# Generative Graph Pattern Machine

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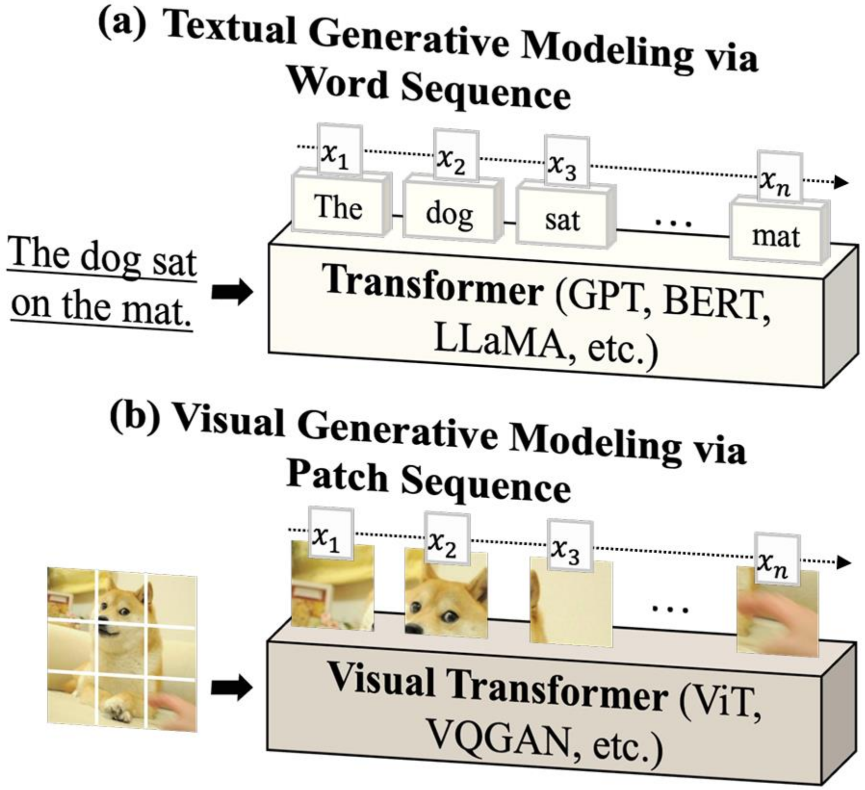
# What Are Vocabularies in Text and Image?

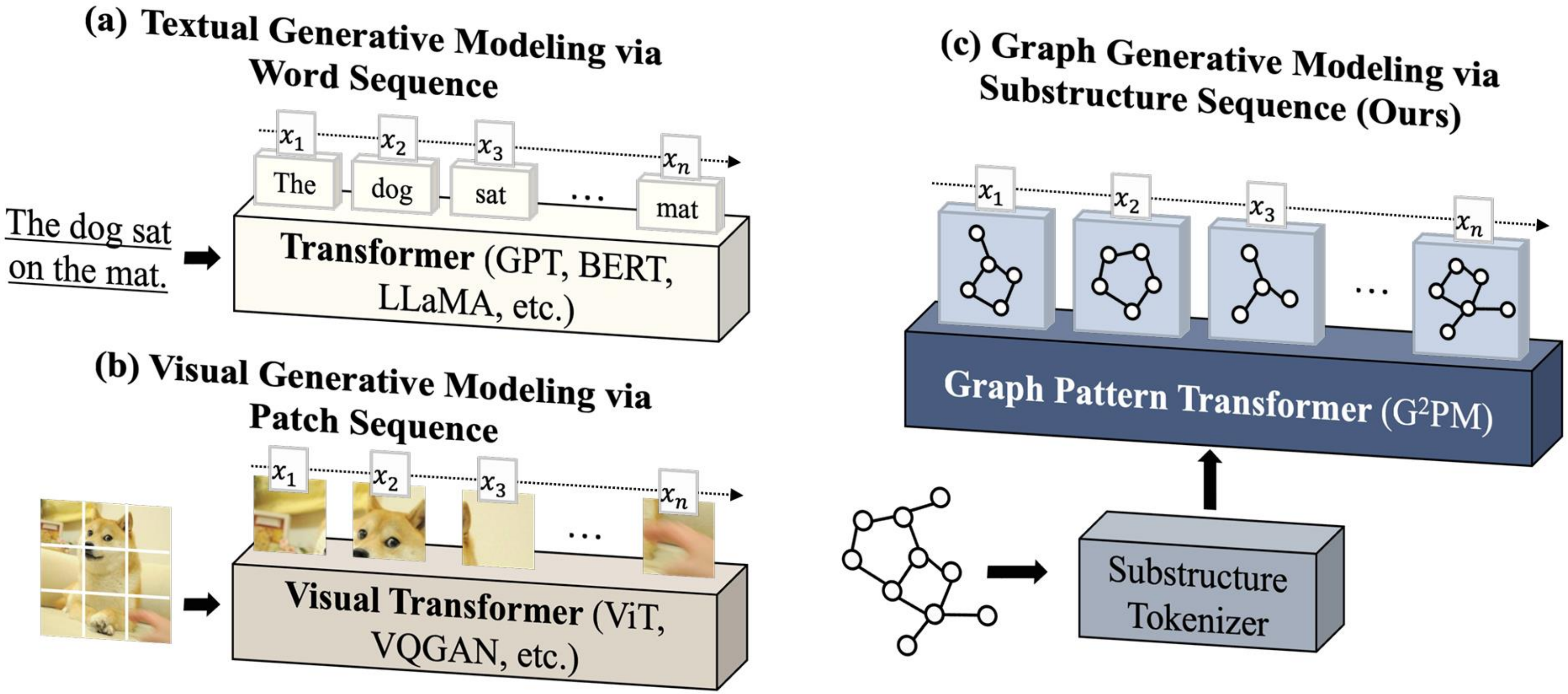
- Text vocabulary preserves textual tokens
- Image vocabulary preserves image concepts.




*Wang, Z., Zhang, Z., Ma, T., Chawla, N. V., Zhang, C., & Ye, Y. Beyond Message Passing: Neural Graph Pattern Machine. In Forty-second International Conference on Machine Learning.*

# Extending Vocabulary to Graphs

- **Graph vocabulary preserves substructure information.**
  - Social network: triangle structure, star-like structure
  - Molecule graph: ring-like structure, like benzene rings.

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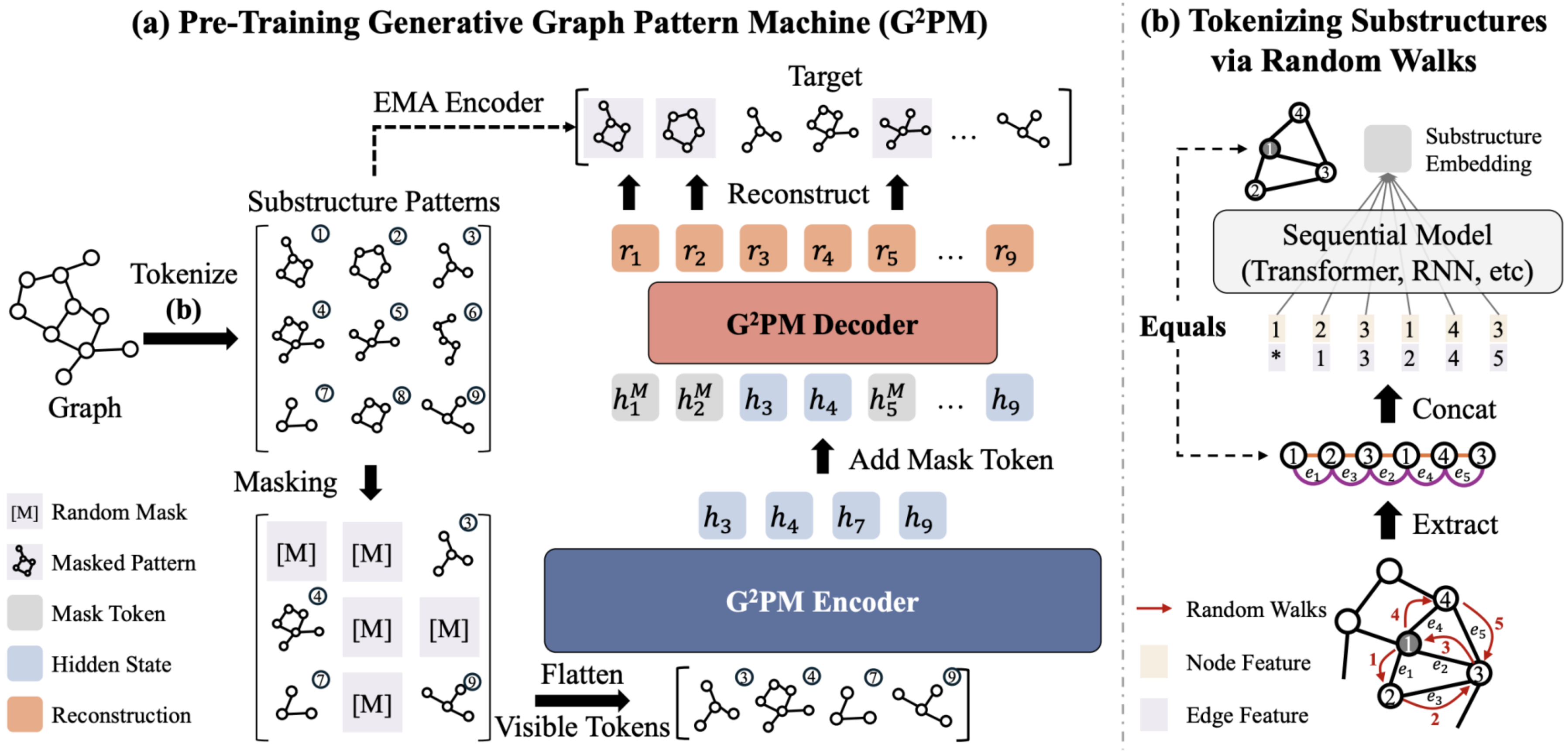
# Generative Graph Pattern Machine

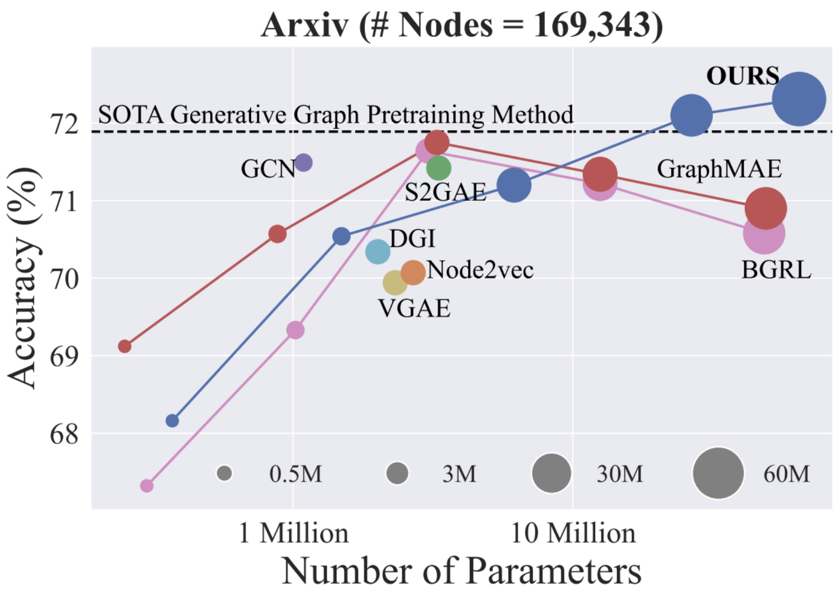
- **Learning from graph vocabularies**
  - Masked token prediction enables self-supervised learning.

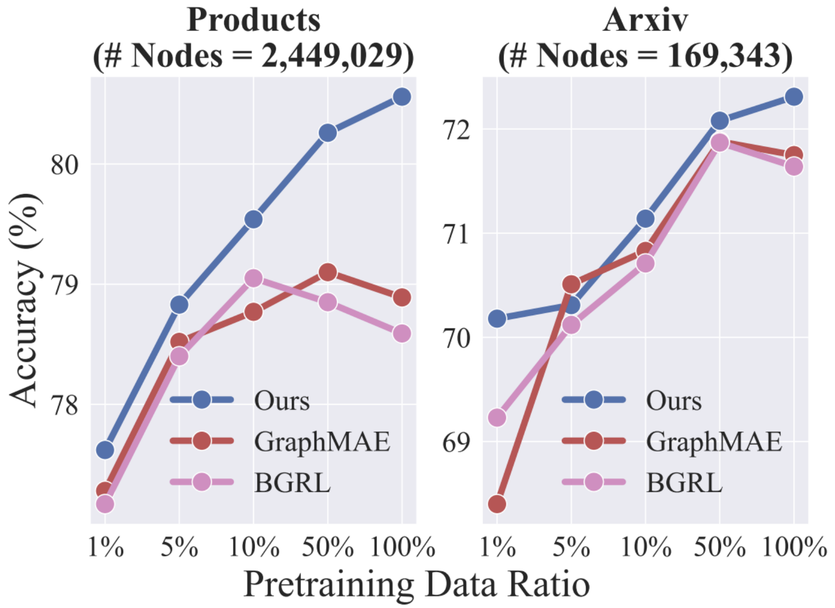



Wang, Z., Zhang, Z., Ma, T., Zhang, C., & Ye, Y. (2025). Scalable Graph Generative Modeling via Substructure Sequences. NeurIPS 25.

# Generative Graph Pattern Machine ($G^2PM$) [NeurIPS'25]

- **$G^2PM$ Enable Scalability on Graphs**
  - **Model Scaling**: $G^2PM$ achieves scalability up to 60M parameters, whereas existing methods saturate on 3M parameters.
  - **Data Scaling**: $G^2PM$ shows robust improvements with more training data, whereas existing methods peak at small data ratios.

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# Generative Graph Pattern Machine ($G^2PM$) [NeurIPS'25]

- $G^2PM$ Enable Scalability on Graphs
- **$G^2PM$ Enable Transferability Across Graphs**
  - Cross-domain transfer learning.
  - Cross-domain pre-training.

Table 4: **Cross-domain transferability** performance across diverse source and target datasets. Parentheses indicate the performance gap compared to training from scratch on the target graph.

| Source | Arxiv | | HIV | |
|---|---|---|---|---|
| **Target** | **Products** | **HIV** | **Arxiv** | **PCBA** |
| GNN [55, 68] | 78.3 (1.2 ↓) | 70.1 (5.7 ↓) | 71.1 (1.0 ↓) | 71.9 (**1.6 ↑**) |
| GPM [63] | 82.0 (0.6 ↓) | 74.3 (2.7 ↓) | 71.4 (1.5 ↓) | 76.4 (**1.3 ↑**) |
| BGRL [48] | 78.8 (**0.2 ↑**) | 72.5 (3.8 ↓) | 68.6 (1.9 ↓) | 72.9 (0.6 ↓) |
| GraphMAE [21] | 77.5 (1.4 ↓) | 74.7 (3.1 ↓) | 69.9 (1.9 ↓) | 73.4 (**0.2 ↑**) |
| $G^2PM$ | **81.3** (**0.7 ↑**) | **76.8** (1.9 ↓) | **72.6** (**0.3 ↑**) | **77.9** (**2.3 ↑**) |

Table 5: **Cross-domain pre-training** results on text-attributed graphs processed by [32], where node features are aligned via a textual encoder.

| **Pretrain** | **Arxiv + FB15K237 + ChemBL** | | |
|---|---|---|---|
| **Downstream** | **Arxiv (Academia)** | **FB15K237 (Knowledge Graph)** | **HIV (Molecule)** |
| BGRL [48] | 70.8 ± 0.2 | 86.5 ± 0.3 | 68.5 ± 1.6 |
| GraphMAE [21] | 70.3 ± 0.3 | 87.8 ± 0.4 | 64.1 ± 0.5 |
| OFA [32] | 71.4 ± 0.3 | 84.7 ± 1.3 | 72.0 ± 1.6 |
| GFT [60] | 71.9 ± 0.1 | **89.3 ± 0.2** | 72.3 ± 2.0 |
| $G^2PM$ | **72.5 ± 0.1** | 88.9 ± 0.5 | **74.1 ± 1.3** |

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