

## Lecture 3 - Network Measures

Wednesday, January 21, 2026 6:17 PM

### Plan for today:

- Discuss paper presentations
  - o 15-20 minutes
  - o What to include?
    - Intro: What problem is the paper trying to address/solve?
    - Background: What other relevant work has considering this problem or other similar problems.
    - Methods: How exactly are the authors addressing/solving the problem under considerations?
    - Results: What experiments have the authors performed to validate their approach or assumptions or theoretical results?
    - Discussion: What are the broad takeaways from the methods and results with respect to prior work and the problem as a whole?
    - Future Work: What are the next steps this work could take?
  - o For examples see: gmslota.com -> Publications -> 'slides' OR
  - o gmslota.com -> Presentations -> 'slides'
- Go over lec02.py code example
- k-edge-connectivity and network flow
- Network measures and distributions
- Code example????????

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## Review of last class

k-connectivity

→ network resilience

→ how many vertices to remove to disconnect the graph

directed graphs

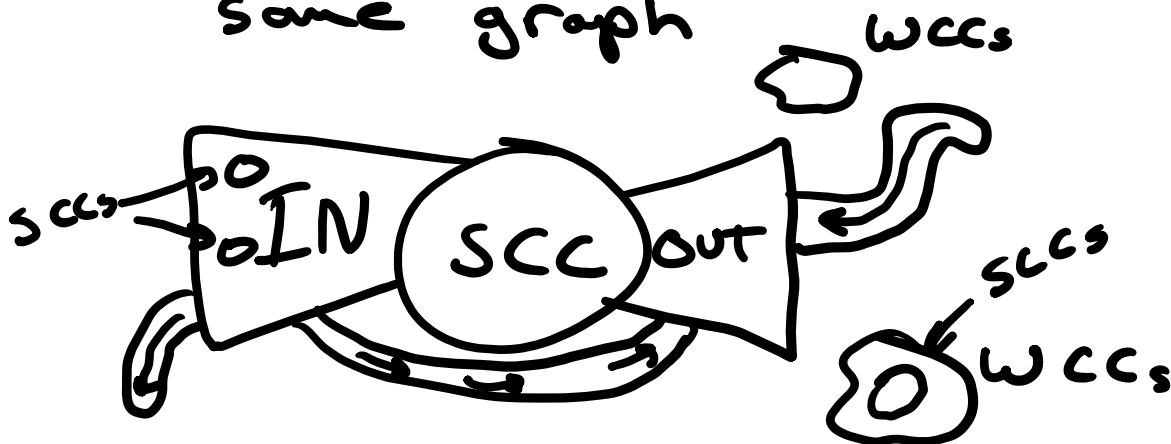
# directed graphs

- edge have direction



- strong/weak connectivity

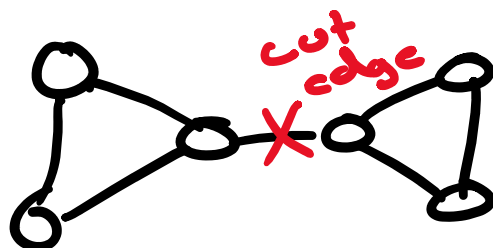
$\Rightarrow$  Connectivity in general gives us insight into some global or underlying structure of some graph



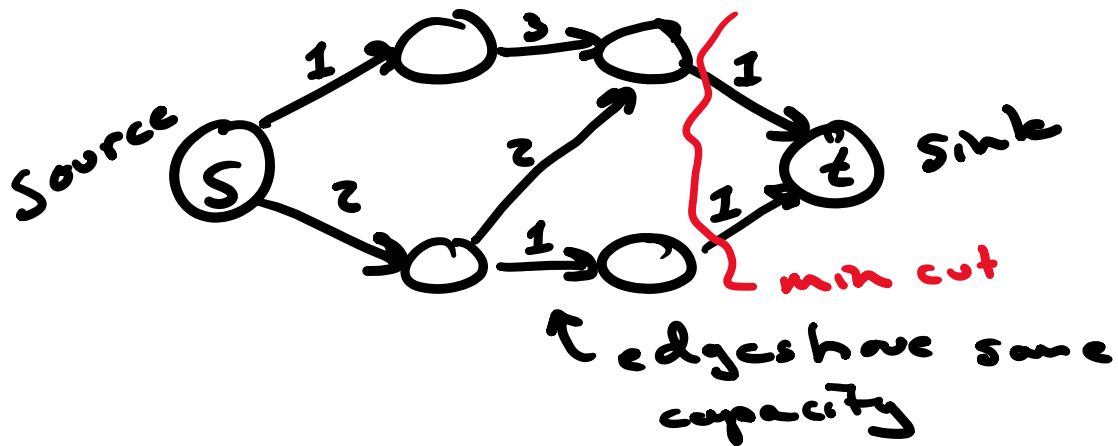
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## k-edge-connectivity

$\hookrightarrow$  how many edges to remove to disconnect some  $G$



# Algorithmic approaches Network Flow



Goal: determine max flow

$$\text{max flow} = \text{min cut} \\ (\text{weighted cut})$$

To determine a min cut  $G$ :  
consider all possible  $u, v$  pairs  
as source, sink

Solve for max flow

min cut?

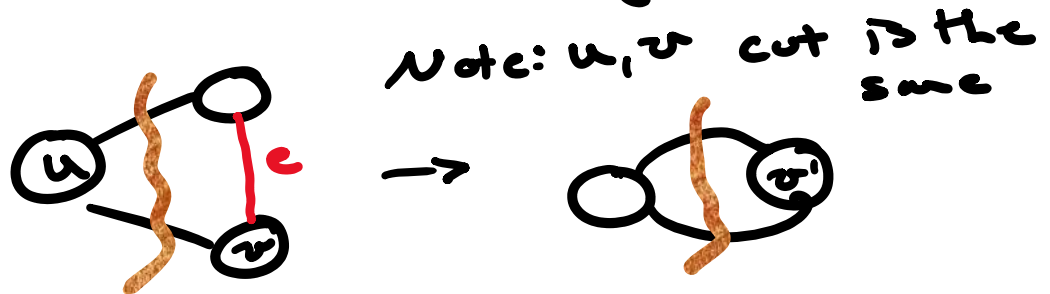
$$\Rightarrow O(n^4)$$

Faster algorithms (using variants  
of flow)  
 $\Rightarrow O(n^2)$

$$\Rightarrow O(n^2) \quad \text{of flow}$$

## Other approaches

→ consider edge contraction



To contract edge  $e$

→ delete  $e$

→ we combine the endpoints of  $e$ , retaining all other adjacencies

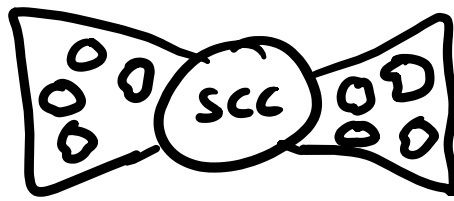
## auxiliary graph construction

↳ transformation of  $G$  into some  $G'$  using edge contraction or similar techniques

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A little more on strong connectivity

context: strong connectivity  
decompositions



← where are all of  
the strong  
components?

Bring it to "Network measures"

↳ largest SCC size, proportionally

↳ total # of SCCs

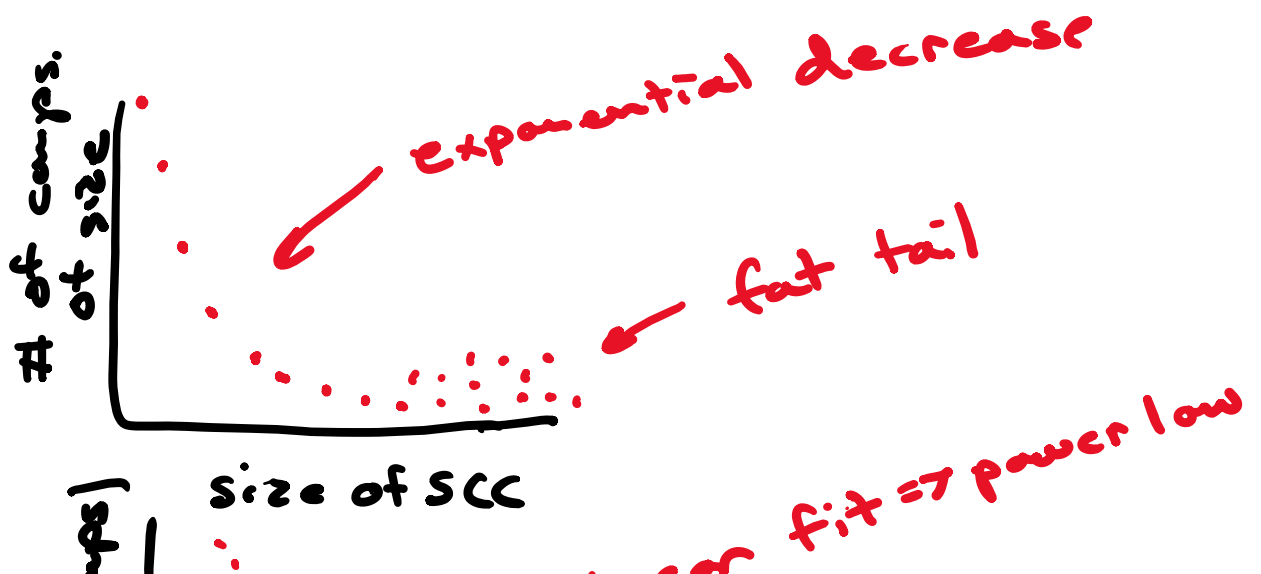
↳ size distributions of SCCs

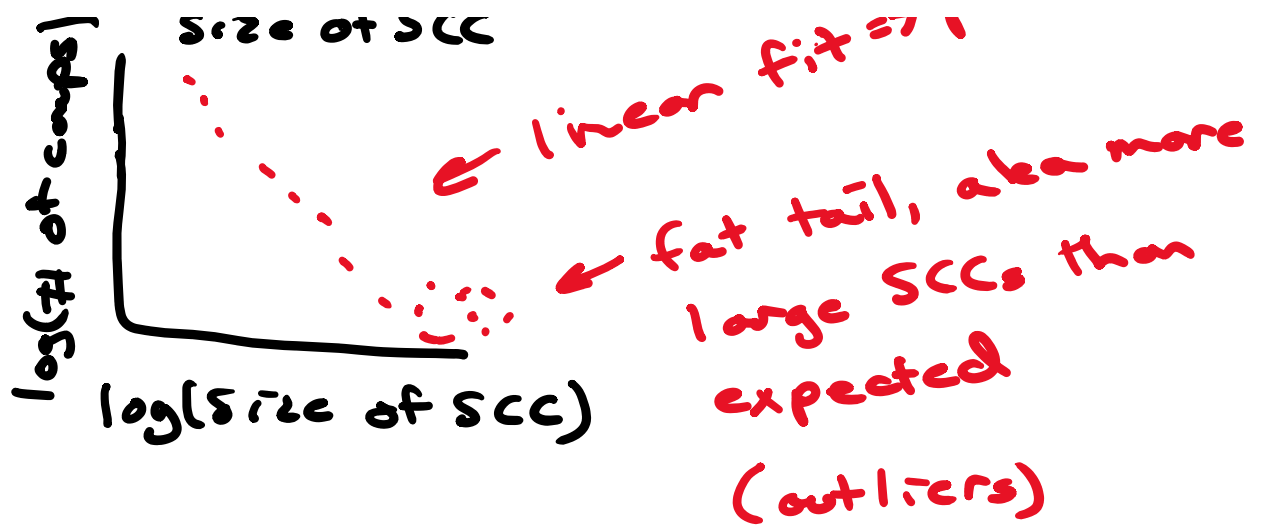
↳ How many size-1 SCCs?

How many size 2 SCCs?

...

max size SCCs?





Note: many properties of our real-world fit the above "shape"

- power-law-ish fit
- fat tail

E.g. component size distributions

{ degree distributions  
 "cluster" size distributions  
 (dense subgraph)

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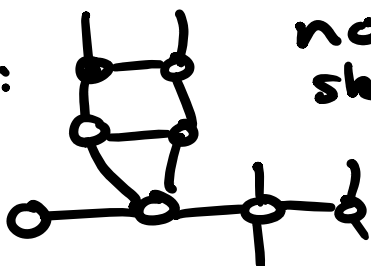
Degree Distributions

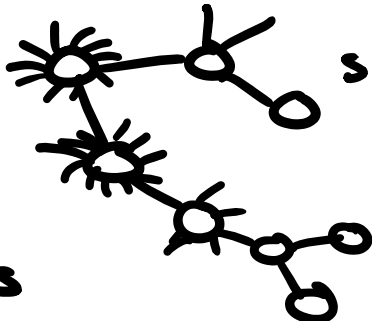
# of vertices with a given degree, over all degrees in  $G$

Why do we care?

→ This simple measure that captures and drives a lot of the network measure and topology

Eg. "Skew" → existence of power-law  
→ gini coefficient

Road networks:  not skewed

Social networks:  skewed

→ our other measures usually follow the notion skewedness that arises from degree distribution

Side note: Random graph generation and hypothesis testing

→ If we generate some  $G'$  with

- ↪ If we generate same  $G'$  with an equivalent D.D. as  $G$ , but with randomly wired edges,
  - we can measure the difference in properties of  $G$  and  $G'$  to explicitly determine the relative "importance" of those properties
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More detail on power-law degree distributions

$$\boxed{P(k) \sim k^{-\gamma}}$$

probability of degree  $k$        $\uparrow$  proportional       $\leftarrow$  power-law exponent

All together: frequency of a degree decreases exponentially with the magnitude of the degree

To actually measure degree dists. and compare them

and compare them

(recall: measurements are useless  
in a vacuum)  
(sp?)

1. compute Gini coefficient  
or similar given a distribution
2. Determine  $\gamma$  power-law exponent  
↳ less straightforward

$$\gamma = 1 + n \left[ \sum_{v \in V} \log\left(\frac{d(v)}{d_{\min}}\right) \right]^{-1}$$

$\gamma$  = power-law exponent

$d(v)$  = degree of  $v$

$d_{\min}$  = min degree (probably 1)

$n$  = number of verts in our  
distribution

Most real-world graphs

$1 \leq \gamma \leq 3$  for their degree dist.

↑  
more  
skewed

↑  
less  
skewed

As we've noted:

This relation generally holds for more than just degrees

↳ connectivity distributions  
cluster sizes  
shortest path lengths

All together, this gives us

$\Rightarrow$  scale-free graphs

Generally: Fat-tailed distributions with power-law fits define many measurable properties of real networks

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How to <sub>graph</sub> mine?

Can compare degree distributions  
connectivity distributions  
cluster distributions

cluster distributions

→ pairwise against other networks

OR

against a null model

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Main takeaways:

1. Measurements should not exist in a vacuum

2. Real graphs are usually skewed  
→ arising from power-law degree distribution driving other properties