

American Dialect Society's Word of the year for 2023: enshittification

Enshittification: aka 'platform decay', is the pattern of decreasing quality of online platforms that act as two- or multi-sided markets. E.g., Amazon, Google, Facebook

Step 1: Create a useful product to attract users (market 1).

Step 2: Monetize those users to sell ads (market 2).

Step 3: Get greedy, hurt market 1 to financially benefit from market 2.

Step 4: Start losing users, hurt market 2 to retain market 1.

Step 5: Basically, piss everyone off and destroy your brand.

Step 6: Die.

Review of last class

k-connectivity

- related to network resilience

→ how many vertices to remove to disconnect the graph

directed graphs

- edges are directed



strong/weak connectivity

strong: $\forall u, v \in V \exists (0) \leq n \exists u, v$ -path

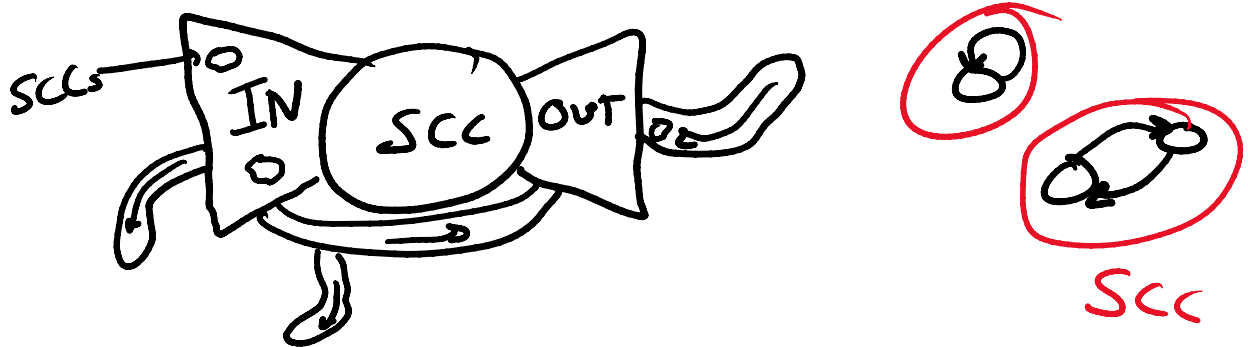


weak: same as undirected

connectivity if we ignore

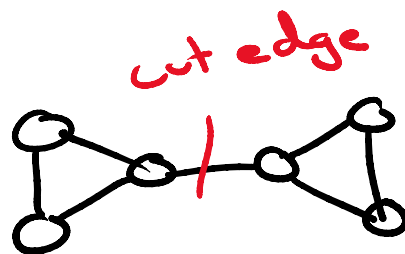
Connectivity if we ignore direction of edge

Connectivity in general gives insight into some global or underlying structure of same graph



k -edge-connectivity

↳ how many edges to disconnect a graph



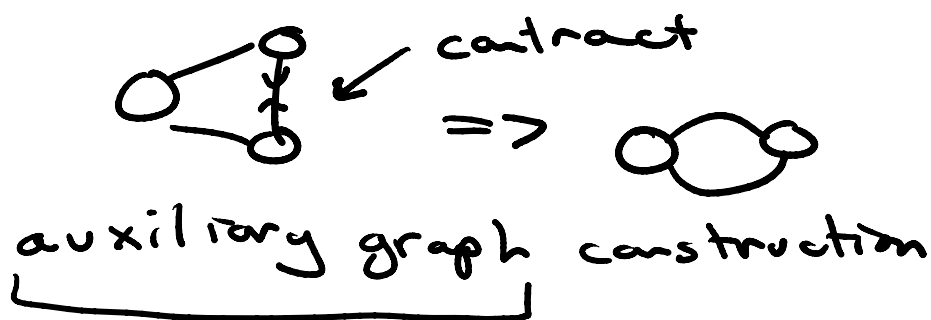
Algorithmic approaches

Network Flow $O(n^4)$

Faster algorithms

Karzanov algos $\sim O(n^2)$

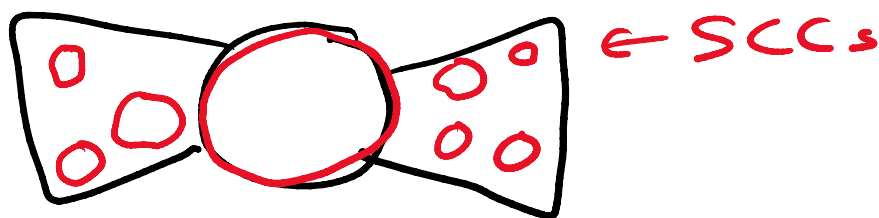
Kardan algos $\sim O(n^2)$
edge contraction



transformation using
contraction or other
technique

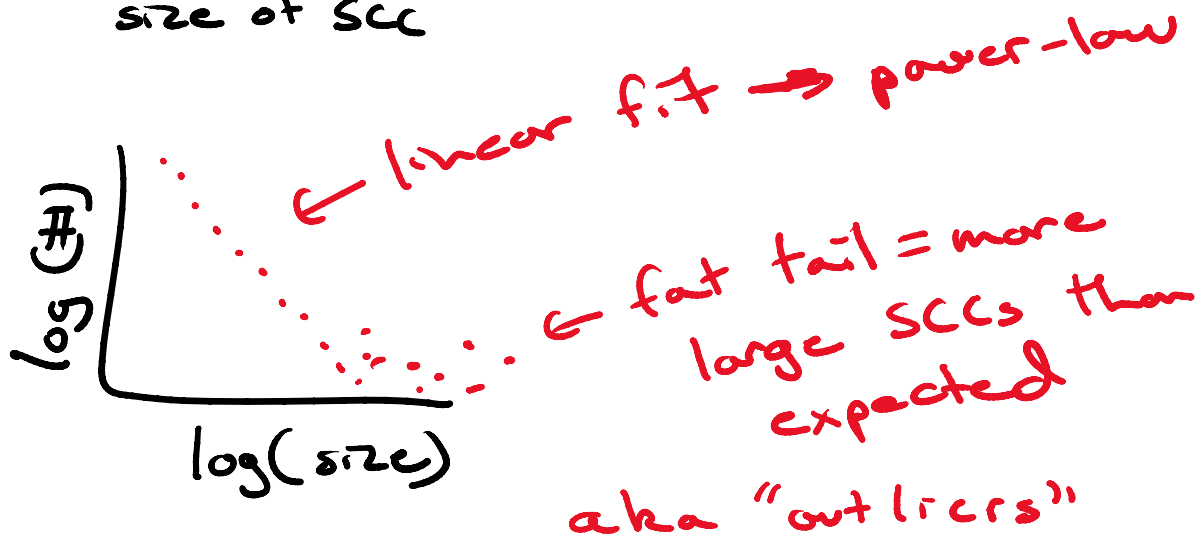
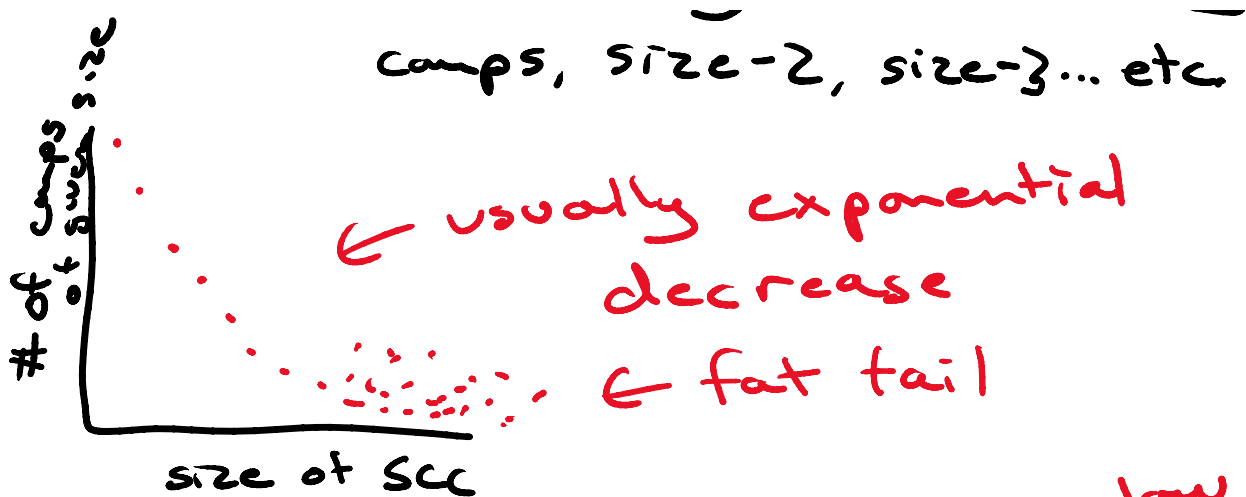
More on strong connectivity

Context: strong connectivity
decompositions



In terms of network measures:
size distributions of strong
components

size
↳ how many size-1 strong
comps, size-2, size-3... etc



Many many properties of our real-world networks fit the above plot "shape"

- power-law fit at the head
- fat tail

Eg. component size distributions

degree distributions, "cluster"

size distribution dense subgraph
↑
degrees vs. # of vertices w/degree

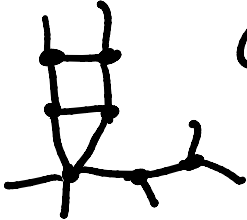
→ degrees vs. # of vertices w/ a degree

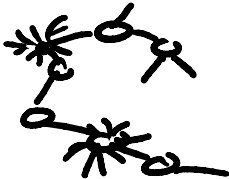
More on degree distributions

Why are they useful?

→ can capture a lot of properties of the given network

Eg.: "skew" → gini coefficient
→ power law fit

Road network:  (not skewed)

Social network:  (more skewed)

- Random graph generation and hypothesis testing

↳ Given same G with same degree distribution, how are the measured properties different than a random graph with the same degree distribution

More detail on power-law ^{degree} distributions
→ power-law exponent

1 core ...

$$P(k) \sim k^{-\gamma} \leftarrow \text{power-law exponent}$$

\uparrow probability of degree k
 \uparrow proportional

→ all together: frequency of a degree decreases exponentially as the degree increases

To actually compare degree distributions
 (recall: measurements are relatively useless in a vacuum)
 (sp?)

- Calculate Gini coefficient
 ↳ straight forward
- Determine γ power-law exponent
 ↳ not as straightforward

One way to get γ : MLE

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

γ = power-law exponent

$d(v)$ = degree of v

$d(v)$ = degree of v

d_{min} = minimum over $d(v) \rightarrow 1$

$n = |V(G)|$ = number of vertices in G

Most real-world graphs

$$1 \leq \gamma \leq 3$$

↑
less skewed

↑
more skewed

As we've noted:

this relation holds for more than
simply degree distributions

Also: - connectivity size distributions
- cluster sizes
- shortest path lengths

All these together

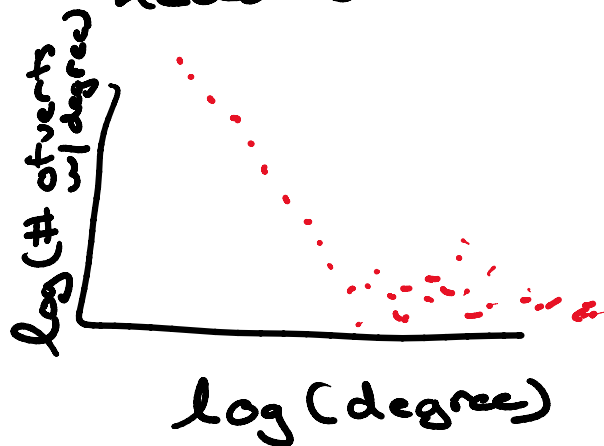
\Rightarrow scale-free graph

Generally, as we've stated:

↳ ... inhibition with

generally, no well-defined

→ Fat-tailed distribution with a power-law fit to the head of the distribution



Mining connectivity structure
How ???

- Identifying cut vertices/edges
- k -(edge-)connectivity decays for vary k
- look at component size distributions for varying k
- General reachability or how maximal k -components are connected

are connected

- k-core identification

→ maximal subgraph S where

$$\forall v \in V(S): d_S(v) \geq k$$

