Recovering Participant Identities in Meetings from a Probabilistic Description of Vocal Interaction

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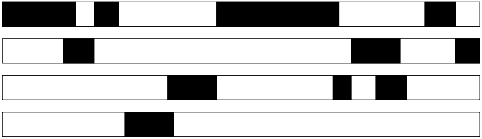
Language Technologies Institute, Carnegie Mellon University

23 September, 2008

Outline

Vocal Interaction (Dabbs & Ruback, 1987)



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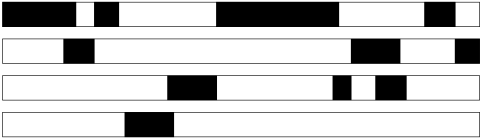

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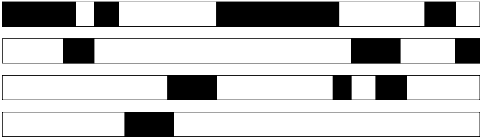

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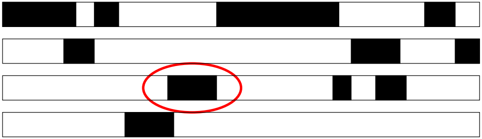

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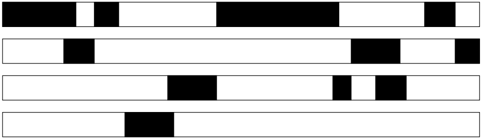

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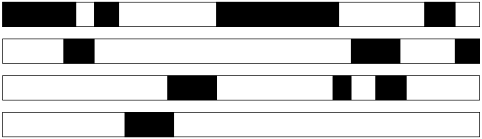

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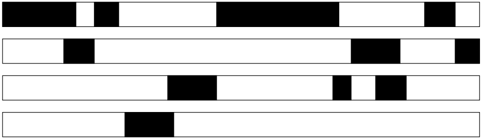

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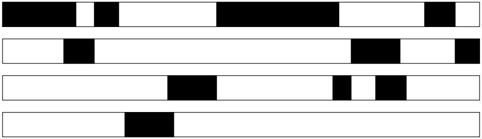

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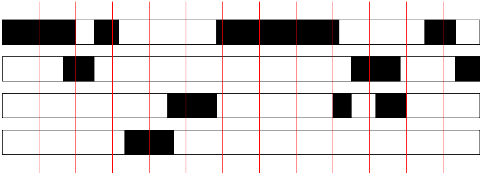

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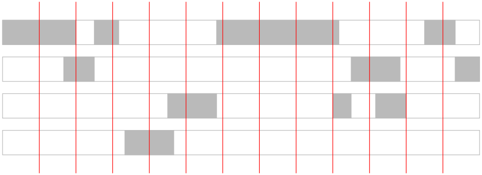

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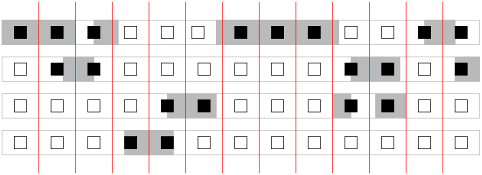

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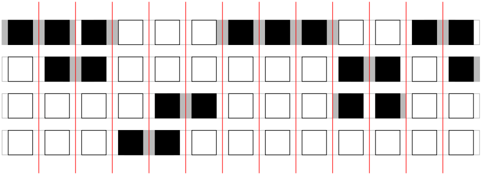

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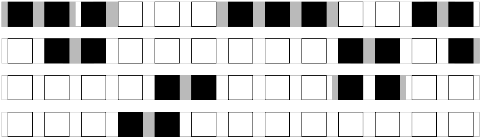

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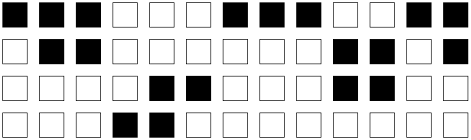

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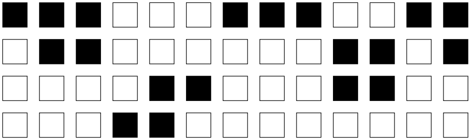

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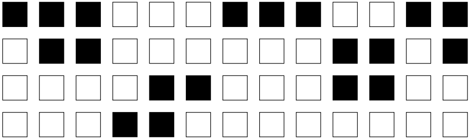

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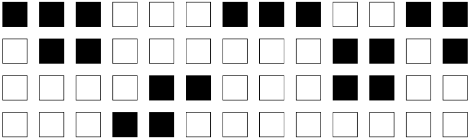

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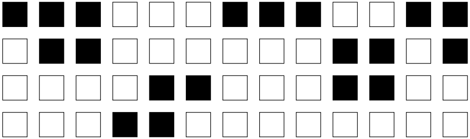

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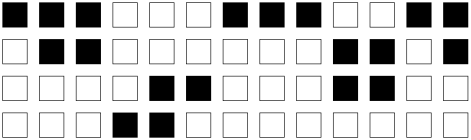

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   - social psychology predicts that preferences of relative timing in talkspurt deployment are predictive of speaker's place in social hierarchy
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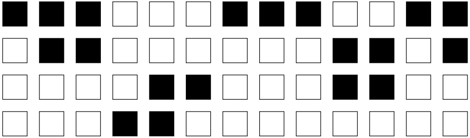

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  - attribute each of K identities to one of K channels
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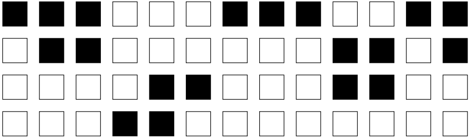

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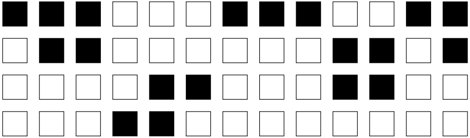

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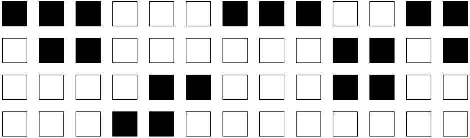

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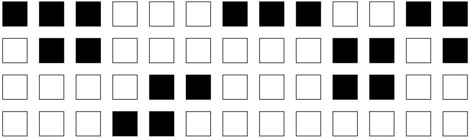

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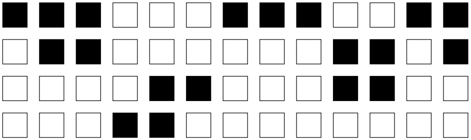

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Static characterization using long-term (entire meeting) observation of vocal interaction:

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   - dominance rankings: Rienks & Heylen, MLMI 2005
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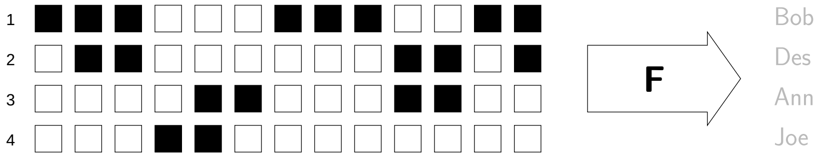

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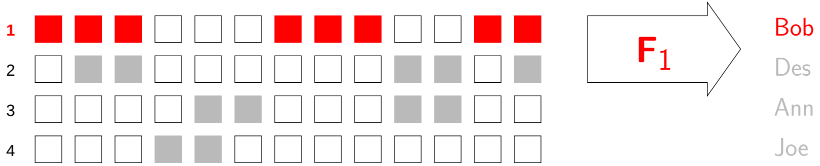

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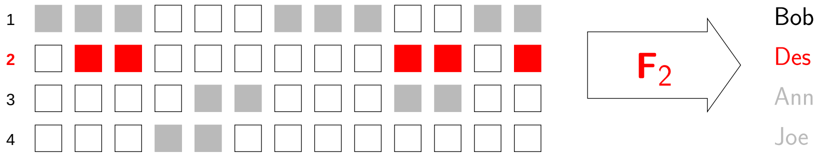

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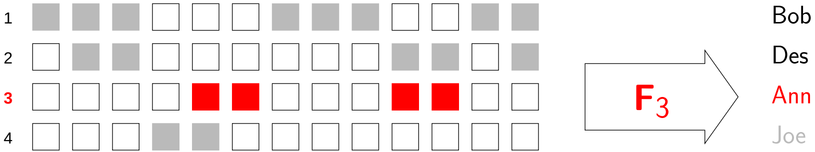

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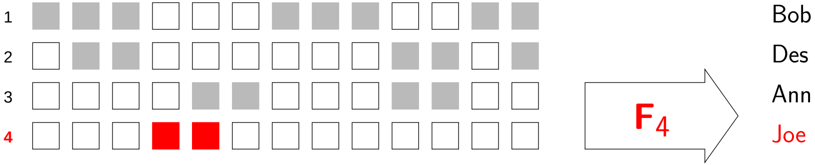

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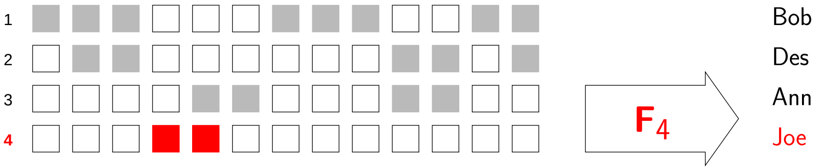

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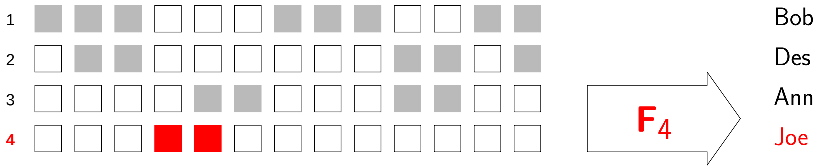

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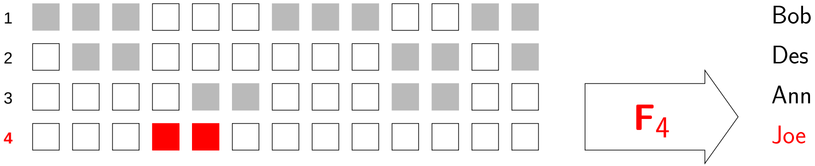

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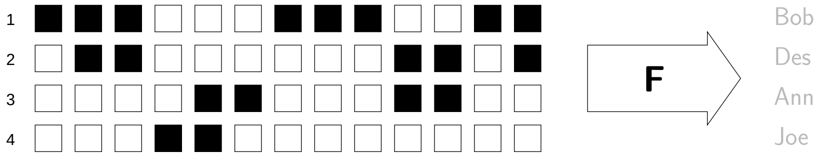

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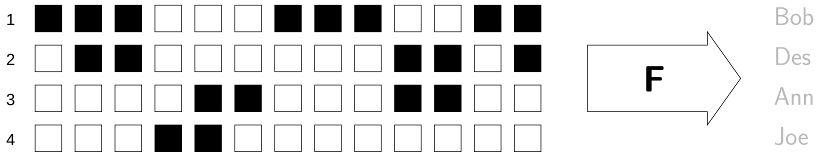
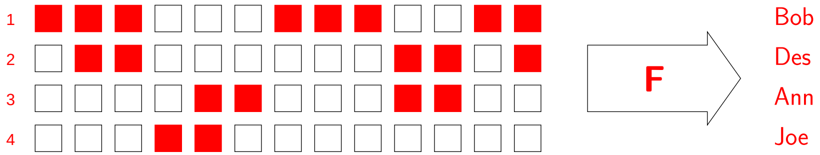
Solution: model participants **jointly**

Recognizing Participants Jointly



1. **F** describes interaction between **all** K participants

Recognizing Participants Jointly



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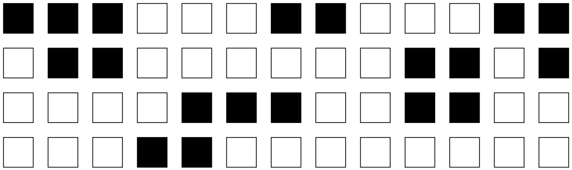
Feature Types in F

1. probability of vocalizing (V)
2. probability of initiating vocalization (VI) in prior silence
3. probability of continuing vocalization (VC) in prior non-overlap
4. probability of initiating overlap (OI) in prior non-overlap
5. probability of continuing overlap (OC) in prior overlap



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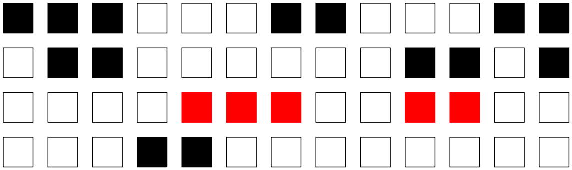

f_k^V

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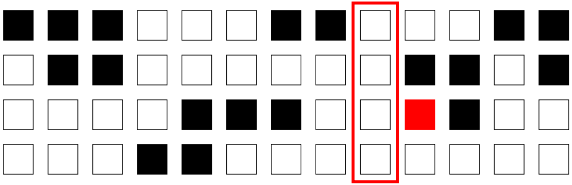

f_k^{VI}

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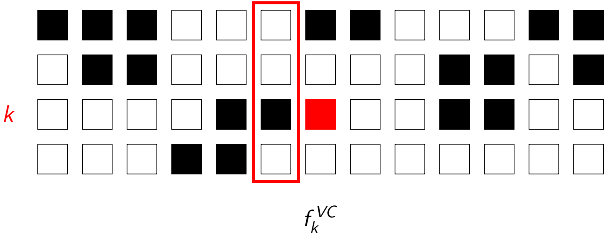

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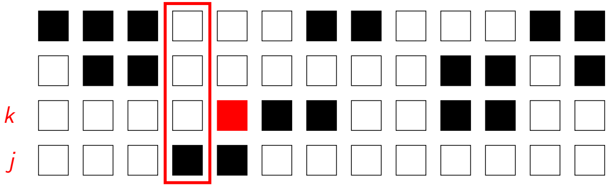

$f_{k,j}^{OI}$

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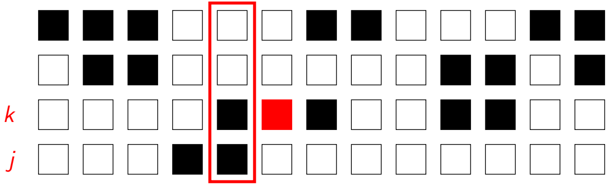

$f_{k,j}^{OC}$

Problem 1: Assigning Known Participant Identities

- know the identities of the K participants,

$$\mathcal{G} \quad = \quad \{\textsc{Ann}, \textsc{Bob}, \textsc{Cyp}\}$$

- but don't know which channel each participant is on

$$\mathbf{g} \in \mathbb{G} \quad = \quad \{\ [\mathrm{A}, \mathrm{B}, \mathrm{C}],\ [\mathrm{A}, \mathrm{C}, \mathrm{B}],\ [\mathrm{B}, \mathrm{A}, \mathrm{C}],\ \cdots\ \}$$

GOAL: find the correct permutation $\mathbf{g}^*$, of $K!$ alternatives

1. compute features $\mathbf{F}$
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Problem 2: Assigning Unknown Participant Identities

- do not know the identities of the K participants,

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- must draw K from $\|\mathcal{P}\| \gg \|\mathcal{G}\|$ alternatives

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The Need for a Greedy Search

- assuming (1) a finite number $|\mathcal{P}|$ of candidate participants,
- and (2) existence of a non-unique UNK participant,
- the number of candidate K-assignments is

$$|\mathbb{G}| = \sum_{j=0}^{K} \frac{K!}{(K-j)!\,j!} \cdot \frac{(|\mathcal{P}|-1)!}{(|\mathcal{P}|-1-j)!}$$

Proposed Search Algorithm:

1. set $\mathbf{g}[k] = \text{UNK}$, for all $1 \le k \le K$
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Data

- ICSI Meeting Corpus (Janin *et al*, 2003)
  - naturally occurring, $3 \leq K \leq 9$
  - TrainSet: 33 meetings
  - DevSet: 18 meetings
  - EvalSet: 16 meetings
- 14 participants occur $\geq$7 times in TrainSet,

$$\mathcal{P} = \{S_1, S_2, \cdots, S_{13}, S_{14}, \text{Unk}\}$$

- time-aligned segmentations for all meetings

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- always guessing Unk (majority) class: 22.9%
- always guessing non-Unk majority class: 11.9%

- top-5 feature type family combination: **69.5%**

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100	**60.2**	56.8	**42.4**
200	**60.2**	53.4	35.6
400	55.1	**58.5**	31.4
800	47.5	47.5	38.1
1600	54.2	56.8	32.2

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Generalization

	training	DevSet	EvalSet
Problem 1	TrainSet	69.5	53.9
	TrainSet & DevSet	—	57.8
Problem 2	TrainSet	29.7	30.4
	TrainSet & DevSet	—	34.3

- evident: system optimized on Problem 1 for DevSet
- Problem 2 (drawing from $\mathcal{P}$ and permutation) much harder
- additional training data helps

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   - are predictive of participant identity (stronger)
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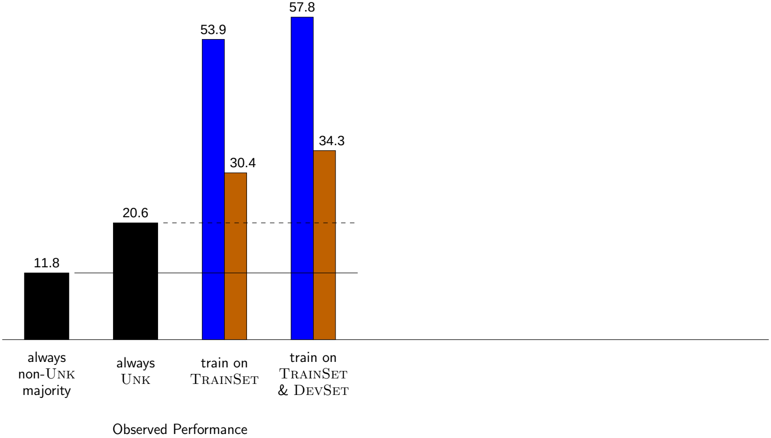
Future Work


11.8
20.6
53.9
30.4
57.8
34.3
always non-Unk majority
always Unk
train on TrainSet
train on TrainSet & DevSet
Observed Performance

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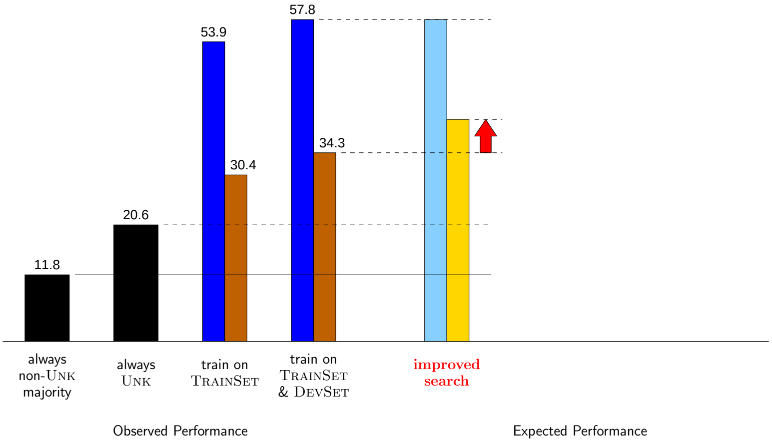
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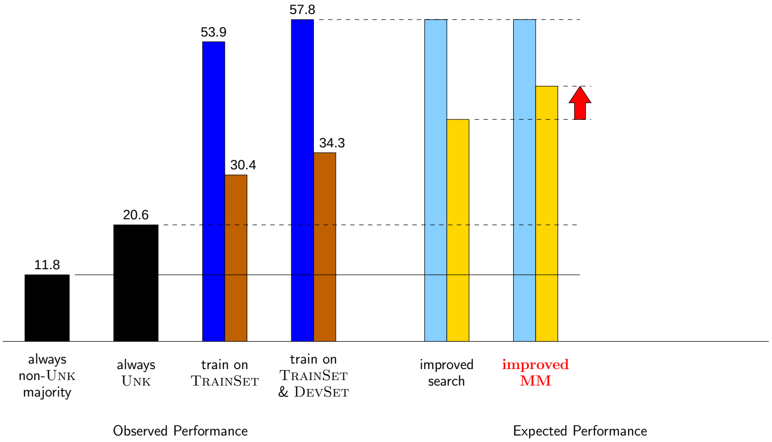
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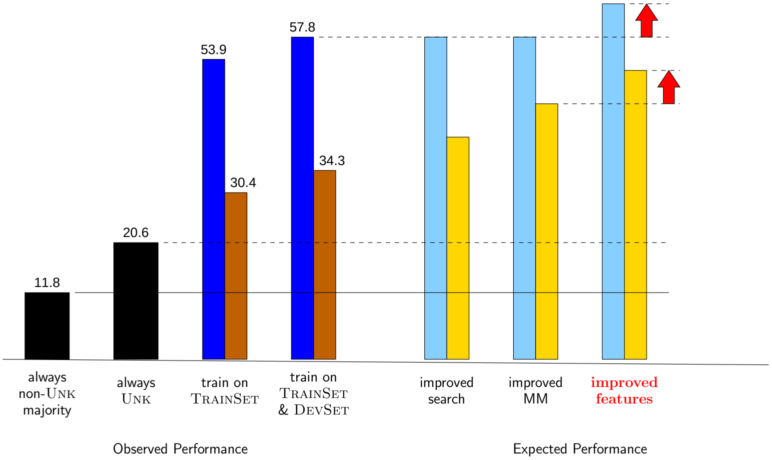
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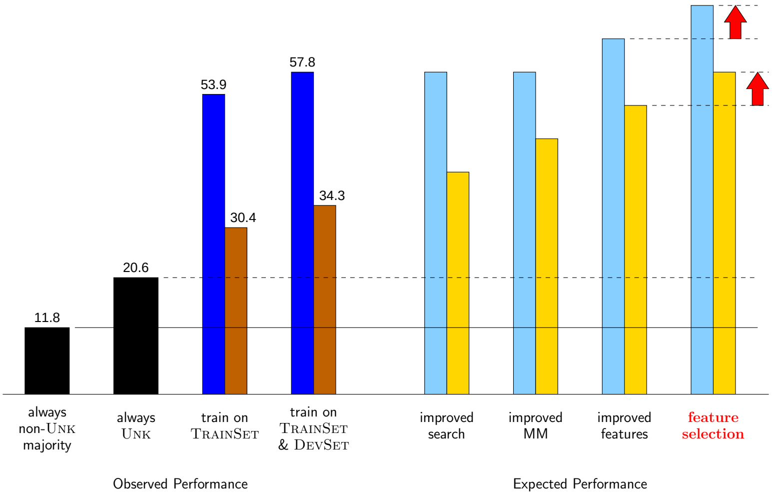

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Thank you for attending.

Thanks also to:

- Liz Shriberg, for access to the ICSI MRDA Corpus