
On the Evolution of Finite-Sized Complex Networks with Constrained Link Addition

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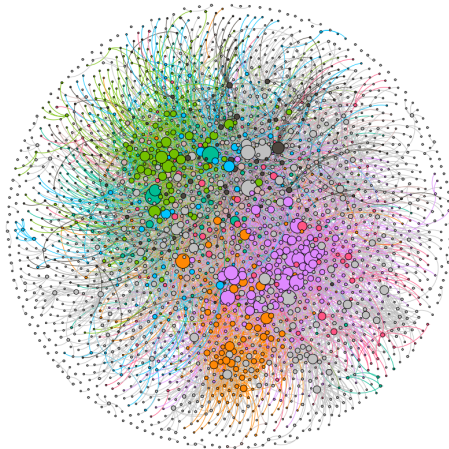


December 19, 2018



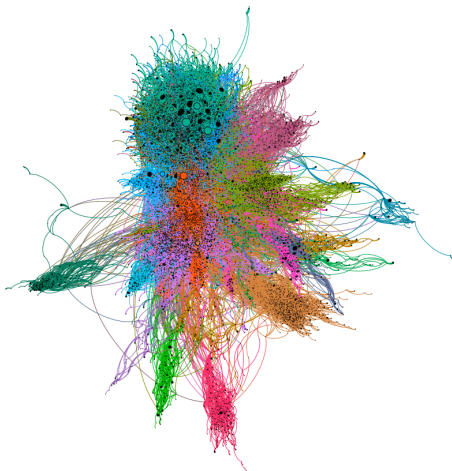
EuroSis network consists of 1285 nodes and 7586 links. The network represents web interaction of 12 European countries in the context of science community actors. The graph is generated with Gephi 0.9.1 and the network layout is ForceAtlas.

Real-world network examples (cont'd...)



The protein-protein biochemical interaction network of Yeast with 2361 nodes and 7182 edges. [The protein-protein interaction networks show contacts established during the bio-chemical reaction in the body of yeast.](#) The graph is generated with Gephi 0.9.1 and the network layout is Fruchterman-Reingold.

Real-world network examples (cont'd...)



The network of autonomous systems (ASs) in the Internet with 22,963 nodes and 48,434 links. A node in the network represents an AS and an edge represents interconnection between two ASs. The graph is generated with Gephi 0.9.1 and the network layout is ForceAtlas 2.



Key observation: Real-world network examples

- Network growth w.r.t. **nodes**



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- Network growth w.r.t. **nodes**
- There is not much literature on the evolution of **finite-sized complex networks**
 - Size of the **network is growing** w.r.t. **new links**
 - The **network size is relatively static**



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 - Size of the **network is growing** w.r.t. **new links**
 - The **network size is relatively static**
- Some real-world examples:
 - **Relationships in community networks**
 - **Transportation networks**
 - **Sensor networks**
 - **Social networks of closed community**
 - **Many more...**

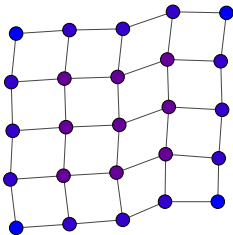
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Our key contribution

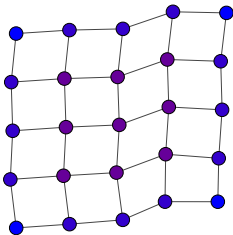
Study the **gradual evolution of finite-sized complex networks** with **constrained link addition**

Evolution of a finite-sized grid network

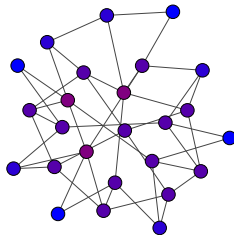


(a) A 5×5 regular grid network

Evolution of a finite-sized grid network

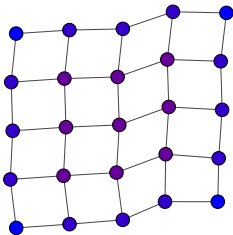


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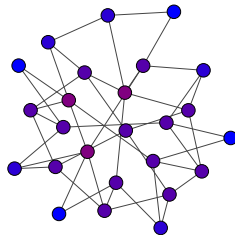


(b) The grid transforms to a small-world network

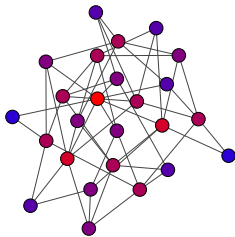
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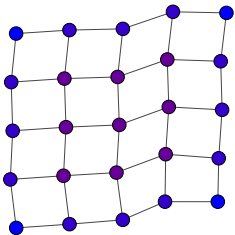


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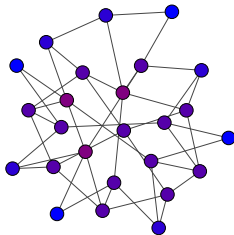


(c) It gradually transforms to a scale-free network

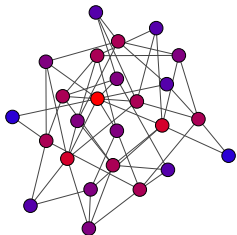
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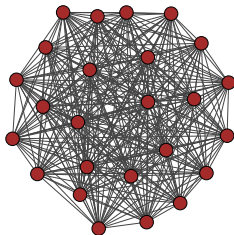
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(c) It gradually transforms to a scale-free network



(d) The grid becomes fully connected with unconstrained link addition



Outline of the talk

- 1 Related work
- 2 Constrained link addition
- 3 Experimental results
- 4 Observations and conclusion



Related work



Evolution of real-world complex networks

- **Barabási et al.**¹ first observed the **formation of real-world networks to be scale-free**
 - **Growth** and **preferential attachment**
 - **Fitness of nodes**²
- **Real-world scale-free networks** can also be **evolved with rewiring**³ where $\gamma \simeq 1$
- **Papadopoulos et al.**⁴ claimed the formation of scale-free networks
 - **Involves no luck**⁵
 - Optimization of **popularity** and **similarity**

¹Albert-László Barabási and Réka Albert. "Emergence of scaling in random networks". In: *Science* 286.5439 (1999), pp. 509–512.

²Ginestra Bianconi and A-L Barabási. "Competition and multiscaling in evolving networks". In: *EPL (Europhysics Letters)* 54.4 (2001), p. 436.

³Gábor Timár, Sergey N Dorogovtsev, and José Fernando F Mendes. "Scale-free networks with exponent one". In: *Physical Review E* 94.2 (2016), p. 022302.

⁴Fragkiskos Papadopoulos et al. "Popularity versus similarity in growing networks". In: *Nature* 489.7417 (2012), pp. 537–540.

⁵Albert-László Barabási. "Network science: Luck or reason". In: *Nature* 489.7417 (2012), pp. 507–508.



Evolution of real-world networks (cont'd. . .)

- **We found⁶** that
 - **Greed** is one of the key reasons for **evolution of real-world scale-free networks**

⁶Abhishek Chakraborty and B. S. Manoj. “The reason behind the scale-free world”. In: *IEEE Sensors Journal* 14.11 (2014), pp. 4014–4015.

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- Greedy decision-based approach **transforms a regular network to a scale-free network**
 - Hub nodes attract **unconstrained log-ranged links (LLs)** due to **long-ranged link affinity (LRA)**

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 - **First LL always connects** between $0.2N^{th}$ and $0.8N^{th}$ **anchor nodes** in a string topology network⁷

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We study what happens when constrained LLs are added based on greedy decision making

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Observations on constrained LL addition



Constrained LL addition: Assumptions

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Constrained LL addition: Assumptions

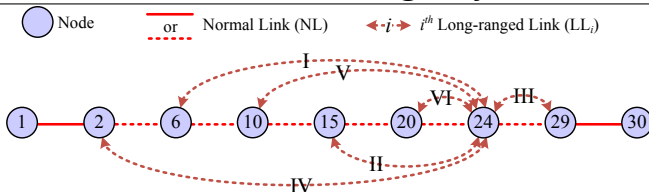
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- **Constrained LL addition** is carried out for **1D and 2D network topologies**
 - **LL_{MaxLen} : Maximum possible length of an LL in 1D**
 - **$LL_{MaxLen2D}$: Maximum possible length of an LL in 2D**



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Addition of unconstrained LLs with greedy decision making:



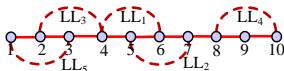
An example unconstrained LL addition in a 30-node string



What do we mean by constrained LL addition?



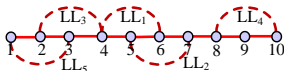
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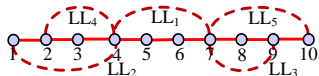
(a) **LL addition with $LL_{MaxLen} = 2$**



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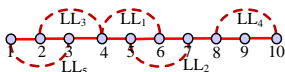
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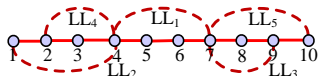
(b) LL addition with $LL_{MaxLen} = 3$



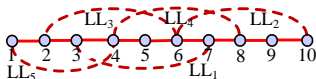
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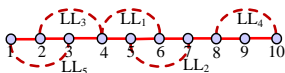
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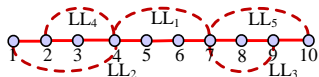
(c) LL addition with $LL_{MaxLen} = 4$



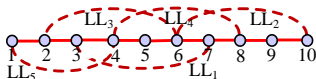
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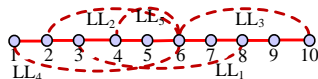
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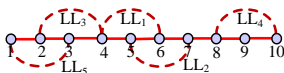
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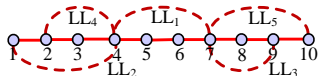
(d) LL addition with $LL_{MaxLen} = 5$



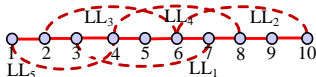
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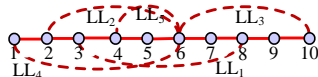
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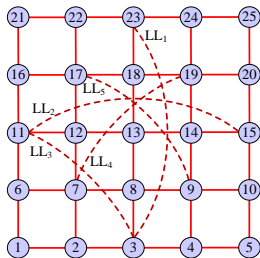
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(e) LL addition in grid with $LL_{MaxLen2D} = 4$



Greedy decision-based constrained LL addition

Greedy Decision-based Constrained LL Addition

```

Initialization:  $LL_{Max}$ 
1: for  $i = 1 \rightarrow k$  do
2:   for  $p = 1 \rightarrow N$  do
3:     for  $q = 1 \rightarrow N$  do
4:       if  $2 \leq LL_{Len}(p, q) \leq LL_{Max}$  &&  $(p, q) \notin \mathcal{E}$  then
5:         Construct  $i^{th}$  LL between nodes  $p$  and  $q$ 
6:         Estimate APL value of the network
7:         Save the APL value
8:         Remove the constructed LL
9:       end if
10:    end for
11:  end for
12:  Searches for optimal APL value to construct  $i^{th}$  LL
13:  if More than one optimal APL LL possibilities exist then
14:    Randomly select one node pair with the optimal value of APL
15:  end if
16:  Add  $i^{th}$  LL between selected node pair giving the lowest APL
17:  Update network graph
18: end for
  
```

// (LL_{MaxLen} or $LL_{MaxLen2D}$)
 // k : Number of LLs to be added



Experimental results and discussion



Experimental setup

- A set of **constrained LLs are added with greedy decision to minimize APL**⁸

⁸B. S. Manoj, Abhishek Chakraborty, and Rahul Singh. *Complex networks: A networking and signal processing perspective*. Prentice Hall PTR, New Jersey, USA, 2018.



Experimental setup

- A set of **constrained LLs are added with greedy decision to minimize APL**⁸
- $\left\lceil \frac{N}{2} \right\rceil$ **constrained LLs are deployed** in an N -node string
 - **Range of an LL (1D): $2 \leq LL \leq \left\lceil \frac{N}{2} \right\rceil$**
 - With various sized networks (**from 50 to 200 nodes**)

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- $\left\lceil \frac{N^2}{2} \right\rceil$ **constrained LLs are deployed** in an $N \times N$ -node grid
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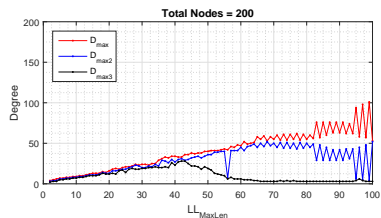
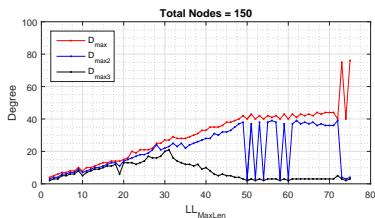
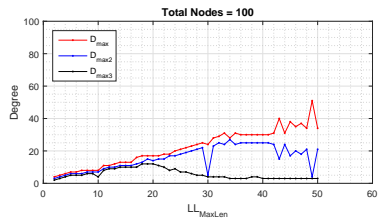
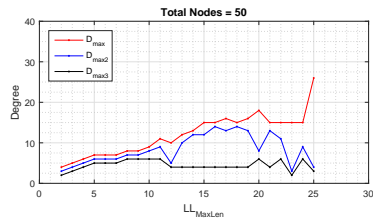
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- **Observations are made** for the following parameters
 - **Nodal degree** w.r.t. different **LL_{Max} values**
(**D_{max}, D_{max2}, and D_{max3}**)
 - **Average length of constrained LLs**

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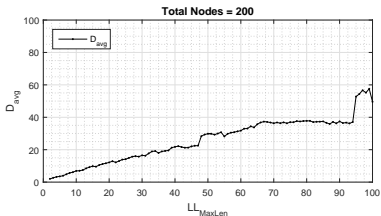
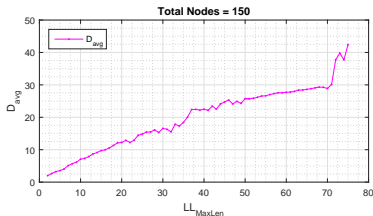
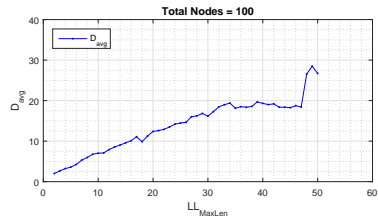
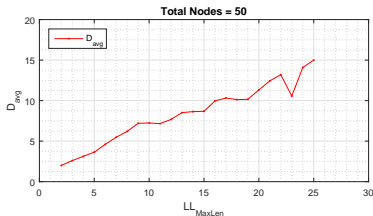
Observations on string networks



Plot of the maximum degree (D_{max}), the second maximum degree (D_{max2}), and the third maximum degree (D_{max3}) with respect to different LL_{MaxLen} values for 50-, 100-, 150-, and 200-node string networks



Observations on string networks (cont'd...)



Plot of the average length of an LL (D_{avg}) with respect to different LL_{MaxLen} values for 50-, 100-, 150-, and 200-node string networks



Key observations from simulation results

■ Observations on nodal degree

- Differences among D_{max} , D_{max2} , and D_{max3} values are more as

$$LL_{MaxLen} \rightarrow \left\lceil \frac{N}{2} \right\rceil$$

- With increasing LL_{MaxLen} , a single node becomes hub



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- At $LL_{MaxLen} \leq 0.2N$, network behaves like **small-world** as no hub-node emerges
- In $0.3N < LL_{MaxLen} < 0.4N$, **presence of multiple hub-nodes**
- For $LL_{MaxLen} \simeq 0.6N$, **first LL is connected between the anchor nodes**, i.e., between $0.2N$ and $0.8N$ nodes



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- In $0.3N < LL_{MaxLen} < 0.4N$, **presence of multiple hub-nodes**
- For $LL_{MaxLen} \simeq 0.6N$, **first LL is connected between the anchor nodes, i.e., between $0.2N$ and $0.8N$ nodes**

■ Observations on average length of a constrained LL

- **Average length of an LL is approximately $0.6 \times LL_{MaxLen}$**



Key observations from simulation results

■ Observations on nodal degree

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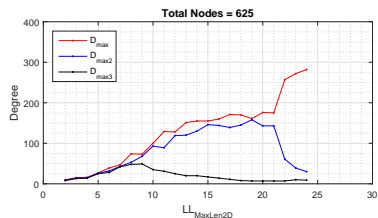
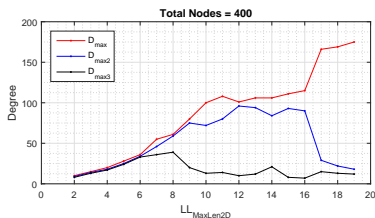
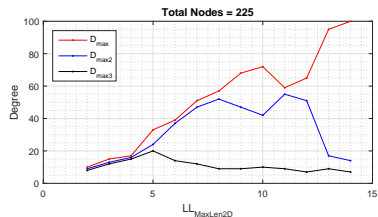
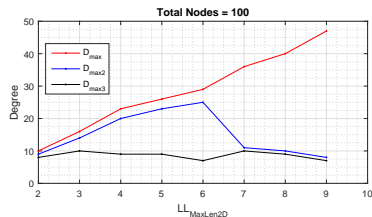
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- When $0.3N < LL_{MaxLen} < 0.4N$, **D_{avg} greatly varies** in the network



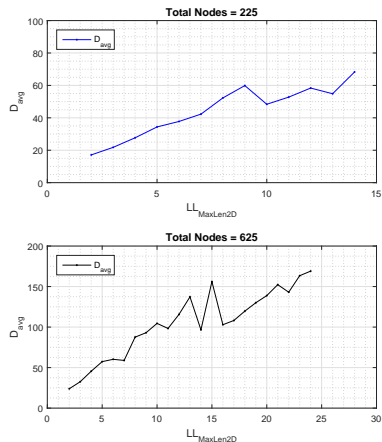
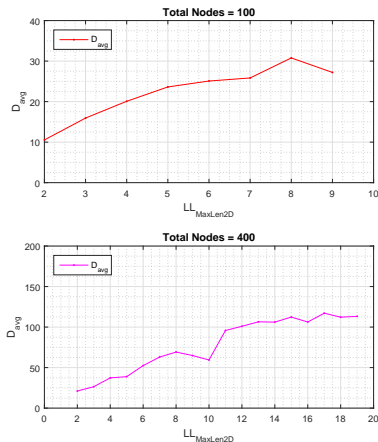
Observations on grid networks



Plot of the maximum degree (D_{max}), the second maximum degree (D_{max2}), and the third maximum degree (D_{max3}) with respect to different $LL_{MaxLen2D}$ values for 10×10 -, 15×15 -, 20×20 -, and 25×25 -node grid networks



Observations on grid networks (cont'd...)



Plot of the average length of an LL (D_{avg}) with respect to different $LL_{MaxLen2D}$ values for 10×10 -, 15×15 -, 20×20 -, and 25×25 -node grid networks



Key observations from simulation results

■ Observations on nodal degree

- Differences among D_{max} , D_{max2} , and D_{max3} values are more as $LL_{MaxLen2D} \rightarrow N$
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- **Average length of an LL** is approximately $0.8 \times LL_{MaxLen2D}$



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- There is a **minimal change in D_{avg} value** in the range $LL_{MaxLen2D} < N$
- As $LL_{MaxLen2D} \rightarrow N$, a single hub node gradually emerges in the network



Observations and conclusion

- **Unconstrained LL addition may result in edge saturation**



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Evolution of a length constrained finite-sized network

Regular network → **small-world network** → **scale-free network**
→ **scale-free network with truncated degree distribution**^a

^a**Truncated degree distribution means that the distribution is a conditional distribution imposed by certain restriction**



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Various phases of network evolution and average length of an LL

Network Types	Phases of Evolution	Range of LL (w.r.t. N)
String	Small-world characteristics	$2 \leq LL_{MaxLen} \leq 0.2N$
	Scale-free characteristics (multiple hub nodes)	$0.3N < LL_{MaxLen} < 0.4N$
	Scale-free characteristics (one hub node emerges with most of the LLs)	$LL_{MaxLen} \geq 0.4N$
	Average length of an LL = $0.6 \times LL_{MaxLen}$	
Grid	Small-world characteristics	$2 \leq LL_{MaxLen2D} \leq 0.2N$
	Scale-free characteristics (multiple hub nodes)	$0.3N < LL_{MaxLen2D} < 0.6N$
	Scale-free characteristics (one hub node emerges with most of the LLs)	$LL_{MaxLen2D} \geq 0.6N$
	Average length of an LL = $0.8 \times LL_{MaxLen2D}$	



QUESTIONS?

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THANK YOU.

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