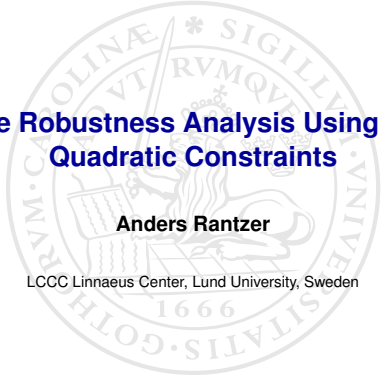


# Scalable Robustness Analysis Using Integral Quadratic Constraints

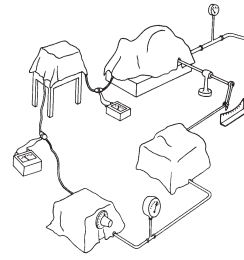
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## A Challenge

### To Verify Performance of Complex Systems



- Complexity:** Total model need not fit memory
- Confidentiality:** Component suppliers do not reveal details
- Transparency:** Interpretations. Design rules.

## Outline

- **Positive Definite Decomposition**
  - Scalable IQC analysis
  - Positive and Monotone Systems
  - Concluding remarks

## Positive Definite Decomposition

The sparse matrix on the left is positive semi-definite if and only if it can be written as a sum of positive semi-definite matrices with the structure on the right.

$$\begin{pmatrix} \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & & & 0 \\ & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & & \\ & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & \\ & & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & \\ 0 & & & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} \end{pmatrix} = \begin{pmatrix} \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & & & 0 \\ & 0 & & & \\ & & 0 & & \\ & & & 0 & \\ & & & & 0 \end{pmatrix} + \begin{pmatrix} & & & & \\ & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & & \\ & & & & \\ & & & & \\ & & & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} \end{pmatrix} + \dots + \begin{pmatrix} & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} \end{pmatrix}$$

## Proof idea

The decomposition follows immediately from the band structure of the Cholesky factors:

$$\begin{pmatrix} \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & & & 0 \\ & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & & \\ & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & \\ & & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & \\ 0 & & & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} \end{pmatrix} = \begin{pmatrix} \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & & & \\ & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & & \\ & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & & \\ & & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} & \\ & & & & \boxed{\begin{matrix} x & x & x \\ x & x & x \\ x & x & x \end{matrix}} \end{pmatrix}$$

[Martin and Wilkinson, 1965]

## Example: Vehicle formation

The first vehicle is controlled to maintain a constant speed:

$$x_1 = G_1 C_1 x_1 + w_1$$

Every other vehicle controls the distance to preceding vehicle:

$$x_k = G_k C_k (x_{k-1} - x_k) + w_k \quad k = 1, \dots, N$$

Is it true that  $|x| \leq \gamma |w|$  for all  $w$ ?

(Other requirements can be handled similarly.)

## Example: Vehicle formation

$$w = \begin{bmatrix} 1 + G_1 C_1 & & & & 0 \\ -G_2 C_2 & \ddots & & & \\ & \ddots & \ddots & & \\ 0 & & \underbrace{-G_N C_N \quad 1 + G_N C_N}_{M(s)} & & \end{bmatrix} x$$

Hence  $|x| \leq \gamma |w|$  if and only if  $(1 + G_k C_k)^{-1}$  stable for all  $k$  and

$$M(i\omega)^* M(i\omega) - \gamma^{-2} = \begin{bmatrix} * & * & & & \\ * & * & * & & \\ & * & * & \ddots & \\ & & \ddots & * & * \\ & & & * & * \end{bmatrix}$$

is positive semi-definite for all  $\omega$ .

## Example: Vehicle formation

The vehicle formation satisfies  $|x| \leq \gamma |w|$  for all  $w$  if and only if there exist  $K_1, \dots, K_N$  with  $K_N = 0$ ,  $K_1 = |1 + G_1 C_1|^2$  such that

$$\begin{bmatrix} |G_k C_k|^2 + K_{k-1} - \gamma^{-2} & C_k^* G_k^* (1 + G_k C_k) \\ (1 + G_k C_k)^* G_k C_k & |1 + G_k C_k|^2 - K_k - \gamma^{-2} \end{bmatrix} \geq 0$$

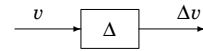
for  $k = 2, \dots, N$ .

- **Complexity:** Separate test for each vehicle  $2, \dots, N$ .
- **Confidentiality:** Distributed search for  $K_2, \dots, K_{N-1}$ .
- **Transparency:** Use  $H_\infty$  optimization to improve  $C_k$ .
- If  $C_k, G_k$  transfer functions, then  $K_k$  frequency dependent.
- Simplify  $K_k$  by model reduction.

## Outline

- Positive Definite Decomposition
- **Scalable IQC analysis**
- Positive and Monotone Systems
- Concluding remarks

## Integral Quadratic Constraint



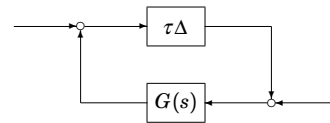
The (possibly nonlinear) operator  $\Delta$  on  $\mathbf{L}_2^m[0, \infty)$  is said to satisfy the IQC defined by  $\Pi$  if

$$\int_{-\infty}^{\infty} \begin{bmatrix} \widehat{v}(i\omega) \\ (\Delta v)(i\omega) \end{bmatrix}^* \Pi(i\omega) \begin{bmatrix} \widehat{v}(i\omega) \\ (\Delta v)(i\omega) \end{bmatrix} d\omega \geq 0$$

for all  $v \in \mathbf{L}_2[0, \infty)$ .

$\Delta$ structure	$\Pi(i\omega)$	Condition
$\Delta$ passive	$\begin{bmatrix} 0 & I \\ I & 0 \end{bmatrix}$	
$\ \Delta(i\omega)\  \leq 1$	$\begin{bmatrix} x(i\omega)I & 0 \\ 0 & -x(i\omega)I \end{bmatrix}$	$x(i\omega) \geq 0$
$\delta \in [-1, 1]$	$\begin{bmatrix} X(i\omega) & Y(i\omega) \\ Y(i\omega)^* & -X(i\omega) \end{bmatrix}$	$X = X^* \geq 0$ $Y = -Y^*$
$\delta(t) \in [-1, 1]$	$\begin{bmatrix} X & Y \\ Y^T & -X \end{bmatrix}$	
$\Delta(s) = e^{-\theta s} - 1$	$\begin{bmatrix} x(i\omega)\rho(\omega)^2 & 0 \\ 0 & -x(i\omega) \end{bmatrix}$	$\rho(\omega) = 2 \max_{ \theta  \leq \theta_0} \sin(\theta\omega/2)$

## IQC Stability Theorem



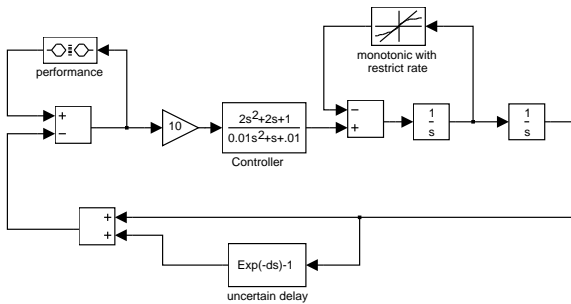
Let  $G(s)$  be stable and proper and let  $\Delta$  be causal.

For all  $\tau \in [0, 1]$ , suppose the loop is well posed and  $\tau\Delta$  satisfies the IQC defined by  $\Pi(i\omega)$ . If

$$\begin{bmatrix} G(i\omega) \\ I \end{bmatrix}^* \Pi(i\omega) \begin{bmatrix} G(i\omega) \\ I \end{bmatrix} < 0 \quad \text{for } \omega \in [0, \infty)$$

then the feedback system is input/output stable.

## The IQC toolbox



```
>> iqc_gui('fricSYSTEM')
```

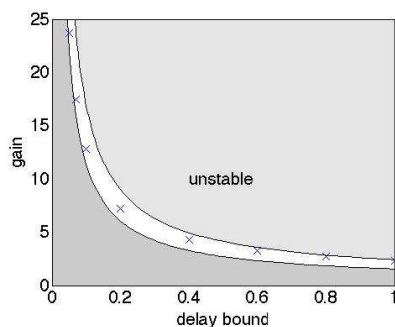
extracting information from fricSYSTEM ...

```
scalar inputs: 5
states: 10
simple q-forms: 7
```

Solving with 62 decision variables ...

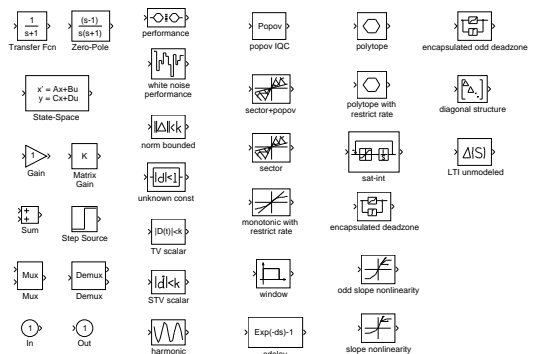
```
ans = 4.7139
```

## Verification by IQCs



IQCs prove stability below the lower line.

## A library of analysis objects



## S-procedure for IQC Analysis

Find  $\tau_1, \dots, \tau_n \geq 0$  such that  $\sigma_0(h) + \sum_k \tau_k \sigma_k(h)$  becomes negative semi-definite:

$$\begin{pmatrix} * & * & * \\ * & * & * \\ * & * & * \end{pmatrix} + \tau_1 \begin{pmatrix} * & * & * \\ * & * & * \\ * & * & * \end{pmatrix} + \tau_2 \begin{pmatrix} * & * & * \\ * & * & * \\ * & * & * \end{pmatrix}$$

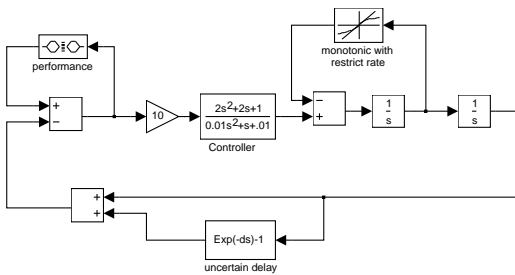
## Decomposing IQC Analysis

Find  $\tau_1, \dots, \tau_n \geq 0$  such that  $\sigma_0(h) + \sum_k \tau_k \sigma_k(h)$  has a negative semi-definite decomposition:

$$\begin{pmatrix} * & * & * \\ * & * & * \\ * & * & * \end{pmatrix} + \tau_1 \begin{pmatrix} * & * & * \\ * & * & * \\ * & * & * \end{pmatrix} + \tau_2 \begin{pmatrix} * & * & * \\ * & * & * \\ * & * & * \end{pmatrix} = \begin{pmatrix} * & * & * \\ * & * & * \\ * & * & * \end{pmatrix} + \begin{pmatrix} * & * & * \\ * & * & * \\ * & * & * \end{pmatrix} + \begin{pmatrix} * & * & * \\ * & * & * \\ * & * & * \end{pmatrix} + \begin{pmatrix} * & * & * \\ * & * & * \\ * & * & * \end{pmatrix}$$

Distributed certificates!

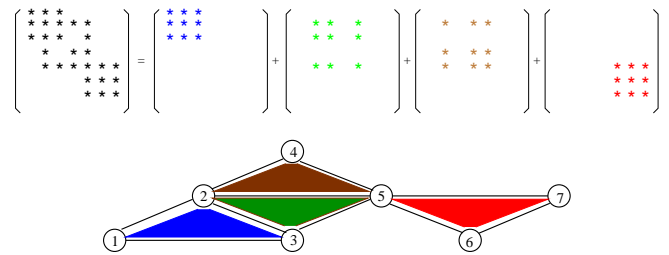
## Distributed Verification



[Feron (2010)]: "The credible autocoder produces not only a target code that implements control-system specifications but also documents the target code with its properties and their proofs."

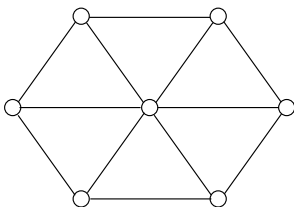
## Chordal Decompositions

Cholesky factors inherit the sparsity structure of the symmetric matrix if and only if the sparsity pattern corresponds to a "chordal" graph.



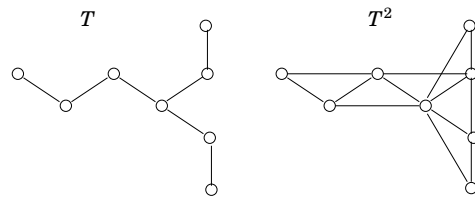
[Blair & Peyton, An introduction to chordal graphs and clique trees, 1992]

## Example: Non-chordal graph



## Example: Chordal graphs

If  $T$  is a tree, then  $T^k$  is chordal for every  $k \geq 1$ .



## Theorem on Positive Extension

A matrix with entries specified according to a chordal graph has a positive definite completion if and only if all fully specified principal minors are positive definite. [Grone, et.al, 1984]

$$\begin{pmatrix} 3 & 2 & 1 & * & * & * & * \\ 2 & 4 & 2 & 1 & * & * & * \\ 1 & 2 & 4 & 1 & 1 & * & * \\ * & 1 & 1 & 3 & 1 & 1 & * \\ * & * & 1 & 1 & 5 & 2 & 1 \\ * & * & * & 1 & 2 & 4 & 1 \\ * & * & * & * & 1 & 1 & 3 \end{pmatrix}$$

## Network congestion control

Maximize  $\sum_i U_i(x)$  over  $x_i \geq 0$  subject to  $\sum_i R_{li} x_i \leq c_l$

Alternatively:  $\min_{p_l \geq 0} \max_{x_i \geq 0} \sum_i [U_i(x_i) - \sum_l p_l (R_{li} x_i - c_l)]$

A model for Internet dynamics can look like this:

$$\dot{x}_i(t) = k_i x_i(t) \left( 1 - \frac{\sum_l R_{li} p_l(t - \tau_{li})}{U'_i(x_i(t))} \right)$$

$$\beta_l \dot{p}_l(t) + p_l(t) = \sum_i x_i(t - \tau_{li})$$

Scalable stability conditions by Low, Paganini, Doyle, Papachristodolou, Vinnicombe, Lestas, Pates, ...

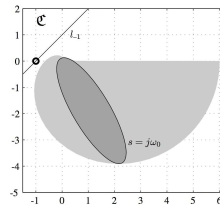
Is there a connection to scalable IQC analysis?

## Network congestion control

Yes!

[Pates/Vinnicomb 2012]:

Separate the ellipse  
 $\left\{ \frac{z^* L(i\omega) z}{z^* z} : z \in \mathbb{C}^n \right\}$  from  $-1$



$$\begin{pmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix} = \begin{pmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix} + \begin{pmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix} - \begin{pmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix} - \begin{pmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix}$$

Sources for conservatism: fixed decomposition  
 fixed separating hyperplane

## Outline

- o Positive Definite Decomposition
- o Scalable IQC analysis
- **Positive and Monotone Systems**
- o Concluding remarks

## Positive systems

A linear system is called *positive* if the state and output remain nonnegative as long as the initial state and the inputs are nonnegative:

$$\frac{dx}{dt} = Ax + Bu \quad y = Cx$$

Equivalently,  $A$ ,  $B$  and  $C$  have nonnegative coefficients except for the diagonal of  $A$ .

**Examples:**

- ▶ Probabilistic models.
- ▶ Economic systems.
- ▶ Chemical reactions.
- ▶ Traffic Networks.

## A Scalable Stability Test



Stability of  $\dot{x} = Ax$  follows from existence of  $\xi_k > 0$  such that

$$\underbrace{\begin{bmatrix} a_{11} & a_{12} & 0 & a_{14} \\ a_{21} & a_{22} & a_{23} & 0 \\ 0 & a_{32} & a_{33} & a_{32} \\ a_{41} & 0 & a_{43} & a_{44} \end{bmatrix}}_A \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \end{bmatrix} < \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

The first node verifies the inequality of the first row.

The second node verifies the inequality of the second row.

...

*Verification is scalable!*

## Search for Stabilizing Gains

Suppose  $\begin{bmatrix} a_{11} - \ell_1 & a_{12} & 0 & a_{14} \\ a_{21} + \ell_1 & a_{22} - \ell_2 & a_{23} & 0 \\ 0 & a_{32} + \ell_2 & a_{33} & a_{32} \\ a_{41} & 0 & a_{43} & a_{44} \end{bmatrix} \geq 0$  for  $\ell_1, \ell_2 \in [0, 1]$ .

For stabilizing gains  $\ell_1, \ell_2$ , find  $0 < \mu_k < \xi_k$  such that

$$\begin{bmatrix} a_{11} & a_{12} & 0 & a_{14} \\ a_{21} & a_{22} & a_{23} & 0 \\ 0 & a_{32} & a_{33} & a_{32} \\ a_{41} & 0 & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \end{bmatrix} + \begin{bmatrix} -1 & 0 \\ 1 & -1 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} < \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

and set  $\ell_1 = \mu_1 / \xi_1$  and  $\ell_2 = \mu_2 / \xi_2$ . Every row gives a local test.

Distributed synthesis by linear programming (gradient search).

## Examples

- ▶ Cloud computing / server farms
- ▶ Heating and ventilation in buildings
- ▶ Traffic flow dynamics
- ▶ Production planning and logistics

## Combination Therapy is a Control Problem

Evolutionary dynamics:

$$\dot{x} = \left( A - \sum_i u_i D^i \right) x$$

Each state  $x_k$  is the concentration of a mutant. (There can be hundreds!) Each input  $u_i$  is a drug dosage.

$A$  describes the mutation dynamics without drugs, while  $D^1, \dots, D^m$  are diagonal matrices modeling drug effects.

Determine  $u_1, \dots, u_m \geq 0$  with  $u_1 + \dots + u_m \leq 1$  such that  $x$  decays as fast as possible!

[Jonsson, Rantzer, Murray, ACC 2014]

## Optimizing Decay Rate

Stability of the matrix  $A - \sum_i u_i D^i + \gamma I$  is equivalent to existence of  $\xi > 0$  with

$$\left( A - \sum_i u_i D^i + \gamma I \right) \xi < 0$$

For row  $k$ , this means

$$A_k \xi - \sum_i u_i D_k^i \xi_k + \gamma \xi_k < 0$$

or equivalently

$$\frac{A_k \xi}{\xi_k} - \sum_i u_i D_k^i + \gamma < 0$$

Maximizing  $\gamma$  is convex optimization in  $(\log \xi_i, u_i, \gamma)$  !

## Using Measurements of Virus Concentrations

Evolutionary dynamics:

$$\dot{x}(t) = \left( A - \sum_i u_i(t) D^i \right) x(t)$$

Can we get faster decay using time-varying  $u(t)$  based on measurements of  $x(t)$  ?

## Using Measurements of Virus Concentrations

The evolutionary dynamics can be written as a convex monotone system:

$$\frac{d}{dt} \log x_k(t) = \frac{A_k x(t)}{x_k(t)} - \sum_i u_i(t) D_k^i$$

Hence the decay of  $\log x_k$  is a convex function of the input and optimal trajectories can be found even for large systems.

## Convex Monotone Systems

The system

$$\dot{x}(t) = f(x(t), u(t)), \quad x(0) = a$$

is a *monotone system* if its linearization is a positive system. It is a *convex monotone system* if every row of  $f$  is also convex.

**Theorem.** [Rantzer/ Bernhardsson (2014)]

For a convex monotone system  $\dot{x} = f(x, u)$ , each component of the trajectory  $\phi_t(a, u)$  is a convex function of  $(a, u)$ .

## Example

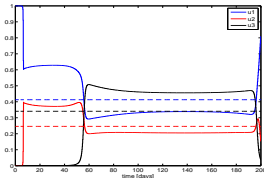
$$A = \begin{bmatrix} -\delta & \mu & \mu & 0 \\ \mu & -\delta & 0 & \mu \\ \mu & 0 & -\delta & \mu \\ 0 & \mu & \mu & -\delta \end{bmatrix}$$

clearance rate  $\delta = 0.24 \text{ day}^{-1}$ , mutation rate  $\mu = 10^{-4} \text{ day}^{-1}$  and replication rates for viral variants and therapies as follows

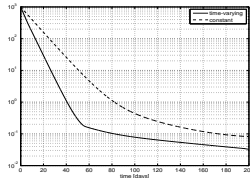
Variant	Therapy 1	Therapy 2	Therapy 3
Wild type ( $x_1$ )	$D_1^1 = 0.05$	$D_1^2 = 0.10$	$D_1^3 = 0.30$
Genotype 1 ( $x_2$ )	$D_2^1 = 0.25$	$D_2^2 = 0.05$	$D_2^3 = 0.30$
Genotype 2 ( $x_3$ )	$D_3^1 = 0.10$	$D_3^2 = 0.30$	$D_3^3 = 0.30$
HR type ( $x_4$ )	$D_4^1 = 0.30$	$D_4^2 = 0.30$	$D_4^3 = 0.15$

## Example

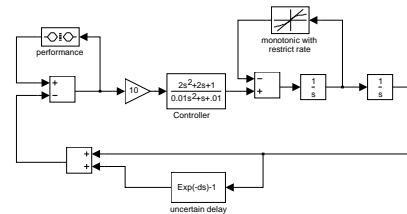
Optimized drug doses:



Total virus population:



## Summary



IQC analysis scales using positive definite decompositions !

$$\begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} = \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix} + \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix} + \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix} + \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix}$$

Scalability comes from monotonicity.