

CSE 373

DECEMBER 1ST – GRAPH MADNESS

ASSORTED MINUTIAE

- **Project 3**
 - Maximum of 3 late days
 - Resubmission for all 3 parts by next Wednesday
- **Written Assignment**
 - Extra Credit
- **Next week:**
 - Monday office hours: 12:00-2:00 in my office
 - No office hours next Friday: email me to make an appointment

TODAY'S LECTURE

- **Isometric Graphs**
- **Last graphs problem**
 - Network Flow (Disclaimer)
- **Graph problem symmetry**

NEXT WEEK

- **Algorithm Design**
- **Computability and Complexity**
- **Exam Review**

FINAL EXAM

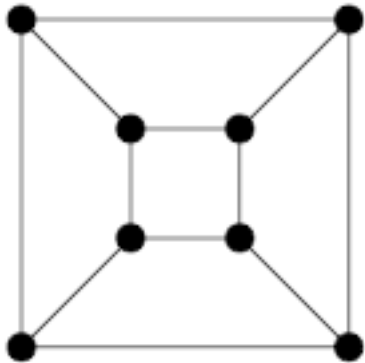
- **Topics list out this weekend**
- **Tue; December 12, 2017, 2:30-4:20**
 - Kane 220
- **Section, exam review**
- **Next Friday, exam review**
- **Practice Exam by next Tuesday**

GRAPHS

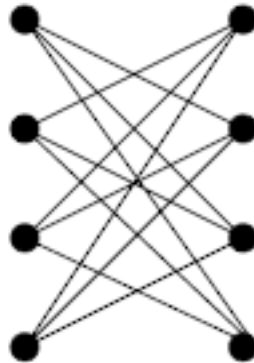
- **Talked a lot about graph representations**
- **Runtimes and memory**
- **How difficult can graphs be?**
 - Is it easier or more difficult to understand certain parts?

GRAPHS

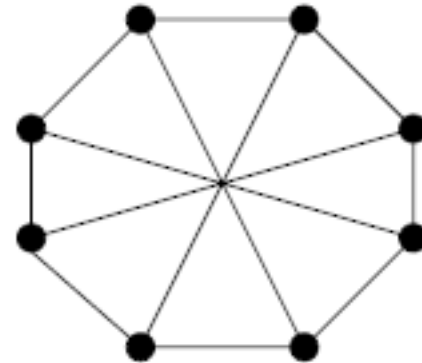
- Which of these 3 graphs do you think would be easiest to run Dijkstra's algorithm on?



G_1



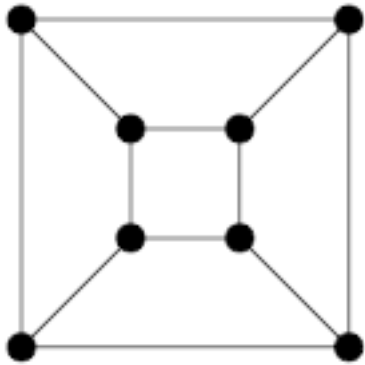
G_2



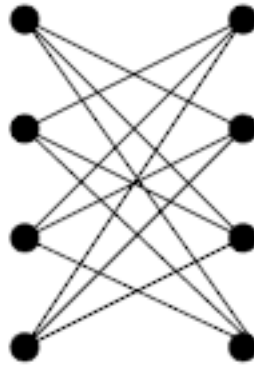
G_3

GRAPHS

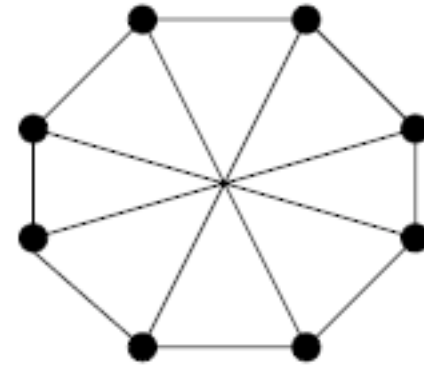
- Which of these 3 graphs do you think would be easiest (for the computer) to run Dijkstra's algorithm on?



G_1



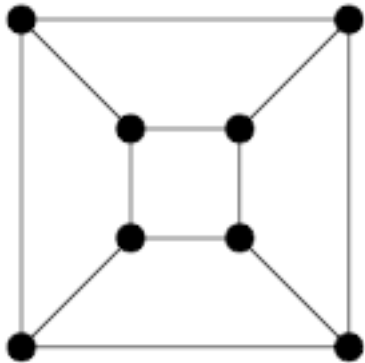
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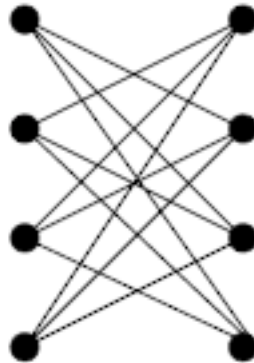
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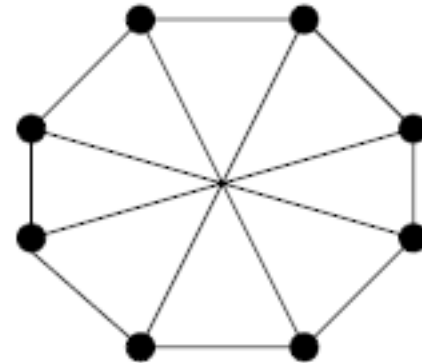
- G_1 and G_2 are the same graph, i.e. they are *isomorphic*



G_1



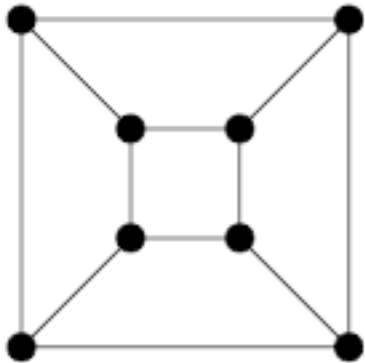
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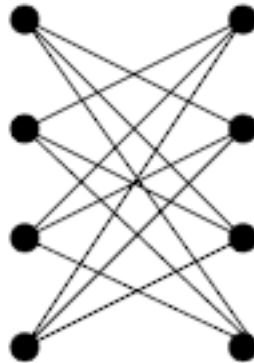
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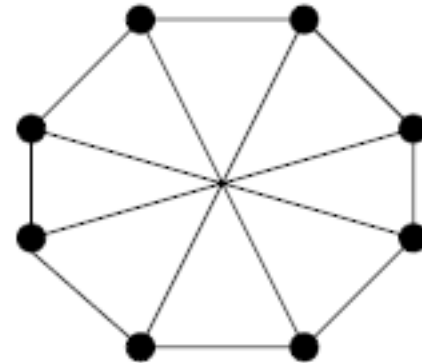
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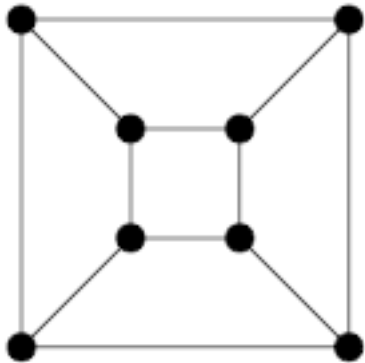
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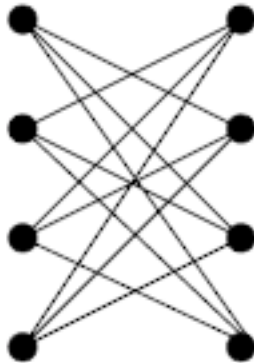
G_3

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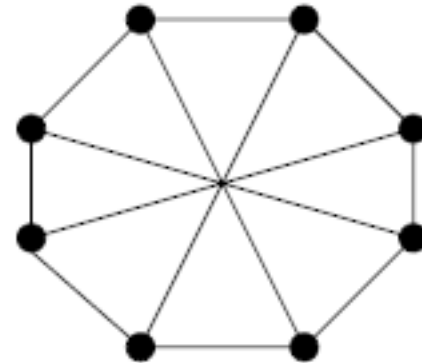
- G_1 and G_2 are the same graph, i.e. they are *isomorphic*
- G_3 is not. Can you prove it?



G_1



G_2



G_3

GRAPHS

- **Graphs have a sneaky way of appearing different all the time**
 - This isn't just true of the graph itself, but it can also be true of graph problems that we want to solve

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- **Graphs have a sneaky way of appearing different all the time**
 - This isn't just true of the graph itself, but it can also be true of graph problems that we want to solve
 - Makes graph theory incredibly interesting, but difficult to discuss

NETWORK FLOW

- **Determine the maximum flow from a source vertex to a sink in a graph**

NETWORK FLOW

- **Determine the maximum flow from a source vertex to a sink in a graph**
 - Graph: $G(V,E)$
 - Source vertex, s
 - Sink vertex, t
 - Each edge's weight represents the traffic a particular edge can carry (must be non-negative)

MAXIMUM FLOW

- Consider breaking graph into two subgraphs
 - $G(V, E_1)$ and $G(V, E_2)$ where $|E_1| = |E_2|$, but their weights are different
 - For each weight in E , $E_{1w} + E_{2w} = E_w$
 - The first is the **flow graph** and the second is the **residual graph**

MAXIMUM FLOW

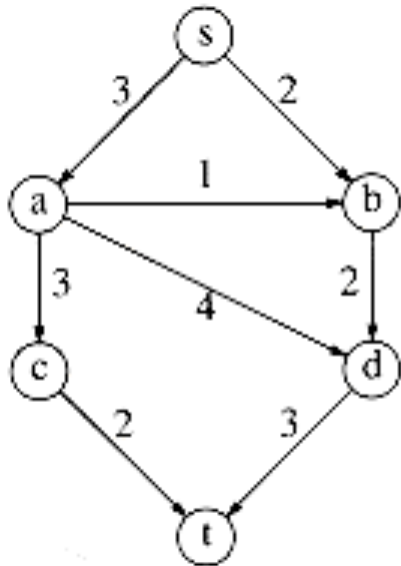
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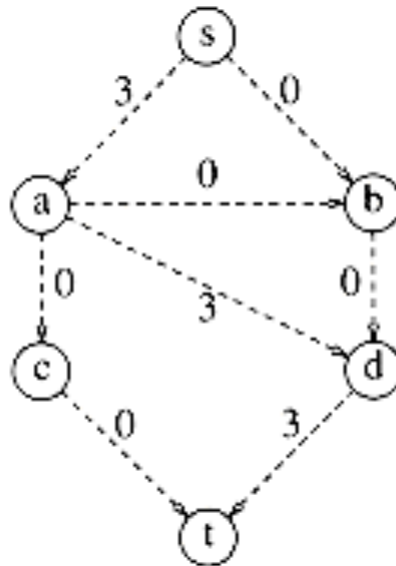
- **Consider breaking graph into two subgraphs**
 - For the flow graph, except the source and sink, the weights of all edges in must equal the weight of edges out
 - The residual graph can never have negative weights

MAXIMUM FLOW

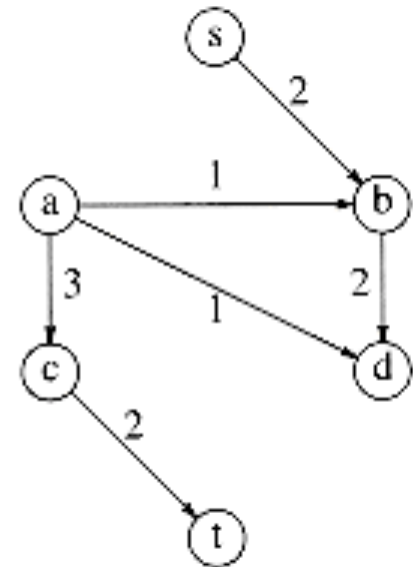
Graph



Flow



Residual



NAÏVE ALGORITHM

- **Start where the the residual is the graph and the flow is empty**
- **While there is a path from s to t in the residual**
 - Find the minimum edge weight along the path
 - For each in the path
 - Add the minimum weight for each edge in the path to the flow
 - Subtract the minimum weight for each edge from the residual

EXAMPLE

EXAMPLE

- **What went wrong?**

EXAMPLE

- **What went wrong?**

- If we select paths in the wrong order, we might not get the correct solution
- This is an example of a greedy-first algorithm
- Need to have an opportunity to back-track
- Well, let's add a reversal (augmenting) edge into the residual!

FORD-FULKERSON

Algorithm [\[edit \]](#)

Let $G(V, E)$ be a graph, and for each edge from u to v , let $c(u, v)$ be the capacity and $f(u, v)$ be the flow. We want to find the maximum flow from the source s to the sink t . After every step in the algorithm the following is maintained:

Capacity constraints:	$\forall (u, v) \in E \ f(u, v) \leq c(u, v)$	The flow along an edge can not exceed its capacity.
Skew symmetry:	$\forall (u, v) \in E \ f(u, v) = -f(v, u)$	The net flow from u to v must be the opposite of the net flow from v to u (see example).
Flow conservation:	$\forall u \in V : u \neq s \text{ and } u \neq t \Rightarrow \sum_{w \in V} f(u, w) = 0$	That is, unless u is s or t . The net flow to a node is zero, except for the source, which "produces" flow, and the sink, which "consumes" flow.
Value(f):	$\sum_{(s,u) \in E} f(s, u) = \sum_{(v,t) \in E} f(v, t)$	That is, the flow leaving from s must be equal to the flow arriving at t .

This means that the flow through the network is a *legal flow* after each round in the algorithm. We define the **residual network** $G_f(V, E_f)$ to be the network with capacity $c_f(u, v) = c(u, v) - f(u, v)$ and no flow. Notice that it can happen that a flow from v to u is allowed in the residual network, though disallowed in the original network: if $f(u, v) > 0$ and $c(v, u) = 0$ then $c_f(v, u) = c(v, u) - f(v, u) = f(u, v) > 0$.

Algorithm Ford–Fulkerson

Inputs Given a Network $G = (V, E)$ with flow capacity c , a source node s , and a sink node t

Output Compute a flow f from s to t of maximum value

1. $f(u, v) \leftarrow 0$ for all edges (u, v)
2. While there is a path p from s to t in G_f , such that $c_f(u, v) > 0$ for all edges $(u, v) \in p$:
 1. Find $c_f(p) = \min\{c_f(u, v) : (u, v) \in p\}$
 2. For each edge $(u, v) \in p$
 1. $f(u, v) \leftarrow f(u, v) + c_f(p)$ (*Send flow along the path*)
 2. $f(v, u) \leftarrow f(v, u) - c_f(p)$ (*The flow might be "returned" later*)

The path in step 2 can be found with for example a [breadth-first search](#) or a [depth-first search](#) in $G_f(V, E_f)$. If you use the former, the algorithm is called [Edmonds–Karp](#).

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- **Oh boy, that got complicated really quickly**
 - $O(|V||E|^2)$

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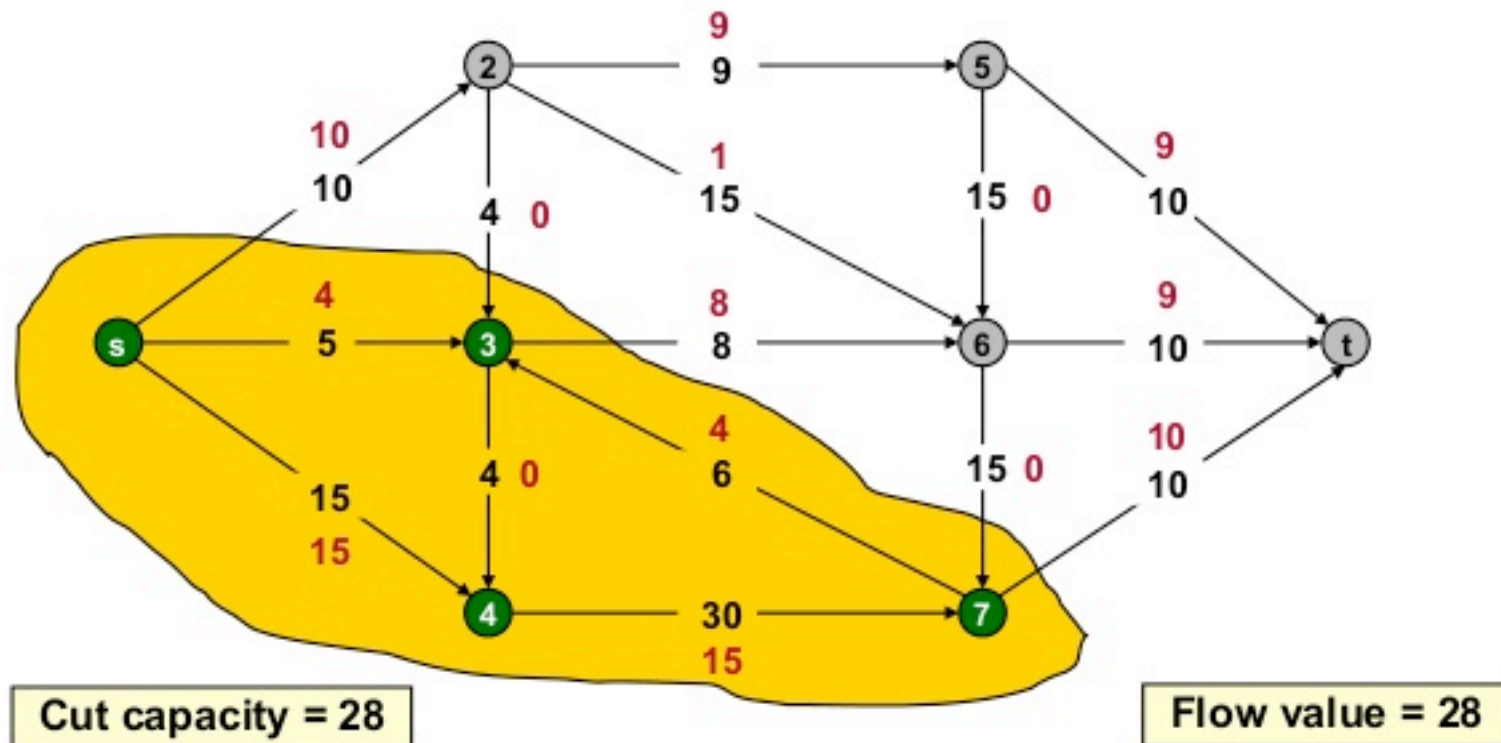
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Max-Flow Min-Cut Theorem

MAX-FLOW MIN-CUT THEOREM (Ford-Fulkerson, 1956): In any network, the value of the max flow is equal to the value of the min cut.

- "Good characterization."
- Proof IOU.



PROBLEM SYMMETRY

- **Solving max-flow is the same as solving the min-cut**
 - What algorithm do we use to solve the min-cut?

FORD-FULKERSON

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FORD-FULKERSON

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FORD-FULKERSON

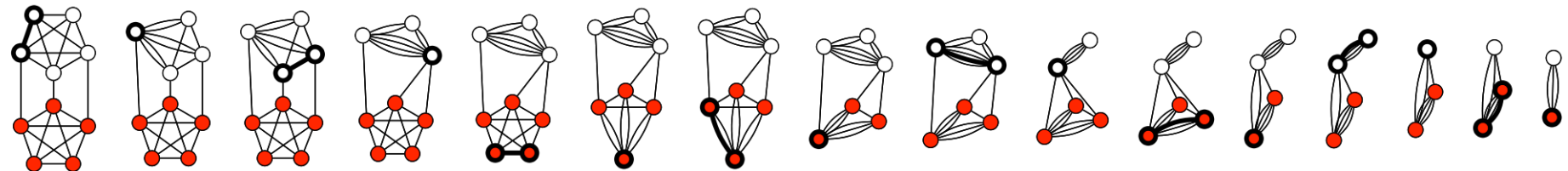
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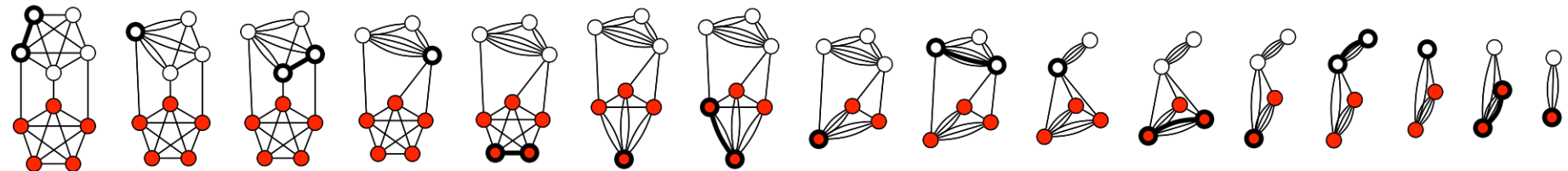
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- **Contract edges at random!**
 - How many edges will you contract to get two subgraphs?



KARGER'S ALGORITHM

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- **Contract edges at random!**
 - How many edges will you contract to get two subgraphs?
 - Only $|V|-2$



KARGER'S ALGORITHM

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- **Does this work?**
 - Success probability of $2/|E|$
 - Run it $O(E)$ times, and you have a bounded success rate!
 - $O(|V||E|)$

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 - Suppose we have an unweighted graph, how might we find the max-cut?
 - Swap all the edges in the graph and solve the min-cut!

REDUCTIONS

- **Anytime you can use one algorithm to solve another, this is called a reduction**
 - What if we wanted to find the graph of maximum flow that also has minimum weight?

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- **Anytime you can use one algorithm to solve another, this is called a reduction**
 - What if we wanted to find the graph of maximum flow that also has minimum weight?
 - This problem is so difficult, no one has found a way to solve it efficiently

TAKE AWAYS

- **We'll talk about approximation and algorithm design more next week**
 - Graph problems can get very difficult very quickly
 - Many problems are related
 - Proving that solving one problem gives a solution to another is called a *reduction*