

Matrices Revisited, Part I

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Recap: Linear Dependence for Single Numbers

One of the simplest ways a single number y can depend on a single number x is *linearly*: $y = mx + c$, with m and c constant. This means that if we increase x by a certain amount Δx and then increase it by the same amount again, y will increase by a certain amount Δy and then increase by the same amount again.

$$\begin{aligned}x &\rightarrow x + \Delta x \rightarrow x + 2\Delta x \\ \implies y &\rightarrow y + \Delta y \rightarrow y + 2\Delta y\end{aligned}$$

(Specifically, $\Delta y = m\Delta x$.) In other words, a given change in x always produces the same change in y . Note that this is not true for any non-linear relationship between x and y , for example $y = x^2$ or $y = e^x$.

NB a linear relationship, when plotted on a graph, is a straight line; m is the gradient and c is the y -intercept.

Why We Need Matrices: Abstract, part I

Matrices are what allow us to have the same situation when \mathbf{x} and \mathbf{y} are no longer single numbers but *collections* of numbers, i.e. vectors: $\mathbf{x} = (x_1, x_2, \dots)$, $\mathbf{y} = (y_1, y_2, \dots)$. A naïve generalisation of $y = mx + c$ would be $\mathbf{y} = m\mathbf{x} + \mathbf{c}$ (recall that a vector is multiplied by a single number elementwise, thus: $c\mathbf{x} = (cx_1, cx_2, \dots)$). In fact, each element of \mathbf{x} can affect each element of \mathbf{y} independently. So, if there are M elements in \mathbf{x} and N in \mathbf{y} , the equivalent of what was the gradient now consists of $M \times N$ numbers: it's a matrix. The definition of how matrix multiplication works, matching each row in the matrix with the vector in turn and adding as you go, e.g.

$$\begin{pmatrix} a & b & c \\ d & e & f \\ g & h & i \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} ax_1 + bx_2 + cx_3 \\ dx_1 + ex_2 + fx_3 \\ gx_1 + hx_2 + ix_3 \end{pmatrix}$$

guarantees the property of linearity we are looking for. Let's see this in the simplest case of a 2×2 matrix...

Why We Need Matrices: Abstract, part II

Let $\mathbf{y} = \mathbf{M} \cdot \mathbf{x} + \mathbf{c}$:

$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} = \begin{pmatrix} ax_1 + bx_2 + c_1 \\ cx_1 + dx_2 + c_2 \end{pmatrix}$$

When we add the same vector \mathbf{g} twice to \mathbf{x} ,

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \rightarrow \begin{pmatrix} x_1 + g_1 \\ x_2 + g_2 \end{pmatrix} \rightarrow \begin{pmatrix} x_1 + 2g_1 \\ x_2 + 2g_2 \end{pmatrix},$$

\mathbf{y} increases twice thus:

$$\begin{aligned} \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} &\rightarrow \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} x_1 + g_1 \\ x_2 + g_2 \end{pmatrix} + \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} = \begin{pmatrix} a(x_1 + g_1) + b(x_2 + g_2) + c_1 \\ c(x_1 + g_1) + d(x_2 + g_2) + c_2 \end{pmatrix} \\ &\rightarrow \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} x_1 + 2g_1 \\ x_2 + 2g_2 \end{pmatrix} + \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} = \begin{pmatrix} a(x_1 + 2g_1) + b(x_2 + 2g_2) + c_1 \\ c(x_1 + 2g_1) + d(x_2 + 2g_2) + c_2 \end{pmatrix} \end{aligned}$$

Why We Need Matrices: Abstract, part III

What just happened? \mathbf{y} increased by the same vector twice. That vector is

$$\Delta \mathbf{y} = \begin{pmatrix} ag_1 + bg_2 \\ cg_1 + dg_2 \end{pmatrix} = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} g_1 \\ g_2 \end{pmatrix}$$

So the same change in \mathbf{x} produces the same change in \mathbf{y} (the behaviour we were looking for). The reason this happened is because $\mathbf{M} \cdot (\mathbf{x} + \mathbf{g}) = \mathbf{M} \cdot \mathbf{x} + \mathbf{M} \cdot \mathbf{g}$. This is the same as saying that matrix multiplication is a *linear operation*, like differentiation (see the calculus notes at <http://www.imperial.ac.uk/people/c.wymant>).

Why We Need Matrices: Practical

Because in public health and epidemiology, one collection of numbers very often affects another collection of numbers.

The Next-Generation Matrix \mathbf{K} , part I

Definition: K_{ij} is the total number of i -type people (or people in group i , if you like) infected by one j -type person throughout the course of their infection.

i and j run over the same set of possible types (type '1', type '2' etc.) so \mathbf{K} is square. The diagonal entries of \mathbf{K} are the numbers of infections people transmit to the same type as themselves; off-diagonal entries enumerate transmissions between different types. A *diagonal matrix* (all off-diagonal elements are zero) describes no mixing: people only transmit to their own group.

$\sum_i K_{ij}$ (i.e. the sum of the j th column) is the total number of people infected by one j -type person throughout the course of their infection.

e.g. $\mathbf{K} = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \implies$

a person in group 1 infects a people in group 1 and c people in group 2; a person in group 2 infects b people in group 1 and d people in group 2.

An Aside: Understanding a *Generation* of Infecteds

Consider the exact analogy between infection as a process of 'epidemiological birth' (producing a new infected individual) and the process of actual birth, i.e. population growth. Date of infection/transmission corresponds to date of birth. Just as the individuals in one generation of a family do not all have the same age, one generation of individuals has a variety of dates of infection. Individuals in one generation of a family may even have non-overlapping lives: a child may die before his/her sibling is born, giving non-overlap within generation one; death of a grandchild before his/her cousin is born gives non-overlap in generation two; etc. Thus, infecteds in the same generation can have infections that do not overlap in time.

As the N th generation of a family can be connected to the 'root' of the family through N processes of birth but no fewer, the N th generation of infecteds in an epidemic can be connected to the founder through N transmission contacts but no fewer.

The connection between a generational view and a real-time view of an epidemic is a mathematically challenging problem, considered in e.g. doi:10.1016/j.mbs.2008.08.009 by Neil and Christophe.

The Next-Generation Matrix \mathbf{K} , part II

If we write the numbers of people of each type, in a given generation of infecteds, in a vector $\mathbf{N} = (N_1, N_2, \dots)$, then the numbers in the next generation are given by the vector $\mathbf{K} \cdot \mathbf{N}$. The numbers in the generation after that are given by the vector $\mathbf{K} \cdot (\mathbf{K} \cdot \mathbf{N}) = \mathbf{K}^2 \cdot \mathbf{N}$. Multiplication by \mathbf{K} gives the next generation, hence the name.

Eigenvalues and Eigenvectors

Vectors can be proportional to each other or not.

Proportional \iff in the same direction in space \iff differ only by a factor.

e.g. $\begin{pmatrix} 2 \\ 3 \end{pmatrix} \propto \begin{pmatrix} 1 \\ 1.5 \end{pmatrix}$ because $\begin{pmatrix} 2 \\ 3 \end{pmatrix} = 2 \times \begin{pmatrix} 1 \\ 1.5 \end{pmatrix}$, and they point in the same direction. (Try drawing them both on a 2D plot: the vector $\begin{pmatrix} 2 \\ 3 \end{pmatrix}$ can be shown by an arrow from the origin to the point $x = 2, y = 3$.) A closely related idea is the fact that $6'' \times 4''$ photos have the same proportion as $9'' \times 6''$, but this is different from $7'' \times 5''$.

The *eigenvectors* of a matrix are those vectors that point in the same direction when multiplied by the matrix; they are merely multiplied by a constant, called the *eigenvalue*.

e.g. $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$ is an eigenvector of $\begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix}$ because $\begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 3 \\ 3 \end{pmatrix} = 3 \times \begin{pmatrix} 1 \\ 1 \end{pmatrix}$, which is in the same direction as the original vector. We see that the eigenvalue is 3. $\begin{pmatrix} 1 \\ 2 \end{pmatrix}$ is *not* an eigenvector of $\begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix}$ because $\begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ 2 \end{pmatrix} = \begin{pmatrix} 4 \\ 5 \end{pmatrix}$, which is in a different direction.