

# Are Stable Instances Easy?

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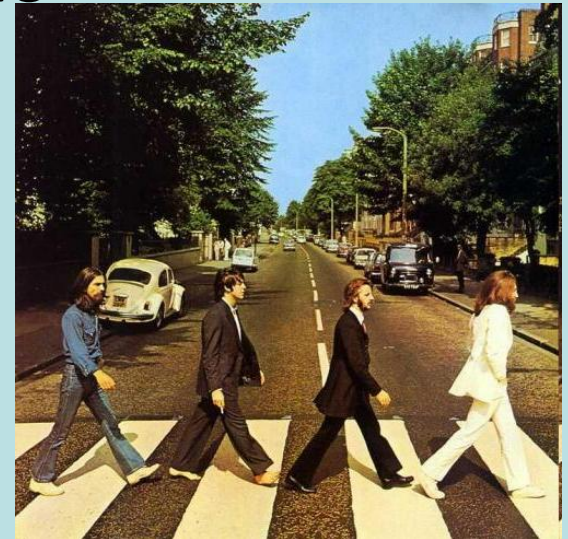
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# Clustering Problems

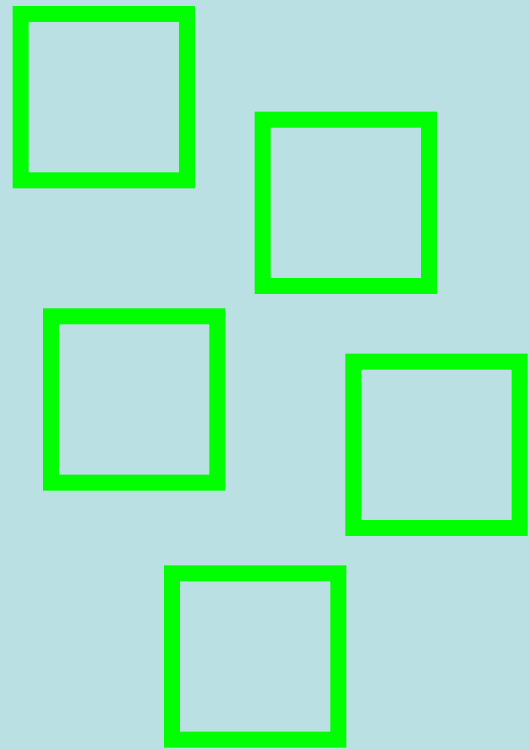
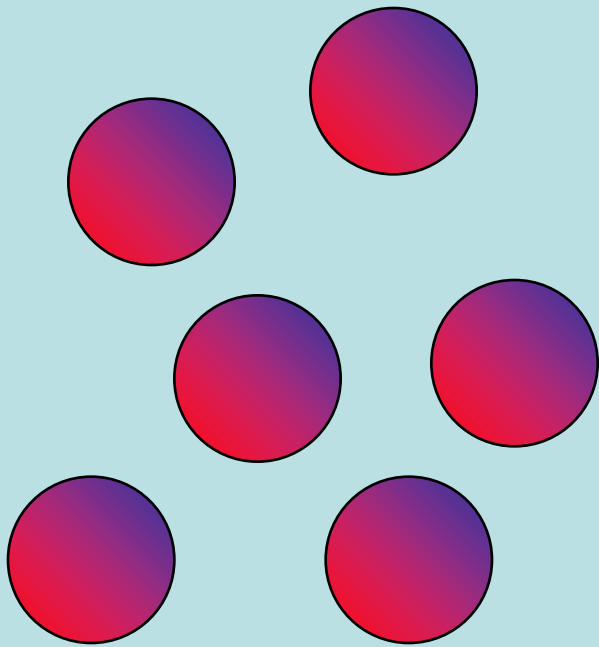
Abundant in science:

- Clustering proteins by edit distance
- Clustering genes by expression profiles
- Clustering pixels in an image into foreground and background

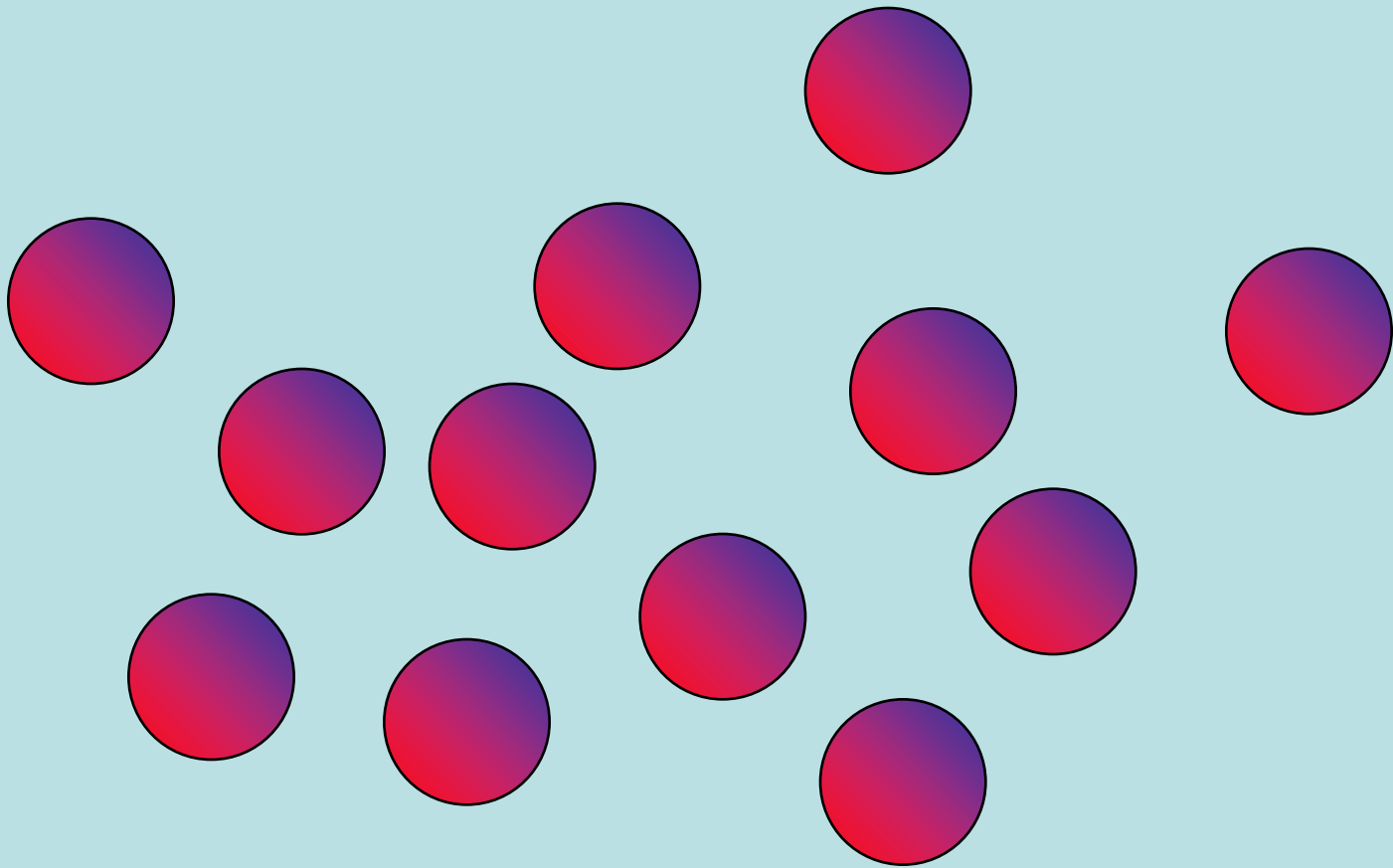
Like all good things: NP-hard



# What is the solution?

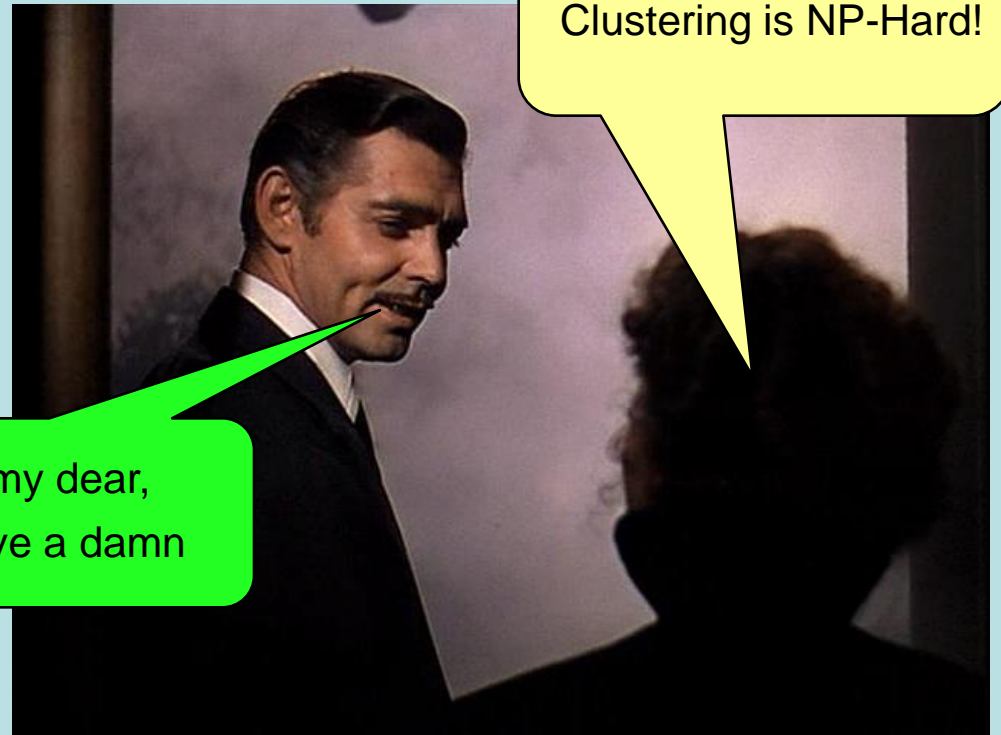


# What is the solution?



# Clustering Problems

Are they really hard when we actually care?



Frankly, my dear,  
I don't give a damn

Rhett, Rhett,  
Clustering is NP-Hard!

# Clustering Problems

**Which instances are interesting?**

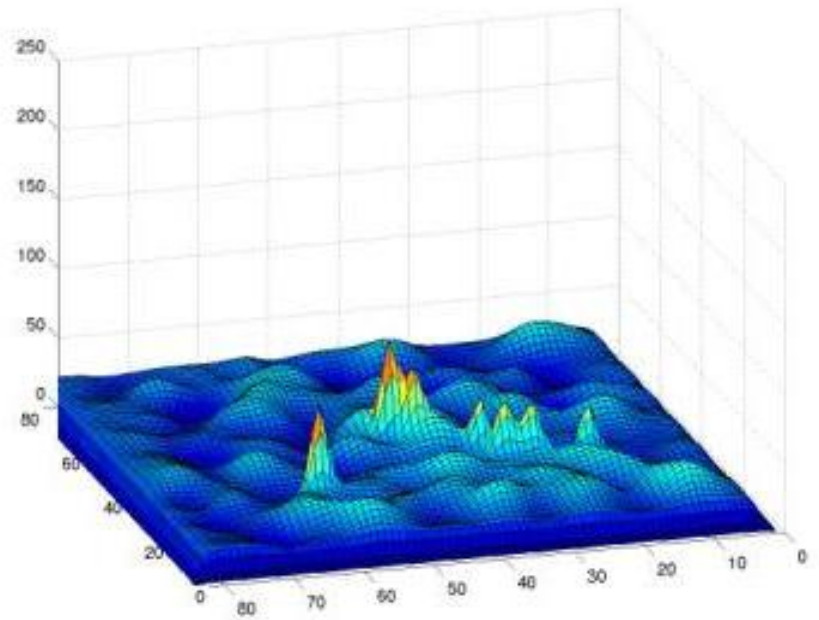
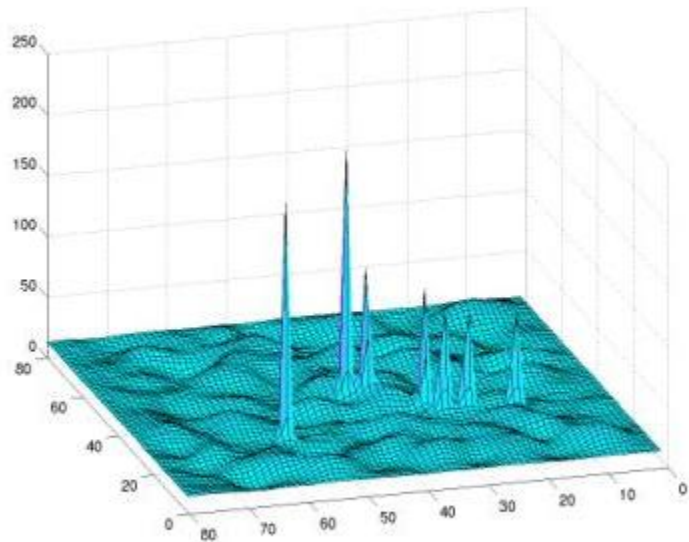
Are interesting instances easy to solve?

Are interesting instances easy to approximate?

Are interesting instances amenable to practical heuristics?

# Related work

**Smoothed Analysis** (Spielman & Teng 2001):  
Don't say it's hard if the hard instances are  
“singular” points.



# Related work

**THE  $(c, \epsilon)$ -PROPERTY** (Balcan, Blum and Gupta 2008):

All  $c$ -approximations of the optimal solution are  $\epsilon$ -close to it.

Then an  $O(\epsilon)$ -close clustering is easily found (*K-means*, *k-medians* and *min-sum\**).



# Related work

**Clusterability** (Ostrovsky, Rabani, Schulman and Swamy 2006):

Optimal  $k$ -clustering is much better than  $(k-1)$ -clustering.

Then there's a PTAS.

**More Clusterability** (Ackerman & Ben David)

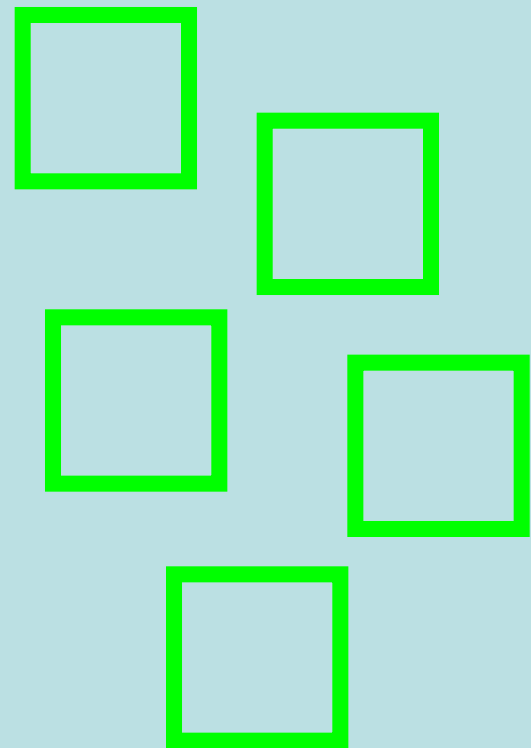
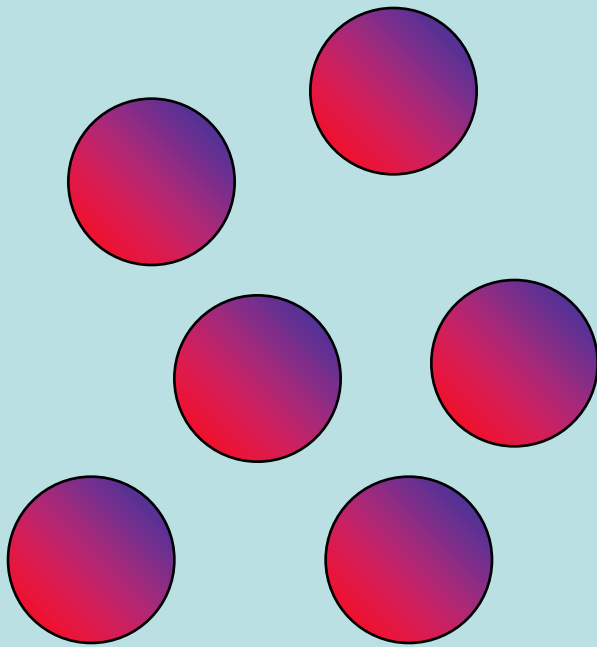
# Stability

We don't care about small perturbations (we never have exact measurements anyway).

Small perturbations should not change ***the structure*** of the optimal solution.

# Stability

Small perturbations do not change the structure of the optimal solution



# Stability

**$\gamma$ -perturbation:** multiply inputs by numbers between 1 and  $\gamma$ .

**$\gamma$ -stability:**  $\gamma$ -perturbations do not change the structure of the optimal solution.

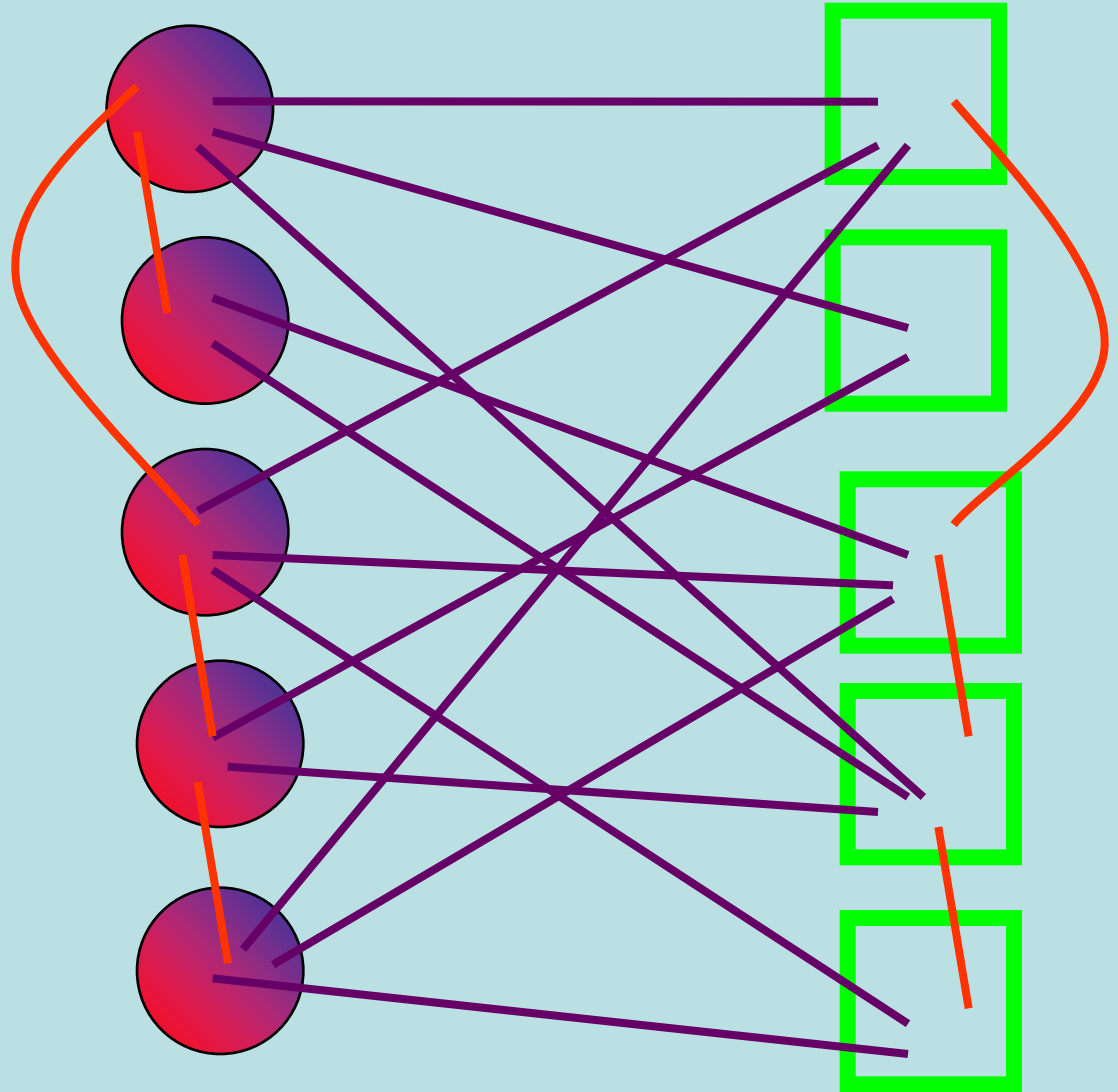
**Are Stable Instances Easy?**

# Max Cut

Maximize weight  
of **crossing** edges

Minimize weight  
of **internal** edges

Minimize weight  
of **internal** edges  
- **crossing** edges

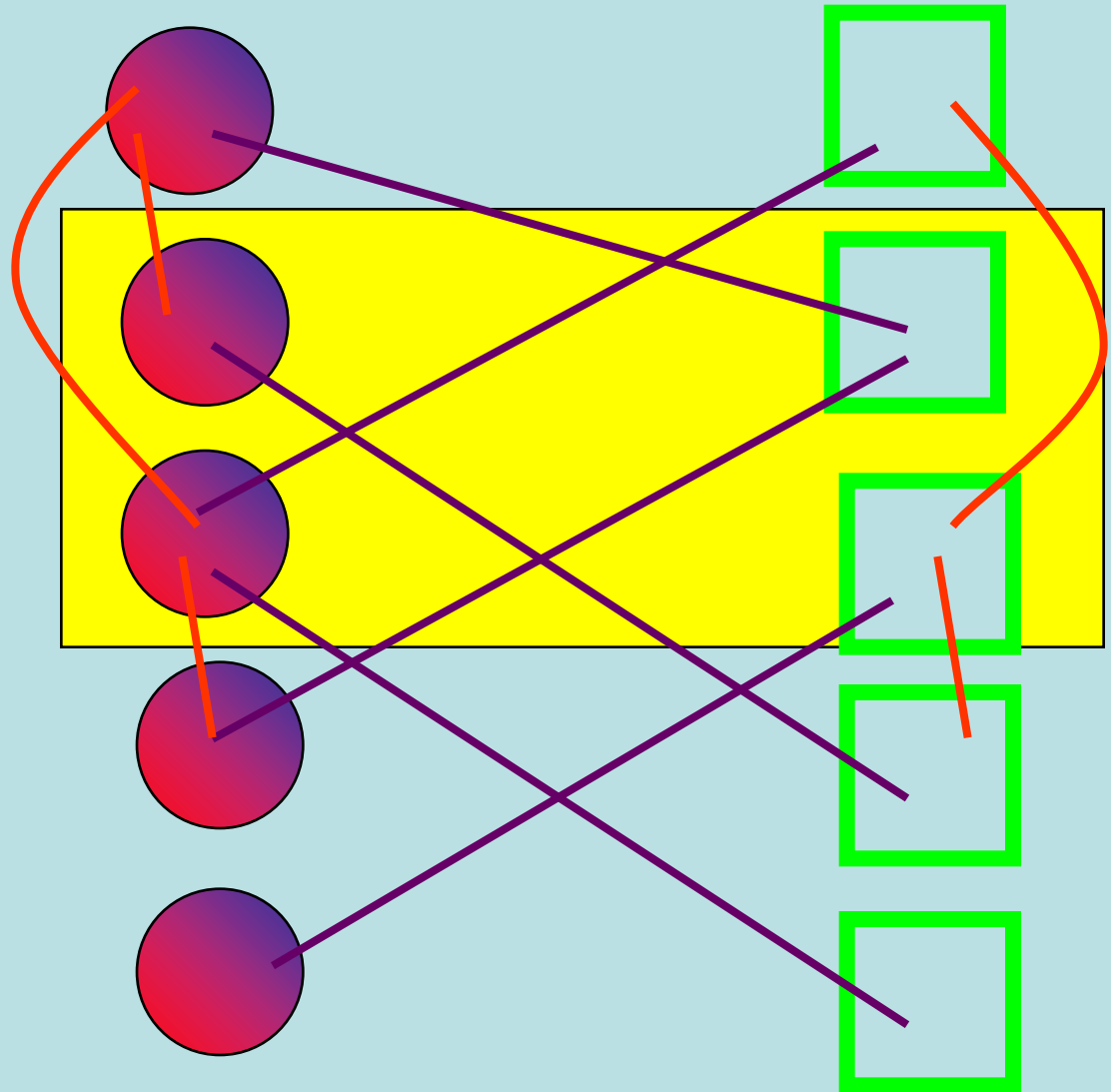


# Max Cut

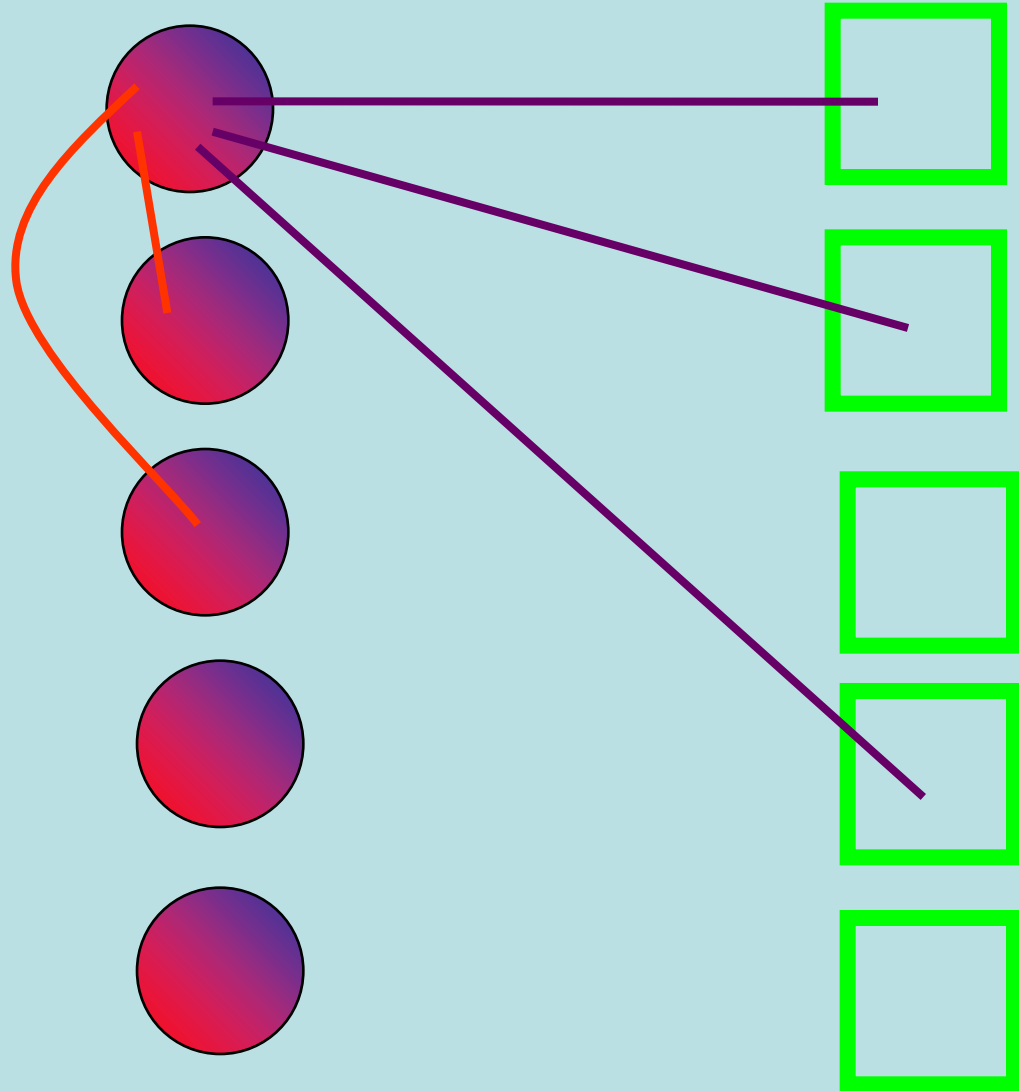
For every subset -  
Weight of **crossing**  $\geq$   
Weight of **internal**

$\gamma$ -Stability:

For every subset -  
Weight of **crossing**  $\geq$   
 $\gamma \times$  (Weight of **internal**)



# Max Cut



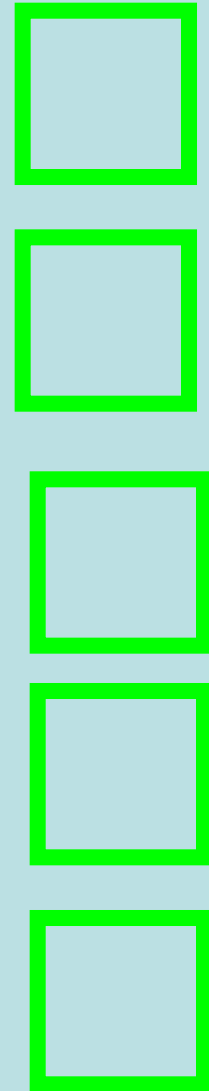
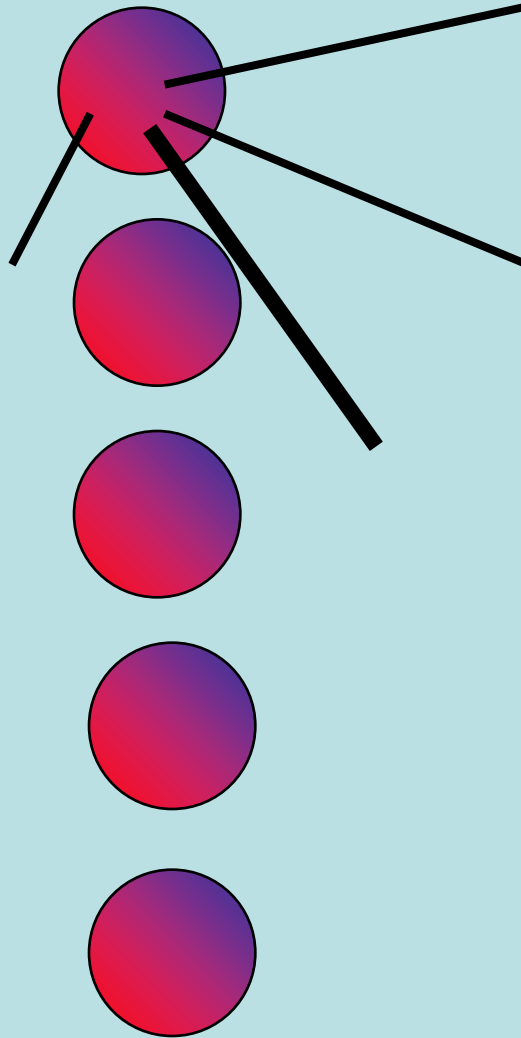
$\gamma$ -Local Stability:

For every vertex -

Weight of **crossing**  $\geq$   
 $\gamma \times$  (Weight of **internal**)

# Combinatorial algorithm

Suppose the graph  
is 4-stable...

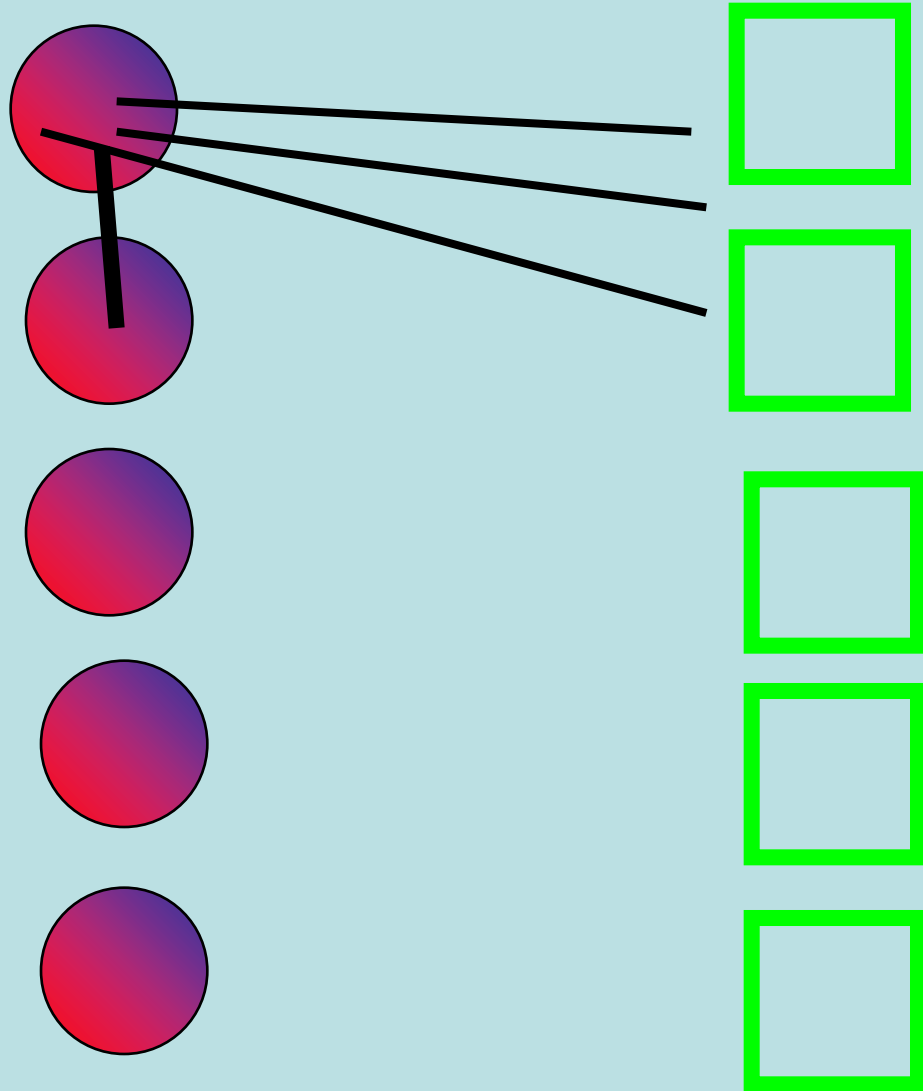




# Combinatorial algorithm

Suppose the graph  
is 4-stable...

Look at the heaviest  
edge (at each  
vertex) – it can't be  
internal...

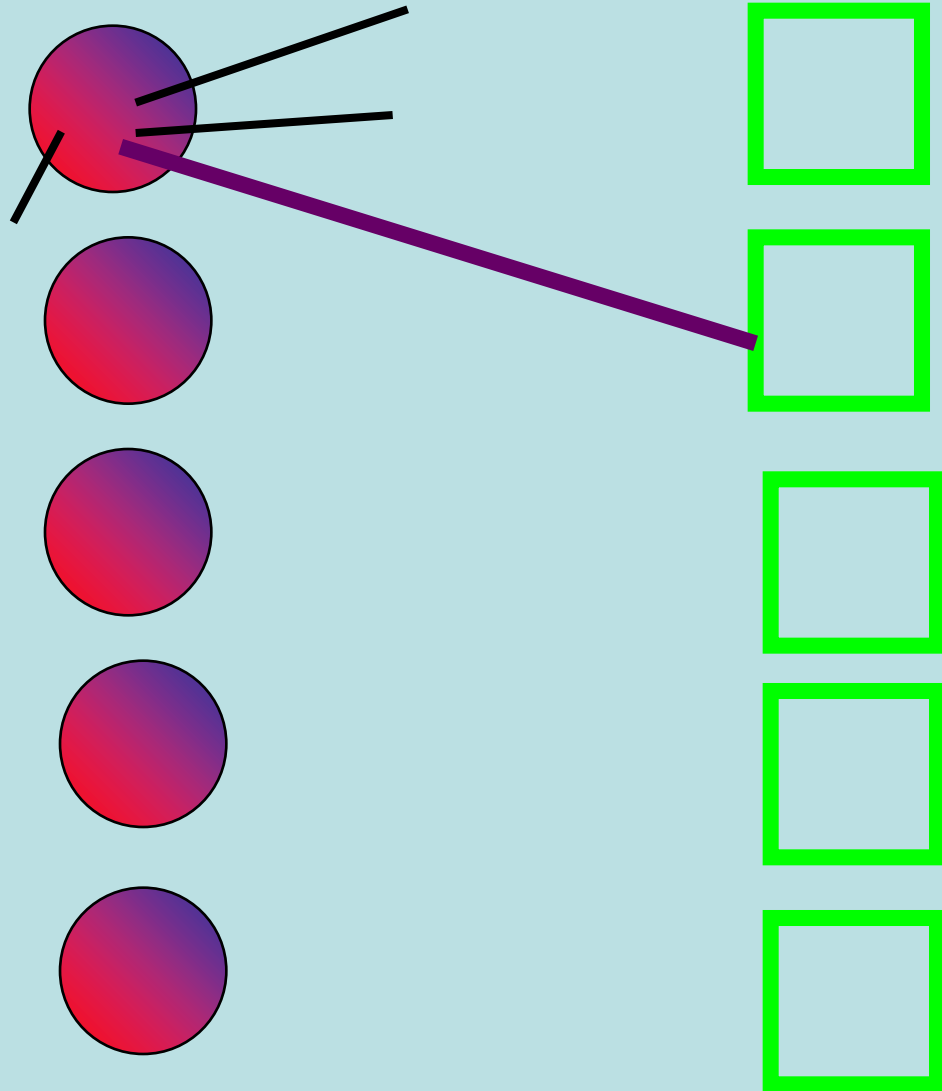


# Combinatorial algorithm

Suppose the graph is 4-stable...

Look at the heaviest edge (of each vertex) – it can't be internal...

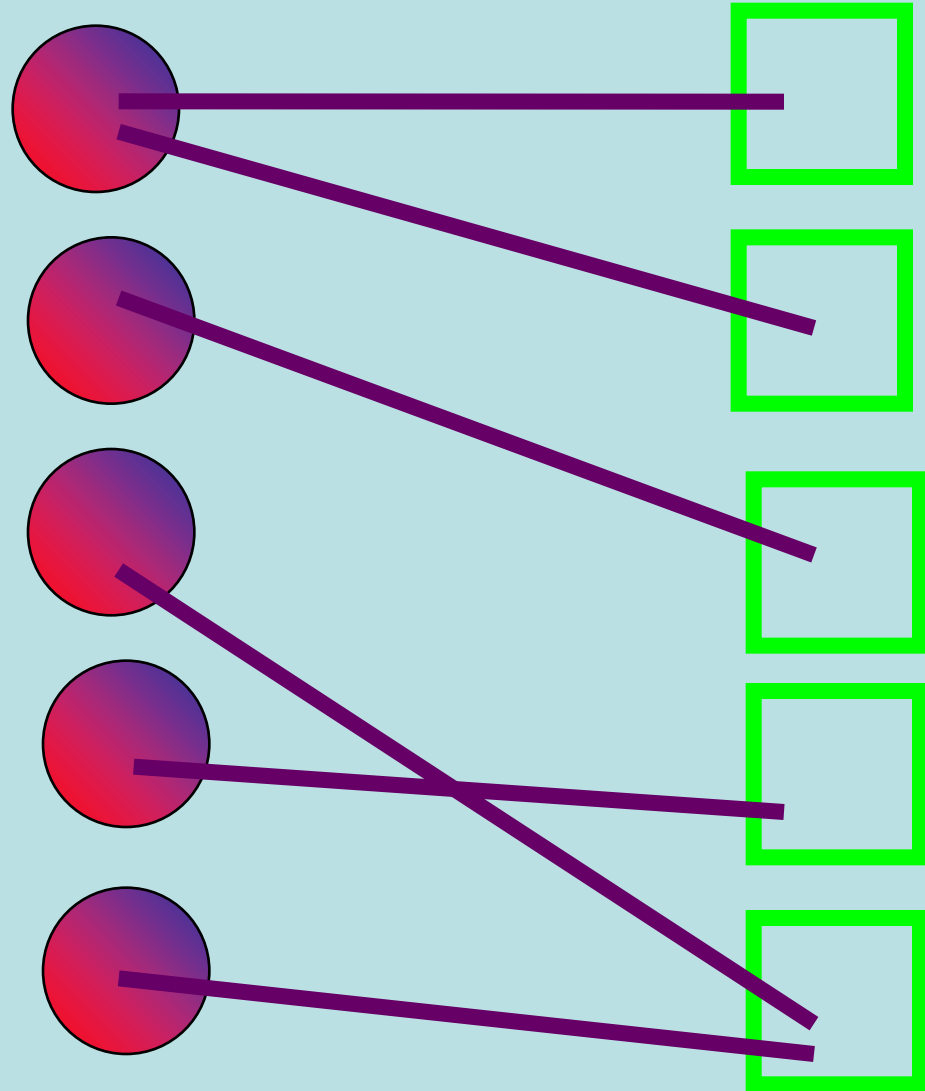
Its vertices must be on different side of the Max Cut.



# Combinatorial algorithm

Continue this way  
as long as you can  
rely on stability...

You can go all the  
way if  $\gamma \geq \sqrt{\Delta n}$



# Combinatorial algorithm II

For simple graphs with minimal degree  $\delta$ ,

Max-Cut is easy when  $\gamma \geq 4n/\delta$ .

# Spectral Algorithm

**Max Cut:** minimize  $x^tAx$  with  $x_i$  in  $\{-1, 1\}$

**Stability:** the same  $x$  will minimize  $x^t(A \cdot P)x$

( $P$  symmetric, and entries between 1 and  $\gamma$ )

**Eigenvector:** minimize  $u^tAu$  (all of  $u$  with norm 1)

$U = |uu^t|$  : What  $x$  in  $\{-1, 1\}^n$  minimizes  $x^t(A \cdot U)x$ ?

- The sign vector of  $u$  ( $A \cdot U = |u^t|A|u|$ )
- The Max Cut (if entries of  $U$  between 1 and  $\gamma$ )

# Spectral Algorithm

**Spectral partitioning:** Partition the graph according to the sign of the eigenvector associated with the least eigenvalue.

Works if entries of U between 1 and  $\gamma$  :

$$\gamma \geq (|\max u_i \cdot u_j / \min u_i \cdot u_j|)^2$$

(u eigenvector associated with least eigenvalue)

# Spectral Algorithm

**Second Least Eigenvalue:** If  $G$  is a  $\gamma$ -locally stable,  $d$ -regular graph:

$$\gamma > 2d/(\lambda_{n-1}+d) - 1$$

Max-Cut solvable for 3-regular graphs with

$$\lambda_{n-1} > -1$$

Boppana '87

# Spectral Algorithm

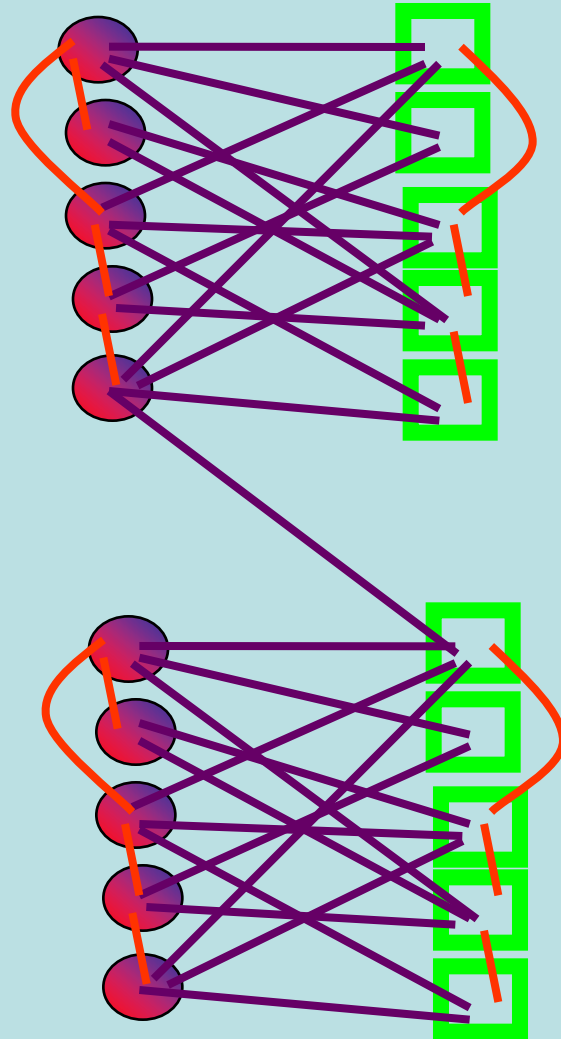
**Expanders:** If  $G$  is a  $\gamma$ -locally stable,  $(d, \lambda)$ -expander with:

$$\gamma > (5d + \lambda) / (d - \lambda)$$

Spectral Algorithm works unless there are small cuts.



# $(\gamma, \epsilon)$ -Stability



# $(\gamma, \epsilon)$ -Stability

1.  $\gamma$ -stability (local stability)
2. Adding an  $\epsilon$ -fraction of edges does not change the structure of the optimal solution, while increasing degrees by at most  $2\epsilon$ .

**Easy when:  $\gamma > 12 / \epsilon^2$**

# Conclusion & Open Problems

- **Are stable instances easy?**
  - Dense simple graphs
  - Eigenvalue separation (expanders)
  - $(\gamma, \epsilon)$ -Stability
- **Are stable instances hard?**
- **When does spectral partitioning work?**
- **Approximations?**
- **Alternative definitions?**