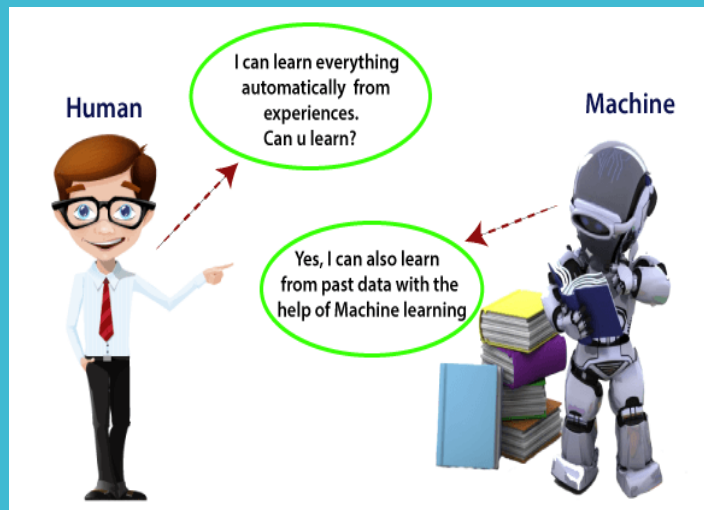














Recommendation System



How does Humans Behave

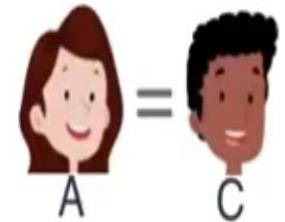
| | M 1 | M 2 | M 3 | M 4 | M 5 |
|---|-----|-----|-----|-----|-----|
|  | 3 | 3 | 3 | 3 | 3 |
|  | 3 | 3 | 3 | 3 | 3 |
|  | 3 | 3 | 3 | 3 | 3 |
|  | 3 | 3 | 3 | 3 | 3 |

| | M 1 | M 2 | M 3 | M 4 | M 5 |
|---|-----|-----|-----|-----|-----|
|  | 3 | 1 | 1 | 3 | 1 |
|  | 1 | 2 | 4 | 1 | 3 |
|  | 3 | 1 | 1 | 3 | 1 |
|  | 4 | 3 | 5 | 4 | 4 |





| | M 1 | M 2 | M 3 | M 4 | M 5 |
|---|-----|-----|-----|-----|-----|
|  | 1 | 3 | 2 | 5 | 4 |
|  | 2 | 1 | 1 | 1 | 5 |
|  | 3 | 2 | 3 | 1 | 5 |
|  | 2 | 4 | 1 | 5 | 2 |

How does Humans Behave

| | M1 | M2 | M3 | M4 | M5 | |
|--|----|----|----|----|----|---|
|  | 3 | 1 | 1 | 3 | 1 | ← |
|  | | | | | | |
|  | 3 | 1 | 1 | 3 | 1 | ← |
|  | | | | | | |



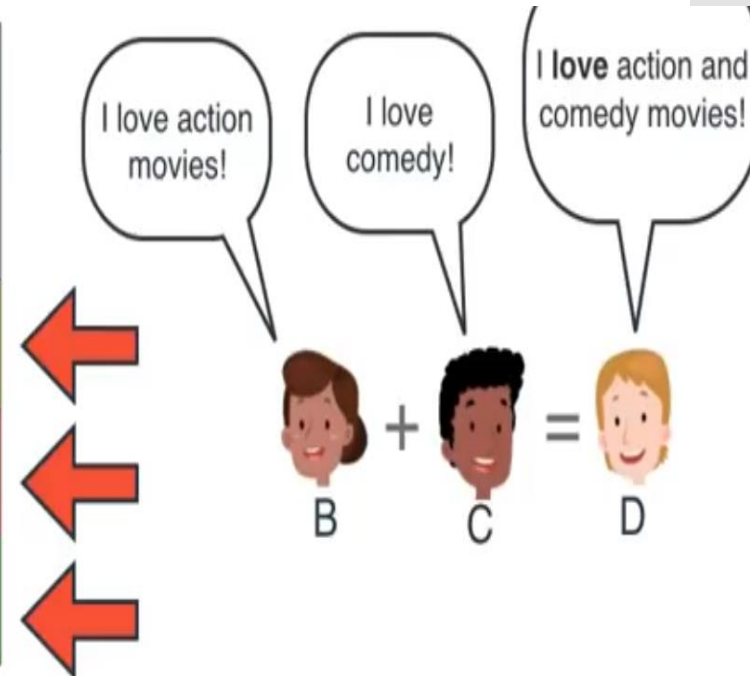
How does Humans Behave

| | M1 | M2 | M3 | M4 | M5 |
|---|----|----|----|----|----|
|  | 3 | 1 | 1 | 3 | 1 |
|  | 1 | 2 | 4 | 1 | 3 |
|  | 3 | 1 | 1 | 3 | 1 |
|  | 4 | 3 | 5 | 4 | 4 |







How does Humans Behave

| | M1 | M2 | M3 | M4 | M5 |
|--|----|----|----|----|----|
|  | | | | | |
|  | 1 | 2 | 4 | 1 | 3 |
|  | 3 | 1 | 1 | 3 | 1 |
|  | 4 | 3 | 5 | 4 | 4 |



How does Recommender System Behaves

| | M1 | M2 | M3 | M4 | M5 |
|---|----|----|----|----|----|
|  | 3 | 1 | 1 | 3 | 1 |
|  | 1 | 2 | 4 | 1 | 3 |
|  | 3 | 1 | 1 | 3 | |
|  | 4 | 3 | 5 | 4 | 4 |

Figuring out
the
dependencies?

Using Matrix
Factorization

- **Depends on different Features**

Figuring out
the
dependencies?

Using Matrix
Factorization

•



Comedy



Action



4

0

Figuring out
the
dependencies?

Using Matrix
Factorization

•



Comedy



Action



4

0

Figuring out
the
dependencies?

Using Matrix
Factorization

•



Comedy



Action



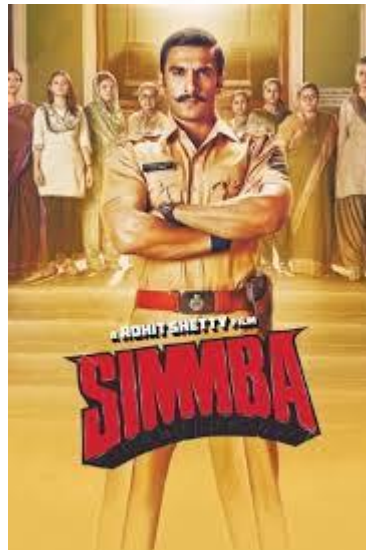
3.5

0.5

Figuring out
the
dependencies?

Using Matrix
Factorization

•



Comedy



3.0



Action



1.0

Figuring out
the
dependencies?

Using Matrix
Factorization

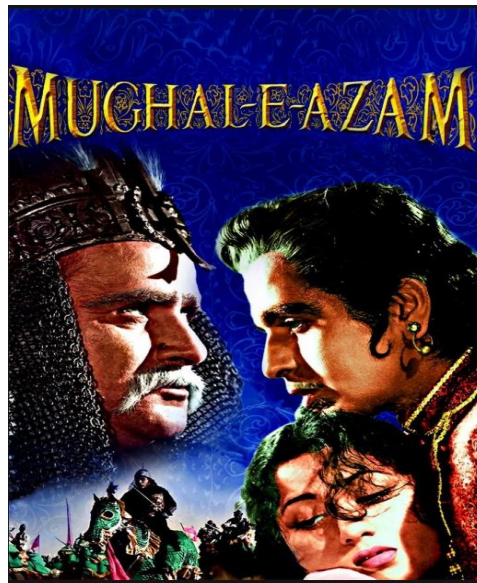
•



Comedy


















Action





0

0.5

| |  Comedy |  Action |
|----|---|---|
| M1 | 3 | 1 |
| M2 | 1 | 2 |
| M3 | 1 | 4 |
| M4 | 3 | 1 |
| M5 | 1 | 3 |

| |  Comedy |  Action |
|---|--|---|
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |

| |  Comedy |  Action |
|----|---|---|
| M1 | 3 | 1 |
| M2 | 1 | 2 |
| M3 | 1 | 4 |
| M4 | 3 | 1 |
| M5 | 1 | 3 |

| |  Comedy |  Action |
|---|---|--|
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |

=

| | M1 | M2 | M3 | M4 | M5 |
|--|----|----|----|----|----|
|  | 3 | 1 | 1 | 3 | 1 |
|  | 1 | 2 | 4 | 1 | 3 |
|  | 3 | 1 | 1 | 3 | 1 |
|  | 4 | 3 | 5 | 4 | 4 |



Matrix Factorization







| | M1 | M2 | M3 | M4 | M5 |
|--------|----|----|----|----|----|
| Comedy | 3 | 1 | 1 | 3 | 1 |
| Action | 1 | 2 | 4 | 1 | 3 |

| | Comedy | Action |
|---|--------|--------|
| A | ✓ | ✗ |
| B | ✗ | ✓ |
| C | ✓ | ✗ |
| D | ✓ | ✓ |

| | M1 | M2 | M3 | M4 | M5 |
|---|----|----|----|----|----|
| A | 3 | 1 | 1 | 3 | 1 |
| B | 1 | 2 | 4 | 1 | 3 |
| C | 3 | 1 | 1 | 3 | 1 |
| D | 4 | 3 | 5 | 4 | 4 |

Matrix Factorization

| | M1 | M2 | M3 | M4 | M5 |
|---|----|----|----|----|----|
|  Comedy | 3 | 1 | 1 | 3 | 1 |
|  Action | 1 | 2 | 4 | 1 | 3 |

| |  Comedy |  Action |
|--|---|---|
|  A | 1 | 0 |
|  B | 0 | 1 |
|  C | 1 | 0 |
|  D | 1 | 1 |

| | M1 | M2 | M3 | M4 | M5 |
|---|----|----|----|----|----|
|  | 3 | 1 | 1 | 3 | 1 |
|  | 1 | 2 | 4 | 1 | 3 |
|  | 3 | 1 | 1 | 3 | 1 |
|  | 4 | 3 | 5 | 4 | 4 |



1000
Movies

2000 Users

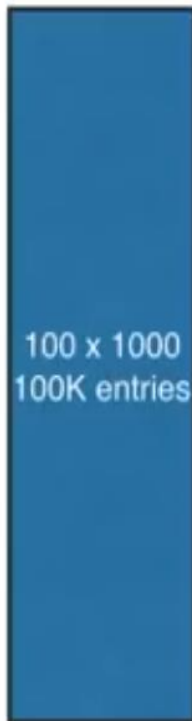
Matrix Factorization

2000 Users



100
Features

1000
Movies







100 Features



1000
Movies

2000 Users

| | M1 | M2 | M3 | M4 | M5 |
|----|-----|-----|-----|-----|-----|
| F1 | 1.2 | 3.1 | 0.3 | 2.5 | 0.2 |
| F2 | 2.4 | 1.5 | 4.4 | 0.4 | 1.1 |

| | F1 | F2 |
|---|-----|-----|
|  A | 0.2 | 0.5 |
|  B | 0.3 | 0.4 |
|  C | 0.7 | 0.8 |
|  D | 0.4 | 0.5 |

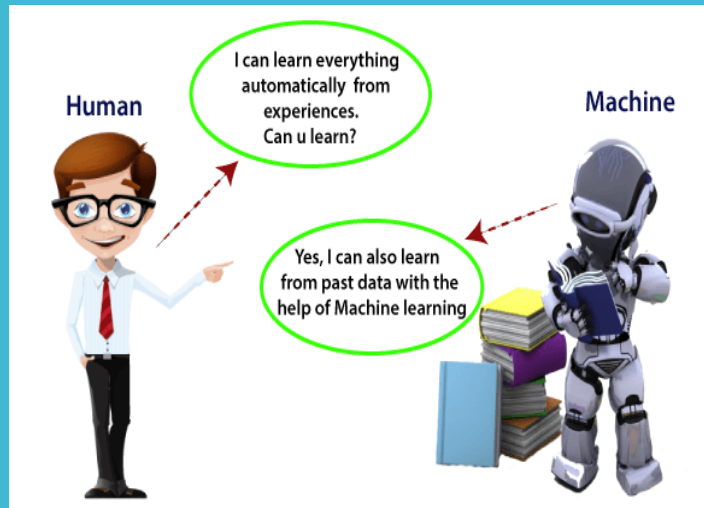
| | M1 | M2 | M3 | M4 | M5 |
|---|------|------|------|------|------|
|  | 1.44 | 1.37 | 2.26 | 0.7 | 0.59 |
|  | 1.32 | 1.53 | 1.85 | 0.91 | 0.5 |
|  | 2.76 | 3.37 | 3.73 | 2.07 | 1.02 |
|  | 1.68 | 1.99 | 2.32 | 1.2 | 0.63 |

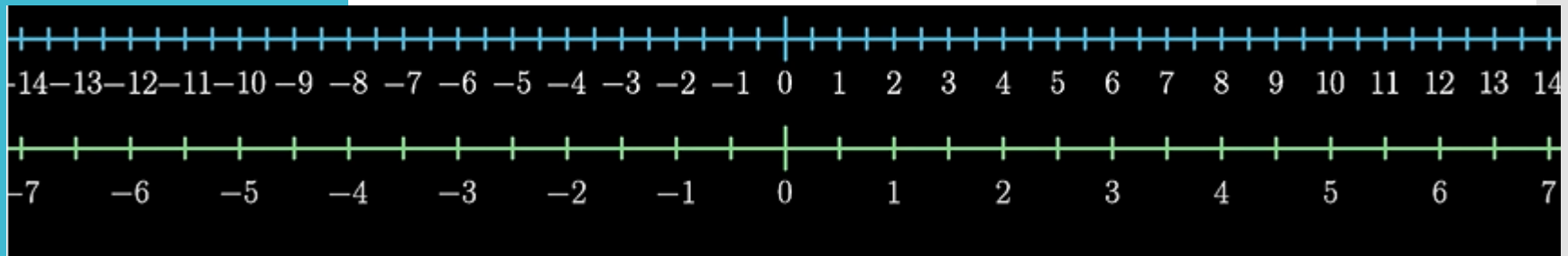
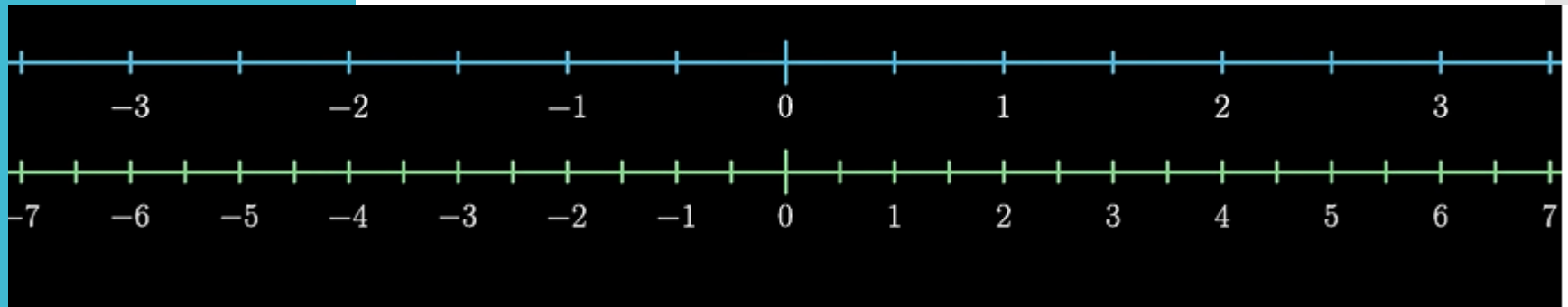
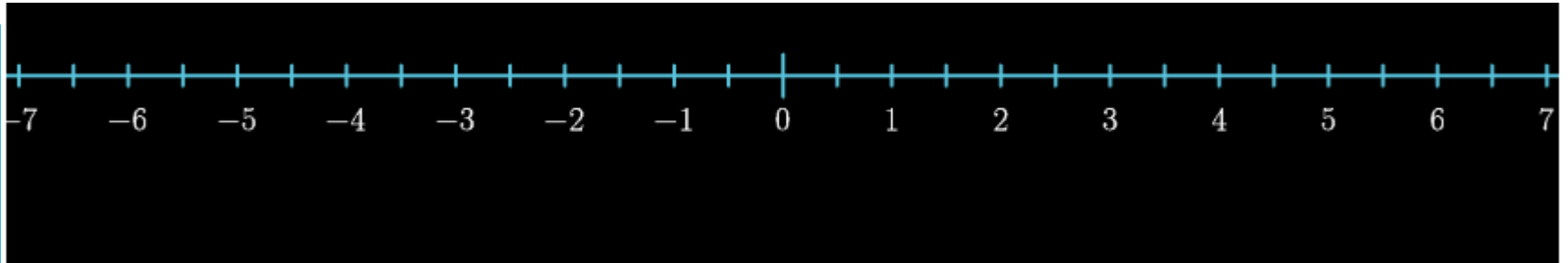
| | M1 | M2 | M3 | M4 | M5 |
|----|----|----|----|----|----|
| F1 | 3 | 1 | 1 | 3 | 1 |
| F2 | 1 | 2 | 4 | 1 | 3 |

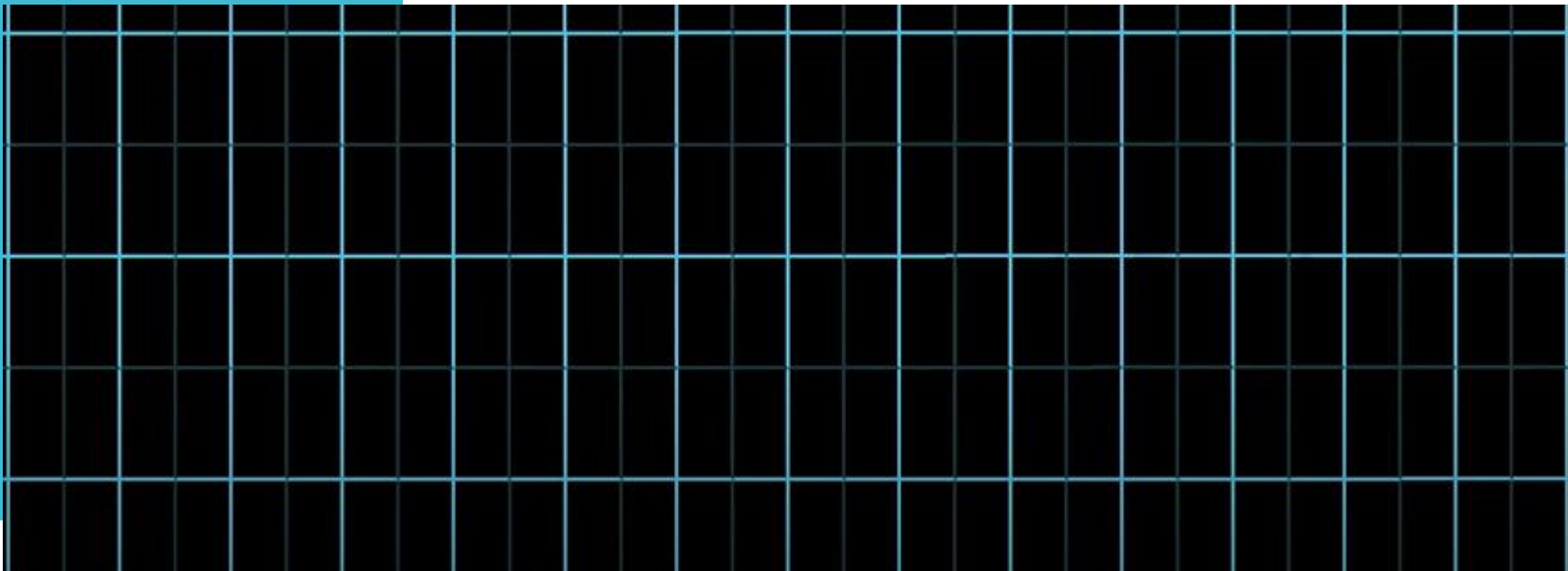
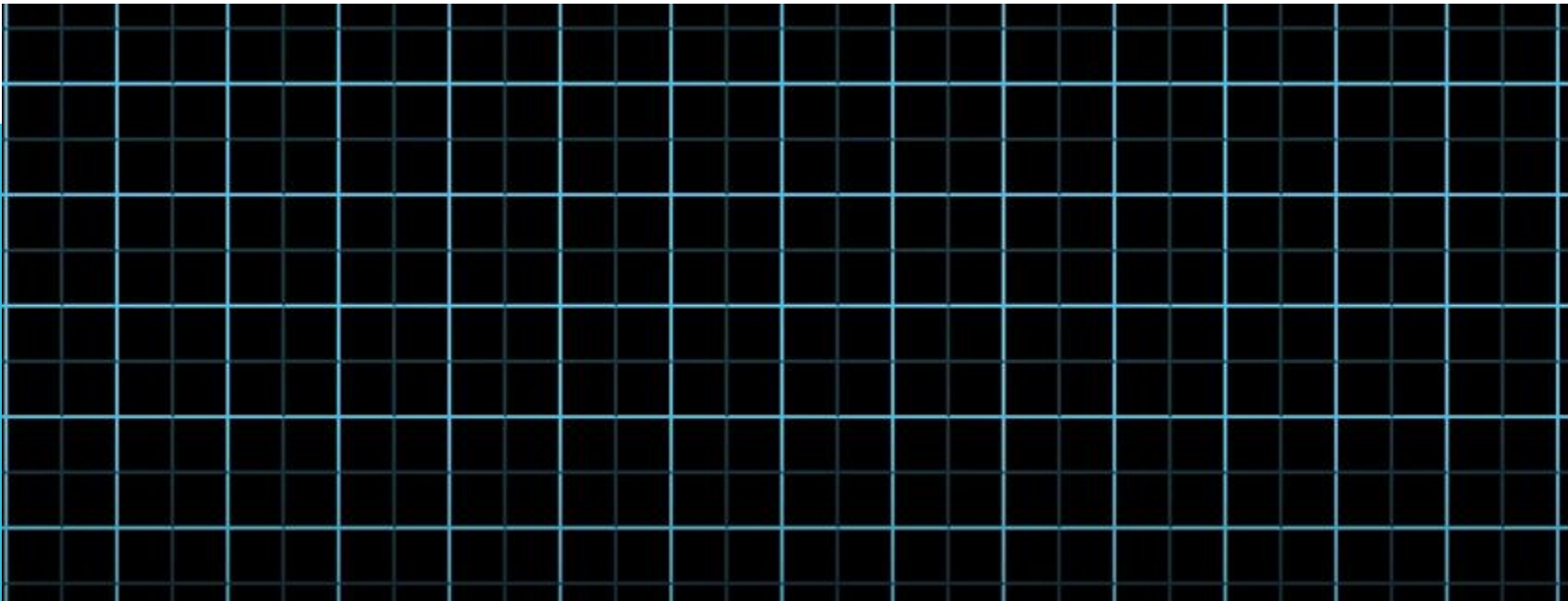
| | F1 | F2 |
|---|----|----|
| A | 1 | 0 |
| B | 0 | 1 |
| C | 1 | 0 |
| D | 1 | 1 |

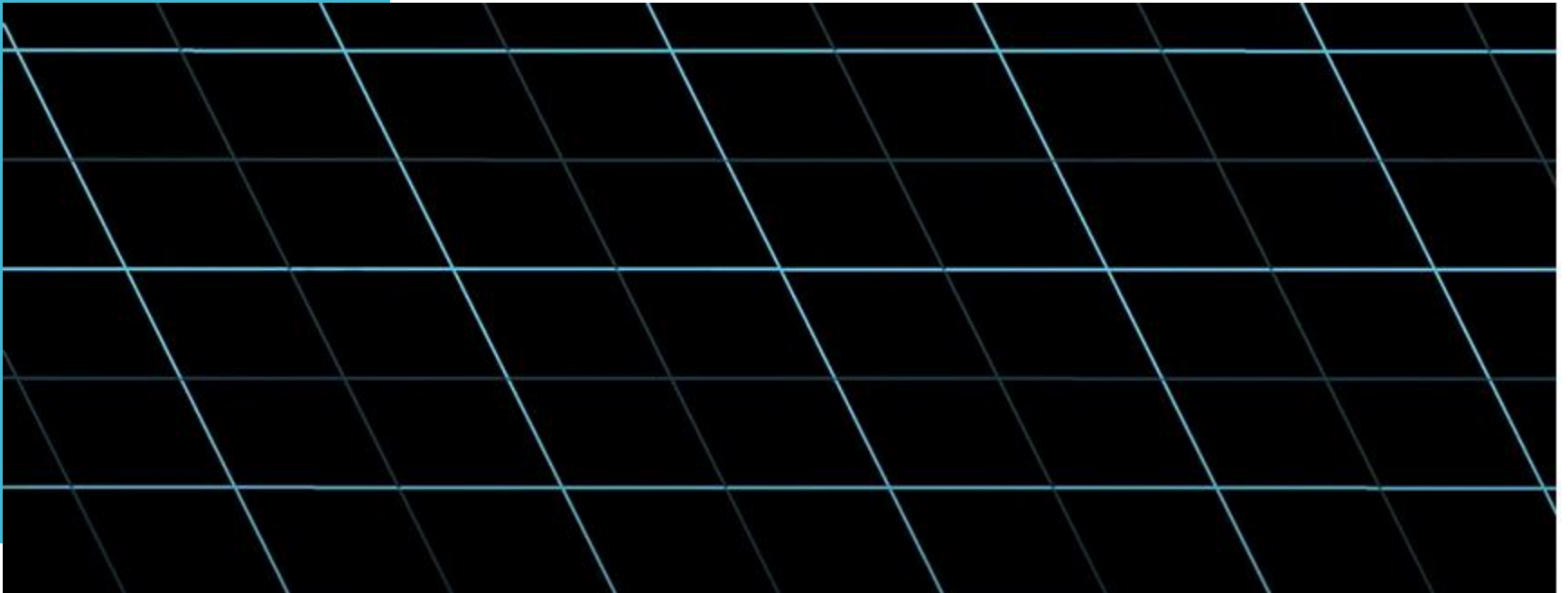
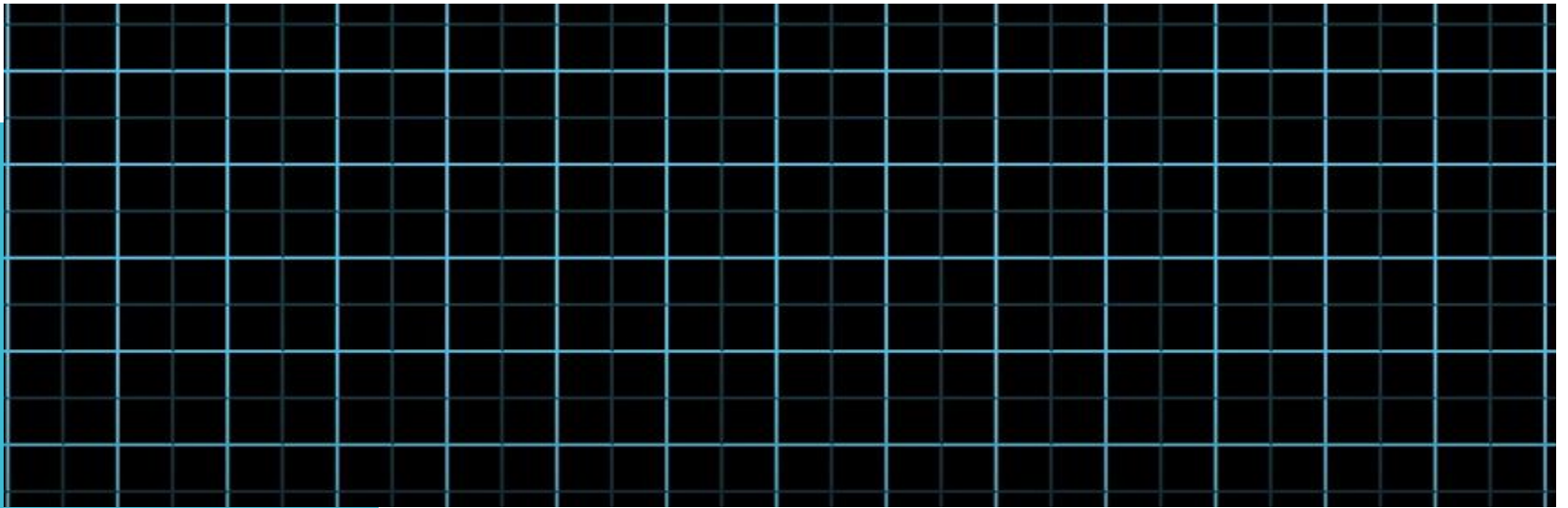
| | M1 | M2 | M3 | M4 | M5 |
|---|----|----|----|----|----|
| A | 3 | | 1 | | 1 |
| B | 1 | | 4 | 1 | |
| C | 3 | 1 | | 3 | 1 |
| D | | 3 | | 4 | 4 |

Linear Transformation







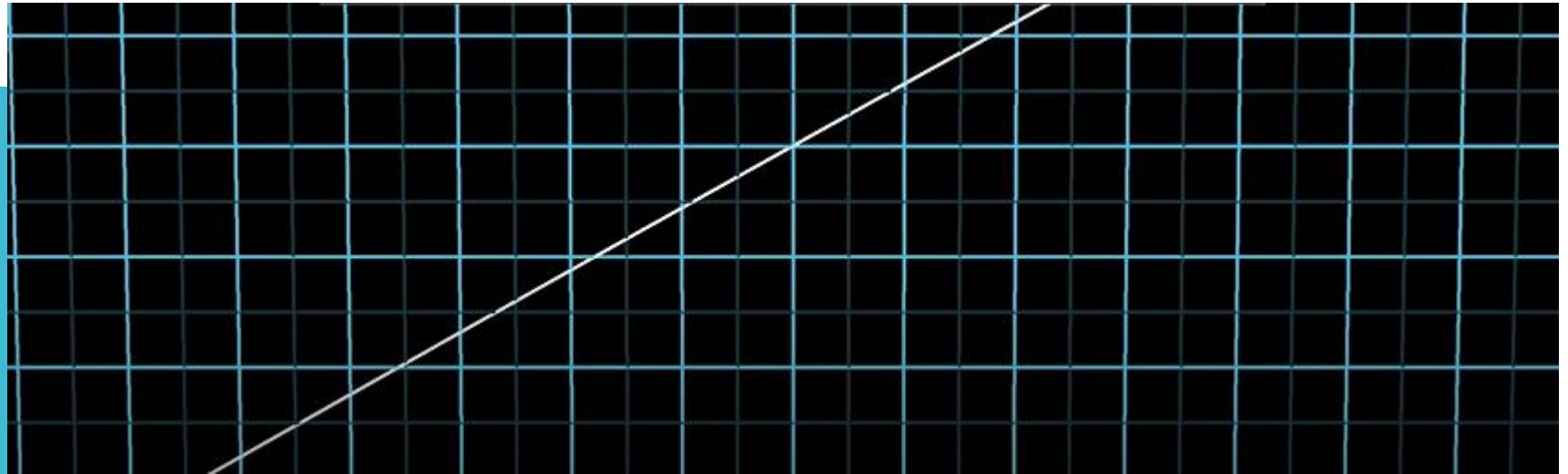


Linearity Property

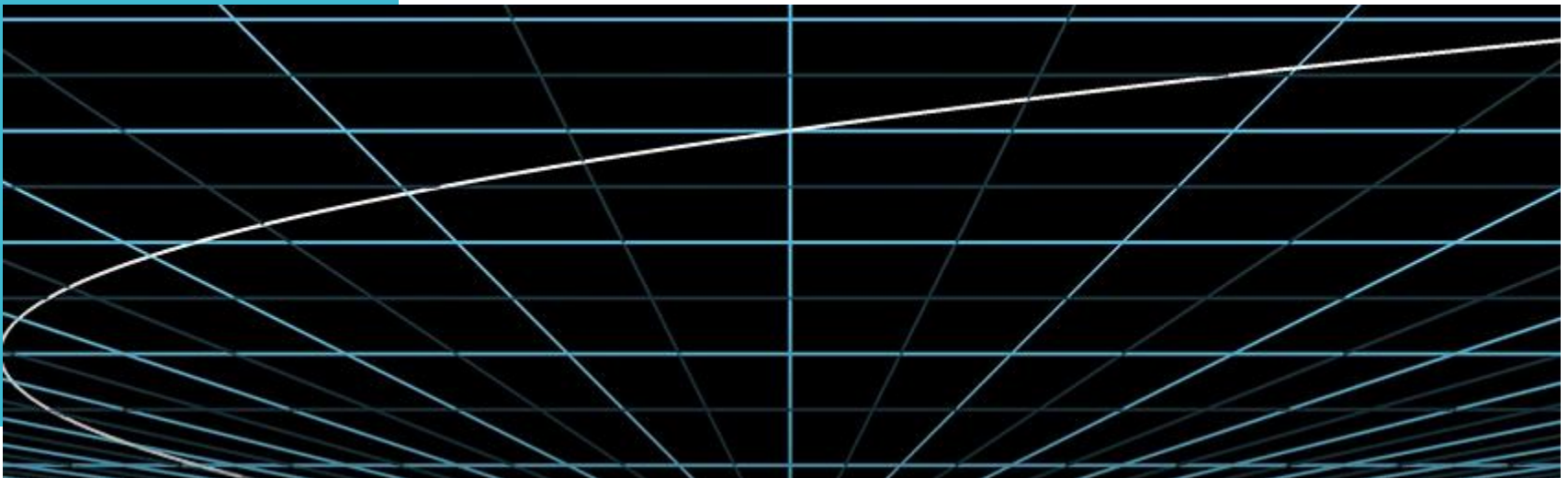
what makes a transformation linear is the following geometric rule: The *origin must remain fixed*, and *all lines must remain lines*.

$$f(\mathbf{v} + \mathbf{w}) = f(\mathbf{v}) + f(\mathbf{w})$$

$$f(c\mathbf{v}) = cf(\mathbf{v})$$



Non-Linear Transformation



<https://youtu.be/XUwg5PFP1RE>

2-D Linear Transformation

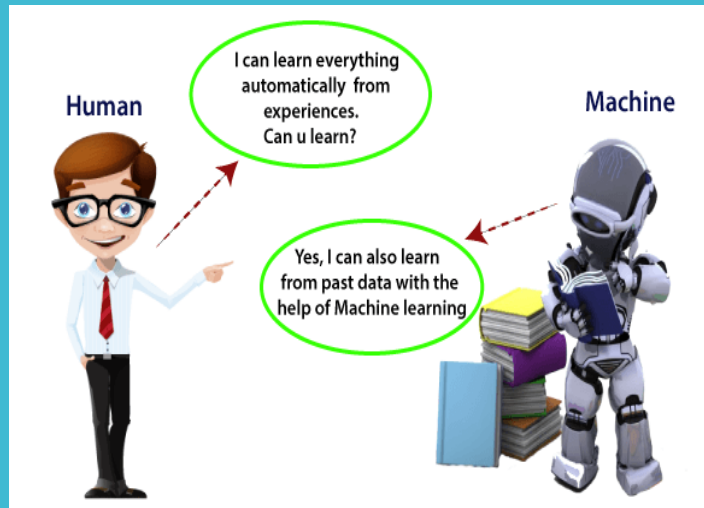
$$\mathbf{A} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

In this matrix, the first *column* tells us where $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$ lands, and the second *column* tells us where $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$ lands. Now we can describe where any vector

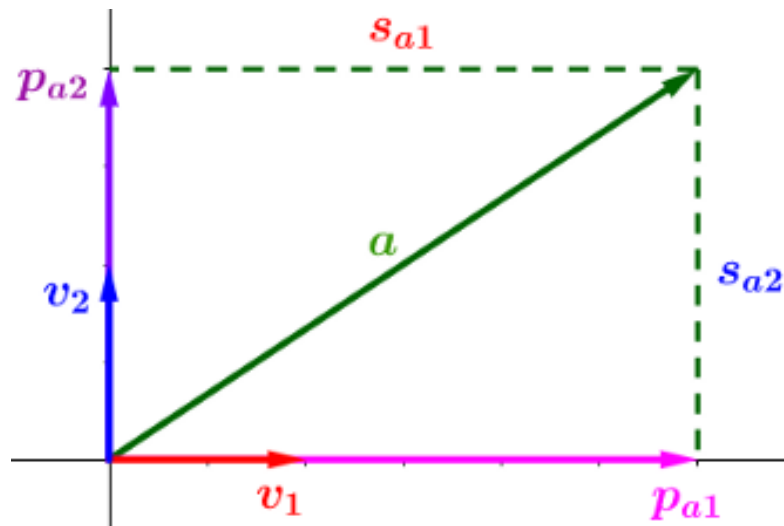
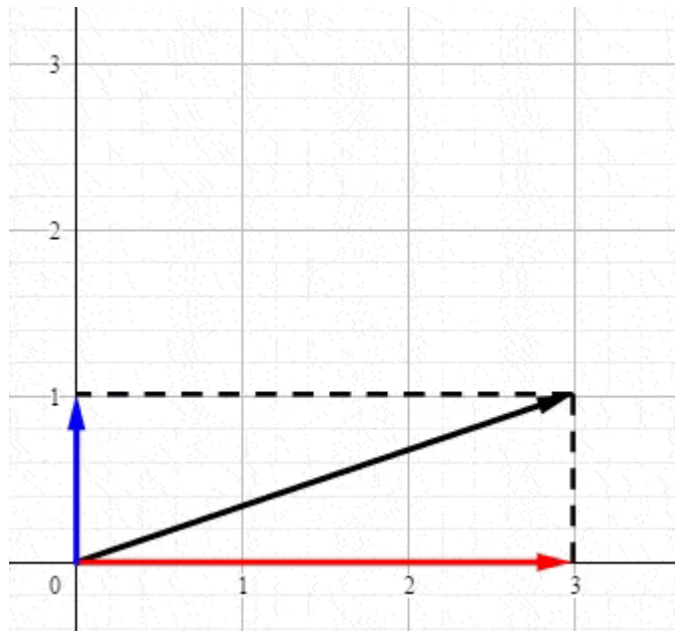
$\mathbf{v} = \begin{bmatrix} x \\ y \end{bmatrix}$ lands very compactly as the matrix-vector product

$$\mathbf{A}\mathbf{v} = \begin{bmatrix} ax + by \\ cx + dy \end{bmatrix}.$$

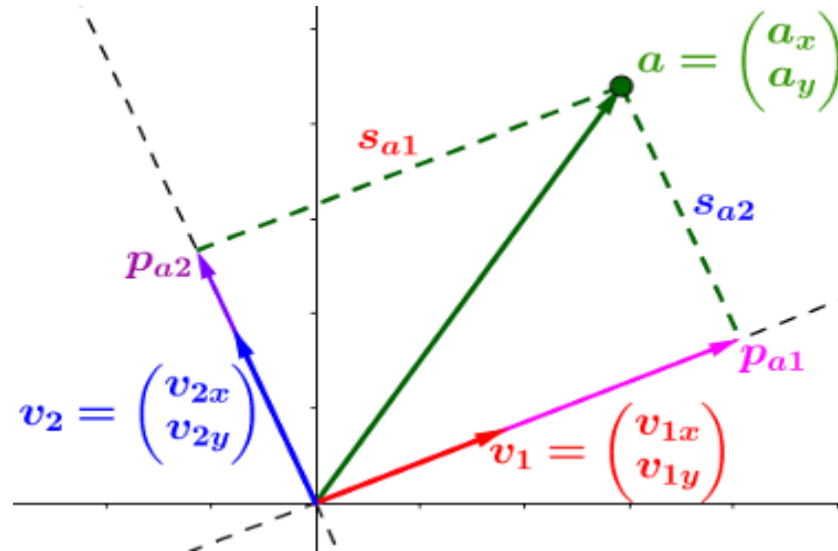
Singular Value Decomposition



SVD Projection



SVD Projection



Projecting a on v_1 and v_2

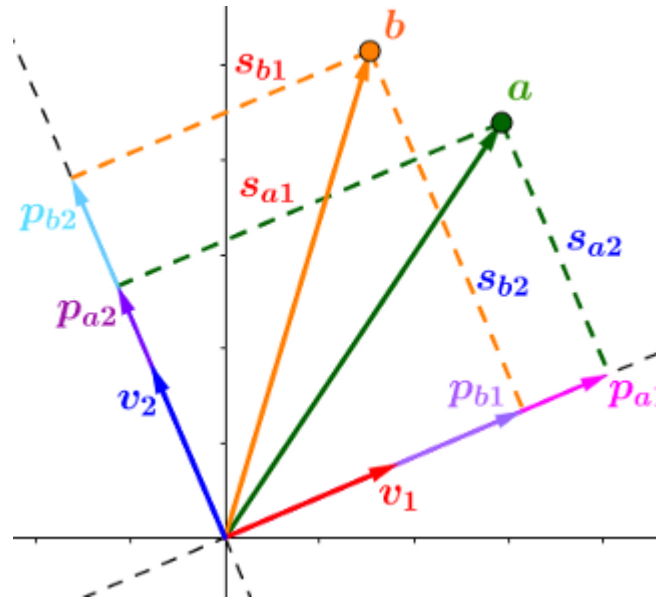
$$a^T \cdot v_1 = (a_x \ a_y) \cdot \begin{pmatrix} v_{1x} \\ v_{1y} \end{pmatrix} = s_{a1}$$

$$a^T \cdot v_2 = (a_x \ a_y) \cdot \begin{pmatrix} v_{2x} \\ v_{2y} \end{pmatrix} = s_{a2}$$

Combining both the axis projections, v_1 and v_2 :

$$a^T \cdot V = (a_x \ a_y) \cdot \begin{pmatrix} v_{1x} & v_{2x} \\ v_{1y} & v_{2y} \end{pmatrix} = (s_{a1} \ s_{a2})$$

SVD Projection



$$a^T \cdot v_1 = \begin{pmatrix} a_x & a_y \end{pmatrix} \begin{pmatrix} v_{1x} \\ v_{1y} \end{pmatrix} = \begin{pmatrix} s_{a1} \end{pmatrix}$$

$$A \cdot V = \begin{pmatrix} a_x & a_y \\ b_x & b_y \end{pmatrix} \cdot \begin{pmatrix} v_{1x} & v_{2x} \\ v_{1y} & v_{2y} \end{pmatrix} = \begin{pmatrix} s_{a1} & s_{a2} \\ s_{b1} & s_{b2} \end{pmatrix} = S$$

SVD Projection

$$A \cdot V = S$$

Diagram illustrating the SVD equation $A \cdot V = S$ with annotations:

- A : Matrix of points
- \cdot : The dot product performs the projection
- V : Matrix of decomposition axes
- S : Matrix of the lengths of projections

Because V contains orthonormal columns, its inverse = its transpose (property of orthogonal matrices).

$$A = S V^{-1} = S V^T$$

Any set of vectors (A) can be expressed in terms of their lengths of projections (S) on some set of orthogonal axes (V).

SVD Projection

$$S = \begin{pmatrix} s_{a1} & s_{a2} \\ s_{b1} & s_{b2} \end{pmatrix}$$

$$\text{Magnitude of 1st column} = \sigma_1 = \sqrt{(s_{a1})^2 + (s_{b1})^2}$$

$$\text{Magnitude of 2nd column} = \sigma_2 = \sqrt{(s_{a2})^2 + (s_{b2})^2}$$

$$S = \begin{pmatrix} \frac{s_{a1}}{\sigma_1} & \frac{s_{a2}}{\sigma_2} \\ \frac{s_{b1}}{\sigma_1} & \frac{s_{b2}}{\sigma_2} \end{pmatrix} \begin{pmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{pmatrix} = \begin{pmatrix} u_{a1} & u_{a2} \\ u_{b1} & u_{b2} \end{pmatrix} \begin{pmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{pmatrix}$$

$\downarrow \qquad \qquad \downarrow$
 $U \qquad \qquad \Sigma$

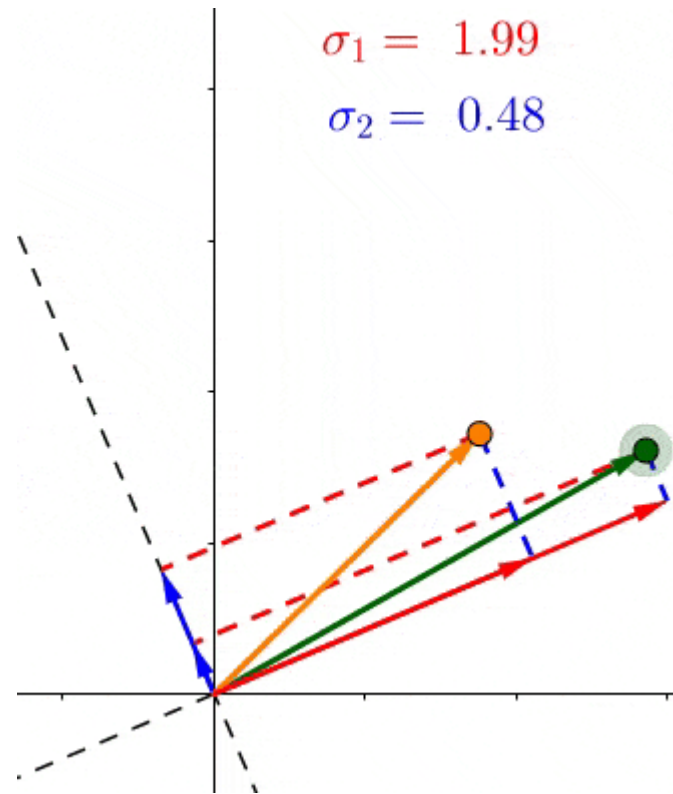
SVD Projection

$$A \cdot V = S$$

Matrix of points The dot product performs the projection Matrix of decomposition axes Matrix of the lengths of projections

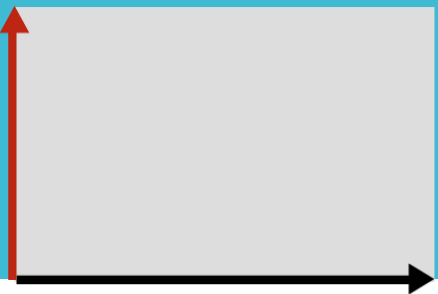
$$A = U \Sigma V^T$$

SVD Projection



SVD in Recommendation System

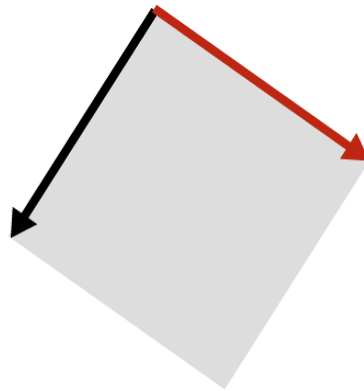
A



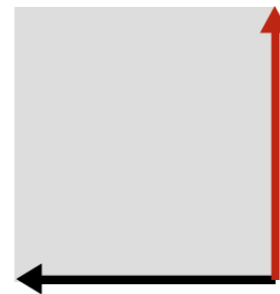
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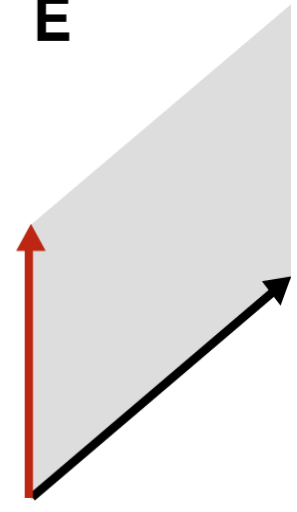
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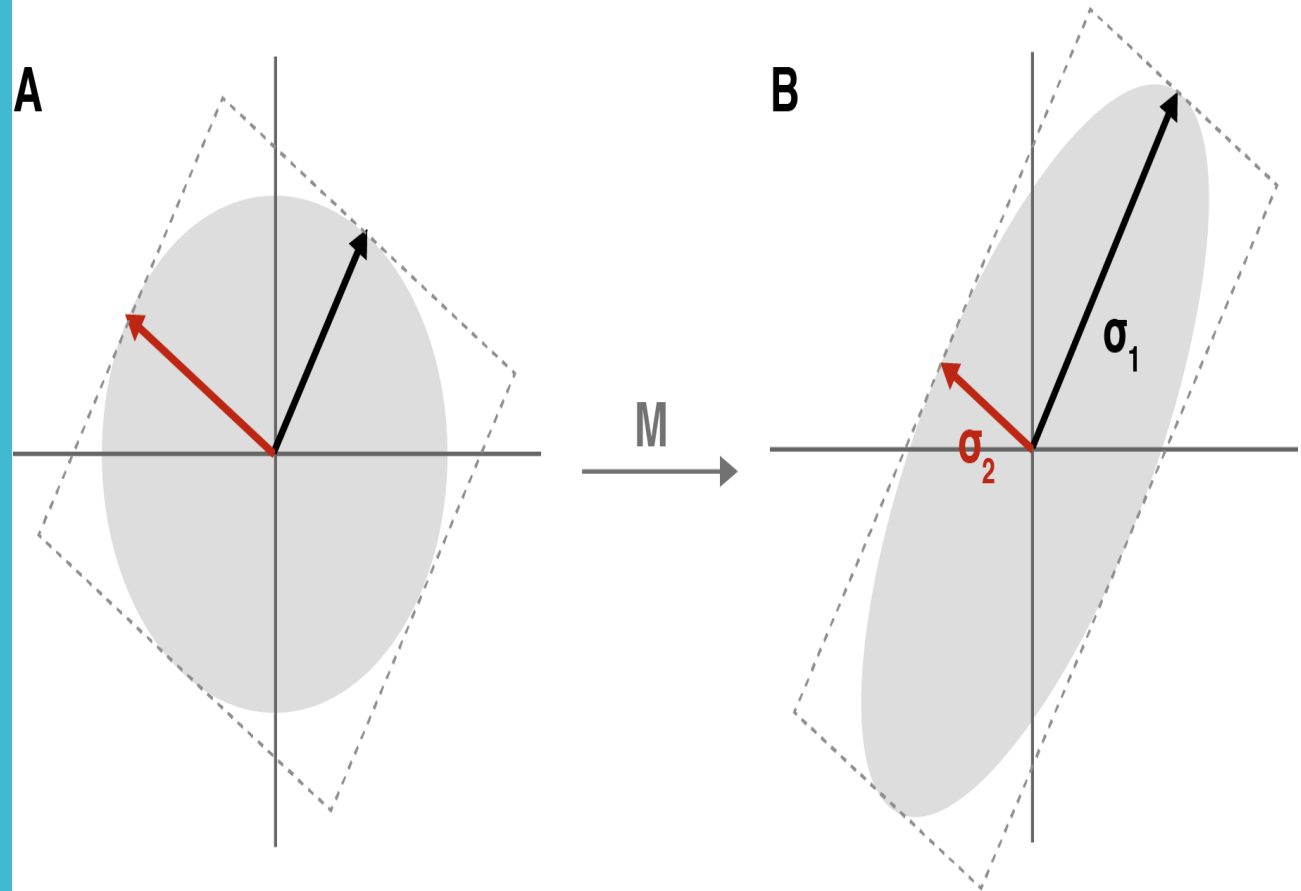
D



E



SVD in Recommendation System



SVD in Recommendation System

The factorisation of this matrix is done by the singular value decomposition. It finds factors of matrices from the factorisation of a high-level (user-item-rating) matrix.

The singular value decomposition is a method of decomposing a matrix into three other matrices.

$$A = USV^T$$

Where A is a $m \times n$ utility matrix,

U is a $m \times r$ orthogonal left singular matrix, which represents the relationship between users and latent factors,

S is a $r \times r$ diagonal matrix, which describes the strength of each latent factor and

V is a $r \times n$ diagonal right singular matrix, which indicates the similarity between items and latent factors.

Recommendation System

Refer Apply Recommendation.ipynb

| | Harry Potter | Star Wars | Tomb Raider |
|--------|--------------|-----------|-------------|
| User 1 | 3 | 1 | |
| User 2 | 3 | | 4 |
| User 3 | 1 | 4 | |
| User 4 | | 2 | 1 |