# Topics in Algorithms 2005 Max Cuts

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### Undirected Unweighted Max Cut

- Cut: Partition of the vertex set
- Max Cut: Number of edges between the two sides of the partition should be maximized



#### Status

- Max Cut is NP-Complete!! Unlike Min-cut.
- If we can solve this problem we can solve the 3-SAT problem and we can solve any problem which can be solved in nondeterministic polynomial time by a Turing Machine.



### **NP-Completeness**

Show that Max Cut is NP-Complete:

- Reduce from 3-SAT
- Given a 3-SAT formula f find a graph G and a number k such that
  - f is sat implies G has a cut of size k.
  - f is not sat implies G has no cut of size k or larger.

# **Reduction from 3-SAT**

#### Reduce from 3-SAT:

- Put 2 vertices for each variable x, one for x and one for  $\underline{x}$ 
  - Connect pairs of vertices x, <u>x</u> by k edges
- Put one vertex for each clause
  - Connect literals in that clause to it
- The Max Cut will always split complement literal pairs why??
- Ideally, the Max Cut should now equal the number of clauses satisfied plus nk where n is number of variables
- Problems!
  - A clause could have more than 1 satisfying literal
  - Clause vertices could get split as well

# Reduction from 3-SAT

#### Reduce from 3-SAT:

- We need to ensure that each satisfied clause contributes the exact same amount to each cut and each unsatisfied clause contributes a lesser amount. How do we ensure this??
- We need to handle splitting of clause vertices. How?

#### Trick

- Work with heterogeneous 3-SAT instead
- 3-SAT in which satisfiability requires the assignment to have at least one true and one false in each clause
- Heterogeneous 3-SAT is also NP-Complete. Exercise??

# Reduction from hetero-3-SAT

Reduce from hetero-3-SAT with m clauses and n variables:

- Put 2m vertices for each variable x, m for x and m for  $\underline{x}$ 
  - There are 2 vertices associated with each clause
  - Connect all m<sup>2</sup> pairs of vertices x,<u>x</u> by k edges each forcing them to come on different sides
- For each clause
  - Connect the three literals for this clause together.
- The Max Cut is knm<sup>2</sup>+2#satisfiable clauses. Why??

# **Approximation Algorithms**

• Can we find a near optimal solution in polynomial time?

- E.g., What if we take a random cut? How does it compare to the min-cut?
  - Show that the expected number of edges in the random cut is #edges/2. Exercise!!
  - Thus a random cut is a expected factor <sup>1</sup>/<sub>2</sub> approximation

# **Approximation Algorithms**

- How about a greedy algorithm. Switch sides for a vertex if it improves the cut.
  - Will this terminate??
  - What approximation factor does it get??

### Beating the 1/2 factor

Can you write max-cut as a linear/concave program (so local and global maxima are the same)?

 $Max_{e=(i,j)} (1-x_i.x_j)/2$ For each vertex  $X_i, X_i = -1$  or  $X_i = 1$ 

- Issues
  - Not Linear. Is the objective function concave?
  - Hoe does one relax the -1,1 constraints?
    - Linear relaxation: x<sub>i</sub> >= -1 and x<sub>i</sub> <= 1</p>
  - How does one solve a concave problem in polynomial time?
  - How does one round linear solutions to integer solutions?

## Concavity

 A twice differentiable function is concave if and only if its Hessian is negative semidefinite, i.e., for vectors v



# Maximizing Concave Functions

There are polynomial time algorithms to maximize concave function over any convex set (eg one obtained by intersection of linear inequalities)

 Reference: Solving Convex Programs by Random Walks By Bertsimas and Vempala

### Beating the 1/2 factor

$$Max_{e=(i,j)} (1-x_i.x_j)/2$$
  
For each vertex  $x_i$ ,  $-1 \le x_i \le 1$ 

- Issues
  - How does one round linear solutions to integer solutions?
  - Think about this? Not sure what is known.

#### **Another Relaxation**

$$\frac{Max_{e=(i,j)} (1-x_i.x_j)/2}{For each vertex X_i, -1 <= X_i <= 1}$$

- Relax X<sub>i</sub>s to be vectors or length 1
- Issues
  - Is the feasible region convex?
  - How does one round?

# SemiDefinite Formulation



- The feasible region is convex
- The objective function is linear
- So solvable in polynomial time
- In addition, a nice geometric interpretation
- Due to Goemans and Williamson

# SemiDefinite Formulation



- Rounding
  - Solving the program yields a set of unit length vectors
  - Use a random hyperplane through the origin to split the vectors into 2; this gives a cut
  - How does the size of this cut compare to that of the semidef program optimum??

## SemiDefinite Formulation



 $d_{ij} = X_{i} X_{j}$ 

X<sub>i</sub>

,X<sub>i</sub>



So the approx factor is 2  $\operatorname{arccos}(d_{ij}) / \pi (1 - d_{ij})$ 

How low can  $2\theta/\pi$  (1- cos  $\theta$ ) be?? Exercise??

#### References

#### Bertsimas, Vempala on convex programming

#### Goemans-Williamson's paper on Max-Cut

#### Exercise

- Max-2-SAT
- Given a 2 SAT formula find an assignment which satisfies as many clauses as possible
- Can you give a simple randomized algorithm followed by a SemiDefinite relaxation and then Rounding algorithm?

#### Thank You