

Geometric Deep Learning Self-Study Group

Session 4

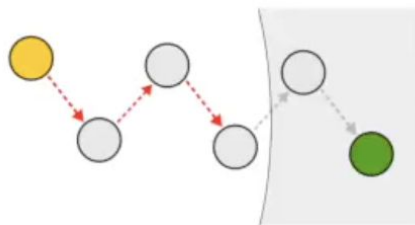
October 13, 2025

Aaron Margolis

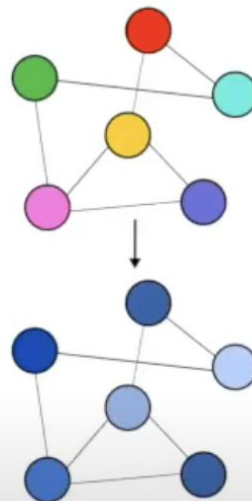
<https://armargolis.github.io/>

Session Outline

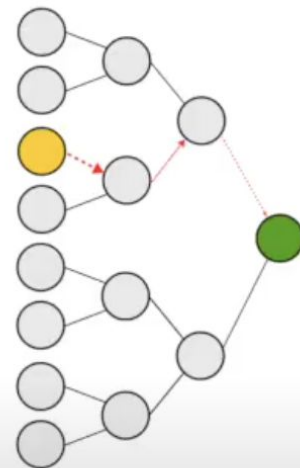
Expressivity/
Under-reaching



Under-reaching



Over-smoothing



Over-squashing

Tutorials

Group Discussion - Possible Project

Remaining Sessions:

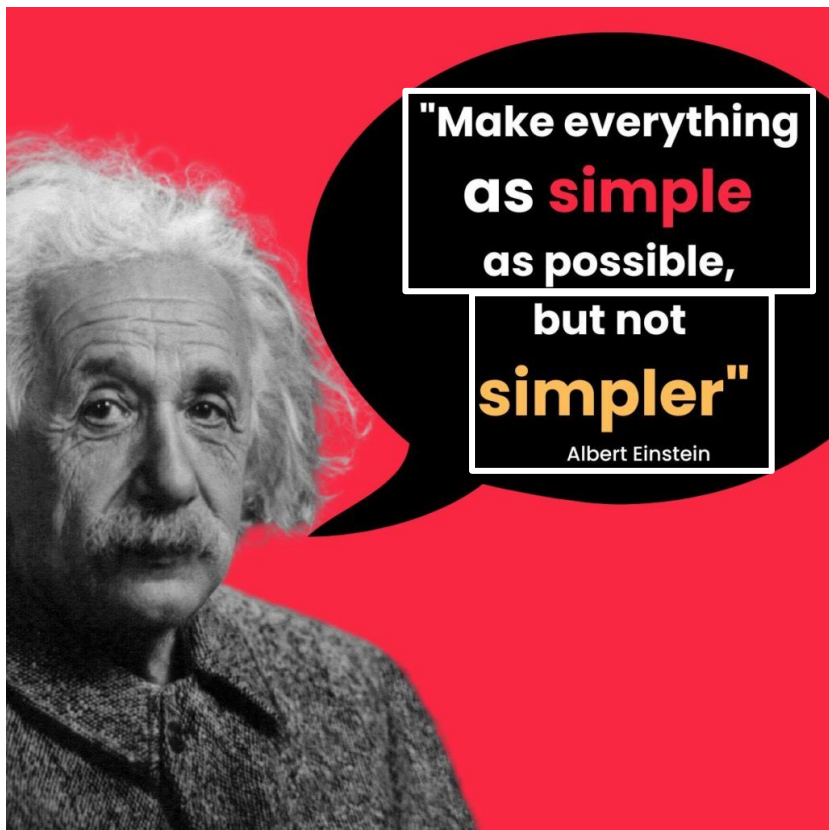
Oct 13: Expressivity

Nov 3: Over-smoothing, Over-squashing and Curvature

Nov 17: Equivariance

Dec 1: Manifolds

Expressivity and Oversquashing



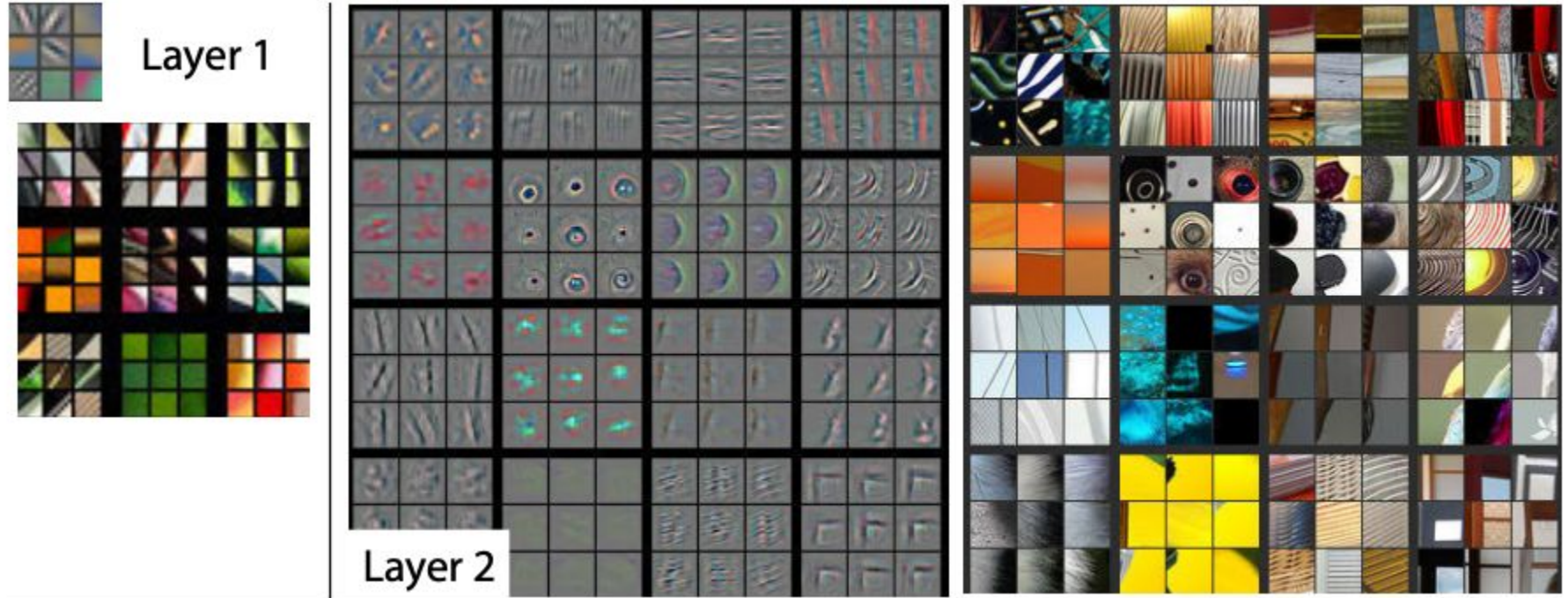
Avoid
Oversmoothing
and
oversquashing

Why dense layers at the
beginning don't work

Achieve
Minimum
Expressivity

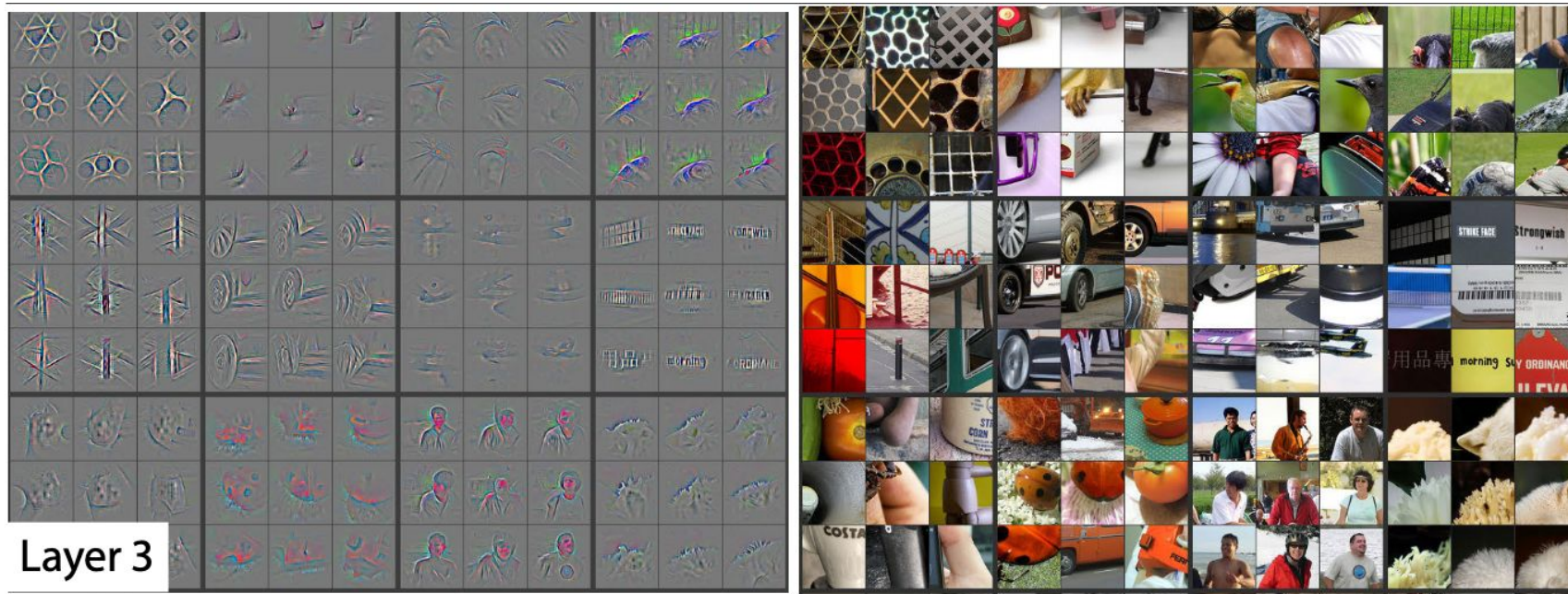
Why you need multiple
convolutional layers

Expressivity

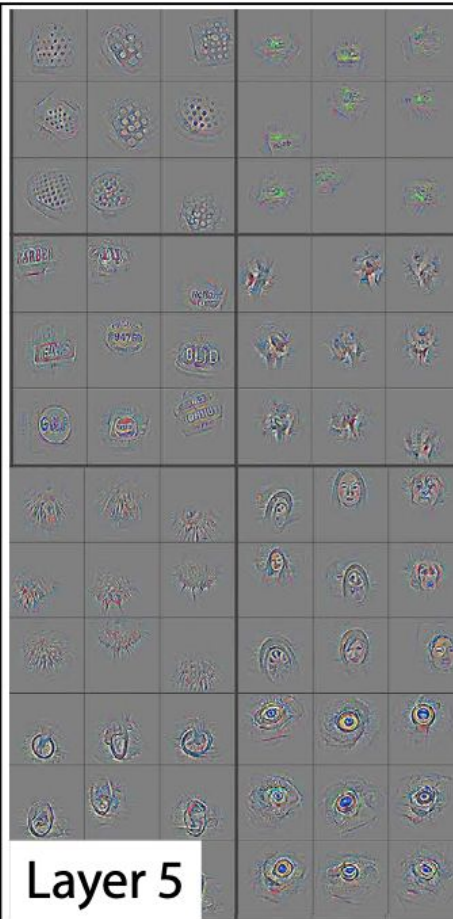
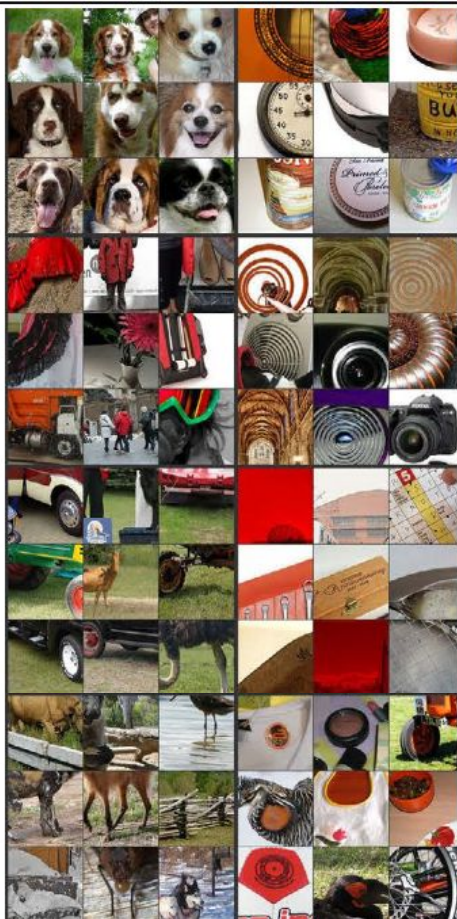
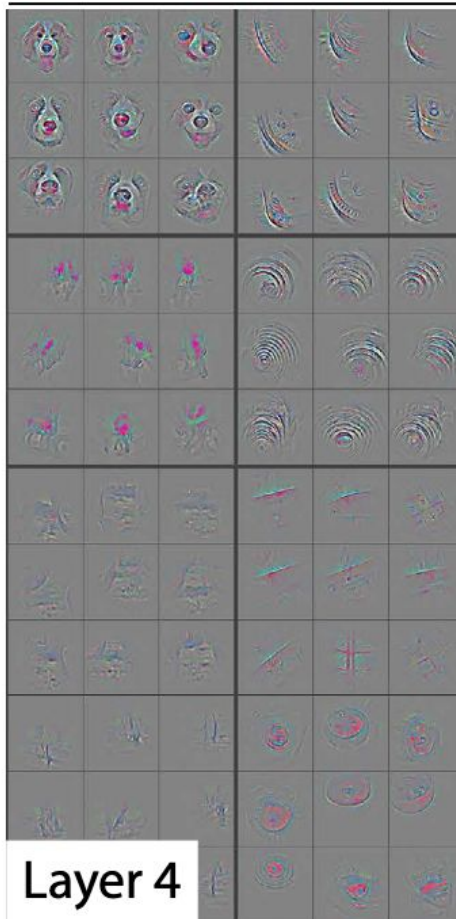


Source: Visualizing and Understanding Convolutional Networks
By Matthew D. Zeiler, Rob Fergus

Expressivity

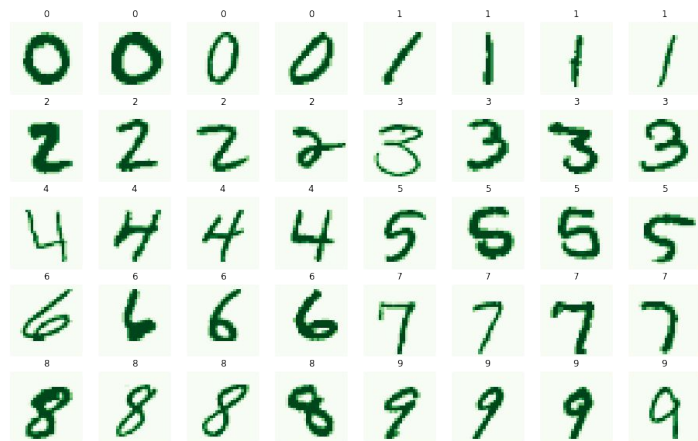


Source: Visualizing and Understanding Convolutional Networks
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5,000 images 28 by 28 images = 3,920,000 data points

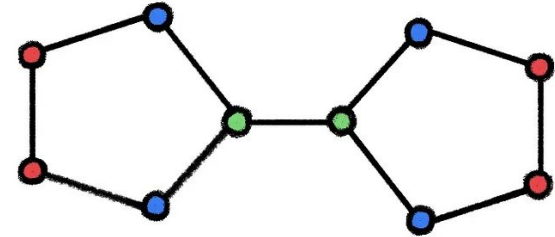
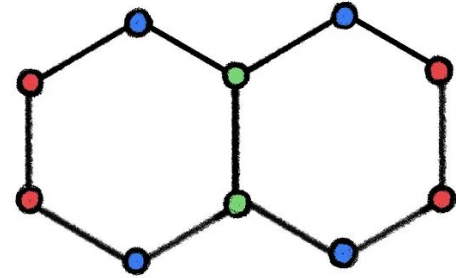
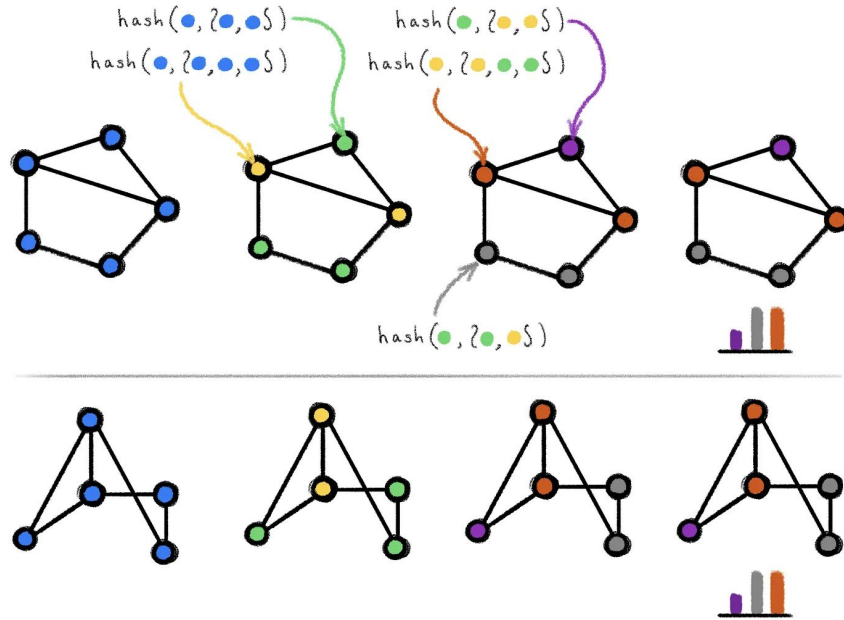
Input images (28 by 28)



<https://www.kaggle.com/code/gpreda/simple-introduction-to-cnn-for-mnist-99-37>

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 32)	320
batch_normalization (Batch Normalization)	(None, 28, 28, 32)	128
conv2d_1 (Conv2D)	(None, 26, 26, 32)	9248
batch_normalization_1 (Batch Normalization)	(None, 26, 26, 32)	128
conv2d_2 (Conv2D)	(None, 13, 13, 32)	25632
max_pooling2d (MaxPooling2D)	(None, 6, 6, 32)	0
batch_normalization_2 (Batch Normalization)	(None, 6, 6, 32)	128
dropout (Dropout)	(None, 6, 6, 32)	0
conv2d_3 (Conv2D)	(None, 3, 3, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 1, 1, 64)	0
batch_normalization_3 (Batch Normalization)	(None, 1, 1, 64)	256
conv2d_4 (Conv2D)	(None, 1, 1, 64)	36928
dropout_1 (Dropout)	(None, 1, 1, 64)	0
flatten (Flatten)	(None, 64)	0
dense (Dense)	(None, 128)	8320
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 10)	1290
Total params: 100,874		
Trainable params: 100,554		
Non-trainable params: 320		

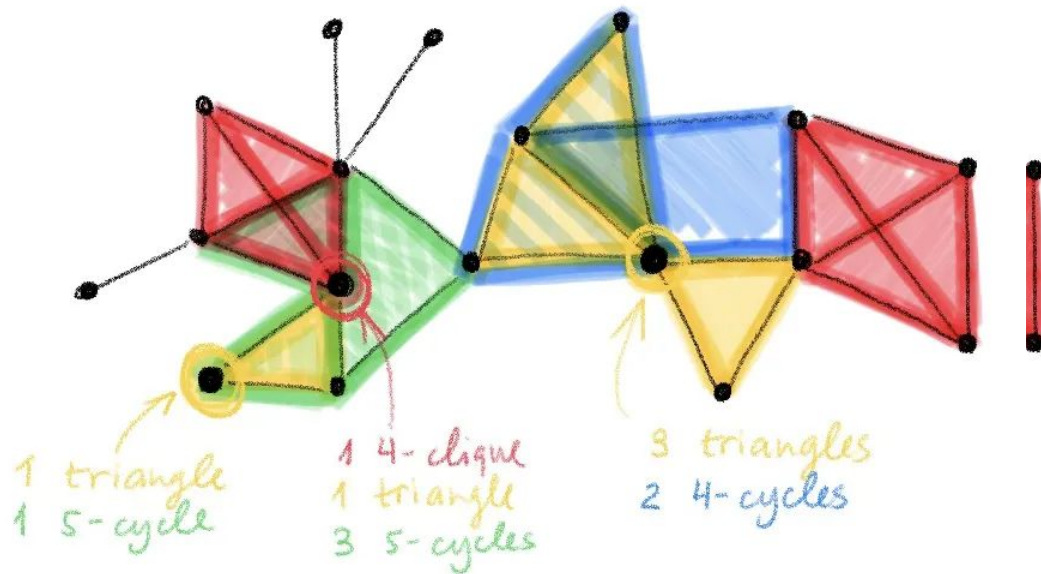
Node Embeddings, Expressive Power and Limitations



Source: Bronstein

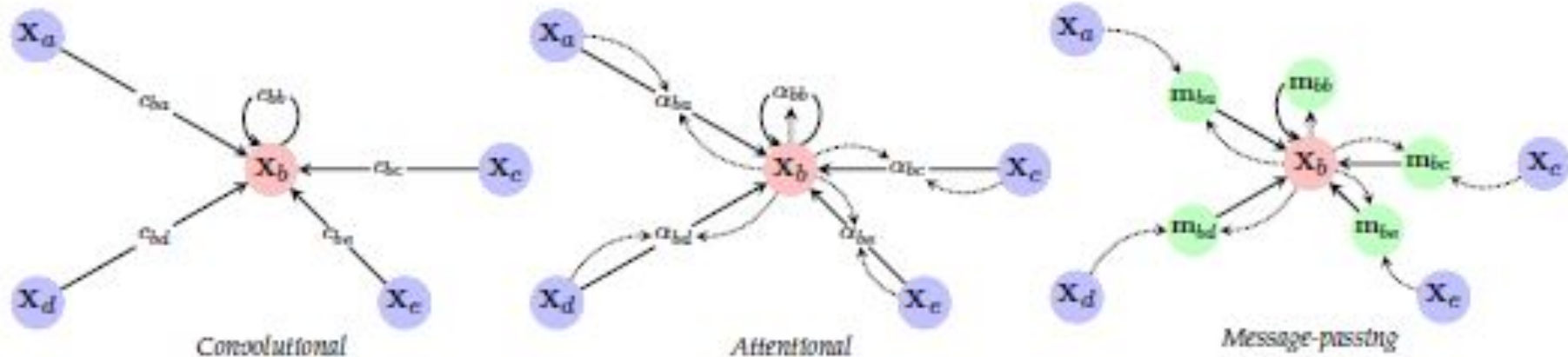
<https://medium.com/data-science/expressive-power-of-graph-neural-networks-and-the-weisfeiler-lehman-test-b883db3c7c49?sk=5c2a28ccd38db3a7b6f80f161e825a5a>

We need something more powerful than GNNs



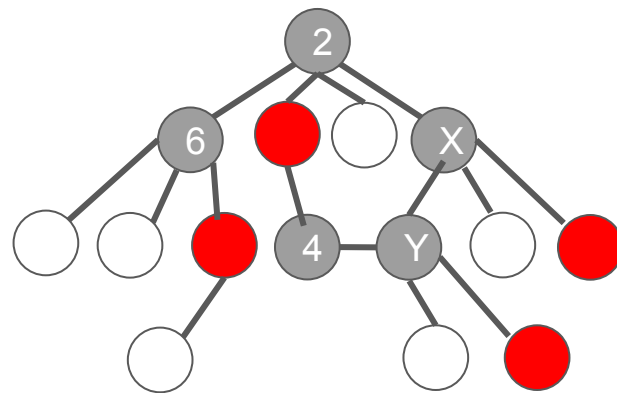
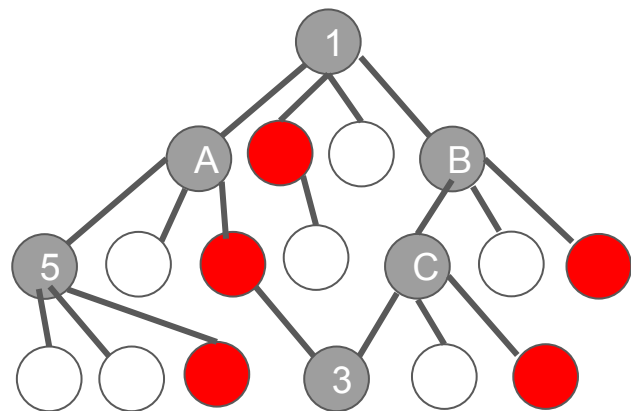
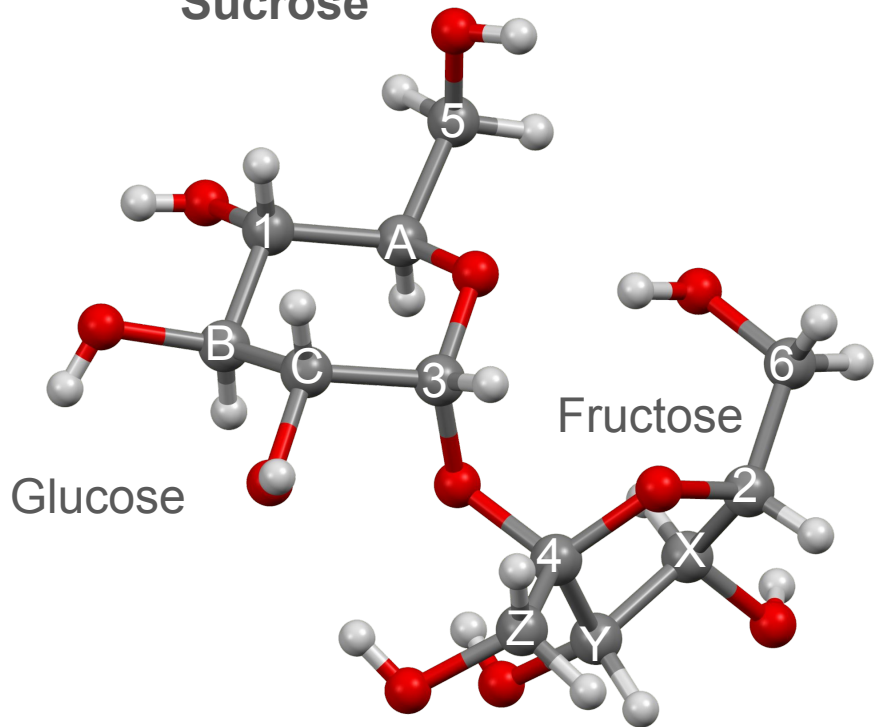
Source:
<https://medium.com/data-science/beyond-weisfeiler-lehman-using-substructures-for-provably-expressive-graph-neural-networks-d476ad665fa3?sk=bc0d14c28a380b4d51debc4935345b73>

More powerful techniques



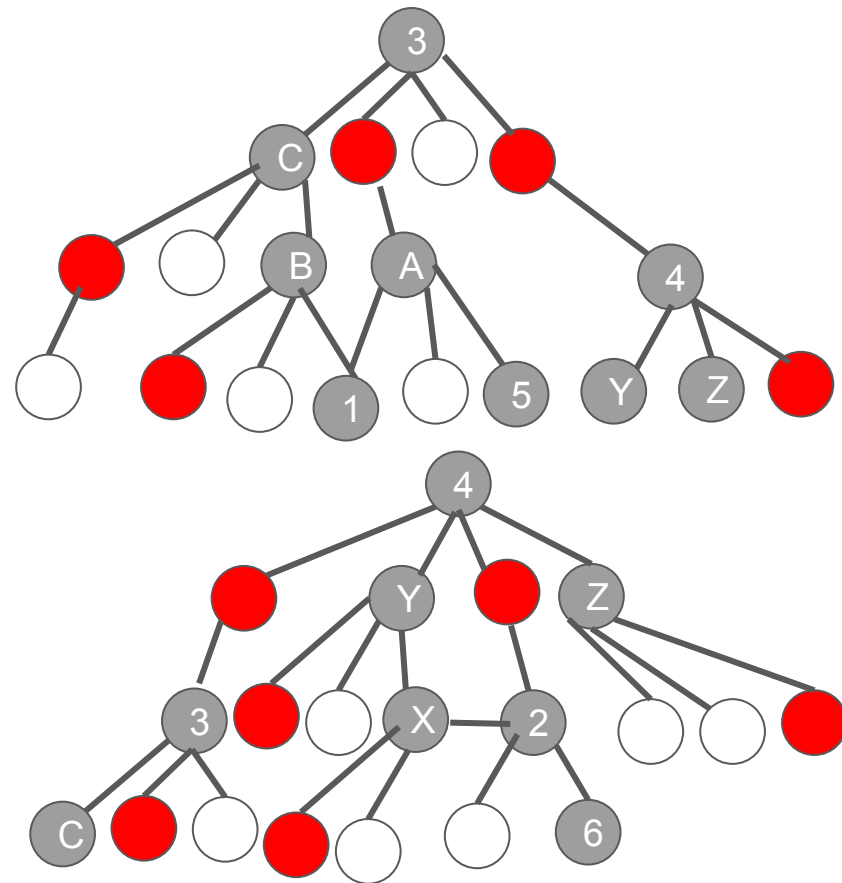
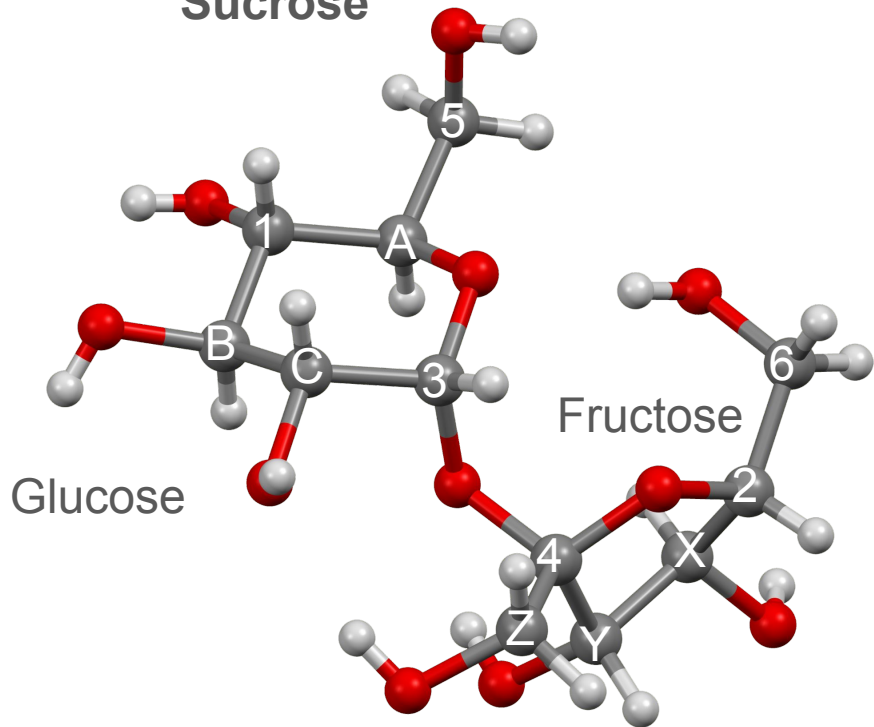
Trees as Inputs: Real World Example

Sucrose



Trees as Inputs: Real World Example

Sucrose



Next Meeting Nov 3

Readings (blogs by Bronstein and collaborators):

Expressive power of graph neural networks and the Weisfeiler-Lehman test

Beyond Weisfeiler-Lehman: using substructures for provably expressive graph neural networks

[GNNs through the lens of Differential Geometry and Algebraic Topology](#)

Over-squashing, Bottlenecks, and Graph Ricci curvature

Lectures:

Discrete Ollivier-Ricci curvature for data visualization and analysis by Abigail Hickok Watch the first 10 minutes to understand discrete curvature

[Curvature and Over-Squashing in GNNs by Francesco Giovanni](#) You can skip the first 10 minutes

Tutorials: Molecular Property Prediction with GNNs, Parts 2-5

To present, fill out this form:

https://docs.google.com/forms/d/e/1FAIpQLSfjuvRWuHfQ9M11uz9PUng_3j_trOAcTyDG2a5yPoMvMWgflQ/viewform?usp=header

References and Resources

Main Reference:

Geometric Deep Learning: Grids, Groups, Graphs, Geodesics, and Gauges

Michael M. Bronstein, Joan Bruna, Taco Cohen, Petar Veličković

<https://geometricdeeplearning.com/book/> We'll use the chapters rather than the big pdf

Additional References:

Mathematical Foundations of Geometric Deep Learning by Borde and Bronstein

<https://www.arxiv.org/abs/2508.02723>

Introduction to Geometric Deep Learning by Patrick Nicolas

<https://patricknicolas.substack.com/p/introduction-to-geometric-deep-learning>

Further Reading:

Valence Labs

<https://portal.valencelabs.com>

Graph Learning on Wednesdays

<https://sites.google.com/view/graph-learning-on-weds>