# Dynamic Depth-Width Optimization for Capsule Graph Convolutional Network

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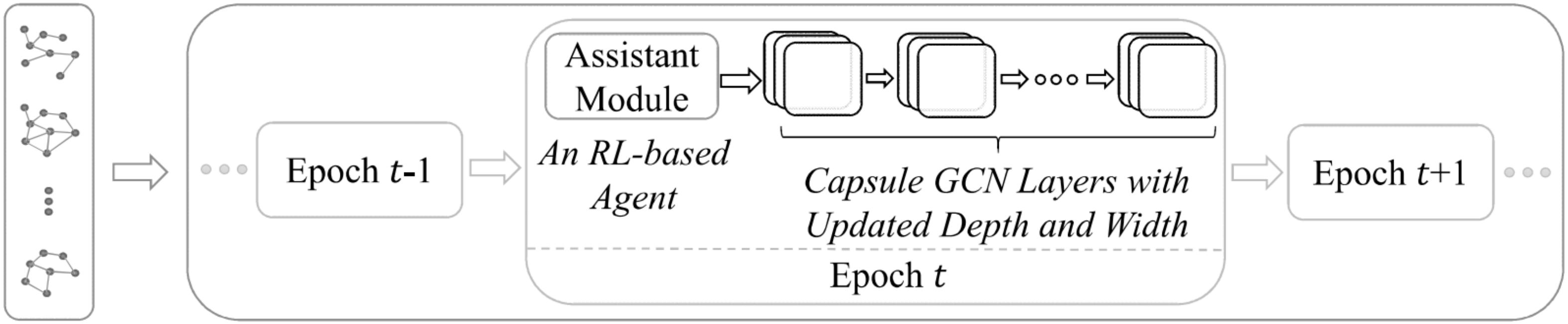
# Problems & Ideas

- Problems of classic Graph Convolutional Networks (GCNs):
  - Neglect the detailed mutual relations among different node features such as position, direction, and connection.
  - Use static model structures to conduct training, which inherently restricts their representation abilities on different datasets.
- Ideas: A capsule-based GCN model with the exploration of the optimal depth-width settings on different datasets is proposed, taking both search efficiency and accuracy results into account.




Architecure of the proposed method (dubbed DynaCGCN). The reinforcement learning (RL) based assistant module in DynaCGCN dynamically adjusts the depth and width of capsule graph convolutional layers.

# Main Contributions

- Contributions:
  - We design a reinforcement learning (RL) based assistant module to optimize the depth and width of capsule graph convolutional layers across sliding epoch windows;
  - We move the RL procedure into only one full training and choose one action (i.e., one alteration to depth and width) at one time in a sliding epoch window, rather than evaluating different candidate depth-width settings simultaneously.

| Model | MUTAG | ENZYMES | NCI1 | PROTEINS | IMDB-BINARY | IMDB-MULTI | COLLAB |
|---|---|---|---|---|---|---|---|
| **GK** | 81.58 ± 2.11 | 32.7 ± 1.20 | 62.49 ± 0.27 | 71.67 ± 0.55 | 65.87 ± 0.98 | 43.89 ± 0.38 | 72.84 ± 0.28 |
| **WL** | 82.05 ± 0.36 | 52.22 ± 1.26 | 82.19 ± 0.18 | 74.68 ± 0.49 | 73.40 ± 4.63 | 49.33 ± 4.75 | 79.02 ± 1.77 |
| **DGK** | 87.44 ± 2.72 | 53.43 ± 0.91 | 80.31 ± 0.46 | 75.68 ± 0.54 | 66.96 ± 0.56 | 44.55 ± 0.52 | 73.09 ± 0.25 |
| **AWE** | 87.87 ± 9.76 | 35.77 ± 5.93 | - | - | 74.45 ± 5.83 | 51.54 ± 3.61 | 73.93 ± 1.94 |
| **PSCN** | 88.95 ± 4.37 | - | 76.34 ± 1.68 | 75.00 ± 2.51 | 71.00 ± 2.29 | 45.23 ± 2.84 | 72.60 ± 2.15 |
| **DGCNN** | 85.83 ± 1.66 | 51.00 ± 7.29 | 74.44 ± 0.47 | 75.54 ± 0.94 | 70.03 ± 0.86 | 47.83 ± 0.85 | 73.36 ± 0.49 |
| **GIN** | **89.40 ± 5.60** | - | 82.70 ± 1.70 | 76.20 ± 2.80 | **75.10 ± 5.10** | **52.30 ± 2.80** | **80.20 ± 1.90** |
| **SOM-GCNN** | - | 50.01 ± 2.92 | 82.32 ± 0.52 | 75.22 ± 0.61 | - | - | - |
| **FGNN** | - | **65.17 ± 6.00** | 69.83 ± 2.20 | 75.75 ± 3.70 | 70.77 ± 5.00 | 49.09 ± 3.50 | 70.19 ± 1.50 |
| **GCAPS-CNN** | - | 61.83 ± 5.39 | **82.72 ± 2.38** | 76.40 ± 4.17 | 71.69 ± 3.40 | 48.50 ± 4.10 | 77.71 ± 2.51 |
| **CapsGNN** | 85.26 ± 5.43 | 53.27 ± 6.15 | 79.98 ± 1.69 | **77.59 ± 2.85** | 72.30 ± 4.57 | 50.27 ± 2.59 | 77.24 ± 2.79 |
| **DynaCGCN** | **91.76 ± 1.27** | **62.21 ± 2.78** | **83.27 ± 1.35** | **78.57 ± 1.83** | **77.18 ± 2.03** | **54.77 ± 1.98** | **82.63 ± 1.47** |

Test accuracies on four biochemical datasets and three social datasets. The bold values represent the methods with top-2 performance on each dataset..