NYU

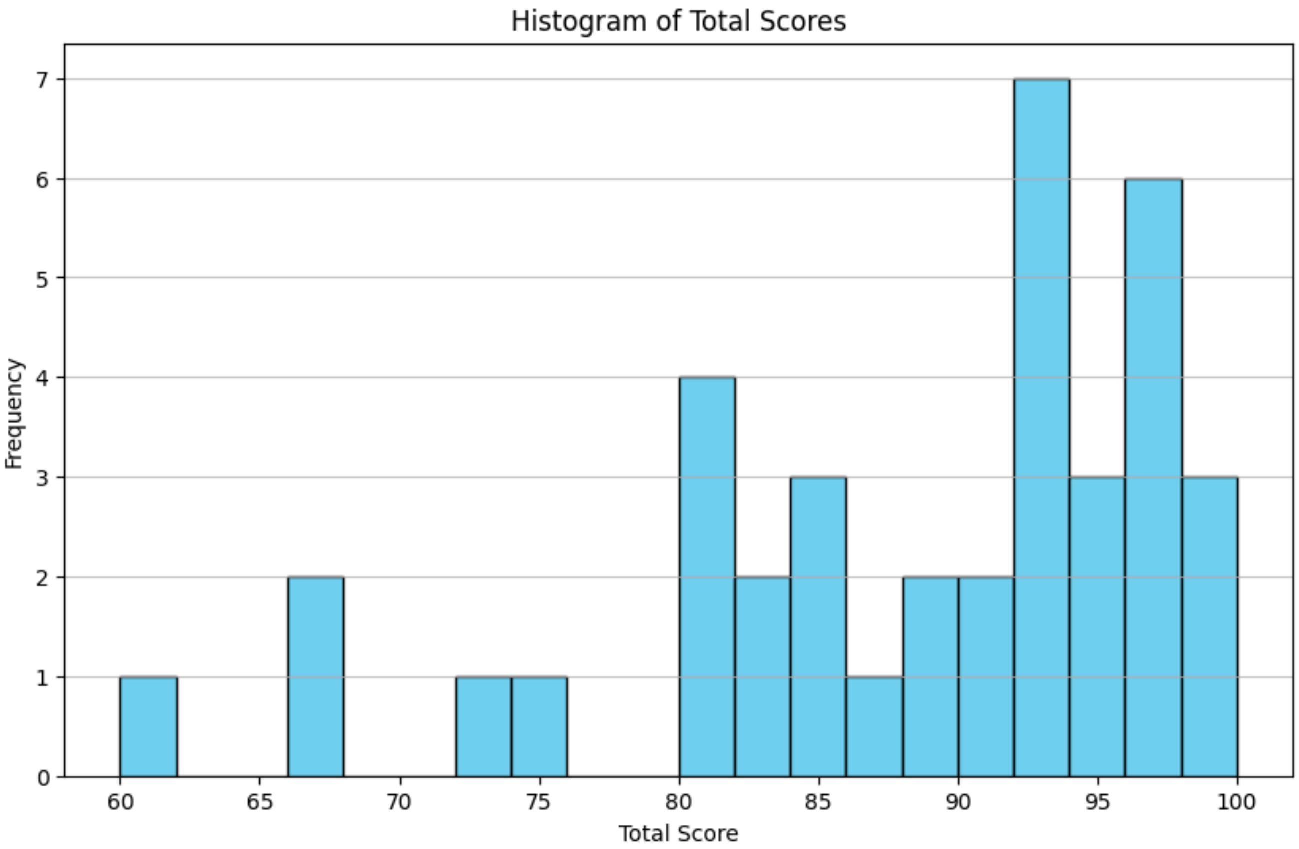
Linear Algebra

Lecture 13

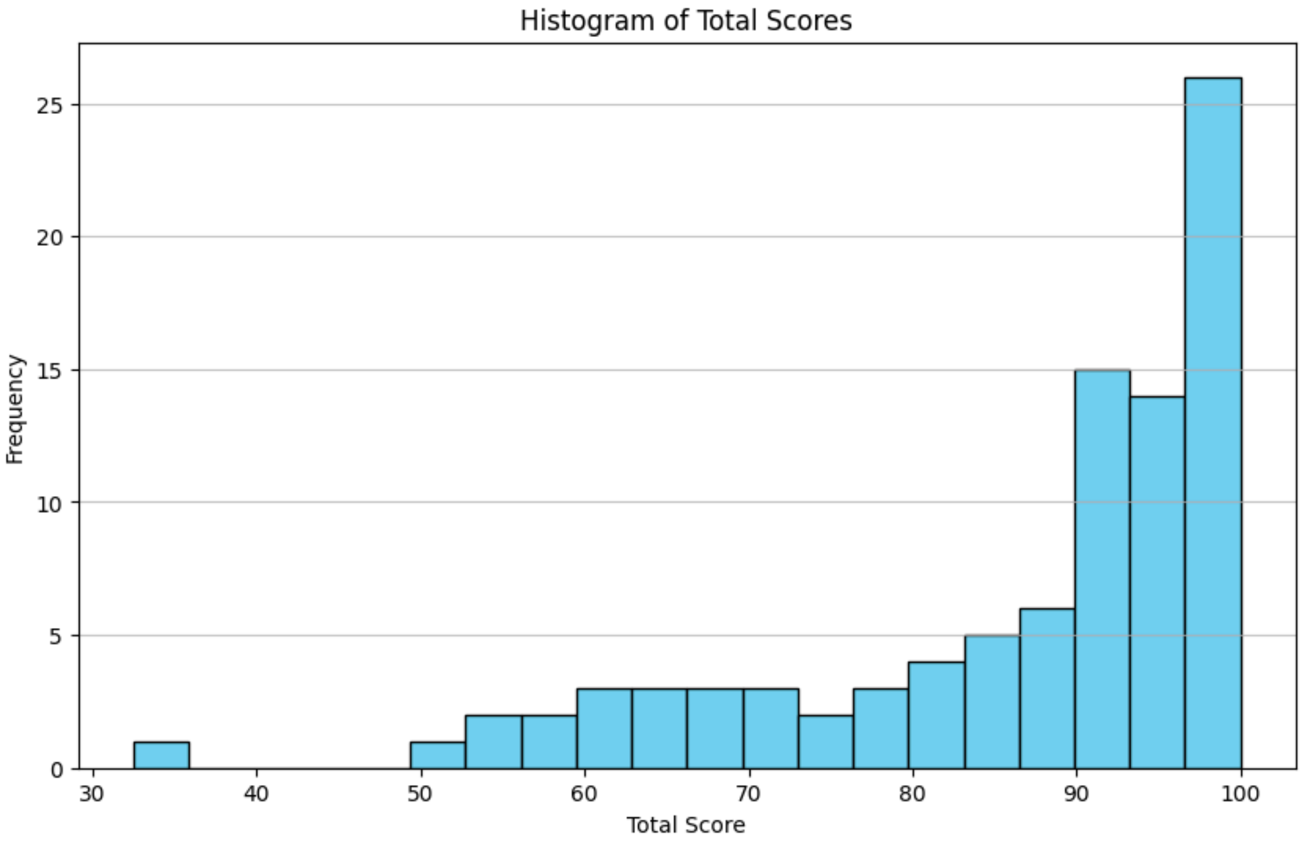
Least Squares

Dr. Yiping Lu

- Mean 87.95 median 91.75



- Mean 86.7 median 92.6

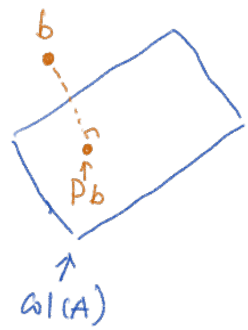


- Projection

Solve Equation $Ax = b$

but $b \notin Col(A)$ → No Solutions

"best guess" ← least square solution!



$$Ax = b \Rightarrow A^TAx = A^Tb$$

A^TA is always are square matrix

- rank (A^TA) = rank (A) ⇒ if A is full column rank. A^TA is invertible

⇓

$A = [\vec{a_1} \cdots \vec{a_r}]$ → A^TA is invertible

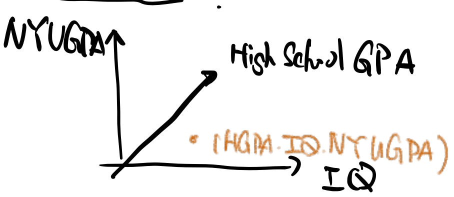
$\vec{a_1} \cdots \vec{a_r}$ are the basis of $Col(A)$

- $x = (A^TA)^{-1}A^Tb$

$$Pb = Ax = A(A^TA)^{-1}A^T b$$

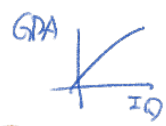
$A(A^TA)^{-1}A^T$ ← P : Projection Matrix

Application



$y \approx c_1 \cdot x_1 + c_2 \cdot x_2$

NYUGPA ≃ c_1 · HGPA + c_2 · IQ



$$y = \begin{bmatrix} NYUGPA_1 \\ \vdots \\ NYUGPA_n \end{bmatrix} \quad x_1 = \begin{bmatrix} HGPA_1 \\ \vdots \\ HGPA_n \end{bmatrix} \quad x_2 = \begin{bmatrix} IQ_1 \\ \vdots \\ IQ_n \end{bmatrix}$$

$A = [x_1 \quad x_2]$ $\quad \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} = (A^TA)^{-1}A^Ty$

Application 2

NYUGPA ≃ $a\, IQ^2 + c_2\, IQ + c_3 \cdot 1$

$$y = \begin{bmatrix} NYGPA_1 \\ \vdots \\ NYUGPA_n \end{bmatrix} \quad x_1 = \begin{bmatrix} IQ_1^2 \\ \vdots \\ IQ_n^2 \end{bmatrix} \quad x_2 = \begin{bmatrix} IQ_1 \\ \vdots \\ IQ_n \end{bmatrix} \quad x_3 = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$$

$A = [x_1 \quad x_2 \quad x_3]$ $\quad \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} = (A^TA)^{-1}A^Ty$

This Meeting is Being Recorded

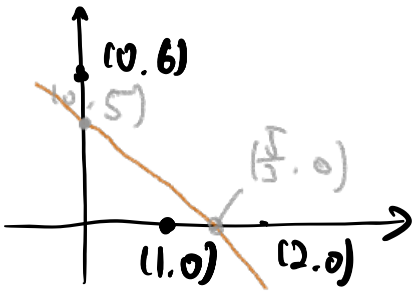
Strang Sections 4.3 – Least Squares Approximations

Course notes adapted from N. Hammoud's NYU lecture notes.

Best-Fit Line

Example

Example: Find the best-fit line through the points $(0,6)$, $(1,0)$, and $(2,0)$.



$y = ax + b$

$y = -3x + 5$

$y = ax + b$

$$6 \approx a \cdot 0 + b \qquad (0, 6)$$
$$0 \approx a \cdot 1 + b \qquad (1, 0)$$
$$0 \approx a \cdot 2 + b \qquad (2, 0)$$

$$\begin{bmatrix} 6 \\ 0 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix} \quad \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$A = \begin{bmatrix} 0 & 1 \\ 1 & 1 \\ 2 & 1 \end{bmatrix} \qquad b = \begin{bmatrix} 6 \\ 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} a \\ b \end{bmatrix} = (A^T A)^{-1} (A^T b) \rightarrow \hat{a} = -3, \quad \hat{b} = 5.$$

$$A^T A = \begin{bmatrix} 5 & 3 \\ 3 & 3 \end{bmatrix} \qquad A^T b = \begin{bmatrix} 0 \\ 6 \end{bmatrix}$$

Example

Example: Find the best-fit line through the points $(0, 6)$, $(1, 0)$, and $(2, 0)$.

Example

Example: Find the best-fit line through the points $(0, 6)$, $(1, 0)$, and $(2, 0)$.

Least Squares Solution

Least Squares Solution

Let A be an $m \times n$ matrix.

Definition

A **least squares solution** to $Ax = b$ is a vector $\widehat{x}$ in $\mathbf{R}^n$ such that

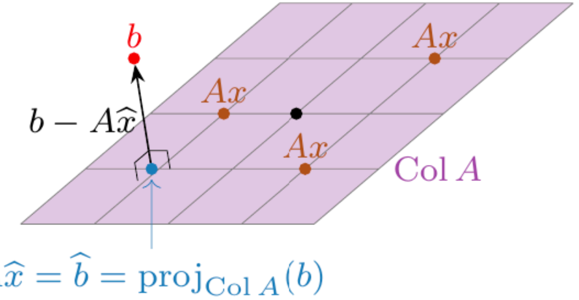
$$\|b - A\widehat{x}\| \leq \|b - Ax\|$$

for all x in $\mathbf{R}^n$.

Error of the Eq $Ax=b$

$\|x\| = \sqrt{x_1^2 + \cdots + x_n^2}$

Note that $b - A\widehat{x}$ is in $(\mathrm{Col}\, A)^{\perp}$.



In other words, a least squares solution $\widehat{x}$ solves $Ax = b$ *as closely as possible.*

Equivalently, a least squares solution to $Ax = b$ is a vector $\widehat{x}$ in $\mathbf{R}^n$ such that

$$A\widehat{x} = \widehat{b} = \mathrm{proj}_{\mathrm{Col}\, A}(b).$$

This is because $\widehat{b}$ is the closest vector to b such that $A\widehat{x} = \widehat{b}$ is consistent.

Least Squares Solution

Theorem

The least squares solutions to $Ax = b$ are the solutions to

$$(A^T A)\widehat{x} = A^T b.$$

This is just another $Ax = b$ problem, but with a *square* matrix $A^T A$!
Note we compute $\widehat{x}$ directly, without computing $\widehat{b}$ first.

Theorem

Let A be an $m \times n$ matrix. The following are equivalent:

1. $Ax = b$ has a *unique* least squares solution for all b in $\mathbf{R}^n$.
2. The columns of A are linearly independent.
3. $A^T A$ is invertible.

In this case, the least squares solution is $(A^T A)^{-1}(A^T b)$.

Least Squares Solution – Yesterday's Example

Find the least squares solutions to $Ax = b$ where:

$$A = \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{pmatrix} \qquad b = \begin{pmatrix} 6 \\ 0 \\ 0 \end{pmatrix}.$$

We have

$$A^T A = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 1 & 2 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{pmatrix} = \begin{pmatrix} 3 & 3 \\ 3 & 5 \end{pmatrix}$$

and

$$A^T b = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 1 & 2 \end{pmatrix} \begin{pmatrix} 6 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 6 \\ 0 \end{pmatrix}.$$

Row reduce:

$$\left(\begin{array}{cc|c} 3 & 3 & 6 \\ 3 & 5 & 0 \end{array}\right) \rightsquigarrow \left(\begin{array}{cc|c} 1 & 0 & 5 \\ 0 & 1 & -3 \end{array}\right).$$

So the only least squares solution is $\widehat{x} = \begin{pmatrix} 5 \\ -3 \end{pmatrix}$.

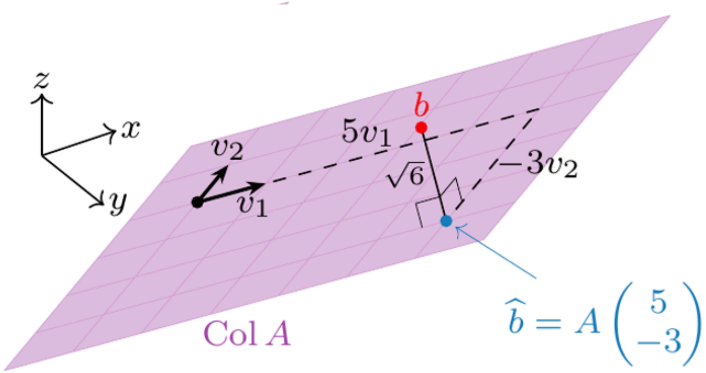
Least Squares Solution – Worked Example

How close did we get?

$$\widehat{b} = A\widehat{x} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} 5 \\ -3 \end{pmatrix} = \begin{pmatrix} 5 \\ 2 \\ -1 \end{pmatrix}$$

The distance from b is

$$\|b - A\widehat{x}\| = \left\| \begin{pmatrix} 6 \\ 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 5 \\ 2 \\ -1 \end{pmatrix} \right\| = \left\| \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix} \right\| = \sqrt{1^2 + (-2)^2 + 1^2} = \sqrt{6}.$$



Least Squares Solution

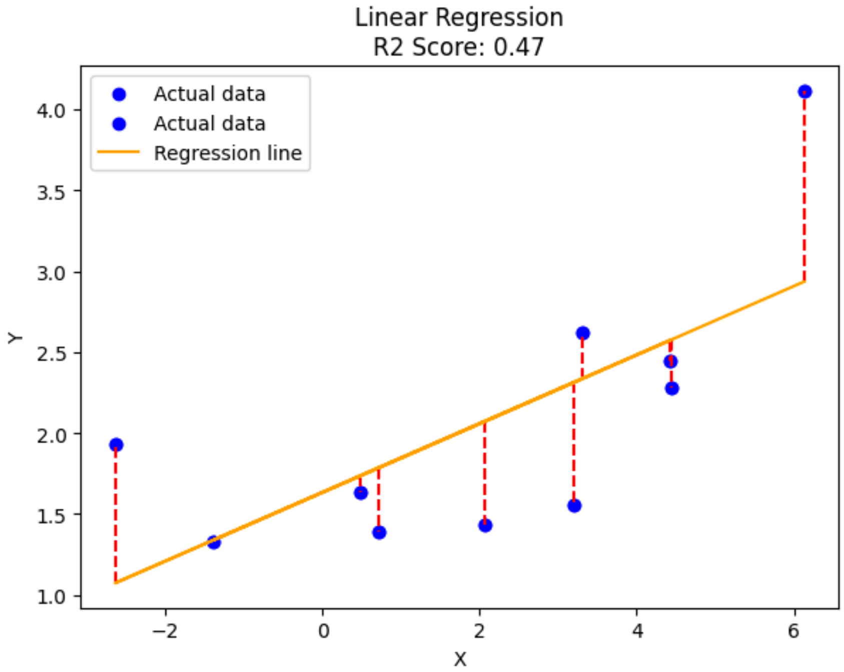
Example: Find the least squares solution to $\begin{bmatrix} 4 & 0 \\ 0 & 2 \\ 1 & 1 \end{bmatrix} \vec{x} = \begin{bmatrix} 2 \\ 0 \\ 11 \end{bmatrix}$.

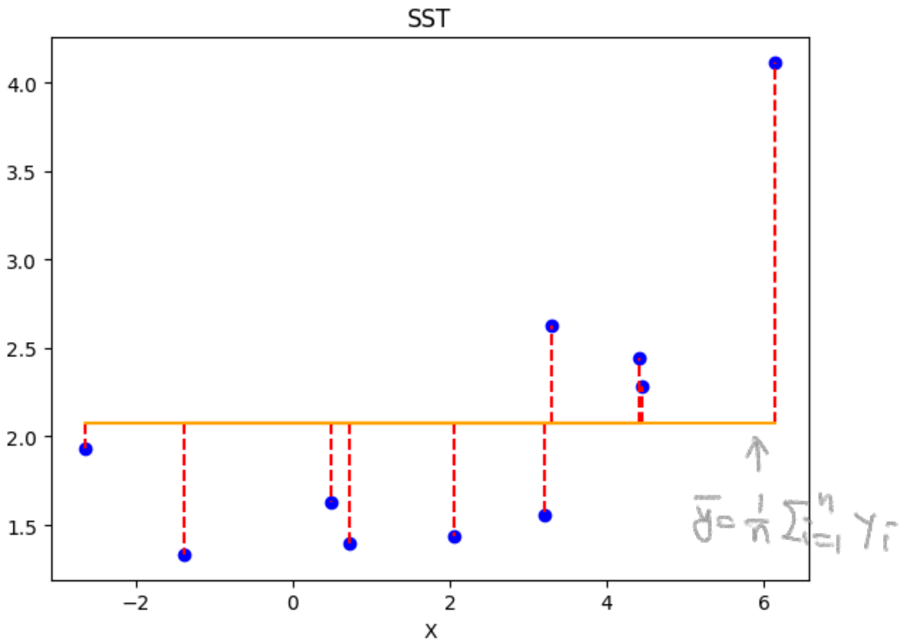
Least Squares Solution

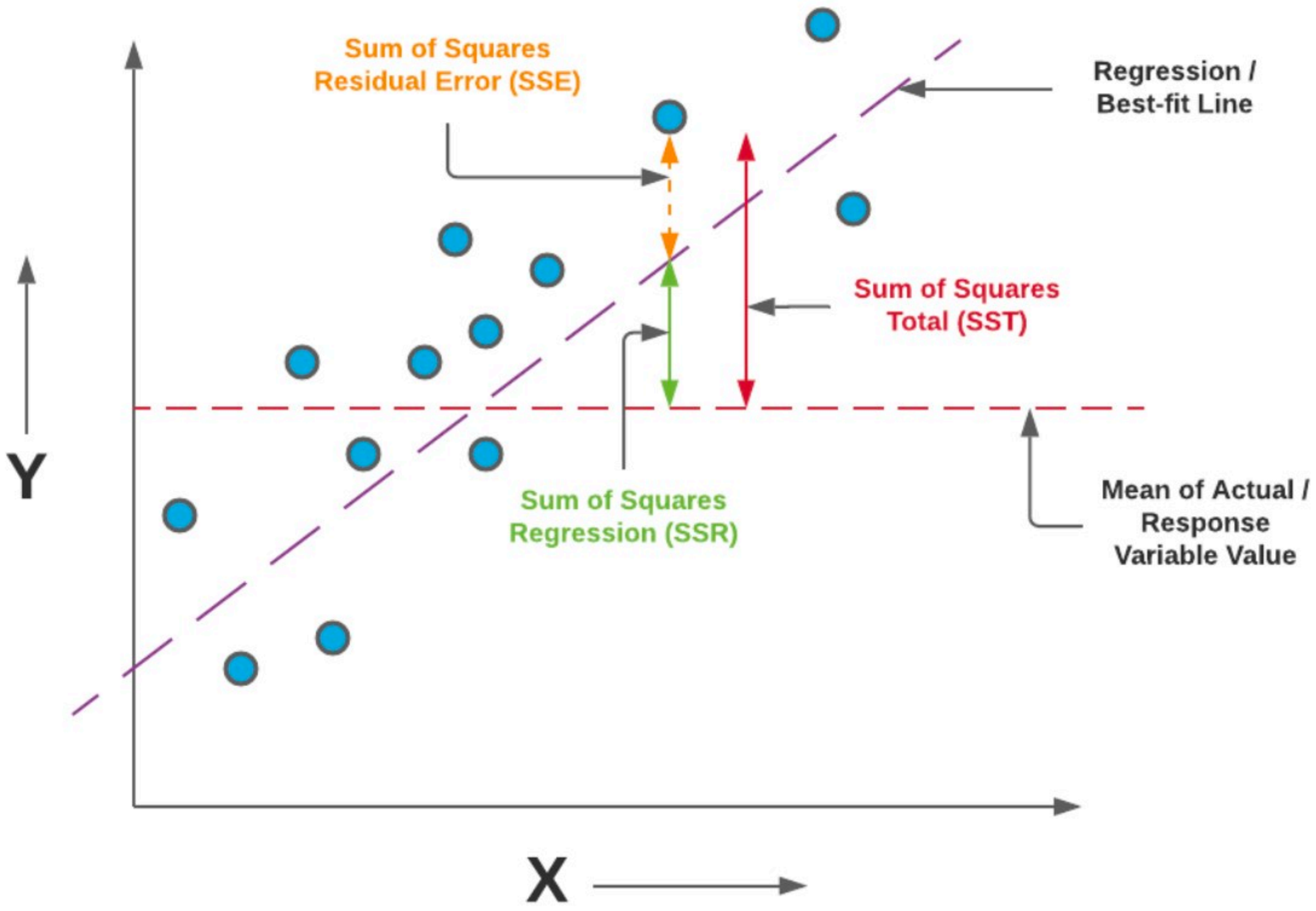
Find the least squares solution to $\begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 0 & 1 \end{bmatrix} \vec{x} = \begin{bmatrix} 1 \\ 3 \\ 8 \\ 2 \end{bmatrix}$.

R2 Score

$$\text{R2 score} = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \qquad \text{R2 score} = 1 - \frac{SS_R}{SS_M}$$

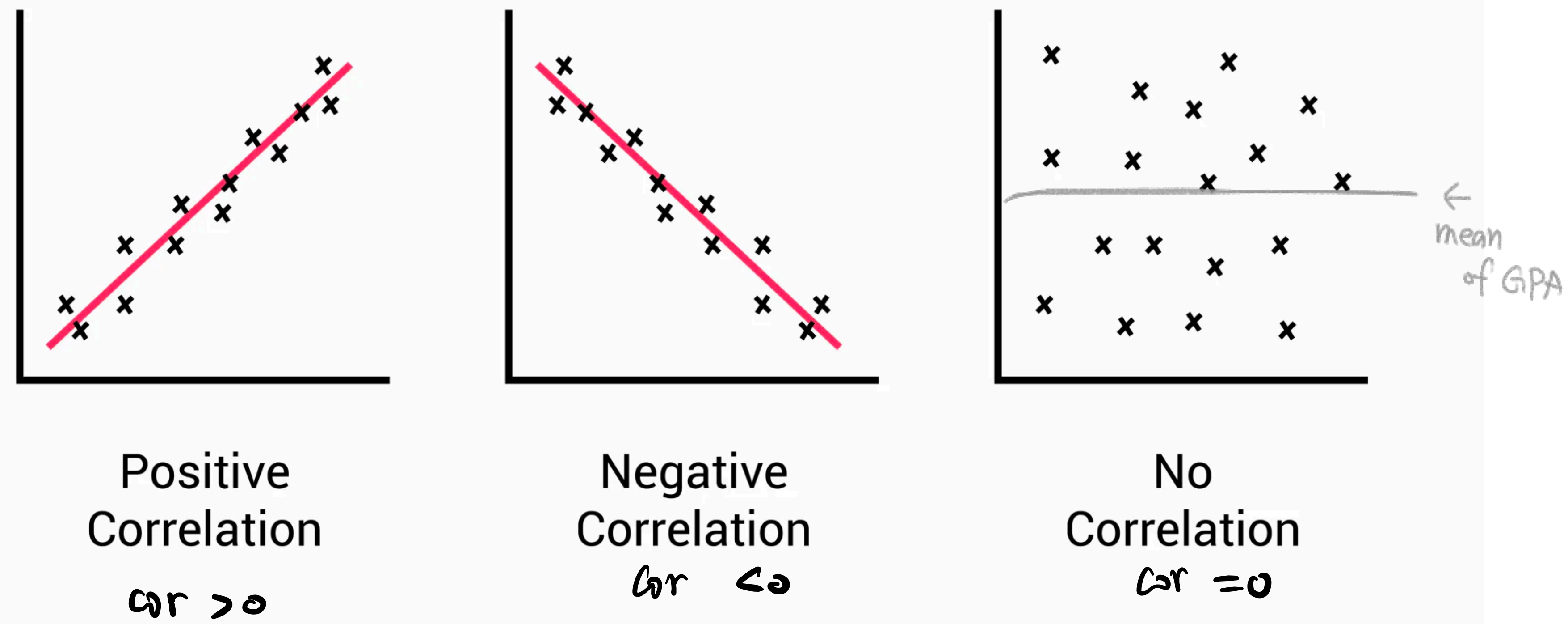





Sum of Squares
Residual Error (SSE)
Regression /
Best-fit Line
Sum of Squares
Total (SST)
Y
Sum of Squares
Regression (SSR)
Mean of Actual /
Response
Variable Value
X

Correlation

$\mathrm{cor}(x, y) = \frac{x \cdot y}{\|x\| \|y\|}$ = cos of θ (θ: angle between x and y)



Correlation = R2 Square for only 1 feature (Not Required)

- Thm $(\text{Correlation})^2$=R2 square when we only 1 feature to do linear regression

use x to predict y. $y \approx c\cdot x$

best $c = \dfrac{(x\cdot y)}{(x\cdot x)}$ $\left((A^TA)^{-1}A^Ty \right)$

Error of best linear fit. $y - c\cdot x = y - \dfrac{(x\cdot y)}{(x\cdot x)}x$

$$\text{R2 score} = 1 - \frac{\sum\left(y_i - \frac{(x\cdot y)}{(x\cdot x)}x_i\right)^2}{\sum y_i^2} = 1 - \frac{(y - cx)\cdot(y - cx)}{y\cdot y} = \frac{(x\cdot y)^2}{(x\cdot x)(y\cdot y)}$$

$$1 - \frac{(x\cdot y)^2}{(x\cdot x)(y\cdot y)} = \frac{1}{y\cdot y}\left[y\cdot y - \frac{(x\cdot y)^2}{x\cdot x}\right] = \frac{(y-cx)\cdot(y-cx)}{y\cdot y}$$

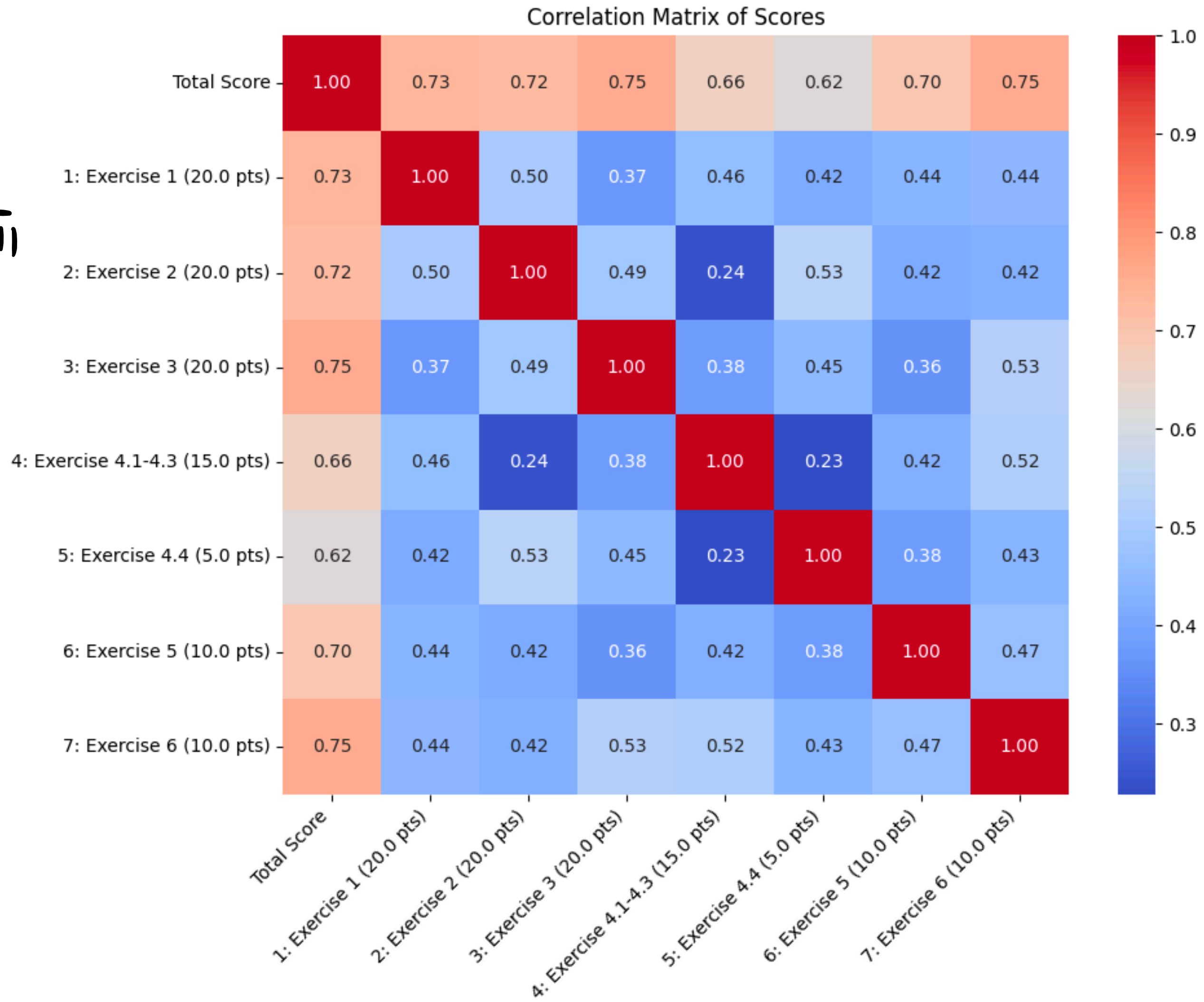
$$\frac{(y-cx)\cdot(y-cx)}{y\cdot y} = \frac{1}{y\cdot y}\left[y - \frac{(x\cdot y)}{(x\cdot x)}x\right]\cdot\left[y - \frac{x\cdot y}{x\cdot x}x\right]$$

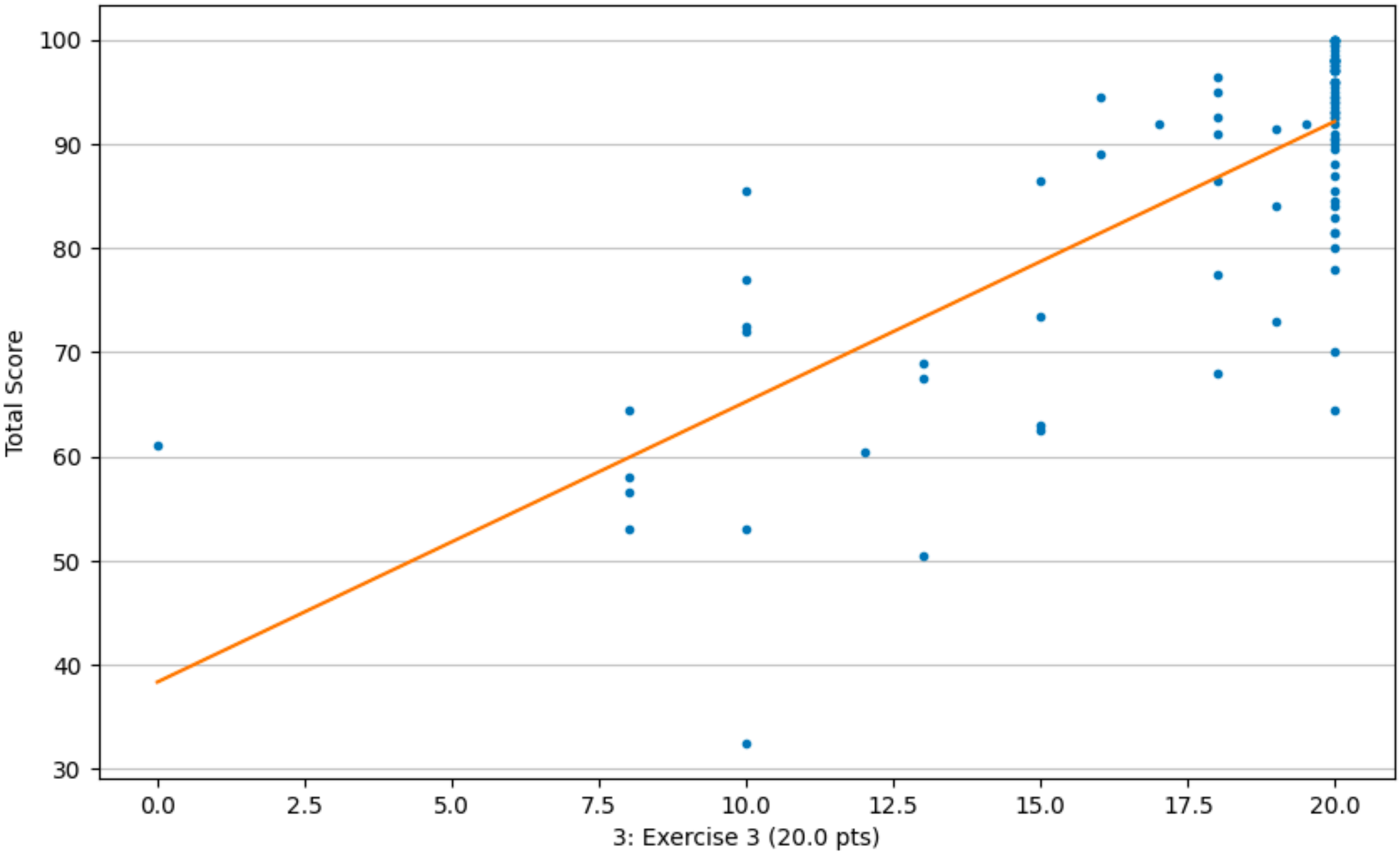
$$= \frac{1}{y\cdot y}\left[y\cdot y - \frac{x\cdot y}{x\cdot x}(x\cdot y) - \frac{(x\cdot y)}{(x\cdot x)}(x\cdot y) + \frac{(x\cdot y)^2}{(x\cdot x)^2}x\cdot x\right]$$

You midterm score

$$\frac{x \cdot y}{\|x\| \cdot \|y\|}$$

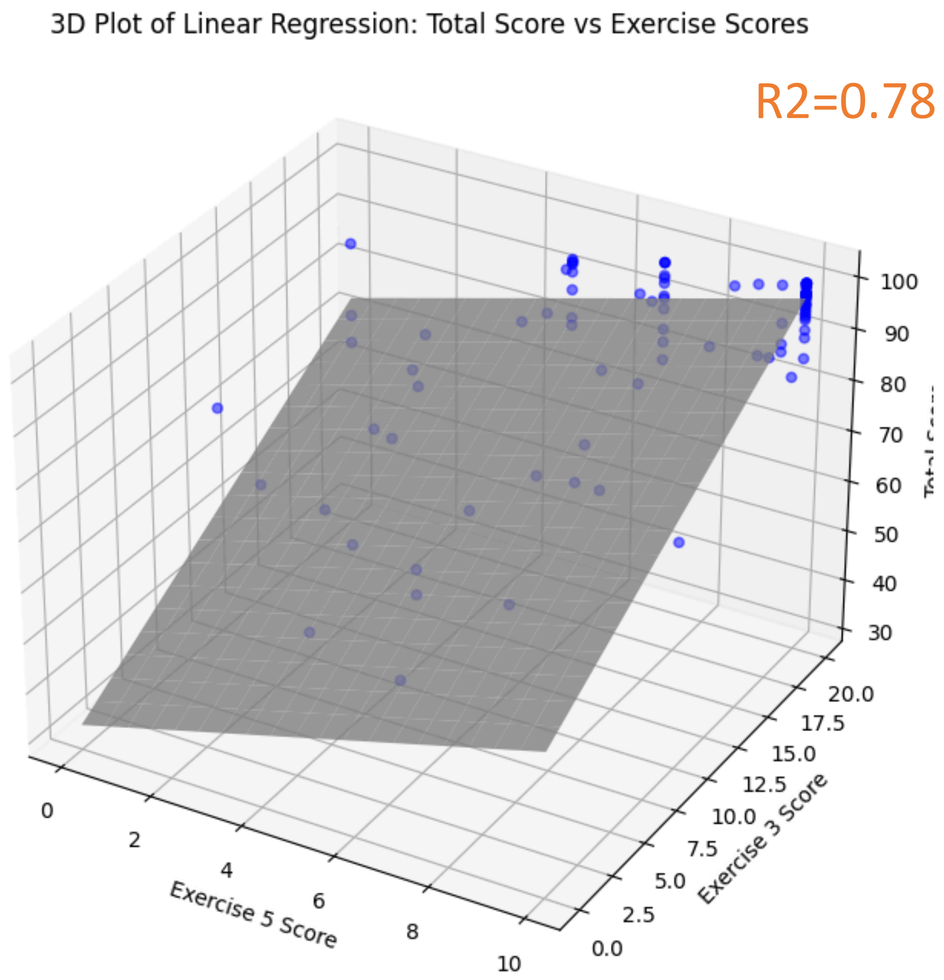
$$cor(x \cdot x) = \frac{x \cdot x}{\|x\| \cdot \|x\|} = 1$$

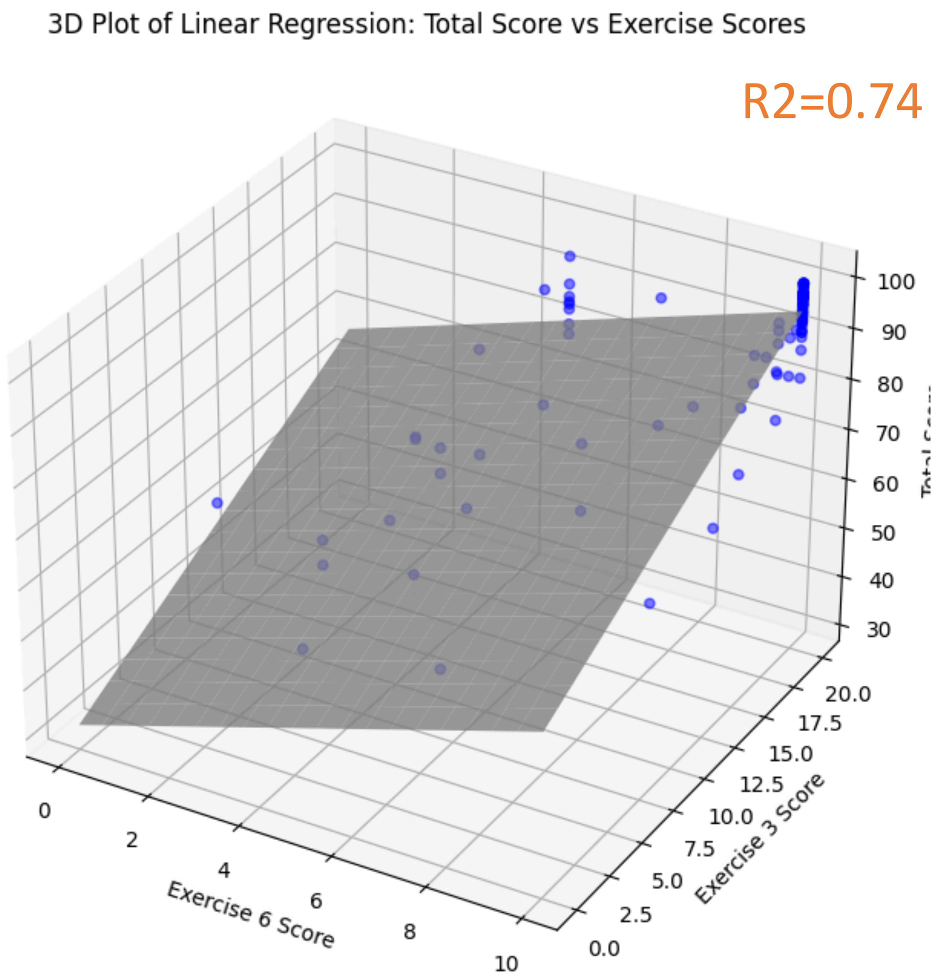




Total Score
3: Exercise 3 (20.0 pts)
100
90
80
70
60
50
40
30
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

Exercise 5 and 6 which is *more powerful*?





Try to Design a Linear Algebra Test using Linear Algebra

```
# Preparing the data
feature_columns = ['1: Exercise 1 (20.0 pts)', '2: Exercise 2 (20.0 pts)',
                   '3: Exercise 3 (20.0 pts)', '4: Exercise 4.1-4.3 (15.0 pts)',
                   '5: Exercise 4.4 (5.0 pts)', '6: Exercise 5 (10.0 pts)',
                   '7: Exercise 6 (10.0 pts)']
X_features = scores_data[feature_columns]
y_total_score = scores_data['Total Score']

# Standardizing the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_features)

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_total_score, test_size=0.2, random_state=42)

# Fitting the Lasso regression model
lasso = Lasso(alpha=5)
lasso.fit(X_train, y_train)

# Getting the coefficients
lasso_coefficients = lasso.coef_

# Displaying the coefficients
coefficients_df = pd.DataFrame({'Feature': feature_columns, 'Coefficient': lasso_coefficients})
coefficients_df
```

	Feature	Coefficient
0	1: Exercise 1 (20.0 pts)	0.324832
1	2: Exercise 2 (20.0 pts)	0.000000
2	3: Exercise 3 (20.0 pts)	3.082411
3	4: Exercise 4.1-4.3 (15.0 pts)	1.556173
4	5: Exercise 4.4 (5.0 pts)	0.000000
5	6: Exercise 5 (10.0 pts)	1.712245
6	7: Exercise 6 (10.0 pts)	2.447044

Lasso:
best linear fit with possible fewer entries

Larger alpha leads to more zeros!
(Means less problems in exam can know
Your's status of learning!)

Try to Design a Linear Algebra Test using Linear Algebra

```
# Preparing the data
feature_columns = ['1: Exercise 1 (20.0 pts)', '2: Exercise 2 (20.0 pts)',
                   '3: Exercise 3 (20.0 pts)', '4: Exercise 4.1-4.3 (15.0 pts)',
                   '5: Exercise 4.4 (5.0 pts)', '6: Exercise 5 (10.0 pts)',
                   '7: Exercise 6 (10.0 pts)']
X_features = scores_data[feature_columns]
y_total_score = scores_data['Total Score']

# Standardizing the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_features)

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_total_score, test_size=0.2, random_state=42)

# Fitting the Lasso regression model
lasso = Lasso(alpha=10)
lasso.fit(X_train, y_train)

# Getting the coefficients
lasso_coefficients = lasso.coef_

# Displaying the coefficients
coefficients_df = pd.DataFrame({'Feature': feature_columns, 'Coefficient': lasso_coefficients})
coefficients_df
```

	Feature	Coefficient
0	1: Exercise 1 (20.0 pts)	0.000000
1	2: Exercise 2 (20.0 pts)	0.000000
2	3: Exercise 3 (20.0 pts)	0.698581
3	4: Exercise 4.1-4.3 (15.0 pts)	0.000000
4	5: Exercise 4.4 (5.0 pts)	0.000000
5	6: Exercise 5 (10.0 pts)	0.000000
6	7: Exercise 6 (10.0 pts)	0.883778

Lasso:
best linear fit with possible fewer entries

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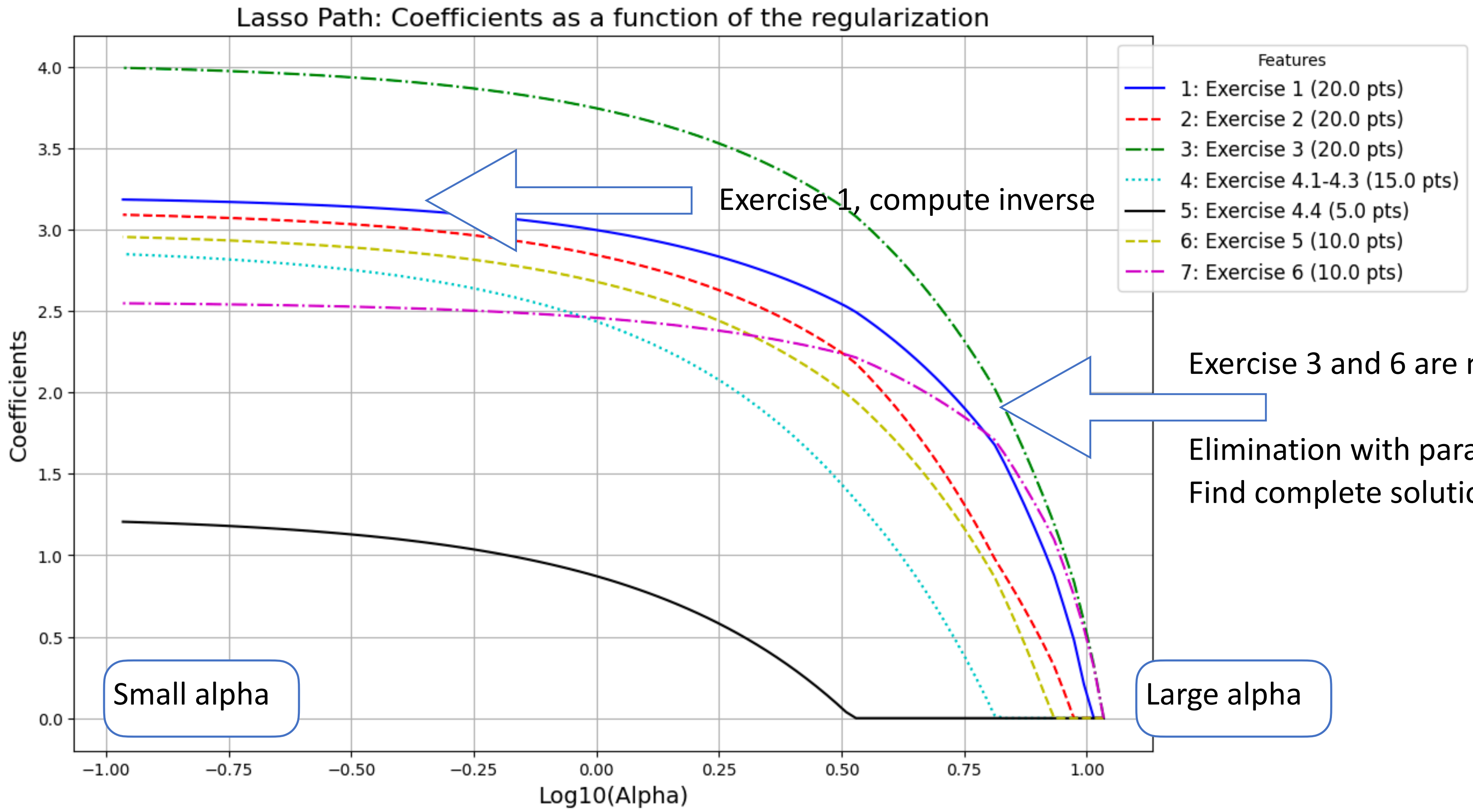
Try to Design a Linear Algebra Test using Linear Algebra

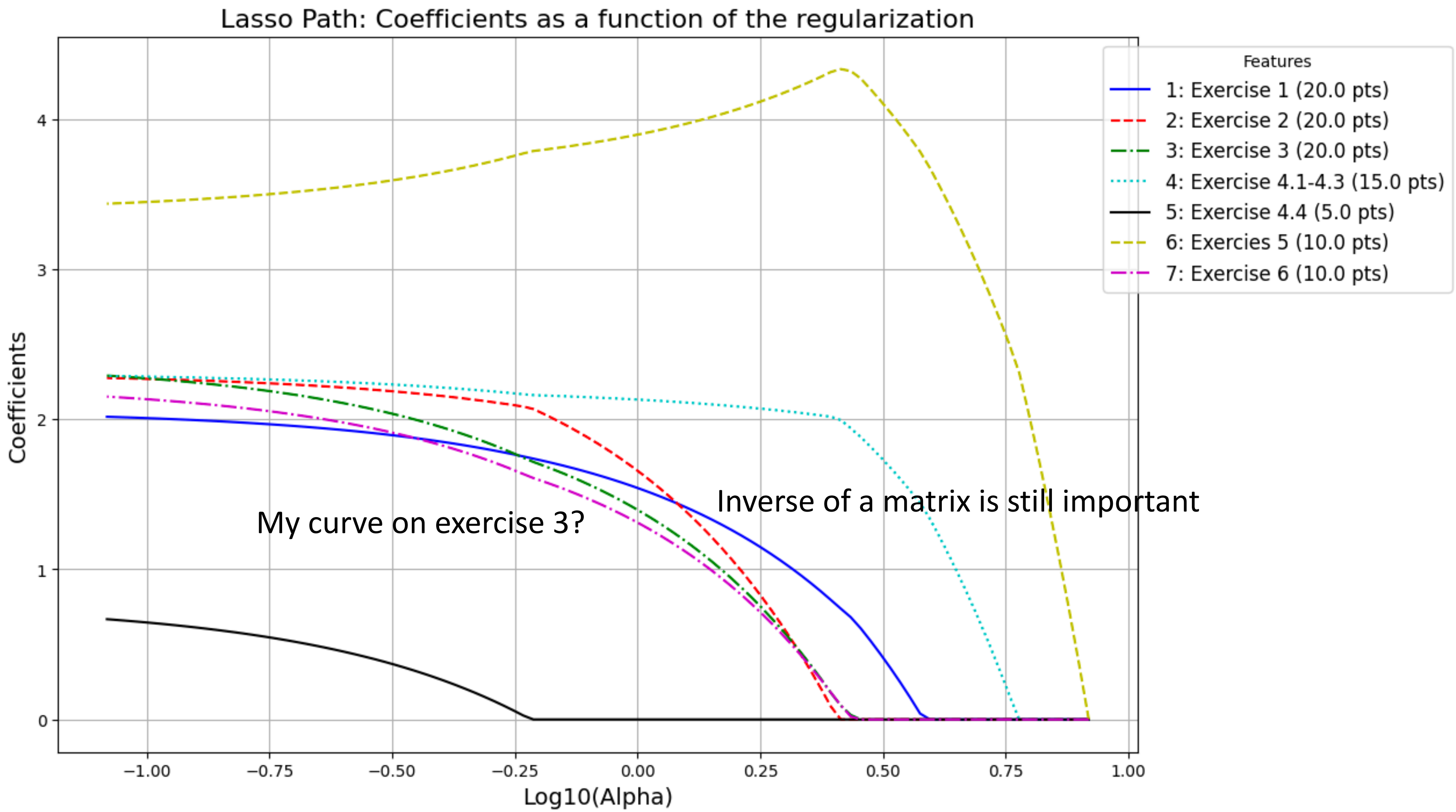


Exercise 3 and 6 are most important

Elimination with parameterized matrix

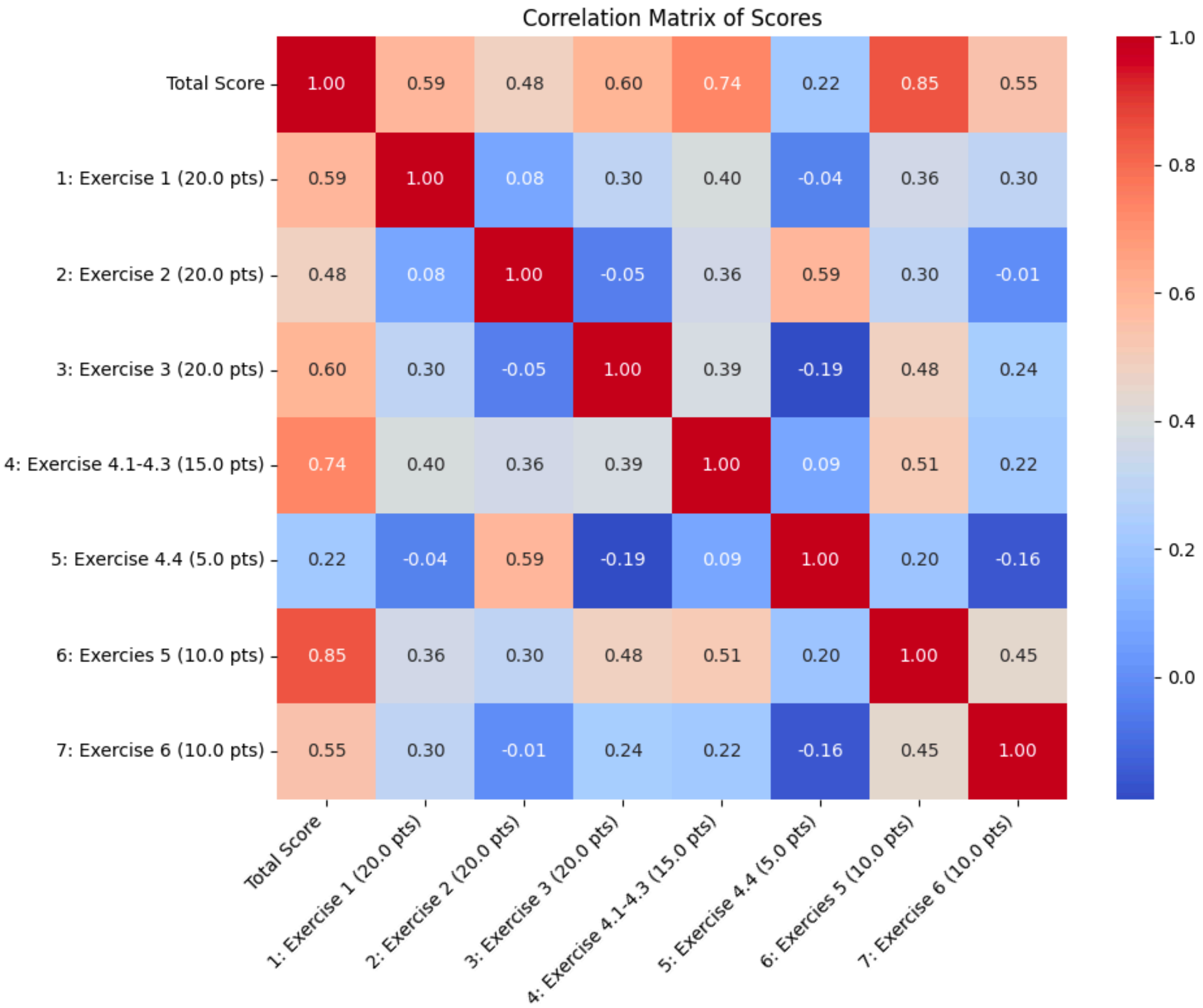
Find complete solution of Ax=b

What is robust and what is not



Inverse of a matrix is still important

My curve on exercise 3?


Correlation Matrix of Scores
Total Score
1: Exercise 1 (20.0 pts)
2: Exercise 2 (20.0 pts)
3: Exercise 3 (20.0 pts)
4: Exercise 4.1-4.3 (15.0 pts)
5: Exercise 4.4 (5.0 pts)
6: Exercies 5 (10.0 pts)
7: Exercise 6 (10.0 pts)
1.00 0.59 0.48 0.60 0.74 0.22 0.85 0.55
0.59 1.00 0.08 0.30 0.40 -0.04 0.36 0.30
0.48 0.08 1.00 -0.05 0.36 0.59 0.30 -0.01
0.60 0.30 -0.05 1.00 0.39 -0.19 0.48 0.24
0.74 0.40 0.36 0.39 1.00 0.09 0.51 0.22
0.22 -0.04 0.59 -0.19 0.09 1.00 0.20 -0.16
0.85 0.36 0.30 0.48 0.51 0.20 1.00 0.45
0.55 0.30 -0.01 0.24 0.22 -0.16 0.45 1.00
1.0
0.8
0.6
0.4
0.2
0.0

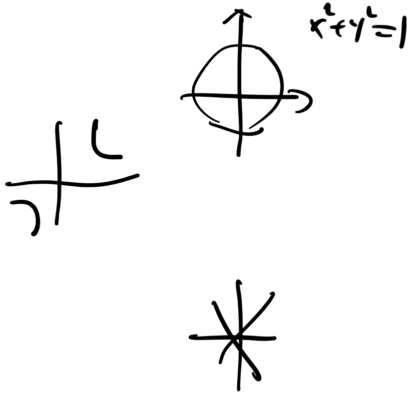
Worked Example – Best Fit Ellipse

Best Fit Ellipse

Find the best fit ellipse for the points $(0,2)$, $(2,1)$, $(1,-1)$, $(-1,-2)$, $(-3,1)$.

The general equation for an ellipse is

$$x^2 + Ay^2 + Bxy + Cx + Dy + E = 0$$



Best Fit Ellipse

Find the best fit ellipse for the points $(0,2)$, $(2,1)$, $(1,-1)$, $(-1,-2)$, $(-3,1)$.

The general equation for an ellipse is

$$x^2 + Ay^2 + Bxy + Cx + Dy + E = 0$$

So we want to solve:

$$\begin{aligned}
(0)^2 + \quad A(2)^2 + \quad B(0)(2) + \quad C(0) + \quad D(2) + E &= 0 \\
(2)^2 + \quad A(1)^2 + \quad B(2)(1) + \quad C(2) + \quad D(1) + E &= 0 \\
(1)^2 + A(-1)^2 + \quad B(1)(-1) + \quad C(1) + D(-1) + E &= 0 \\
(-1)^2 + A(-2)^2 + B(-1)(-2) + C(-1) + D(-2) + E &= 0 \\
(-3)^2 + \quad A(1)^2 + \quad B(-3)(1) + C(-3) + \quad D(1) + E &= 0
\end{aligned}$$

Best Fit Ellipse

Find the best fit ellipse for the points $(0,2)$, $(2,1)$, $(1,-1)$, $(-1,-2)$, $(-3,1)$.

The general equation for an ellipse is

$$x^2 + Ay^2 + Bxy + Cx + Dy + E = 0$$

So we want to solve:

$$\begin{aligned}
(0)^2 + \quad A(2)^2 + \quad B(0)(2) + \quad C(0) + \quad D(2) + E &= 0 \\
(2)^2 + \quad A(1)^2 + \quad B(2)(1) + \quad C(2) + \quad D(1) + E &= 0 \\
(1)^2 + A(-1)^2 + \quad B(1)(-1) + \quad C(1) + D(-1) + E &= 0 \\
(-1)^2 + A(-2)^2 + B(-1)(-2) + C(-1) + D(-2) + E &= 0 \\
(-3)^2 + \quad A(1)^2 + \quad B(-3)(1) + C(-3) + \quad D(1) + E &= 0
\end{aligned}$$

In matrix form:

$$\begin{pmatrix} 4 & 0 & 0 & 2 & 1 \\ 1 & 2 & 2 & 1 & 1 \\ 1 & -1 & 1 & -1 & 1 \\ 4 & 2 & -1 & -2 & 1 \\ 1 & -3 & -3 & 1 & 1 \end{pmatrix} \begin{pmatrix} A \\ B \\ C \\ D \\ E \end{pmatrix} = \begin{pmatrix} 0 \\ -4 \\ -1 \\ -1 \\ -9 \end{pmatrix}.$$

Best Fit Ellipse

$$A = \begin{pmatrix} 4 & 0 & 0 & 2 & 1 \\ 1 & 2 & 2 & 1 & 1 \\ 1 & -1 & 1 & -1 & 1 \\ 4 & 2 & -1 & -2 & 1 \\ 1 & -3 & -3 & 1 & 1 \end{pmatrix} \qquad b = \begin{pmatrix} 0 \\ -4 \\ -1 \\ -1 \\ -9 \end{pmatrix}.$$

$$A^T A = \begin{pmatrix} 35 & 6 & -4 & 1 & 11 \\ 6 & 18 & 10 & -4 & 0 \\ -4 & 10 & 15 & 0 & -1 \\ 1 & -4 & 0 & 11 & 1 \\ 11 & 0 & -1 & 1 & 5 \end{pmatrix} \qquad A^T b = \begin{pmatrix} -18 \\ 18 \\ 19 \\ -10 \\ -15 \end{pmatrix}$$

Best Fit Ellipse

$$A = \begin{pmatrix} 4 & 0 & 0 & 2 & 1 \\ 1 & 2 & 2 & 1 & 1 \\ 1 & -1 & 1 & -1 & 1 \\ 4 & 2 & -1 & -2 & 1 \\ 1 & -3 & -3 & 1 & 1 \end{pmatrix} \qquad b = \begin{pmatrix} 0 \\ -4 \\ -1 \\ -1 \\ -9 \end{pmatrix}.$$

$$A^T A = \begin{pmatrix} 35 & 6 & -4 & 1 & 11 \\ 6 & 18 & 10 & -4 & 0 \\ -4 & 10 & 15 & 0 & -1 \\ 1 & -4 & 0 & 11 & 1 \\ 11 & 0 & -1 & 1 & 5 \end{pmatrix} \qquad A^T b = \begin{pmatrix} -18 \\ 18 \\ 19 \\ -10 \\ -15 \end{pmatrix}$$

Row reduce:

$$\left(\begin{array}{ccccc|c} 35 & 6 & -4 & 1 & 11 & -18 \\ 6 & 18 & 10 & -4 & 0 & 18 \\ -4 & 10 & 15 & 0 & -1 & 19 \\ 1 & -4 & 0 & 11 & 1 & -10 \\ 11 & 0 & -1 & 1 & 5 & -15 \end{array}\right) \rightsquigarrow \left(\begin{array}{ccccc|c} 1 & 0 & 0 & 0 & 0 & 16/7 \\ 0 & 1 & 0 & 0 & 0 & -8/7 \\ 0 & 0 & 1 & 0 & 0 & 15/7 \\ 0 & 0 & 0 & 1 & 0 & -6/7 \\ 0 & 0 & 0 & 0 & 1 & -52/7 \end{array}\right)$$

$(A^TA)^{-1}(A^Tb)$

Best Fit Ellipse

$$A = \begin{pmatrix} 4 & 0 & 0 & 2 & 1 \\ 1 & 2 & 2 & 1 & 1 \\ 1 & -1 & 1 & -1 & 1 \\ 4 & 2 & -1 & -2 & 1 \\ 1 & -3 & -3 & 1 & 1 \end{pmatrix} \qquad b = \begin{pmatrix} 0 \\ -4 \\ -1 \\ -1 \\ -9 \end{pmatrix}.$$

$$A^T A = \begin{pmatrix} 35 & 6 & -4 & 1 & 11 \\ 6 & 18 & 10 & -4 & 0 \\ -4 & 10 & 15 & 0 & -1 \\ 1 & -4 & 0 & 11 & 1 \\ 11 & 0 & -1 & 1 & 5 \end{pmatrix} \qquad A^T b = \begin{pmatrix} -18 \\ 18 \\ 19 \\ -10 \\ -15 \end{pmatrix}$$

Row reduce:

$$\left(\begin{array}{ccccc|c} 35 & 6 & -4 & 1 & 11 & -18 \\ 6 & 18 & 10 & -4 & 0 & 18 \\ -4 & 10 & 15 & 0 & -1 & 19 \\ 1 & -4 & 0 & 11 & 1 & -10 \\ 11 & 0 & -1 & 1 & 5 & -15 \end{array}\right) \rightsquigarrow \left(\begin{array}{ccccc|c} 1 & 0 & 0 & 0 & 0 & 16/7 \\ 0 & 1 & 0 & 0 & 0 & -8/7 \\ 0 & 0 & 1 & 0 & 0 & 15/7 \\ 0 & 0 & 0 & 1 & 0 & -6/7 \\ 0 & 0 & 0 & 0 & 1 & -52/7 \end{array}\right)$$

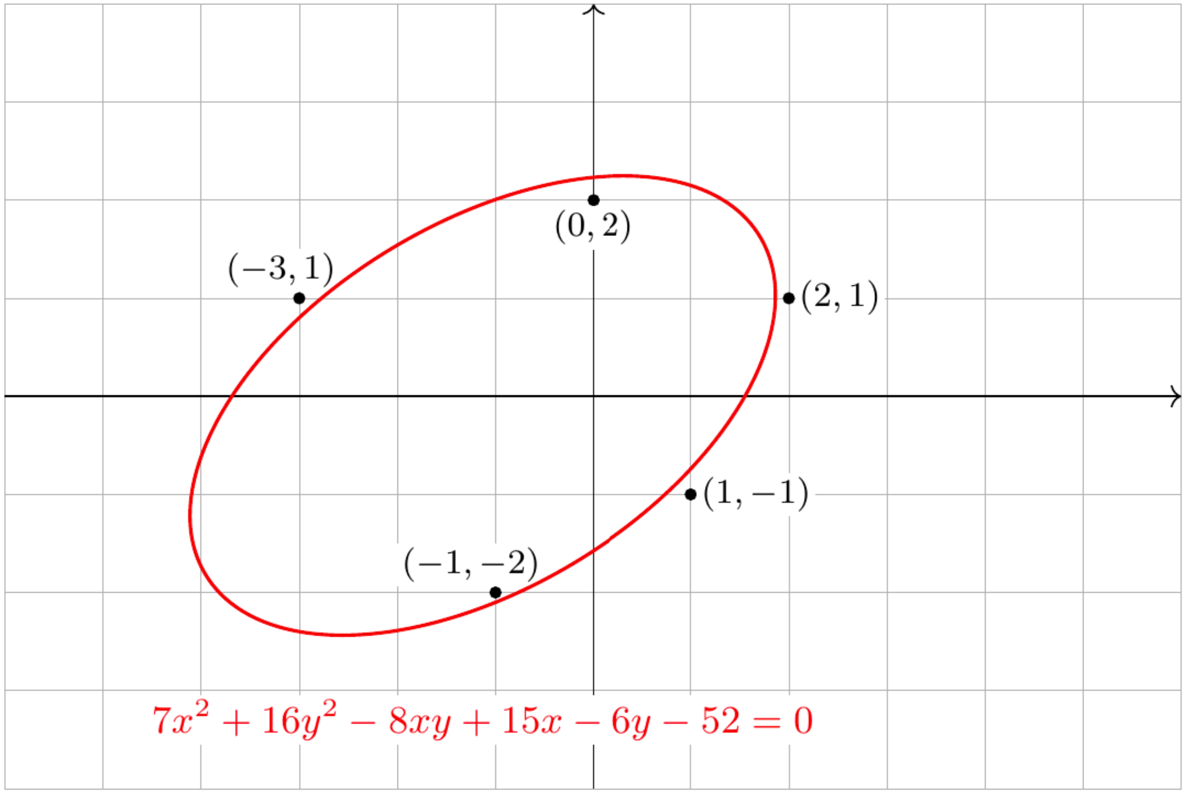
Best fit ellipse:

$$x^2 + \frac{16}{7}y^2 - \frac{8}{7}xy + \frac{15}{7}x - \frac{6}{7}y - \frac{52}{7} = 0$$

or

$$7x^2 + 16y^2 - 8xy + 15x - 6y - 52 = 0.$$

Best Fit Ellipse



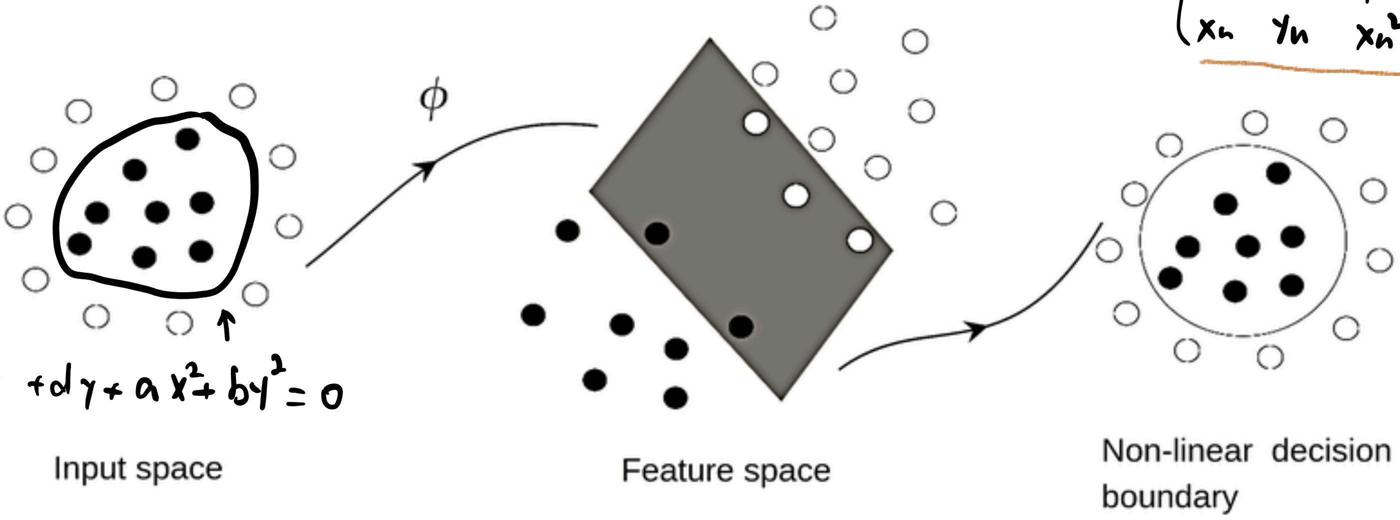
Remark: Gauss invented the method of least squares to do exactly this: he predicted the (elliptical) orbit of the asteroid Ceres as it passed behind the sun in 1801.

Kernel Trick

$$A = \begin{bmatrix} x_1 & y_1 & x_1^2 & y_1^2 \\ \vdots & \vdots & \vdots & \vdots \\ x_n & y_n & x_n^2 & y_n^2 \end{bmatrix}$$

→ new data

→ new data



$cx + dy + ax^2 + by^2 = 0$

$$(A^\top A)^{-1} A^\top b$$

4x4

$y = A(A^\top A)^{-1} A^\top b$

$A^\top A.$

$(AA^\top)^{-1} A$