Some Terms used in Deep Learning

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Activation Function

To allow Neural Networks to learn complex decision boundaries, we apply a nonlinear activation function to some of its layers. Commonly used functions include sigmoid, tanh, ReLU (Rectified Linear Unit) and variants of these.

Adadelta

Adadelta is a gradient descent based learning algorithm that adapts the learning rate per parameter over time. It was proposed as an improvement over Adagrad, which is more sensitive to hyperparameters and may decrease the learning rate too aggressively. Adadelta It is similar to rmsprop and can be used instead of vanilla SGD.

Adagrad

Adagrad is an adaptive learning rate algorithms that keeps track of the squared gradients over time and automatically adapts the learning rate per-parameter. It can be used instead of vanilla SGD and is particularly helpful for sparse data, where it assigns a higher learning rate to infrequently updated parameters.

Adam

Adam is an adaptive learning rate algorithm similar to rmsprop, but updates are directly estimated using a running average of the first and second moment of the gradient and also include a bias correction term.

Affine Layer

A fully-connected layer in a Neural Network. **Affine means that each neuron in the previous layer is connected to each neuron in the current layer**. In many ways, this is the “standard” layer of a Neural Network.

Affine layers are often added on top of the outputs of Convolutional Neural Networks or Recurrent Neural Networks before making a final prediction. An affine layer is typically of the form y = f(Wx + b) where x are the layer inputs, W the parameters, b a bias vector, and f a nonlinear activation function

Attention Mechanism

Attention Mechanisms are inspired by human visual attention, the ability to focus on specific parts of an image. Attention mechanisms can be incorporated in both Language Processing and Image Recognition architectures to help the network learn what to "focus" on when making predictions.

Alexnet

Alexnet is the name of the Convolutional Neural Network architecture that won the ILSVRC 2012 competition by a large margin and was responsible for a resurgence of interest in CNNs for Image Recognition.

It consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. Alexnet was introduced in ImageNet Classification with Deep Convolutional Neural Networks.

Autoencoder

An Autoencoder is a Neural Network model whose goal is to predict the input itself, typically through a "bottleneck" somewhere in the network.

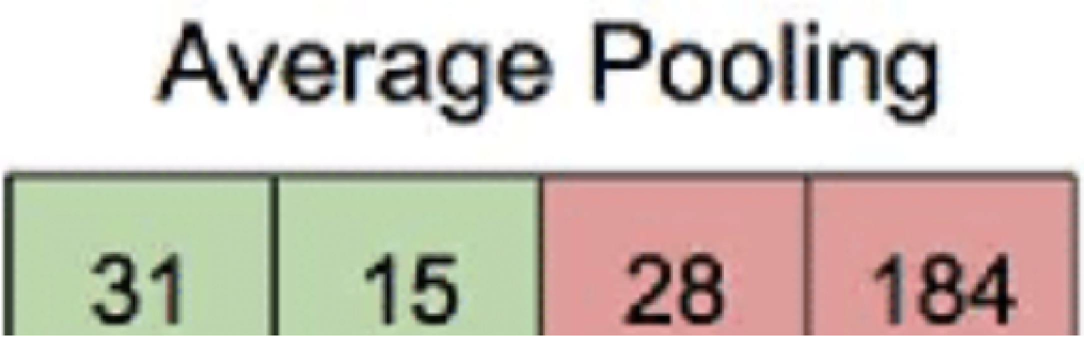
By **introducing a bottleneck, we force the network to learn a lower-dimensional representation of the input, effectively compressing the input into a good representation.**

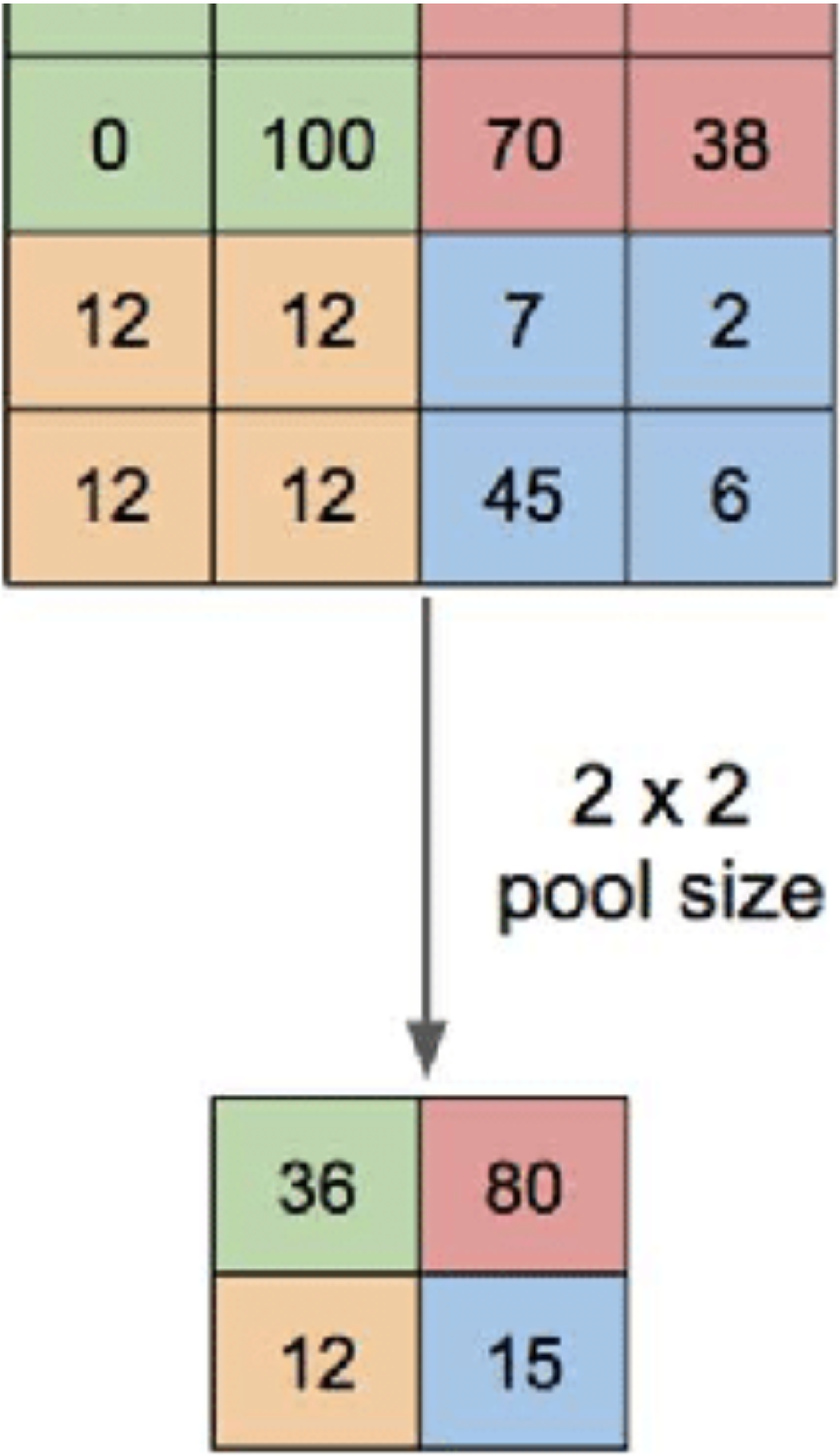
Autoencoders are related to PCA and other dimensionality reduction techniques, but can learn more complex mappings due to their nonlinear nature.

A wide range of autoencoder architectures exist, including Denoising Autoencoders, Variational Autoencoders, or Sequence Autoencoders.

Average-Pooling

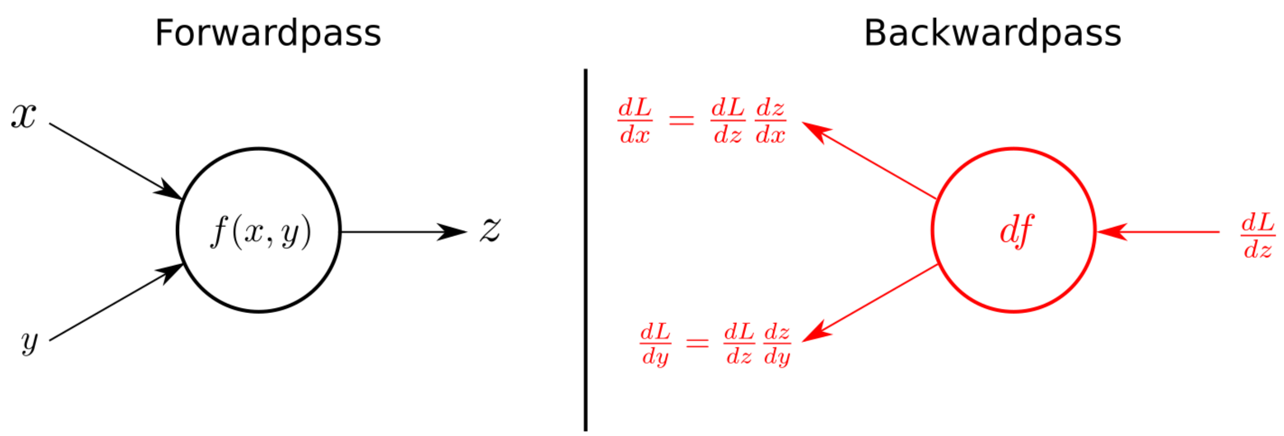
Average-Pooling is a pooling technique used in Convolutional Neural Networks for Image Recognition. It works by sliding a window over patches of features, such as pixels, and taking the average of all values within the window. It compresses the input representation into a lower-dimensional representation.





- Backpropagation

Backpropagation is an algorithm to efficiently calculate the gradients in a Neural Network, or more generally, a feedforward computational graph. It boils down to applying the chain rule of differentiation starting from the network output and propagating the gradients backward.



Backpropagation Through Time (BPTT)

Backpropagation Through Time is the **Backpropagation algorithm applied to Recurrent Neural Networks (RNNs)**.

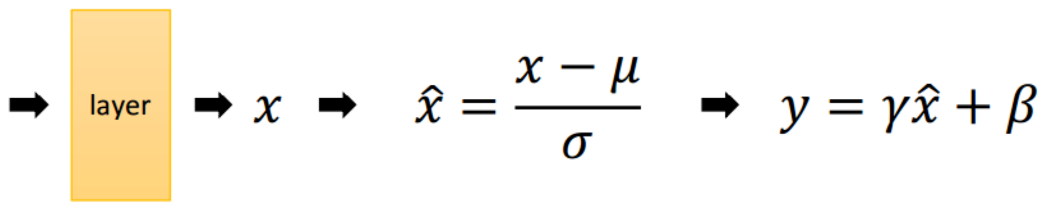
BPTT can be seen as the standard backpropagation algorithm applied to an RNN, where **each time step represents a layer and the parameters are shared across layers**.

Because an RNN shares the same parameters across all time steps, the errors at one time step must be backpropagated "through time" to all previous time steps, hence the name. When dealing with long sequences (hundreds of inputs), a truncated version of BPTT is often used to reduce the computational cost. Truncated BPTT stops backpropagating the errors after a fixed number of steps.

Batch Normalization

Batch Normalization is a technique that normalizes layer inputs per mini-batch. **It speed up training, allows for the usage of higher learner rates, and can act as a regularizer. Batch Normalization has been found to be very effective for Convolutional and Feedforward Neural Networks but hasn't been successfully applied to Recurrent Neural Networks.**

Batch Normalization (BN)



- μ: mean of x in mini-batch
- σ: std of x in mini-batch
- γ: scale
- β: shift

- μ, σ: functions of x, analogous to responses
- γ, β: parameters to be learned, analogous to weights

Bidirectional RNN

A Bidirectional Recurrent Neural Network is a type of Neural Network that contains two RNNs going into different directions.

The forward RNN reads the input sequence from start to end, while the backward RNN reads it from end to start.

The two RNNs are stacked on top of each others and their states are typically combined by appending the two vectors.

Bidirectional RNNs are often used in Natural Language problems, where we want to take the context from both before and after a word into account before making a prediction.

Caffe

Caffe is a deep learning framework developed by the Berkeley Vision and Learning Center. Caffe is particularly popular and performant for vision tasks and CNN models.

Categorical Cross-Entropy Loss

The categorical cross-entropy loss is also known as the negative log likelihood. It is a popular loss function for categorization problems and measures the similarity between two probability distributions, typically the true labels and the predicted labels.

It is given by L = -sum(y * log(y_prediction)) where y is the probability distribution of true labels (typically a one-hot vector) and y_prediction is the probability distribution of the predicted labels, often coming from a softmax.

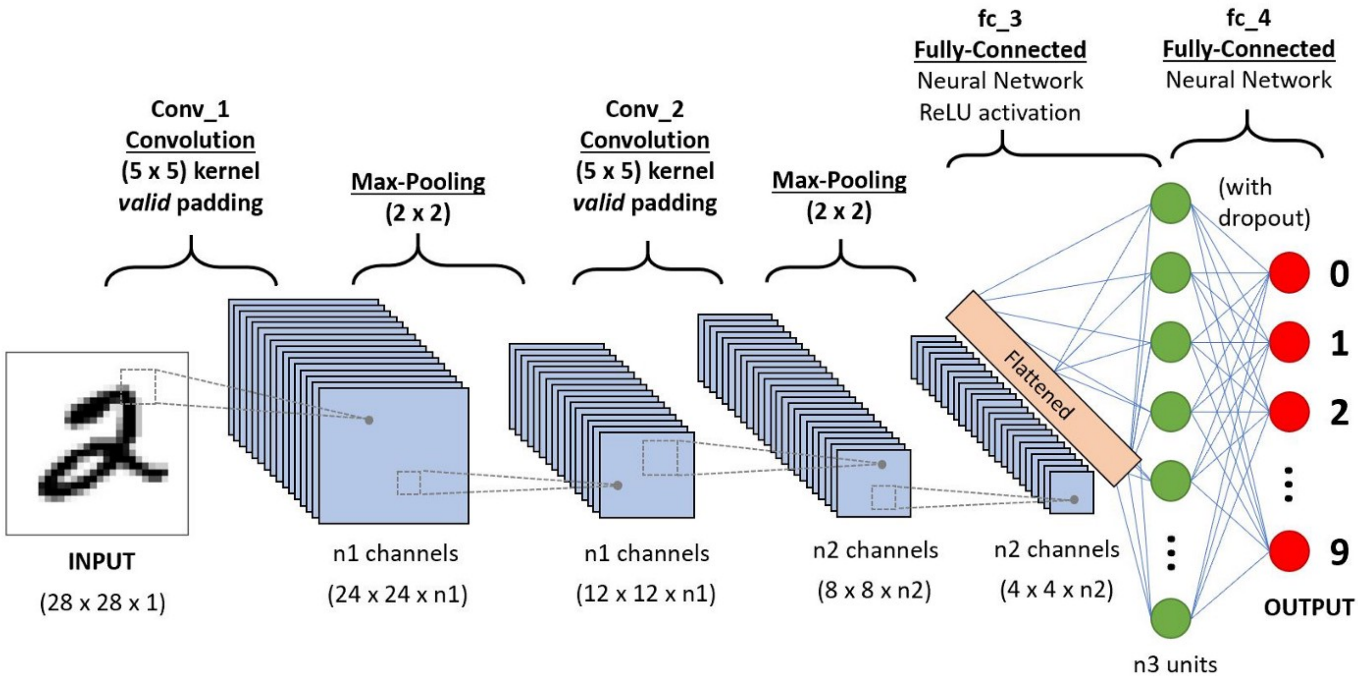
Channel

Input data to Deep Learning models can have multiple channels.

The canonical examples are images, which have red, green and blue color channels. A image can be represented as a 3-dimensional Tensor with the dimensions corresponding to channel, height, and width. Natural Language data can also have multiple channels, in the form of different types of embeddings.

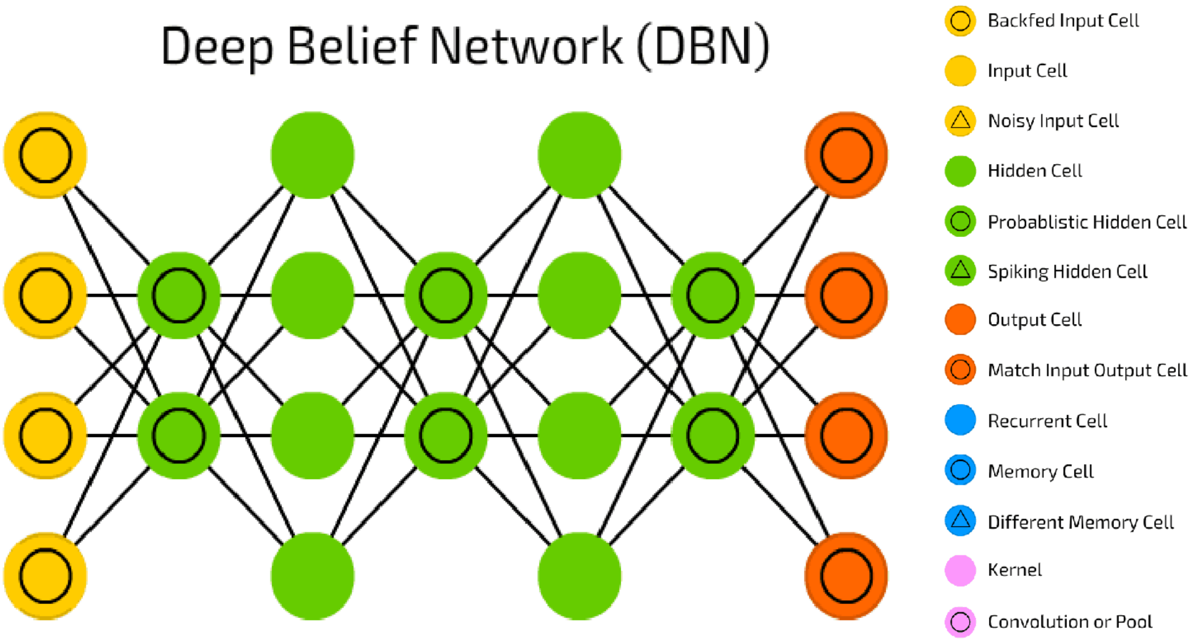
Convolutional Neural Network (CNN, ConvNet)

A CNN uses convolutions to connected extract features from local regions of an input. Most CNNs contain a combination of convolutional, pooling and affine layers. CNNs have gained popularity particularly through their excellent performance on visual recognition tasks, where they have been setting the state of the art for several years.



Deep Belief Network (DBN)

DBNs are a type of probabilistic graphical model that learn a hierarchical representation of the data in an unsupervised manner. DBNs consist of multiple hidden layers with connections between neurons in each successive pair of layers. DBNs are built by stacking multiple RBNs on top of each other and training them one by one.



Deep Dream

A technique invented by Google that tries to distill the knowledge captured by a deep Convolutional Neural Network. The technique can generate new images, or transform existing images and give them a dreamlike flavor, especially when applied recursively.

Dropout

Dropout is a regularization technique for Neural Networks that prevents overfitting. It prevents neurons from co-adapting by randomly setting a fraction of them to 0 at each training iteration. Dropout can be interpreted in various ways, such as randomly sampling from an exponential number of different networks. **Dropout layers first gained popularity through their use in CNNs, but have since been applied to other layers, including input embeddings or recurrent networks.**

Exploding Gradient Problem

The Exploding Gradient Problem is the opposite of the Vanishing Gradient Problem. In Deep Neural Networks gradients may explode during backpropagation, resulting number overflows. A common technique to deal with exploding gradients is to perform Gradient Clipping.

Fine-Tuning

Fine-Tuning refers to the technique of initializing a network with parameters from another task (such as an unsupervised training task), and then updating these parameters based on the task at hand.

Gradient Clipping

Gradient Clipping is a technique to prevent exploding gradients in very deep networks, typically Recurrent Neural Networks. There exist various ways to perform gradient clipping, but the a common one is to normalize the gradients of a parameter vector when its L2 norm exceeds a certain threshold according to new_gradients = gradients * threshold / l2_norm(gradients).

GloVe

GloVe is an unsupervised learning algorithm for obtaining vector representations (embeddings) for words. GloVe vectors serve the same purpose as word2vec but have different vector representations due to being trained on co-occurrence statistics.

GoogleLeNet

The name of the Convolutional Neural Network architecture that won the ILSVRC 2014 challenge. The network uses Inception modules to reduce the parameters and improve the utilization of the computing resources inside the network.

GRU

The Gated Recurrent Unit is a simplified version of an LSTM unit with fewer parameters. Just **like an LSTM cell, it uses a gating mechanism to allow RNNs to efficiently learn long-range dependency by preventing the vanishing gradient problem**. The GRU consists of a reset and update gate that determine which part of the old memory to keep vs. update with new values at the current time step.

Highway Layer

A Highway Layer is a type of Neural Network layer that uses a gating mechanism to control the information flow through a layer. *Stacking multiple Highway Layers allows for training of very deep networks. *

Highway Layers work by learning a gating function that chooses which parts of the inputs to pass through and which parts to pass through a transformation function, such as a standard affine layer for example.

The basic formulation of a Highway Layer is T * h(x) + (1 - T) * x, where T is the learned gating function with values between 0 and 1, h(x) is an arbitrary input transformation and x is the input. Note that all of these must have the same size.

Inception Module

Inception Modules are used in Convolutional Neural Networks to allow for more efficient computation and deeper Networks trough a dimensionality reduction with stacked 1×1 convolutions.

Keras

Kears is a Python-based Deep Learning library that includes many high-level building blocks for deep Neural Networks. It can run on top of either TensorFlow, Theano, or CNTK.

LSTM

Long Short-Term Memory networks were invented to prevent the vanishing gradient problem in Recurrent Neural Networks by using a memory gating mechanism. Using LSTM units to calculate the hidden state in an RNN we help to the network to efficiently propagate gradients and learn long-range dependencies.

Max-Pooling

A pooling operations typically used in Convolutional Neural Networks. A max-pooling layer selects the maximum value from a patch of features. Just like a convolutional layer, pooling layers are parameterized by a window (patch) size and stride size.

Pooling layers help to reduce the dimensionality of a representation by keeping only the most salient information, and in the case of image inputs, they provide basic invariance to translation (the same maximum values will be selected even if the image is shifted by a few pixels). Pooling layers are typically inserted between successive convolutional layers.

Momentum

Momentum is an extension to the Gradient Descent Algorithm that accelerates or damps the parameter updates. In practice, including a momentum term in the gradient descent updates leads to better convergence rates in Deep Networks.

Multilayer Perceptron (MLP)

A **Multilayer Perceptron is a Feedforward Neural Network with multiple fully-connected layers that use nonlinear activation functions to deal with data which is not linearly separable**. An MLP is the most basic form of a multilayer Neural Network, or a deep Neural Networks if it has more than 2 layers.

Neural Machine Translation (NMT)

An NMT system uses Neural Networks to translate between languages, such as English and French.

NMT systems can be trained end-to-end using bilingual corpora, which differs from traditional Machine Translation systems that require hand-crafted features and engineering.

NMT systems are typically implemented using encoder and decoder recurrent neural networks that encode a source sentence and produce a target sentence, respectively.

Restricted Boltzmann Machine (RBN)

RBMs are a type of probabilistic graphical model that can be interpreted as a stochastic artificial neural network. RBNs learn a representation of the data in an unsupervised manner. An RBN consists of visible and hidden layer, and connections between binary neurons in each of these layers. RBNs can be efficiently trained using Contrastive Divergence, an approximation of gradient descent.

Recurrent Neural Network (RNN)

A RNN models sequential interactions through a hidden state, or memory. It can take up to N inputs and produce up to N outputs. For example, an input sequence may be a sentence with the outputs being the part-of-speech tag for each word (N-to-N). An input could be a sentence, and the output a sentiment classification of the sentence (N-to-1).

An input could be a single image, and the output could be a sequence of words corresponding to the description of an image (1-to-N). At each time step, an RNN calculates a new hidden state ("memory") based on the current input and the previous hidden state. The "recurrent" stems from the facts that at each step the same parameters are used and the network performs the same calculations based on different inputs.

Recursive Neural Network

Recursive Neural Networks are a generalization of Recurrent Neural Networks to a tree-like structure. The same weights are applied at each recursion.

Just like RNNs, Recursive Neural Networks can be trained end-to-end using backpropagation. While it is possible to learn the tree structure as part of the optimization problem, Recursive Neural Networks are often applied to problem that already have a predefined structure, like a parse tree in Natural Language Processing.

ReLU

Short for Rectified Linear Unit(s). ReLUs are often used as activation functions in Deep Neural Networks.

They are defined by f(x) = max(0, x). The advantages of ReLUs over functions like tanh include that they tend to be sparse (their activation easily be set to 0), and that they suffer less from the vanishing gradient problem.

ReLUs are the most commonly used activation function in Convolutional Neural Networks. There exist several variations of ReLUs, such as Leaky ReLUs, Parametric ReLU (PReLU) or a smoother softplus approximation.

ResNet

Deep Residual Networks won the ILSVRC 2015 challenge. These networks work by introducing shortcut connection across stacks of layers, allowing the optimizer to learn "easier" residual mappings instead of the more complicated original mappings. These shortcut connections are similar to Highway Layers, but they are data-independent and don't introduce additional parameters or training complexity. ResNets achieved a 3.57% error rate on the ImageNet test set.

RMSProp

RMSProp is a gradient-based optimization algorithm. It is similar to Adagrad, but introduces an additional decay term to counteract Adagrad's rapid decrease in learning rate.

Seq2Seq

A Sequence-to-Sequence model reads a sequence (such as a sentence) as an input and produces another sequence as an output. It differs from a standard RNN in that the input sequence is completely read before the network starts producing any output. Typically, seq2seq models are implemented using two RNNs, functioning as encoders and decoders. Neural Machine Translation is a typical example of a seq2seq model.

SGD

Stochastic Gradient Descent (Wikipedia) is a gradient-based optimization algorithm that is used to learn network parameters during the training phase. The gradients are typically calculated using the backpropagation algorithm.

In practice, people use the minibatch version of SGD, where the parameter updates are performed based on a batch instead of a single example, increasing computational efficiency. Many extensions to vanilla SGD exist, including Momentum, Adagrad, rmsprop, Adadelta or Adam.

Softmax

The softmax function is typically used to convert a vector of raw scores into class probabilities at the output layer of a Neural Network used for classification.

It normalizes the scores by exponentiating and dividing by a normalization constant. If we are dealing with a large number of classes, a large vocabulary in Machine Translation for example, the normalization constant is expensive to compute.

There exist various alternatives to make the computation more efficient, including Hierarchical Softmax or using a sampling-based loss such as NCE.

TensorFlow

TensorFlow is an open source C++/Python software library for numerical computation using data flow graphs, particularly Deep Neural Networks. It was created by Google. In terms of design, it is most similar to Theano, and lower-level than Caffe or Keras.

Vanishing Gradient Problem

The vanishing gradient problem arises in very deep Neural Networks, typically Recurrent Neural Networks, that use activation functions whose gradients tend to be small (in the range of 0 from 1).

Because these small gradients are multiplied during backpropagation, they tend to “vanish” throughout the layers, preventing the network from learning long-range dependencies. Common ways to counter this problem is to use activation functions like ReLUs that do not suffer from small gradients, or use architectures like LSTMs that explicitly combat vanishing gradients. The opposite of this problem is called the exploding gradient problem.

VGG

VGG refers to convolutional neural network model that secured the first and second place in the 2014 ImageNet localization and classification tracks, respectively. The VGG model consist of 16–19 weight layers and uses small convolutional filters of size 3×3 and 1×1.