

Econ 204 2011

Lecture 10

Outline

1. Diagonalization of Real Symmetric Matrices
2. Application to Quadratic Forms
3. Linear Maps Between Normed Spaces

Announcements :

- PS 3 due
- PS 4 posted due Tues
- PS 5
- posted marked slides from yest.
- posted edited slides for lec. 9

How Might This Matter

- Why does diagonalizability matter?

Consider a two-dimensional linear difference equation:

$$\begin{pmatrix} c_{t+1} \\ k_{t+1} \end{pmatrix} = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} c_t \\ k_t \end{pmatrix} \quad \forall t = 0, 1, 2, 3, \dots$$

given an initial condition c_0, k_0 , or, setting

$$y_t = \begin{pmatrix} c_t \\ k_t \end{pmatrix} \quad \forall t \quad \text{and} \quad B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$$

we can rewrite this more compactly as

$$y_{t+1} = By_t \quad \forall t$$

where $b_{ij} \in \mathbf{R}$ each i, j .

We want to find a solution y_t , $t = 1, 2, 3, \dots$ given initial condition y_0 . (Why?)

Such a dynamical system will arise for example as a characterization of the solution to a standard infinite-horizon optimal growth problem (202a, lecture 2).

If B is diagonalizable, this can be easily solved after a change of basis. If B is diagonalizable, choose an invertible 2×2 real matrix P such that

$$P^{-1}BP = D = \begin{pmatrix} d_1 & 0 \\ 0 & d_2 \end{pmatrix}$$

Then

$$\begin{aligned} y_{t+1} = By_t \quad \forall t &\iff P^{-1}y_{t+1} = P^{-1}By_t \quad \forall t \\ &\iff \underbrace{(P^{-1}y_{t+1})}_{\bar{y}_{t+1}} = \underbrace{(P^{-1}BP)}_D \underbrace{(P^{-1}y_t)}_{\bar{y}_t} \quad \forall t \\ &\iff \bar{y}_{t+1} = D\bar{y}_t \quad \forall t \end{aligned} = \begin{pmatrix} d_1 & 0 \\ 0 & d_2 \end{pmatrix} \bar{y}_t$$

where $\bar{y}_t = P^{-1}y_t \quad \forall t$

$$\bar{y}'_{t+1} = d_1 \bar{y}_t \quad \forall t \quad \bar{y}'_0$$

where $\bar{y}_t = P^{-1}y_t \quad \forall t$.

Since D is diagonal, after a change of basis to \bar{y}_t , we need to solve two **independent** linear univariate difference equations, which is easy:

$$\bar{y}_{it} = d_i^t \bar{y}_{i0} \quad \forall t$$

- Not all real $n \times n$ matrices are diagonalizable (not even all invertible $n \times n$ matrices are)...so can we identify some classes that are? *yesterday:*
 - basis of eigenvectors (\Leftrightarrow)
 - n distinct eigenvalues (\Rightarrow)
- Some types of matrices appear more frequently than others – especially real symmetric $n \times n$ matrices (matrix representation of second derivatives of C^2 functions, quadratic forms...). *e.g. second order conditions in optimization problems, convexity & concavity checks, ~*

- Recall that an $n \times n$ real matrix A is *symmetric* if $a_{ij} = a_{ji}$ for all i, j , where a_{ij} is the $(i, j)^{\text{th}}$ entry of A .

Rest of this section: work in \mathbb{R}^n

- vector space
- norm
- inner product

Orthonormal Bases

Definition 1. Let

$$\delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$$

A basis $V = \{v_1, \dots, v_n\}$ of \mathbb{R}^n is orthonormal if $v_i \cdot v_j = \delta_{ij}$.

In other words, a basis is orthonormal if each basis element has unit length ($\|v_i\|^2 = v_i \cdot v_i = 1 \ \forall i$), and distinct basis elements are perpendicular ($v_i \cdot v_j = 0$ for $i \neq j$).

Orthonormal Bases

Remark: Suppose that $x = \sum_{j=1}^n \alpha_j v_j$ where $\{v_1, \dots, v_n\}$ is an orthonormal basis of \mathbf{R}^n . Then

$$\begin{aligned} x \cdot v_k &= \left(\sum_{j=1}^n \alpha_j v_j \right) \cdot v_k \\ &= \sum_{j=1}^n \alpha_j (v_j \cdot v_k) \\ &= \sum_{j=1}^n \alpha_j \delta_{jk} = \begin{cases} \alpha_k & k=j \\ 0 & k \neq j \end{cases} \\ &= \alpha_k \end{aligned}$$

so

$$x = \sum_{j=1}^n (x \cdot v_j) v_j$$

Orthonormal Bases

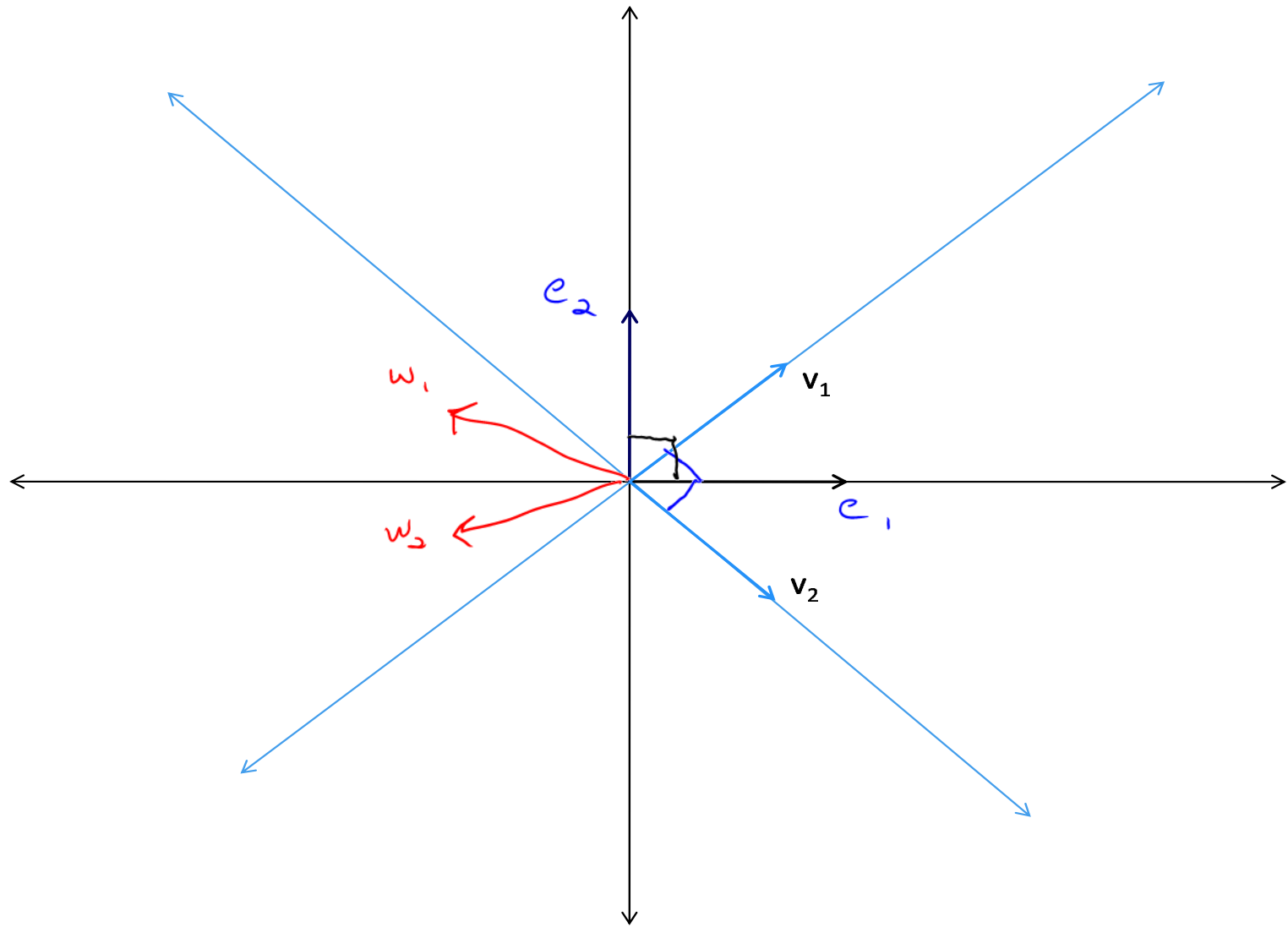
Example: The standard basis of \mathbf{R}^n is orthonormal.

(Why?)

e.g. $\mathbb{R}^2 = (1, 0), (0, 1)$

others? $(\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}), (\frac{1}{\sqrt{2}}, -\frac{1}{\sqrt{2}})$

also, many bases that are not orthonormal



Unitary Matrices

Recall that for a real $n \times m$ matrix A , A^\top denotes the transpose of A : the $(i, j)^{th}$ entry of A^\top is the $(j, i)^{th}$ entry of A .

So the i^{th} row of A^\top is the i^{th} column of A .

Definition 2. A real $n \times n$ matrix A is unitary if $A^\top = A^{-1}$.

Notice that by definition every unitary matrix is invertible.

Unitary Matrices

Theorem 1. *A real $n \times n$ matrix A is unitary if and only if the columns of A are orthonormal.*

Proof. Let v_j denote the j^{th} column of A .

$$\begin{aligned} A^T &= A^{-1} && \iff A^T A = I && = (\delta_{ij}) \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases} \\ &&& \iff v_i \cdot v_j = \delta_{ij} \quad \forall i, j \\ &&& \iff \{v_1, \dots, v_n\} \text{ is orthonormal} \end{aligned}$$

□

Unitary Matrices

If A is unitary, let V be the set of columns of A and W be the standard basis of \mathbf{R}^n . Since A is unitary, it is invertible, so V is a basis of \mathbf{R}^n .

$$A^T = A^{-1} = \text{Mtx}_{V,W}(\text{id}) = \begin{array}{l} \text{change of basis} \\ \text{from } W \text{ to } V \\ \uparrow \\ \text{standard basis} \end{array}$$

Since V is orthonormal, the transformation between bases W and V preserves all geometry, including lengths and angles.

Diagonalization of Real Symmetric Matrices

Theorem 2. Let $T \in L(\mathbb{R}^n, \mathbb{R}^n)$ and W be the standard basis of \mathbb{R}^n . Suppose that $Mtx_W(T)$ is symmetric. Then the eigenvectors of T are all real, and there is an orthonormal basis $V = \{v_1, \dots, v_n\}$ of \mathbb{R}^n consisting of eigenvectors of T , so that $Mtx_W(T)$ is diagonalizable:

$$C = Mtx_W(T) = \underbrace{Mtx_{W,V}(id)}_{\text{unitary}} \cdot \underbrace{Mtx_V(T)}_{\text{diagonal}} \cdot \underbrace{Mtx_{V,W}(id)}_{\text{unitary}}$$

where $Mtx_V T$ is diagonal and the change of basis matrices $Mtx_{V,W}(id)$ and $Mtx_{W,V}(id)$ are unitary.

i.e. $C = \begin{matrix} P^{-1} D P \\ P^T D P \end{matrix}$ where $\begin{cases} D \text{ diagonal} \\ \{\lambda_1, \dots, \lambda_n\} \\ P \text{ unitary} \end{cases}$

The proof of the theorem requires a lengthy digression into the linear algebra of *complex* vector spaces. A brief outline is in the notes.

Quadratic Forms

Example: Let

$$f(x) = \alpha x_1^2 + \beta x_1 x_2 + \gamma x_2^2$$

Let

write as $f(x) = x^T A x$, A symmetric

$$A = \begin{pmatrix} \alpha & \frac{\beta}{2} \\ \frac{\beta}{2} & \gamma \end{pmatrix}$$

$$x^T A x = (x_1 \ x_2) \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

so A is symmetric and

$$\begin{aligned}x^T Ax &= (x_1, x_2) \begin{pmatrix} \alpha & \frac{\beta}{2} \\ \frac{\beta}{2} & \gamma \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \\ &= (x_1, x_2) \begin{pmatrix} \alpha x_1 + \frac{\beta}{2} x_2 \\ \frac{\beta}{2} x_1 + \gamma x_2 \end{pmatrix} \\ &= \alpha x_1^2 + \beta x_1 x_2 + \gamma x_2^2 \\ &= f(x)\end{aligned}$$

Notice $f(0) = 0$.

Can we determine anything about
 $f(x)$ $x \neq 0$?

e.g. $f(x) \geq 0 \forall x$? easy if $\beta = 0$

Quadratic Forms

general form:

Consider a quadratic form

$$f(x_1, \dots, x_n) = \sum_{i=1}^n \alpha_{ii} x_i^2 + \sum_{i < j} \beta_{ij} x_i x_j \quad (1)$$

Let

$$\alpha_{ij} = \begin{cases} \frac{\beta_{ij}}{2} & \text{if } i < j \\ \frac{\beta_{ji}}{2} & \text{if } i > j \end{cases}$$

above diagonal

below diagonal

Let

$$A = \begin{pmatrix} \alpha_{11} & \cdots & \alpha_{1n} \\ \vdots & \ddots & \vdots \\ \alpha_{n1} & \cdots & \alpha_{nn} \end{pmatrix} \text{ so } f(x) = x^T A x$$

real symmetric

Quadratic Forms

A is symmetric, so let $V = \{v_1, \dots, v_n\}$ be an orthonormal basis of eigenvectors of A with corresponding eigenvalues $\lambda_1, \dots, \lambda_n$.

$$\begin{aligned} \text{Then } A &= U^\top D U \\ \text{where } D &= \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix} \\ \text{and } U &= \text{Mtx}_{V,W}(\text{id}) \text{ is unitary} \end{aligned}$$

The columns of U^\top (the rows of U) are the coordinates of v_1, \dots, v_n , expressed in terms of the standard basis W . Given $x \in \mathbf{R}^n$, recall

$$x = \sum_{i=1}^n \gamma_i v_i \text{ where } \gamma_i = x \cdot v_i$$

Quadratic Forms

So

$$\begin{aligned}
 f(x) &= f\left(\sum \gamma_i v_i\right) \\
 &= \left(\sum \gamma_i v_i\right)^\top A \left(\sum \gamma_i v_i\right) \\
 &= \left[\left(\sum \gamma_i v_i\right)^\top U^\top\right] D U \left(\sum \gamma_i v_i\right) \\
 &= \left(U \sum \gamma_i v_i\right)^\top D \left(U \sum \gamma_i v_i\right) \\
 &= \left(\sum \gamma_i U v_i\right)^\top D \left(\sum \gamma_i U v_i\right) \\
 &= (\gamma_1, \dots, \gamma_n) D \begin{pmatrix} \gamma_1 \\ \vdots \\ \gamma_n \end{pmatrix} \\
 &= \sum \lambda_i \gamma_i^2
 \end{aligned}$$

↑
eigenvalues of
A

$$(EF)^\top = F^\top E^\top$$

U linear

U is change of
basis from
w to v \Rightarrow
 $U v_i = (0, \dots, 1, \dots, 0)$

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$\forall i$
 $= \text{cnd}_v(v_i)$

Quadratic Forms

The equation for the level sets of f is

$$\sum_{i=1}^n \lambda_i \gamma_i^2 = C$$

- If $\lambda_i \geq 0$ for all i , the level set is an ellipsoid, with principal axes in the directions v_1, \dots, v_n . The length of the principal axis along v_i is $\sqrt{C/\lambda_i}$ if $C \geq 0$ (if $\lambda_i = 0$, the level set is a degenerate ellipsoid with principal axis of infinite length in that direction). The level set is empty if $C < 0$.

$\Rightarrow f$ has global min at 0, $f(x) \geq 0 \forall x$

- If $\lambda_i \leq 0$ for all i , the level set is an ellipsoid, with principal axes in the directions v_1, \dots, v_n . The length of the principal

$\Rightarrow f$ has global max at 0, $f(x) \leq 0 \forall x$

axis along v_i is $\sqrt{C/\lambda_i}$ if $C \leq 0$ (if $\lambda_i = 0$, the level set is a degenerate ellipsoid with principal axis of infinite length in that direction). The level set is empty if $C > 0$.

- If $\lambda_i > 0$ for some i and $\lambda_j < 0$ for some j , the level set is a hyperboloid. For example, suppose $n = 2$, $\lambda_1 > 0$, $\lambda_2 < 0$. The equation is

$$\begin{aligned} C &= \lambda_1 \gamma_1^2 + \lambda_2 \gamma_2^2 \\ &= \left(\sqrt{\lambda_1 \gamma_1} + \sqrt{|\lambda_2| \gamma_2} \right) \left(\sqrt{\lambda_1 \gamma_1} - \sqrt{|\lambda_2| \gamma_2} \right) \end{aligned}$$

$\Rightarrow f$ has a saddle point at 0
min with respect to v_i
max with respect to v_j

This is a hyperbola with asymptotes

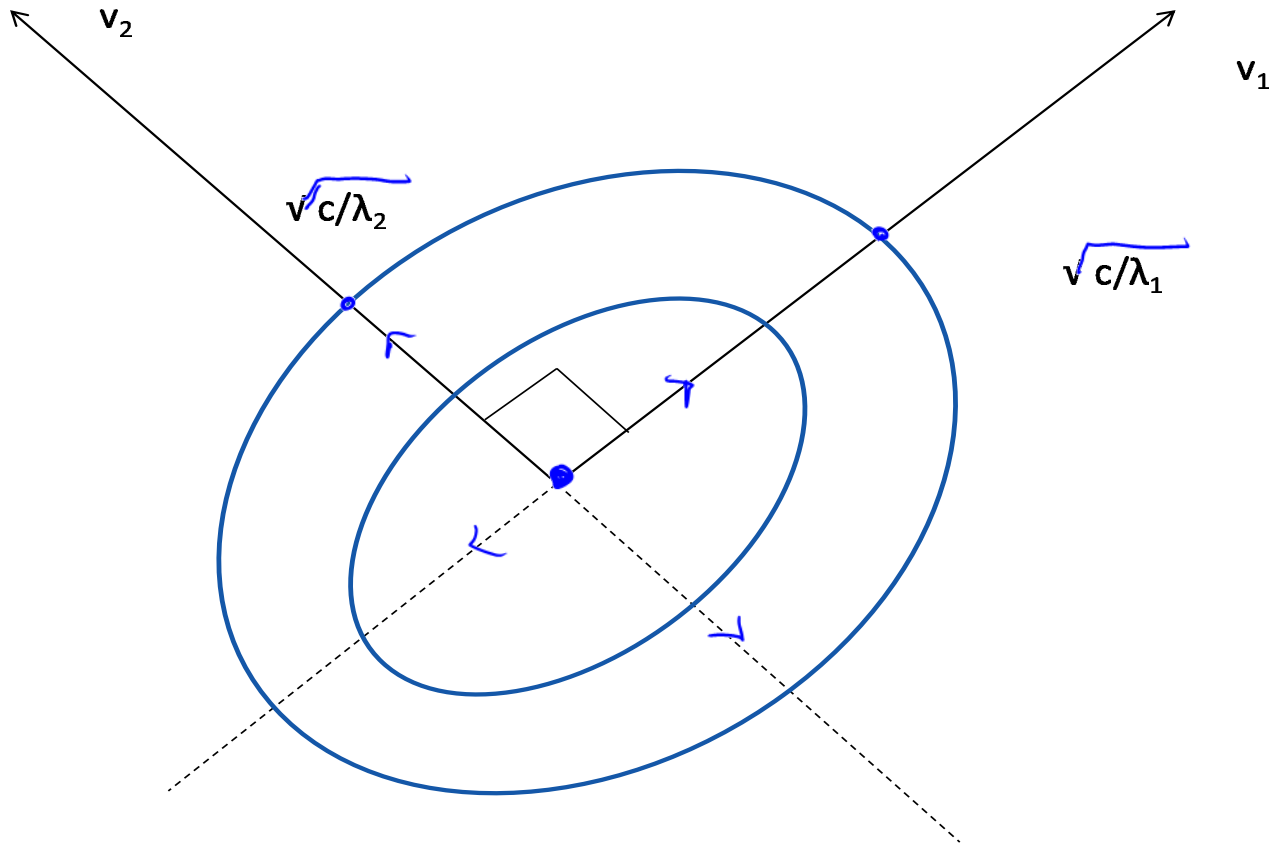
$$0 = \sqrt{\lambda_1 \gamma_1} + \sqrt{|\lambda_2| \gamma_2}$$

$$\Rightarrow \gamma_1 = -\sqrt{\frac{|\lambda_2|}{\lambda_1}} \gamma_2$$

$$0 = \left(\sqrt{\lambda_1 \gamma_1} - \sqrt{|\lambda_2| \gamma_2} \right)$$

$$\Rightarrow \gamma_1 = \sqrt{\frac{|\lambda_2|}{\lambda_1}} \gamma_2$$

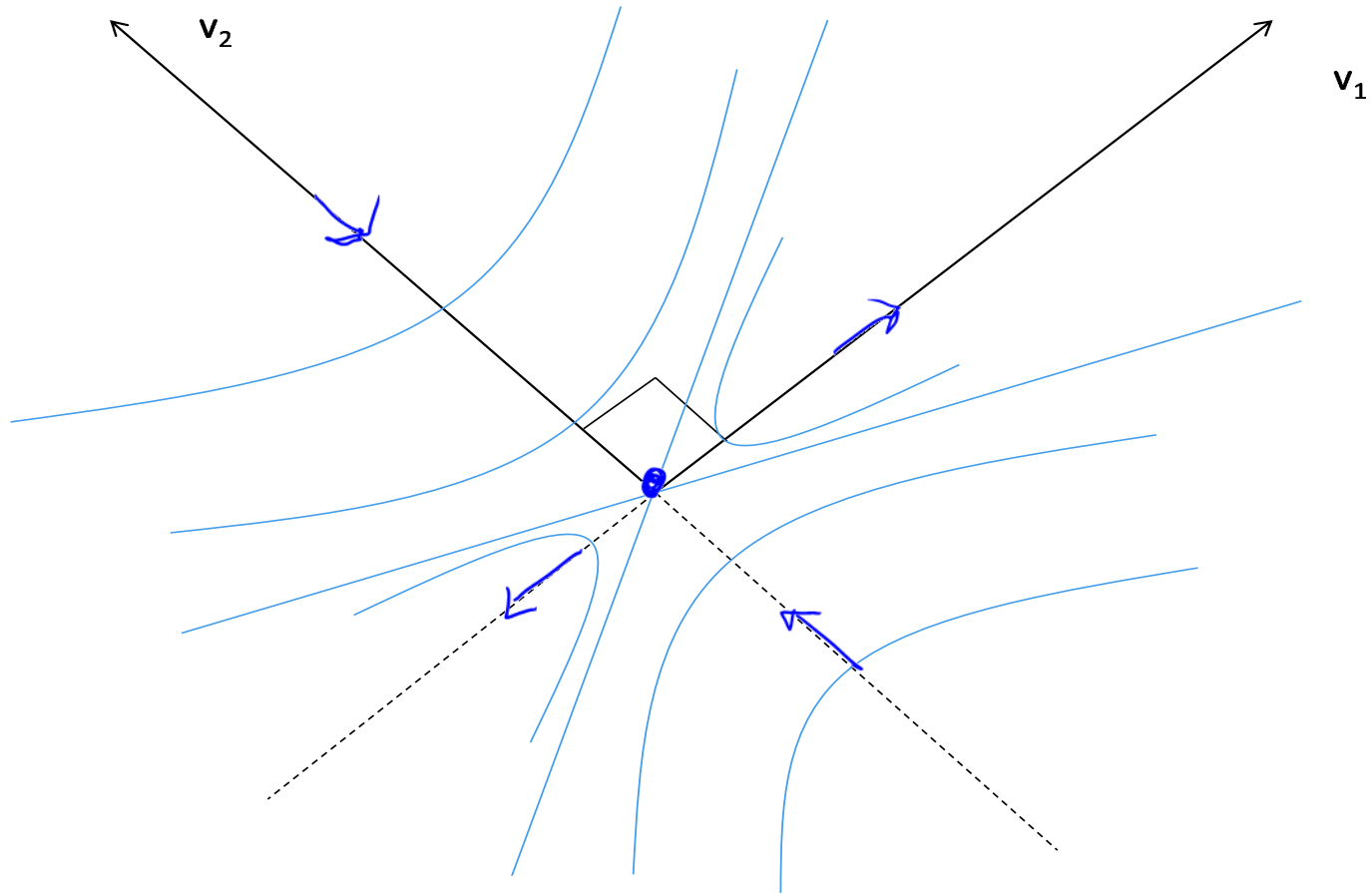
$$\lambda_1 > 0, \lambda_2 > 0$$



f has global min at 0

$$\lambda_1 > 0, \lambda_2 < 0$$

$$\gamma_1 = \sqrt{|\lambda_2|/\lambda_1}$$



f has a saddle point at 0

Quadratic Forms

This proves the following corollary of Theorem 2.

Corollary 1. *Consider the quadratic form (1).*

- 1. f has a global minimum at 0 if and only if $\lambda_i \geq 0$ for all i ; the level sets of f are ellipsoids with principal axes aligned with the orthonormal eigenvectors v_1, \dots, v_n .*
- 2. f has a global maximum at 0 if and only if $\lambda_i \leq 0$ for all i ; the level sets of f are ellipsoids with principal axes aligned with the orthonormal eigenvectors v_1, \dots, v_n .*

3. *If $\lambda_i < 0$ for some i and $\lambda_j > 0$ for some j , then f has a saddle point at 0 ; the level sets of f are hyperboloids with principal axes aligned with the orthonormal eigenvectors v_1, \dots, v_n .*

Bounded Linear Maps

over \mathbb{R}

Definition 3. Suppose X, Y are normed vector spaces and $T \in L(X, Y)$. We say T is bounded if

$$\exists \beta \in \mathbf{R} \text{ s.t. } \|T(x)\|_Y \leq \beta \|x\|_X \quad \forall x \in X$$

Note this implies that T is Lipschitz with constant β .

why not

$$\|T(x)\|_Y \leq \beta \quad \forall x ??$$

$$T(\alpha x) = \alpha T(x) \quad \forall \alpha \in \mathbb{R}$$

$$\Rightarrow \|T(\alpha x)\| = |\alpha| \|T(x)\| \quad \forall \alpha \in \mathbb{R}$$

Bounded Linear Maps

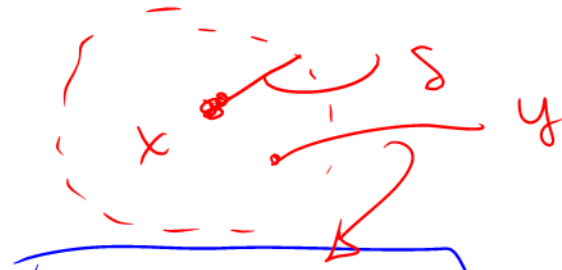
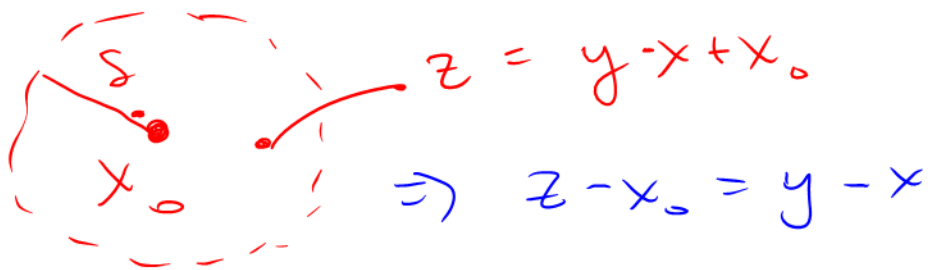
Much more is true:

Theorem 3 (Thms. 4.1, 4.3). *Let X and Y be normed vector spaces and $T \in L(X, Y)$. Then*

- T is continuous at some point $x_0 \in X$*
- \iff *T is continuous at every $x \in X$*
- \iff *T is uniformly continuous on X*
- \iff *T is Lipschitz*
- \iff *T is bounded*

Proof. Suppose T is continuous at x_0 . Fix $\varepsilon > 0$. Then there exists $\delta > 0$ such that

$$\left(\forall \bar{z} \mid \|\bar{z} - x_0\| < \delta \right) \implies \|T(\bar{z}) - T(x_0)\| < \varepsilon$$



Now suppose x is any element of X . If $\|y - x\| < \delta$, let $z =$

$z = y - x + x_0$, so $\|z - x_0\| = \|y - x\| < \delta$.

$\|T(y) - T(x)\|$

$= \|T(y - x)\|$

$= \|T(y - x + x_0 - x_0)\|$

$= \|T(z) - T(x_0)\|$

$< \varepsilon$

T linear

$= \|T(z - x_0)\|$

T linear

which proves that T is continuous at every x , and uniformly continuous.

We claim that T is bounded if and only if T is continuous at 0. Suppose T is not bounded. Then

$\exists \{x_n\}$ s.t. $\|T(x_n)\| > n\|x_n\| \quad \forall n$

Note that $x_n \neq 0$. Let $\varepsilon = 1$. Fix $\delta > 0$ and choose n such that $\frac{1}{n} < \delta$. Let

$$\begin{aligned}
 x'_n &= \frac{x_n}{n\|x_n\|} && = \frac{1}{n} \frac{x_n}{\|x_n\|} \\
 \|x'_n\| &= \frac{\|x_n\|}{n\|x_n\|} \\
 &= \frac{1}{n} \\
 &< \delta \\
 \|T(x'_n) - T(0)\| &= \|T(x'_n)\| \\
 &\stackrel{0}{=} \frac{1}{n\|x_n\|} \|T(x_n)\| && \text{defn of } x'_n \\
 &> \frac{n\|x_n\|}{n\|x_n\|} && + T \text{ linear} \\
 &= 1 && \text{defn of } x_n \\
 &= \varepsilon
 \end{aligned}$$

Since this is true for every δ , T is not continuous at 0. Therefore, T continuous at 0 implies T is bounded. Now, suppose T is bounded, so find M such that $\|T(x)\| \leq M\|x\|$ for every $x \in X$. Given $\varepsilon > 0$, let $\delta = \varepsilon/M$. Then

$$\|x - 0\| < \delta \Rightarrow \|x\| < \delta$$

$$\Rightarrow \|T(x) - T(0)\| = \|T(x)\| < M\delta$$

$$\Rightarrow \|T(x) - T(0)\| < \varepsilon = M\delta$$

defn of M

so T is continuous at 0.

Thus, we have shown that continuity at some point x_0 implies uniform continuity, which implies continuity at every point, which implies T is continuous at 0, which implies that T is bounded, which implies that T is continuous at 0, which implies that T is

continuous at some x_0 , so all of the statements except possibly the Lipschitz statement are equivalent.

Suppose T is bounded, with constant M . Then

$$\begin{aligned}\|T(x) - T(y)\| &= \|T(x - y)\| \\ &\leq M\|x - y\|\end{aligned}$$

T linear

so T is Lipschitz with constant M ; conversely, if T is Lipschitz with constant M , then T is bounded with constant M . So all the statements are equivalent. \square

Bounded Linear Maps

Every linear map on a finite-dimensional normed vector space is bounded (and thus continuous, uniformly continuous, and Lipschitz continuous).

Theorem 4 (Thm. 4.5). *Let X and Y be normed vector spaces, with $\dim X < \infty$. Every $T \in L(X, Y)$ is bounded.*

↳ n some n ∈ ℕ.

Proof. See de la Fuente.



Topological Isomorphism

Definition 4. A topological isomorphism *between normed vector spaces X and Y* is a linear transformation $T \in L(X, Y)$ that is invertible (one-to-one, onto), continuous, and has a continuous inverse.

Two normed vector spaces X and Y are topologically isomorphic if there is a topological isomorphism $T : X \rightarrow Y$.

The Space $B(X, Y)$

Suppose X and Y are normed vector spaces. We define

$$\begin{aligned} B(X, Y) &= \{T \in L(X, Y) : T \text{ is bounded}\} \\ \|T\|_{B(X, Y)} &= \sup \left\{ \frac{\|T(x)\|_Y}{\|x\|_X}, x \in X, x \neq 0 \right\} \\ &= \sup \{\|T(x)\|_Y : \|x\|_X = 1\} \end{aligned}$$

We skip the proofs of the rest of these results – read dIF.

$$\frac{\|T(x)\|_Y}{\|x\|_X} = \frac{1}{\|x\|_X} \|T(x)\|_Y$$

The Space $B(X, Y)$

Theorem 5 (Thm. 4.8). *Let X, Y be normed vector spaces. Then*

$$\left(B(X, Y), \|\cdot\|_{B(X, Y)} \right)$$

is a normed vector space.

The Space $B(\mathbf{R}^n, \mathbf{R}^m)$

Theorem 6 (Thm. 4.9). Let $T \in L(\mathbf{R}^n, \mathbf{R}^m)$ ($= B(\mathbf{R}^n, \mathbf{R}^m)$) with matrix $A = (a_{ij})$ with respect to the standard bases. Let

$$M = \max\{|a_{ij}| : 1 \leq i \leq m, 1 \leq j \leq n\}$$

Then

$$M \leq \|T\| \leq M\sqrt{mn}$$

.

Compositions

Theorem 7 (Thm. 4.10). *Let $R \in L(\mathbf{R}^m, \mathbf{R}^n)$ and $S \in L(\mathbf{R}^n, \mathbf{R}^p)$.
Then*

$$\|S \circ R\| \leq \|S\| \|R\|$$

Invertibility

Define $\Omega(\mathbf{R}^n) = \{T \in L(\mathbf{R}^n, \mathbf{R}^n) : T \text{ is invertible}\}$

Theorem 8 (Thm. 4.11'). *Suppose $T \in L(\mathbf{R}^n, \mathbf{R}^n)$ and E is the standard basis of \mathbf{R}^n . Then*

T is invertible

$$\iff \ker T = \{0\}$$

$$\iff \det(Mtx_E(T)) \neq 0$$

$$\iff \det(Mtx_{V,V}(T)) \neq 0 \text{ for every basis } V$$

$$\iff \det(Mtx_{V,W}(T)) \neq 0 \text{ for every pair of bases } V, W$$

Invertibility

invertible

Theorem 9 (Thm. 4.12). *If $S, T \in \Omega(\mathbf{R}^n)$, then $S \circ T \in \Omega(\mathbf{R}^n)$ and*

$$(S \circ T)^{-1} = T^{-1} \circ S^{-1}$$

Invertibility

Theorem 10 (Thm. 4.14). *Let $S, T \in L(\mathbf{R}^n, \mathbf{R}^n)$. If T is invertible and*

$$\|T - S\| < \frac{1}{\|T^{-1}\|}$$

then S is invertible. In particular, $\Omega(\mathbf{R}^n)$ is open in $L(\mathbf{R}^n, \mathbf{R}^n) = B(\mathbf{R}^n, \mathbf{R}^n)$.

Theorem 11 (Thm. 4.15). *The function $(\cdot)^{-1} : \Omega(\mathbf{R}^n) \rightarrow \Omega(\mathbf{R}^n)$ that assigns T^{-1} to each $T \in \Omega(\mathbf{R}^n)$ is continuous.*