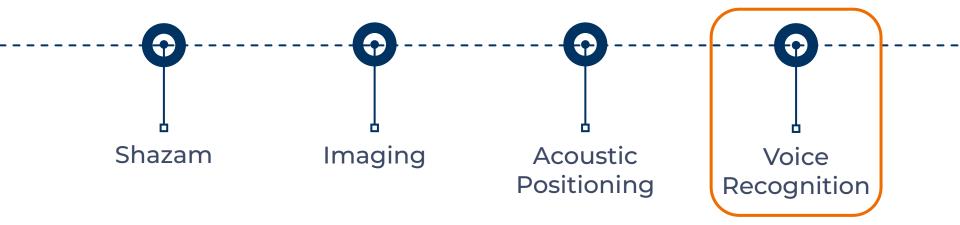
EECS 16A Voice Recognition 1

Welcome! We'll be starting at Berkeley Time.

Semester Outline



Today's Agenda

- Voice Classification Problem Overview
- SVD / PCA Conceptual Review
- Using SVD / PCA for Voice Classification
- Tips for Best Performance

Voice Recognition Problem

- We have a set of:
 - Words
 - 40 recordings of someone speaking each word
- We want to come up with a model that can be given a new recording of the spoken word and predict which word it is!

 In other words, given a training dataset, "train" a classifier model that takes audio signals.

Organization of our Data

- Each recording is a vector of some numbers that represent our sampled audio signal
- Given our data, what can we do to classify a new recording?
 What are some features that we can compare?

```
Recording 0 = [-64, 30, 24, 52, ...]

Recording 1 = [-54, 86, 78, 64, ...]

Recording 2 = [32, 64, 50, -110 ...]

Recording 3 = [-40, 70, 4, -36, ...]
```

Features

 In this lab, we are going to stack all the recordings into a matrix where the row is each recording and each audio sample (column) is a feature (things that distinguish one datapoint from another).

feature	е	0	1	2	3	
Recording 0 =	[-64 ,	30,	24,	52,]
Recording 1 =	[-54 ,	86,	78 ,	64,]
Recording 2 =	[32,	64,	50,	-110]
Recording 3 =	[-40,	70,	4,	-36,]

:

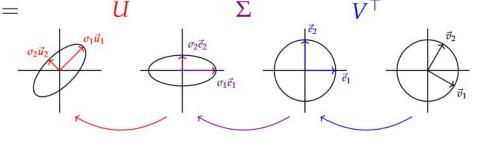
Singular Value Decomposition (SVD)

- What is SVD?
 - Decompose a matrix into 3
 separate matrices with
 unique properties
- U
 - Orthonormal eigenvectors of AA^T
 - A rotation matrix!
- S
 - o Diagonal matrix of singular values
 - Think of as a scaling matrix!
- V
 - Orthonormal eigenvectors of A^TA
 - Another rotation matrix!

$$A_{m \times n} = U_{m \times m} S_{m \times n} V_{n \times n}^{T}$$

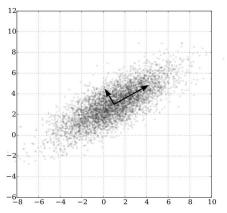
$$\begin{pmatrix} A & U & S & V^T \\ x_{11} & x_{12} & x_{1n} \\ & \ddots & \\ x_{m1} & & x_{mn} \end{pmatrix} = \begin{pmatrix} u_{11} & u_{m1} \\ & \ddots \\ & u_{1m} & u_{mm} \end{pmatrix} \begin{pmatrix} \sigma_1 & 0 \\ & \sigma_{\sigma_1} \\ 0 & & 0 \end{pmatrix} \begin{pmatrix} v_{11} & v_{1n} \\ & \ddots \\ v_{n1} & v_{nn} \end{pmatrix}$$

$$m \times n \qquad m \times m \qquad m \times n \qquad n \times n$$

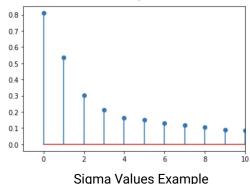


Principal Components Analysis (PCA)

- $PCA = \underline{P}$ rincipal \underline{C} omponent \underline{A} nalysis
 - Principal components: basis vectors that maximize variance in our data
 - Oftentimes, we can capture most of the data's behavior with just a few principal components!
 - Fewer dimensions is easier to work with
- How do we compute PCA?
 - Let's use SVD!!!!
 - Take the vectors that correspond with the highest singular values since those are the "most important" transformations of a matrix
 - The principal components of our setup are the vectors from V – why?



Principal Components of Data Example



What are our PCA Vectors?

Theorem 9 (Linear Algebra of the Full SVD)

Let $A \in \mathbb{R}^{m \times n}$ have rank $r \leq \min\{m, n\}$. Let $A = U\Sigma V^{\top}$ be an SVD of A.

(i) $Col(U_r) = Col(A)$.

(ii)
$$\operatorname{Col}(V_r) = \operatorname{Col}(A^\top) = \operatorname{Row}(A)$$
.



(iii)
$$\operatorname{Col}(U_{m-r}) = \operatorname{Null}(A^{\top}).$$

(iv)
$$Col(V_{n-r}) = Null(A)$$
.

(v)
$$AA^{\top} = U\Sigma\Sigma^{\top}U^{\top}$$
.

(vi)
$$A^{\top}A = V\Sigma^{\top}\Sigma V^{\top}$$
.

(vii)
$$AV_r = U_r \Sigma_r$$
.

Each row is one datapoint, we want to capture the variance across all our datapoints!

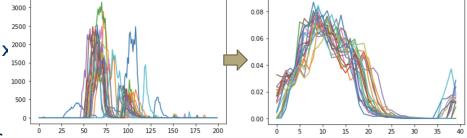
Voice Classification with PCA

Our voice classification system:

- 1. Data Pre-Processing
- 2. SVD and PCA Computation
- 3. Mean Centroid Classification
- 4. Validation + Hyperparameter Tuning

Data Preprocessing/Word Alignment

- Trim and align each recording to locate and isolate the spoken word
 - value needed to trigger a word
 start
 - Pre-length how many timesteps before we hit this threshold did we start speaking the word
 - Length how long the sample is



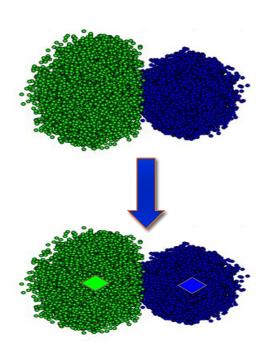
Word example: "meat"

Computing PCA via SVD

- Split our data into (70%) training and (30%) testing data
 - Use training data for the steps below, save testing data for Part 6
- Stack the aligned words in a data matrix
- Zero-mean ("demean") the data using the mean of each timestep (each "feature") in preparation for SVD

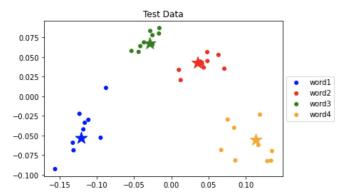
Mean Centroid Classification

- We now have:
 - Labelled training data (70% of Original Data)
 - Axes of most variation (PCA basis vectors)
- Project data onto basis vectors
- Find projected centroid (mean) for each word
 - To classify new points (unlabelled data), project it onto these basis vectors and finding which centroid it is closest to



Verify your Classifier

- Using the 30% of data set aside, verify the accuracy of our classifier
 - Project test data onto our PCA vectors
 - Subtract projected mean vector
 - Assign to closest centroid in 3D space
 - Check if classified centroid is the same as the data label
- Aim for at least 80% accuracy on all words with the test data!
 - In machine learning, it is standard practice to follow this "set aside" method to verify that the classification works and isn't overfitting



Word Choice Guidelines

- Speech pattern recognition, not word recognition
 - Actual word doesn't matter, but the speech pattern for the word does!
 - Enunciate syllables well to make clear distinctions
- Generally, try to use words with:
 - Different syllables (e.g. pear, apple, banana, watermelon)
 - Different endings (hard vs. soft, , e.g back vs. shoe)
- Remember the way you say each word, as you'll have to replicate it later!
 - Can record yourself with your phone so you have a record of how you said each word

Data Collection Guidelines

- We will provide 4 word datasets
- You will collect 40 recordings of one word of your choosing, making the total 5 words

Feedback

Please provide feedback with this anonymous feedback form!!

https://tinyurl.com/fb-student-fa24