Dimensionality Reduction

UV Decomposition
Singular-Value Decomposition
CUR Decomposition

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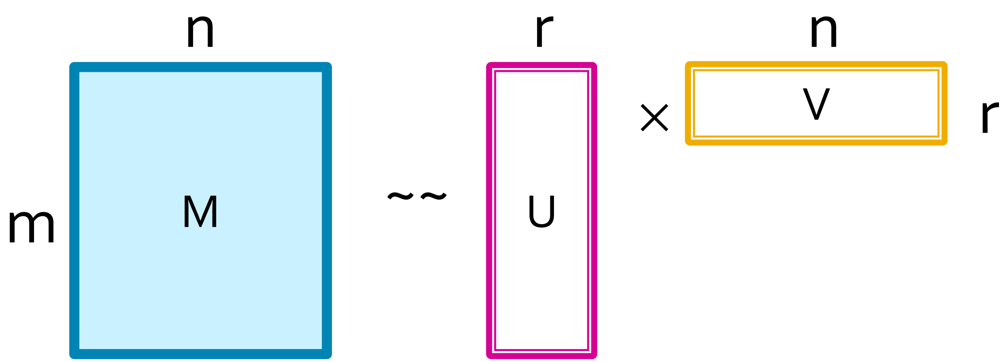
Reducing Matrix Dimension

- Often, our data can be represented by an m-by-n matrix.
- And this matrix can be closely approximated by the product of two matrices that share a small common dimension r.

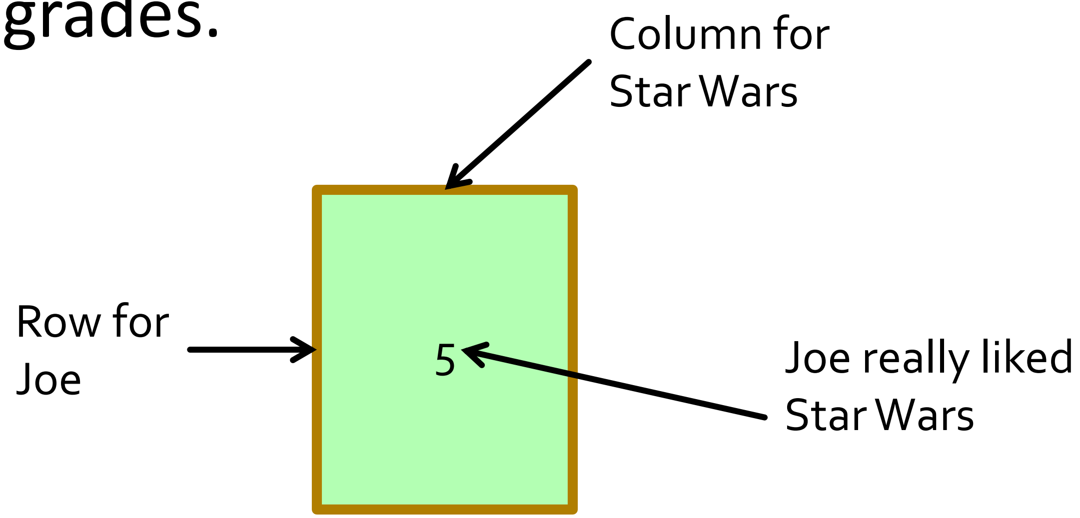


Why Is That Even Possible?

- There are hidden, or *latent* factors that – to a close approximation – explain why the values are as they appear in the matrix.
- Two kinds of data may exhibit this behavior:
  1. Matrices representing a many-many-relationship.
  2. Matrices that are really a relation (as in a relational database).

Matrices as Relationships

- Our data can be a many-many relationship in the form of a matrix.
  - Example: people vs. movies; matrix entries are the ratings given to the movies by the people.
  - Example: students vs. courses; entries are the grades.



Matrices as Relationships – (2)

- Often, the relationship can be explained closely by latent factors.
  - Example: genre of movies or books.
    - I.e., Joe liked Star Wars because Joe likes science-fiction, and Star Wars is a science-fiction movie.
  - Example: good at math?

Matrices as Relational Data

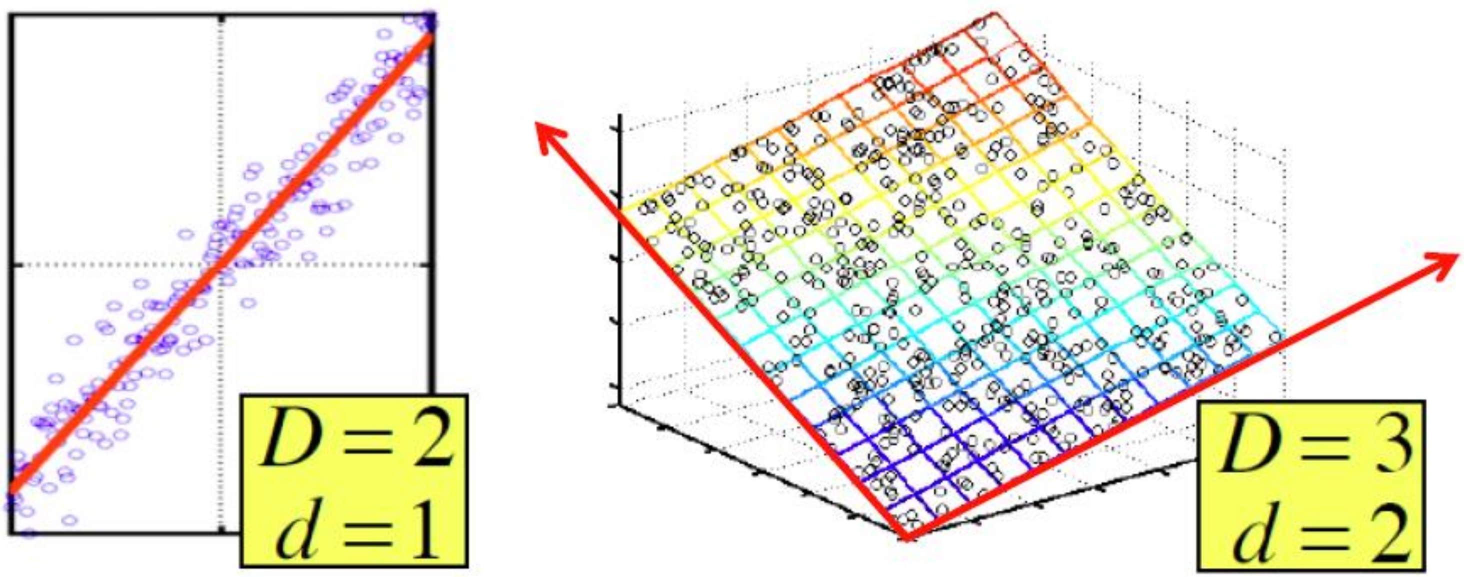
- Another closely related form of data is a collection of rows (tuples), each representing one entity.
- Columns represent attributes of these entities.
- Example: Stars can be represented by their mass, brightness in various color bands, diameter, and several other properties.
- But it turns out that there are only two independent variables (latent factors): mass and age.

Example: Stars

Star	Mass	Luminosity	Color	Age
Sun	1.0	1.0	Yellow	4.6B
Alpha Centauri	1.1	1.5	Yellow	5.8B
Sirius A	2.0	25	White	0.25B

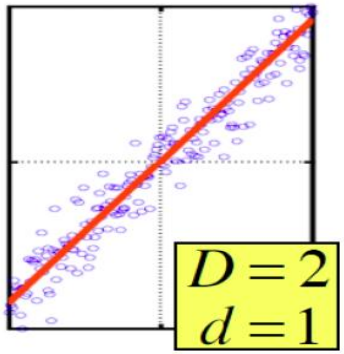
The matrix

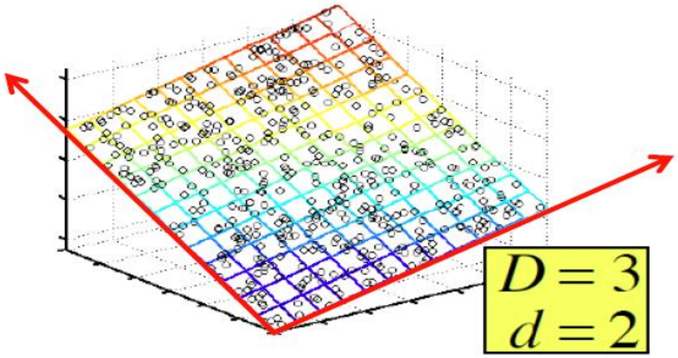
D-Dimensional Data Lying Close to a d-Dimensional Subspace



Intuition

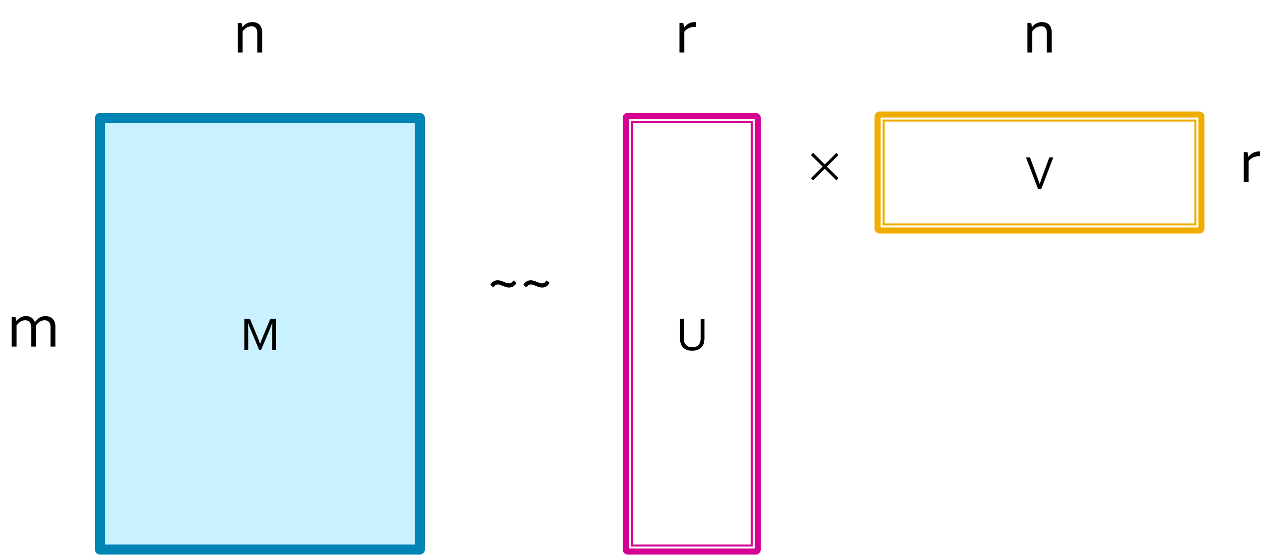
- The axes of the subspace can be chosen by:
  - The first dimension is the direction in which the points exhibit the greatest variance.
  - The second dimension is the direction, orthogonal to the first, in which points show the greatest variance.
  - And so on…, until you have “enough” dimensions.





UV Decomposition

- The simplest form of matrix decomposition is to find a pair of matrixes, the first (U) with few columns and the second (V) with few rows, whose product is close to the given matrix M.



Latent Factors

- This decomposition works well if r is the number of “hidden factors” that explain the matrix M.
- Example: m_{ij} is the rating person i gives to movie j; u_{ik} measures how much person i likes genre k; v_{kj} measures the extent to which movie j belongs to genre k.

Measuring the Error

- Common way to evaluate how well P = UV approximates M is by *RMSE* (root-mean-square error).
- Average $(m_{ij} – p_{ij})^2$ over all i and j.
- Take the square root.
  - Square-rooting changes the scale of error, but doesn't really effect which choice of U and V is best.

Example: RMSE

$$M = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \qquad U = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \qquad V = \begin{bmatrix} 1 & 2 \end{bmatrix} \qquad P = \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$$

RMSE = sqrt((0+0+1+0)/4) sqrt(0.25) = 0.5

$$M = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \qquad U = \begin{bmatrix} 1 \\ 3 \end{bmatrix} \qquad V = \begin{bmatrix} 1 & 2 \end{bmatrix} \qquad P = \begin{bmatrix} 1 & 2 \\ 3 & 6 \end{bmatrix}$$

RMSE = sqrt((0+0+0+4)/4) sqrt(1.0) = 1.0

Optimizing U and V

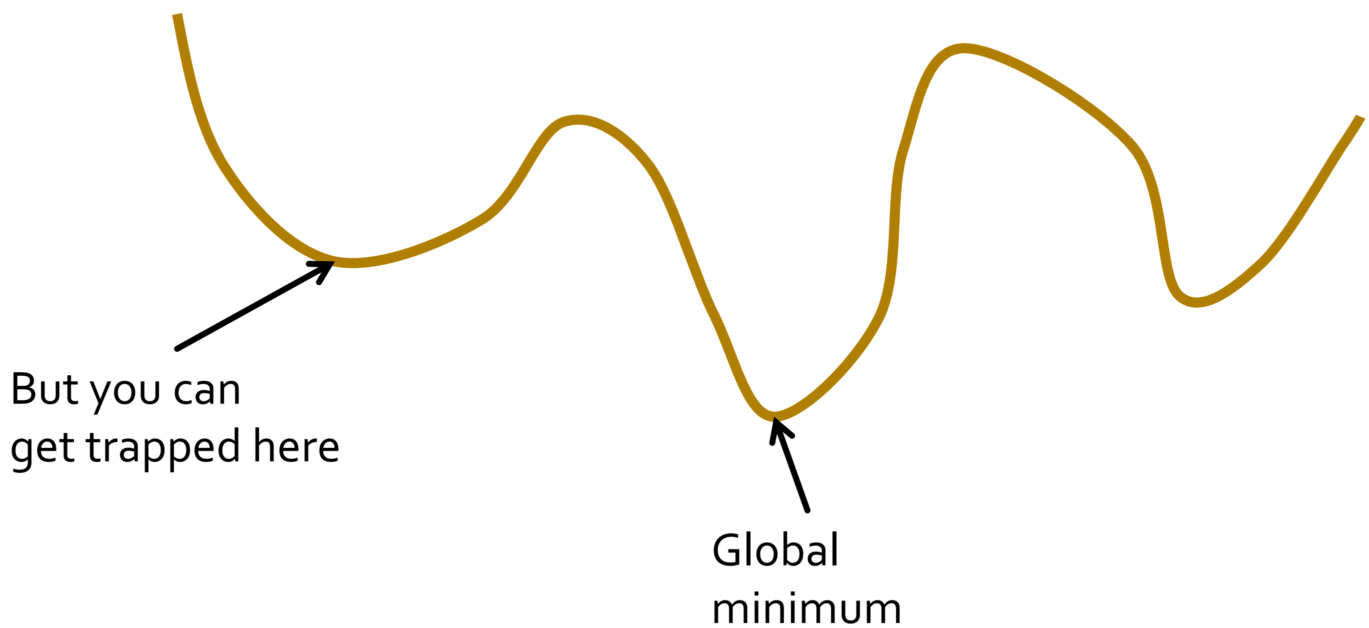
- Pick r, the number of latent factors.
- Think of U and V as composed of variables, u_{ik} and v_{kj}.
- Express the RMSE as (the square root of)

$$E = \Sigma_{ij} (m_{ij} - \Sigma_k u_{ik} v_{kj})^2.$$

- *Gradient descent*: repeatedly find the derivative of E with respect to each variable and move each a small amount in the direction that lowers the value of E.
  - Many options – more later in the course.

Local Versus Global Minima

- Expressions like this usually have many minima.
- Seeking the nearest minimum from a starting point can trap you in a local minimum, from which no small improvement is possible.



Avoiding Local Minima

- Use many different starting points, chosen at random, in the hope that one will be close enough to the global minimum.
- *Simulated annealing*: occasionally try a leap to someplace further away in the hope of getting out of the local trap.
  - Intuition: the global minimum might have many nearby local minima.
    - As Mt. Everest has most of the world's tallest mountains in its vicinity.

Application: Recommendations

- UV decomposition can be used even when the entire matrix M is not known.
- Example: recommendation systems, where M represents known ratings of movies (e.g.) by people.
- Jure will cover recommendation systems next week.

Singular-Value Decomposition

- Rank of a Matrix
- Orthonormal Bases
- Eigenvalues/Eigenvectors
- Computing the Decomposition
- Eliminating Dimensions

Why SVD?

- Gives a decomposition of any matrix into a product of three matrices.
- There are strong constraints on the form of each of these matrices.
  - Results in a decomposition that is essentially unique.
- From this decomposition, you can choose any number r of intermediate concepts (latent factors) in a way that minimizes the RMSE error given that value of r.

Rank of a Matrix

- The *rank* of a matrix is the maximum number of rows (or equivalently columns) that are linearly independent.
  - I.e., no nontrivial sum is the all-zero vector.
- Example: No two rows dependent.
  - One would have to be a multiple of the other.
- But **any** 3 rows are dependent.
  - Example: First + third – twice the second = [0,0,0].
- Similarly, the 3 columns are dependent.
- Therefore, rank = 2.

1	2	3
4	5	6
7	8	9
10	11	12

Important Fact About Rank

- If a matrix has rank r, then it can be decomposed exactly into matrices whose shared dimension is r.
- Example, in Sect. 11.3 of MMDS, of a 7-by-5 matrix with rank 2 and an exact decomposition into a 7-by-2 and a 2-by-5 matrix.

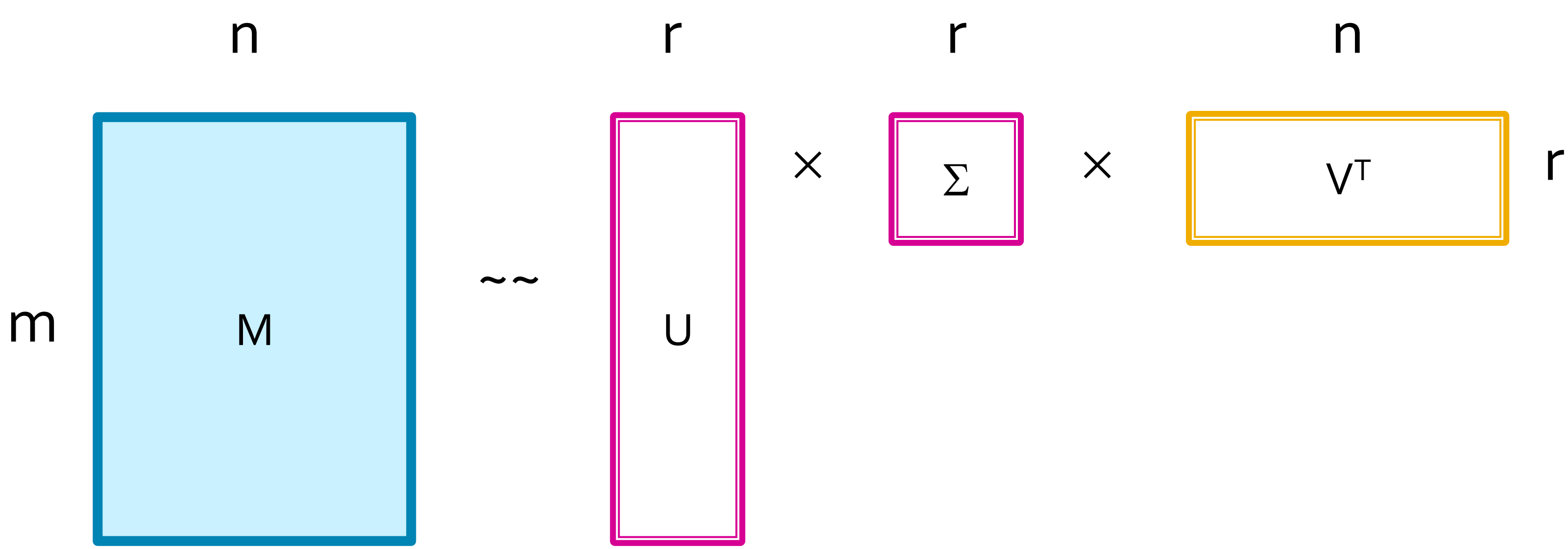
Orthonormal Bases

- Vectors are *orthogonal* if their dot product is 0.
- Example: [1,2,3].[1,-2,1] = 0, so these two vectors are orthogonal.
- A *unit vector* is one whose length is 1.
  - *Length* = square root of sum of squares of components.
    - No need to take square root if we are looking for length = 1.
- Example: [0.8, -0.1, 0.5, -0.3, 0.1] is a unit vector, since 0.64 + 0.01 + 0.25 + 0.09 + 0.01 = 1.
- An *orthonormal basis* is a set of unit vectors any two of which are orthogonal.

Example: Columns Are Orthonormal

$3/\sqrt{116}$	$1/2$	$7/\sqrt{116}$	$1/2$
$3/\sqrt{116}$	$-1/2$	$7/\sqrt{116}$	$-1/2$
$7/\sqrt{116}$	$1/2$	$-3/\sqrt{116}$	$-1/2$
$7/\sqrt{116}$	$-1/2$	$-3/\sqrt{116}$	$1/2$

Form of SVD



Special conditions:

U and V are column-orthonormal
(so V^T has orthonormal rows)

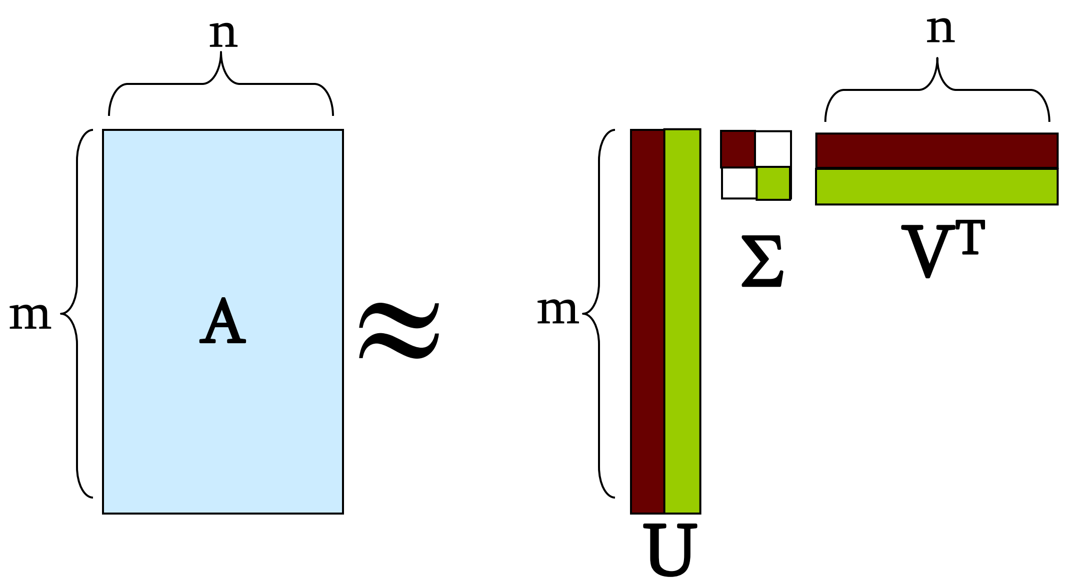
Σ is a diagonal matrix

Facts About SVD

- The values of Σ along the diagonal are called the *singular values*.
- It is always possible to decompose M exactly, if r is the rank of M.
- But usually, we want to make r much smaller, and we do so by setting to 0 the smallest singular values.
  - Which has the effect of making the corresponding columns of U and V useless, so they may as well not be there.

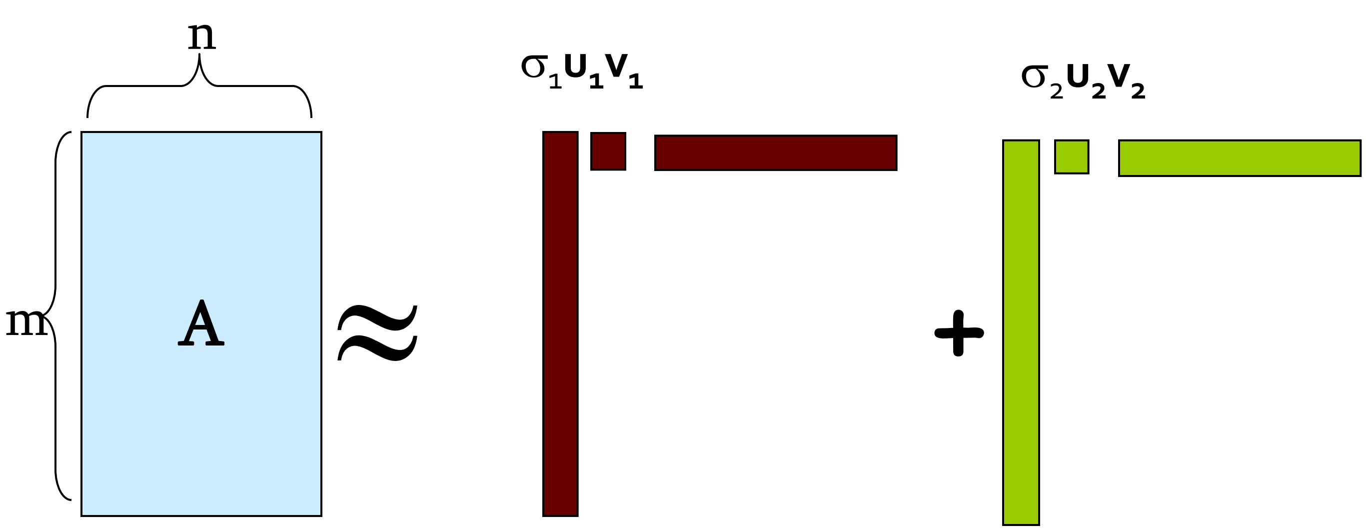
Linkage Among Components of U, V, Σ

$$\mathbf{A} \approx \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T = \sum_i \sigma_i \mathbf{u}_i \circ \mathbf{v}_i^{\mathrm{T}}$$



Each Singular Value Affects One Column of U and V

$$\mathbf{A} \approx \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T = \sum_i \sigma_i \mathbf{u}_i \circ \mathbf{v}_i^{\mathrm{T}}$$



If we set $\sigma_2 = 0$, then the green columns may as well not exist.

σ_i … scalar
u_i … vector
v_i … vector

Jure's Example Decomposition

- The following is Example 11.9 from MMDS.
- It modifies the simpler Example 11.8, where a rank-2 matrix can be decomposed exactly into a 7-by-2 U and a 5-by-2 V.

Example: Users-to-Movies

- $A = U\,\Sigma\,V^T$ - example: **Users to Movies**

$$
\begin{array}{cc}
 & \begin{matrix}\text{Matrix} & \text{Alien} & \text{Serenity} & \text{Casablanca} & \text{Amelie}\end{matrix} \\
\begin{matrix}\uparrow\\ \text{SciFi}\\ \downarrow\\ \\ \uparrow\\ \text{Romnce}\\ \downarrow\end{matrix} &
\begin{bmatrix}
\mathbf{1} & \mathbf{1} & \mathbf{1} & 0 & 0 \\
\mathbf{3} & \mathbf{3} & \mathbf{3} & 0 & 0 \\
\mathbf{4} & \mathbf{4} & \mathbf{4} & 0 & 0 \\
\mathbf{5} & \mathbf{5} & \mathbf{5} & 0 & 0 \\
0 & \mathbf{2} & 0 & \mathbf{4} & \mathbf{4} \\
0 & 0 & 0 & \mathbf{5} & \mathbf{5} \\
0 & \mathbf{1} & 0 & \mathbf{2} & \mathbf{2}
\end{bmatrix}
\end{array}
=
\begin{bmatrix}
\mathbf{0.13} & 0.02 & -0.01 \\
\mathbf{0.41} & 0.07 & -0.03 \\
\mathbf{0.55} & 0.09 & -0.04 \\
\mathbf{0.68} & 0.11 & -0.05 \\
0.15 & \mathbf{-0.59} & \mathbf{0.65} \\
0.07 & \mathbf{-0.73} & \mathbf{-0.67} \\
0.07 & \mathbf{-0.29} & \mathbf{0.32}
\end{bmatrix}
\times
\begin{bmatrix}
\mathbf{12.4} & 0 & 0 \\
0 & \mathbf{9.5} & 0 \\
0 & 0 & \mathbf{1.3}
\end{bmatrix}
\times
\begin{bmatrix}
\mathbf{0.56} & \mathbf{0.59} & \mathbf{0.56} & 0.09 & 0.09 \\
0.12 & -0.02 & 0.12 & \mathbf{-0.69} & \mathbf{-0.69} \\
0.40 & \mathbf{-0.80} & 0.40 & 0.09 & 0.09
\end{bmatrix}
$$

Example: Users-to-Movies

- $A = U \Sigma V^T$ - example: **Users to Movies**

$$
\begin{array}{cc}
 & \begin{array}{ccccc} \text{Matrix} & \text{Alien} & \text{Serenity} & \text{Casablanca} & \text{Amelie} \end{array} \\
\begin{array}{c} \\ \\ \text{SciFi} \\ \\ \\ \text{Romnce} \\ \\ \end{array} &
\begin{bmatrix}
\mathbf{1} & \mathbf{1} & \mathbf{1} & 0 & 0 \\
\mathbf{3} & \mathbf{3} & \mathbf{3} & 0 & 0 \\
\mathbf{4} & \mathbf{4} & \mathbf{4} & 0 & 0 \\
\mathbf{5} & \mathbf{5} & \mathbf{5} & 0 & 0 \\
0 & \mathbf{2} & 0 & \mathbf{4} & \mathbf{4} \\
0 & 0 & 0 & \mathbf{5} & \mathbf{5} \\
0 & \mathbf{1} & 0 & \mathbf{2} & \mathbf{2}
\end{bmatrix}
\end{array}
=
\begin{array}{c}
\begin{array}{ccc} \text{SciFi-concept} & \text{Romance-concept} & \end{array} \\
\begin{bmatrix}
\mathbf{0.13} & 0.02 & -0.01 \\
\mathbf{0.41} & 0.07 & -0.03 \\
\mathbf{0.55} & 0.09 & -0.04 \\
\mathbf{0.68} & 0.11 & -0.05 \\
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\end{bmatrix}
\end{array}
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\end{bmatrix}
\times
\begin{bmatrix}
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0.12 & -0.02 & 0.12 & \mathbf{-0.69} & \mathbf{-0.69} \\
0.40 & \mathbf{-0.80} & 0.40 & 0.09 & 0.09
\end{bmatrix}
$$

Example: Users-to-Movies

- $A = U \Sigma V^T$ - example:

U is "user-to-concept" similarity matrix

SciFi-concept

Romance-concept

$$
\begin{array}{c c}
 & \begin{array}{ccccc} \text{Matrix} & \text{Alien} & \text{Serenity} & \text{Casablanca} & \text{Amelie} \end{array} \\
\begin{array}{c} \\ \\ \text{SciFi} \\ \\ \\ \text{Romnce} \\ \\ \end{array} &
\begin{bmatrix}
\mathbf{1} & \mathbf{1} & \mathbf{1} & 0 & 0 \\
\mathbf{3} & \mathbf{3} & \mathbf{3} & 0 & 0 \\
\mathbf{4} & \mathbf{4} & \mathbf{4} & 0 & 0 \\
\mathbf{5} & \mathbf{5} & \mathbf{5} & 0 & 0 \\
0 & \mathbf{2} & 0 & \mathbf{4} & \mathbf{4} \\
0 & 0 & 0 & \mathbf{5} & \mathbf{5} \\
0 & \mathbf{1} & 0 & \mathbf{2} & \mathbf{2}
\end{bmatrix}
\end{array}
=
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\mathbf{0.56} & \mathbf{0.59} & \mathbf{0.56} & 0.09 & 0.09 \\
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0.40 & \mathbf{-0.80} & 0.40 & 0.09 & 0.09
\end{bmatrix}
$$

Example: Users-to-Movies

- $A = U \Sigma V^T$ - example:

SciFi-concept

"strength" of the SciFi-concept

$$
\begin{array}{cc}
 & \begin{array}{ccccc} \text{Matrix} & \text{Alien} & \text{Serenity} & \text{Casablanca} & \text{Amelie} \end{array} \\
\begin{array}{c} \\ \text{SciFi} \\ \\ \\ \\ \text{Romnce} \\ \\ \end{array} &
\begin{bmatrix}
\mathbf{1} & \mathbf{1} & \mathbf{1} & 0 & 0 \\
\mathbf{3} & \mathbf{3} & \mathbf{3} & 0 & 0 \\
\mathbf{4} & \mathbf{4} & \mathbf{4} & 0 & 0 \\
\mathbf{5} & \mathbf{5} & \mathbf{5} & 0 & 0 \\
0 & \mathbf{2} & 0 & \mathbf{4} & \mathbf{4} \\
0 & 0 & 0 & \mathbf{5} & \mathbf{5} \\
0 & \mathbf{1} & 0 & \mathbf{2} & \mathbf{2}
\end{bmatrix}
\end{array}
=
\begin{bmatrix}
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0.15 & \mathbf{-0.59} & \mathbf{0.65} \\
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\end{bmatrix}
\times
\begin{bmatrix}
\mathbf{12.4} & 0 & 0 \\
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\times
\begin{bmatrix}
\mathbf{0.56} & \mathbf{0.59} & \mathbf{0.56} & 0.09 & 0.09 \\
0.12 & -0.02 & 0.12 & \mathbf{-0.69} & \mathbf{-0.69} \\
0.40 & \mathbf{-0.80} & 0.40 & 0.09 & 0.09
\end{bmatrix}
$$

Example: Users-to-Movies

- $A = U \Sigma V^T$ - example:

V is "movie-to-concept" similarity matrix

SciFi-concept

$$
\begin{array}{cc}
 & \begin{array}{ccccc} \text{Matrix} & \text{Alien} & \text{Serenity} & \text{Casablanca} & \text{Amelie} \end{array} \\
\begin{array}{c} \text{SciFi} \\ \\ \\ \\ \text{Romnce} \\ \\ \\ \end{array} &
\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 3 & 3 & 3 & 0 & 0 \\ 4 & 4 & 4 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 2 & 0 & 4 & 4 \\ 0 & 0 & 0 & 5 & 5 \\ 0 & 1 & 0 & 2 & 2 \end{bmatrix}
\end{array}
=
\begin{bmatrix} \mathbf{0.13} & 0.02 & -0.01 \\ \mathbf{0.41} & 0.07 & -0.03 \\ \mathbf{0.55} & 0.09 & -0.04 \\ \mathbf{0.68} & 0.11 & -0.05 \\ 0.15 & \mathbf{-0.59} & \mathbf{0.65} \\ 0.07 & \mathbf{-0.73} & \mathbf{-0.67} \\ 0.07 & \mathbf{-0.29} & \mathbf{0.32} \end{bmatrix}
\times
\begin{bmatrix} \mathbf{12.4} & 0 & 0 \\ 0 & \mathbf{9.5} & 0 \\ 0 & 0 & \mathbf{1.3} \end{bmatrix}
\times
\begin{bmatrix} \mathbf{0.56} & \mathbf{0.59} & \mathbf{0.56} & 0.09 & 0.09 \\ 0.12 & -0.02 & 0.12 & \mathbf{-0.69} & \mathbf{-0.69} \\ 0.40 & \mathbf{-0.80} & 0.40 & 0.09 & 0.09 \end{bmatrix}
$$

SciFi-concept

Lowering the Dimension

- **Q:** **How exactly is dimensionality reduction done?**
- **A: Set smallest singular values to zero**

$$
\begin{bmatrix}
\mathbf{1} & \mathbf{1} & \mathbf{1} & 0 & 0 \\
\mathbf{3} & \mathbf{3} & \mathbf{3} & 0 & 0 \\
\mathbf{4} & \mathbf{4} & \mathbf{4} & 0 & 0 \\
\mathbf{5} & \mathbf{5} & \mathbf{5} & 0 & 0 \\
0 & \mathbf{2} & 0 & \mathbf{4} & \mathbf{4} \\
0 & 0 & 0 & \mathbf{5} & \mathbf{5} \\
0 & \mathbf{1} & 0 & \mathbf{2} & \mathbf{2}
\end{bmatrix}
\approx
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\end{bmatrix}
\times
\begin{bmatrix}
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\end{bmatrix}
\times
\begin{bmatrix}
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\end{bmatrix}
$$

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\mathbf{4} & \mathbf{4} & \mathbf{4} & 0 & 0 \\
\mathbf{5} & \mathbf{5} & \mathbf{5} & 0 & 0 \\
0 & \mathbf{2} & 0 & \mathbf{4} & \mathbf{4} \\
0 & 0 & 0 & \mathbf{5} & \mathbf{5} \\
0 & \mathbf{1} & 0 & \mathbf{2} & \mathbf{2}
\end{bmatrix}
\approx
\begin{bmatrix}
\mathbf{0.13} & 0.02 & \cancel{-0.01} \\
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\mathbf{0.55} & 0.09 & \cancel{-0.04} \\
\mathbf{0.68} & 0.11 & \cancel{-0.05} \\
0.15 & \mathbf{-0.59} & \cancel{\mathbf{0.65}} \\
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\end{bmatrix}
\times
\begin{bmatrix}
\mathbf{12.4} & 0 & 0 \\
0 & \mathbf{9.5} & 0 \\
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\end{bmatrix}
\times
\begin{bmatrix}
\mathbf{0.56} & \mathbf{0.59} & \mathbf{0.56} & 0.09 & 0.09 \\
0.12 & -0.02 & 0.12 & \mathbf{-0.69} & \mathbf{-0.69} \\
\cancel{0.40} & \cancel{\mathbf{-0.80}} & \cancel{0.40} & \cancel{0.09} & \cancel{0.09}
\end{bmatrix}
$$

Lowering the Dimension

- **Q:** **How exactly is dimensionality reduction done?**
- **A: Set smallest singular values to zero**

$$\begin{bmatrix} \mathbf{1} & \mathbf{1} & \mathbf{1} & 0 & 0 \\ \mathbf{3} & \mathbf{3} & \mathbf{3} & 0 & 0 \\ \mathbf{4} & \mathbf{4} & \mathbf{4} & 0 & 0 \\ \mathbf{5} & \mathbf{5} & \mathbf{5} & 0 & 0 \\ 0 & \mathbf{2} & 0 & \mathbf{4} & \mathbf{4} \\ 0 & 0 & 0 & \mathbf{5} & \mathbf{5} \\ 0 & \mathbf{1} & 0 & \mathbf{2} & \mathbf{2} \end{bmatrix} \approx \begin{bmatrix} \mathbf{0.13} & 0.02 \\ \mathbf{0.41} & 0.07 \\ \mathbf{0.55} & 0.09 \\ \mathbf{0.68} & 0.11 \\ 0.15 & \mathbf{-0.59} \\ 0.07 & \mathbf{-0.73} \\ 0.07 & \mathbf{-0.29} \end{bmatrix} \times \begin{bmatrix} \mathbf{12.4} & 0 \\ 0 & \mathbf{9.5} \end{bmatrix} \times \begin{bmatrix} \mathbf{0.56} & \mathbf{0.59} & \mathbf{0.56} & 0.09 & 0.09 \\ 0.12 & -0.02 & 0.12 & \mathbf{-0.69} & \mathbf{-0.69} \end{bmatrix}$$

Lowering the Dimension

- **Q:** **How exactly is dimensionality reduction done?**
- **A: Set smallest singular values to zero**

$$\begin{bmatrix} \mathbf{1} & \mathbf{1} & \mathbf{1} & 0 & 0 \\ \mathbf{3} & \mathbf{3} & \mathbf{3} & 0 & 0 \\ \mathbf{4} & \mathbf{4} & \mathbf{4} & 0 & 0 \\ \mathbf{5} & \mathbf{5} & \mathbf{5} & 0 & 0 \\ 0 & \mathbf{2} & 0 & \mathbf{4} & \mathbf{4} \\ 0 & 0 & 0 & \mathbf{5} & \mathbf{5} \\ 0 & \mathbf{1} & 0 & \mathbf{2} & \mathbf{2} \end{bmatrix} \approx \begin{bmatrix} \mathbf{0.92} & \mathbf{0.95} & \mathbf{0.92} & 0.01 & 0.01 \\ \mathbf{2.91} & \mathbf{3.01} & \mathbf{2.91} & -0.01 & -0.01 \\ \mathbf{3.90} & \mathbf{4.04} & \mathbf{3.90} & 0.01 & 0.01 \\ \mathbf{4.82} & \mathbf{5.00} & \mathbf{4.82} & 0.03 & 0.03 \\ 0.70 & \mathbf{0.53} & 0.70 & \mathbf{4.11} & \mathbf{4.11} \\ -0.69 & 1.34 & -0.69 & \mathbf{4.78} & \mathbf{4.78} \\ 0.32 & \mathbf{0.23} & 0.32 & \mathbf{2.01} & \mathbf{2.01} \end{bmatrix}$$

Frobenius Norm and Approximation Error

- The *Frobenius norm* of a matrix is the square root of the sum of the squares of its elements.
- The *error* in an approximation of one matrix by another is the Frobenius norm of the difference.
  - Same as the RMSE.
- Important fact: The error in the approximation of a matrix by SVD, subject to picking r singular values, is minimized by zeroing all but the largest r singular values.

Energy

- So what's a good value for r?
- Let the *energy* of a set of singular values be the sum of their squares.
- Pick r so the retained singular values have at least 90% of the total energy.
- Example: With singular values 12.4, 9.5, and 1.3, total energy = 245.7.
- If we drop 1.3, whose square is only 1.7, we are left with energy 244, or over 99% of the total.
- But also dropping 9.5 leaves us with too little.

Finding Eigenpairs

- We want to describe how the SVD is actually computed.
- Essential is a method for finding the *principal* eigenvalue (the largest one) and the corresponding eigenvector of a symmetric matrix.
  - M is *symmetric* if $m_{ij} = m_{ji}$ for all i and j.
- Start with any "guess eigenvector" $\mathbf{x}_0$.
- Construct $\mathbf{x}_{k+1} = M\mathbf{x}_k / ||M\mathbf{x}_k||$ for k = 0, 1,…
  - ||…|| denotes the Frobenius norm.
- Stop when consecutive $\mathbf{x}_k$'s show little change.

Example: Iterative Eigenvector

$$M = \begin{matrix} 1 & 2 \\ 2 & 3 \end{matrix} \qquad \mathbf{x}_0 = \begin{matrix} 1 \\ 1 \end{matrix}$$

$$\frac{M\mathbf{x}_0}{||M\mathbf{x}_0||} = \begin{matrix} 3 \\ 5 \end{matrix} \;/\sqrt{34} = \begin{matrix} 0.51 \\ 0.86 \end{matrix} = \mathbf{x}_1$$

$$\frac{M\mathbf{x}_1}{||M\mathbf{x}_1||} = \begin{matrix} 2.23 \\ 3.60 \end{matrix} \;/\sqrt{17.93} = \begin{matrix} 0.53 \\ 0.85 \end{matrix} = \mathbf{x}_2$$

Finding the Principal Eigenvalue

- Once you have the principal eigenvector $\mathbf{x}$, you find its eigenvalue λ by $\lambda = \mathbf{x}^T M \mathbf{x}$.
- In proof: $\mathbf{x}\lambda = M\mathbf{x}$ for this λ, since $\mathbf{x}\,\mathbf{x}^T M \mathbf{x} = M\mathbf{x}$.
  - Why? $\mathbf{x}$ is a unit vector, so $\mathbf{x}\,\mathbf{x}^T = 1$.
- Example: If we take $\mathbf{x}^T = [0.54, 0.87]$, then $\lambda =$

$$[0.53\ 0.85] \begin{bmatrix} 1 & 2 \\ 2 & 3 \end{bmatrix} \begin{bmatrix} 0.53 \\ 0.85 \end{bmatrix} = 4.25$$

Finding More Eigenpairs

- Eliminate the portion of the matrix M that can be generated by the first eigenpair, λ and **x**.
- $M^* := M - \lambda \mathbf{x}\,\mathbf{x}^T$.
- Recursively find the principal eigenpair for M*, eliminate the effect of that pair, and so on.
- Example:

$$M^* = \begin{bmatrix} 1 & 2 \\ 2 & 3 \end{bmatrix} - 4.25 \begin{bmatrix} 0.53 \\ 0.85 \end{bmatrix} [0.53\ 0.85] = \begin{bmatrix} -0.19 & 0.09 \\ 0.09 & 0.07 \end{bmatrix}$$

How to Compute the SVD

- Start by supposing $M = U\Sigma V^T$.
- $M^T = (U\Sigma V^T)^T = (V^T)^T\Sigma^T U^T = V\Sigma U^T$.
  - Why? (1) Rule for transpose of a product (2) the transpose of the transpose and the transpose of a diagonal matrix are both the identity function.
- $M^TM = V\Sigma U^TU\Sigma V^T = V\Sigma^2V^T$.
  - Why? U is orthonormal, so U^TU is an identity matrix.
  - Also note that Σ^2 is a diagonal matrix whose i-th element is the square of the i-th element of Σ.
- $M^TMV = V\Sigma^2V^TV = V\Sigma^2$.
  - Why? V is also orthonormal.

Computing the SVD –(2)

- Starting with $M^TMV = V\Sigma^2$, note that therefore the i-th column of V is an eigenvector of M^TM, and its eigenvalue is the i-th element of Σ^2.
- Thus, we can find V and Σ by finding the eigenpairs for M^TM.
  - Once we have the eigenvalues in Σ^2, we can find the singular values by taking the square root of these eigenvalues.
- Symmetric argument, starting with MM^T, gives us U.

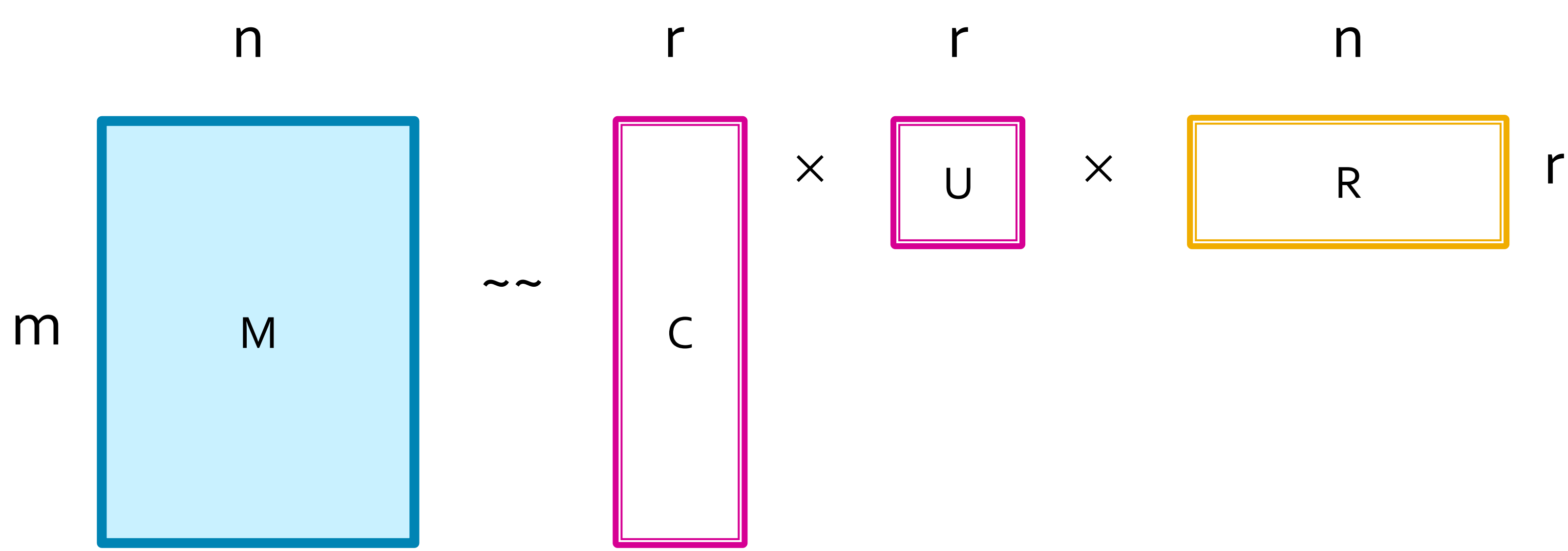
CUR Decomposition

The Sparsity Issue
Picking Random Rows and Columns

Sparsity

- It is common for the matrix M that we wish to decompose to be very sparse.
- But U and V from a UV or SVD decomposition will not be sparse even so.
- CUR decomposition solves this problem by using only (randomly chosen) rows and columns of M.

Form of CUR Decomposition



r chosen as you like.

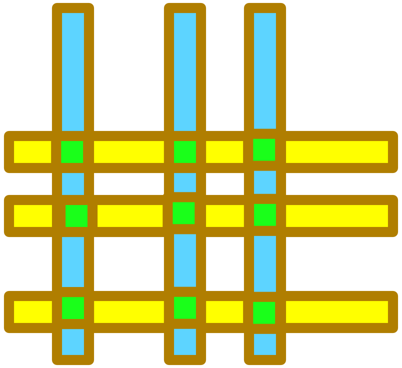
C = randomly chosen columns of M.

R = randomly chosen rows of M

U is tricky – more about this.

Construction of U

- U is r-by-r, so it is small, and it is OK if it is dense and complex to compute.
- Start with W = intersection of the r columns chosen for C and the r rows chosen for R.
- Compute the SVD of W to be $X\Sigma Y^T$.
- Compute Σ^+, the *Moore-Penrose inverse* of Σ.
  - Definition, next slide.
- $U = Y(\Sigma^+)^2X^T$.



Moore-Penrose Inverse

- If Σ is a diagonal matrix, its More-Penrose inverse is another diagonal matrix whose i-th entry is:
  - $1/\sigma$ if σ is not 0.
  - 0 if σ is 0.
- Example:

$$\Sigma = \begin{matrix} 4 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{matrix} \qquad \Sigma^+ = \begin{matrix} 0.25 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0 \end{matrix}$$

Which Rows and Columns?

- To decrease the expected error between M and its decomposition, we must pick rows and columns in a nonuniform manner.
- The *importance* of a row or column of M is the square of its Frobinius norm.
  - That is, the sum of the squares of its elements.
- When picking rows and columns, the probabilities must be proportional to importance.
- Example: [3,4,5] has importance 50, and [3,0,1] has importance 10, so pick the first 5 times as often as the second.