# Modeling Vocal Interaction for Text-Independent Classification of Conversation Type

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September 2, 2007

# What Is Vocal Interaction?

- the patterns of vocal activity for all participants to a conversation
  - no words $\longrightarrow$ a **text-independent** representation of multi-party conversation
- as used in psycholinguistics (Dabbs & Ruback, 1987)
- in telecommunications: "on-off patterns" (Brady, 1967)
- studied since the 1930s

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- a basic competence in conversation understanding
- type is most often taken for granted
  - ie. *"My project is about cocktail parties. Why would I ever need to know that a cocktail party is not a business meeting?"*
- searching & indexing in heterogenous multi-party conversation recordings (or portions)
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# Defining Conversation Type

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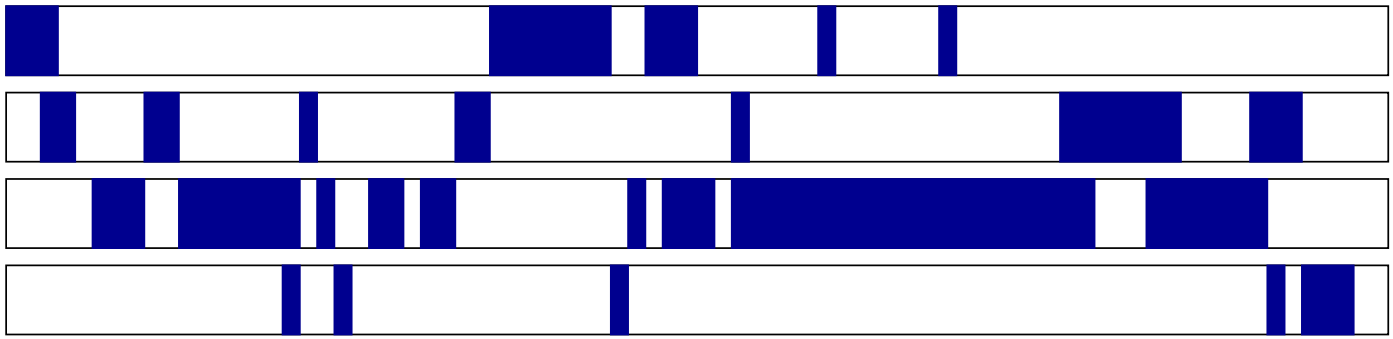

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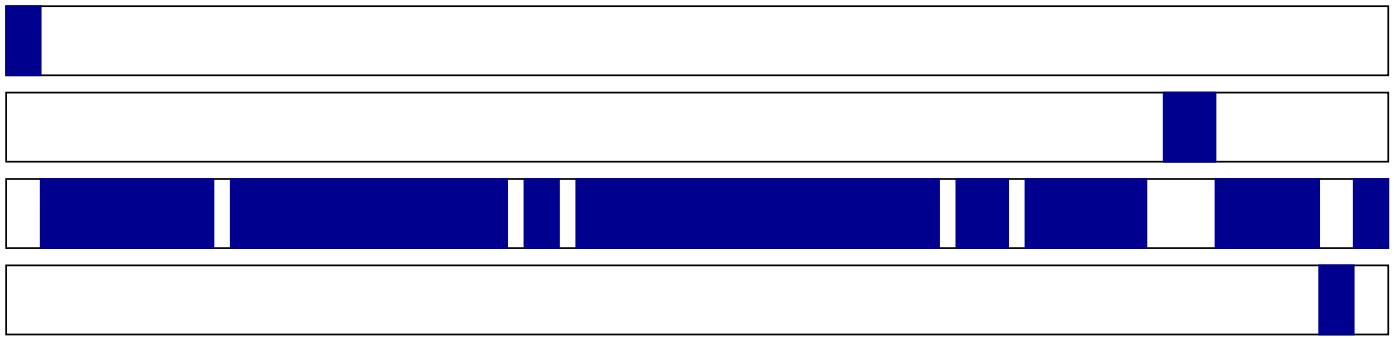

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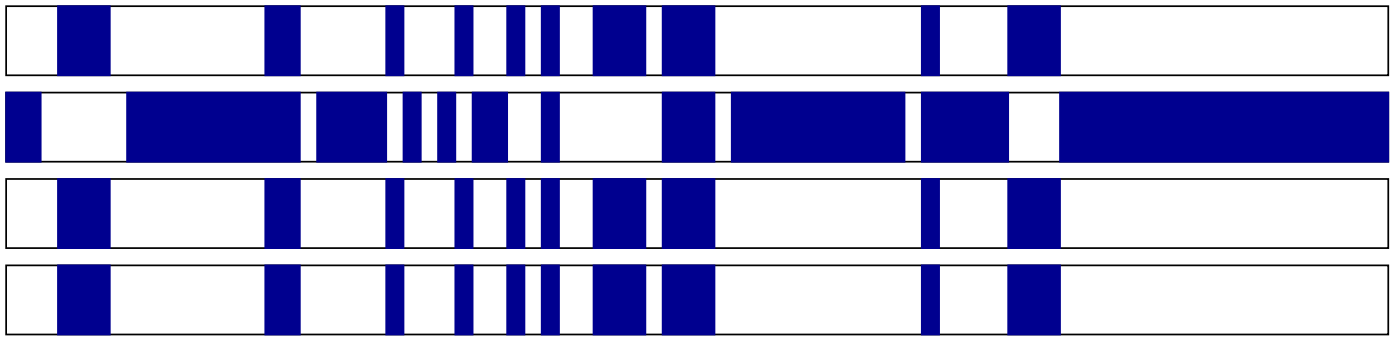

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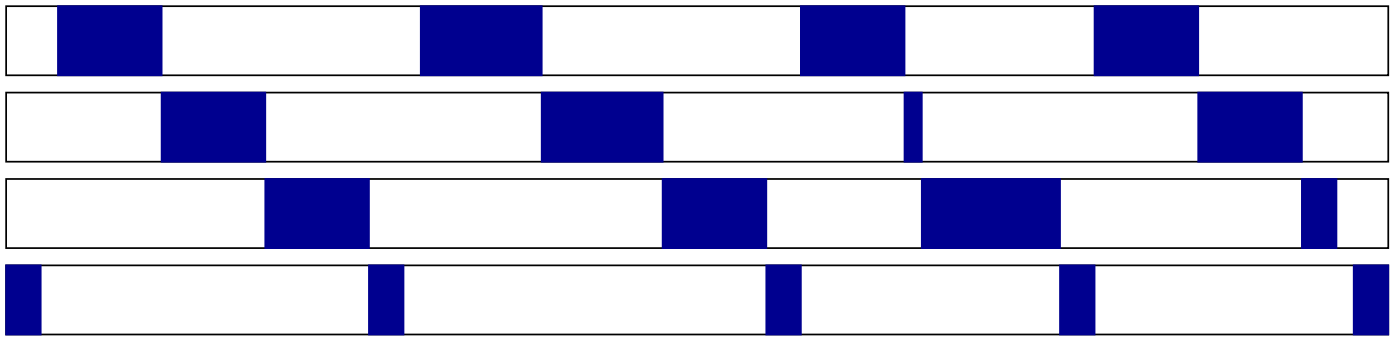

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# Related Work

- **none** on conversation type classification
- various, on evolving conversation state
  - (Banerjee & Rudnicky, 2004)
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- several related text-independent tasks
  - participant dominance detection (Rienks et al, 2005), 4-party
  - interaction group recognition (Brdiczka et al, 2005), 4-party
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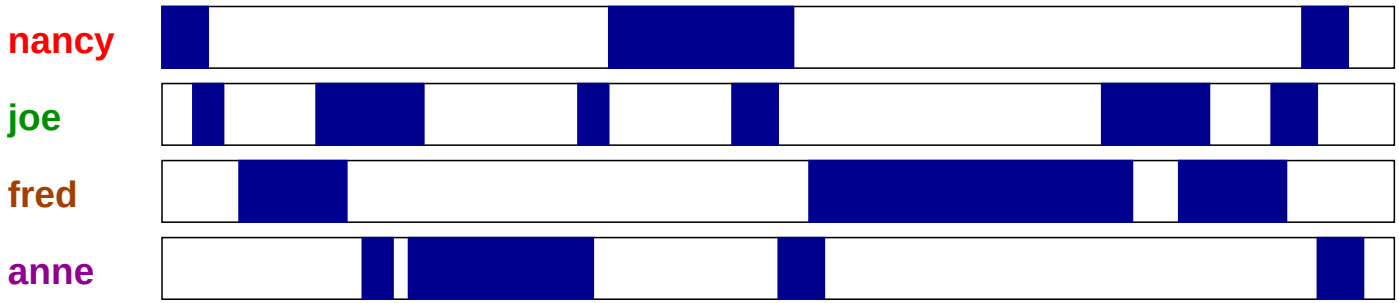


- at time $t$, each of $K$ participants is in one of 2 discrete states, vocalizing ($\mathcal{V}$) or not vocalizing ($\mathcal{N}$)
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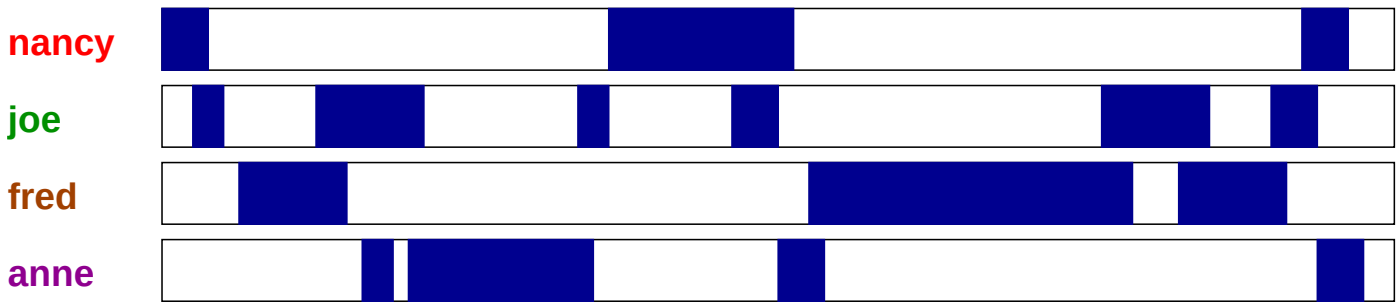


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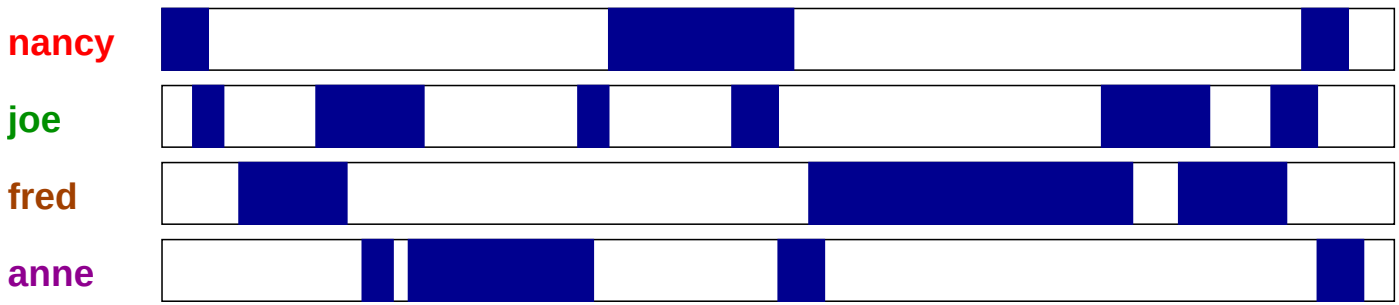


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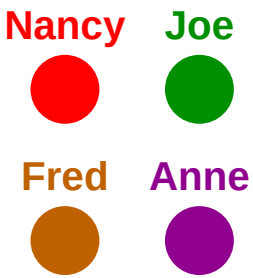
# Modeling Groups

- assume that $\mathcal{C}$ is a 1st order Markov process, produced by the ordered **group** $\mathcal{G}$ of $\|\mathcal{G}\| \equiv K$ specific participants




$\mathcal{G}$

- participants are drawn from a known population $\mathcal{P}$ of size $\|\mathcal{P}\|$
- the number of distinct groups of size $\|\mathcal{G}\| \leq \|\mathcal{P}\|$ is

$$N_{\mathcal{G}} = \frac{\|\mathcal{P}\|!}{(\|\mathcal{P}\| - \|\mathcal{G}\|)!}$$

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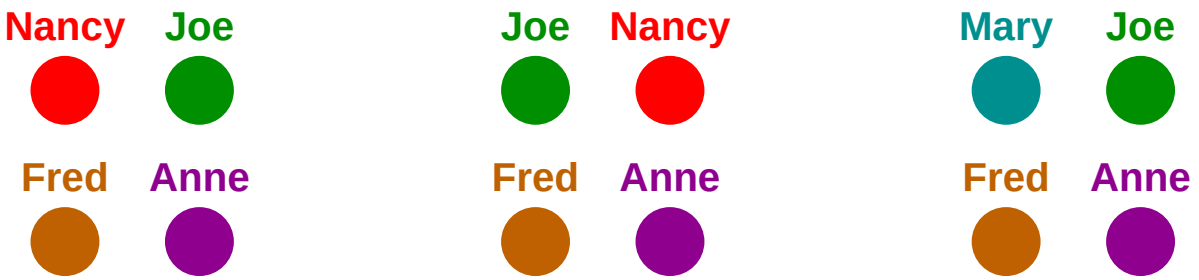


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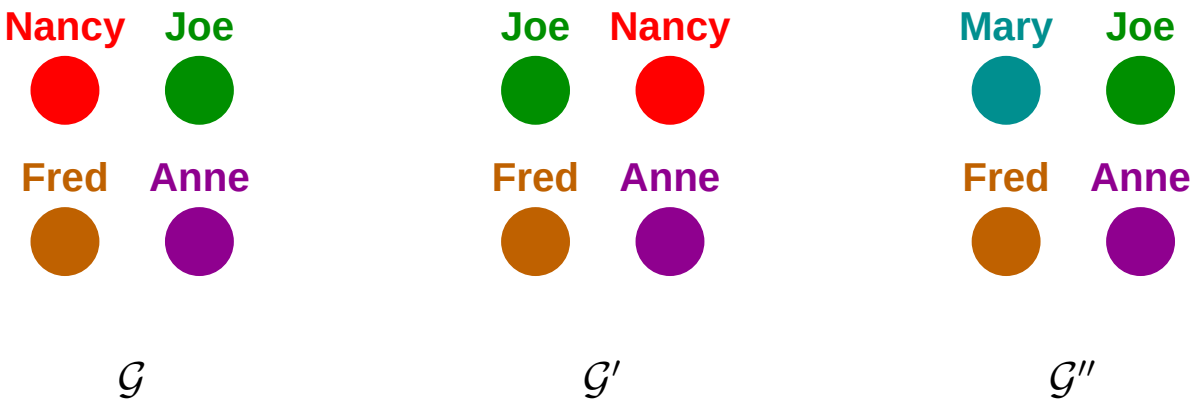


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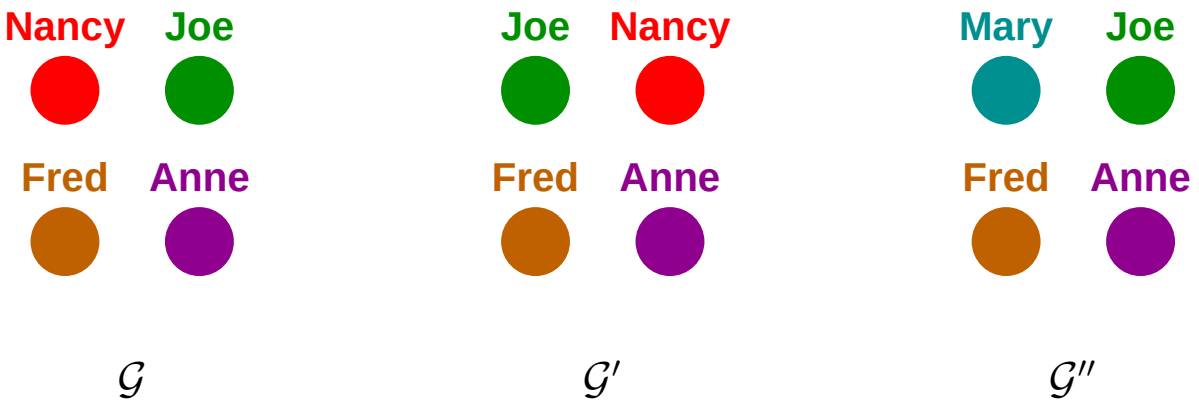


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# Conversation Type Classification

- participant identities, and therefore $\mathcal{G}$, are **hidden variables**
- given a set of features $\mathbf{F}$ extracted from $\mathcal{C}$,

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\mathcal{T}^* &= \arg\max_{\mathcal{T}} P(\mathcal{T} \mid \mathbf{F}) \\
&= \arg\max_{\mathcal{T}} \sum_{\mathcal{G}} P(\mathcal{G}, \mathcal{T}, \mathbf{F}) \\
&= \arg\max_{\mathcal{T}} \sum_{\mathcal{G}} P(\mathcal{T}) \times \underbrace{P(\mathcal{G} \mid \mathcal{T})}_{\text{Membership Model}} \times \underbrace{P(\mathbf{F} \mid \mathcal{G}, \mathcal{T})}_{\text{Behavior Model}}
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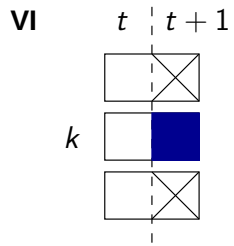


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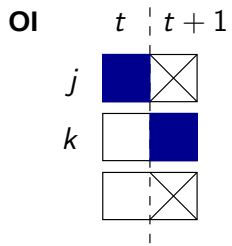

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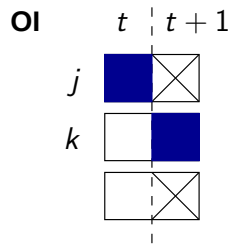


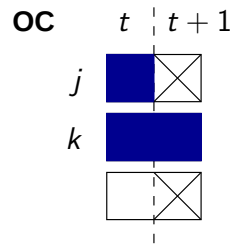

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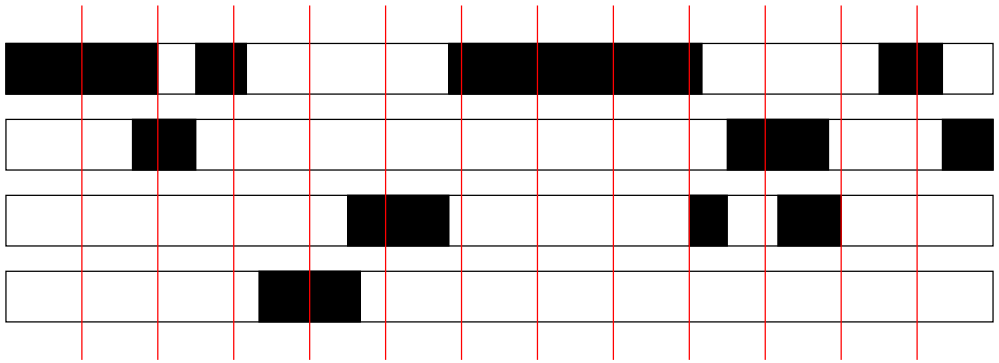

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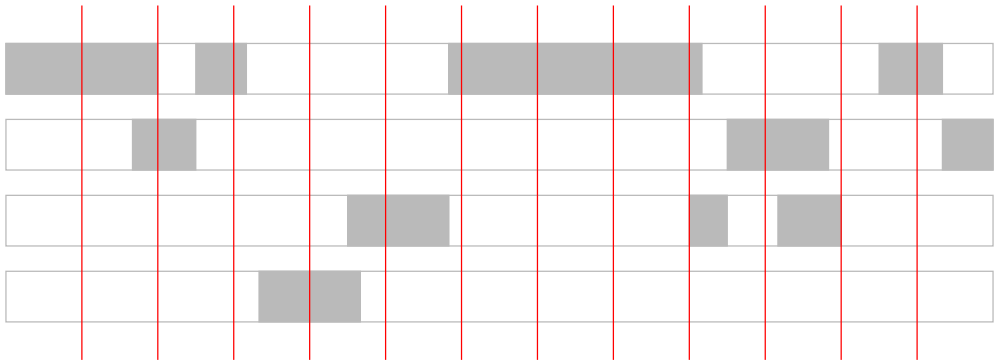

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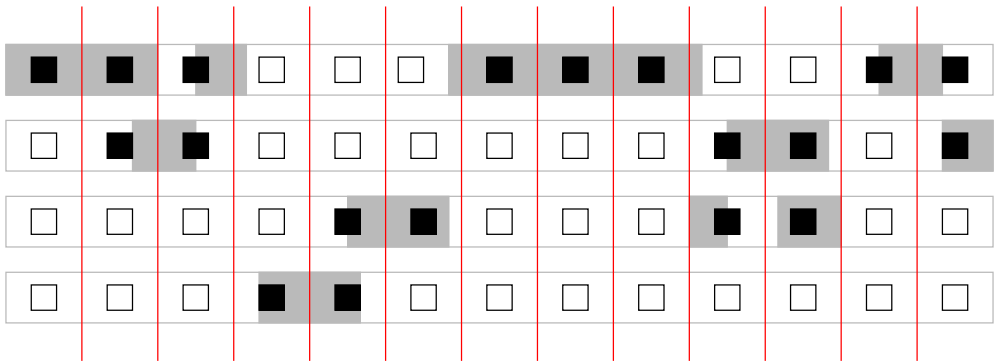

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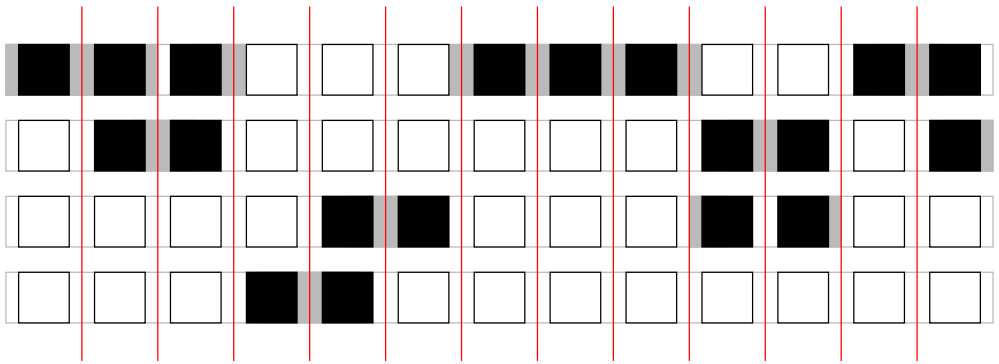

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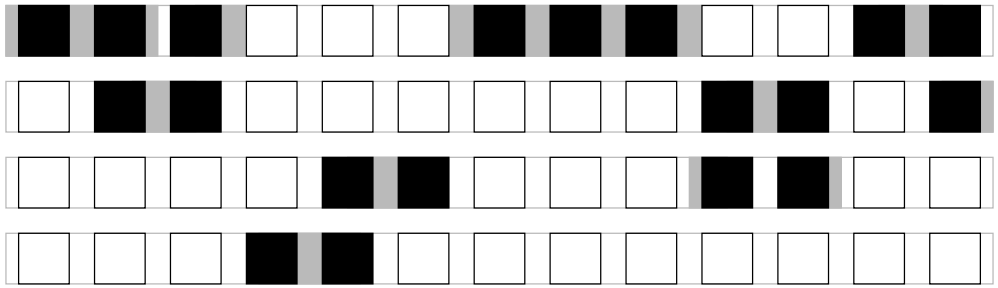

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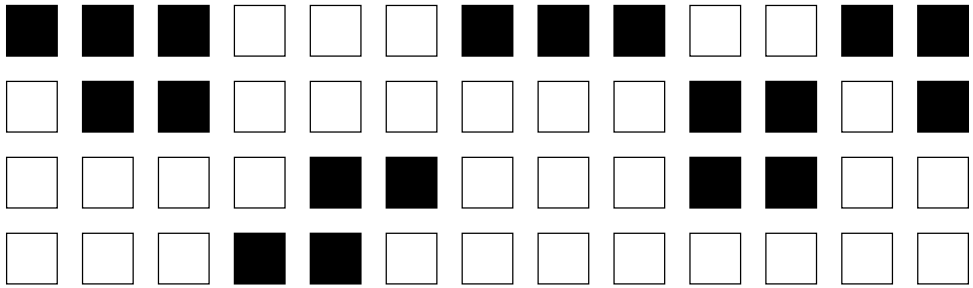

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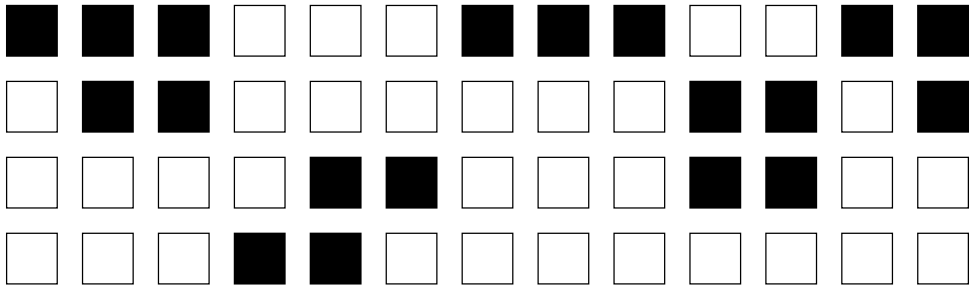

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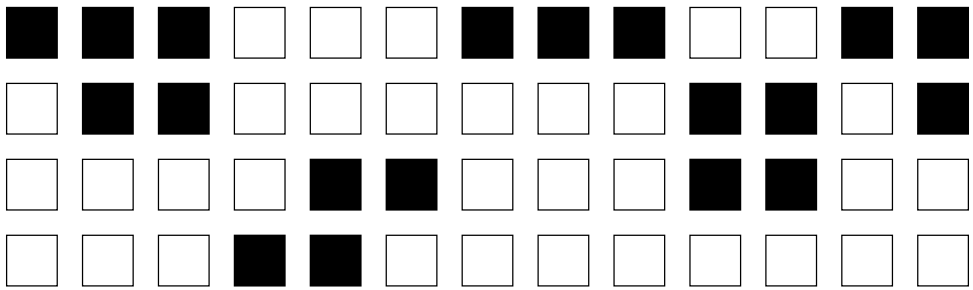

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# Alternate Feature Estimation Method

- use a variant of a model from stochastic dynamics, the **Ising model** (Glauber, 1963)
- assume the conditional probability of vocal activity state transition, for each $k$

$$P\left(\mathbf{q}_{t+1}[k] = \mathcal{V} \,|\, \mathbf{q}_t = \mathbf{S}_i\right) \quad = \quad y_k\left(\mathbf{S}_i\right)$$

- where

$$y_k\left(\mathbf{x}\right) \quad = \quad \frac{1}{1 + e^{-\beta\left(\sum_{j=1}^{K} w_{k,j} x_j + b_k\right)}}$$

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# Behavior Model

- for each conversation type $\mathcal{T}$ and each group $\mathcal{G}$, require the likelihood of **F** (as estimated from the observed vocal interaction record)

$$P(\mathbf{F} \mid \mathcal{G}, \mathcal{T}) = \prod_{k=1}^{K} P\left(f_k^{VI} \mid \theta^{VI}_{\mathcal{T},\mathcal{G}[k]}\right) P\left(f_k^{VC} \mid \theta^{VC}_{\mathcal{T},\mathcal{G}[k]}\right) \times \prod_{j \neq k}^{K} P\left(f_{k,j}^{OI} \mid \theta^{OI}_{\mathcal{T},\mathcal{G}[k],\mathcal{G}[j]}\right) P\left(f_{k,j}^{OC} \mid \theta^{OC}_{\mathcal{T},\mathcal{G}[k],\mathcal{G}[j]}\right)$$

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# The ICSI Meeting Corpus

(Janin et al, 2003), (Shriberg et al, 2004)

- naturally occurring project-oriented conversations
- for our purposes, 4 types of longitudinal collections:

| type | # of meetings | # of possible participants | # of participants | | |
|---|---|---|---|---|---|
| | | | mod | min | max |
| Bed | 15 | 13 | 6 | 4 | 7 |
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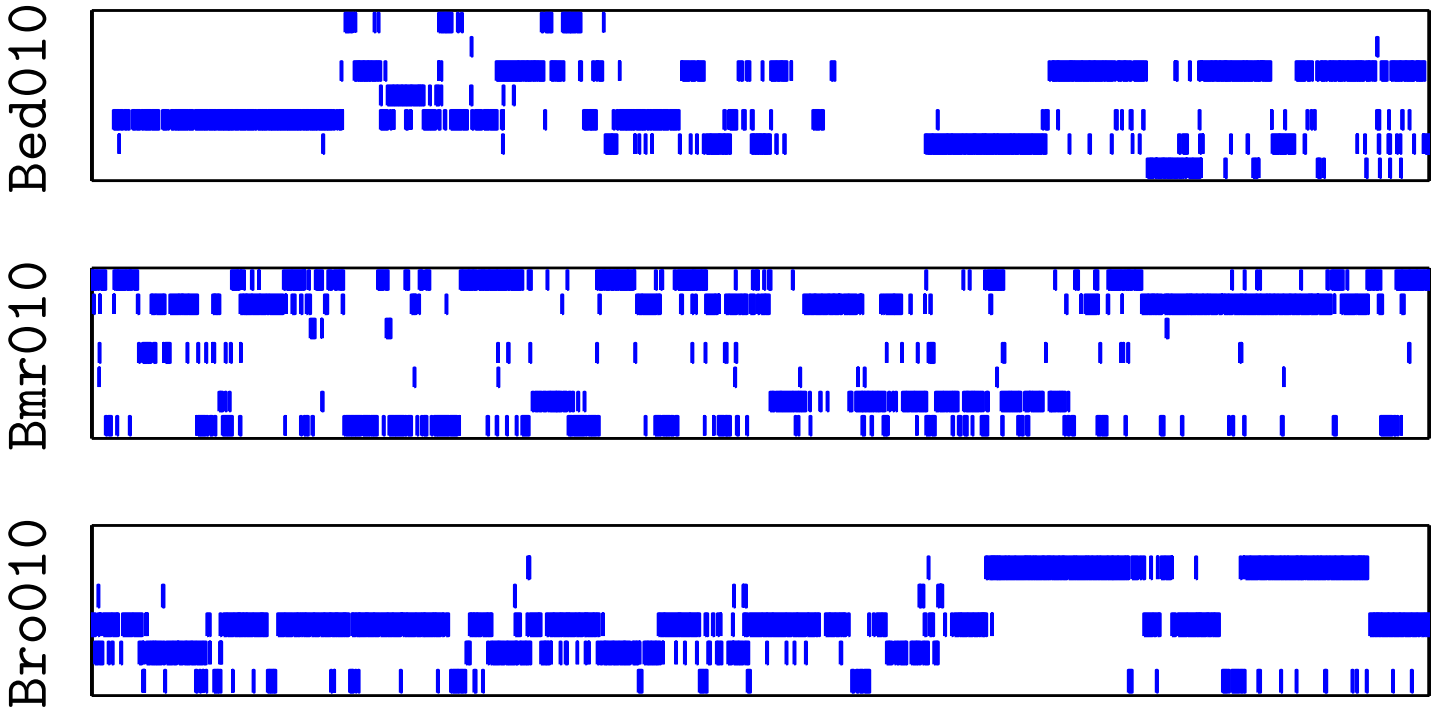
# Differences Between Meeting Types

- 36-minute excerpts (from 1000 sec to 2000 sec)



# Baseline

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- compute a single feature $f_k^T$: **vocalizing time proportion**
  - employed for assessing speaker diarization performance (Jin et al, 2004), (Mirghafori & Wooters, 2006)
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# Feature Comparison

| Feature(s) | ML Estimation | | NN Estimation | |
|---|---|---|---|---|
| | w/o $f_k^T$ | w/ $f_k^T$ | w/o $f_k^T$ | w/ $f_k^T$ |
| baseline | — | 65.7 | — | 65.7 |
| $f_k^{VI}$ | 59.7 | 67.2 | 56.7 | 65.7 |
| $f_k^{VC}$ | 62.7 | 77.6 | 56.7 | 71.6 |
| $\langle f_{k,j}^{OI} \rangle_j$ | 35.8 | 52.2 | 64.2 | 67.2 |
| $\langle f_{k,j}^{OC} \rangle_j$ | 53.7 | 67.2 | 64.2 | 80.6 |
| $f_{k,j}^{OI}$ | 41.8 | 46.3 | 67.2 | 64.2 |
| $f_{k,j}^{OC}$ | 61.2 | 68.7 | 73.1 | 79.1 |

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- the baseline feature $f_k^T$ outperforms most other features

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- by themselves, specific participant-pair features outperform each participant's average participant-pair features

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- most features, when combined with $f_k^T$, lead to improved performance

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- all NN-estimated features together yield **82.1%**
- an optimal NN-estimated feature subset (forward selection) yields **83.6%**

# Feature Comparison

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|---|---|---|---|---|
| | w/o $f_k^T$ | w/ $f_k^T$ | w/o $f_k^T$ | w/ $f_k^T$ |
| baseline | — | 65.7 | — | 65.7 |
| $f_k^{VI}$ | 59.7 | 67.2 | 56.7 | 65.7 |
| $f_k^{VC}$ | 62.7 | 77.6 | 56.7 | 71.6 |
| $\langle f_{k,j}^{OI} \rangle_j$ | 35.8 | 52.2 | 64.2 | 67.2 |
| $\langle f_{k,j}^{OC} \rangle_j$ | 53.7 | 67.2 | 64.2 | 80.6 |
| $f_{k,j}^{OI}$ | 41.8 | 46.3 | 67.2 | 64.2 |
| $f_{k,j}^{OC}$ | 61.2 | 68.7 | 73.1 | 79.1 |

- all NN-estimated features together yield **82.1%**
- an optimal NN-estimated feature subset (forward selection) yields **83.6%**

# Discussion

- 3-way confusion matrix, optimal NN-estimated feature subset

| Estimated | Actual Type | | |
|---|---|---|---|
| | Bed | Bmr | Bro |
| Bed | **11** | 1 | 3 |
| Bmr | 2 | **26** | 1 |
| Bro | 3 | 1 | **19** |

  - Bmr (discussions among peers) is the most distinct type
  - Bed and Bro (both more structured meetings) are more similar to each other than to Bmr

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- classification paradigm with several novel elements:
  1. exclusively text-independent features, from vocal interaction patterns
  2. participant groups, allowing for modeling multi-participant behaviors
  3. Ising model assumption of $\mathcal{C}$ transition probabilities
- meeting sub-type classification accuracy: 83%
- relative error reduction of 52% over the baseline
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# Future Work

- use automatic, rather than manual, segmentation
- include verbal (words, DAs) features
- explore the dual problem of role/participant detection:

$$\begin{aligned} \mathcal{G}^* &= \arg\max_{\mathcal{G}} P(\mathcal{G} \mid \mathbf{F}) \\ &= \arg\max_{\mathcal{G}} \sum_{\mathcal{T}} P(\mathcal{G}, \mathcal{T}, \mathbf{F}) \\ &= \arg\max_{\mathcal{G}} \sum_{\mathcal{T}} P(\mathcal{T}) \times P(\mathcal{G} \mid \mathcal{T}) \times P(\mathbf{F} \mid \mathcal{G}, \mathcal{T}) \end{aligned}$$

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# Thanks!

We'd also like to thank:

- Liz Shriberg
  - lots of helpful discussion
  - access to the ICSI MRDA annotation
- CHIL project for funding