



SEMI-SUPERVISED CLASSIFICATION WITH GRAPH CONVOLUTIONAL NETWORKS

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Motivation

Semi-Supervised vs. Supervised vs. Unsupervised Learning

- Supervised Learning $X - Y$
- Unsupervised X
- Semi-Supervised X - some Y

Efficient community detection

- Only a portion of the data needs to be labeled



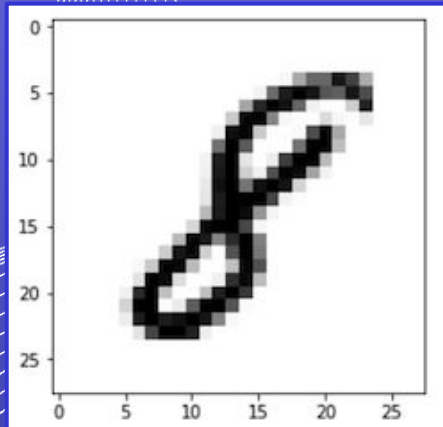


01

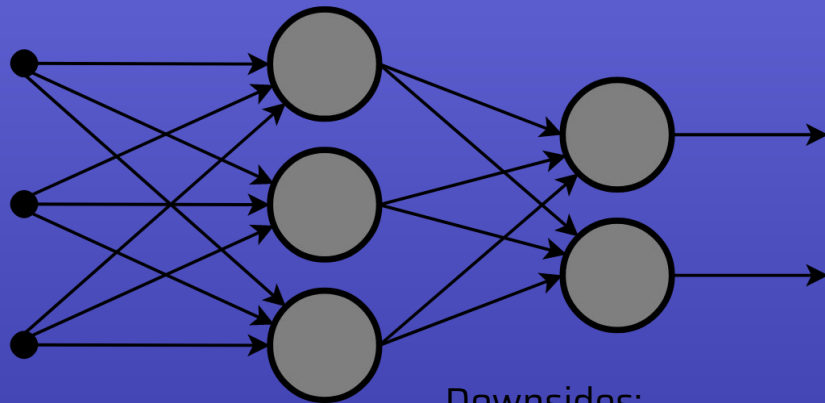
Convolutions

Why use convolutional network layers?

Traditional Neural Networks



28x28 Image



784 Input Parameters

Downsides:

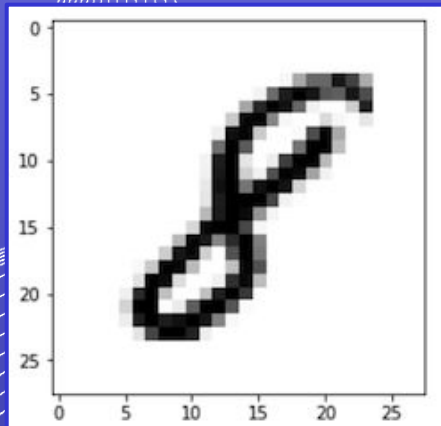
Number of parameters quickly explodes
(10 Nodes, 1 Hidden Layer) = 7000+
Parameters

- High Training Costs
- Overfitting

Assumes all pixels are independent



Convolutional Neural Networks



28x28 Image

3	1	1	2	8	4
1	0	7	3	2	6
2	3	5	1	1	3
1	4	1	2	6	5
3	2	1	3	7	2
9	2	6	2	5	1

Original image 6x6

"Convolution"

\times

1	0	-1
1	0	-1
1	0	-1

Filter 3x3

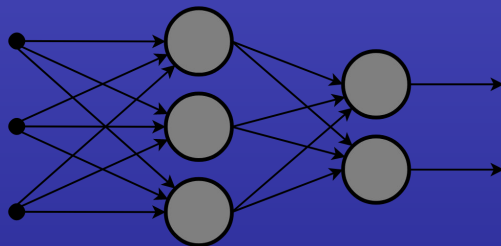
=

-7	...		
...	...		

Output 4x4

Result of the element-wise product and sum of the filter matrix and the original image

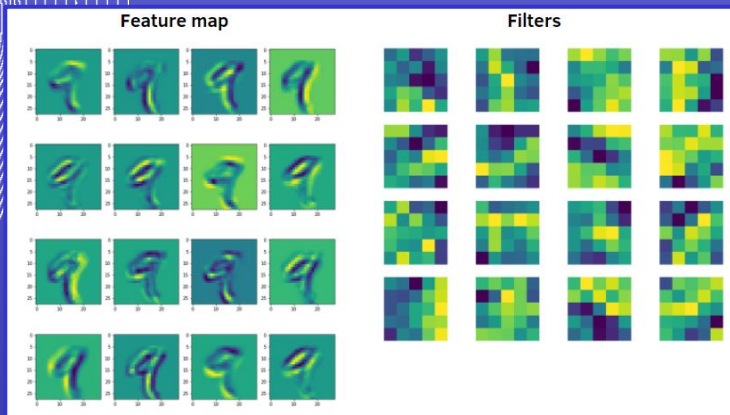
16 Inputs



+

4x4 Image

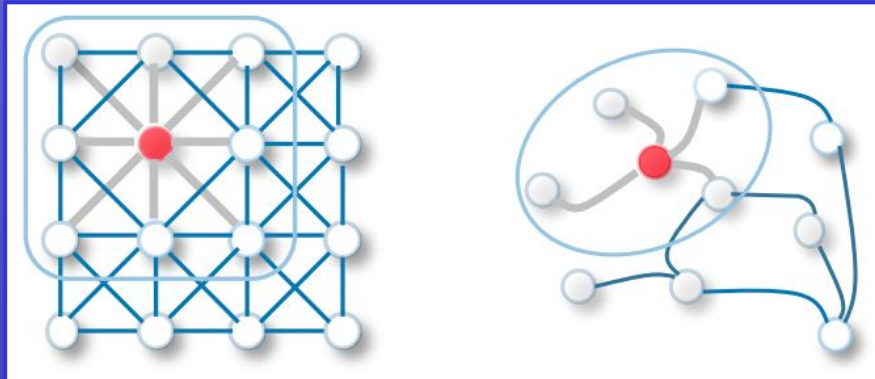
Convolutional Neural Networks



Advantages

- Reduced parameters, less training time
- Preserves correlation between neighboring pixels
- Greatly increased accuracy
- Literal breakthrough in image recognition technology

Convolutional Neural Networks



Instead of neighboring pixels, we'll assume that neighboring nodes contain useful information, this is the basis for GCN's





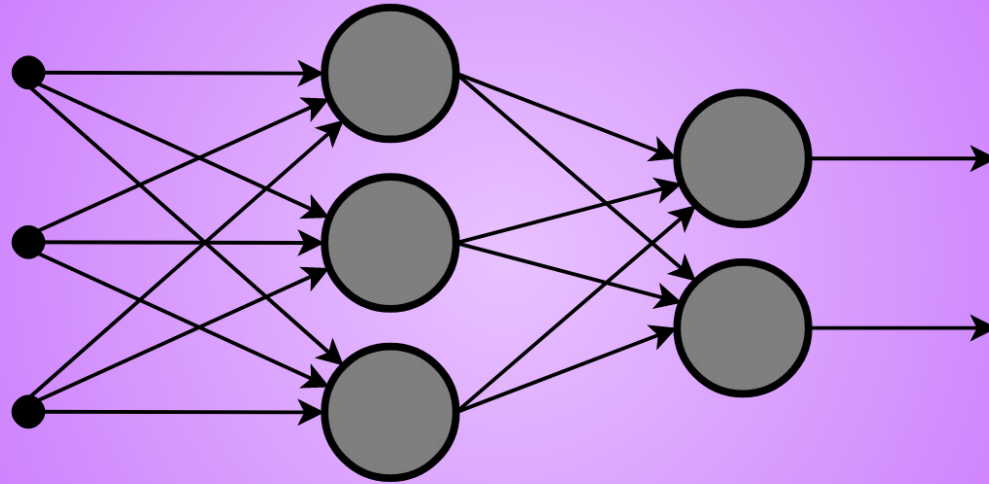
02

Graph Convolutions

How do convolutions generalize to network data?



The Forward Pass



$$Z = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} X \Theta$$



Loss Function - Cross Entropy

$$\mathcal{L} = - \sum_{l \in \mathcal{Y}_L} \sum_{f=1}^F Y_{lf} \ln Z_{lf}$$

S		T
0.775	$L_{CE}(S,T)$	1
0.116		0
0.039		0
0.070		0
		0

Loss = 0.3677

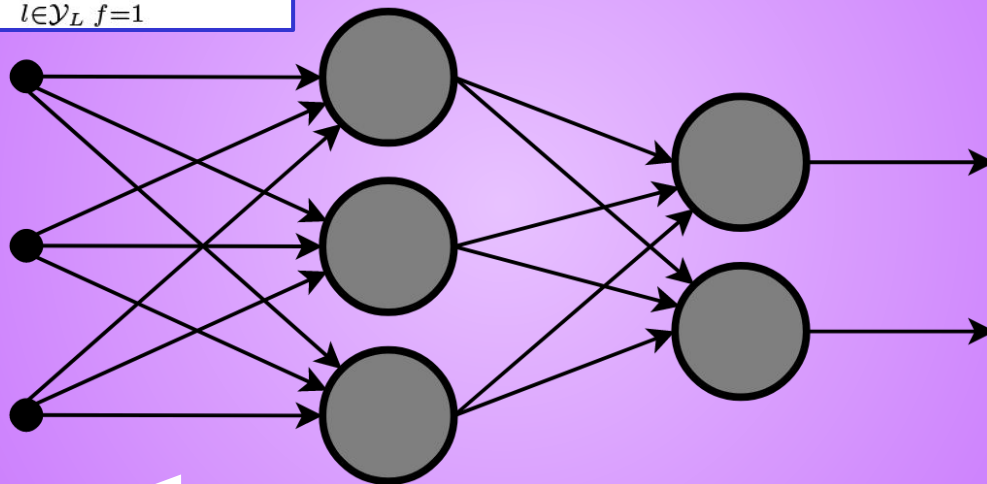
S		T
0.938	$L_{CE}(S,T)$	1
0.028		0
0.013		0
0.023		0
		0

Loss = 0.095



Backpropagation

$$\mathcal{L} = - \sum_{l \in \mathcal{Y}_L} \sum_{f=1}^F Y_{lf} \ln Z_{lf}$$



$$\mathbf{a}_{n+1} = \mathbf{a}_n - \gamma \nabla F(\mathbf{a}_n)$$

Stochastic Gradient Descent



03

Experimental Design

Applying GCN's to a myriad of datasets.

Experimental Design

- GCNs were tested in a number of experiments:
 - Semi-supervised document classification
 - Semi-supervised entity classification
 - Bipartite graph extracted from NELL
- Host of datasets are selected for testing

Datasets and Design

- Datasets used include:
 - Citation Networks: Citeseer (3.6%), Cora (5.2%) , and Pubmed (0.3%)
 - NELL (0.1%)
 - Random Graphs: Training time
- Two-layer GCNs are trained and evaluated on a test set of 1000 labeled examples, with comparisons against:
 - ManiReg, DeepWalk, and Planetoid

Datasets

	Nodes	Edges	Classes	Features
Citeseer	3327	4732	6	3703
Cora	2708	5429	7	1433
Pubmed	19717	44338	3	500
NELL	65755	266144	210	5414




04

Results

How do GCN's perform?

Semi-Supervised Classification

	Citeseer	Cora	Pubmed	nELL
ManiReg	60.1	59.5	70.7	21.8
DeepWalk	43.2	67.2	65.3	58.1
Planetoid	64.7	75.7	77.2	61.9
 GCN	70.3	81.5	79.0	66.0

Results and Limitations

- GCNs outperformed other methods by a large margin
 - GCNs remain computationally efficient
- Limitations:
 - Memory Requirement
 - Directed Edges
 - Initial Assumptions:
 - Locality (implicit to GCN)





Thanks!

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