## Matrix-vector and vector-matrix multiplication

Two ways to multiply a matrix by a vector:

- matrix-vector multiplication
- vector-matrix multiplication

For each of these, two equivalent definitions:

- ▶ in terms of linear combinations
- ▶ in terms of dot-products

### Matrix-vector multiplication in terms of linear combinations

**Linear-Combinations Definition of matrix-vector multiplication:** Let M be an  $R \times C$  matrix.

▶ If **v** is a *C*-vector then

$$M * \mathbf{v} = \sum_{c \in C} \mathbf{v}[c]$$
 (column  $c$  of  $M$ )

$$\begin{bmatrix} 1 & 2 & 3 \\ 10 & 20 & 30 \end{bmatrix} * [7,0,4] = 7[1,10] + 0[2,20] + 4[3,30]$$

▶ If **v** is *not* a *C*-vector then

$$M * \mathbf{v} = \mathsf{ERROR}!$$

$$\begin{bmatrix} 1 & 2 & 3 \\ 10 & 20 & 30 \end{bmatrix} * [7,0] = ERROR!$$

## Matrix-vector multiplication in terms of linear combinations

## Matrix-vector multiplication in terms of linear combinations: Lights Out

A solution to a Lights Out configuration is a linear combination of "button vectors."

For example, the linear combination

can be written as

$$\begin{bmatrix} \bullet \\ \bullet \end{bmatrix} = \begin{bmatrix} \bullet & \bullet \\ \bullet & \bullet \end{bmatrix} \begin{bmatrix} \bullet & \bullet \\ \bullet & \bullet \end{bmatrix} \begin{bmatrix} \bullet \\ \bullet$$

# Solving a matrix-vector equation: Lights Out

Solving an instance of 
$$Lights Out$$
  $\Rightarrow$  Solving a matrix-vector equation

$$\begin{bmatrix} \bullet \\ \bullet \end{bmatrix} = \begin{bmatrix} \bullet & \bullet \\ \bullet & \bullet \end{bmatrix} \begin{bmatrix} \bullet & \bullet \\ \bullet & \bullet \end{bmatrix} \begin{bmatrix} \bullet \\ \bullet$$

## Solving a matrix-vector equation

### Fundamental Computational Problem: Solving a matrix-vector equation

- input: an  $R \times C$  matrix A and an R-vector **b**
- output: the C-vector  $\mathbf{x}$  such that  $A * \mathbf{x} = \mathbf{b}$

# Solving a matrix-vector equation: $2 \times 2$ special case

Simple formula to solve

$$\begin{bmatrix} a & c \\ b & d \end{bmatrix} * [x, y] = [p, q]$$

if  $ad \neq bc$ :

$$x = \frac{dp - cq}{ad - bc}$$
 and  $y = \frac{aq - bp}{ad - bc}$ 

For example, to solve

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} * [x, y] = [-1, 1]$$

we set

$$x = \frac{4 \cdot -1 - 2 \cdot 1}{1 \cdot 4 - 2 \cdot 3} = \frac{-6}{-2} = 3$$

and

$$y = \frac{1 \cdot 1 - 3 \cdot -1}{1 \cdot 4 - 2 \cdot 3} = \frac{4}{-2} = -2$$

Later we study algorithms for more general cases.

#### The solver module

We provide a module solver that defines a procedure solve(A, b) that tries to find a solution to the matrix-vector equation  $A\mathbf{x} = \mathbf{b}$ Currently solve(A, b) is a black box

```
er project along(p, v):
sigma = ((b*v)/(v*v)) if v*v != 0 else 0
return sigma * v
                       def solve(A, b):
def project orthogonal(b
                              0.R = factor(A)
   for v in vlist:
      b = b - project_
                              col_label_list =
                              return triangular
lef aug_project_orthogon
  sigmadict = {len(vli ...
   for i.v in enumerate(vlist):
       sigma = (b*v)/def transformation(A,one=1, col_label_)
                         """Given a matrix A, and optionally
      sigmadict[i] =
      b = b - sigma*t),
                           compute matrix M such that M is
  return (b. siamadi
                           U = M*A is in echelon form.
lef orthogonalize(vlis
                        row_labels, col_labels = A.D
  vstarlist =
                        m = len(row_labels)
   for v in vlist:
                        row_label_list = sorted(row_labels
    vstarlist.append
                        rowlist = [Vec(col_labels, {c:A[r,c
   return vstarlist
                        M_rows = transformation_rows(rowlis
ef aua orthogonalize(
   vstarlist = \square
```

but we will learn how to code it in the coming weeks.

Let's use it to solve this *Lights Out* instance...

### Vector-matrix multiplication in terms of linear combinations

Vector-matrix multiplication is different from matrix-vector multiplication:

Let M be an  $R \times C$  matrix.

**Linear-Combinations Definition of matrix-vector multiplication:** If  $\mathbf{v}$  is a C-vector then

$$M * \mathbf{v} = \sum_{c \in C} \mathbf{v}[c]$$
 (column  $c$  of  $M$ )

**Linear-Combinations Definition of vector-matrix multiplication:** If  $\mathbf{w}$  is an R-vector then

$$\mathbf{w} * M = \sum_{r \in R} \mathbf{w}[r] \text{ (row } r \text{ of } M\text{)}$$

$$\begin{bmatrix} 3,4 \end{bmatrix} * \begin{bmatrix} 1 & 2 & 3 \\ 10 & 20 & 30 \end{bmatrix} = 3[1,2,3] + 4[10,20,30]$$

### Vector-matrix multiplication in terms of linear combinations: JunkCo











l _+	NΛ	
Let	IVI	=

	metal	concrete	plastic	water	electricity
garden gnome	0	1.3	.2	.8	.4
hula hoop	0	0	1.5	.4	.3
slinky	.25	0	0	.2	.7
silly putty	0	0	.3	.7	.5
salad shooter	.15	0	.5	.4	.8

total resources used =  $[\alpha_{\mathsf{gnome}}, \alpha_{\mathsf{hoop}}, \alpha_{\mathsf{slinky}}, \alpha_{\mathsf{putty}}, \alpha_{\mathsf{shooter}}] * \mathsf{V}$ 

Suppose we know total resources used and we know M.

To find the values of  $\alpha_{\rm gnome}, \alpha_{\rm hoop}, \alpha_{\rm slinky}, \alpha_{\rm putty}, \alpha_{\rm shooter}$ 

solve a *vector-matrix* equation  $\mathbf{b} = \mathbf{x} * M$  where  $\mathbf{b}$  is vector of total resources used.

## Solving a matrix-vector equation

### Fundamental Computational Problem: Solving a matrix-vector equation

- ▶ input: an  $R \times C$  matrix A and an R-vector  $\mathbf{b}$
- output: the C-vector  $\mathbf{x}$  such that  $A * \mathbf{x} = \mathbf{b}$

If we had an algorithm for solving a *matrix-vector* equation, could also use it to solve a *vector-matrix* equation, using transpose.

## The solver module, and floating-point arithmetic

For arithmetic over  $\mathbb{R}$ , Python uses floats, so round-off errors occur:

```
>>> 10.0**16 + 1 == 10.0**16
True
```

Consequently algorithms such as that used in solve(A, b) do not find exactly correct solutions.

To see if solution  $\mathbf{u}$  obtained is a reasonable solution to  $A * \mathbf{x} = \mathbf{b}$ , see if the vector  $\mathbf{b} - A * \mathbf{u}$  has entries that are close to zero:

```
>>> A = listlist2mat([[1,3],[5,7]])
>>> u = solve(A, b)
>>> b - A*u
```

The vector  $\mathbf{b} - A * \mathbf{u}$  is called the *residual*. Easy way to test if entries of the residual are close to zero: compute the dot-product of the residual with itself:

Vec({0, 1},{0: -4.440892098500626e-16, 1: -8.881784197001252e-16})

```
>>> res = b - A*u
>>> res * res
9.860761315262648e-31
```

## Checking the output from solve(A, b)

For some matrix-vector equations  $A * \mathbf{x} = \mathbf{b}$ , there is no solution.

In this case, the vector returned by solve(A, b) gives rise to a largeish residual:

```
>>> A = listlist2mat([[1,2],[4,5],[-6,1]])
>>> b = list2vec([1,1,1])
>>> u = solve(A, b)
>>> res = b - A*u
>>> res * res
```

0.24287856071964012

Later in the course we will see that the residual is, in a sense, as small as possible.

Some matrix-vector equations are *ill-conditioned*, which can prevent an algorithm using floats from getting even approximate solutions, even when solutions exists:

```
>>> A = listlist2mat([[1e20,1],[1,0]])

>>> b = list2vec([1,1])

>>> u = solve(A, b)

>>> b - A*u

Vec({0, 1},{0: 0.0, 1: 1.0})
```

We will not study conditioning in this course.