

# **Polyhedral Homotopy Method for Nash Equilibrium Problem**

**(joint work with Xindong Tang)**

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**AMA Colloquium Series on Young Scholars in Optimization and Data Science**

# Discrete Math

## Nash Equilibrium Problem

Consider a 2-player game with 2 strategies for each player

		2nd	
		C	D
1st	A	8	4
	B	6	7

1st player payoff

		2nd	
		C	D
1st	A	4	6
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2nd player payoff

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(B,D) is a Nash equilibrium

(A,D) is not a Nash equilibrium

# Nash Equilibrium Problem

## Nash equilibrium (NE)

In game theory, a state that a player can achieve the desired outcome by not changing their initial strategy.

It is a state that every player's objective is optimized for given other players' strategies.

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> solve( $x^5 - 3x + 1$ )  
RootOf(_Z5 - 3_Z + 1, index = 1), RootOf(_Z5 - 3_Z + 1, index = 2), RootOf(_Z5 - 3_Z + 1, index  
= 3), RootOf(_Z5 - 3_Z + 1, index = 4), RootOf(_Z5 - 3_Z + 1, index = 5)
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```

```
> fsolve(x5 - 3 x + 1)  
-1.388791984, 0.3347341419, 1.214648043
```



# Algebra + Numerical Analysis

## How to solve an equation? (Geometric point of view)

How to find roots of  $f(x) = x^5 - 3x + 1$ ?

Consider  $g(x) = x^5 - 1$  (whose roots are the 5-th roots of unity  $\xi_1, \dots, \xi_5$ ).

Then,  $H(x, t) = (1 - t)f(x) + tg(x)$  finds roots of  $f(x)$  as  $t$  goes from 1 to 0.

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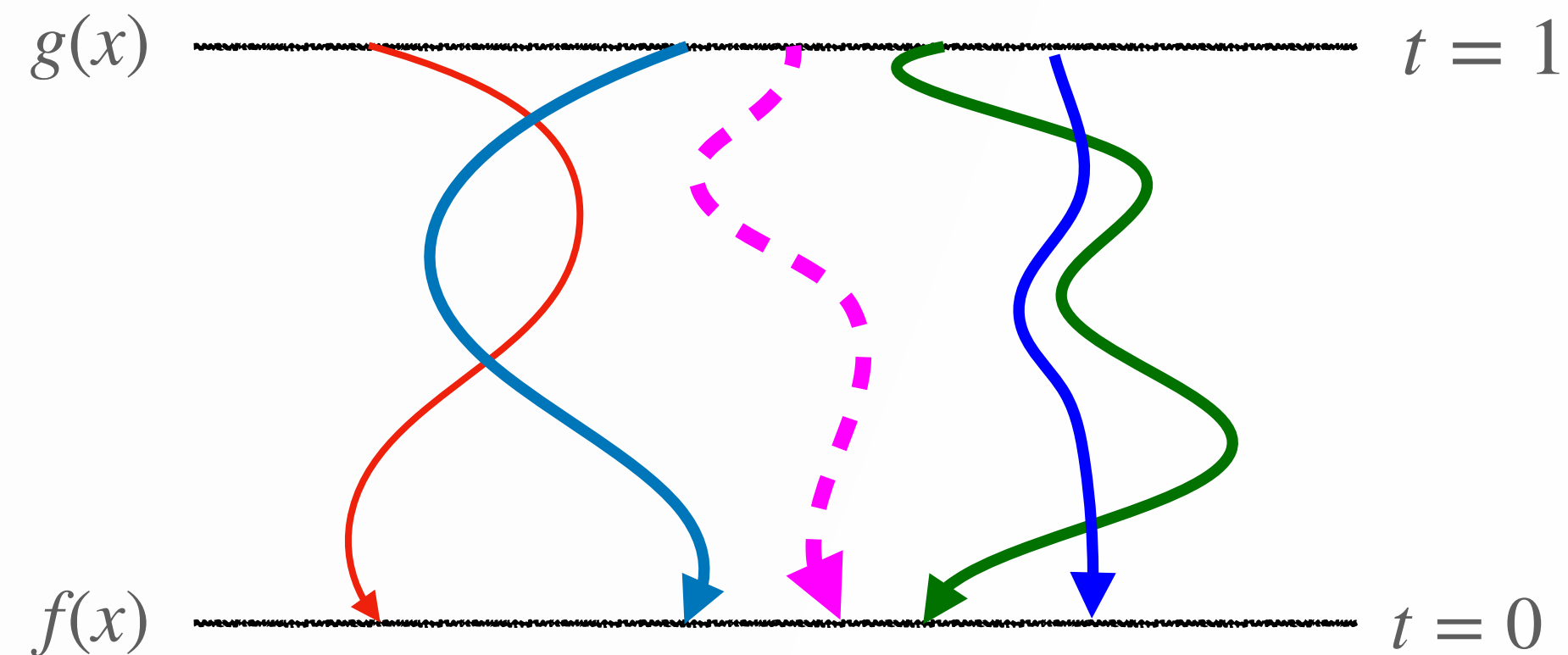
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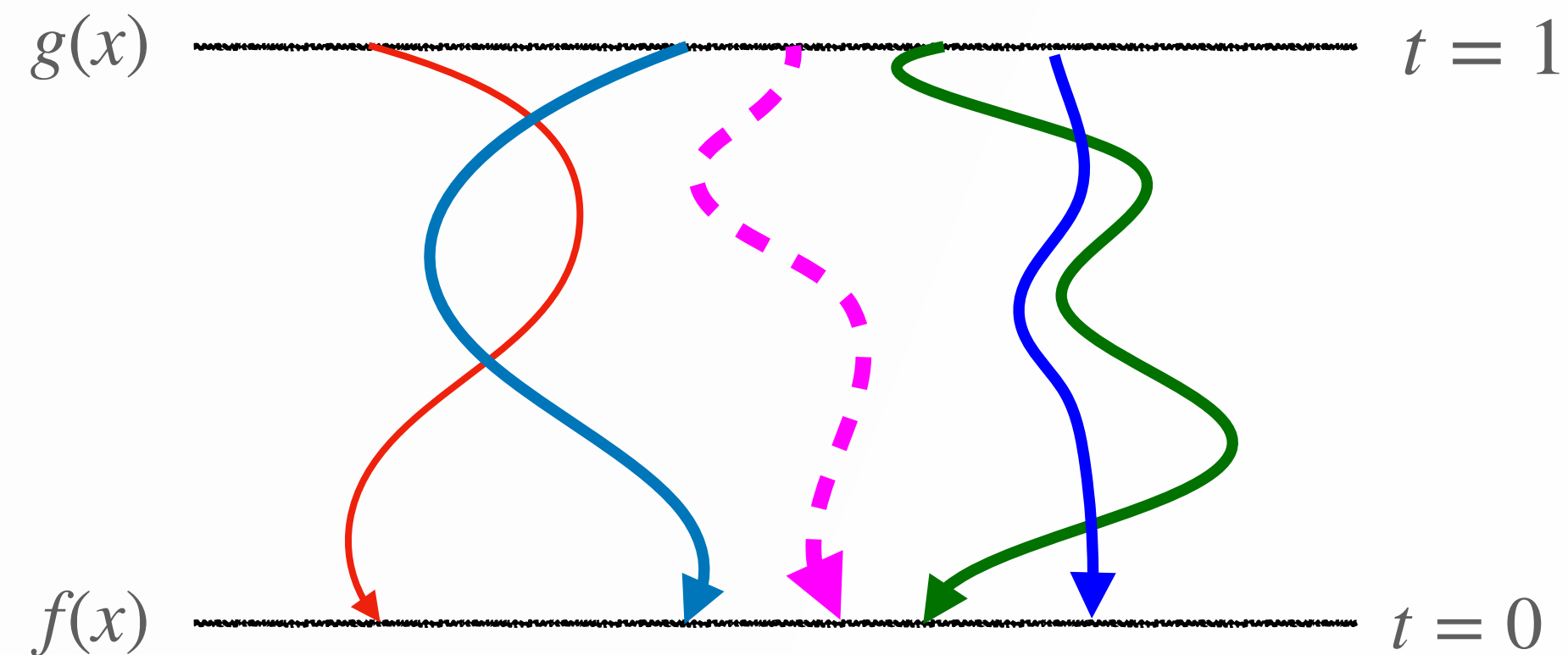
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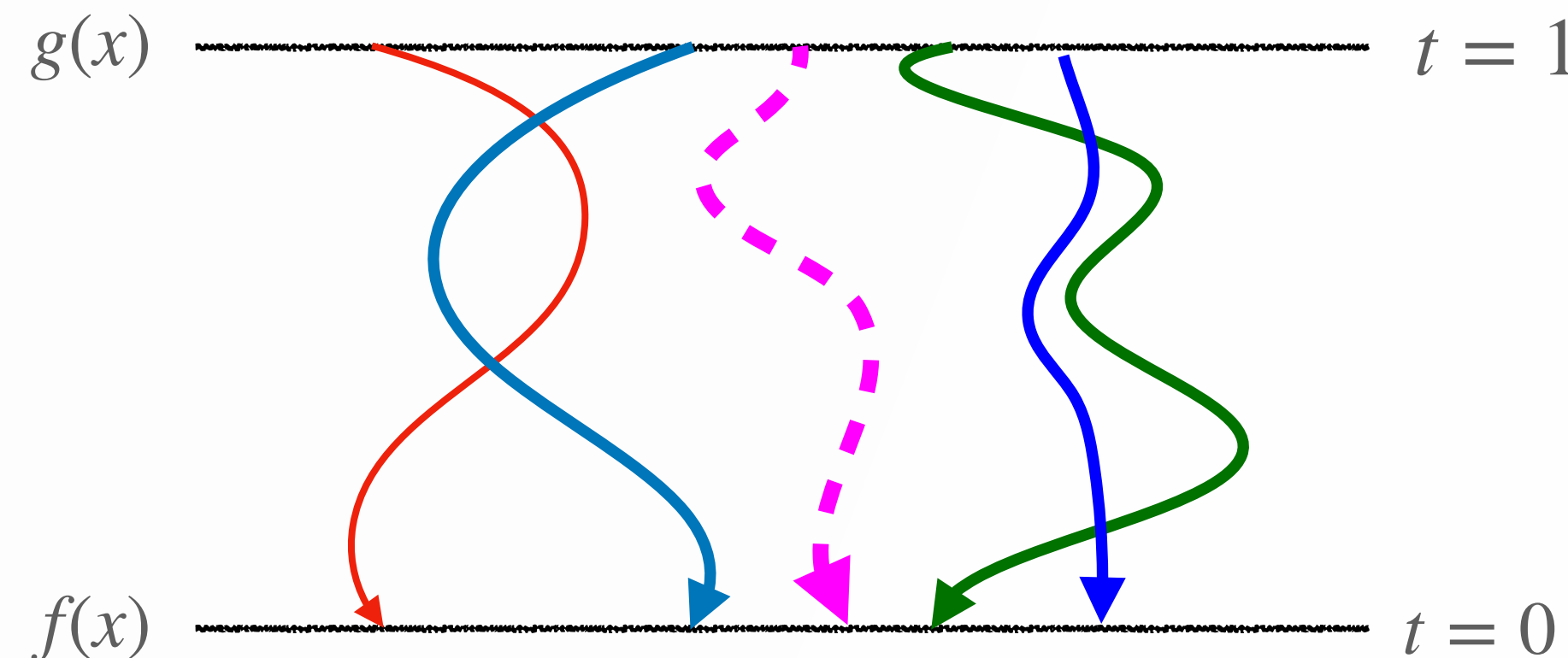
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Then,  $H(x, t) = (1 - t)f(x) + tg(x)$  finds roots of  $f(x)$  as  $t$  goes from 1 to 0. **(Homotopy method)**

# **Nash Equilibrium Problem + Numerical Algebraic Geometry**

# Why Homotopy Method?

- Current known methods for NEP are based on optimization methods.
  - Heavily relies on the convexity of feasible sets.
- Previous works focus on finding one NE (or finding all NEs one-by-one).
  - Homotopy methods can be proper for finding all NEs at once.

# Nash Equilibrium Problem

NEP as an **optimization problem**.

Consider  $N$ -player game.

$$x_i := (x_{i,1}, \dots, x_{i,n_i}) \in \mathbb{R}^{n_i}$$

the  $i$ -th player's strategy.

$$x := (x_1, \dots, x_N) \in \mathbb{R}^{n_1 + \dots + n_N}$$

a vector for all players' strategies.

$$x_{-i} := (x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$$

all strategies except  $i$ -th player's strategy.

$$f_i \in \mathbb{C}[x]$$

the  $i$ -th player's objective function.

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the  $i$ -th player's constraints ( $j = 1, \dots, m_i$ )



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NEP as an **optimization problem**.

Find a tuple  $u = (u_1, \dots, u_N)$  such that  $u_i$  is a optimizer of the  $i$ -th player's optimization :

$$F_i : \begin{cases} \min_{x_i \in \mathbb{R}^{n_i}} & f_i(u_1, \dots, u_{i-1}, x_i, u_{i+1}, \dots, u_N) \\ \text{s.t.} & g_{i,j}(u_1, \dots, u_{i-1}, x_i, u_{i+1}, \dots, u_N) = 0 \quad \text{if } j \in \mathcal{E}_i \\ & g_{i,j}(u_1, \dots, u_{i-1}, x_i, u_{i+1}, \dots, u_N) \geq 0 \quad \text{if } j \in \mathcal{J}_i \end{cases}$$

where  $\mathcal{E}_i$  and  $\mathcal{J}_i$  are sets of indices for equality constraints and inequality constraints respectively.

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$$X_i := \{x_i \in \mathbb{R}^{n_i} \mid g_{i,j}(x_i) = 0, \quad g_{i,j}(x_i) \geq 0\}$$

the feasible set of  $F_i$

**regular NEP**

the feasible set  $X_i$  doesn't depend on  $x_{-i}$ .

**generalized NEP (GNEP)**

the feasible set  $X_i$  depends on  $x_{-i}$ .

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all  $f_i$  and  $g_{i,j}$  are polynomials.



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# Optimality Conditions for GNEPs

## KKT system

If  $x_i$  is a minimizer of  $F_i$ , then there is a Lagrange multiplier vector

$\lambda_i := (\lambda_{i,1}, \dots, \lambda_{i,m_i})$  satisfying the first-order

**Karush-Kuhn-Tucker (KKT) condition.**

$$\left\{ \begin{array}{l} \nabla_{x_i} f_i(x) - \sum_{j=1}^{m_i} \lambda_{i,j} \nabla_{x_i} g_{i,j}(x) = 0 \\ \lambda_{i,j} g_{i,j}(x) = 0 \quad \text{for all } j \\ g_{i,j}(x) = 0 \quad \text{if } j \in \mathcal{E}_i \\ g_{i,j}(x) \geq 0 \text{ and } \lambda_{i,j} \geq 0 \quad \text{if } j \in \mathcal{J}_i \end{array} \right.$$

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If  $x$  is a generalized Nash equilibrium, then the KKT condition holds for all  $i = 1, \dots, N$ .

Then, we have the following KKT system for each  $i = 1, \dots, N$ .

$$F_i := \begin{cases} \nabla_{x_i} f_i(x) - \sum_{j=1}^{m_i} \lambda_{i,j} \nabla_{x_i} g_{i,j}(x) = 0 \\ g_{i,j}(x) = 0 \quad \text{for } j = 1, \dots, m_i \end{cases}$$

Find all solutions of the KKT system  $F := (F_1, \dots, F_N)$ .  
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## Example

Consider 2-player GNEP

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# Optimality Conditions for GNEPs

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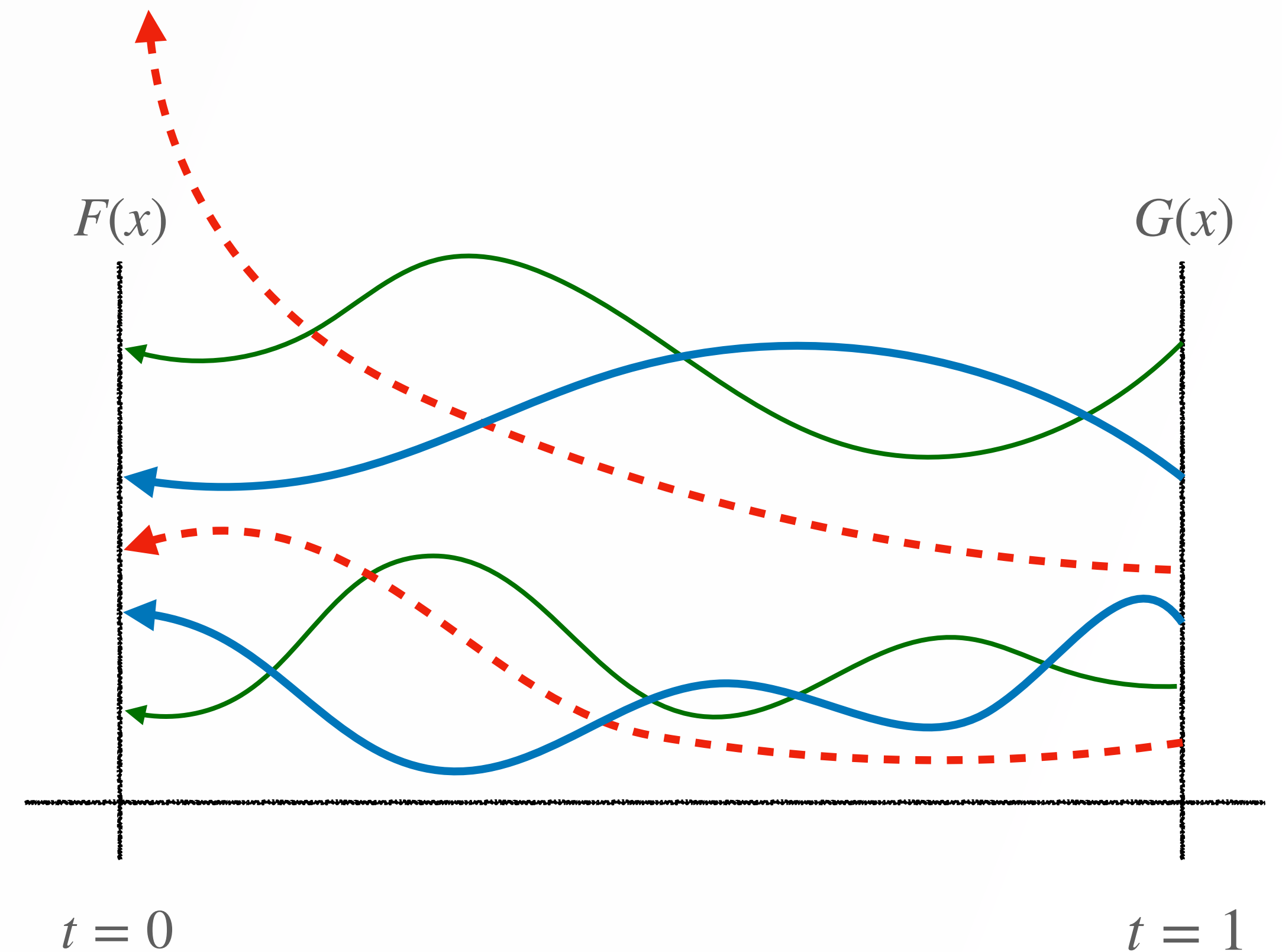
These systems provide the system  $F := \{F_1, F_2\}$

# Homotopy Continuation

Finding solutions by tracking homotopy

$$H(t, x) = t\gamma G(x) + (1 - t)F(x), \quad t \in [0, 1]$$

Solve  $F$  (**target system**) by constructing a homotopy with  $G$  (**start system**) whose solutions are known.



# Homotopy Continuation

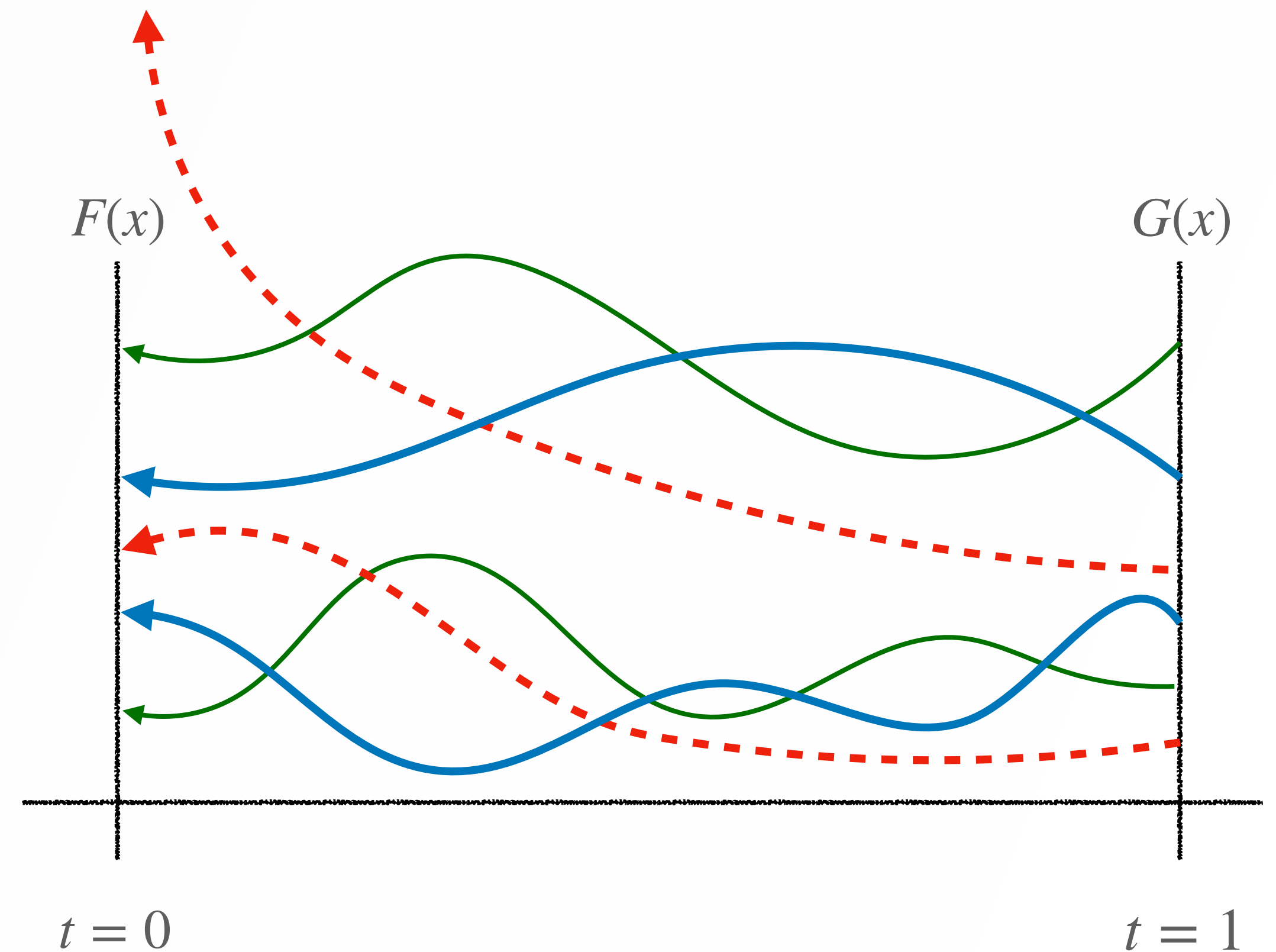
## How to choose start system?

The choice of start system determines the number of homotopy paths to track.

Bézout homotopy (Bézout bound = product of degrees)

polyhedral homotopy (BKK bound)

multihomogeneous start system



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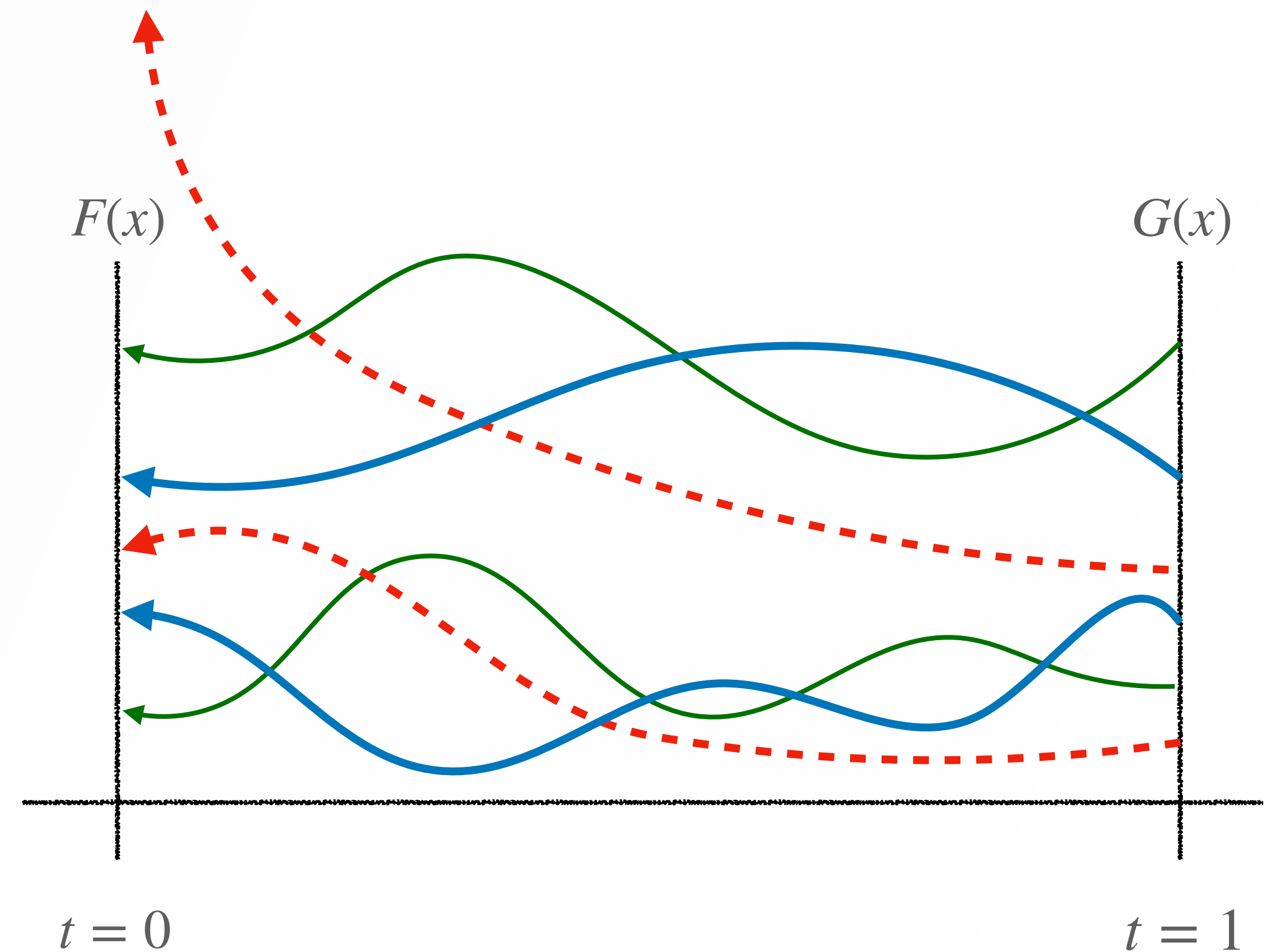
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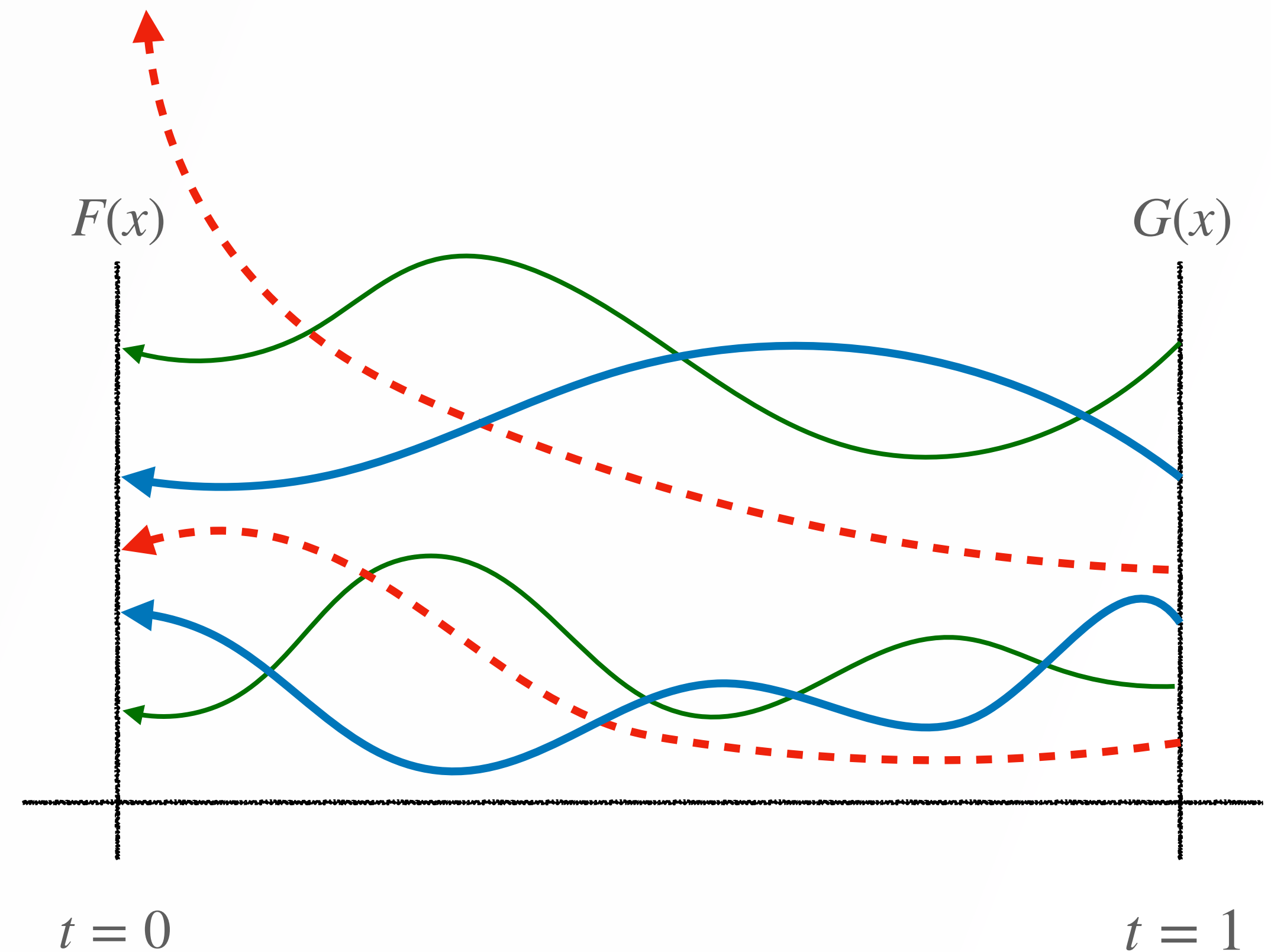
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# Polyhedral Homotopy Continuation

## Bernstein theorem

**Theorem [Bernstein 1975].**  $F := \{f_1, \dots, f_n\} \subset \mathbb{C}[x_1, \dots, x_n]$  : a square polynomial system.

$Q_i$  : the Newton polytope of  $f_i$ . Then,  $(\# \text{ isolated roots in } (\mathbb{C} \setminus \{0\})^n) \leq MV(Q_1, \dots, Q_n)$ .

$MV(Q_1, \dots, Q_n)$  is the **mixed volume** of  $Q_1, \dots, Q_n$ .

The mixed volume above is called the **BKK bound**.

The polyhedral homotopy tracks BKK bound many paths.

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$f \in \mathbb{C}[x_1, \dots, x_n]$  : a polynomial.

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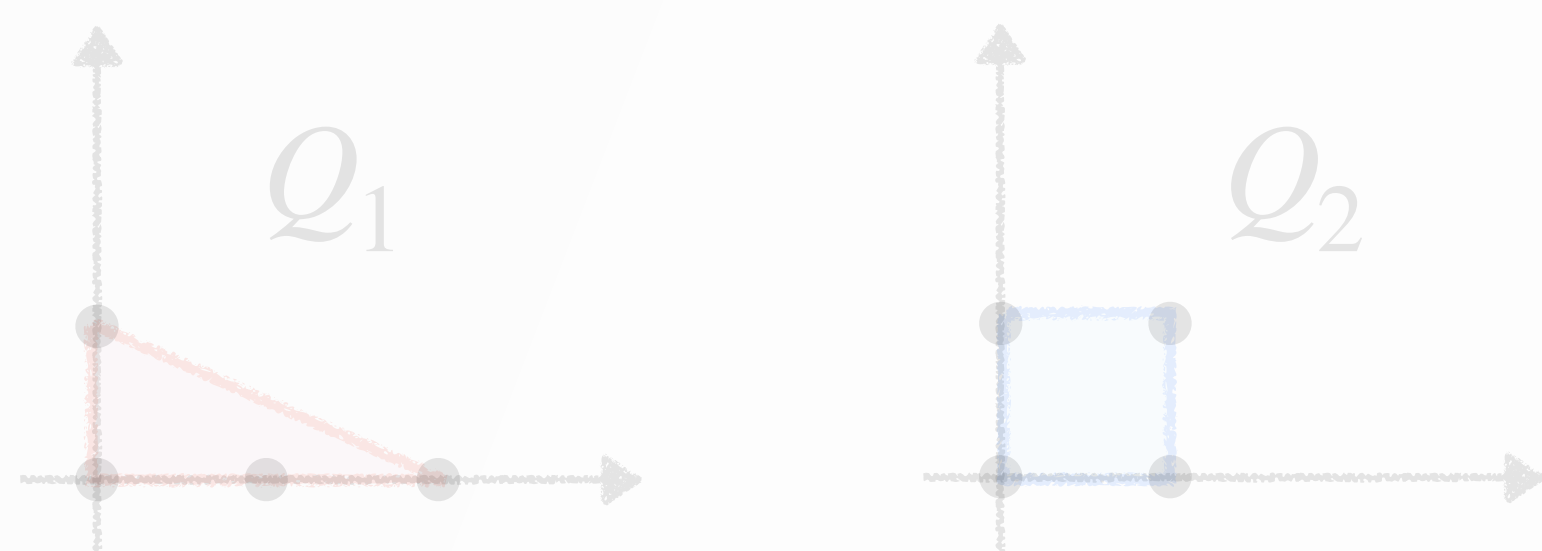
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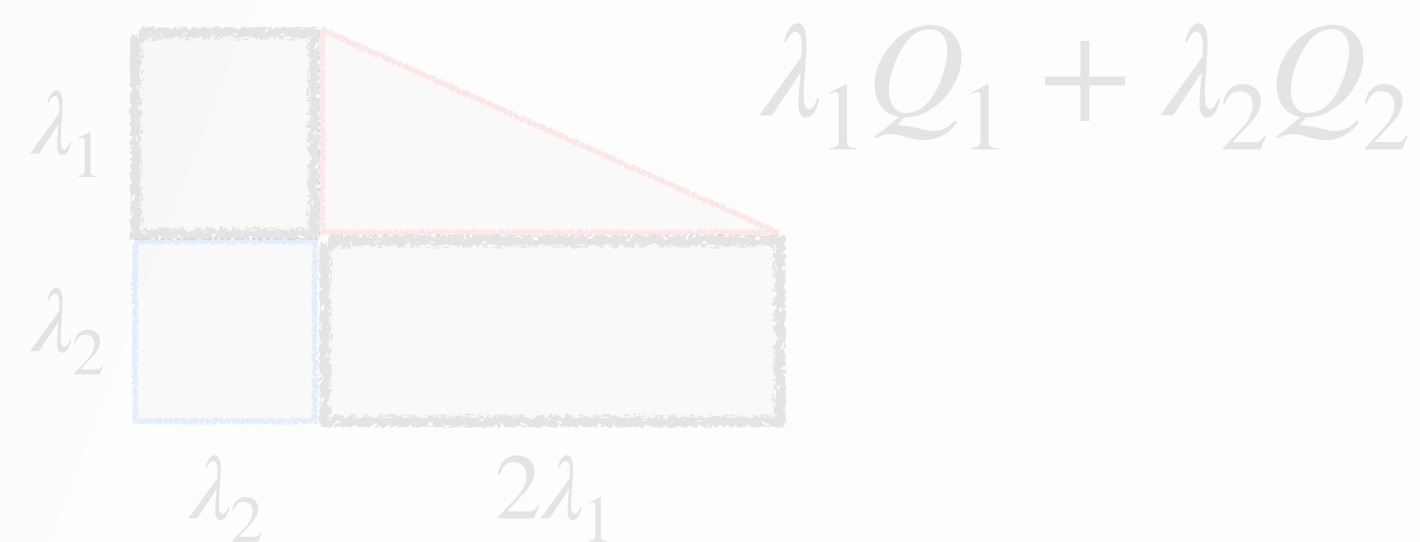
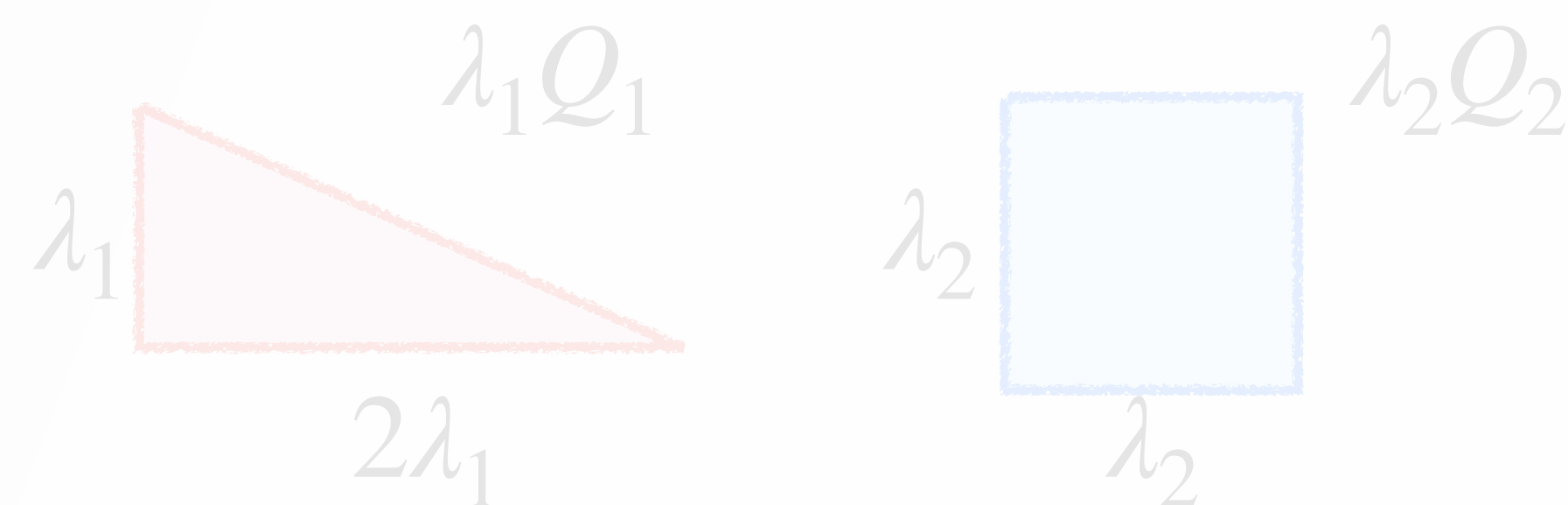
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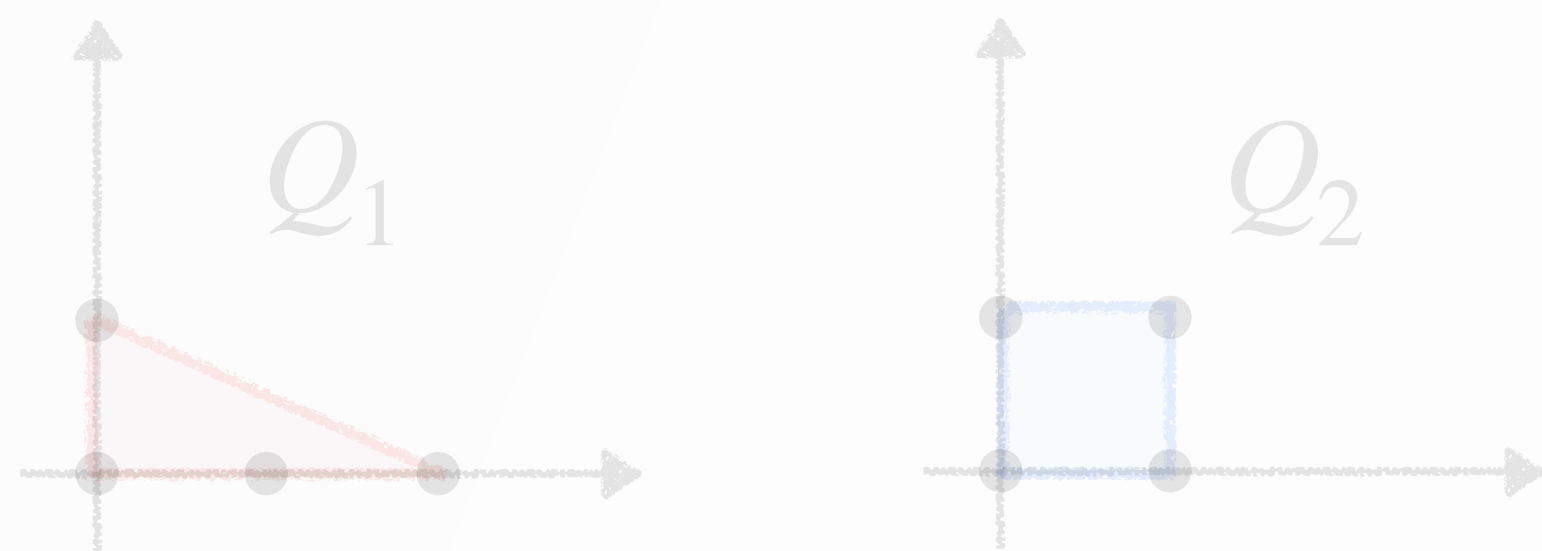
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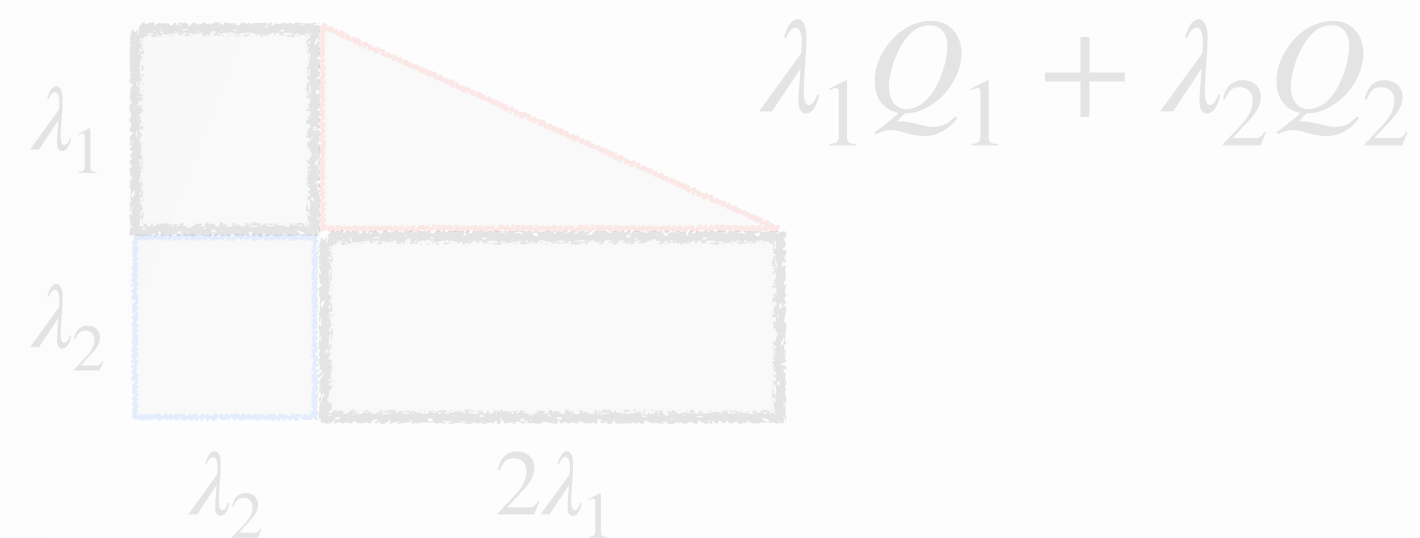
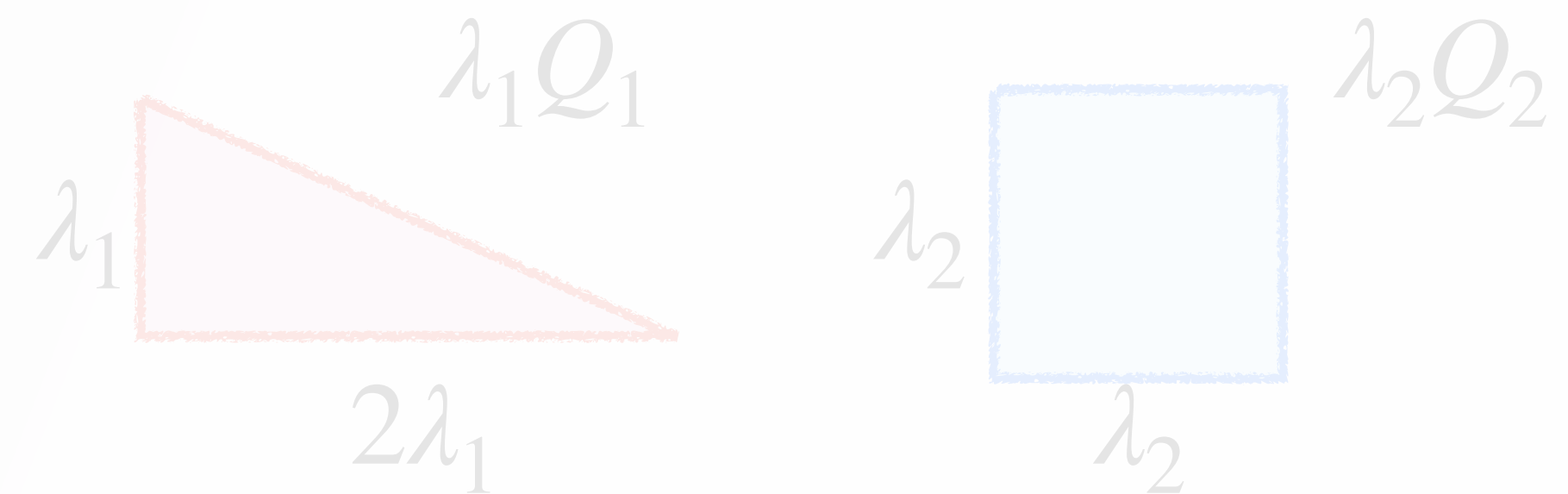
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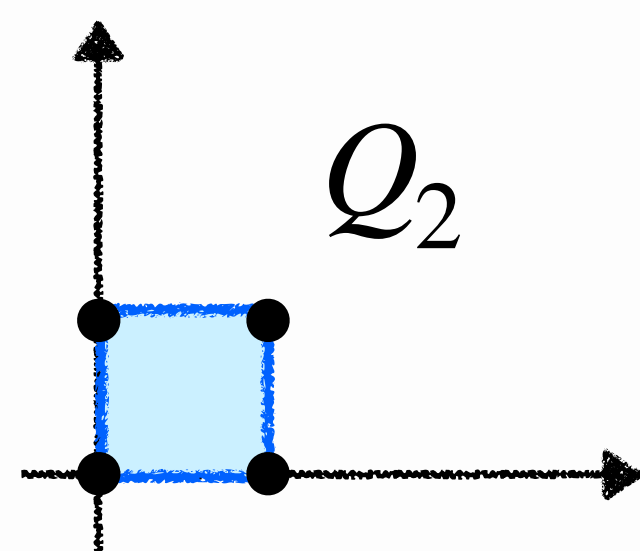
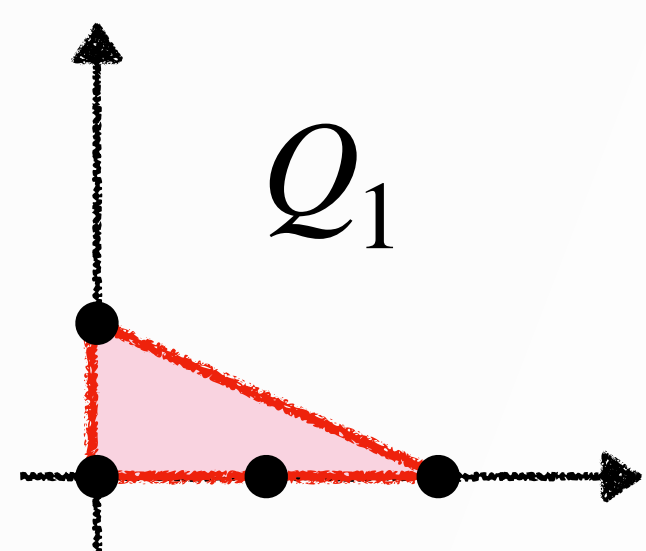
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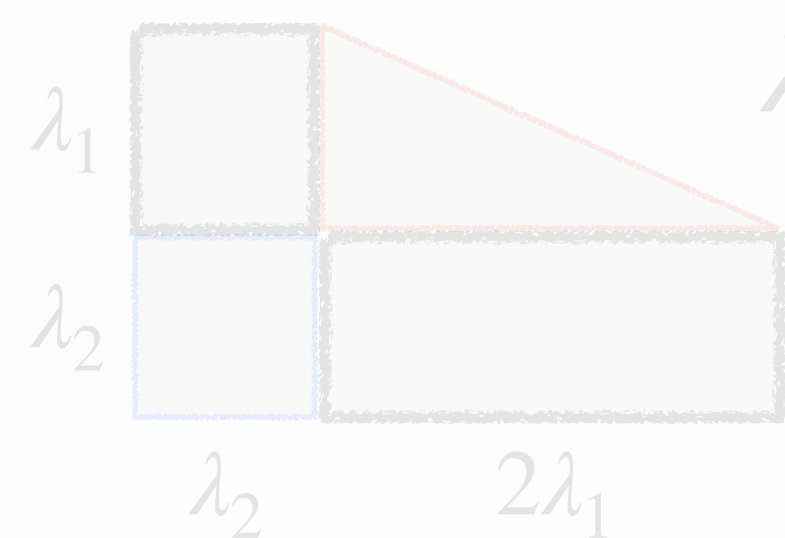
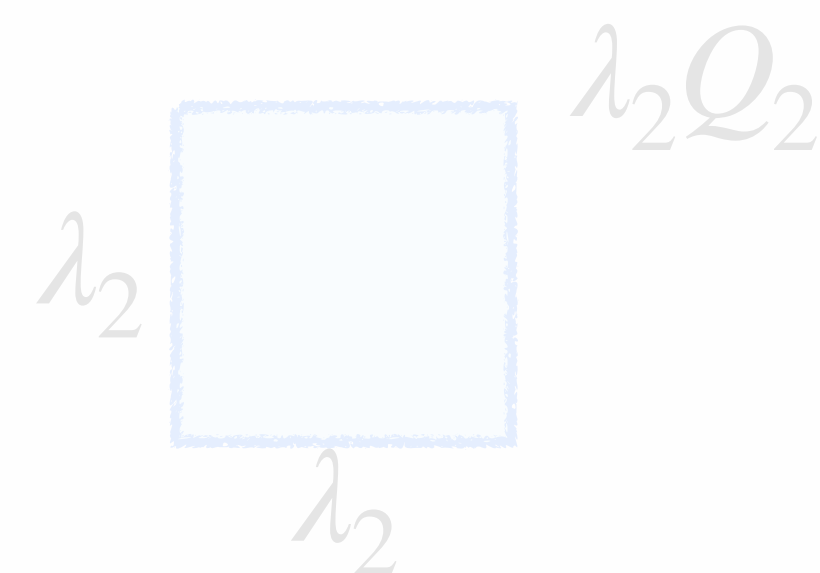
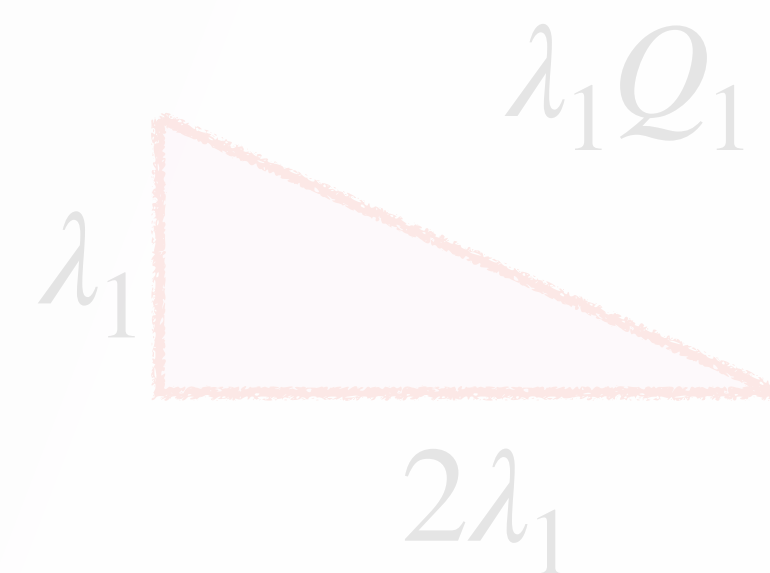
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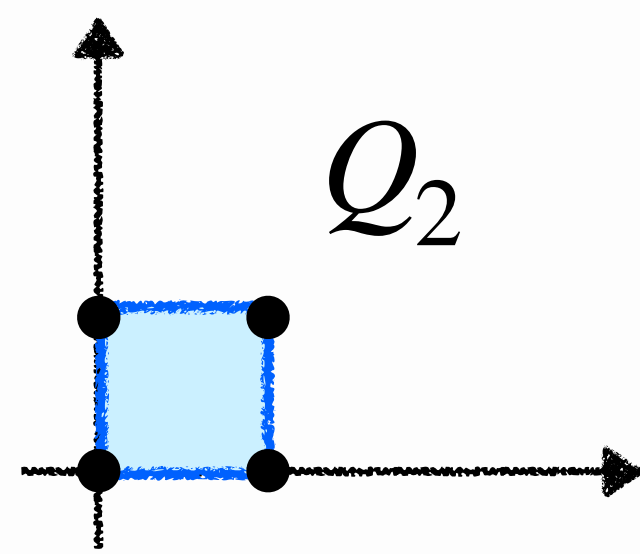
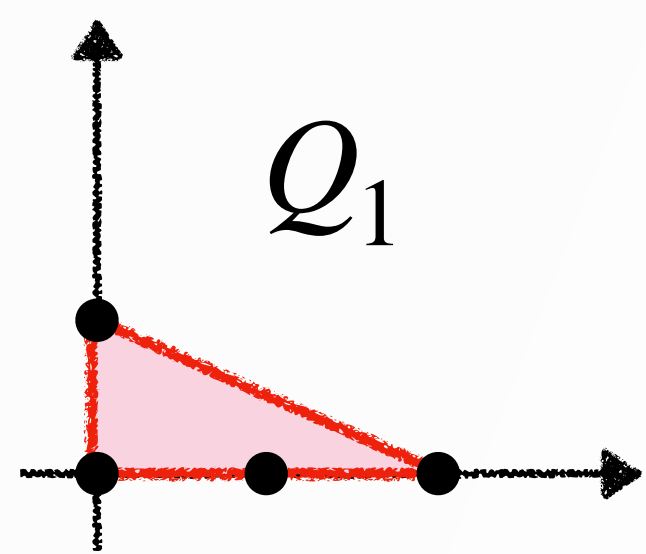
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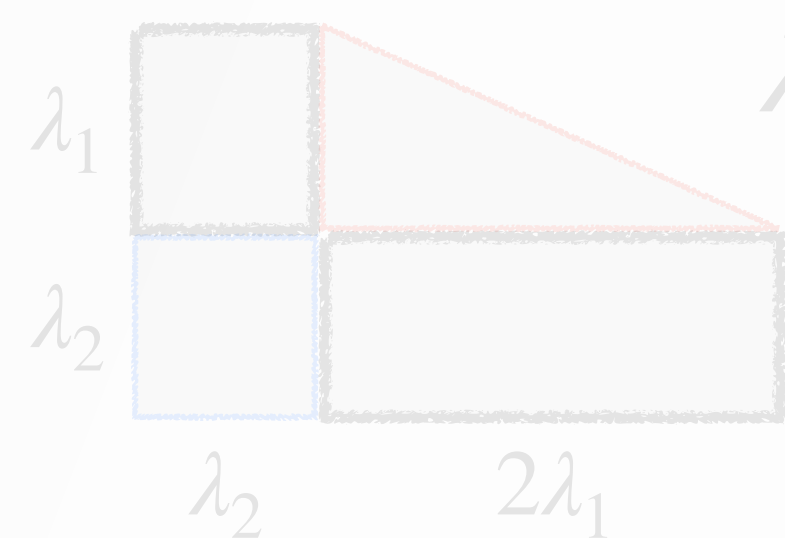
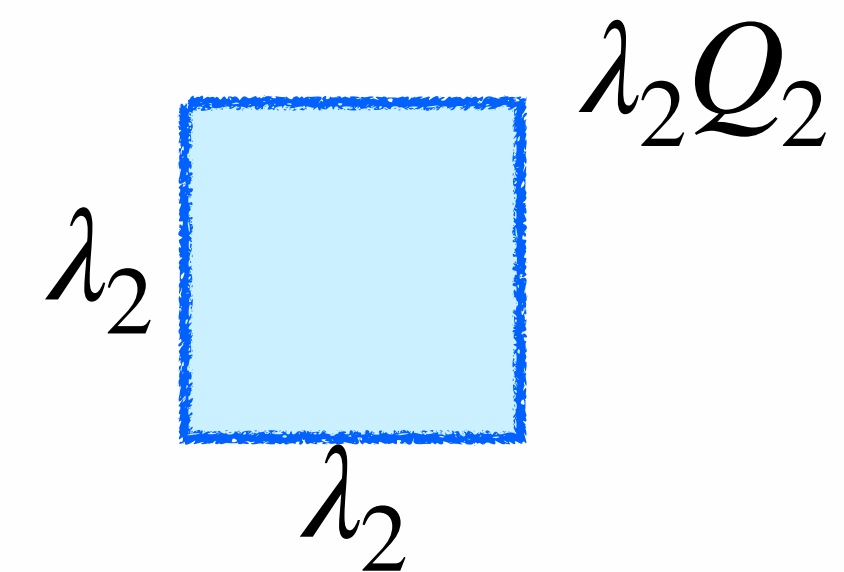
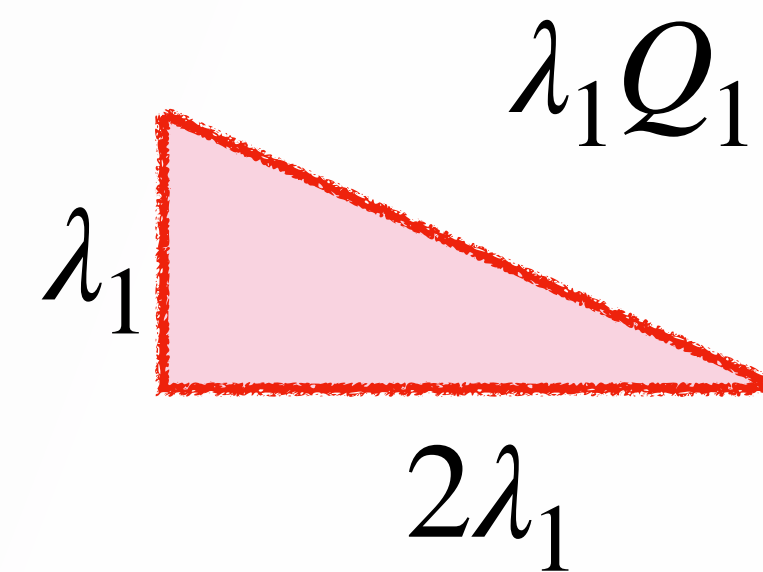
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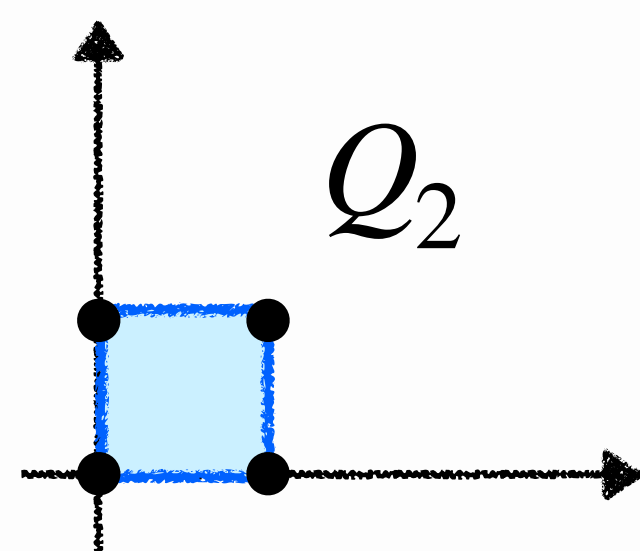
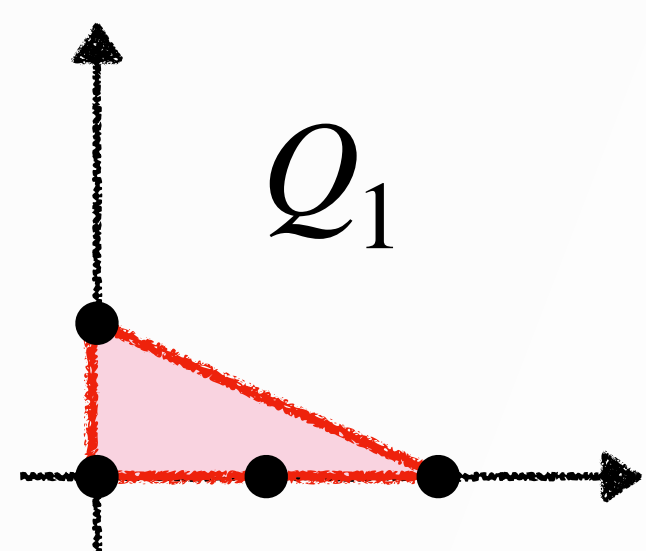
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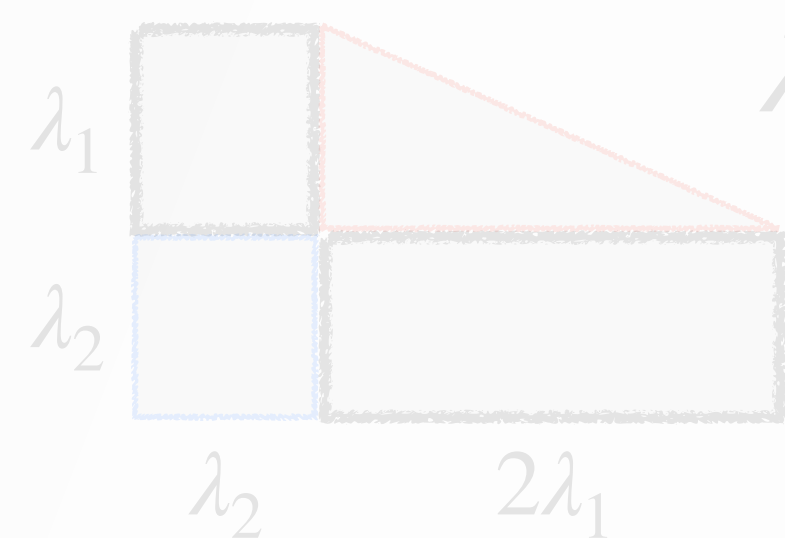
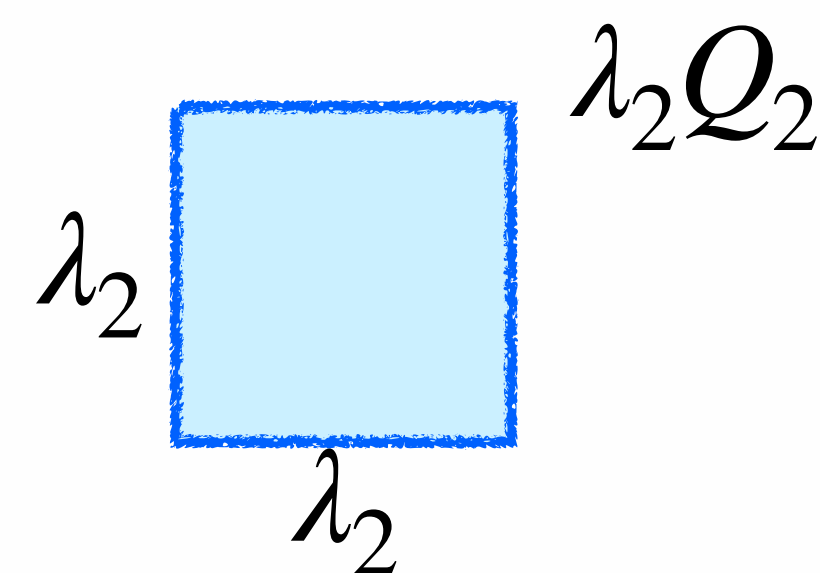
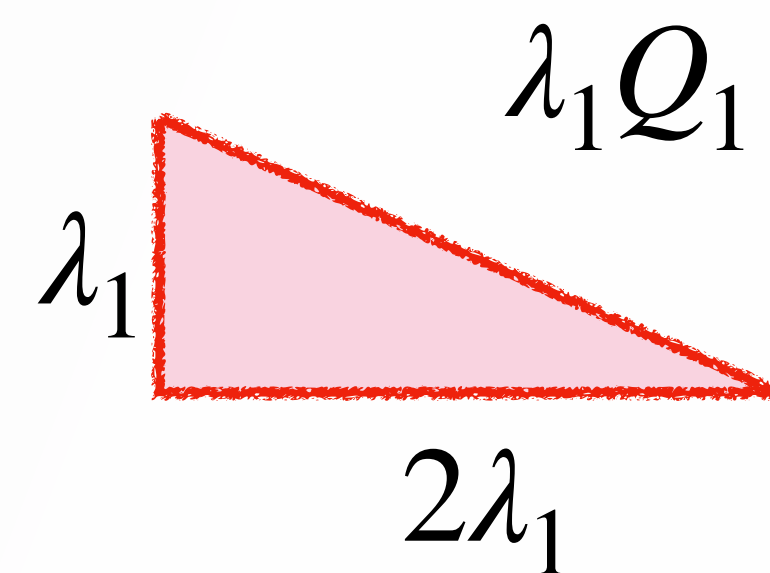
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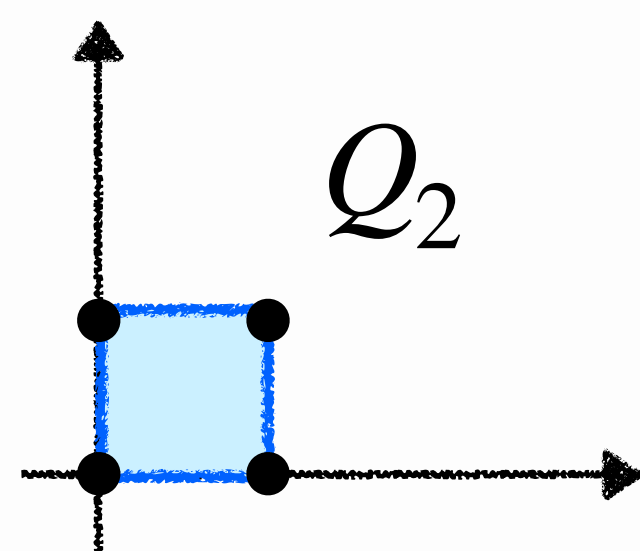
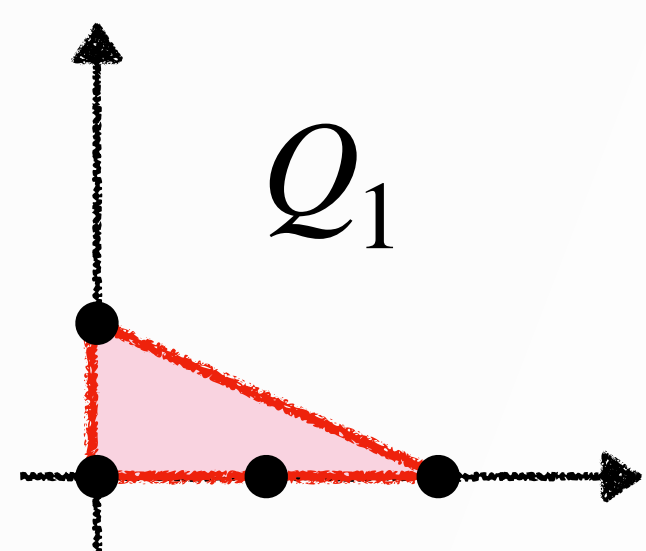
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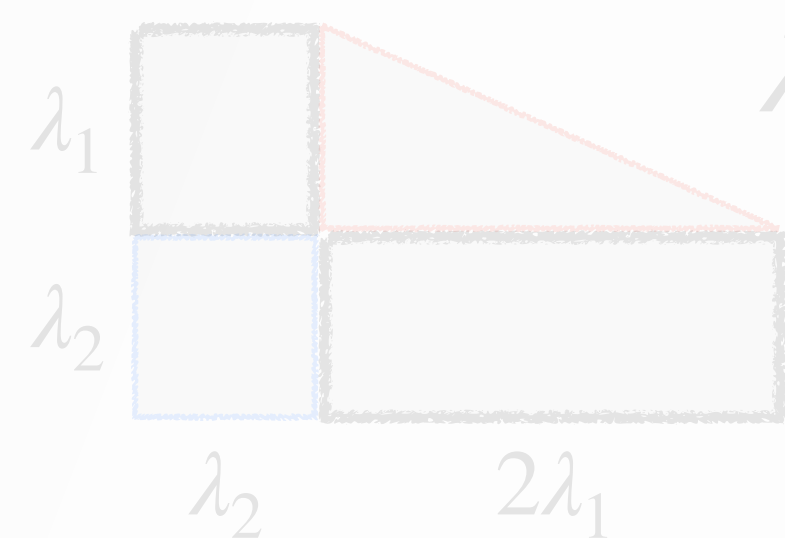
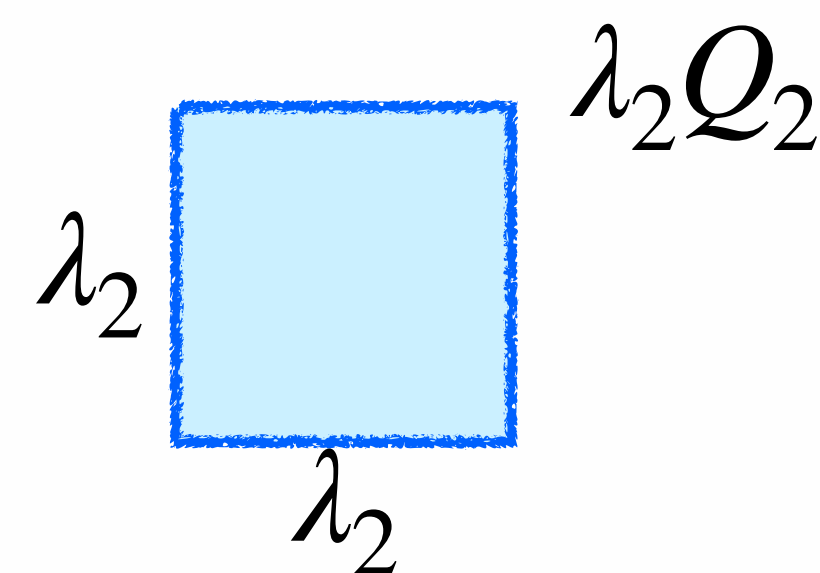
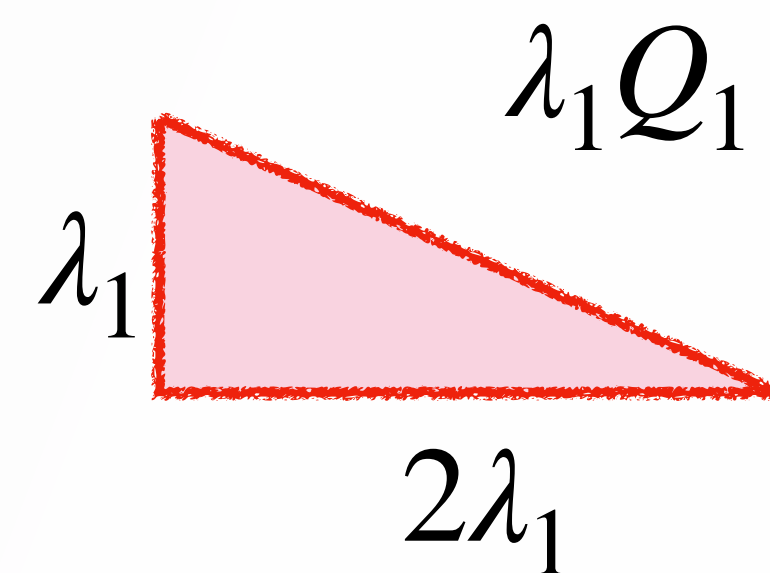
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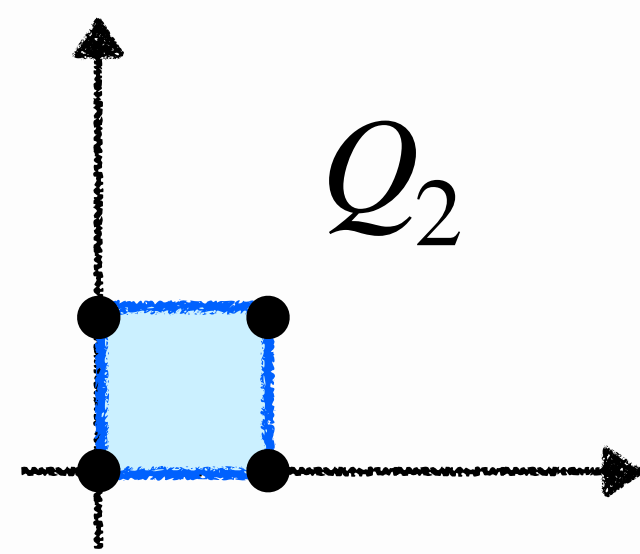
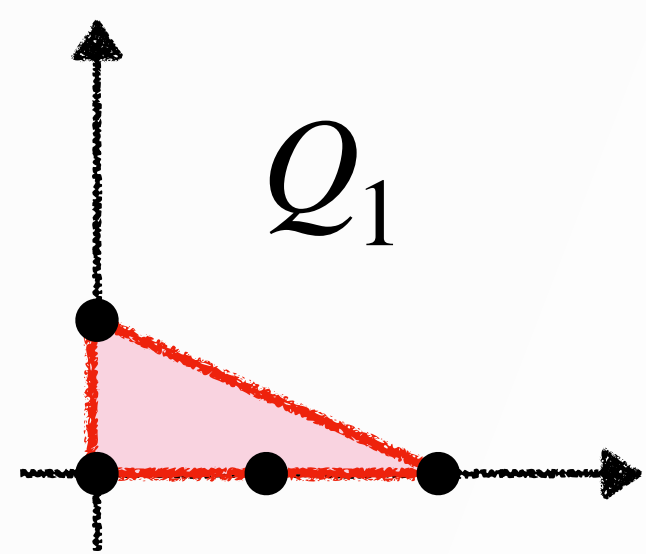
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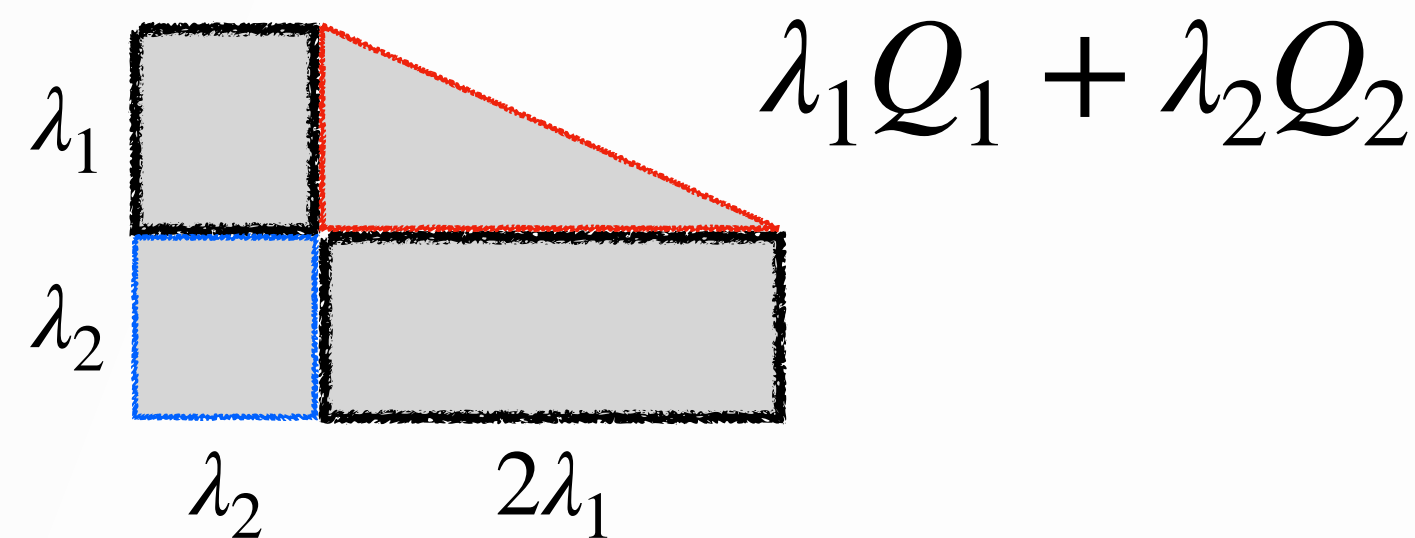
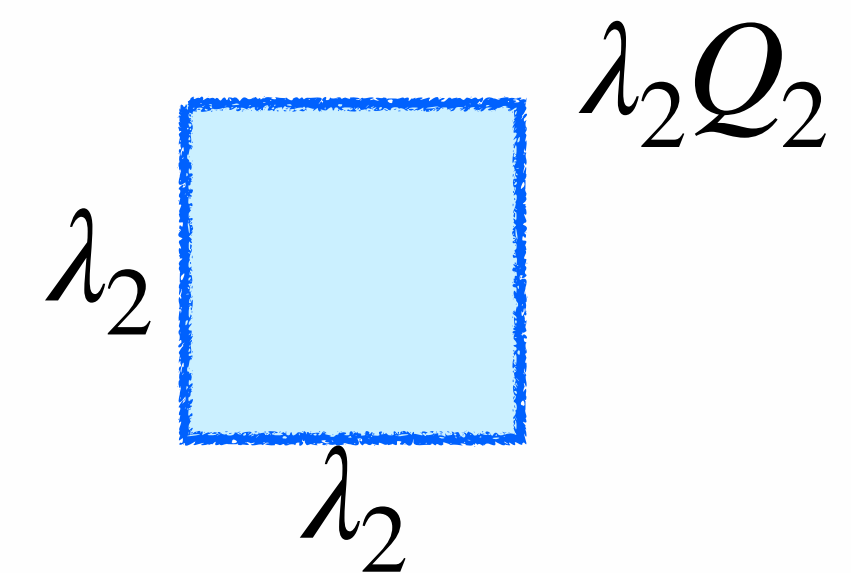
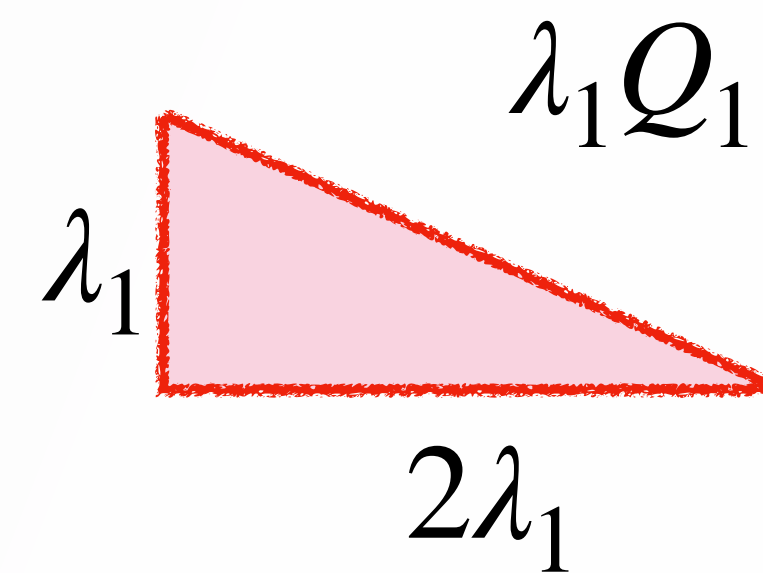
# Polyhedral Homotopy Continuation

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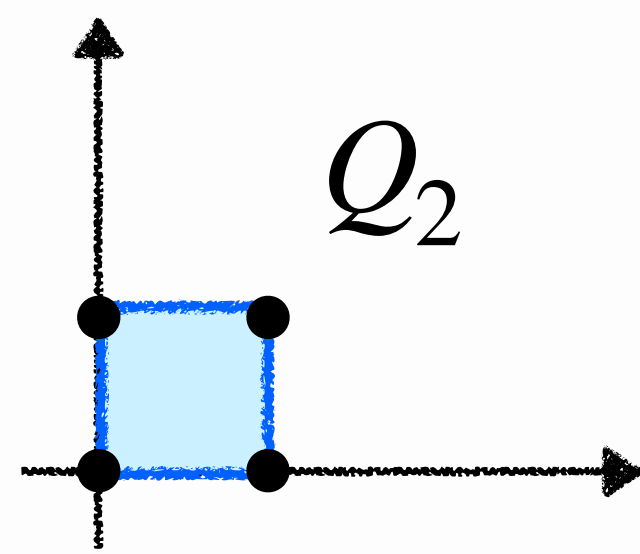
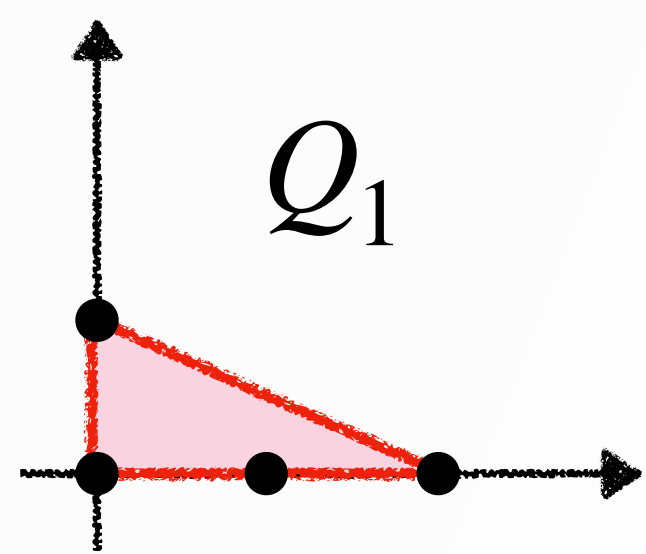
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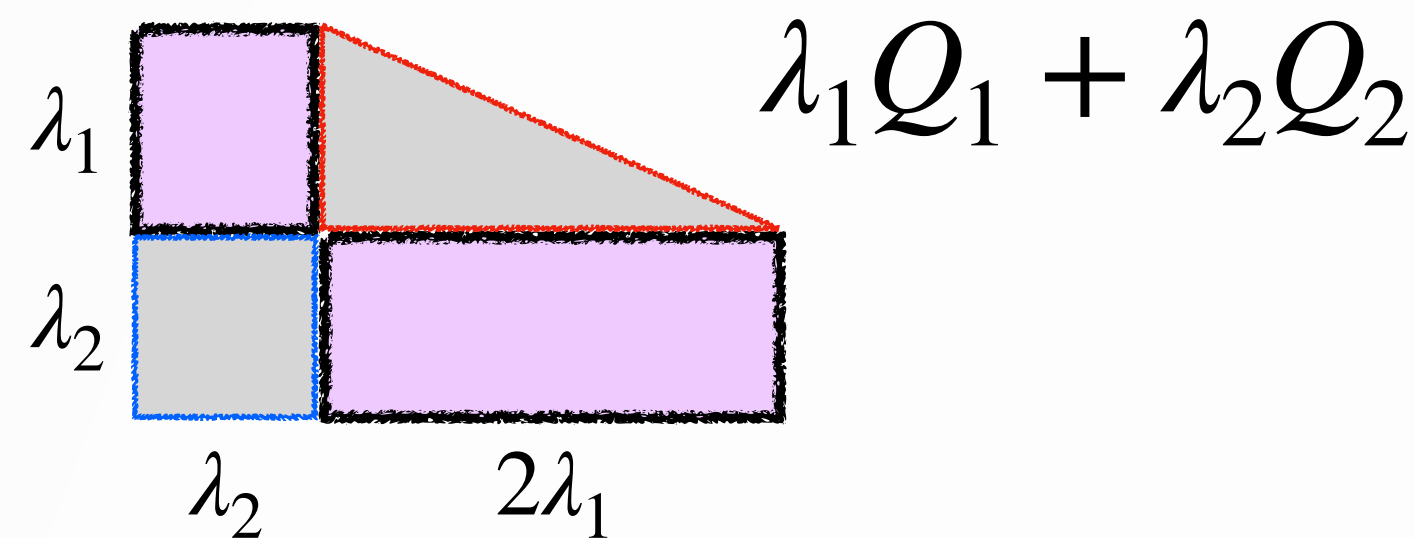
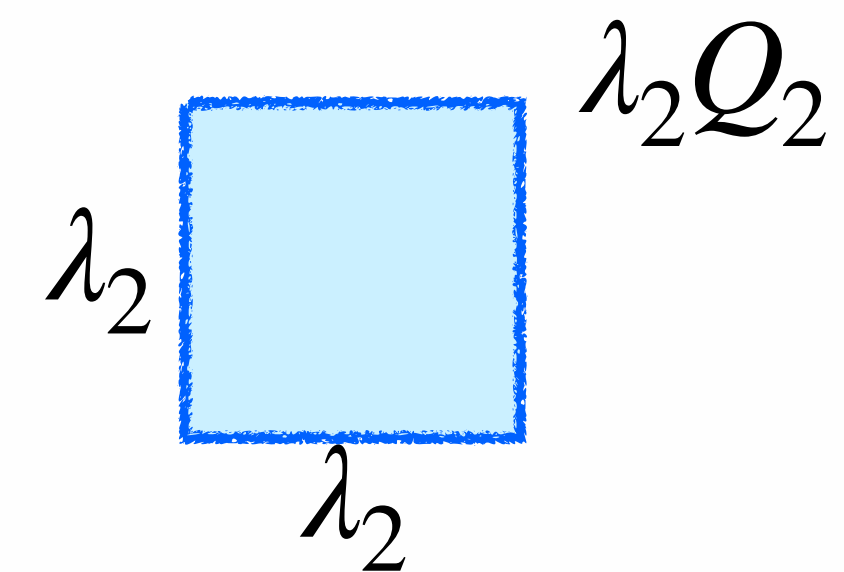
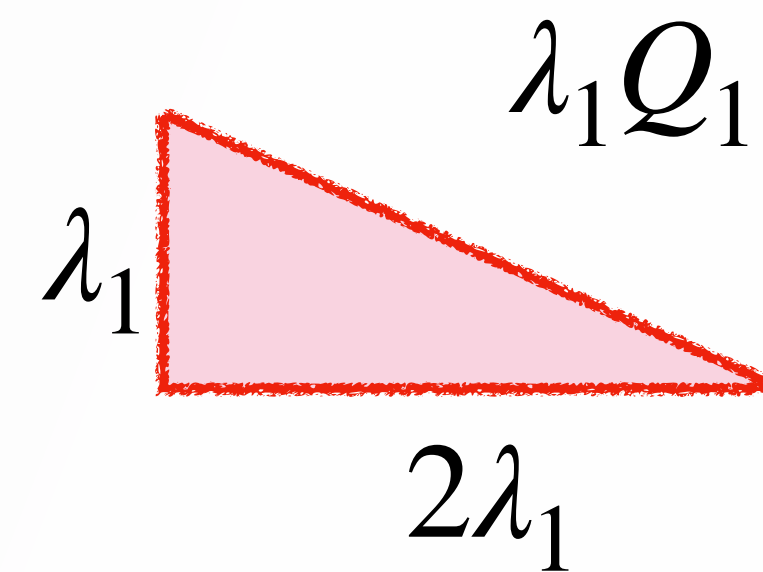
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# Bernstein Generic System

## The second part of Bernstein theorem

**Theorem [Bernstein 1975].**  $F := \{f_1, \dots, f_n\} \subset \mathbb{C}[x_1, \dots, x_n]$  : a square polynomial system.

$Q_i$  : the Newton polytope of  $f_i$ . Then,  $(\# \text{ isolated roots in } (\mathbb{C} \setminus \{0\})^n) \leq MV(Q_1, \dots, Q_n)$ .

The equality holds if and only if the **facial system**  $F^w := \{f_1^w, \dots, f_n^w\}$  has no solutions in  $(\mathbb{C} \setminus \{0\})^n$  for any weight vector  $w \in \mathbb{Z}^n$ .

When a system achieves the BKK bound, we say that the system is **Bernstein generic**.

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# Bernstein Generic System

## Facial system

$$f = \sum_{a \in A} c_a x^a \in \mathbb{C}[x_1, \dots, x_n]$$

a polynomial with the support  $A \subset \mathbb{Z}^n$ .

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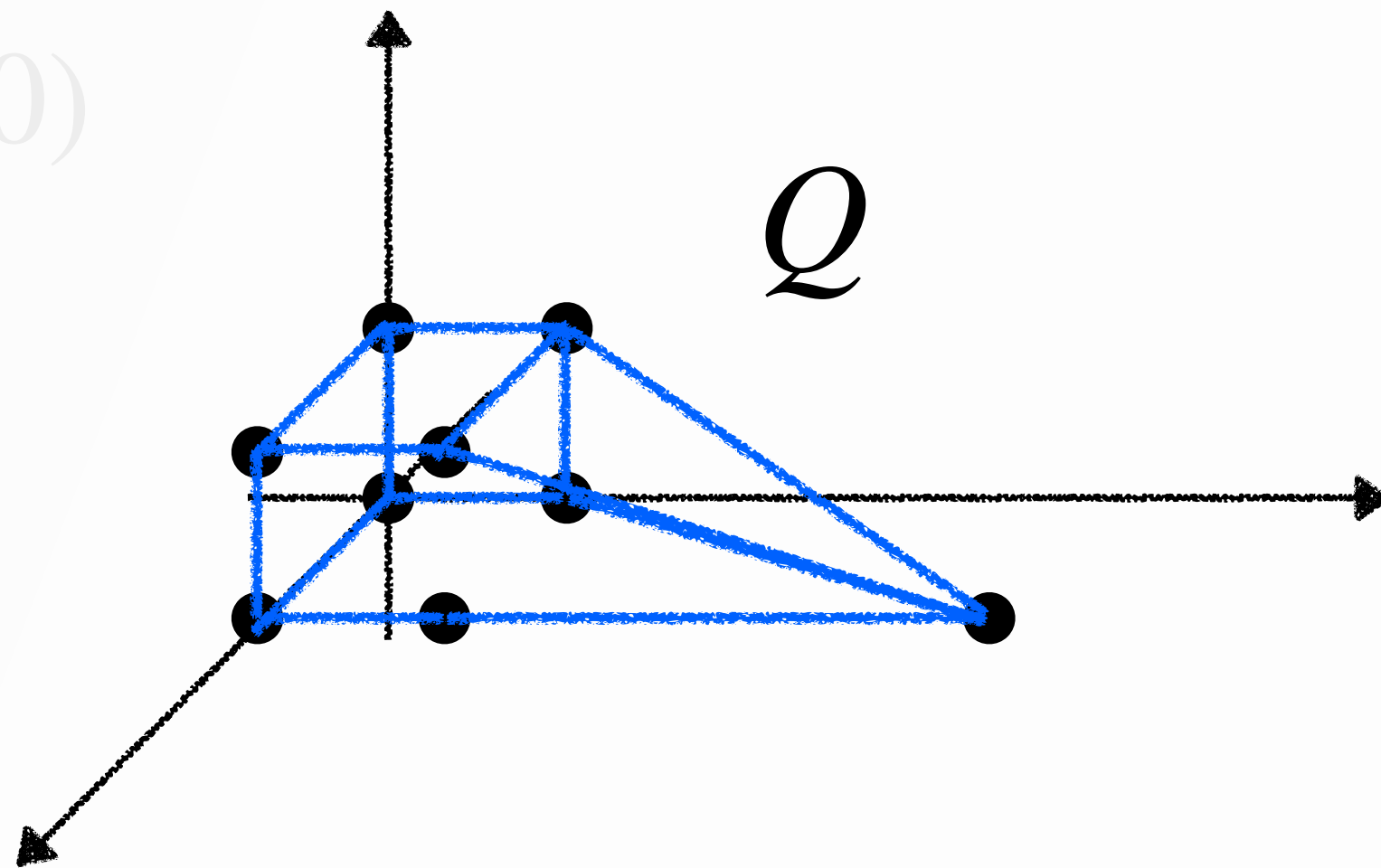
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**Example**  $f = c_1xy^4 + c_2xyz + c_3xy + c_4yz + c_5xz + c_6x + c_7y + c_8z + c_9$ .

$$w = (-1, 0, 0)$$

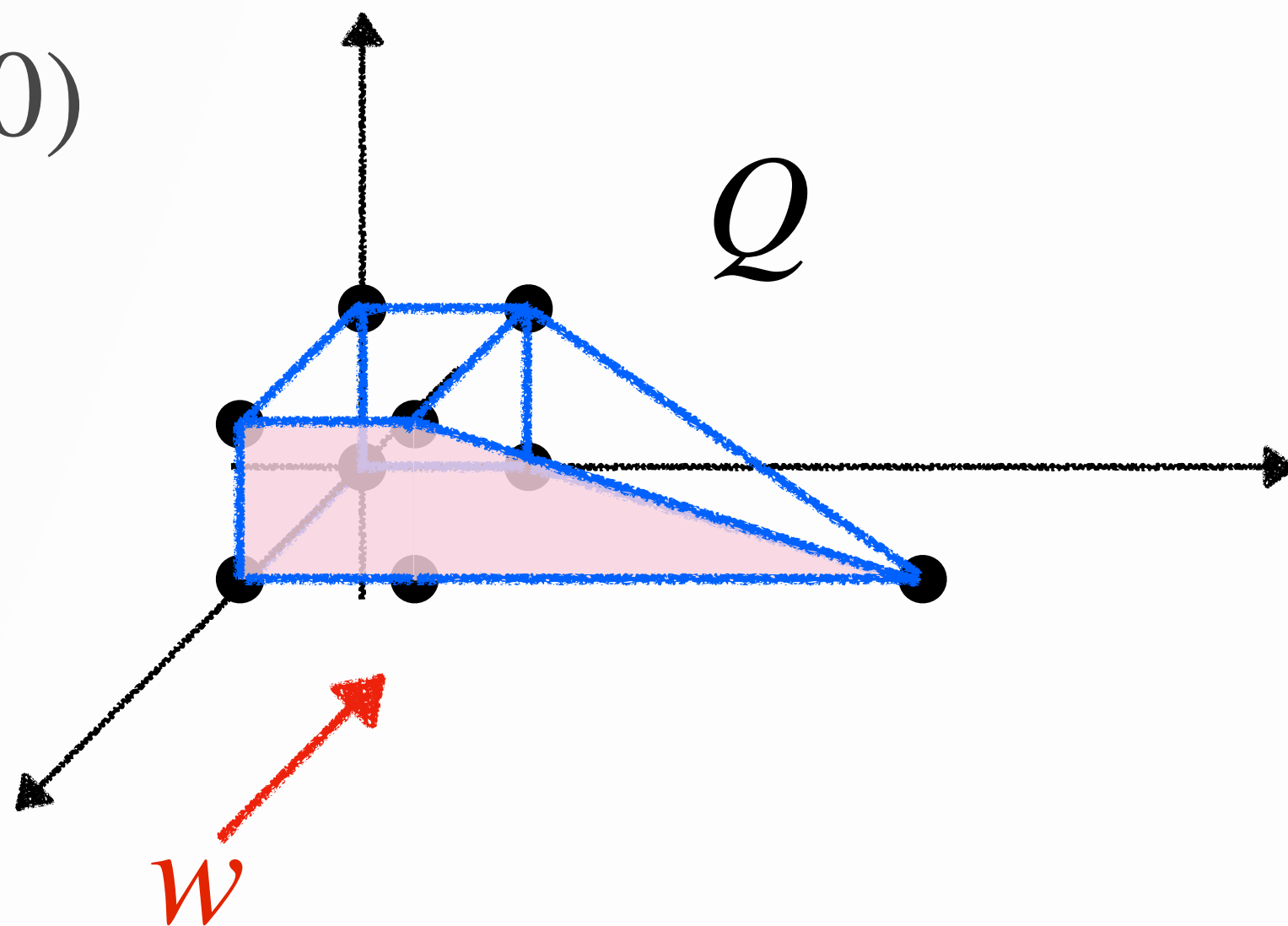


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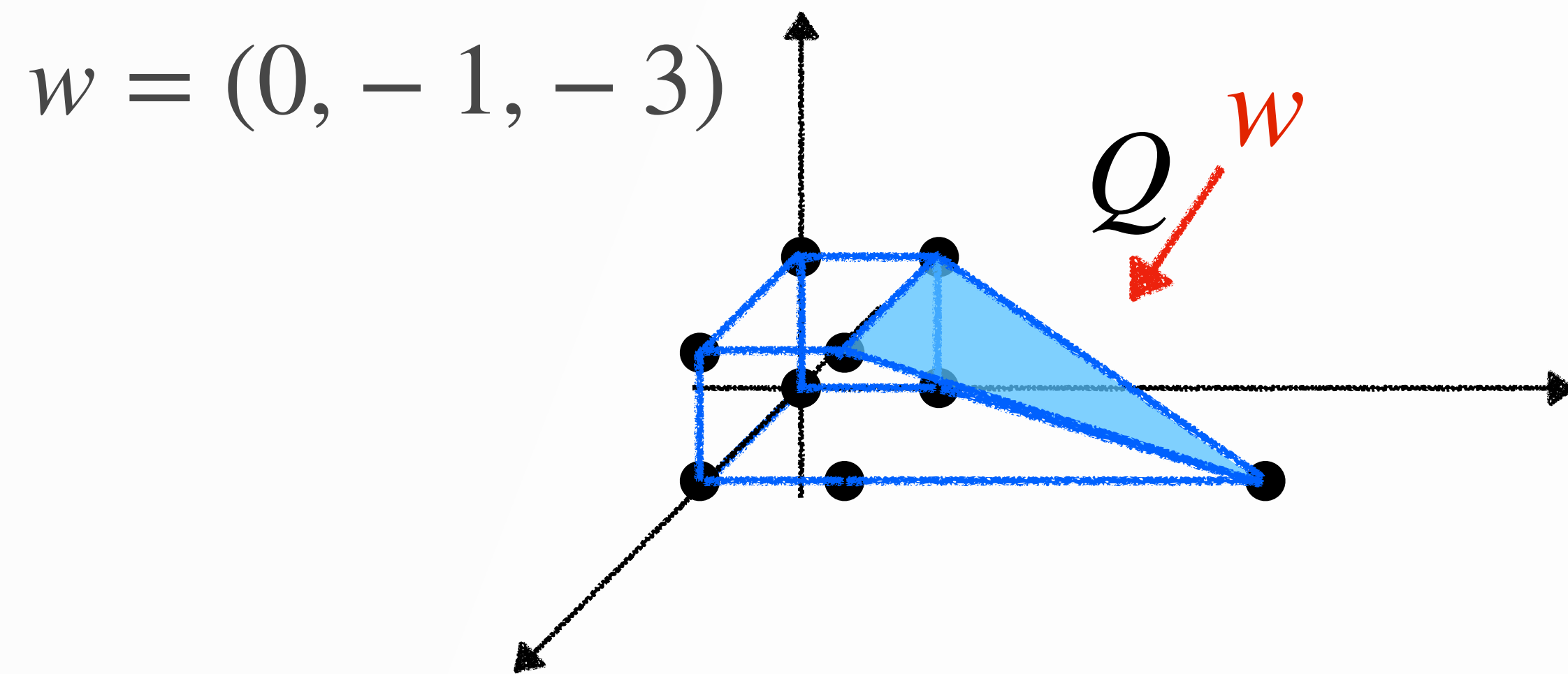
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$$f^w = c_1xy^4 + c_2xyz + c_4yz$$



# Solving KKT System

**Theorem [L.-Tang].** Suppose that for each  $i = 1, \dots, N$ , polynomials  $f_i$  and  $g_{i,j}$  are generic for all  $j = 1, \dots, m_i$ . Then the KKT system  $F = \{F_1, \dots, F_N\}$  is Bernstein general.

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# Selecting GNEs from KKT Points

$\mathcal{K}_{\mathbb{C}}$  : the set of KKT points  $(x, \lambda)$  obtained by the homotopy method.

$\mathcal{K}$  : the set of real KKT points with  $\lambda \geq 0$  and  $g_{i,j}(x) \geq 0$ .

$$\mathcal{K} = \{(x, \lambda) \in \mathcal{K}_{\mathbb{C}} \cap \mathbb{R}^N \mid \lambda_{i,j} \geq 0, g_{i,j}(x) \geq 0\}$$

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For  $u = (u_1, \dots, u_N) \in \mathcal{P}$ , consider the following optimization problem:

$$\left\{ \begin{array}{ll} \delta_i := \min_{x_i \in \mathbb{R}^{n_i}} & f_i(x_i, u_{-i}) - f_i(u_i, u_{-i}) \\ \text{s.t.} & g_{i,j}(x_i, u_{-i}) = 0 \quad \text{if } j \in \mathcal{E}_i \\ & g_{i,j}(x_i, u_{-i}) \geq 0 \quad \text{if } j \in \mathcal{J}_i \end{array} \right.$$

If  $u$  is a GNE, then each  $u_i$  is a minimizer.

We solve the optimization problem using the moment-SOS relaxation.

# Experiments

## Example 1) Non-convex Problem

$$\begin{aligned} \text{1st player : } & \begin{cases} \min_{x_1 \in \mathbb{R}^2} & 3x_{2,1}(x_{1,1})^3 + 5(x_{1,2})^3 - 2 \sum_{j=1}^2 x_{1,j} \cdot \sum_{j=1}^2 x_{2,j} \\ \text{s.t.} & 5x_{1,1} - 2x_{1,2} + 3x_{2,2} - 1 \geq 0, \quad 3 - x_{2,1} \cdot x_1^T x_1 \geq 0, \\ & x_{1,1} \geq -2, \quad x_{1,2} \geq 1; \end{cases} \\ \text{2nd player : } & \begin{cases} \min_{x_2 \in \mathbb{R}^2} & (2x_{1,1} + 3x_{1,2})(x_{2,1})^3 - 3x_{2,1} + 7(x_{2,2})^2 + 5x_{1,1}x_{1,2}x_{2,2} \\ \text{s.t.} & 7x_{1,2} + 3x_{2,2} - 5x_{2,1}^2 + 3 \geq 0, \quad 2x_{2,1} \geq -1, \\ & 2 - x_{2,2} \geq 0, \quad 5 + x_{2,2} \geq 0. \end{cases} \end{aligned}$$

The KKT system has the mixed volume 480, Solving using `HomotopyContinuation.jl`, it 480 KKT points and gives a unique GNE in 5.75 seconds (4 seconds to compute KKT points, 1.75 seconds for selecting).

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# Experiments

## Example 2) Convex Problem

Example A.3 of **[Facchinei-Kanzow 2010]**

A 3-player game with objectives  $f_i = \frac{1}{2}x_i^\top A_i x_i + x_i^\top (B_i x_{-i} + b_i)$  where

$$A_1 = \begin{bmatrix} 20 & 5 & 3 \\ 5 & 5 & -5 \\ 3 & -5 & 15 \end{bmatrix}, A_2 = \begin{bmatrix} 11 & -1 \\ -1 & 9 \end{bmatrix}, A_3 = \begin{bmatrix} 48 & 39 \\ 39 & 53 \end{bmatrix},$$

$$B_1 = \begin{bmatrix} -6 & 10 & 11 & 20 \\ 10 & -4 & -17 & 9 \\ 15 & 8 & -22 & 21 \end{bmatrix}, B_2 = \begin{bmatrix} 20 & 1 & -3 & 12 & 1 \\ 10 & -4 & 8 & 16 & 21 \end{bmatrix}, B_3 = \begin{bmatrix} 10 & -2 & 22 & 12 & 16 \\ 9 & 19 & 21 & -4 & 20 \end{bmatrix}, b_1 = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}, b_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, b_3 = \begin{bmatrix} -1 \\ 2 \end{bmatrix}.$$

Constraints are given  $-10 \leq x \leq 10$ ,  $g_{1,1} = 20 - x_{1,1} - x_{1,2} - x_{1,3} \geq 0$ ,  $g_{1,2} = x_{2,1} - x_{3,2} - x_{1,1} - x_{1,2} + x_{1,3} + 5 \geq 0$ ,

$g_{2,1} = x_{1,2} + x_{1,3} - x_{3,1} - x_{2,1} + x_{2,2} + 7 \geq 0$ ,  $g_{3,1} = x_{1,1} + x_{1,3} - x_{2,1} - x_{3,2} + 4 \geq 0$ .

# Experiments

## Example 2) Convex Problem

Example A.3 of **[Facchinei-Kanzow 2010]**

The mixed volume : 12096

Solution found : 11631 KKT points

GNE found : 5 GNEs found with 4 newly found

Elapsed time : 177 seconds

# Experiments

## Comparison

Comparison with known methods on Example 1) and 2) :

Interior point method (**Dreves-Facchinei-Kanzow-Sagratella 2011**)

Augmented Lagrangian method (**Kanzow-Steck 2016**)

Gauss-Seidel method (**Nie-Tang-Xu 2021**)

Semidefinite relaxation (**Nie-Tang 2021**)

# Experiments

## Comparison

**IPM** : Interior point method, **ALM** : Augmented Lagrangian method, **GSM** : Gauss-Seidel method, **SDP** : Semidefinite relaxation, **PHC** : Solved by using the polyhedral homotopy method (`HomotopyContinuation.jl`)

		IPM	ALM	GSM	SDP	PHC
Example 1)	Time	Fail	Fail	11.47	17.89	5.75
	Error			$4 \cdot 10^{-7}$	$1 \cdot 10^{-6}$	$2 \cdot 10^{-8}$
Example 2)	Time	3.12	1.50	Fail	11.55	177
	Error	$2 \cdot 10^{-7}$	$1 \cdot 10^{-7}$		$2 \cdot 10^{-7}$	$1 \cdot 10^{-6}$ (5 GNEs)

# Experiments

## Example 3) Random nonconvex GNEP

Consider  $N$ -player GNEP whose  $i$ -th player's optimization problem is

$$\begin{cases} \min_{x_i \in \mathbb{R}^{n_i}} & f_i(x_i, x_{-i}) \\ \text{s.t.} & -x_i^\top A_i x_i + x_{-i}^\top B_i x_i + c_i^\top x \geq d_i \end{cases}$$

where  $A_i = R_i^\top R_i$  with randomly generated  $R_i \in \mathbb{R}^{n_i \times n_i}$  and  $B_i \in \mathbb{R}^{n_i \times (n - n_i)}$ ,  $c_i \in \mathbb{R}^n$ ,  $d_i \in \mathbb{R}$ .

The objective  $f_i$  is a dense polynomial of degree  $d$  with randomly generated real coefficients.

For various  $(d, N, n_i)$ -values, solve the problem 100 times and record the success rate (for finding mixed volume many KKT points) and elapsed time (solving KKT + selecting GNEs).

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# Experiments

## Example 3) Random nonconvex GNEP

$d$	$N$	$n_i$	Mixed volume	Success rate	Average time
2	2	2	25	100 %	0.0563 + 1.1330
	2	3	49	100 %	0.1802 + 1.5098
	3	2	125	100 %	0.8473 + 3.1890
3	2	2	100	100 %	0.1893 + 2.5667
	2	3	484	100 %	2.1800 + 5.7500
	3	2	1000	97 %	5.2550 + 14.4360
4	2	2	289	100 %	0.8270 + 4.4256
	2	3	2809	95 %	24.5330 + 21.9054
	3	2	4913	95 %	44.0899 + 40.6792

**Thank you for your attention**