

Thm. If $F = \mathbb{C}$ and V is a finite-dimensional vector space, then any $T \in \mathcal{L}(V)$ has an eigenvalue.

Idea. By the Prop, all we need to do is find some $\lambda \in \mathbb{C}$ for which the map $T - \lambda \cdot I_V$ is not injective.

If I have a bunch of candidate eigenvalues $\lambda_1, \dots, \lambda_k$ I can test them all at once by checking if the composition

$$(T - \lambda_1 I_V) \circ (T - \lambda_2 I_V) \circ \dots \circ (T - \lambda_k I_V)$$

is injective. this looks like a factored polynomial.

If this sends some non-zero $v \in V$ to $\vec{0}$, then at least one of the $T - \lambda_i I_V$ s is not injective.

Recall in the proof:

$$0 = \underbrace{(a_0 + a_1 T + a_2 T^2 + \dots + a_n T^n)}_{p(T)}(v)$$

$$= c(T - \lambda_1 I)(T - \lambda_2 I) \dots (T - \lambda_n I)(v).$$

Need to check that "polynomials over operators" behave the same way as the usual polynomials.

We know that there is a map

$$\mathcal{P}(F) \xrightarrow{\Phi \leftarrow \text{Phi}} \{ \text{polynomials in } T \}$$
$$\sum c_i z^i \mapsto \sum c_i T^i.$$

Does this map respect multiplication? AKA

$$\text{Does } \Phi(p(z) \cdot q(z)) = \Phi(p(z)) \circ \Phi(q(z))?$$

Thm. If V is finite-dimensional and $T \in \mathcal{L}(V)$ then the following are equivalent:

(1) T is diagonalizable

(2) V has a basis consisting of eigenvectors of T .

(3) There exists k 1-dim. invariant subspaces Z_1, \dots, Z_k s.t. $V = Z_1 \oplus \dots \oplus Z_k$.

(4) $V = E(\lambda_1) \oplus \dots \oplus E(\lambda_k)$, where $\lambda_1, \dots, \lambda_k$ are distinct eigenvalues.

(5) $\dim(V) = \dim(E(\lambda_1)) + \dots + \dim(E(\lambda_k))$.

Pf. (1) \Leftrightarrow (2).

If T is diagonalizable, then there is some basis $\{v_1, \dots, v_n\}$ of V such that the matrix of T w.r.t.

this basis is $\begin{matrix} & \begin{matrix} v_1 & v_2 & \dots & v_n \end{matrix} \\ \begin{matrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{matrix} & \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{bmatrix} \end{matrix}$ (by definition).

$$T(v_i) = \lambda_i \cdot v_i.$$

So v_i is an eigenvector for T .

Conversely, if $\{v_1, \dots, v_n\}$ is a basis of eigenvectors, then \exists scalars $\lambda_1, \dots, \lambda_n$ s.t. $T(v_i) = \lambda_i v_i$.

The matrix of T w.r.t. this basis is $\begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$.

This is a diagonal matrix, so T is diagonalizable.

Pf. (5) \Rightarrow (2).

For each $E(\lambda_i)$ choose a basis $\{v_1^i, v_2^i, \dots, v_{n_i}^i\}$.

The list of all basis elements of all $E(\lambda_i)$ has size equal to n by assumption.

$$[\dim(E(\lambda_1)) + \dots + \dim(E(\lambda_k))] =$$

$$\# \{v_1^1, \dots, v_{n_1}^1\} + \dots + \# \{v_1^k, \dots, v_{n_k}^k\} = n$$

$$\text{So } \{v_1^1, \dots, v_{n_1}^1, \dots, v_1^k, \dots, v_{n_k}^k\} \quad \begin{matrix} \parallel \\ \text{dim}(V) \end{matrix} \quad]$$

is a basis if it is a linearly independent list.

When is $\{v_1^1, v_2^1, \dots, v_{n_1}^1\}$

$$a_1 v_{i_1}^1 + a_2 v_{i_2}^2 + \dots + a_k v_{i_k}^k = 0 ?$$

\downarrow

$$z_1 + z_2 + \dots + z_k = 0 ?$$

\uparrow \uparrow \uparrow

$$E(\lambda_1) \quad E(\lambda_2) \quad E(\lambda_k)$$

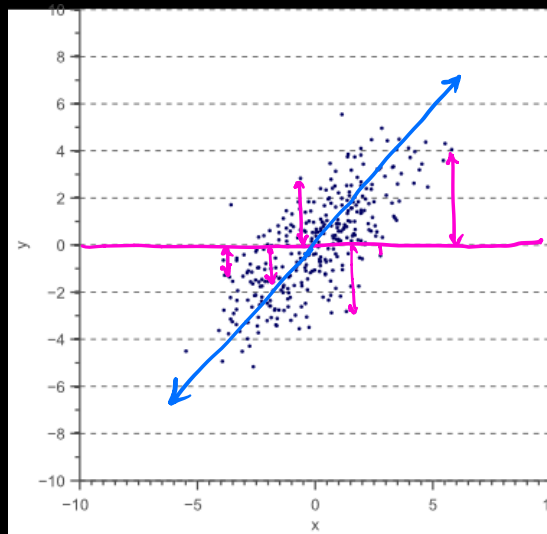
Each z_i is an eigenvector belonging to a distinct eigenvalue.

$$\Rightarrow z_1 = z_2 = \dots = z_k = 0.$$

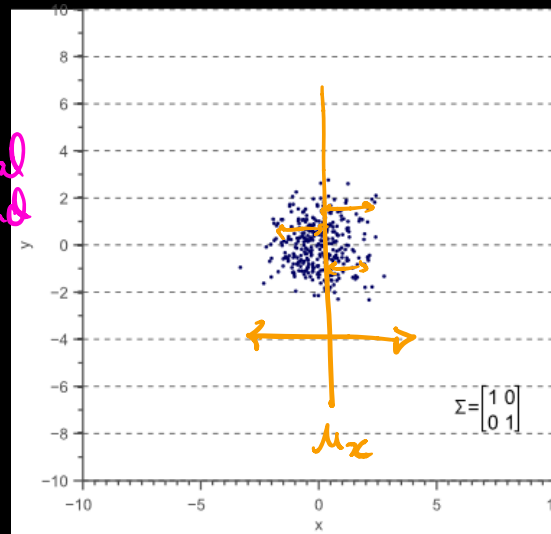
$$\Rightarrow a_1 = a_2 = \dots = a_k = 0.$$

□

Application: The shape of data. [Ref: computer vision for dummies]



μ_y
vertical spread



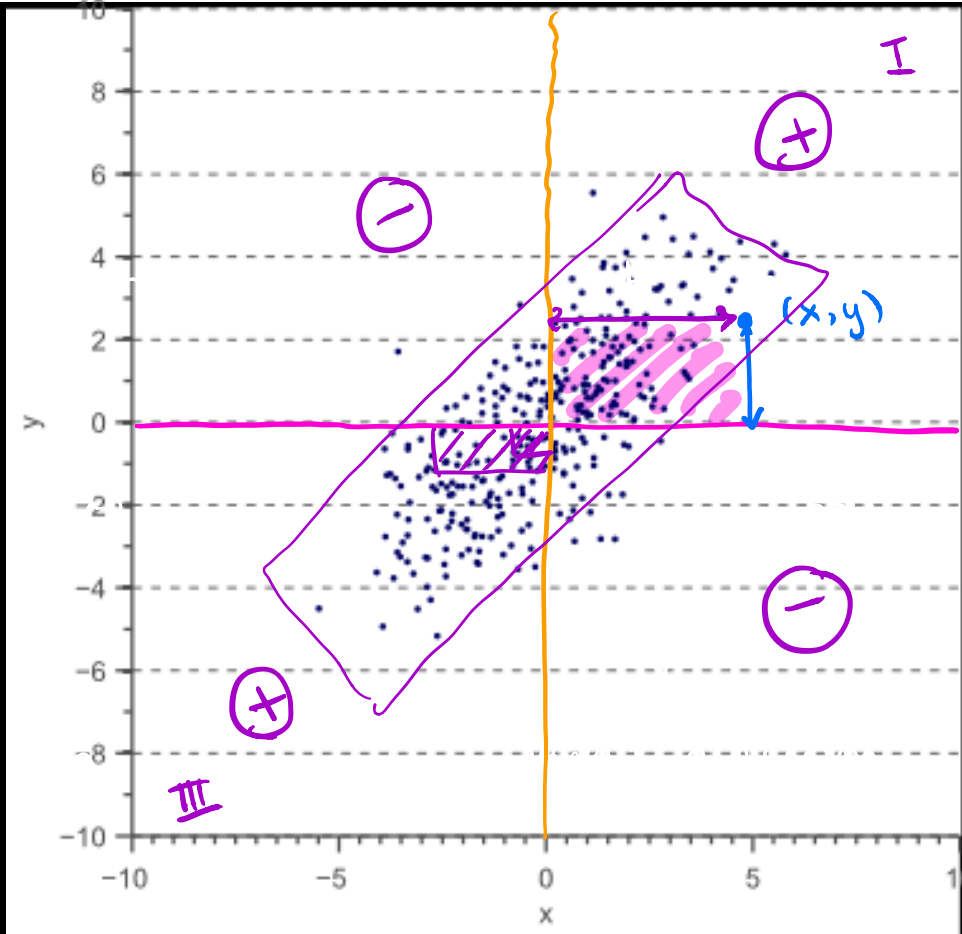
Say I have data points $(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)$.

Want to understand: how spread out is my data?

What is the standard deviation?

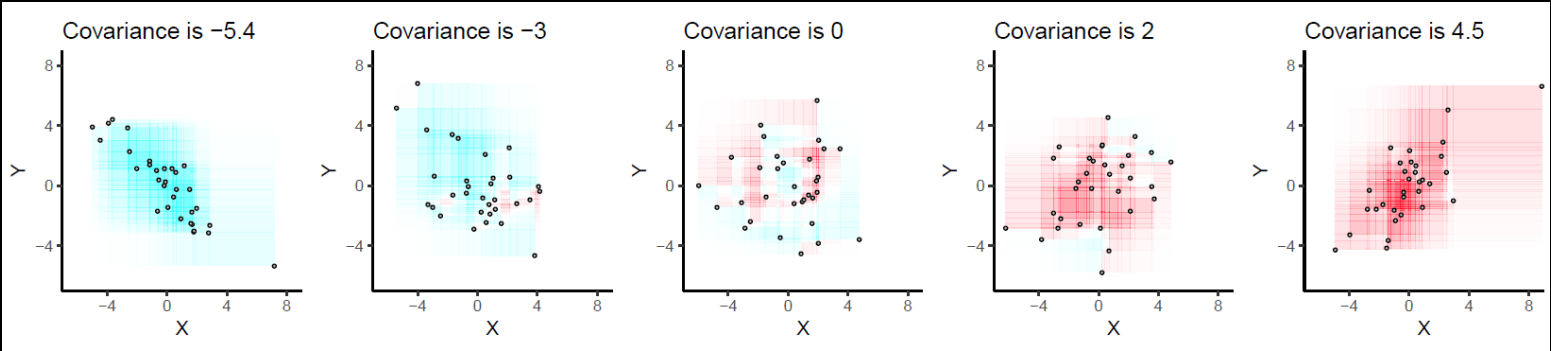
$$\sigma(y, y) = \frac{1}{N-1} \sum_{i=1}^N (y_i - \mu_y)^2$$

$$\sigma(x, x) = \frac{1}{N-1} \sum_{i=1}^N (x_i - \mu_x)^2$$



Covariance

$$\sigma(x, y) = \frac{1}{N-1} \sum_{i=1}^N \underbrace{(x_i - \mu_x)}_{\text{blue bracket}} \cdot \underbrace{(y_i - \mu_y)}_{\text{purple bracket}}$$

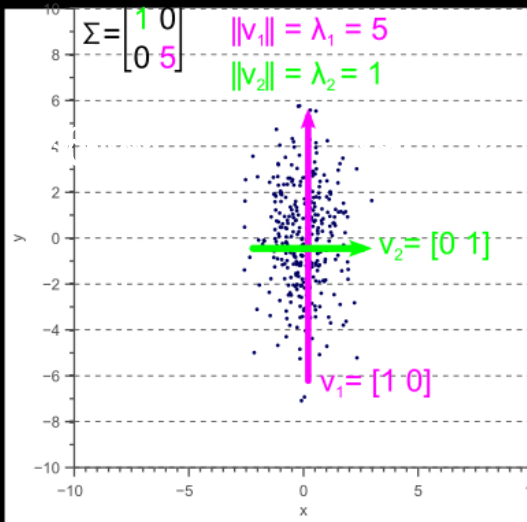
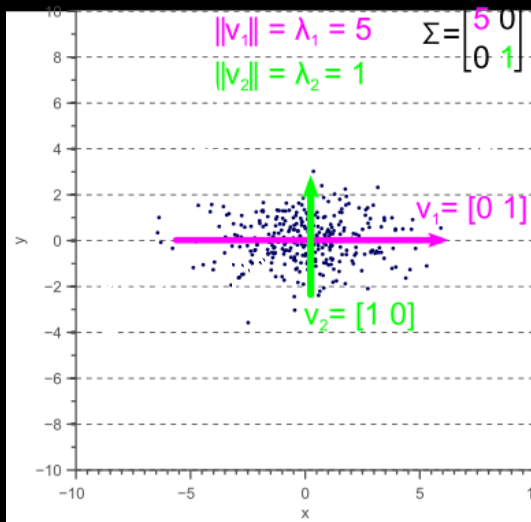


We can organize all "spread" into into a matrix, called the covariance matrix.

$$\Sigma = \begin{bmatrix} \sigma(x,x) & \sigma(y,x) \\ \sigma(x,y) & \sigma(y,y) \end{bmatrix}$$

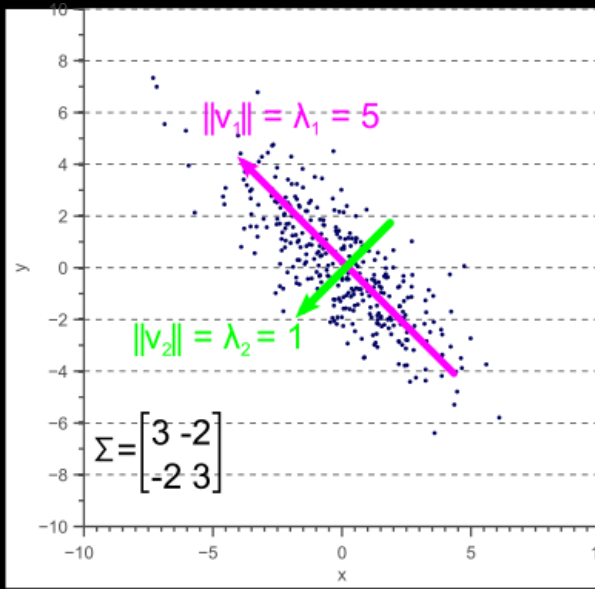
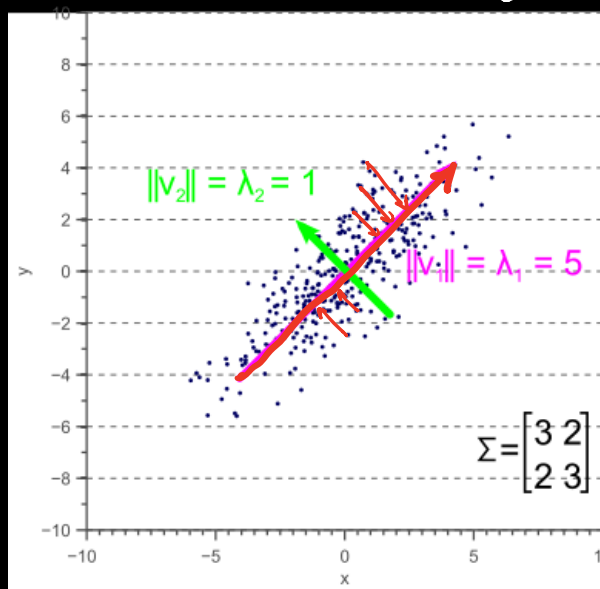
If $\sigma(x,y) = \sigma(y,x) = 0$, Σ has a very nice interpretation:

capital sigma



in this case, Σ is a diagonal matrix.

CRAZY FACT: the eigenvectors of Σ point in the directions of maximal spread!
Eigenvalues tell you by how much.

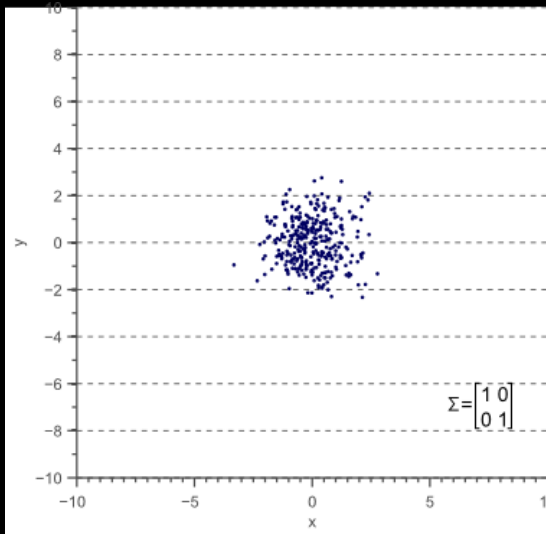


Principle component analysis.

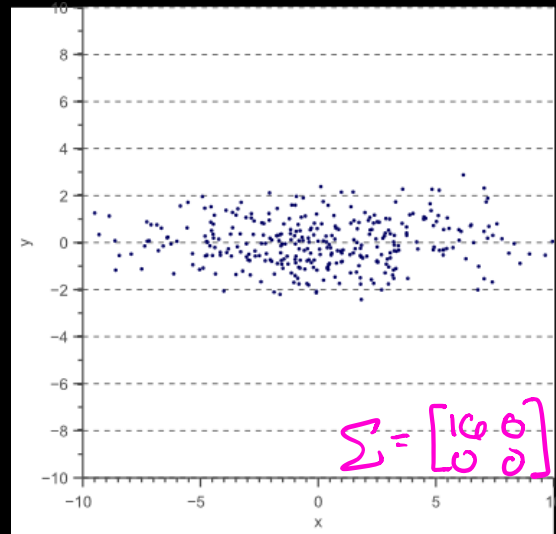
Crucial fact: Σ is always diagonalizable.

You can always find the principle components.

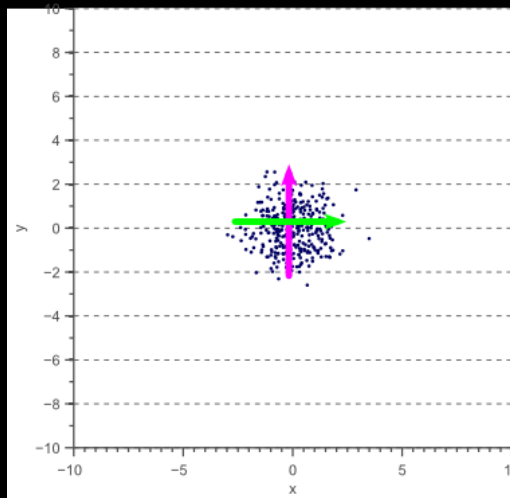
There always exists "white data", data for which $\Sigma = \text{identity}$, and a linear transformation T



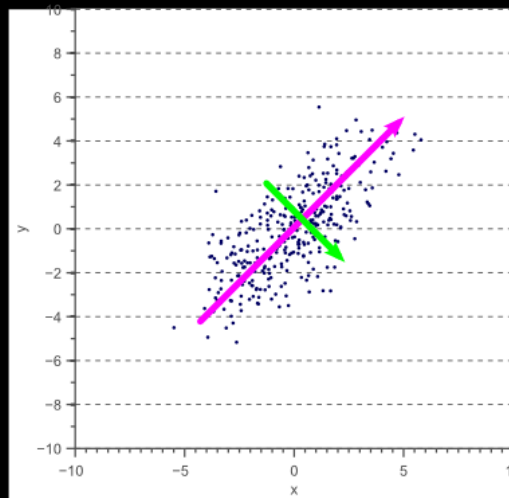
$$T \rightarrow \begin{bmatrix} 4 & 0 \\ 0 & 0 \end{bmatrix}$$



$$\Sigma = T^2.$$



T



$$\Sigma = T \cdot T^t$$