# Graph Metanetworks for Processing Diverse Neural Architectures

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## Metanetworks: Processing NN Weights

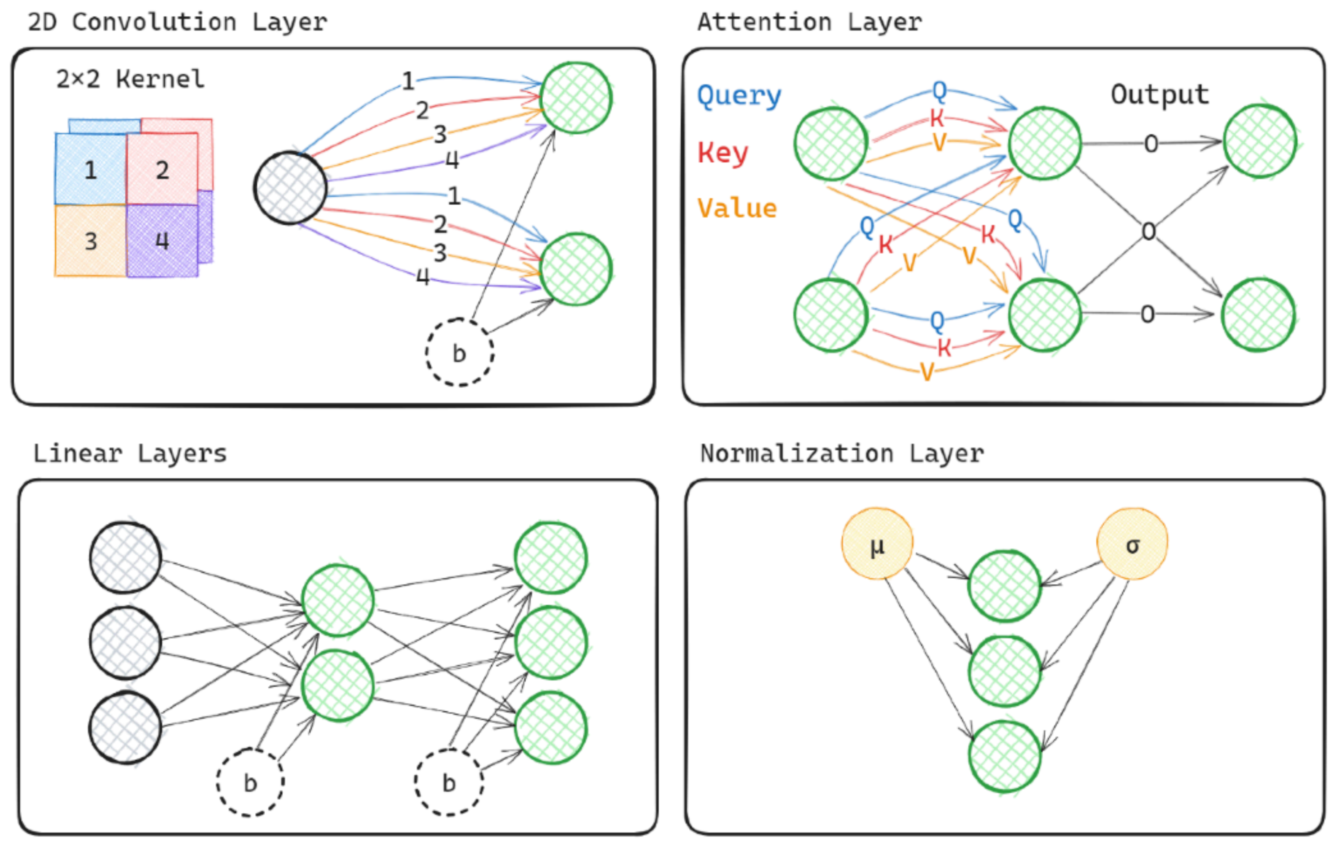
We develop new **metanetworks**: neural networks that take as input other neural networks' weights.

**Metanetwork Applications:**

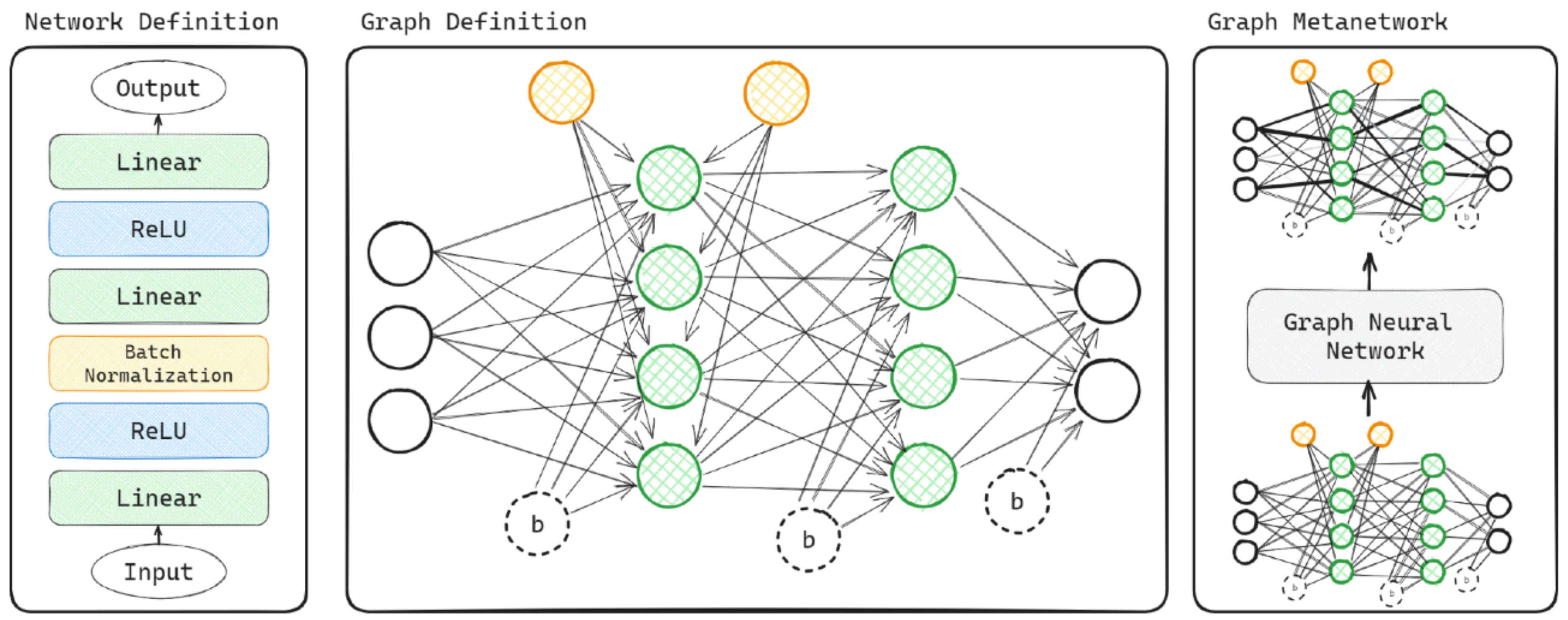
- Predicting generalization from weights
- Generating neural network weights
- Learned optimizers: $[\theta_t, \nabla_\theta L(\theta_t)] \mapsto \theta_{t+1}$
- Editing neural network weights

## Example Graph Constructions

One node per neuron / channel
One edge per parameter




## Our Graph Metanetworks (GMNs)

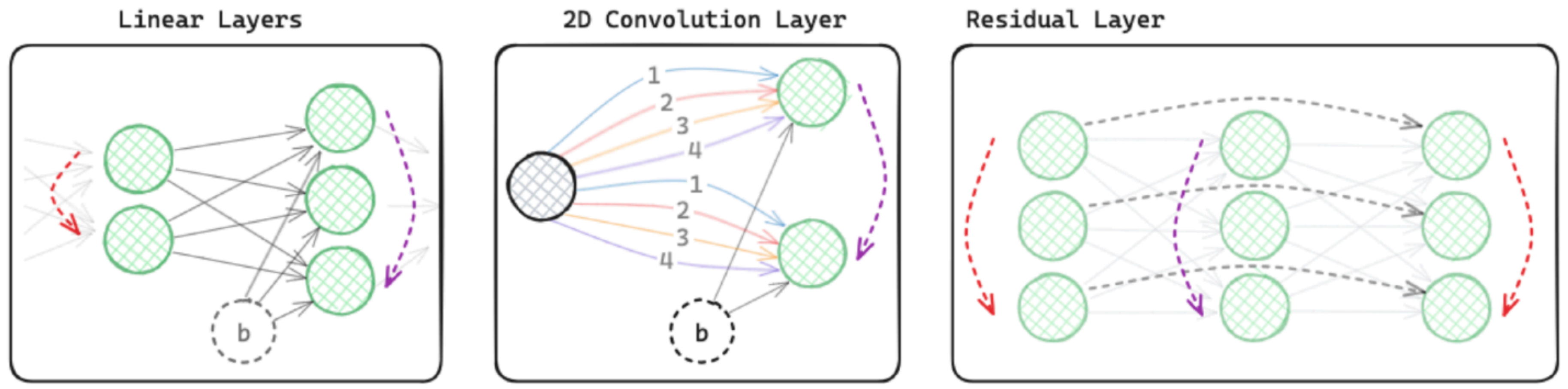



1. Convert input neural network to graph
2. Process with GNN / Graph Transformer

## Equivariance to Parameter Symmetries

**We prove:** any graph automorphism of the computation graph of an NN is a permutation parameter symmetry.

**GMNs are equivariant to permutation parameter symmetries** because GNNs are equivariant to graph automorphisms




## Expressivity

**GMNs can provably simulate:**

- Previous metanetworks: StatNN (Unterthiner et al. 2020) and NP-NFN (Zhou et al. 2023)
- Forward pass of input neural networks

## Experiments

- GMNs are SOTA metanets on several tasks
- Predicting CIFAR-10 test accuracy of diverse input image classifiers (CNNs, 1D CNNs, ResNets, ViTs, and DeepSets):

| | | Diverse Architectures | |
|---|---|---|---|
| | Metanet | $R^2$ | $\tau$ |
| 50% | DeepSets (Zaheer et al., 2017) | .562±.020 | .559±.011 |
| | DMC (Eilertsen et al., 2020) | .957±.009 | .883±.007 |
| | GMN (Ours) | **.975**±.002 | **.908**±.004 |
| 5% | DeepSets (Zaheer et al., 2017) | .126±.015 | .290±.010 |
| | DMC (Eilertsen et al., 2020) | .810±.046 | .758±.013 |
| | GMN (Ours) | **.918**±.002 | **.828**±.005 |
| OOD | DeepSets (Zaheer et al., 2017) | .128±.071 | .380±.014 |
| | DMC (Eilertsen et al., 2020) | −.134 ± .147 | .566±.055 |
| | GMN (Ours) | **.768**±.063 | **.780**±.030 |