

Subgraphs, Motifs, and Scaling in a Dynamic Airline Network

arXiv:1807.02585

Steve Lawford

ENAC, University of Toulouse

Online, 26 August 2022
(Econophysics Colloquium)

Joint work with Marius Agasse-Duval

Introduction

- ▶ Small-scale topological structure of dynamic airline network
 - ▶ Graph-theoretic research on transportation networks typically focuses on macro or micro measures (diameter, centrality)
 - ▶ Little known about subgraph-level behaviour (scaling, motifs), sometimes called “mesoscopic” measures
- (1) **Count small subgraphs** — exact analytic enumeration
 - (2) **Investigate scaling** — power law between subgraph counts and edges, evidence for model evolution (“phase transition”)
 - (3) **Identify motifs** — statistically significant wrt. random graphs

Framework for study of simple undirected graphs

- ▶ Real-world network as graph

$$G = (V, E), \quad n = |V|, \quad m = |E|$$

- ▶ Adjacency matrix

$$g = (g)_{ij}, \quad (g)_{ii} = 0, \quad (g)_{ij} = (g)_{ji}, \quad (g)_{ij} \in \{0, 1\}$$

- ▶ Edge, neighbourhood, degree, density

$$(i, j) \in E, \quad \Gamma_G(i) = \{j : (i, j) \in E\}$$

$$k_i = |\Gamma_G(i)|, \quad d(G) = 2m/n(n-1)$$

Small connected non-isomorphic subgraphs (3, 4 nodes)



3-star $M_3^{(3)}$



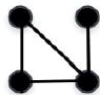
Triangle $M_7^{(3)}$



4-star $M_{11}^{(4)}$



4-path $M_{13}^{(4)}$



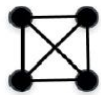
Tadpole $M_{15}^{(4)}$



4-circle $M_{30}^{(4)}$



Diamond $M_{31}^{(4)}$



4-complete $M_{63}^{(4)}$

Subgraph $M_a^{(b)}$ is $G' = (V', E') \subseteq G$ with $V' \subseteq V$ and $E' \subseteq E$, such that $(i, j) \in E' \implies i, j \in V'$ (induced subgraph $\tilde{M}_a^{(b)}$ has every possible edge)

Small connected non-isomorphic subgraphs (5 nodes)



5-star $M_{75}^{(5)}$



5-arrow $M_{77}^{(5)}$



Cricket $M_{79}^{(5)}$



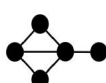
5-path $M_{86}^{(5)}$



Bull $M_{87}^{(5)}$



Banner $M_{94}^{(5)}$



Stingray $M_{95}^{(5)}$



Lollipop $M_{117}^{(5)}$



Spinning top $M_{119}^{(5)}$



Kite $M_{127}^{(5)}$



Ufo $M_{222}^{(5)}$



Chevron $M_{223}^{(5)}$



Hourglass $M_{235}^{(5)}$



5-circle $M_{236}^{(5)}$



House $M_{237}^{(5)}$



Crown $M_{239}^{(5)}$



Envelope $M_{254}^{(5)}$



Lamp $M_{255}^{(5)}$



Arrowhead $M_{507}^{(5)}$



Cat's cradle $M_{511}^{(5)}$

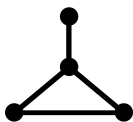


5-complete $M_{1023}^{(5)}$

e.g. $M_a^{(b)}$, $b = 5$, $a = \sum_{i=1}^{b-1} \sum_{j=i+1}^b 2^{\binom{b-i}{2} + (b-j)} (g)_{ij}$, $119_{10} = 0001110111_2$
 (spinning top)

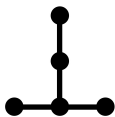
Counting subgraphs by decomposition

Let g be the adjacency matrix and let k_i be the degree of node i



tadpole

$$|M_{15}^{(4)}| = \frac{1}{2} \sum_{k_i > 2} (g^3)_{ii} (k_i - 2)$$

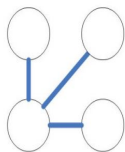


5-arrow

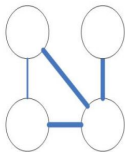
$$|M_{77}^{(5)}| = \sum_{\substack{(i,j) \in E \\ \text{both directions}}} \binom{k_i - 1}{2} (k_j - 1) - 2|M_{15}^{(4)}|$$

Generally, analytic formulae for subgraphs can be expressed in terms of [simpler subgraphs](#) (Noga Alon et al., 1997; Estrada, 2011)

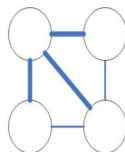
Counting induced subgraphs by linear combination



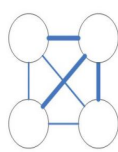
(a) 4-star $M_{11}^{(4)}$.



(b) Tadpole $M_{15}^{(4)}$.



(c) Diamond $M_{31}^{(4)}$.



(d) 4-complete $M_{63}^{(4)}$.

$$|\tilde{M}_{11}^{(4)}| = |M_{11}^{(4)}| - |\tilde{M}_{15}^{(4)}| - 2|\tilde{M}_{31}^{(4)}| - 4|M_{63}^{(4)}|$$

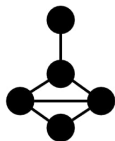
$$|\tilde{M}_{15}^{(4)}| = |M_{15}^{(4)}| - 4|\tilde{M}_{31}^{(4)}| - 12|M_{63}^{(4)}|$$

$$|\tilde{M}_{31}^{(4)}| = |M_{31}^{(4)}| - 6|M_{63}^{(4)}|$$

$$\implies |\tilde{M}_{11}^{(4)}| = |M_{11}^{(4)}| - |M_{15}^{(4)}| + 2|M_{31}^{(4)}| - 4|M_{63}^{(4)}|$$

Exact enumeration much harder for larger subgraphs

Let g be the adjacency matrix and k_i the degree of node i , and $S(i,j) = \Gamma_G(i) \cap \Gamma_G(j)$ the common neighbourhood of nodes i, j



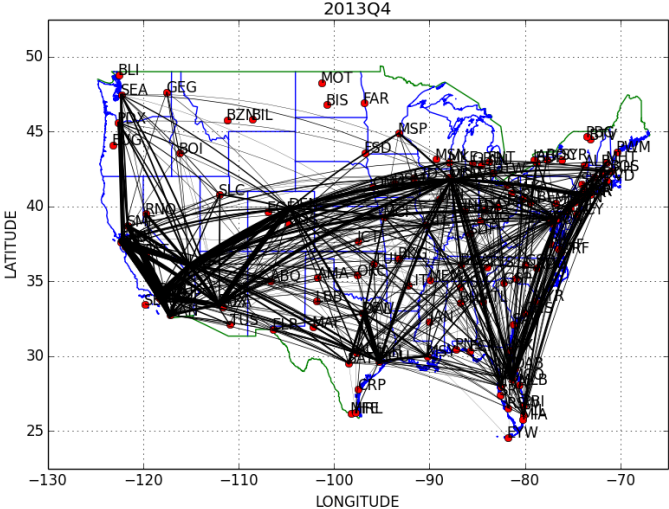
spinning top

$$|M_{119}^{(5)}| = \sum_{\substack{(i,j) \in E \\ k_i > 2, k_j > 2}} ((g^2)_{ij} - 1) \sum_{\substack{r \in S(i,j) \\ k_r > 1}} (k_r - 2) - 12 |M_{63}^{(4)}|$$

$$|\tilde{M}_{119}^{(5)}| = |M_{119}^{(5)}| - 3 |M_{127}^{(5)}| - 2 |M_{239}^{(5)}| - 2 |M_{254}^{(5)}| + 8 |M_{255}^{(5)}| + 8 |M_{507}^{(5)}| - 24 |M_{511}^{(5)}| + 60 |M_{1023}^{(5)}|$$

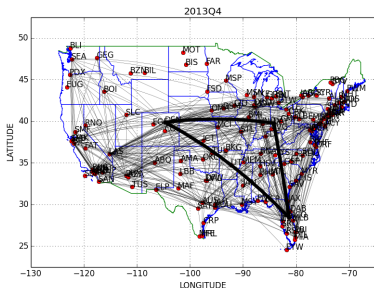
Much work on [efficient algorithms](#) to make subgraph counting feasible for larger subgraphs and networks (Ribeiro et al., 2021)

Route-map data for Southwest Airlines (1)

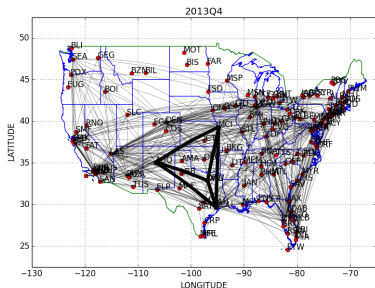


DB1B, 1999Q1 – 2013Q4, unidirectional route-level, direct tickets

Route-map data for Southwest Airlines (2)¹



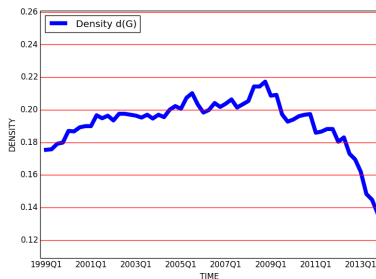
Triangle $M_7^{(3)}$



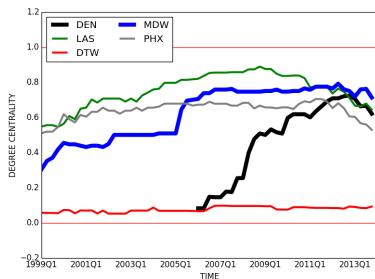
4-complete $M_{63}^{(4)}$

¹Dayton–Denver–Orlando and Albuquerque–Dallas–Houston–Kansas City

Network dynamics — local and global



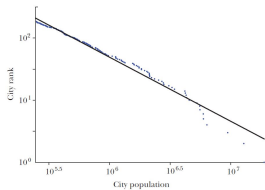
Density



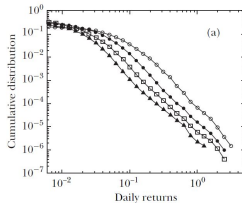
Degree centrality

- ▶ Number of airports has increased much faster than routes
- ▶ Heterogeneity in degree centrality over time, different airports
- ▶ Diameter and average path length very similar to Erdős-Rényi $G(n, p)$ but much higher clustering, suggesting small world, and **subgraph counts generally much higher** than in $G(n, p)$

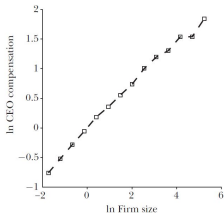
Power laws in economics and biology (Gabaix, 2016)²



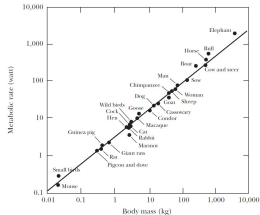
$$\beta \approx -1 \text{ (Zipf's law)}$$



$$\beta \approx -3 \text{ (cubic law)}$$



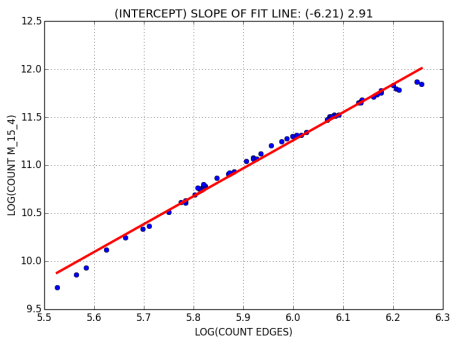
$$\beta \approx 1/3 \text{ (Robert's law)}$$



$$\beta \approx 3/4 \text{ (Kleiber's law)}$$

²Clockwise from top-left: city rank and population, stock return distribution and return, metabolic rate and body mass, CEO compensation and firm size

How do subgraphs scale with network size?³

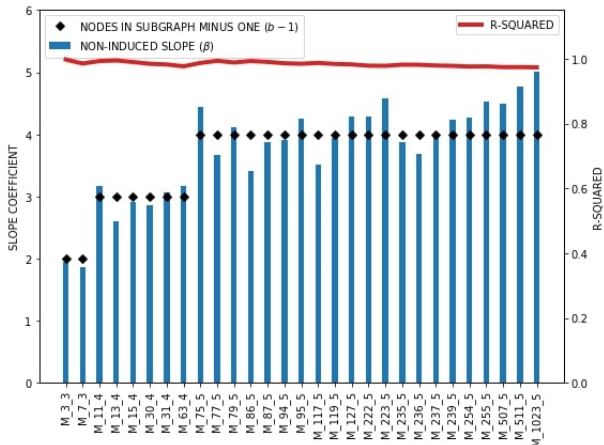


tadpole

- ▶ Evidence that $|M_a^{(b)}| = A m^\beta$ with $\beta \approx b - 1$
- ▶ Erdős-Rényi $G(n, p)$, general scaling result (Bollobás, 1985; Itzkovitz & Uri Alon, 2005) $\implies \beta = b/2$ as n large

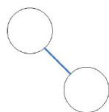
³“Networks are full of power laws . . .” but do they arise from optimality or randomness? “It would be nice to know.” (Gabaix, 2016, pp.200–201)

Evidence for power law $|M_a^{(b)}| = A m^\beta$, full-sample

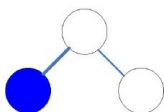


- Close match between estimated slope β (blue), and $b - 1$ (black) for *all* subgraphs $b = 3, 4, 5$; R-squared very high (red)

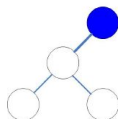
Scaling not robust to evolution in toy model (1)



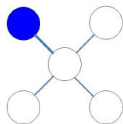
(a) $\ell = 2$ nodes.



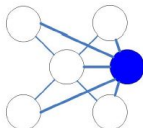
(b) $\ell = 3$ nodes.



(c) $\ell = 4$ nodes.



(d) $\ell = n^* = 5$ nodes.



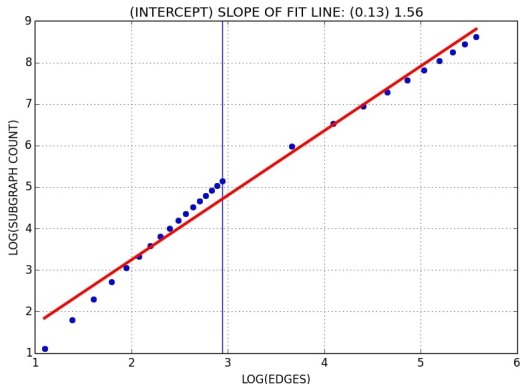
(e) $\ell = 6$ nodes.



(f) $\ell = 7$ nodes.

- ▶ (Regime 1, $n < n^*$) Grows as n -star
e.g. $|M_3^{(3)}| \sim 2^{-1}m^2$, as n^* large
- ▶ (Regime 2, $n \geq n^*$) Tends to n -complete
e.g. $|M_3^{(3)}| \sim 2^{1/2}m^{3/2}$, as n large relative to n^*

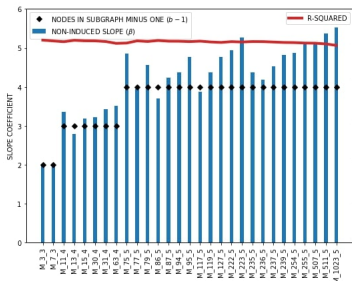
Scaling not robust to evolution in toy model (2)



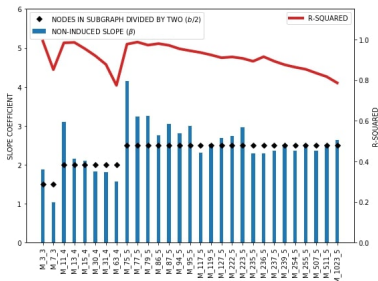
3-star

- ▶ Setting $n = 30$ and $n^* = 20$, least squares on full-sample gives $\beta = 1.56$ and $R^2 = 0.983$ for 3-star subgraph counts

Evidence for power law $|M_a^{(b)}| = A m^\beta$, two regimes



Regime 1



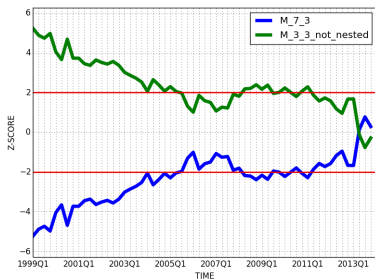
Regime 2

- ▶ In Regime 1, evidence that $\beta \approx b - 1$
- ▶ In Regime 2, evidence that $\beta \approx b/2$
- ▶ Which **theoretical or real graphs** have similar scaling?
What could cause such a “**phase transition**”?

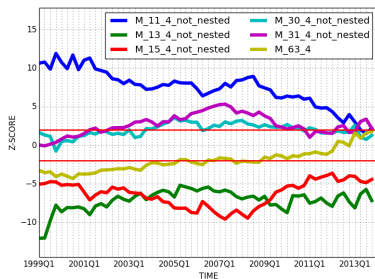
Which induced subgraphs are motifs?

- ▶ Do any subgraphs arise more (less) often than in G random? (Milo et al., 2002; many papers 2002–2004; Chen et al., 2013)
- ▶ Null ensemble: degree-preserving rewiring of edges to randomize observed G , control for observed lower-degree induced subgraphs by simulated annealing (Milo et al., 2002)
- ▶ Motifs unique local topologies, basic structural elements that *may perform specialized functions individually or in interaction*

The z-scores for 3-node and 4-node induced subgraphs



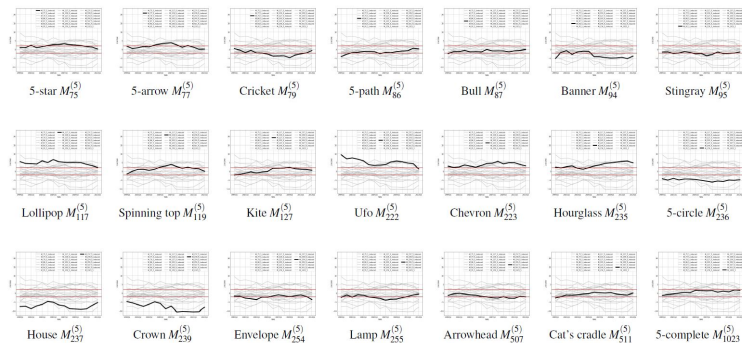
3-node



4-node

- ▶ The 3-star $\tilde{M}_3^{(3)}$ less significant over time, triangle $M_7^{(3)}$ opposite interpretation, **but density and clustering have fallen!**
- ▶ The 4-star $\tilde{M}_{11}^{(4)}$ is a strong motif for much of the sample, the 4-path $\tilde{M}_{13}^{(4)}$ and tadpole $\tilde{M}_{15}^{(4)}$ are strong anti-motifs

The z-scores for 5-node induced subgraphs



5-node

- ▶ Some heterogeneity across subgraphs, significance of motifs stable over time, curious given observed dynamics and scaling

Conclusions

- ▶ Frame real-world transportation network as a mathematical graph, investigate local topology, **some features of random graphs but striking differences too** (scaling, motifs)
- ▶ Quantitative evidence for **power law** between subgraph counts and edges, possible **“phase transition”** in underlying model
- ▶ Efficient detection of motifs on 3–5 nodes, **some surprising quantitative results** (density falls but “clustered” motifs more significant, time-varying scaling but motifs “stable” over time)

Extensions and speculation

- ▶ Develop a better qualitative and quantitative understanding of subgraph-based scaling in economic and transportation networks (better data, larger networks, larger subgraphs, bias-reducing econometrics, theoretical models, universality)
- ▶ Expand toolkit of subgraph-based “mesoscopic” measures, subgraphs as “fingerprints” of real-world networks? (network typology, components of econometric or statistical models)
- ▶ Do *small* subgraphs provide insight into the “reconstruction conjecture” (Kelly, 1957; Ulam, 1960) or analogous results? (are graphs uniquely determined by small/large subgraphs?)