Using Past Speaker Behavior to Better Predict Turn Transitions

Thesis Presentation

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Outline

1 Motivation

2 Theoretical Model

3 Data Preparation

4 Data Exploration

5 Machine Learning Models

6 Summary

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Section 1

Motivation

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   - Prosodic (Ford 1996,Stolcke 2002,Ferrer 2003)
   - Pragmatic (Ford 2001)

Thesis Statement

Conversant's past behavior can help predict turn transitions

Past behavior represented by Summary features

Acknowledgement

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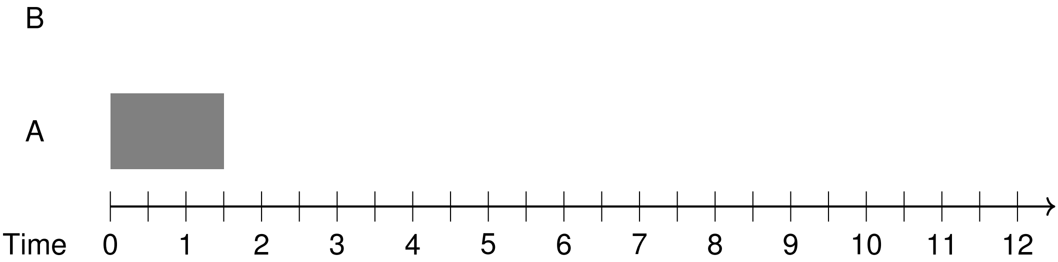
3. Thesis advisor and collaborator : Prof. Peter Heeman.

Section 2

Theoretical Model

Relative Turn Length

Timing Diagram



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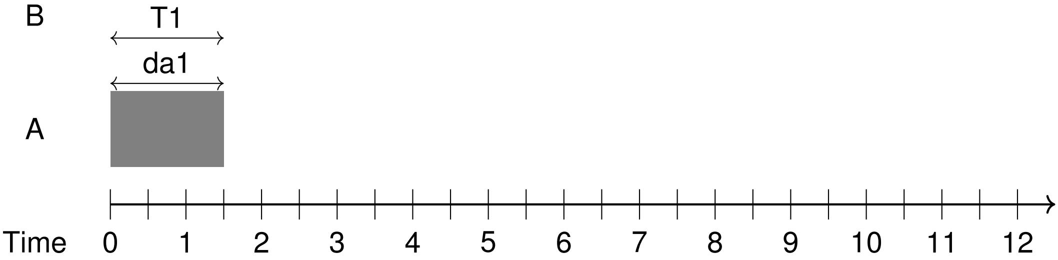

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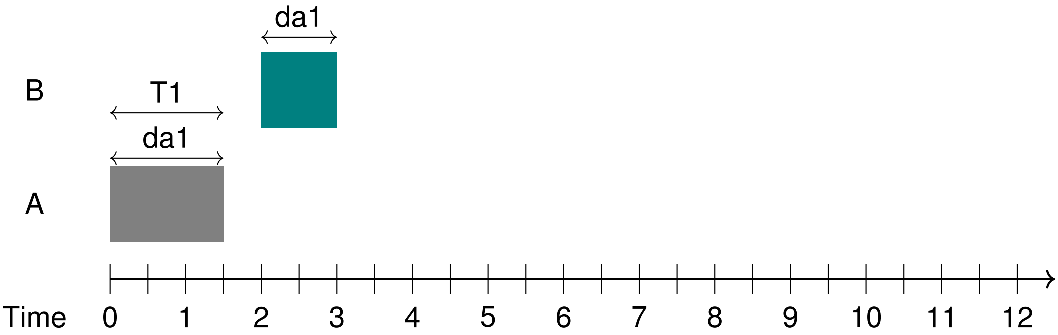

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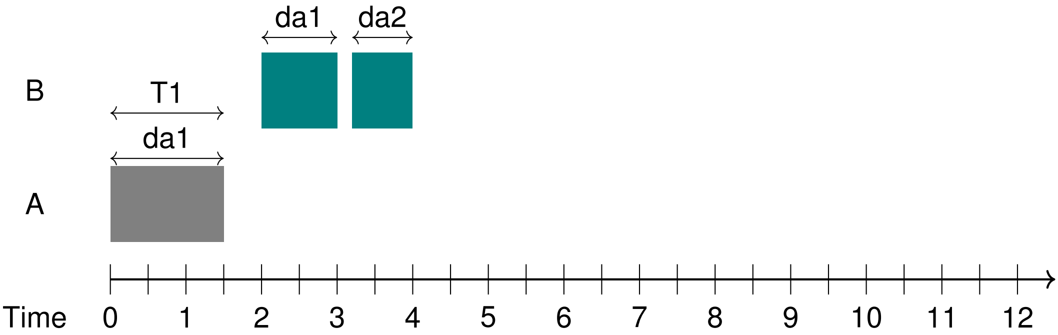

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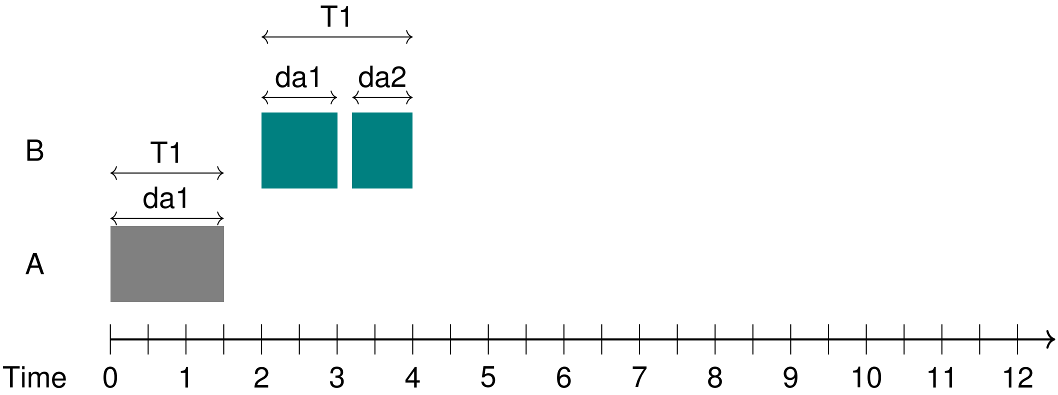

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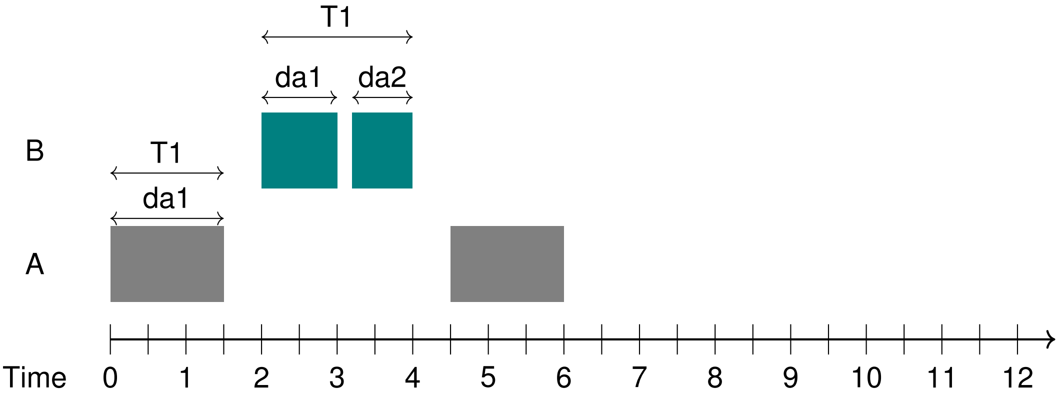

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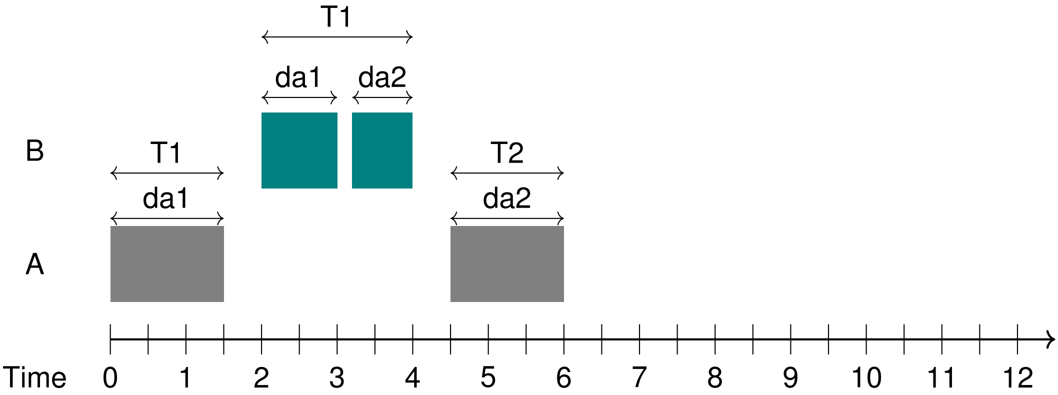

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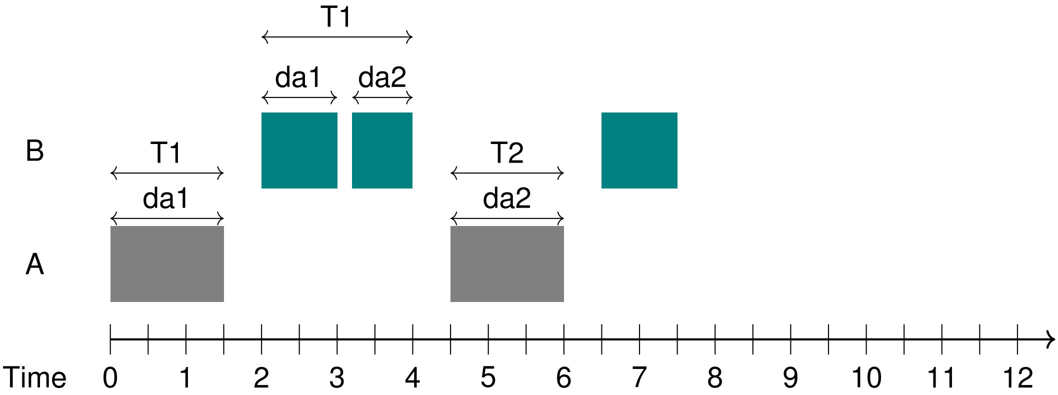

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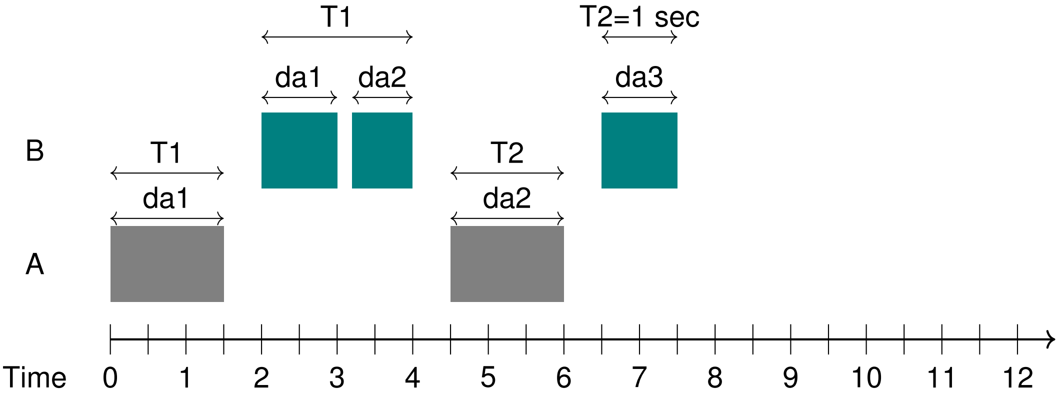

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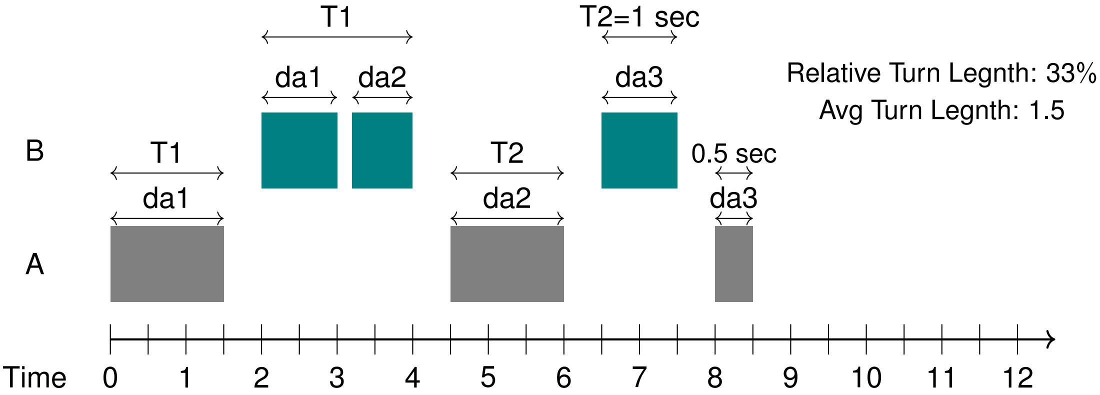

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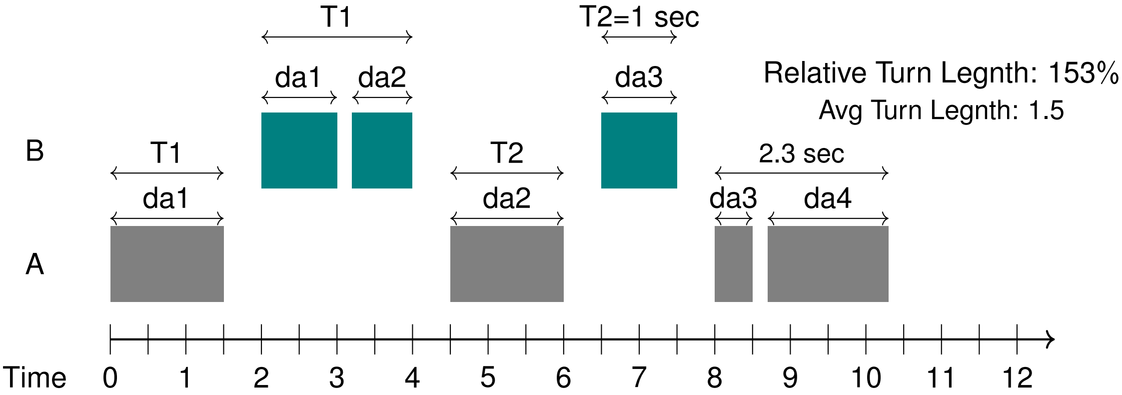

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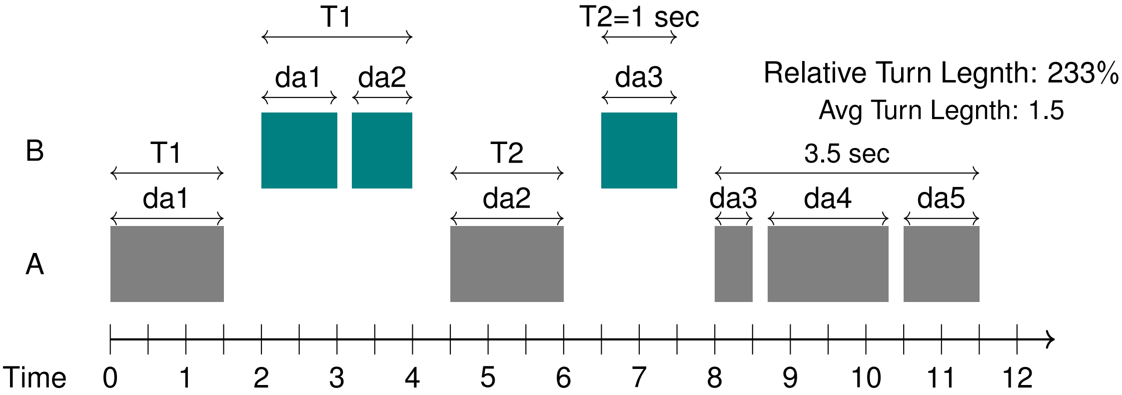
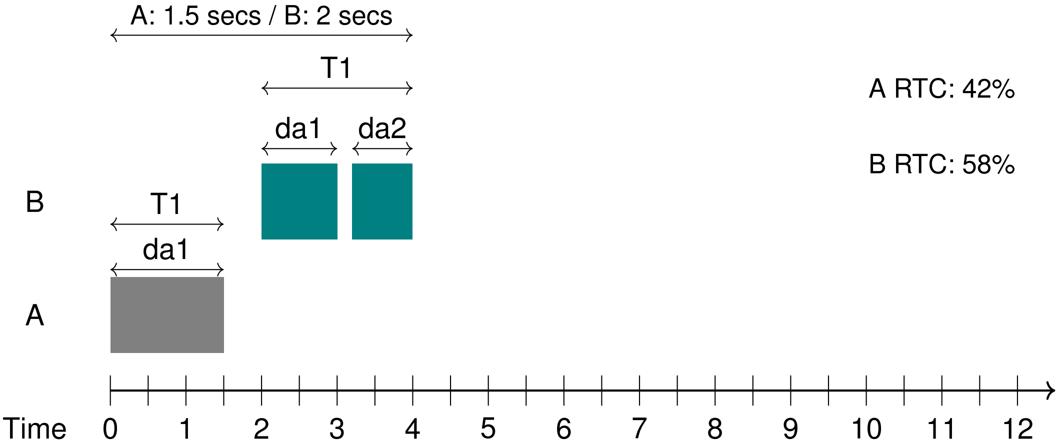


Relative Floor Control

Timing Diagram



A RTC: 42%

B RTC: 58%

Relative Floor Control

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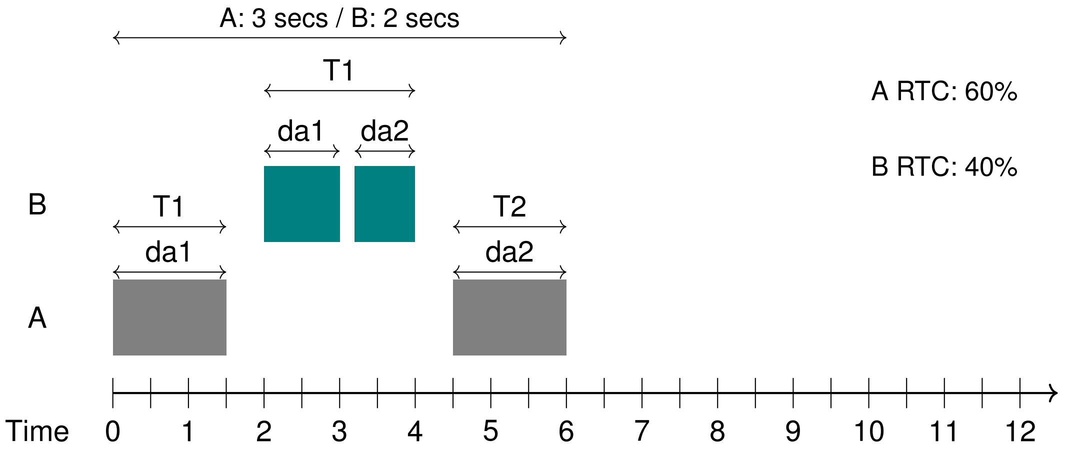

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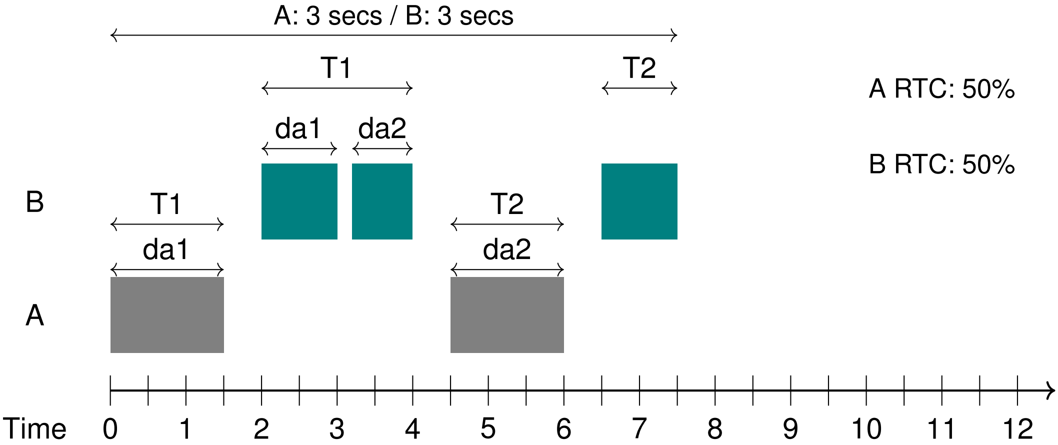
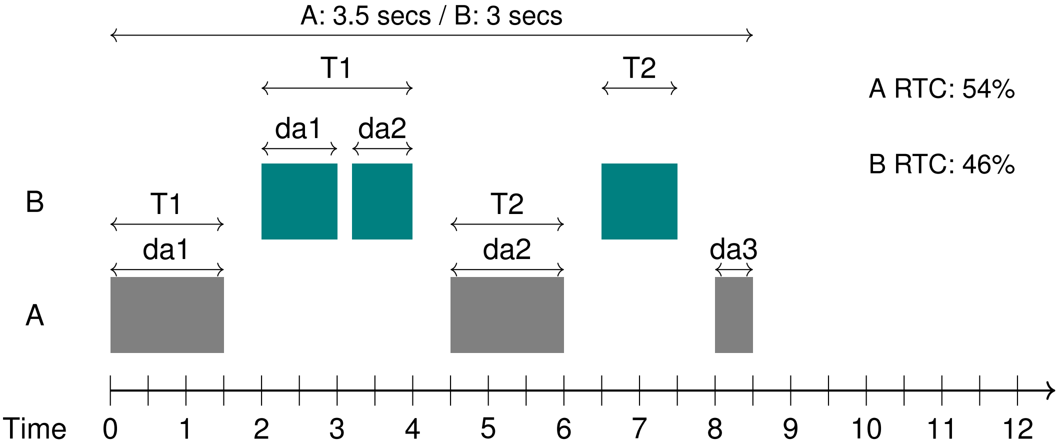


A RTC: 50%

B RTC: 50%

Relative Floor Control
Timing Diagram



Relative Floor Control

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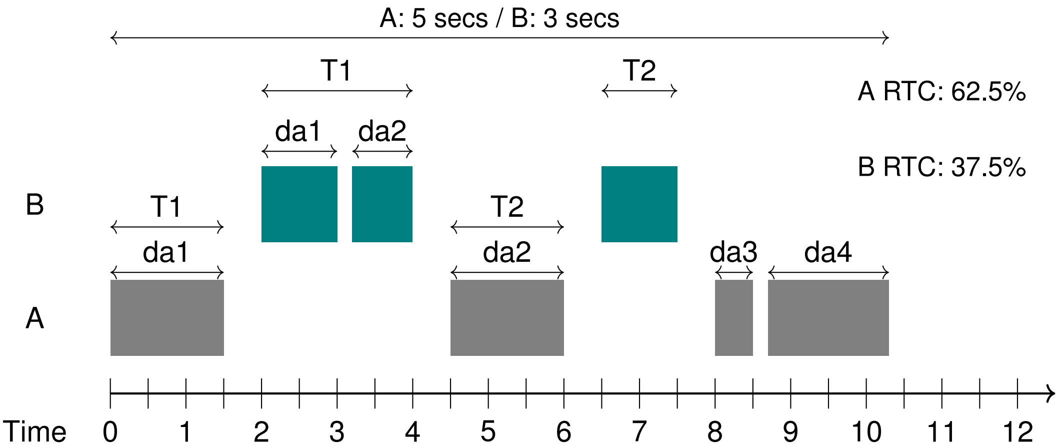

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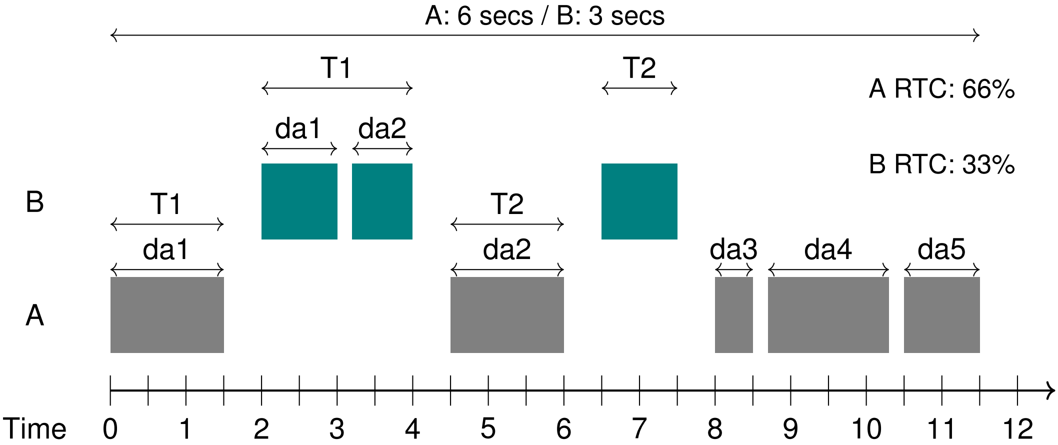

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Section 3

Data Preparation

Corpus

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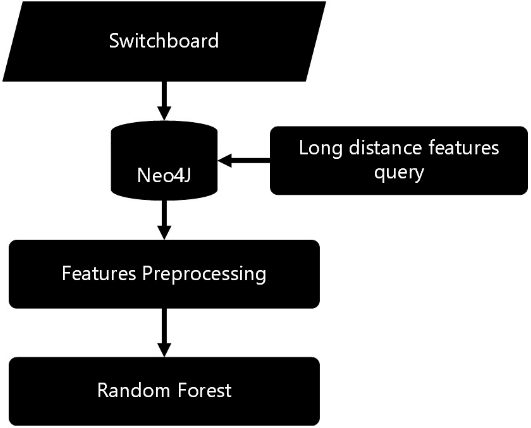
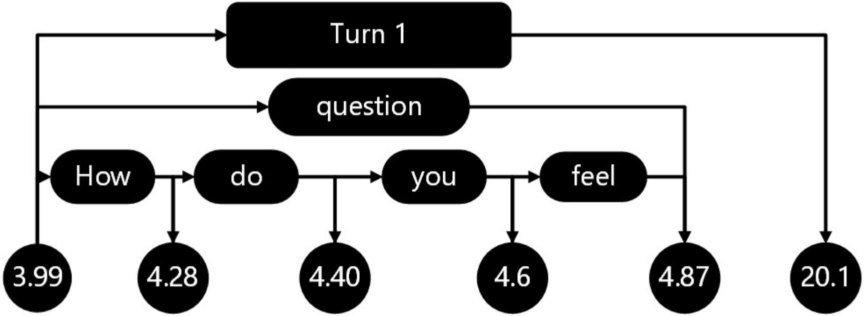
4. In our research the corpus contain 642 conversations.

Preprocessing pipeline



Conversation representation



Preprocessing

- Removed 11 dialogue acts that were coded as other in switchboard.
- Skip the first 120 seconds of the conversation.
  - Gives time for conversant to form the conversional image.
  - Reduces the dialogue acts from 50633 to 37508.
- Reduce data sparsity by collapsing 65 dialog acts into 9.

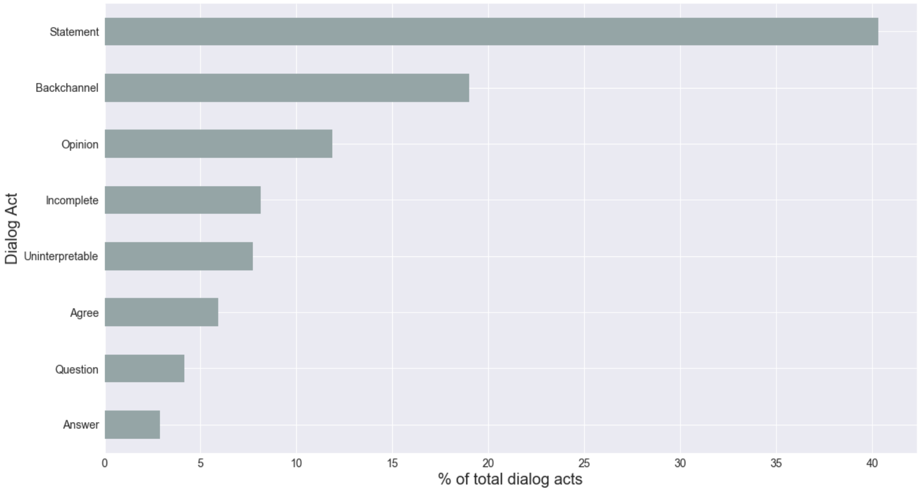
Switchboard dialog acts	Dialog act classes
sd,h,bf	statement
sv,ad,sv@	statement - opinion
aa,aar̂	agree accept
%.%-,%@	abandon
b,bh	backchannel
qy,qo,qh	question
no,ny,ng,arp	answer
+	+
o@,+@	NA

Table: Mapping from dialog act to dialog act class

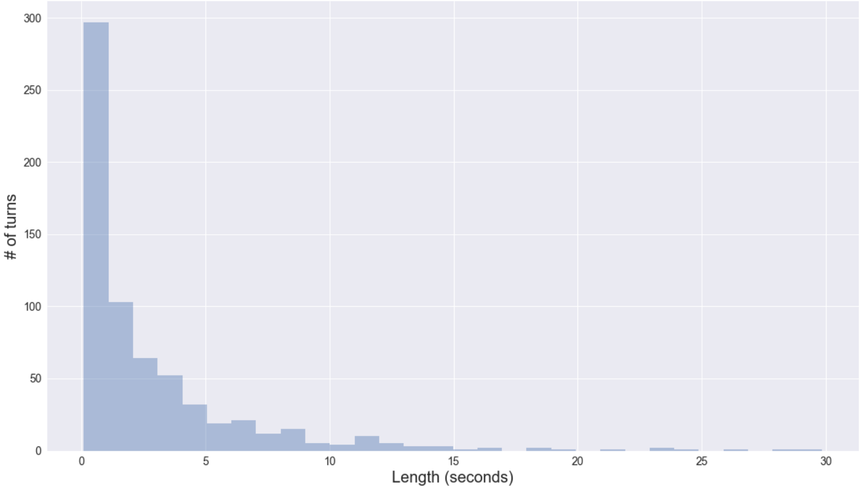
Section 4

Data Exploration

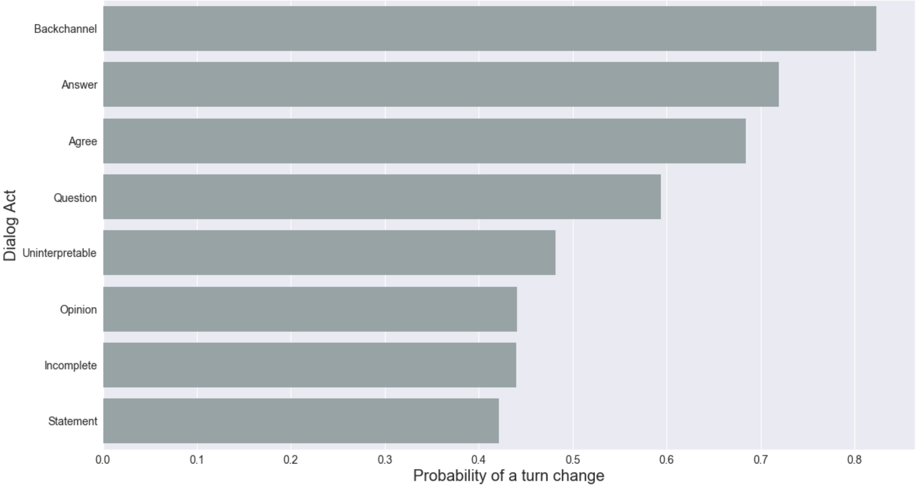
Dialog act relative count



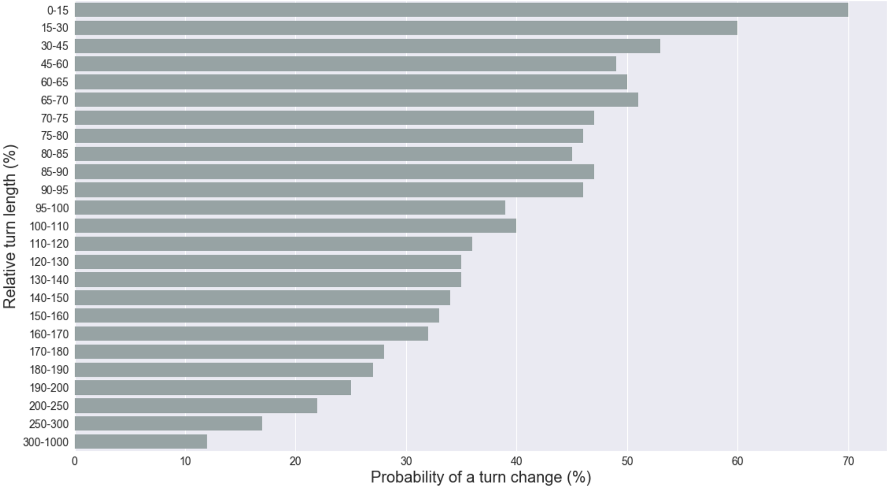
Turn Length Distribution



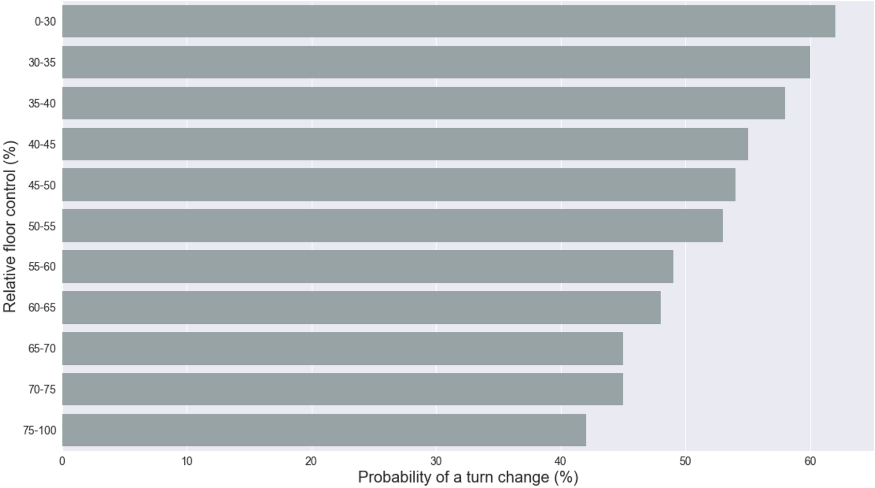
Dialog act probability of turn change



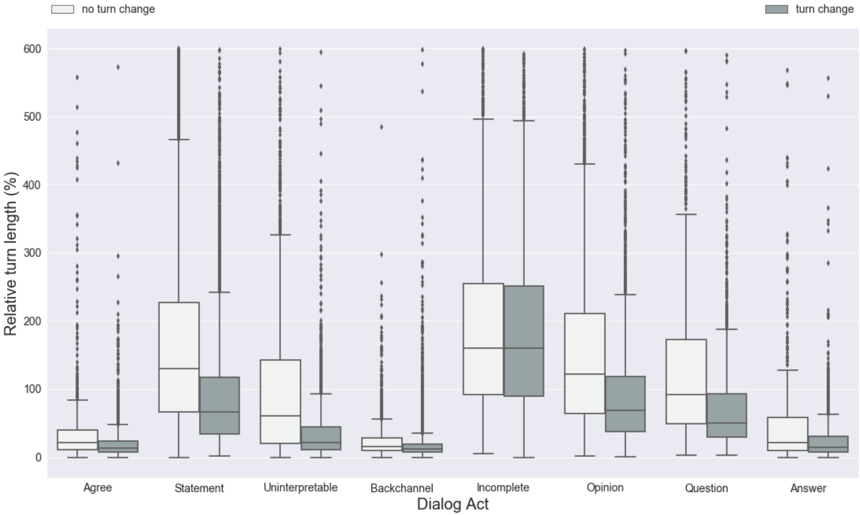
Relative Turn Length effect on probability of turn change



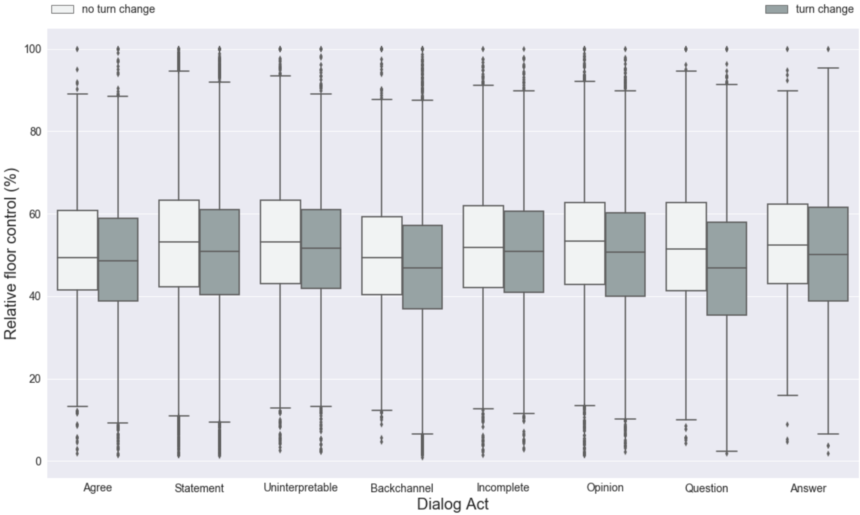
Relative Turn Control effect on probability of a turn change



Relative turn length for dialog act type



Relative floor control by dialog act



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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.
- 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%

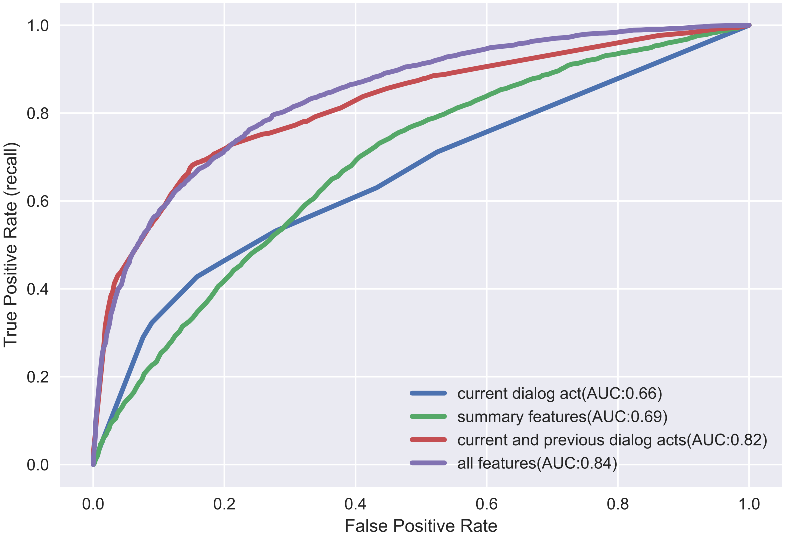
Table: Precision, recall and F1 results using Random Forests

Result for Gradient Boosting

	Accuracy	F1	Precision	Recall	AUC
baseline 1	62.79%	57.81%	74.98%	47.04%	65.99%
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

Summary

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   - Short turn (Low RTL) leads to turn change
   - In long turn the speaker will actually hold the floor.

Future work

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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.