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# Minimizing Operations in Matrix/Vector Multiplication

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CS 591MH

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# Matrix/Vector Multiplication

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$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} r_1^T \\ \hline r_2^T \\ \hline \vdots \\ \hline r_m^T \end{bmatrix} \begin{bmatrix} x \end{bmatrix} = \begin{bmatrix} r_1^T x \\ r_2^T x \\ \vdots \\ r_m^T x \end{bmatrix}$$

$$y = Ax$$

# Optimization Problem

Objective: To generate code to minimize the number of multiply add pairs (MAPs) in matrix/vector multiplication

e.g.  $r_2 = \alpha r_1$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} r_1^T \\ \hline \alpha r_1^T \\ \hline \vdots \\ \hline r_m^T \end{bmatrix} \begin{bmatrix} x \end{bmatrix} = \begin{bmatrix} r_1^T x \\ \alpha y_1 \\ \vdots \\ r_m^T x \end{bmatrix}$$

## Possible Optimizations - 0 Rows

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$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$$y_3 = 0 \quad \boxed{0 \text{ MAPs}}$$

## Possible Optimizations - 1 NZ Rows

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$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} 2 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$$y_1 = 2x_1 \quad \boxed{1 \text{ MAP}}$$

## Possible Optimizations - 2 NZ Rows

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$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 2 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$$y_2 = 2x_1 + 2x_2 \quad \boxed{2 \text{ MAPs}}$$

## Possible Optimizations - 3 NZ Rows

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$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 4 & 4 & 4 & 4 \\ 0 & 0 & 1 & 1 \\ 2 & 2 & 2 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$$y_4 = 2x_1 + 2x_2 + 2x_3 \quad \boxed{3 \text{ MAPs}}$$

## Possible Optimizations - Same Rows

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$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$$y_4 = y_2 \quad \boxed{0 \text{ MAPs}}$$



## Possible Optimizations - Scalar Multiple Rows

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$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 4 & 4 & 4 & 4 \\ 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$$y_2 = 4y_1 \quad \boxed{1 \text{ MAP}}$$

## Possible Optimizations - Partial Scalar Multiple Rows

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$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 4 & 4 & 4 & 4 \\ 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$$y_2 = 4y_4 + 4x_4 \quad \boxed{2 \text{ MAPs}}$$

## Possible Optimizations - Linear Dependency Rows

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$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 4 & 4 & 4 & 4 \\ 0 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$$y_2 = 4y_3 + 4y_4 \quad \boxed{2 \text{ MAPs}}$$

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WHY?

# Application

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- Work by Kirby, et al., University of Chicago
- Finite element "Compilers"
  - FIAT (FE gen.), FFC (variational forms -> code )
  - FErari (optimizer)
- Construction of FE Matrices extremely expensive for large unstructured problems, especially for high order bases
- Methods for reducing redundant operations in building stiffness matrices
  - Many local stiffness matrices built
  - Generate code to optimize construction of local stiffness matrices

# 2D Laplace - Local Stiffness Matrix Assembly

- Elemental bilinear form:

$$\begin{aligned}
 (\nabla u, \nabla v)_e &= \det(J) (\nabla u, \nabla v)_{\hat{e}} \\
 &= \det(J) \left[ \left( \frac{\partial u}{\partial r} \frac{\partial r}{\partial x}, \frac{\partial v}{\partial r} \frac{\partial r}{\partial x} \right)_{\hat{e}} + \left( \frac{\partial u}{\partial r} \frac{\partial r}{\partial x}, \frac{\partial v}{\partial s} \frac{\partial s}{\partial x} \right)_{\hat{e}} + \left( \frac{\partial u}{\partial s} \frac{\partial s}{\partial x}, \frac{\partial v}{\partial r} \frac{\partial r}{\partial x} \right)_{\hat{e}} + \left( \frac{\partial u}{\partial s} \frac{\partial s}{\partial x}, \frac{\partial v}{\partial s} \frac{\partial s}{\partial x} \right)_{\hat{e}} + \right. \\
 &\quad \left. \left( \frac{\partial u}{\partial r} \frac{\partial r}{\partial y}, \frac{\partial v}{\partial r} \frac{\partial r}{\partial y} \right)_{\hat{e}} + \left( \frac{\partial u}{\partial r} \frac{\partial r}{\partial y}, \frac{\partial v}{\partial s} \frac{\partial s}{\partial y} \right)_{\hat{e}} + \left( \frac{\partial u}{\partial s} \frac{\partial s}{\partial y}, \frac{\partial v}{\partial r} \frac{\partial r}{\partial y} \right)_{\hat{e}} + \left( \frac{\partial u}{\partial s} \frac{\partial s}{\partial y}, \frac{\partial v}{\partial s} \frac{\partial s}{\partial y} \right)_{\hat{e}} \right] \\
 &= \det(J) \left[ \frac{\partial r}{\partial x} \left( \frac{\partial u}{\partial r}, \frac{\partial v}{\partial r} \right)_{\hat{e}} \frac{\partial r}{\partial x} + \frac{\partial r}{\partial x} \left( \frac{\partial u}{\partial r}, \frac{\partial v}{\partial s} \right)_{\hat{e}} \frac{\partial s}{\partial x} + \frac{\partial s}{\partial x} \left( \frac{\partial u}{\partial s}, \frac{\partial v}{\partial r} \right)_{\hat{e}} \frac{\partial r}{\partial x} + \frac{\partial s}{\partial x} \left( \frac{\partial u}{\partial s}, \frac{\partial v}{\partial s} \right)_{\hat{e}} \frac{\partial s}{\partial x} + \right. \\
 &\quad \left. \frac{\partial r}{\partial y} \left( \frac{\partial u}{\partial r}, \frac{\partial v}{\partial r} \right)_{\hat{e}} \frac{\partial r}{\partial y} + \frac{\partial r}{\partial y} \left( \frac{\partial u}{\partial r}, \frac{\partial v}{\partial s} \right)_{\hat{e}} \frac{\partial s}{\partial y} + \frac{\partial s}{\partial y} \left( \frac{\partial u}{\partial s}, \frac{\partial v}{\partial r} \right)_{\hat{e}} \frac{\partial r}{\partial y} + \frac{\partial s}{\partial y} \left( \frac{\partial u}{\partial s}, \frac{\partial v}{\partial s} \right)_{\hat{e}} \frac{\partial s}{\partial y} \right] \\
 &\vdots \\
 &= \det(J) \left[ \frac{\partial r}{\partial x} (\mathbf{u}^T D_{rr} \mathbf{v}) \frac{\partial r}{\partial x} + \frac{\partial r}{\partial x} (\mathbf{u}^T D_{rs} \mathbf{v}) \frac{\partial s}{\partial x} + \frac{\partial s}{\partial x} (\mathbf{u}^T D_{sr} \mathbf{v}) \frac{\partial r}{\partial x} + \frac{\partial s}{\partial x} (\mathbf{u}^T D_{ss} \mathbf{v}) \frac{\partial s}{\partial x} + \right. \\
 &\quad \left. \frac{\partial r}{\partial y} (\mathbf{u}^T D_{rr} \mathbf{v}) \frac{\partial r}{\partial y} + \frac{\partial r}{\partial y} (\mathbf{u}^T D_{rs} \mathbf{v}) \frac{\partial s}{\partial y} + \frac{\partial s}{\partial y} (\mathbf{u}^T D_{sr} \mathbf{v}) \frac{\partial r}{\partial y} + \frac{\partial s}{\partial y} (\mathbf{u}^T D_{ss} \mathbf{v}) \frac{\partial s}{\partial y} \right]
 \end{aligned}$$

$$D_{rr}(i, j) = \left( \frac{\partial \phi_i}{\partial r}, \frac{\partial \phi_j}{\partial r} \right)_{\hat{e}}, \quad D_{rs}(i, j) = \left( \frac{\partial \phi_i}{\partial r}, \frac{\partial \phi_j}{\partial s} \right)_{\hat{e}}, \quad D_{sr}(i, j) = \left( \frac{\partial \phi_i}{\partial s}, \frac{\partial \phi_j}{\partial r} \right)_{\hat{e}}, \quad D_{ss}(i, j) = \left( \frac{\partial \phi_i}{\partial s}, \frac{\partial \phi_j}{\partial s} \right)_{\hat{e}}$$

# 2D Laplace - Local Stiffness Matrix Assembly

$$(\nabla u, \nabla v)_e = \mathbf{u}^T \left( \det(J) \left[ \frac{\partial r}{\partial x} (D_{rr}) \frac{\partial r}{\partial x} + \frac{\partial r}{\partial x} (D_{rs}) \frac{\partial s}{\partial x} + \frac{\partial s}{\partial x} (D_{sr}) \frac{\partial r}{\partial x} + \frac{\partial s}{\partial x} (D_{ss}) \frac{\partial s}{\partial x} + \right. \right. \\ \left. \left. \frac{\partial r}{\partial y} (D_{rr}) \frac{\partial r}{\partial y} + \frac{\partial r}{\partial y} (D_{rs}) \frac{\partial s}{\partial y} + \frac{\partial s}{\partial y} (D_{sr}) \frac{\partial r}{\partial y} + \frac{\partial s}{\partial y} (D_{ss}) \frac{\partial s}{\partial y} \right] \right) \mathbf{v}$$

$$S^e = \det(J) \left[ \frac{\partial r}{\partial x} D_{rr} \frac{\partial r}{\partial x} + \frac{\partial r}{\partial x} D_{rs} \frac{\partial s}{\partial x} + \frac{\partial s}{\partial x} D_{sr} \frac{\partial r}{\partial x} + \frac{\partial s}{\partial x} D_{ss} \frac{\partial s}{\partial x} + \right. \\ \left. \frac{\partial r}{\partial y} D_{rr} \frac{\partial r}{\partial y} + \frac{\partial r}{\partial y} D_{rs} \frac{\partial s}{\partial y} + \frac{\partial s}{\partial y} D_{sr} \frac{\partial r}{\partial y} + \frac{\partial s}{\partial y} D_{ss} \frac{\partial s}{\partial y} \right]$$

- Terms not grouped by element dependency
- $8 * (\# \text{ bases})^2$  MAPs

$$S^e = D_{rr} \left[ \det(J) \left( \frac{\partial r}{\partial x} \frac{\partial r}{\partial x} + \frac{\partial r}{\partial y} \frac{\partial r}{\partial y} \right) \right]_e + D_{rs} \left[ \det(J) \left( \frac{\partial r}{\partial x} \frac{\partial s}{\partial x} + \frac{\partial r}{\partial y} \frac{\partial s}{\partial y} \right) \right]_e + \\ D_{sr} \left[ \det(J) \left( \frac{\partial s}{\partial x} \frac{\partial r}{\partial x} + \frac{\partial s}{\partial y} \frac{\partial r}{\partial y} \right) \right]_e + D_{ss} \left[ \det(J) \left( \frac{\partial s}{\partial x} \frac{\partial s}{\partial x} + \frac{\partial s}{\partial y} \frac{\partial s}{\partial y} \right) \right]_e$$

## 2D Laplace - Tensor K

$$\begin{aligned}
 S^e = & D_{rr} \left[ \det(J) \left( \frac{\partial r}{\partial x} \frac{\partial r}{\partial x} + \frac{\partial r}{\partial y} \frac{\partial r}{\partial y} \right) \right]_e + D_{rs} \left[ \det(J) \left( \frac{\partial r}{\partial x} \frac{\partial s}{\partial x} + \frac{\partial r}{\partial y} \frac{\partial s}{\partial y} \right) \right]_e + \\
 & D_{sr} \left[ \det(J) \left( \frac{\partial s}{\partial x} \frac{\partial r}{\partial x} + \frac{\partial s}{\partial y} \frac{\partial r}{\partial y} \right) \right]_e + D_{ss} \left[ \det(J) \left( \frac{\partial s}{\partial x} \frac{\partial s}{\partial x} + \frac{\partial s}{\partial y} \frac{\partial s}{\partial y} \right) \right]_e
 \end{aligned}$$

$$S_{i,j}^e = \sum_m^2 \sum_n^2 G_{m,n}^e K_{i,j,m,n} = K_{i,j} : G^e$$

$$G^e = \begin{bmatrix} \left[ \det(J) \left( \frac{\partial r}{\partial x} \frac{\partial r}{\partial x} + \frac{\partial r}{\partial y} \frac{\partial r}{\partial y} \right) \right]_e & \left[ \det(J) \left( \frac{\partial r}{\partial x} \frac{\partial s}{\partial x} + \frac{\partial r}{\partial y} \frac{\partial s}{\partial y} \right) \right]_e \\ \left[ \det(J) \left( \frac{\partial s}{\partial x} \frac{\partial r}{\partial x} + \frac{\partial s}{\partial y} \frac{\partial r}{\partial y} \right) \right]_e & \left[ \det(J) \left( \frac{\partial s}{\partial x} \frac{\partial s}{\partial x} + \frac{\partial s}{\partial y} \frac{\partial s}{\partial y} \right) \right]_e \end{bmatrix}$$

$$K_{i,j} = \begin{bmatrix} D_{rr}(i,j) & D_{rs}(i,j) \\ D_{sr}(i,j) & D_{ss}(i,j) \end{bmatrix} = \begin{bmatrix} \left( \frac{\partial \phi_i}{\partial r}, \frac{\partial \phi_j}{\partial r} \right)_{\hat{e}} & \left( \frac{\partial \phi_i}{\partial r}, \frac{\partial \phi_j}{\partial s} \right)_{\hat{e}} \\ \left( \frac{\partial \phi_i}{\partial s}, \frac{\partial \phi_j}{\partial r} \right)_{\hat{e}} & \left( \frac{\partial \phi_i}{\partial s}, \frac{\partial \phi_j}{\partial s} \right)_{\hat{e}} \end{bmatrix}$$



## 2D Laplace - Tensor K

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$$K_{i,j} = \begin{bmatrix} \left( \frac{\partial \phi_i}{\partial r}, \frac{\partial \phi_j}{\partial r} \right)_{\hat{e}} & \left( \frac{\partial \phi_i}{\partial r}, \frac{\partial \phi_j}{\partial s} \right)_{\hat{e}} \\ \left( \frac{\partial \phi_i}{\partial s}, \frac{\partial \phi_j}{\partial r} \right)_{\hat{e}} & \left( \frac{\partial \phi_i}{\partial s}, \frac{\partial \phi_j}{\partial s} \right)_{\hat{e}} \end{bmatrix}$$

	$\phi_{0,0}$	$\phi_{1,0}$	$\phi_{0,1}$			
$\phi_{0,0}$	1	1	0	-1	-1	0
$\phi_{1,0}$	1	1	0	-1	-1	0
$\phi_{0,1}$	0	0	0	0	0	0
	-1	-1	0	1	1	0
	-1	-1	0	1	1	0
	0	0	0	0	0	0

$K$

$$S_{i,j}^e = K_{i,j} : G^e$$

$$S_{1,2} = -G_{1,2} - G_{2,2}$$

p=1

# Optimization Problem

3	3	0	-4	0	1	-4	0	0	0	1	0
3	3	0	-4	0	1	-4	0	0	0	1	0
0	0	8	4	0	-4	0	4	-8	-4	0	0
-4	-4	4	8	0	-4	4	0	-4	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
1	1	-4	-4	0	3	0	0	4	0	-1	0
-4	-4	0	4	0	0	8	4	0	-4	-4	0
0	0	4	0	0	0	4	8	-4	-8	-4	0
0	0	-8	-4	0	4	0	-4	8	4	0	0
0	0	-4	0	0	0	-4	-8	4	8	4	0
1	1	0	0	0	-1	-4	-4	0	4	3	0
0	0	0	0	0	0	0	0	0	0	0	0

- Example of tensor  $K$
- 2D Laplace
- Triangles
- $p=2$
- Each Block a “row”
- Optimize Frobenius product

$$S_{i,j}^e = K_{i,j} : G^e$$

# Initial Implementation

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- Modified 2D Helmholtz Matlab code from CS598LO
- "Tensor" representation of local stiffness matrix
- Several optimizations (only binary relationships)
  - 0 block
  - Same block
  - 1 NZ, 2NZ, 3NZ
  - Scalar multiple block
  - Partial scalar multiple block
- Graph model for more complex block relationships
- Implementation generates an optimal (minimal MAPs) set of operations to build stiffness matrix
  - Optimal for block relationships used
- Now have C++ matrix/vector multiplication optimization code using FErari tensors

# Initial Implementation Example

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$S =$

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

# Initial Implementation Example - 0 Blocks

3	3	0	-4	0	1	-4	0	0	0	1	0
3	3	0	-4	0	1	-4	0	0	0	1	0
0	0	8	4	0	-4	0	4	-8	-4	0	0
-4	-4	4	8	0	-4	4	0	-4	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
1	1	-4	-4	0	3	0	0	4	0	-1	0
-4	-4	0	4	0	0	8	4	0	-4	-4	0
0	0	4	0	0	0	4	8	-4	-8	-4	0
0	0	-8	-4	0	4	0	-4	8	4	0	0
0	0	-4	0	0	0	-4	-8	4	8	4	0
1	1	0	0	0	-1	-4	-4	0	4	3	0
0	0	0	0	0	0	0	0	0	0	0	0

No change to S

# Initial Implementation Example

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$S =$

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

# Initial Implementation Example - Same Blocks

3	3	0	-4	0	1	-4	0	0	0	1	0
3	3	0	-4	0	1	-4	0	0	0	1	0
0	0	8	4	0	-4	0	4	-8	-4	0	0
-4	-4	4	8	0	-4	4	0	-4	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
1	1	-4	-4	0	3	0	0	4	0	-1	0
-4	-4	0	4	0	0	8	4	0	-4	-4	0
0	0	4	0	0	0	4	8	-4	-8	-4	0
0	0	-8	-4	0	4	0	-4	8	4	0	0
0	0	-4	0	0	0	-4	-8	4	8	4	0
1	1	0	0	0	-1	-4	-4	0	4	3	0
0	0	0	0	0	0	0	0	0	0	0	0

0 MAPs

$$S_{i,j} = S_{k,l}$$

# Initial Implementation Example

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S =

0	0	0	0	0	0
0	0	$S(1,2)$	0	0	0
0	$S(2,1)$	0	0	0	0
0	$S(2,4)$	0	$S(2,2)$	0	$S(1,4)$
0	$S(2,5)$	0	$S(4,5)$	$S(2,2)$	$S(3,5)$
0	0	0	$S(4,1)$	$S(5,3)$	0



## Initial Implementation Example - Scalar Multiple

3	3	0	-4	0	1	-4	0	0	0	1	0
3	3	0	-4	0	1	-4	0	0	0	1	0
0	0	8	4	0	-4	0	4	-8	-4	0	0
-4	-4	4	8	0	-4	4	0	-4	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
1	1	-4	-4	0	3	0	0	4	0	-1	0
-4	-4	0	4	0	0	8	4	0	-4	-4	0
0	0	4	0	0	0	4	8	-4	-8	-4	0
0	0	-8	-4	0	4	0	-4	8	4	0	0
0	0	-4	0	0	0	-4	-8	4	8	4	0
1	1	0	0	0	-1	-4	-4	0	4	3	0
0	0	0	0	0	0	0	0	0	0	0	0

1 MAP

$$$S_{i,j} = \alpha S_{k,l}$$$

# Initial Implementation Example

$S =$

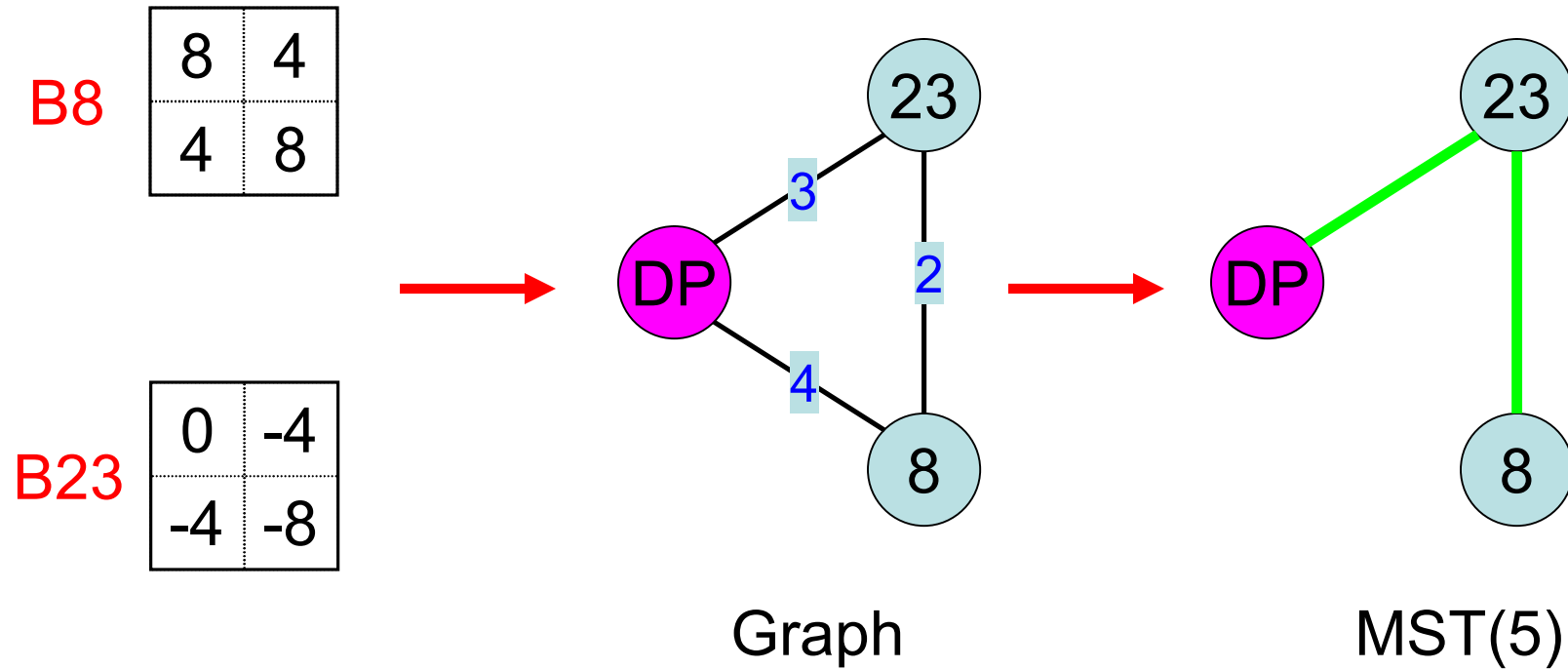
0	0	$-\frac{1}{4}S(1,2)$	0	0	$-\frac{1}{4}S(1,4)$
0	0	$S(1,2)$	0	0	0
$-\frac{1}{4}S(2,1)$	$S(2,1)$	0	0	0	$-\frac{1}{4}S(3,5)$
0	$S(2,4)$	0	$S(2,2)$	0	$S(1,4)$
0	$S(2,5)$	0	$S(4,5)$	$S(2,2)$	$S(3,5)$
$-\frac{1}{4}S(4,1)$	0	$-\frac{1}{4}S(5,3)$	$S(4,1)$	$S(5,3)$	0

# Initial Implementation Example

3	3	0	-4	0	1	-4	0	0	0	1	0
3	3	0	-4	0	1	-4	0	0	0	1	0
0	0	8	4	0	-4	0	4	-8	-4	0	0
-4	-4	4	8	0	-4	4	0	-4	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
1	1	-4	-4	0	3	0	0	4	0	-1	0
-4	-4	0	4	0	0	8	4	0	-4	-4	0
0	0	4	0	0	0	4	8	-4	-8	-4	0
0	0	-8	-4	0	4	0	-4	8	4	0	0
0	0	-4	0	0	0	-4	-8	4	8	4	0
1	1	0	0	0	-1	-4	-4	0	4	3	0
0	0	0	0	0	0	0	0	0	0	0	0

- Build graph from remaining blocks
- One vertex for each block
- One dot product vertex
- Weighted edges
- Weights – work to determine a block given another block
- Find MST

# Graph Problem



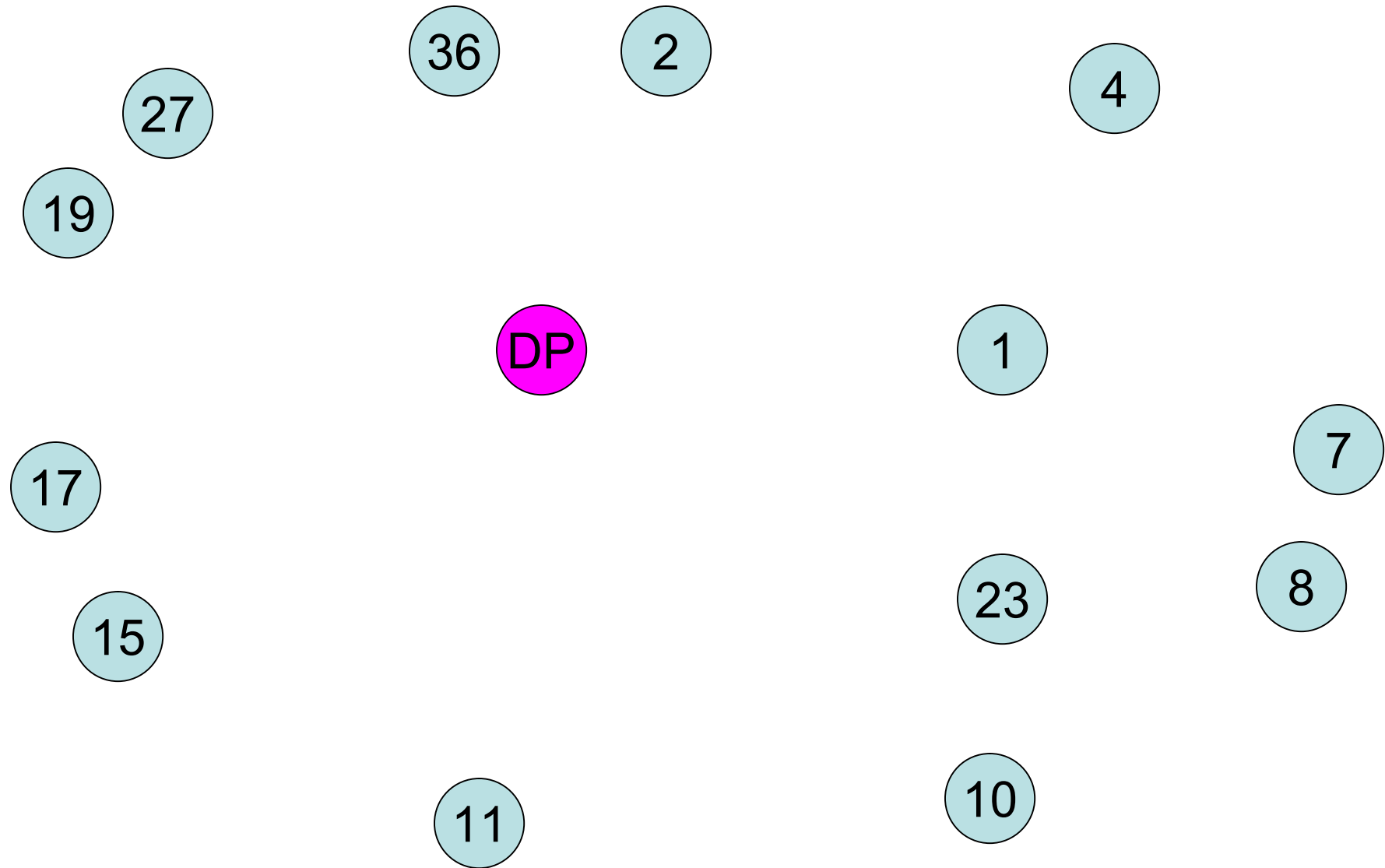
$$S_8 = -S_{23} + 8G_{1,1}$$

# Initial Implementation Example

3	3	0	-4	0	1	-4	0	0	0	1	0
3	3	0	-4	0	1	-4	0	0	0	1	0
0	0	8	4	0	-4	0	4	-8	-4	0	0
-4	-4	4	8	0	-4	4	0	-4	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
1	1	-4	-4	0	3	0	0	4	0	-1	0
-4	-4	0	4	0	0	8	4	0	-4	-4	0
0	0	4	0	0	0	4	8	-4	-8	-4	0
0	0	-8	-4	0	4	0	-4	8	4	0	0
0	0	-4	0	0	0	-4	-8	4	8	4	0
1	1	0	0	0	-1	-4	-4	0	4	3	0
0	0	0	0	0	0	0	0	0	0	0	0

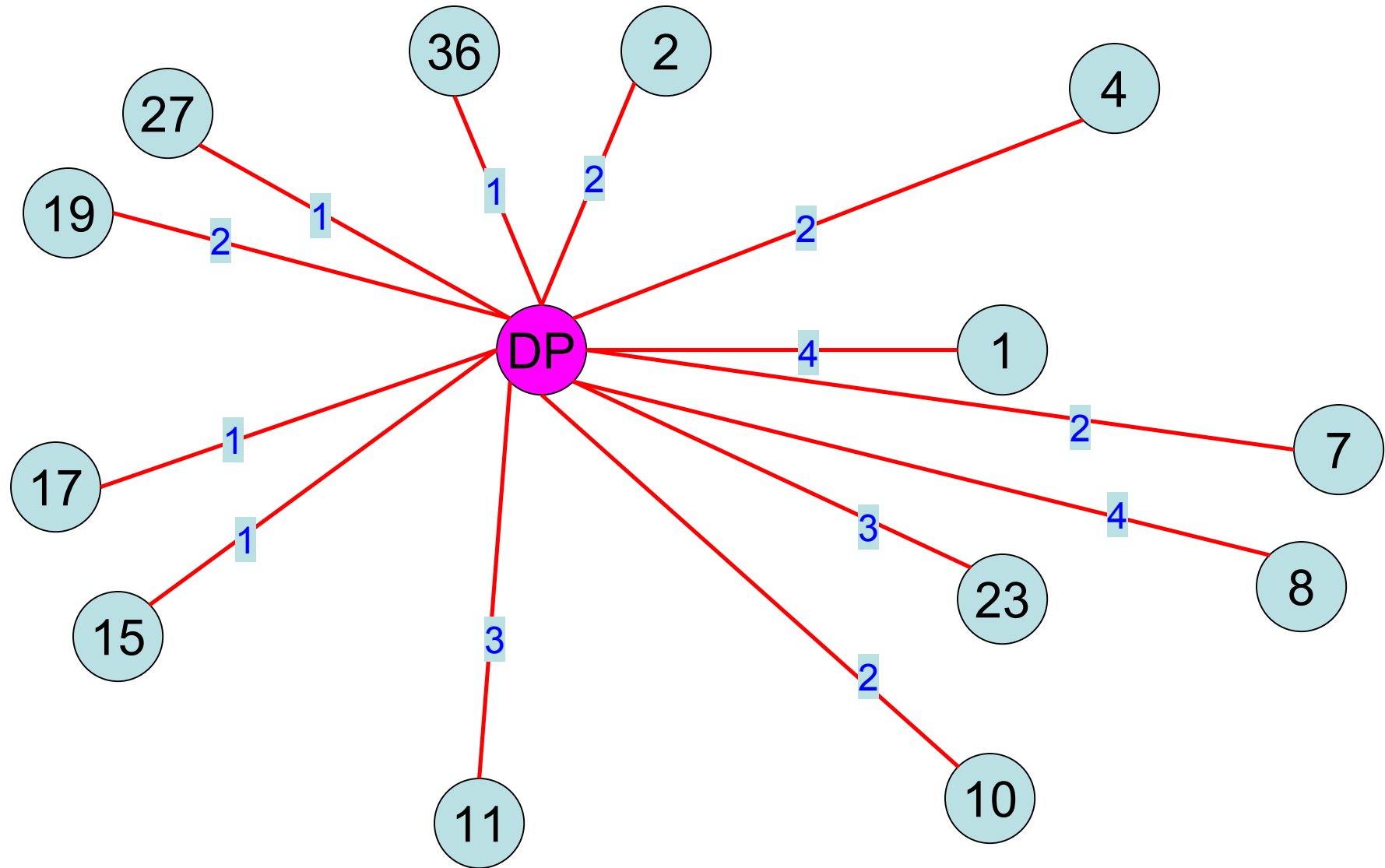
# Graph Vertices

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# Graph - Dot Product Edges

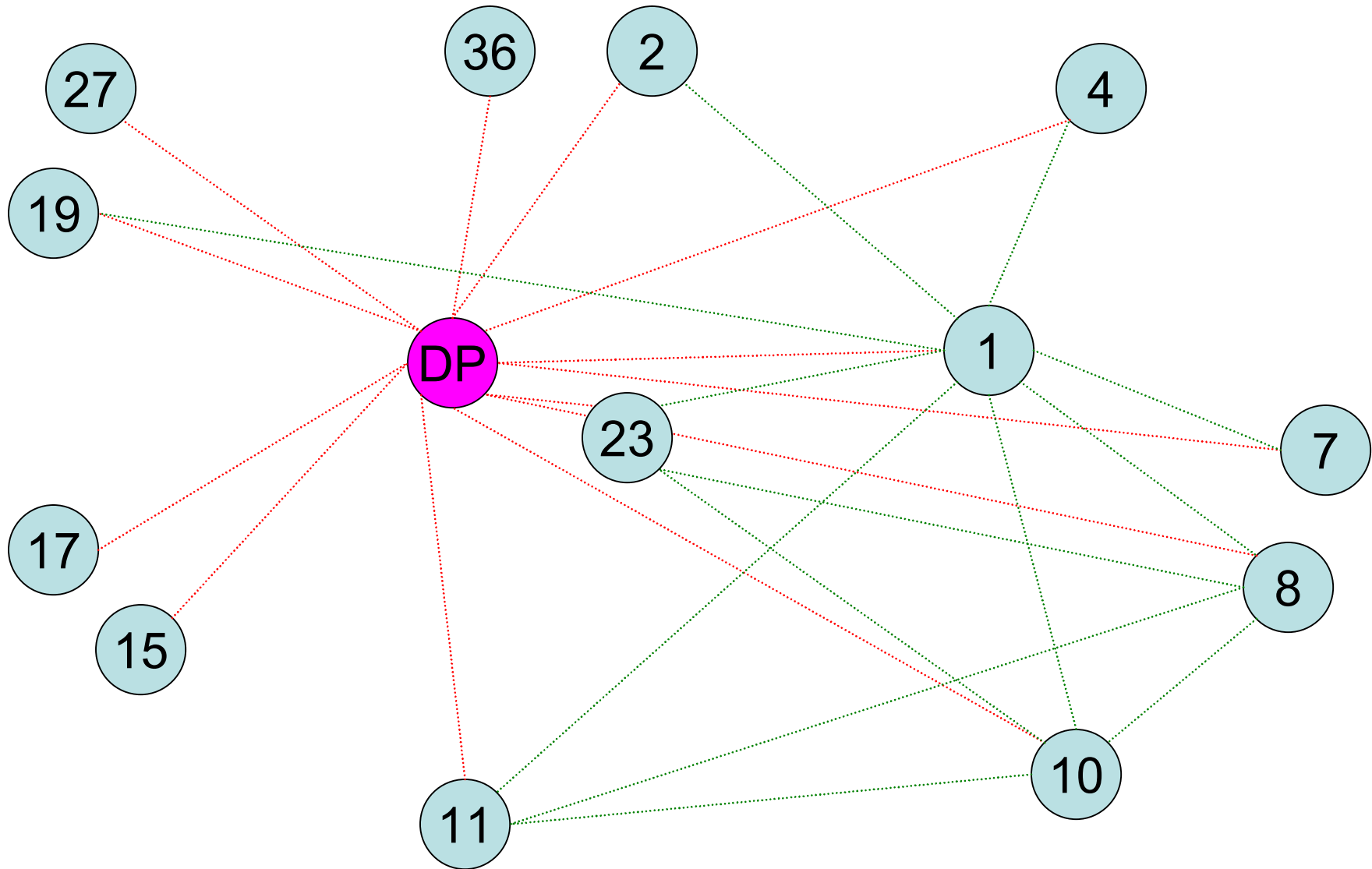
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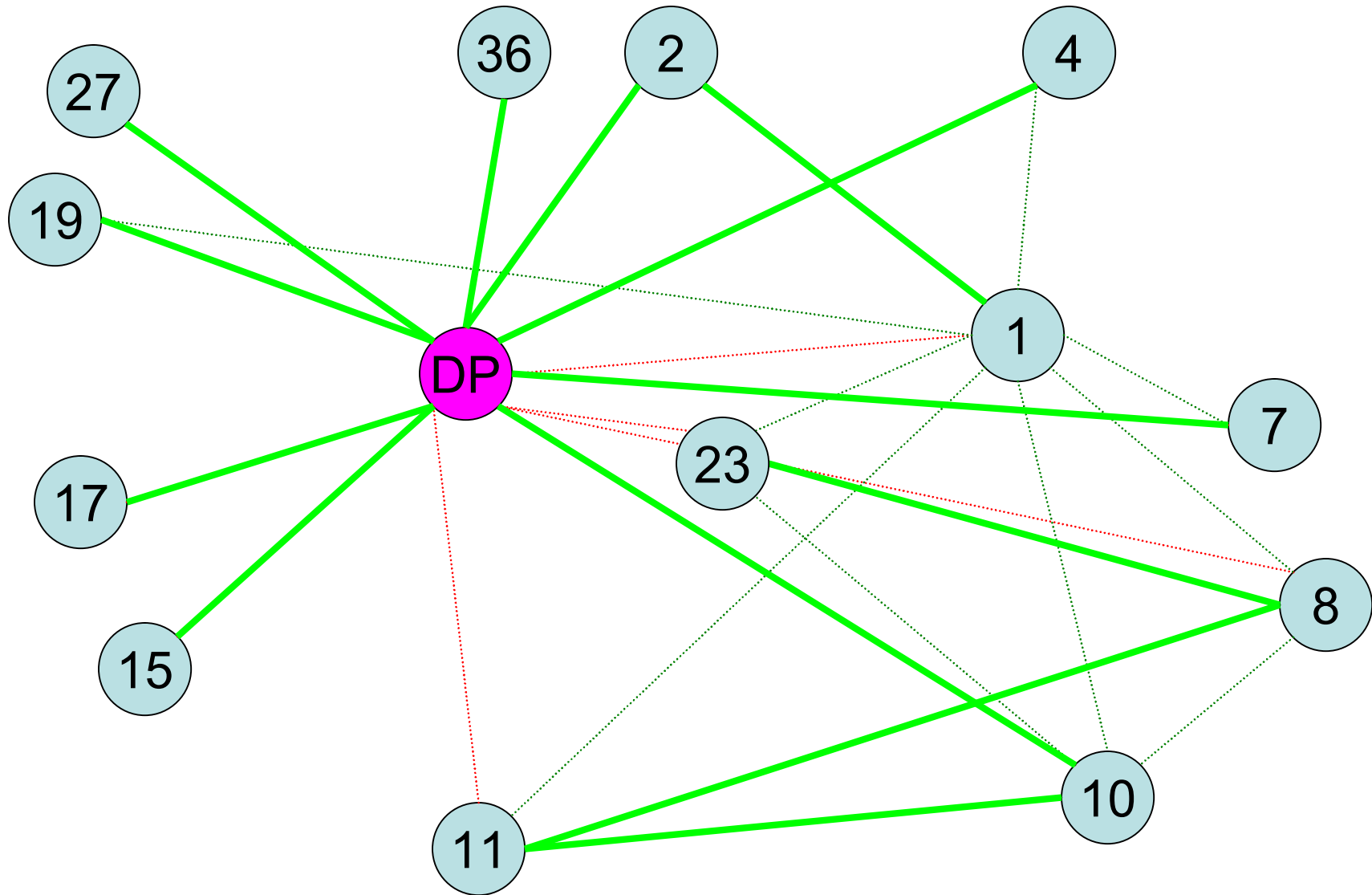




# Graph



# Kruskal's Algorithm -> MST



# Operations Generated for Each Entry in S

$$S = \begin{array}{|c|c|c|c|c|c|} \hline \begin{array}{l} -\frac{3}{4}S(1,2) \\ +3G(1,1) \\ +3G(2,1) \end{array} & \begin{array}{l} -4G(1,2) \\ -4G(2,2) \end{array} & -\frac{1}{4}S(1,2) & \begin{array}{l} -4G(1,1) \\ -4G(2,1) \end{array} & \mathbf{0} & -\frac{1}{4}S(1,4) \\ \hline \begin{array}{l} -4G(2,1) \\ -4G(2,2) \end{array} & \begin{array}{l} -S(2,5) \\ +8G(2,2) \end{array} & S(1,2) & \begin{array}{l} 4G(1,2) + \\ 4G(2,1) \end{array} & \begin{array}{l} -S(2,4) \\ -8G(1,1) \end{array} & \mathbf{0} \\ \hline -\frac{1}{4}S(2,1) & S(2,1) & 3G(2,2) & \mathbf{0} & 4G(2,1) & -\frac{1}{4}S(3,5) \\ \hline \begin{array}{l} -4G(1,1) \\ -4G(1,2) \end{array} & S(2,4) & \mathbf{0} & S(2,2) & \begin{array}{l} -S(2,2) \\ +8G(1,1) \end{array} & S(1,4) \\ \hline \mathbf{0} & S(2,5) & 4G(1,2) & S(4,5) & S(2,2) & S(3,5) \\ \hline -\frac{1}{4}S(4,1) & \mathbf{0} & -\frac{1}{4}S(5,3) & S(4,1) & S(5,3) & 3G(1,1) \\ \hline \end{array}$$

144 MAPs



29 MAPs

# Code Generation

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$S(1,2) = -4 * G(1,2) - 4 * G(2,2);$   
 $S(1,4) = -4 * G(1,1) - 4 * G(2,1);$   
 $S(2,1) = -4 * G(2,1) - 4 * G(2,2);$   
 $S(2,4) = 4 * G(1,2) + 4 * G(2,1);$   
 $S(3,3) = 3 * G(2,2);$   
 $S(3,5) = 4 * G(2,1);$   
 $S(4,1) = -4 * G(1,1) - 4 * G(1,2);$   
 $S(5,3) = 4 * G(1,2);$   
 $S(6,6) = 3 * G(1,1);$   
 $S(1,1) = -0.75 * S(1,2) + 3 * G(1,1) + 3 * G(2,1);$   
 $S(2,5) = -1 * S(2,4) - 8 * G(1,1);$   
 $S(2,2) = -1 * S(2,5) + 8 * G(2,2);$   
 $S(4,5) = -1 * S(2,2) + 8 * G(1,1);$   
 $S(1,3) = -0.25 * S(1,2);$   
 $S(1,6) = -0.25 * S(1,4);$

$S(3,1) = -0.25 * S(2,1);$   
 $S(3,6) = -0.25 * S(3,5);$   
 $S(6,1) = -0.25 * S(4,1);$   
 $S(6,3) = -0.25 * S(5,3);$   
 $S(2,3) = S(1,2);$   
 $S(3,2) = S(2,1);$   
 $S(4,2) = S(2,4);$   
 $S(4,4) = S(2,2);$   
 $S(4,6) = S(1,4);$   
 $S(5,2) = S(2,5);$   
 $S(5,4) = S(4,5);$   
 $S(5,5) = S(2,2);$   
 $S(5,6) = S(3,5);$   
 $S(6,4) = S(4,1);$   
 $S(6,5) = S(5,3);$

# Initial Results

Order	Entries	Base MAPs	Opt. MAPs
1	9	36	15(14)
2	36	144	29(28)
3	100	400	155
4	225	900	443
5	441	1764	814
6	784	3136	1387
7	1296	5184	2211

- Greatly reduced MAPs when building stiffness matrix
- Reduction for lower order FE simple
  - Many zeros in K
- Reduction for higher order FE more interesting
  - Fewer zeros in K
  - More complex algorithms necessary

# Limitation of Graph Model

3	3	0	-4	0	1	-4	0	0	0	1	0
3	3	0	-4	0	1	-4	0	0	0	1	0
0	0	8	4	0	-4	0	4	-8	-4	0	0
-4	-4	4	8	0	-4	4	0	-4	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
1	1	-4	-4	0	3	0	0	4	0	-1	0
-4	-4	0	4	0	0	8	4	0	-4	-4	0
0	0	4	0	0	0	4	8	-4	-8	-4	0
0	0	-8	-4	0	4	0	-4	8	4	0	0
0	0	-4	0	0	0	-4	-8	4	8	4	0
1	1	0	0	0	-1	-4	-4	0	4	3	0
0	0	0	0	0	0	0	0	0	0	0	0

$$S_{1,1} = 3S_{1,3} + 3S_{1,6}$$

2 MAPs

- Edges connect 2 vertices
- Can exploit only binary block relationships
- Need hypergraphs with hyperedges

# Linear Dependence Hyperedge Representation

$$S_1 = 3S_3 + 3S_6$$

B1

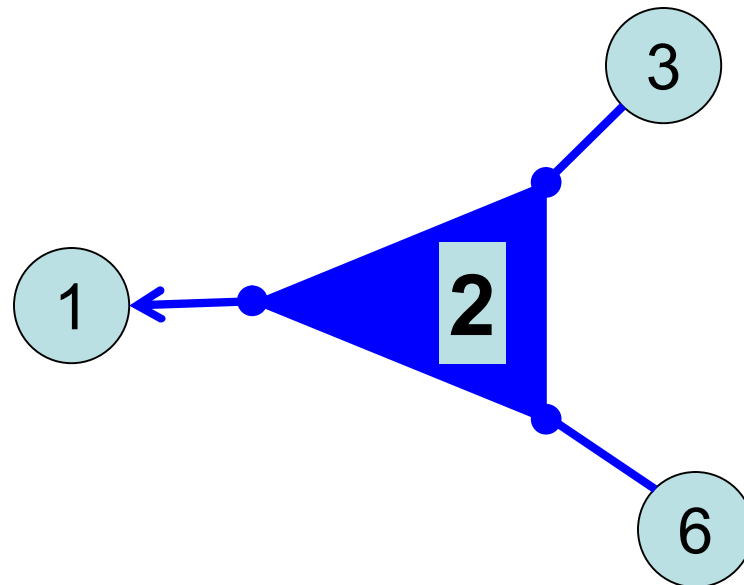
3	3
3	3

B3

0	1
0	1

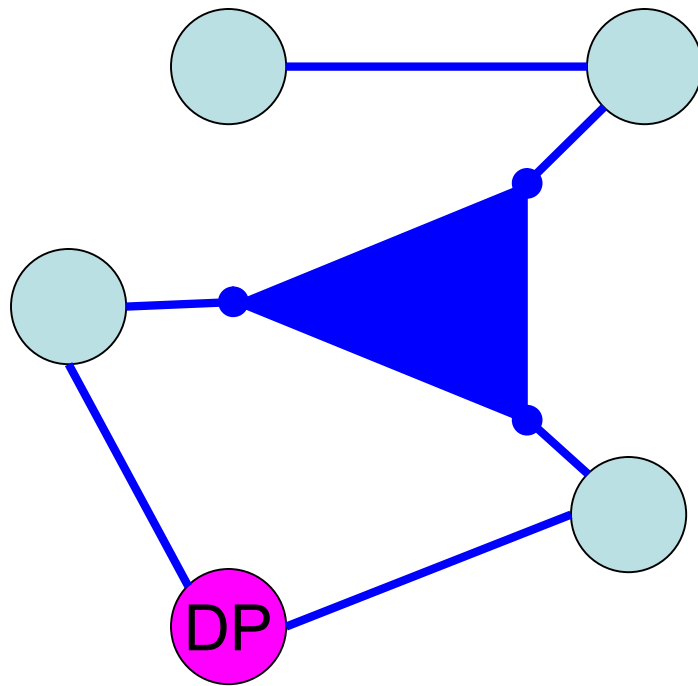
B6

1	0
1	0

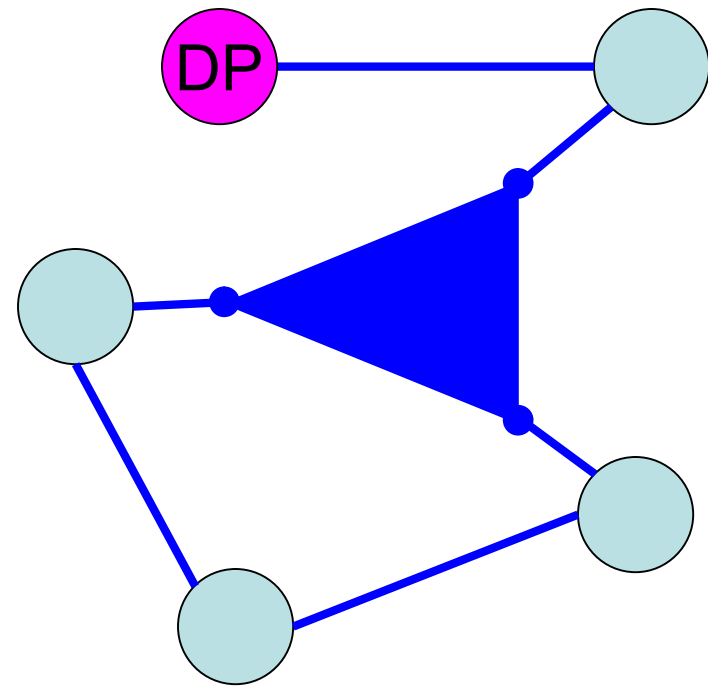


# Argument for Directed Hyperedge Representation

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Feasible



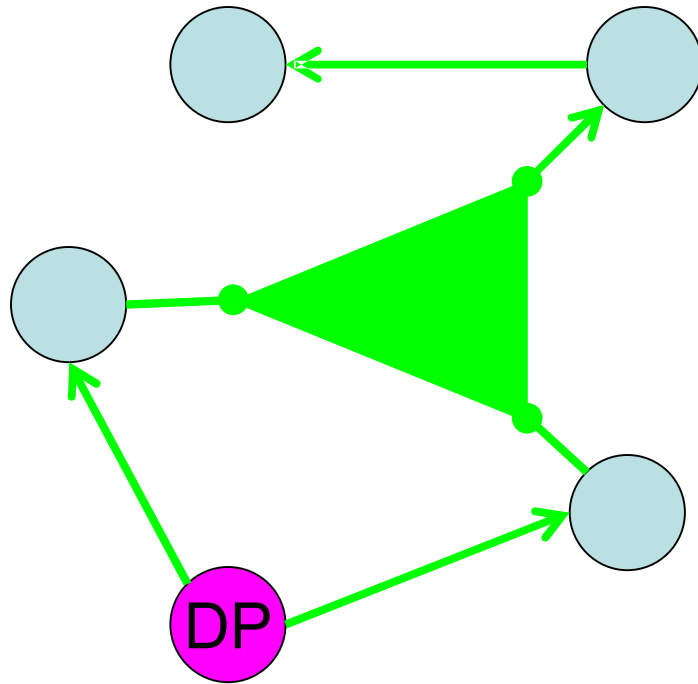
Infeasible

Undirected – almost the same graph

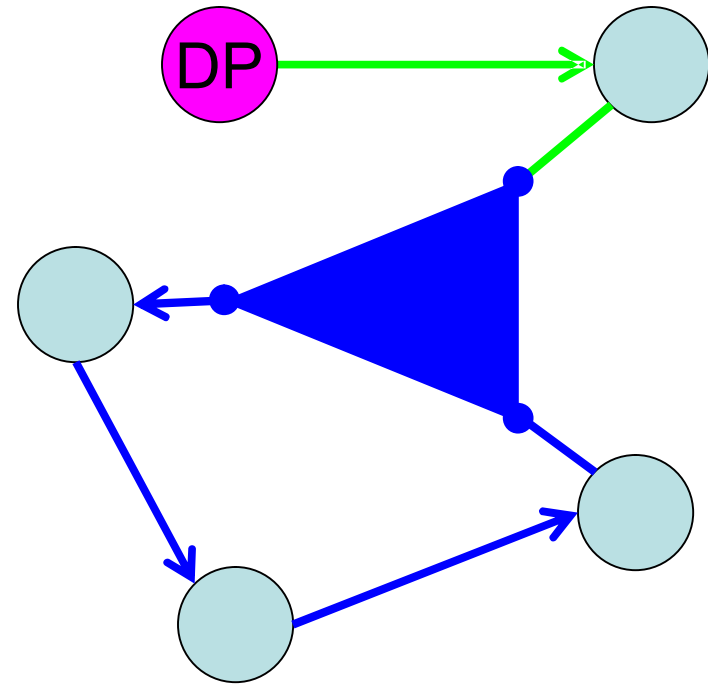


# Argument for Directed Hyperedge Representation

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Feasible

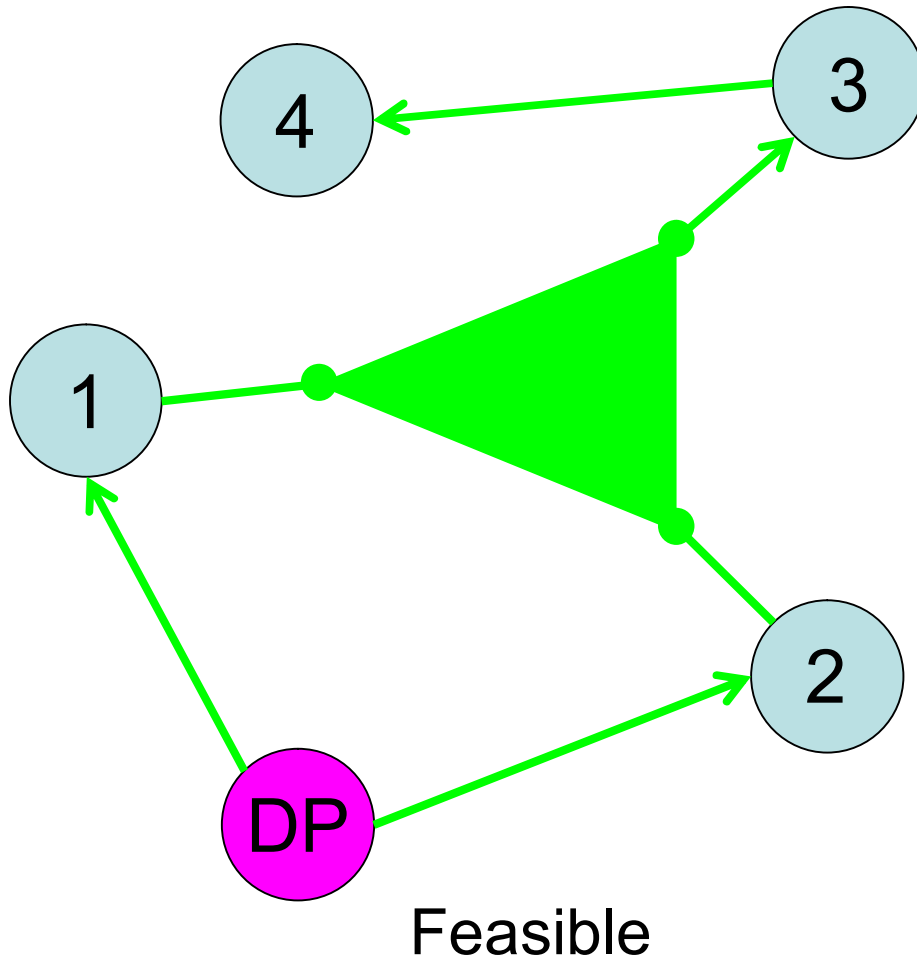


Infeasible

- Directed – clearly different graphs
- Disadvantage – more edges needed

# Directed Hypergraph Problem

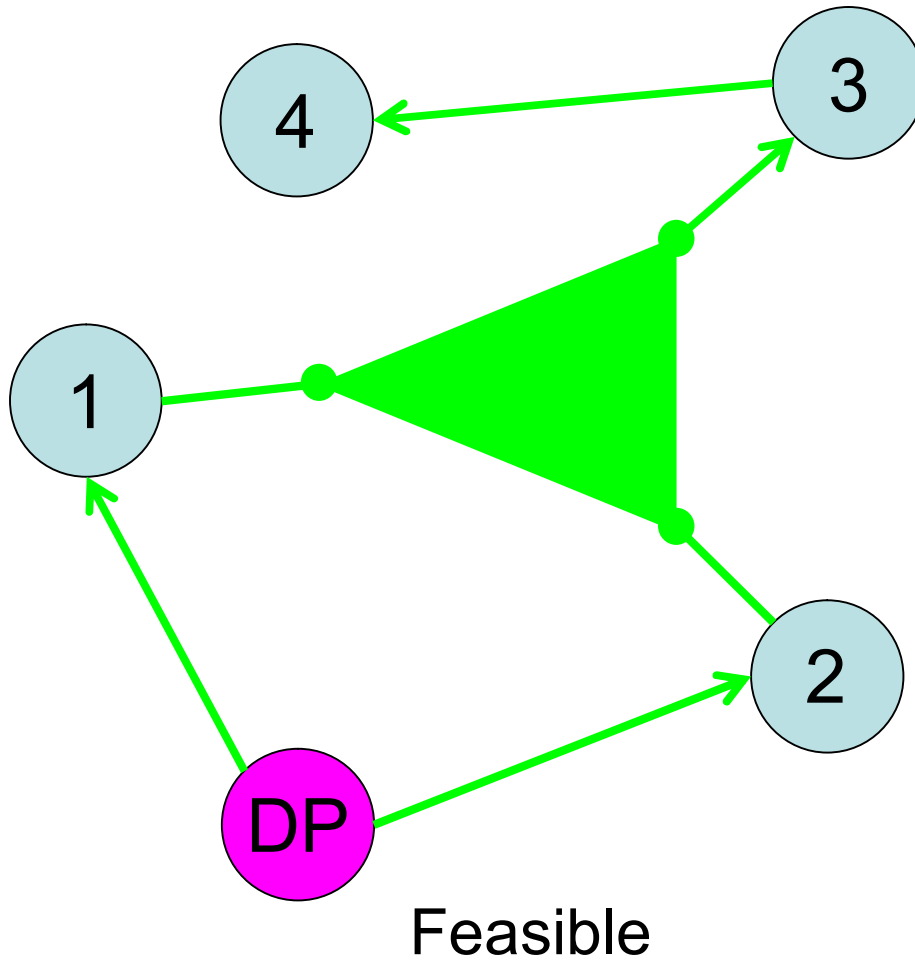
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- How do we characterize feasible solutions?
- Solution not necessarily MST

# Feasible Directed Hypergraph Solution

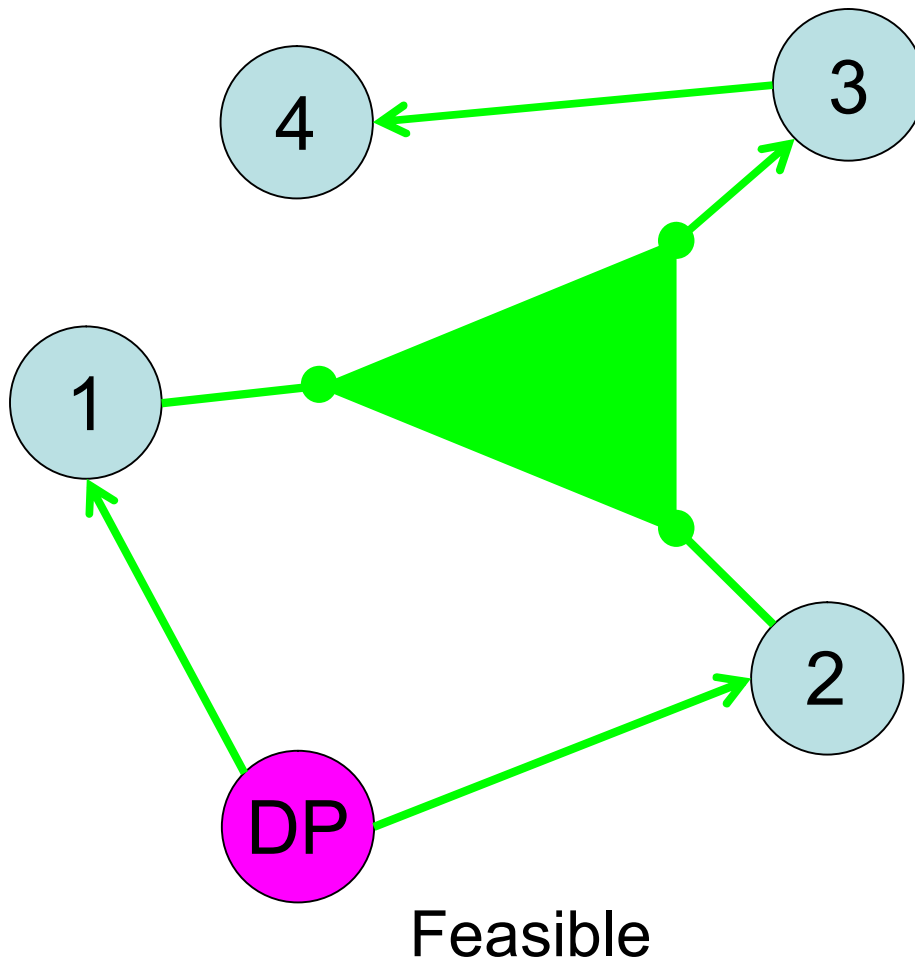
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Every vertex reachable  
via valid path from DP

# Feasible Directed Hypergraph Solution

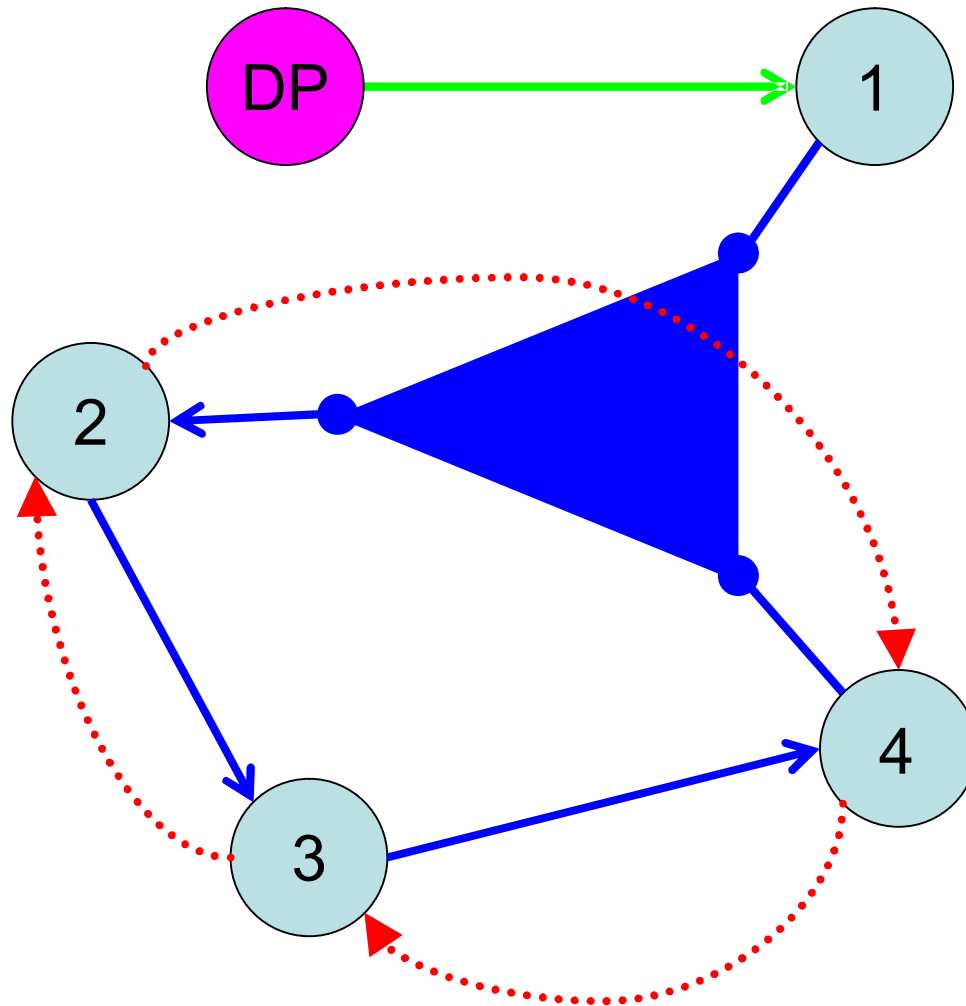
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- Graph Connected
- All vertices are sinks except for DP
- No dependency cycles

# Dependency Cycle

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# Combinatorial Optimization Problem

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$\min c^T x_e$  ← Objective function

$c$  ← Vector of edge costs

$x_e$  ← Vector of binary variables

- Mathematical formulation into combinatorial optimization problem
- Use IP software to solve this problem
- Optimal solution when IP problem solved exactly
- IP is NP-hard

# Notation

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$$X(F) := \sum_{e \in F} x_e$$

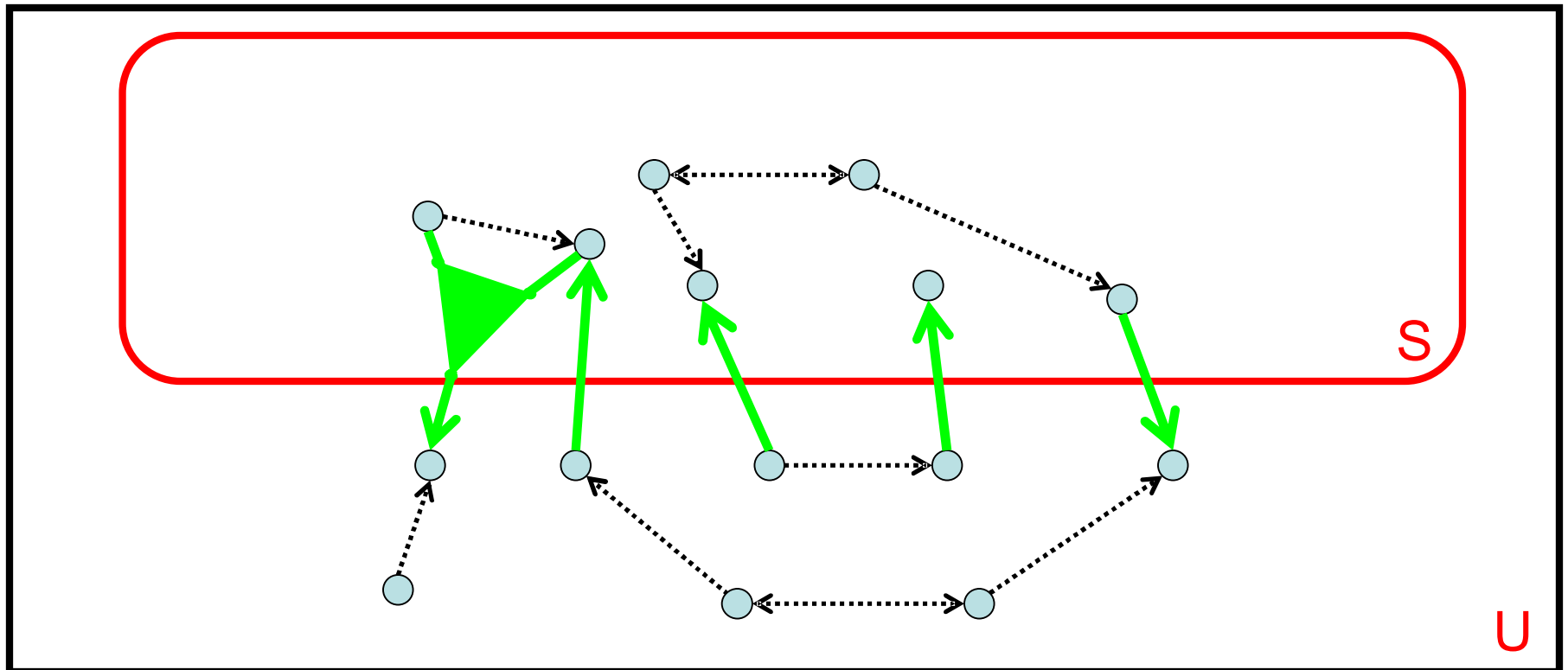
Set of edges



## Notation

$$\delta(\mathcal{S}) := \{e \in E : V_e \cap \mathcal{S} \neq \emptyset, \\ V_e \cap \bar{\mathcal{S}} \neq \emptyset\}$$

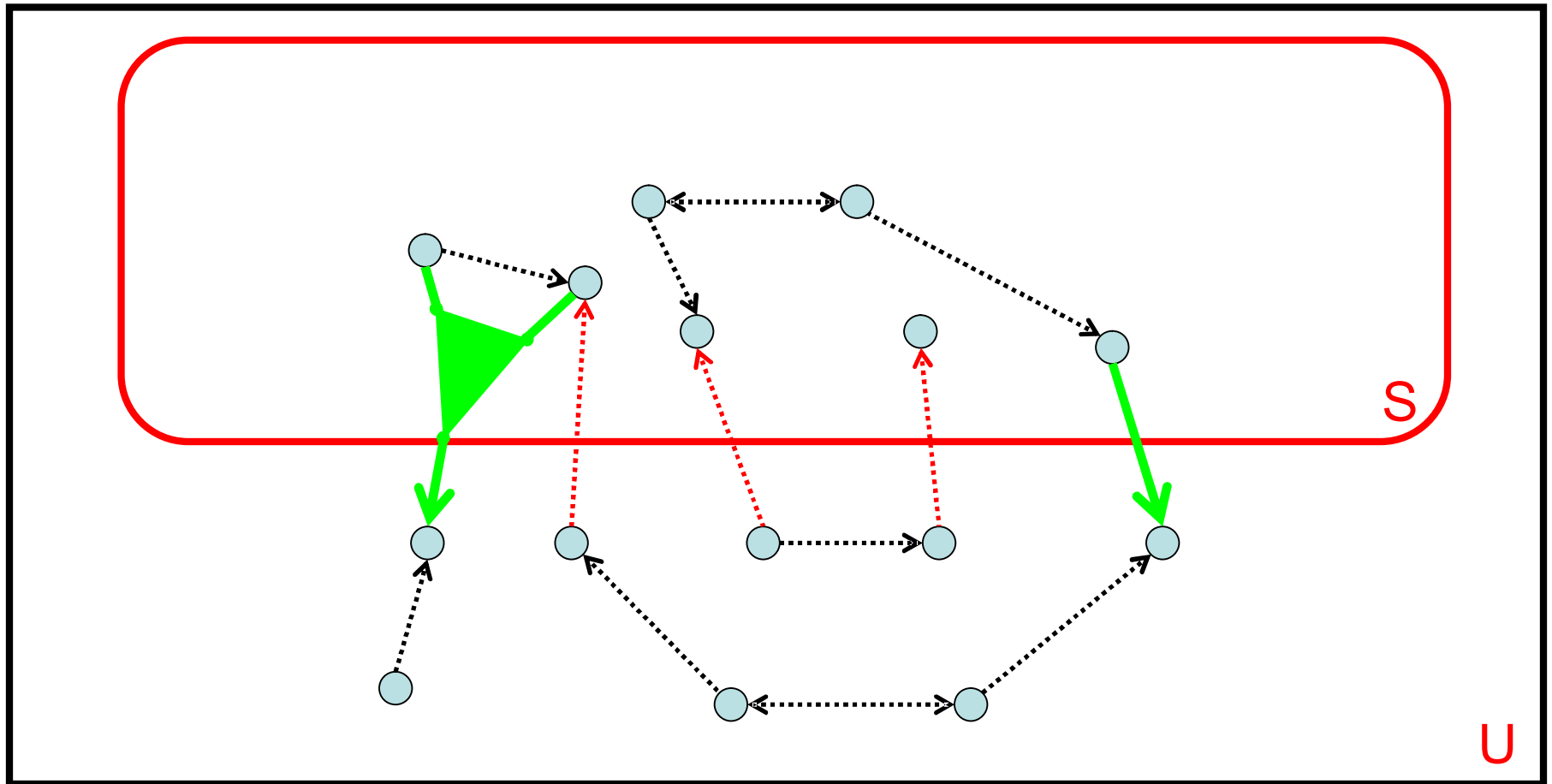
Set of vertices





# Notation

$$\delta^-(S) := \{e \in E : V_e \cap S \neq \emptyset, V_e \cap \bar{S} = \text{sink}(e)\}$$



# Combinatorial Optimization Problem

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$$\min c^T x_e$$

*s.t.*

$$\sum_{e:v=\text{sink}(e)} x_e = 1, \quad \forall v \neq v_{DP}$$

$$X(\delta^-(S)) \geq 1, \quad \forall S \subset V : v_{DP} \in S$$

# Combinatorial Optimization Problem

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$$\min c^T x_e$$

*s.t.*

All vertices sinks except for DP

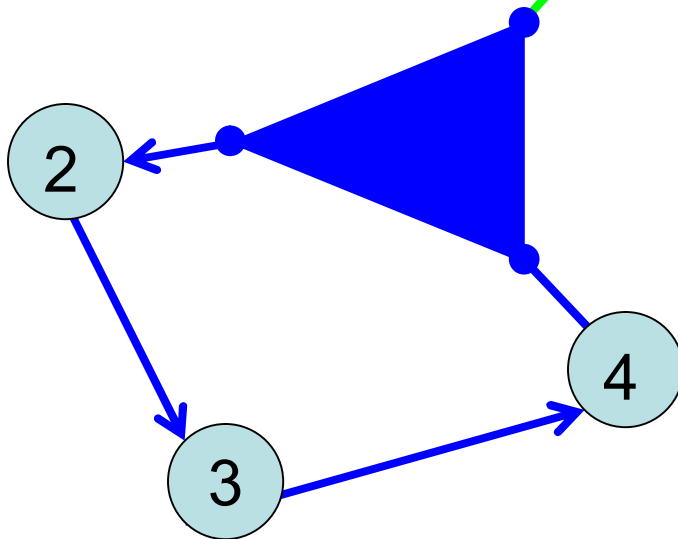
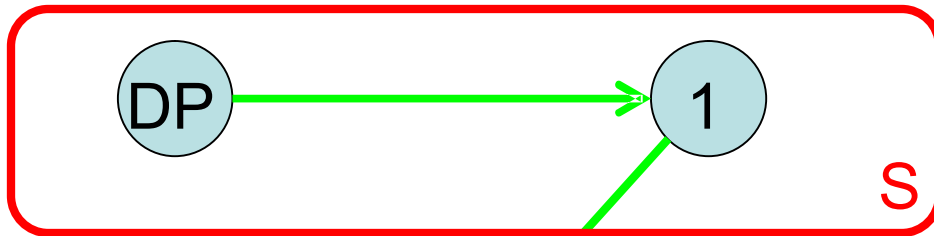
$$\sum_{e:v=\text{sink}(e)} x_e = 1, \quad \forall v \neq v_{DP}$$

$$X(\delta^-(S)) \geq 1, \quad \forall S \subset V : v_{DP} \in S$$

Connectivity, no dependency cycles

# Example 1: Applying 2<sup>nd</sup> Condition

$$X(\delta^-(S)) \geq 1, \forall S \subset V : v_{DP} \in S$$

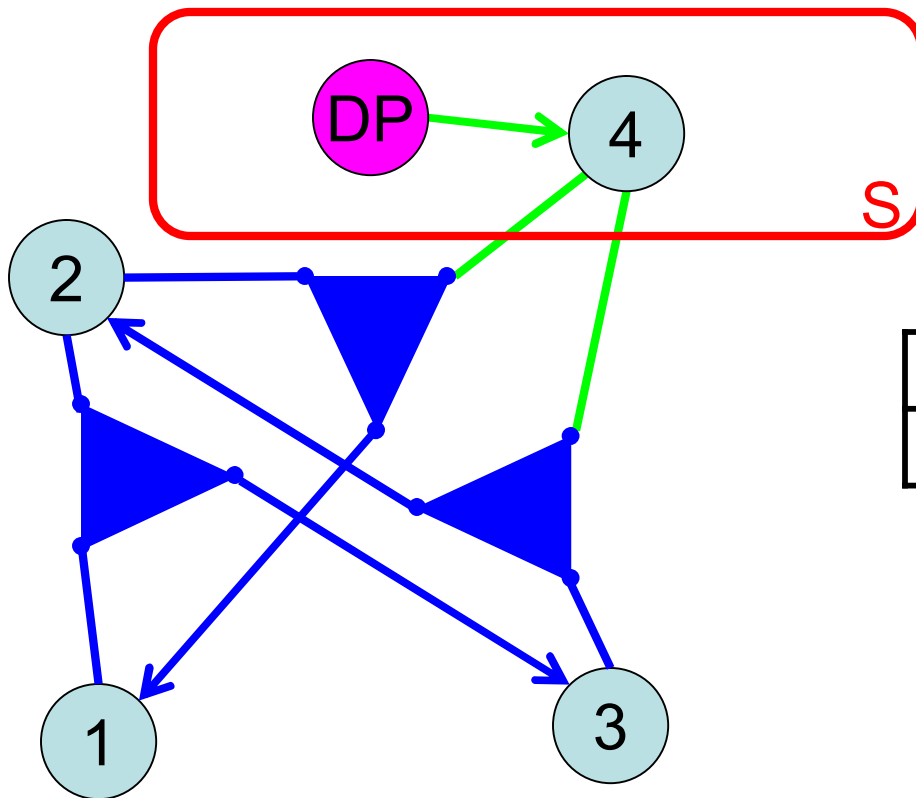


$S$	$e \in \delta^-(S) : x_e = 1$
$\{DP, 1\}$	<b>X</b>

Infeasible

## Example 2: Applying 2<sup>nd</sup> Condition

$$X(\delta^-(S)) \geq 1, \forall S \subset V : v_{DP} \in S$$

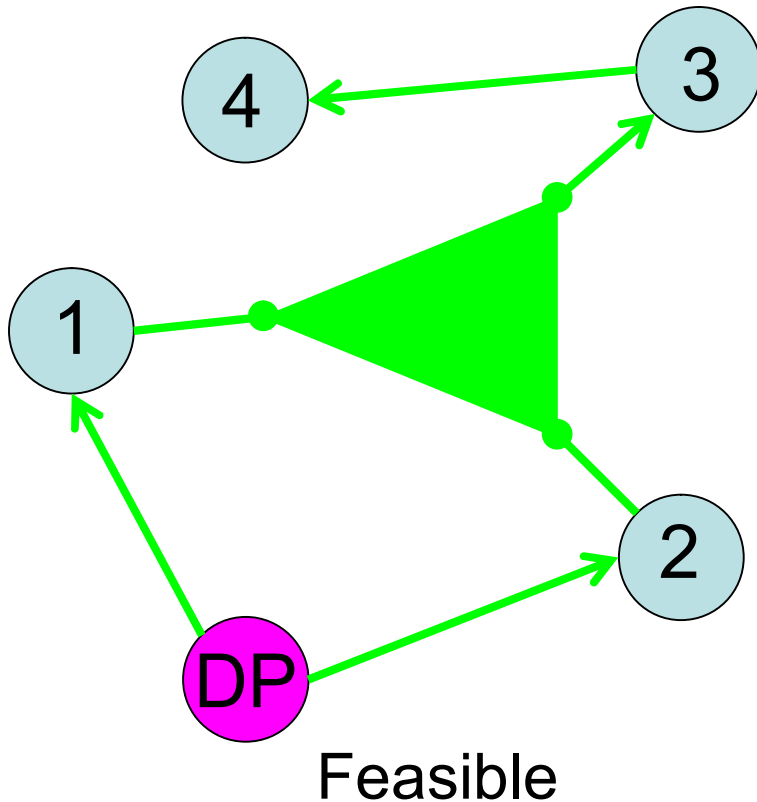


$S$	$e \in \delta^-(S) : x_e = 1$
$\{DP, 4\}$	<b>X</b>

Infeasible

## Example 3: Applying 2<sup>nd</sup> Condition

$$X(\delta^-(S)) \geq 1, \forall S \subset V : v_{DP} \in S$$



S	$e \in \delta^-(S) : x_e = 1$
{DP}	{DP, 1}
{DP, 1}	{DP, 2}
{DP, 2}	{DP, 1}
{DP, 3}	{DP, 1}
{DP, 4}	{DP, 1}
{DP, 1, 2}	{1, 2, 3}
{DP, 1, 3}	{DP, 2}
{DP, 1, 4}	{DP, 2}
{DP, 2, 3}	{DP, 1}
{DP, 2, 4}	{DP, 1}
{DP, 3, 4}	{DP, 1}
{DP, 1, 2, 3}	{3, 4}
{DP, 1, 2, 4}	{1, 2, 3}
{DP, 1, 3, 4}	{DP, 2}
{DP, 2, 3, 4}	{DP, 1}

# Acknowledgements

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Boman, Erik. Unpublished notes and correspondence. SNL. 2005.

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Kirby, R. C., Anders Logg, L. Ridgeway Scott, Andy R. Terrel (2005). "Topological optimization of the evaluation of finite element matrices." University of Chicago Technical Reports: 1-22.

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Professor Olson, et al. 2D Helmholtz code.