# Using Past Speaker Behavior to Better Predict Turn Transitions

Thesis Presentation

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# Outline

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Section 1

# Motivation

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   - Pragmatic (Ford 2001)

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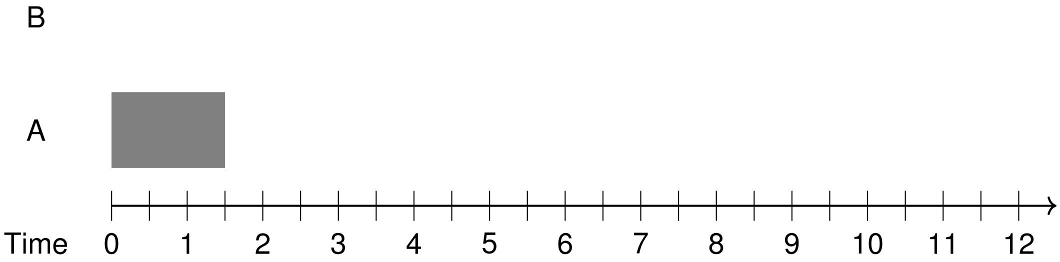
   - Relative turn length: current turn length so far (in seconds and words) relative to the speaker's average turn length
   - Relative Floor Control: the speaker's control of the conversation floor (in seconds and words) relative to the total conversation length
   - Computed for every dialog act.

Section 2

# Theoretical Model

# Relative Turn Length

## Timing Diagram



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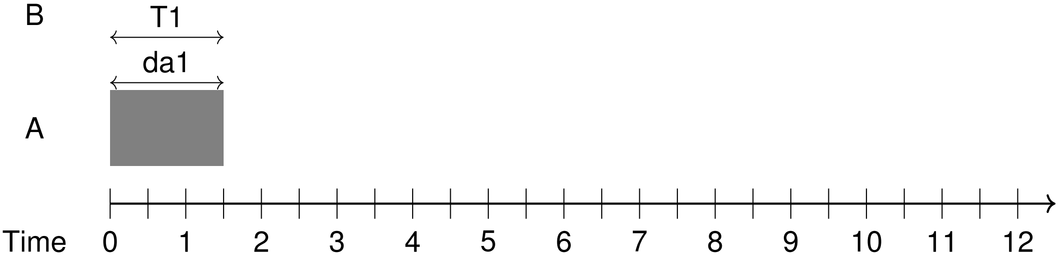

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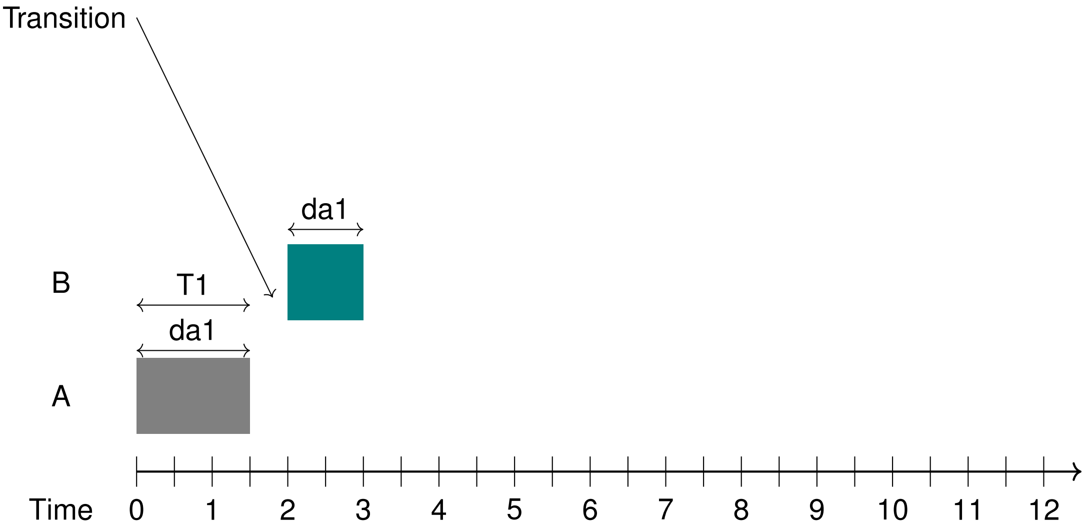

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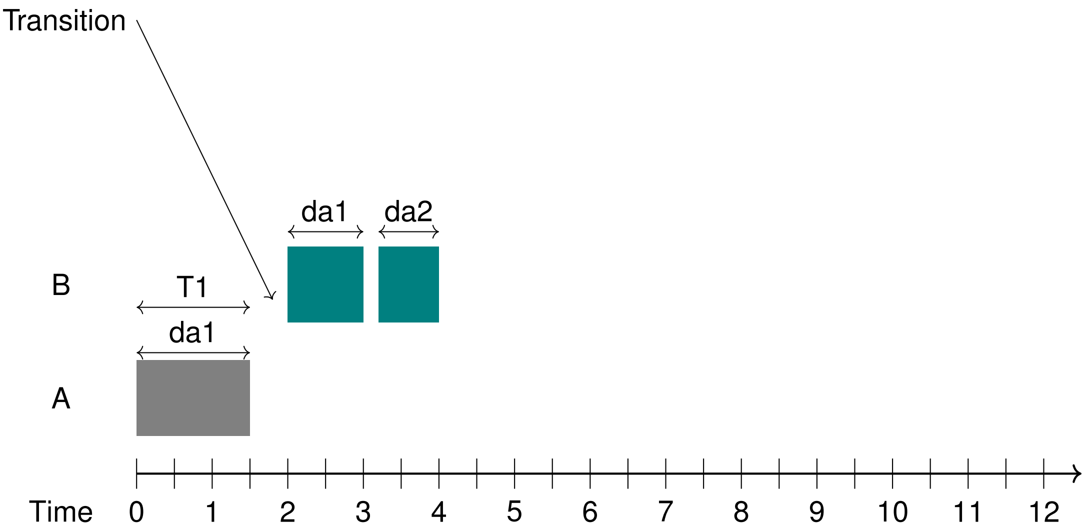

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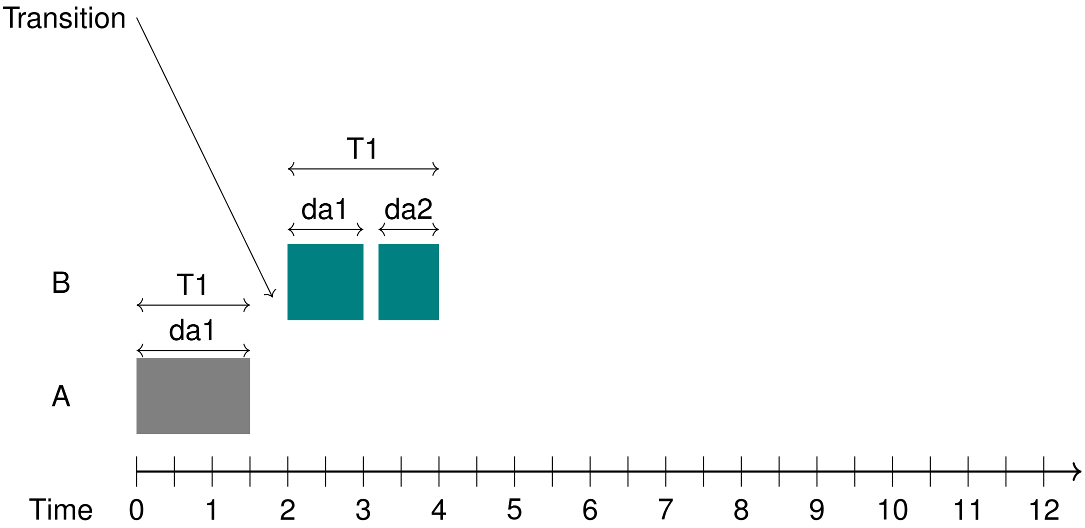

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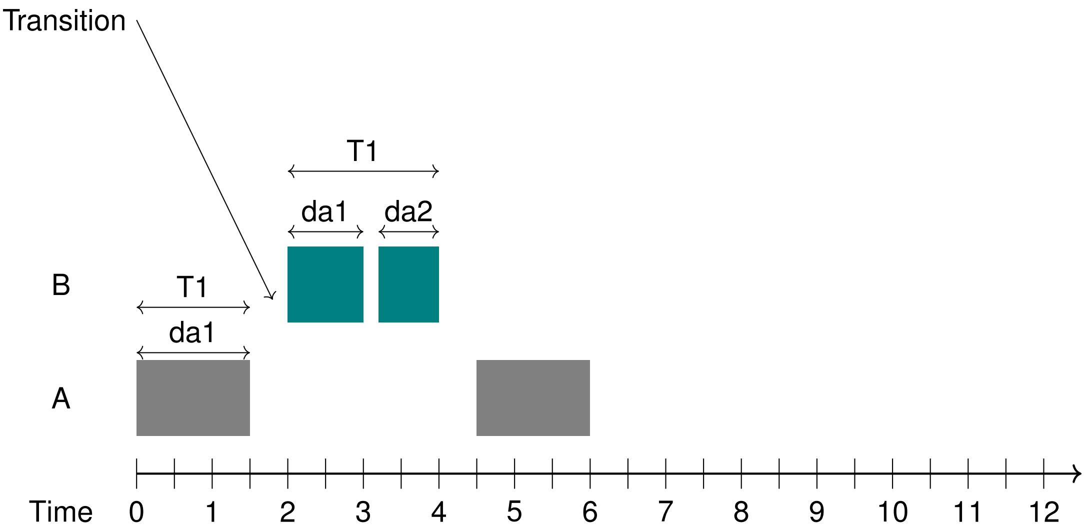

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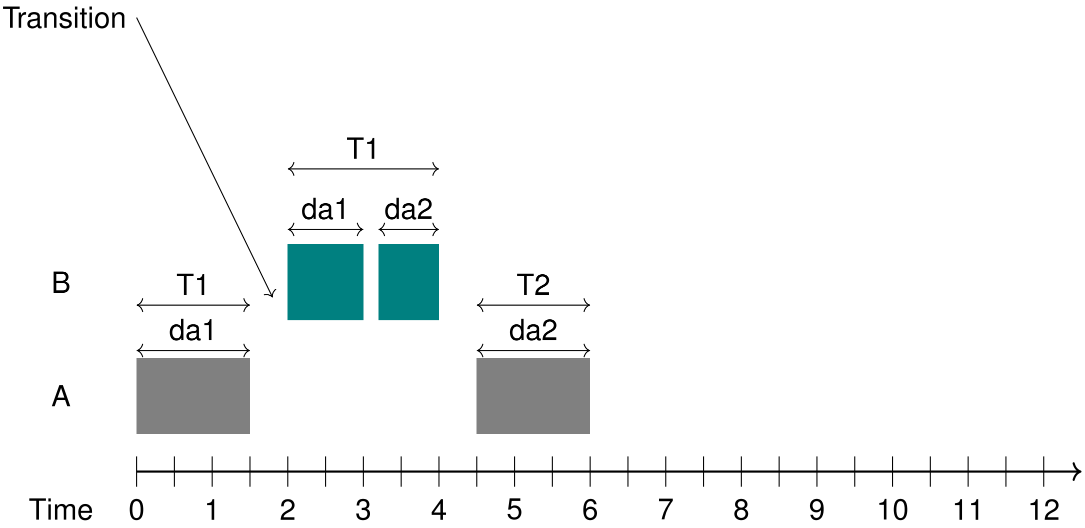

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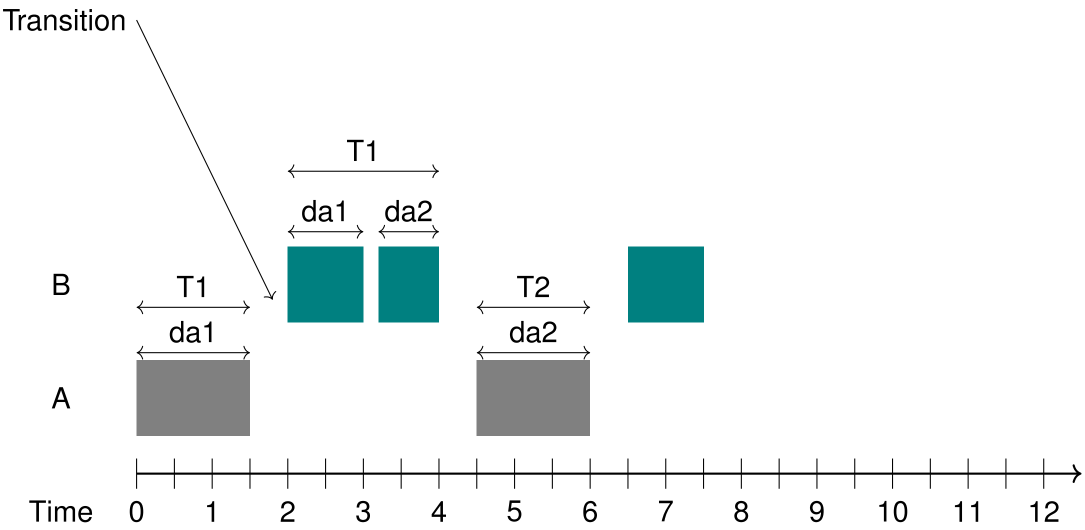

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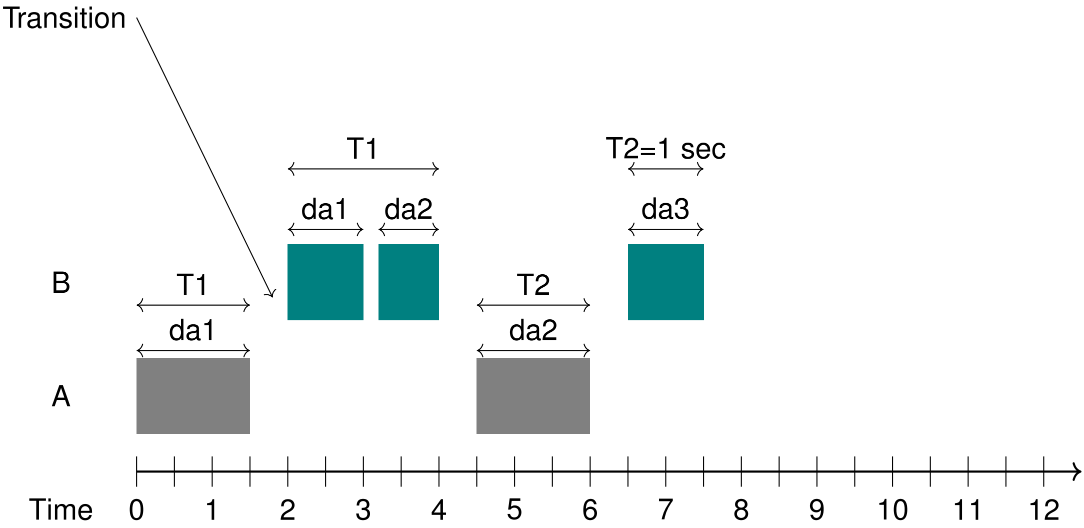

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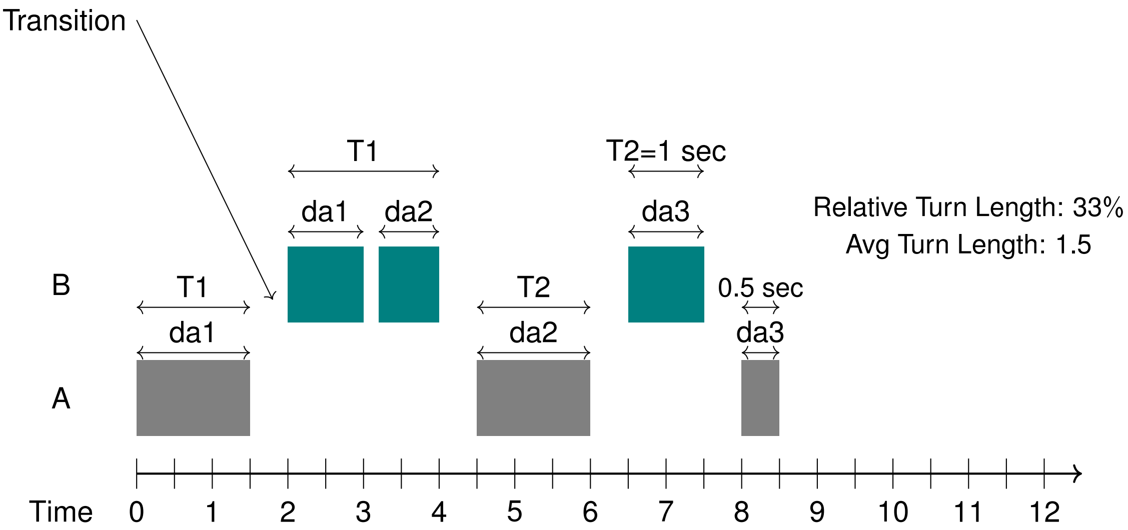

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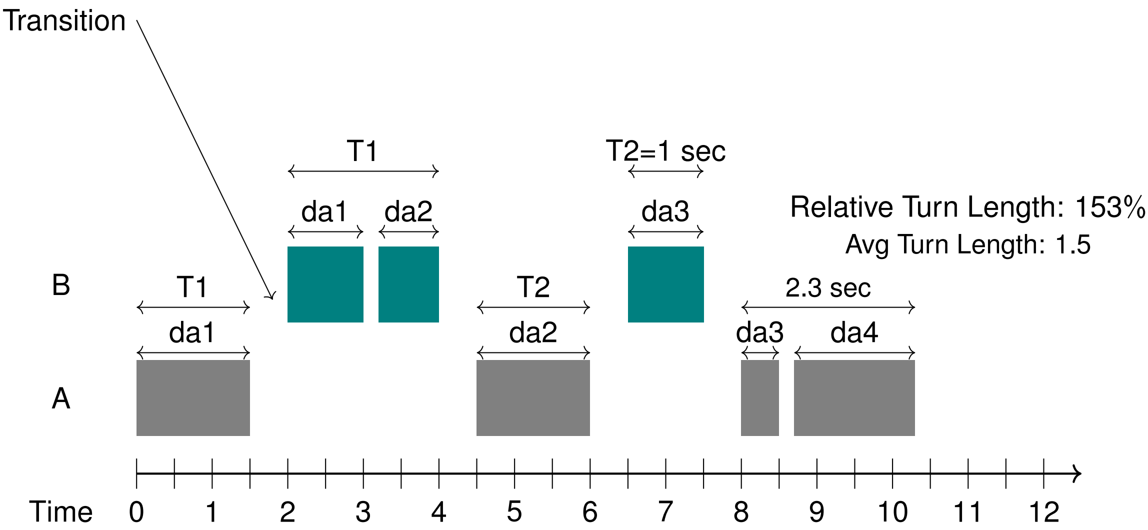

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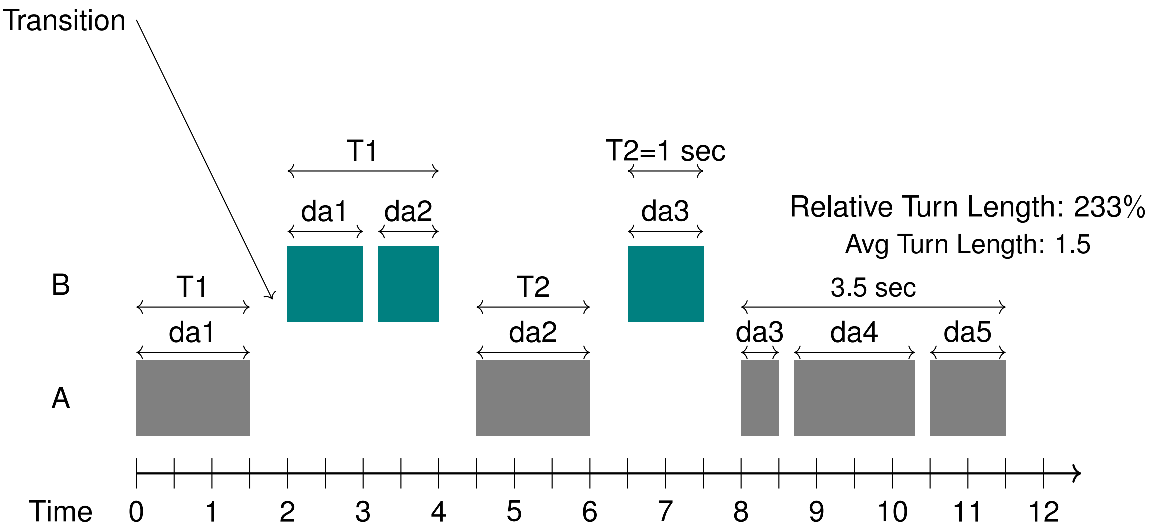

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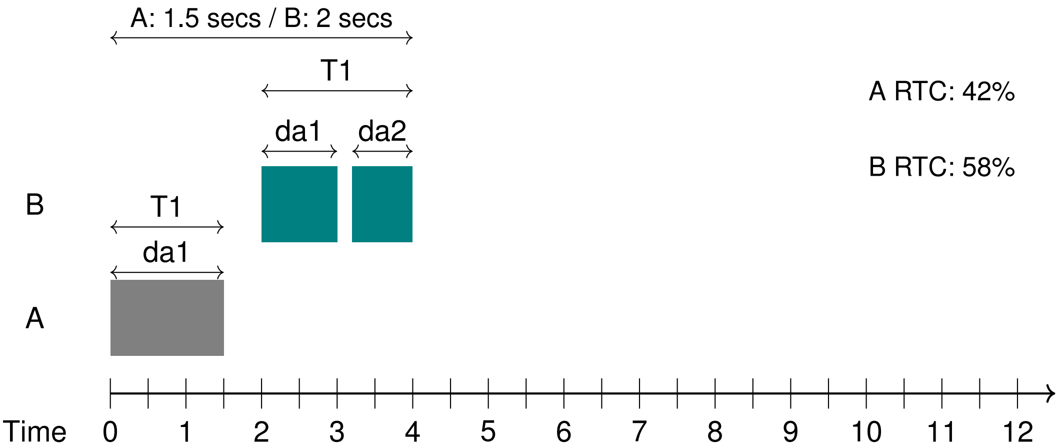


A RTC: 42%

B RTC: 58%

# Relative Floor Control

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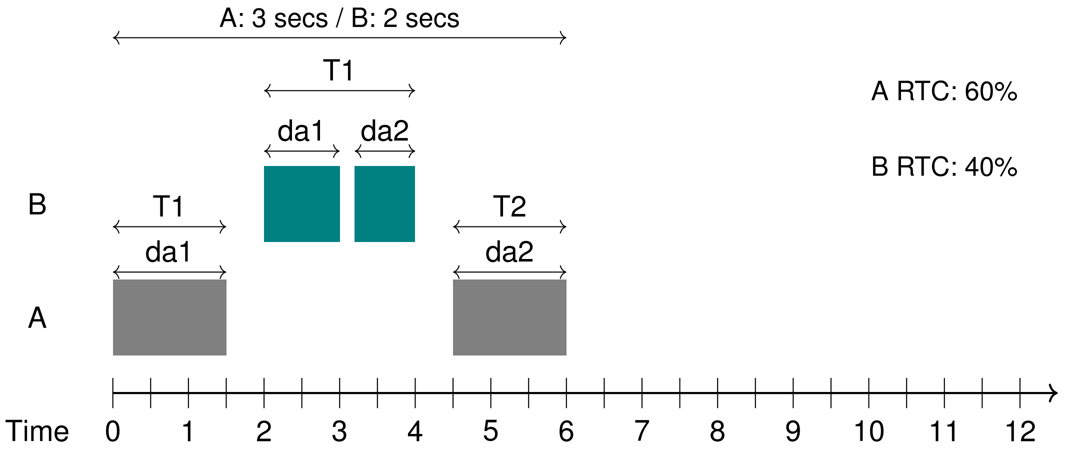

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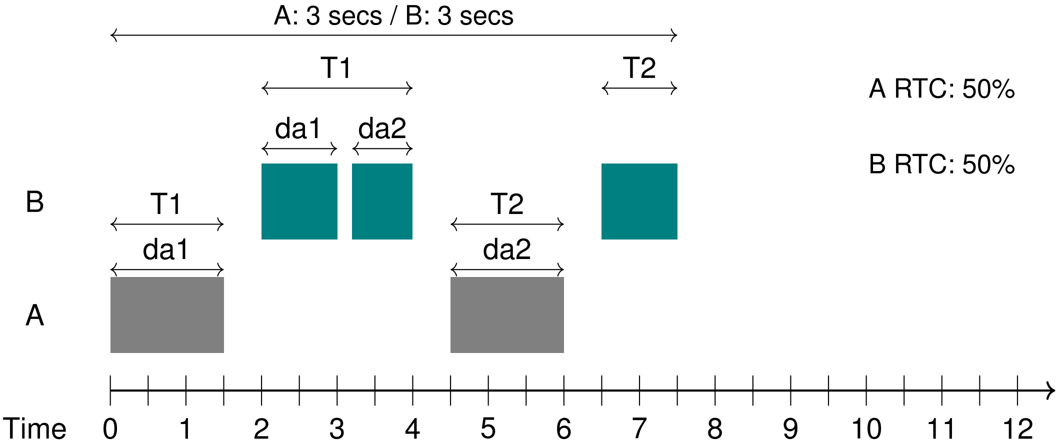


A RTC: 50%

B RTC: 50%

# Relative Floor Control

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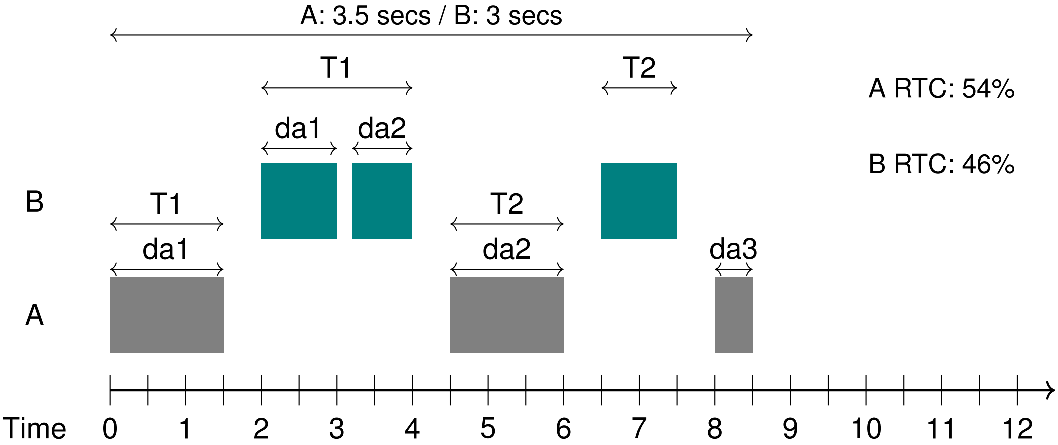

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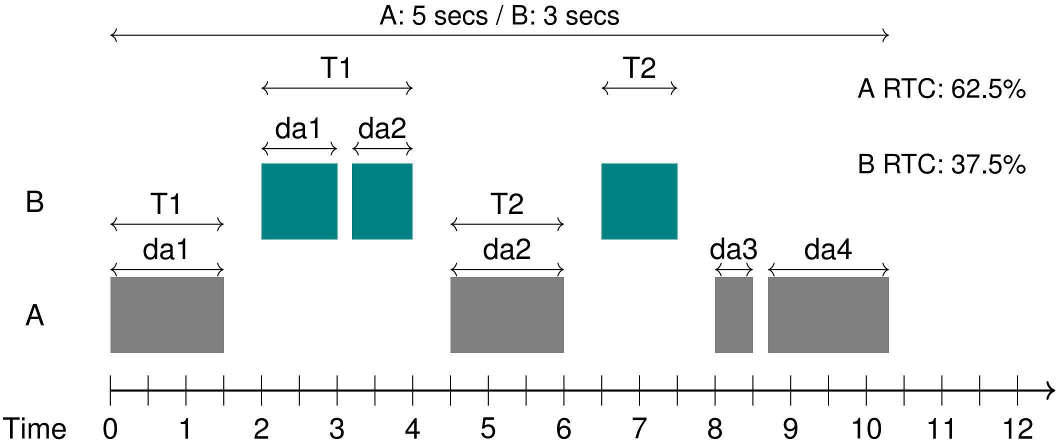

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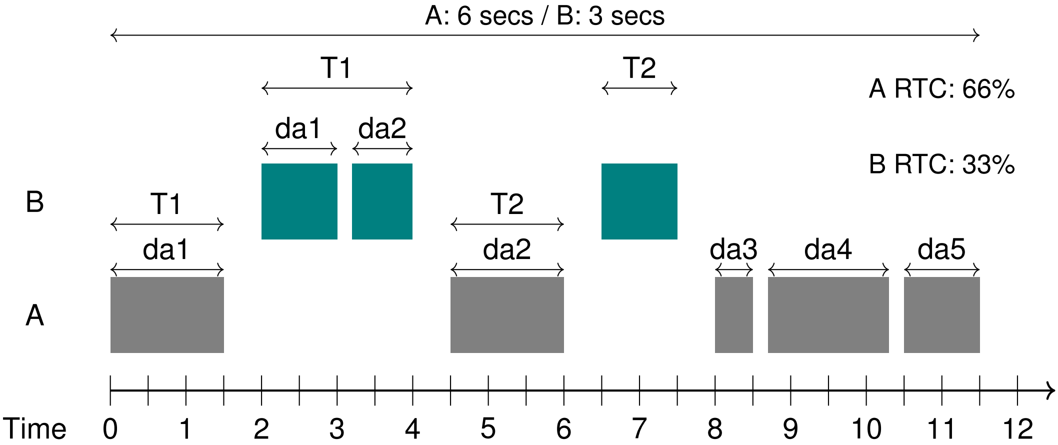

Section 3

# Data Preparation

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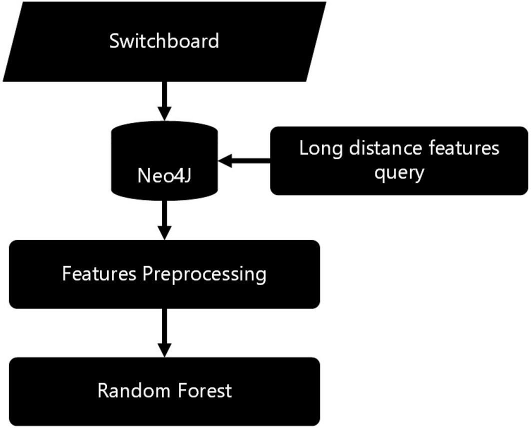
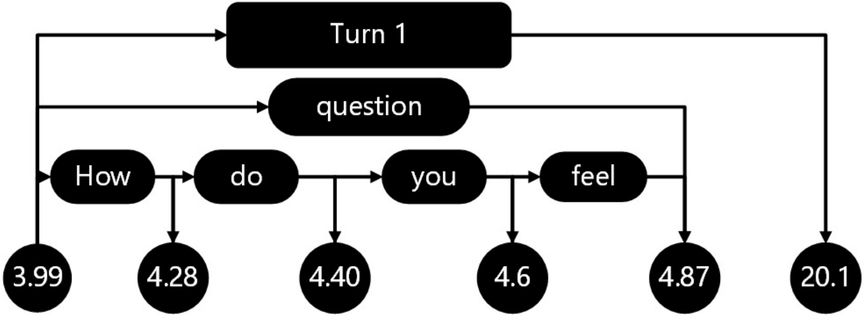
3. 2483 conversation, involving 520 speakers
4. In our research we used the NXT version (S. Calhoun, 2010) of the corpus which contain 642 annotated conversations (XML)

# Preprocessing pipeline



# Conversation representation



# Preprocessing

- Removed 11 dialogue acts that were coded as other in switchboard.
- Reduce data sparsity by collapsing 65 dialog acts into 9.
- Performed using python-pandas.

| Switchboard dialog acts | Dialog act classes |
|---|---|
| sd,h,bf | statement |
| sv,ad,sv@ | statement - opinion |
| aa,aar̂ | agree accept |
| %.%-,%@ | abandon |
| b,bh | backchannel |
| qy,qo,qh | question |
| no,ny,ng,arp | answer |
| + | + |
| o@,+@ | NA |

Table: Mapping from dialog act to dialog act class

Section 4

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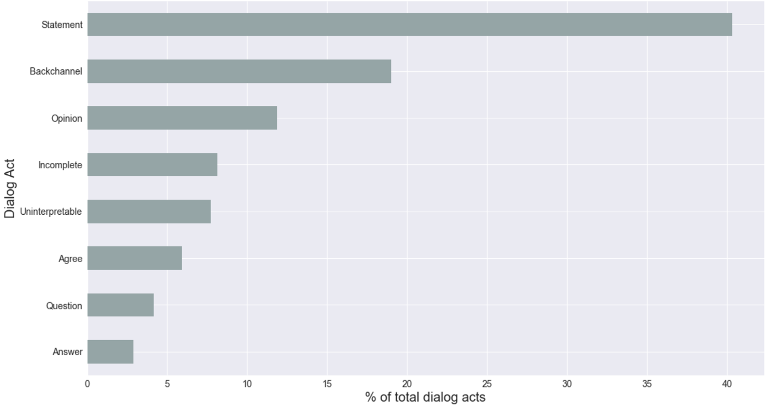
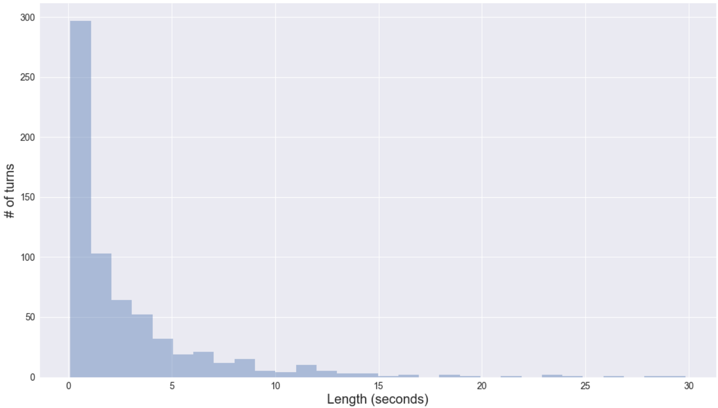
3. Done using python pandas for data preparation and python seaborn for data visualization

# Dialog act relative count



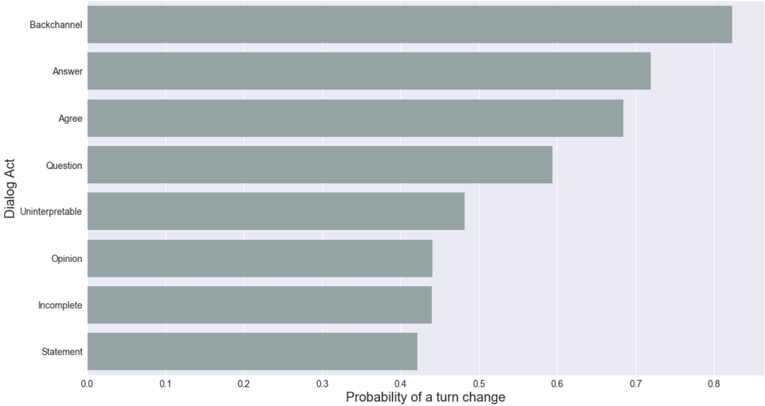

- Mainly Statements and Backchannels.
- Representative of casual conversations.

# Turn Length Distribution



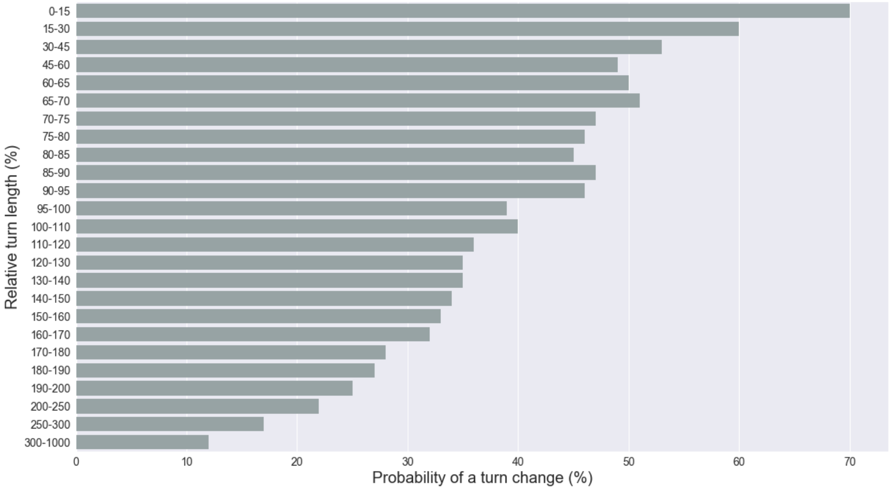

- Very skewed distribution
- Long flat tail

# Dialog act probability of turn change



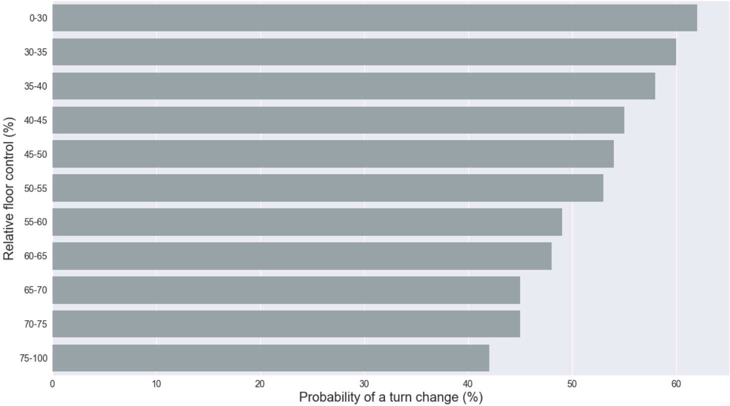

- Backchannels mostly leads to turn change (Explain the previous slide)

# Relative Turn Length effect on probability of turn change



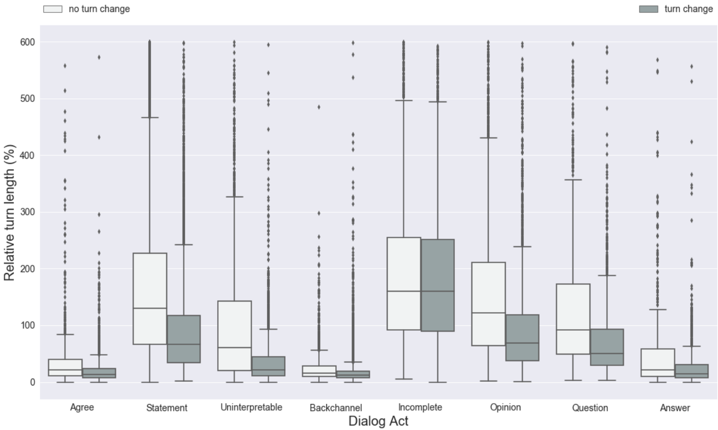

- Dialog act with small relative length lead to turn change.
- As the speaker has the floor for more time, the speaker tends to hold it.

# Relative Turn Control effect on probability of a turn change



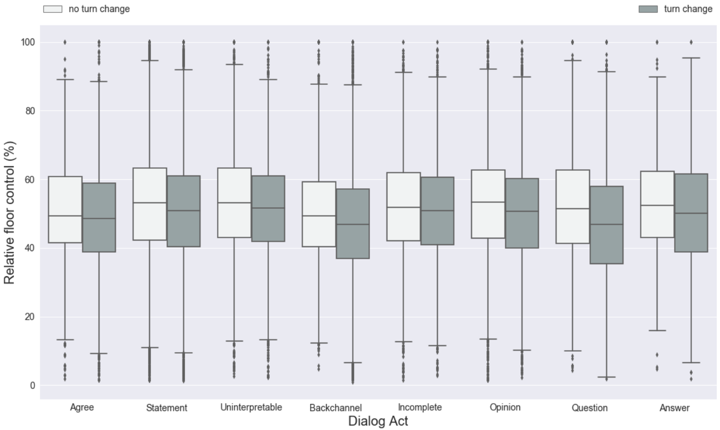

- High values of floor control correlate with the willingness of the current speaker to give up the floor.

# Relative turn length for dialog act type




- The median relative turn length that led to a turn change is smaller than when it does not.
- High RTL do not lead to turn change. Holds across dialog acts

# Relative floor control by dialog act




- The median is mainly 50% across dialog acts
- The median for relative floor control is slightly higher for each dialogue act when it not followed by a turn change, than when it is

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   - for small relative turn length, this is due to short turn with single dialog act which is likely to be back channel or an answer, both of which have low relative
   - for high relative turn length, we attribute to the flat tail of turn length distribution - the chance that the current dialog act will lead to a turn change are smaller and smaller and hence the speaker will likely keep the floor

Section 5

# Machine Learning Models

# Classifiers

- Used random forests (N=200) / Gradient Boosting to train and test the following models
  - baseline 1: current dialog act label.
  - baseline 2: current and previous dialog acts.
  - summary model: just the summary features.
  - full model: summary features and the current and previous dialog acts.
- Used pandas for data pre processing and scikit-learn for model training and evaluation.
- Evaluation was done using 10 fold cross validation.
- Run grid search to find the optimal hyper parameters.

# Result for Random Forest Classifier

| | Accuracy | F1 | Precision | Recall | AUC |
|---|---|---|---|---|---|
| baseline 1 | 62.79% | 57.81% | 74.98% | 47.04% | 65.99% |
| baseline 2 | 74.89% | 74.87% | 81.84% | 69.00% | 81.11% |
| summary | 65.54% | 69.32% | 67.22% | 71.36% | 69.46% |
| full | 75.75% | 77.59% | 77.50% | 77.83% | 83.78% |

Table: Precision, recall and F1 results using Random Forests

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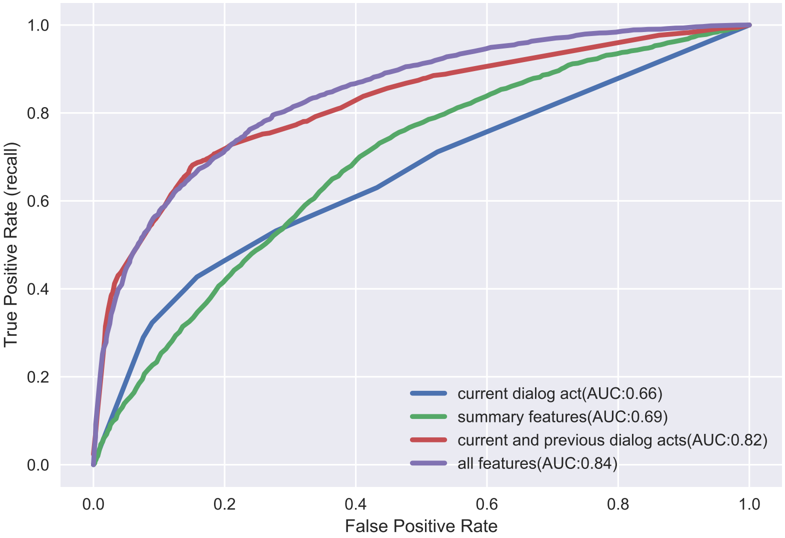
| baseline 2 | 74.88% | 74.82% | 81.92% | 68.86% | 81.10% |
| summary | 67.91% | 71.30% | 69.20% | 73.55% | 72.64% |
| all | 76.57% | 78.74% | 77.44% | 80.11% | 84.84% |

Table: Precision, recall and F1 results using Gradient boost classifier

# ROC curves and AUC of different models



# Sensitivity to Measurement Start Time

| | 0s | 15s | 30s | 45s | 60s | **120s** | 180s |
|---|---|---|---|---|---|---|---|
| baseline 1 | 65.99% | 66.10% | 66.12% | 66.09% | 66.02% | 65.98% | 66.05% |
| baseline 2 | 81.11% | 81.21% | 81.24% | 81.20% | 81.15% | 80.92% | 80.68% |
| summary | 69.46% | 69.51% | 69.43% | 69.49% | 69.57% | 69.10% | 69.21% |
| full | 83.78% | 83.87% | 83.85% | 83.80% | 83.61% | 83.19% | 82.80% |

Table: AUC Score in relation to the start of the dialog

Section 6

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2. However, the affect for our data is the opposite of our initial assumption
   - Short turn (Low RTL) leads to turn change
   - In long turn the speaker will actually hold the floor.

# Future work

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4. Perform the experiments where back channels are not considered as turn change.

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1. Combine the summary features with other local features (semantic/prosadic)
2. Test the hypothesis on another type of corpus (for example task based corpus)
3. Instead of measuring the affect from the start of the conversation, use moving averages with different window length.
4. Perform the experiments where back channels are not considered as turn change.
5. In general, any local features can be turned into a summary feature by taking the avarage over past turn. Hence this area of research can be expanded to other local features.

# Acknowledgement

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