

# Solving multivariate polynomial systems (Assignment 2)

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In this paper, we will develop mathematical theories and algorithms for the following problem.

**In:**  $f \in \mathbb{C}[x_1, \dots, x_n]^n$

**Out:**  $S \subset \mathbb{C}^n$ , the set of complex solutions of  $f$ .

## 1 Solving by Multiplication Matrix (Pham systems)

### 1.1 Theory

**Definition 1 (Pham system)** A system  $f \in \mathbb{C}[x_1, \dots, x_n]^n$  is called a Pham system if it has the following form:

$$\begin{aligned} f_1 &= x_1^{d_1} + \sum_{e_1 + \dots + e_n < d_1} a_{1,e} x_1^{e_1} \cdots x_n^{e_n} \\ &\vdots \\ f_n &= x_n^{d_n} + \sum_{e_1 + \dots + e_n < d_n} a_{n,e} x_1^{e_1} \cdots x_n^{e_n} \end{aligned}$$

**Definition 2 (Monomial Basis)** The monomial basis for  $(d_1, \dots, d_n)$  is given by

$$\omega = [x_1^{e_1} \cdots x_n^{e_n} : 0 \leq e_1 < d_1, \dots, 0 \leq e_n < d_n]$$

They are ordered in the decreasing order in the total degree where  $x_n > x_{n-1} > \dots > x_1$ .

**Definition 3 (Multiplication matrix)** Let  $g \in \mathbb{C}[x_1, \dots, x_n]$ . Then the multiplication matrix  $M_g$  for  $g$  is defined by

$$g \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_m \end{bmatrix} \equiv_f M_g \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_m \end{bmatrix}$$

**Theorem 4** Let  $g \in \mathbb{C}[x_1, \dots, x_n]$  be random. Let  $V$  be the set of all the eigenvectors of  $M_g$ . Then, with probability one, we have

$$S = \{[v_{m-1}/v_m, \dots, v_{m-n}/v_m] : v \in V\}$$

**Proof.** Let  $f(z) = 0$ , and by Theorem 9 in project 1, we know that  $\left\{ \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_m \end{bmatrix} : f(z_i) = 0 \right\}$  spans  $M_g$ .

Given that  $g$  is random, for all  $i \neq j$ ,  $g(z_i) \neq g(z_j)$ , then we get that  $\begin{bmatrix} v_1 \\ \vdots \\ v_m \end{bmatrix} = v_m \begin{bmatrix} \omega_1(z_i) \\ \vdots \\ \omega_m(z_i) \end{bmatrix}$  Observe that

$x_n > x_{n-1} > \dots > x_1$ ,  $\omega_m = 1$ , thus we get  $\begin{bmatrix} v_1/v_m \\ \vdots \\ 1 \end{bmatrix} = v_m \begin{bmatrix} \omega_1(z_i) \\ \vdots \\ \omega_m(z_i) \end{bmatrix}$  Hence with probability one, we get  $S = \{[v_{m-1}/v_m, \dots, v_{m-n}/v_m] : v \in V\}$  ■

## 1.2 Algorithms

### Algorithm 5 (MulMat)

**In:**  $f \in \mathbb{C}[x_1, \dots, x_n]^n$  a Pham system,  $g \in \mathbb{C}[x_1, \dots, x_n]$

**Out:**  $M$ , the multiplication matrix of  $g$  modulo  $f$

1.  $\omega =$  Monomial Basis of function  $f$
2.  $n =$  number of omegas
3.  $M = \text{Remainder}(g\omega_i, \omega_j)$  with size  $n \times n$
4. Return  $M$

### Algorithm 6 (SolveByMulMat)

**In:**  $f \in \mathbb{C}[x_1, \dots, x_n]^n$  a Pham system,  $g \in \mathbb{C}[x_1, \dots, x_n]$  random linear

**Out:**  $S \subset \mathbb{C}^n$ , the set of complex solutions of  $f$ .

1.  $M = \text{MultMat}(fs, vs, g)$
2.  $E = \text{Eigenvalue}(M)$
3.  $S = E[i - k][j]/E[i][j]$  with  $k = 1 \dots n$
4. Return  $S$

## 2 Solving by Univariate Resultant (General systems)

### 2.1 Theory

**Definition 7 (Sylvester matrix)** Let  $f = \sum_{i=0}^m a_i x^i, g = \sum_{i=0}^n b_i x^i \in \mathbb{C}[x]$ , where  $a_m = b_n \neq 0$ . Then the Sylvester matrix  $S$  of  $f, g$  is defined as

$$S = \begin{bmatrix} a_m & a_{m-1} & \cdots & \cdots & a_0 & & & \\ & \ddots & \ddots & & & \ddots & & \\ & & a_m & a_{m-1} & \cdots & \cdots & a_0 & \\ b_n & b_{n-1} & \cdots & b_0 & & & & \\ & \ddots & \ddots & & \ddots & & & \\ & & \ddots & \ddots & & \ddots & & \\ & & & b_n & b_{n-1} & \cdots & b_0 & \end{bmatrix}$$

where there are  $n$  rows of the coefficients of  $f$  and  $m$  rows of the coefficients of  $g$ .

**Definition 8 (Subresultant)** The  $k$ -th subresultant of  $f$  and  $g$  with respect to  $x$ , written as  $R_{x,k}(f, g)$  is defined as

$$R_{x,k}(f, g) = \sum_{i=0}^k |S_{k,i}| x^i$$

where  $S_{k,i}$  is the submatrix of the Sylvester matrix  $S$ , consisting of

1. the first  $n - k$  rows of the coefficients of  $f$
2. the first  $m - k$  rows of the coefficients of  $g$
3. the first  $n + m - 2k - 1$  columns and the  $n + m - k - i$ -th column

**Theorem 9** Let  $f = a_m(x - \alpha_1) \cdots (x - \alpha_m)$  and  $g = b_n(x - \beta_1) \cdots (x - \beta_n)$ . Then we have

$$R_{x,0}(f, g) = a_m^n b_n^m \prod_{i,j} (\alpha_i - \beta_j)$$

**Proof.** For the sake of simple presentation of the proof idea, let us consider  $\deg f = 3$  and  $\deg g = 2$ . The idea can be easily generalize to arbitrary degrees.

Let  $|V| \neq 0$ , then we get the Sylvester matrix

$$\begin{bmatrix} a_3 & a_2 & a_1 & a_0 & 0 \\ 0 & a_3 & a_2 & a_1 & 0 \\ b_2 & b_1 & b_0 & 0 & 0 \\ 0 & b_2 & b_1 & b_0 & 0 \\ 0 & 0 & b_2 & b_1 & b_0 \end{bmatrix}$$

then from class, we are given the matrix

$$\begin{bmatrix} a_3 & a_2 & a_1 & a_0 & 0 \\ 0 & a_3 & a_2 & a_1 & 0 \\ b_2 & b_1 & b_0 & 0 & 0 \\ 0 & b_2 & b_1 & b_0 & 0 \\ 0 & 0 & b_2 & b_1 & b_0 \end{bmatrix} \begin{bmatrix} 1 & a_1^4 & \dots & a_3^4 \\ & 1 & a_1^3 & \dots & a_3^3 \\ & & a_1^2 & \dots & a_3^2 \\ & & a_1^1 & \dots & a_3^1 \\ & & a_1^0 & \dots & a_3^0 \end{bmatrix} = \begin{bmatrix} a_3 & a_2 & \alpha_1^1 f(\alpha_1) & \dots & \alpha_3^0 f(\alpha_3) \\ 0 & a_3 & \alpha_1^0 f(\alpha_1) & \dots & \alpha_3^0 f(\alpha_3) \\ b_2 & b_1 & \alpha_1^2 g(\alpha_1) & \dots & \alpha_3^2 g(\alpha_3) \\ 0 & b_2 & \alpha_1^1 g(\alpha_1) & \dots & \alpha_3^1 g(\alpha_3) \\ 0 & 0 & \alpha_1^0 g(\alpha_1) & \dots & \alpha_3^0 g(\alpha_3) \end{bmatrix}$$

Since  $\alpha$  is the roots of  $f$ , we have

$$\begin{bmatrix} a_3 & a_2 & 0 & \dots & 0 \\ 0 & a_3 & 0 & \dots & 0 \\ b_2 & b_1 & \alpha_1^2 g(\alpha_1) & \dots & \alpha_3^2 g(\alpha_3) \\ 0 & b_2 & \alpha_1^1 g(\alpha_1) & \dots & \alpha_3^1 g(\alpha_3) \\ 0 & 0 & \alpha_1^0 g(\alpha_1) & \dots & \alpha_3^0 g(\alpha_3) \end{bmatrix}$$

thus

$$|\text{LHS}| = |S||V|$$

and

$$|\text{RHS}| = \alpha_3^2 \begin{bmatrix} \alpha_1^2 g(\alpha_1) & \dots & \alpha_3^2 g(\alpha_3) \\ \alpha_1^1 g(\alpha_1) & \dots & \alpha_3^1 g(\alpha_3) \\ \alpha_1^0 g(\alpha_1) & \dots & \alpha_3^0 g(\alpha_3) \end{bmatrix} \cdot |V| = a_3^2 g(\alpha_1) \dots g(\alpha_3) \begin{bmatrix} \alpha_1^2 & \dots & \alpha_3^2 \\ \alpha_1^1 & \dots & \alpha_3^1 \\ \alpha_1^0 & \dots & \alpha_3^0 \end{bmatrix} = a_3^2 g(\alpha_1) \dots g(\alpha_3) |V|$$

. Hence

$$|S| = a_3^2 b_2 (\alpha_1 - \beta_1) \dots (\alpha_1 - \beta_2)$$

⋮

$$\begin{aligned} & b_2(\alpha_3 - \beta_1) \dots (\alpha_3 - \beta_2) \\ &= a_3^2 b_2^3 \prod_{i,j} (\alpha_i - \beta_j) \end{aligned}$$

■

**Theorem 10**  $R_{x,k} \in \langle f, g \rangle$ .

**Proof.** For the sake of simple presentation of the proof idea, let us consider  $\deg f = 3$  and  $\deg g = 2$  and  $k = 1$ . Consider the Sylvester matrix

$$\begin{bmatrix} a_3 & a_2 & a_1 & a_0 & 0 \\ 0 & a_3 & a_2 & a_1 & 0 \\ b_2 & b_1 & b_0 & 0 & 0 \\ 0 & b_2 & b_1 & b_0 & 0 \\ 0 & 0 & b_2 & b_1 & b_0 \end{bmatrix}$$

Using the sub-resultant elimination method we get the matrix

$$\begin{aligned} \begin{bmatrix} a_3 & a_2 & a_1 \\ b_2 & b_1 & b_0 \\ 0 & b_2 & b_1 \end{bmatrix} x^1 + \begin{bmatrix} a_3 & a_2 & a_0 \\ b_2 & b_1 & 0 \\ 0 & b_2 & b_1 \end{bmatrix} x^0 &= \begin{bmatrix} a_3 & a_2 & a_1 x^1 + a_0 x^0 \\ b_2 & b_1 & b_0 x^1 \\ 0 & b_2 & b_1 x^1 + b_0 x^0 \end{bmatrix} = \begin{bmatrix} a_3 & a_2 & a_3 x^3 + a_2 x^2 + a_1 x^1 + a_0 x^0 \\ b_2 & b_1 & b_2 x^3 + b_1 x^2 + b_0 x^1 \\ 0 & b_2 & b_2 x^2 + b_1 x^1 + b_0 x^0 \end{bmatrix} \\ &= \begin{bmatrix} a_3 & a_2 & 1 \\ b_2 & b_1 & 0 \\ 0 & b_2 & b_1 \end{bmatrix} f + \begin{bmatrix} a_3 & a_2 & 0 \\ b_2 & b_1 & x \\ 0 & b_2 & 1 \end{bmatrix} g \in \langle f, g \rangle \end{aligned}$$

■

**Definition 11 (Triangular form)** For the sake of simplicity, we will define it for  $n = 4$ . The triangular form of  $f$  is defined as

$$\tilde{f} = (\tilde{f}_1, \dots, \tilde{f}_4)$$

where

$$\begin{aligned} \tilde{f}_1 &= R_{x_1,1}(f_1, f_2) \\ \tilde{f}_2 &= R_{x_2,1}(f_{12}, f_{13}) \\ \tilde{f}_3 &= R_{x_3,1}(f_{23}, f_{24}) \\ \tilde{f}_4 &= f_{34} \end{aligned}$$

where again

$$\begin{aligned} f_{12} &= R_{x_1,0}(f_1, f_2) \\ f_{13} &= R_{x_1,0}(f_1, f_3) & f_{23} &= R_{x_2,0}(f_{12}, f_{13}) \\ f_{14} &= R_{x_1,0}(f_1, f_4) & f_{24} &= R_{x_2,0}(f_{12}, f_{14}) & f_{34} &= R_{x_3,0}(f_{23}, f_{24}) \end{aligned}$$

**Definition 12 (Near-diagonal form)** The near diagonal form of  $f$  is defined as  $u \in \mathbb{C}[x_n]$  and  $p \in \mathbb{C}(t)^n$  obtained from back-substitution from  $\tilde{f}$  so that

$$\begin{aligned} u &= \tilde{f}_n \\ x_1 &= p_1(x_n) \\ &\vdots \\ x_{n-1} &= p_{n-1}(x_n) \end{aligned}$$

**Theorem 13** Let  $f \in \mathbb{C}[x_1, \dots, x_n]^n$  and let  $g \in \mathbb{C}[x_1, \dots, x_n]$  be random linear. Let  $u \in \mathbb{C}[t]$  and  $p \in \mathbb{C}(t)^n$  be the near-diagonal form of  $(f_1, \dots, f_n, g - t)$ . Then we have

$$S \subset \{p(t) : u(t) = 0\}$$

**Proof.** Fill in..... ■

## 2.2 Algorithm

### Algorithm 14 (Triangularize)

**In:**  $f \in \mathbb{C}[x_1, \dots, x_n]^n$

**Out:**  $f_t \in \mathbb{C}[x_1, \dots, x_n]^n$ , triangular form of  $f$

1.  $n = \text{number of equations}$
2.  $ft = \text{list of resultant}$
3.  $ft[i] = R_{x_1}(f_1, f_2)(x_2, x_3)$
4.  $ft[i + 1] = R_{x_1}(f_1, f_3)(x_2, x_3)$
5. Repeat resultant  $n$  times
6. Return  $ft$

### Algorithm 15 (Near-diagonalize)

**In:**  $f \in \mathbb{C}[x_1, \dots, x_n]^n$

**Out:**  $f_t \in \mathbb{C}[x_1, \dots, x_n]^n$ , near-diagonal form of  $f$

1.  $ft = \text{Triangularize}(fs, vs)$
2. Solve for  $g_n(x_n)$
3. Back substitute  $g_1, g_2, \dots, g_{n-1}$
4. Return list of  $g$

### Algorithm 16 (SolveByUniRes)

**In:**  $f \in \mathbb{C}[x_1, \dots, x_n]^n$ ,  $g \in \mathbb{C}[x_1, \dots, x_n]$  random linear

**Out:**  $S \subset \mathbb{C}^n$ , the set of complex solutions of  $f$  (possibly with extraneous ones)

1.  $g = \text{NearDiagonalize}(f)$
2.  $t = \text{solution of } g$
3.  $S = \text{back substitution of } t$
4. Return  $S$

### 3 Solving by Multivariate Resultant (General systems)

#### 3.1 Theory

**Definition 17 (Macaulay matrix)** Let  $f \in \mathbb{C}[x_1, \dots, x_n]^{n+1}$ . Let

1.  $D = (d_1 - 1) + \dots + (d_{n+1} - 1) + 1$  where  $d_i = \deg f_i$
2.  $T = \{x^e : |e| \leq D\}$ , ordered in the decreasing order in the total degree where  $x_n > x_{n-1} > \dots > x_1$ .
3.  $T_1 = \{t \in T : x_1^{d_1} | t\}$   
 $T_2 = \{t \in T \setminus T_1 : x_2^{d_2} | t\}$   
 $\vdots$   
 $T_n = \{t \in T \setminus T_1 \setminus \dots \setminus T_{n-1} : x_n^{d_n} | t\}$   
 $T_{n+1} = T \setminus T_1 \setminus \dots \setminus T_n$

The Macaulay matrix  $M$  of  $f$  is defined such that

$$\begin{bmatrix} T_1/x_1^{d_1} & f_1 \\ \vdots & \\ T_n/x_n^{d_n} & f_n \\ T_{n+1} & f_{n+1} \end{bmatrix} = M \begin{bmatrix} T_1 \\ \vdots \\ T_n \\ T_{n+1} \end{bmatrix}$$

**Theorem 18** If  $f$  has a common solution then  $|M| = 0$ .

**Proof.** Fill in..... ■

**Definition 19 (Eigen matrix)** Let  $f \in \mathbb{C}[x_1, \dots, x_n]^n$  and  $g \in \mathbb{C}[x_1, \dots, x_n]$ . Let  $M$  be the Macaulay matrix of  $(f_1, \dots, f_n, g)$ . Let  $M = \begin{bmatrix} A & B \\ C & D \end{bmatrix}$  where  $D$  is square with  $d_1 \dots d_n$ . The Eigen-matrix  $E$  of  $g$  modulo  $f$  is defined by  $E = -CA^{-1}B + D$ .

**Theorem 20** Let  $g \in \mathbb{C}[x_1, \dots, x_n]$  be random linear. Let  $E$  be the eigen-matrix of  $g$  modulo  $f$ . Let  $V$  be the set of all the eigenvectors of  $E$ . Then, with probabilities one, we have

$$S = \{[v_{m-1}/v_m, \dots, v_{m-n}/v_m] : v \in V\}$$

**Proof.** From class we proved that  $T_n(\alpha)$  is an eigenvector of  $E$  and we obtain the result

$$\begin{bmatrix} \vdots \\ v_{m-1} \\ v_m \end{bmatrix} \propto \begin{bmatrix} \vdots \\ \alpha_1 \\ 1 \end{bmatrix}$$

Hence  $\alpha_1 = v_{m-1}/v_m, \alpha_2 = v_{m-2}/v_m \dots \alpha_n = v_{m-n}/v_m$ , and we get

$$S = \{v_{m-1}/v_m, \dots, v_{m-n}/v_m\}$$

■

### 3.2 Algorithm

#### Algorithm 21 (Macaulay matrix)

**In:**  $f \in \mathbb{C}[x_1, \dots, x_n]^{n+1}$

**Out:** *The Macaulay matrix of  $f$*

1.  $D = \text{number of partition}$
2.  $D = (\deg f_1 - 1) + \dots (\deg f_n - 1) + 1$
3.  $\omega = \text{MonToDeg}(D)$
4. *Partition  $\omega$  into  $T_1, \dots, T_n$*
5. *Construct matrix  $M$  from  $T_1, \dots, T_n$*
6. *Return  $M$*

#### Algorithm 22 (Eigen matrix)

**In:**  $f \in \mathbb{C}[x_1, \dots, x_n]^n$ ,  $g \in \mathbb{C}[x_1, \dots, x_n]$

**Out:**  $E$ , *the eigen matrix of  $g$  modulo  $f$*

1.  $M = \text{MacaulayMatrix}(f)$
2.  $E = -CA^{-1}B + D$
3. *Return  $E$*

#### Algorithm 23 (SolveByMultiRes)

**In:**  $f \in \mathbb{C}[x_1, \dots, x_n]^n$ ,  $g \in \mathbb{C}[x_1, \dots, x_n]$  *random linear*

**Out:**  $S \subset \mathbb{C}^n$ , *the set of complex solutions of  $f$*

1.  $E = \text{EigenMatrix}(f)$
2.  $V = \text{eigenvectors of } E$
3.  $S = \{v_{m-1}/v_m, \dots, v_{m-n}/v_m\}$
4. *Return  $S$*