# **Outline of Today's Lecture**



1. Basics of deep learning



2. Deep learning for graphs  $\checkmark$ 



3. Graph Convolutional Networks



4. GNNs subsume CNNs and **Transformers** 



# **Architecture Comparison**

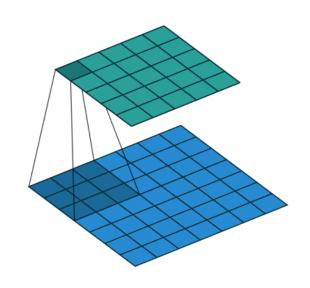


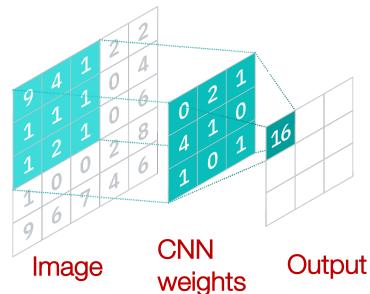
How does GNNs compare to prominent architectures such as Convolutional Neural Nets, and Transformers?

# Convolutional Neural Network



Convolutional neural network (CNN) layer with 3x3 filter:





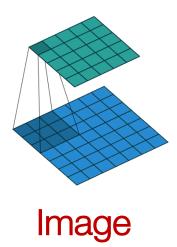
CNN formulation: 
$$\mathbf{h}_v^{(l+1)} = \sigma(\sum_{u \in \mathbf{N}(v) \cup \{v\}} \mathbf{W}_l^u \mathbf{h}_u^{(l)}), \quad \forall l \in \{0, \dots, L-1\}$$

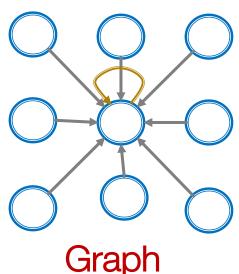
N(v) represents the 8 neighbor pixels of v.



## Convolutional neural network (CNN) layer with

3x3 filter:

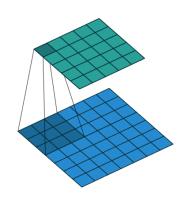




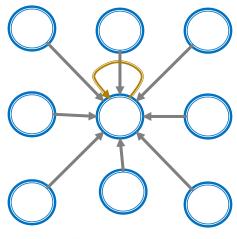
GNN formulation (previous slide):  $\mathbf{h}_v^{(l+1)} = \sigma(\mathbf{W}_l \sum_{u \in \mathbf{N}(v)} \frac{\mathbf{h}_u^{(l)}}{|\mathbf{N}(v)|} + \mathbf{B}_l \mathbf{h}_v^{(l)}), \forall l \in \{0, \dots, L-1\}$ 



# Convolutional neural network (CNN) layer with 3x3 filter:







#### Graph

GNN formulation: 
$$\mathbf{h}_v^{(l+1)} = \sigma(\mathbf{W_l} \sum_{u \in \mathbf{N}(v)} \frac{\mathbf{h}_u^{(l)}}{|\mathbf{N}(v)|} + \mathbf{B}_l \mathbf{h}_v^{(l)}), \forall l \in \{0, \dots, L-1\}$$

CNN formulation: 
$$\mathbf{h}_v^{(l+1)} = \sigma(\sum_{u \in \mathbf{N}(v)} \mathbf{W}_l^u \mathbf{h}_u^{(l)} + \mathbf{B}_l \mathbf{h}_v^{(l)}), \forall l \in \{0, \dots, L-1\}$$

**Key difference**: We can learn different  $W_l^u$  for different "neighbor" u for pixel v on the image. The reason is we can pick an order for the 9 neighbors using **relative position** to the center pixel: {(-1,-1). (-1,0), (-1, 1), ..., (1, 1)}



Convolutional neural network (CNN) layer with 3x3 filter:

- CNN can be seen as a special GNN with fixed neighbor size and ordering:
  - The size of the filter is pre-defined for a CNN.
  - The advantage of GNN is it processes arbitrary graphs with different degrees for each node.

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# Convolutional neural network (CNN) layer with 3x3 filter:

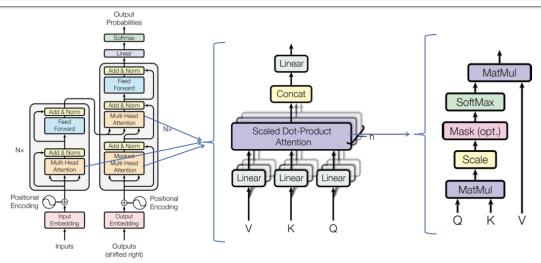
- CNN can be seen as a special GNN with fixed neighbor size and ordering.
- CNN is not permutation equivariant.
  - Switching the order of pixels will leads to different outputs.

**Key difference**: We can learn different  $W_l^u$  for different "neighbor" u for pixel v on the image. The reason is we can pick an order for the 9 neighbors using **relative position** to the center pixel: {(-1,-1). (-1,0), (-1, 1), ..., (1, 1)}

### **Transformer**

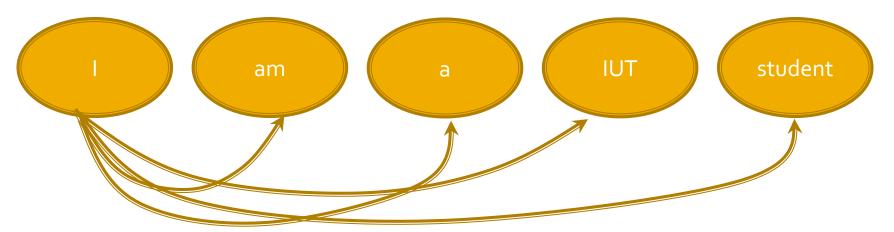


Transformer is one of the most popular architectures that achieves great performance in many sequence modeling tasks.



#### **Key component: self-attention**

 Every token/word attends to all the other tokens/words via matrix calculation.

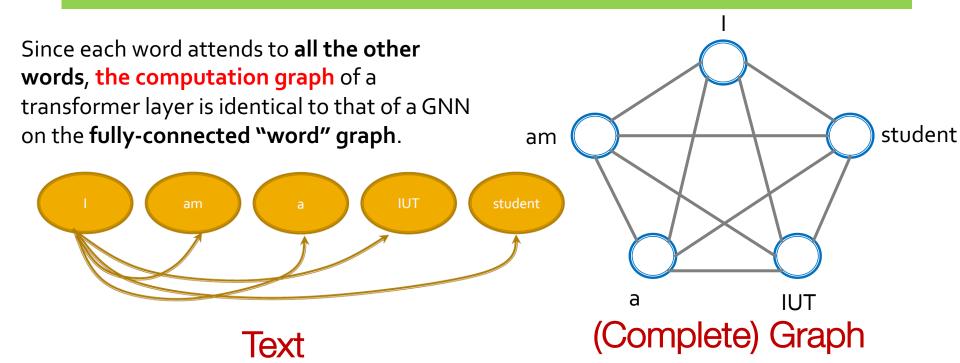


## **GNN vs. Transformer**



A nice blog plot for this: <a href="https://towardsdatascience.com/transformers-are-graph-neural-networks-bca9f75412aa">https://towardsdatascience.com/transformers-are-graph-neural-networks-bca9f75412aa</a>

# Transformer layer can be seen as a special GNN that runs on a fully-connected "word" graph!



# Summary



#### In this lecture, we introduced

- Basics of neural networks
  - Loss, Optimization, Gradient, SGD, non-linearity, MLP
- Idea for Deep Learning for Graphs
  - Multiple layers of embedding transformation
  - At every layer, use the embedding at previous layer as the input
  - Aggregation of neighbors and self-embeddings
- Graph Convolutional Network
  - Mean aggregation; can be expressed in matrix form
- GNN is a general architecture
  - CNN and Transformer can be viewed as a special GNN