Challenges of Generating Structurally Diverse Graphs



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Motivation

How to use diverse graphs?

- Analyze graph algorithms
- Evaluate heuristic/neural approximations of graph algorithms
- Evaluate GNNs and their expressive power
- Use as training data



Problem setup

What we want:

 Generate graphs with diverse structural properties

Why not sample graphs uniformly at random?

• They are similar



Joint distribution of graph characteristics of Erdős– Rényi models with parameter p = 0.5 (ER-0.5) and with uniformly-chosen p (ER-mix)

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- Each graph G_i has n nodes

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- Choose some graph distance $Dig(G_i,G_jig)$
- Define diversity as a function of all pairwise distances
- We use **Energy** as a measure of diversity:

$$-\frac{2}{N(N-1)}\sum_{i< j}\frac{1}{D(G_i, G_j)}$$

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• Why not, e.g., average distance? See the paper

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Greedy algorithm

Greedy algorithm

- Uses a large pre-generated set of different graphs, e.g., from random graph models
- Greedily selects graphs from this set to optimize diversity

- Greedy algorithm
- Genetic algorithm

Genetic algorithm

- Define crossover and mutation operations
- Select parent graphs and generate a child graph that inherits structural traits from its parents
- Update population with a new graph if this increases diversity
- Iterate the procedure

- Greedy algorithm
- Genetic algorithm
- Local optimization (LocalOpt)

LocalOpt algorithm

- Start with a sufficiently diverse set
- Iteratively modify each graph by making small random changes
- Accept the change if diversity increases
- Iterate the procedure

- Greedy algorithm
- Genetic algorithm
- Local optimization (LocalOpt)
- Iterative graph generative modeling (IGGM)

IGGM algorithm

- Train a generative model on a set of random graphs
- Use the model to produce a large set of candidate graphs
- Select a diverse subset from the generated set (e.g., via Greedy)
- Train a generative model on this more diverse set
- Repeat the procedure

- Greedy algorithm
- Genetic algorithm
- Local optimization (LocalOpt)
- Iterative graph generative modeling (IGGM)

The above approaches can be combined in different ways

Results

• Generated graphs have various structural patterns:



Results

• Graphs have more diverse combinations of characteristics than random graphs:



Open challenges

- Analysis of diversity measures
- Developing more scalable approaches
- Developing more sophisticated algorithms
- Conditioning on specific properties of graphs
- Applying diverse graphs in practice

Yandex Research

Thank you!

