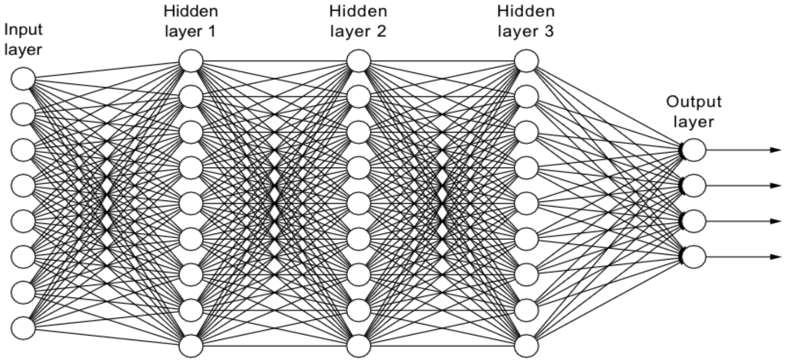
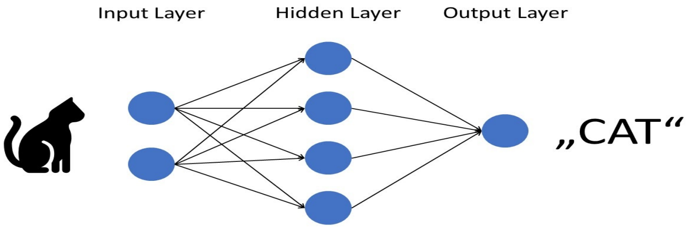
Machine Learning 5: Convolutional Neural Networks



Recap



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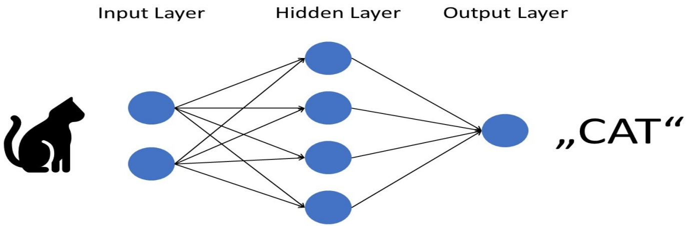

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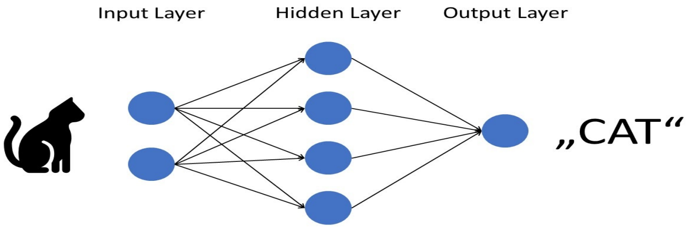

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- These features are created through **non-linearly transforming** (e.g. sigmoid function) a bf weighted combination of the input features.

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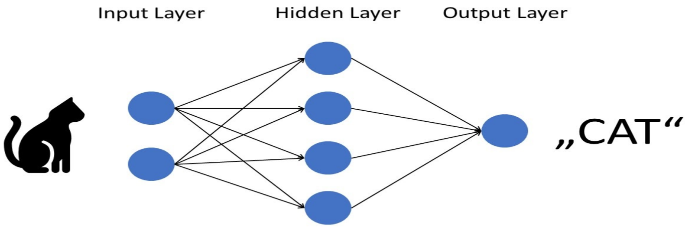

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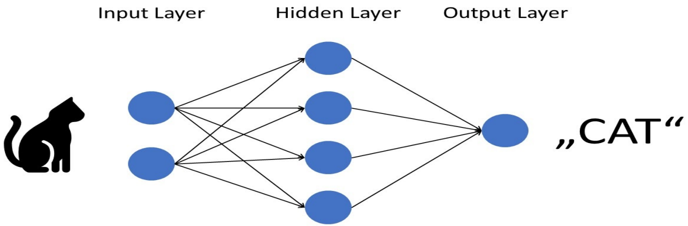

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- Typically each hidden layer of a neural network is **fully connected**, i.e. each neuron in layer N is connected to each neuron in layer $N \pm 1$.

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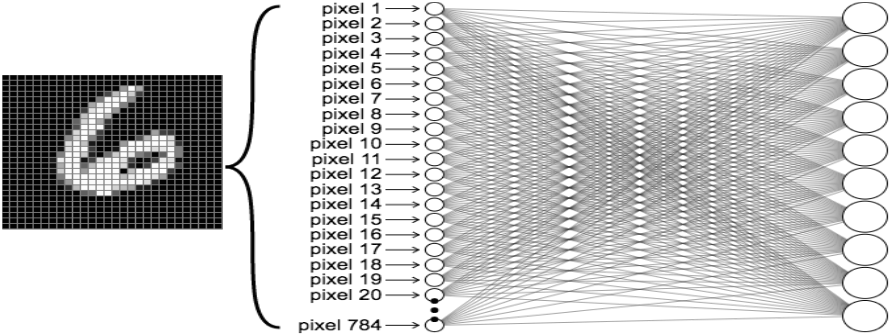

Convolutions

One way to solve this problem is to make use of the fact that our input is an image. This image can be represented as a volume, for example a $200 \times 200 \times 3$ cuboid.

Segments of this volume can then be convolved with weight arrays to produce a new volume. We can perform successive such convolutions to finally ending up with a reduced output volume, for example 1×2 for the face-not face classification.

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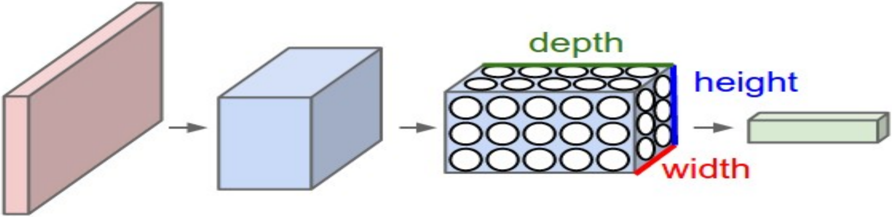

Credit: `https://cs231n.github.io/convolutional-networks/`

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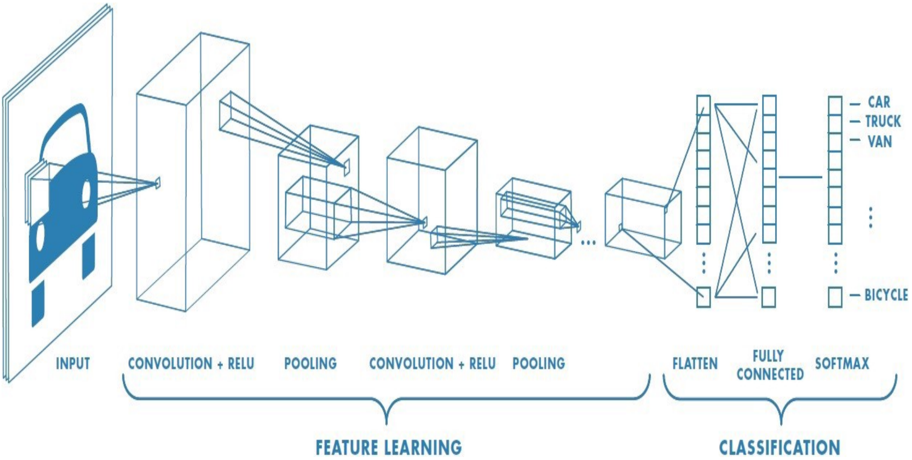
When it is applied to a segment of the image an element-wise multiplication is performed and then the products are summed to give the output ‘pixel’.

See animation at at
https://cs231n.github.io/convolutional-networks/

The layers of a CNN



Credit: `https://medium.com/@_sumitsaha_`

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Pooling layer: A pooling layer acts to reduce the volume and hence number of weights for a successive Conv layer. It does this by moving through the input volume at a stride greater than 1 pixel at a time. One example is max pooling which applies a `Max` function to select most important input features.

Flatten and Dense layer: Unrolls the volume into a vector of values and then the dense layer is a fully connected normal neural network hidden layer with neurons equal to the number of classes.

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Dropout: Dropout is a technique which acts as a regularisation of the network. During training, random activations are not considered in the layer prior to a dropout operation. This creates 'noise' in the training process. By forcing the weights to account for this, we make each individual weight less important, and consequently we reduce over-fitting.