

Shifrin 1.2. The Dot Product

①

Recall: $x \in \mathbb{R}^n$ is given by $x = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$.

$$x \pm y = \begin{bmatrix} x_1 \pm y_1 \\ \vdots \\ x_n \pm y_n \end{bmatrix} \quad c x = \begin{bmatrix} c x_1 \\ \vdots \\ c x_n \end{bmatrix}$$

Definition. The dot product or inner product of $x, y \in \mathbb{R}^n$ is the scalar

$$x \cdot y = x_1 y_1 + \dots + x_n y_n$$

This is a kind of multiplication for vectors (but be careful - the output is not a vector), and it has similar properties:

1. $x \cdot y = y \cdot x$ \leftarrow commutative

2. $x \cdot x = \|x\|^2 \geq 0$, $\|x\| = 0 \Leftrightarrow x = 0$

3. $c(x \cdot y) = (cx) \cdot y = x \cdot (cy)$

4. $x \cdot (y + z) = x \cdot y + x \cdot z$

\uparrow distributes over vector addition

②

We can use these properties to do vector algebra that looks much like the ordinary (scalar) algebra you already know.

Lemma. $\|x+y\|^2 = \|x\|^2 + 2x \cdot y + \|y\|^2$

Proof. $\|x+y\|^2 = (x+y) \cdot (x+y)$

$$= x \cdot x + x \cdot y + y \cdot x + y \cdot y$$

$$= x \cdot x + 2x \cdot y + y \cdot y$$

$$= \|x\|^2 + 2x \cdot y + \|y\|^2. \quad \square$$

~~the~~

Definition. We say $x, y \in \mathbb{R}^n$ are orthogonal ~~if~~ or perpendicular if $x \cdot y = 0$.

Definition. Given $x, y \in \mathbb{R}^n$, we let ③

$$X^{\parallel} = \frac{X \cdot y}{\|y\|^2} y, \quad X^{\perp} = X - \frac{X \cdot y}{\|y\|^2} y$$

Proposition. We have

1. X^{\parallel} is parallel to y
2. X^{\perp} is orthogonal to y
3. $X = X^{\parallel} + X^{\perp}$

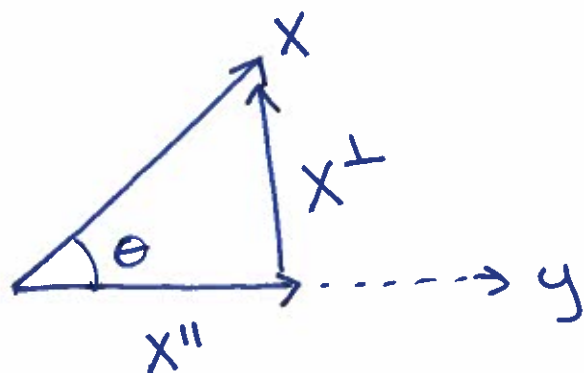
Proof. The only one that's not easy is 2.

$$\begin{aligned} X^{\perp} \cdot y &= \left(X - \frac{X \cdot y}{\|y\|^2} y \right) \cdot y \\ &= X \cdot y - \frac{X \cdot y}{\|y\|^2} y \cdot y \\ &= 0. \end{aligned}$$

□

Now suppose we have (in \mathbb{R}^2)

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we know

$$\cos \theta = \frac{\|x''\|}{\|x\|} = \frac{\left\| \frac{x \cdot y}{\|y\|^2} y \right\|}{\|x\|}$$

hypotenuse \rightarrow \leftarrow adjacent side

$$= \frac{x \cdot y}{\|y\|^2} \frac{\|y\|}{\|x\|}$$

so

$$= \frac{x \cdot y}{\|x\| \|y\|}$$

Lemma. In \mathbb{R}^2 , the angle θ between x and y is given by

$$\theta = \arccos \left(\frac{x \cdot y}{\|x\| \|y\|} \right).$$

Definition. The angle between $x, y \in \mathbb{R}^n$ is the unique θ in $[0, \pi]$ so that

$$\cos \theta = \frac{x \cdot y}{\|x\| \|y\|}$$

Now we ~~can~~ show something important.

Cauchy-Schwarz Inequality.

If $x, y \in \mathbb{R}^n$, then $|x \cdot y| \leq \|x\| \|y\|$.

Further, $|x \cdot y| = \|x\| \|y\|$ if and only if one vector is a scalar multiple of the other.

Proof. If $y = 0$ then $|x \cdot y| = 0 = \|x\| \|y\|$ and $y = 0x$, so we're done.
 \uparrow scalar 0!

If $y \neq 0$, we consider

$$g(t) = \|x + ty\|^2 = \|x\|^2 + 2t x \cdot y + t^2 \|y\|^2$$

Now $g(t)$ is a square (and a norm) ⑦

So $g(t) \geq 0$ for all t . At the min,

$$g(t_0) = \|x\|^2 - 2 \frac{(x \cdot y)^2}{\|y\|^2} + \frac{(x \cdot y)^2}{\|y\|^2} \frac{\|y\|^2}{\|y\|^2}$$

$$= \|x\|^2 - \frac{(x \cdot y)^2}{\|y\|^2}$$

so

$$\|x\|^2 - \frac{(x \cdot y)^2}{\|y\|^2} \geq 0$$

~~and~~

$$\|x\|^2 \geq \frac{(x \cdot y)^2}{\|y\|^2}$$

$$\|x\|^2 \|y\|^2 \geq (x \cdot y)^2$$

and (taking square roots)

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$$\|x\| \|y\| \geq |x \cdot y|$$

Now ~~if~~ $\|x\| \|y\| = |x \cdot y| \iff$ ^{if and only if} $g(t_0) = 0,$

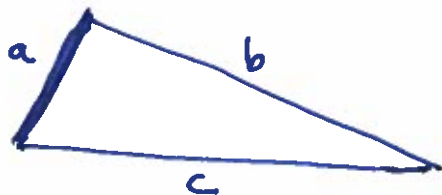
or $\|x - t_0 y\|^2 = 0$. In this case

$x = t_0 y$ and x is a scalar

multiple of y . \square

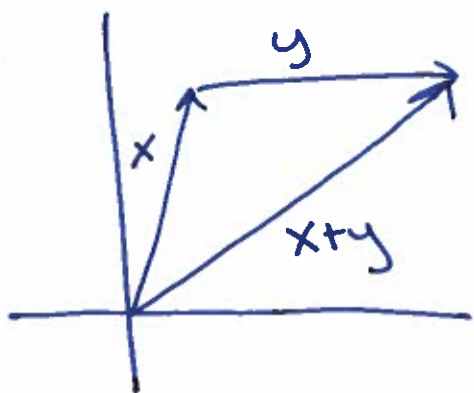
We can now use this to prove.

Triangle Inequality. The sum of the lengths of two sides of a triangle is \geq the length of the third side.



$$\begin{aligned} a + b &\geq c \\ b + c &\geq a \\ c + a &\geq b \end{aligned}$$

Proof.



If we write $\triangle ABC$ in vector form, we must show $\|x+y\| \leq \|x\| + \|y\|$.

But

$$\|x+y\|^2 = \|x\|^2 + 2x \cdot y + \|y\|^2$$

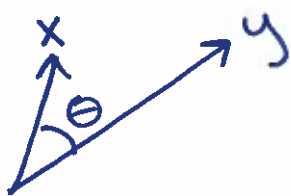
$$\leq \|x\|^2 + 2\|x\|\|y\| + \|y\|^2$$

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

So $\|x+y\| \leq \|x\| + \|y\|$. \square

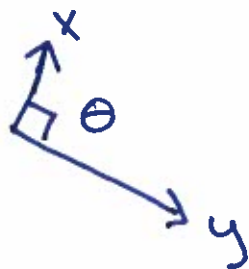
Note: We used the fact that all these norms are ≥ 0 . Where?

Examples.



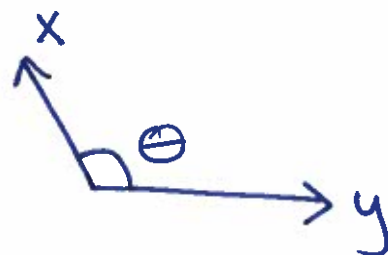
$$\theta < \pi/2$$

$$x \cdot y > 0$$



$$\theta = \pi/2$$

$$x \cdot y = 0$$



$$\theta > \pi/2$$

$$x \cdot y < 0$$

Suppose we define two vectors by data about n people.

$$\vec{x} = \begin{bmatrix} \vdots \\ x_i \\ \vdots \end{bmatrix}$$

$$x_i = \begin{cases} 1, & \text{if student } i \text{ is wearing hat} \\ -1, & \text{if not} \end{cases}$$

$$\vec{y} = \begin{bmatrix} \vdots \\ y_i \\ \vdots \end{bmatrix}$$

$$y_i = \begin{cases} 1, & \text{if student } i \text{ is wearing sunglasses} \\ -1, & \text{if not} \end{cases}$$

Suppose that $\mathbf{1} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$.

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Definition. The mean or average of $X \in \mathbb{R}^n$ is given by $\mu_X = \frac{1}{n} X \cdot \mathbf{1} = \frac{1}{n} \sum X_i$.

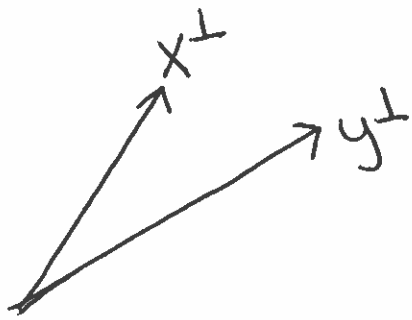
We can "zero mean" X by taking the component of X orthogonal to $\mathbf{1}$.

$$\begin{aligned} X^\perp &= X - \frac{X \cdot \mathbf{1}}{\|\mathbf{1}\|^2} \mathbf{1} \\ &= X - \frac{X \cdot \mathbf{1}}{n^2} \mathbf{1} \\ &= X - \left(\frac{1}{n} X \cdot \mathbf{1} \right) \frac{1}{n} \mathbf{1} \\ &= X - \mu_X \cdot \frac{1}{n} \mathbf{1} \end{aligned}$$

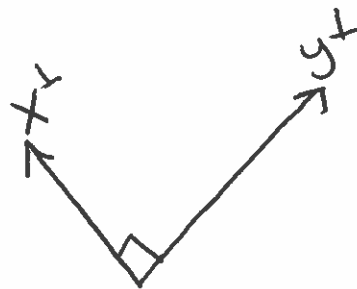
Definition. The Pearson correlation coefficient (or r) between x and y is

$$r = \frac{x^\perp \cdot y^\perp}{\|x^\perp\| \|y^\perp\|} = \cos \Theta$$

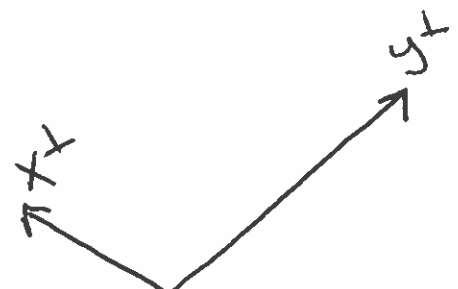
where Θ is the angle between x^\perp, y^\perp .



positively correlated
or "correlated"



uncorrelated



negatively correlated
or "anticorrelated"

We will keep returning to this picture

statistics \longleftrightarrow high dimensional geometry