



COMP 6651

Algorithm Design Techniques

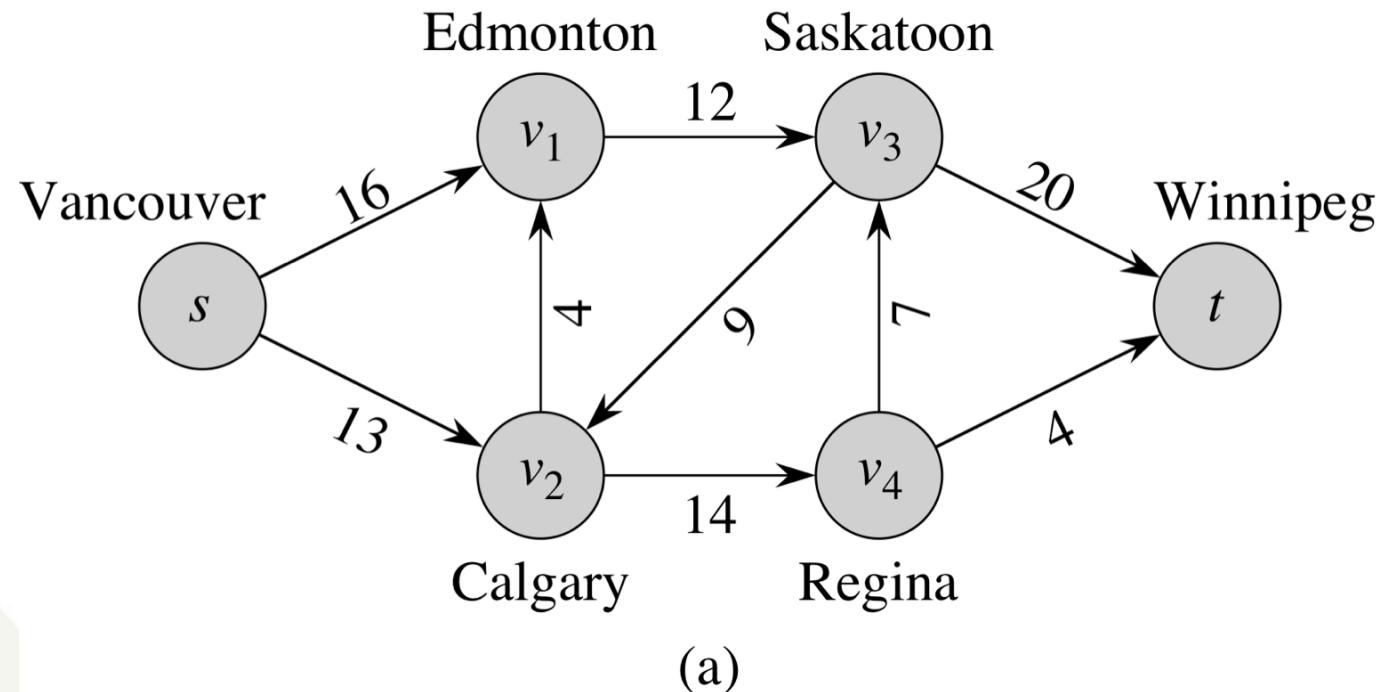
Week 9

Max flow. Graph-cut.

Ack: Some slides from Fredo Durand MIT, Daniel Helper from Haifa University and the web

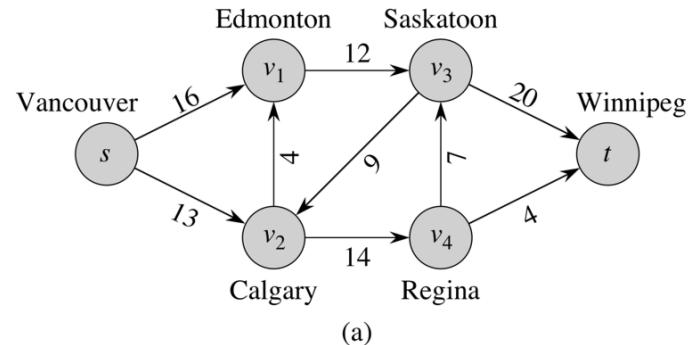
Theory

- Max flow problem



Theory

- Max flow problem



Capacity constraint: For all $u, v \in V$, we require $0 \leq f(u, v) \leq c(u, v)$.

Flow conservation: For all $u \in V - \{s, t\}$, we require

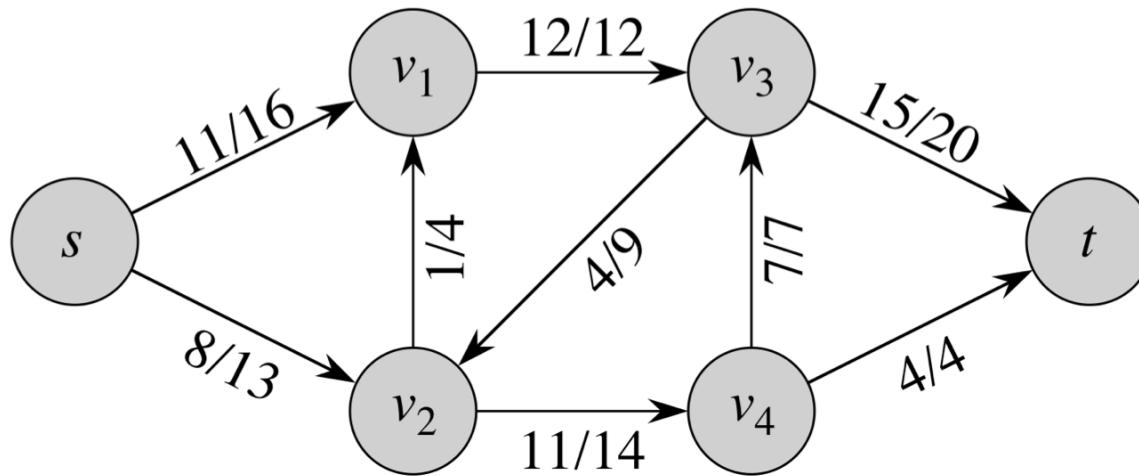
$$\sum_{v \in V} f(v, u) = \sum_{v \in V} f(u, v).$$

When $(u, v) \notin E$, there can be no flow from u to v , and $f(u, v) = 0$.

$$|f| = \sum_{v \in V} f(s, v) - \sum_{v \in V} f(v, s),$$

Theory

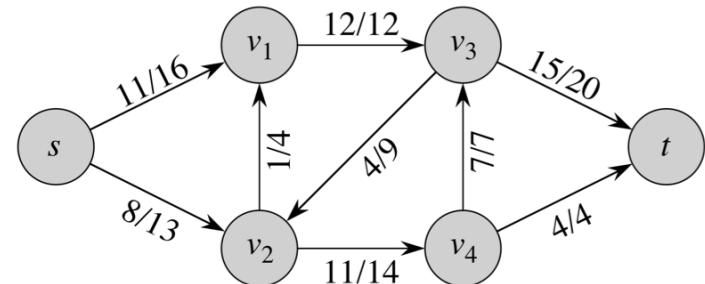
- Max flow problem



(b)

Theory

- Max flow problem
- Ford-Fulkerson algorithm



(b)

Capacity constraint: For all $u, v \in V$, we require $0 \leq f(u, v) \leq c(u, v)$.

Flow conservation: For all $u \in V - \{s, t\}$, we require

$$\sum_{v \in V} f(v, u) = \sum_{v \in V} f(u, v) .$$

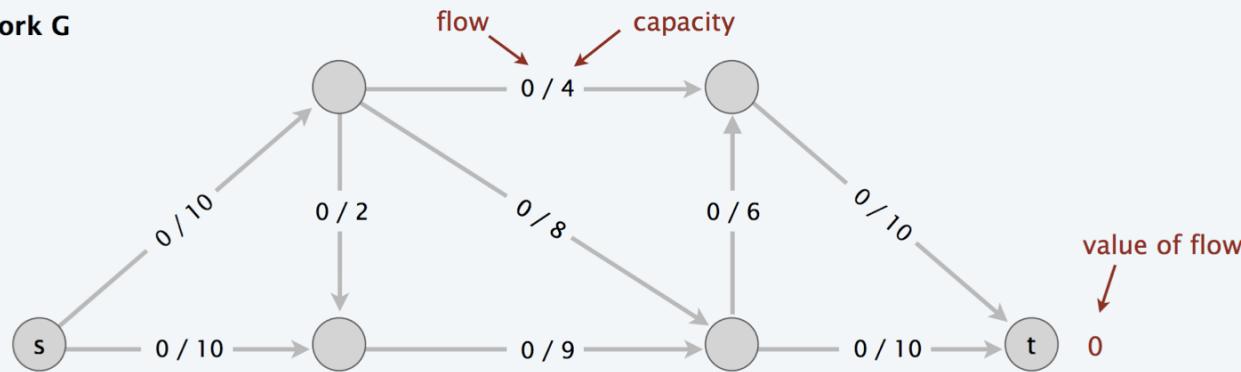
When $(u, v) \notin E$, there can be no flow from u to v , and $f(u, v) = 0$.

$$|f| = \sum_{v \in V} f(s, v) - \sum_{v \in V} f(v, s) ,$$

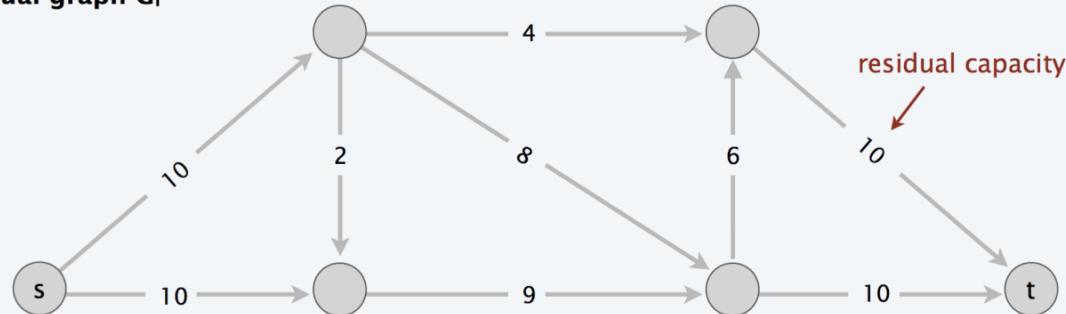
Theory

- Max flow problem - example

network G



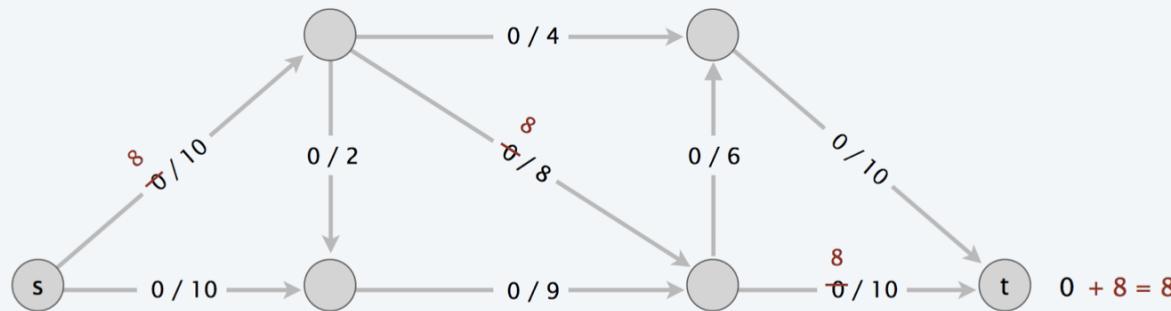
residual graph G_f



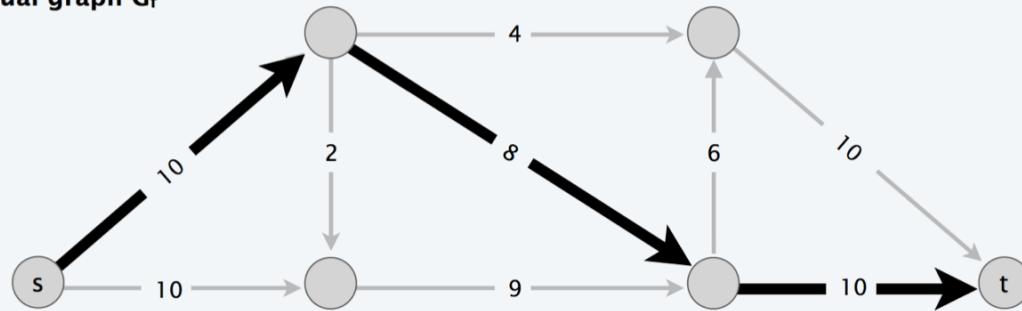
Theory

- Max flow problem - example

network G



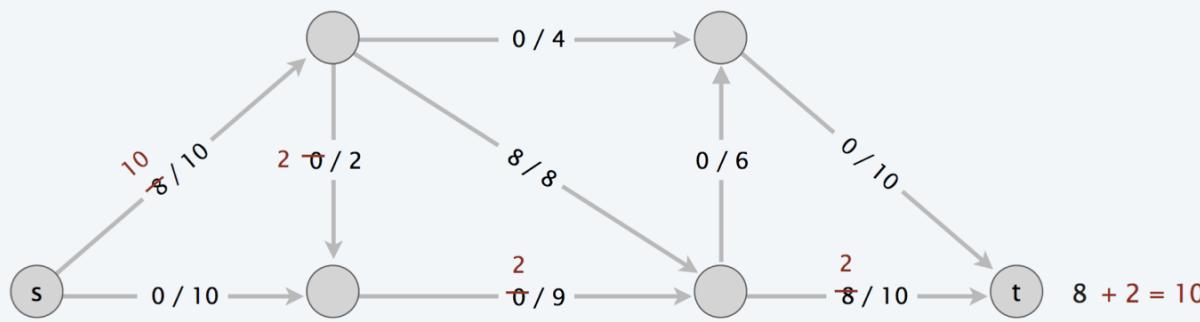
residual graph G_f



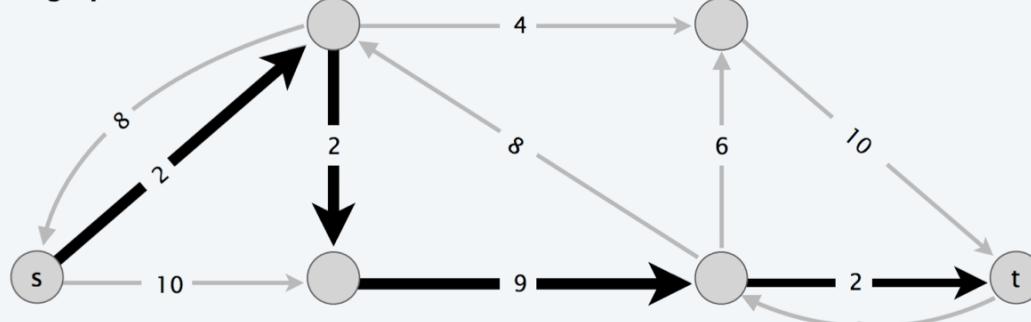
Theory

- Max flow problem - example

network G



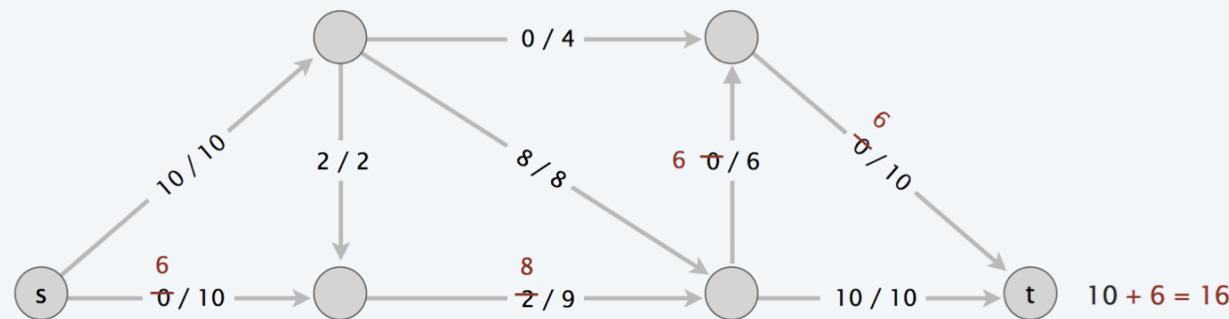
residual graph G_f



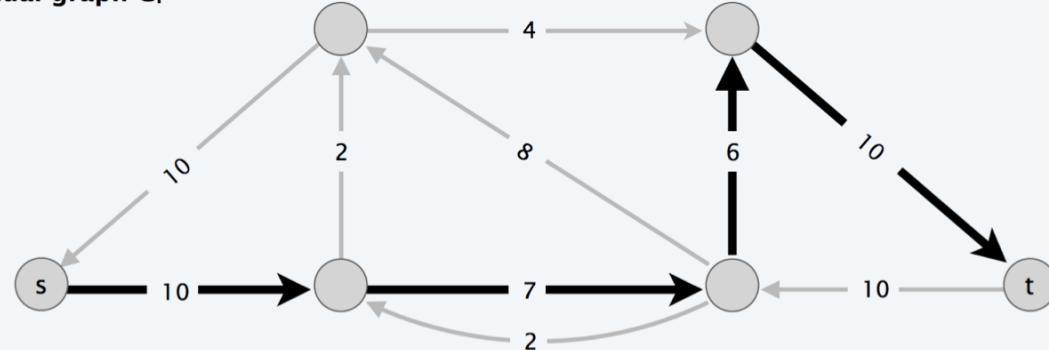
Theory

- Max flow problem - example

network G



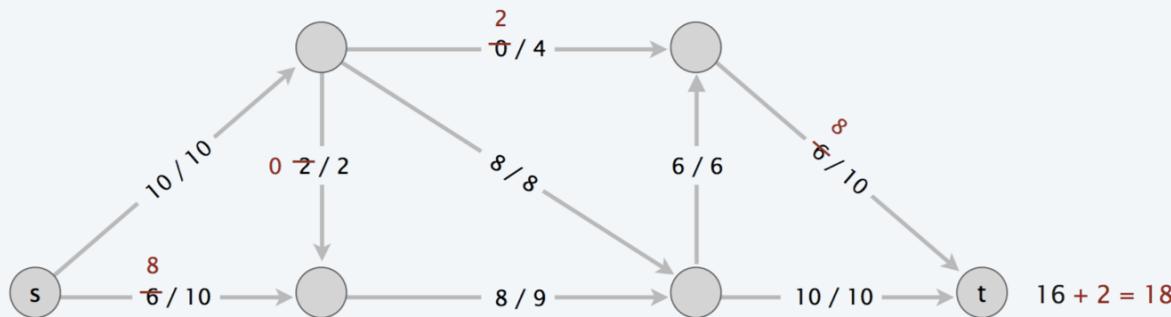
residual graph G_f



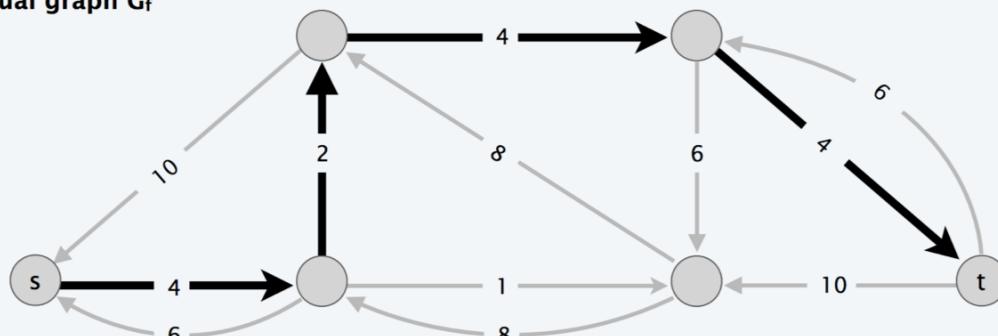
Theory

- Max flow problem - example

network G

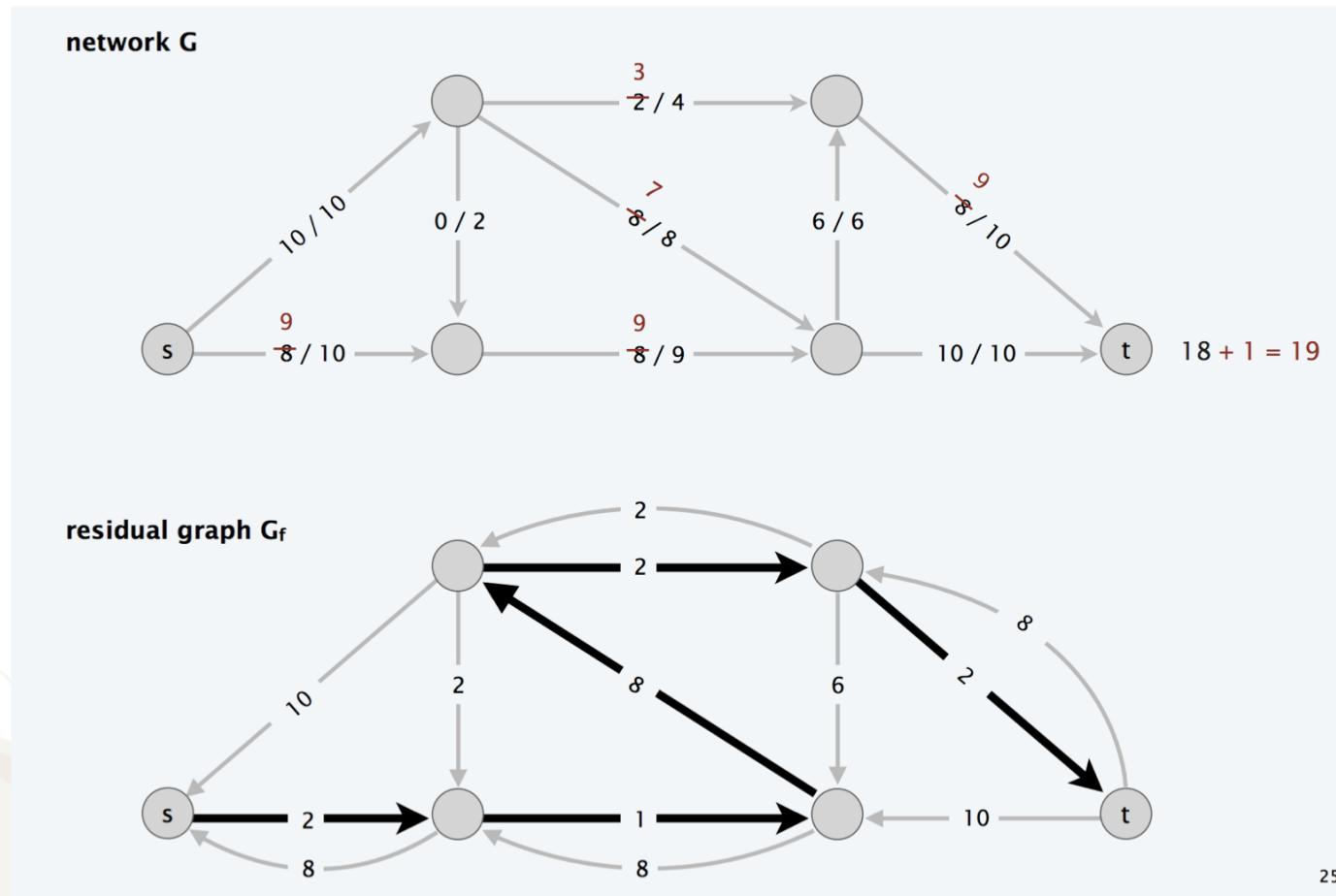


residual graph G_f



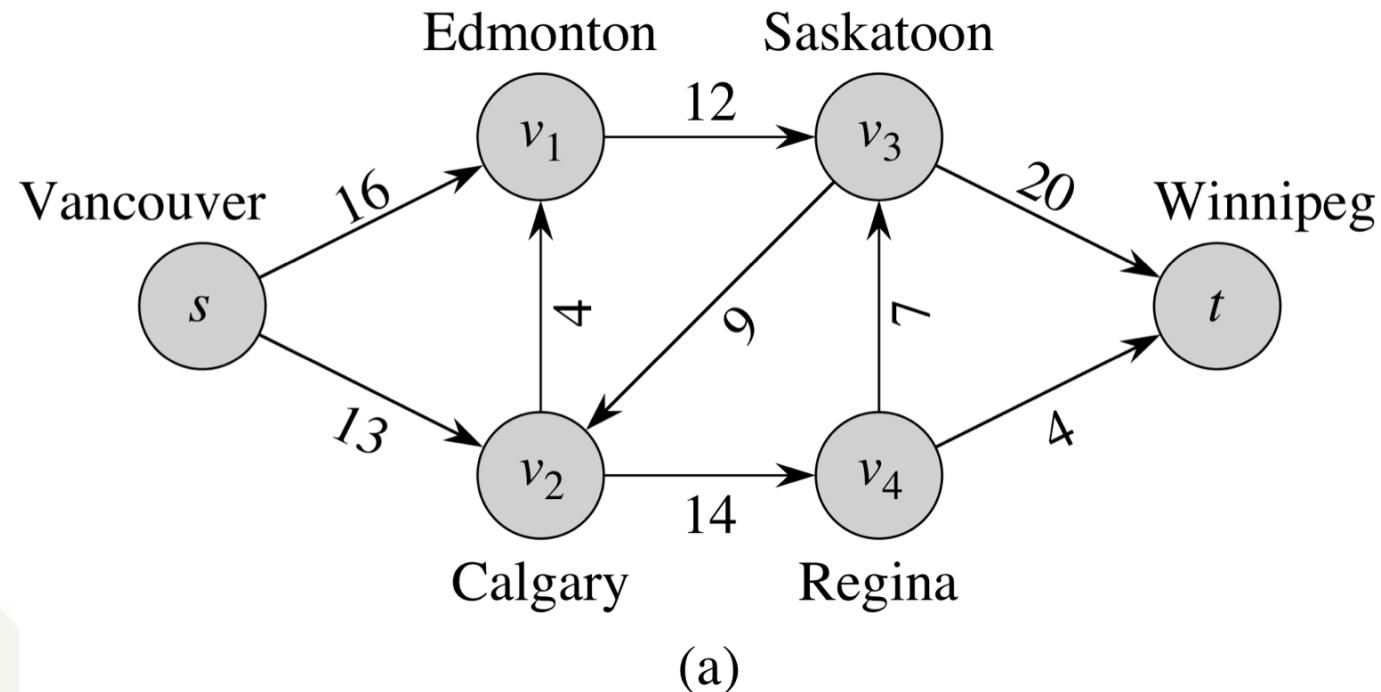
Theory

- Max flow problem - example



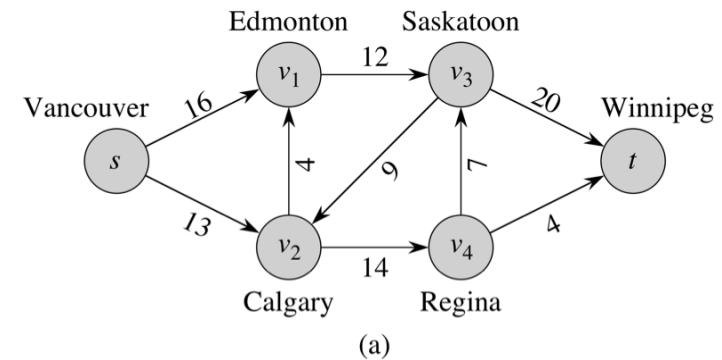
Theory

- Min Graph-cut \leftrightarrow Max flow problem



Theory

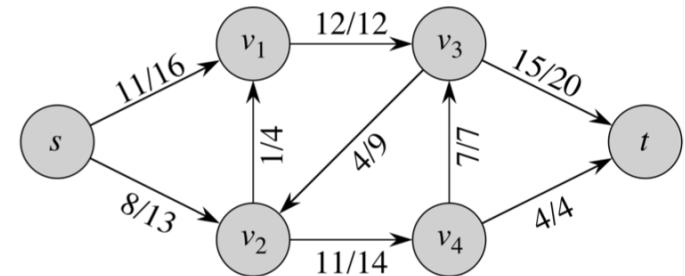
- Min Graph-cut \leftrightarrow Max flow problem
- Remove edges that partition the graph into two disjoint components



$$c(S, T) = \sum_{u \in S} \sum_{v \in T} c(u, v)$$

Theory

- Min Graph-cut \leftrightarrow Max flow problem
- What is the relation?



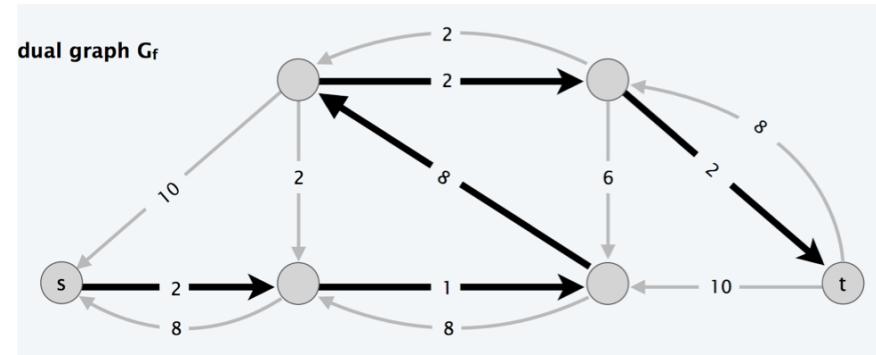
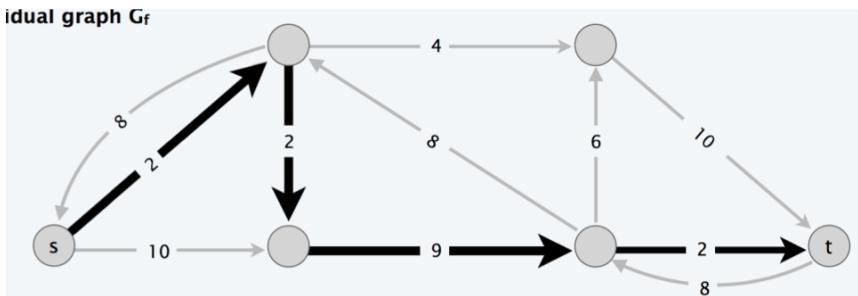
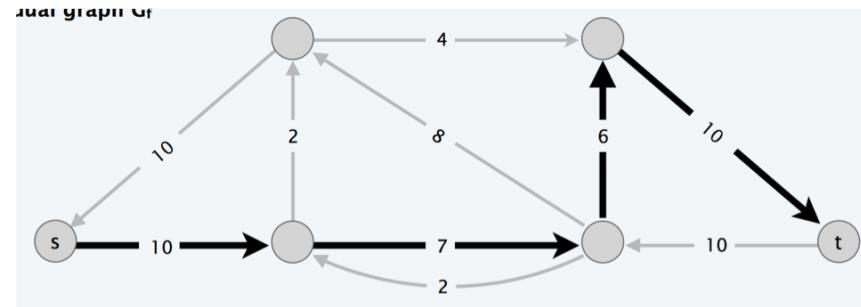
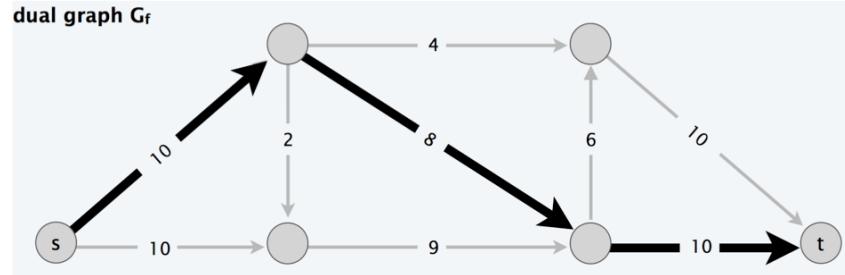
(b)

$$c(S, T) = \sum_{u \in S} \sum_{v \in T} c(u, v)$$

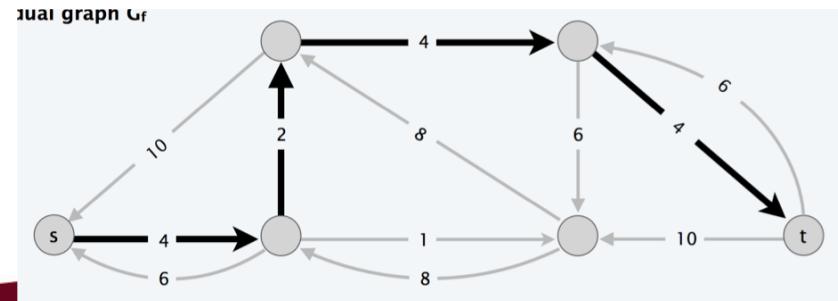
- Cost of the min cut equals min flow

- How to get the min-cut
- Keep all residual graphs

Theory

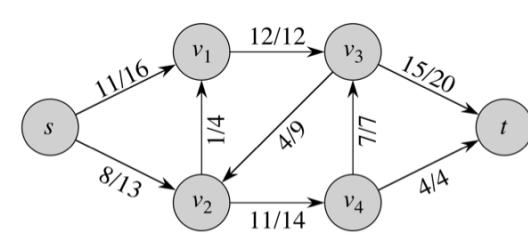
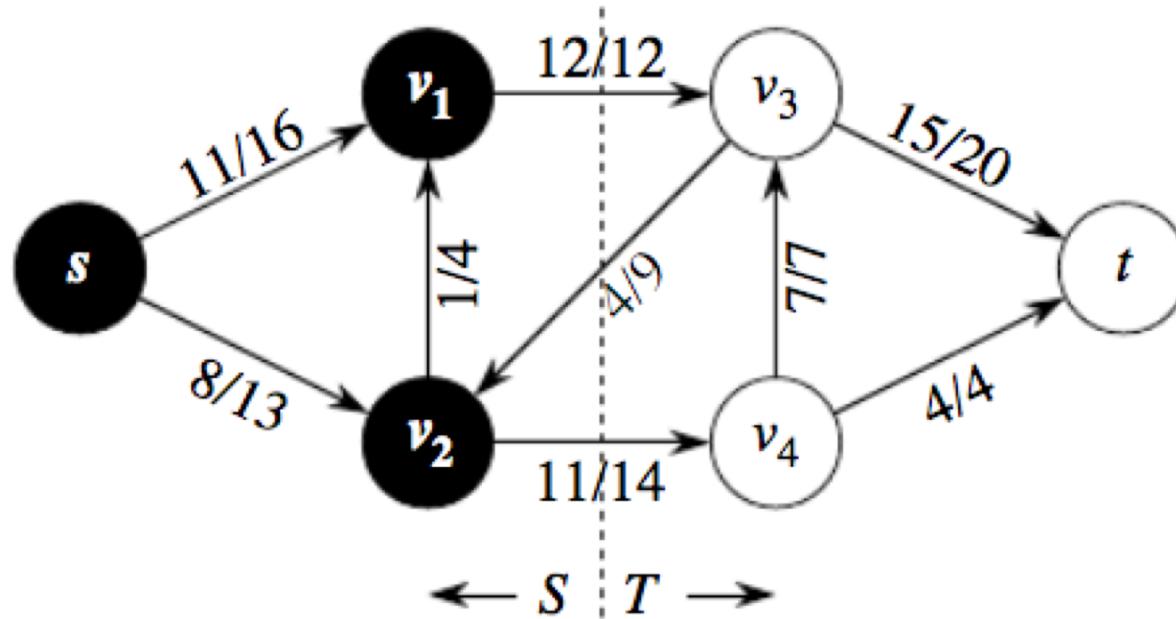


- Remove 1 edge from each
- Minimum sum
- Dynamic programming



a
try

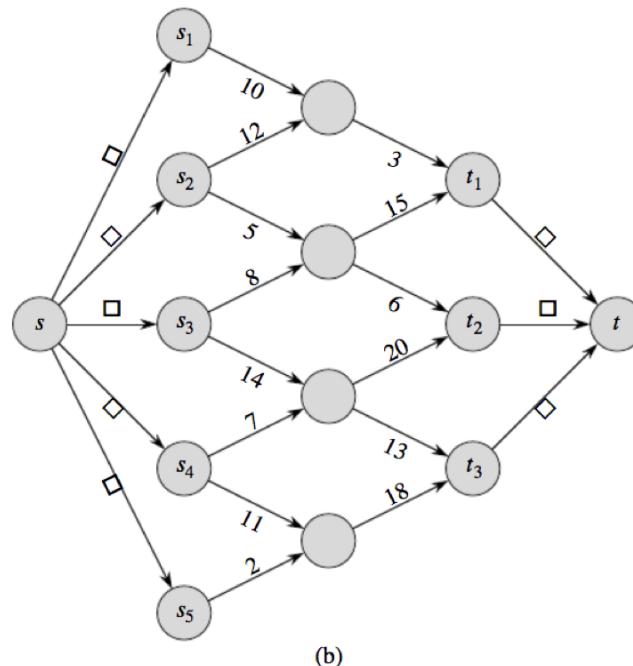
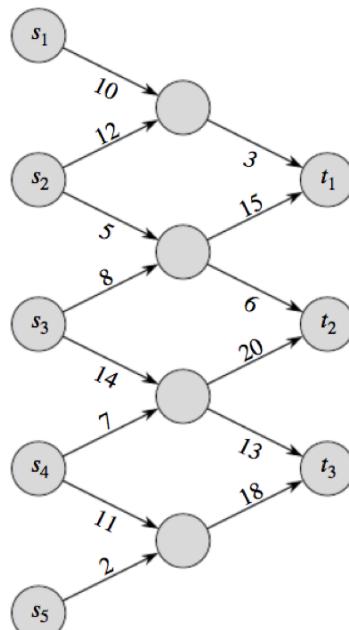
Theory



(b)

Theory

- Multiple sources and sinks



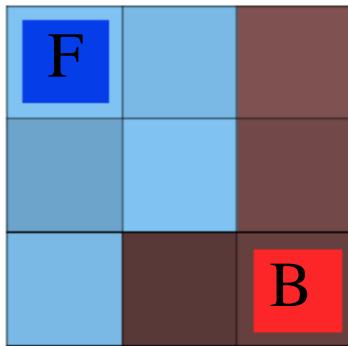
Theory

- Complexity
 - Planar graphs
 - Planar graphs on grid
- Undirected graph
 - Very similar
 - A bit simpler

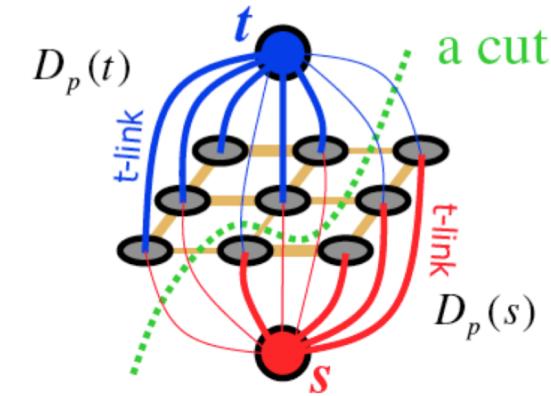
Image Segmentation using graph Cuts

How we apply to image segmentation?

Image forms a canonical graph



F	F	B
F	F	B
F	B	B



Reducing to finding min cut

BUT

Problem is defining the weights/capacities

Who are s and t ?

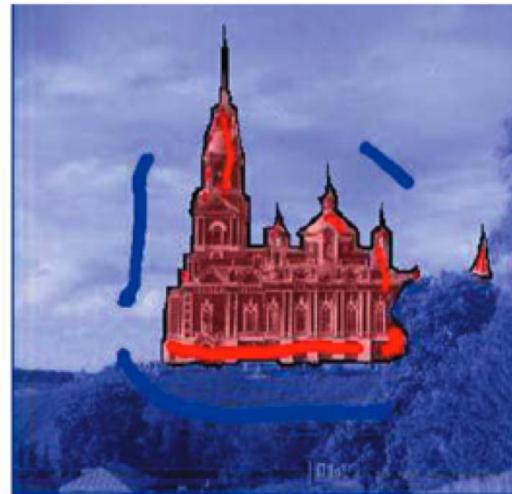
Image Segmentation using graph Cuts

Need an initial rough segmentation

1. Manual
2. Other heuristics
 1. Blurriness
 2. Depth



(a) A woman from a village



(b) A church in Mozhaisk (near Moscow)

Image Segmentation using graph Cuts

How do we assign weights

1. Inf to edges from/to s and t
2. Use common split in computer vision: data + smoothness (regularization)
3. Compute probabilities that
 1. pixels are in different groups (regularization)
 2. Pixel belongs to F or G (data term) How?
 1. Initial clustering
 2. Blurriness
 3. Average color
4. Convert to energy (-log(p))

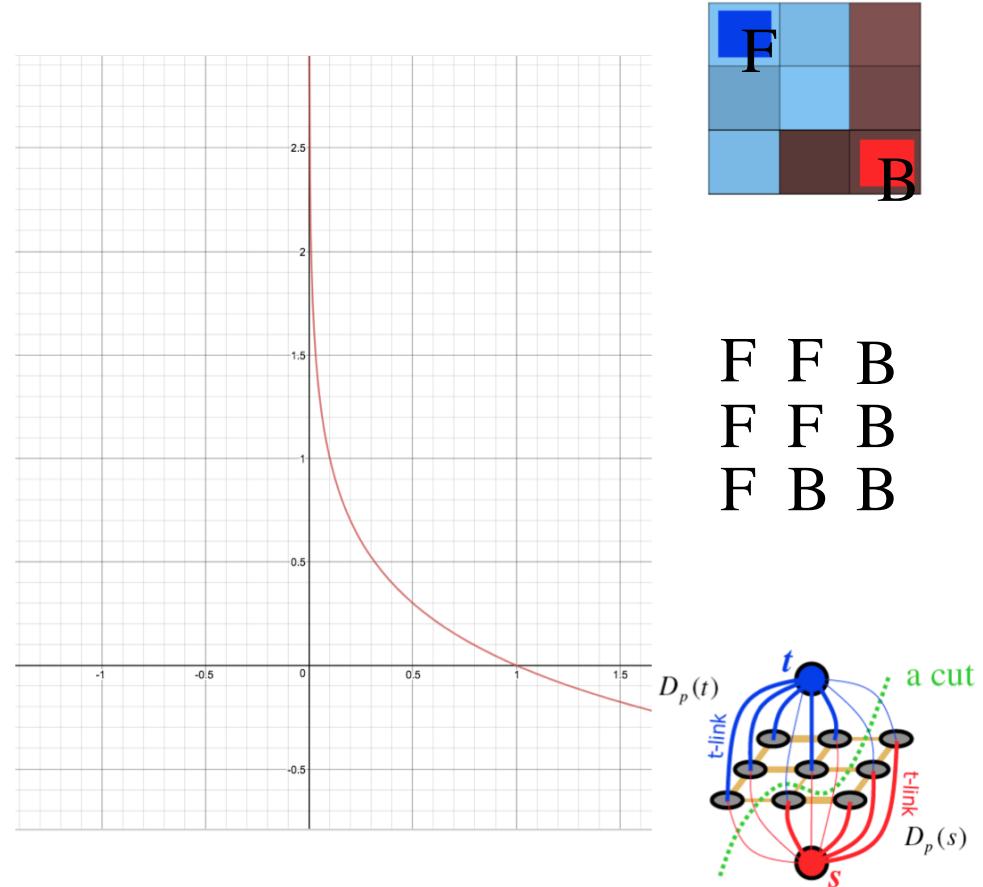
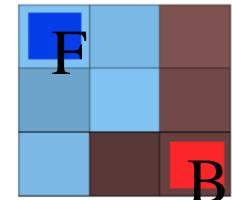


Image Segmentation using graph Cuts

- What is better graph-cut clustering?
 - Graph-cut:
 - Both unary and neighboring probability (Random Markov Fields)
 - Clustering:
 - Allows more clusters
 - Hidden Markov Model
 - Generalizes to multiple clusters
 - Not using graph-cut
- It is not the only approach
- Graph cut used a lot in classification
- Graphical models used a lot in visual computing



F F B
F F B
F B B

