

GATs

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Pauckert

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References

Graph Attention Networks

Justin Pauckert

Discrete Optimization and Machine Learning
TU Berlin

July 5, 2021

Graph Data

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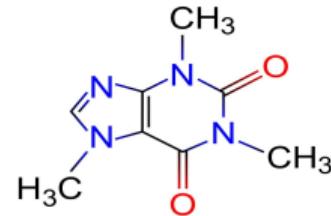
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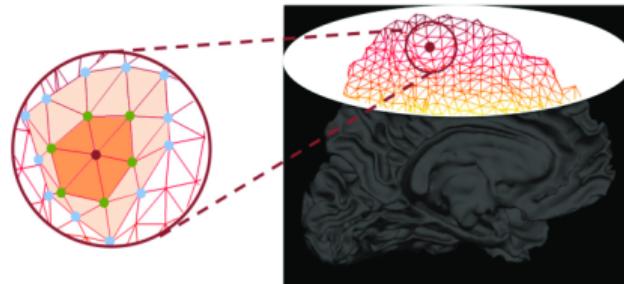
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Traffic



Chemistry



Neuroscience

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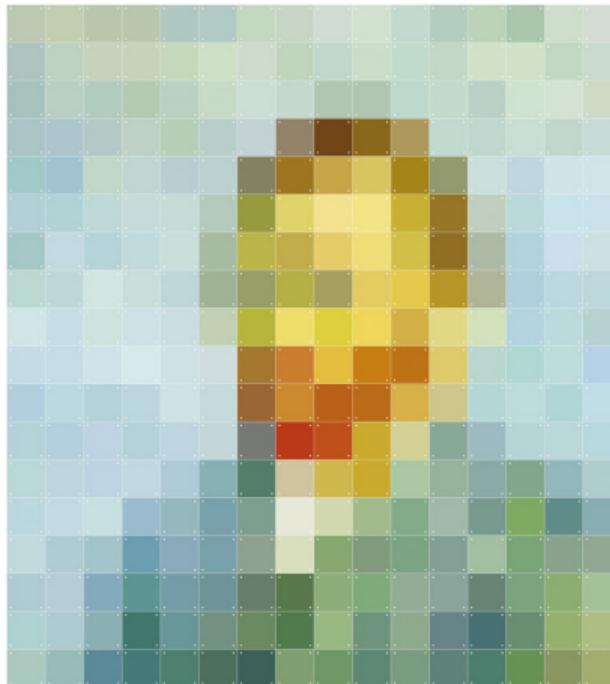
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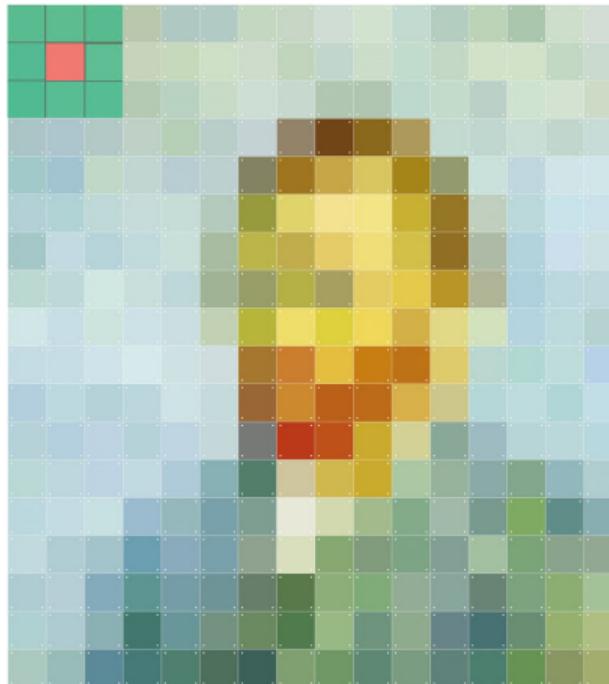
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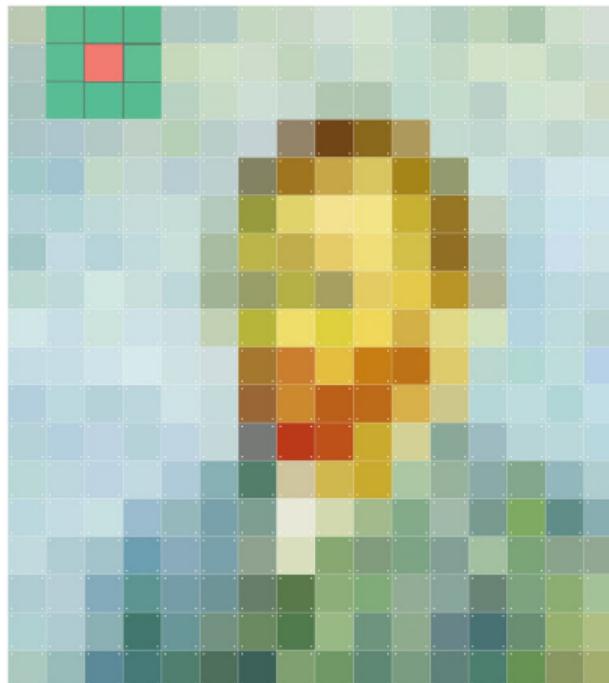
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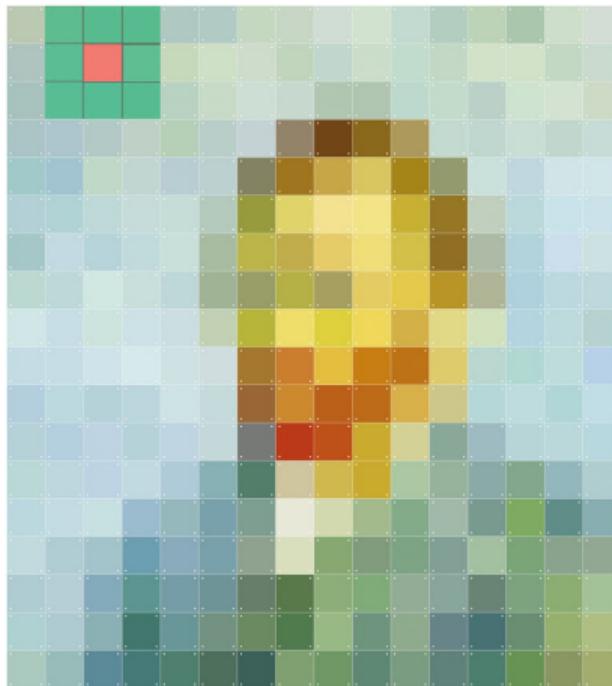
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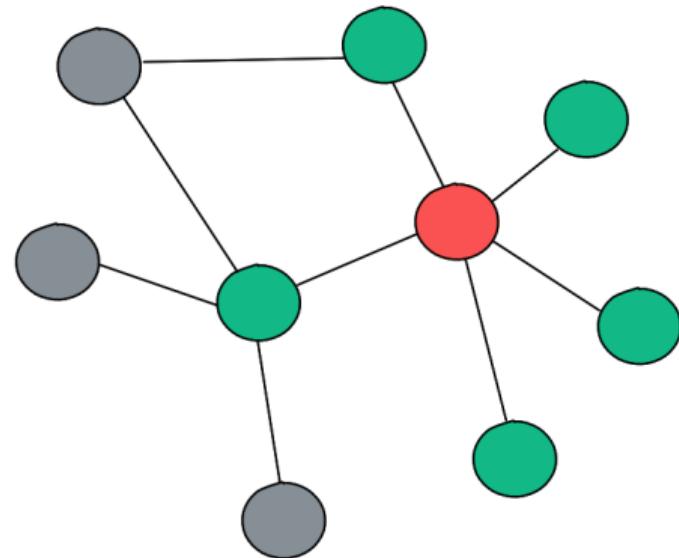
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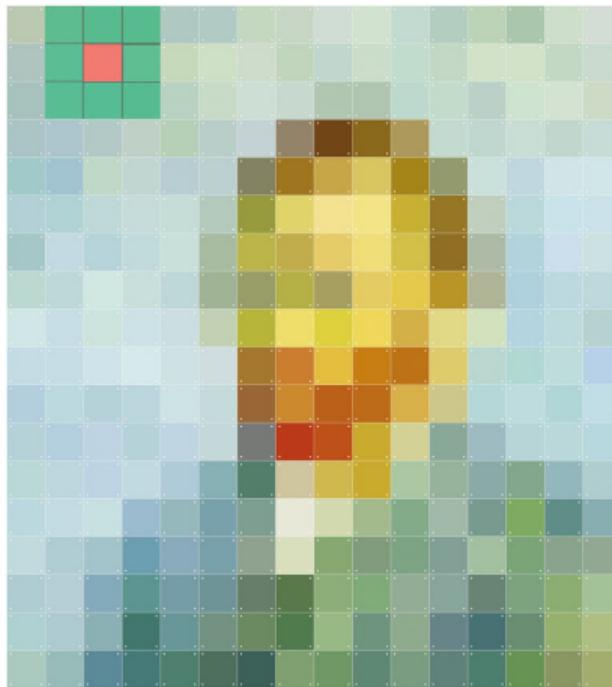
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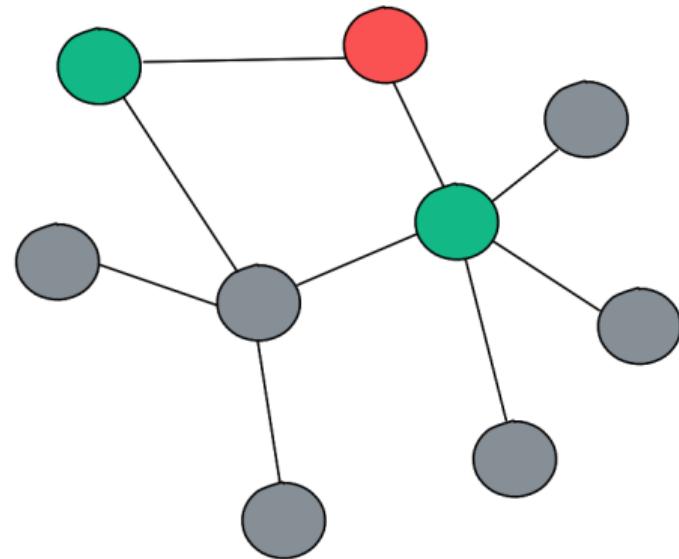
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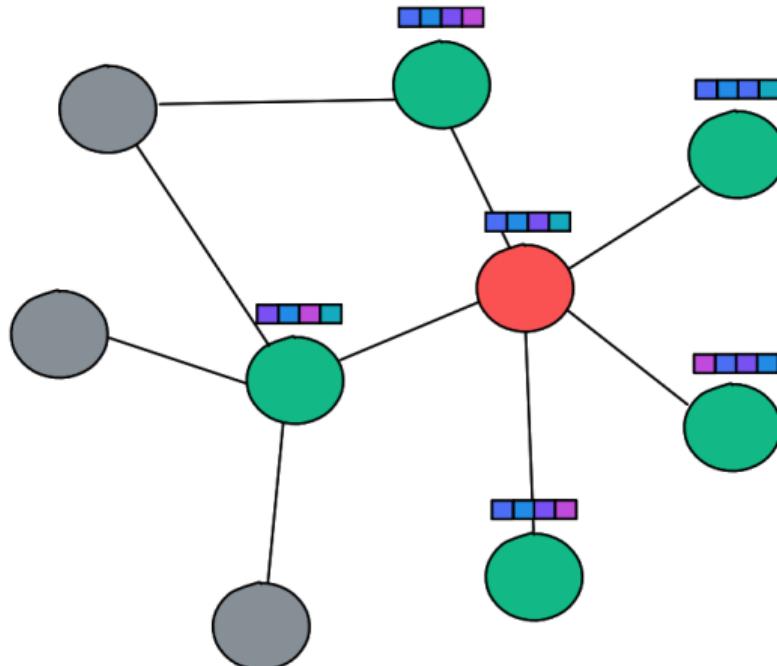
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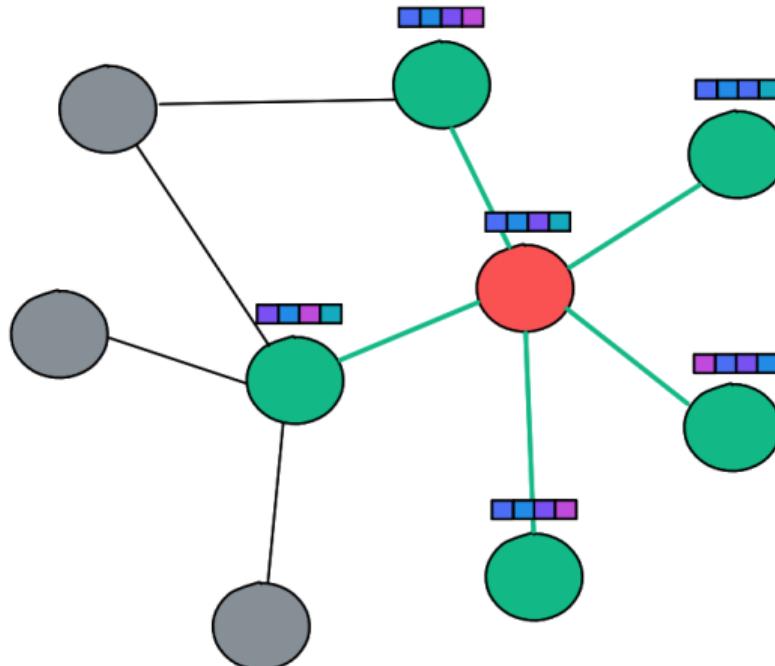
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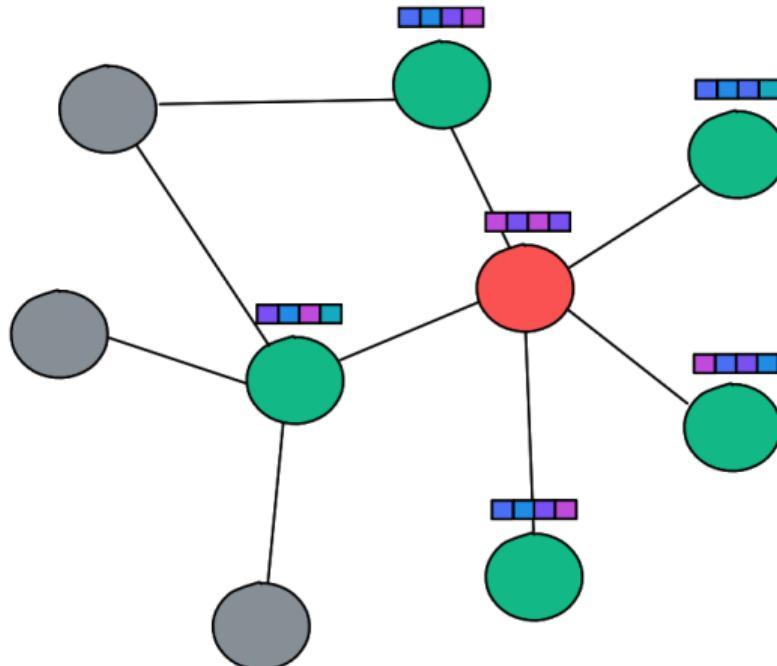
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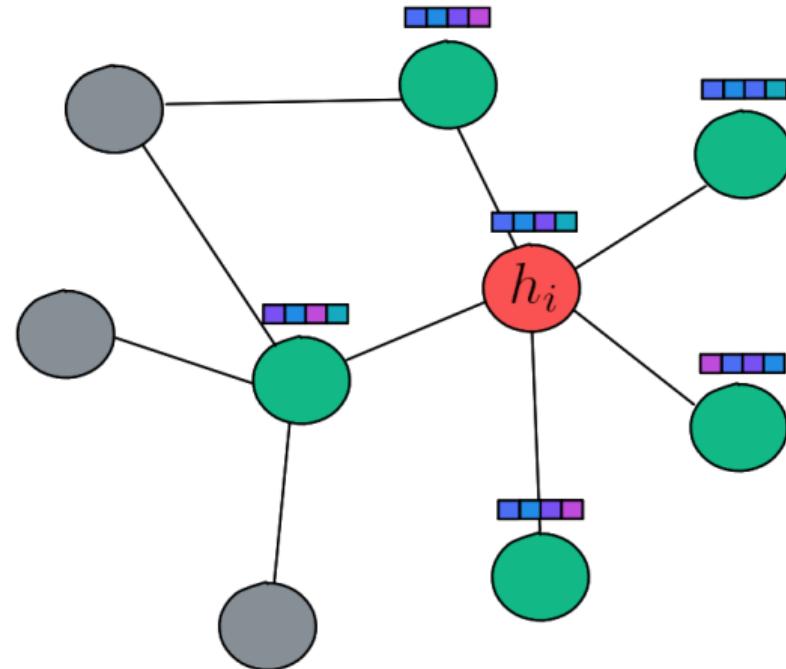
References

$$h_i \in \mathbb{R}^F, h'_i \in \mathbb{R}^{F'}$$

feature weight matrix $\mathbf{W} \in \mathbb{R}^{F' \times F}$

shared attention mechanism

$$a : \mathbb{R}^{F'} \times \mathbb{R}^F \rightarrow \mathbb{R}$$



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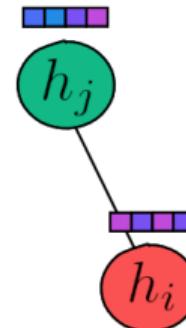
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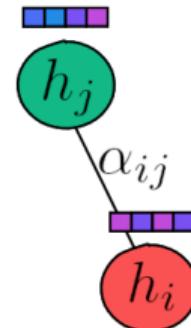
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normalized attention coefficients

$$\alpha_{ij} = \text{softmax}_j(e_{ij})$$



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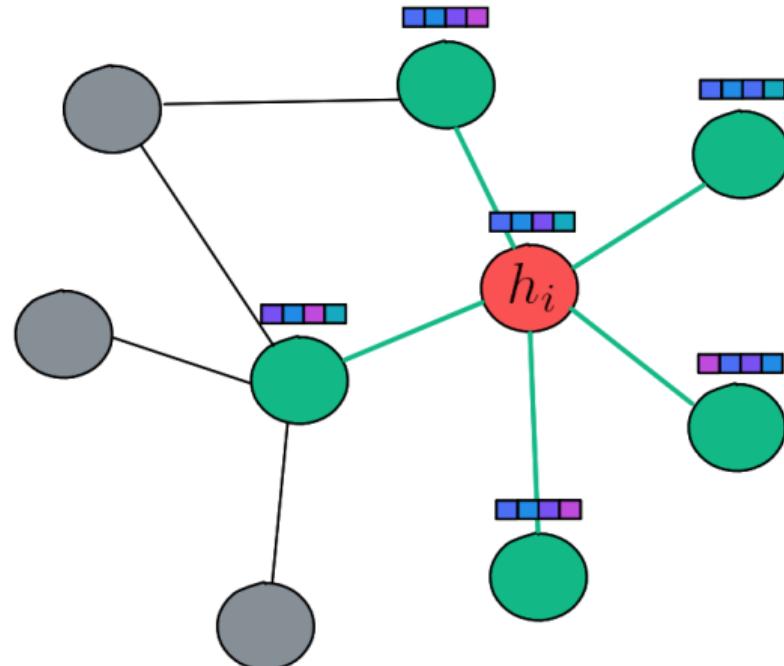
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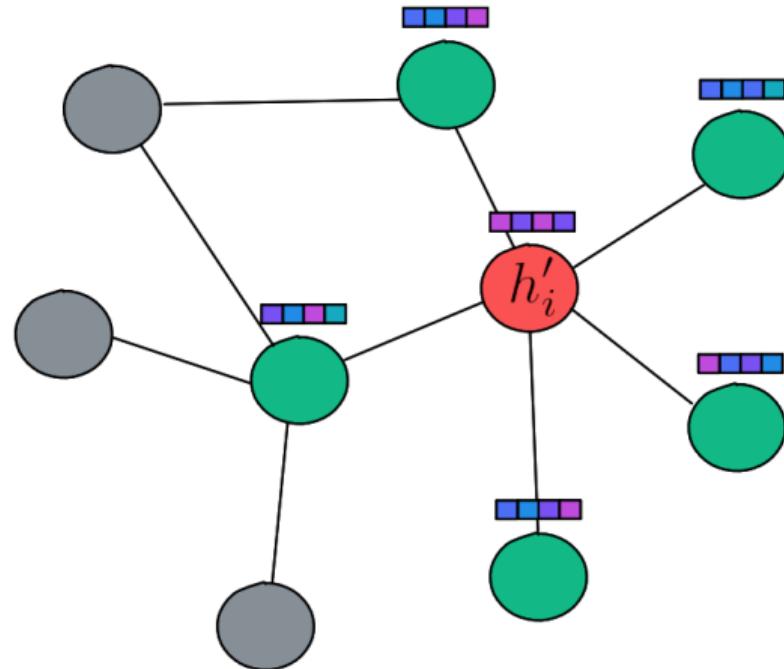
$$e_{ij} = a(\mathbf{W}h_i, \mathbf{W}h_j)$$

normalized attention coefficients

$$\alpha_{ij} = \text{softmax}_j(e_{ij})$$

output with nonlinearity σ

$$h'_i = \sigma\left(\sum_{j \in \mathcal{N}_i} \alpha_{ij} \mathbf{W}h_j\right)$$



Multi-Head Attention

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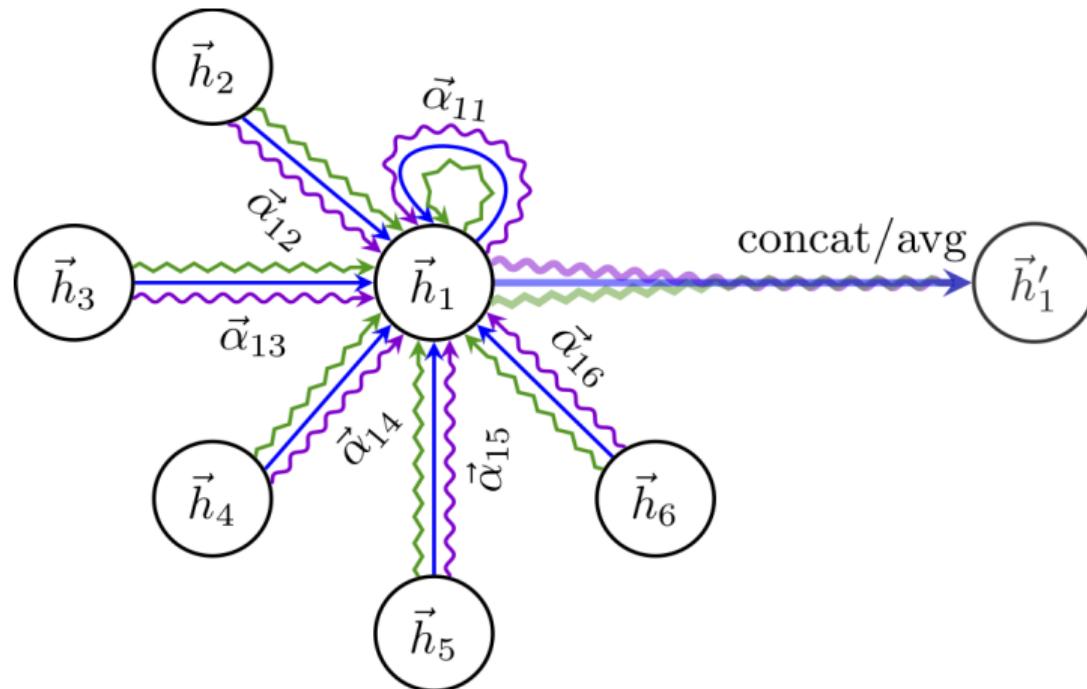
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Veličković et al. 2018

Improvements over previous methods

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- shared attention mechanism allows usage for **inductive** learning tasks
- previous inductive methods did not include all neighbors
- attention weights lead to more interpretability

Results using GATs

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- Classification of Brain Surface Areas (Cucurull *et al.*, 2018)
- Explainable Text Models (Rao *et al.*, 2021)

Brain Mesh Segmentation

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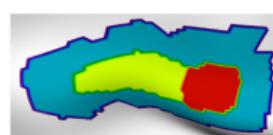
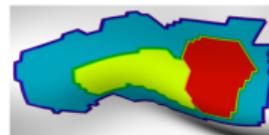
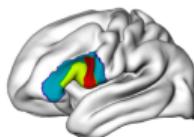
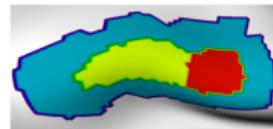
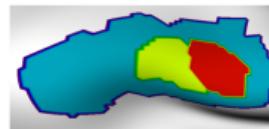
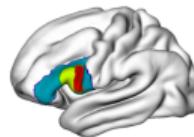
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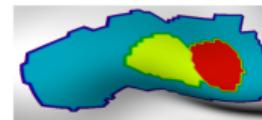
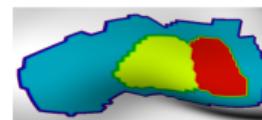
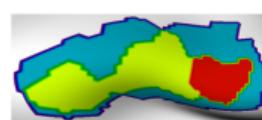
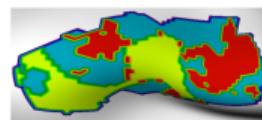
References



(a) Left hemisphere

(b) Ground truth

(c) NodeAVG



(d) NodeMLP

(e) Jakobsen et al. [21]

(f) GCN

(g) GAT

Cucurull *et al.* 2018

Explainable Text Visual Question Answering Models

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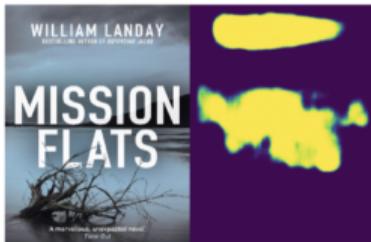
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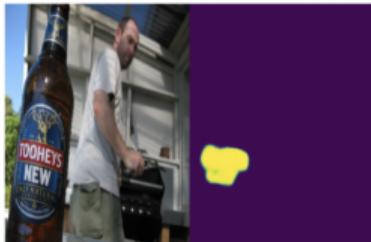
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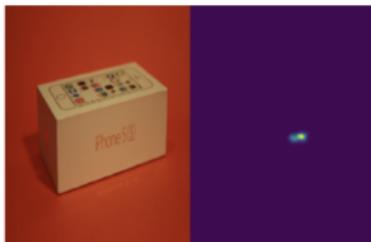
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Q: who wrote this?
A: william landay
Expl: william landay is printed on the book



Q: Is this a bottle of toohey's?
A: yes
Expl: yes the bottle says so



Q: What type of phone is this for?
A: iphone 5s
Expl: iphone 5 is printed on the box

Explainable Text Visual Question Answering Models

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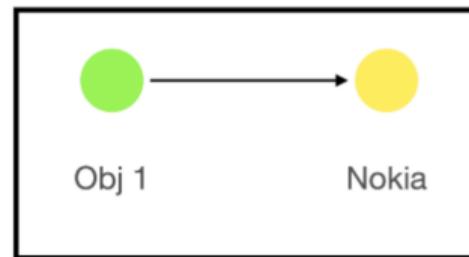
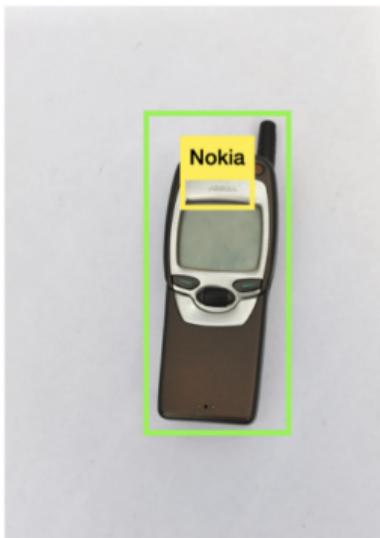


Figure 4: An example of how to build the graph

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Q: Who's light shines upon you?
A: love
Expl: it is written on the poster



Q: what does the glass say?
A: komatsu
Expl: it is written on the glass

Figure 6: Examples where the MTXNet model fails.

Related Work and Limitations

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- Benchmarking Graph Neural Networks (Dwivedi *et al.* 2020)
- Do we need deep graph neural networks? (Bronstein 2020)

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Cora and Citeseer are not large enough

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Table 6: Performance on the TU datasets with 10-fold cross validation (higher is better). Two runs of all the experiments using the same hyperparameters but different random seeds are shown separately to note the differences in ranking and variation for reproducibility. The top 3 performance scores are highlighted as **First**, **Second**, **Third**.

Dataset	Model	L	#Param	seed 1				seed 2			
				Test Acc. \pm s.d.	Train Acc. \pm s.d.	#Epoch	Epoch/Total	Test Acc. \pm s.d.	Train Acc. \pm s.d.	#Epoch	Epoch/Total
ENZYMES	MLP	4	101481	55.833 \pm 3.516	93.062 \pm 7.551	332.30	0.18s/0.17hr	53.833 \pm 4.717	87.854 \pm 10.765	327.80	0.19s/0.18hr
	GCN	4	103407	65.833 \pm 4.610	97.688 \pm 3.064	343.00	0.69s/0.67hr	64.833 \pm 7.089	93.042 \pm 4.982	334.30	0.74s/0.70hr
	GraphSage	4	105595	65.000 \pm 4.944	100.000 \pm 0.000	294.20	1.62s/1.34hr	68.167 \pm 5.449	100.000 \pm 0.000	287.30	1.76s/1.42hr
	MoNet	4	105307	63.000 \pm 8.090	95.229 \pm 5.864	333.70	0.53s/0.49hr	62.167 \pm 4.833	93.562 \pm 5.897	324.40	0.68s/0.62hr
	GAT	4	101274	68.500 \pm 5.241	100.000 \pm 0.000	299.30	0.70s/0.59hr	68.500 \pm 4.622	100.000 \pm 0.000	309.10	0.76s/0.66hr
	GatedGCN	4	103409	65.667 \pm 4.899	99.979 \pm 0.062	316.80	2.31s/2.05hr	70.000 \pm 4.944	99.979 \pm 0.062	313.20	2.63s/2.30hr
	GIN	4	104864	65.333 \pm 6.823	100.000 \pm 0.000	402.10	0.53s/0.61hr	67.667 \pm 5.831	100.000 \pm 0.000	404.90	0.60s/0.68hr
	RingGNN	2	103538	18.667 \pm 1.795	20.104 \pm 2.166	337.30	7.12s/6.71hr	45.333 \pm 4.522	56.792 \pm 6.081	497.50	8.05s/11.16hr
	3WLGNN	3	104658	61.000 \pm 6.799	98.875 \pm 1.571	381.80	9.22s/9.83hr	57.667 \pm 9.522	96.729 \pm 5.525	336.50	11.80s/11.09hr

Dwivedi *et al.* 2020

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different tasks favor different models

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Table 2: Benchmarking results for MP-GCNs and WL-GNNs across 7 medium-scale graph classification/regression and node/link prediction datasets. Results are averaged over 4 runs with 4 different seeds. **Red**: the best model, **Violet**: good models.

Model	L	NODE CLASSIFICATION						CLUSTER			
		#Param	Test Acc. \pm s.d.	PATTERN Train Acc. \pm s.d.	#Epoch	Epoch/Total	#Param	Test Acc. \pm s.d.	Train Acc. \pm s.d.	#Epoch	Epoch/Total
MLP	4	105263	50.519 \pm 0.000	50.487 \pm 0.014	42.25	8.95s/0.11hr	106015	20.973 \pm 0.004	20.938 \pm 0.002	42.25	5.83s/0.07hr
GCN	4	100923	63.880 \pm 0.074	65.126 \pm 0.135	105.00	118.85s/3.51hr	101655	53.445 \pm 2.029	54.041 \pm 2.197	70.00	65.72s/1.30hr
	16	500823	71.892 \pm 0.334	78.409 \pm 1.592	81.50	492.19s/11.31hr	501687	68.498 \pm 0.976	71.729 \pm 2.212	79.75	270.28s/6.08hr
	4	101739	50.516 \pm 0.001	50.473 \pm 0.014	43.75	93.41s/1.17hr	102187	50.454 \pm 0.145	54.374 \pm 0.203	64.00	53.56s/0.97hr
	16	502842	50.492 \pm 0.001	50.487 \pm 0.005	46.50	391.19s/5.19hr	503350	63.844 \pm 0.110	86.710 \pm 0.167	57.75	225.61s/3.70hr
MoNet	4	103775	85.482 \pm 0.037	85.569 \pm 0.044	89.75	35.71s/0.90hr	104227	58.064 \pm 0.131	58.454 \pm 0.183	76.25	24.29s/0.52hr
	16	511487	85.582 \pm 0.038	85.720 \pm 0.068	81.75	68.49s/1.58hr	511999	66.407 \pm 0.540	67.727 \pm 0.649	77.75	47.82s/1.05hr
GAT	4	109936	75.824 \pm 1.823	77.883 \pm 1.632	96.00	20.92s/0.57hr	110700	57.732 \pm 0.323	58.331 \pm 0.342	67.25	14.17s/0.27hr
	16	526990	78.271 \pm 0.186	90.212 \pm 0.476	53.50	50.33s/0.77hr	527874	70.587 \pm 0.447	76.074 \pm 1.362	73.50	35.94s/0.75hr
GatedGCN	4	104003	84.480 \pm 0.122	84.474 \pm 0.155	78.75	139.01s/3.09hr	104355	60.404 \pm 0.419	61.618 \pm 0.536	94.50	79.97s/2.13hr
	16	502223	85.568 \pm 0.088	86.007 \pm 0.123	65.25	644.71s/11.91hr	502615	73.840 \pm 0.326	87.880 \pm 0.908	60.00	400.07s/6.81hr
GatedGCN-PE	16	502457	86.508\pm0.085	86.801 \pm 0.133	65.75	647.94s/12.08hr	504253	76.082\pm0.196	88.919 \pm 0.720	57.75	399.66s/6.58hr

Dwivedi *et al.* 2020

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How far can we go with GATs?

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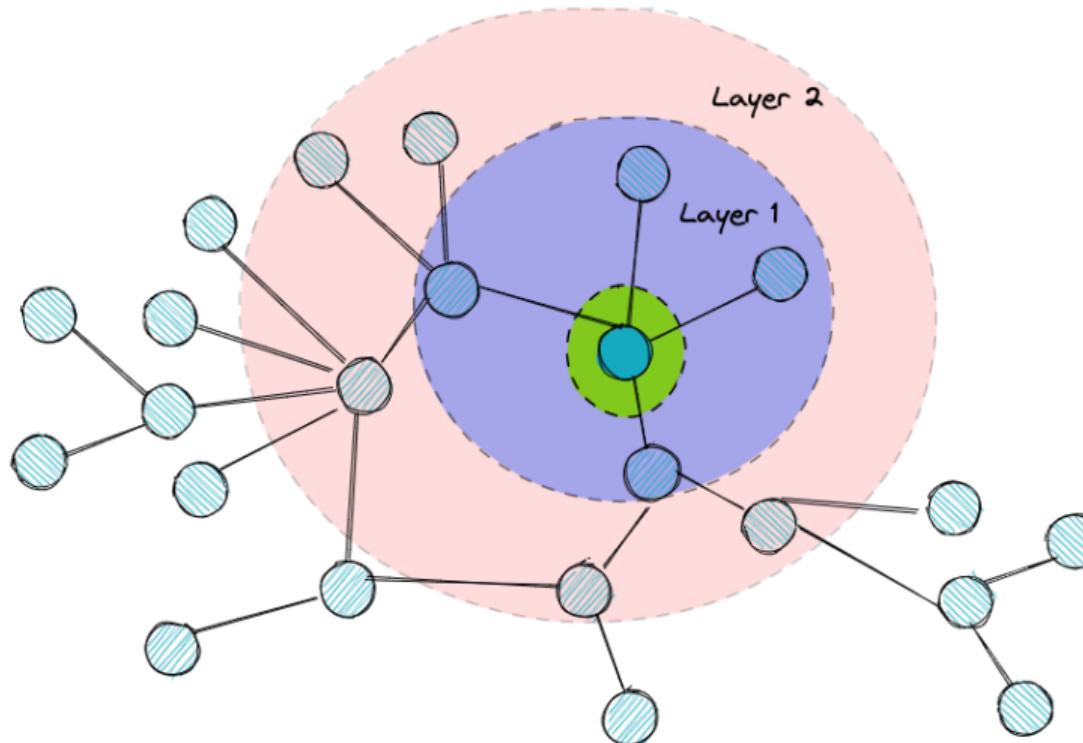
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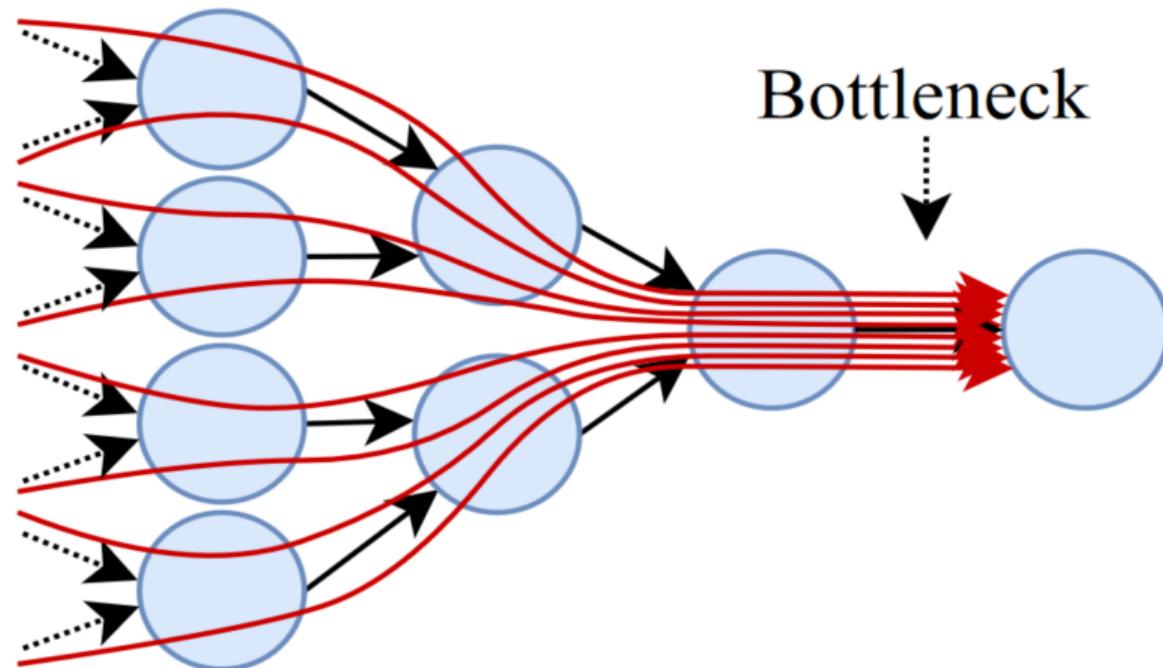
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Alon & Yahav 2021

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Veličković *et al.* 2018

Graph Attention Networks

arXiv 1710.10903

github.com/PetarV-/GAT



Cucurull *et al.* 2018

Convolutional neural networks for mesh-based parcellation of the cerebral cortex

MIDL 2018 Conference Submission

<https://openreview.net/forum?id=rkKvBAiiz>



Rao *et al.* 2021

A First Look: Towards Explainable TextVQA Models via Visual and Textual Explanations

arXiv 2105.02626

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Dwivedi *et al.* 2020

Benchmarking Graph Neural Networks

arXiv 2003.00982



Bronstein 2020

Do we need deep graph neural networks?

<https://towardsdatascience.com/do-we-need-deep-graph-neural-networks-be62d3ec5c59>



Alon & Yahav 2021

On the Bottleneck of Graph Neural Networks and its Practical Implications

arXiv 2006.05205