

Why.N.How: Linear Algebra

Adrian KC Lee ScD

Research Fellow, MGH



Martinos Center
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Format of tutorial

- ▶▶ Why do we care about Linear Algebra?
- ▶▶ What is a vector?
 - ▶ Geometric interpretation.
 - ▶ Vector operations, “Norms,” Projections.
 - ▶ Independence, Basis set.
- ▶▶ What is a matrix?
 - ▶ Determinants, Inverse.
 - ▶ Under-determined solution / null-space / MEG.
 - ▶ Over-determined solution / LMMSE / fMRI.

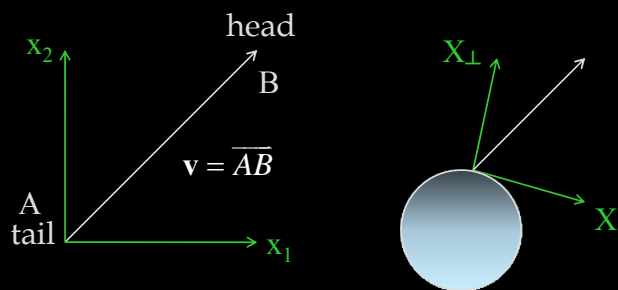


Why Linear Algebra?

- ▶▶ What is linear algebra?
 - ▶ Study of vectors, systems of linear equations...
- ▶▶ Who cares?
 - ▶ Extensive applications in neurosciences.
 - ▶ Nice geometric interpretation of complex mathematical concepts, e.g., spectral coherence.
- ▶▶ How do we use MATLAB?
 - ▶ MATrix LABoratory: fundamental knowledge in linear algebra matters!!



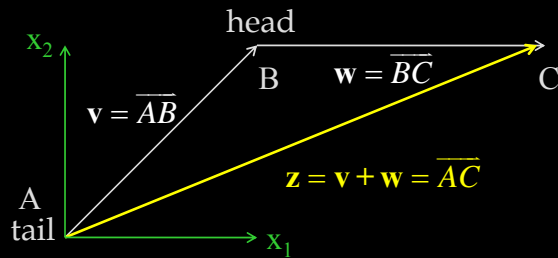
What is a vector?



- ▶▶ Physical interpretation: a geometric entity characterized by a magnitude and a direction.
- ▶▶ Commonly encountered in Euclidean space.
 - ▶ In MEG: tangential and normal decomposition.



Vector Addition

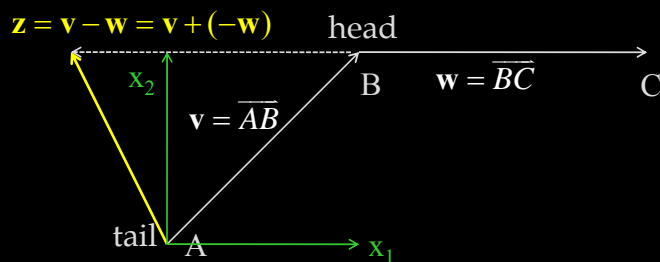


$$\mathbf{v} = \begin{pmatrix} 2 \\ 2 \end{pmatrix} \quad \mathbf{w} = \begin{pmatrix} 3 \\ 0 \end{pmatrix}$$

$$\mathbf{z} = \mathbf{v} + \mathbf{w} = \begin{pmatrix} 2 \\ 2 \end{pmatrix} + \begin{pmatrix} 3 \\ 0 \end{pmatrix} = \begin{pmatrix} 5 \\ 2 \end{pmatrix}$$



Vector Subtraction



$$\mathbf{v} = \begin{pmatrix} 2 \\ 2 \end{pmatrix} \quad \mathbf{w} = \begin{pmatrix} 3 \\ 0 \end{pmatrix}$$

$$\mathbf{z} = \mathbf{v} - \mathbf{w} = \mathbf{v} + (-\mathbf{w}) = \begin{pmatrix} 2 \\ 2 \end{pmatrix} + \begin{pmatrix} -3 \\ 0 \end{pmatrix} = \begin{pmatrix} -1 \\ 2 \end{pmatrix}$$



“Norm”

$$\mathbf{v} = \begin{pmatrix} -3 \\ 4 \end{pmatrix}$$

$$\|\mathbf{x}\| = \sqrt{x_1^2 + x_2^2 + x_3^2 + \dots + x_n^2}$$

$$= \left(|x_1|^p + |x_2|^p + |x_3|^p + \dots + |x_n|^p \right)^{1/p}$$

$$\|\mathbf{v}\| = \sqrt{(-3)^2 + (4)^2} = 5 \quad \|\mathbf{x}\|_\infty = \max\{|x_1|, |x_2|, \dots, |x_p|\}$$

- ▶ “Norm” is a measure of distance of a vector.
- ▶ Default norm: L2-norm
- ▶ Other norms: L1-norm; L ∞ -norm.



Scalar Multiplication / Unit Vector

$$\mathbf{v} = \begin{pmatrix} -3 \\ 4 \end{pmatrix} \quad \frac{1}{2}\mathbf{v}$$

$$\frac{1}{2}\mathbf{v} = \frac{1}{2} \begin{pmatrix} -3 \\ 4 \end{pmatrix} = \begin{pmatrix} -1.5 \\ 2 \end{pmatrix}$$

$$\hat{\mathbf{v}} = \frac{\mathbf{v}}{\|\mathbf{v}\|} \quad \|\mathbf{v}\| = \sqrt{(-3)^2 + (4)^2} = 5$$

$$\hat{\mathbf{v}} = \frac{1}{5} \begin{pmatrix} -3 \\ 4 \end{pmatrix}$$

- ▶ Unit vector factors out the magnitude,
- ▶ Watch out for MATLAB vectors (e.g., PCA), they give you unit vectors.



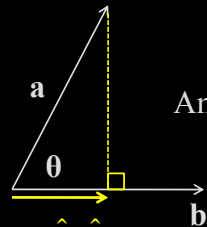
Dot product / Projection

Dot Product:

$$a_1 b_1 + \dots + a_n b_n = \|\mathbf{a}\| \|\mathbf{b}\| \cos \theta$$

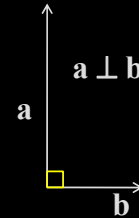
Angle between 2 vectors:

$$\cos \theta = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$$



$$(\mathbf{a} \cdot \hat{\mathbf{b}}) \hat{\mathbf{b}}$$

Projection



$\mathbf{a} \perp \mathbf{b}$

- ▶ Two vectors are orthogonal if their dot product equals to 0, i.e., If $\mathbf{a} \perp \mathbf{b}$, then $\mathbf{a} \cdot \mathbf{b} = 0$
- ▶ Note: $\mathbf{a} \cdot \mathbf{a} = \|\mathbf{a}\|^2$.

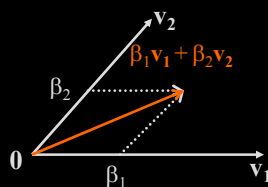


Independence / Basis set

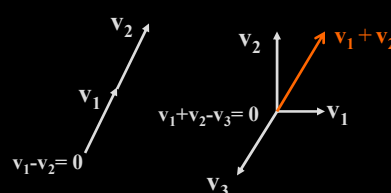
Definition: $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ is independent if and only if no vector in this set can be written as a linear combination of the rest:

$$\beta_1 \mathbf{v}_1 + \dots + \beta_n \mathbf{v}_n = \mathbf{0} \quad \text{iff} \quad \forall \beta_i = 0$$

Independent set of vectors in \mathbb{R}^2



Dependent set of vectors in \mathbb{R}^2



- ▶ Unique weights for decomposition into an independent set.
- ▶ Basis set: a set of independent vectors that span V ,
 - » e.g., \mathbf{v}_1 and \mathbf{v}_2 form a basis set for \mathbb{R}^2 but not \mathbb{R}^3 .



Matrix (Addition / Scalar Multiplication / Transpose)

- ▶ Matrix: rectangular table of elements
 - ▶ used to describe linear equations.

$$\begin{array}{l}
 \mathbf{A} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \begin{array}{l} m \text{ rows} \\ n \text{ columns} \end{array} \\
 \text{Matrix } m \times n
 \end{array}
 \quad
 \mathbf{A} = \begin{bmatrix} 2 & 4 \\ 4 & 11 \end{bmatrix}; \mathbf{B} = \begin{bmatrix} 1 & 3 \\ 1 & 2 \end{bmatrix}$$

$$\mathbf{A} + \mathbf{B} = \begin{bmatrix} 2+1 & 4+3 \\ 4+1 & 11+2 \end{bmatrix} = \begin{bmatrix} 3 & 7 \\ 4 & 13 \end{bmatrix}$$

$$\mathbf{B}^T = \begin{bmatrix} 1 & 1 \\ 3 & 2 \end{bmatrix} \quad \mathbf{A} = \begin{bmatrix} 3.2 & 3.4 \\ 3.4 & 3.11 \end{bmatrix} = \begin{bmatrix} 6 & 12 \\ 12 & 33 \end{bmatrix}$$



Note: \mathbf{A} is symmetric, i.e., $\mathbf{A}^T = \mathbf{A}$

Matrix Multiplication

- ▶ Matrix multiplication is NOT commutative:
 - ▶ i.e., generally, $\mathbf{AB} \neq \mathbf{BA}$

$$\mathbf{A} = \begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix}; \mathbf{B} = \begin{bmatrix} 2 & 3 \\ 1 & 0 \end{bmatrix}$$

$$\mathbf{A}\mathbf{B} = \begin{bmatrix} 1.2+2.1 & 1.3+2.0 \\ 0.2+1.1 & 0.3+1.0 \end{bmatrix} = \begin{bmatrix} 4 & 3 \\ 1 & 0 \end{bmatrix}$$

$$\mathbf{B}\mathbf{A} = \begin{bmatrix} 2.1+3.0 & 2.2+3.1 \\ 1.1+0.0 & 1.2+0.1 \end{bmatrix} = \begin{bmatrix} 2 & 7 \\ 1 & 2 \end{bmatrix}$$



Matrix Multiplication

▶ Dimension of matrices must match

$$\mathbf{C}_{(m,p)} = \mathbf{A}_{(m,n)} \mathbf{B}_{(n,p)}$$

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 2 \\ -1 & 3 & 1 \end{bmatrix}; \mathbf{B} = \begin{bmatrix} 3 & 1 \\ 2 & 1 \\ 1 & 0 \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} 1 \cdot 3 + 0 \cdot 2 + 2 \cdot 1 & 1 \cdot 1 + 0 \cdot 1 + 2 \cdot 0 \\ -1 \cdot 3 + 3 \cdot 2 + 1 \cdot 1 & -1 \cdot 1 + 3 \cdot 1 + 1 \cdot 0 \end{bmatrix} = \begin{bmatrix} 5 & 1 \\ 4 & 2 \end{bmatrix}$$



Solving Linear Equations

$$\begin{aligned} a_{11}x_1 + \cdots + a_{1n}x_n &= b_1 \\ &\vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n &= b_n \end{aligned}$$

$$\mathbf{Ax} = \mathbf{b}$$

$$\begin{array}{l} \mathbf{A} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \begin{array}{l} \text{m rows} \\ \text{n columns} \end{array} \\ \text{m x n} \\ \text{Matrix} \end{array} \quad \mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix}$$

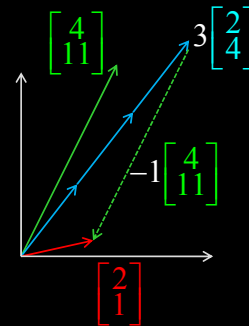
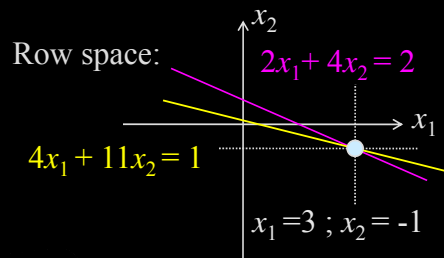


Matrix (Geometric interpretation)

$$\mathbf{Ax} = \mathbf{b} \quad \mathbf{A} = \begin{bmatrix} 2 & 4 \\ 4 & 11 \end{bmatrix} \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

Solve for \mathbf{x} :

$$\mathbf{x} = \begin{bmatrix} 3 \\ -1 \end{bmatrix} \quad \text{Column space: } x_1 \begin{bmatrix} 2 \\ 4 \end{bmatrix} + x_2 \begin{bmatrix} 4 \\ 11 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$



How to solve for \mathbf{x} in $\mathbf{Ax} = \mathbf{b}$?

(M equations = N unknowns)

► How many equations do I need to solve for 3 unknowns?

- In general: M equations, N unknowns.
- Can we guarantee a unique solution when $M=N$?

Demonstration:

<http://demonstrations.wolfram.com/PlanesSolutionsAndGaussianEliminationOfA33LinearSystem/>



Solve $\mathbf{Ax} = \mathbf{b}$ by finding \mathbf{A}^{-1}

(M equations = N unknowns)

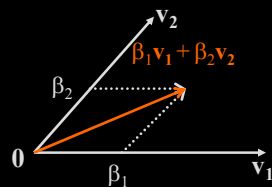
- ▶▶ If $\mathbf{Ax} = \mathbf{b}$ and we want to solve for \mathbf{x} :
 - ▶ We want $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$
- ▶▶ Does \mathbf{A}^{-1} always exist?
 - ▶ Only if \mathbf{A} is a square matrix (i.e., $M=N$).
 - ▶ Only if determinant of \mathbf{A} is not 0.
- ▶▶ How do we find determinant and \mathbf{A}^{-1} ?
 - ▶ Can use Gaussian elimination to find determinant.
 - ▶ Can use Cramer's rule to find \mathbf{A}^{-1} .
 - ▶ Or use MATLAB ☺!!!!



Undetermined case

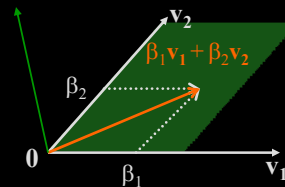
(M equations < N unknowns)

Independent set of vectors in \mathbb{R}^2



- ▶▶ $M = N$
- ▶▶ Vectors span 2 dimension
 - ▶ Rank = 2.
 - ▶ Nullity = $N - R = 0$.

Independent set of vectors in \mathbb{R}^3

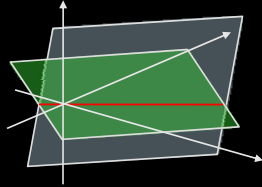


- ▶▶ $M < N$
- ▶▶ Vectors span 2 dimension
 - ▶ Rank = 2.
 - ▶ Nullity = $N - R = 1$.



Null-space

(M equations $<$ N unknowns)



▶ $M < N$

▶ Rank = 2

▶ Nullity = 1

▶ There is no unique solution since we are in an underdetermined case.

▶ Any point lying on the red line is a valid solution!

▶ How do we find A^{-1} when A is not square ($M \neq N$)?

▶ Pseudo-inverse.

▶ “Do the best we can do, given what we have.”



Undetermined soln in MEG

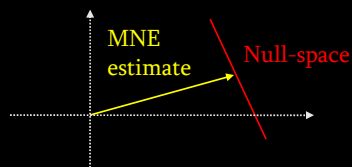
▶ In MEG:

▶ 306 sensors ($M = 306$ equations).

▶ 6000 dipole estimates ($N = 6000$ unknowns).

▶ $M \ll N$.

▶ MNE: uniqueness comes from other constraints.



▶ Side topics:

▶ How to obtain pseudo-inverse?

▶ Singular Value Decomposition.

▶ Eigenvalues, eigenvectors.

▶ $Ax = \lambda x$



Overdetermined case (M equations > N unknowns)

▶▶ Experiment:

▶ Relationship between number of people wanting me to stop talking (y) as a function of time (t).

▶ Model: $\hat{y} = C_0 + C_1 t$

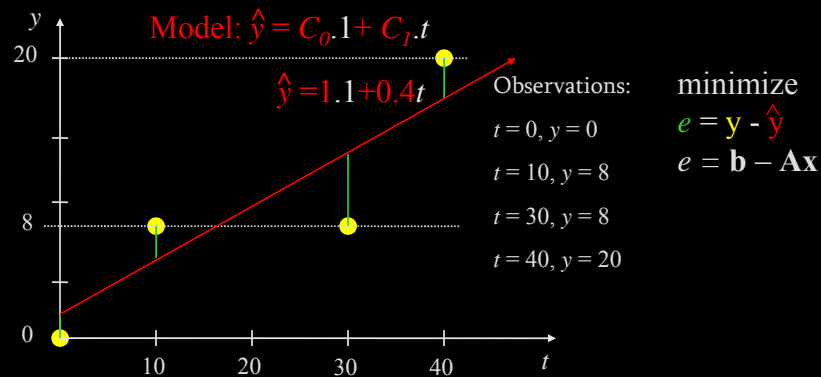
» C_0 : baseline Care-Factor; C_1 : drift in Attention.

» Data collected (y : reported distractions) at time $t_1=0$ ($y=y_1$); $t_2=10$ ($y=y_2$); $t_3=30$ ($y=y_3$); $t_4=40$ ($y=y_4$).

$$\mathbf{Ax} = \mathbf{b} \quad \begin{array}{l} C_0 + t_1 C_1 = y_1 \\ C_0 + t_2 C_1 = y_2 \\ C_0 + t_3 C_1 = y_3 \\ C_0 + t_4 C_1 = y_4 \end{array} \quad \mathbf{A} = \begin{bmatrix} 1 & 0 \\ 1 & 10 \\ 1 & 30 \\ 1 & 40 \end{bmatrix} \quad \mathbf{x} = \begin{bmatrix} C_0 \\ C_1 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix}$$



Results (Linear regression)

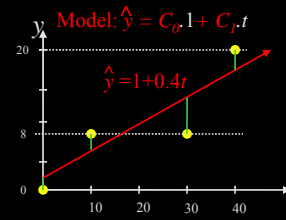
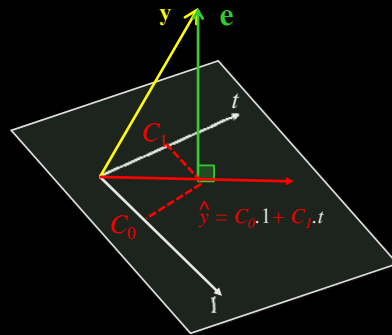


$$\mathbf{Ax} = \mathbf{b}$$



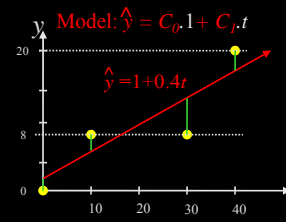
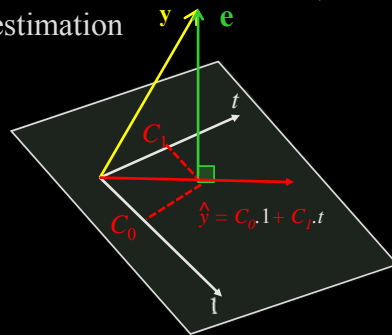
LMMSE

- ▶ Framework: estimate a set of weights (C_0 and C_1) such that the error (e) between our observed data (\mathbf{b}) and our weighted design matrix (\mathbf{A}) is minimum,
 - ▶ i.e., “minimize” $\mathbf{e} = \mathbf{b} - \mathbf{A}\mathbf{x} = \mathbf{y} - (C_0 \cdot 1 + C_1 \cdot t)$
 - ▶ Linearly Minimize by Mean Square Error: $\|\mathbf{e}\|^2$



LMMSE / GLM

- ▶ Closed form solution (LMMSE)
 - ▶ Find \mathbf{x} that minimizes $\|\mathbf{Ax} - \mathbf{b}\|^2$
 - ▶ Least square solution to $\mathbf{Ax} = \mathbf{b}$: $\mathbf{x} = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{b}$
- ▶ Now consider Random variables as vectors (GLM):
 - ▶ Least square solution to $\mathbf{X}\beta = \mathbf{Y}$: $\beta = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}$
 - ▶ where \mathbf{Y} = Observed data; \mathbf{X} = Design matrix; β = Parameter estimation

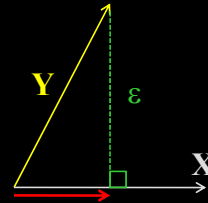


GLM in a nut-shell (fMRI context)

$$Y = X\beta + \varepsilon$$

- ▶ Y : BOLD signal at various time at a single voxel
- ▶ X : Designed matrix
- ▶ β : Estimation of each component in X (Parameters estimation)
- ▶ ε : Noise (also known as residuals, i.e., anything that is not modeled by X)

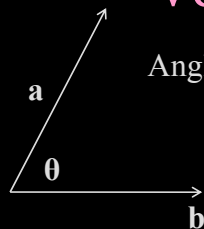
Error (ε) is orthogonal to all our modeled parameters:



β = Projection onto each modeled parameter in Design matrix X

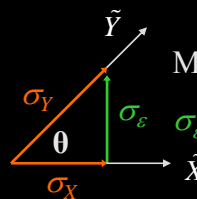


Vectors \rightarrow Statistics



Angle between 2 vectors:

$$\cos \theta = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$$



Min. MSE: σ_ε^2

$$\sigma_\varepsilon^2 = \sigma_Y^2 - (\sigma_Y \cos \theta)^2$$

$$\sigma_{YX} = E[\tilde{Y}\tilde{X}] = \sigma_Y \sigma_X \cos \theta$$

$$\cos \theta = \frac{\sigma_{YX}}{\sigma_Y \sigma_X} = \rho$$

$$MMSE = \sigma_Y^2 (1 - \rho^2)$$

ρ = correlation coefficient

Y : Data, X : estimate

Coherence measure
(Gross *et al*, 2001):

$$\frac{|\mathbf{C}_{x,y}(f)|^2}{\mathbf{C}_{x,x}(f)\mathbf{C}_{y,y}(f)}$$



Useful Resources

▶▶ MIT OpenCourseWare:

- ▶ 18.06 Linear Algebra (Strang's Lecture series)

- ▶ <http://ocw.mit.edu/OcwWeb/Mathematics/18-06Spring-2005/CourseHome/>

▶▶ Good link between Linear Algebra and MATLAB:

- ▶ http://www.ling.upenn.edu/courses/ling525/linear_algebra_review.html

▶▶ Why.N.How Wiki:

- ▶ https://gate.nmr.mgh.harvard.edu/wiki/whynhow/index.php/Main_Page

