11-755/18-797 Machine Learning for Signal Processing

# Fundamentals of Linear Algebra – part 2

Class 3 4 Sep 2012

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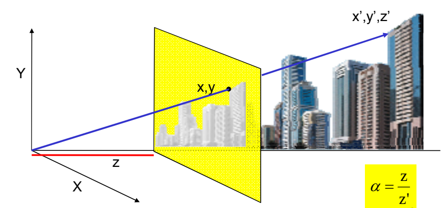
## Overview

- Vectors and matrices
- Basic vector/matrix operations
- Various matrix types
- Projections

- More on matrix types
- Matrix determinants
- Matrix inversion
- Eigenanalysis
- Singular value decomposition



## Central Projection




$\alpha = \frac{z}{z'}$

$x = \alpha x'$

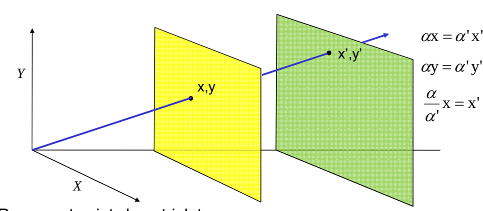
$y = \alpha y'$

$\frac{x}{x'} = \frac{y}{y'} = \frac{z}{z'}$ Property of a line through origin

- The positions on the "window" are scaled along the line
- To compute (x,y) position on the window, we need z (distance of window from eye), and (x',y',z') (location being projected)



## Homogeneous Coordinates




$\alpha x = \alpha' x'$

$\alpha y = \alpha' y'$

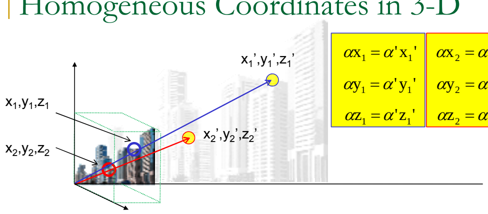
$\frac{\alpha}{\alpha'} x = x'$

- Represent points by a triplet
  - Using yellow window as reference:
  - (x,y) = (x,y,1)
  - (x',y') = (x,y,c') c' = α'/α
  - Locations on line generally represented as (x,y,c)
    - x'= x/c' , y'= y/c'

$\frac{\alpha}{\alpha'} x = x'$ $\frac{\alpha}{\alpha'} y = y'$



## Homogeneous Coordinates in 3-D

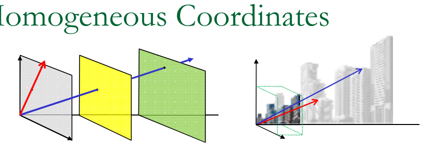



| | |
|---|---|
| $\alpha x_1 = \alpha' x_1'$ | $\alpha x_2 = \alpha' x_2'$ |
| $\alpha y_1 = \alpha' y_1'$ | $\alpha y_2 = \alpha' y_2'$ |
| $\alpha z_1 = \alpha' z_1'$ | $\alpha z_2 = \alpha' z_2'$ |

- Points are represented using FOUR coordinates
  - (X,Y,Z,c)
  - "c" is the "scaling" factor that represents the distance of the actual scene
- Actual Cartesian coordinates:
  - $X_{actual} = X/c$, $Y_{actual} = Y/c$, $Z_{actual} = Z/c$

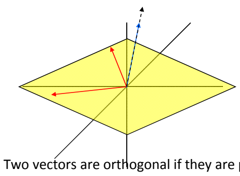


## Homogeneous Coordinates



- In both cases, constant "c" represents distance along the line with respect to a reference window
  - In 2D the plane in which all points have values (x,y,1)
- Changing the reference plane changes the representation
- I.e. there may be *multiple* Homogenous representations (x,y,c) that represent the same cartesian point (x' y')

## Orthogonal/Orthonormal vectors



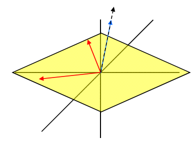
$$A = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \qquad B = \begin{bmatrix} u \\ v \\ w \end{bmatrix}$$

$$AB = 0 \quad \Rightarrow \quad xu + yv + zw = 0$$

- Two vectors are orthogonal if they are perpendicular to one another
  - A.B = 0
  - A vector that is perpendicular to a plane is orthogonal to *every* vector on the plane
- Two vectors are ortho*normal* if
  - They are orthogonal
  - The length of each vector is 1.0
  - Orthogonal vectors can be made orthonormal by normalizing their lengths to 1.0



## Orthogonal matrices



$$\begin{bmatrix} \sqrt{0.5} & -\sqrt{0.125} & \sqrt{0.375} \\ \sqrt{0.5} & \sqrt{0.125} & -\sqrt{0.375} \\ 0 & \sqrt{0.75} & 0.5 \end{bmatrix}$$

- Orthogonal Matrix : $AA^T = A^TA = I$
  - The matrix is square
  - All row vectors are orthonormal to one another
    - Every vector is perpendicular to the hyperplane formed by all other vectors
  - All column vectors are also orthonormal to one another
  - **Observation:** In an orthogonal matrix if the length of the row vectors is 1.0, the length of the column vectors is also 1.0
  - **Observation**: In an orthogonal matrix no more than one row can have all entries with the same polarity (+ve or –ve)

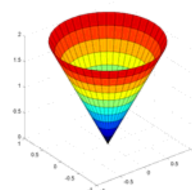


## Orthogonal and Orthonormal Matrices

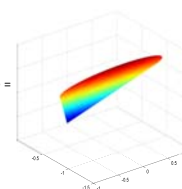
- Orthogonal matrices will retain the **length** and **relative angles between** transformed vectors
  - Essentially, they are combinations of rotations, reflections and permutations
  - Rotation matrices and permutation matrices are all orthonormal matrices
- If the entries of the matrix are not unit length, it cannot be orthogonal
  - $AA^T = I$ or $A^TA = I$, but not both
  - $AA^T$ = Diagonal or $A^TA$ = Diagonal, but not both
  - If all the entries are the same length, we can get $AA^T = A^TA$ = Diagonal, though
- A non-square matrix cannot be orthogonal
  - $AA^T=I$ or $A^TA = I$, but not both



## Matrix Rank and Rank-Deficient Matrices



P * Cone =



- Some matrices will eliminate one or more dimensions during transformation
  - These are *rank deficient* matrices
  - The rank of the matrix is the dimensionality of the transformed version of a full-dimensional object



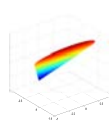
## Matrix Rank and Rank-Deficient Matrices

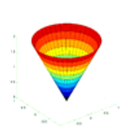
P =

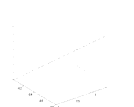
| | | |
|---|---|---|
| 1.0000 | 0 | 0 |
| 0 | 0.2500 | -0.4330 |
| 0 | -0.4330 | 0.7500 |

P2 =

| | | |
|---|---|---|
| 0.5000 | -0.2500 | 0.4330 |
| -0.2500 | 0.1250 | -0.2165 |
| 0.4330 | -0.2165 | 0.3750 |







Rank = 2

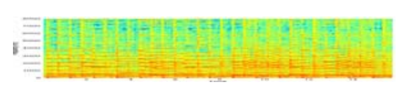
Rank = 1

- Some matrices will eliminate one or more dimensions during transformation
  - These are *rank deficient* matrices
  - The rank of the matrix is the dimensionality of the transformed version of a full-dimensional object

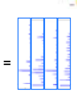


## Projections are often examples of rank-deficient transforms

M =

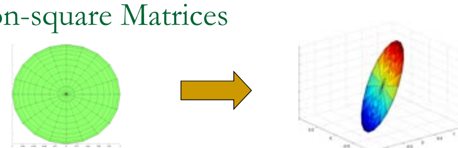


W =



- $P = W (W^TW)^{-1} W^T$ ; Projected Spectrogram = P*M
- The original spectrogram can never be recovered
  - P is rank deficient
- P explains all vectors in the new spectrogram as a mixture of only the 4 vectors in W
  - There are only a maximum of 4 ***independent*** bases
  - Rank of P is 4

## Non-square Matrices



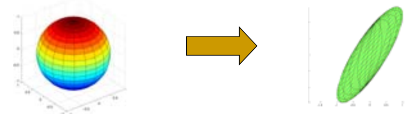
$$\begin{bmatrix} x_1 & x_2 & . & . & x_N \\ y_1 & y_2 & . & . & y_N \end{bmatrix} \quad \begin{bmatrix} .8 & .9 \\ .1 & .9 \\ .6 & 0 \end{bmatrix} \quad \begin{bmatrix} \hat{x}_1 & \hat{x}_2 & . & . & \hat{x}_N \\ \hat{y}_1 & \hat{y}_2 & . & . & \hat{y}_N \\ \hat{z}_1 & \hat{z}_2 & . & . & \hat{z}_N \end{bmatrix}$$

X = 2D data   P = transform   PX = 3D, rank 2

- Non-square matrices add or subtract axes
  - More rows than columns → add axes
    - But does not increase the dimensionality of the data



## Non-square Matrices



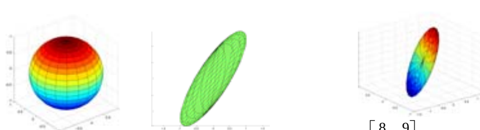
$$\begin{bmatrix} x_1 & x_2 & . & . & x_N \\ y_1 & y_2 & . & . & y_N \\ z_1 & z_2 & . & . & z_N \end{bmatrix} \quad \begin{bmatrix} .3 & 1 & .2 \\ .5 & 1 & 1 \end{bmatrix} \quad \begin{bmatrix} \hat{x}_1 & \hat{x}_2 & . & . & \hat{x}_N \\ \hat{y}_1 & \hat{y}_2 & . & . & \hat{y}_N \end{bmatrix}$$

X = 3D data, rank 3   P = transform   PX = 2D, rank 2

- Non-square matrices add or subtract axes
  - More rows than columns → add axes
    - But does not increase the dimensionality of the data
  - Fewer rows than columns → reduce axes
    - May reduce dimensionality of the data



## The Rank of a Matrix



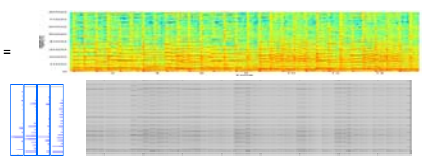
$$\begin{bmatrix} .3 & 1 & .2 \\ .5 & 1 & 1 \end{bmatrix} \qquad \begin{bmatrix} .8 & .9 \\ .1 & .9 \\ .6 & 0 \end{bmatrix}$$

- The matrix rank is the dimensionality of the transformation of a full-dimensioned object in the original space
- The matrix can never *increase* dimensions
  - Cannot convert a circle to a sphere or a line to a circle
- The rank of a matrix can never be greater than the lower of its two dimensions



## The Rank of Matrix

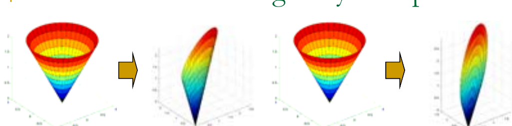
M =



- Projected Spectrogram = P * M
  - Every vector in it is a combination of only 4 bases
- The rank of the matrix is the *smallest* no. of bases required to describe the output
  - E.g. if note no. 4 in P could be expressed as a combination of notes 1,2 and 3, it provides no additional information
  - Eliminating note no. 4 would give us the same projection
  - The rank of P would be 3!



## Matrix rank is unchanged by transposition

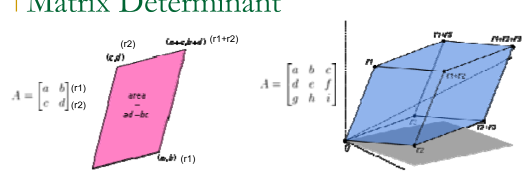


$$\begin{bmatrix} 0.9 & 0.5 & 0.8 \\ 0.1 & 0.4 & 0.9 \\ 0.42 & 0.44 & 0.86 \end{bmatrix} \qquad \begin{bmatrix} 0.9 & 0.1 & 0.42 \\ 0.5 & 0.4 & 0.44 \\ 0.8 & 0.9 & 0.86 \end{bmatrix}$$

- If an N-dimensional object is compressed to a K-dimensional object by a matrix, it will also be compressed to a K-dimensional object by the transpose of the matrix

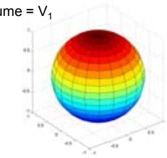
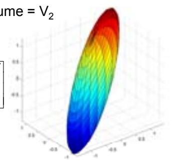


## Matrix Determinant




- The determinant is the "volume" of a matrix
- Actually the volume of a parallelepiped formed from its row vectors
  - Also the volume of the parallelepiped formed from its column vectors
- Standard formula for determinant: in text book

## Matrix Determinant: Another Perspective

Volume = $V_1$  $\begin{bmatrix} 0.8 & 0 & 0.7 \\ 1.0 & 0.8 & 0.8 \\ 0.7 & 0.9 & 0.7 \end{bmatrix}$ Volume = $V_2$ 

- The determinant is the ratio of N-volumes
  - If $V_1$ is the volume of an N-dimensional object "O" in N-dimensional space
    - O is the complete set of points or vertices that specify the object
  - If $V_2$ is the volume of the N-dimensional object specified by A*O, where A is a matrix that transforms the space
  - $|A| = V_2 / V_1$



## Matrix Determinants

- Matrix determinants are *only defined for square matrices*
  - They characterize volumes in linearly transformed space of the same dimensionality as the vectors
- Rank deficient matrices have determinant 0
  - Since they compress full-volumed N-dimensional objects into zero-volume N-dimensional objects
    - E.g. a 3-D sphere into a 2-D ellipse: The ellipse has 0 volume (although it does have area)
- Conversely, all matrices of determinant 0 are rank deficient
  - Since they compress full-volumed N-dimensional objects into zero-volume objects



## Multiplication properties

- Properties of vector/matrix products
  - Associative

$$\mathbf{A}\cdot(\mathbf{B}\cdot\mathbf{C}) = (\mathbf{A}\cdot\mathbf{B})\cdot\mathbf{C}$$

  - Distributive

$$\mathbf{A}\cdot(\mathbf{B}+\mathbf{C}) = \mathbf{A}\cdot\mathbf{B}+\mathbf{A}\cdot\mathbf{C}$$

  - NOT commutative!!!

$$\mathbf{A}\cdot\mathbf{B} \neq \mathbf{B}\cdot\mathbf{A}$$

    - *left multiplications ≠ right multiplications*
  - Transposition

$$(\mathbf{A}\cdot\mathbf{B})^T = \mathbf{B}^T\cdot\mathbf{A}^T$$



## Determinant properties

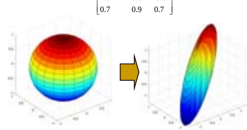
- Associative for square matrices $|\mathbf{A}\cdot\mathbf{B}\cdot\mathbf{C}| = |\mathbf{A}|\cdot|\mathbf{B}|\cdot|\mathbf{C}|$
  - Scaling volume sequentially by several matrices is equal to scaling once by the product of the matrices
- Volume of sum != sum of Volumes $|(\mathbf{B}+\mathbf{C})| \neq |\mathbf{B}|+|\mathbf{C}|$
- Commutative
  - The order in which you scale the volume of an object is irrelevant

$$|\mathbf{A}\cdot\mathbf{B}| = |\mathbf{B}\cdot\mathbf{A}| = |\mathbf{A}|\cdot|\mathbf{B}|$$



## Matrix Inversion

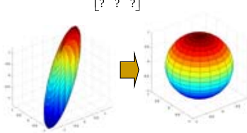
$$T = \begin{bmatrix} 0.8 & 0 & 0.7 \\ 1.0 & 0.8 & 0.8 \\ 0.7 & 0.9 & 0.7 \end{bmatrix}$$



- A matrix transforms an N-dimensional object to a different N-dimensional object
- What transforms the new object back to the original?
  - The *inverse transformation*

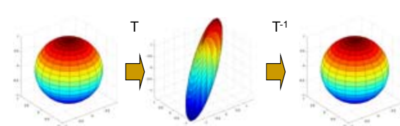
$$Q = \begin{bmatrix} ? & ? & ? \\ ? & ? & ? \\ ? & ? & ? \end{bmatrix} = T^{-1}$$

- The inverse transformation is called the matrix inverse





## Matrix Inversion

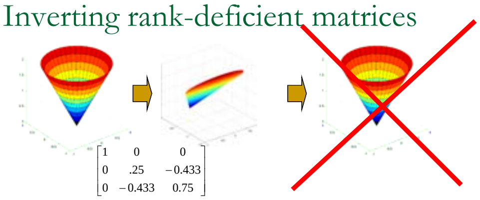



$T^{-1}*T*D = D \rightarrow T^{-1}T = I$

- The product of a matrix and its inverse is the identity matrix
  - Transforming an object, and then inverse transforming it gives us back the original object

$T*T^{-1}*D = D \rightarrow TT^{-1} = I$

# Inverting rank-deficient matrices



$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & .25 & -0.433 \\ 0 & -0.433 & 0.75 \end{bmatrix}$$

- Rank deficient matrices "flatten" objects
  - In the process, multiple points in the original object get mapped to the same point in the transformed object
- It is not possible to go "back" from the flattened object to the original object
  - Because of the many-to-one forward mapping
- Rank deficient matrices have no inverse



# Revisiting Projections and Least Squares

- Projection computes a *least squared error* estimate
- For each vector V in the music spectrogram matrix
  - Approximation: $V_{approx}$ = a*note1 + b*note2 + c*note3..

$$T = \begin{bmatrix} \text{note1} & \text{note2} & \text{note3} \end{bmatrix} \qquad V_{approx} = T \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

  - Error vector E = $V - V_{approx}$
  - Squared error energy for V e(V) = norm$(E)^2$
- Projection computes $V_{approx}$ for all vectors such that Total error is minimized
- **But WHAT ARE "a" "b" and "c"?**



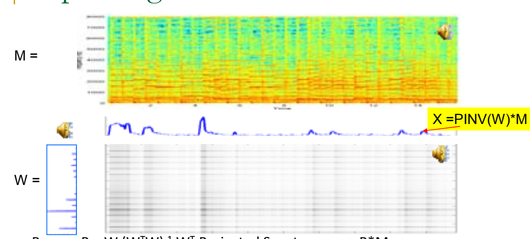
# The Pseudo Inverse (PINV)

$$V_{approx} = T \begin{bmatrix} a \\ b \\ c \end{bmatrix} \Rightarrow V \approx T \begin{bmatrix} a \\ b \\ c \end{bmatrix} \Rightarrow \begin{bmatrix} a \\ b \\ c \end{bmatrix} = PINV(T) * V$$

- We are approximating spectral vectors V as the transformation of the vector $[a\ b\ c]^T$
  - Note – we're viewing the collection of bases in T as a transformation
- The solution is obtained using the *pseudo inverse*
  - This give us a *LEAST SQUARES* solution
    - If T were square and invertible Pinv(T) = $T^{-1}$, and $V = V_{approx}$



# Explaining music with one note

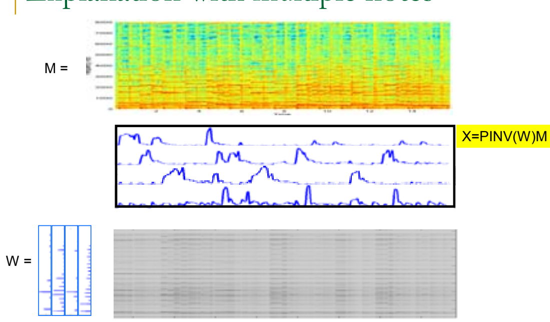



- Recap: P = W $(W^TW)^{-1}$ $W^T$, Projected Spectrogram = P*M
- **Approximation: M = W*X**
- The amount of W in each vector = X = PINV(W)*M
- W*Pinv(W)*M = Projected Spectrogram
  - W*Pinv(W) = Projection matrix!!

PINV(W) = $(W^TW)^{-1}W^T$



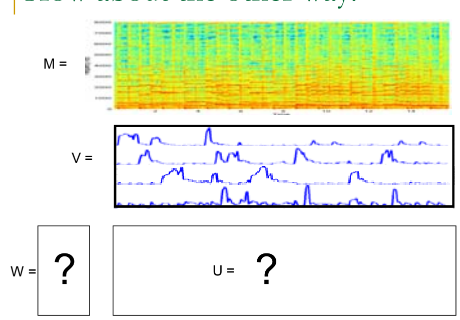
# Explanation with multiple notes




- X = Pinv(W) * M; Projected matrix = W*X = W*Pinv(W)*M



# How about the other way?




- WV \approx M W = M * Pinv(V) U = WV

## Pseudo-inverse (PINV)

- Pinv() applies to non-square matrices
- Pinv ( Pinv (A))) = A
- A*Pinv(A)= projection matrix!
  - Projection onto the columns of A
- If A = K x N matrix and K > N, A projects N-D vectors into a higher-dimensional K-D space
  - Pinv(A) = NxK matrix
  - Pinv(A)*A = I in this case
- Otherwise A * Pinv(A) = I



## Matrix inversion (division)

- The inverse of matrix multiplication
  - Not element-wise division!!
- Provides a way to "undo" a linear transformation
  - Inverse of the unit matrix is itself
  - Inverse of a diagonal is diagonal
  - Inverse of a rotation is a (counter)rotation (its transpose!)
  - Inverse of a rank deficient matrix does not exist!
    - But pseudoinverse exists
- For square matrices: Pay attention to multiplication side!

$$\mathbf{A}\cdot\mathbf{B}=\mathbf{C},\ \ \mathbf{A}=\mathbf{C}\cdot\mathbf{B}^{-1},\ \ \mathbf{B}=\mathbf{A}^{-1}\cdot\mathbf{C}$$

- If matrix not square use a matrix pseudoinverse:

$$\mathbf{A}\cdot\mathbf{B}\approx\mathbf{C},\ \ \mathbf{A}=\mathbf{C}\cdot\mathbf{B}^{+},\ \ \mathbf{B}=\mathbf{A}^{+}\cdot\mathbf{C}$$

- MATLAB syntax: inv(a), pinv(a)



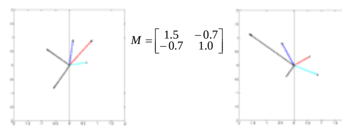
## Eigenanalysis

- If something can go through a process mostly unscathed in character it is an *eigen*-something
  - Sound example:
- A vector that can undergo a matrix multiplication and keep pointing the same way is an *eigenvector*
  - Its length can change though
- How much its length changes is expressed by its corresponding *eigenvalue*
  - Each eigenvector of a matrix has its eigenvalue
- Finding these "eigenthings" is called eigenanalysis



## EigenVectors and EigenValues

Black vectors are eigen vectors



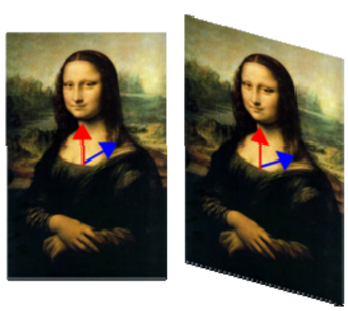

- Vectors that do not change angle upon transformation
  - They may change length

$$MV = \lambda V$$

  - V = eigen vector
  - λ = eigen value
  - `Matlab: [V, L] = eig(M)`
    - L is a diagonal matrix whose entries are the eigen values
    - V is a maxtrix whose columns are the eigen vectors

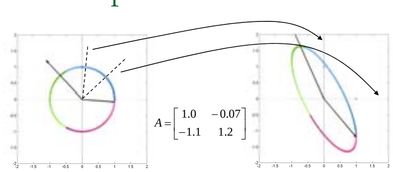


## Eigen vector example



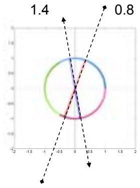


## Matrix multiplication revisited




- Matrix transformation "transforms" the space
  - Warps the paper so that the normals to the two vectors now lie along the axes

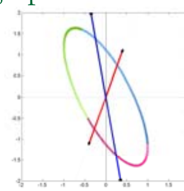
## A stretching operation




- Draw two lines
- Stretch / shrink the paper along these lines by factors $\lambda_1$ and $\lambda_2$
  - The factors could be negative – implies flipping the paper
- The result is a transformation of the space



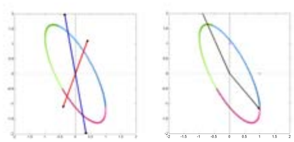
## A stretching operation



- Draw two lines
- Stretch / shrink the paper along these lines by factors $\lambda_1$ and $\lambda_2$
  - The factors could be negative – implies flipping the paper
- The result is a transformation of the space



## Physical interpretation of eigen vector

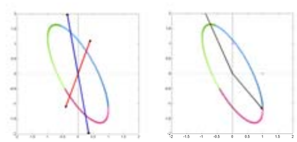


- The result of the stretching is exactly the same as transformation by a matrix
- The axes of stretching/shrinking are the eigenvectors
  - The degree of stretching/shrinking are the corresponding eigenvalues
- The EigenVectors and EigenValues convey all the information about the matrix



## Physical interpretation of eigen vector

$$V = [V_1 \quad V_2]$$
$$\Lambda = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$
$$M = V \Lambda V^{-1}$$



- The result of the stretching is exactly the same as transformation by a matrix
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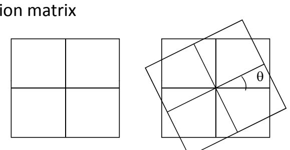
## Eigen Analysis

- Not all square matrices have nice eigen values and vectors
  - E.g. consider a rotation matrix

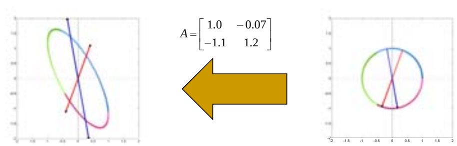
$$\mathbf{R}_\theta = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \quad X = \begin{bmatrix} x \\ y \end{bmatrix} \quad X_{new} = \begin{bmatrix} x' \\ y' \end{bmatrix}$$




  - This rotates every vector in the plane
    - No vector that remains unchanged
- In these cases the Eigen vectors and values are complex



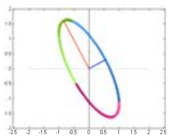
## Singular Value Decomposition



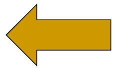
$$A = \begin{bmatrix} 1.0 & -0.07 \\ -1.1 & 1.2 \end{bmatrix}$$

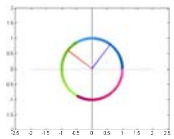
- Matrix transformations convert circles to ellipses
- Eigen vectors are vectors that do not change direction in the process
- There is another key feature of the ellipse to the left that carries information about the transform
  - Can you identify it?

## Singular Value Decomposition



$$A = \begin{bmatrix} 1.0 & -0.07 \\ -1.1 & 1.2 \end{bmatrix}$$

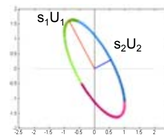




- The major and minor axes of the transformed ellipse define the ellipse
  - They are at right angles
- These are transformations of right-angled vectors on the original circle!



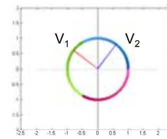
## Singular Value Decomposition




$$A = \begin{bmatrix} 1.0 & -0.07 \\ -1.1 & 1.2 \end{bmatrix}$$

$A = U\ S\ V^T$

matlab:
[U,S,V] = svd(A)




- U and V are orthonormal matrices
  - Columns are orthonormal vectors
- S is a diagonal matrix
- The *right singular vectors* of V are transformed to the *left singular vectors* in U
  - And scaled by the *singular values* that are the diagonal entries of S

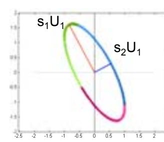


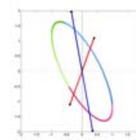
## Singular Value Decomposition

- The left and right singular vectors are not the same
  - If A is not a square matrix, the left and right singular vectors will be of different dimensions
- The singular values are always real
- The largest singular value is the largest amount by which a vector is scaled by A
  - Max (|Ax| / |x|) = $s_{max}$
- The smallest singular value is the smallest amount by which a vector is scaled by A
  - Min (|Ax| / |x|) = $s_{min}$
  - This can be 0 (for low-rank or non-square matrices)



## The Singular Values



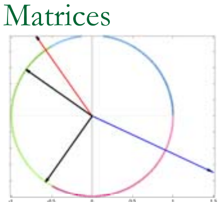



- Square matrices: The product of the singular values is the determinant of the matrix
  - This is also the product of the *eigen* values
  - I.e. there are two different sets of axes whose products give you the area of an ellipse
- For any "broad" rectangular matrix A, the largest singular value of any square submatrix B cannot be larger than the largest singular value of A
  - An analogous rule applies to the smallest singular value
  - This property is utilized in various problems, such as compressive sensing



## Symmetric Matrices

$$\begin{bmatrix} 1.5 & -0.7 \\ -0.7 & 1 \end{bmatrix}$$

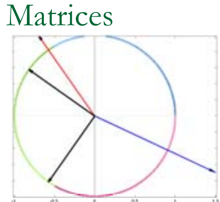


- Matrices that do not change on transposition
  - Row and column vectors are identical
- The left and right singular vectors are identical
  - U = V
  - $A = U\ S\ U^T$
- They are identical to the *eigen vectors* of the matrix



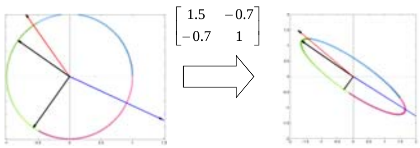
## Symmetric Matrices

$$\begin{bmatrix} 1.5 & -0.7 \\ -0.7 & 1 \end{bmatrix}$$



- Matrices that do not change on transposition
  - Row and column vectors are identical
- Symmetric matrix: Eigen vectors and Eigen values are always real
- Eigen vectors are always orthogonal
  - At 90 degrees to one another

## Symmetric Matrices




- Eigen vectors point in the direction of the major and minor axes of the ellipsoid resulting from the transformation of a spheroid
  - The eigen values are the lengths of the axes

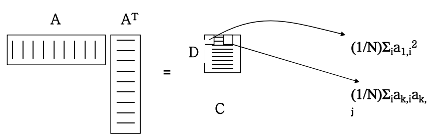


## Symmetric matrices

- Eigen vectors $V_i$ are orthonormal
  - $V_i^T V_i = 1$
  - $V_i^T V_j = 0$, i != j
- Listing all eigen vectors in matrix form V
  - $V^T = V^{-1}$
  - $V^T V = I$
  - $V V^T = I$
- $M V_i = \lambda V_i$
- In matrix form : $M V = V \Lambda$
  - $\Lambda$ is a diagonal matrix with all eigen values
- $M = V \Lambda V^T$



## The Correlation and Covariance Matrices




- Consider a set of column vectors represented as a DxN matrix A
- The correlation matrix is
  - $C = (1/N) AA^T$
    - If the average value (mean) of the vectors in A is 0, C is called the ***covariance*** matrix
    - **covariance = correlation + mean * mean$^T$**
- Diagonal elements represent average of the squared value of each dimension
  - Off diagonal elements represent how two components are related
    - How much knowing one lets us guess the value of the other



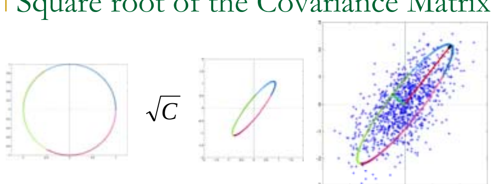
## Correlation / Covariance Matrix

$$C = V \Lambda V^T$$
$$Sqrt(C) = V.Sqrt(\Lambda).V^T$$
$$Sqrt(C).Sqrt(C) = V.Sqrt(\Lambda).V^T V.Sqrt(\Lambda).V^T$$
$$= V.Sqrt(\Lambda).Sqrt(\Lambda)V^T = V \Lambda V^T = C$$

- The correlation / covariance matrix is symmetric
  - Has orthonormal eigen vectors and real, non-negative eigen values
- The *square root* of a correlation or covariance matrix is easily derived from the eigen vectors and eigen values
  - The eigen values of the *square root* of the covariance matrix are the square roots of the eigen values of the covariance matrix
  - These are also the “singular values” of the data set



## Square root of the Covariance Matrix



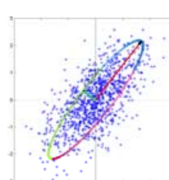

- The square root of the covariance matrix represents the elliptical scatter of the data
- The eigenvectors of the matrix represent the major and minor axes



## The Correlation Matrix

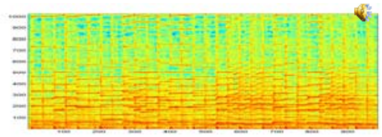
Any vector $V = a_{V,1}$ * eigenvec1 + $a_{V,2}$ *eigenvec2 + ..

$\Sigma_V a_{V,i}$ = eigenvalue(i)



- Projections along the N eigen vectors with the largest eigen values represent the N greatest “energy-carrying” components of the matrix
- Conversely, N “bases” that result in the least square error are the N best eigen vectors

## An audio example



- The spectrogram has 974 vectors of dimension 1025
- The covariance matrix is size 1025 x 1025
- There are 1025 eigenvectors



## Eigen Reduction

$M = spectrogram$ 1025x1000

$C = M.M^T$ 1025x1025

V = 1025x1025 $[V, L] = eig(C)$

$V_{reduced} = [V_1 \quad . \quad . \quad V_{25}]$ 1025x25

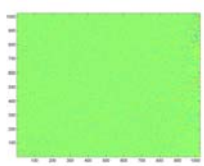
$M_{lowdim} = Pinv(V_{reduced})M$ 25x1000

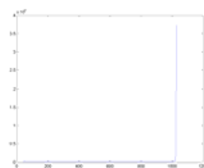
$M_{reconstructed} = V_{reduced} M_{lowdim}$ 1025x1000

- Compute the Correlation
- Compute Eigen vectors and values
- Create matrix from the 25 Eigen vectors corresponding to 25 highest Eigen values
- Compute the weights of the 25 eigenvectors
- To reconstruct the spectrogram – compute the projection on the 25 eigen vectors



## Eigenvalues and Eigenvectors





- Left panel: Matrix with 1025 eigen vectors
- Right panel: Corresponding eigen values
  - Most eigen values are close to zero
    - The corresponding eigenvectors are "unimportant"

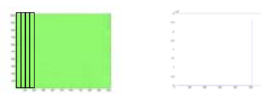
$M = spectrogram$

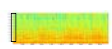
$C = M.M^T$

$[V, L] = eig(C)$



## Eigenvalues and Eigenvectors





Vec = a1 *eigenvec1 + a2 * eigenvec2 + a3 * eigenvec3 …

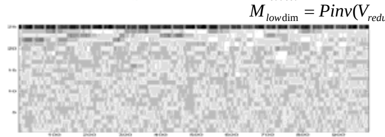
- The vectors in the spectrogram are linear combinations of all 1025 eigen vectors
- The eigen vectors with low eigen values contribute very little
  - The average value of $a_i$ is proportional to the square root of the eigenvalue
  - Ignoring these will not affect the composition of the spectrogram



## An audio example

$V_{reduced} = [V_1 \quad . \quad . \quad V_{25}]$

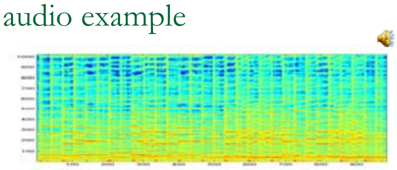
$M_{lowdim} = Pinv(V_{reduced})M$



- The same spectrogram projected down to the 25 eigen vectors with the highest eigen values
  - Only the 25-dimensional weights are shown
    - The weights with which the 25 eigen vectors must be added to compose a least squares approximation to the spectrogram



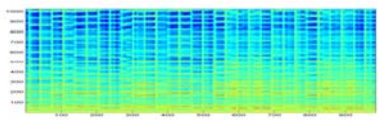
## An audio example



$M_{reconstructed} = V_{reduced} M_{lowdim}$

- The same spectrogram constructed from only the 25 eigen vectors with the highest eigen values
  - Looks similar
    - With 100 eigenvectors, it would be indistinguishable from the original
  - Sounds pretty close
  - But now sufficient to store 25 numbers per vector (instead of 1024)

## With only 5 eigenvectors



- The same spectrogram constructed from only the 5 eigen vectors with the highest eigen values
  - Highly recognizable



## Correlation vs. Covariance Matrix

- Correlation:
  - The N eigen vectors with the largest eigen values represent the N greatest "energy-carrying" components of the matrix
  - Conversely, N "bases" that result in the least square error are the N best eigen vectors
    - Projections onto these eigen vectors retain the most energy in the data.
- Covariance:
  - the N eigen vectors with the largest eigen values represent the N greatest *"variance-carrying"* components of the matrix
  - Conversely, N "bases" that retain the maximum possible variance are the N best eigen vectors



## Eigenvectors, Eigenvalues and Covariances

- The eigenvectors and eigenvalues (singular values) derived from the correlation matrix are important
- Do we need to actually compute the correlation matrix?
  - No
- Direct computation using Singular Value Decomposition

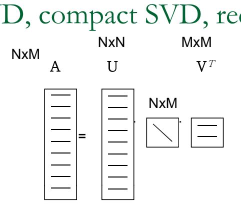


## SVD vs. Eigen decomposition

- Singluar value decomposition is analogous to the eigen decomposition of the correlation matrix of the data
  - SVD: $D = U S V^T$
  - $DD^T = U S V^T V S U^T = U S^2 U^T$
- The "left" singluar vectors are the eigen vectors of the correlation matrix
  - Show the directions of greatest importance
- The corresponding singular values are the square roots of the eigen values of the correlation matrix
  - Show the importance of the eigen vector



## Thin SVD, compact SVD, reduced SVD




- Thin SVD: Only compute the first N columns of U
  - All that is required if N < M
- Compact SVD: Only the left and right singular vectors corresponding to non-zero singular values are computed



## Why bother with eigens/SVD

- Can provide a unique insight into data
  - Strong statistical grounding
  - Can display complex interactions between the data
  - Can uncover irrelevant parts of the data we can throw out
- Can provide *basis functions*
  - A set of elements to compactly describe our data
  - Indispensable for performing compression and classification
- Used over and over and still perform amazingly well

*Eigenfaces*
Using a linear transform of the above "eigenvectors" we can compose various faces

## Making vectors and matrices in MATLAB

- Make a row vector:
  `a = [1 2 3]`
- Make a column vector:
  `a = [1;2;3]`
- Make a matrix:
  `A = [1 2 3;4 5 6]`
- Combine vectors
  `A = [b c]` or `A = [b;c]`
- Make a random vector/matrix:
  `r = rand(m,n)`
- Make an identity matrix:
  `I = eye(n)`
- Make a sequence of numbers
  `c = 1:10` or `c = 1:0.5:10` or `c = 100:-2:50`
- Make a ramp
  `c = linspace( 0, 1, 100)`



## Indexing

- To get the *i*-th element of a vector
  `a(i)`
- To get the *i*-th *j*-th element of a matrix
  `A(i,j)`
- To get from the *i*-th to the *j*-th element
  `a(i:j)`
- To get a *sub-matrix*
  `A(i:j,k:l)`
- To get segments
  `a([i:j k:l m])`



## Arithmetic operations

- Addition/subtraction
  `C = A + B` or `C = A - B`
- Vector/Matrix multiplication
  `C = A * B`
  - Operant sizes must match!
- Element-wise operations
  - Multiplication/division
    `C = A .* B` or `C = A ./ B`
  - Exponentiation
    `C = A.^B`
  - Elementary functions
    `C = sin(A)` or `C = sqrt(A)`, …



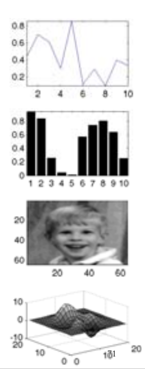
## Linear algebra operations

- Transposition
  `C = A'`
  - If `A` is complex also conjugates use `C = A.'` to avoid that
- Vector norm
  `norm(x)` (also works on matrices)
- Matrix inversion
  `C = inv(A)` if `A` is square
  `C = pinv(A)` if `A` is not square
  - `A` might not be invertible, you'll get a warning if so
- Eigenanalysis
  `[u,d] = eig(A)`
  - `u` is a matrix containing the eigenvectors
  - `d` is a diagonal matrix containing the eigenvalues
- Singular Value Decomposition
  `[u,s,v] = svd(A)` or `[u,s,v] = svd(A,0)`
  - "thin" versus regular SVD
  - `s` is diagonal and contains the singular values



## Plotting functions

- 1-d plots
  `plot(x)`
  - if `x` is a vector will plot all its elements
  - If `x` is a matrix will plot all its column vectors
  
  `bar(x)`
  - Ditto but makes a bar plot
- 2-d plots
  `imagesc(x)`
  - plots a matrix as an image
  
  `surf(x)`
  - makes a surface plot





## Getting help with functions

- The `help` function
  - Type `help` followed by a function name
- Things to try

```
help help
help +
help eig
help svd
help plot
help bar
help imagesc
help surf
help ops
help matfun
```

- Also check out the tutorials and the mathworks site