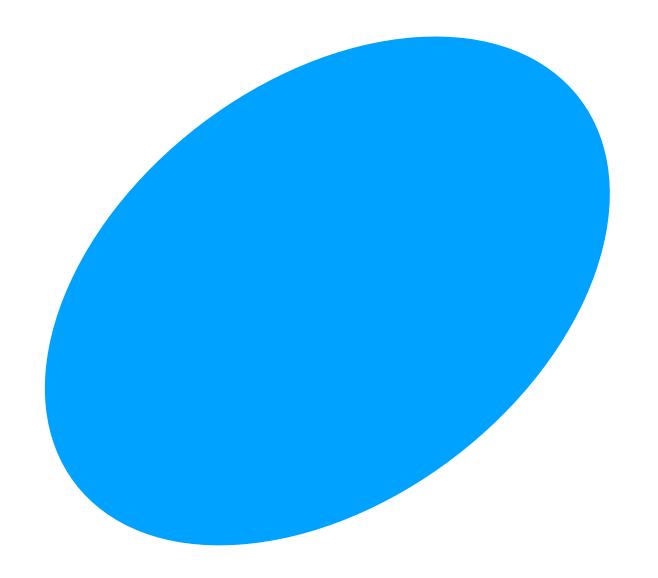
(2D) Linear transformations

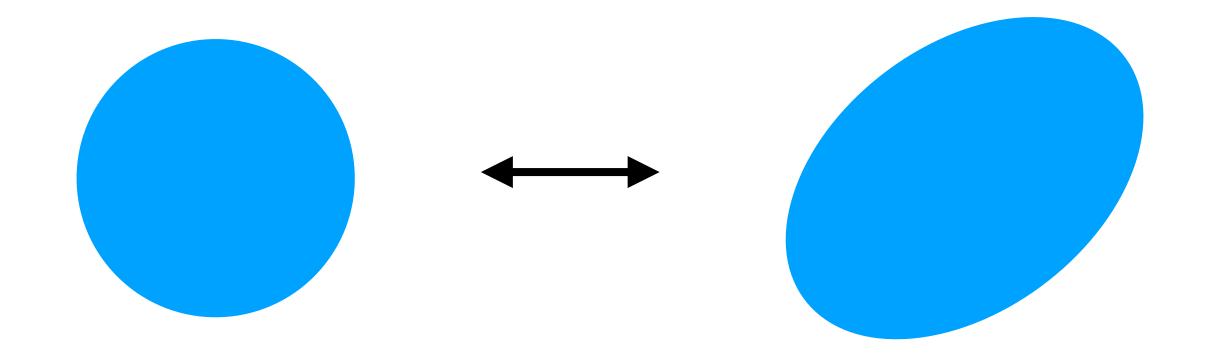
UCSD CSE 167 Tzu-Mao Li

Motivation: rendering an ellipse

testing whether a point is inside an ellipse is slightly more complex

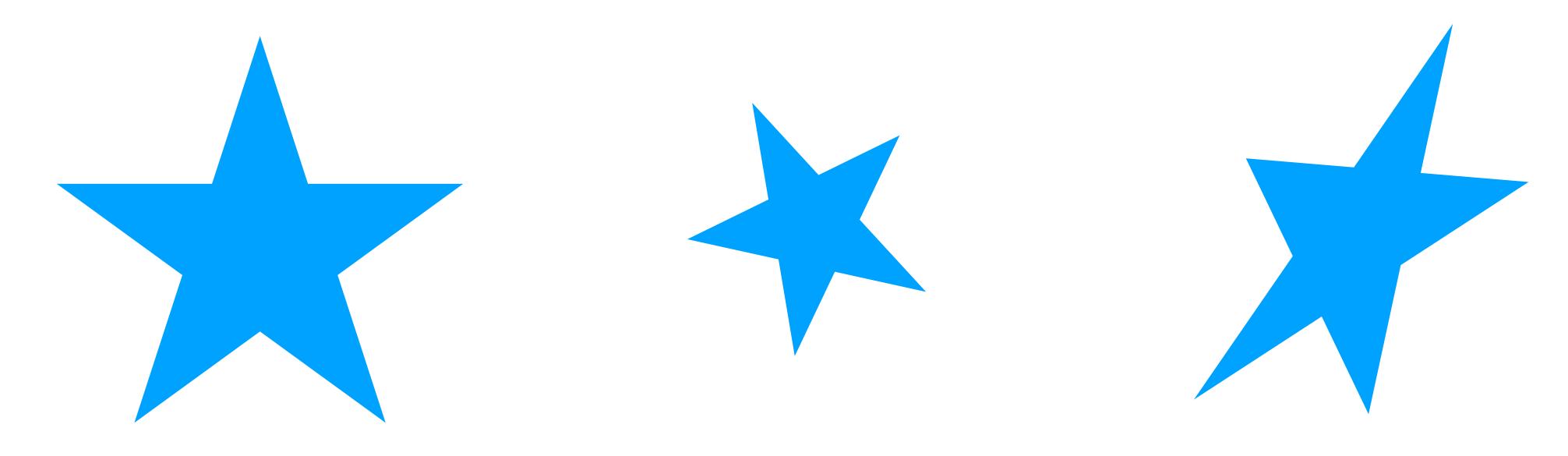


Idea: map the ellipse to a simple circle

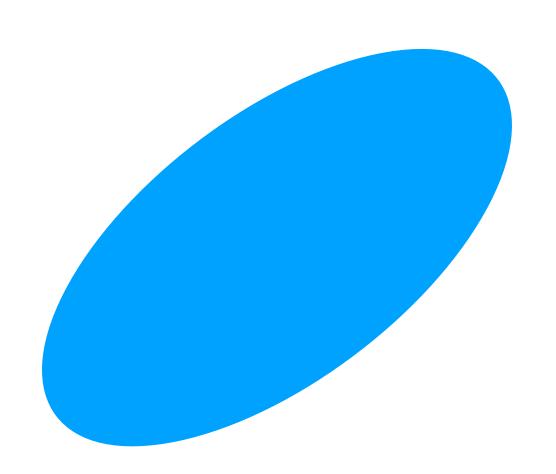


Motivation 2: instancing

only want to store one star

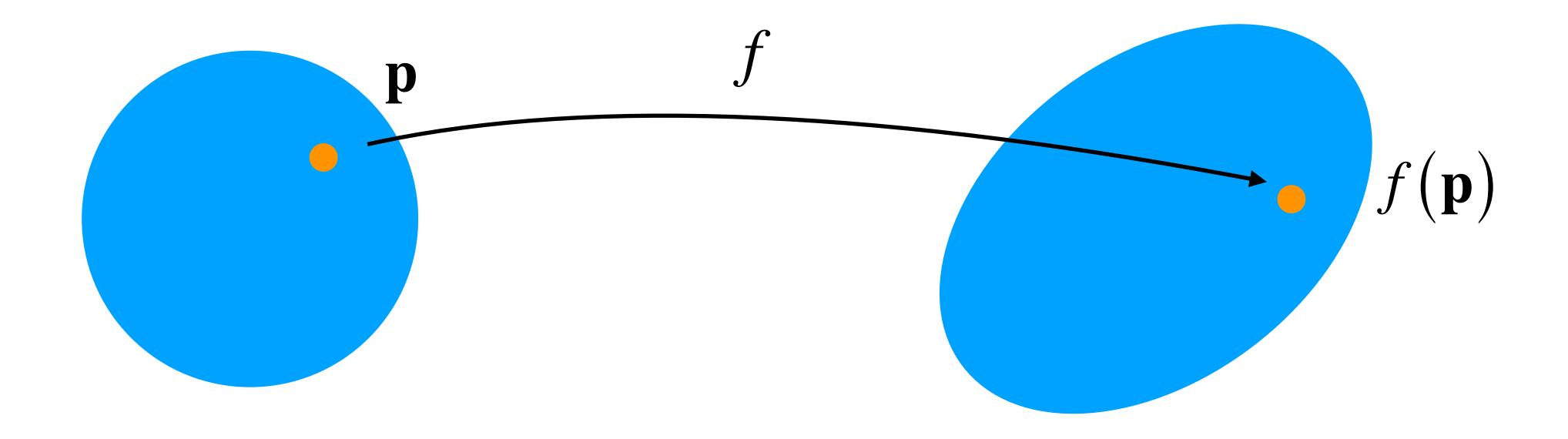


Motivation 3: animation



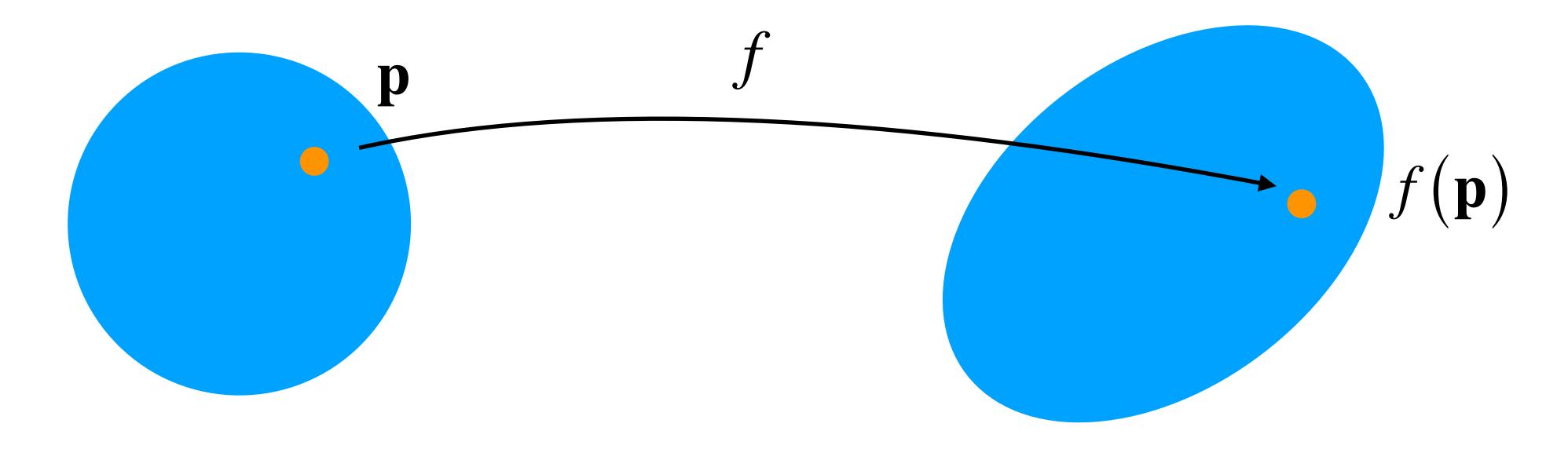
Transformation

each point \mathbf{p} is mapped to a point $f(\mathbf{p})$



Linear Transformation

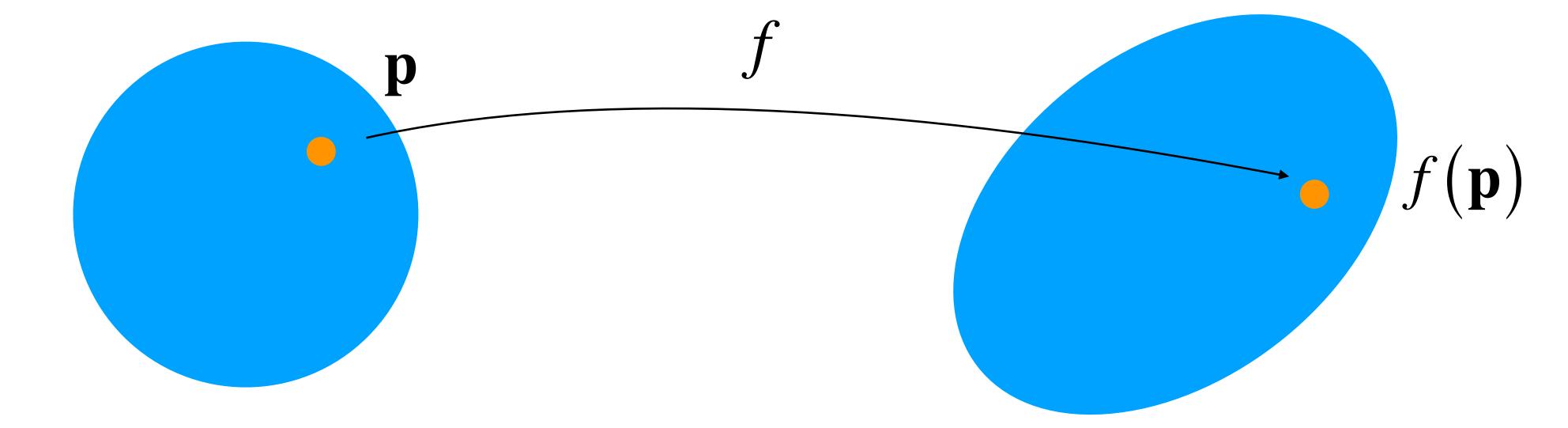
each point ${\bf p}$ is mapped to a point $f({\bf p})$ by a linear function f



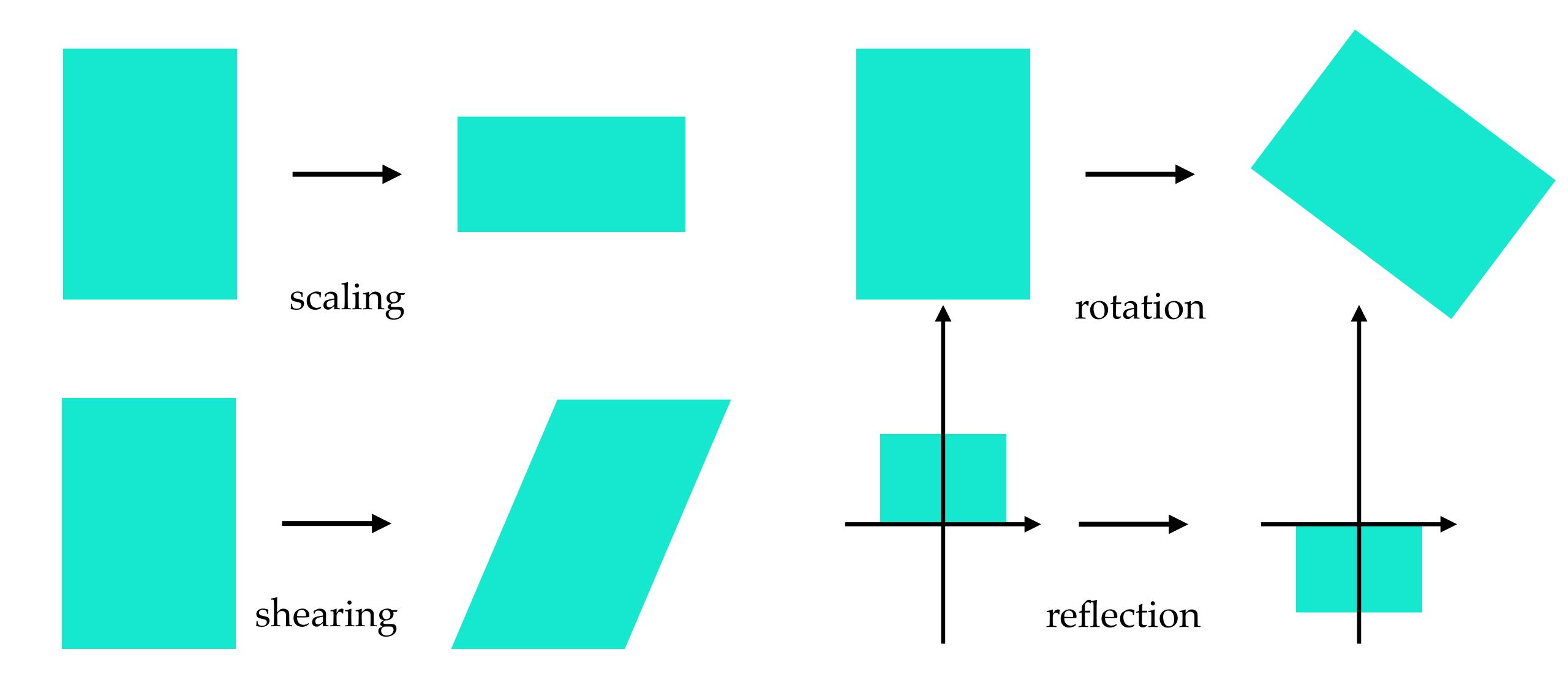
(we will define linearity later)

Why linear transformation?

- linear transformations are easier to analyze and well understood
 - e.g., there are well-established ways to compute their inverses
- linear transformations are expressive
- non-linear transformations can often be broken down to many small linear transformations



Things linear transformation can do

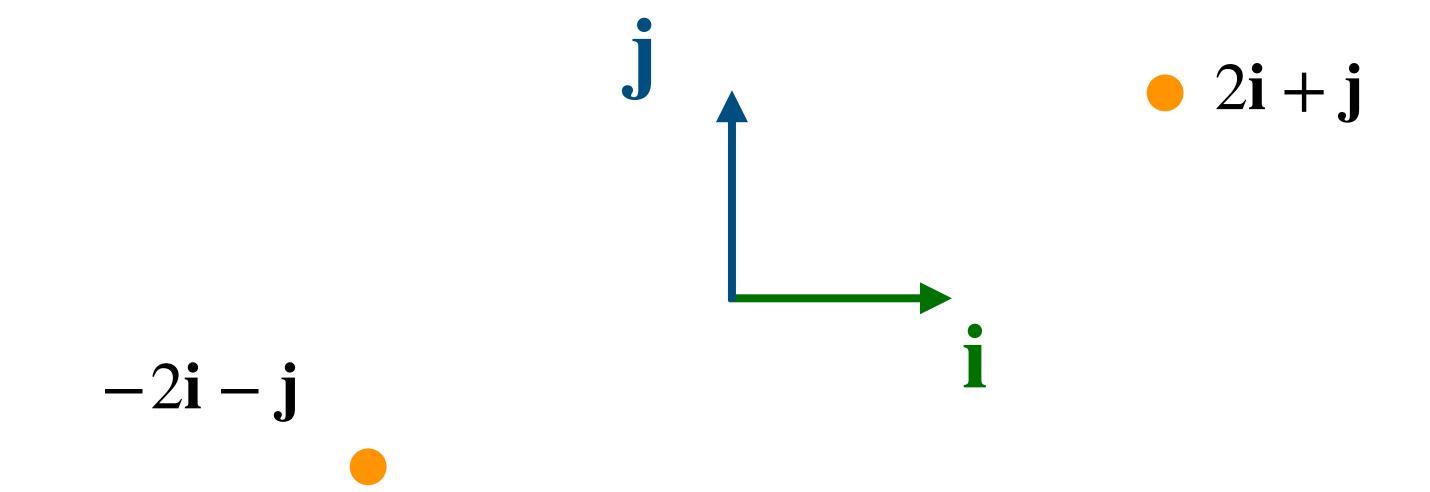


Linear algebra

- excellent resources:
 - Essence of Linear Algebra https://www.youtube.com/playlist? list=PLZHQObOWTQDPD3MizzM2xVFitgF8hE_ab
 - Immersive Linear Algebra http://immersivemath.com/ila/index.html

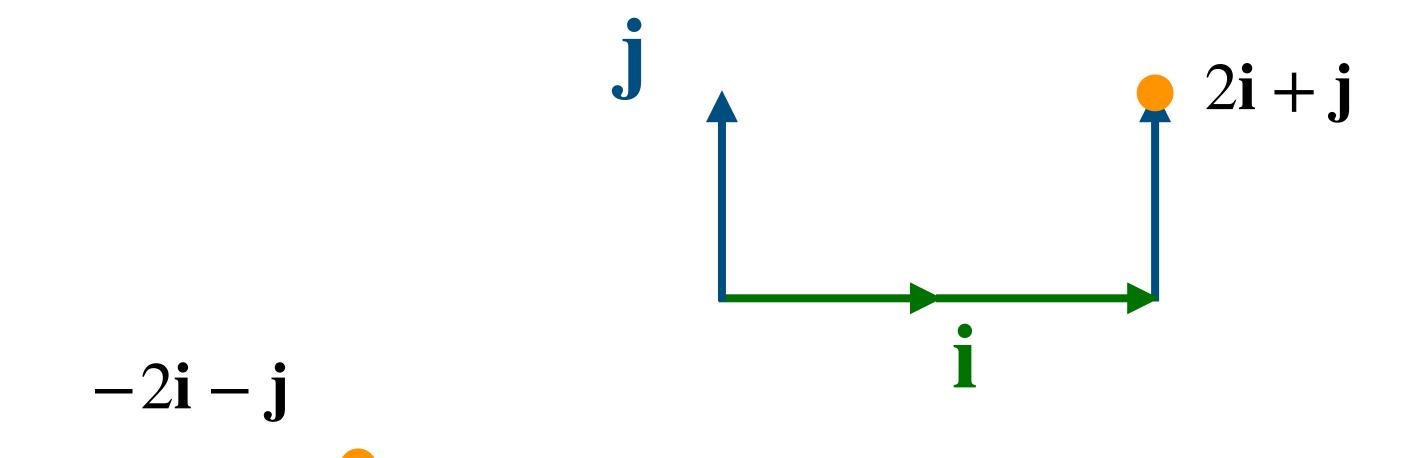
Linear basis

each point in the 2D space can be written as a linear combination of two basis vectors \mathbf{i} and \mathbf{j}



Linear basis

each point in the 2D space can be written as a linear combination of two basis vectors \mathbf{i} and \mathbf{j}



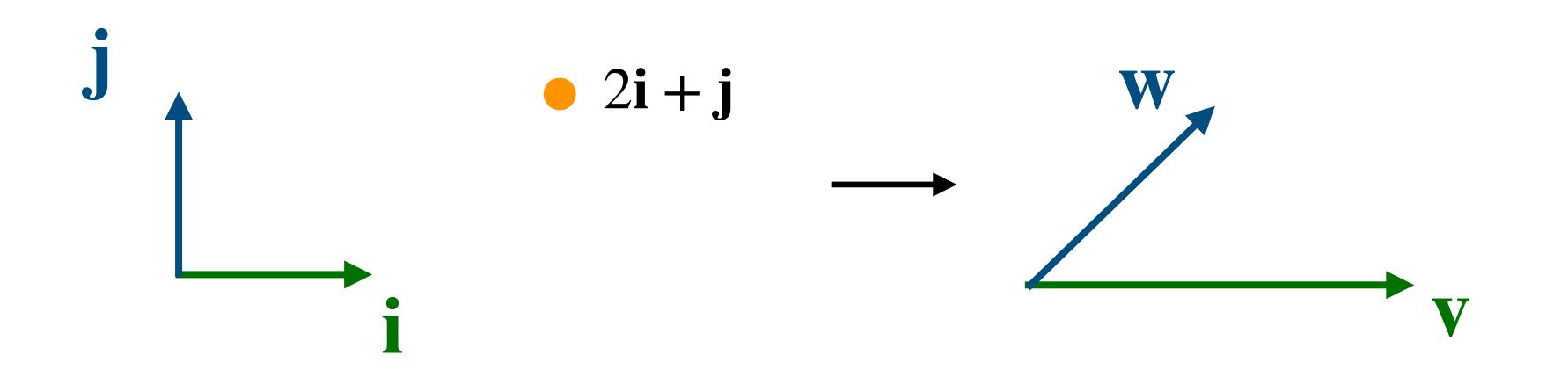
Linear basis

we can use a different linear basis to represent the same 2D space (and they don't need to be perpendicular to each other!)

$$\mathbf{v} \qquad \mathbf{2i} + \mathbf{j} = \frac{1}{2}\mathbf{v} + \mathbf{w}$$

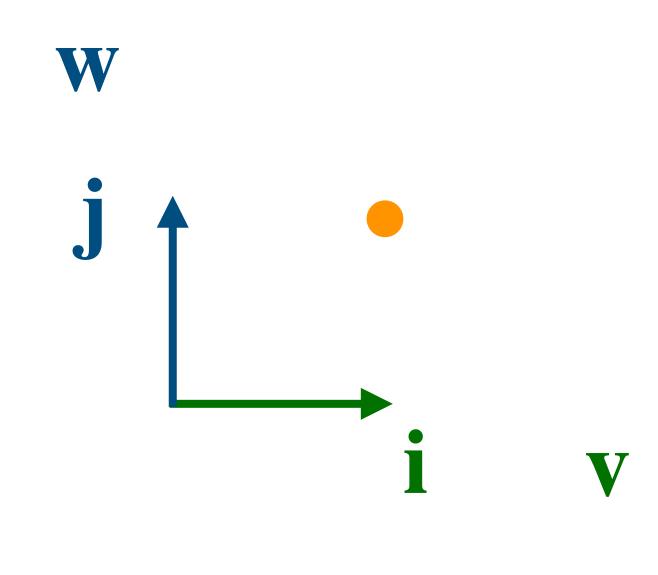
$$-2\mathbf{i} - \mathbf{j} = -\frac{1}{2}\mathbf{v} - \mathbf{w}$$

Linear transformation = preserves the coordinates, but changes the basis

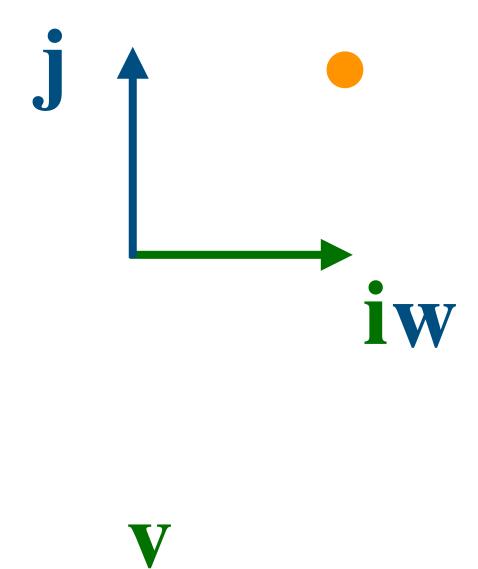


 $2\mathbf{v} + \mathbf{w}$

Example: scaling



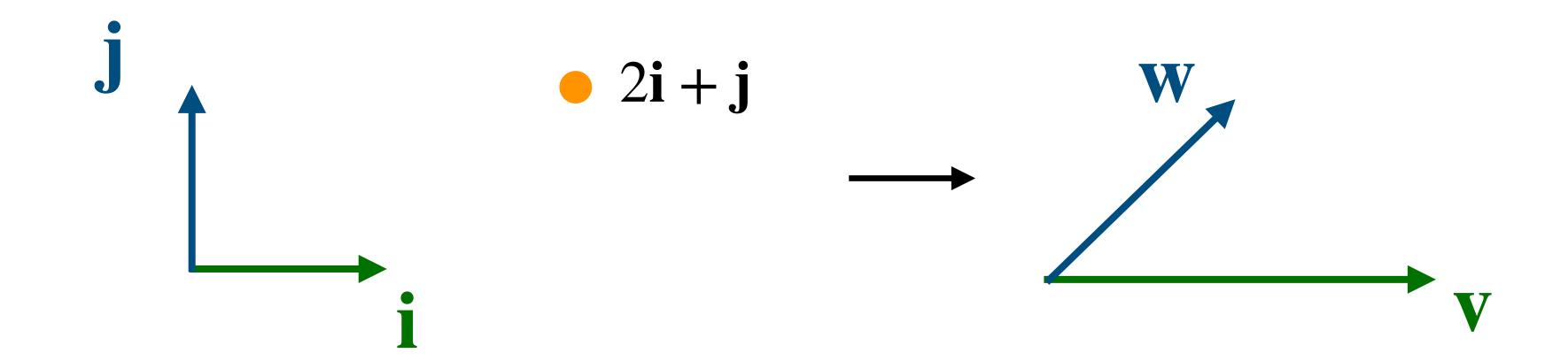
Example: rotation



Computing linear transformation

• step 1: write down the new basis in terms of the old basis

$$\mathbf{v} = 2\mathbf{i}$$
 $\mathbf{w} = \mathbf{i} + \mathbf{j}$



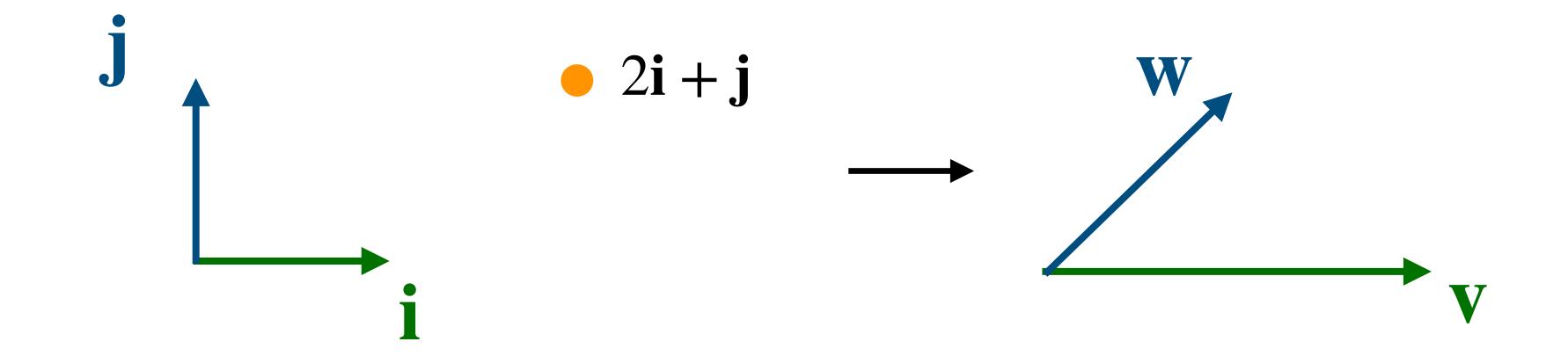
 $2\mathbf{v} + \mathbf{w}$

Computing linear transformation

• step 1: write down the new basis in terms of the old basis

$$\mathbf{v} = 2\mathbf{i}$$
 $\mathbf{w} = \mathbf{i} + \mathbf{j}$

• step 2: substitute $2\mathbf{v} + \mathbf{w} = 2(2\mathbf{i}) + (\mathbf{i} + \mathbf{j}) = 5\mathbf{i} + \mathbf{j}$



 $2\mathbf{v} + \mathbf{w}$

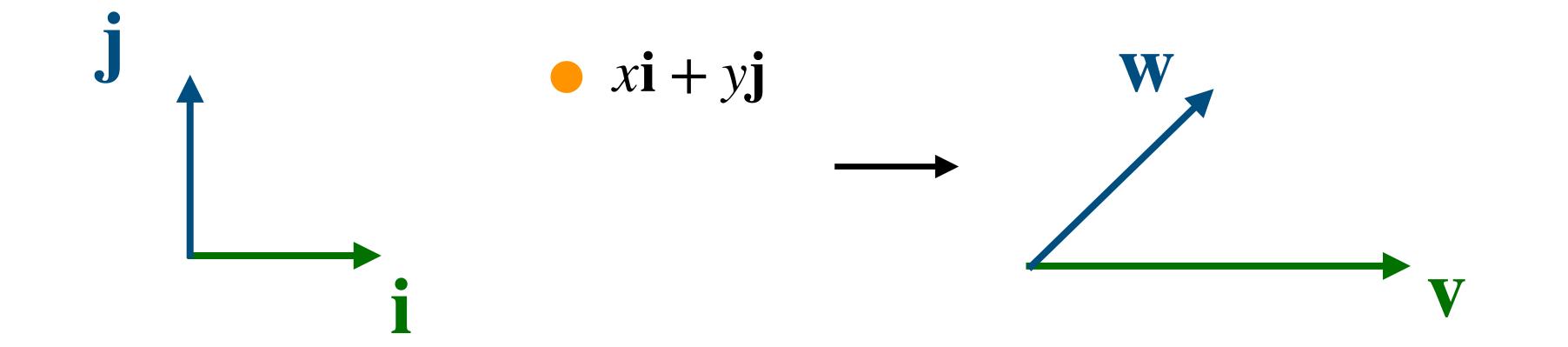
Computing linear transformation

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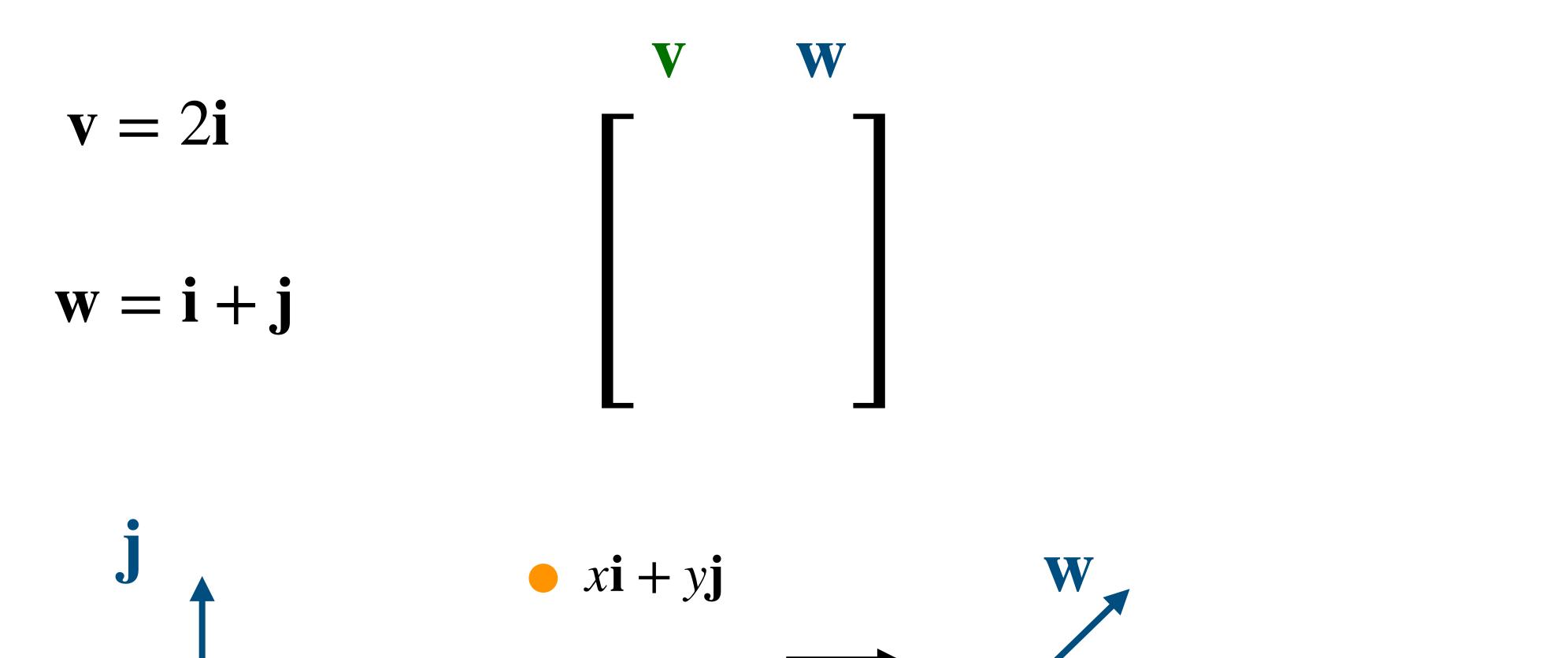
• step 2: substitute

$$x\mathbf{v} + y\mathbf{w} = x(2\mathbf{i}) + y(\mathbf{i} + \mathbf{j}) = (2x + y)\mathbf{i} + y\mathbf{j}$$



xv + yw

Representing linear transformation as a matrix



 $x\mathbf{v} + y\mathbf{w}$

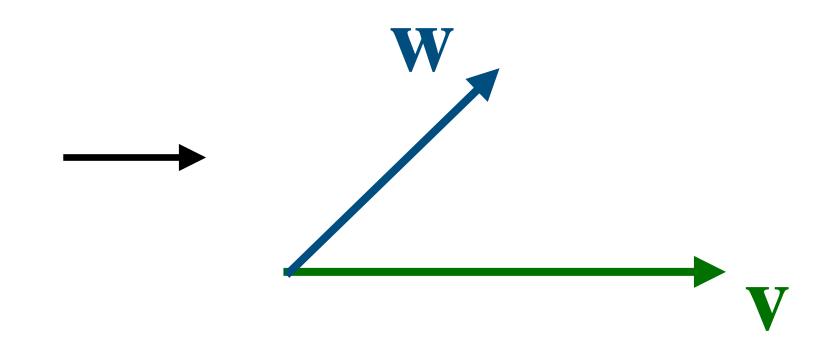
Representing linear transformation as a matrix

$$\mathbf{v} = 2\mathbf{i}$$

$$\mathbf{w} = \mathbf{i} + \mathbf{j}$$

where does i go?

-xi + yj



xv + yw

Representing linear transformation as a matrix

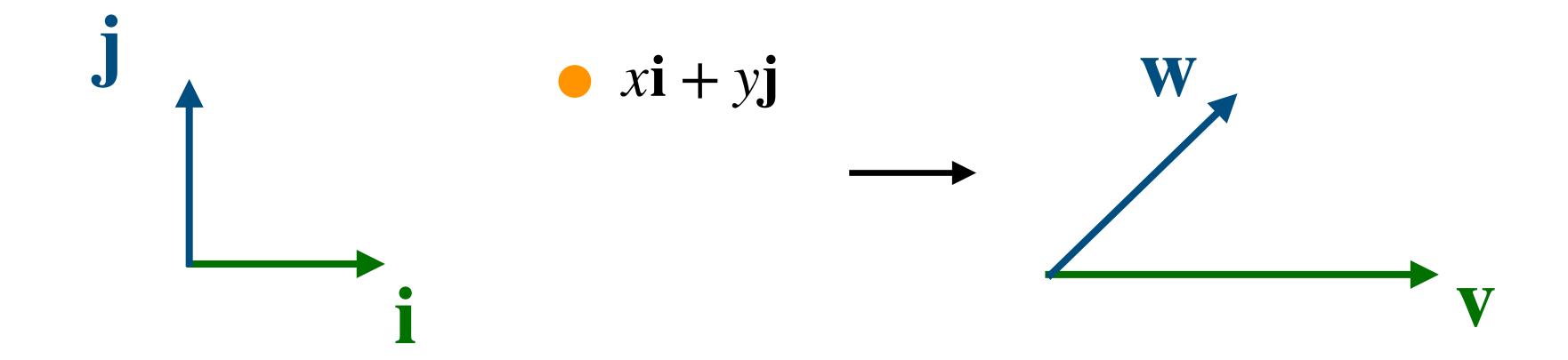
$$\mathbf{v} = 2\mathbf{i}$$

$$\mathbf{w} = \mathbf{i} + \mathbf{j}$$

$$\mathbf{v} = \mathbf{w}$$

$$\begin{bmatrix} 2 & 1 \\ 0 & 1 \end{bmatrix}$$

$$\mathbf{v} = \mathbf{i} + \mathbf{j}$$
where does \mathbf{j} go?



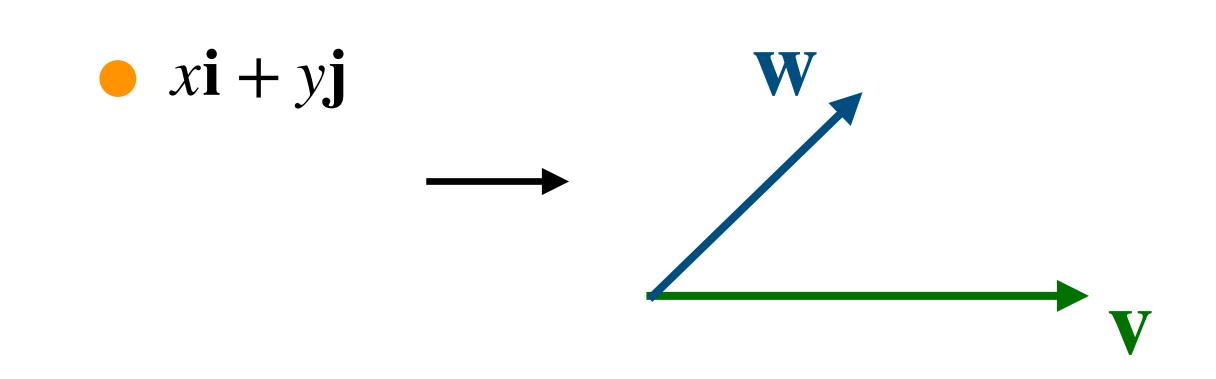
 $x\mathbf{v} + y\mathbf{w}$

Applying linear transformation as matrix-vector product

$$\mathbf{v} = 2\mathbf{i}$$

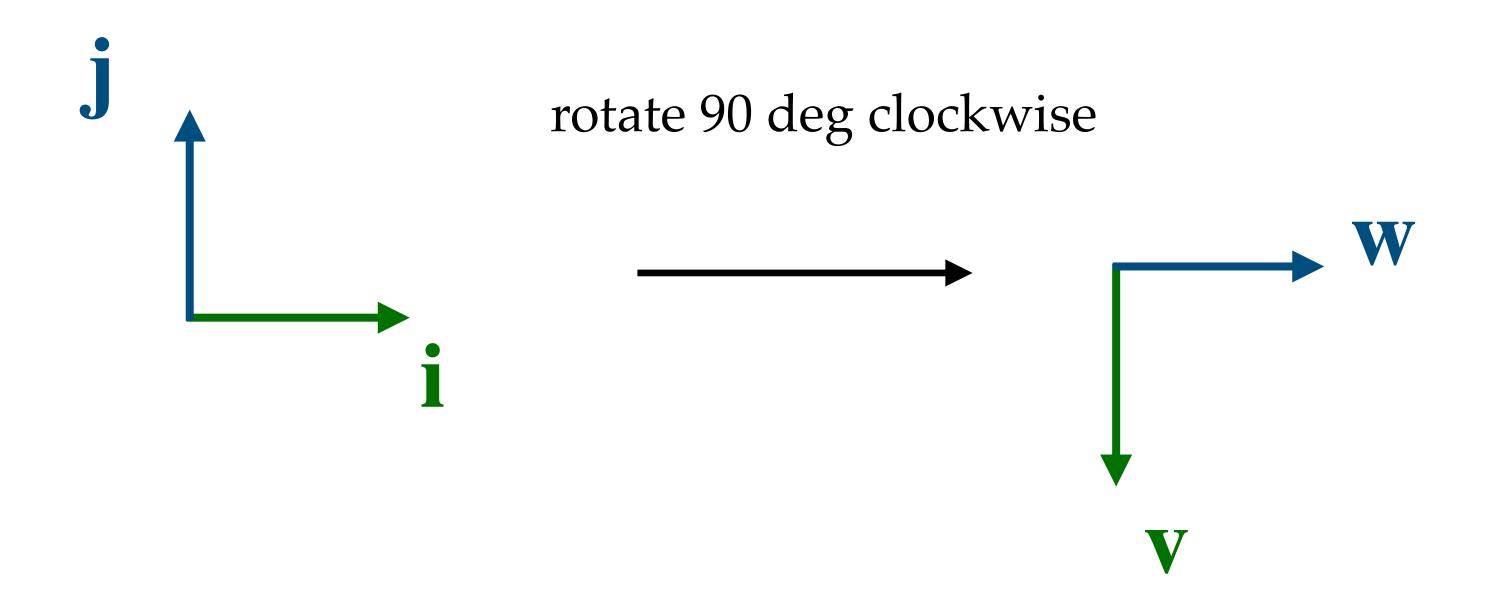
$$\mathbf{w} = \mathbf{i} + \mathbf{j}$$

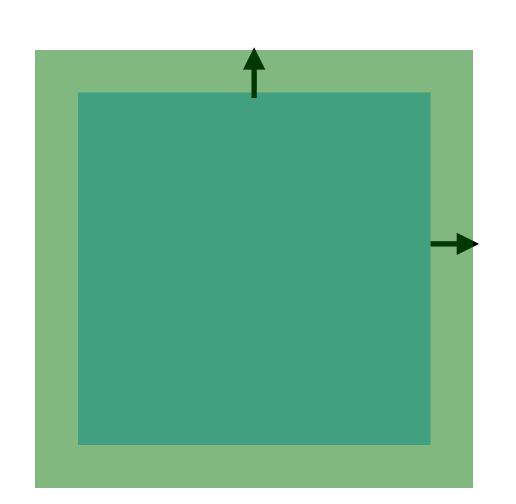
$$\begin{bmatrix} \mathbf{v} & \mathbf{w} \\ 2 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2x + y \\ y \end{bmatrix}$$



xv + yw

Quiz: what is the matrix form of this transformation?

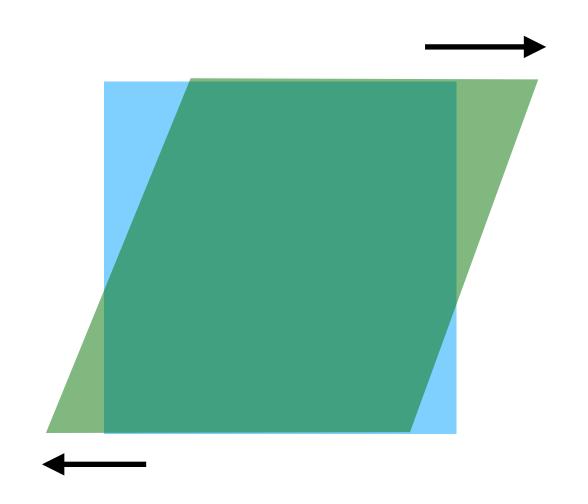




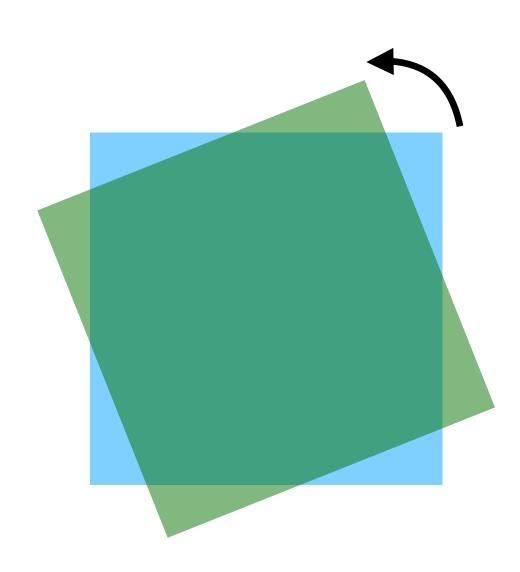
scaling

$$S_{x}$$
 O S_{y}

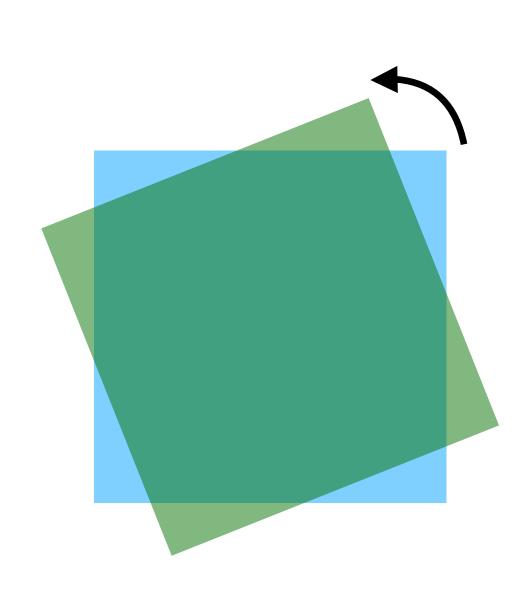
x shearing



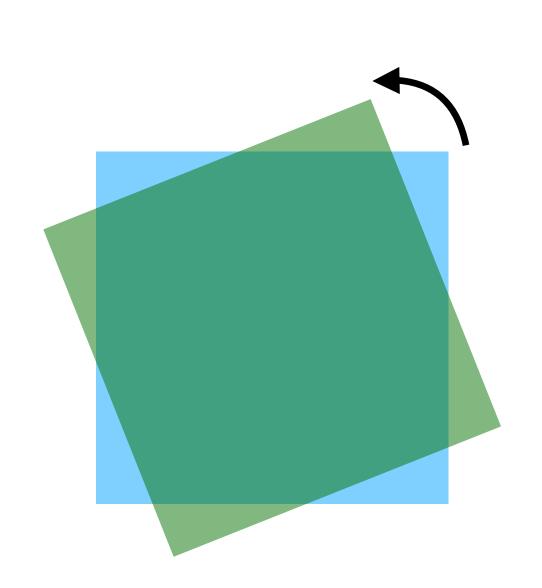
$$\begin{bmatrix} 1 & \lambda_x \\ 0 & 1 \end{bmatrix}$$



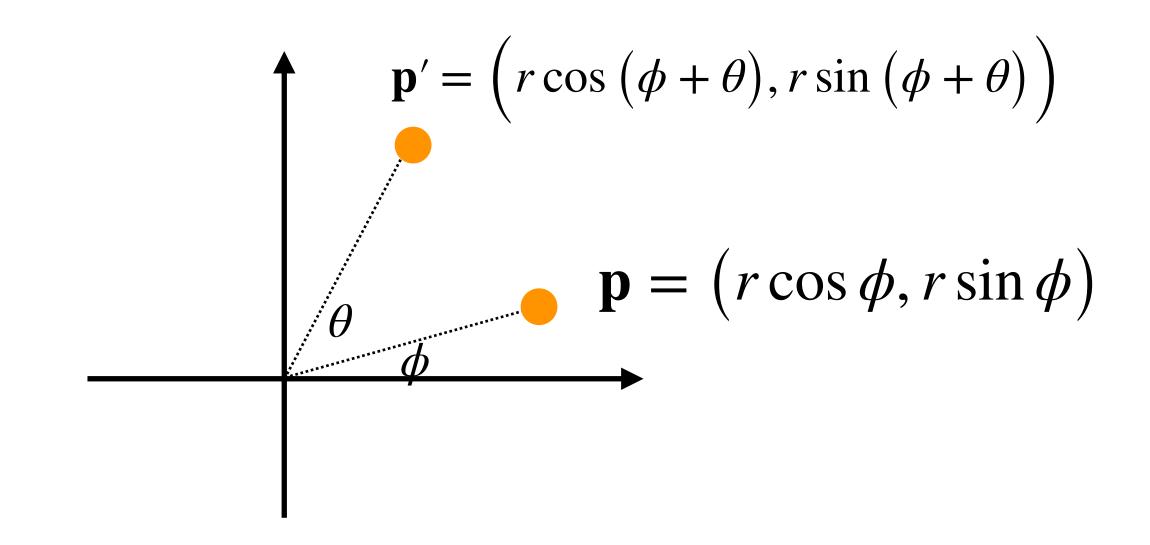
$$\begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$

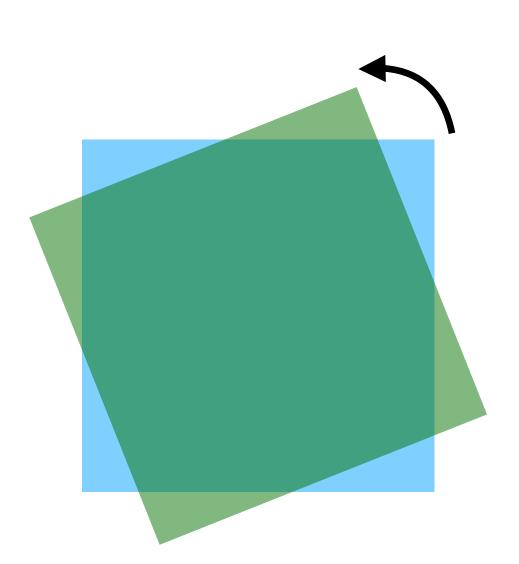


$$\begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$



$$\begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$





 $\cos(\phi + \theta) = \cos(\phi)\cos(\theta) - \sin(\phi)\sin(\theta)$ $\sin(\phi + \theta) = \sin(\phi)\cos(\theta) + \cos(\phi)\sin(\theta)$

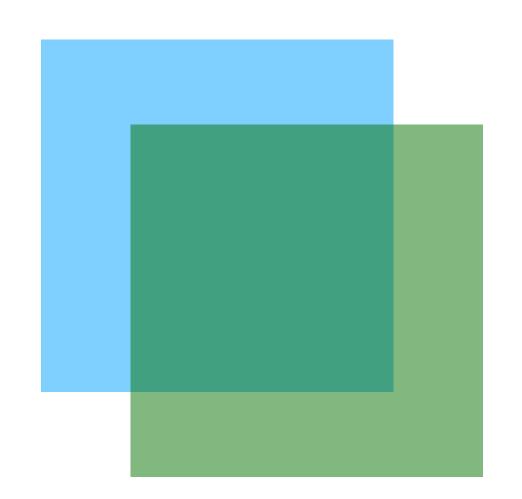
$$\begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$

$$\mathbf{p}' = \left(r\cos\left(\phi + \theta\right), r\sin\left(\phi + \theta\right)\right)$$

$$\mathbf{p} = \left(r\cos\phi, r\sin\phi\right)$$

What about translation?

we can't write translation as a 2x2 matrix! (the basis vectors don't encode the information of where is the origin)



-> translation is not a 2D linear transformation!

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

Trick: augmented matrix

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

$$\downarrow$$

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & t_x \\ c & d & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

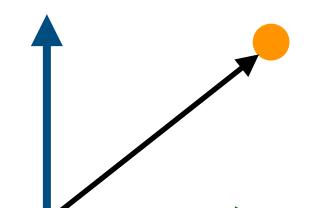
Trick: augmented matrix

 $\begin{bmatrix} a & b & t_x \\ c & d & t_y \\ 0 & 0 & 1 \end{bmatrix}$

the 2D transformations represented by this matrix are called **affine transformation**

Augmented matrices allow us to distinguish **points** and **vectors**

points: locations in space



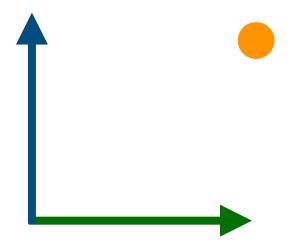
vectors: offsets in space

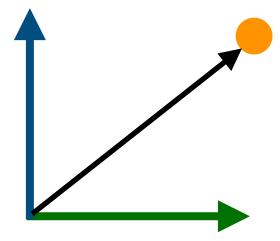


Augmented matrices allow us to distinguish **points** and **vectors**

points: locations in space

vectors: offsets in space





points are affected by translation

vectors are not affected by translation

Augmented matrices allow us to distinguish **points** and **vectors**

setting the third coordinate to 0 allows us to "turn off" the translation feature

$$\begin{bmatrix} a & b & t_x \\ c & d & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} a & b & t_x \\ c & d & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 0 \end{bmatrix}$$

points are affected by translation

vectors are not affected by translation

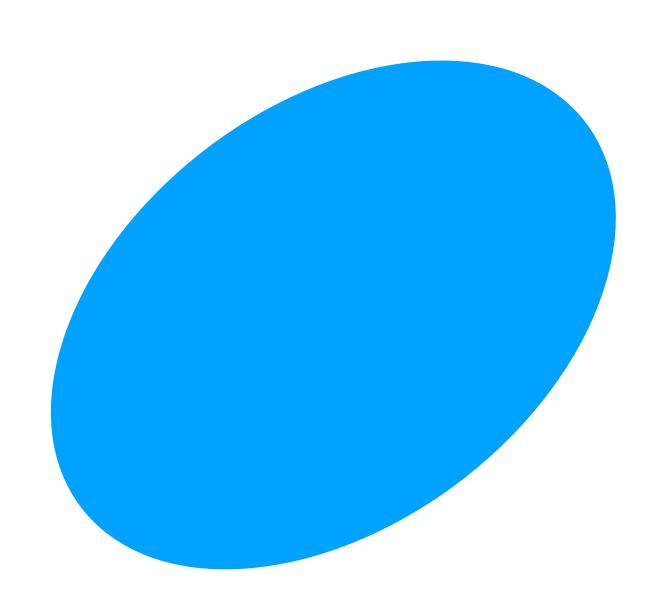
Combining multiple transformations = multiplying matrices

e.g., first scale (S), then rotate (R), then translate (T)

translate
$$\left(\text{rotate}\left(\text{scale}\left(\mathbf{p}\right)\right)\right) = TRS\mathbf{p}$$

we can premultiply the TRS matrices if we want to apply them to many ps

How do we use linear transformation to render an ellipse?

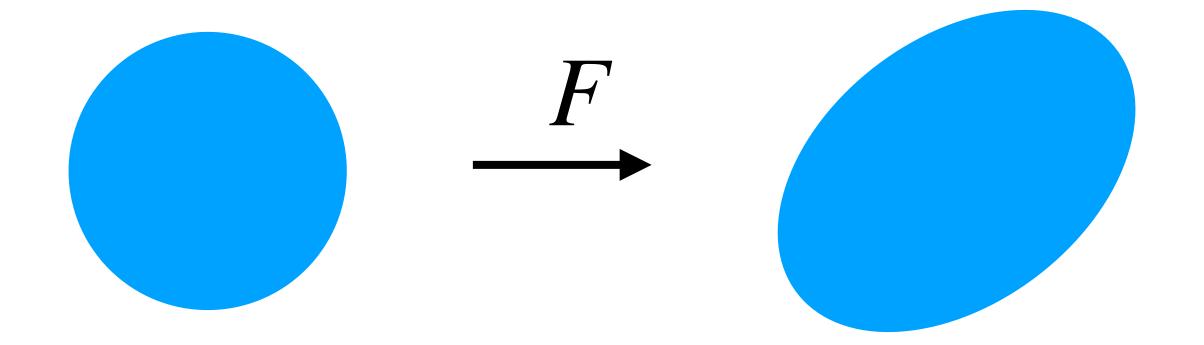


Object space vs "canvas space"

I invented this term

object space

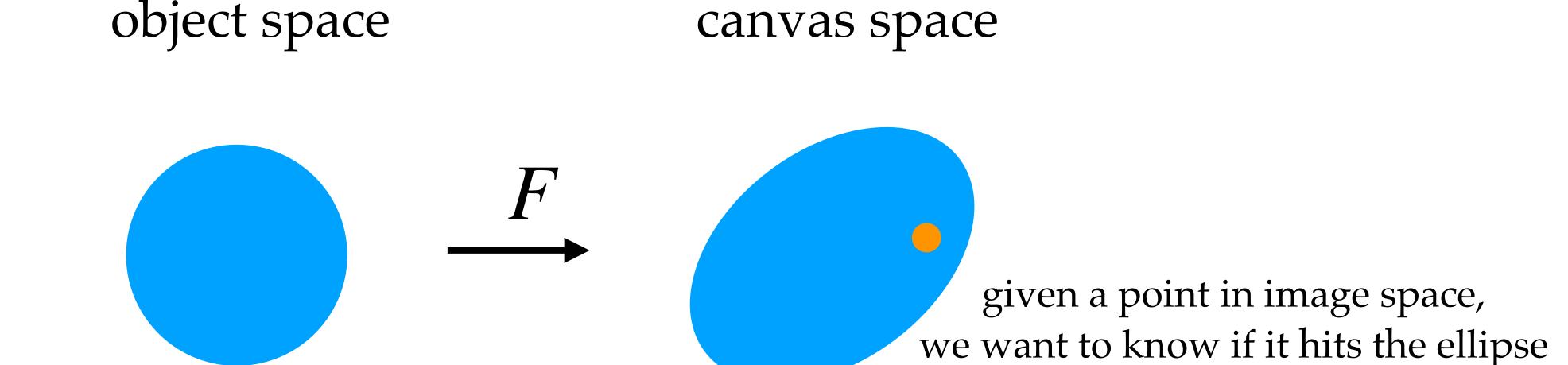
canvas space



the space we define the object and test whether a point is inside the circle

the space we actually see the transformed circle

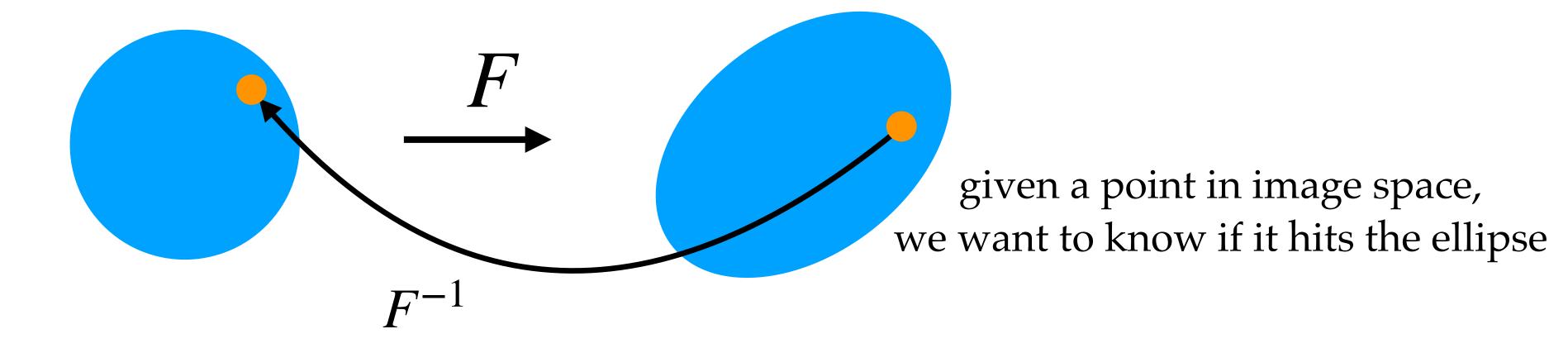
Rendering by testing in object space



Rendering by testing in object space

object space

canvas space



we apply the inverse transform F^{-1} to the point, converting it from image space to object space

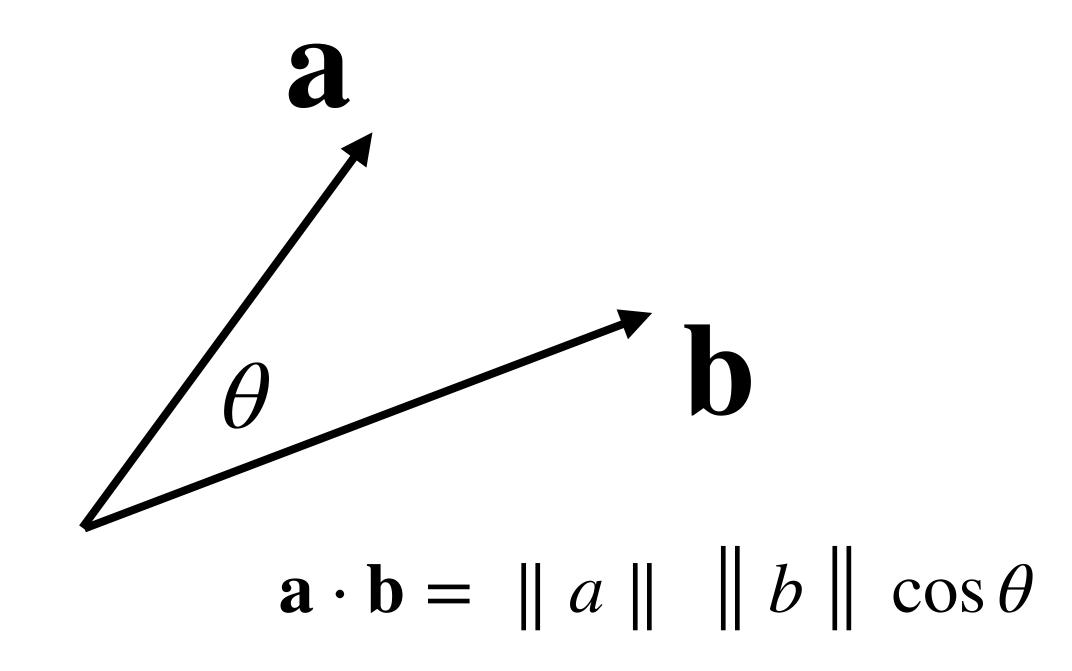
Rendering by testing in object space

object space canvas space we test in object space which is much simpler F given a point in image space, we want to know if it hits the ellipse

we apply the inverse transform F^{-1} to the point, converting it from canvas space to object space

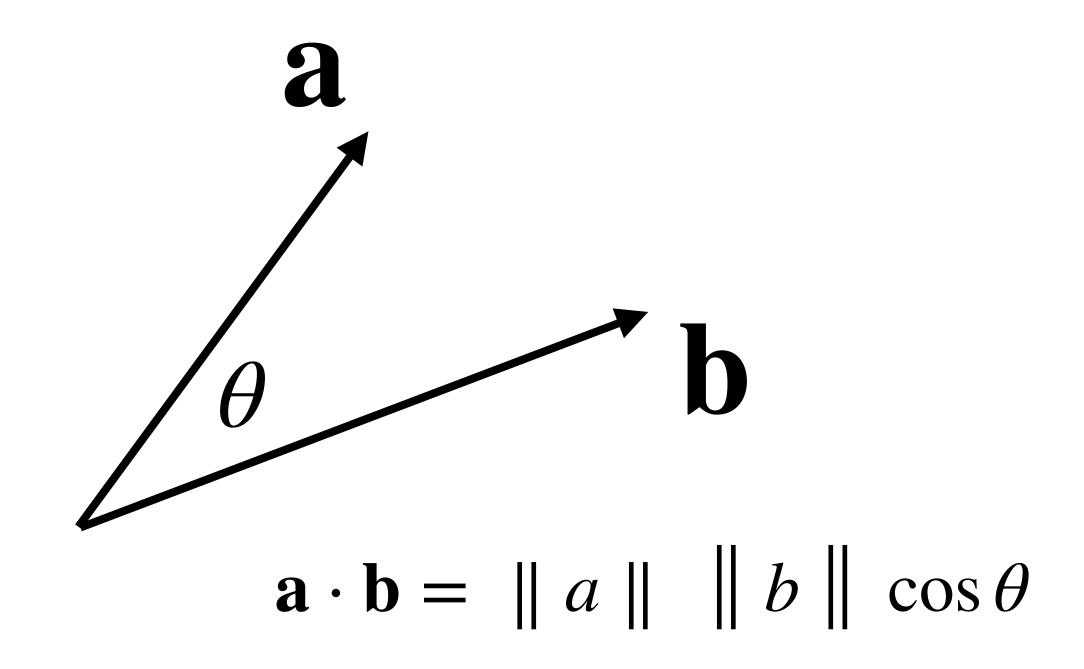
Dot product

dot products measure projected length of vectors



Dot product

dot products measure projected length of vectors



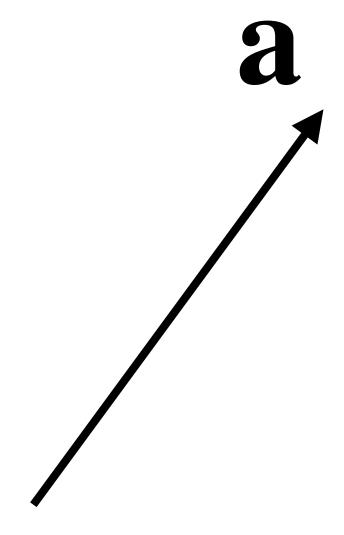
but we can also compute it by element-wise products — why?

$$\mathbf{a} \cdot \mathbf{b} = \mathbf{a}_x \mathbf{b}_x + \mathbf{a}_y \mathbf{b}_y$$

we can see $\mathbf{a} \cdot \mathbf{b}$ as applying a linear transformation \mathbf{a}^T to \mathbf{b}

$$\mathbf{a} \cdot \mathbf{b} = \mathbf{a}^T \mathbf{b}$$

$$\mathbf{a}^T = \begin{bmatrix} \mathbf{a}_x & \mathbf{a}_y \end{bmatrix}$$

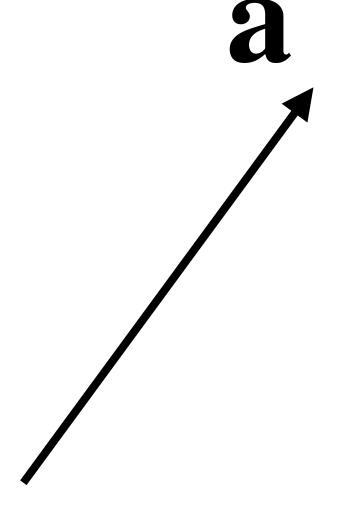


we can see $\mathbf{a} \cdot \mathbf{b}$ as applying a linear transformation \mathbf{a}^T to \mathbf{b}

let's for now assume a is a unit vector

$$\mathbf{a} \cdot \mathbf{b} = \mathbf{a}^T \mathbf{b}$$

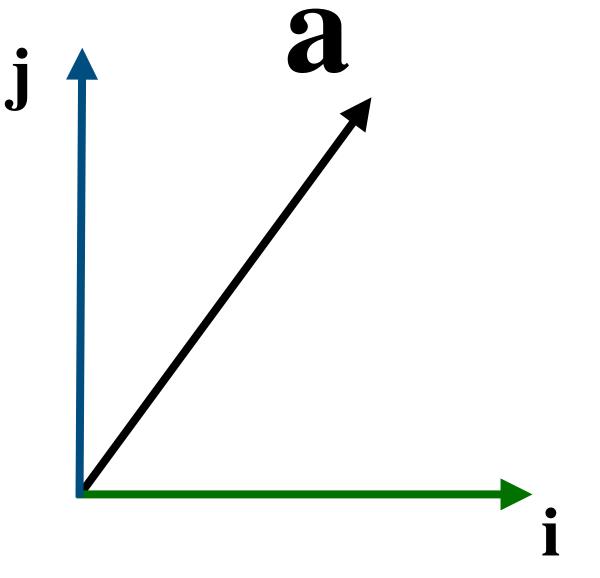
$$\mathbf{a}^T = \begin{bmatrix} \mathbf{a}_x & \mathbf{a}_y \end{bmatrix}$$



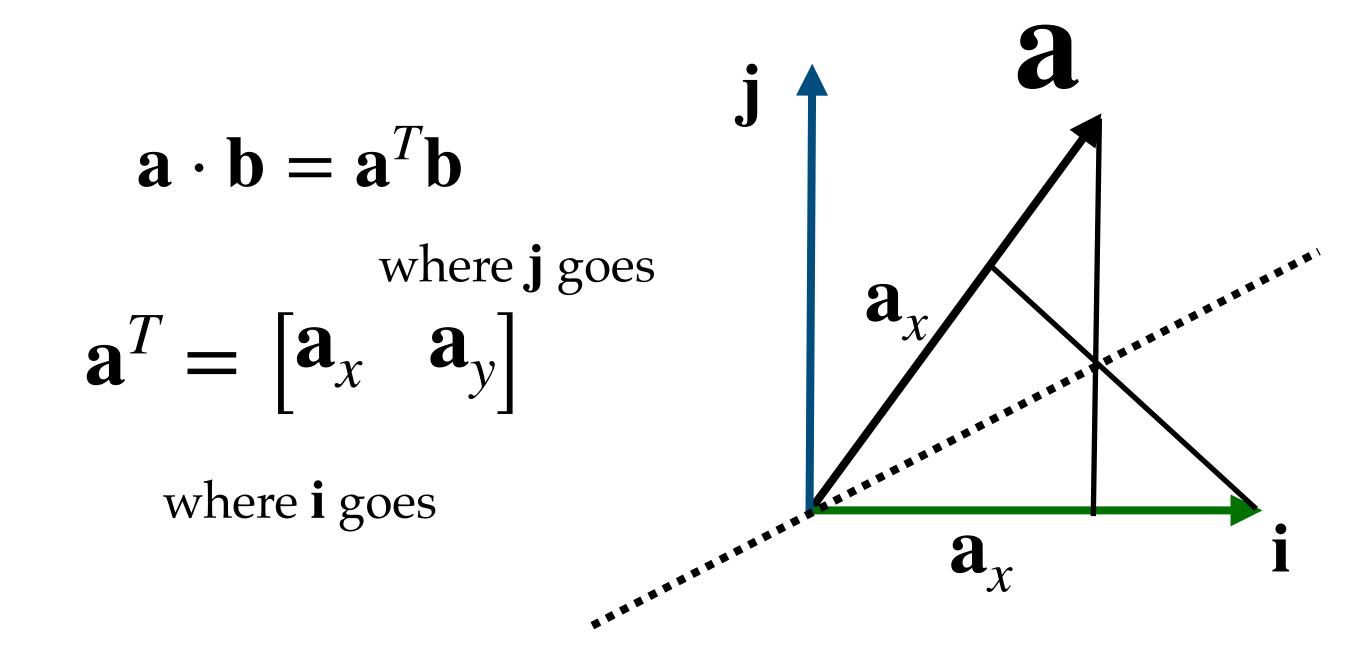
we can see $\mathbf{a} \cdot \mathbf{b}$ as applying a linear transformation \mathbf{a}^T to \mathbf{b}

let's for now assume a is a unit vector

$$\mathbf{a} \cdot \mathbf{b} = \mathbf{a}^T \mathbf{b}$$
where \mathbf{j} goes
 $\mathbf{a}^T = \begin{bmatrix} \mathbf{a}_x & \mathbf{a}_y \end{bmatrix}$
where \mathbf{i} goes



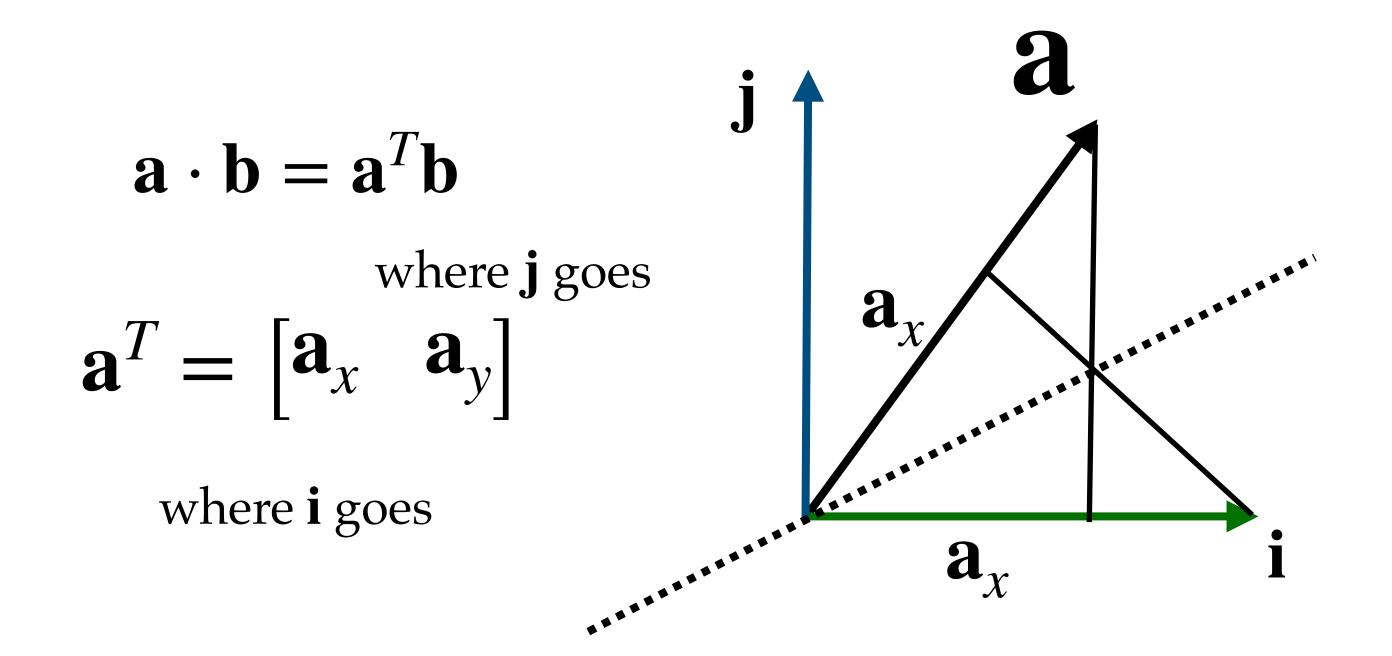
we can see $\mathbf{a} \cdot \mathbf{b}$ as applying a linear transformation \mathbf{a}^T to \mathbf{b}



let's for now assume a is a unit vector

 \mathbf{a}_{x} happens to be the projection length of \mathbf{i} !

we can see $\mathbf{a} \cdot \mathbf{b}$ as applying a linear transformation \mathbf{a}^T to \mathbf{b}

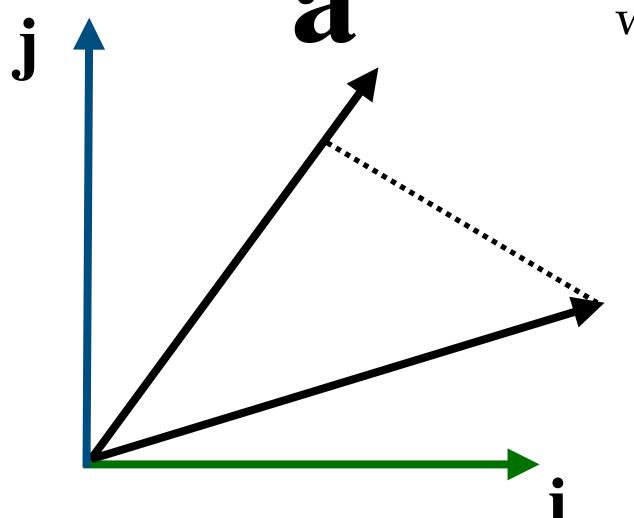


 \mathbf{a}_{x} happens to be the projection length of \mathbf{i} !

if **a** is not a unit vector, just need to scale the result by its length

we can see $\mathbf{a} \cdot \mathbf{b}$ as applying a linear transformation \mathbf{a}^T to \mathbf{b}

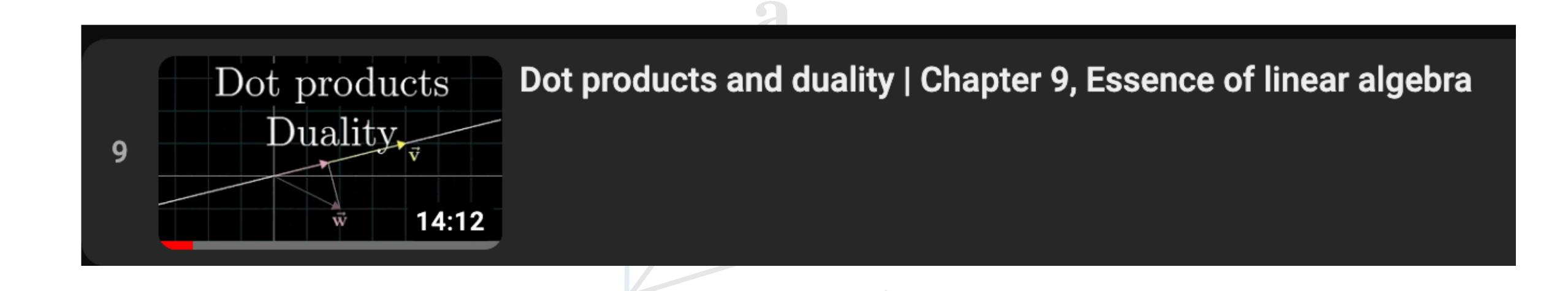
$$\mathbf{a} \cdot \mathbf{b} = \mathbf{a}^T \mathbf{b}$$



we can decompose \mathbf{b} into linear combination of \mathbf{i} and \mathbf{j}

therefore, $\mathbf{a} \cdot \mathbf{b} = \text{projecting } \mathbf{b} \text{ to } \mathbf{a} \text{ and scale by}$ $\mathbf{a}' \text{s length}$

See the 3Blue1Brown video!



https://www.youtube.com/watch?v=LyGKycYT2v0

Next: Cameras

