Graph Generative Models for Network Topology Design

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What is an Optical Network Topology?

Optical networks refer to **communication networks** that use optical fibers to transmit data as light signals. **Optical network topology design** refers to the **process of determining the physical layout** and connectivity of optical networks.

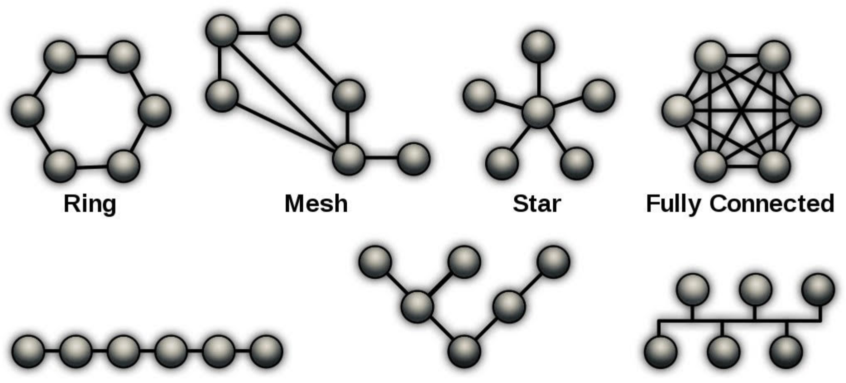


Figure 1. Types of Network Topologies (Source: Wikipedia).

Why do we need to automate network topology design?

- **Efficiency:** Reducing cost and time in designing the topology for core networks.
- **Optimisation:** Physical Topology Design affects metrics such as throughput, resilience and capacity.
- **Intelligence:** Extracting, reproducing and learning the patterns and intelligence of design
- **Scalability:** Potential to extend the existing topologies with automation on graphs.

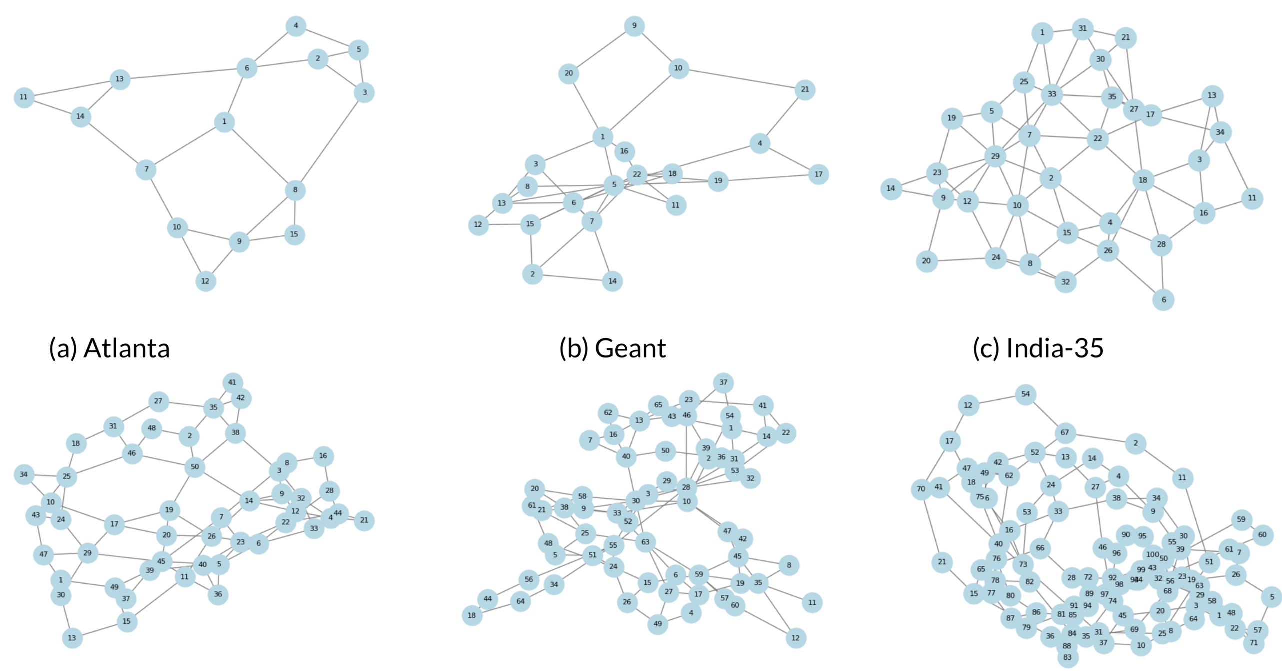
(a) BT Europe (b) BT North America

Figure 2. Backbone Networks (Source: Internet Topology Zoo (ITZ).

State of the Art: Designing a Network Topology

Optical Network Topology as a Graph:

- **Topology as a Graph:** Core network for long-haul data transmission is represented as a graph.
- **Nodes:** Nodes are network elements (Optical Add-Drop Multiplexer, Optical Cross-Connect, Optical Transport System, Optical Switch, Optical Router) at specific geo-locations.
- **Edges:** Edges represent fiber-optic links between nodes and are established using fiber cables that contain multiple fiber strands, with each strand capable of carrying different wavelength channels (Wavelength Division Multiplexing (WDM))



(a) Atlanta (b) Geant (c) India-35
(d) Germany-50 (e) TA2 (f) CORONET-GLOBAL

Figure 3. Real World Core Optical Network Topologies from SNDLib [[3]]

State of the Art: Optical Network Topology Design

- **Topology Design Based on Industrial Approach:** Factors influencing design choices can be:
  - **Requirement-Based:** Traffic Distribution, Fiber Placement Location, Scale/Type of Network, Network Survivability
  - **External:** Budget, Economic Feasibility, Geographic Terrain, Population, Political Factors, Existing Structural, Plumbing, Transportation, Electrical Infrastructure.
- **Research on Automated Topology Generation:** The layout of computer networks do not adhere to any generalised model [2].
  - **Probabilistic Graph Generative Models** Barabasi–Albert (BA), Erdos–Renyi (ER), Watts-Strogatz (WS), Gabriel Graphs (GG), Waxman Models (WX), Signal to Noise Barabasi–Albert (SNR-BA) [3]
  - **Deep Learning Based Approaches** Generative Adversarial Networks (GANs) [1].

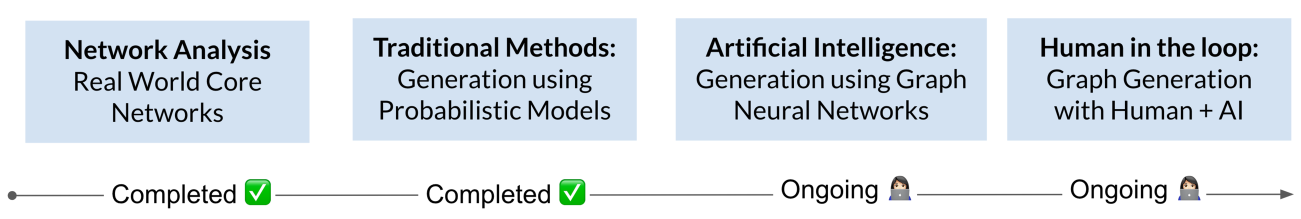


Figure 4. Research Objectives and Processes

References

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The internet topology zoo.
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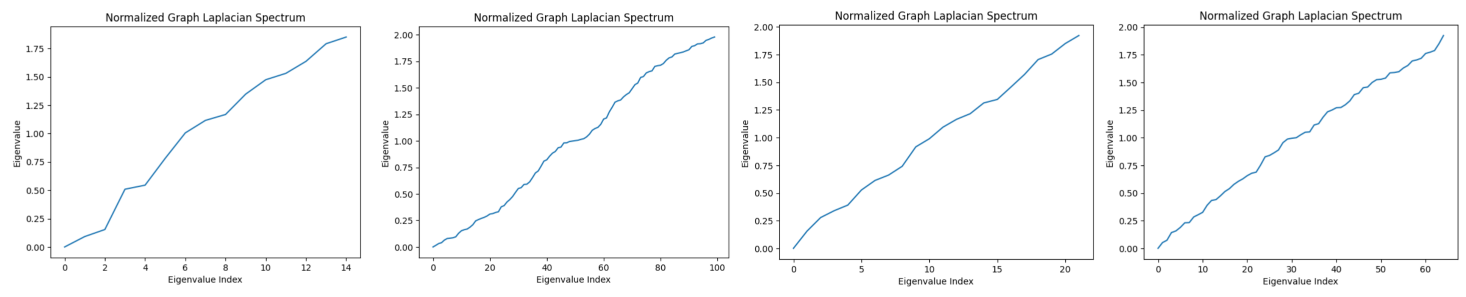
What are the properties of real-world core optical networks?

Results: We analysed 24 real world core networks and found the **range of average node degree to be between 4.572 to 2.400 with an average of 3.249** [3].

Metric	Min	Max	Average	Std. Dev
Number of Nodes	12	100	37.7917	22.1163
Number of Edges	15	136	60.5417	31.7914
Density	0.0275	0.2727	0.1236	0.0692
Graph Diameter	3	17	8.0833	3.8098
Graph Radius	2	9	4.6667	1.9927
Average Shortest Path Length	2.1364	6.6741	3.6625	1.3648
Average Node Degree	**2.4**	**4.5714**	**3.27108**	**0.6446**
Average Clustering Coefficient	0	0.5582	0.19152	0.1733
Transitivity	0	0.375	0.1661	0.138
Assortativity Coefficient	-0.377	0.3209	-0.0015	0.1768
Algebraic Connectivity	0.194	68.6863	15.486	20.2107
Spectral Radius	11.8161	843.9364	317.4452	346.2178
Modularity	0.0715	0.5253	0.3738	0.1284
Leading Eigenvalue	23.3289	2289.7727	694.6322	774.823

Table 1. Graph Metrics of Real World Core Networks

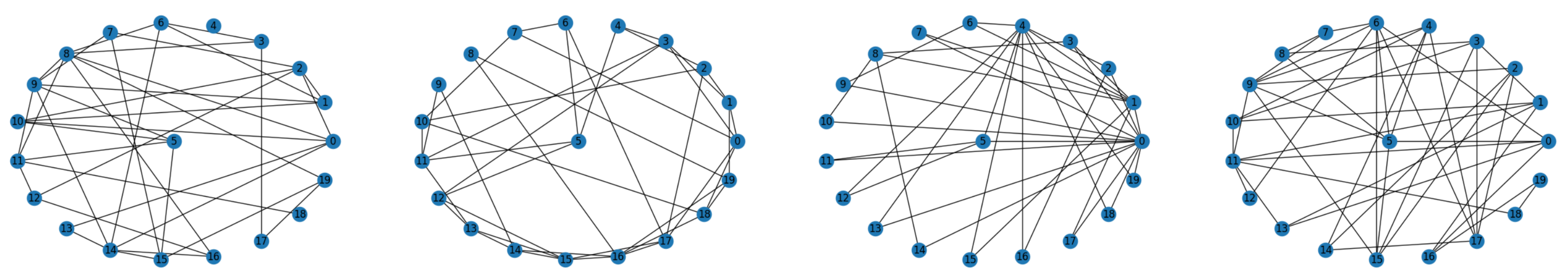


(a) Atlanta (b) CORONET-GLOBAL (c) Germany-50 (d) TA2

Figure 5. Normalised Graph Laplacian Spectrum of Real World Core Networks

Can we Automate Network Design using Generative Probabilistic Models?

We employ **ER (Erdős-Rényi), BA (Barabási-Albert), WS (Watts-Strogatz), and WX (Waxman) models.**

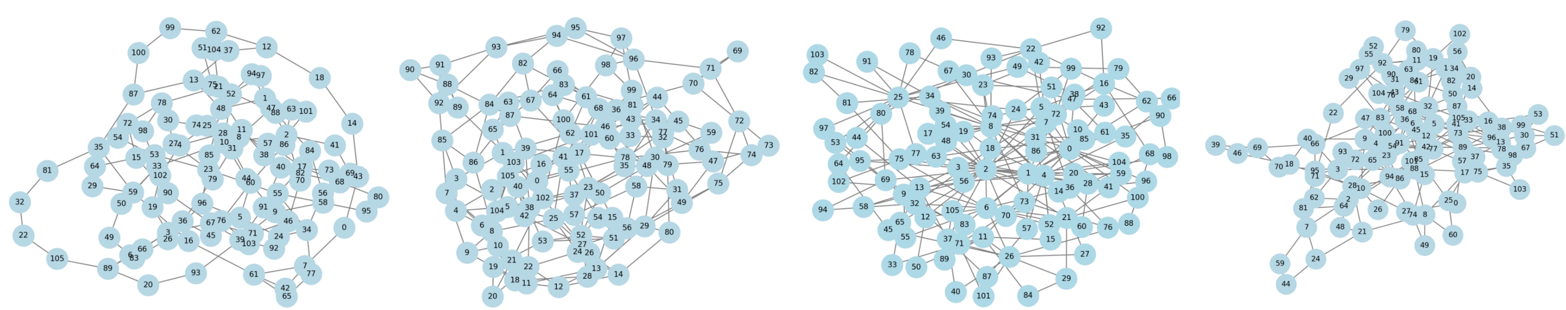


(a) Erdős-Rényi Graph (b) Watts Strogatz Graph (c) Barabási–Albert Graph (d) Waxman Model Graph

Figure 6. Graphs Generated Traditional Generative Models With 20 Nodes (No Constraints)

Metric	ER Model	WS Model	BA Model	WX Model
Number of Nodes	20	20	20	20
Number of Edges	37	40	36	43
Average Node Degree	**3.7**	**4.0**	**3.6**	**4.3**
Average Clustering Coefficient	0.153	0.173	0.409	0.237

Table 2. Network Analysis of Generated Graphs - 20 Nodes

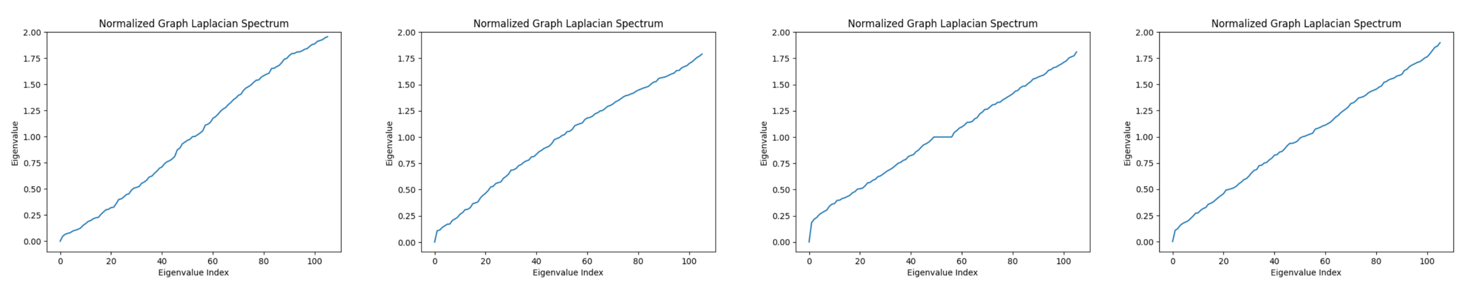


(a) Erdős-Rényi Graph (b) Watts Strogatz Graph (c) Barabási–Albert Graph (d) Waxman Model Graph

Figure 7. Graphs Generated Traditional Generative Models With 106 nodes (Min Node Degree = 2)

Metric	ER Model	WS Model	BA Model	WX Model
Number of Nodes	106	106	106	106
Number of Edges	141	212	208	200
Average Node Degree	**2.7**	**4**	**3.9**	**3.77**
Average Clustering Coefficient	0.014	0.184	0.125	0.095

Table 3. Network Analysis of Generated Graphs - 106 Nodes



(a) ER-106 (b) WS-106 (c) BA-106 (d) WX-106

Figure 8. Normalised Graph Laplacian Spectrum of Generated Graphs with 106 nodes (Min Node Degree = 2)

Summary

- **Simulation of Core Networks:** Constrained and Unconstrained ER, BA, WS, WX models
- **Graph Similarity:** Comparison of Network and Spectral Metrics among Real & Generated graphs.
- **Limitations:** We can only optimise for one graph metric at a time and cannot employ multiple objectives or constraints. The model is not learning from existing network topologies and cannot use node or edge features. Computation of optimal parameters can be expensive.
- **Next: Graph Autoencoders and Variational Autoencoders** are specifically designed for graph structured data. They encode the graph structure into a low-dimensional latent space and learn to reconstruct the original graph

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