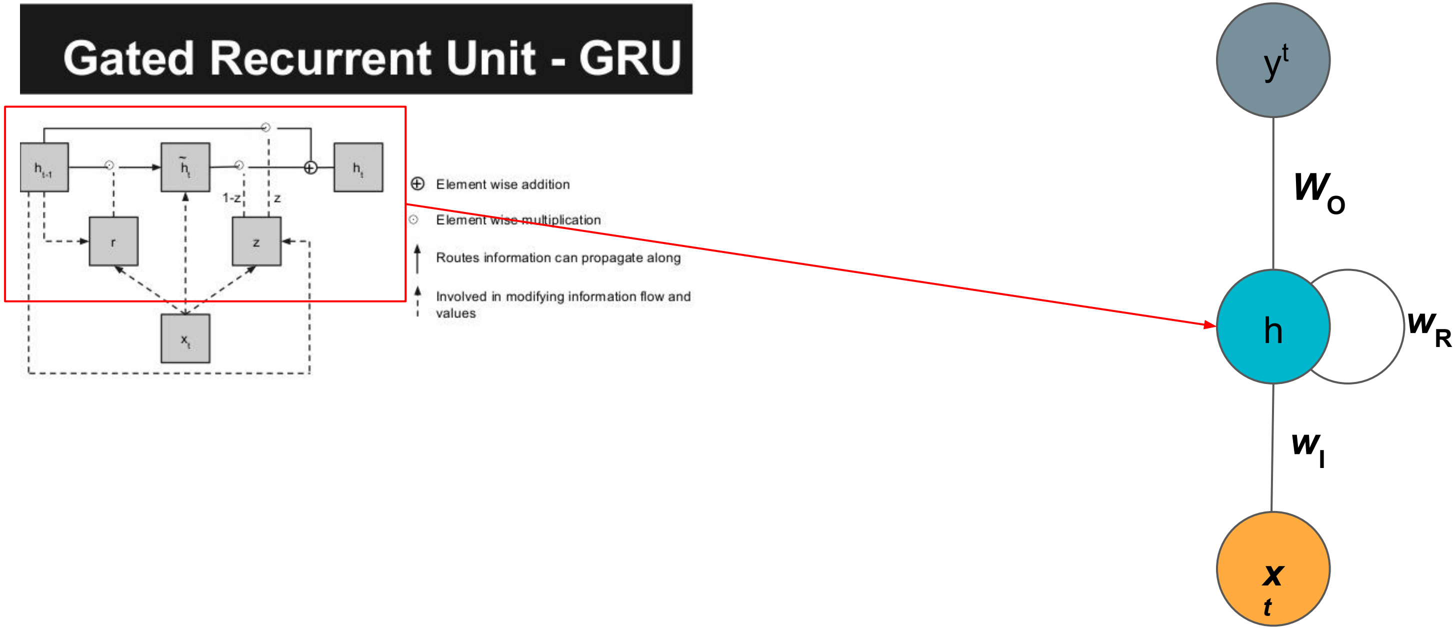
$$r_t = \sigma(W_r h_{t-1})$$

$$\tilde{h}_t = tanh(W \cdot [r_t * h_{t-1}])$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Indico and Alec Radford: https://www.youtube.com/watch?v=VINCQghQRuM

Gated Recurrent Units



Gated Recurrent Unit - GRU

⊕ Element wise addition

⊙ Element wise multiplication

↑ Routes information can propagate along

⇡ Involved in modifying information flow and values

Indico and Alec Radford: https://www.youtube.com/watch?v=VINCQghQRuM

What about LSTM?

GRU cells are a recent tweak on LSTM cells.

Their function is similar, allowing an RNN to have longer term dependencies.

However LSTM cells are a bit more complicated and in practice the two perform about the same.

“We compared the GRU to the LSTM and its variants, and found that the GRU outperformed the LSTM on nearly all tasks except language modelling with the naive initialization, but also that the LSTM nearly matched the GRU’s performance once its forget gate bias was initialized to 1.”

“An Empirical Exploration of Recurrent Network Architectures” - http://jmlr.org/proceedings/papers/v37/jozefowicz15.pdf

Rafal Jozefowicz, Wojciech Zaremba, Ilya Sutskever

Resources for LSTM?

Andrej Karpathy: Unreasonable Effectiveness of RNNs

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

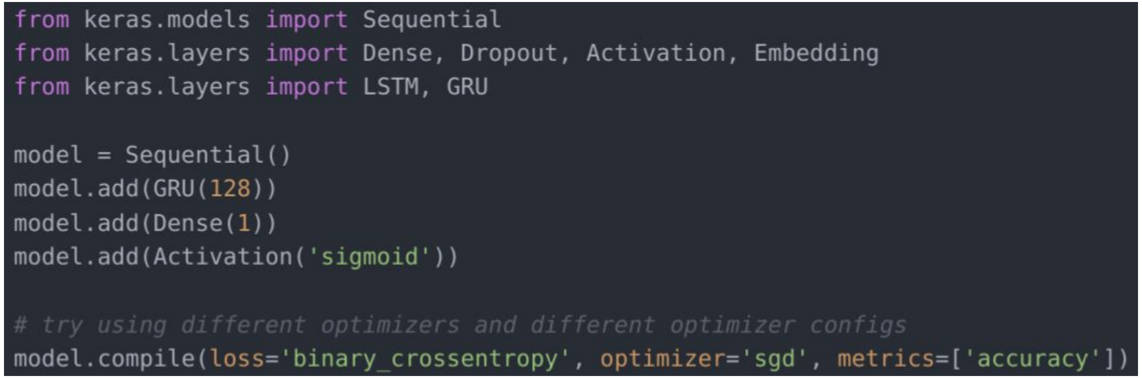
Christopher Olah: Understanding LSTM Networks

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

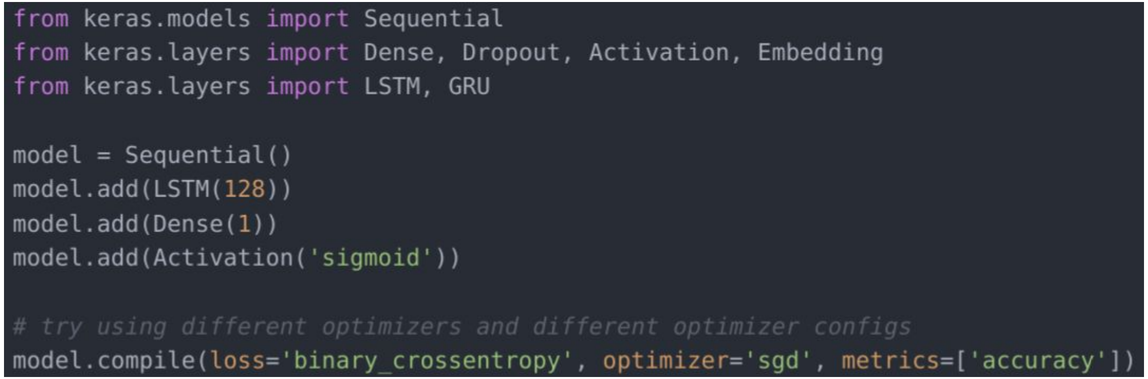
A Beginners Guide to Recurrent Neural Networks and LSTM

https://deeplearning4j.org/lstm

Coding GRU and LSTM



```python
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Embedding
from keras.layers import LSTM, GRU

model = Sequential()
model.add(GRU(128))
model.add(Dense(1))
model.add(Activation('sigmoid'))

# try using different optimizers and different optimizer configs
model.compile(loss='binary_crossentropy', optimizer='sgd', metrics=['accuracy'])
```



```python
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```

Hands on Practice

Word Embeddings

Word Embeddings

Word embeddings represent a major breakthrough in the way that we represent words to computers.

The biggest change is that we no longer represent words as discrete objects. Instead we represent words in a continuous semantic space. This allows us to easily handle things like; synonyms, categories (names, vehicles, …), antonyms, and others.

The main idea is that we create a shallow neural network that will learn a mapping between the words and their new embeddings.

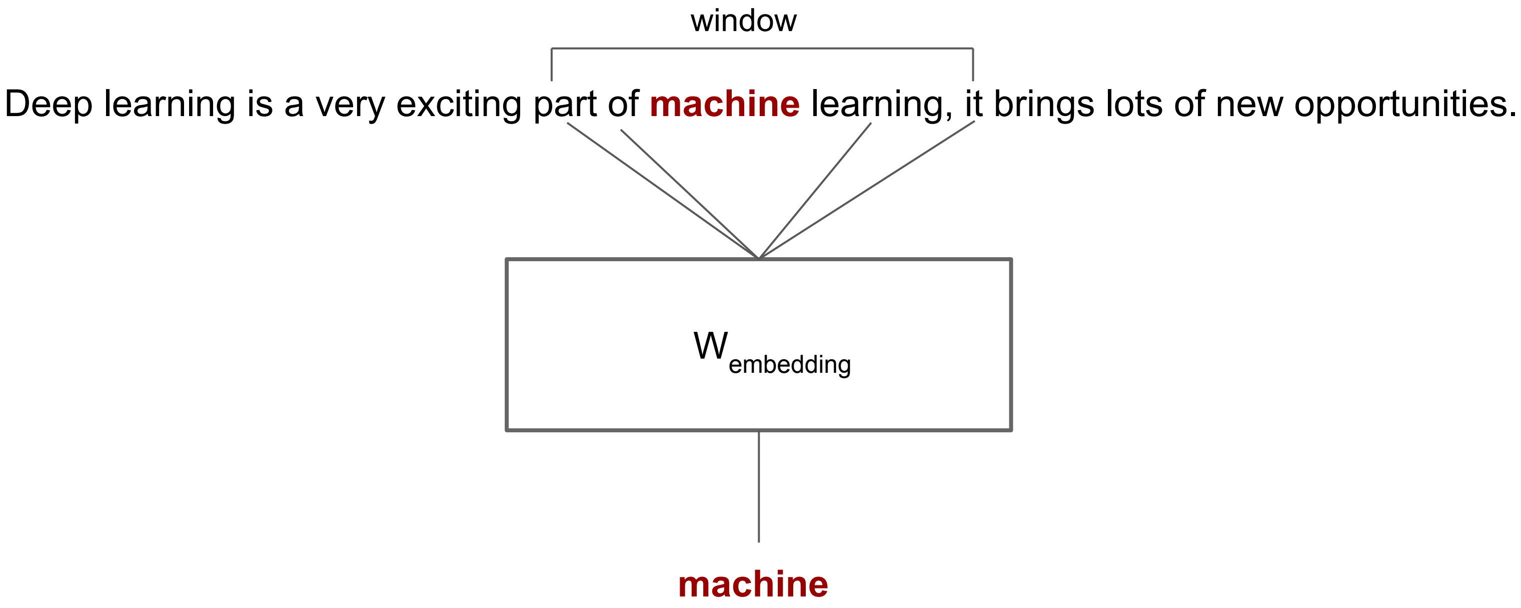
Word Embeddings

The insight that made this possible that was to treat words that are close to each other as being related.

We try to predict each word by looking at it’s surrounding context.

“You will know a word by the company that it keeps” - John Rupert Firth

Continuous Bag of Words



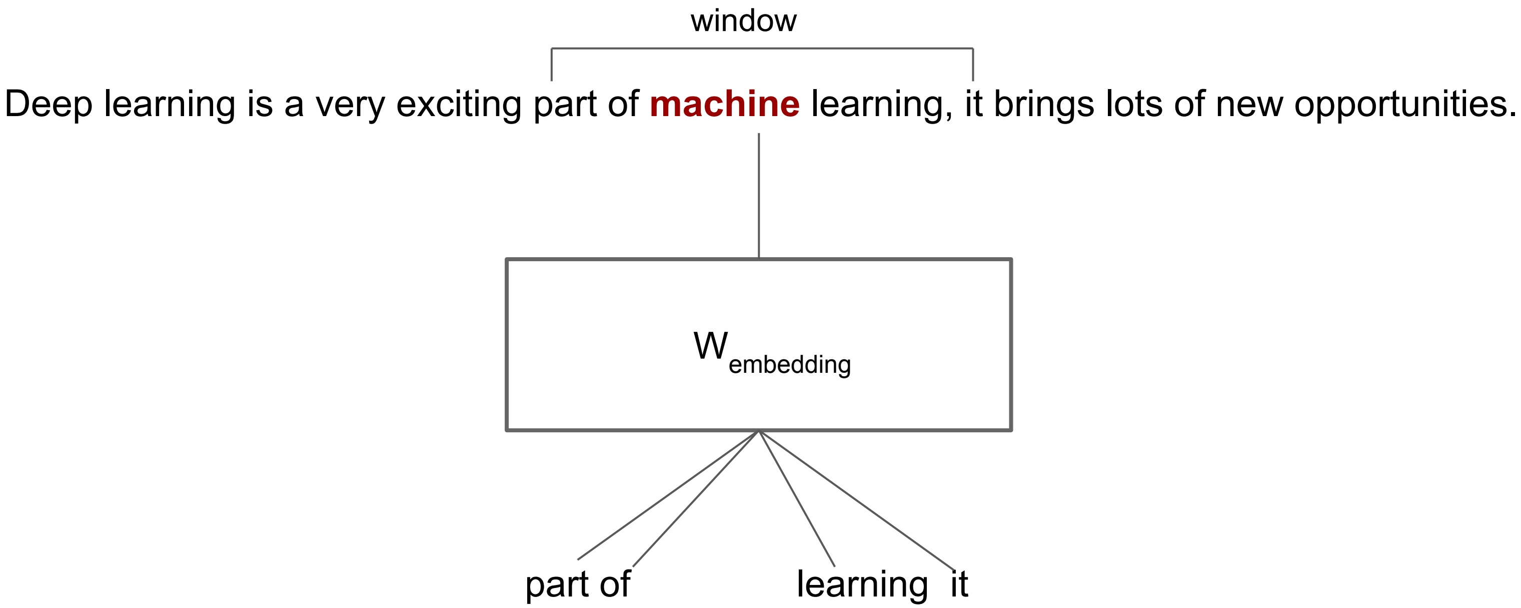
window

Deep learning is a very exciting part of **machine** learning, it brings lots of new opportunities.

$W_{embedding}$

machine

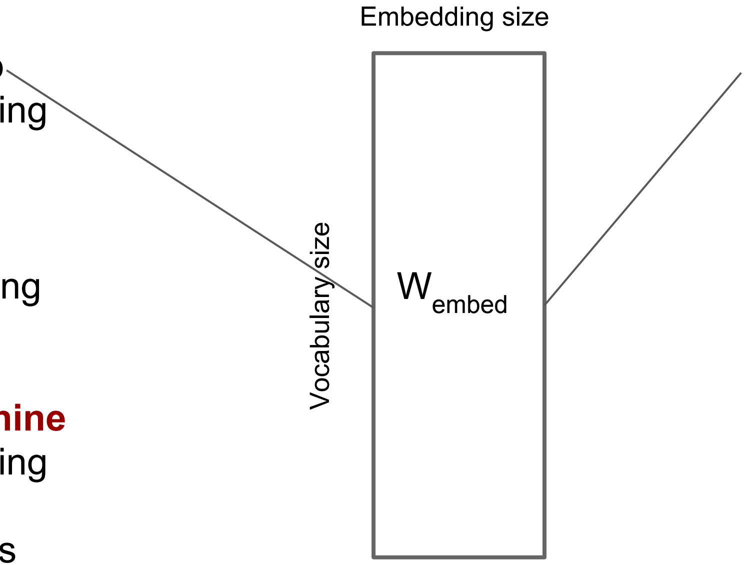
Skip-Gram



Deep learning is a very exciting part of **machine** learning, it brings lots of new opportunities.

Retrieving the Embeddings

Deep
learning
is
a
very
exciting
part
of
machine
learning
it
brings
...



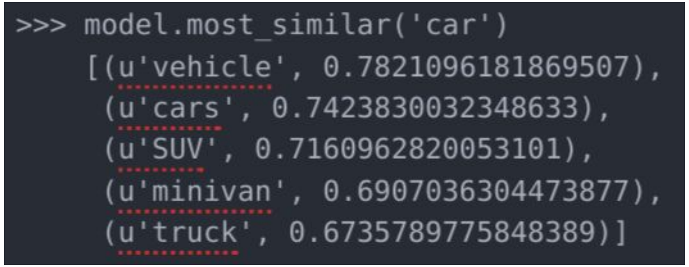
Deep = [0.7 0.2 0.8 0.4 ...]

Once the model is trained, the $W_{embedding}$ matrix turns into a lookup table.

To retrieve the embeddings we just take each row vector that corresponds to each word in the embedding matrix.

The shape of the embedding matrix is [n_vocab, embed_size].

Finding Similar Words



```
>>> model.most_similar('car')
    [(u'vehicle', 0.7821096181869507),
     (u'cars', 0.7423830032348633),
     (u'SUV', 0.7160962820053101),
     (u'minivan', 0.6907036304473877),
     (u'truck', 0.6735789775848389)]
```

$$\frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

By using the cosine similarity between the vectors representing each word we can query the model for the most similar words.

If we search for the words that are most similar to car we get; vehicle, cars, SUV, minivan and truck.

This type of thing is impossible if we represent words only as discrete objects.

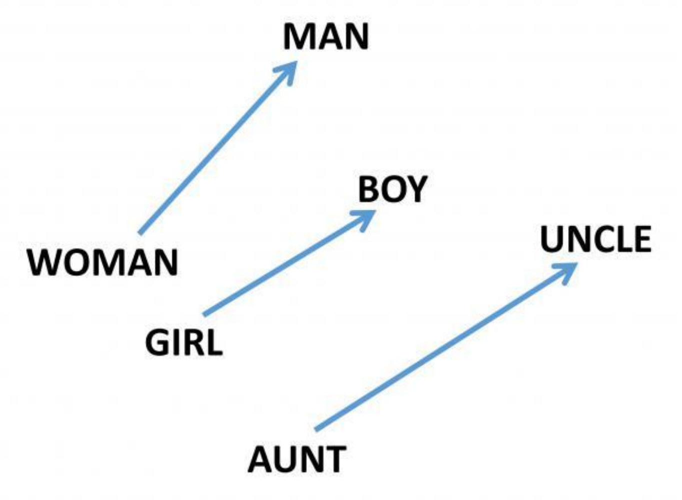
Useful Properties

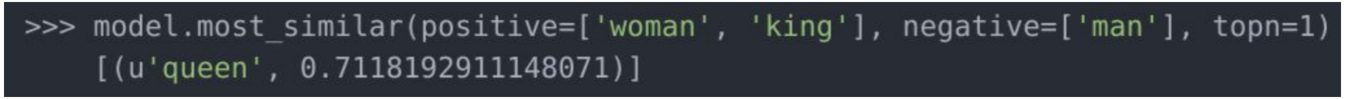
These embeddings end up encoding some really useful information.

The difference between ‘woman’ - ‘man’, ‘girl’ - ‘boy’, and ‘aunt’ - ‘uncle’ are all vectors with roughly the same direction.

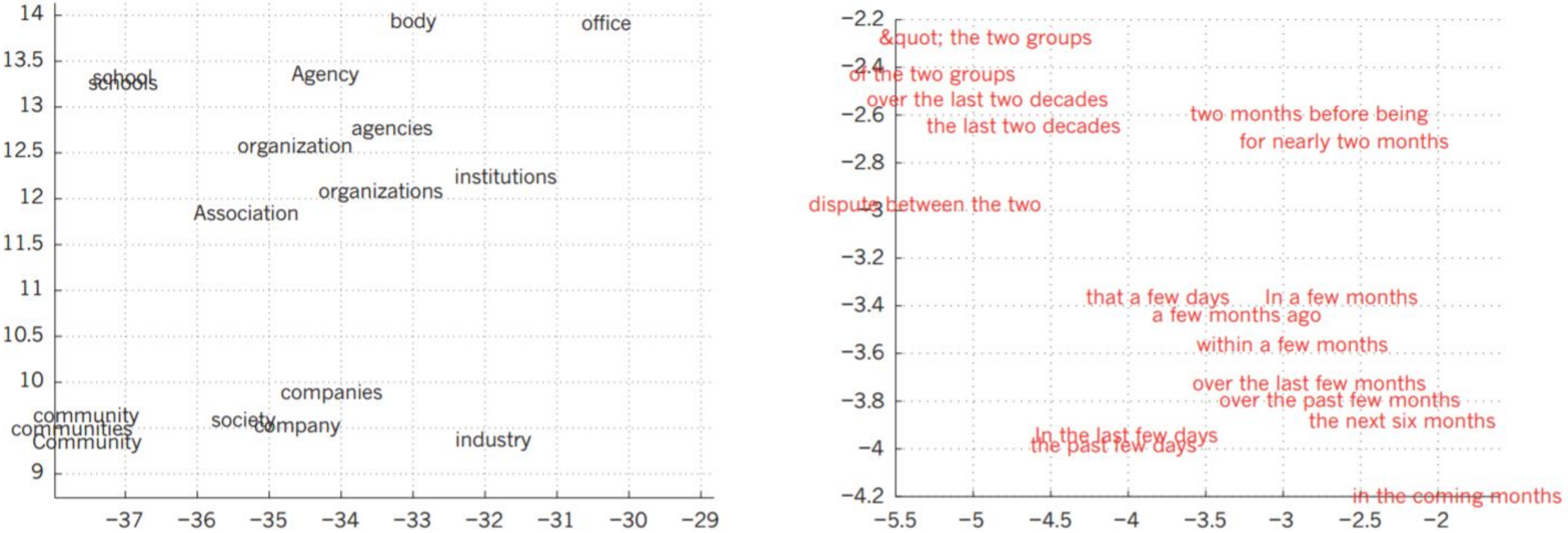
This tells us that the gender information is implicitly encoded in the word embeddings.

The same is true for many other comparisons that we can make between words.



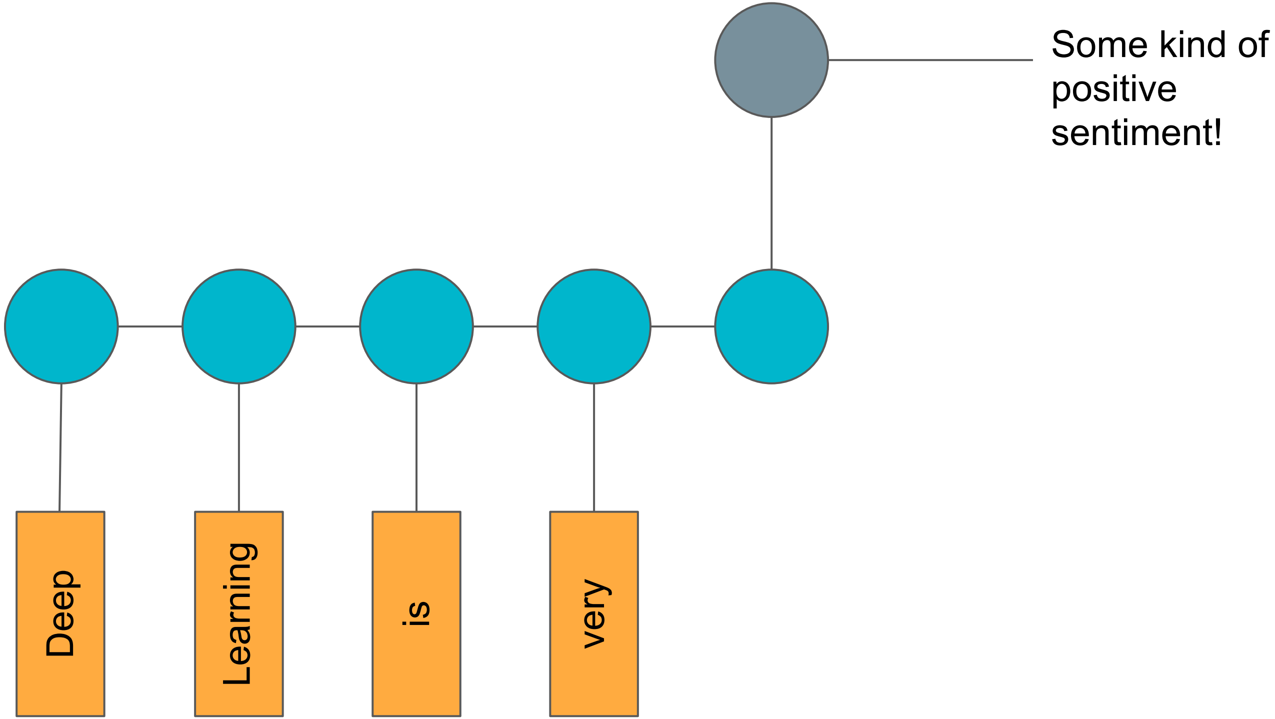


```
>>> model.most_similar(positive=['woman', 'king'], negative=['man'], topn=1)
    [(u'queen', 0.7118192911148071)]
```



http://www.cs.toronto.edu/~hinton/absps/NatureDeepReview.pdf

A Match Made in Heaven



Some kind of positive sentiment!

In Summary

Deep learning is a popular machine learning method for tasks that attempt to mimic human perception.

1) Images

2) Text

3) Audio

4) Speech

In Summary

We typically define neural networks by their computational graphs and most computations are done as matrix multiplies.

The ‘dogma’ of deep learning is that we are using these graphs to learn ways of representing the input data in a form that makes it easiest for the given task.

The final classifier layer is simple, the real work is done above it.

We can also extract and use these internal representations for other tasks.

See our image classification example, and the word embeddings slides.

In Summary

Neural networks are usually trained with Stochastic Gradient Descent and it’s variations.

A typical workflow for images would be taking a network pretrained on ImageNet and fine tuning it for your needs. Like what we did in our examples.

RNNs are still a little bit more tricky to work with. Usually takes some time to nail down the best hyperparameters.

Word embeddings are an incredibly powerful way of representing words by extracting the internal representations of the neural network.

Useful Links

Deep Learning Book - amazing resource for everything from theory to application

http://www.deeplearningbook.org/

Tensorflow - Tutorials and code examples if you want something more low level than Keras.

https://www.tensorflow.org/

Keras - High level wrapper for tensorflow or theano. Most useful for those looking to do applied work instead of research.

https://keras.io/

Useful Links

Theano - primarily developed as a research tool for deep learning. Functions a lot like TensorFlow. Some people call TensorFlow theano 2.0.

http://deeplearning.net/software/theano/

Torch - another popular framework for deep learning. Uses Lua instead of python.

http://torch.ch/

Stanfords DL tutorial - quick low level introduction to deep learning.

http://deeplearning.stanford.edu/tutorial/

Useful Links

Hugo Larochelle’s neural network class - Great video series of neural networks

https://www.youtube.com/playlist?list=PL6Xpj9I5qXYEcOhn7TqghAJ6NAPrNmUBH

Deep Learning for Natural Language Processing

http://cs224d.stanford.edu/

Convolutional Neural Networks for Visual Recognition

http://cs231n.stanford.edu/