

# Deconvoluting Graph Convolutional Networks

Answering the whats, whys and hows

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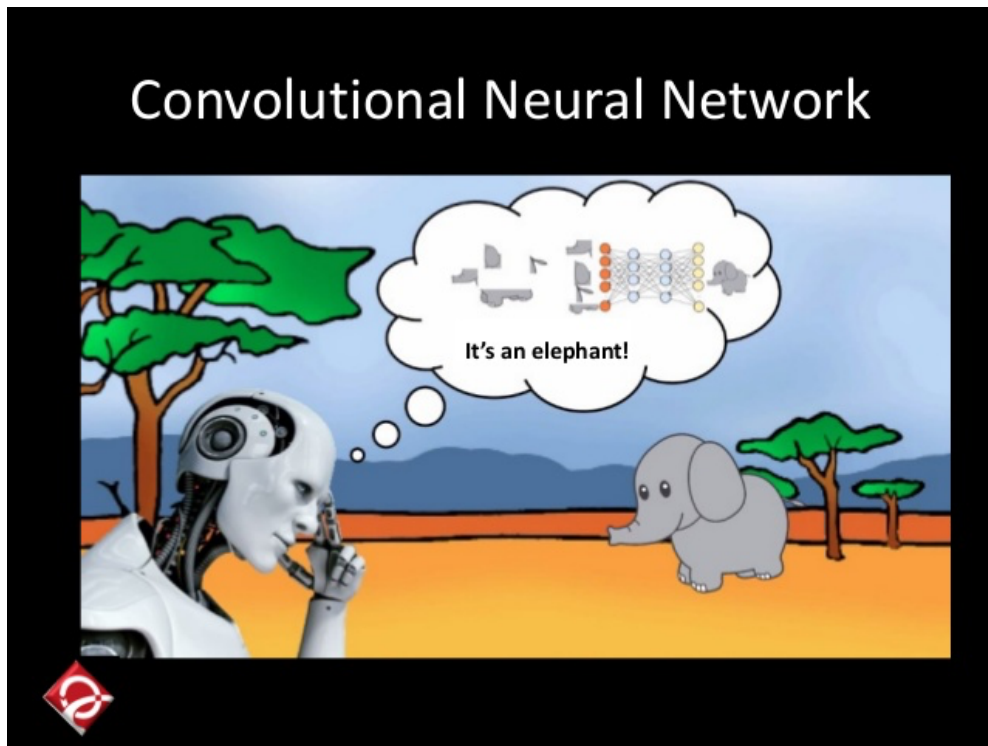
# Outline

- Convolutional Neural Networks
- Why Graph Convolutional Networks (GCN)?
- Convolution in GCN
- Applications

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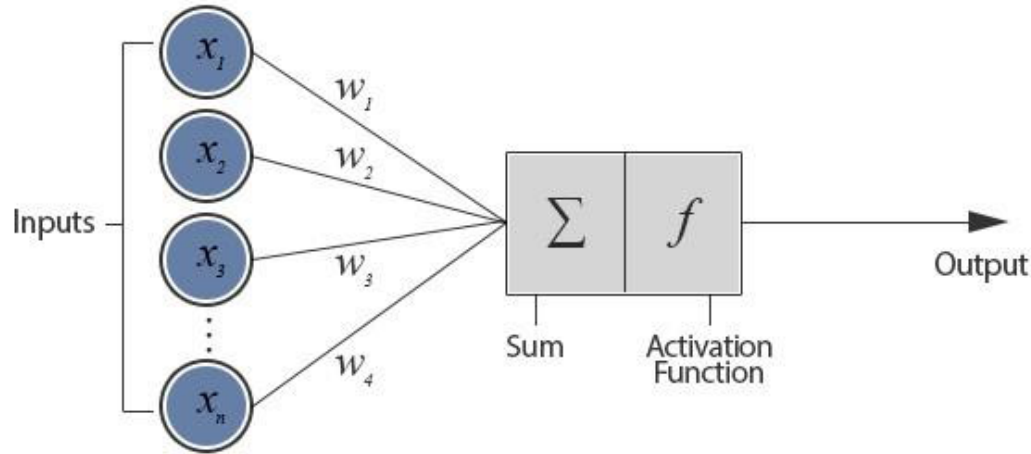
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# Convolutional Neural Networks - The revolution



- AlexNet brought about a revolution with its simple architecture and good performance
- This network achieved a top-5 error rate of 15.3% in ImageNet-2012 challenge
- Has just 8 layers, 5 convolutional followed by 3 fully-connected

# Neural Networks - The starting point

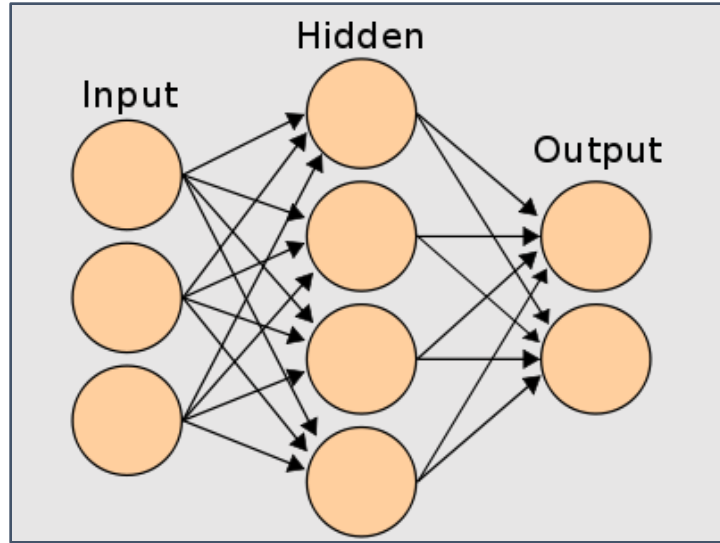


A perceptron

- Perceptron consists of weights  $w$ , summing function and an activation function
- Output =  $f(Wx + b)$

$$f(Wx + b)$$

# Neural Networks - The starting point



A multi-layer perceptron model

Multi-layer perceptron (MLP) models do not take spatial structure into account and suffer from curse of dimensionality!

# Convolutional Neural Networks (CNN)

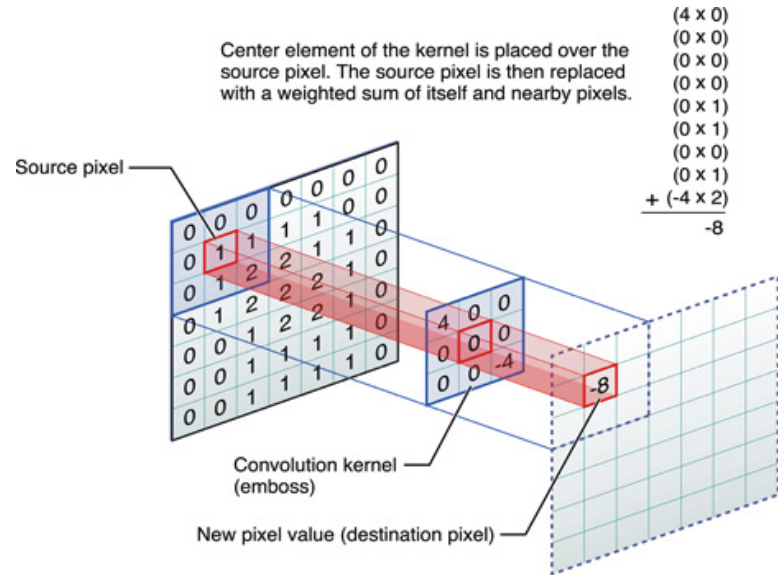
- Operates on images - captures the spatial structure
- Consists of learnable set of filters which perform 2D convolution on the image to get activation map

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

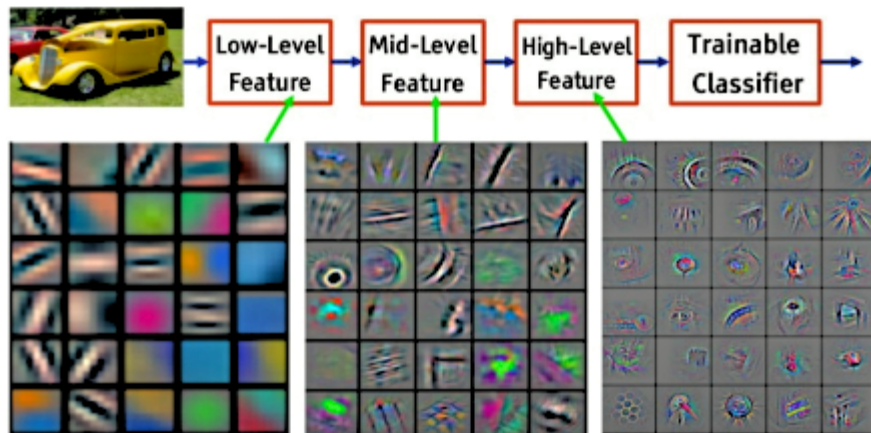
Image

4		

Convolved  
Feature



# Convolutional Neural Network - Activation Maps

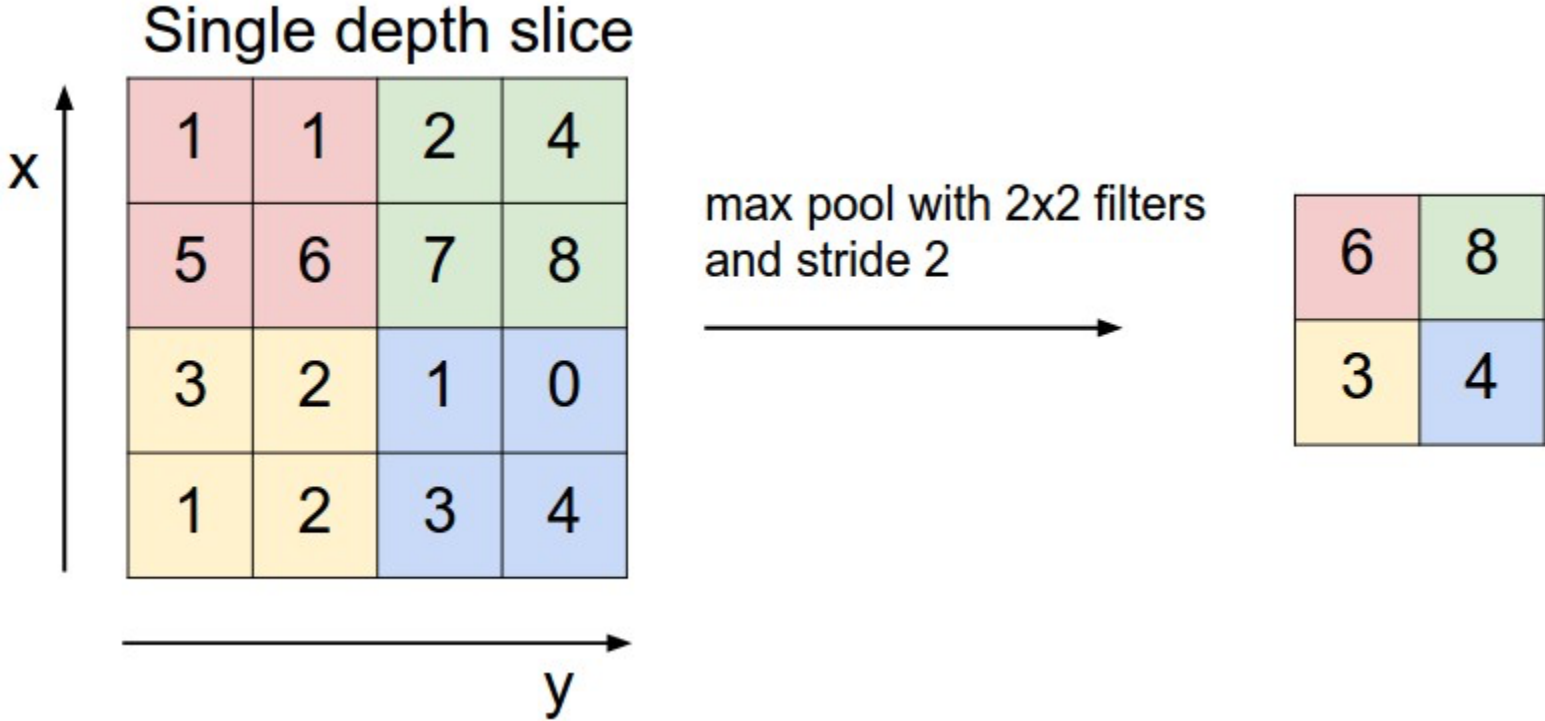


Example activation maps

- The 2D image obtained after convolution with filter is called activation map
- There can be multiple such maps in a given layer depending on number of filters
- Maps in the initial layers learn low level features like edges and deeper layers learn high-level features

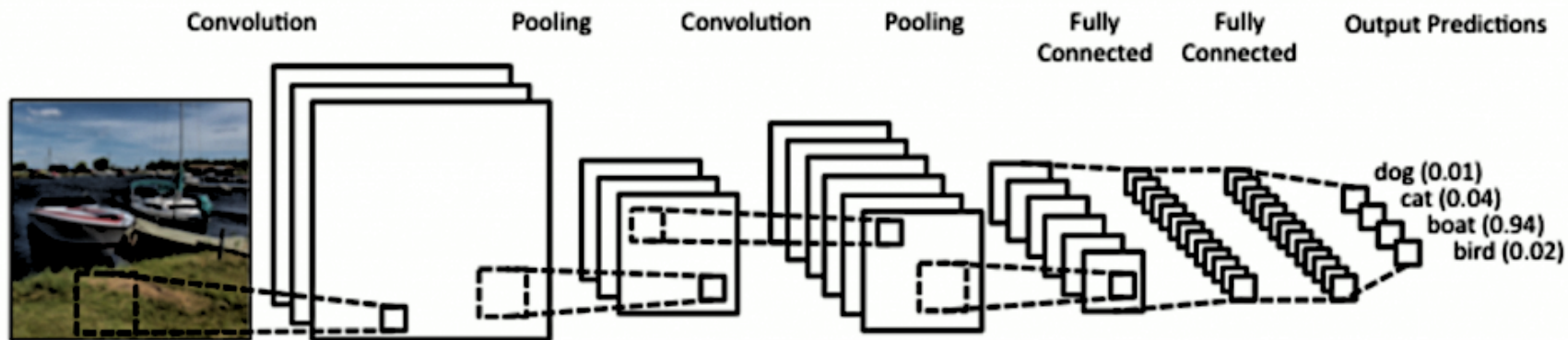


# Convolutional Neural Network - Pooling



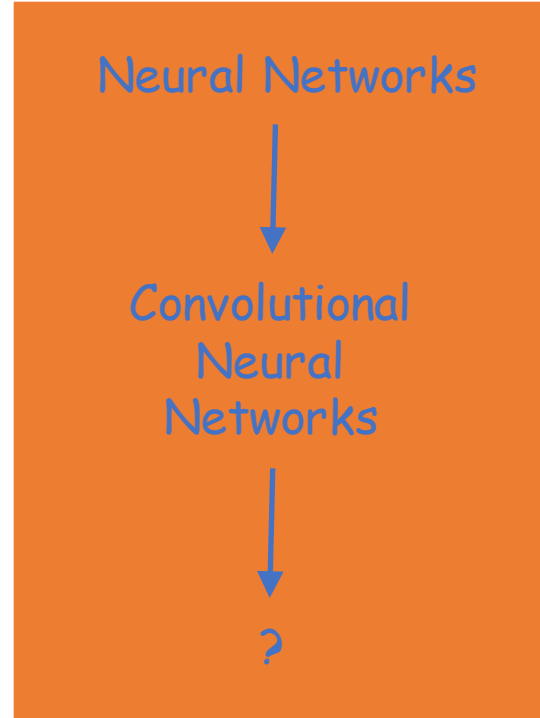
Max-pooling operation

# Convolutional Neural Network



An example architecture of a CNN being used for classification

What next?

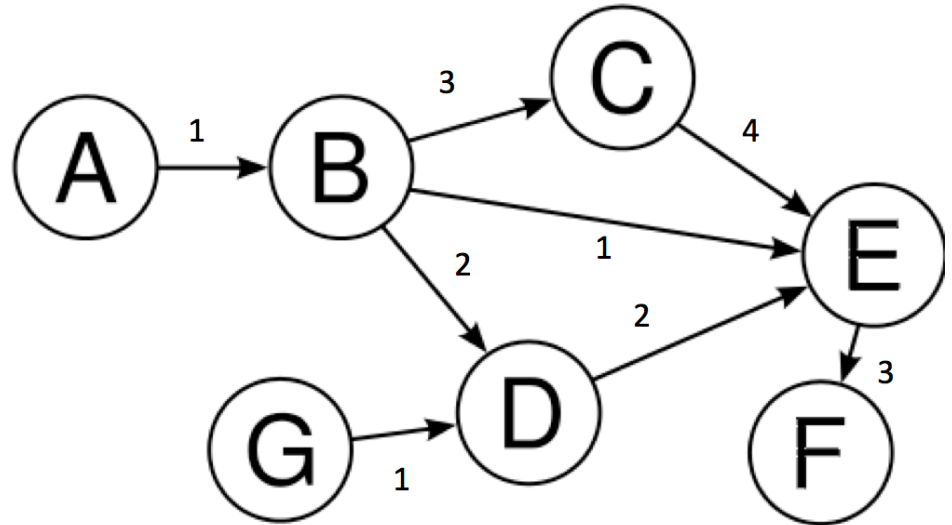


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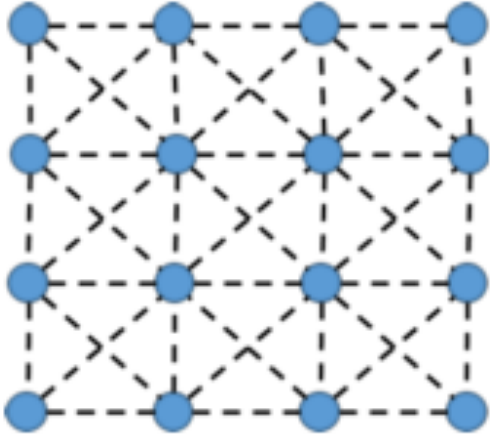
# Graphs

- A graph (directed or undirected) consists of a set of vertices  $V$  (or nodes) and a set of edges  $E$
- Edges can be weighted (weights can be scalar or vector) or binary
- Nodes are represented by attribute values (can be scalar or vector)



A directed graph

# Image as a Graph



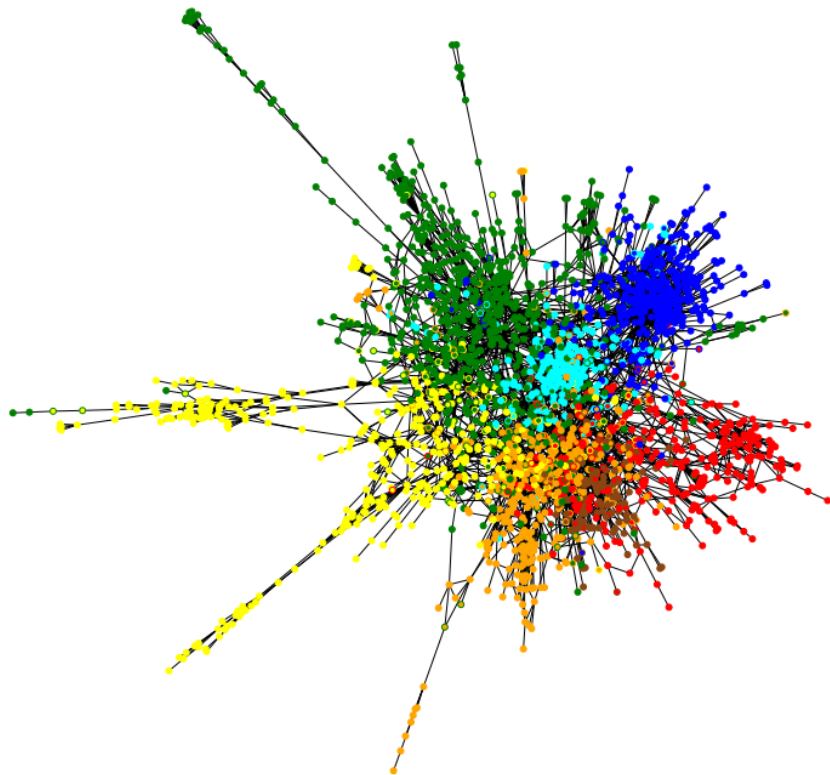
- Each pixel has 8 neighbors
- The node attributes are scalar values for grayscale image and 3-dimensional for RGB images
- The edge weights are binary (0 or 1), either present or absent

# Graph Convolutional Networks (GCN)

Why?

There arises many scenarios where the inherent structure of the data is that of a graph (for e.g. social networks) and one has to learn from it, one can employ GCN for classification/segmentation/clustering tasks!

# Graph Convolutional Networks (GCN)



The Cora dataset

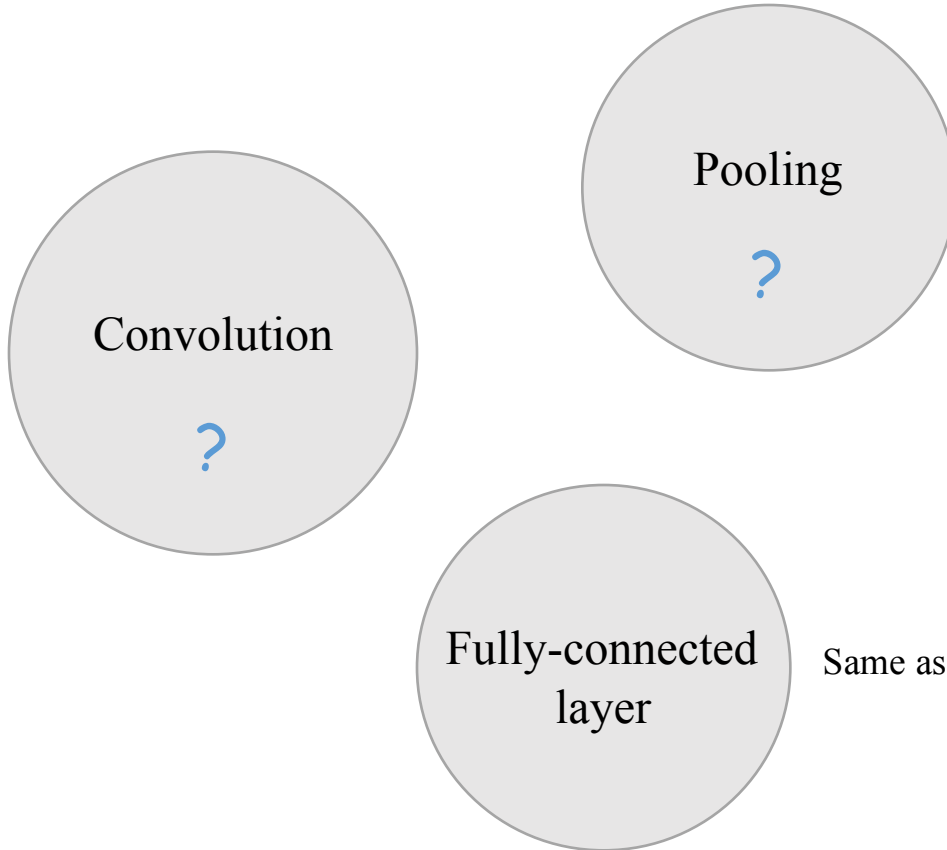


# Graph Convolutional Networks (GCN)

What?

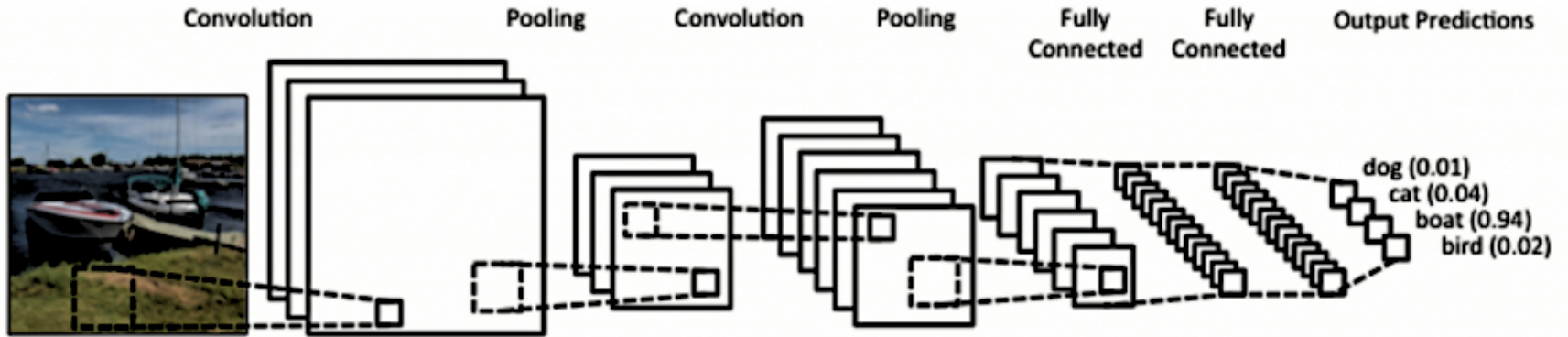
The architecture is similar to a traditional CNN but it takes graphs as input, also the convolution and pooling operations are different in principle

# CNN vs GCN



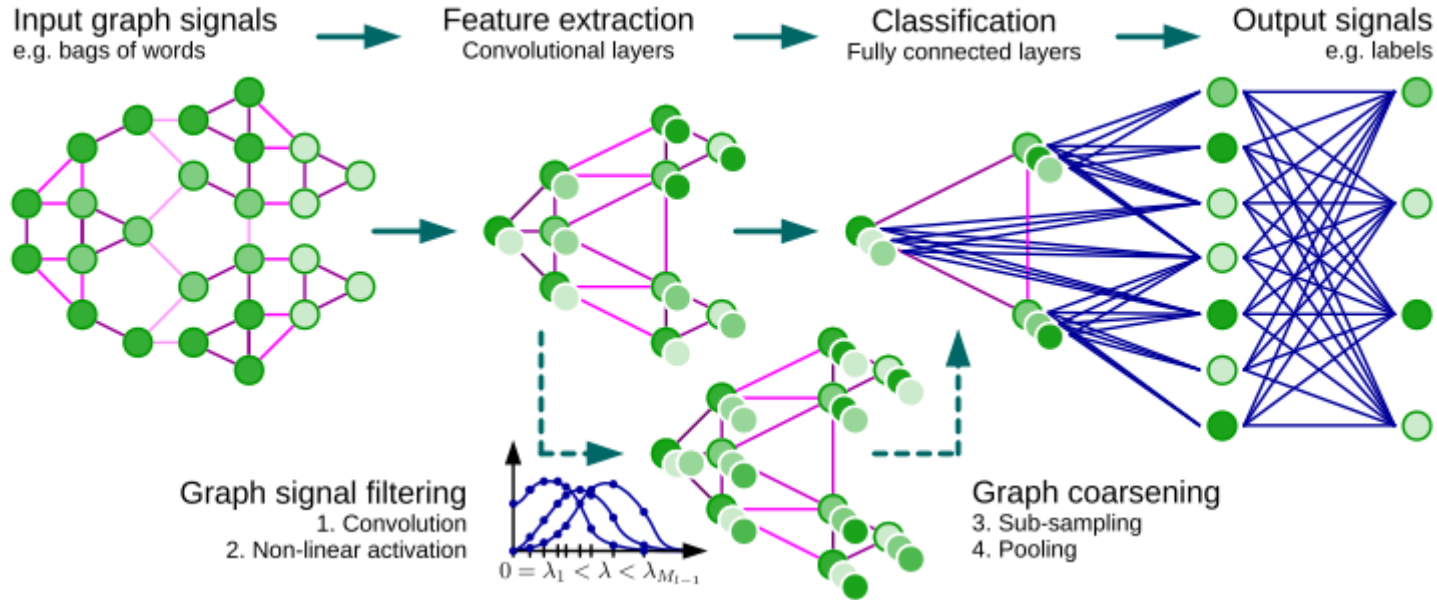
The three integral operations

# CNN vs GCN



An example architecture of a CNN being used for classification

# CNN vs GCN



An example architecture of a GCN being used for classification

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# Convolution in GCN

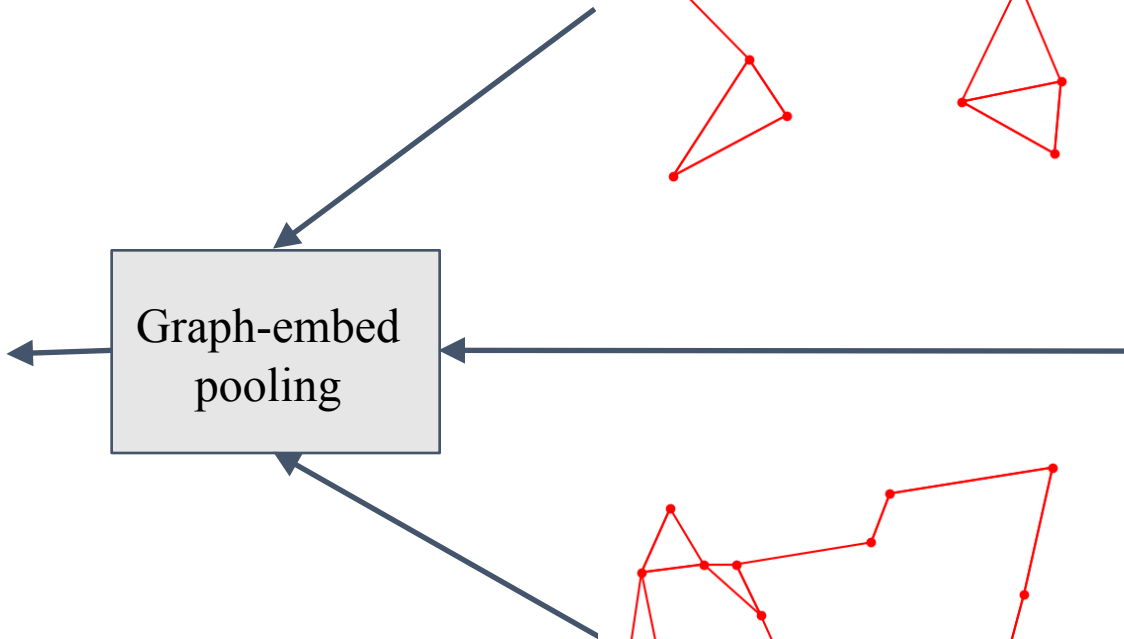
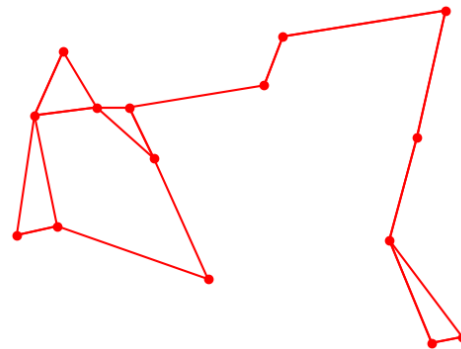
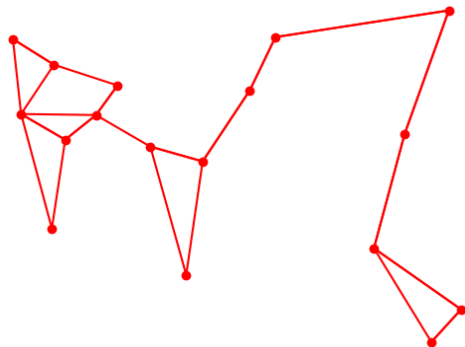
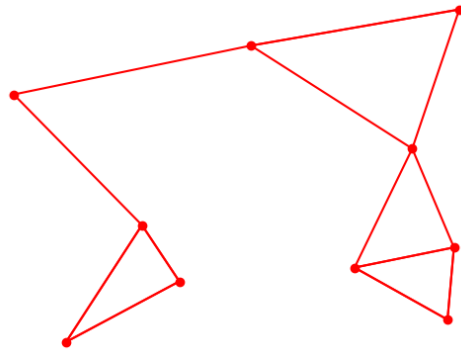
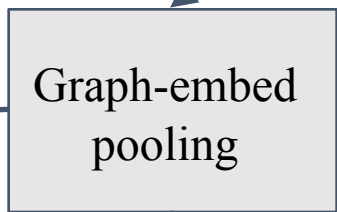
- Spectral and Spatial approach exist for performing convolution in graphs
- Spectral approach has the limitation of the graph structure being same for all samples i.e. **homogeneous** structure
- It is a hard constraint, as most of the real-world graph data has different structures and size for different samples i.e. **heterogeneous structure**
- Spatial approach comes to the rescue!

# Spatial approach

- Does not require homogeneous graph structure
- In turn, requires preprocessing of graph to enable learning on it
- Recall in CNN, images had to be **same size** before being fed to the CNN
- So, in case of GCN also all the heterogeneous graph structures need to be **mapped to a fixed-size output** before learning is performed on it
- Luckily an approach exists - Graph Embed Pooling!

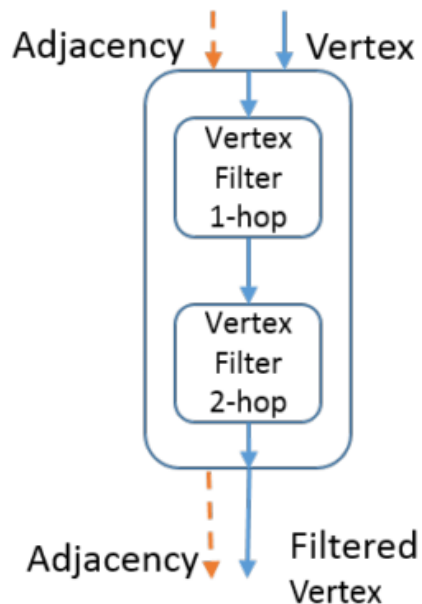
# Spatial approach

Fixed  
structure  
graph!

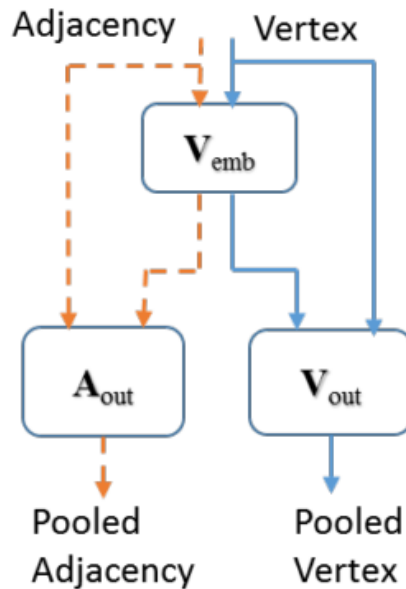




# Spatial approach



(a) Graph Convolution



(b) Graph Pooling

Graph Convolution transforms only the Vertex values whereas Graph Pooling transforms both the Vertex values as well as the Adjacency Matrix

# Spatial approach - Convolution

- Convolution of the vertices  $V$  with the filter  $H$  require matrix multiplication of the form,

$$\mathbf{V}_{out} = \mathbf{H}\mathbf{V}_{in} \text{ where } \mathbf{V}_{in}, \mathbf{V}_{out} \in \mathbb{R}^N$$

- The filter  $H$  is defined as the  $k$ -th degree polynomial of the graph adjacency matrix  $A$ ,

$$\mathbf{H} = h_0\mathbf{I} + h_1\mathbf{A} + h_2\mathbf{A}^2 + \dots + h_k\mathbf{A}^k, \mathbf{H} \in \mathbb{R}^{N \times N}$$

- Generally we have,

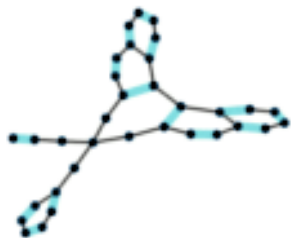
$$\mathbf{H} \approx h_0\mathbf{I} + h_1\mathbf{A}$$

- In case of node attributes being vector, the matrix  $H$  can be designed accordingly

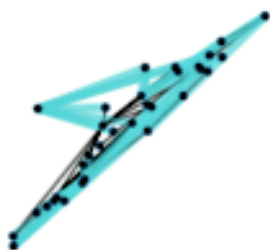
# Spatial approach - Pooling

- Just like in CNN, here too pooling has to be performed
- Graph embed pooling is the approach, it serves two purposes -
  - pooling of graphs to reduce size (and increase receptive field)
  - mapping of input to a fixed size output graph
- Unlike max-pooling in CNN, here a convolutional layer is learnt whose output gives the embedding matrix
- Using the embedding matrix, the vertex attributes and adjacency matrix are transformed

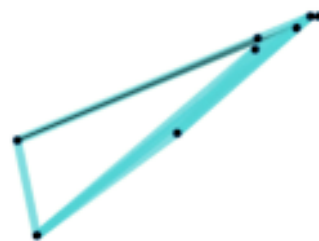
# Spatial approach



(a) Input graph.



(b) Pool to 32 vertex.



(c) Pool to 8 vertex.

Graph Embed Pooling  
demonstrated, geometry should not  
be taken literally

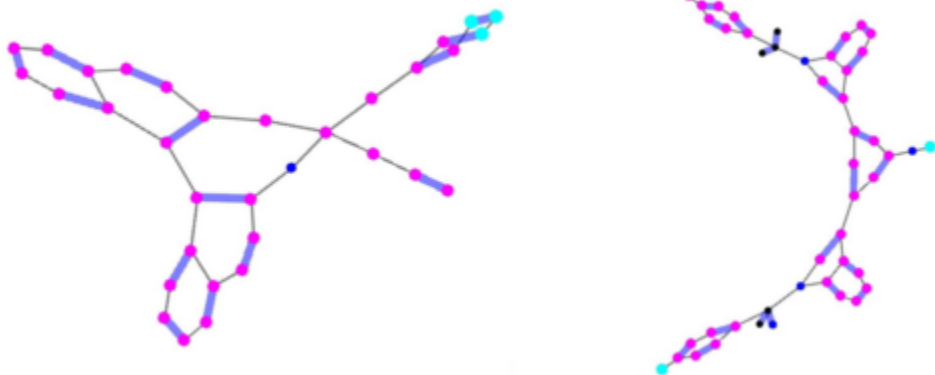
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# Applications

- Classification
  - Images/segments modelled as graph being labeled into classes
  - Chemical compound classification
- Clustering/Segmentation (subset of classification)
  - Image pixels, modelled as a graph, being labeled into semantic classes
  - Research paper classification depending on the citation and references relationship between different documents (Cora dataset)
  - To organize information in large datasets for faster access, say for social network analysis

# Applications



Samples of chemical compounds  
which will be classified into positive  
or negative sample for detection of  
lung cancer

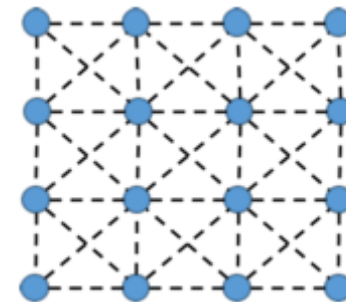
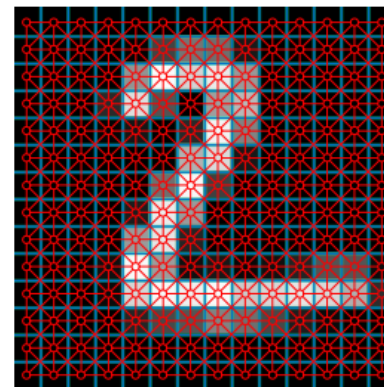
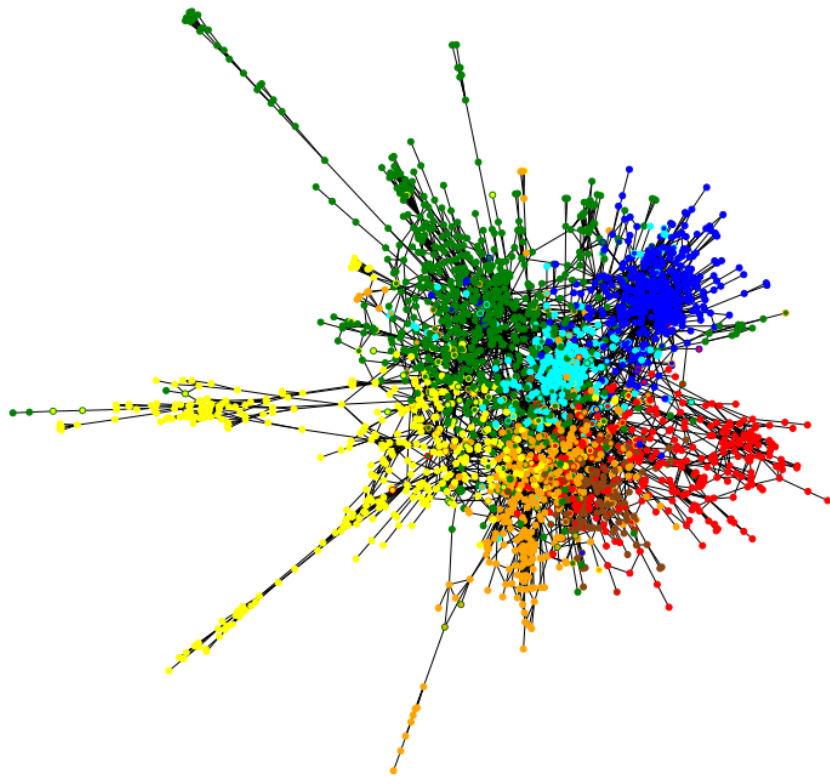


Image represented as a  
graph



MNIST digit image as  
a graph

# Applications



The Cora dataset



# Important References

1. David I Shuman, Sunil K Narang, Pascal Frossard, Antonio Ortega, and Pierre Vandergheynst. The Emerging Field of Signal Processing on Graphs. *IEEE Signal Processing Magazine*, 30(3):83–98, 2013.
2. Aliaksei Sandryhaila and José M F Moura. Discrete Signal Processing on Graphs. *IEEE Transactions on Signal Processing*, 61(7):1644–1656, 2013.
3. Bruna et al. Spectral networks and locally connected networks on graphs. In *International Conference on Learning Representations (ICLR)*, 2014.
4. Michael Edwards and Xianghua Xie. Graph Based Convolutional Neural Network. *arXiv:1609.08965*, 2016.
5. Michaël Defferrard, Xavier Bresson, and Pierre Vandergheynst. Convolutional Neural Networks on Graphs with Fast Localized Spectral Filtering. 2016.
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Questions?



Thank You

