

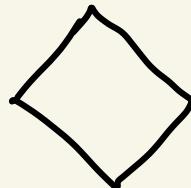

Recall: Equivalence of Norms

Given any two norms on \mathbb{R}^n ,
we have 2 unit spheres. (1
for each norm) and we
start \cup showed that you can
stick each sphere inside of the
other.

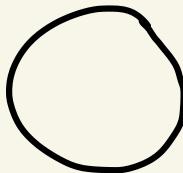
More explicitly:

Then Given $\|\cdot\|_1$ and $\|\cdot\|_2$
necessity
(not L^1 and L^2 norms), $\exists c, d \neq 0$
such that $\forall v \in \mathbb{R}^n$
 $c\|v\|_1 \leq \|v\|_2 \leq d\|v\|_1$
(c, d work $\forall v$)

$$\| \cdot \|_1$$

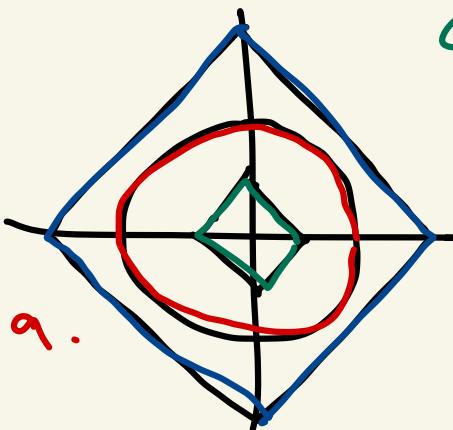


$$\| \cdot \|_2$$



Thm says

This
is
backwards!
See page 9.



$$\begin{aligned} c\|v\|_1 &\leq \|v\|_2 \\ &\leq d\|v\|_1 \end{aligned}$$

$$c = \min \left\{ \|u\|_2 \mid \|u\|_1 = 1 \right\} *$$

$$d = \max \left\{ \|u\|_2 \mid \|u\|_1 = 1 \right\} *$$

Know this
though.

Well for all unit vectors of $\|\cdot\|_1$

$c \leq \|u\|_2 \leq d$ by definition

but then given $v \in \mathbb{R}^n$,

$\frac{v}{\|v\|_1}$ is a unit vector $\|\cdot\|_1$.

$$c \leq \left\| \frac{v}{\|v\|_1} \right\|_2 \leq d$$

$$c \leq \frac{1}{\|v\|_1} \|v\|_2 \leq d$$

$$c\|v\|_1 \leq \|v\|_2 \leq d\|v\|_2. \quad \square$$

(The hard part is showing
 $c > 0$, $d < \infty$.)

Ex L^2 -norm and L^∞ -norm on \mathbb{R}^n .

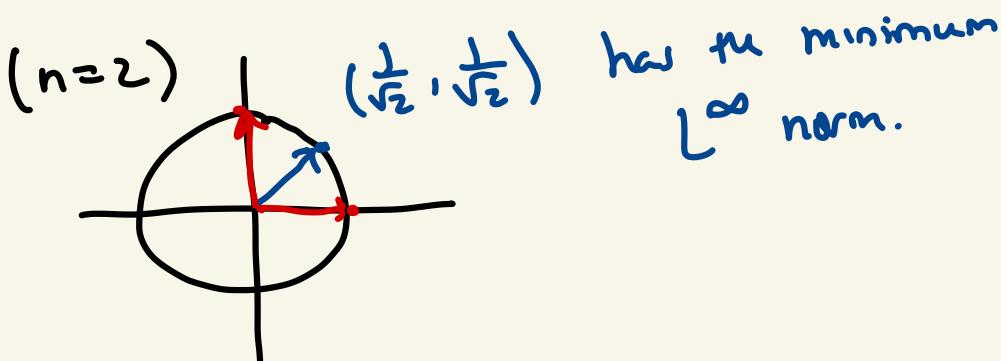
$$c \|v\|_2 \leq \|v\|_\infty \leq d \|v\|_2.$$

$$\begin{aligned} c \sqrt{v_1^2 + \dots + v_n^2} &\leq \max \{ |v_1|, \dots, |v_n| \} \\ &\leq d \sqrt{v_1^2 + \dots + v_n^2} \end{aligned}$$

$$c = \min \{ \|u\|_\infty \mid \|u\|_2 = 1 \}$$

$$\|u\|_2 = 1 \quad u_1^2 + u_2^2 + \dots + u_n^2 = 1$$

Need to minimize the max of the u_i .



In general

$$c = \min \left\{ \max \{ |u_i| \} \mid u_1^2 + \dots + u_n^2 = 1 \right\}$$

$$= \frac{1}{\sqrt{n}}.$$

So $\bar{u} = \left(\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}}, \dots, \frac{1}{\sqrt{n}} \right)$

achieves the minimum.

$$d = \max \left\{ \|u\|_\infty \mid \|u\|_2 = 1 \right\}$$

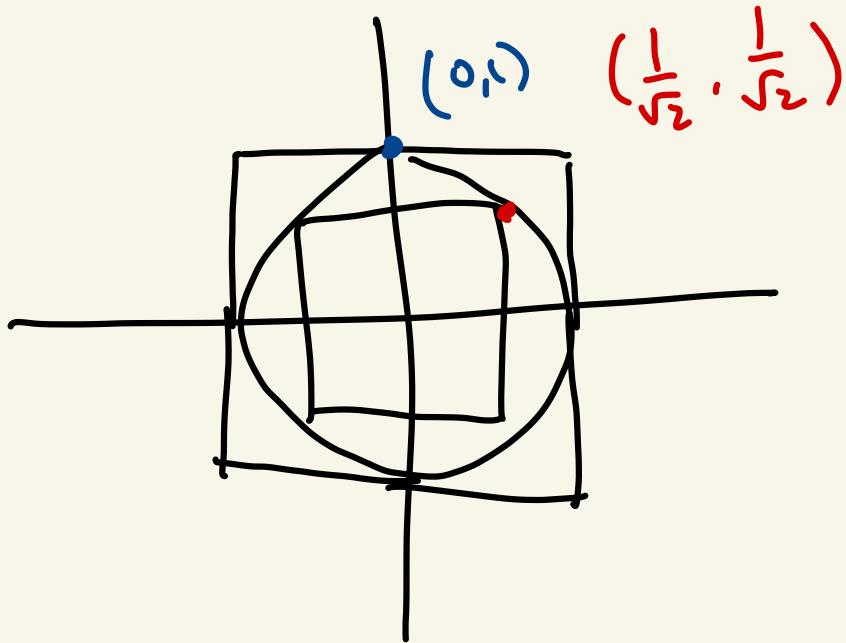
$u_i \leq 1$ and if we let

$$e_i = (0, 0, \dots, 1, \dots 0)$$

$$\|e_i\| = 1.$$

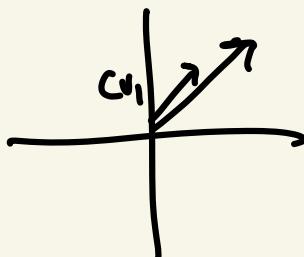
$$\Rightarrow d = 1. \quad \text{Therefore, ...}$$

$$\underbrace{\frac{1}{\sqrt{n}} \|v\|_2 \leq \|v\|_\infty \leq \|v\|_2}_{\text{---}}$$



$$c \|v\|_1 \leq \|v\|_2$$

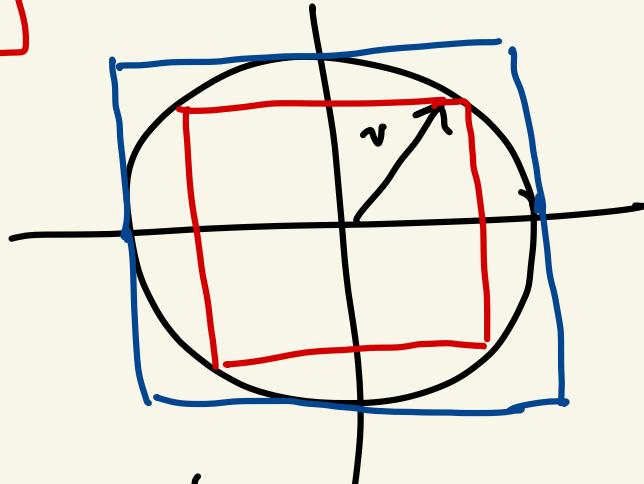
$$\|cv\|_1 \leq \|v\|_2$$



$$\begin{aligned}
 & \frac{1}{\sqrt{n}} \sqrt{v_1^2 + \dots + v_n^2} \\
 &= \sqrt{\frac{v_1^2}{n} + \dots + \frac{v_n^2}{n}} \leq \max \left\{ |v_1|, \dots, |v_n| \right\} \\
 &\leq \sqrt{v_1^2 + \dots + v_n^2}
 \end{aligned}$$

Suppose $\|v\|_2 = 1$

$$\frac{1}{\sqrt{2}} \leq \|v\|_\infty \leq 1$$



So the $\frac{1}{\sqrt{2}} \|v\|_2 \leq \|v\|_\infty \leq \|v\|_2$.

In general,

$$c \|\mathbf{v}\|_1 \leq \|\mathbf{v}\|_n \leq d \|\mathbf{v}\|_1.$$

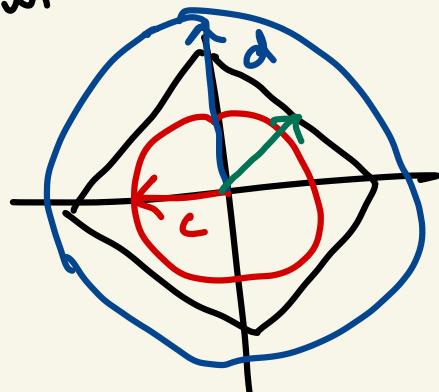
Given $\|\mathbf{v}\|_1$ then what is
 $\|\mathbf{v}\|_2$?

Suppose $\|\mathbf{v}\|_1 = 1$

then what are bounds
for $\|\mathbf{v}\|_2$?

$$c \leq \|\mathbf{v}\|_2 \leq d.$$

so it's



Note: This only works in \mathbb{R}^n .

If you try to compare different norms; in say $C([a,b])$, then you won't get far.

Matrix Norms :

Recall: $M_{n \times n}(\mathbb{R})$ is also a vector space.

Given a norm $\|\cdot\|$ on \mathbb{R}^n

we can define a norm on

$M_{n \times n}(\mathbb{R})$ by

$$\|A\| = \max \left\{ \|A\mathbf{u}\| \mid \|\mathbf{u}\| = 1 \right\}$$

$$\|A\| = \max \left\{ \|Au\| \mid \|u\| = 1 \right\}.$$

- $\|A\| \geq 0$. Need to show
 $\|A\| = 0 \Rightarrow A = 0$.

Let $\|A\| = 0$. Then

$$\max \left\{ \|A\vec{u}\| \right\} = 0.$$

$$\Rightarrow \|A\vec{u}\| = 0 \text{ for all unit vectors.}$$

But then if $\vec{v} \neq 0$, then

$$\left\| A \frac{\vec{v}}{\|\vec{v}\|} \right\| = 0 \quad \left(\text{since } \frac{\vec{v}}{\|\vec{v}\|} \text{ is a unit vector} \right)$$

$$\Rightarrow \|Av\| = 0 \text{ as well.}$$

$$\Rightarrow Av = 0 \text{ if } v \text{ since}$$

$\|\cdot\|$ is a norm on \mathbb{R}^n .

$\ker(A) = \mathbb{R}^n$, which means
 $A = 0$.

$$\begin{aligned}\|cA\| &= \max \left\{ \|cAu\| \right\} \\ &= \max \left\{ |c| \|Au\| \right\} \\ &= |c| \max \left\{ \|Au\| \right\} \\ &= |c| \|A\|\end{aligned}$$
$$\begin{aligned}\|A+B\| &= \max \left\{ \|(A+B)u\| \right\} \\ &\leq \max \left\{ \|Au\| + \|Bu\| \right\} \\ &\leq \max \left\{ \|Au\| \right\} + \max \left\{ \|Bu\| \right\} \\ &= \|A\| + \|B\|\end{aligned}$$

□

Take $\| \cdot \|_\infty$ on \mathbb{R}^n and
we'll define it on $M_{n \times n}(\mathbb{R})$.

$$\| A \|_\infty = \max \left\{ \| A \vec{u} \|_\infty \mid \| \vec{u} \|_\infty = 1 \right\}$$

Claim : $\| A \|_\infty = \text{largest row sum}$

$$= \max \left\{ \sum_{j=1}^n |a_{ij}| \mid i=1, \dots, n \right\}$$

Ex $\begin{bmatrix} -1 & 2 & 3 \\ 5 & -2 & 1 \\ 7 & -3 & 5 \end{bmatrix} = A$

$$|-1| + |2| + |3| = 6$$

$$|5| + |-2| + |1| = 8$$

$$|7| + |-3| + |5| = 15$$

$$\| A \|_\infty = 15 = \max \{ \| A \vec{u} \|_\infty \}$$

Pf :

$$\begin{aligned}\|A\|_{\infty} &= \max \left\{ \boxed{\|Au\|_{\infty}} \mid \|u\|_{\infty} = 1 \right\} \\ &= \max \left\{ \max \left\{ \text{entries of } Au \right\} \mid \|u\| = 1 \right\} \\ &= \max \left\{ \underbrace{\left| \sum a_{ij} u_j \right|}_{i^{\text{th}} \text{ entry of } Au} \mid \|u\| = 1 \right\} \\ &\leq \max \left\{ \sum |a_{ij} u_j| \mid \|u\| = 1 \right\} \\ &= \max \left\{ \sum |a_{ij}| u_j \Big| \stackrel{\wedge}{\substack{1}} \mid \|u\|_{\infty} = 1 \right\} \\ &\leq \max \left\{ \sum_{j=1}^n |a_{ij}| \Big| i = 1, \dots, n \right\} \\ &= \text{largest row sum}\end{aligned}$$

Suppose row i achieves the largest row sum.

$\sum_{j=1}^n |a_{ij}|$ is the largest row sum.

Let $u \in S_1$ for the L^∞ norm.
defined by

$$u_j = 1 \text{ if } a_{ij} > 0$$

$$u_j = -1 \text{ if } a_{ij} < 0.$$

Ex $A = \begin{bmatrix} -1 & 2 & 3 \\ 5 & -2 & 1 \\ 7 & -3 & 5 \end{bmatrix}$

3 row is the biggest
 $u = (\underline{1}, \underline{-1}, \underline{1})$

$\|A\|_\infty \geq \|A_u\|_\infty$ for $u = (\pm 1, \pm 1, \dots)$
 In particular

But $\|A\vec{u}\|_\infty = \sum_{j=1}^n |a_{ij}|$ for the
 ith row

= largest row
 sum.

$$\begin{bmatrix} -1 & 2 & 3 \\ 5 & -2 & 1 \\ 7 & -3 & 5 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 8 \\ 15 \end{bmatrix}$$

$$\begin{aligned} (A)_{i,*} u &= \sum a_{ij} u_j \\ &= \sum |a_{ij}| \end{aligned}$$

$\|A\|_\infty \geq$ largest row sum

$\implies \|A\|_\infty =$ largest row sum

L^2 -norm on $M_{2 \times 2}(\mathbb{R})$ ($n=2$)

$$\left\| \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix} \right\|_2$$

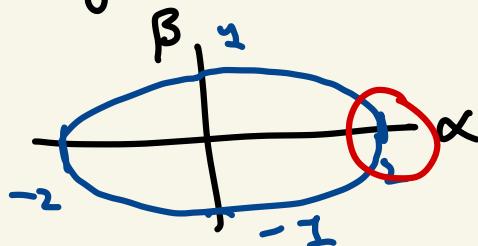
$$= \max \left\{ \left\| \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \right\|_2 \mid \begin{array}{l} x^2 + y^2 = 1 \end{array} \right\}$$

$$= \max \left\{ \left\| \begin{pmatrix} 2x \\ y \end{pmatrix} \right\|_2 \mid x^2 + y^2 = 1 \right\}$$

$$\begin{pmatrix} 2x \\ y \end{pmatrix} \mid x^2 + y^2 = 1$$

$$\text{Let } \alpha = 2x \Rightarrow \left(\frac{\alpha}{2}\right)^2 + \beta^2 = 1$$

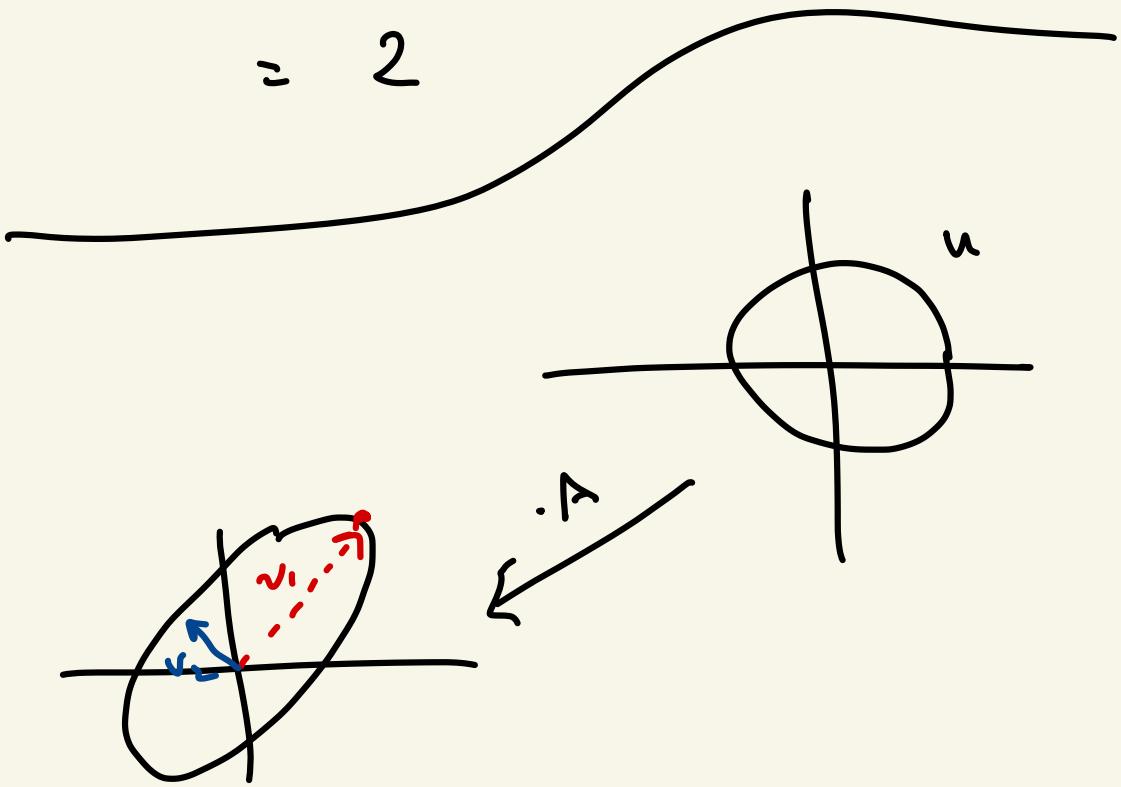
$$\beta = y$$



$$\begin{aligned} & \| \begin{pmatrix} 2 \\ 0 \end{pmatrix} \|_2 \\ &= \max \left\{ \left\| \begin{pmatrix} \alpha \\ \beta \end{pmatrix} \right\|_2 \mid \right. \\ & \quad \left. \left(\frac{\alpha}{2} \right)^2 + \beta^2 = 1 \right\} \end{aligned}$$

$$= \| \begin{pmatrix} 2 \\ 0 \end{pmatrix} \|_2$$

$$= 2$$



The norm $\|A\| = \max \{\|A_{i,j}\|\}$

satisfies $\|AB\| \leq \|A\| \cdot \|B\|$.

\Rightarrow define infinite series of matrices

$$\sum \frac{1}{n!} A^n = e^A \quad (\text{diff eq topic})$$

3.4 Positive Definite matrices

Back to inner products ...

Let $\langle \cdot, \cdot \rangle$ be an inner product on \mathbb{R}^n .

Recall the standard basis on \mathbb{R}^n

$$e_1 = \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, e_2 = \begin{pmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{pmatrix}$$

$$\dots, e_n = \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{pmatrix}.$$

$$\vec{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} = x_1 \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} + \dots + x_n \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{pmatrix}$$

$$= x_1 e_1 + x_2 e_2 + \dots + x_n e_n. *$$

$$\langle x, y \rangle = \left\langle \sum_{i=1}^n x_i e_i, \sum_{j=1}^n y_j e_j \right\rangle$$

$$= \sum_{i=1}^n \langle x_i e_i, \sum_{j=1}^n y_j e_j \rangle$$

$$= \sum_{i=1}^n x_i \langle e_i, \sum_{j=1}^n y_j e_j \rangle$$

$$= \sum_{i=1}^n x_i \sum_{j=1}^n \langle e_i, y_j e_j \rangle$$

$$= \sum_{i=1}^n x_i \sum_{j=1}^n y_j \langle e_i, e_j \rangle$$

$$= \sum_{i,j=1}^n x_i y_j \underbrace{\langle e_i, e_j \rangle}_{\in \mathbb{R}}$$

Define $k_{ij} = \langle e_i, e_j \rangle$.

what are these?

$$= \sum_{i,j=1}^n k_{ij} x_i y_j$$

Every inner product has formula

that is a linear combination of $x_i y_j$

(3.1.2d $x_1^2 y_1^2 + x_2^2 y_2^2$ not an inner product)

Define $K \in M_{n \times n}(\mathbb{R})$

$$(K)_{ij} = k_{ij} = \langle e_i, e_j \rangle$$

Ex: If $\langle x, y \rangle = \bar{x} \cdot \bar{y}$

then $e_1 \cdot e_1 = 1$ $e_1 \cdot e_2 = 0$

$$e_2 \cdot e_1 = 0 \quad e_2 \cdot e_2 = 1$$

$$K = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

3.1.2a $\langle x, y \rangle = 2x_1y_1 + 3x_2y_2$

$$K = \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix}$$

(3.9) $\langle x, y \rangle = x_1y_1 - x_1y_2 - x_2y_1 + 4x_2y_2$

$$K = \begin{bmatrix} 1 & -1 \\ -1 & 4 \end{bmatrix} \curvearrowleft$$

$\langle \cdot, \cdot \rangle$ on $\mathbb{R}^n \rightsquigarrow$ matrix K

which matrix K \rightsquigarrow inner products?

Claim: $\langle x, y \rangle = x^T K y$ (x^T is a row vector)

$$\text{pf: } x^T K y = (x, \dots, x_n) K \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$$

$$= (x, \dots, x_n) \left(\sum_{j=1}^n k_{ij} y_j \right)_{i=1, \dots, n}$$

$$= \sum_{i, j=1}^n k_{ij} x_i y_j = \langle x, y \rangle \quad \square$$

Any inner product is just
 $x^T K y$, $x, y \in \mathbb{R}^n$.

Our question simplifies to

which matrices K make
an inner product of the form
 $\langle x, y \rangle = x^T K y^2$.

- Bilinear $x^T K y$ is bilinear no matter what K is

- Symmetry $y^T K x = x^T K y \quad \forall x, y$
If we let $x = e_i$ $y = e_j$

$$e_i^T K e_j = e_j^T K e_i$$

"

"

$$\langle e_i, e_j \rangle$$

$$\langle e_j, e_i \rangle$$

"

$$(K)_{ij}$$

$$(K)_{ji}$$

- Since $k_{ij} = k_{ji} \Rightarrow$
 $K^T = K$ so that
 K is symmetric.

- Positivity

$$\langle x, x \rangle > 0 \quad \text{if } x \neq 0$$

$$\langle 0, 0 \rangle = 0$$

$0^T K 0 = 0$ no matter what K is.

$$\langle x, x \rangle = x^T K x > 0 \quad \text{if } x \neq 0.$$

Def Define the polynomial $g(x)$

$$= \langle x, x \rangle = \sum_{i,j}^n k_{ij} x_i x_j$$

$$K = \begin{bmatrix} 1 & -1 \\ -1 & 4 \end{bmatrix} . \quad \leftarrow \text{positive definite} .$$

$$\rightsquigarrow g(x_1, x_2) \\ = (x_1 \ x_2) \begin{pmatrix} 1 & -1 \\ -1 & 4 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

$$= x_1^2 - 2x_1 x_2 + 4x_2^2 > 0$$

$$= (x_1 - x_2)^2 + 3x_2^2 > 0$$

Def A symmetric matrix K is
positive definite if

$$g(x) = x^T K x > 0 \text{ for all } x \neq 0.$$

Every inner product $\langle \cdot, \cdot \rangle$ on \mathbb{R}^n
 is of the form $\langle x, y \rangle = x^T K y$
 for a positive definite matrix
 K. (1-1 correspondence ?)

We've narrowed down the study of
 inner products to positive def.
 matrices.

- - - - - - - -

Note: Positive def has no
 relation to the entries being
 positive.

$\begin{bmatrix} 1 & -1 \\ -1 & 4 \end{bmatrix}$ was pos. def. despite having
 negative entries.

$\begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix}$ is not pos def. despite
 having all positive entries.

Gram matrices :

let V be an inner product space.

Let $v_1, \dots, v_n \in V$. The

Gram matrix for the vectors is
the $n \times n$ matrix K

$$\text{w } (K)_{ij} = \langle v_i, v_j \rangle .$$

Def: A matrix K is positive
semi-definite if

$$g(x) = x^T K x \geq 0.$$

$\begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix}$ is positive semi-def.
but not positive-def.

Thm let V be an inner product space. let K be the Gram matrix for the set $v_1, \dots, v_n \in V$.

Then K is positive semi-definite. *

Furthermore, K is positive definite if v_1, \dots, v_n are independent.

If $v_1, \dots, v_n \in V$ all you have to do is check whether

$$K = \begin{pmatrix} \langle v_1, v_1 \rangle & \cdots & \cdots \\ \vdots & \ddots & \cdot \\ \vdots & \cdots & \ddots & \langle v_n, v_n \rangle \end{pmatrix}$$

is positive def or not, to see if the v_i are independent.

Pf in book

$$\underline{\text{Ex}} : \text{ let } V = C^0[-\pi, \pi] \\ = "C^0[0, 2\pi]$$

$$\text{let } f(x) = 5$$

$$g(x) = 2\sin^2(x) - 1$$

$$h(x) = 3\cos^2(bx) \quad (\text{dependent})$$

But we can check using Gram matrix.

$$K = \begin{pmatrix} \langle f, f \rangle & \langle f, g \rangle & \langle f, h \rangle \\ \langle g, f \rangle & \langle g, g \rangle & \langle g, h \rangle \\ \langle h, f \rangle & \langle h, g \rangle & \langle h, h \rangle \end{pmatrix}$$

$$\langle f, g \rangle = \int_{-\pi}^{\pi} f(x)g(x) dx$$

$$K = \begin{pmatrix} 50\pi & 0 & 15\pi \\ 0 & \pi & -\frac{3}{2}\pi \\ 15\pi & -\frac{3}{2}\pi & \frac{27\pi}{4} \end{pmatrix}$$

$$= \frac{\pi}{4} \begin{pmatrix} 200 & 0 & 60 \\ 0 & 4 & -6 \\ 60 & -6 & 27 \end{pmatrix}$$

Is $\begin{pmatrix} 200 & 0 & 60 \\ 0 & 4 & -6 \\ 60 & -6 & 27 \end{pmatrix}$ positive definite?

Prop Any positive def matrix is invertible.

Pf let $\vec{z} \in \ker(K)$

$$\Rightarrow K\vec{z} = 0$$

$$\vec{z}^T K \vec{z} = 0$$

$$\Rightarrow \vec{z} = 0. \quad \text{So } \ker(K) = 0$$

$\Leftrightarrow K$ is invertible.

$\begin{pmatrix} 200 & 0 & 60 \\ 0 & 4 & -6 \\ 60 & -6 & 27 \end{pmatrix}$ not invertible!
 \Rightarrow not pos def.

$\vec{z} = \begin{pmatrix} -3 \\ 15 \\ 10 \end{pmatrix} \Rightarrow \vec{z}^T K \vec{z} = 0.$
 f,s,h are dependent!