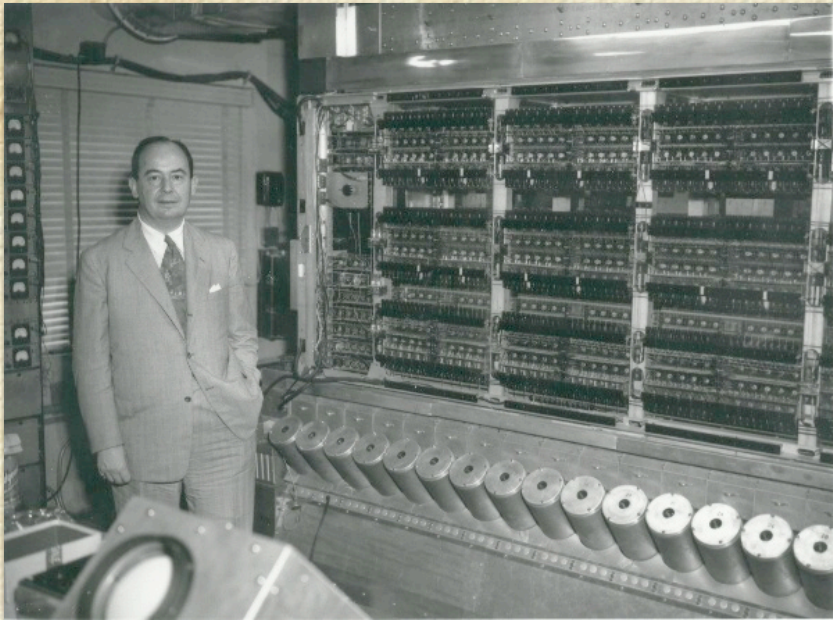


# Geometric optimization of the evaluation of finite element matrices

---

*Robert C. Kirby*  
*Texas Tech University*

# A new day dawns...



Numerical analysis

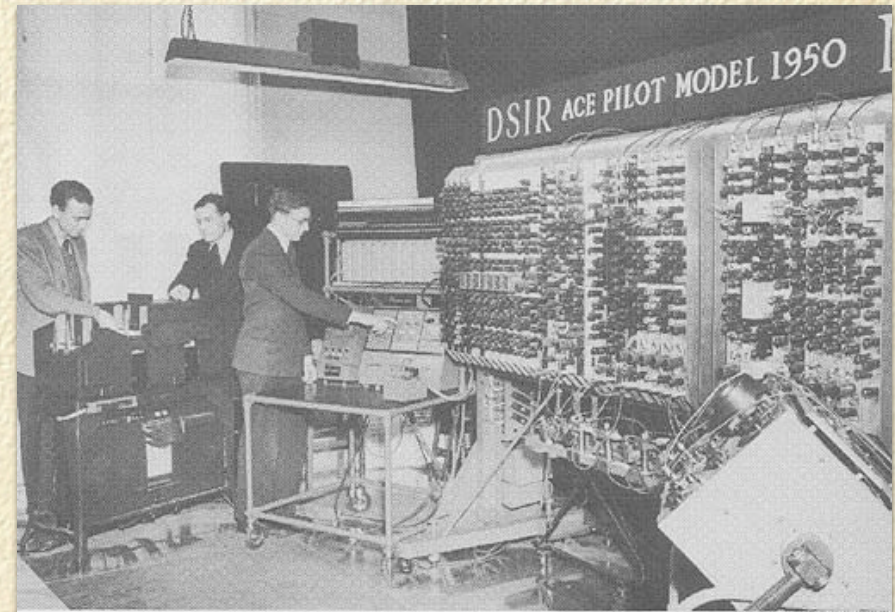
Theoretical CS

Computer engineering

KFLOPS

Cryptography

Turbulence



# Software makes it happen

- Canonical problems
- Parallel libraries
- Performance optimization
- PETSc, Trilinos, HYPRE
- SciDAC/TOPS (DOE)

$$Ax = b$$

$$Ax = \lambda Bx$$

$$F(x) = 0$$

$$f(\dot{x}, x, t, p) = 0$$

$$\min_u \phi(x, u) \text{ s.t.}$$

$$F(x, u) = 0$$

# It's a big gap...

---

Fusion

Biomechanics

Turbulence

etc...



Linear algebra

Newton

Multigrid

MPI

<http://palodurocanyon.com>

# The “Grant” Method

---

- ❑ Immense resources
- ❑ Victory at any cost
- ❑ Patient, decisive
- ❑ Never quit/let up



# I need an ARMY!

---

$$B_t = \nabla \times (u \times B)$$

$$u_t + u \cdot \nabla u - \mu \Delta u + \nabla p = (\nabla \times B) \times B$$

$$\nabla \cdot u = 0$$

$$\nabla \cdot B = 0$$

...and this is still a *model*!

# Too often...



Victory through superior cannon fodder

# Another way to see it

---



- Think like von Neumann, Turing...build a machine.
- ...and spin new mathematical opportunities



# Example: Laplacian

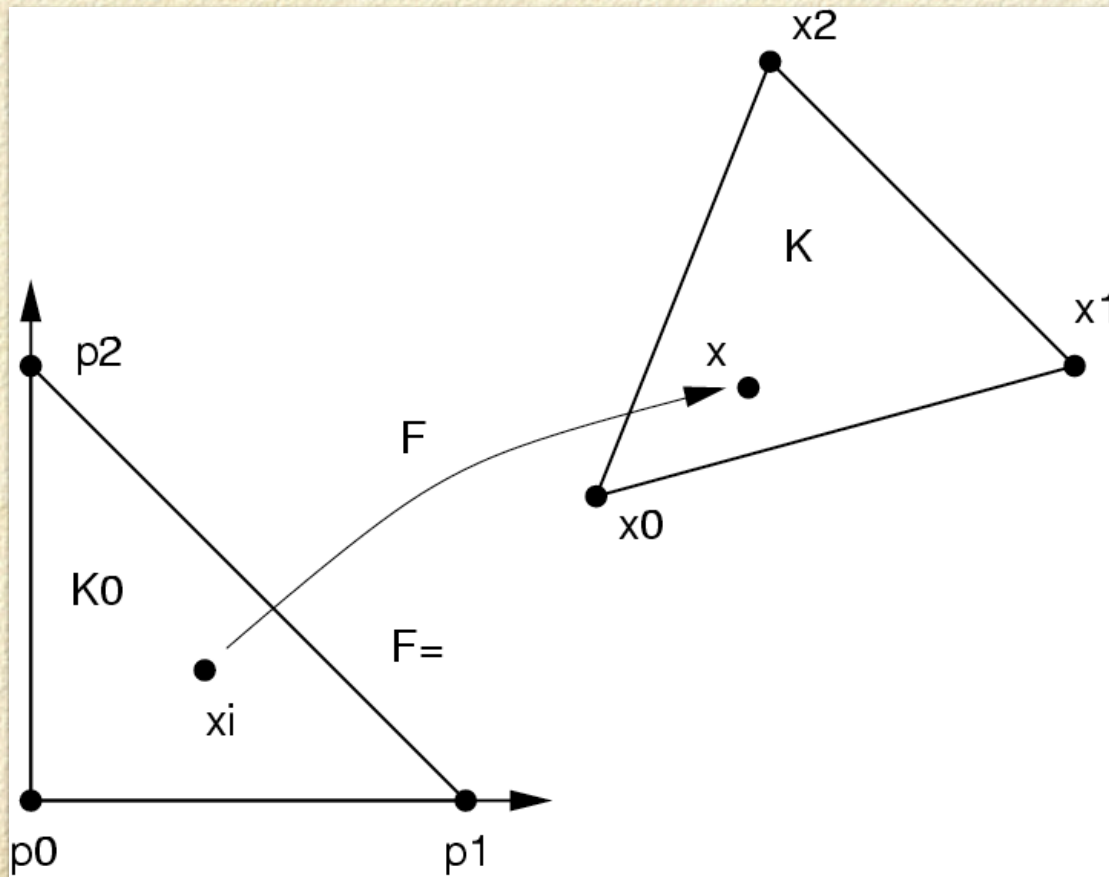
□ Weak form:

$$a(u, v) = \int_{\Omega} \nabla u \cdot \nabla v$$

□ Element matrix:

$$\begin{aligned} A_i^K &= \int_K \nabla \phi_{i_1} \cdot \nabla \phi_{i_2} dx \\ &= \sum_{d=1}^D \int_K D_x^d \phi_{i_1} D_x^d \phi_{i_2} dx \end{aligned}$$

# Element transformation



# Structure of computation

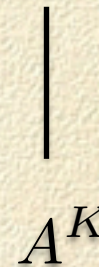
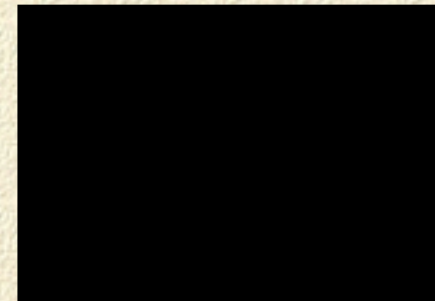
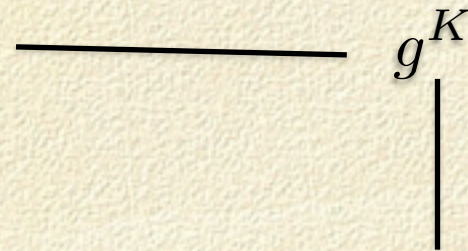
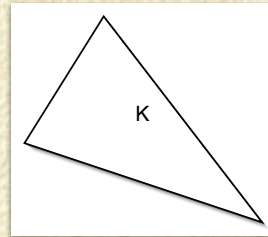
$$\begin{aligned} A_i^K &= \int_K \nabla \phi_{i_1}^{K,1}(x) \cdot \nabla \phi_{i_2}^{K,2}(x) dx \\ &= \det F'_K \sum_{\beta} \frac{\partial X_{\alpha_1}}{\partial x_{\beta}} \frac{\partial X_{\alpha_2}}{\partial x_{\beta}} \int_{K_0} \frac{\partial \Phi_{i_1}^1(X)}{\partial X_{\alpha_1}} \frac{\partial \Phi_{i_2}^2(X)}{\partial X_{\alpha_2}} dX \\ &= \sum_{\alpha} A_{i\alpha}^0 G_K^{\alpha} \end{aligned}$$

Matvec

- Reference element/geometry separated
- Contraction happens on each triangle
- Local matrix inserted into global matrix

# Abstract Problem

---



□  $V \subset \mathbb{R}^d$  fixed

□  $g \in \mathbb{R}^d$  arbitrary

□ Compute  $\{v^t g : v \in V\}$

# A for Poisson (k=2,d=2)

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

# Canonical Form

---

$$A_i^K = \sum_{\gamma \in \mathcal{C}} \int_K \prod_{j=1}^m c_j(i, \gamma) D_x^{\delta_j(i, \gamma)} \phi_{\nu_j(i, \gamma)}^{K, j} [\kappa_j(i, \gamma)] dx$$

$c_j(i, \gamma)$	coefficient
$\nu_j(i, \gamma)$	basis function
$\kappa_j(i, \gamma)$	vector component
$\delta_j(i, \gamma)$	derivative multiindex

# Example

---

$$a(v, u) = \sum_{\gamma_1=1}^d \sum_{\gamma_2=1}^d \int_{\Omega} w \frac{\partial v[\gamma_1]}{\partial x_{\gamma_2}} \frac{\partial u[\gamma_1]}{\partial x_{\gamma_2}} dx$$

$$A_i^K = \sum_{\gamma_1=1}^d \sum_{\gamma_2=1}^d \sum_{\gamma_3=1}^{|V_3^K|} \int_{\Omega} \frac{\partial \phi_{i_1}^{K,1}[\gamma_1]}{\partial x_{\gamma_2}} \frac{\partial \phi_{i_2}^{K,2}[\gamma_1]}{\partial x_{\gamma_2}} w_{\gamma_3} \phi_{\gamma_3}^{K,3} dx,$$

$r$	2
$m$	3
$\iota(i, \gamma)$	$(i_1, i_2, \gamma_3)$
$\delta(i, \gamma)$	$(\gamma_2, \gamma_2, \emptyset)$
$\kappa(i, \gamma)$	$(\gamma_1, \gamma_2, \emptyset)$
$c_j(i, \gamma)$	$(1, 1, w_{\gamma_3})$

# Representation Theorem

$$A_i^K = \sum_{\alpha \in \mathcal{A}} A_{i\alpha}^0 G_K^\alpha \quad \forall i \in \mathcal{I}$$

$$A_{i\alpha}^0 = \sum_{\beta \in \mathcal{B}} \int_{K_0} \prod_{j=1}^m D_X^{\delta'_j(i,\alpha,\beta)} \Phi_{\iota_j(i,\alpha,\beta)}^{K_0,j} [\kappa_j(i,\alpha,\beta)] dX$$

$$G_K^\alpha = \sum_{\beta \in \mathcal{B}'} \det F'_K \prod_{j=1}^m c_j(i,\alpha,\beta) \prod_{j'=1}^m \prod_{k=1}^{|\delta_{j'}(i,\alpha,\beta)|} \frac{\partial X_{\delta'_{j'k}(i,\alpha,\beta)}}{\partial x_{\delta_{j'k}(i,\alpha,\beta)}}$$

Basis for FFC[KL]



# Optimizing evaluation

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

# Optimizing evaluation

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

Zero

# Optimizing evaluation

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

# Optimizing evaluation

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

Sparse

# Optimizing evaluation

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

# Optimizing evaluation

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

Equal

# Optimizing evaluation

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

# Optimizing evaluation

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

Colinear



# Optimizing evaluation

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

# Optimizing evaluation

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

Linear Combination

# Optimizing evaluation

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

# Optimizing evaluation

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

Edit Distance

# Optimizing evaluation

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

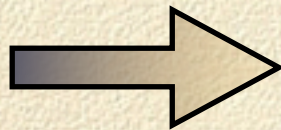
# Topology and flop count

Hamming distance	$H^+(u, v) =  \{i : u_i \neq v_i\} $
Negated Hamming distance	$H^-(u, v) =  \{i : u_i \neq -v_i\} $
Colinearity	$u = \alpha v \rightarrow c(u, v) = 1$

# Topology and flop count

Hamming distance	$H^+(u, v) =  \{i : u_i \neq v_i\} $
Negated Hamming distance	$H^-(u, v) =  \{i : u_i \neq -v_i\} $
Colinearity	$u = \alpha v \rightarrow c(u, v) = 1$

$$\rho(u, v) = k$$

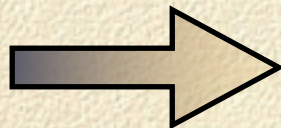


$$u^t g = f(v^t g) \quad (k \text{ MAPs})$$

# Topology and flop count

Hamming distance	$H^+(u, v) =  \{i : u_i \neq v_i\} $
Negated Hamming distance	$H^-(u, v) =  \{i : u_i \neq -v_i\} $
Colinearity	$u = \alpha v \rightarrow c(u, v) = 1$

$$\rho(u, v) = k$$



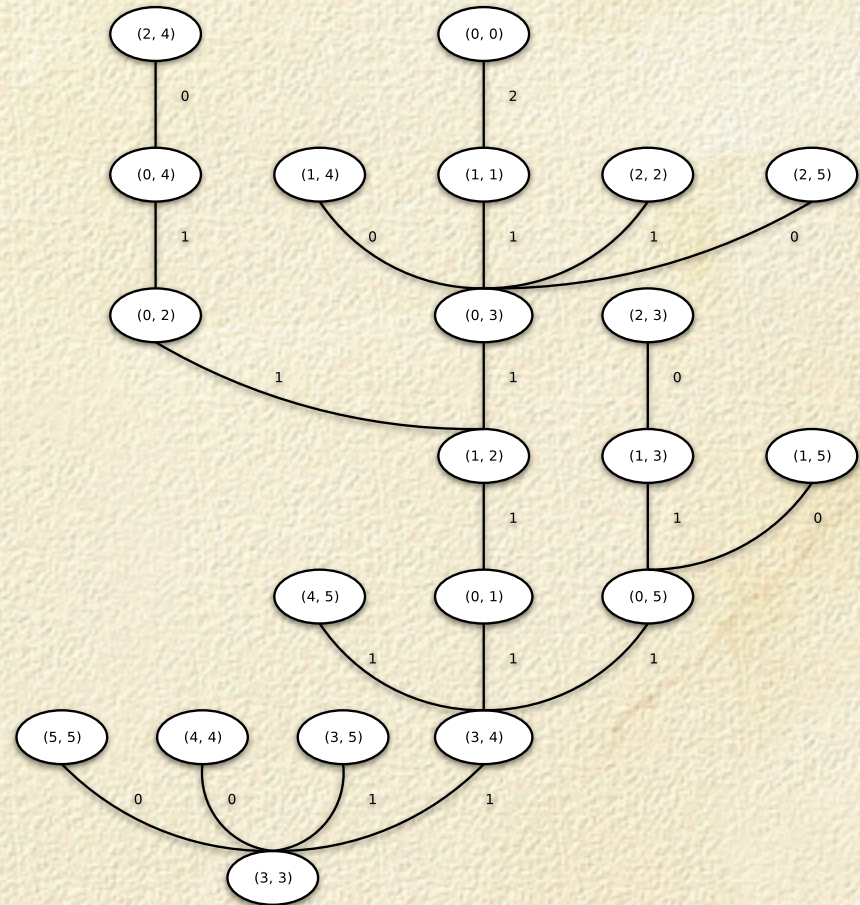
“Complexity-reducing relations”

$$u^t g = f(v^t g) \quad (k \text{ MAPs})$$



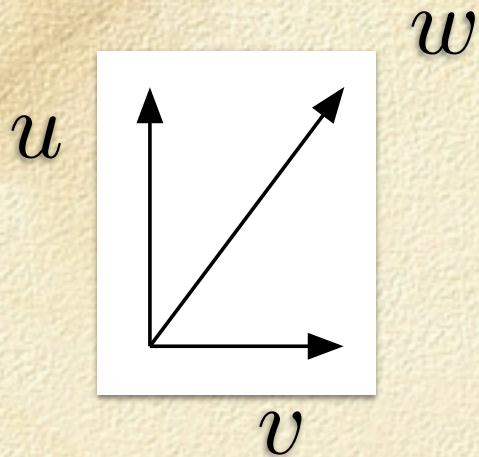
# “Optimal” algorithm

- Do a dot product
- Dot product of vector “nearest” to finished vectors
- Repeat till done
- Prim’s algorithm



Thm: Minimum spanning tree encodes optimal algorithm

# Geometric relations



$$w = \alpha u + \beta v$$



$$w^t g = \alpha(u^t g) + \beta(v^t g) \Rightarrow 2 \text{ MAPs}$$

❑ NOT a graph/  
metric space!

❑ Low-dimensional  
matters most

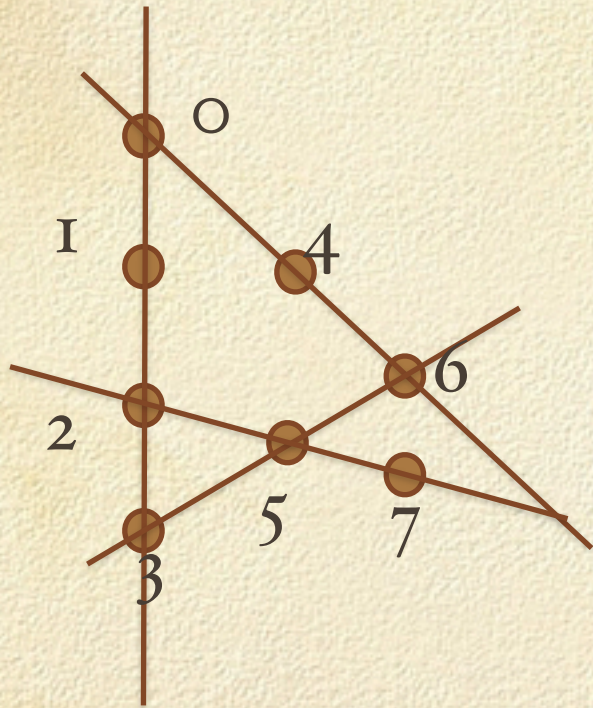
❑ Detection?

# Detection Algorithm

---

- $\mathcal{O}(d^2 N^3)$  via Gaussian elimination
- Better: Project all vectors into  $\mathbb{R}^3$ 
  - Form all pairs of projected vectors
  - Search for colinearity among normal to planes (necessary for coplanarity)
  - Runtime:  $\mathcal{O}(N^{2+\epsilon})$

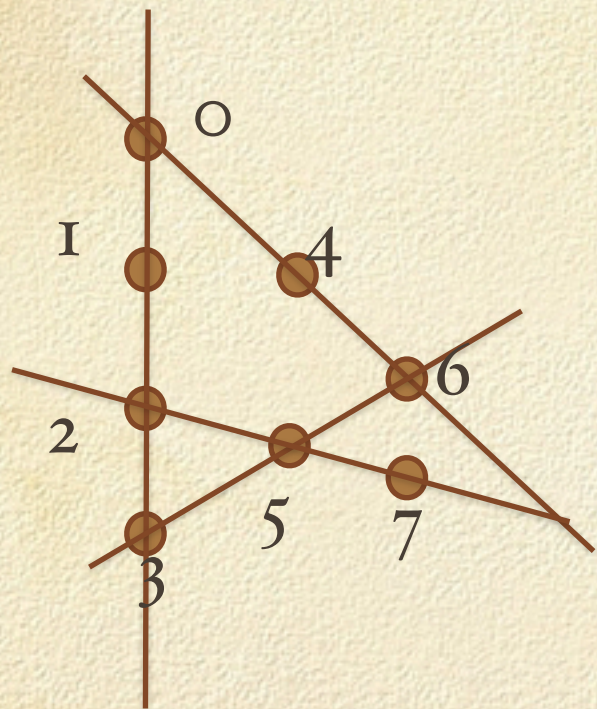
# Finite Linear Space



- Based on incidence between “points” and “lines”
- “Points”: vectors
- “Lines”: planes
- Cf. finite geometry

# Closure

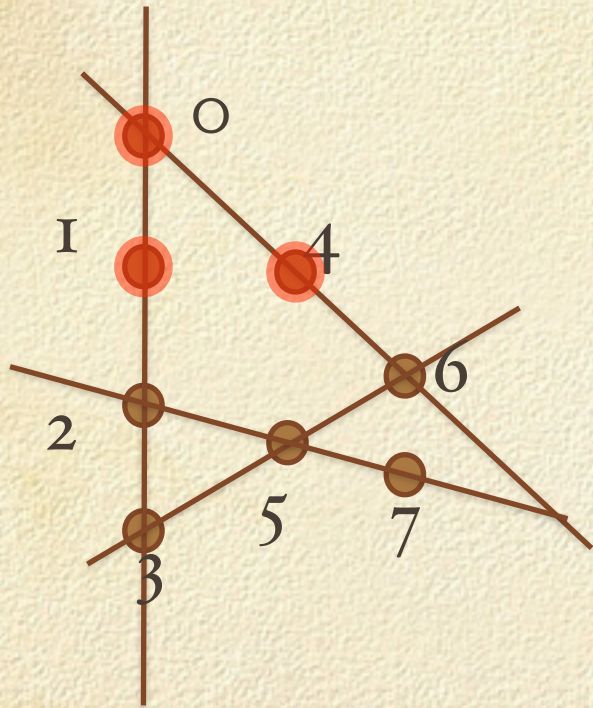
---



$$v \in S \rightarrow v \in \bar{S}$$

$$R(a, b, c) : a, b \in \bar{S} \rightarrow c \in \bar{S}$$

# Generator



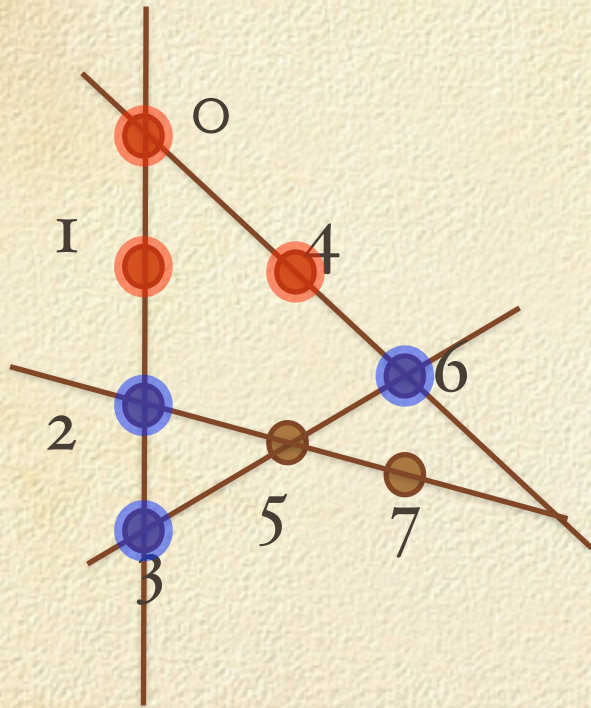
■ e.g.  $\{0,1,4\}$

■ Only do explicit dot products for generator

■ cf. Dijkstra/Prim on “line graph”

# Generator

---

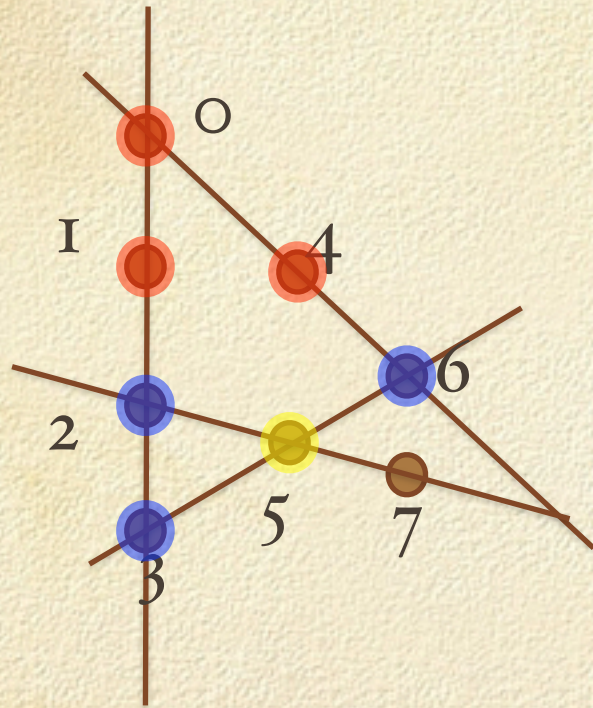


□ e.g. {0,1,4}

□ Only do explicit dot products for generator

□ cf. Dijkstra/Prim on “line graph”

# Generator



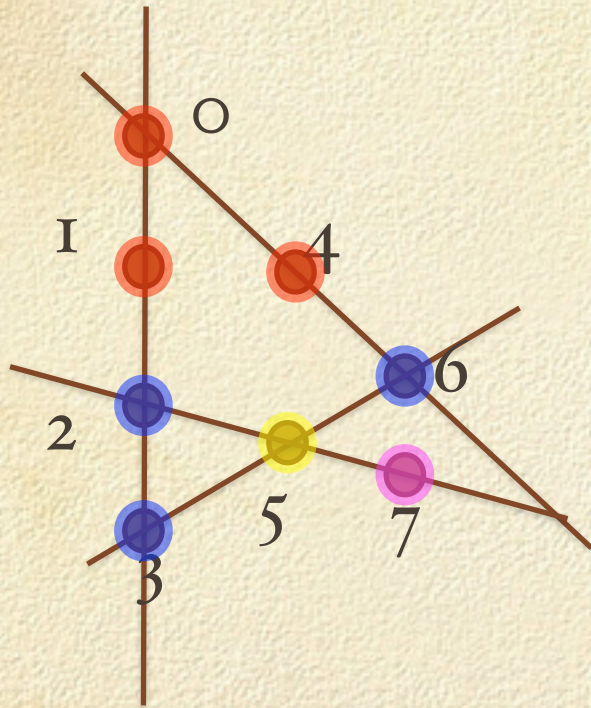
□ e.g.  $\{0,1,4\}$

□ Only do explicit dot products for generator

□ cf. Dijkstra/Prim on “line graph”



# Generator



□ e.g.  $\{0,1,4\}$

□ Only do explicit dot products for generator

□ cf. Dijkstra/Prim on “line graph”

# FLOP reduction

k	n	nz	ne	nc	nr	MAPs
2	55	0	6	0	6	97
3	210	0	42	22	7	329
4	630	0	150	48	67	1117

Effective

Increased  
compile-time  
expense

Combined?

Beats CRR!

# Combinatorial optimization problem

---

$\{v_i\}_{i=1}^{|V|}$  ordering of vectors

$$w_R(v_i) = \begin{cases} 2, & \exists j, k < i : R(\{v_i, v_j, v_k\}) \\ m, & \textit{otherwise} \end{cases}$$

$$w_\rho(v_i) = \min_{j < i} \rho(v_i, v_j)$$

$$w(v_i) = \min(w_{R,i}, w_{\rho,i})$$

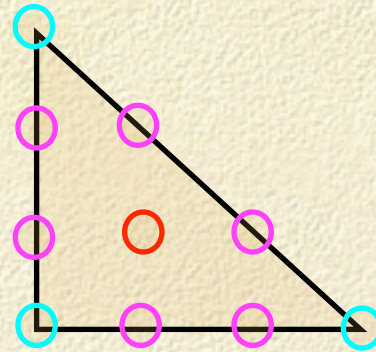
$$\min_{\mathcal{V}} \sum_{i=1}^{|V|} w(v_i)$$

# On the horizon for form evaluation

---

$$A = \prod A_i$$

sparse?



barycentric groups?

$$u \mapsto \nabla u|_{\xi}$$

fast evaluation?

■ Algebraic theory?  
(Püschel for signal processing)

■ Automate spectral elements?