Linear Least-Squares Application in Chemical Kinetic Data

Becky Hanscam

University of Puget Sound Advanced Linear Algebra, Spring 2014



1 Chemical Perspective

- Elementary Reactions
- Arrhenius Equation

2 Least-Square Methods

- Preliminaries
- Normal Equations
- QR Decomposition
- Cholesky Factorization
- SVD

Elementary Reactions Arrhenius Equation





2 Least-Square Methods

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- Normal Equations
- QR Decomposition
- Cholesky Factorization
- SVD

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3 = 9 Q Q

Elementary Reactions Arrhenius Equation

Elementary Reactions

$A + B \rightarrow C + D$

$NO(g) + O_3(g) \rightarrow NO_2(g) + O_2(g)$

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Elementary Reactions Arrhenius Equation



Chemical Perspective Elementary Reactions

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Elementary Reactions Arrhenius Equation

Arrhenius Equation



Elementary Reactions Arrhenius Equation

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Elementary Reactions Arrhenius Equation

Arrhenius Equation

$$\ln k = \frac{-E_a}{R} \frac{1}{T} + \ln A$$
$$y = m x + b$$

Elementary Reactions Arrhenius Equation

Arrhenius Equation

$$\ln k = \frac{-E_a}{R} \frac{1}{T} + \ln A$$
$$y = m x + b$$

$$A = e^b = e^{\ln k}$$
$$E_a = -mR$$

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Elementary Reactions Arrhenius Equation

Arrhenius Equation

$$\ln k = \frac{-E_a}{R} \frac{1}{T} + \ln A$$
$$y = m x + b$$
$$\mathbf{k} = m \mathbf{T_0} + b$$

$A = e^b = e^{\ln k}$	
$E_2 = -mR$	
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Elementary Reactions Arrhenius Equation

Arrhenius Equation

$$\ln k = \frac{-E_a}{R} \frac{1}{T} + \ln A$$

$$y = m \times + b$$

$$\mathbf{k} = m \mathbf{T_0} + b$$

$$\begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} = \begin{bmatrix} t_1 & 1 \\ t_2 & 1 \\ \vdots & \vdots \\ t_n & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix}$$

$$A = e^b = e^{\ln k}$$
$$E_a = -mR$$

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Elementary Reactions Arrhenius Equation

Arrhenius Equation

$$\ln k = \frac{-E_a}{R} \frac{1}{T} + \ln A$$

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$$\mathbf{k} = T \mathbf{x}$$

$$A = e^{b} = e^{\ln k}$$
$$E_{a} = -mR$$

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Elementary Reactions Arrhenius Equation

Arrhenius Equation

Table : Temperature Dependence of the Rate Constant in the Formationof Nitrogen Dioxide and Oxygen Gas

Т (К)	$k (M^{-1}s^{-1})$	ln <i>k</i>	$rac{1}{T}$ (K ⁻¹)
300	$1.21 imes10^{10}$	23.216	$3.33 imes10^{-3}$
325	$1.67 imes10^{10}$	23.539	$3.08 imes10^{-3}$
350	$2.20 imes10^{10}$	23.841	$2.86 imes10^{-3}$
375	$2.79 imes10^{10}$	24.052	$2.67 imes10^{-3}$
400	$3.45 imes10^{10}$	24.264	$2.50 imes10^{-3}$
425	$4.15 imes10^{10}$	24.449	$2.35 imes10^{-3}$

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Elementary Reactions Arrhenius Equation

Arrenhius Equation

$$\begin{bmatrix} 3.33 \times 10^{-3} & 1\\ 3.08 \times 10^{-3} & 1\\ 2.86 \times 10^{-3} & 1\\ 2.67 \times 10^{-3} & 1\\ 2.50 \times 10^{-3} & 1\\ 2.35 \times 10^{-3} & 1 \end{bmatrix} \begin{bmatrix} m\\ b \end{bmatrix} = \begin{bmatrix} 23.216\\ 23.539\\ 23.841\\ 24.052\\ 24.264\\ 24.264\\ 24.449 \end{bmatrix}$$

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Preliminaries

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Preliminaries Normal Equations QR Decomposition Cholesky Factorization SVD

Preliminaries

Theorem

If T is size $m \times n$ with $m \ge n$, then T has full rank if and only if its columns form a linearly independent set.

$$T = \begin{bmatrix} t_1 & 1 \\ t_2 & 1 \\ \vdots & \vdots \\ t_n & 1 \end{bmatrix}$$

T has full rank.

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Normal Equations

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Normal Equations

Use when...

- no rounding errors
- speed is important

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Normal Equations

Use when...

no rounding errors

speed is important

Benefits:

- T can be any size
- T has full rank so x will always be unique

Image: A (1)

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Preliminaries Normal Equations QR Decomposition Cholesky Factorization SVD

Normal Equations

Theorem

The least-squares solution to $T\mathbf{x} = \mathbf{k}$ is also a solution to $T^*T\mathbf{x} = T^*\mathbf{k}$, the normal equations, where the function $r(\mathbf{x}) = ||T\mathbf{x} - \mathbf{k}||^2$ is minimized.

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Normal Equations

 $T^*T\mathbf{x} = T^*\mathbf{k}$

$$\begin{bmatrix} 4.7656 \times 10^{-5} & 0.01679 \\ 0.01679 & 6 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = \begin{bmatrix} 0.40025 \\ 143.334 \end{bmatrix}$$

 $m = -1256.73203263 \Rightarrow E_a = 10.44847012 \frac{kJ}{mol} \\ b = 27.405755138 \Rightarrow A = 7.983038593 \times 10^{11}$

QR Decomposition

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Preliminaries Normal Equations **QR Decomposition** Cholesky Factorization SVD

QR Decomposition via the Gram-Schmidt Procedure

Use when...

- rounding errors are present
- speed is not important

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Preliminaries Normal Equations **QR Decomposition** Cholesky Factorization SVD

QR Decomposition via the Gram-Schmidt Procedure

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Preliminaries Normal Equations **QR Decomposition** Cholesky Factorization SVD

QR Decomposition via the Gram-Schmidt Procedure

Theorem

Suppose that T is an $m \times n$ matrix of rank n. Then there exists an $m \times n$ matrix Q whose columns form an orthonormal set, and an upper-triangular matrix R of size n with positive diagonal entries, such that T = QR.

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QR Decomposition

 $\begin{aligned} \mathcal{T} &= [\mathbf{t}_1 | \mathbf{t}_2] \\ &= [\mathbf{u}_1 | \mathbf{u}_2] \begin{bmatrix} 1 & \frac{-\mathbf{t}_1^* \mathbf{t}_2}{\mathbf{t}_1^* \mathbf{t}_1} \\ 0 & 1 \end{bmatrix}^{-1} \\ &= [\mathbf{q}_1 | \mathbf{q}_2] \begin{bmatrix} \frac{1}{\|\mathbf{u}_1\|} & \frac{-\mathbf{t}_1^* \mathbf{t}_2}{\mathbf{t}_1^* \mathbf{t}_1} \\ 0 & \frac{1}{\|\mathbf{u}_2\|} \end{bmatrix}^{-1} \\ &= QR \end{aligned}$

Gram-Schmidt on \boldsymbol{t}_1 and \boldsymbol{t}_2

 \boldsymbol{u}_1 and \boldsymbol{u}_2 scaled by their norm

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QR Decomposition via the Gram-Schmidt Procedure

$$T = \begin{bmatrix} 0.4824 & -0.5954 \\ 0.4462 & -0.2926 \\ 0.4143 & -0.0262 \\ 0.3868 & 0.2039 \\ 0.3621 & 0.4098 \\ 0.3404 & 0.5914 \end{bmatrix} \begin{bmatrix} 6.9034 \times 10^{-3} & 2.4322 \\ 0 & 0.2909 \end{bmatrix} = QR$$

Preliminaries Normal Equations **QR Decomposition** Cholesky Factorization SVD

QR Decomposition via the Gram-Schmidt Procedure

From the normal equations: $R\mathbf{x} = Q^*\mathbf{k}$

 $m = -1256.73203263 \Rightarrow E_a = 10.44847012 \frac{kJ}{mol}$ $b = 27.405755138 \Rightarrow A = 7.983038593 \times 10^{11}$

Notes:

- Preserves entry values when calculated over RDF
- Solutions equal to those calculated directly from the normal equations

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Cholesky Factorization

Use when...

- no rounding errors
- speed is important

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Cholesky Factorization

Use when...

no rounding errors

speed is important

Benefits:

- T can be any size
- T has full rank so x will always be unique

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Cholesky Factorization

Definition

If $\langle \mathbf{x}, A\mathbf{x} \rangle > 0$ for all \mathbf{x} then A is a symmetric positive definite matrix where $\mathbf{x} \neq 0$.

$$T^* T = \begin{bmatrix} 4.7656 \times 10^{-5} & 0.01679 \\ 0.01679 & 6 \end{bmatrix}$$

T is a symmetric positive definite matrix.

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Cholesky Factorization

Theorem

If T^*T is symmetric positive definite then there exists a unique upper triangular matrix G with positive diagonal entries such that $T^*T = G^*G$.

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Cholesky Factorization

Proof:

$$T^*T = A = \begin{bmatrix} a & \mathbf{y}^* \\ \hline \mathbf{y} & B \end{bmatrix}$$

$$= \begin{bmatrix} \sqrt{a} & \mathbf{0}^* \\ \frac{1}{\sqrt{a}}\mathbf{y} & I \end{bmatrix} \begin{bmatrix} 1 & \mathbf{0}^* \\ \hline \mathbf{0} & B - \frac{1}{a}\mathbf{y}\mathbf{y}^* \end{bmatrix} \begin{bmatrix} \sqrt{a} & \frac{1}{\sqrt{a}}\mathbf{y}^* \\ \hline \mathbf{0} & I \end{bmatrix}$$

 $= G_1^* A_1 G_1$

After *n* interations:

$$A = G_n^* \dots G_2^* G_1^* I G_1 G_2 \dots G_n = G^* G$$

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Cholesky Factorization

Note:

The entry in the upper left corner of the matrix $B - \frac{1}{a}\mathbf{y}\mathbf{y}^*$ is always positive.

$$a = \langle \mathbf{e}_2, A_1 G_1^{-1} \mathbf{e}_2 \rangle > 0$$
 where $\mathbf{x} = G_1^{-1} \mathbf{e}_2$

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Cholesky Factorization

$$T^*T = \begin{bmatrix} 4.7656 \times 10^{-5} & 0.01679 \\ 0.01679 & 6 \end{bmatrix}$$
$$= \begin{bmatrix} 6.90 \times 10^{-3} & 0 \\ 2.4322 & 0.29093 \end{bmatrix} \begin{bmatrix} 6.90 \times 10^{-3} & 2.4322 \\ 0 & 0.29093 \end{bmatrix}$$
$$= G^*G.$$

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Cholesky Factorization

From the normal equations: $G^*G\mathbf{x} = T^*\mathbf{k}$

$$\begin{array}{l} m = -1256.74352341 \ \Rightarrow E_a = 10.44856565 \ \frac{kJ}{mol} \\ b = 27.4057876928 \ \Rightarrow A = 7.983289484 \times 10^{11} \end{array}$$

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Use when...

- T is rank deficient
- speed is not important

Preliminaries Normal Equations QR Decomposition Cholesky Factorization SVD



Use when...

- T is rank deficient
- speed is not important

Benefits:

- Method is rank revealing
- Only method that holds when T is rank deficient
- T has full rank so x will always be unique

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Theorem

If T is a real $m \times n$ matrix then there exists orthogonal matrices

$$U = [\mathbf{u}_1|...|\mathbf{u}_m]$$
 and $V = [\mathbf{v}_1|...|\mathbf{v}_n]$,

where U is size m and V is size n, such that $T = USV^*$. S is a diagonal matrix with diagonal entries $\sqrt{\delta_1}, ..., \sqrt{\delta_n}$, where $\delta_1, ..., \delta_n$ are eigenvalues of the matrix T^*T .

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SVD

- The eigenvalues of T^*T , δ_1, δ_2 , are $\{6.72278 \times 10^{-7}, 6\}$
- The singular values of T are $s_1 = \sqrt{\delta_1} = 8.199 \times 10^{-4}$ and $s_2 = \sqrt{\delta_2} = 2.4495$

$$S = [s_1 \mathbf{e}_1 | s_2 \mathbf{e}_2] = \begin{bmatrix} 8.199 \times 10^{-4} & 0\\ 0 & 2.4495\\ 0 & 0\\ 0 & 0\\ 0 & 0\\ 0 & 0 \end{bmatrix}$$

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The eigenvectors for δ_1 and δ_2 are \mathbf{x}_1 and \mathbf{x}_2 $V^* = [\mathbf{x}_1 | \mathbf{x}_2]^* = \begin{bmatrix} -0.999996 & 0.002798 \\ -0.002798 & -0.999996 \end{bmatrix}$

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SVD

$U = [\mathbf{y}_1 | \mathbf{y}_2 | \mathbf{y}_3 | \mathbf{y}_4 | \mathbf{y}_5 | \mathbf{y}_6]$

	-0.6484	-0.4082	-0.6426	-0.3462	-0.0027	-0.0339
	-0.3435	-0.4082	0.6061	0.3246	-0.4845	-0.2459
	-0.0752	-0.4082	0.3353	0.1676	0.5944	0.7266
_	0.1565	-0.4082	0.1014	0.3999	-0.0264	-0.5969
	0.3638	-0.4082	-0.1078	-0.7408	0.4113	0.2215
	0.5468	-0.4082	-0.2924	0.1949	-0.4920	-0.0713

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SVD



the system is inconsistent.

Let $C = SV^*$ and $\mathbf{b} = U^*\mathbf{k}$, then solve the system $C^*C\mathbf{x} = C^*\mathbf{b}$.

 $m = -1256.73203461 \implies E_a = 10.44847014 \frac{kJ}{mol}$ $b = 27.4057551435 \implies A = 7.983038637 \times 10^{11}$

Note: When T is rank deficient, **x** is given directly.



Table : Results of Various Least-squares Methods for the Calculation ofthe Activation Energy and Frequency Factor

Calculation Method	E_a (kJ/mol)	A
Estimation	10.4	8.0×10^{11}
Normal Equations	10.44847012	$7.983038593 imes 10^{11}$
QR Decomposition	10.44847012	$7.983038593 imes 10^{11}$
Singular Value Decomposition	10.44847014	$7.983038637 imes 10^{11}$
Cholesky Factorization	10.44856565	$7.983289484 imes 10^{11}$

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Figure : Energy profile for reaction $NO(g) + O_3(g) \rightarrow NO_2(g) + O_2(g)$

$$E_a = 10.448 \ \frac{kJ}{mol} \ A = 7.983 \times 10^{11}$$

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