

Orthogonality and Isotropy of Speaker and Phonetic Information in self-supervised speech representations

Previous work suggests geometric properties of a representation space reflects its quality.

Orthogonality between phone and speaker subspaces supports simple disentanglement (Liu et al., 2023).

Isotropy in a representation space implies all dimensions are utilized uniformly, which proves helpful in some tasks (e.g. modeling semantic similarity), but harmful in others (e.g. clustering).

In this work, we propose a quantitative measure, *Cumulative Residual Variance*, to evaluate:

- Questions**
- To what extent do different SSL models exhibit these two geometric properties?
 - How do these properties relate to performance on phone and speaker classification?

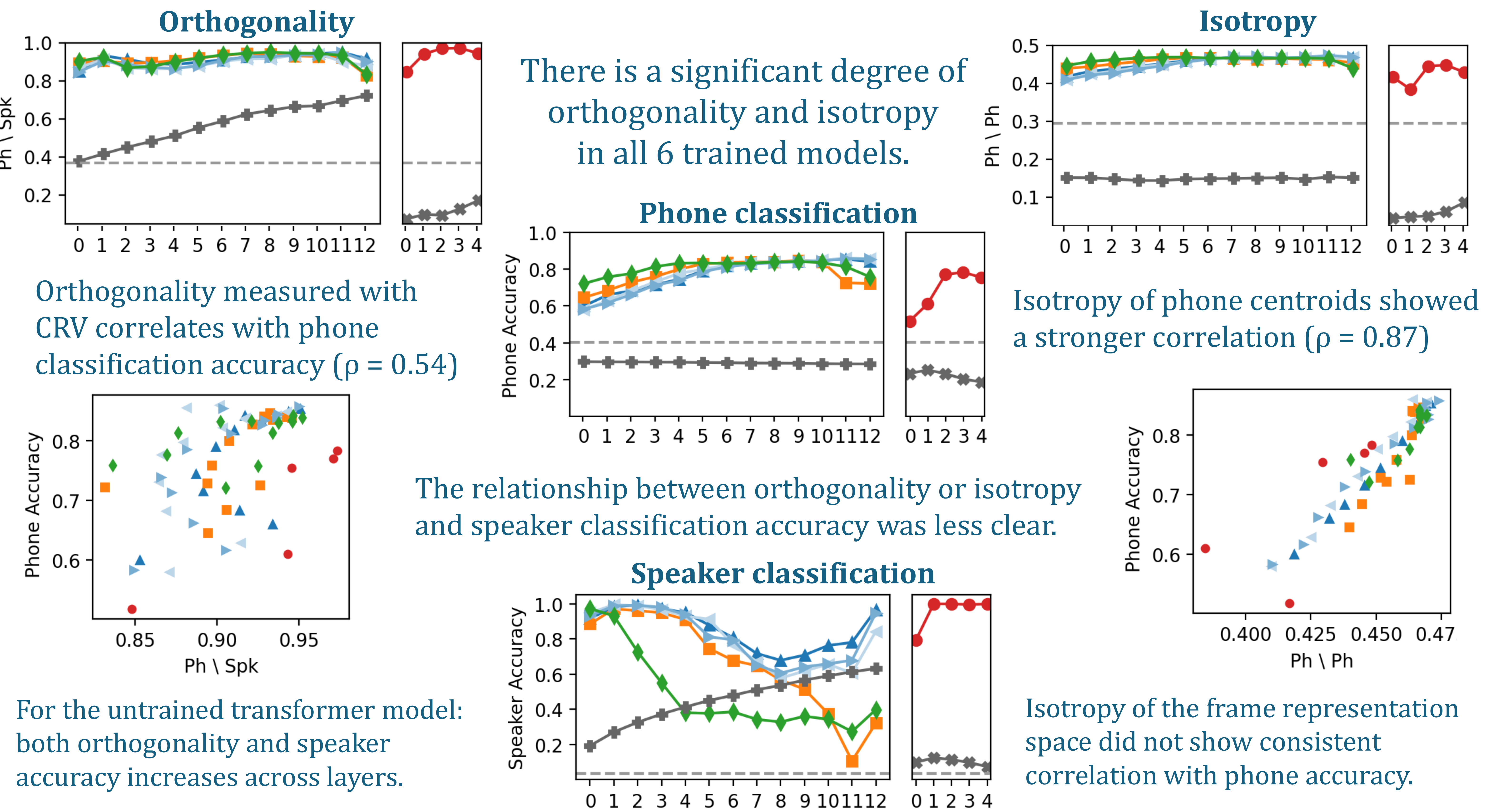
Results

We compared six self-supervised speech models ...

... across all layers within each model

... with untrained models

... with acoustic features



Across the models, layer-wise trend for speaker information shows far greater variation than phonetic information.

Cumulative residual Variance

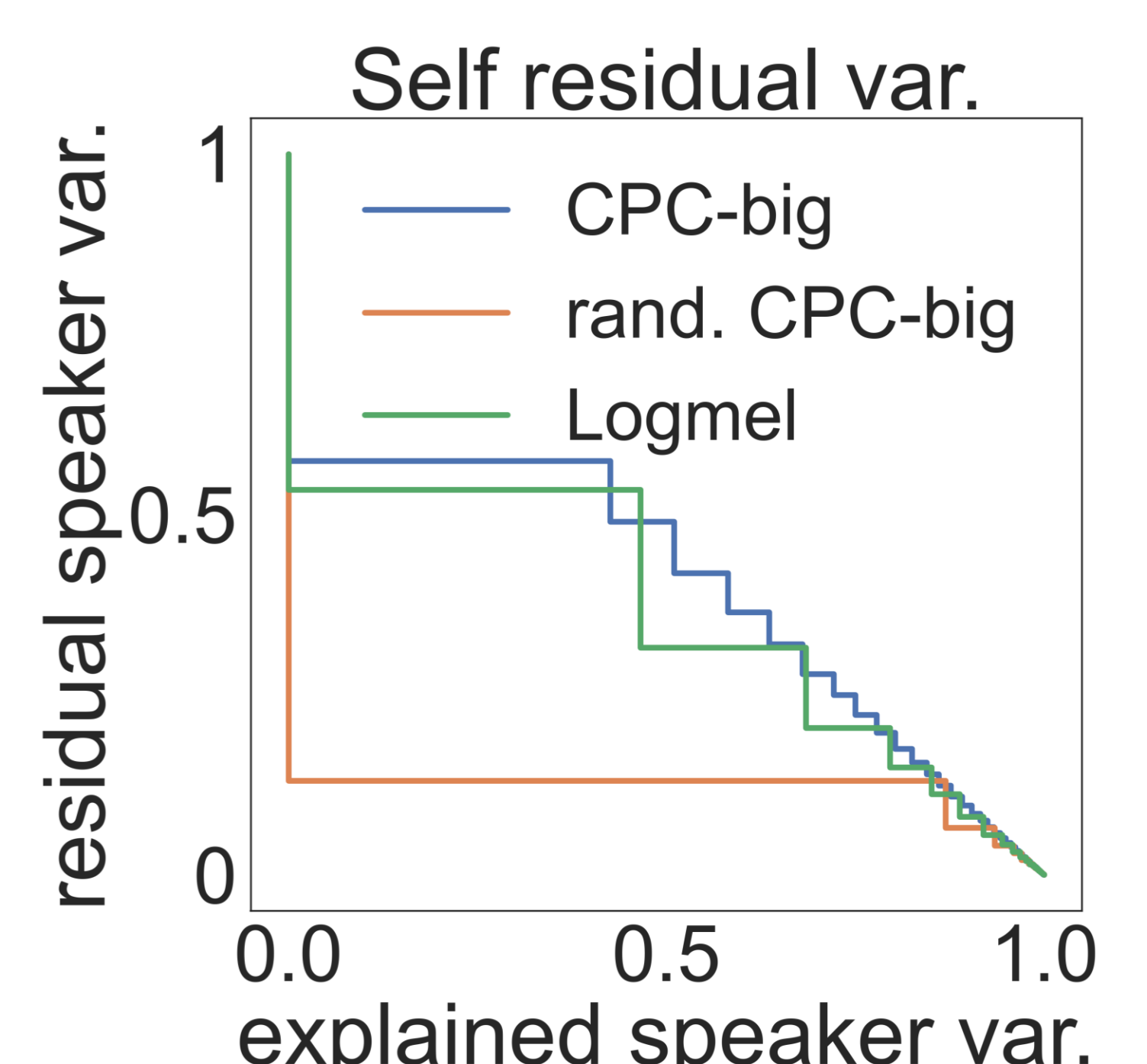
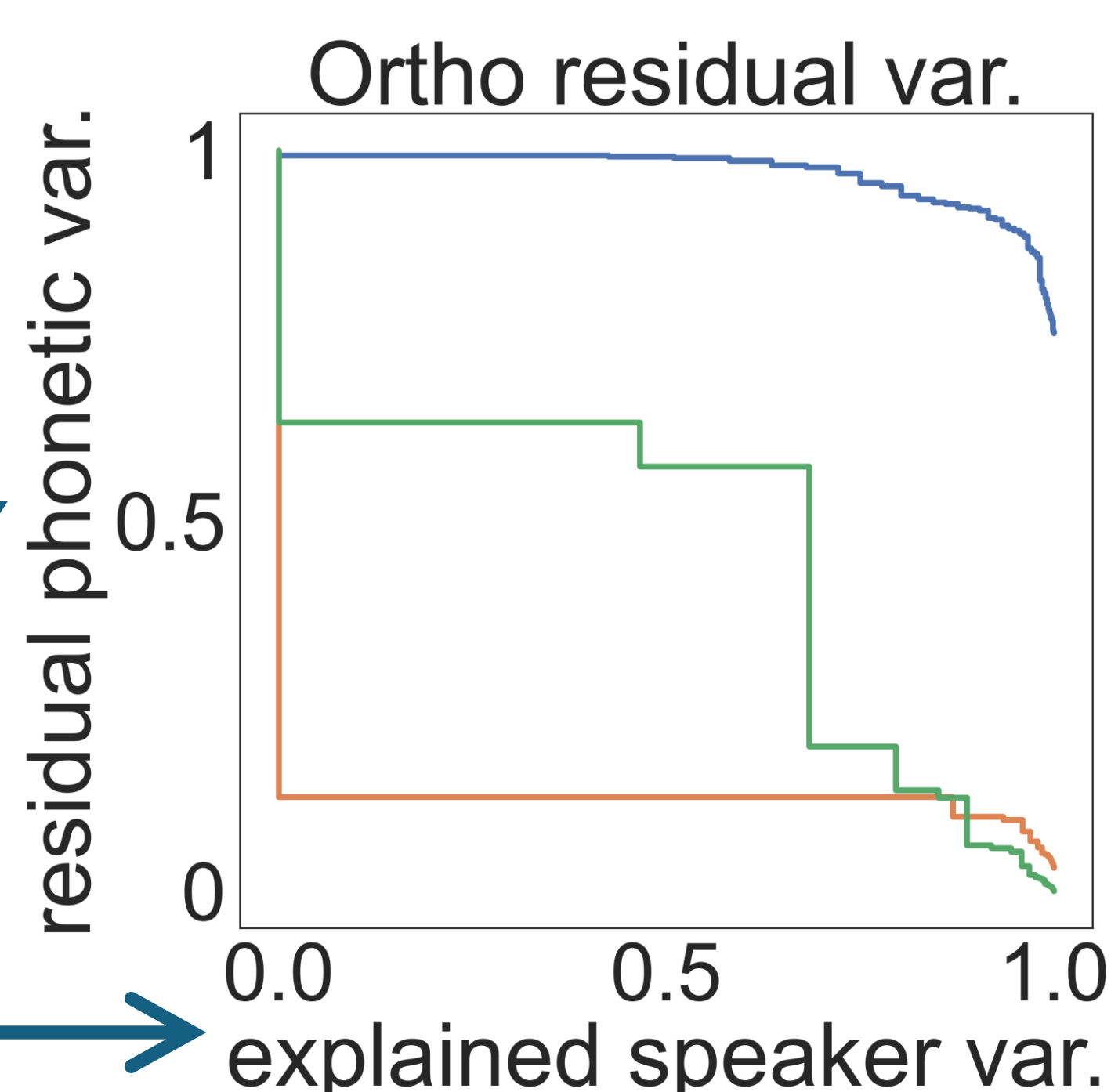
Given X (speaker centroids), Y (phone centroids):
 $X_0 = X, Y_0 = Y, v_i$ = the i -th principal direction of X .
 For $i = 0$ to n ,

- Project Y_i to the orthogonal complement of v_i

$$Y_{i+1} = Y_i - (Y_i v_i) v_i^T$$

- Measure the variance remaining in Y_{i+1}
- Compute the variance explained in X_{i+1} ($\sum_{j=1}^i \lambda_j$)

Plot



The area under the curve gives the residual phonetic variance w.r.t. speaker, or ph\spk.

AUC -> spk\spk.