

# A FRAMEWORK FOR THE AUTOMATIC INFERENCE OF STOCHASTIC TURN-TAKING STYLES

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## Goals

A **stochastic turn-taking model** predicts a speaker's speech activity at instant  $t$ , given that speaker's and their interlocutors' speech activity at preceding instants.

### It is known that ...

For conversant-independent models, training with more data helps **on average**.

For conversant-dependent models, **within-conversation** adaptation helps.

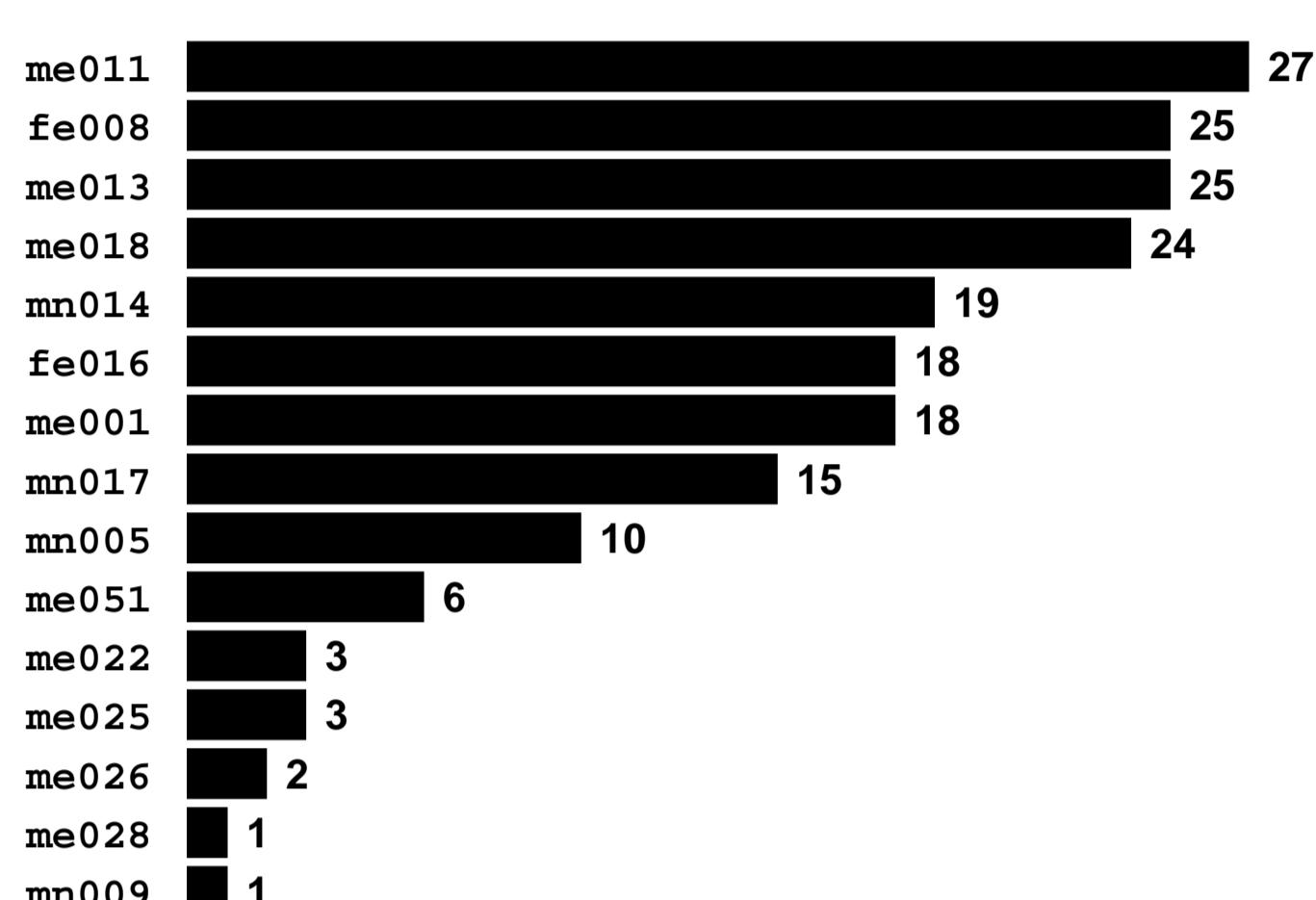
### But it is not known ...

1. Whether conversants are self-consistent **across conversations**, implying quasi-stationary turn-taking styles?
2. **What** may account for the variability observed in models?

## Longitudinal, Conversational Dataset

### “Bmr” Subset of ICSI Meeting Corpus

- ▶ recorded over the course of a year
- ▶ allegedly **natural** turn-taking: “would have been held even if they were not recorded”
- ▶ total 29 conversations
- ▶ average 48.4 minutes per conversation
- ▶ total 15 participants
- ▶ average 6.8 participants per conversation
- ▶ total 197 conversation sides



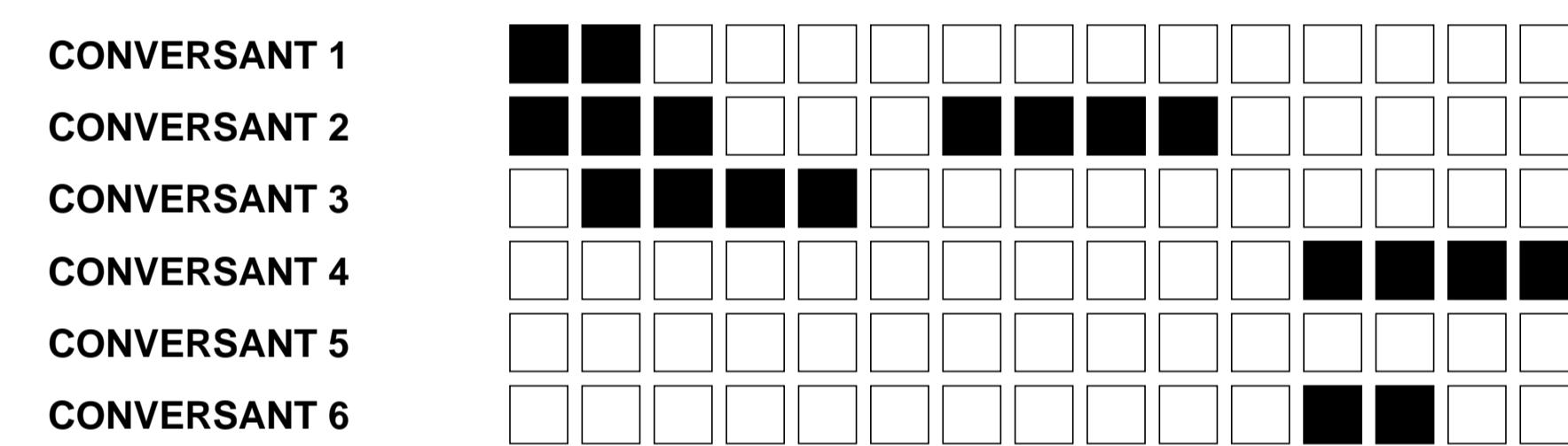
## Findings from Dataset

1. Intra-person (within-class) variability is smaller than inter-person (between-class) variability.
2. People are surprisingly self-consistent, even in the extremely impoverished representation of speech/non-speech over 500 ms.
3. Longer-conversation observations exhibit smaller intra-person (within-class) variability.
4. Greater “talkativity” exhibits larger inter-person (between-class) variability.
5. Stochastic turn-taking models appear to be correlated with conversational-group role.
6. Person-discriminative aspects of stochastic turn-taking models appear to lie on a low-dimensionality manifold.

## 1. Inference of Turn-Taking Models

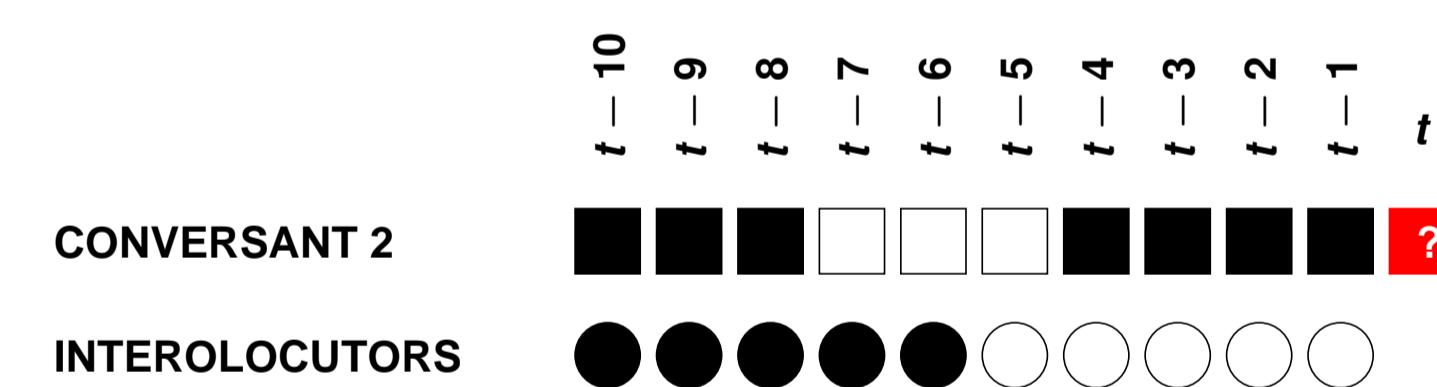
### Construct Speech/Non-speech Chronogram

- a. Throw away voice, words, prosody, etc.
- b. Discretize using 100-ms frames



### Infer an STT Model for Each Conversant

- c. Compute exclusive-OR of interlocutors
- d. Train n-gram stochastic turn-taking model



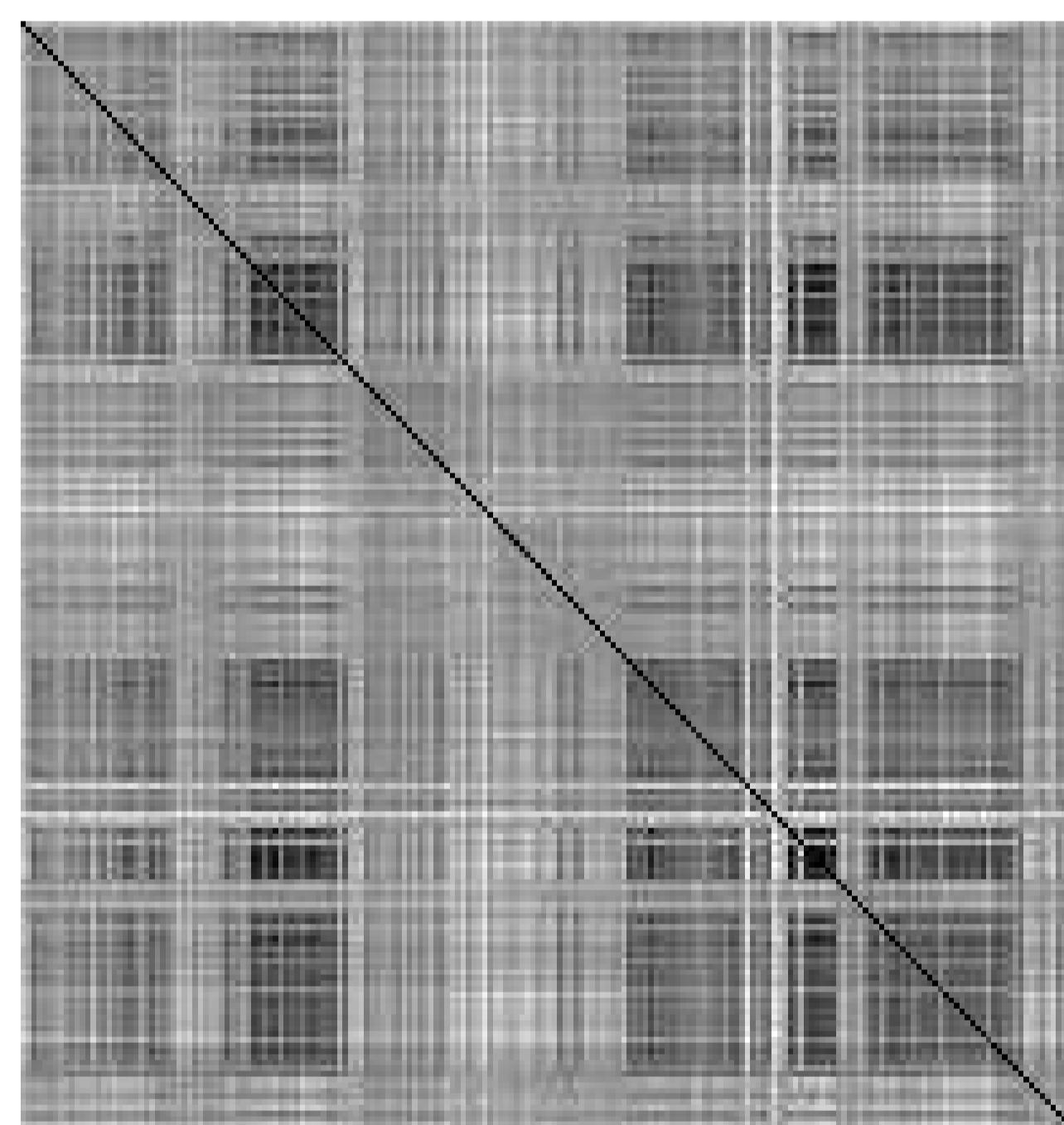
Unsmoothed model characterizes participant's contextualized speech deployment timing in one conversation (ie. one “side”).

## 2. Computation of Inter-Model Distances

### Compute Jensen-Shannon (JS) Distance

- a. n-grams are conditional probability models
- b. JS distance is symmetric and bounded

### Form Distance Matrix Over All Model Pairs



Can perform distance-based clustering and/or classification of conversational sides directly from complete matrix.

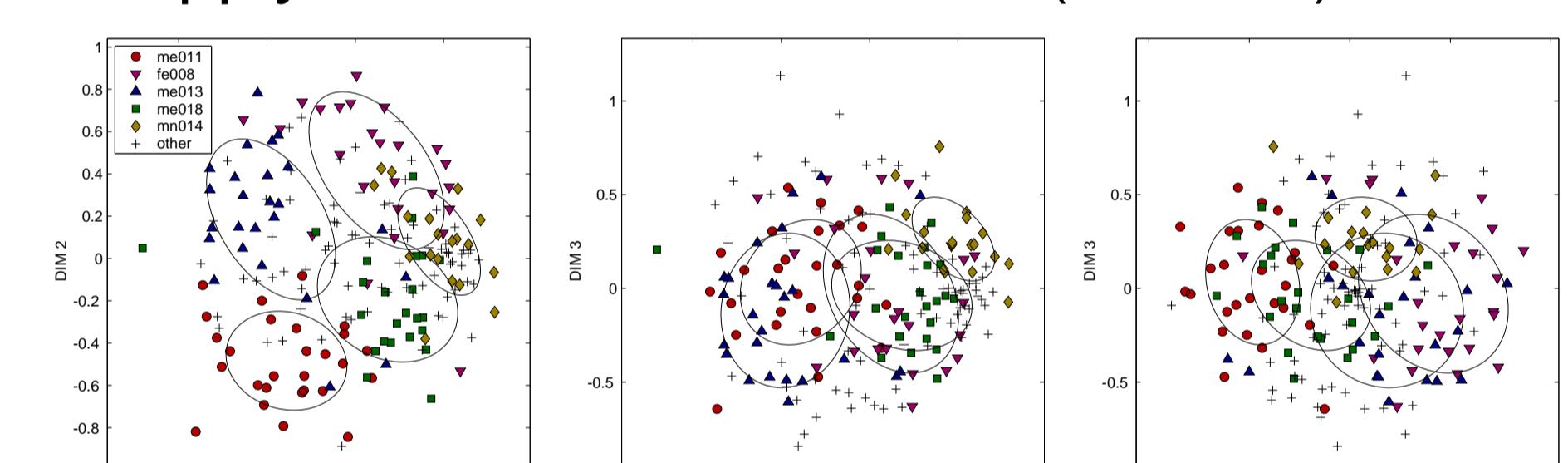
## 3. Nearest-Neighbor (NN) Classification

### Classify Participants Directly from Matrix

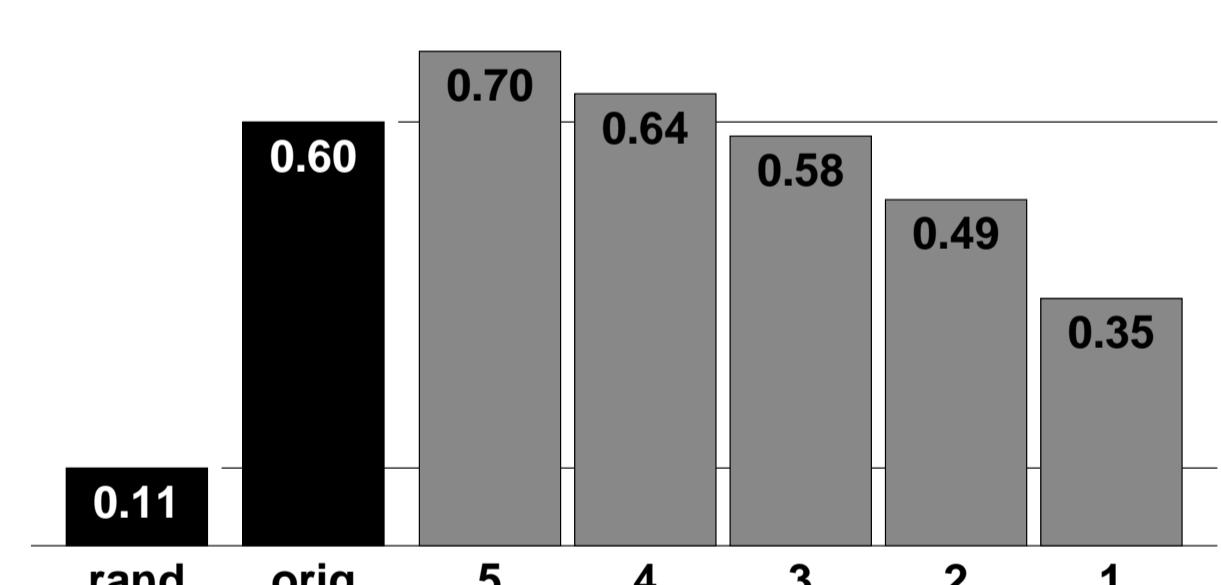
- a. Accuracy of 60% is achieved

### Classify After Multi-Dimensional Scaling

- b. Apply MDS to  $N$  dimensions ( $N$  small)



- c. Recompute distances
- d. Repeat NN classification

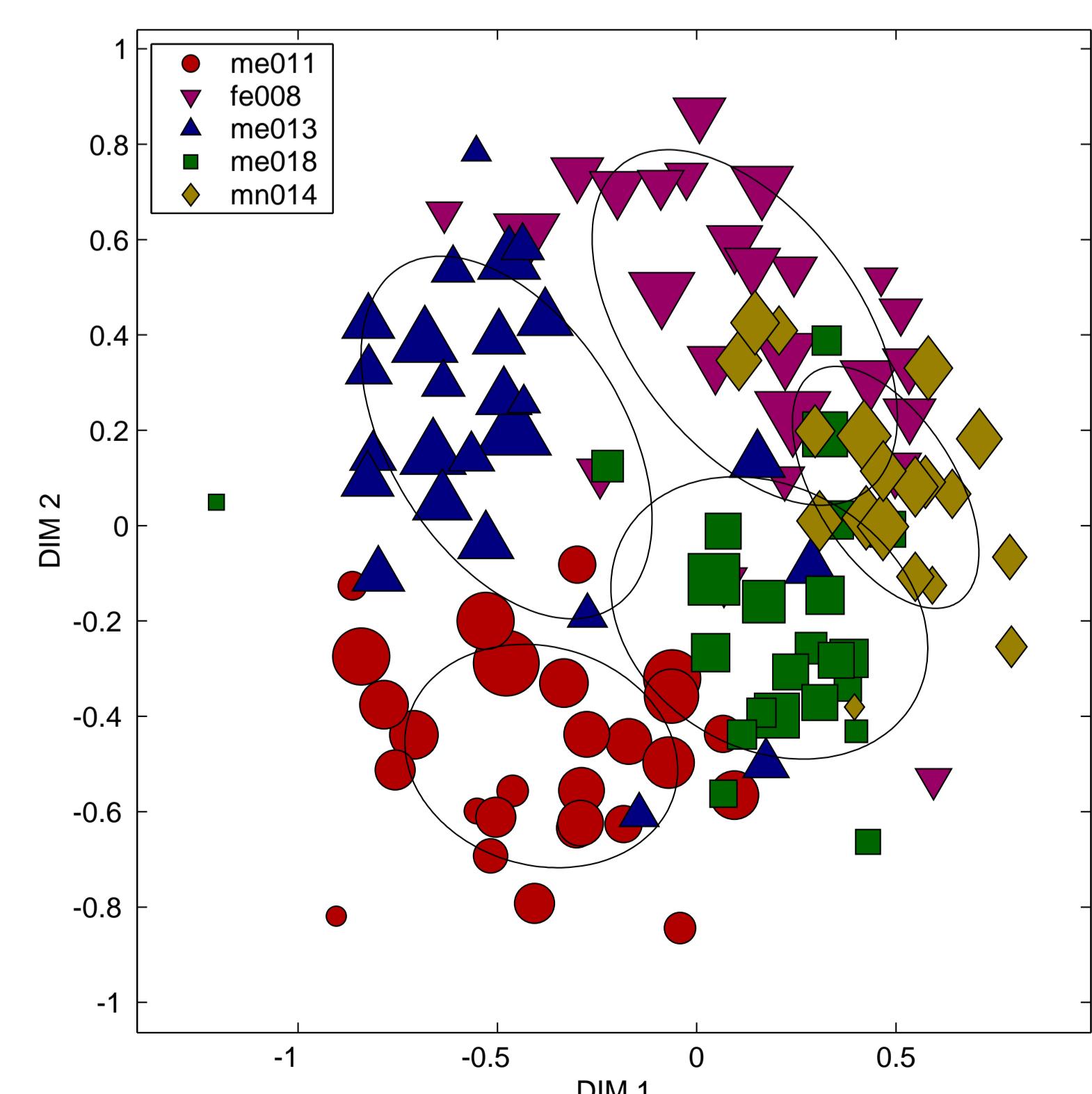


The space of models appears to lie on a low-dimensional manifold.

## Intra-Person: Duration of Observation

### Variability due to duration of sides

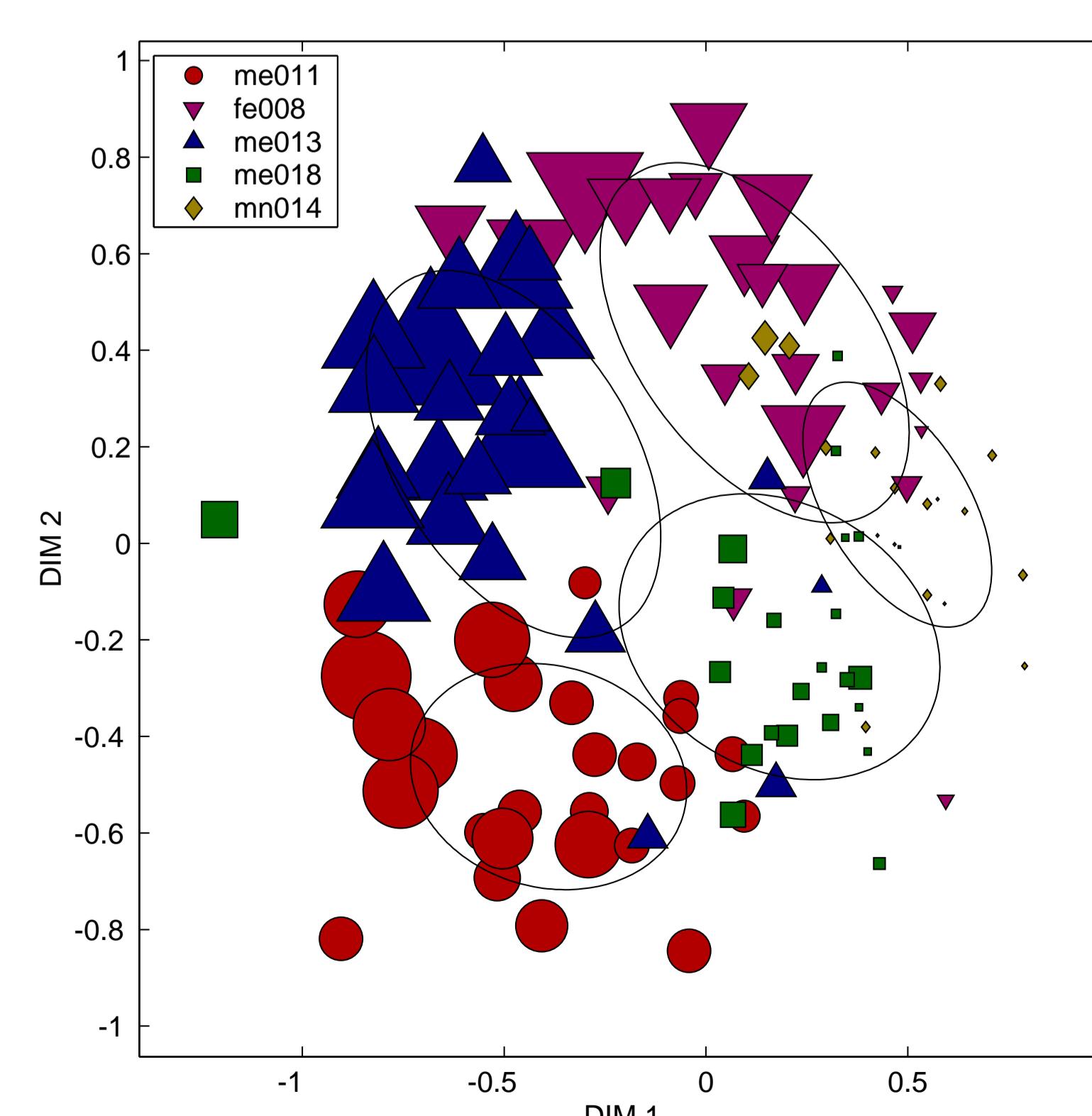
bigger markers → longer sides



## Intra-Person: Unconditional “Talkativity”

### Variability due to the proportion of speech

bigger markers → talkative sides



## Inter-Person: Organization Seniority

### Variability due to organizational role

self-reported seniority as proxy

