Set 1: Basics

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Scalars, Vectors and Matrices

Scalars and their operations are assumed to be from

- the field of real numbers ($\mathbb{R}$)
- the field of complex numbers ($\mathbb{C}$)
  - complex number: $\alpha = \beta + i\gamma$ where i here is used to represent the root of -1 (occasionally we will use j for this but it will be made clear when this is done)
  - β and γ are the real and imaginary parts of α respectively
  - complex conjugate $\bar{\alpha} = \beta - i\gamma$
  - the absolute value of α denoted $|\alpha|$ is $\sqrt{\alpha\bar{\alpha}} = \sqrt{\beta^2 + \gamma^2}$

Scalars, Vectors and Matrices

- $\mathbb{R}^n$ – a vector is an one-dimensionally ordered list of n real scalars
  - addition of vectors is componentwise scalar addition
  - scalar vector product multiplies each component of the vector with the scalar
- $\mathbb{C}^n$ – a vector is an one-dimensionally ordered list of n complex scalars
  - addition of vectors is componentwise complex scalar addition
  - scalar vector product multiplies each complex component of the vector with the complex scalar

Example – $\mathbb{R}^3$

Vectors:

$$x = \begin{pmatrix} 1 \\ 3 \\ -52 \end{pmatrix} \quad y = \begin{pmatrix} 10 \\ -4 \\ 2 \end{pmatrix}$$

Basic Operations:

$$x + y = \begin{pmatrix} 11 \\ -1 \\ -50 \end{pmatrix} \quad 2x = \begin{pmatrix} 2 \\ 6 \\ -104 \end{pmatrix} \quad 3y = \begin{pmatrix} 30 \\ -12 \\ 6 \end{pmatrix}$$

Linear Combination:

$$2x + 3y = \begin{pmatrix} 32 \\ -6 \\ -98 \end{pmatrix}$$

Example – $\mathbb{R}^3$

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

$$e_3 = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \qquad e = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

Scalars, Vectors and Matrices

Definition 1.1. An $m \times n$ matrix of scalars from $\mathbb{R}$ or $\mathbb{C}$ is a two-dimensionally ordered arrangement of mn scalars

$$A = \begin{pmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1n} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2n} \\ \vdots & \vdots & & \vdots \\ \alpha_{m1} & \alpha_{m2} & \cdots & \alpha_{mn} \end{pmatrix}$$

The set of $m \times n$ matrices with scalar elements from $\mathbb{R}$ is denoted $\mathbb{R}^{m \times n}$

The set of $m \times n$ matrices with scalar elements from $\mathbb{C}$ is denoted $\mathbb{C}^{m \times n}$

Matrix Operations

Matrix scaling $A, B \in \mathbb{R}^{m \times n}$ and $\gamma \in \mathbb{R}$:

$$B = \gamma A = A\gamma \;\text{ has elements }\; \beta_{ij} = \gamma \alpha_{ij}$$

Matrix addition $A, B, C \in \mathbb{R}^{m \times n}$:

$$C = A + B = B + A \;\text{ has elements }\; \gamma_{ij} = \beta_{ij} + \alpha_{ij}$$

This is the collection of vectors $\mathbb{R}^{mn}$ and the associated scalar field and operations

Matrix Vector Product

Definition 1.2. If

$$A = \begin{pmatrix} a_1 & a_2 & \cdots & a_n \end{pmatrix} \in \mathbb{R}^{m \times n}$$

and the vector $x \in \mathbb{R}^n$

$$x = \begin{pmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_n \end{pmatrix}$$

then

$$Ax = a_1\xi_1 + a_2\xi_2 + \cdots + a_n\xi_n$$

Matrix Operations

If $A \in \mathbb{R}^{n_1 \times n_2}$, $B \in \mathbb{R}^{n_2 \times n_3}$, then $C \in \mathbb{R}^{n_1 \times n_3}$ is

Scalar definintion:

$$C = AB \text{ has elements } \gamma_{ij} = \Sigma_{k=1}^{n_2} \alpha_{ik} \beta_{kj}$$

Matrix-vector definition:

$$C = AB \rightarrow c_i = Ab_i \;\; i = 1, \ldots, n_3 \text{ where } c_i = Ce_i, \;\; b_i = Be_i$$

Outer product definition:

$$C = AB = \Sigma_{i=1}^{n_2} a_i b_i^T \text{ where } a_i = Ae_i, \;\; b_i^T = e_i^T B$$

Inner product definintion:

$$C = AB \text{ has elements } \gamma_{ij} = a_i^T b_j \text{ where } b_i = Be_i, \;\; a_i^T = e_i^T A$$

Matrix Operations

- the matrix product is not commutative
- the matrix product is associative
- the matrix product is distributive, i.e., $A(B+C) = AB + AC$
- All scalars and vectors can be replaced with submatrices of appropriate dimension to yield block forms of the matrix product

Matrix Operations

Definition 1.3. The transpose of $A \in \mathbb{R}^{m\times n}$, denoted A^T, and the hermitian transpose of $A \in \mathbb{C}^{m\times n}$, denoted A^H, are the $n \times m$ matrices

$$A^T = \begin{pmatrix} \alpha_{11} & \alpha_{21} & \cdots & \alpha_{m1} \\ \alpha_{12} & \alpha_{22} & \cdots & \alpha_{m2} \\ \vdots & \vdots & & \vdots \\ \alpha_{1n} & \alpha_{2n} & \cdots & \alpha_{mn} \end{pmatrix} \quad A^H = \begin{pmatrix} \bar{\alpha}_{11} & \bar{\alpha}_{21} & \cdots & \bar{\alpha}_{m1} \\ \bar{\alpha}_{12} & \bar{\alpha}_{22} & \cdots & \bar{\alpha}_{m2} \\ \vdots & \vdots & & \vdots \\ \bar{\alpha}_{1n} & \bar{\alpha}_{2n} & \cdots & \bar{\alpha}_{mn} \end{pmatrix}$$

Vector Space

Definition 1.4. Given scalars $\mathcal{F}$, a set of vectors $\mathcal{V}$, a vector addition operation $x = y + z$ for $x, y, z \in \mathcal{V}$, and a scalar-vector product operation $y = \alpha x$ for $x, y \in \mathcal{V}$ and $\alpha \in \mathcal{F}$, we have a vector space if the following properties hold:

$$\begin{aligned}
x + y &= y + x && (1)\\
(x + y) + z &= x + (y + z) && (2)\\
x + 0_v &= x && (3)\\
x + (-1_s)x &= 0_v && (4)\\
(\alpha\beta)x &= \alpha(\beta x) && (5)\\
(\alpha +_s \beta)x &= \alpha x + \beta x && (6)\\
\alpha(x + y) &= \alpha x + \alpha y && (7)\\
1_s x &= x && (8)
\end{aligned}$$

Scalar and Vector 0

$$\begin{aligned}
0_v &= a + (-1)a \quad prop4 \\
&= 1a + (-1)a \quad prop8 \\
&= (0+1)a + (-1)a \quad scalar\ 0+1=1 \\
&= (0a+1a) + (-1)a \quad prop6 \\
&= 0a + (1a + (-1)a) \quad prop2 \\
&= 0a + (a + (-1)a) \quad prop8 \\
&= 0a + (0) \quad prop4 \\
&= 0a \quad prop3
\end{aligned}$$

Examples

- $\mathcal{P}_n$ – the set of polynomials of degree less than or equal to n
  - isomorphic to $\mathbb{C}^{n+1}$
  - elements can be written as a linear combination of $n+1$ monomials therefore finite dimensional space
- $\mathcal{P}_\infty$ – the set of polynomials of any degree
  - any element can be written as a finte sum of monomials
  - infinite dimensional since it is not the same finite sum size for all vectors
- $\mathcal{L}^2_\omega[\alpha,\beta] = \{f : [\alpha,\beta] \to \mathbb{R},\ \ \int_\alpha^\beta f^2(x)\omega(x)dx < \infty\}$
  - infinite dimensional
  - need concept of convergence to discuss infinite linear combination that represents each vector

Algebraic Structure

- The algebraic structure of a vector space considers:
  - Subspaces
  - Linear Transformations
  - Bases
  - Linear Independence
- The algebraic structure of the vector spaces $\mathbb{R}^n$ and $\mathbb{C}^n$ is **common to all finite dimensional vector spaces**. We will use $\mathbb{R}^n$ in most of our discussions but the results can be adapted to $\mathbb{C}^n$ and all other such vector spaces.
- By definition a vector space $\mathcal{V}$ is closed under linear combinations, but an arbitrary subset of the space is not necessarily closed, e.g., a finite set or the set of vectors with nonnegative elements.

Subspace

Definition 1.5. A subset $\mathcal{S} \subseteq \mathbb{R}^n$ is a **subspace** if it is closed under linear combination, i.e., if $x_1, x_2, \ldots, x_k \in \mathcal{S}$ then for any scalars α_i, $i = 1, \ldots, k$

$$\alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_k x_k \in \mathcal{S}$$

and in fact the subspace is itself a vector space (and hence all of our results apply within $\mathcal{S}$).

Definition 1.6. Let $\mathcal{S} \subseteq \mathbb{R}^n$ be a subset (finite or infinite). The set of all linear combinations of vectors in $\mathcal{S}$ is called the **span** of $\mathcal{S}$ and is a subspace.

Example 1.1. $\mathbb{R}^n = span(e_1, e_2, \ldots, e_n)$

Matrices and Transformations

Definition 1.7. Given $A \in \mathbb{C}^{m\times n}$, consider $b = Ax$ for all $x \in \mathbb{C}^n$.

- The span of the columns of A is a subspace of $\mathbb{C}^m$ called the **range** of A and is denoted $\mathcal{R}(A)$.
- Since $A(\alpha x + \beta y) = \alpha Ax + \beta Ay$, A defines a linear function

$$F(A) : \mathbb{C}^n \to \mathcal{R}(A) \subseteq \mathbb{C}^m$$

- Any linear function $F : \mathbb{C}^n \to \mathbb{C}^m$ has a unique A defining it.

Independence

Definition 1.8. The set of vectors $x_1, \ldots, x_k$ are **linearly independent** if

$$\alpha_1 x_1 + \cdots + \alpha_k x_k = 0 \to \alpha_i = 0$$

for $i = 1, \ldots, k$. If this does not hold then the vectors are **linearly dependent**.

Note that:

- A set of vectors being linearly dependent implies one of the vectors can be written as a linear combination of the others.
- Any set that contains the 0 vector is linearly dependent.

Examples

$$x = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \quad y = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}$$

are linearly independent in $\mathbb{R}^3$.

$$x = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \quad y = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} \quad z = \begin{pmatrix} 3 \\ 3 \\ 1 \end{pmatrix}$$

are linearly dependent

Bases

Definition 1.9. A set of vectors $x_1, x_2, \ldots, x_k \in \mathcal{S} \subseteq \mathbb{R}^n$ is a **basis** for the subspace $\mathcal{S}$ if

- $x_1, x_2, \ldots, x_k$ are linearly independent,
- $span(x_1, x_2, \ldots, x_k) = \mathcal{S}$

Note that:

- A subspace has many bases but every basis contains k vectors and the unique integer k is the dimension of the subspace ($k = dim(\mathcal{S})$).
- $k = dim(\mathcal{S})$ is the number of degrees of freedom in $\mathcal{S}$, i.e., $\mathcal{S}$ is essentially $\mathbb{R}^k$ embedded in $\mathbb{R}^n$.
- Any collection of vectors in $\mathcal{S}$ with $k + 1$ or more vectors is linearly dependent.

Matrix Implications

- Linear independent columns of $A \in \mathbb{C}^{m\times n} \leftrightarrow \forall x \neq 0,\ Ax \neq 0$
- Linear dependent columns of $A \in \mathbb{C}^{m\times n} \leftrightarrow \exists x \neq 0 \ \ni Ax = 0$
- $\mathcal{N}(A) = \{x \in \mathcal{C}^n | Ax = 0\}$ is a subspace called the **null space** of A. (Also called the kernel denoted $\ker(A)$.)
- $\#$ of independent columns =dimension of $\mathcal{R}(A) =$ **column rank** of A
- $\#$ of independent rows =dimension of $\mathcal{R}(A) =$ **row rank** of A
- If $b = Ax \in \mathcal{R}(A)$ and $rank(A) = n$ then the linear function defined by A is one-to-one and onto $\mathcal{R}(A)$ and x is unique.

Analytic Properties

In addition to the algebraic properties discussed so far we can also define analytic properties of vector spaces and the associated linear transformations,

- size
- distance
- angle

These are analyzed via:

- norms
- inner products

Size and Distance

Definition 1.10. A vector norm, $\|x\|$, is a function $\mathbb{C}^n \to \mathbb{R}$ that satisfies

- $\|x\| \geq 0$ and $x = 0 \leftrightarrow \|x\| = 0$ (definiteness)
- $\|\alpha x\| = |\alpha|\|x\|$ (homogeneity)
- $\|x + y\| \leq \|x\| + \|y\|$ (triangle inequality)

We can also deduce

$$\|x - y\| \geq |\|x\| - \|y\||$$

Examples Vector Norms

Let $x \in \mathbb{C}^n$ with elements $e_i^H x = \xi_i$.

$$\begin{aligned}
\|x\|_1 &= \Sigma_{i=1}^n |\xi_i| \\
\|x\|_2 &= \sqrt{\Sigma_{i=1}^n |\xi_i|^2} \\
\|x\|_p &= \left(\Sigma_{i=1}^n |\xi_i|^p\right)^{1/p} \\
\|x\|_\infty &= \max_{1 \leq i \leq n} |\xi_i|
\end{aligned}$$

Norm Equivalence

Theorem 1.1. *Let $\mu(x)$ and $\nu(x)$ be vector norms then there exist constants, i.e., independent of x, $\sigma > 0$ and $\tau > 0$ such that*

$$\sigma\mu(x) \leq \nu(x) \leq \tau\mu(x)$$

Norm Equivalence

In other words, for analytical purposes, all norms are equivalent.
Convergence in one vector norm implies convergence in any other.

Note that σ and τ may be dependent on n.

$$\|x\|_2 \leq \|x\|_1 \leq \sqrt{n}\|x\|_2$$

$$\|x\|_\infty \leq \|x\|_2 \leq \sqrt{n}\|x\|_\infty$$

$$\|x\|_\infty \leq \|x\|_1 \leq n\|x\|_\infty$$

Matrix Norms

Definition 1.11. A matrix norm on $\mathbb{C}^{m\times n}$ denoted $\|A\|$ maps $\mathbb{C}^{m\times n} \to \mathbb{R}$ and satisfies

- $\|A\| \geq 0$ and $A = 0 \leftrightarrow \|A\| = 0$
- $\|\alpha A\| = |\alpha|\|A\|$
- $\|A + B\| \leq \|A\| + \|B\|$

Examples of matrix norms

Let $A \in \mathbb{C}^{m\times n}$ with elements $e_i^H A e_j = \alpha_{ij}$.

$$\begin{aligned}
\|A\|_1 &= \max_{1\le j\le n} \Sigma_{i=1}^{m} |\alpha_{ij}| = \max_{1\le j\le n} \|Ae_j\|_1 \\
\|A\|_\infty &= \max_{1\le i\le m} \Sigma_{j=1}^{n} |\alpha_{ij}| = \max_{1\le i\le m} \|e_i^H A\|_1 \\
\|A\|_2 &= \max_{\|x\|_2=1} \|Ax\|_2 \\
\|A\|_p &= \max_{\|x\|_p=1} \|Ax\|_p \\
\|A\|_F &= \sqrt{\Sigma_{i=1}^{m}\Sigma_{j=1}^{n}|\alpha_{ij}|^2} = \sqrt{\Sigma_{i=1}^{n}\|Ae_i\|_2^2}
\end{aligned}$$

Examples of matrix norms

- The Frobenius norm $\|A\|_F$ is essentially the vector 2 norm applied to the matrix as if it was a element of $\mathbb{C}^{mn}$.
- $\|A\|_F^2 = trace(A^H A)$ where the trace is the sum of the diagonal elements.
- While all matrix norms are equivalent for analytical purposes, they **differ considerably in their ease of computation**.

Matrix 2 Norm

- Definition given requires optimization

$$\|A\|_2 = \max_{\|x\|_2=1} \|Ax\|_2$$

- $\|A\|_2$ can be related to eigenvalues and singular values but these are also “infinite” computations
- Bounds can be derived in terms of $\|A\|_1$ and $\|A\|_\infty$, i.e., equivalence can be used for approximation

$$\|A\|_2 \leq \sqrt{\|A\|_1 \|A\|_\infty}$$

Consistent Matrix Norms

Definition 1.12. The matrix norms $\|\cdot\|_\alpha$,$\|\cdot\|_\beta$,$\|\cdot\|_\gamma$ are **consistent** if

$$\|AB\|_\alpha \leq \|A\|_\beta \|B\|_\gamma$$

whenever the product exists.

Lemma 1.2. *The matrix p-norm defines a family of consistent matrix norms. Specifically, for $A \in \mathbb{C}^{m\times n}$,$B \in \mathbb{C}^{n\times r}$ and $x \in \mathbb{C}^n$*

$$\|AB\|_p \leq \|A\|_p \|B\|_p$$
$$\|Ax\|_p \leq \|A\|_p \|x\|_p$$

Induced Matrix Norms

Definition 1.13. The matrix norm $\|\cdot\|$ is **subordinate** to vector norms $\|\cdot\|_\alpha$ and $\|\cdot\|_\beta$ if

$$\|Ax\|_\alpha \leq \|A\|\|x\|_\beta$$

and the matrix norm therefore bounds the expansion/contraction of the linear transformation defined by A.

Definition 1.14. Given vector norms $\|\cdot\|_\alpha$ and $\|\cdot\|_\beta$ the induced matrix norm $\|\cdot\|_{\alpha,\beta}$ is

$$\|A\|_{\alpha,\beta} = \max_{\|x\|_\alpha=1} \|Ax\|_\beta$$

Induced Matrix Norms

Theorem 1.3. *Given a vector norm $\|\cdot\|_\alpha$ on $\mathbb{C}^n$ or $\mathbb{R}^n$ the induced matrix norm $\|\cdot\|_\beta$ for an $n \times n$ matrix*

1. $\|Ax\|_\alpha \leq \|A\|_\beta \|x\|_\alpha$ *(subordinate)*
2. $\|I\|_\beta = 1$
3. $\|AB\|_\beta \leq \|A\|_\beta \|B\|_\beta$ *(submultiplicative)*

Convergence

Both vector sequences and matrix sequences can therefore be said to converge to limit vectors and limit matrices by considering convergence in $\mathbb{R}$.

Definition 1.15. For the vector sequence $\{x_k\}$ and the matrix sequence $\{A_k\}$

$$\lim_{k\to\infty} x_k = x \leftrightarrow \lim_{k\to\infty} \|x_k - x\| = 0$$
$$\lim_{k\to\infty} A_k = A \leftrightarrow \lim_{k\to\infty} \|A_k - A\| = 0$$

Componentwise convergence for both follows.

Angles in n-dimensional Spaces

Definition 1.16. An inner product (or scalar product) on a vector space $\mathcal{V}$ is a map $< \cdot, \cdot >: \mathcal{V} \times \mathcal{V} \to F$ where the field F is either $\mathbb{R}$ or $\mathbb{C}$ that satisfies

1. $< \alpha x + \beta z, y > = \alpha < x, y > + \beta < z, y >$, with $x, y, z \in \mathcal{V}$ and $\alpha, \beta \in F$. (linearity)
2. $< x, y > = \overline{< y, x >}$ (hermitian)
3. $< x, x > \geq 0$ and $< x, x > = 0 \leftrightarrow x = 0$ (definiteness)

Inner Product

- $< x, y >= x^H y$ is an inner product for $\mathbb{C}^n$
- $< x, y >= x^T y$ is an inner product for $\mathbb{R}^n$
- There are other inner products for $\mathbb{C}^n$ and $\mathbb{R}^n$.
- $\|x\| = \sqrt{< x, x >}$ is a norm.

Angles in n-dimensional Spaces

Lemma 1.4. *For* $x, y \in \mathbb{C}^n$

- $|x^H y| \leq \|x\|_p \|y\|_q$ *with* $\frac{1}{p} + \frac{1}{q} = 1$ *(Hoelder inequality)*
- $|x^H y| \leq \|x\|_2 \|y\|_2$ *(Cauchy-Schwarz inequality)*
- $|x^H y| \leq \|x\|_1 \|y\|_\infty$

Angles in n-dimensional Spaces

Angles can be defined by making the Cauchy-Schwarz inequality an equality.

Definition 1.17. Let x and y be two nonzero vectors in $\mathbb{C}^n$ then the cosine of the **angle between the one-dimensional subspaces defined by the vectors,** $0 \leq \theta \leq \pi/2$, is defined

$$|x^H y| = cos\theta \|x\|_2 \|y\|_2$$

Definition 1.18. Let x and y be two nonzero vectors in $\mathbb{C}^n$ then the cosine of the **angle between the vectors**, $0 \leq \theta < 2\pi$ or $-\pi \leq \phi \leq \pi$, is defined

$$x^H y = cos\theta \|x\|_2 \|y\|_2 = cos\phi \|x\|_2 \|y\|_2$$

Generalization from $\mathbb{R}^2$

Consider $x, y \in \mathbb{R}^2$ positive quadrant.

$$x^T y = \cos\theta \|x\| \|y\|$$

$$\tilde{x}^T \tilde{y} = \cos\theta$$

$$\tilde{x} = (\cos\theta_1, \sin\theta_1) \text{ and } \|\tilde{x}\| = 1$$

$$\tilde{y} = (\cos\theta_2, \sin\theta_2) \text{ and } \|\tilde{y}\| = 1$$

where θ_1 and θ_2 are angles from $(1, 0)$

$$\tilde{x}^T \tilde{y} = \cos\theta_1 \cos\theta_2 + \sin\theta_1 \sin\theta_2 = \cos(\theta_1 - \theta_2) = \cos\theta$$

Orthogonality

Definition 1.19. The vectors x and y are said to be orthogonal if their inner product is 0, i.e., $< x, y >= x^H y = 0$.

This generalizes the Pythagorean Theorem to multidimensional and complex vectors:

$$\begin{aligned} \|x+y\|_2^2 &= (x+y)^H(x+y) \\ &= x^H x + y^H y + 2Re(x^H y) \\ &= x^H x + y^H y \\ &= \|x\|_2^2 + \|y\|_2^2 \end{aligned}$$

Polarization and Parallelograms

Theorem 1.5. *Let $\mathcal{V}$ be a vector space over $\mathbb{R}$ (similar statments can be made for $\mathbb{C}$) with and inner product $< x, y >$. If the norm is defined by$\|x\| = \sqrt{< x, x >}$ then we have*

- $\|x + y\|^2 = \|x\|^2 + \|y\|^2 + 2 < x, y >$
- $\|x - y\|^2 = \|x\|^2 + \|y\|^2 - 2 < x, y >$ *(cosine law)*
- $\|x + y\|^2 + \|x - y\|^2 = 2(\|x\|^2 + \|y\|^2)$ *(parallelogram law)*
- $\|x + y\|^2 - \|x - y\|^2 = 4 < x, y >$ *(polarization identity)*

Polarization and Parallelograms

The reverse is also true.

Theorem 1.6. *Let $\mathcal{V}$ be a normed vector space over $\mathbb{R}$ (similar statments can be made for $\mathbb{C}$). If the norm satisfies the parallelogram law then the polarization identity defines an inner product for $\mathcal{V}$. That is*

$$\|x+y\|^2 + \|x-y\|^2 = 2(\|x\|^2 + \|y\|^2)$$

$$\Downarrow$$

$$< x, y >= \frac{1}{4}\{\|x+y\|^2 - \|x-y\|^2\}$$

$$\Downarrow$$

$$\|x+y\|^2 = \|x\|^2 + \|y\|^2 + 2 < x, y >$$

and $\|x-y\|^2 = \|x\|^2 + \|y\|^2 - 2 < x, y >$