DSC 140B

Representation Learning

Lecture 03 | Part 1

Functions of a Vector

Functions of a Vector

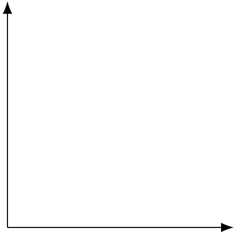
- In ML, we often work with functions of a vector: $f : \mathbb{R}^d \to \mathbb{R}^{d'}$.
- Example: a prediction function, $H(\vec{x})$.
- Functions of a vector can return:
  - a number: $f : \mathbb{R}^d \to \mathbb{R}^1$
  - a vector $\vec{f} : \mathbb{R}^d \to \mathbb{R}^{d'}$
  - something else?

Transformations

- A **transformation** $\vec{f}$ is a function that takes in a vector, and returns a vector *of the same dimensionality*.
- That is, $\vec{f} : \mathbb{R}^d \to \mathbb{R}^d$.

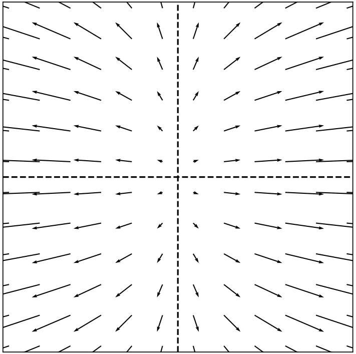
Visualizing Transformations

- A transformation is a **vector field**.
  - Assigns a vector to each point in space.
  - Example: $\vec{f}(\vec{x}) = (3x_1, x_2)^T$



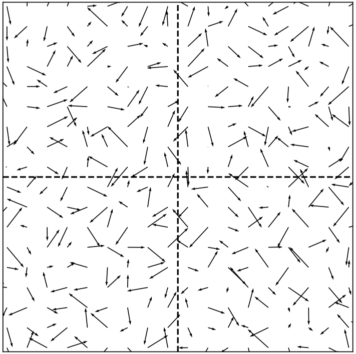
Example

- $\vec{f}(\vec{x}) = (3x_1, x_2)^T$



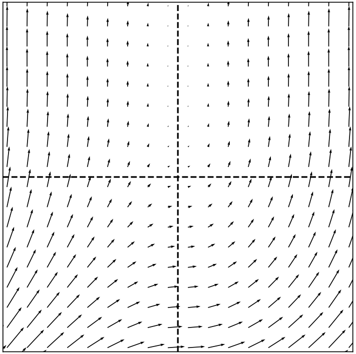
Arbitrary Transformations

- Arbitrary transformations can be quite complex.



Arbitrary Transformations

- Arbitrary transformations can be quite complex.



Linear Transformations

- Luckily, we often[1] work with simpler, **linear transformations**.

- A transformation f is linear if:

$$\vec{f}(\alpha\vec{x} + \beta\vec{y}) = \alpha\vec{f}(\vec{x}) + \beta\vec{f}(\vec{y})$$

[1] Sometimes, just to make the math tractable!

Checking Linearity

- To check if a transformation is linear, use the definition.

- **Example:** $\vec{f}(\vec{x}) = (x_2, -x_1)^T$

Exercise

Let $\vec{f}(\vec{x}) = (x_1 + 3, x_2)$. Is $\vec{f}$ a linear transformation?

Implications of Linearity

- Suppose $\vec{f}$ is a linear transformation. Then:

$$\begin{aligned}\vec{f}(\vec{x}) &= \vec{f}(x_1\hat{e}^{(1)} + x_2\hat{e}^{(2)}) \\ &= x_1\vec{f}(\hat{e}^{(1)}) + x_2\vec{f}(\hat{e}^{(2)})\end{aligned}$$

- I.e., $\vec{f}$ is **totally determined** by what it does to the basis vectors.

The **Complexity** of Arbitrary Transformations

- Suppose f is an **arbitrary** transformation.
- I tell you $\vec{f}(\hat{e}^{(1)}) = (2, 1)^T$ and $\vec{f}(\hat{e}^{(2)}) = (-3, 0)^T$.
- I tell you $\vec{x} = (x_1, x_2)^T$.
- What is $\vec{f}(\vec{x})$?

The **Simplicity** of Linear Transformations

- Suppose f is a **linear** transformation.
- I tell you $\vec{f}(\hat{e}^{(1)}) = (2, 1)^T$ and $\vec{f}(\hat{e}^{(2)}) = (-3, 0)^T$.
- I tell you $\vec{x} = (x_1, x_2)^T$.
- What is $\vec{f}(\vec{x})$?

Exercise

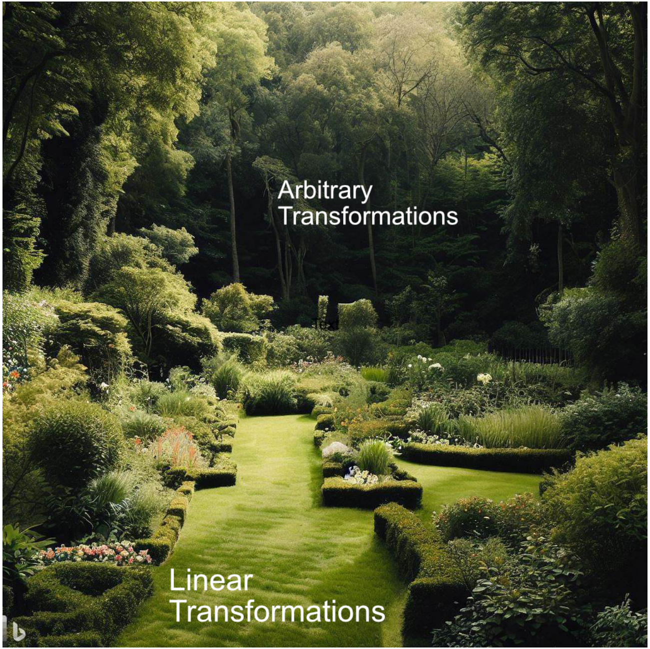
- Suppose f is a **linear** transformation.
- I tell you $\vec{f}(\hat{e}^{(1)}) = (2, 1)^T$ and $\vec{f}(\hat{e}^{(2)}) = (-3, 0)^T$.
- I tell you $\vec{x} = (3, -4)^T$.
- What is $\vec{f}(\vec{x})$?

Key Fact

- Linear functions are determined **entirely** by what they do on the basis vectors.

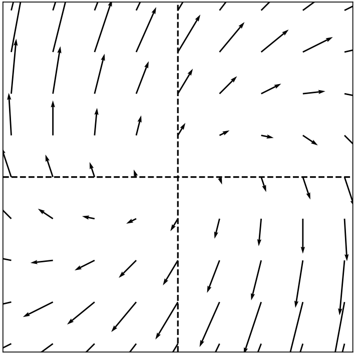
- I.e., to tell you what f does, I only need to tell you $\vec{f}(\hat{e}^{(1)})$ and $\vec{f}(\hat{e}^{(2)})$.

- This makes the math easy!


Arbitrary Transformations
Linear Transformations

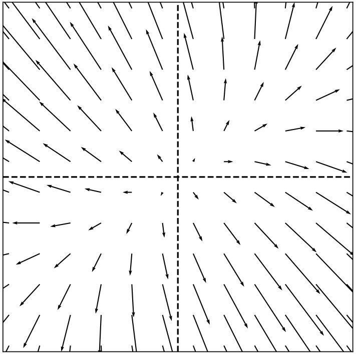
Example Linear Transformation

- $\vec{f}(\vec{x}) = (x_1 + 3x_2, -3x_1 + 5x_2)^T$



Another Example Linear Transformation

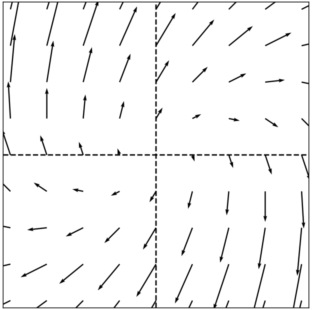
- $\vec{f}(\vec{x}) = (2x_1 - x_2, -x_1 + 3x_2)^T$

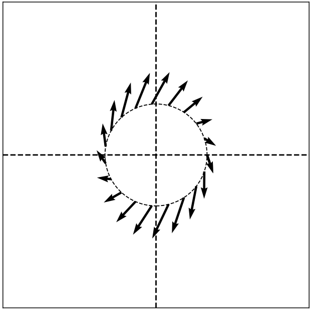


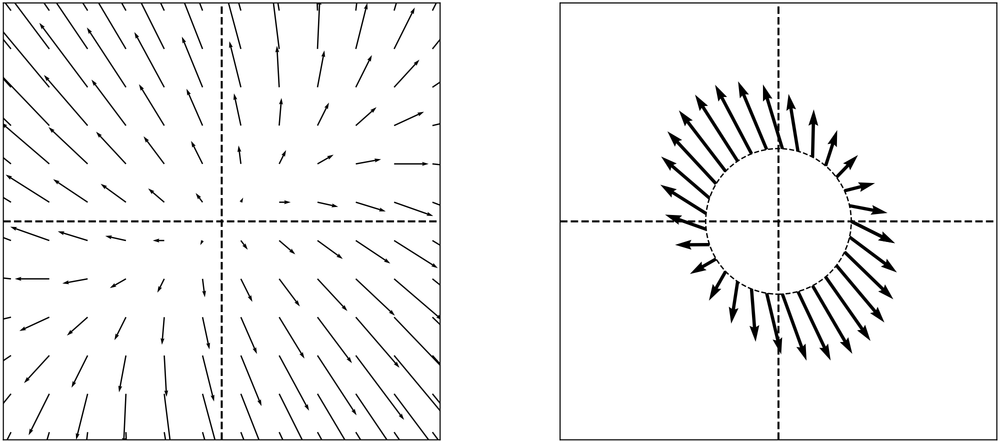
Note

- Because of linearity, along any given direction $\vec{f}$ changes only in scale.

$$\vec{f}(\lambda\hat{x}) = \lambda\vec{f}(\hat{x})$$







Linear Transformations and Bases

- We have been writing transformations in coordinate form. For example:

$$\vec{f}(\vec{x}) = (x_1 + x_2, x_1 - x_2)^T$$

- To do so, we assumed the **standard basis**.

- If we use a different basis, the formula for $\vec{f}$ changes.

Example

- Suppose that in the standard basis, $\vec{f}(\vec{x}) = (x_1 + x_2, x_1 - x_2)^T$.
- Let $\hat{u}^{(1)} = \frac{1}{\sqrt{2}}(1, 1)^T$ and $\hat{u}^{(2)} = \frac{1}{\sqrt{2}}(-1, 1)^T$.
- Write $[\vec{x}]_{\mathcal{U}} = (z_1, z_2)^T$.
- What is $[\vec{f}(\vec{x})]_{\mathcal{U}}$ in terms of z_1 and z_2?

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Representation Learning

Lecture 03 | Part 2

Matrices

Matrices?

- I thought this week was supposed to be about linear algebra... Where are the matrices?

Matrices?

- I thought this week was supposed to be about linear algebra... Where are the matrices?
- What is a matrix, anyways?

What is a matrix?

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix}$$

Recall: Linear Transformations

- A **transformation** $\vec{f}(\vec{x})$ is a function which takes a vector as input and returns a vector of the same dimensionality.

- A transformation $\vec{f}$ is **linear** if

$$\vec{f}(\alpha\vec{u} + \beta\vec{v}) = \alpha\vec{f}(\vec{u}) + \beta\vec{f}(\vec{v})$$

Recall: Linear Transformations

- **Key** consequence of **linearity**: to compute $\vec{f}(\vec{x})$, only need to know what $\vec{f}$ does to basis vectors.

- Example:

$$\vec{x} = 3\hat{e}^{(1)} - 4\hat{e}^{(2)} = \begin{pmatrix} 3 \\ -4 \end{pmatrix}$$

$$\vec{f}(\hat{e}^{(1)}) = -\hat{e}^{(1)} + 3\hat{e}^{(2)}$$

$$\vec{f}(\hat{e}^{(2)}) = 2\hat{e}^{(1)}$$

$$\vec{f}(\vec{x}) =$$

Matrices

- **Idea**: Since $\vec{f}$ is defined by what it does to basis, place $\vec{f}(\hat{e}^{(1)})$, $\vec{f}(\hat{e}^{(2)})$, ... into a table as columns

- This is the **matrix** representing[2] $\vec{f}$

$$\vec{f}(\hat{e}^{(1)}) = -\hat{e}^{(1)} + 3\hat{e}^{(2)} = \begin{pmatrix} -1 \\ 3 \end{pmatrix}$$

$$\vec{f}(\hat{e}^{(2)}) = 2\hat{e}^{(1)} = \begin{pmatrix} 2 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} -1 & 2 \\ 3 & 0 \end{pmatrix}$$

---

[2] with respect to the standard basis $\hat{e}^{(1)}, \hat{e}^{(2)}$

Exercise

Write the matrix representing $\vec{f}$ with respect to the standard basis, given:

$$\vec{f}(\hat{e}^{(1)}) = (1, 4, 7)^T$$
$$\vec{f}(\hat{e}^{(2)}) = (2, 5, 7)^T$$
$$\vec{f}(\hat{e}^{(3)}) = (3, 6, 9)^T$$

Exercise

Suppose $\vec{f}$ has the matrix below:

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix}$$

Let $\vec{x} = (-2, 1, 3)^T$. What is $\vec{f}(\vec{x})$?

Main Idea

A square $(n \times n)$ matrix can be interpreted as a compact representation of a linear transformation $f : \mathbb{R}^n \to \mathbb{R}^n$.

What is matrix multiplication?

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix} \begin{pmatrix} -2 \\ 1 \\ 3 \end{pmatrix} = \begin{pmatrix} \quad \\ \quad \\ \quad \end{pmatrix}$$

A low-level definition

$$(A\vec{x})_i = \sum_{j=1}^{n} A_{ij} x_j$$

A low-level interpretation

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix} \begin{pmatrix} -2 \\ 1 \\ 3 \end{pmatrix} = -2 \begin{pmatrix} 1 \\ 4 \\ 7 \end{pmatrix} + 1 \begin{pmatrix} 2 \\ 5 \\ 8 \end{pmatrix} + 3 \begin{pmatrix} 3 \\ 6 \\ 9 \end{pmatrix}$$

In general...

$$\begin{pmatrix} \uparrow & \uparrow & \uparrow \\ \vec{a}^{(1)} & \vec{a}^{(2)} & \vec{a}^{(3)} \\ \downarrow & \downarrow & \downarrow \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = x_1 \vec{a}^{(1)} + x_2 \vec{a}^{(2)} + x_3 \vec{a}^{(3)}$$

Matrix Multiplication

$$\vec{x} = x_1\hat{e}^{(1)} + x_2\hat{e}^{(2)} + x_3\hat{e}^{(3)} = (x_1, x_2, x_3)^T$$

$$\vec{f}(\vec{x}) = x_1\vec{f}(\hat{e}^{(1)}) + x_2\vec{f}(\hat{e}^{(2)}) + x_3\vec{f}(\hat{e}^{(3)})$$

$$A = \begin{pmatrix} \uparrow & \uparrow & \uparrow \\ \vec{f}(\hat{e}^{(1)}) & \vec{f}(\hat{e}^{(2)}) & \vec{f}(\hat{e}^{(3)}) \\ \downarrow & \downarrow & \downarrow \end{pmatrix}$$

$$\begin{aligned} A\vec{x} &= \begin{pmatrix} \uparrow & \uparrow & \uparrow \\ \vec{f}(\hat{e}^{(1)}) & \vec{f}(\hat{e}^{(2)}) & \vec{f}(\hat{e}^{(3)}) \\ \downarrow & \downarrow & \downarrow \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \\ &= x_1\vec{f}(\hat{e}^{(1)}) + x_2\vec{f}(\hat{e}^{(2)}) + x_3\vec{f}(\hat{e}^{(3)}) \end{aligned}$$

Matrix Multiplication

- Matrix A represents a linear transformation $\vec{f}$
  - With respect to the standard basis
  - If we use a different basis, the matrix changes!
- Matrix multiplication $A\vec{x}$ **evaluates** $\vec{f}(\vec{x})$

What are they, *really*?

- Matrices are sometimes just tables of numbers.
- But they often have a deeper meaning.

Main Idea

A square ($n \times n$) matrix can be interpreted as a compact representation of a linear transformation $\vec{f} : \mathbb{R}^n \to \mathbb{R}^n$.

What's more, if A represents $\vec{f}$, then $A\vec{x} = \vec{f}(\vec{x})$; that is, multiplying by A is the same as evaluating $\vec{f}$.

Example

$$\vec{x} = 3\hat{e}^{(1)} - 4\hat{e}^{(2)} = \begin{pmatrix} 3 \\ -4 \end{pmatrix}$$

$$A =$$

$$\vec{f}(\hat{e}^{(1)}) = -\hat{e}^{(1)} + 3\hat{e}^{(2)}$$

$$\vec{f}(\hat{e}^{(2)}) = 2\hat{e}^{(1)}$$

$$A\vec{x} =$$

$$\vec{f}(\vec{x}) =$$

Note

- All of this works because we assumed $\vec{f}$ is **linear**.
- If it isn't, evaluating $\vec{f}$ isn't so simple.

Note

- All of this works because we assumed $\vec{f}$ is **linear**.
- If it isn't, evaluating $\vec{f}$ isn't so simple.
- Linear algebra = simple!

Matrices in Other Bases

- The matrix of a linear transformation wrt the **standard basis**:

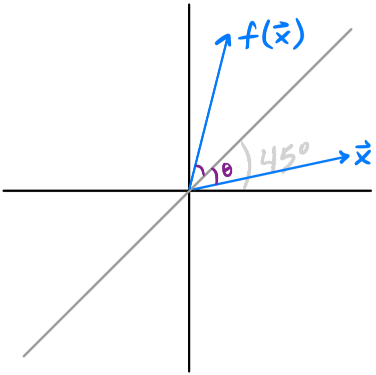
$$\begin{pmatrix} \uparrow & \uparrow & \uparrow & \\ \vec{f}(\hat{e}^{(1)}) & \vec{f}(\hat{e}^{(2)}) & \cdots & \vec{f}(\hat{e}^{(d)}) \\ \downarrow & \downarrow & \downarrow & \end{pmatrix}$$

- With respect to basis $\mathcal{U}$:

$$\begin{pmatrix} \uparrow & \uparrow & \uparrow & \\ [\vec{f}(\hat{u}^{(1)})]_{\mathcal{U}} & [\vec{f}(\hat{u}^{(2)})]_{\mathcal{U}} & \cdots & [\vec{f}(\hat{u}^{(d)})]_{\mathcal{U}} \\ \downarrow & \downarrow & \downarrow & \end{pmatrix}$$

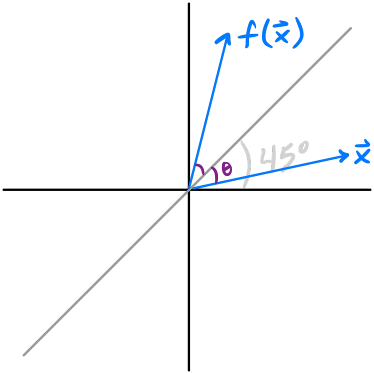
Matrices in Other Bases

- Consider the transformation $\vec{f}$ which "mirrors" a vector over the line of 45°.



- What is its matrix in the standard basis?

Matrices in Other Bases



- Let $\hat{u}^{(1)} = \frac{1}{\sqrt{2}}(1, 1)^T$
- Let $\hat{u}^{(2)} = \frac{1}{\sqrt{2}}(-1, 1)^T$
- What is $[\vec{f}(\hat{u}^{(1)})]_{\mathcal{U}}$?
- $[\vec{f}(\hat{u}^{(2)})]_{\mathcal{U}}$?
- What is the matrix?

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Lecture 03 | Part 3

The Spectral Theorem

Eigenvectors

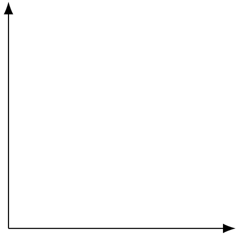
- Let A be an $n \times n$ matrix. An **eigenvector** of A with **eigenvalue** λ is a nonzero vector $\vec{v}$ such that $A\vec{v} = \lambda\vec{v}$.

Eigenvectors (of Linear Transformations)

- Let $\vec{f}$ be a linear transformation. An **eigenvector** of $\vec{f}$ with **eigenvalue** λ is a nonzero vector $\vec{v}$ such that $f(\vec{v}) = \lambda\vec{v}$.

Geometric Interpretation

- When $\vec{f}$ is applied to one of its eigenvectors, $\vec{f}$ simply scales it.
  - Possibly by a negative amount.



Symmetric Matrices

- Recall: a matrix A is **symmetric** if $A^T = A$.

The Spectral Theorem[3]

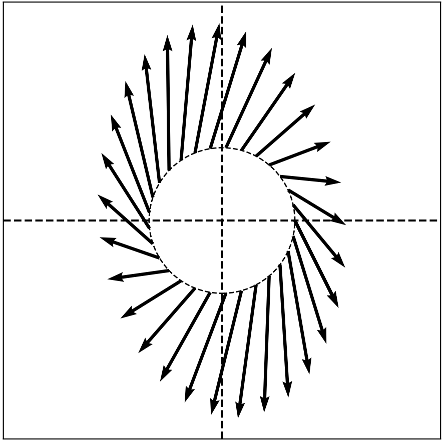
- **Theorem**: Let A be an $n \times n$ *symmetric* matrix. Then there exist n eigenvectors of A which are all mutually orthogonal.

[3] for symmetric matrices

What?

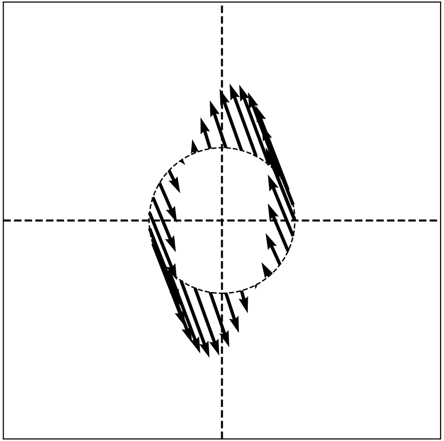
- What does the spectral theorem mean?
- What is an eigenvector, really?
- Why are they useful?

Example Linear Transformation



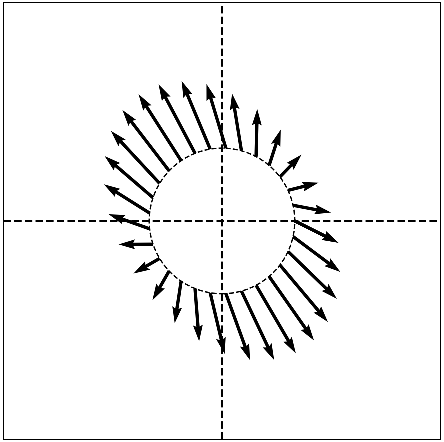
$$A = \begin{pmatrix} 5 & 5 \\ -10 & 12 \end{pmatrix}$$

Example Linear Transformation



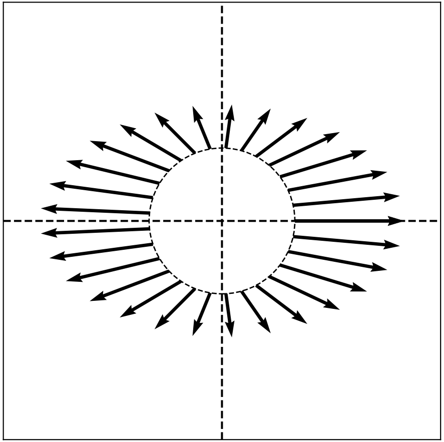
$$A = \begin{pmatrix} -2 & -1 \\ -5 & 3 \end{pmatrix}$$

Example Symmetric Linear Transformation



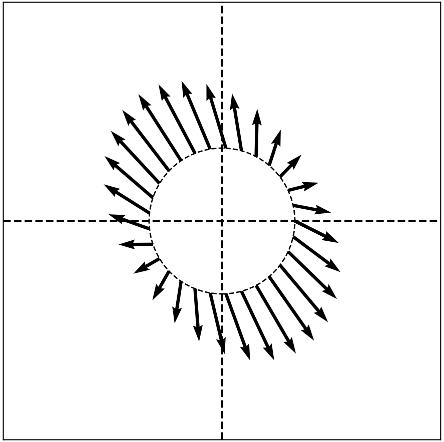
$$A = \begin{pmatrix} 2 & -1 \\ -1 & 3 \end{pmatrix}$$

Example Symmetric Linear Transformation



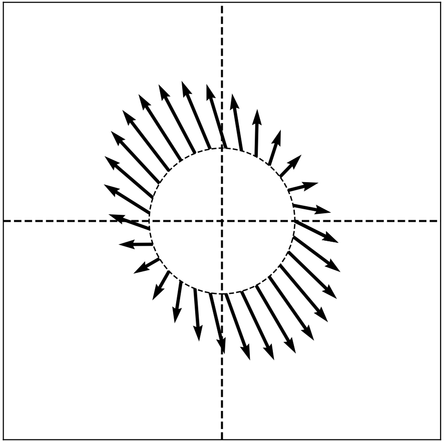
$$A = \begin{pmatrix} 5 & 0 \\ 0 & 2 \end{pmatrix}$$

Observation #1



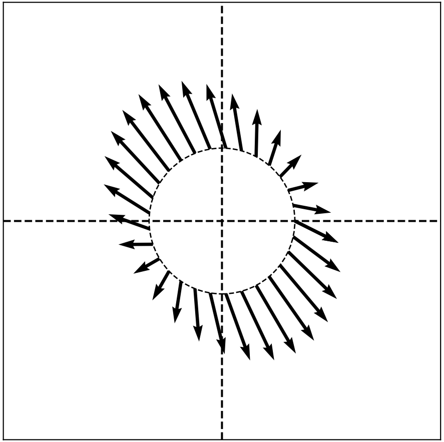
- Symmetric linear transformations have **axes of symmetry**.

Observation #2



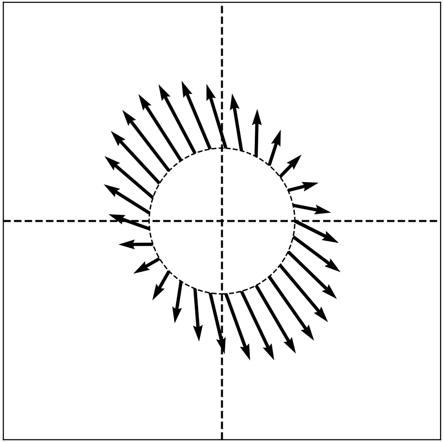
- The axes of symmetry are **orthogonal** to one another.

Observation #3



- The action of $\vec{f}$ along an axis of symmetry is simply to scale its input.

Observation #4



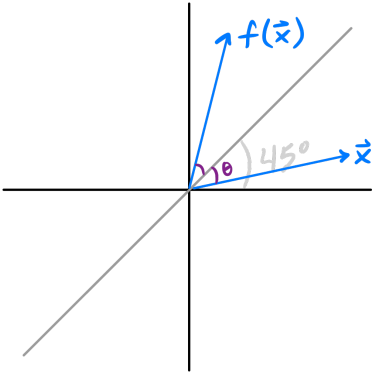
- The size of this scaling can be different for each axis.

Main Idea

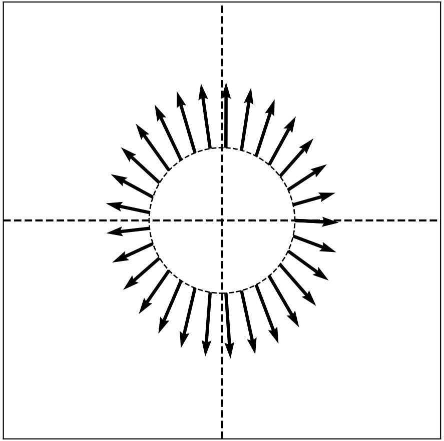
The **eigenvectors** of a symmetric linear transformation (matrix) are its axes of symmetry. The **eigenvalues** describe how much each axis of symmetry is scaled.

Exercise

Consider the linear transformation which mirrors its input over the line of 45°. Give two orthogonal eigenvector of the transformation.

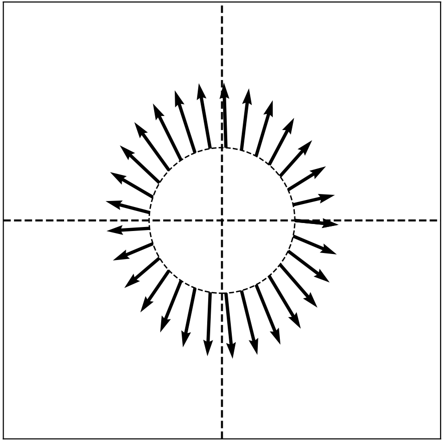


Off-diagonal elements



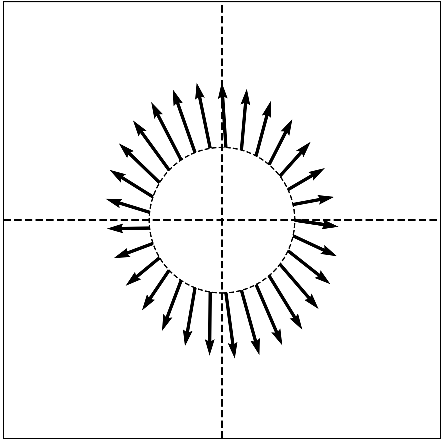
$$A = \begin{pmatrix} 5 & -0.1 \\ -0.1 & 2 \end{pmatrix}$$

Off-diagonal elements



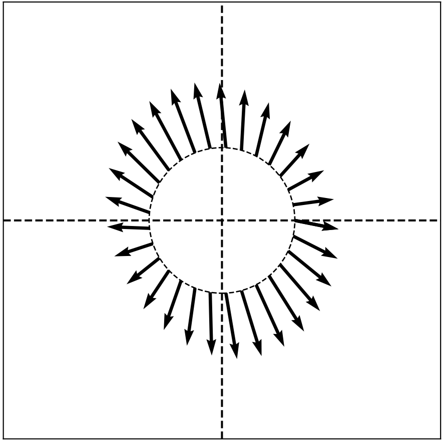
$$A = \begin{pmatrix} 5 & -0.2 \\ -0.2 & 2 \end{pmatrix}$$

Off-diagonal elements



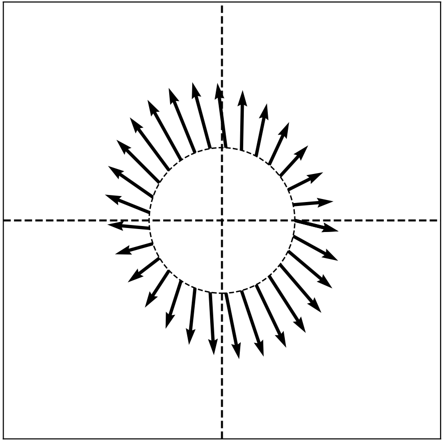
$$A = \begin{pmatrix} 5 & -0.3 \\ -0.3 & 2 \end{pmatrix}$$

Off-diagonal elements



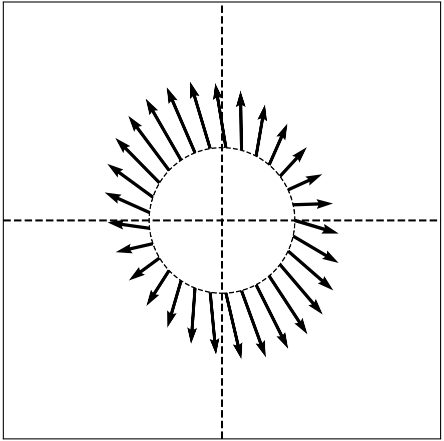
$$A = \begin{pmatrix} 5 & -0.4 \\ -0.4 & 2 \end{pmatrix}$$

Off-diagonal elements



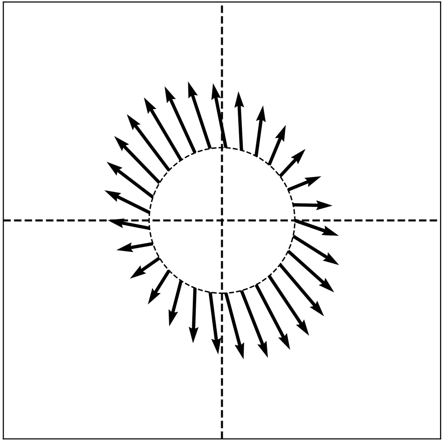
$$A = \begin{pmatrix} 5 & -0.5 \\ -0.5 & 2 \end{pmatrix}$$

Off-diagonal elements



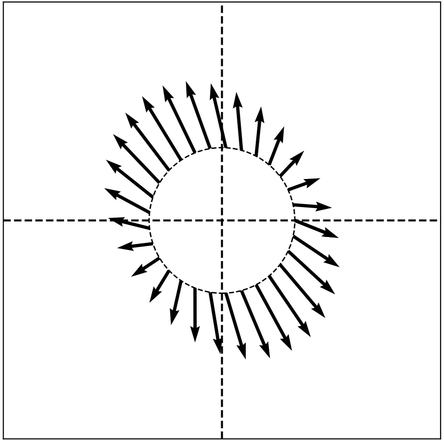
$$A = \begin{pmatrix} 5 & -0.6 \\ -0.6 & 2 \end{pmatrix}$$

Off-diagonal elements



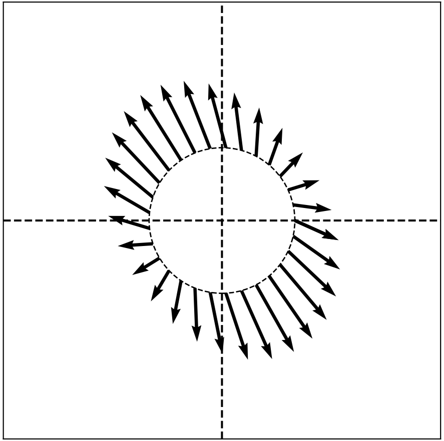
$$A = \begin{pmatrix} 5 & -0.7 \\ -0.7 & 2 \end{pmatrix}$$

Off-diagonal elements



$$A = \begin{pmatrix} 5 & -0.8 \\ -0.8 & 2 \end{pmatrix}$$

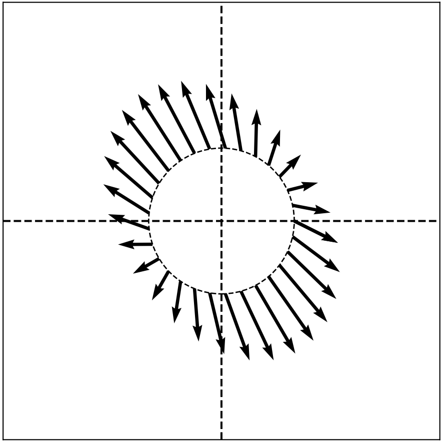
Off-diagonal elements



$$A = \begin{pmatrix} 5 & -0.9 \\ -0.9 & 2 \end{pmatrix}$$

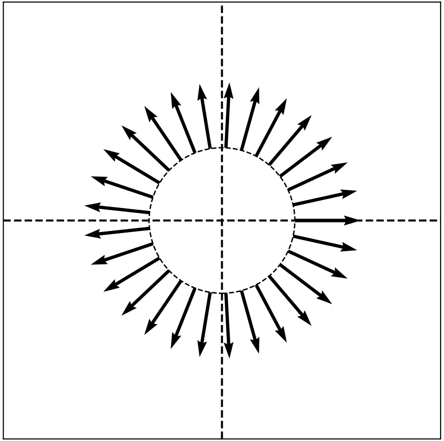
The Spectral Theorem[4]

- **Theorem**: Let A be an $n \times n$ *symmetric* matrix. Then there exist n eigenvectors of A which are all mutually orthogonal.



[4] for symmetric matrices

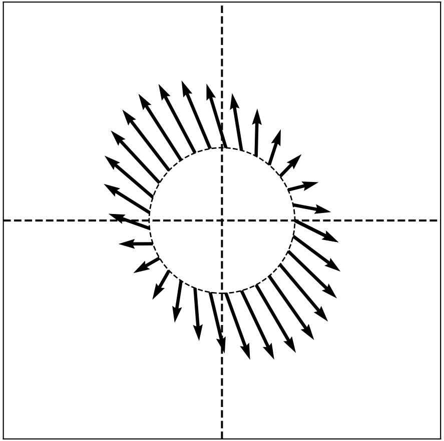
What about total symmetry?



- Every vector is an eigenvector.

$$A = \begin{pmatrix} 3 & 0 \\ 0 & 3 \end{pmatrix}$$

Computing Eigenvectors



```
>> A = np.array([[2, -1], [-1, 3]])
>> np.linalg.eigh(A)
(array([1.38196601, 3.61803399]),
 array([[-0.85065081, -0.52573111],
        [-0.52573111,  0.85065081]]))
```