Today

Semidefinite Programming

Today

Semidefinite Programming

...for Approximating MaxCut.

Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\rightarrow$ for all $x \in R^n$, $x^T A x \geq 0$.

Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\quad \rightarrow$ for all $x \in R^n$, $x^T A x \geq 0$.

Hmm...

Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\rightarrow$ for all $x \in R^n$, $x^T Ax \geq 0$.

Hmm...

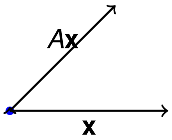
Ax is same direction as x?

Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\rightarrow$ for all $x \in R^n$, $x^T A x \geq 0$.

Hmm...

Ax is same direction as x?

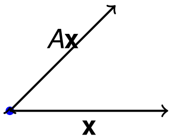


Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\rightarrow$ for all $x \in R^n$, $x^T Ax \geq 0$.

Hmm...

Ax is same direction as x?



Spectral decomposition:

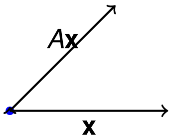
$A = \sum_i \lambda_i v_i v_i^T$.

Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\rightarrow$ for all $x \in R^n$, $x^T Ax \geq 0$.

Hmm...

Ax is same direction as x?



Spectral decomposition:

$A = \sum_i \lambda_i v_i v_i^T$.

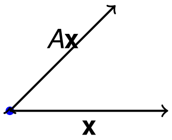
$\lambda_i \geq 0$ – eigenvalue.
v_i – associated eigenvector.

Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\rightarrow$ for all $x \in R^n$, $x^T A x \geq 0$.

Hmm...

Ax is same direction as x?



Spectral decomposition:

$A = \sum_i \lambda_i v_i v_i^T$.

$\lambda_i \geq 0$ – eigenvalue.
v_i – associated eigenvector.

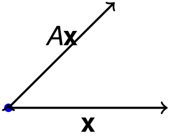
$A = B^T B$

Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\rightarrow$ for all $x \in R^n$, $x^T Ax \geq 0$.

Hmm...

Ax is same direction as x?



Spectral decomposition:

$A = \sum_i \lambda_i v_i v_i^T$.

$\lambda_i \geq 0$ – eigenvalue.
v_i – associated eigenvector.

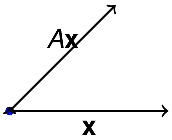
$$A = B^T B \qquad B = \sqrt{\lambda_i} \begin{bmatrix} v_1 \\ v_2 \\ \cdots \end{bmatrix}$$

Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\rightarrow$ for all $x \in R^n$, $x^T A x \geq 0$.

Hmm...

Ax is same direction as x?



Spectral decomposition:

$A = \sum_i \lambda_i v_i v_i^T$.

$\lambda_i \geq 0$ – eigenvalue.
v_i – associated eigenvector.

$$A = B^T B \qquad B = \sqrt{\lambda_i} \begin{bmatrix} v_1 \\ v_2 \\ \cdots \end{bmatrix}$$

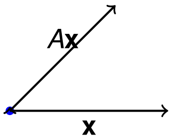
Representation $\rightarrow$ positive semefinite too: $(x^T B^T)(Bx) \geq 0$

Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\rightarrow$ for all $x \in R^n$, $x^T A x \geq 0$.

Hmm...

Ax is same direction as x?



Spectral decomposition:
$A = \sum_i \lambda_i v_i v_i^T$.

$\lambda_i \geq 0$ – eigenvalue.
v_i – associated eigenvector.

$$A = B^T B \qquad B = \sqrt{\lambda_i} \begin{bmatrix} v_1 \\ v_2 \\ \cdots \end{bmatrix}$$

Representation $\rightarrow$ positive semefinite too: $(x^T B^T)(Bx) \geq 0$

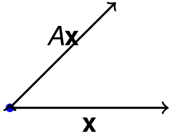
Possibly many such representations.

Positive Semidefinite Matrices

$n \times n$ matrix A positive semidefinite $\rightarrow$ for all $x \in R^n$, $x^T A x \geq 0$.

Hmm...

Ax is same direction as x?



Spectral decomposition:
$A = \sum_i \lambda_i v_i v_i^T$.

$\lambda_i \geq 0$ – eigenvalue.
v_i – associated eigenvector.

$$A = B^T B \qquad B = \sqrt{\lambda_i} \begin{bmatrix} v_1 \\ v_2 \\ \cdots \end{bmatrix}$$

Representation $\rightarrow$ positive semefinite too: $(x^T B^T)(Bx) \geq 0$

Possibly many such representations.

Efficiently computable: cholesky factorization

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i \quad & \geq \quad b_i \\ A \quad & \succeq \quad 0 \end{aligned} \tag{1}$$

Semidefinite Programming.

$$
\begin{aligned}
\max \quad & A.C \\
A.X_i \quad & \geq \quad b_i \\
A \quad & \succeq \quad 0
\end{aligned}
\tag{1}
$$

$A.X$ is matrix inner product:

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i \quad & \geq \quad b_i \\ A \quad & \succeq \quad 0 \end{aligned} \tag{1}$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.

Semidefinite Programming.

$$
\begin{aligned}
\max \quad & A.C \\
A.X_i \quad & \geq \quad b_i \\
A \quad & \succeq \quad 0
\end{aligned}
\tag{1}
$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Semidefinite Programming.

$$
\begin{aligned}
\max \quad & A.C \\
A.X_i & \geq b_i \\
A & \succeq 0
\end{aligned} \tag{1}
$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Linear Programming?

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i \quad & \geq \quad b_i \\ A \quad & \succeq \quad 0 \end{aligned} \tag{1}$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Linear Programming? A must be diagonal.

Semidefinite Programming.

$$
\begin{aligned}
\max \quad & A.C \\
A.X_i \quad & \geq \quad b_i \\
A \quad & \succeq \quad 0
\end{aligned}
\tag{1}
$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Linear Programming? A must be diagonal.
Constraint for each $i \neq j$,

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i \quad & \geq \quad b_i \\ A \quad & \succeq \quad 0 \end{aligned} \tag{1}$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Linear Programming? A must be diagonal.
Constraint for each $i \neq j$,
X_{jk} is 1 at entry jk, 0 elsewhere.

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i & \geq b_i \\ A & \succeq 0 \end{aligned} \tag{1}$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Linear Programming? A must be diagonal.
Constraint for each $i \neq j$,
X_{jk} is 1 at entry jk, 0 elsewhere. b_{jk} is 0.

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i \quad & \geq \quad b_i \\ A \quad & \succeq \quad 0 \end{aligned} \tag{1}$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Linear Programming? A must be diagonal.
Constraint for each $i \neq j$,
X_{jk} is 1 at entry jk, 0 elsewhere. b_{jk} is 0.

Solvable?

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i \quad & \geq \quad b_i \\ A \quad & \succeq \quad 0 \end{aligned} \tag{1}$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Linear Programming? A must be diagonal.
Constraint for each $i \neq j$,
X_{jk} is 1 at entry jk, 0 elsewhere. b_{jk} is 0.

Solvable?
Convex: Solution A and A'.

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i & \geq b_i \\ A & \succeq 0 \end{aligned} \tag{1}$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Linear Programming? A must be diagonal.
Constraint for each $i \neq j$,
X_{jk} is 1 at entry jk, 0 elsewhere. b_{jk} is 0.

Solvable?
Convex: Solution A and A'.
$\mu A + (1 - \mu)A'$ is solution.

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i & \geq b_i \\ A & \succeq 0 \end{aligned} \tag{1}$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.

view A and X as n^2 dimensional vector.

Linear Programming? A must be diagonal.

Constraint for each $i \neq j$,

X_{jk} is 1 at entry jk, 0 elsewhere. b_{jk} is 0.

Solvable?

Convex: Solution A and A'.

$\mu A + (1-\mu)A'$ is solution.

Linear constraints, objective.

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i \quad & \geq \quad b_i \\ A \quad & \succeq \quad 0 \end{aligned} \tag{1}$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Linear Programming? A must be diagonal.
Constraint for each $i \neq j$,
X_{jk} is 1 at entry jk, 0 elsewhere. b_{jk} is 0.

Solvable?
Convex: Solution A and A'.
$\mu A + (1-\mu)A'$ is solution.
Linear constraints, objective.
$x^T Ax, x^T A' x \geq 0 \implies x^T(\mu A + (1-\mu)A')x \geq 0$.

Semidefinite Programming.

$$\begin{aligned} \max \quad & A.C \\ A.X_i & \geq b_i \\ A & \succeq 0 \end{aligned} \tag{1}$$

$A.X$ is matrix inner product: $\sum_{ij} a_{ij} x_{ij}$.
view A and X as n^2 dimensional vector.

Linear Programming? A must be diagonal.
Constraint for each $i \neq j$,
X_{jk} is 1 at entry jk, 0 elsewhere. b_{jk} is 0.

Solvable?
Convex: Solution A and A'.
$\mu A + (1-\mu)A'$ is solution.
Linear constraints, objective.
$x^T A x, x^T A' x \geq 0 \implies x^T(\mu A + (1-\mu)A')x \geq 0$.

Actully: psd is "cone" constraint.

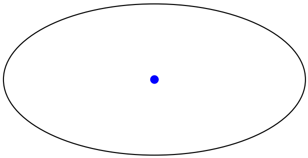
Semidefinite Programming:polynomial time.

Ellipsoid algorithm.

Semidefinite Programming:polynomial time.

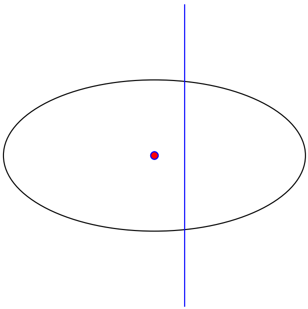
Ellipsoid algorithm.

Enclosing Ellipse.



Semidefinite Programming:polynomial time.

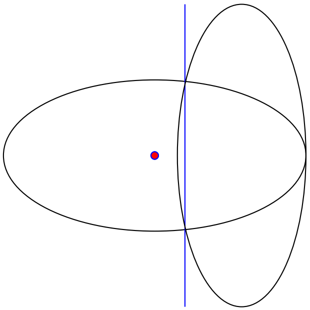
Ellipsoid algorithm.



Enclosing Ellipse.
Center point not feasible.

Semidefinite Programming:polynomial time.

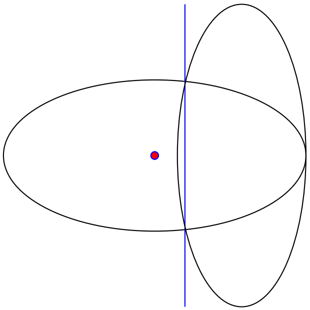
Ellipsoid algorithm.



Enclosing Ellipse.
Center point not feasible.
New Ellipsoid.

Semidefinite Programming:polynomial time.

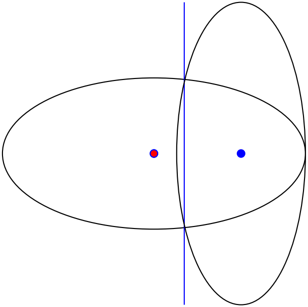
Ellipsoid algorithm.



Enclosing Ellipse.
Center point not feasible.
New Ellipsoid.
$\leq (1 - 1/\text{poly}(n))$ volume.

Semidefinite Programming:polynomial time.

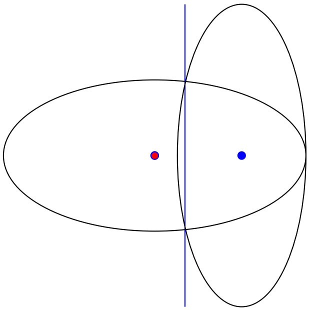
Ellipsoid algorithm.



Enclosing Ellipse.
Center point not feasible.
New Ellipsoid.
$\leq (1 - 1/\text{poly}(n))$ volume.
Center point feasible?

Semidefinite Programming:polynomial time.

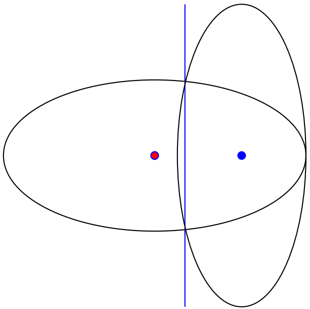
Ellipsoid algorithm.



Enclosing Ellipse.
Center point not feasible.
New Ellipsoid.
  $\leq (1 - 1/\text{poly}(n))$ volume.
Center point feasible?
Linear Programming:
  find violated constraint.

Semidefinite Programming:polynomial time.

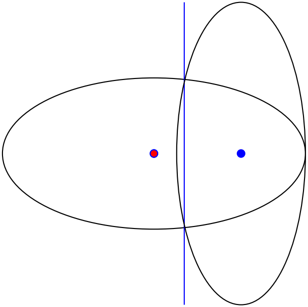
Ellipsoid algorithm.



Enclosing Ellipse.
Center point not feasible.
New Ellipsoid.
$\leq (1 - 1/\text{poly}(n))$ volume.
Center point feasible?
Linear Programming:
find violated constraint.
Semidefinite Programming:
find x where $x^T Ax \leq 0$.

Semidefinite Programming:polynomial time.

Ellipsoid algorithm.

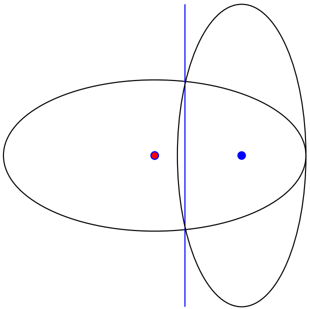


Only get close!

Enclosing Ellipse.
Center point not feasible.
New Ellipsoid.
$\leq (1 - 1/\text{poly}(n))$ volume.
Center point feasible?
Linear Programming:
find violated constraint.
Semidefinite Programming:
find x where $x^T A x \leq 0$.
Compute smallest eigenvalue.

Semidefinite Programming:polynomial time.

Ellipsoid algorithm.



Enclosing Ellipse.
Center point not feasible.
New Ellipsoid.
$\leq (1 - 1/\text{poly}(n))$ volume.
Center point feasible?
Linear Programming:
find violated constraint.
Semidefinite Programming:
find x where $x^T A x \leq 0$.
Compute smallest eigenvalue.

Only get close!
$O(\log \frac{1}{\varepsilon})$ dependence on closeness.

Semidefinite Programming: another view.

$$
\begin{aligned}
\max \quad & A.C \\
A.X_i \quad & \geq \quad b_i \\
A \quad & \succeq \quad 0
\end{aligned}
\tag{2}
$$

Semidefinite Programming: another view.

$$\begin{aligned} \max \quad & A.C \\ A.X_i & \geq b_i \\ A & \succeq 0 \end{aligned} \tag{2}$$

Recall $A = B^T B$.

Semidefinite Programming: another view.

$$\begin{aligned} \max \quad & A.C \\ A.X_i \quad & \geq \quad b_i \\ A \quad & \succeq \quad 0 \end{aligned} \tag{2}$$

Recall $A = B^T B$.

Programming over vectors: $v_1, v_2, \ldots, v_n$.

Semidefinite Programming: another view.

$$
\begin{aligned}
\max \quad & A.C \\
A.X_i \quad & \geq \quad b_i \\
A \quad & \succeq \quad 0
\end{aligned}
\tag{2}
$$

Recall $A = B^T B$.

Programming over vectors: $v_1, v_2, \ldots, v_n$.

Semidefinite Programming: another view.

$$\begin{aligned} \max \quad & A.C \\ A.X_i \quad & \geq \quad b_i \\ A \quad & \succeq \quad 0 \end{aligned} \tag{2}$$

Recall $A = B^T B$.

Programming over vectors: $v_1, v_2, \ldots, v_n$.

Linear Constraints over $v_i \cdot v_j$

Semidefinite Programming: another view.

$$\begin{aligned} \max \quad & A.C \\ A.X_i \quad & \geq \quad b_i \\ A \quad & \succeq \quad 0 \end{aligned} \tag{2}$$

Recall $A = B^T B$.

Programming over vectors: $v_1, v_2, \ldots, v_n$.

Linear Constraints over $v_i \cdot v_j$

quadratic..kind of!

Semidefinite Programming: another view.

$$\begin{aligned} \max \quad & A.C \\ A.X_i & \geq b_i \\ A & \succeq 0 \end{aligned} \tag{2}$$

Recall $A = B^T B$.

Programming over vectors: $v_1, v_2, \ldots, v_n$.

Linear Constraints over $v_i \cdot v_j$

quadratic..kind of!

Semidefinite Programming: another view.

$$\begin{aligned} \max \quad & A.C \\ A.X_i &\geq b_i \\ A &\succeq 0 \end{aligned} \tag{2}$$

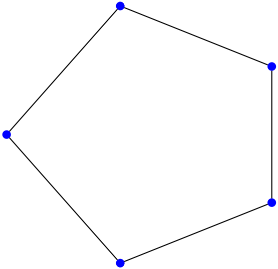
Recall $A = B^T B$.

Programming over vectors: $v_1, v_2, \ldots, v_n$.

Linear Constraints over $v_i \cdot v_j$
quadratic..kind of!

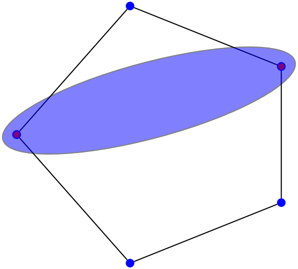
Max Cut

Given a graph $G = (V, E)$, with $w : E \rightarrow R$, find S where $\sum_{e \in S \times S} w_e$ is maximized.



Max Cut

Given a graph $G = (V, E)$, with $w : E \rightarrow R$, find S where $\sum_{e \in S \times S} w_e$ is maximized.



Max Cut Size: 4

Factor half approximation?

Random: choose a side at random.

Factor half approximation?

Random: choose a side at random.

Each edge has probability $\frac{1}{2}$ of being cut.

Factor half approximation?

Random: choose a side at random.

Each edge has probability $\frac{1}{2}$ of being cut.

Expected value of solution is half total edge weight.

Factor half approximation?

Random: choose a side at random.

Each edge has probability $\frac{1}{2}$ of being cut.

Expected value of solution is half total edge weight.

Greedy: choose larger choice.

Factor half approximation?

Random: choose a side at random.

Each edge has probability $\frac{1}{2}$ of being cut.

Expected value of solution is half total edge weight.

Greedy: choose larger choice.

When each node comes, cuts at least half previous edges.

Factor half approximation?

Random: choose a side at random.

Each edge has probability $\frac{1}{2}$ of being cut.

Expected value of solution is half total edge weight.

Greedy: choose larger choice.

When each node comes, cuts at least half previous edges.

Can we do better?

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Maximize $\sum_{ij} w_{ij} \frac{1 - x_i x_j}{2}$.

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Maximize $\sum_{ij} w_{ij} \frac{1 - x_i x_j}{2}$.

Cost of cut indicated by ± 1 vector!

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Maximize $\sum_{ij} w_{ij} \frac{1 - x_i x_j}{2}$.

Cost of cut indicated by ± 1 vector!

Integer?

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Maximize $\sum_{ij} w_{ij} \frac{1 - x_i x_j}{2}$.

Cost of cut indicated by ± 1 vector!

Integer? Quadratic?

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Maximize $\sum_{ij} w_{ij} \frac{1 - x_i x_j}{2}$.

Cost of cut indicated by ± 1 vector!

Integer? Quadratic?

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Maximize $\sum_{ij} w_{ij} \frac{1 - x_i x_j}{2}$.

Cost of cut indicated by ± 1 vector!

Integer? Quadratic?

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Maximize $\sum_{ij} w_{ij} \frac{1 - x_i x_j}{2}$.

Cost of cut indicated by ± 1 vector!

Integer? Quadratic?

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Maximize $\sum_{ij} w_{ij} \frac{1 - v_i \cdot v_j}{2}$.

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Maximize $\sum_{ij} w_{ij} \frac{1 - x_i x_j}{2}$.

Cost of cut indicated by ± 1 vector!

Integer? Quadratic?

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Maximize $\sum_{ij} w_{ij} \frac{1 - v_i \cdot v_j}{2}$.

Semidefinite Program.

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Maximize $\sum_{ij} w_{ij} \frac{1 - x_i x_j}{2}$.

Cost of cut indicated by ± 1 vector!

Integer? Quadratic?

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Maximize $\sum_{ij} w_{ij} \frac{1 - v_i \cdot v_j}{2}$.

Semidefinite Program. Can solve?

Embedding problem.

Assign variables $x_1, \ldots, x_n$ to vertices.

x_i are ± 1.

Maximize $\sum_{ij} w_{ij} \frac{1 - x_i x_j}{2}$.

Cost of cut indicated by ± 1 vector!

Integer? Quadratic?

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Maximize $\sum_{ij} w_{ij} \frac{1 - v_i \cdot v_j}{2}$.

Semidefinite Program. Can solve? (Basically.)

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Maximize $\sum_{ij} w_{ij} \frac{1 - v_i \cdot v_j}{2}$.

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Maximize $\sum_{ij} w_{ij} \frac{1 - v_i \cdot v_j}{2}$.

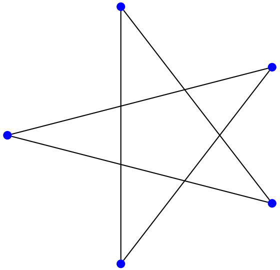
Example?

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Maximize $\sum_{ij} w_{ij} \frac{1 - v_i \cdot v_j}{2}$.

Example?

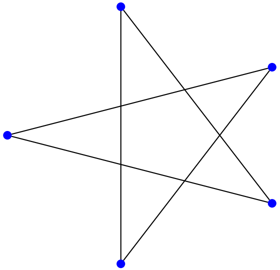


Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Maximize $\sum_{ij} w_{ij} \frac{1 - v_i \cdot v_j}{2}$.

Example?



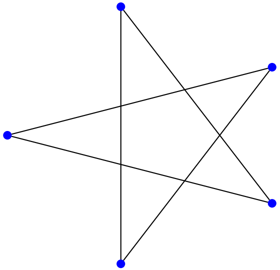
Solution Value: $5\frac{(1-cos(4\pi/5))}{2} \approx 4.52$

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Maximize $\sum_{ij} w_{ij} \frac{1 - v_i \cdot v_j}{2}$.

Example?



Solution Value: $5\frac{(1 - cos(4\pi/5))}{2} \approx 4.52$

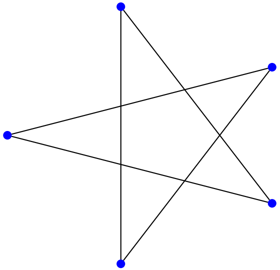
Higher than opt.

Assign vectors $v_1, v_2, \ldots, v_n$ to vertices.

$|v_i| = 1$

Maximize $\sum_{ij} w_{ij} \frac{1 - v_i \cdot v_j}{2}$.

Example?

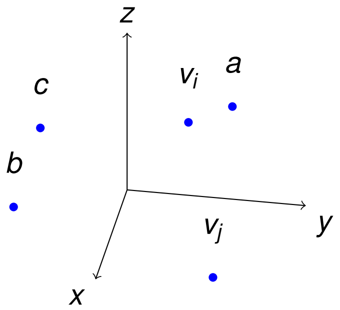


Solution Value: $5\frac{(1 - cos(4\pi/5))}{2} \approx 4.52$

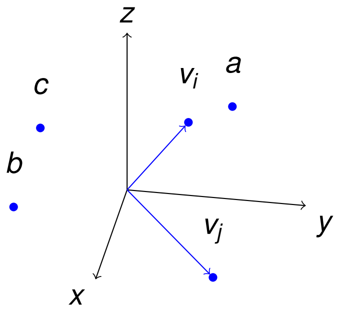
Higher than opt.

Round and not lose too much?

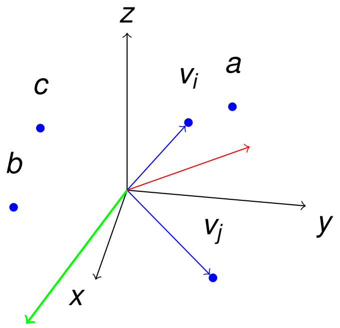
Hyperplane rounding.



Hyperplane rounding.

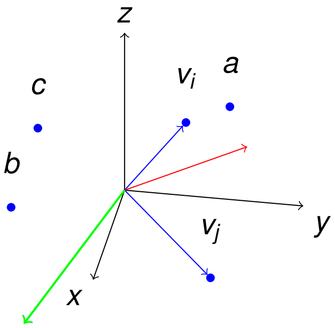


Hyperplane rounding.



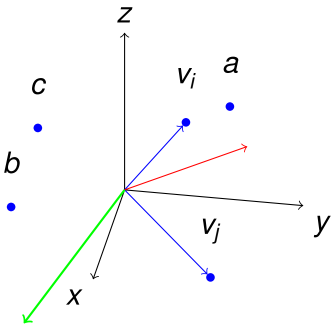
Normal to hyperplane:

Hyperplane rounding.



Normal to hyperplane:
red does not separate!

Hyperplane rounding.



Normal to hyperplane:
red does not separate!
green does.

Hyperplane rounding.

Take a random vector, w

Hyperplane rounding.

Take a random vector, w

Let $S = \{w \cdot v \geq 0\}$

Hyperplane rounding.

Take a random vector, w

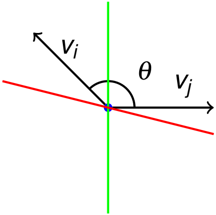
Let $S = \{w \cdot v \geq 0\}$

Claim 1: Expected weight of $(S, V - S)$ is at least 0.878 SDPOPT.

Hyperplane rounding.

Take a random vector, w
  Let $S = \{w \cdot v \geq 0\}$

Claim 1: Expected weight of $(S, V - S)$ is at least 0.878 SDPOPT.

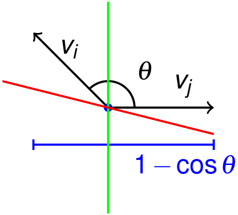


Hyperplane rounding.

Take a random vector, w

Let $S = \{w \cdot v \geq 0\}$

Claim 1: Expected weight of $(S, V - S)$ is at least 0.878 SDPOPT.



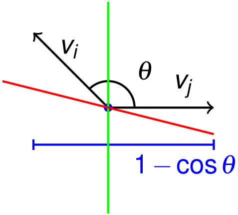
SDP value for edge (i, j).

$\frac{(1-\cos\theta)}{2}$

Hyperplane rounding.

Take a random vector, w
  Let $S = \{w \cdot v \geq 0\}$

Claim 1: Expected weight of $(S, V - S)$ is at least 0.878 SDPOPT.



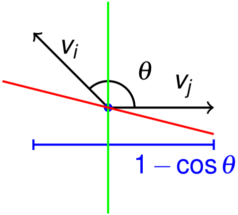
SDP value for edge (i, j).
$\frac{(1-\cos\theta)}{2}$
Prob. of cutting:

Hyperplane rounding.

Take a random vector, w

Let $S = \{w \cdot v \geq 0\}$

Claim 1: Expected weight of $(S, V - S)$ is at least 0.878 SDPOPT.



SDP value for edge (i, j).

$\frac{(1-\cos\theta)}{2}$

Prob. of cutting:

$\frac{\theta}{\pi}$

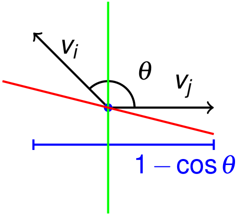
Expected value in rounding!

Hyperplane rounding.

Take a random vector, w

Let $S = \{w \cdot v \geq 0\}$

Claim 1: Expected weight of $(S, V - S)$ is at least 0.878 SDPOPT.



SDP value for edge (i, j).

$\frac{(1-\cos\theta)}{2}$

Prob. of cutting:

$\frac{\theta}{\pi}$

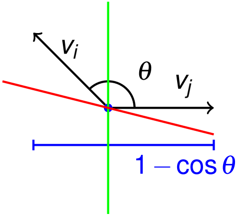
Expected value in rounding!

Ratio is $\frac{2\theta}{\pi(1-\cos\theta)}$.

Hyperplane rounding.

Take a random vector, w
  Let $S = \{w \cdot v \geq 0\}$

Claim 1: Expected weight of $(S, V - S)$ is at least 0.878 SDPOPT.



SDP value for edge (i, j).
$\frac{(1-\cos\theta)}{2}$
Prob. of cutting:
$\frac{\theta}{\pi}$
Expected value in rounding!

Ratio is $\frac{2\theta}{\pi(1-\cos\theta)}$.
Always bigger than .878!

See you on Thursday.