ECON526: Quantitative Economics with Data Science Applications

Foundations of Numerical Linear Algebra

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Going Beyond "`reg y x, robust`"

- Data science, econometrics, and macroeconomics are built on linear algebra.
- Numerical linear algebra has all sorts of pitfalls, which become more critical as we scale up to larger problems.
- Speed differences in choosing better algorithms can be orders of magnitude.
- Crucial to know what goes on under-the-hood in Stata/R/python packages for applied work, even if you don't implement it yourself.
- Material here is related to
  - → QuantEcon Python
  - → QuantEcon Data Science
  - → A First Course in Quantitative Economics with Python

Packages

This section uses the following packages:

```
import numpy as np
import matplotlib.pyplot as plt
import scipy
from numpy.linalg import cond, matrix_rank, norm
from scipy.linalg import inv, solve, det, eig, lu, eigvals
from scipy.linalg import solve_triangular, eigvalsh, cholesky
```

Basic Computational Complexity

Big-O Notation

For a function $f(N)$ and a positive constant C, we say $f(N)$ is $O(g(N))$, if there exist positive constants C and N_0 such that:

$$0 \leq f(N) \leq C \cdot g(N) \quad \text{for all } N \geq N_0$$

- Often crucial to know how problems scale asymptotically (as $N \to \infty$)
- Caution! This is only an asymptotic limit, and can be misleading for small N
  - → $f_1(N) = N^3 + N$ is $O(N^3)$
  - → $f_2(N) = 1000N^2 + 3N$ is $O(N^2)$
  - → For roughly $N > 1000$ use f_2 algorithm, otherwise f_1

Examples of Computational Complexity

- Simple examples:
  - → $\boldsymbol{x} \cdot \boldsymbol{y} = \sum_{n=1}^{N} \boldsymbol{x}_n \boldsymbol{y}_n$ is $O(N)$ since it requires N multiplications and additions
  - → $\boldsymbol{A}\boldsymbol{x}$ for $\boldsymbol{A} \in \mathbb{R}^{N \times N}, \boldsymbol{x} \in \mathbb{R}^N$ is $O(N^2)$ since it requires N dot products, each $O(N)$

Numerical Precision

Machine Epsilon

For a given datatype, ϵ is defined as $\epsilon = \min_{\delta>0} \{\delta : 1 + \delta > 1\}$

- Computers have finite precision. 64-bit typical, but 32-bit on GPUs

```
print(f"machine epsilon for float64 = {np.finfo(float).eps}")
print(f"1 + eps/2 == 1? {1.0 + 1.1e-16 == 1.0}")
print(f"machine epsilon for float32 = {np.finfo(np.float32).eps}")
```

```
machine epsilon for float64 = 2.220446049250313e-16
1 + eps/2 == 1? True
machine epsilon for float32 = 1.1920928955078125e-07
```

Basic Linear Algebra

Norms

- Common measure of size is the Euclidean norm, or L^2 norm for $x \in \mathbb{R}^2$
- Complexity is $O(N)$, square N times then N additions

$$||x||_2 = \sqrt{\sum_{n=1}^{N} x_n^2}$$

```
x = np.array([1, 2, 3]) # Calculating different ways (in order of preference)
print(np.sqrt(sum(xval**2 for xval in x))) # manual with comprehensions
print(np.sqrt(np.sum(np.square(x)))) # broadcasts
print(norm(x)) # built-in to numpy norm(x, ord=2) alternatively
print(f"||x||_2^2 = {norm(x)**2} = {x.T @ x} = {np.dot(x, x)}")
```

```
3.7416573867739413
3.7416573867739413
3.7416573867739413
||x||_2^2 = 14.0 = 14 = 14
```

Solving Systems of Equations

- Solving $Ax = b$ for x is equivalent $A^{-1}Ax = A^{-1}b$
- Then since $A^{-1}A = I$, and $Ix = x$, we have $x = A^{-1}b$
- Careful since matrix algebra is not commutative!

```
A = np.array([[0, 2], [3, 4]]) # or ((0, 2), (3, 4))
b = np.array([2,1])  # Column vector
x = solve(A, b)  # Solve Ax = b for x
x
```

```
array([-1.,  1.])
```

Using the Inverse Directly

- Can replace the `solve` with a calculation of an inverse
- But it can be slower or less accurate than solving the system directly

```
A_inv = inv(A)
A_inv @ b # i.e, A^{-1} * b
```

```
array([-1.,  1.])
```

Linear Combinations

We can think of solving a system as finding the linear combination of columns of A that equal b

```
b_star = x[0] * A[:, 0] + x[1] * A[:, 1] # using x solution
print(f"b = {b}, b_star = {b_star}")
```

```
b = [2 1], b_star = [2. 1.]
```

Column Space and Rank

- The column space of a matrix represents all possible linear combinations of its columns.
- It forms a basis for the space of solutions when solving systems of linear equations represented by the matrix
- The rank of a matrix is the dimension of its column space

```
A = np.array([[0, 2], [3, 4]])
matrix_rank(A)
```

```
2
```

Hence, can solve $\boldsymbol{Ax} = \boldsymbol{b}$ for any $\boldsymbol{b} \in \mathbb{R}^2$ since the column space is the entire space $\mathbb{R}^2$

Singular Matrices

On the other hand, note

```
A = np.array([[1, 2],
              [2, 4]])
matrix_rank(A)
```

```
1
```

So we can only solve $Ax = b$ for $b \propto \begin{bmatrix} 1 \\ 2 \end{bmatrix} \propto \begin{bmatrix} 2 \\ 4 \end{bmatrix}$

Checking Singularity

```
A = np.array([[1, 2], [2, 4]])
# An (expensive) way to check if A is singular is if det(A) = 0
print(det(A) == 0.0)
print(matrix_rank(A) != A.shape[0]) # or check rank
# Check before inverting or use exceptions
try:
    inv(A)
    print("Matrix is not singular (invertible).")
except np.linalg.LinAlgError:
    print("Matrix is singular (non-invertible).")
```

```
True
True
Matrix is singular (non-invertible).
```

Determinant is Not Scale Invariant

- Reminder: numerical precision in calculations makes it hard to compare to zero
- The determinate is useful but depends on the scale of the matrix
- A more robust alternative is the condition number (more next lecture)

```
1  eps, K = 1e-8, 100000
2  A = np.array([[1, 2], [1 + eps, 2 + eps]])
3  print(f"det(A)={det(A):.5g}, det(K*A)={det(K*A):.5g}")
4  print(f"cond(A)={cond(A):.5g}, cond(K*A)={cond(K*A):.5g},")
5  print(f"det(inv(A))={det(inv(A)):.5g}, cond(inv(A))={cond(inv(A)):.5g}")
```

```
det(A)=-1e-08, det(K*A)=-100
cond(A)=1e+09, cond(K*A)=1e+09,
det(inv(A))=-1e+08, cond(inv(A))=1e+09
```

Interpreting Condition Numbers

- The condition number of the matrix A is $\kappa(A) = ||A|| \cdot ||A^{-1}||$, which can be shown in terms of ratio of the largest and smallest eigenvalues
  - → $\kappa(A) = \frac{\lambda_{\max}}{\lambda_{\min}}$ for λ the eigenvalues of A. More soon!
- Crude intuition: for machine epsilon ϵ_{mach} when calculating some x
  - → The relative error, $||x - x_{\text{approx}}||/||x||$ is roughly $\kappa(A) \cdot \epsilon_{\text{mach}}$
  - → Solving $Ax = b$ when $\epsilon_{\text{mach}} = 1e^{-16}$ it amplifies errors in b, etc.
  - → if $\kappa(A) \approx 1e^{16}$ errors amplified so the scale of 100% relative error

Rules of Thumb

- Rule of thumb for standard floating points where $\epsilon_{\text{mach}} = 1e^{-16}$:
  - → $\kappa(A) \approx 1$ well-conditioned
  - → $\kappa(A) < 100$ fairly well-conditioned
  - → $\kappa(A) < 1e^{5}$ moderately ill-conditioned. Take care
  - → $\kappa(A) < 1e^{8}$ ill-conditioned and might introduce significant errors, especially in algorithms which repeatedly use the same calculations
  - → $\kappa(A) > 1e^{8}$ very ill-conditioned and likely to introduce significant errors
- Choose solution algorithms based on “numerical stability” and “conditioning” when worried
- Much more extreme with 32-bit floats such as when using GPUs.

Solving Linear Systems of Equations

Solving Systems with Multiple RHS

- Inverse is nice because you can reuse the A^{-1} to solve $Ax = b$ for many b
- However, you can do this with `solve` as well
- Or can reuse LR factorizations (discussed next)

```
A = np.array([[0, 2], [3, 4]])
B = np.array([[2,3], [1,2]])  # [2,1] and [3,2] as columns
# or: B = np.column_stack([np.array([2, 1]),np.array([3,2])])
X = solve(A, B)  # Solve AX = B for X
print(X)
print(f"Checking: A*{X[:,0]} = {A@X[:, 0]} = {B[:,0]}, column of B")
```

```
[[-1.         -1.33333333]
 [ 1.          1.5       ]]
Checking: A*[-1.  1.] = [2. 1.] = [2 1], column of B
```

LU(P) Decompositions

- We can "factor" any square A into $PA = LU$ for triangular L and U. Invertible can have $A = LU$, called the LU decomposition. "P" is for partial-pivoting
- Singular matrices may not have full-rank L or U matrices

```
1 A = np.array([[1, 2], [2, 4]])
2 P, L, U = lu(A)
3 print(f"L*U =\n{L @ U}")
4 print(f"P*A =\n{P @ A}")
```

```
L*U =
[[2. 4.]
 [1. 2.]]
P*A =
[[2. 4.]
 [1. 2.]]
```

P, U, and L

The P matrix is a permutation matrix of “pivots” the others are triangular

```
1 print(f"P =\n{P}")
2 print(f"L =\n{L}")
3 print(f"U =\n{U}")
```

```
P =
[[0. 1.]
 [1. 0.]]
L =
[[1.  0. ]
 [0.5 1. ]]
U =
[[2. 4.]
 [0. 0.]]
```

LU Decompositions and Systems of Equations

- Pivoting is typically implied when talking about “LU”
- Used in the default `solve` algorithm (without more structure)
- Solving systems of equations with triangular matrices: for $Ax = LUx = b$
  1. Define $y = Ux$
  2. Solve $Ly = b$ for y and $Ux = y$ for x
- Since both are triangular, process is $O(N^2)$ (but LU itself $O(N^3)$)
- Could be used to find `inv`
  - → $A = LU$ then $AA^{-1} = I = LUA^{-1} = I$
  - → Solve for Y in $LY = I$, then solve $UA^{-1} = Y$
- Tight connection to textbook Gaussian elimination (including pivoting)

LU for Non-Singular Matrices

```
A = np.array([[1, 2], [3, 4]])
P, L, U = lu(A)
print(f"L*U =\n{L @ U}")
print(f"P*A =\n{P @ A}")
```

```
L*U =
[[3. 4.]
 [1. 2.]]
P*A =
[[3. 4.]
 [1. 2.]]
```

L, U, P

```
1 print(f"P =\n{P}")
2 print(f"L =\n{L}")
3 print(f"U =\n{U}")
```

```
P =
[[0. 1.]
 [1. 0.]]
L =
[[1.         0.        ]
 [0.33333333 1.        ]]
U =
[[3.         4.        ]
 [0.         0.66666667]]
```

Backwards Substitution Example

$$Ux = b$$

$$U \equiv \begin{bmatrix} 3 & 1 \\ 0 & 2 \end{bmatrix}, \quad b = \begin{bmatrix} 7 \\ 2 \end{bmatrix}$$

Solving bottom row for x_2

$$2x_2 = 2, \quad x_2 = 1$$

Move up a row, solving for x_1, substituting for x_2

$$3x_1 + 1x_2 = 7, \quad 3x_1 + 1 \times 1 = 7, \quad x_1 = 2$$

Generalizes to many rows. For L it is “forward substitution”

Use Triangular Structure if Possible

- Triangular matrices of size N can be solved with back substitution in $O(N^2)$
- Is $O(N^2)$ good or bad? Beats, $O(N^3)$ typical of general methods

```
U = np.array([[3, 1],
              [0, 2]])
b = np.array([7,2])
solve(U,b) # works, but internally does an LU which is O(N^3)
solve_triangular(U, b, lower=False) # fast O(N^2)
```

```
array([2., 1.])
```

Symmetric Matrix Structure

Another common matrix type are symmetric, $A = A^T$

```
A = np.array([[1, 2], [2, 5]]) # also posdef, not singular
b = np.array([1,4])
# With scipy 1.11.3 check with scipy.linalg.issymmetric(A)
solve(A, b, assume_a="sym") # could also use "pos" since positive definite
```

```
array([-3.,  2.])
```

Positive Definite Matrices

- A symmetric matrix A is positive definite if $x^T Ax > 0$ for all $x \neq 0$
- Useful in many areas, such as covariance matrices. Example

```
A = np.array([[1, 2], [2, 5]])
x = np.array([0, 1]) # can't really check for all x
print(f"x^T A x = {x.T @ A @ x}")
```

```
x^T A x = 5
```

- Example of a symmetric matrix that is not positive definite

```
A = np.array([[1, 2], [2, 0]])
print(f"x^T A x = {x.T @ A @ x}")  # one counterexample is enough
```

```
x^T A x = 0
```

- We can check these with eigenvalues

Cholesky Decomposition

- For symmetric positive definite matrices: $L = U^T$,
- Called a Cholesky decomposition: $A = LL^T$ for a lower triangular matrix L.
- Equivalently, could find A = $U^T U$ for an upper triangular matrix U

```
1 A = np.array([[1, 2], [2, 5]])
2 L = cholesky(A, lower=True) # cholesky also defined for upper=True
3 print(L)
4 print(f"L*L^T =\n{L @ L.T}")
```

```
[[1. 0.]
 [2. 1.]]
L*L^T =
[[1. 2.]
 [2. 5.]]
```

Solving Positive Definite Systems

```
A = np.array([[1, 2], [2, 5]])
b = np.array([1,4])
print(solve(A, b, assume_a="pos")) # uses cholesky internally

L = cholesky(A, lower=True)
y = solve_triangular(L, b, lower=True)
x = solve_triangular(L.T, y, lower=False)
print(x)
```

```
[-3.  2.]
[-3.  2.]
```

Cholesky for Covariance Matrices

- Covariance matrices are positive-definite, semi-definite if degenerate
- Key property of Gaussian random variables:
  - → $X \sim N(\mu, \Sigma)$ for $\mu \in \mathbb{R}^N, \Sigma \in \mathbb{R}^{N \times N}$
  - → $X = \mu + AZ$ for $Z \sim N(0_N, I_N)$ where $AA^T = \Sigma$
- That is, A is the Cholesky decomposition of the covariance matrix

Matrices as Linear Transformations

- Recall: for $\boldsymbol{x} \in \mathbb{R}^N$ we should think of a $\boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{A}\boldsymbol{x}$ for $\boldsymbol{A} \in \mathbb{R}^{M \times N}$ as a linear transformation from $\mathbb{R}^N$ to $\mathbb{R}^M$

  → Definition of Linear: $\boldsymbol{f}(\boldsymbol{a}\boldsymbol{x}_1 + \boldsymbol{b}\boldsymbol{x}_2) = \boldsymbol{a}\boldsymbol{f}(\boldsymbol{x}_1) + \boldsymbol{b}\boldsymbol{f}(\boldsymbol{x}_2)$ for scalar $\boldsymbol{a}, \boldsymbol{b}$

- Similarly, the $\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{A}\boldsymbol{x}$ then $\boldsymbol{f}^{-1}(\boldsymbol{y}) = \boldsymbol{A}^{-1}\boldsymbol{y}$ goes from $\mathbb{R}^M$ to $\mathbb{R}^N$

  → If the matrix is square and invertible, we can go back and forth without losing information (i.e., bijective). Otherwise we may be projected onto a lower-dimensional “manifold”.

Norms and Linear Transformations

- The vector norm $||x||_2$ is an important feature in many applications
  - → Hence $||f(x)||_2 = ||Ax||_2$ frequently comes up in economics and datascience
  - → e.g. linear regression is written as minimizing a vector norm

$$\min_{\beta} ||y - X\beta||_2$$

- Matrix structure or decompositions of A help us better understand the $f(x)$ mapping

Orthogonal Matrices

- A square matrix Q is **orthogonal** if: $Q^{-1} = Q^T$, and hence $Q^TQ = QQ^T = I$
  - → For orthogonal Q, $f(x) = Qx$ is interpreted as rotating x without stretching
  - → $y = f(x) = Qx$ then $f^{-1}(y) = Q^{-1}y = Q^Ty$ is rotating y back
  - → Columns are orthonormal: $Q = [q_1| \quad \dots \quad |q_N]$ then
    - ⇾ $q_i \cdot q_j = 0$ for $i \neq j$ and $q_i \cdot q_i = 1$
  - → Rotation means the length doesn't change: $||Qx||_2 = ||x||_2$
  - → Transformations which preserve norms are central in many applications within data science, ML, and economics - especially in high-dimensions

Eigenvalues and Eigenvectors

Eigenvalues and Eigenvectors

- For a square $\boldsymbol{A}$, an eigenvector $\boldsymbol{x}$ and eigenvalue $\boldsymbol{\lambda}$ satisfy

$$\boldsymbol{A}\boldsymbol{x} = \boldsymbol{\lambda}\boldsymbol{x}$$

- $\boldsymbol{A} \in \mathbb{R}^{\boldsymbol{N}\times\boldsymbol{N}}$ has $\boldsymbol{N}$ eigenvalue/eigenvector pairs, possible multiplicity of $\boldsymbol{\lambda}$
- Intuition: $\boldsymbol{x}$ is a direction $\boldsymbol{A}\boldsymbol{x} \propto \boldsymbol{x}$ and $\boldsymbol{\lambda}$ says how much it “stretches”

Properties of Eigenvalues and Eigenvectors

- For any eigenvector x and scalar c then $cx \propto Ax$ as well
- Symmetric matrices have real eigenvalues and orthogonal eigenvectors. i.e. $x_1 \cdot x_2 = 0$ for $x_1 \neq x_2$ eigenvectors. Complex in general
- Singular if and only if it has an eigenvalue of zero
- Positive (semi)definite if and only if all eigenvalues are strictly (weakly) positive
- Diagonal matrix has eigenvalues as its diagonal
- Triangular matrix has eigenvalues as its diagonal

Positive Definite and Eigenvalues

You cannot check $x^T Ax > 0$ for all x. Check if “stretching” is positive

```
A = np.array([[3, 1], [2, 1]])
# A_eigs = np.real(eigvals(A)) # symmetric matrices have real eigenvalues
A_eigs = eigvalsh(A) # specialized for symmetric/hermitian matrices
print(A_eigs)
is_positive_definite = np.all(A_eigs > 0)
is_positive_semi_definite = np.all(A_eigs >= 0) # or eigvals(A) >= -eps
print(f"pos-def? {is_positive_definite}")
print(f"pos-semi-def? {is_positive_semi_definite}")
```

```
[-0.23606798  4.23606798]
pos-def? False
pos-semi-def? False
```

Positive Semi-Definite Matrices **May** Have a Zero Eigenvalue

The simplest positive-semi-definite (but not posdef) matrix is

```
A_eigs = eigvalsh(np.array([[1, 0], [0, 0]]))
print(A_eigs)
is_positive_definite = np.all(A_eigs > 0)
is_positive_semi_definite = np.all(A_eigs >= 0) # or eigvals(A) >= -eps
print(f"pos-def? {is_positive_definite}")
print(f"pos-semi-def? {is_positive_semi_definite}")
```

```
[0. 1.]
pos-def? False
pos-semi-def? True
```

Eigen Decomposition

- For square, symmetric, non-singular matrix A factor into

$$A = Q\Lambda Q^{-1}$$

- Q is a matrix of eigenvectors, Λ is a diagonal matrix of paired eigenvalues
- For symmetric matrices, the eigenvectors are orthogonal and $Q^{-1}Q = Q^{T}Q = I$ which form an orthonormal basis
- Orthogonal matrices can be thought of as rotations without stretching
- More general matrices all have a Singular Value Decomposition (SVD)
- With symmetric A, an interpretation of Ax is that we can first rotate x into the Q basis, then stretch by Λ, then rotate back

Eigendecompositions and Matrix Powers

- Can be used to find A^t for large t (e.g. for Markov chains)
  - $\rightarrow$ P^t, i.e. $P \cdot P \cdot \ldots \cdot P$ for t times
  - $\rightarrow$ $P = Q\Lambda Q^{-1}$ then $P^t = Q\Lambda^t Q^{-1}$ where Λ^t is just the pointwise power
- Related tools such as SVD can help with dimensionality reduction

Spectral/Eigendecomposition of Symmetric Matrix Example

```
A = np.array([[2, 1], [1, 3]])
Lambda, Q = eig(A)
print(f"eigenvectors are column-by-column in Q =\n{Q}")
print(f"eigenvalues are in Lambda = {Lambda}")
print(f"Q Lambda Q^T =\n{Q @ np.diag(np.real(Lambda)) @ Q.T}")
```

```
eigenvectors are column-by-column in Q =
[[-0.85065081 -0.52573111]
 [ 0.52573111 -0.85065081]]
eigenvalues are in Lambda = [1.38196601+0.j 3.61803399+0.j]
Q Lambda Q^T =
[[2. 1.]
 [1. 3.]]
```

Spectral Radius is Maximum Absolute Eigenvalue

- If any $\lambda \in \Lambda$ are > 1 can see this would explode
- Useful for seeing if iteration $x_{t+1} = Ax_t$ from a x_0 explodes
- The **spectral radius** of matrix A is

$$\rho(A) = \max_{\lambda \in \Lambda} |\lambda|$$

Least Squares and the Normal Equations

Least Squares

Given a matrix $\boldsymbol{X} \in \mathbb{R}^{N \times M}$ and a vector $\boldsymbol{y} \in \mathbb{R}^{N}$, we want to find $\beta \in \mathbb{R}^{M}$ such that

$$\min_{\beta} ||y - X\beta||^2, \text{ that is,}$$

$$\min_{\beta} \sum_{n=1}^{N} \frac{1}{N} (y_n - X_n \cdot \beta)^2$$

Where X_n is n'th row. Take FOCS and rearrange to get

$$(X^T X)\beta = X^T y$$

Solving the Normal Equations

- The X is often referred to as the “design matrix”. $X^T X$ as the Gram matrix
- Can form $A = X^T X$ and $b = X^T y$ and solve $A\beta = b$.
  - → Or invert $X^T X$ to get

$$\beta = (X^T X)^{-1} X^T y$$

  - → Note that $X^T X$ is symmetric and, if X is full-rank, positive definite

Solving Regression Models in Practice

- In practice, use the `lstsq` function in scipy
  - → It uses better algorithms using eigenvectors. More stable (see next lecture on conditioning)
  - → One algorithm uses another factoring, the QR decomposition
  - → There, $X = QR$ for Q orthogonal and R upper triangular. See QR Decomposition for more
- Better yet, for applied work use higher-level libraries like `statsmodels` (integrates well with `pandas` and `seaborn`)
  - → See statsmodels docs for R-style notation
  - → See QuantEcon OLS Notes for more.

Example of LLS using Scipy

```
1 N, M = 100, 5
2 X = np.random.randn(N, M)
3 beta = np.random.randn(M)
4 y = X @ beta + 0.05 * np.random.randn(N)
5 beta_hat, residuals, rank, s = scipy.linalg.lstsq(X, y)
6 print(f"beta =\n {beta}\nbeta_hat =\n{beta_hat}")
```

```
beta =
 [-0.37740033 -0.03482823 -0.62279476  1.50312151  0.45715271]
beta_hat =
[-0.38415748 -0.03090123 -0.61707946  1.50418288  0.45413767]
```

Solving using the Normal Equations

Or we can solve it directly. Provide matrix structure (so it can use a Cholesky)

```
1 beta_hat = solve(X.T @ X, X.T @ y, assume_a="pos")
2 print(f"beta =\n {beta}\nbeta_hat =\n{beta_hat}")
```

```
beta =
 [-0.37740033 -0.03482823 -0.62279476  1.50312151  0.45715271]
beta_hat =
[-0.38415748 -0.03090123 -0.61707946  1.50418288  0.45413767]
```

Collinearity in “Tall” Matrices

- Tall $\mathbb{R}^{N \times M}$ “design matrices” have $N > M$ and are “overdetermined”
- The rank of a matrix is full rank if all columns are linearly independent
- You can only identify M parameters with M linearly independent columns

```
X = np.array([[1, 2], [2, 5], [3, 7]]) # 3 observations, 2 variables
X_col = np.array([[1, 2], [2, 4], [3, 6]]) # all proportional
print(f"rank(X) = {matrix_rank(X)}, rank(X_col) = {matrix_rank(X_col)}")
```

```
rank(X) = 2, rank(X_col) = 1
```

Collinearity and Estimation

- If X is not full rank, then $X^T X$ is not invertible. For example:

```
print(f"cond(X'*X)={cond(X.T@X)}, cond(X_col'*X_col)={cond(X_col.T@X_col)}")
```

```
cond(X'*X)=2819.3329786399063, cond(X_col'*X_col)=1.2999933999712892e+16
```

- Note that when you start doing operations on matrices, numerical error creeps in, so you will not get an exact number
- The rule-of-thumb with condition numbers is that if it is 1×10^k then you lose about k digits of precision. So this effectively means it is singular
- Given the singular matrix, this means a continuum of β will solve the problem

`lstsq` Solves it? Careful on Interpretation!

- Since $X_{col}^T X_{col}$ is singular, we cannot use `solve(X.T@X, y)`
- But what about `lstsq` methods?
- As you will see, this gives an answer. Interpretation is hard
- The key is that in the case of non-full rank, you cannot identify individual parameters

  → Related to “Identification” in econometrics

  → Having low residuals is not enough

```
y = np.array([5.0, 10.1, 14.9])
beta_hat, residuals, rank, s = scipy.linalg.lstsq(X_col, y)
print(f"beta_hat_col = {beta_hat}")
print(f"rank={rank}, cols={X.shape[1]}, norm(X*beta_hat_col-y)={norm(residuals)}")
```

```
beta_hat_col = [0.99857143 1.99714286]
rank=1, cols=2, norm(X*beta_hat_col-y)=0.0
```

Fat Design Matrices

- Fat $\mathbb{R}^{N \times M}$ "design matrices" have $N < M$ and are "underdetermined"
- Less common in econometrics, but useful to understand the structure
- A continuum $\beta \in \mathbb{R}^{M - \mathrm{rank}(X)}$ solve this problem

```
1 X = np.array([[1, 2, 3], [0, 5, 7]]) # 2 rows, 3 variables
2 y = np.array([5, 10])
3 beta_hat, residuals, rank, s = scipy.linalg.lstsq(X, y)
4 print(f"beta_hat = {beta_hat}, rank={rank}, ? residuals = {residuals}")
```

```
beta_hat = [0.8 0.6 1. ], rank=2, ? residuals = []
```

Which Solution?

- Residuals are zero here because there are enough parameters to fit perfectly (i.e., it is underdetermined)
- Given the multiple solutions, the `lstsq` is giving

$$\min_{\beta} ||\beta||_2^2 \text{ s.t. } X\beta = y$$

- i.e., the “smallest” coefficients which interpolate the data exactly
- Which trivially fulfills the OLS objective: $\min_\beta ||y - X\beta||_2^2$

Careful Interpreting Underdetermined Solutions

- Useful and common in ML, but be **very** careful when interpreting for economics
  - → Tight connections to Bayesian versions of statistical tests
  - → But until you understand econometrics and “identification” well, **stick to full-rank matrices**
  - → **Advanced topics:** search for “Regularization”, “Ridgeless Regression” and “Benign Overfitting in Linear Regression.”