

Lab 10: Eigenvalues and Eigenvectors, Convexity **Solutions**

EECS 245, Spring 2026 at the University of Michigan

due for completion at 11:59PM Ann Arbor Time on Monday, June 15th, 2026

Name: _____

username: _____

Each lab worksheet will contain several activities, some of which will involve writing code and others that will involve writing math on paper. To receive credit for a lab, you must complete as many of the activities as you can in 2 hours and submit a PDF of your work to Gradescope. We will provide specific instructions on how to submit programming activities (e.g. submitting the notebook or including a screenshot of some output).

Feel free to work with others in the course, but you must submit individually.

Recap: Eigenvalues and Eigenvectors

Let $A = \begin{bmatrix} 6 & 3 \\ 3 & -2 \end{bmatrix}$.

- An **eigenvector** of A is a non-zero vector $\vec{v}$ such that $A\vec{v} = \lambda\vec{v}$ for some scalar λ . The scalar λ is called the **eigenvalue** corresponding to $\vec{v}$. For A 's eigenvectors, multiplying by A is equivalent to multiplying by a scalar.
- The **characteristic polynomial** of A is given by $p(\lambda) = \det(A - \lambda I)$.

$$p(\lambda) = \det(A - \lambda I) = \begin{vmatrix} 6 - \lambda & 3 \\ 3 & -2 - \lambda \end{vmatrix} = (6 - \lambda)(-2 - \lambda) - 3 \cdot 3 = \lambda^2 - 4\lambda - 21 = (\lambda + 3)(\lambda - 7)$$

- The eigenvalues of A are the roots of the characteristic polynomial, so $\lambda_1 = -3$ and $\lambda_2 = 7$.
 - The eigenvector $\vec{v}_1$ satisfies $A\vec{v}_1 = -3\vec{v}_1$.

$$\begin{bmatrix} 6 & 3 \\ 3 & -2 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = -3 \begin{bmatrix} a \\ b \end{bmatrix} \implies b = -3a$$

So any vector of the form $\begin{bmatrix} a \\ -3a \end{bmatrix}$ ($a \neq 0$) is an eigenvector of A corresponding to the

eigenvalue -3 . We could pick $\vec{v}_1 = \begin{bmatrix} 2 \\ -6 \end{bmatrix}$.

- The eigenvector $\vec{v}_2$ satisfies $A\vec{v}_2 = 7\vec{v}_2$. Another way to find it is to solve for the null space of $A - 7I = \begin{bmatrix} -1 & 3 \\ 3 & -9 \end{bmatrix}$. One vector in $\text{nullsp}(A - 7I)$ is $\vec{v}_2 = \begin{bmatrix} 3 \\ 1 \end{bmatrix}$.

Activity 1: Introduction

For each 2×2 matrix A below:

- (i) Find the characteristic polynomial of A , and use it to find the eigenvalues of A .
- (ii) Find one eigenvector for each eigenvalue of A . Verify that each eigenvector is indeed an eigenvector of A by multiplying it by A .
- (iii) **By hand (not using Python or Desmos)**, draw a picture (like the one in Chapter 9.1 titled [Visualizing the eigenvectors of \$A\$](#)) with vectors $\vec{v}_1, A\vec{v}_1, \vec{v}_2, A\vec{v}_2$ as arrows (where $\vec{v}_1$ and $\vec{v}_2$ are the eigenvectors you found above).

a) $A = \begin{bmatrix} 3 & 0 \\ 0 & 4 \end{bmatrix}$

Solution:

- (i) The characteristic polynomial of A is

$$\begin{aligned}\det(A - \lambda I) &= \begin{vmatrix} 3 - \lambda & 0 \\ 0 & 4 - \lambda \end{vmatrix} \\ &= (3 - \lambda)(4 - \lambda)\end{aligned}$$

So, the eigenvalues of A are $\lambda_1 = 3$ and $\lambda_2 = 4$. A is a diagonal matrix, which means its eigenvalues are its diagonal entries.

- (ii) Matching examples we've seen in class (in particular, [this example](#) from Chapter 9.2), an eigenvector for $\lambda_1 = 3$ is $\vec{v}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ and an eigenvector for $\lambda_2 = 4$ is $\vec{v}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$; indeed, $A\vec{v}_1 = 3\vec{v}_1$ and $A\vec{v}_2 = 4\vec{v}_2$.

b) $A = \begin{bmatrix} 3 & 4 \\ 4 & 3 \end{bmatrix}$

Solution:

(i) The characteristic polynomial of A is

$$\begin{aligned}\det(A - \lambda I) &= \begin{vmatrix} 3 - \lambda & 4 \\ 4 & 3 - \lambda \end{vmatrix} \\ &= (3 - \lambda)^2 - 16 \\ &= \lambda^2 - 6\lambda + 9 - 16 \\ &= \lambda^2 - 6\lambda - 7 \\ &= (\lambda + 1)(\lambda - 7)\end{aligned}$$

So, the eigenvalues of A are $\lambda_1 = -1$ and $\lambda_2 = 7$.

(ii) • The eigenvector $\vec{v}_1$ corresponding to $\lambda_1 = -1$ satisfies $A\vec{v}_1 = -1\vec{v}_1$.

$$\begin{bmatrix} 3 & 4 \\ 4 & 3 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = -1 \begin{bmatrix} a \\ b \end{bmatrix}$$

The first component implies $3a + 4b = -a \implies 4a + 4b = 0 \implies a = -b$. So, an eigenvector $\vec{v}_1$ is $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$ (though there are infinitely many other choices; any scalar multiple of $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$ is also an eigenvector for eigenvalue -1). Note that using the second component would give us the same relationship. To verify that we correctly found the eigenvector-eigenvalue pair, multiplying A by $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$ gives

$$A \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 3 - 4 \\ 4 - 3 \end{bmatrix} = \begin{bmatrix} -1 \\ 1 \end{bmatrix} = -1 \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

(We will omit this step moving forward.)

• The eigenvector $\vec{v}_2$ corresponding to $\lambda_2 = 7$ satisfies $A\vec{v}_2 = 7\vec{v}_2$.

$$\begin{bmatrix} 3 & 4 \\ 4 & 3 \end{bmatrix} \begin{bmatrix} c \\ d \end{bmatrix} = 7 \begin{bmatrix} c \\ d \end{bmatrix}$$

The first component implies $3c + 4d = 7c \implies 4c - 4d = 0 \implies c = d$. So, an eigenvector $\vec{v}_2$ is $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$.

To conclude,

$$\lambda_1 = -1, \vec{v}_1 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}, \quad \lambda_2 = 7, \vec{v}_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Activity 2: Rapid Fire

The goal of this activity is to practice spotting eigenvalues and characteristic polynomials quickly. Two quick facts:

- The **sum** of the eigenvalues of a matrix is equal to the **trace** of the matrix (which is the sum of the diagonal entries).
- The **product** of the eigenvalues of a matrix is equal to the **determinant** of the matrix.

a) A 2×2 matrix A has $\text{trace}(A) = 5$ and $\det(A) = 6$. What are the eigenvalues of A ?

Solution: $\lambda_1 = 2, \lambda_2 = 3$.

The eigenvalues of A must sum to 5 and multiply to 6. The only possible solution is $\lambda_1 = 2$ and $\lambda_2 = 3$, which indeed satisfy both conditions. There are infinitely many **matrices** that satisfy these conditions, but the eigenvalues in all of them are 2 and 3.

b) A non-invertible 2×2 matrix has an eigenvalue of 5. What is its characteristic polynomial?

Solution: $p(\lambda) = \lambda^2 - 5\lambda$.

Let A be the matrix in question. Since A is not invertible, 0 is one of its eigenvalues. Since it's a 2×2 matrix, it can only have two eigenvalues, so its two eigenvalues are 0 and 5. So, its characteristic polynomial is a polynomial with roots 0 and 5, i.e.

$$p(\lambda) = (\lambda - 0)(\lambda - 5) = \lambda^2 - 5\lambda$$

c) A 3×3 matrix A has $\det(A) = 20$ and two unique **positive integer** eigenvalues, one of which is repeated twice. In other words, $p(\lambda)$ has the form

$$p(\lambda) = (\lambda - \lambda_1)^2(\lambda - \lambda_2)$$

(λ_1 has an **algebraic multiplicity** of 2. This is a term we'll see more in tomorrow's lecture and [Chapter 9.4](#).)

What are all possible values of λ_1 and λ_2 ?

Solution: $\lambda_1 = 2, \lambda_2 = 5$ or $\lambda_1 = 1, \lambda_2 = 20$.

The product of A 's eigenvalues — including arithmetic multiplicities — is equal to the determinant of A . Since λ_1 has $\text{AM}(\lambda_1) = 2$, it must appear twice in the product of the eigenvalues. So,

$$\lambda_1^2 \lambda_2 = 20$$

We're told that λ_1 and λ_2 are integers. Note that $20 = 2 \cdot 10 = 2 \cdot 2 \cdot 5$. The only possible solutions are $\lambda_1 = 2$ and $\lambda_2 = 5$ (which means $\lambda_1^2 \lambda_2 = (2)^2 \cdot 5 = 20$) or $\lambda_1 = 1$ and $\lambda_2 = 20$ (which means $\lambda_1^2 \lambda_2 = (1)^2 \cdot 20 = 20$).

Activity 3: Quadratic Forms Return

Open Desmos in 3D mode at desmos.com/3d and write $z = x^2 + 2bxy + 16y^2$. This should show you a 3D surface along with a slider for b . Drag the slider to see how the shape of the surface changes for different b 's. You should notice that depending on the value of b , the surface may or may not have a global minimum. Let's explore!

- a) z is a quadratic form, $f(\vec{x}) = \vec{x}^T A \vec{x}$, where $\vec{x} = \begin{bmatrix} x \\ y \end{bmatrix}$ and A is a symmetric matrix. Find A .

Solution: $A = \begin{bmatrix} 1 & b \\ b & 16 \end{bmatrix}$.

To see where this comes from, let's expand $f(\vec{x}) = \vec{x}^T A \vec{x}$:

$$\begin{aligned} f(\vec{x}) &= \vec{x}^T A \vec{x} \\ &= \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & b \\ b & 16 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \\ &= \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} x + by \\ bx + 16y \end{bmatrix} \\ &= x(x + by) + y(bx + 16y) \\ &= x^2 + bxy + bxy + 16y^2 \\ &= x^2 + 2bxy + 16y^2 \end{aligned}$$

So, $A = \begin{bmatrix} 1 & b \\ b & 16 \end{bmatrix}$.

- b) For a vector-to-scalar function $f : \mathbb{R}^n \rightarrow \mathbb{R}$, the **Hessian** of f , denoted $\nabla^2 f$, is the $n \times n$ matrix of second partial derivatives of f . Find $\nabla^2 f$ for $f(\vec{x}) = \vec{x}^T A \vec{x}$.

Solution: $\nabla^2 f = \begin{bmatrix} 2b & 2b \\ 2b & 32 \end{bmatrix}.$

To find the second partial derivatives of f , we first find the first partial derivatives:

$$\begin{aligned} f(\vec{x}) &= \vec{x}^T A \vec{x} = x^2 + 2bxy + 16y^2 \\ \frac{\partial f}{\partial x} &= 2x + 2by \\ \frac{\partial f}{\partial y} &= 2bx + 32y \end{aligned}$$

Since there are two first partial derivatives, there are $2 \times 2 = 4$ second partial derivatives. We can find them all by taking the partial derivatives of the first partial derivatives:

$$\begin{aligned} \frac{\partial^2 f}{\partial x^2} &= \frac{\partial}{\partial x} (2x + 2by) = 2 \\ \frac{\partial^2 f}{\partial x \partial y} &= \frac{\partial}{\partial y} (2x + 2by) = 2b \\ \frac{\partial^2 f}{\partial y \partial x} &= \frac{\partial}{\partial x} (2bx + 32y) = 2b \\ \frac{\partial^2 f}{\partial y^2} &= \frac{\partial}{\partial y} (2bx + 32y) = 32 \end{aligned}$$

Note that $\frac{\partial^2 f}{\partial x \partial y} = \frac{\partial^2 f}{\partial y \partial x}$, which is a general property of second partial derivatives — it doesn't matter which order we take the derivatives in. So, the Hessian is

$$\nabla^2 f = \begin{bmatrix} 2 & 2b \\ 2b & 32 \end{bmatrix}$$

Notice that this is just $2A$!

c) A symmetric matrix A is **positive semidefinite** (PSD) if $\vec{v}^T A \vec{v} \geq 0$ for all $\vec{v} \in \mathbb{R}^n$. In English, this says that A is positive semidefinite if the quadratic form $f(\vec{v}) = \vec{v}^T A \vec{v}$ is always non-negative for all $\vec{v} \in \mathbb{R}^n$. Two relevant facts:

- A differentiable vector-to-scalar function f is **convex** if its Hessian is PSD.
- A symmetric matrix A is PSD if and only if all of its eigenvalues are non-negative.

Using the facts above, find the range of values b for which f is convex, and verify your answer by dragging the slider on Desmos.

Solution: As long as $-4 \leq b \leq 4$, the Hessian is PSD, and f is convex.

Recall from the previous part that the Hessian is

$$\nabla^2 f = \begin{bmatrix} 2 & 2b \\ 2b & 32 \end{bmatrix} = 2A$$

f is convex if and only if $2A$ is PSD, which means that both of $2A$'s eigenvalues are non-negative. Let λ_1 and λ_2 be $2A$'s eigenvalues. Then, we need $\lambda_1 \geq 0$ and $\lambda_2 \geq 0$. How do we ensure this?

Let's recall the facts about the trace and determinant introduced at the start of Activity 2:

- The sum of $2A$'s eigenvalues, $\lambda_1 + \lambda_2$, is equal to the trace of $2A$, $\text{trace}(2A)$, which is the sum of the diagonal entries of $2A$. Here, this is $2 + 32 = 34$.
- The product of $2A$'s eigenvalues, $\lambda_1 \lambda_2$, is equal to the determinant of $2A$, $\det(2A)$, which is $2 \cdot 32 - (2b)^2 = 64 - 4b^2$.

The fact that $\lambda_1 + \lambda_2 = 34$ means that no matter what b is, at least one of the eigenvalues is non-negative, since you can't add two negative numbers and get a positive sum.

So, let's focus our attention on the product of the eigenvalues, $\lambda_1 \lambda_2 = 64 - 4b^2$. We need this to be ≥ 0 , because if it were negative, then one of the eigenvalues would be negative (since multiplying a positive number by a negative number gives a negative number).

Using this reasoning, we need $64 - 4b^2 \geq 0$, which simplifies to $4b^2 \leq 64$, which simplifies to $b^2 \leq 16$, which simplifies to $-4 \leq b \leq 4$. If $|b| > 4$, then one of the eigenvalues would be negative, $2A$ would not be PSD, and f would not be convex.

Notice that in this case, the "test" for convexity ended up simplifying to checking whether the determinant of A is non-negative. That is true, in general, for quadratic forms $f(\vec{x}) = \vec{x}^T A \vec{x}$ where A is a 2×2 symmetric matrix. But if A is 3×3 or larger, the determinant test alone isn't sufficient; it's possible to have a positive determinant and trace but a negative eigenvalue in a 3×3 matrix. What is true in general is that if A is a symmetric $n \times n$ matrix, then $f(\vec{x}) = \vec{x}^T A \vec{x}$ is convex if and only if all of A 's eigenvalues are non-negative.

Activity 4: Understanding Complex Proofs

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a convex function. It turns out that the function $g(\vec{x})$, defined by

$$g(\vec{x}) = f(A\vec{x} + \vec{b})$$

for some $n \times n$ matrix A and vector $\vec{b} \in \mathbb{R}^n$, is also convex, no matter what A and $\vec{b}$ are. We're not going to ask you to prove this on your own: instead, we'll give you a proof and ask you questions to ensure you understand it.

Our **goal** is to show that $g((1-t)\vec{x} + t\vec{y}) \leq (1-t)g(\vec{x}) + tg(\vec{y})$, for all $\vec{x}, \vec{y} \in \mathbb{R}^n$ and $t \in [0, 1]$. We'll start with the "left-hand side" of the definition, and try and leverage f 's convexity.

$$g((1-t)\vec{x} + t\vec{y}) = f\left(A((1-t)\vec{x} + t\vec{y}) + \vec{b}\right) \quad (1)$$

$$= f\left((1-t)A\vec{x} + tA\vec{y} + \vec{b}\right) \quad (2)$$

$$= f\left((1-t)(A\vec{x} + \vec{b}) + t(A\vec{y} + \vec{b})\right) \quad (3)$$

$$\leq (1-t)f(A\vec{x} + \vec{b}) + tf(A\vec{y} + \vec{b}) \quad (4)$$

$$= \boxed{(1-t)g(\vec{x}) + tg(\vec{y})} \quad (5)$$

a) In which line did we use the fact that f is convex?

Solution: Line 4. We simplified the original expression to the form of the formal definition's left side in line 3, and line 4 is where we connect it back to the right side.

b) How did we move from line (1) to line (2), i.e. $f\left(A((1-t)\vec{x} + t\vec{y}) + \vec{b}\right) = f\left((1-t)A\vec{x} + tA\vec{y} + \vec{b}\right)$?

Solution: Distributing A by left multiplying it to the terms in the parentheses.

c) How did we move from line (2) to line (3), i.e. $f\left((1-t)A\vec{x} + tA\vec{y} + \vec{b}\right) = f\left((1-t)(A\vec{x} + \vec{b}) + t(A\vec{y} + \vec{b})\right)$?

Solution: Add $t\vec{b} - t\vec{b}$ to the input expression, that way we can increase the number of terms without changing the value of the expression.

Recall, $g(\vec{x}) = f(A\vec{x} + \vec{b})$, where A is an $n \times n$ matrix and $\vec{x}, \vec{b} \in \mathbb{R}^n$. On the last page, we showed that if f is convex, then g is convex.

Now, let's explore what happens if f is **strictly** convex. Recall, this means that for all (non-equal) $\vec{x}$ and $\vec{y}$ in its domain, and for any $t \in (0, 1)$,

$$f((1-t)\vec{x} + t\vec{y}) < (1-t)f(\vec{x}) + tf(\vec{y})$$

- d) Suppose $\text{rank}(A) = n$. Explain why it's impossible for $A\vec{x} + \vec{b} = A\vec{y} + \vec{b}$ for two different vectors $\vec{x}$ and $\vec{y}$.

Solution: If $\text{rank}(A) = n$, then the columns of A are linearly independent, so $A\vec{x}$ and $A\vec{y}$ must be different for any $\vec{x} \neq \vec{y}$.

- e) Suppose $\text{rank}(A) < n$. Explain why it's possible for $g(\vec{x}) = g(\vec{y})$ for two different vectors $\vec{x}$ and $\vec{y}$. *Hint: Think about $\text{nullsp}(A)$.*

Solution: If $\text{rank}(A) < n$, then A 's columns are linearly dependent, so $A\vec{x}$ and $A\vec{y}$ can be the same vector. In that case, $f(A\vec{x} + \vec{b}) = f(A\vec{y} + \vec{b}) \rightarrow g(\vec{x}) = g(\vec{y})$.

- f) Using the above reasoning, explain why if f is strictly convex, then g is strictly convex if $\text{rank}(A) = n$, and is (not strictly) convex if $\text{rank}(A) < n$.

Solution: We can show this with a proof by cases. In both cases, we'll start from line 4 of the proof on the previous page, but with f being strictly convex.

Case 1: $\text{rank}(A) = n$

$$\begin{aligned} g((1-t)\vec{x} + t\vec{y}) &< (1-t)f(A\vec{x} + \vec{b}) + tf(A\vec{y} + \vec{b}) \\ &< (1-t)g(\vec{x}) + tg(\vec{y}) \end{aligned}$$

Case 2: $\text{rank}(A) < n$

We know from part e) that it's possible for $g(\vec{x}) = g(\vec{y})$. Using proof by contradiction, assume that g is strictly convex.

$$\begin{aligned} g((1-t)\vec{x} + t\vec{y}) &< (1-t)f(A\vec{x} + \vec{b}) + tf(A\vec{y} + \vec{b}) \\ &< (1-t)g(\vec{x}) + tg(\vec{y}) \\ &< (1-t)g(\vec{x}) + tg(\vec{x}) \\ &< g(\vec{x}) \end{aligned}$$

This is a contradiction, because if $t = 0$, then the left side of the inequality is $g(\vec{x})$, leaving us with $g(\vec{x}) < g(\vec{x})$.

- g) What were your thoughts on this type of activity, where we give you a proof and ask you questions about it?

☐ Hated it ☐ Didn't like it ☐ Neutral ☐ Liked it ☐ Loved it