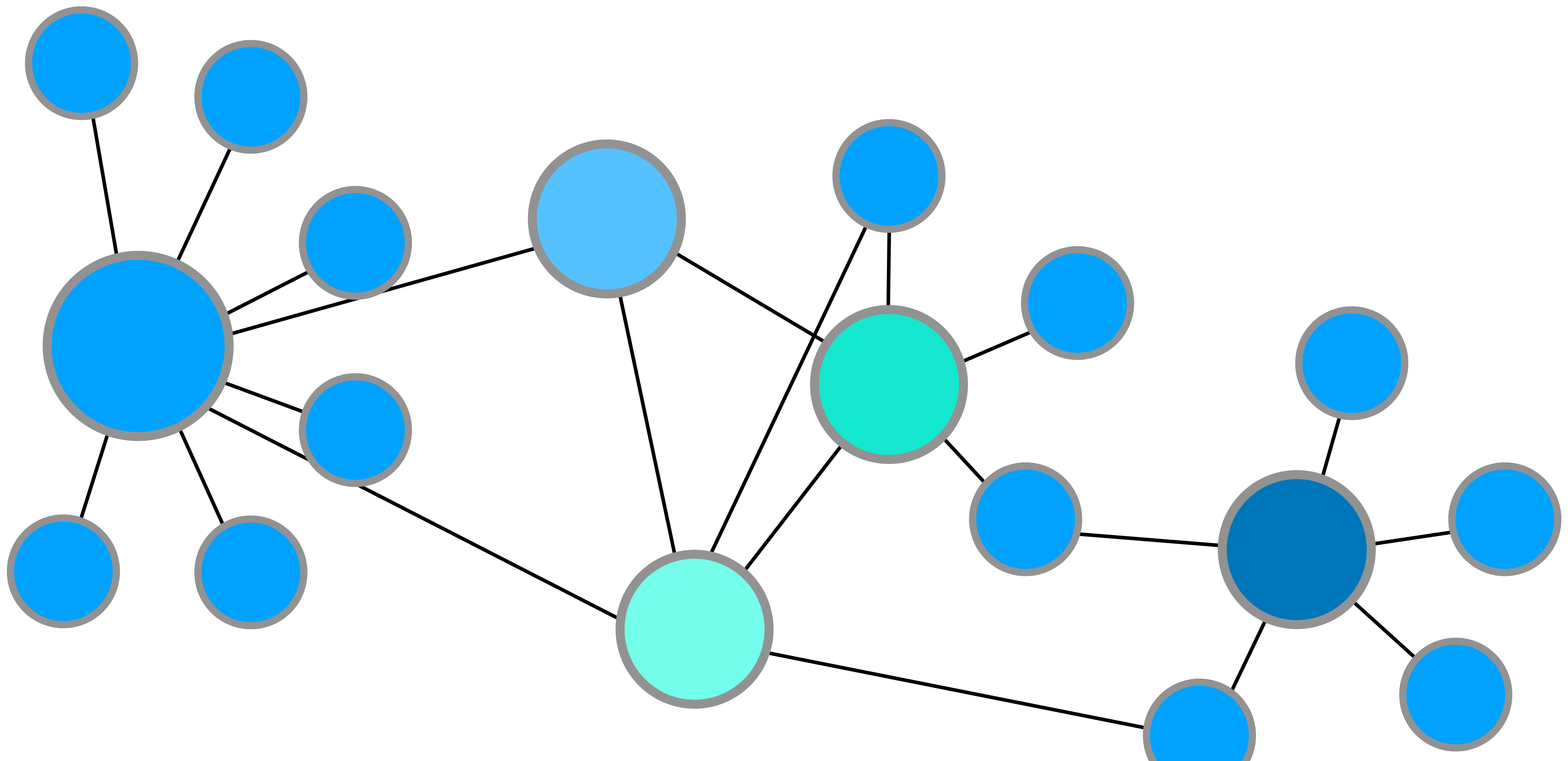
Uncovering network evolution mechanisms using temporal data

Naomi Arnold, Raul Mondragon, Richard Clegg



Models for network topology

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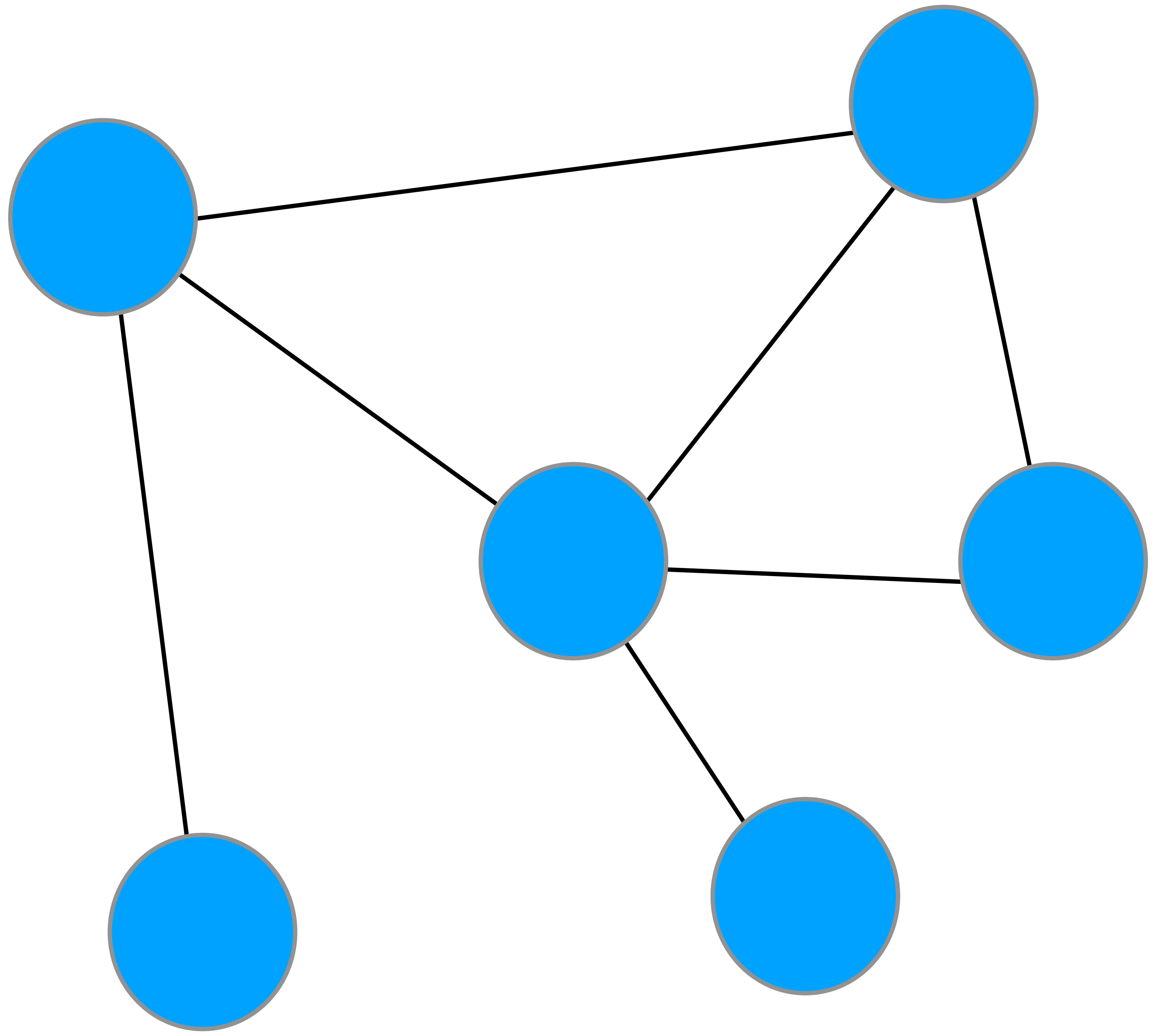

Static Models

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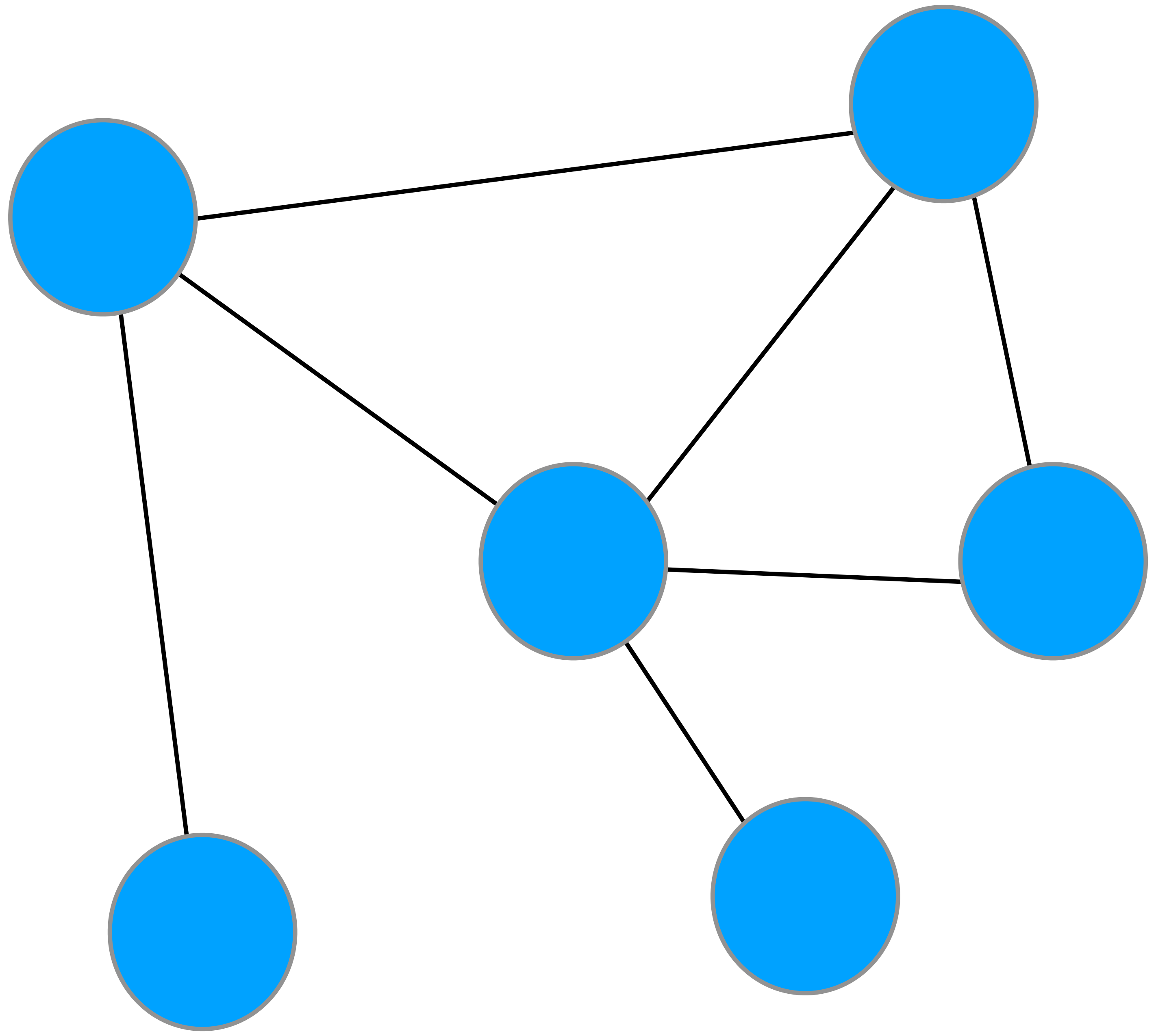

Static Models **Dynamic Models**

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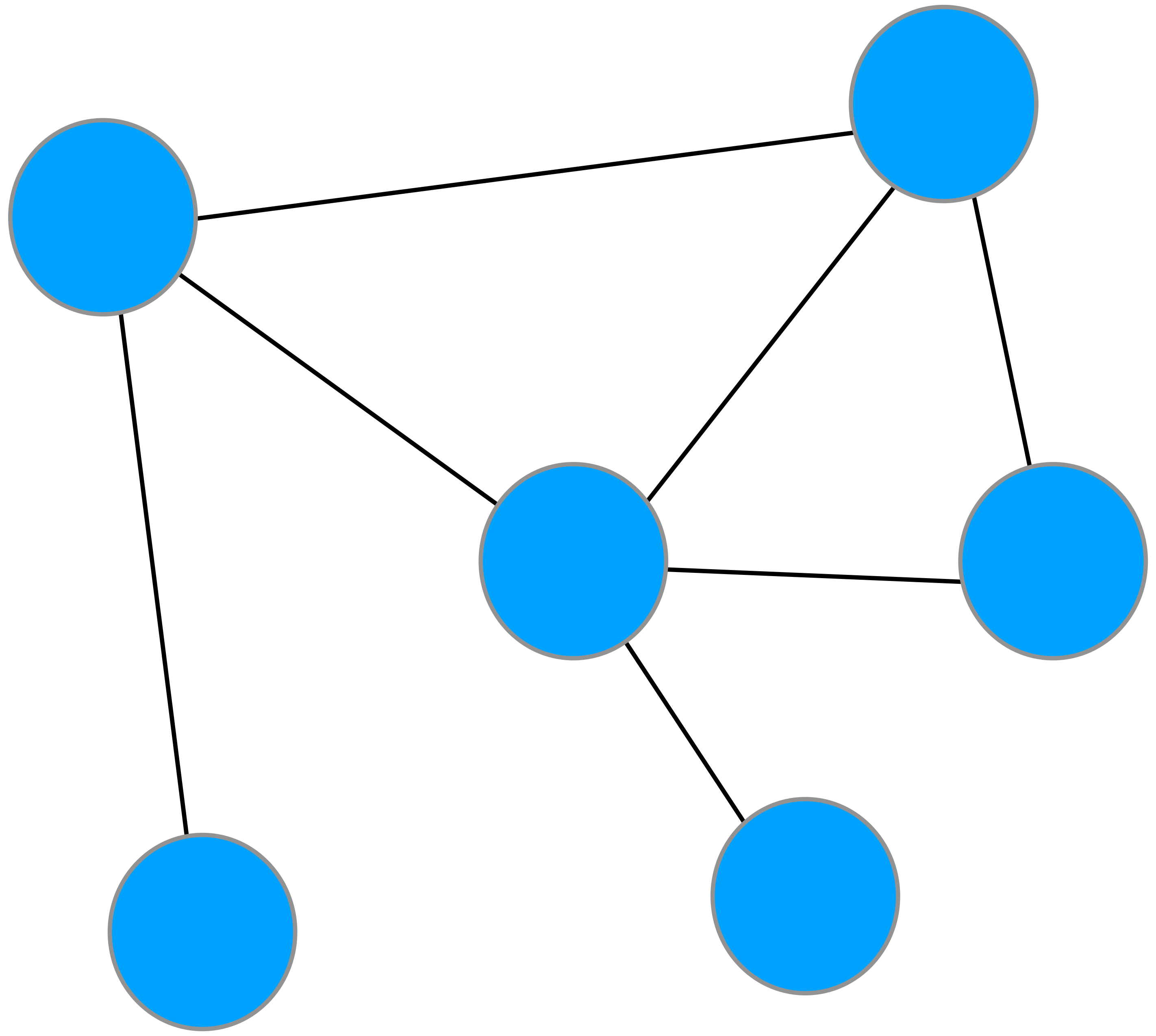

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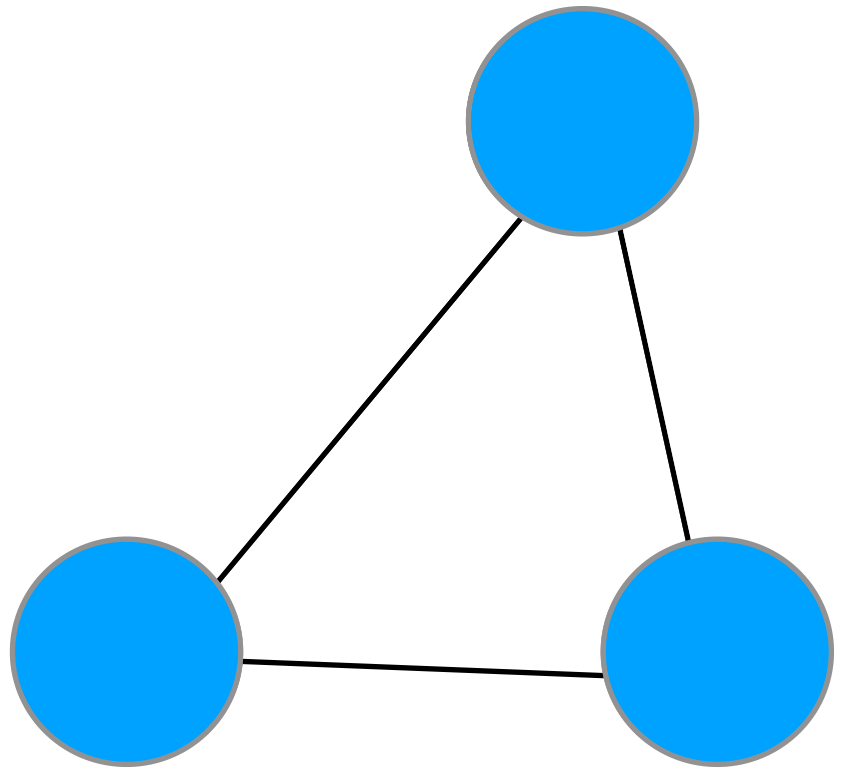

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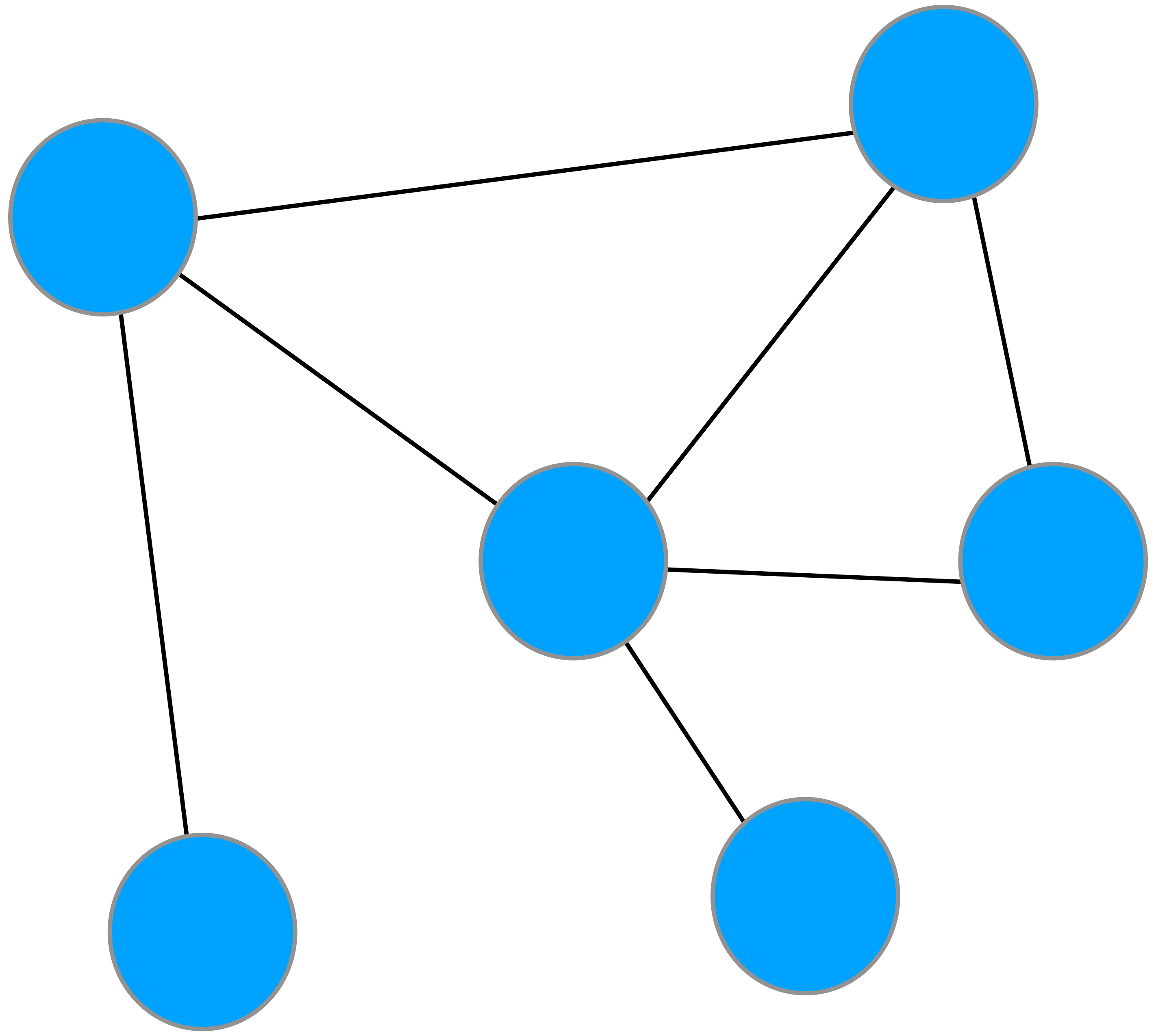

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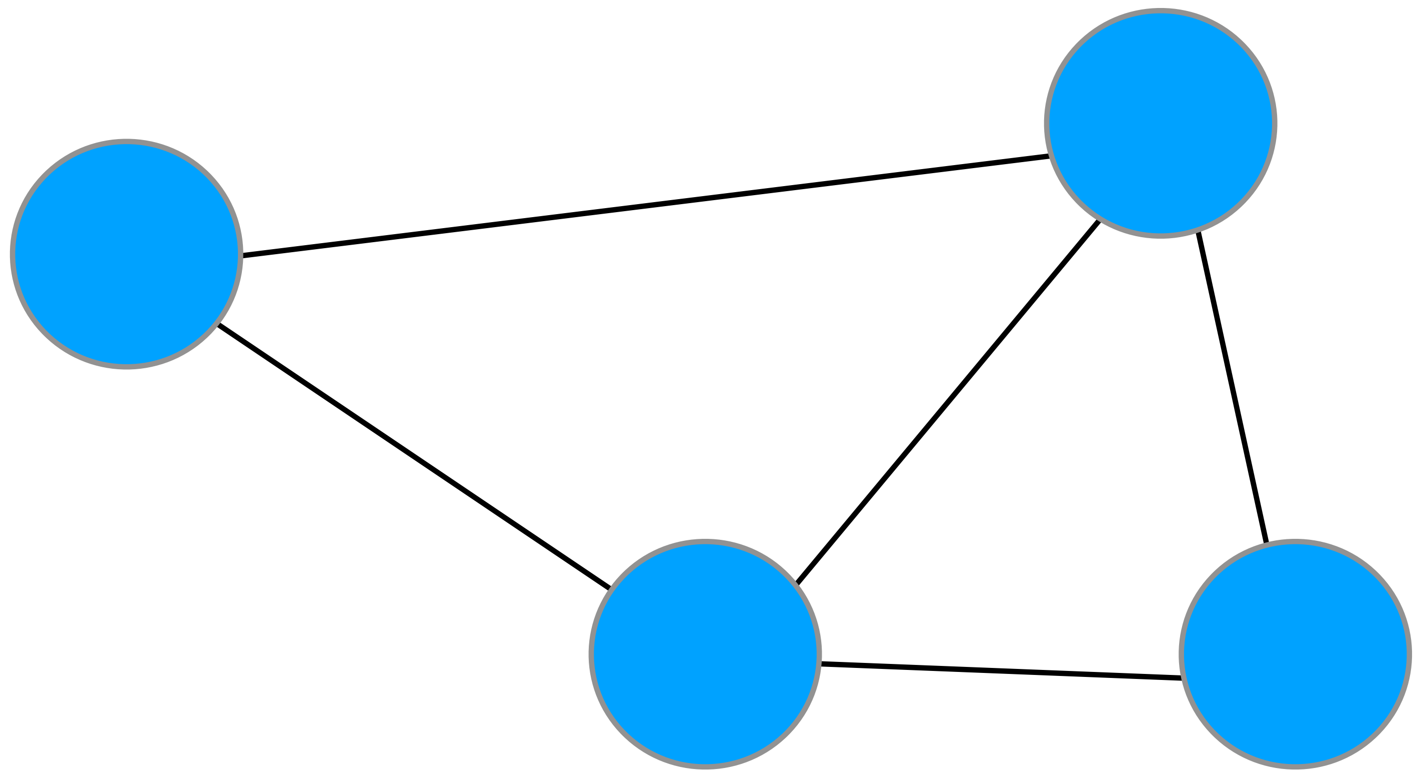

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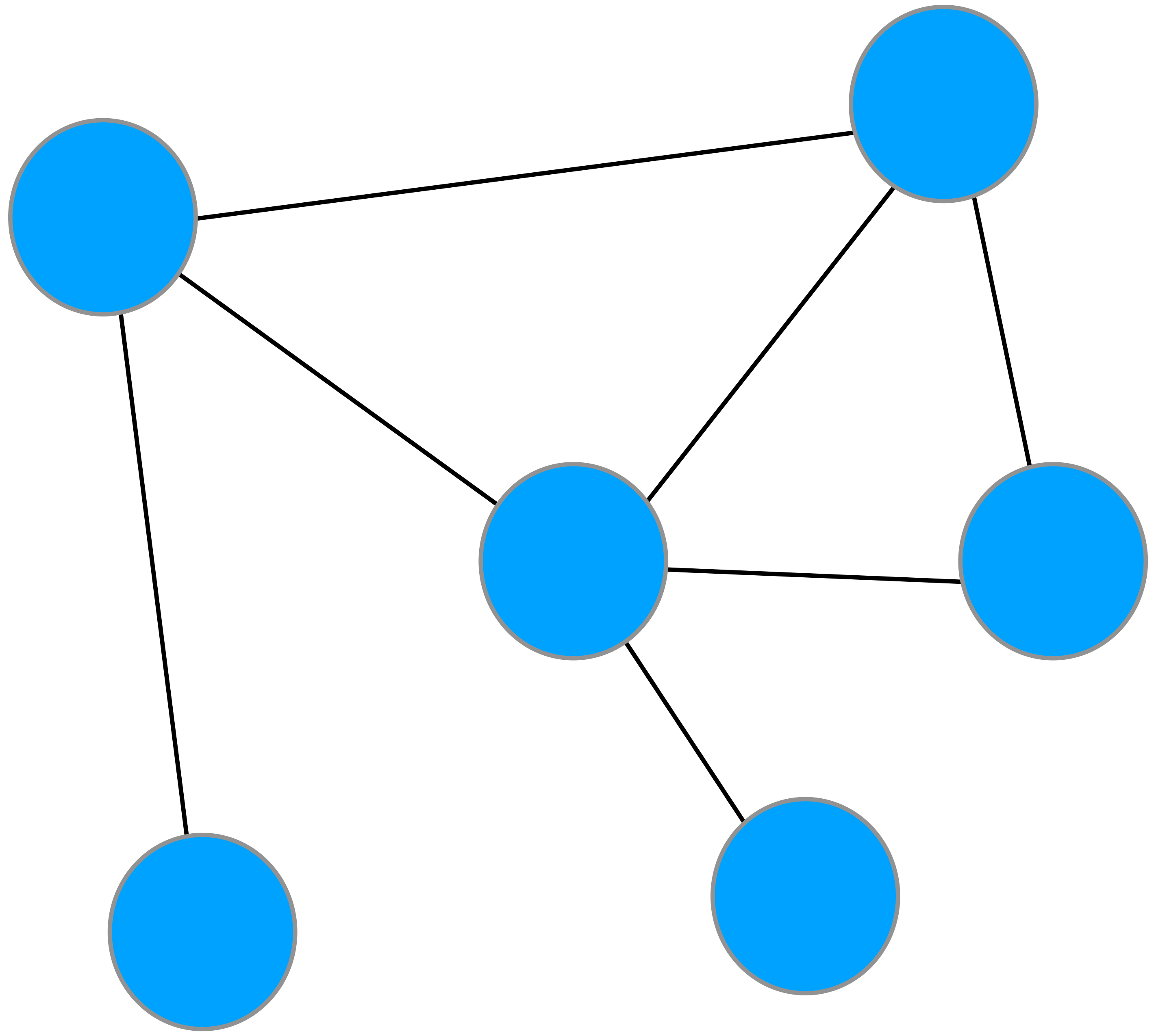

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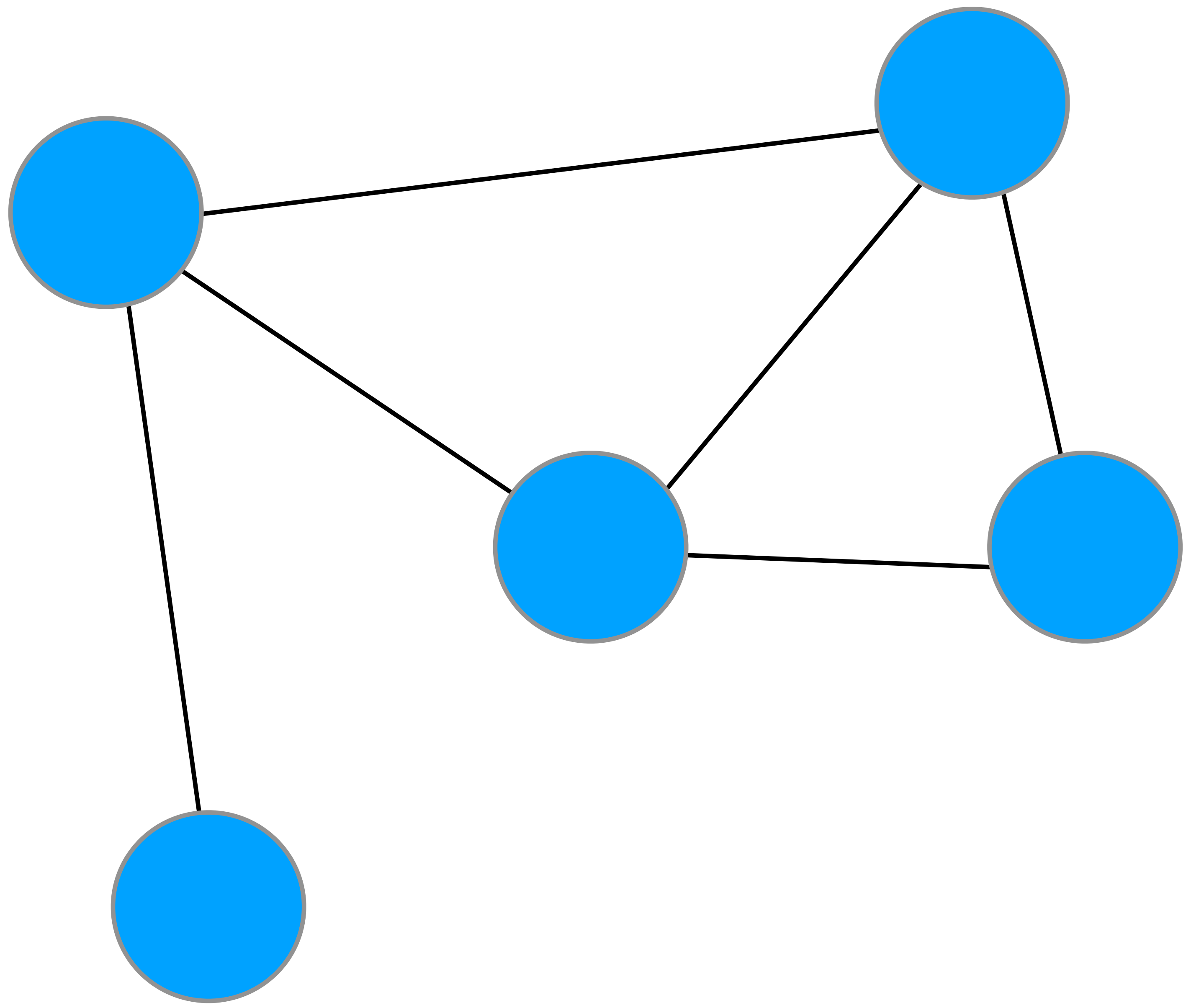

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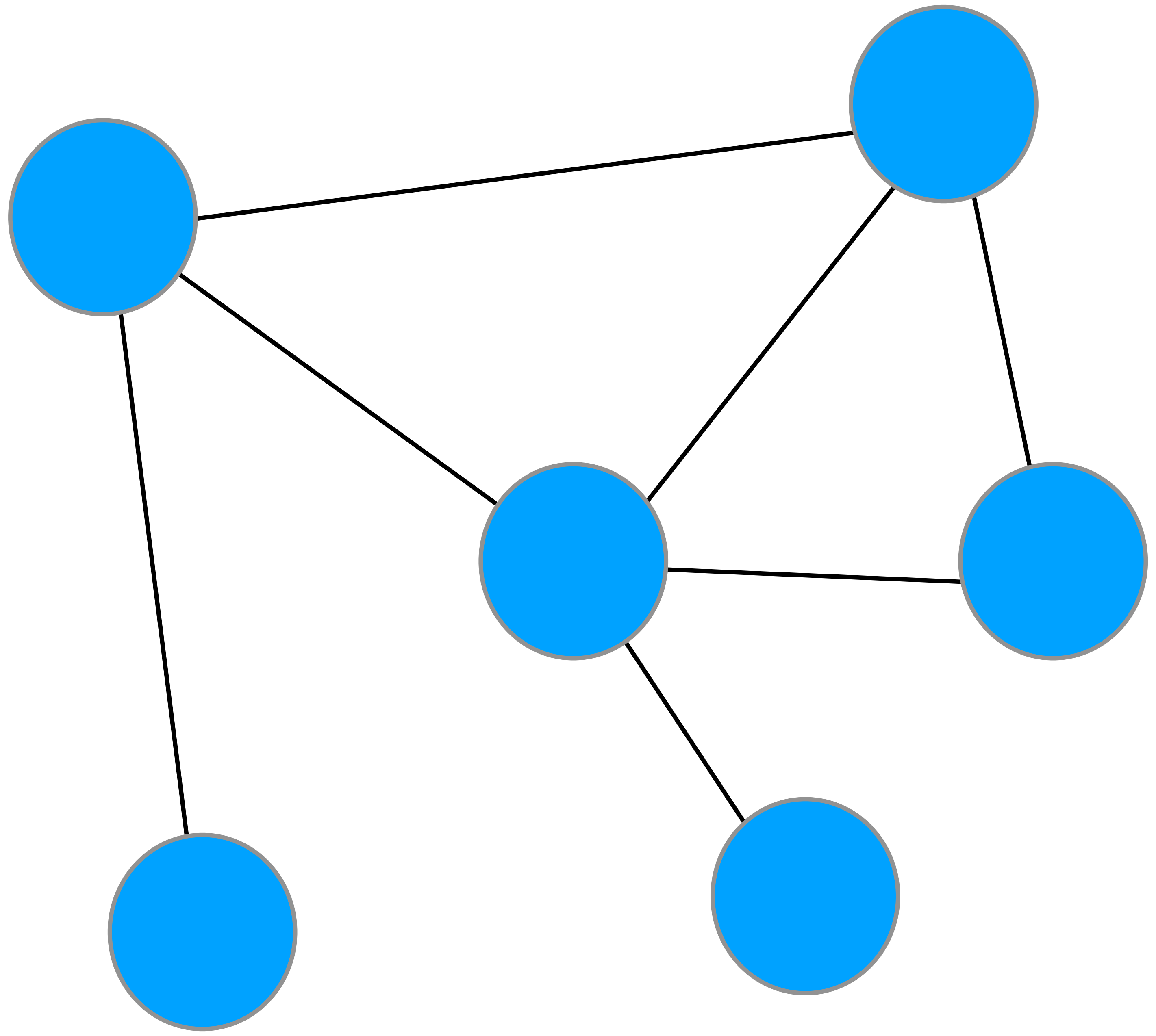

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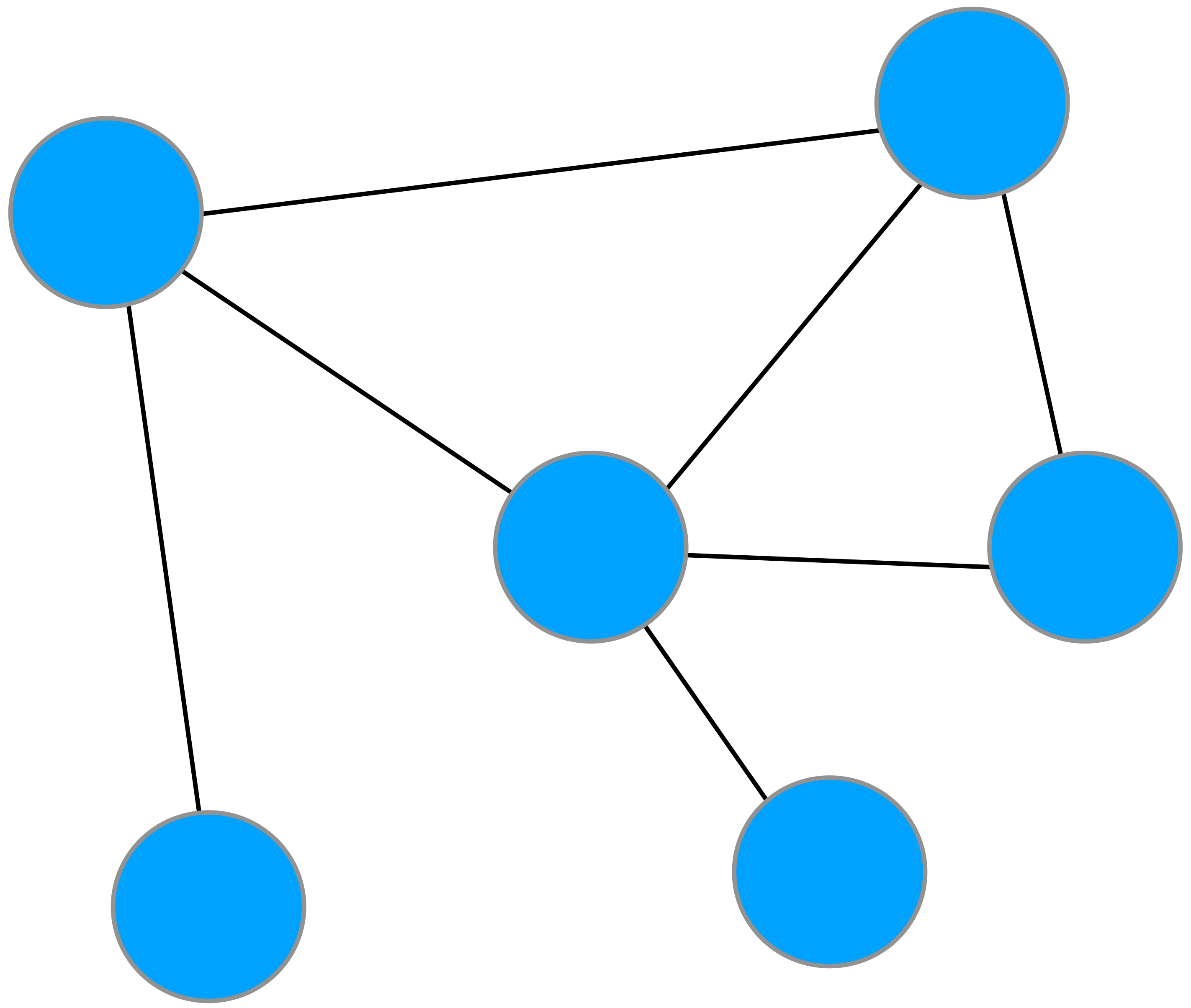

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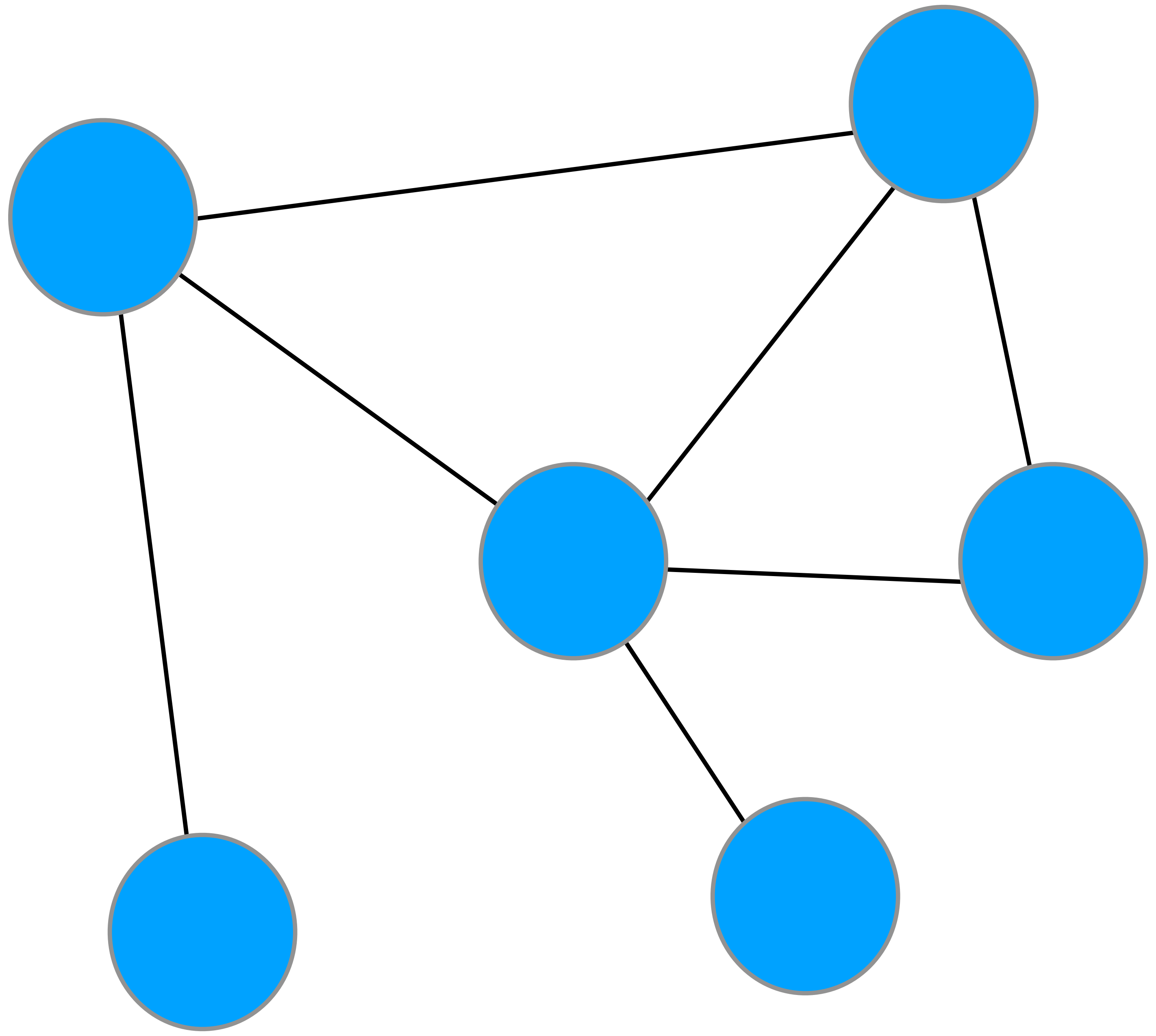

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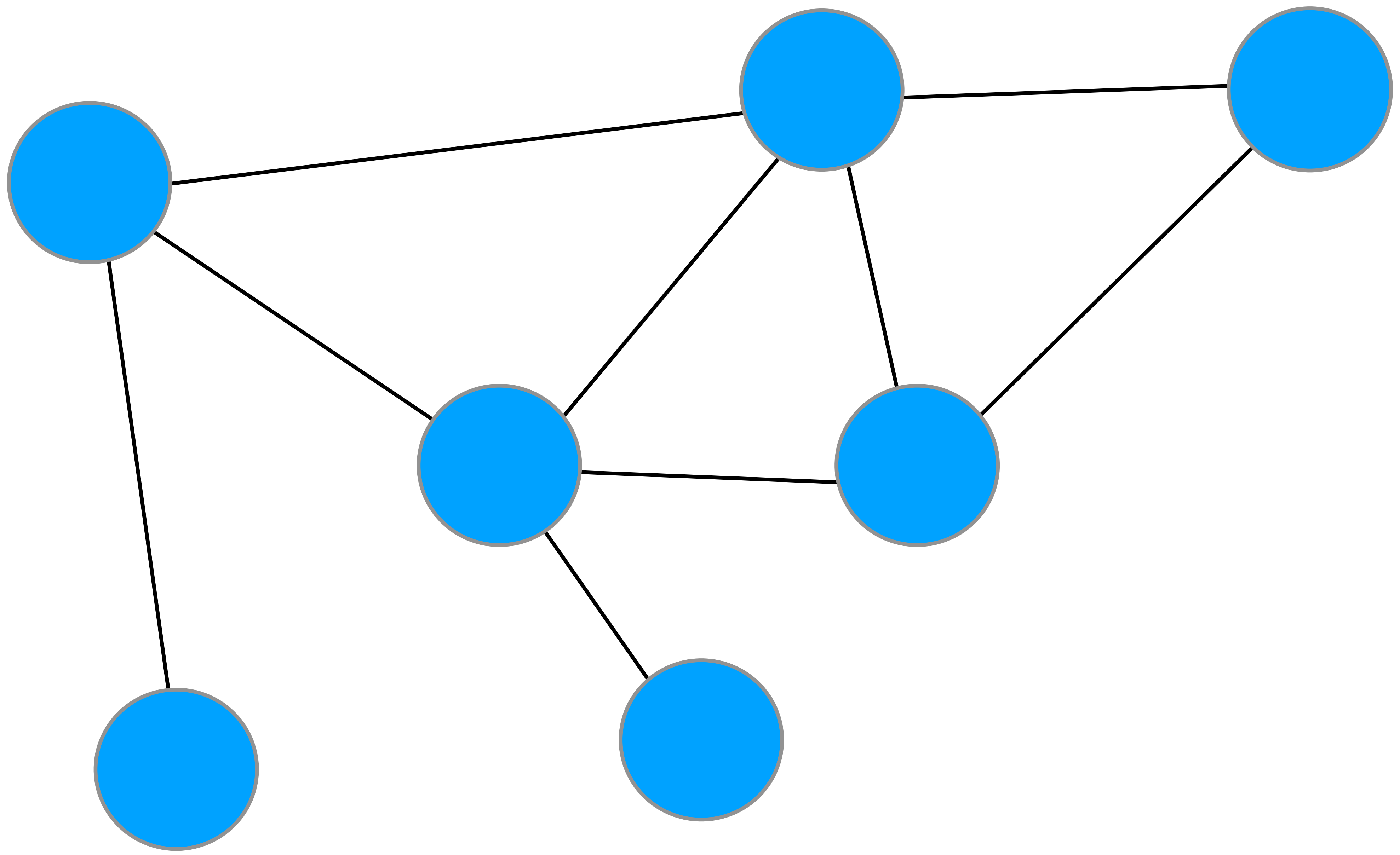

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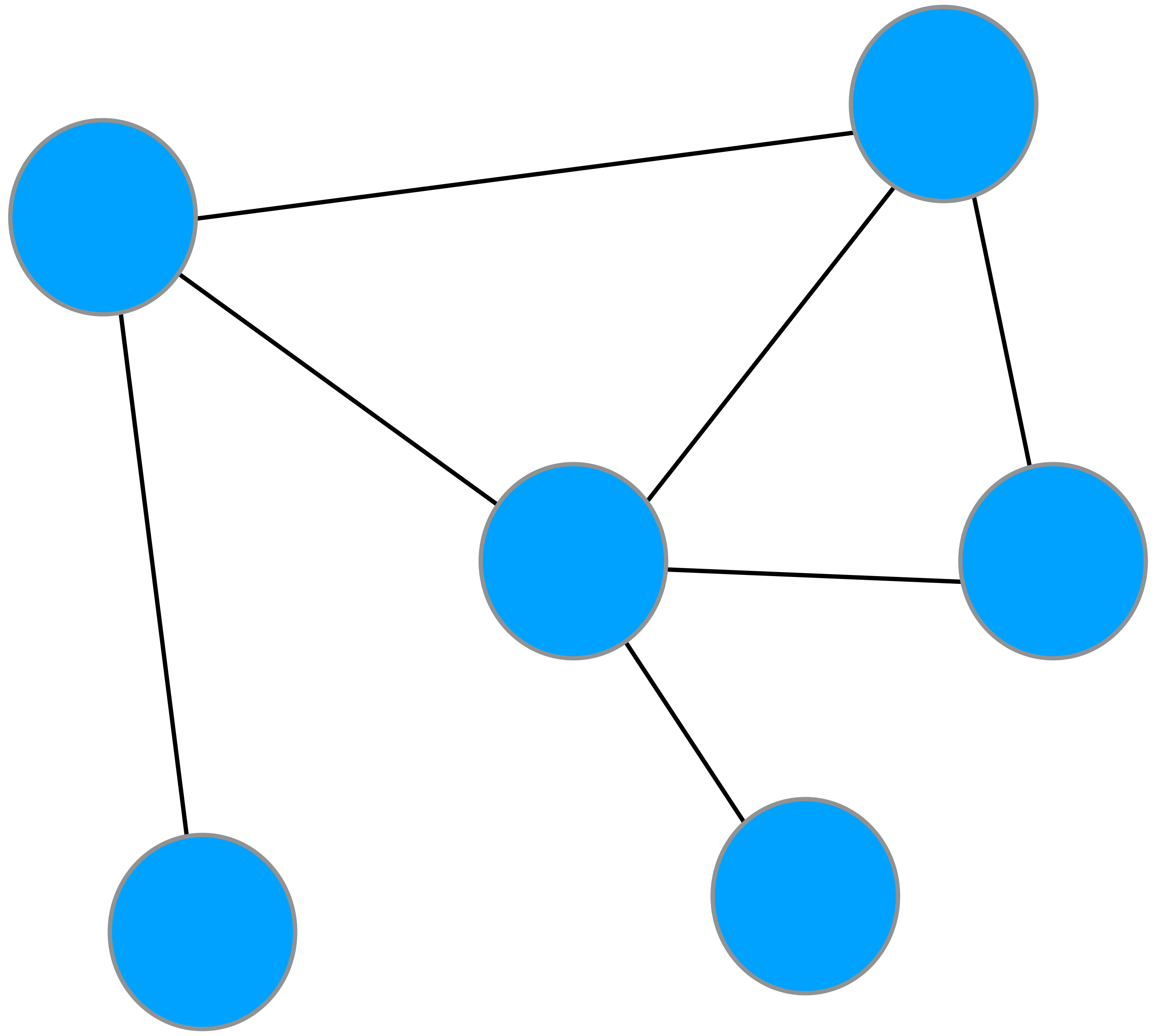

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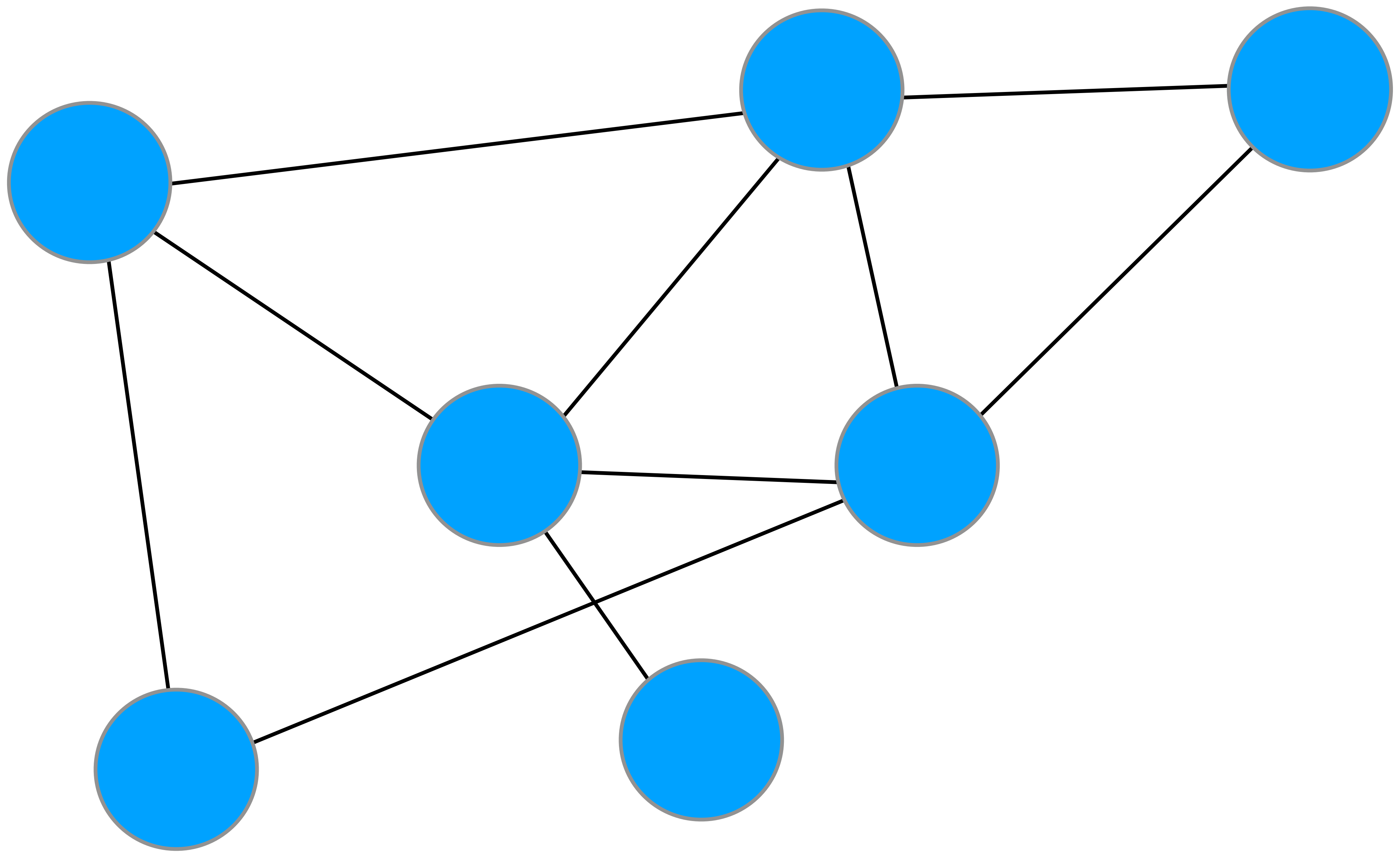

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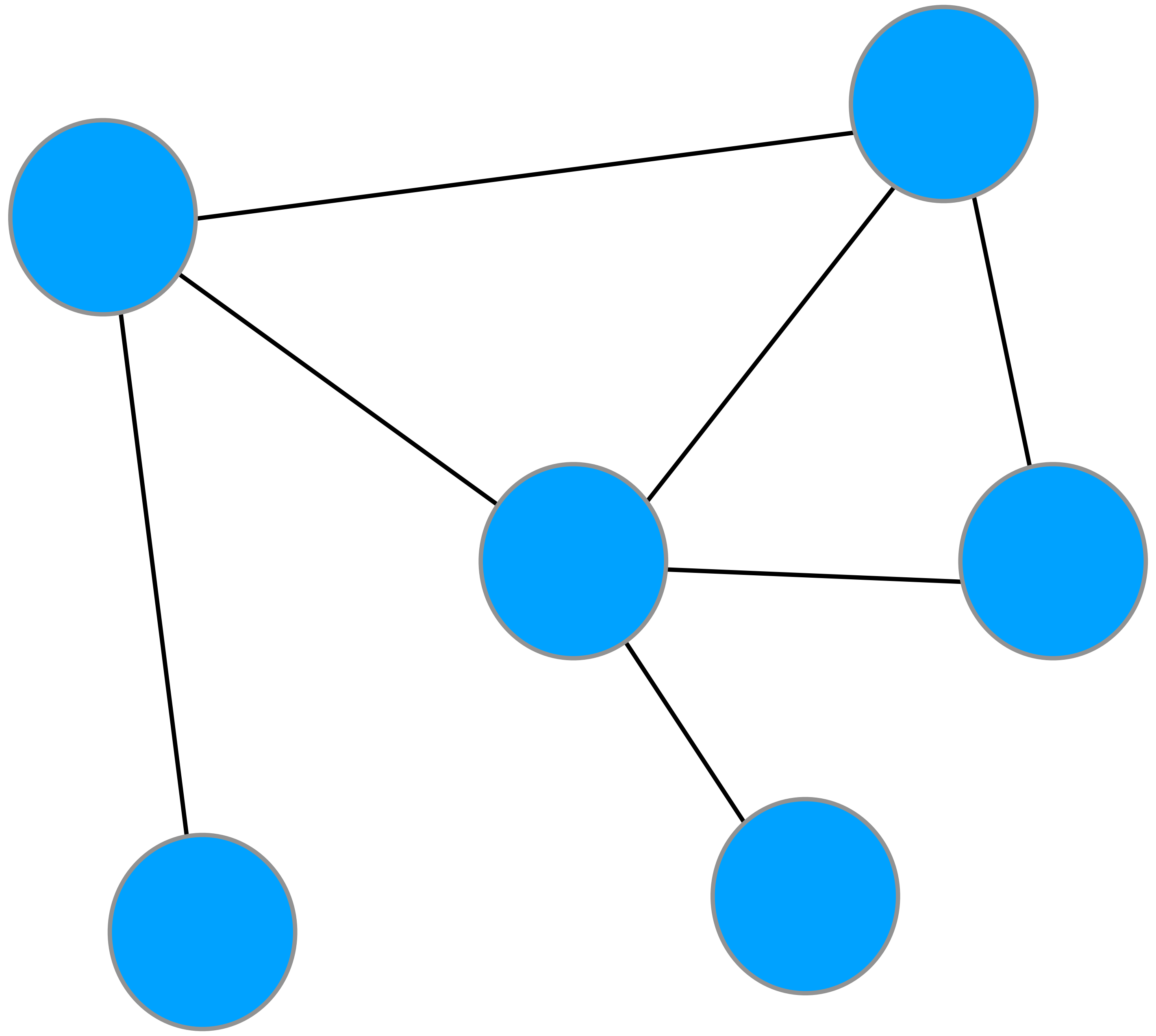

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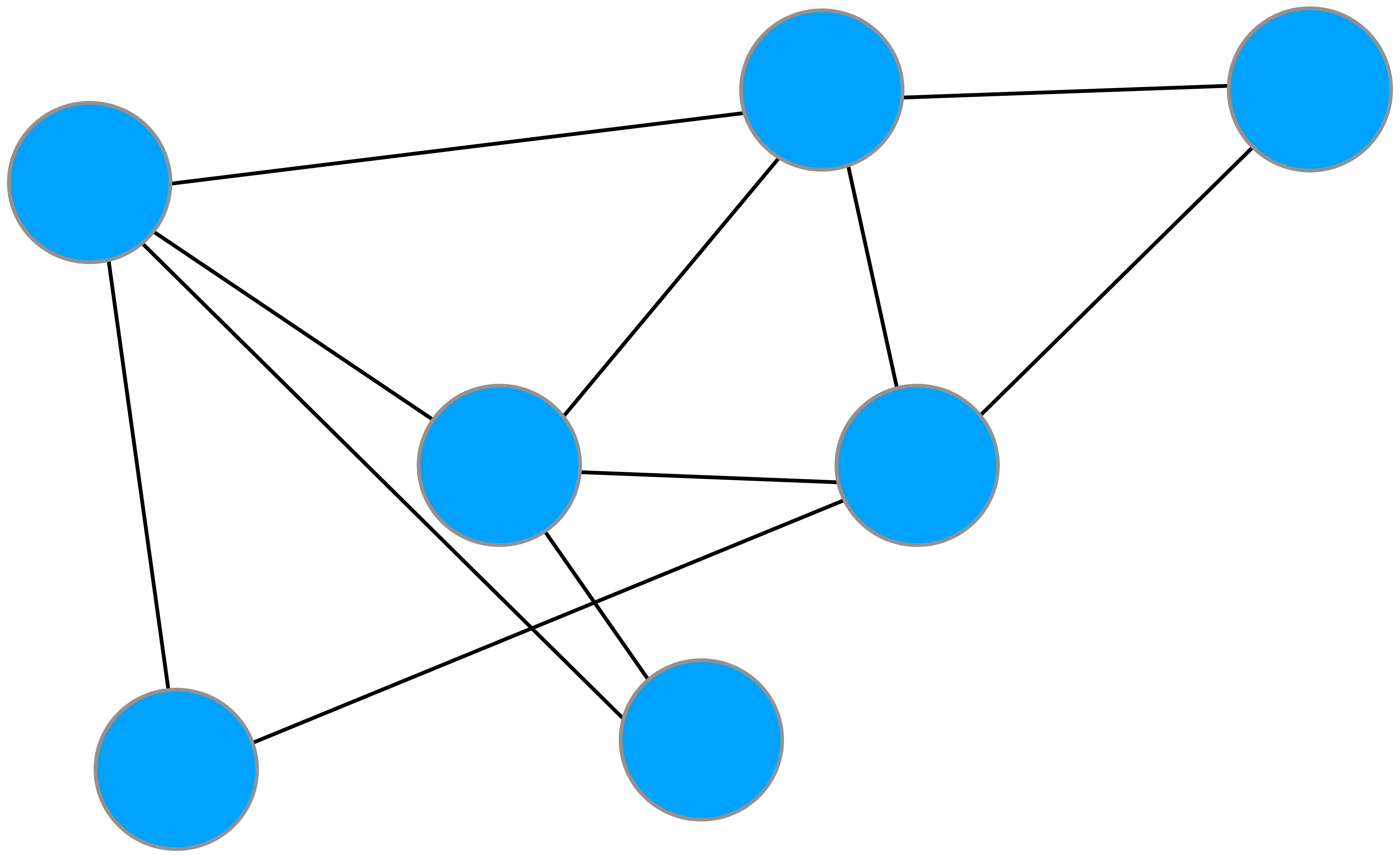

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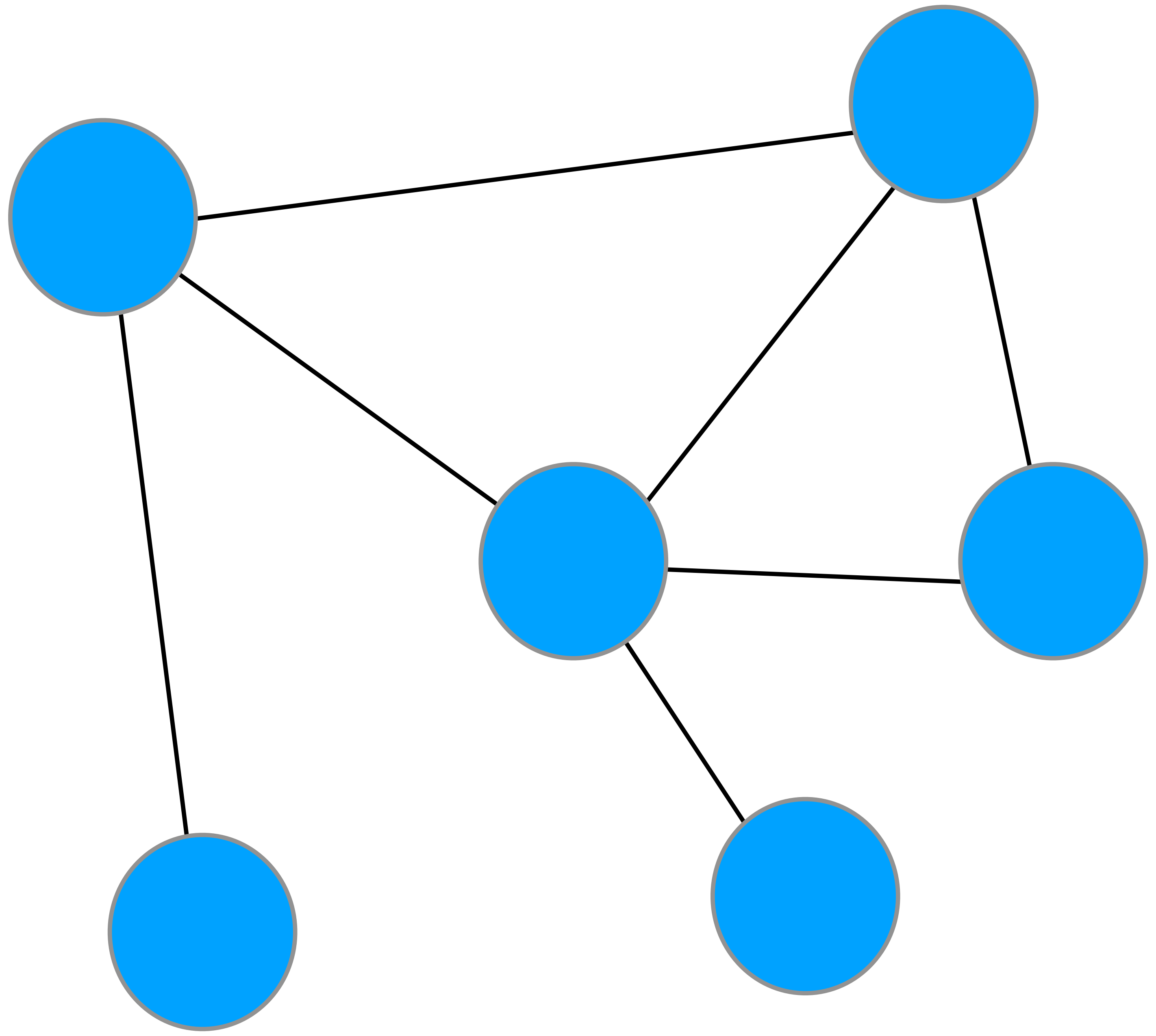

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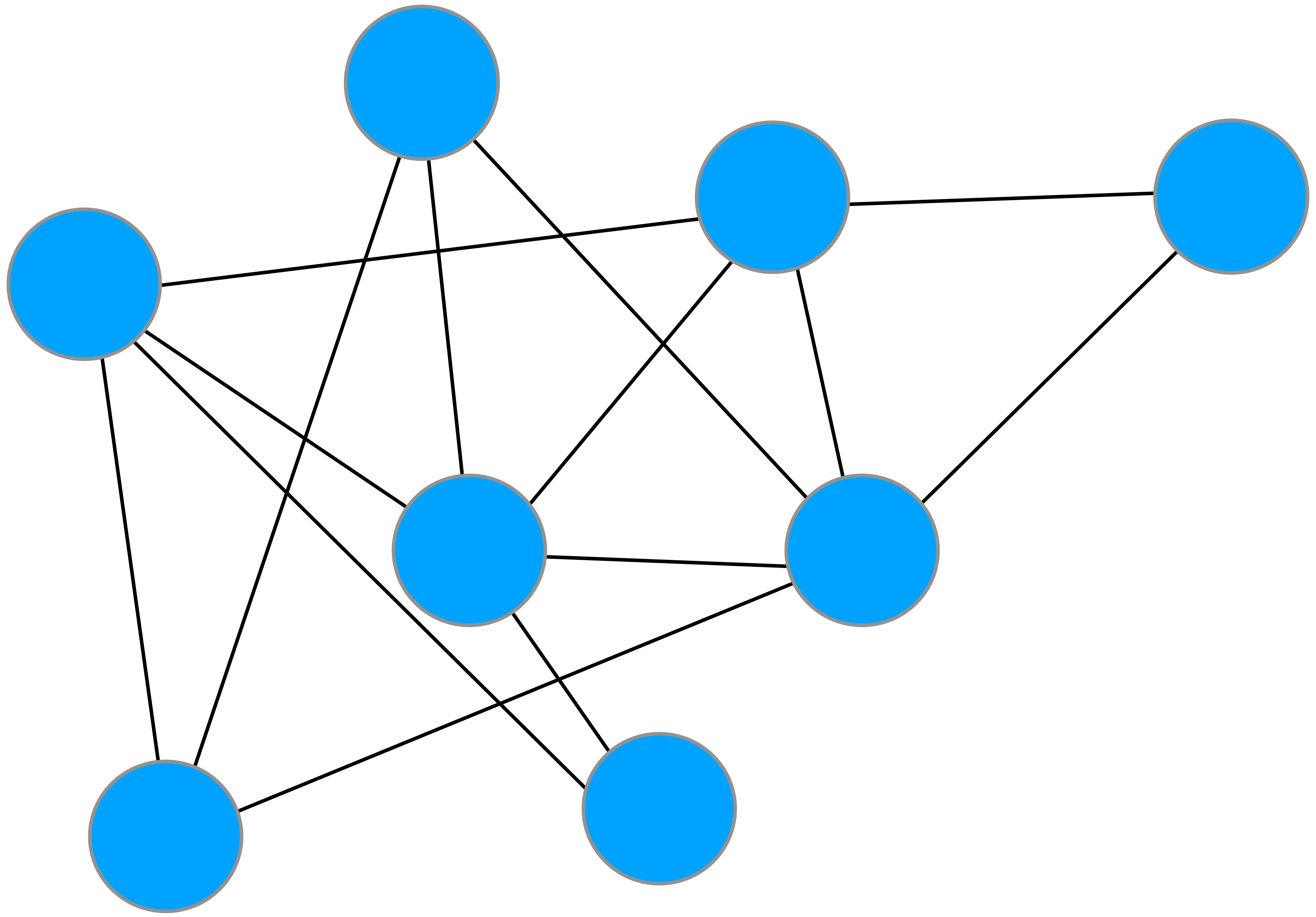

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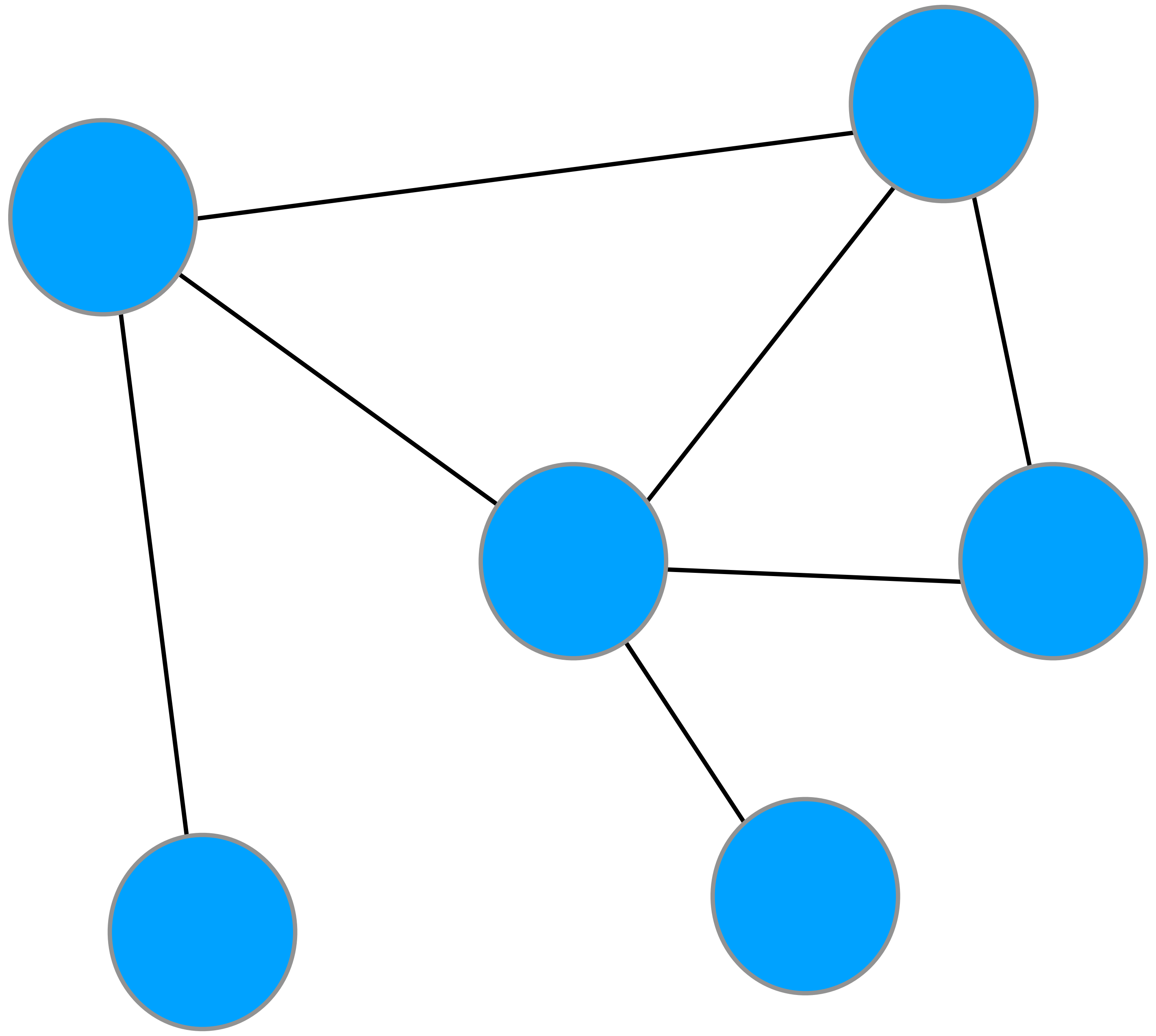

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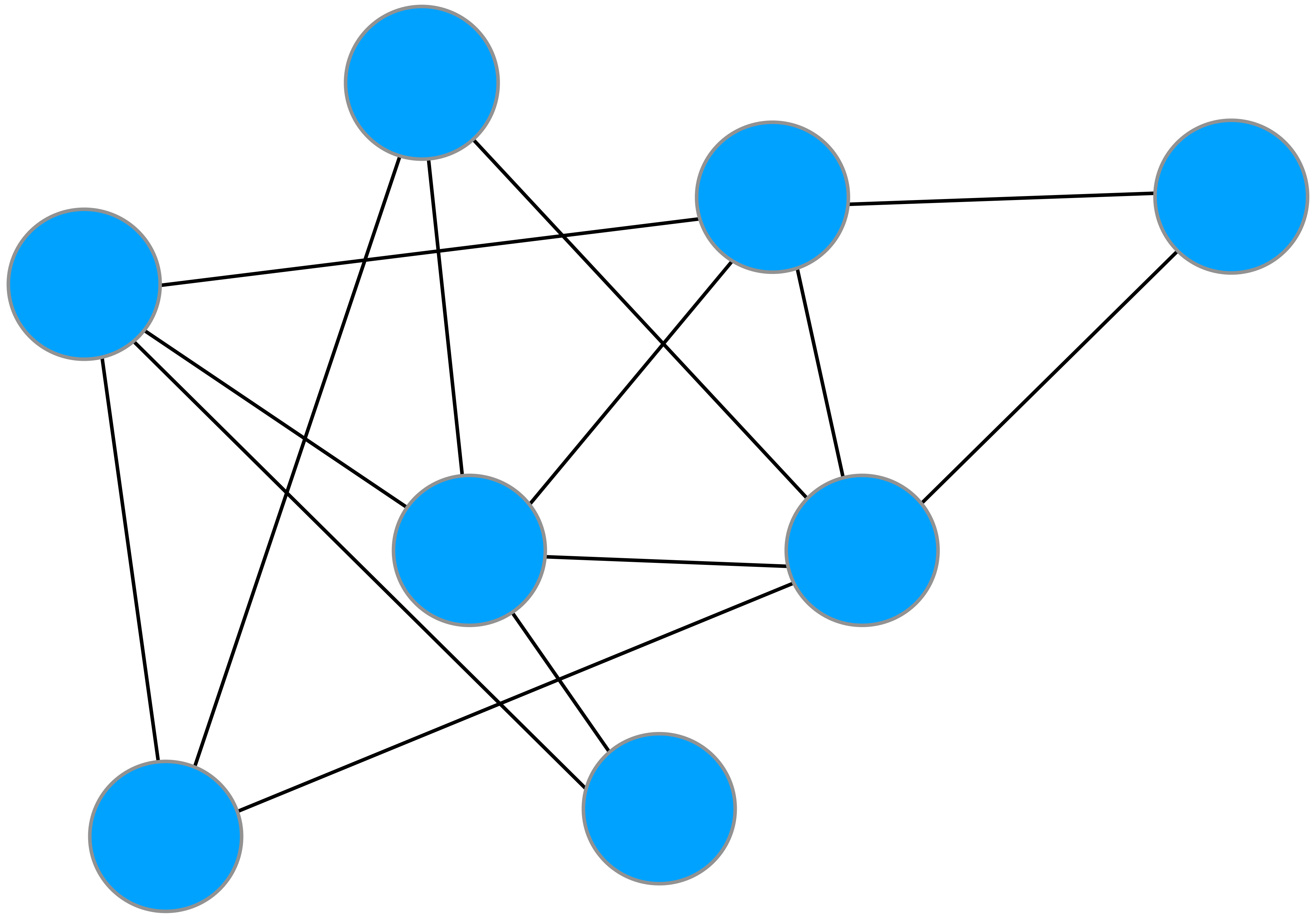

Dynamic Models

Why dynamic: Network Changepoints

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Forks in the blockchain resulting in splitting of transaction network

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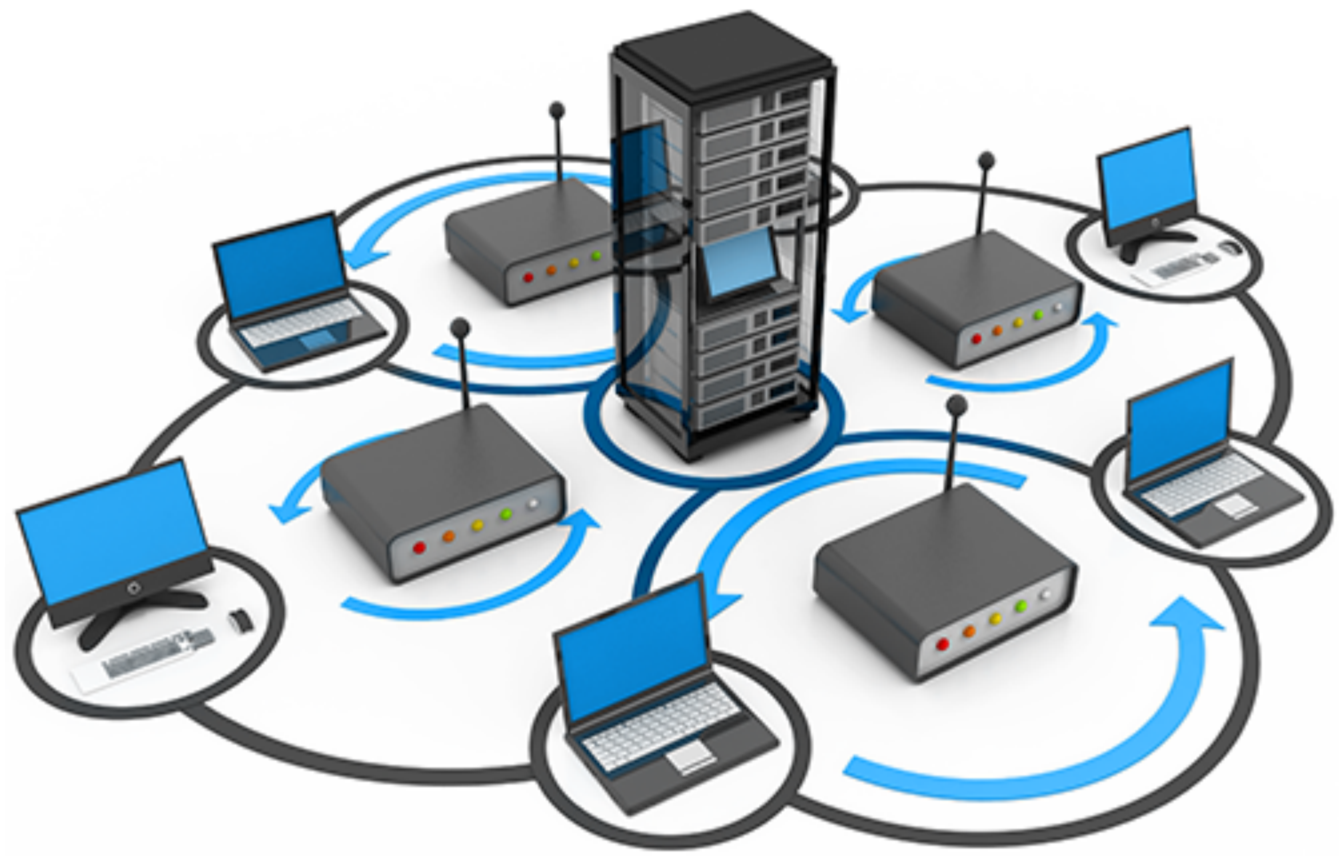
Emergence of IXPs changing peering behaviour



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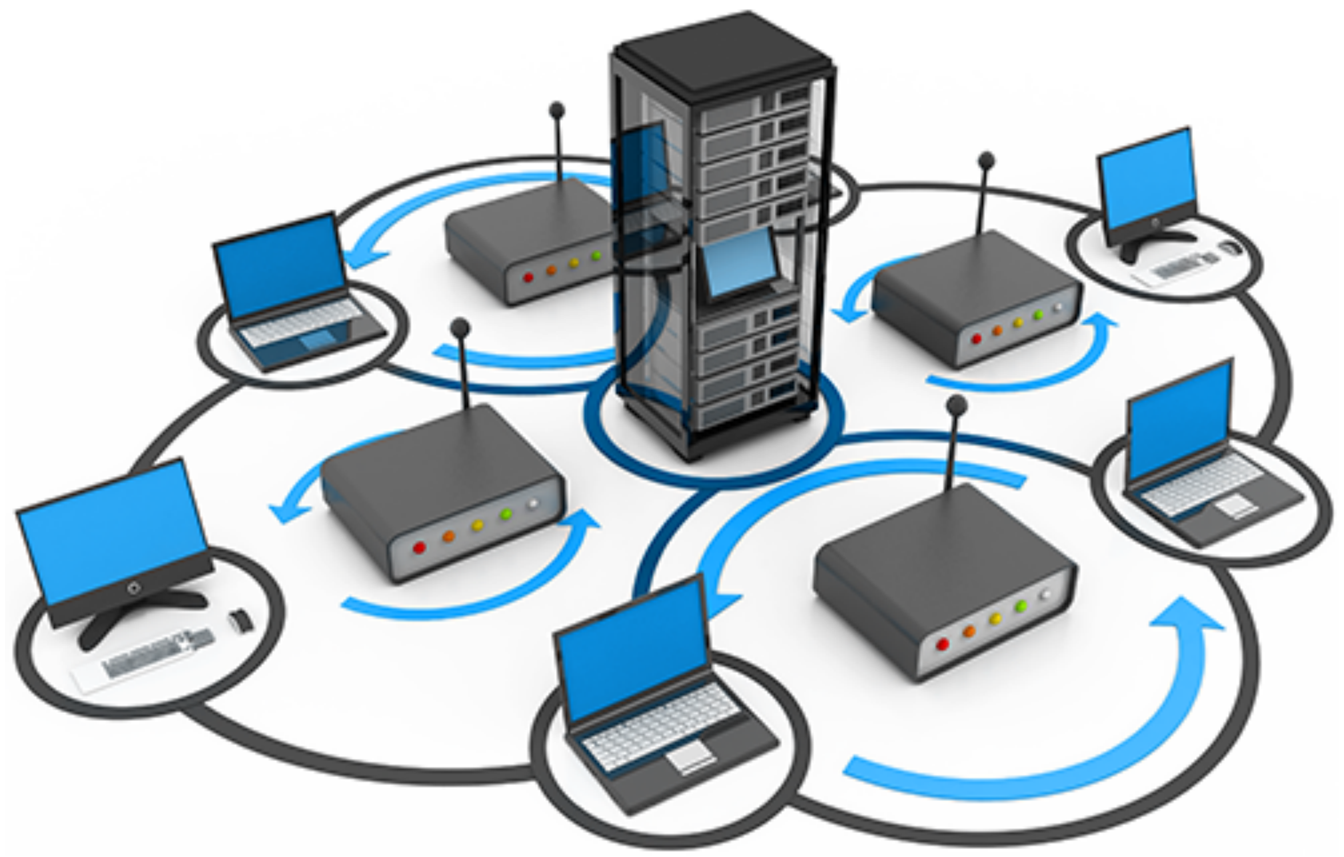
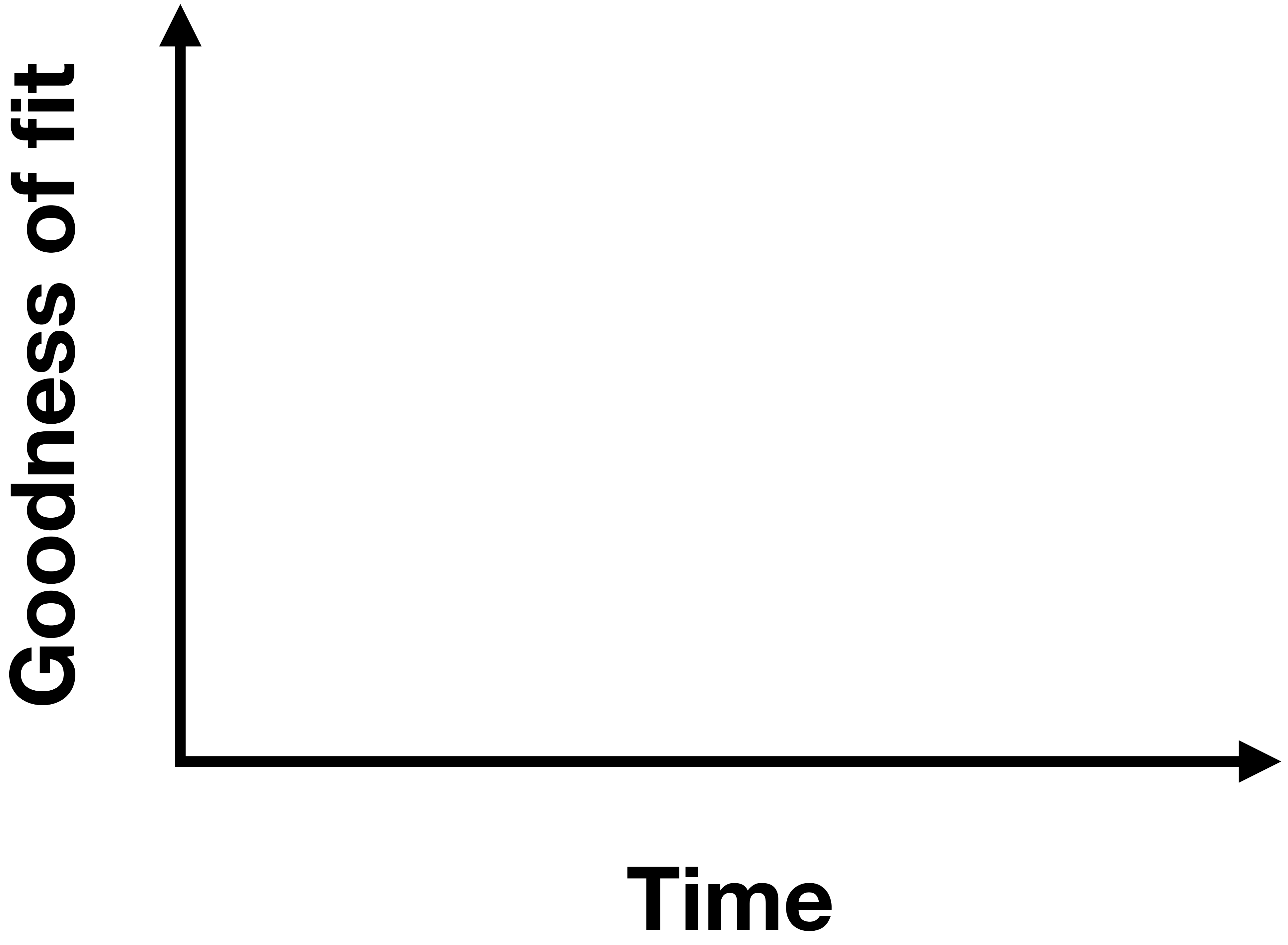


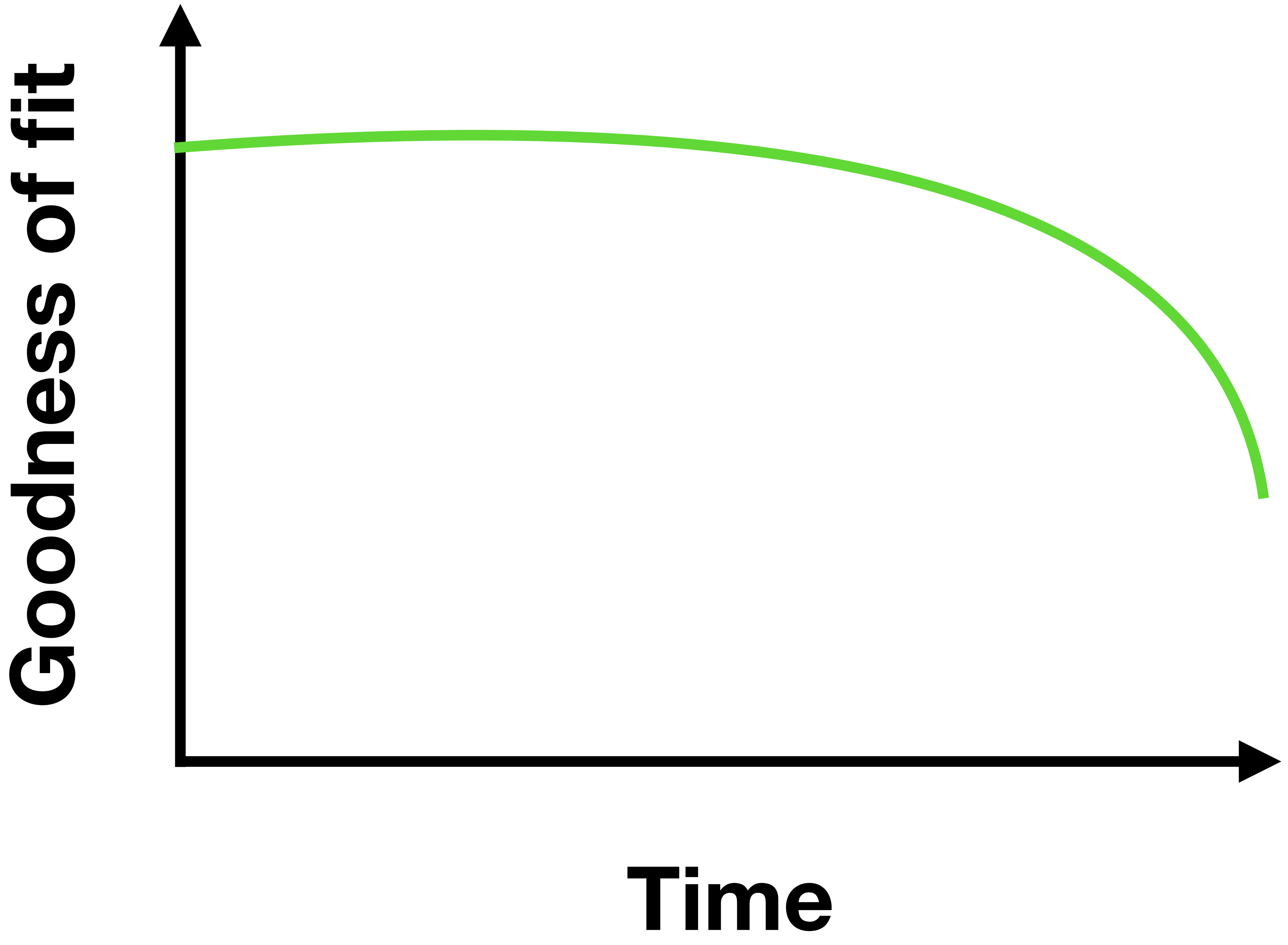
New features which change way in which users connect and interact with each other

Informal idea using network topology models



Suppose we have a sound way of monitoring the goodness of fit of a model for a network that is evolving in time

Informal idea using network topology models



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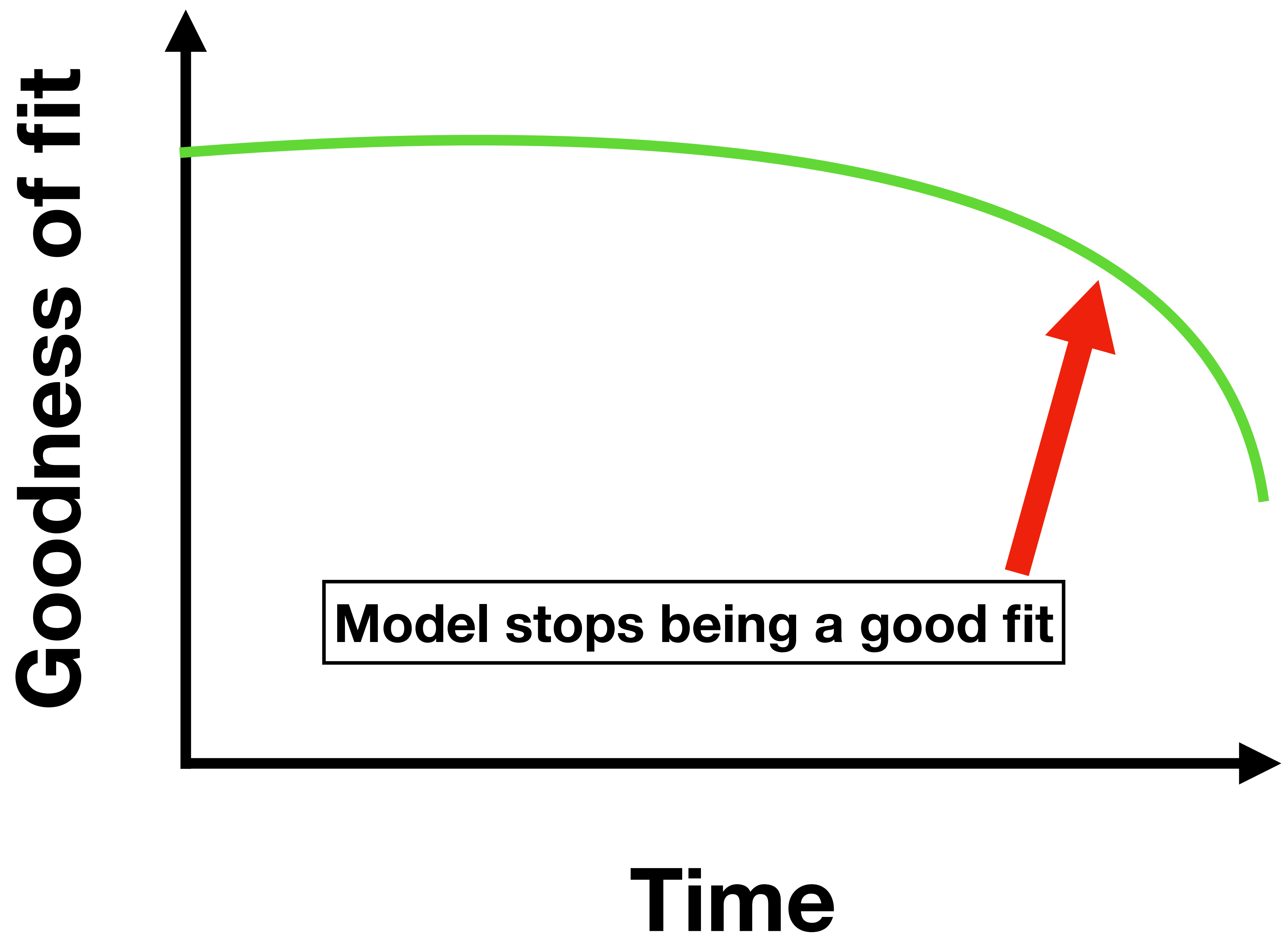

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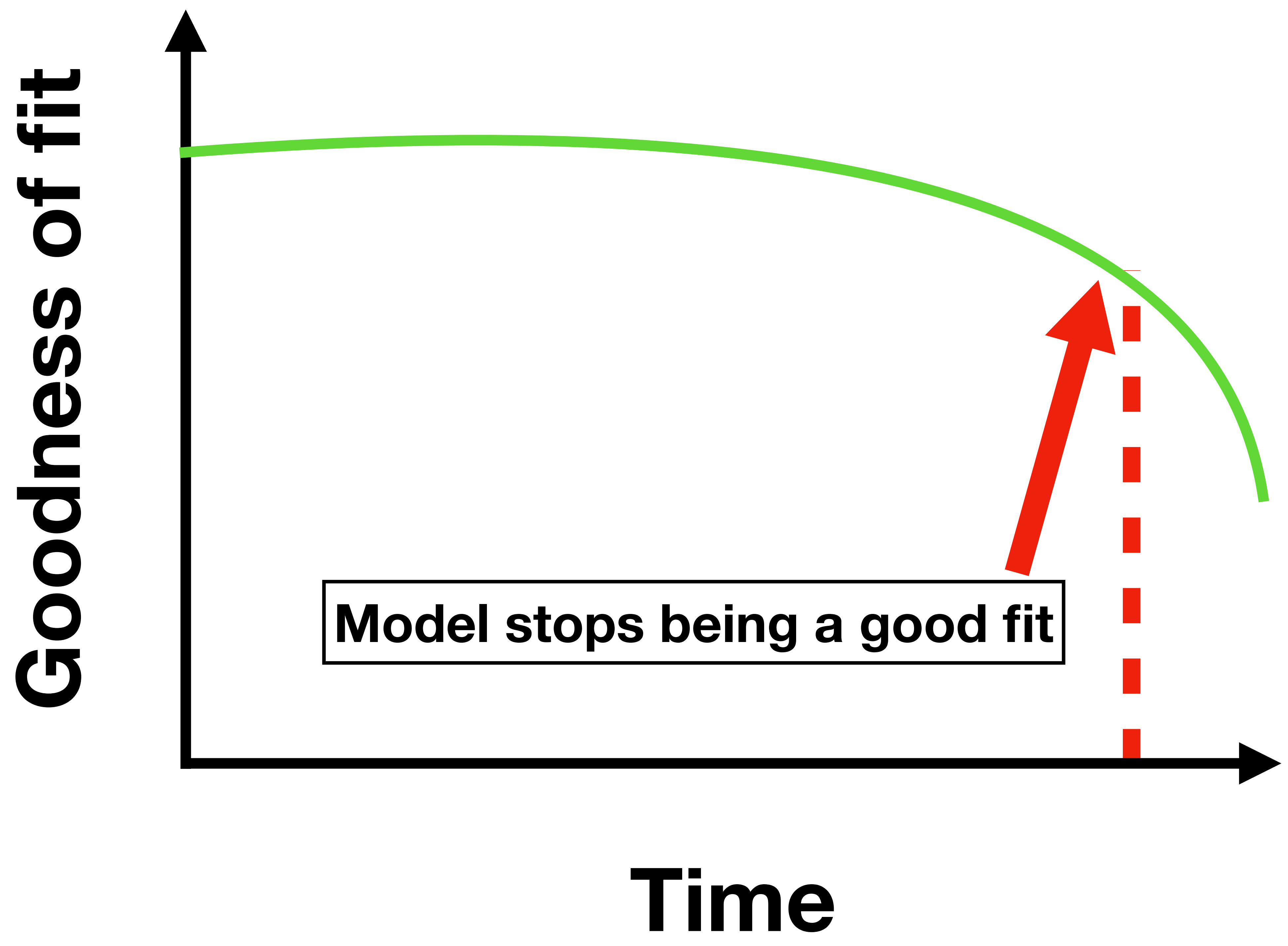

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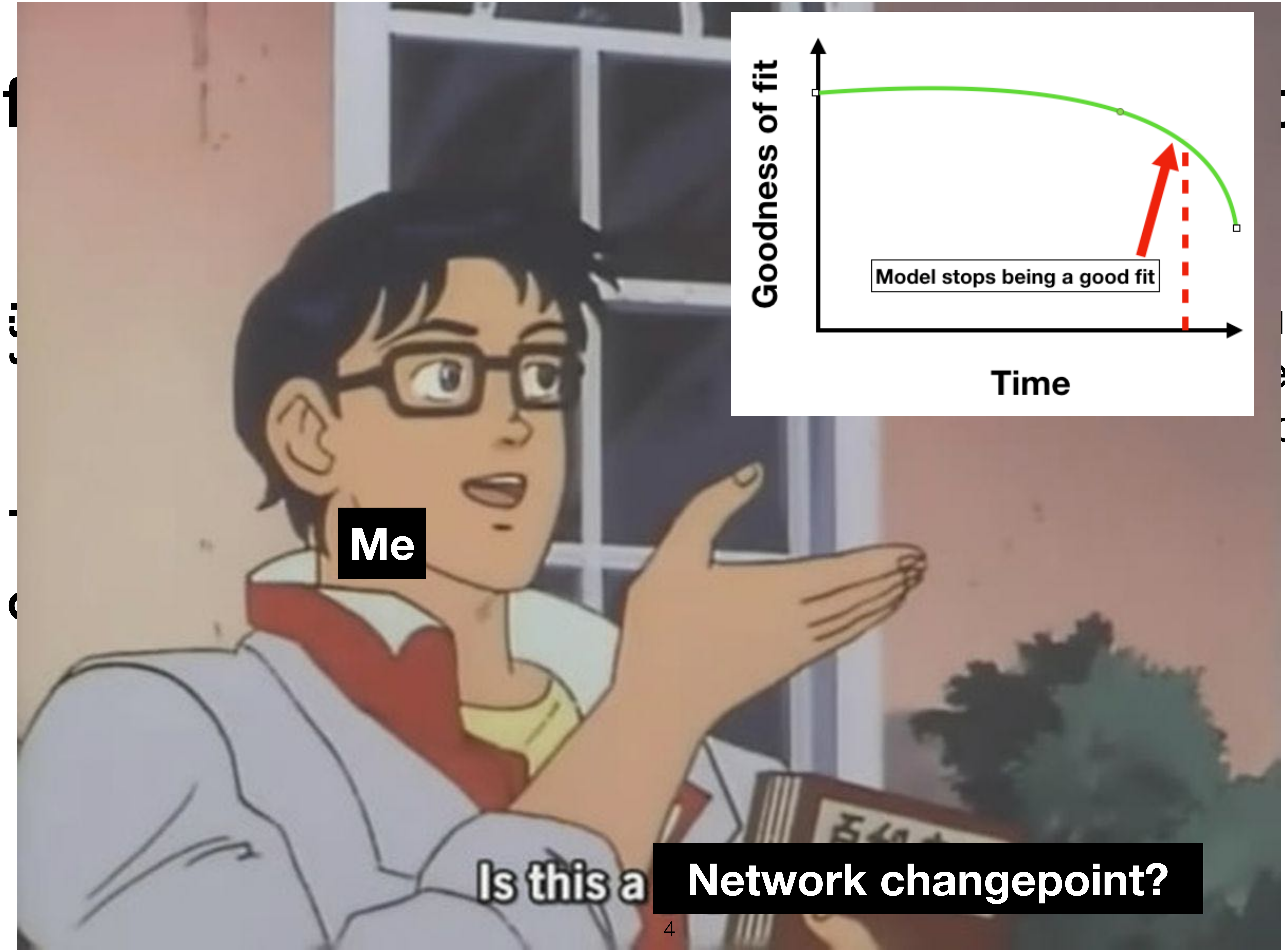

First steps: What is a ‘good model’ for a given evolving network?

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Different explanatory models might generate networks with similar/same statistics

Example: Barabasi-Albert vs Rank-Preference

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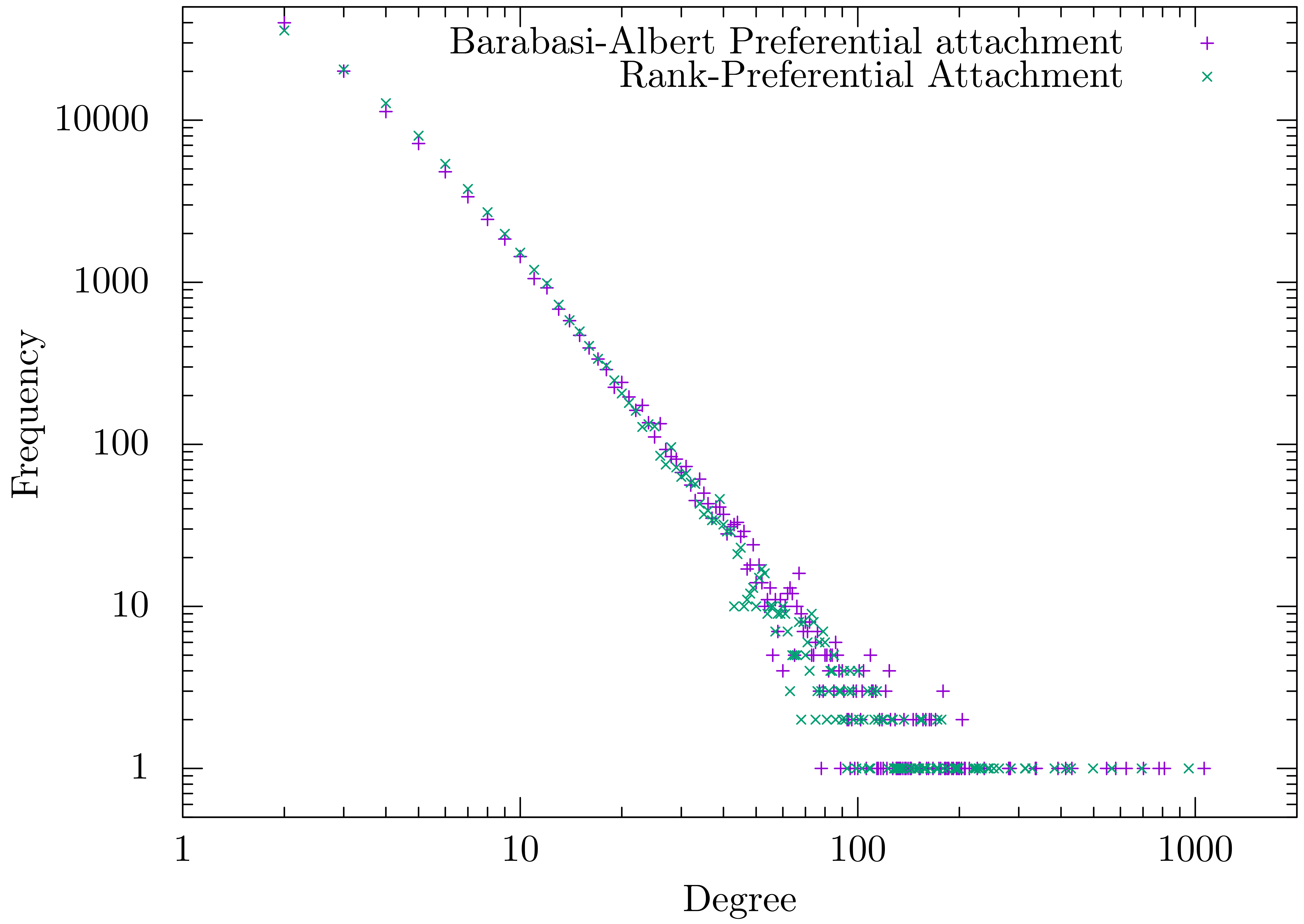
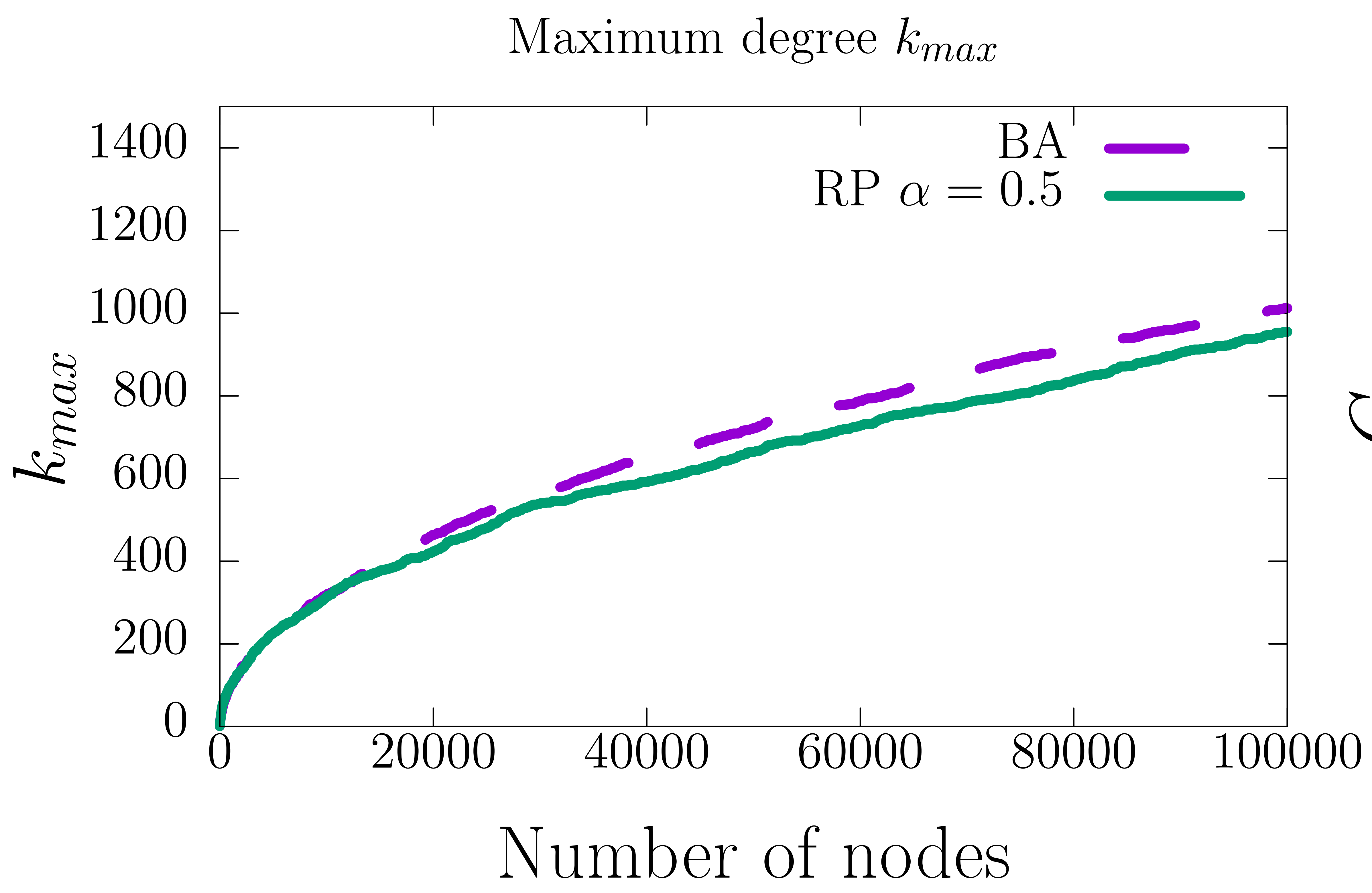
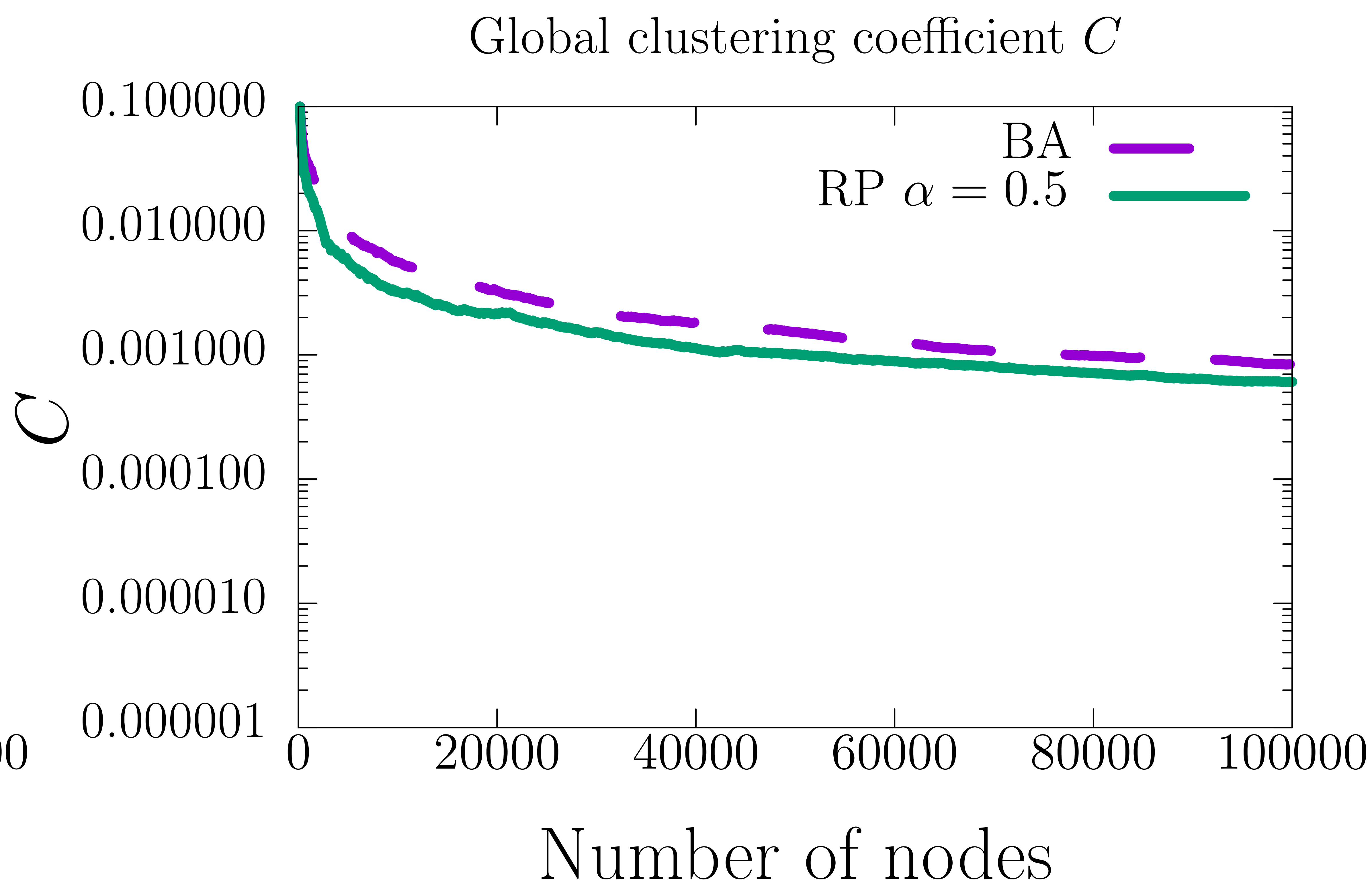


Degree distribution of generated networks

Example: Barabasi-Albert vs Rank-Preference

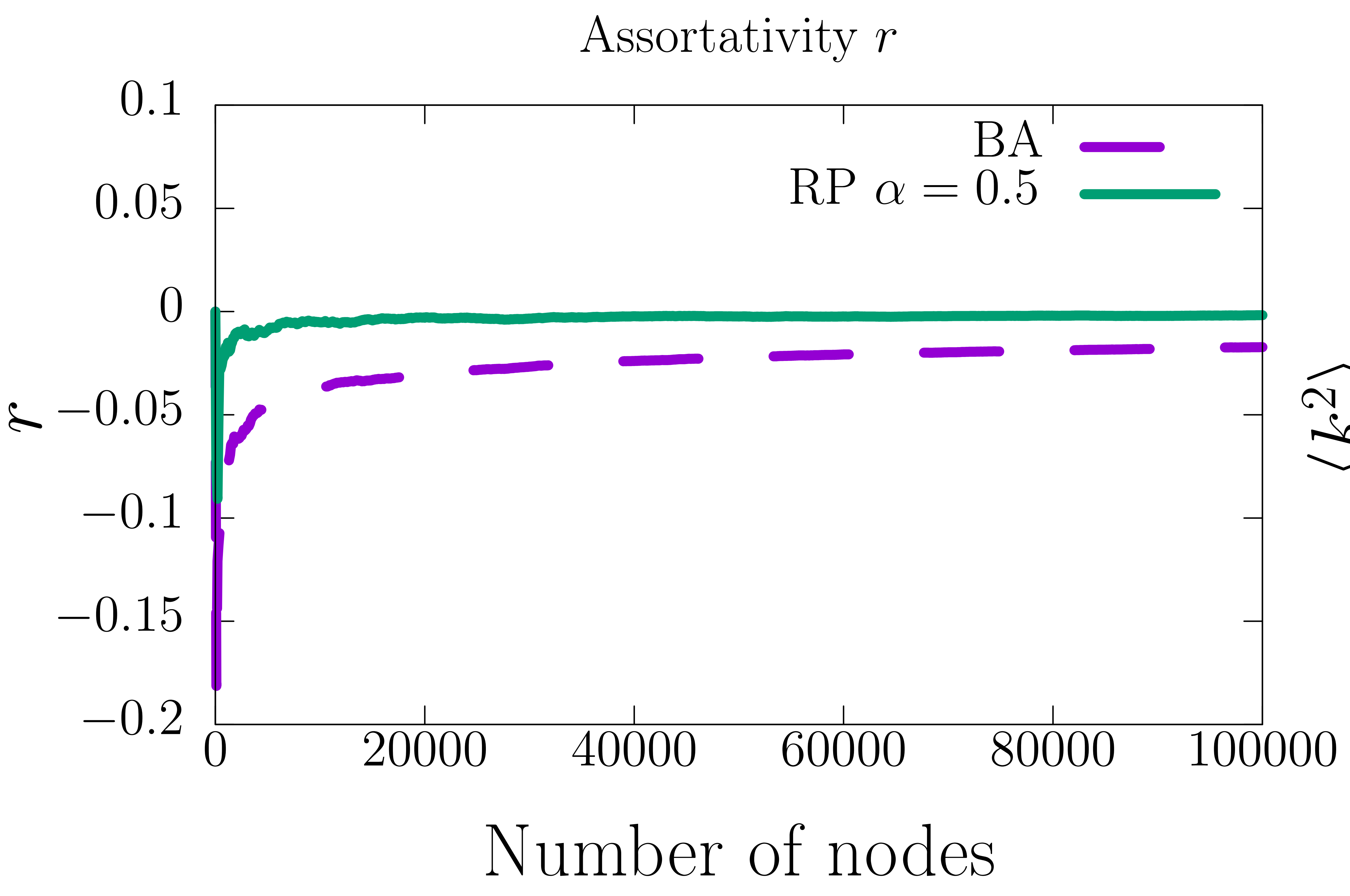


Maximum Degree

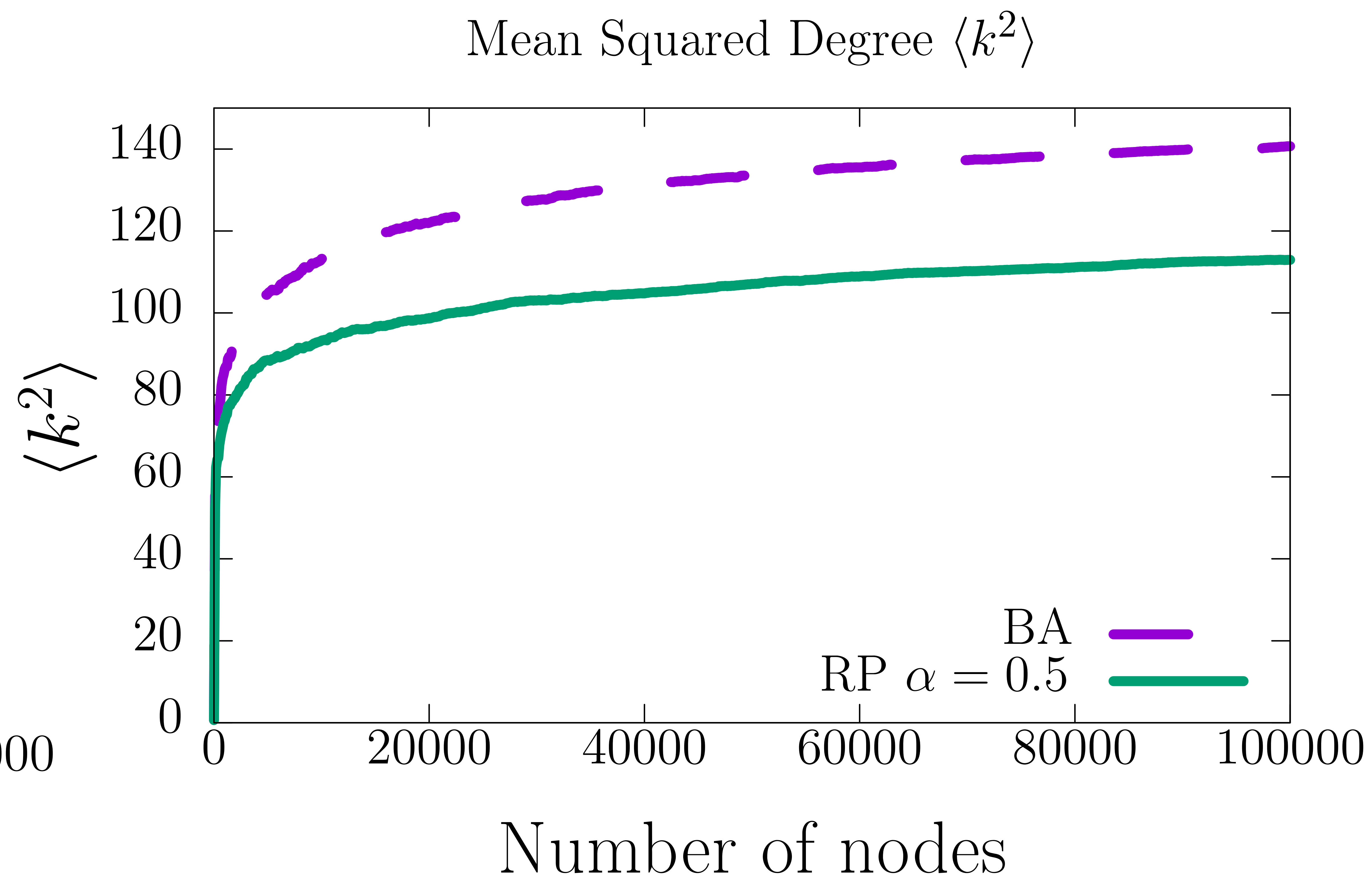


Global Clustering Coefficient

Example: Barabasi-Albert vs Rank-Preference



Degree Assortativity



Mean Squared Degree

Better Measure: Model Likelihood

[R. G. Clegg, B. Parker, M. Rio
Likelihood based assessment of dynamic networks (2016)]

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Evolving network $G(t)$

Candidate probabilistic model $M(\theta)$

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Evolving network $G(t)$

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Likelihood of model: Probability of generating entire evolution of G from model $M(\theta)$

Better Measure: Model Likelihood

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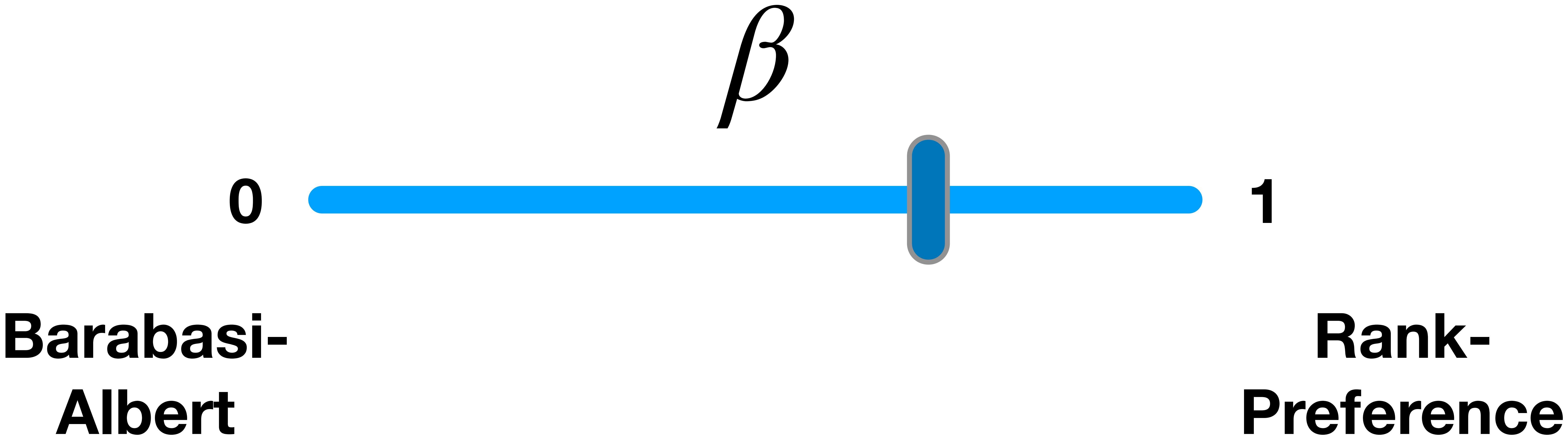
Actually, we can distinguish these using likelihood where single statistics might fail!

Distinguishing networks generated by BA vs RP



Test: given an artificial network grown that is generated from part BA and part RP, can we recover the proportion each model contributed using model likelihood?

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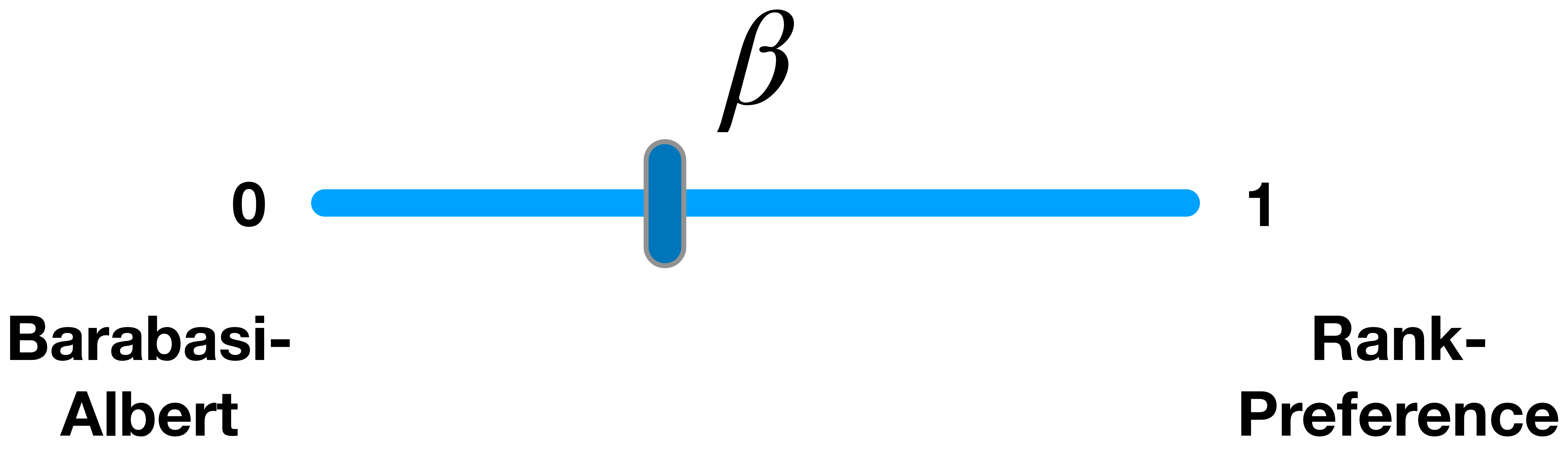

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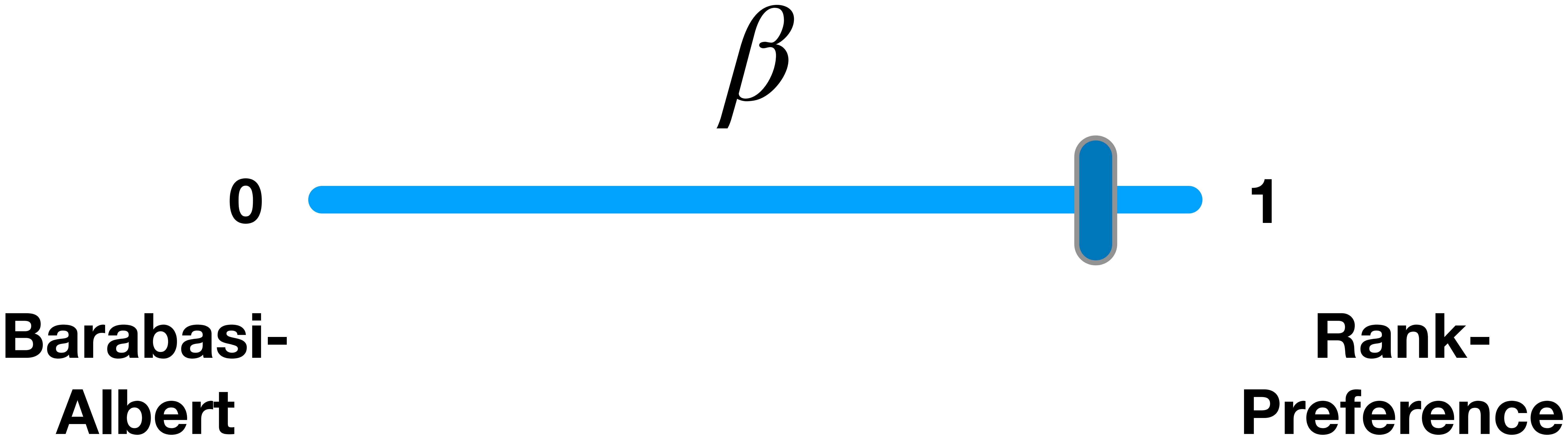

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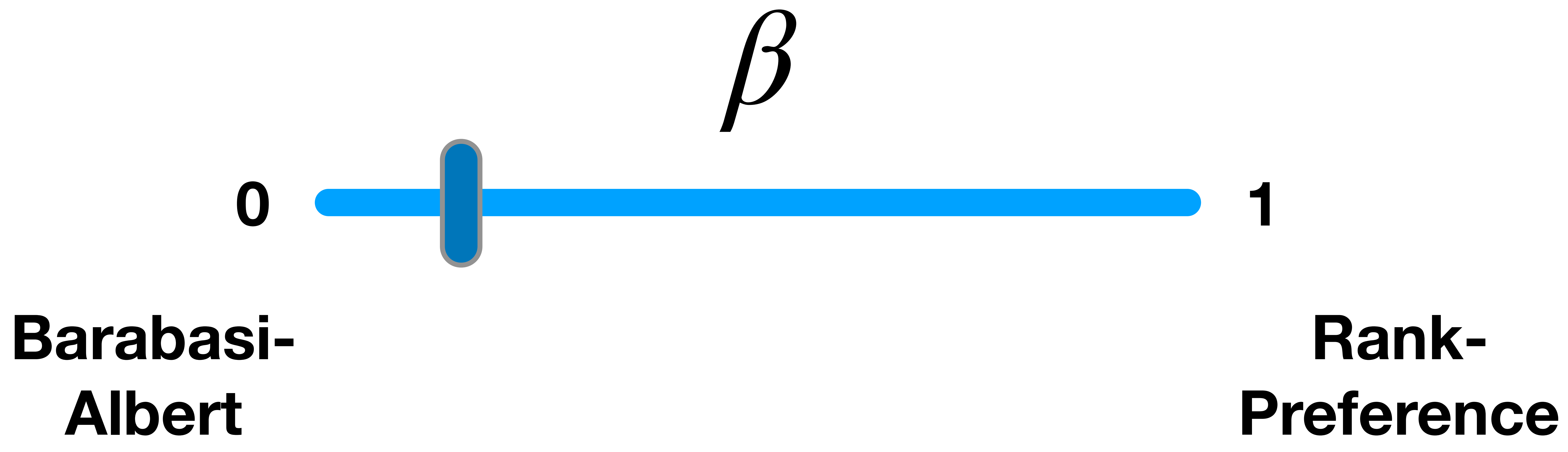

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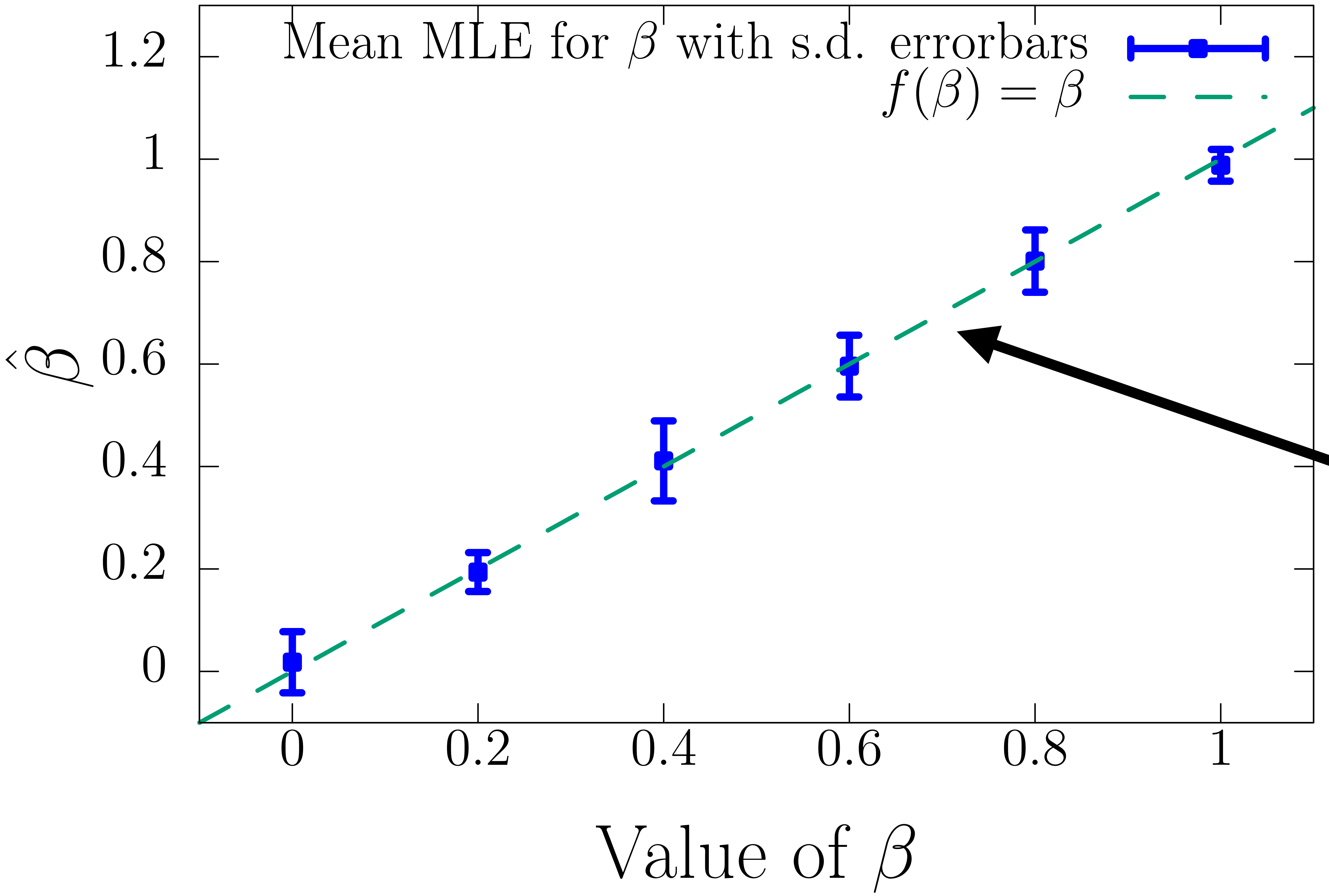
Distinguishing networks generated by BA vs RP

So, we can distinguish between even very similar models



Aim: be close to green line

β

Barabasi-Albert **0** **1** **Rank-Preference**

Example: Modeling the AS topology

University of Oregon
Routeviews dataset

Candidate models to mix:

Positive-Feedback-Preference (PFP)

Nodes chosen uniformly at random

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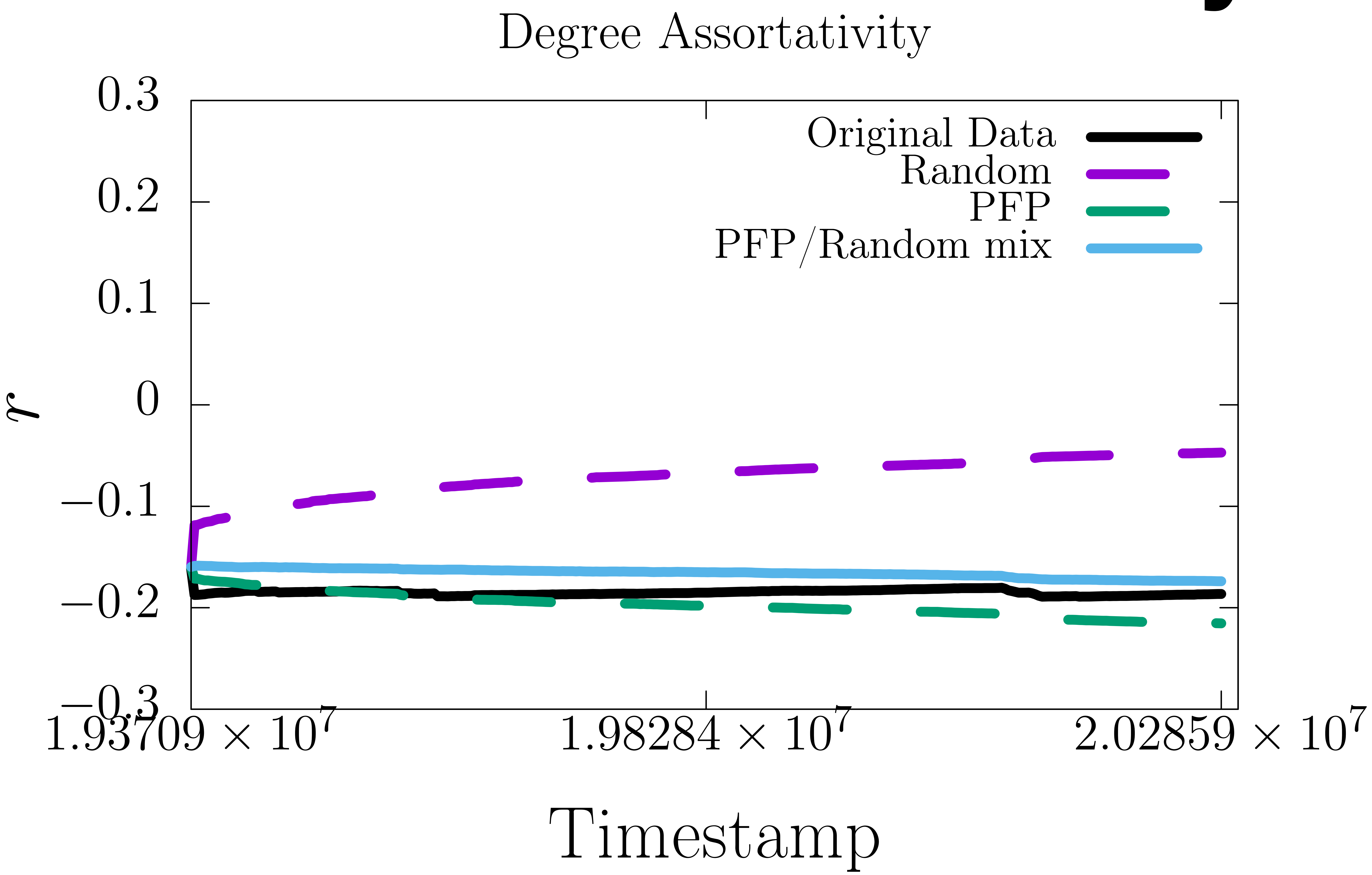
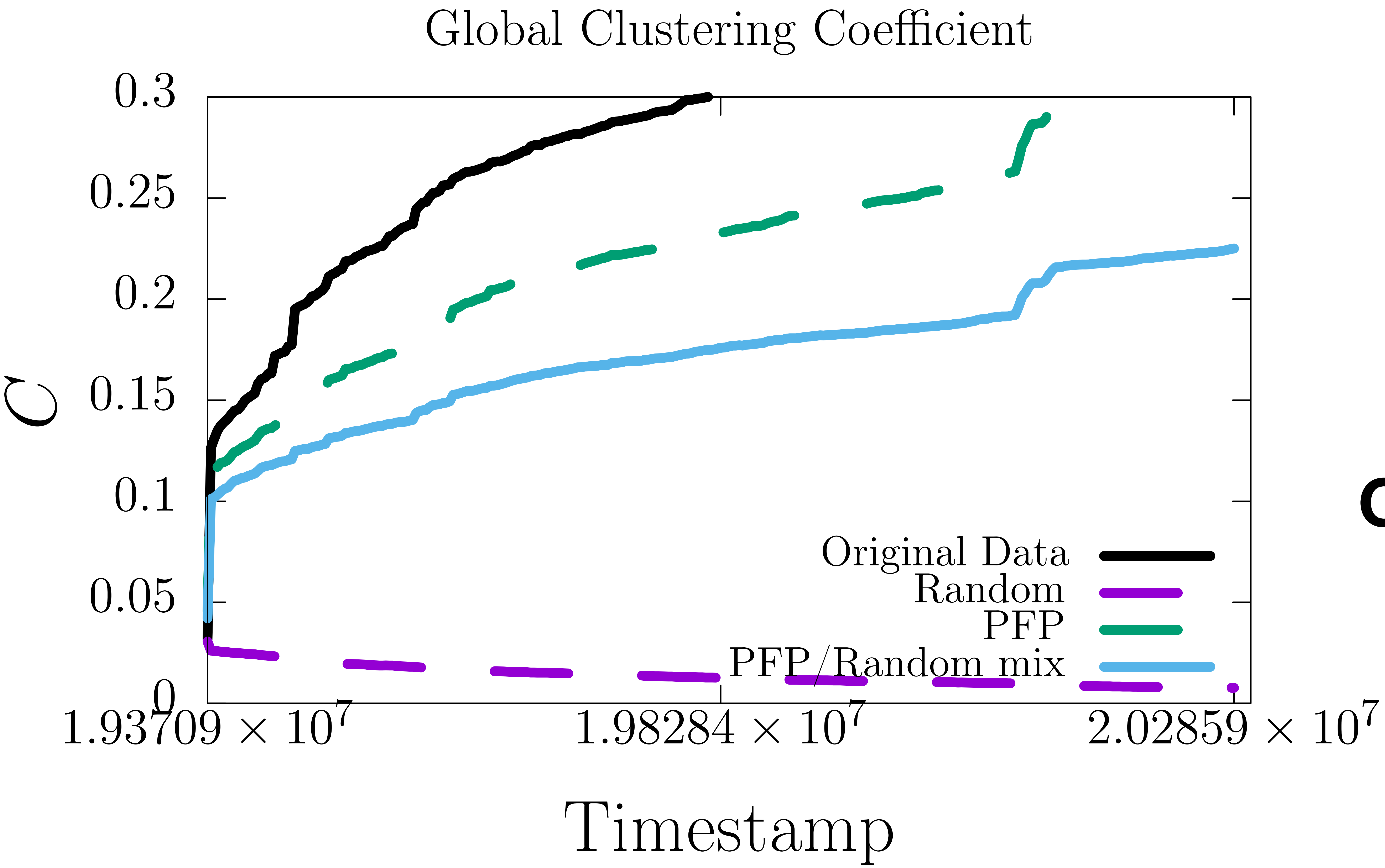
Takeaways



Some stats match well!

Degree Assortativity

Takeaways



Others not so well!

Clustering coefficient

Conclusion and Next Steps

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Thanks for listening!

n.a.arnold@qmul.ac.uk