Classification and clustering of ultrasound tongue images in vowel production

語言所碩二 盧妍蓁語言所博三 翁益寧

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 - Tongue, larynx (vocal cords)
 - Articulatory phonetics and laboratory phonology
 - Speech pathology and therapy
 - Second language acquisition



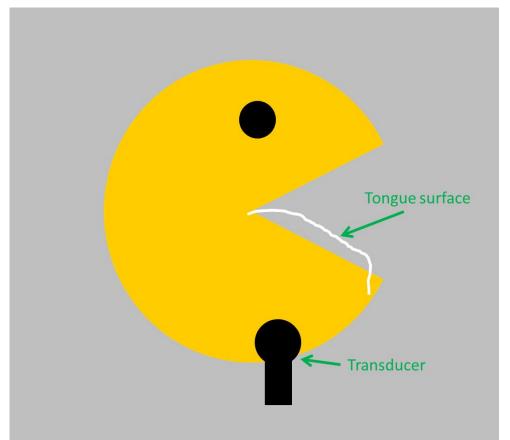


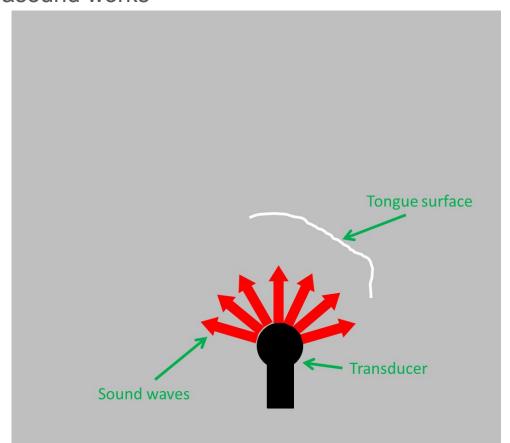
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 - Tongue, larynx (vocal cords)
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- Pros of ultrasound
 - Non-invasive, safe, easy to set-up, accessible
 - Visible in real-time

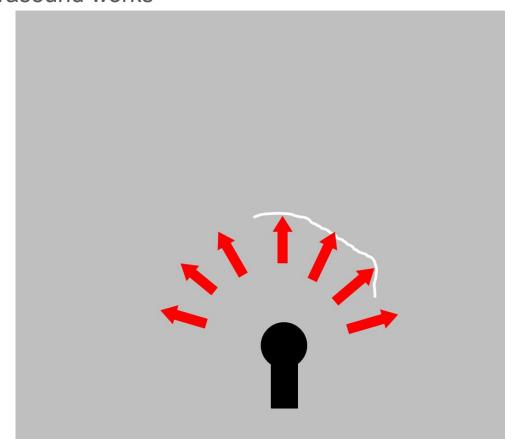


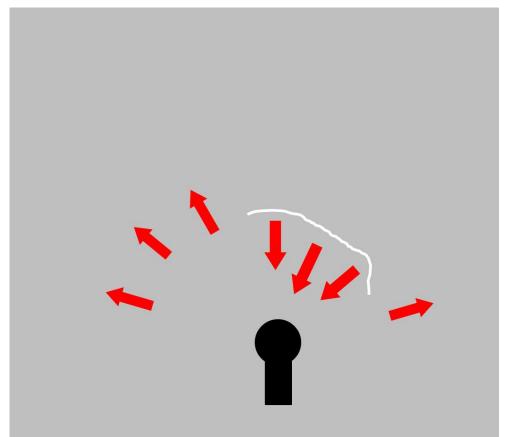


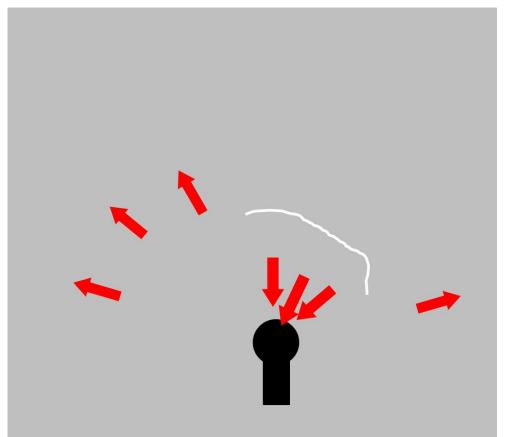




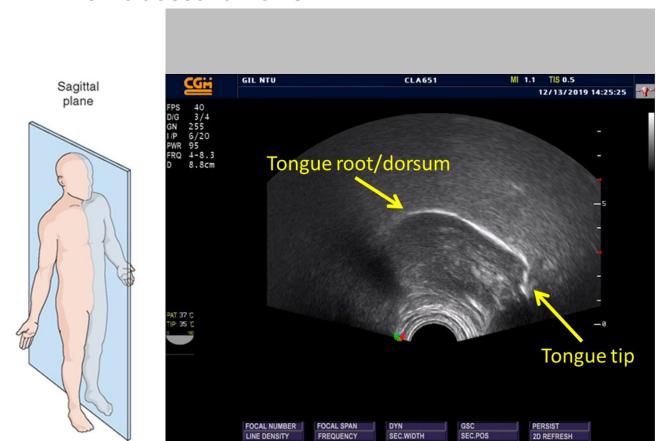








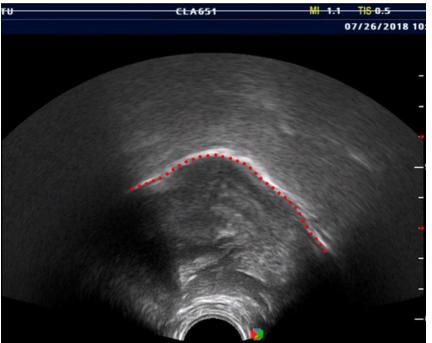




- Traditional method of analyzing ultrasound data is slow and laborious
- Quantifying image data into coordinates (contour tracing)
 - Tongue contour → line (a series of points)
 - Each point described by coordinates (X, Y)

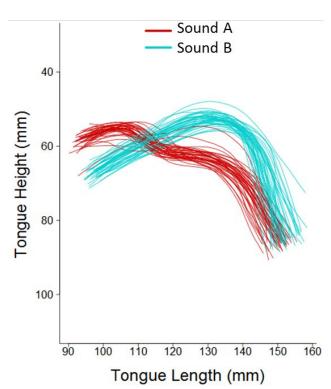


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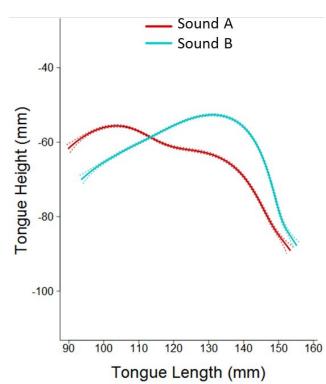
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- Statistical analysis
 - Smoothing Spline ANOVA
 - Generalized Additive Mixed Models



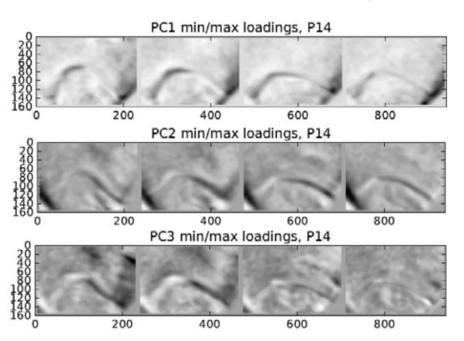
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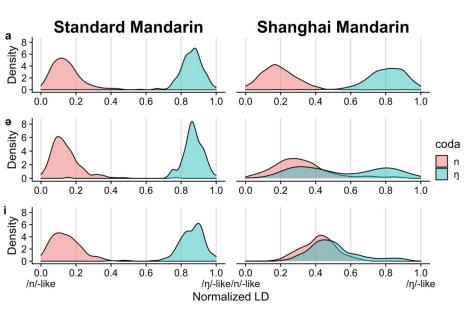


Recent studies started to use raw-image-based analysis methods

Principal Component Analysis



Linear Discriminant Analysis



Kochetov et al. (2019) Manner differences in the Punjabi dentalretroflex contrast: An ultrasound study of time-series data

Faytak et al. (2020) Nasal coda neutralization in Shanghai Mandarin: Articulatory and perceptual evidence

Our goal:

Try out raw-image-based methods for

- Classification of vowels
 - Convolutional Autoencoder
- Visualization of vowel clusters
 - PCA (Principal Component Analysis)
 - t-SNE (t-distributed Stochastic Neighbor embedding) (library install failed)
 - UMAP (Uniform Manifold Approximation and Projection)

- Subjects
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- Materials
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 - Each vowel pronounced 100 times in isolation
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Images from the midpoint of each trial were extracted for analysis

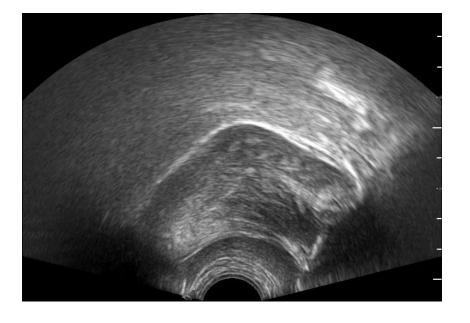
• Speaker 1 /a/ /u/ /i/ /e/ **/o/ /**ə/



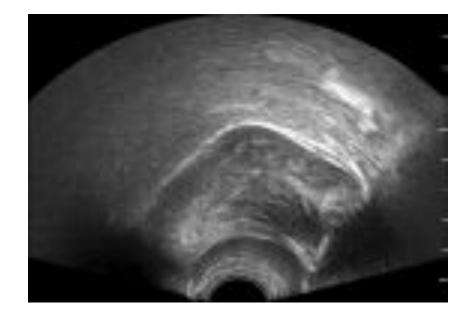
Convert to greyscale



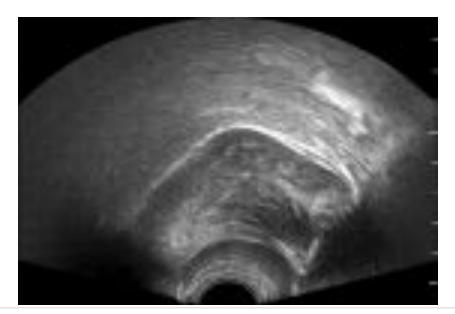
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- Cropping to meaningful area



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- Downscaling to 96 (h) * 140 (w)

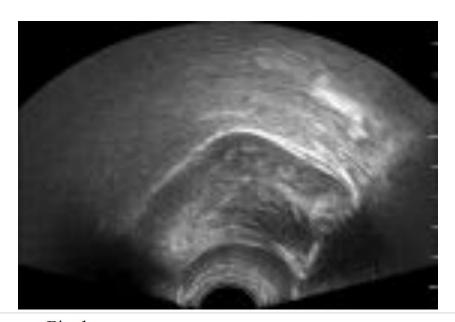


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- Downscaling to 96 (h) * 140 (w)
- Flattening to (1 * 13440) vector
 - Only necessary for some analysis



		Pixel										
Image	P1	P2		P3	P4	P5	•••	P13438	P13439	P13440		
a001		0	0	34	157	255	•••	27	0	0		
a002		0	0	0	58	169	•••	84	2	0		

- Convert to greyscale
- Cropping to meaningful area
- Downscaling to 96 (h) * 140 (w)
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- Normalizing to [0, 1]

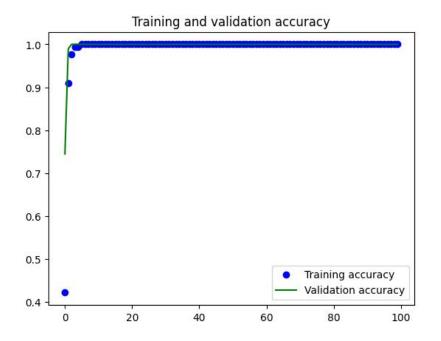


	Pixel										
Image	P1	P2	P3	P4	P5	•••	P13438	P13439	P13440		
a001	0.000	0.000	0.133	0.616	1.000	•••	0.106	0.000	0.000		
a002	0.000	0.000	0.000	0.227	0.663	•••	0.329	0.008	0.000		

• Total 1200 images

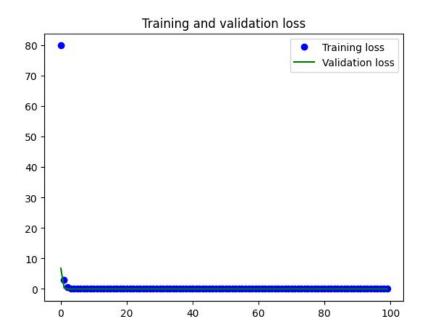
- Training set: 960 images
 - 80% train
 - 20% validation
 - 200 total epochs

• Test set: 240 images



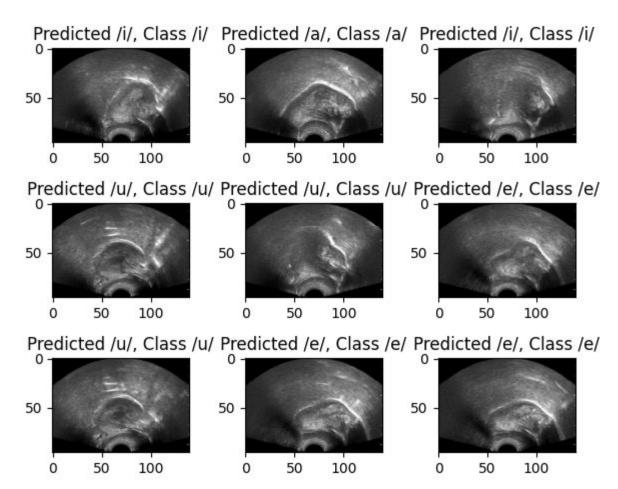
Test loss: 0.095

Test accuracy: 0.992

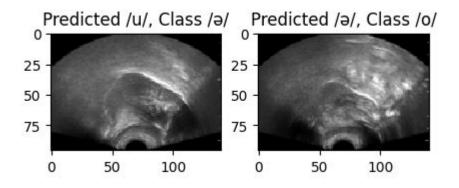


No overfitting Robust performance

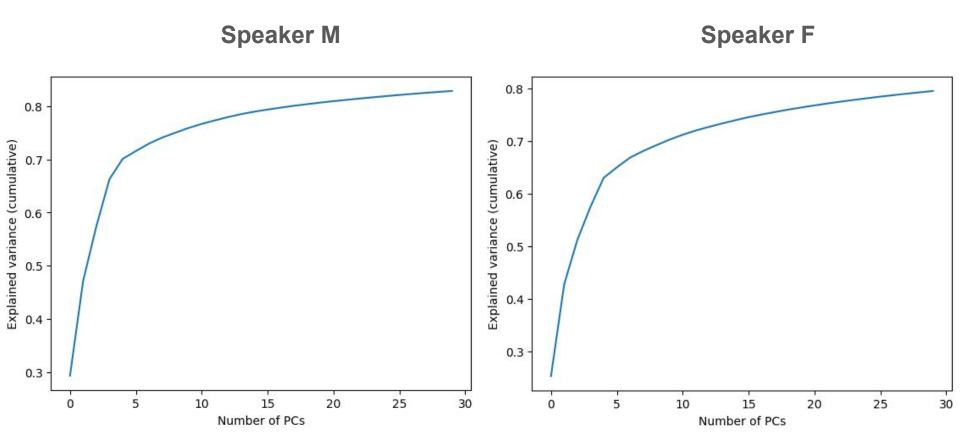
238 correct labels



2 incorrect labels

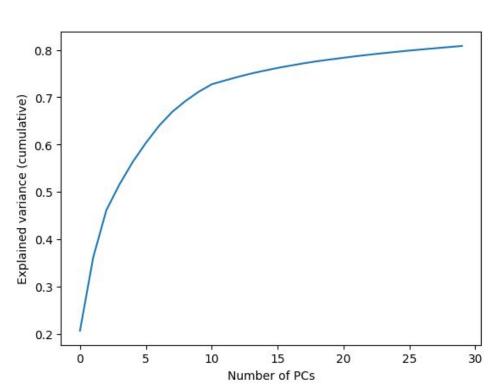


Explained variance (cumulative)

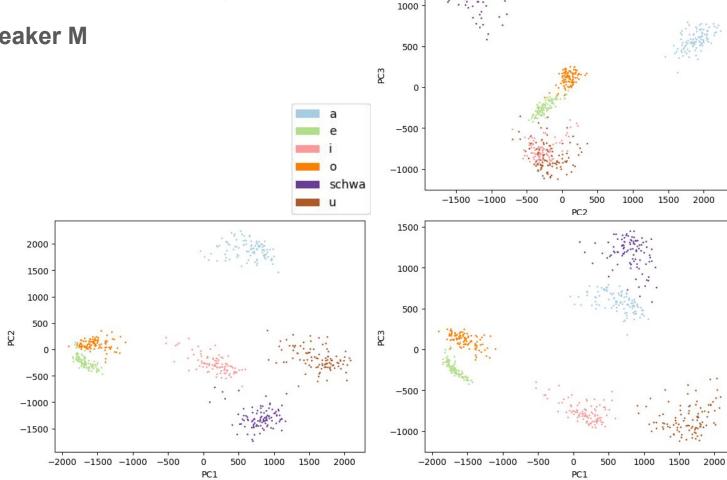


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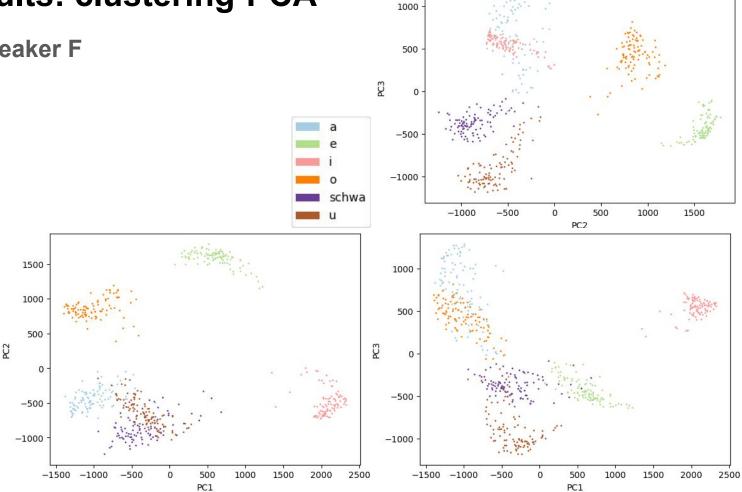


Speaker M



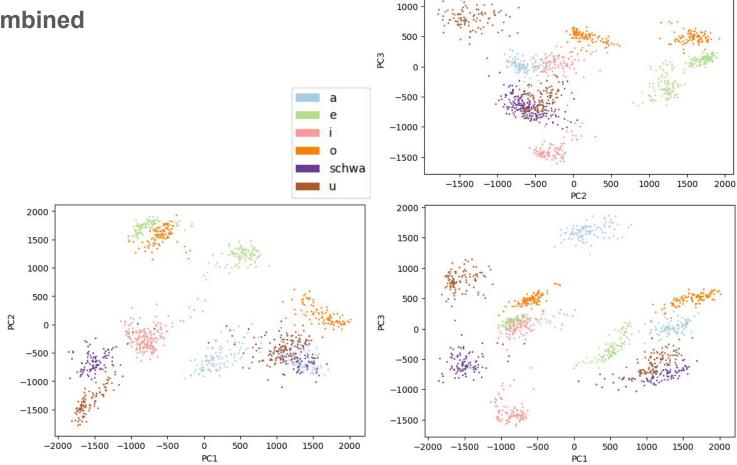
1500

Speaker F



Results: clustering-PCA

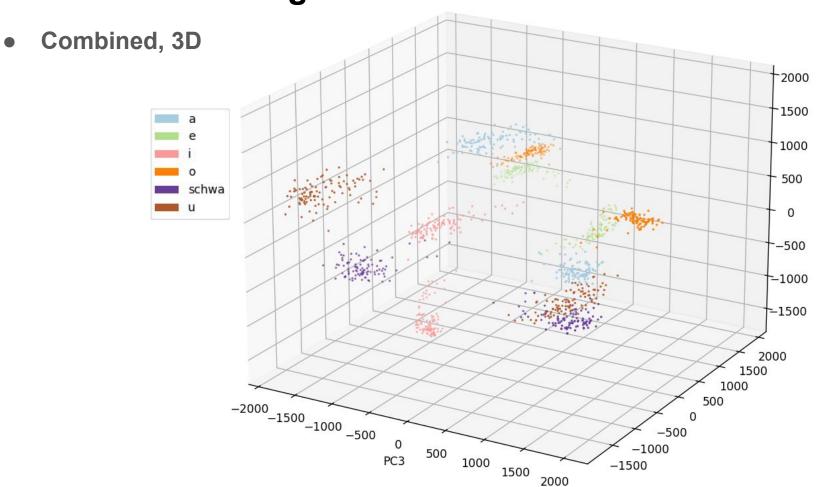
Combined



2000

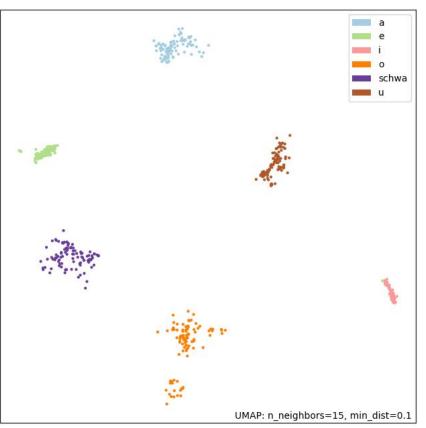
1500

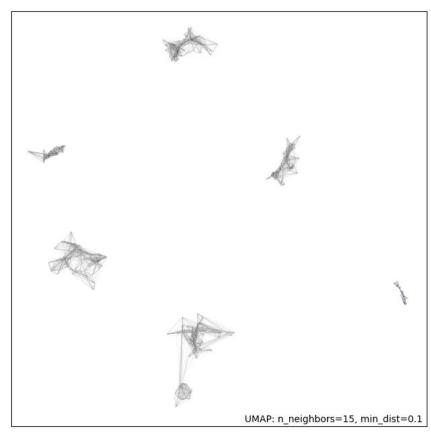
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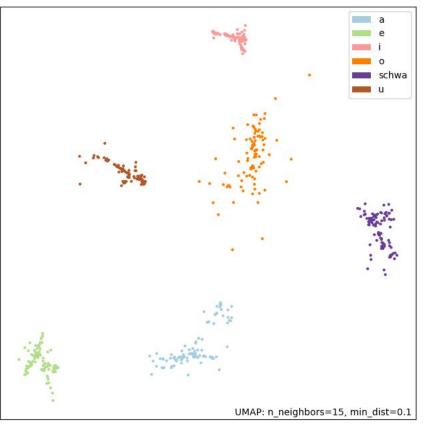
Speaker M

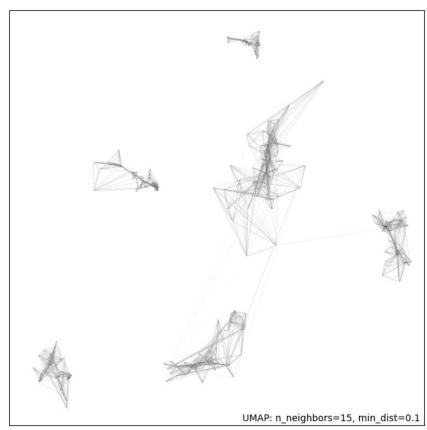
2D embedding





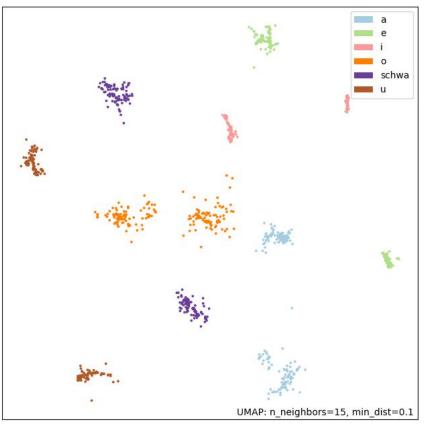
Speaker F 2D embedding

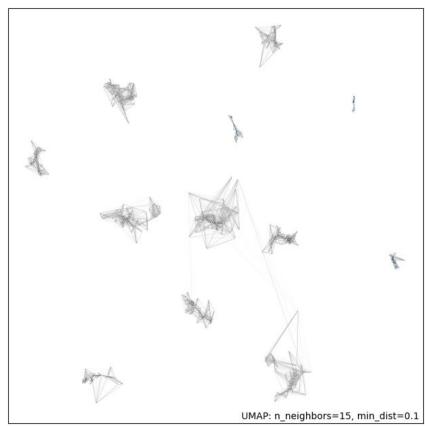




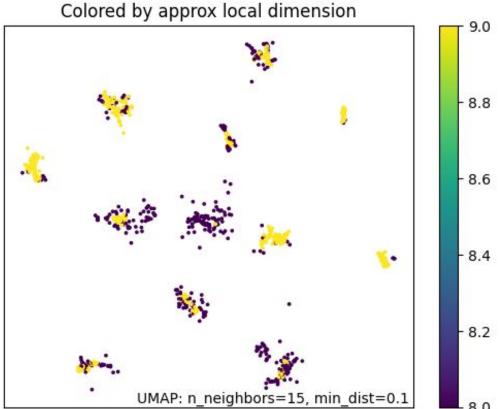
Combined

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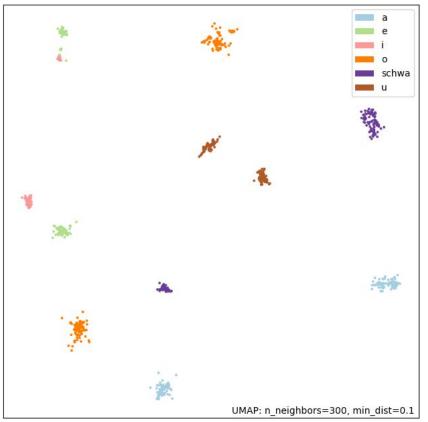


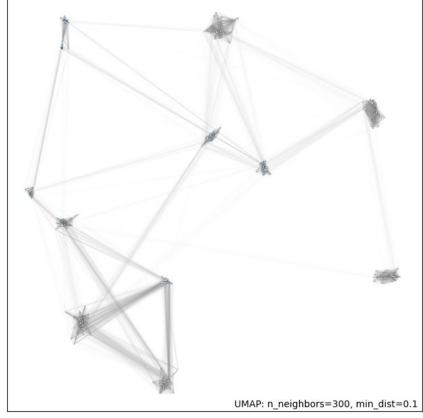


Combined local dimensions



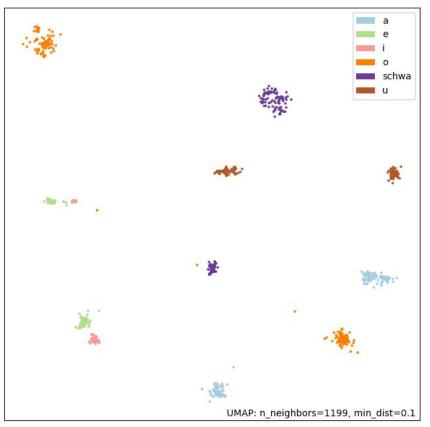
Combined, n_neighbors=300 2D embedding

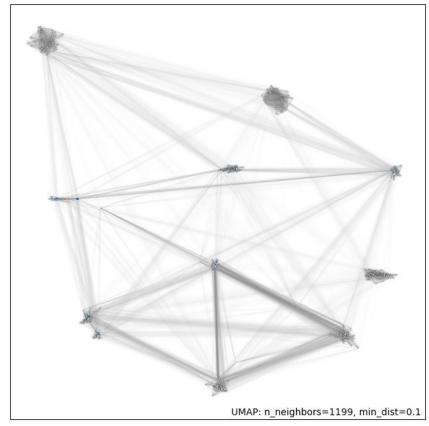


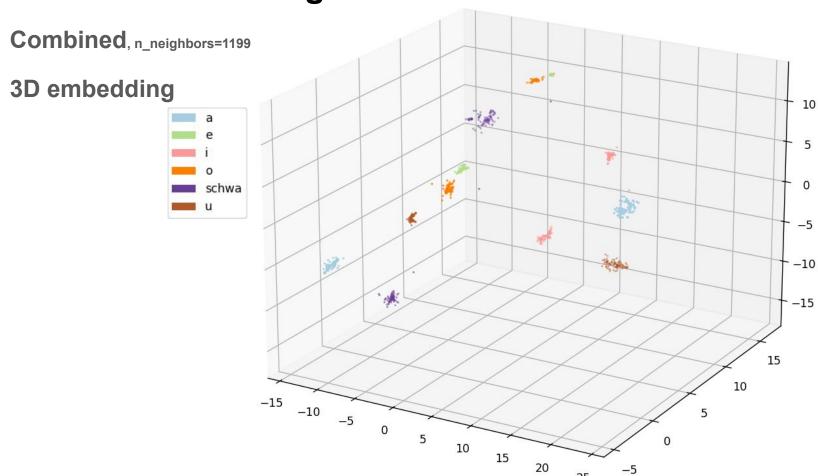


Combined, n_neighbors=1199

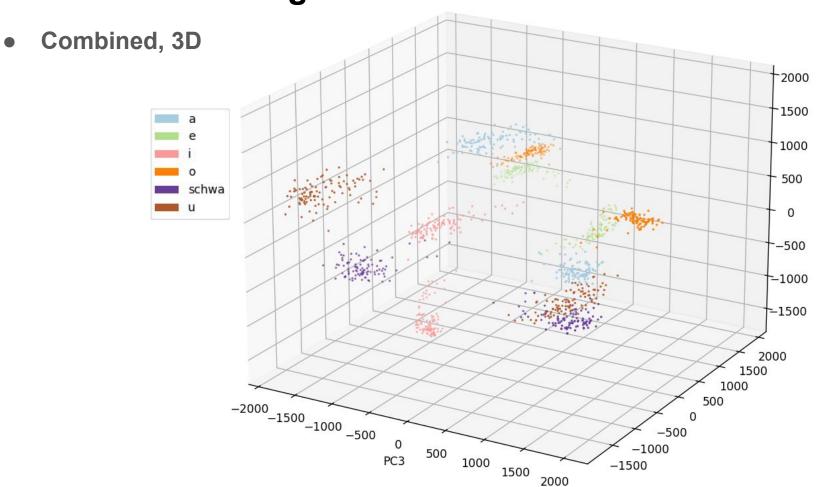
2D embedding







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- The same vowels from different speakers don't seem to cluster together
 - Image normalization

Thank you!