

Quiz

Define the vectors \mathbf{a}_1 and \mathbf{a}_2 as follows:

$$\mathbf{a}_1 = \frac{\# \ \$ \ \%}{2 \ 1 \ -1} \text{ and } \mathbf{a}_2 = \frac{\# \ \$ \ \%}{-1 \ 4 \ 3}$$

Let A be the matrix whose **column**-dict representation is $\{ '@' : \mathbf{a}_1, '&' : \mathbf{a}_2 \}$. Compute A times

the vector $\frac{@ \ \&}{2 \ 4}$

Let B be the matrix whose **row**-dict representation is $\{ '@' : \mathbf{a}_1, '&' : \mathbf{a}_2 \}$. Compute B times the

vector $\frac{\# \ \$ \ \%}{-1 \ 0 \ 3}$.

Matrices as vectors

Soon we study true matrix operations. But first....

A matrix can be interpreted as a vector:

- ▶ an $R \times S$ matrix is a function from $R \times S$ to \mathbb{F} ,
- ▶ so it can be interpreted as an $R \times S$ -vector:
 - ▶ *scalar-vector multiplication*
 - ▶ *vector addition*
- ▶ Our full implementation of Mat class will include these operations.

Transpose

Transpose swaps rows and columns.

	@	#	?
a	2	1	3
b	20	10	30



	a	b
@	2	20
#	1	10
?	3	30

Transpose (and Quiz)

Quiz: Write `transpose(M)`

Answer:

```
def transpose(M):  
    return Mat((M.D[1], M.D[0]), {(q,p):v for (p,q),v in M.f.items()})
```

Computing sparse matrix-vector product

To compute matrix-vector or vector-matrix product,

- ▶ could use dot-product or linear-combinations definition.
- ▶ However, using those definitions, it's not easy to exploit sparsity in the matrix.

“Ordinary” Definition of Matrix-Vector Multiplication: If M is an $R \times C$ matrix and \mathbf{u} is a C -vector then $M * \mathbf{u}$ is the R -vector \mathbf{v} such that, for each $r \in R$,

$$v[r] = \sum_{c \in C} M[r, c] u[c]$$

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Obvious method:

```
1 for i in R:  
2   v[i] :=  $\sum_{j \in C} M[i, j]u[j]$ 
```

But this doesn't exploit sparsity!

Idea:

- ▶ Initialize output vector \mathbf{v} to zero vector.
- ▶ Iterate over nonzero entries of M , adding terms according to ordinary definition.

```
1 initialize  $\mathbf{v}$  to zero vector  
2 for each pair  $(i, j)$  in sparse representation,  
3   v[i] = v[i] +  $M[i, j]u[j]$ 
```

Linear systems using matrices

Recall: A **linear system** is a system of linear equations

$$\begin{aligned} \mathbf{a}_1 \cdot \mathbf{x} &= \beta_1 \\ &\vdots \\ \mathbf{a}_m \cdot \mathbf{x} &= \beta_m \end{aligned}$$

Key idea: Write linear system as a **matrix-vector equation**.

$$\begin{bmatrix} \mathbf{a}_1 \\ \vdots \\ \mathbf{a}_m \end{bmatrix} \mathbf{x} = \mathbf{b} \quad [\beta_1, \dots, \beta_m] \quad [\beta_1, \dots, \beta_m]$$

First advantage of a matrix: Can interpret a row matrix as a column matrix:

$$\left[\begin{array}{c|c|c} \mathbf{v}_1 & \cdots & \mathbf{v}_n \end{array} \right] \mathbf{x} = \mathbf{b}$$

We have many questions about linear systems:

- ▶ How to find a solution?
- ▶ How many solutions?
 - ▶ Does a solution even exist?
 - ▶ When does only one solution exist?
- ▶ What to do if there are no solutions?
- ▶ For which right-hand sides β_1, \dots, β_m does a solution exist?

Matrices will help us **answer these questions** and **use linear systems in other applications**.

Interpret this matrix-vector equation as:
With what coefficients can \mathbf{b} be written as a linear combination of $\mathbf{v}_1, \dots, \mathbf{v}_n$?

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Interpret this matrix-vector equation as:

With what coefficients can \mathbf{b} be written as a linear combination of $\mathbf{v}_1, \dots, \mathbf{v}_n$?

A solution to a *Lights Out* configuration is a linear combination of “button vectors.”

For example, the linear combination

$$\begin{bmatrix} \bullet & \\ \bullet & \end{bmatrix} = 0 \begin{bmatrix} \bullet & \bullet \\ \bullet & \end{bmatrix} + 1 \begin{bmatrix} \bullet & \bullet \\ \bullet & \bullet \end{bmatrix} + 0 \begin{bmatrix} \bullet & \\ \bullet & \bullet \end{bmatrix} + 1 \begin{bmatrix} \bullet & \bullet \\ \bullet & \bullet \end{bmatrix}$$

can be written as

$$\begin{bmatrix} \bullet & \\ \bullet & \end{bmatrix} = \left[\begin{array}{c|c|c|c} \begin{bmatrix} \bullet & \bullet \\ \bullet & \end{bmatrix} & \begin{bmatrix} \bullet & \bullet \\ \bullet & \bullet \end{bmatrix} & \begin{bmatrix} \bullet & \\ \bullet & \bullet \end{bmatrix} & \begin{bmatrix} \bullet & \bullet \\ \bullet & \bullet \end{bmatrix} \end{array} \right] * [0, 1, 0, 1]$$

Solving an instance of *Lights Out*

\Rightarrow

Solving a matrix-vector equation

Linear systems using matrices

A solution to a *Lights Out* configuration is a linear combination of “button vectors.”

For example, the linear combination

$$\begin{array}{|c|} \hline \bullet \\ \hline \bullet \\ \hline \end{array} = 0 \begin{array}{|c|c|} \hline \bullet & \bullet \\ \hline \bullet & \\ \hline \end{array} + 1 \begin{array}{|c|c|} \hline \bullet & \bullet \\ \hline & \bullet \\ \hline \end{array} + 0 \begin{array}{|c|c|} \hline \bullet & \\ \hline \bullet & \bullet \\ \hline \end{array} + 1 \begin{array}{|c|c|} \hline & \bullet \\ \hline \bullet & \bullet \\ \hline \end{array}$$

can be written as

$$\begin{array}{|c|} \hline \bullet \\ \hline \bullet \\ \hline \end{array} = \left[\begin{array}{|c|c|} \hline \bullet & \bullet \\ \hline \bullet & \\ \hline \end{array} \middle| \begin{array}{|c|c|} \hline \bullet & \bullet \\ \hline & \bullet \\ \hline \end{array} \middle| \begin{array}{|c|c|} \hline \bullet & \\ \hline \bullet & \bullet \\ \hline \end{array} \middle| \begin{array}{|c|c|} \hline & \bullet \\ \hline \bullet & \bullet \\ \hline \end{array} \right] * [0, 1, 0, 1]$$

Solving an instance of *Lights Out*

\Rightarrow

Solving a matrix-vector equation

$$\begin{array}{|c|} \hline \bullet \\ \hline \bullet \\ \hline \end{array} = \left[\begin{array}{|c|c|} \hline \bullet & \bullet \\ \hline \bullet & \\ \hline \end{array} \middle| \begin{array}{|c|c|} \hline \bullet & \bullet \\ \hline & \bullet \\ \hline \end{array} \middle| \begin{array}{|c|c|} \hline \bullet & \\ \hline \bullet & \bullet \\ \hline \end{array} \middle| \begin{array}{|c|c|} \hline & \bullet \\ \hline \bullet & \bullet \\ \hline \end{array} \right] * [\alpha_1, \alpha_2, \alpha_3, \alpha_4]$$

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

```
def project_along(b, v):
    sigma = ((b*v)/(v*v)) if v*v != 0 else 0
    return sigma * v

def project_orthogonal(b, vlist):
    for v in vlist:
        b = b - project_along(b, v)
    return b

def aug_project_orthogonal(b, vlist):
    sigmadict = {}
    for i, v in enumerate(vlist):
        sigma = (b*v)/(v*v)
        sigmadict[i] = sigma
        b = b - sigma*v
    return (b, sigmadict)

def orthogonalize(vlist):
    vstarlist = []
    for v in vlist:
        vstarlist.append(v - sum(sigmadict[i]*vlist[i] for i in range(len(vlist))))
    return vstarlist

def aug_orthogonalize(vlist):
    vstarlist = []
    sigmadict = {}
    for i, v in enumerate(vlist):
        vstarlist.append(v - sum(sigmadict[j]*vlist[j] for j in range(i)))
        sigmadict[i] = {}
        for j in range(i):
            sigmadict[i][j] = (v*vlist[j])/(v*vlist[j])

def solve(A, b):
    Q, R = factor(A)
    col_label_list = []
    return triangular_solve(Q, R, b, col_label_list)
```

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

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



The two fundamental spaces associated with a matrix

Want to study linear systems, equivalently *matrix-vector equations* $A\mathbf{x} = \mathbf{b}$

For which right-hand side vectors \mathbf{b} does $A\mathbf{x} = \mathbf{b}$ have a solution?

An $R \times C$ matrix A corresponds to the function $f : \mathbb{F}^C \rightarrow \mathbb{F}^R$ defined by $f(\mathbf{x}) = A\mathbf{x}$

The system $A\mathbf{x} = \mathbf{b}$ has a solution *if and only if* there is some vector \mathbf{v} such that $A\mathbf{v} = \mathbf{b}$.

Thus the system has a solution *if and only if* there is some vector \mathbf{v} in \mathbb{F}^C such that $f(\mathbf{v}) = \mathbf{b}$.

Thus the system has a solution *if and only if* \mathbf{b} is in the image of the function f .

(Remember that the *image* of a function is the set of all possible outputs.)

Question: How can we characterize the image of the function $f(\mathbf{x}) = A\mathbf{x}$?

Answer: Use the **linear-combinations** interpretation.

For any input \mathbf{x} , the output is the linear combination of the **columns** of A where coefficients are the entries of \mathbf{x} .

The set of **all** outputs is thus the set of all linear combinations of the columns of A .

Also known as the *span* of the columns of A

We call this the **column space of A** . Written $\text{Col } A$.

We know it is a vector space.

The two fundamental spaces associated with a matrix

Recall: We are interested in **solution set** of **corresponding homogeneous linear system**

$$\begin{bmatrix} A \end{bmatrix} \mathbf{x} = \mathbf{0}$$

We know this is a vector space.

In context of matrices, we call it the **null space** of the matrix A . Written **Null A**

Summary: The two most important spaces associated with a matrix A are

- ▶ Col A
- ▶ Null A

Solution set of a matrix-vector equation

Proposition: If \mathbf{u}_1 is a solution to $A * \mathbf{x} = \mathbf{b}$ then solution set is $\mathbf{u}_1 + \mathcal{V}$

where $\mathcal{V} = \text{Null } A$

- ▶ If \mathcal{V} is a trivial vector space then \mathbf{u}_1 is the only solution.
- ▶ If \mathcal{V} is not trivial then \mathbf{u}_1 is *not* the only solution.

Corollary: $A * \mathbf{x} = \mathbf{b}$ has at most one solution iff $\text{Null } A$ is a trivial vector space.

Question: How can we tell if the null space of a matrix is trivial?

Answer comes later...

Matrix-matrix multiplication

If

- ▶ A is a $R \times S$ matrix, and
- ▶ B is a $S \times T$ matrix

then it is legal to multiply A times B .

- ▶ In Mathese, written AB
- ▶ In our Mat class, written $A*B$

AB is different from BA .

In fact, one product might be legal while the other is illegal.

Matrix-matrix multiplication: matrix-vector definition

Matrix-vector definition of matrix-matrix multiplication:

For each column-label s of B ,

$$\text{column } s \text{ of } AB = A * (\text{column } s \text{ of } B)$$

Let $A = \begin{bmatrix} 1 & 2 \\ -1 & 1 \end{bmatrix}$ and $B =$ matrix with columns $[4, 3]$, $[2, 1]$, and $[0, -1]$

$$B = \left[\begin{array}{c|c|c} 4 & 2 & 0 \\ 3 & 1 & -1 \end{array} \right]$$

AB is the matrix with column $i = A * (\text{column } i \text{ of } B)$

$$A * [4, 3] = [10, -1]$$

$$A * [2, 1] = [4, -1]$$

$$A * [0, -1] = [-2, -1]$$

$$AB = \left[\begin{array}{c|c|c} 10 & 4 & -2 \\ -1 & -1 & -1 \end{array} \right]$$

Matrix-matrix multiplication: Dot-product definition

Combine

- ▶ *matrix-vector* definition of matrix-matrix multiplication, and
- ▶ *dot-product* definition of matrix-vector multiplication

to get...

Dot-product definition of matrix-matrix multiplication:

Entry rc of AB is the dot-product of row r of A with column c of B .

Example:

$$\begin{bmatrix} 1 & 0 & 2 \\ 3 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & | & 1 \\ 5 & | & 0 \\ 1 & | & 3 \end{bmatrix} = \begin{bmatrix} [1, 0, 2] \cdot [2, 5, 1] & [1, 0, 2] \cdot [1, 0, 3] \\ [3, 1, 0] \cdot [2, 5, 1] & [3, 1, 0] \cdot [1, 0, 3] \\ [2, 0, 1] \cdot [2, 5, 1] & [2, 0, 1] \cdot [1, 0, 3] \end{bmatrix} = \begin{bmatrix} 4 & 7 \\ 11 & 3 \\ 5 & 5 \end{bmatrix}$$

Matrix-matrix multiplication: transpose

$$(AB)^T = B^T A^T$$

Example:

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 5 & 0 \\ 1 & 2 \end{bmatrix} = \begin{bmatrix} 7 & 4 \\ 19 & 8 \end{bmatrix}$$

$$\begin{bmatrix} 5 & 0 \\ 1 & 2 \end{bmatrix}^T \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}^T = \begin{bmatrix} 5 & 1 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix} = \begin{bmatrix} 7 & 19 \\ 4 & 8 \end{bmatrix}$$

You might think “ $(AB)^T = A^T B^T$ ” but this is **false**.

In fact, doesn't even make sense!

- ▶ For AB to be legal, A 's column labels = B 's row labels.
- ▶ For $A^T B^T$ to be legal, A 's row labels = B 's column labels.

Example: $\begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix} \begin{bmatrix} 6 & 7 \\ 8 & 9 \end{bmatrix}$ is legal but $\begin{bmatrix} 1 & 3 & 5 \\ 2 & 4 & 6 \end{bmatrix} \begin{bmatrix} 6 & 8 \\ 7 & 9 \end{bmatrix}$ is not.

Matrix-matrix multiplication: Column vectors

Multiplying a matrix A by a one-column matrix B

$$\begin{bmatrix} & & \\ & A & \\ & & \end{bmatrix} \begin{bmatrix} \mathbf{b} \\ \\ \end{bmatrix}$$

By matrix-vector definition of matrix-matrix multiplication, result is matrix with one column:
 $A * \mathbf{b}$

This shows that matrix-vector multiplication is subsumed by matrix-matrix multiplication.

Convention: Interpret a vector \mathbf{b} as a one-column matrix (“column vector”)

▶ Write vector $[1, 2, 3]$ as $\begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$

▶ Write $A * [1, 2, 3]$ as $\begin{bmatrix} & & \\ & A & \\ & & \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$ or $A\mathbf{b}$