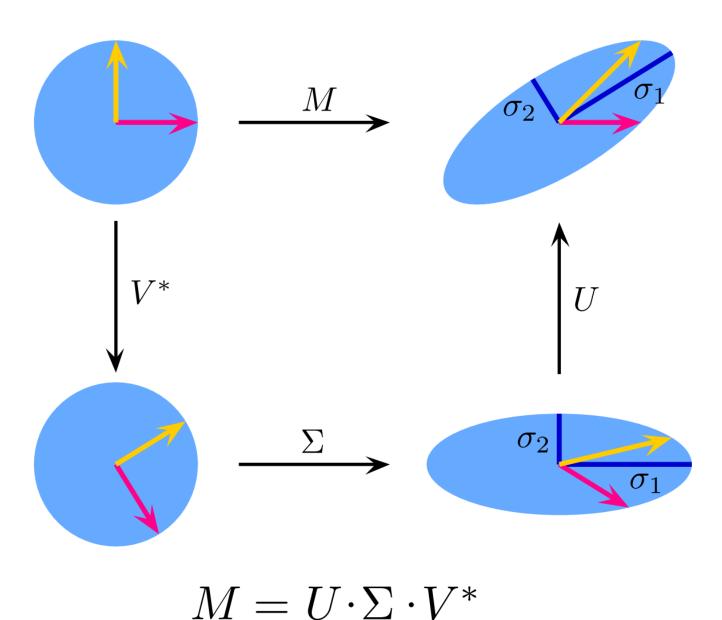
SVD

SVD stands for singular value decomposition.

Sometimes it is useful to decompose transformation matrices in multiple matrices that only do a type of transformation each.

The difference with <u>spectral decomposition</u>, is that SVD doesn't require a <u>symmetric</u> <u>matrix</u>, but just about any <u>matrix</u>.

SVD says that any matrix, regardless of symmetry, rank or shape, can unconditionally be decomposed into 3 special matrices.



Explanation:

$$AV = U\Sigma$$

Where:

- A is any matrix.
- V are the orthonormal vectors that, once transformed by A, remain orthonormal.
- Σ is a diagonal matrix that scales the basis vectors before they are rotated.
- U is the rotation that brings the basis vectors

What does it mean:

$$V=egin{bmatrix} v_1 \ v_2 \end{bmatrix}, & U=egin{bmatrix} u_1 \ u_2 \end{bmatrix}, & \Sigma=egin{bmatrix} \sigma_1 \ \sigma_2 \end{bmatrix}$$
 $Av_1=u_1\sigma_1$ and

$$Av_2=u_2\sigma_2$$

The vectors in U are the vectors of V after being transformed by A(they remain orthonormal by definition of V).

AV:

For some reason we found the pair of vectors that when transformed by A, remain orthonormal.

We now put them through A and end up with orthonormal vectors.

$U\Sigma$:

We have the scaling information in the Σ matrix, then we rotate those scaled vectors to where they are after AV (by applying U, by U definition).

Result:

If we then want A, we divide both sides by V^-1 .

$$A = U\Sigma V^{-1}$$

How do we get U and V?

We make spectral decomposition of AA^T, which returns a symmetrical matrix. We can also do A^TA, which also returns another symmetrical matrix.

Those two matrices have something in common with the original matrix apparently. V and U's columns are the eigenvectors of those two symmetrical matrices.

