Using Past Speaker Behavior to Better Predict Turn Transitions

Thesis Presentation

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Outline

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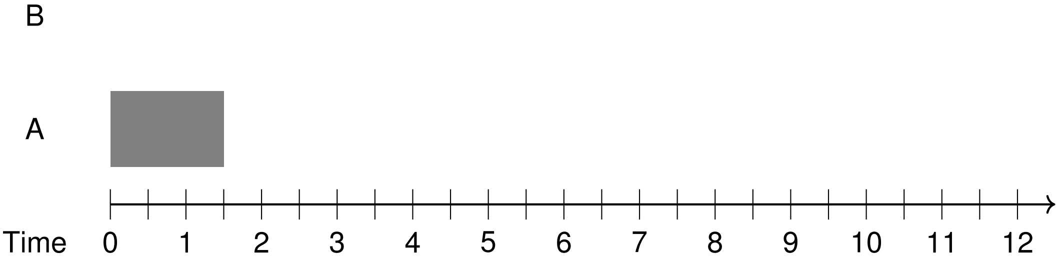
Section 1

Motivation

Relative Turn Length

Timing Diagram



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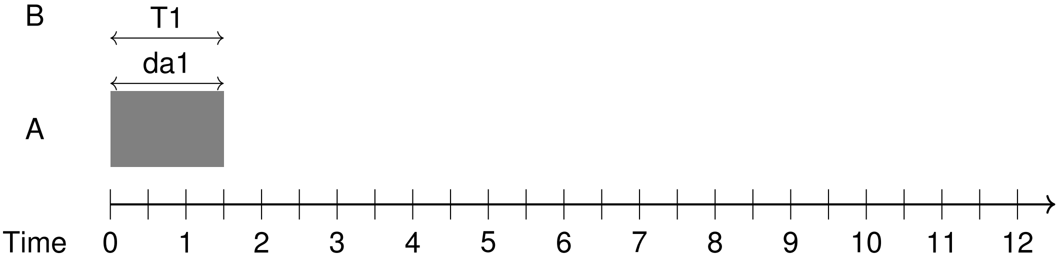

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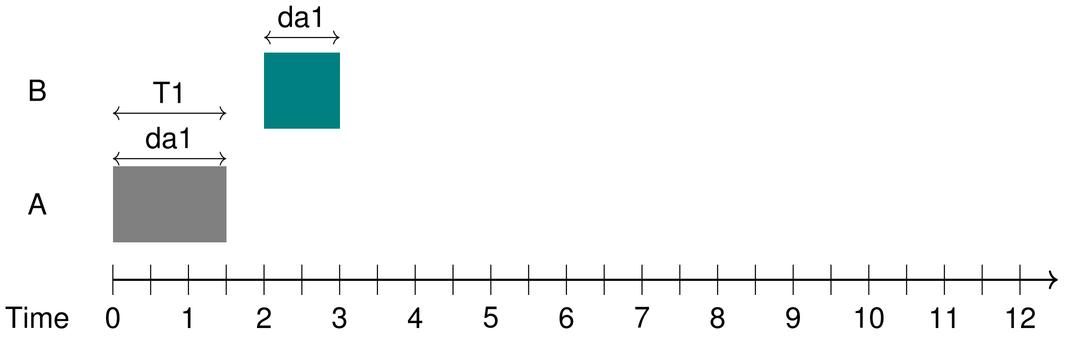

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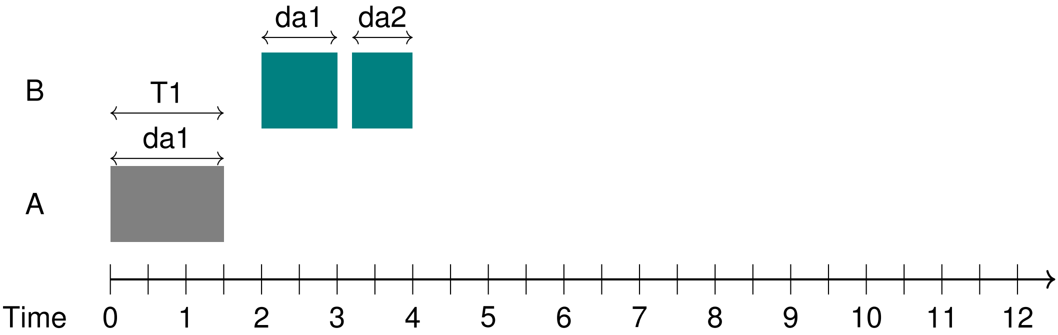

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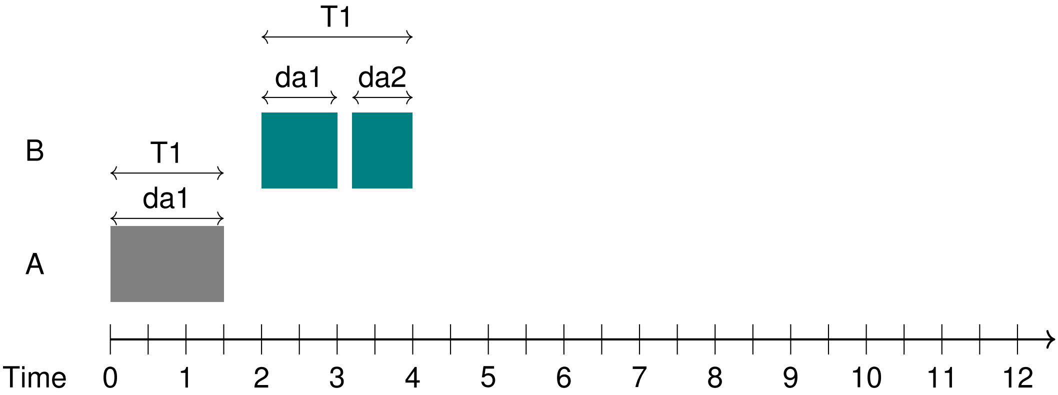

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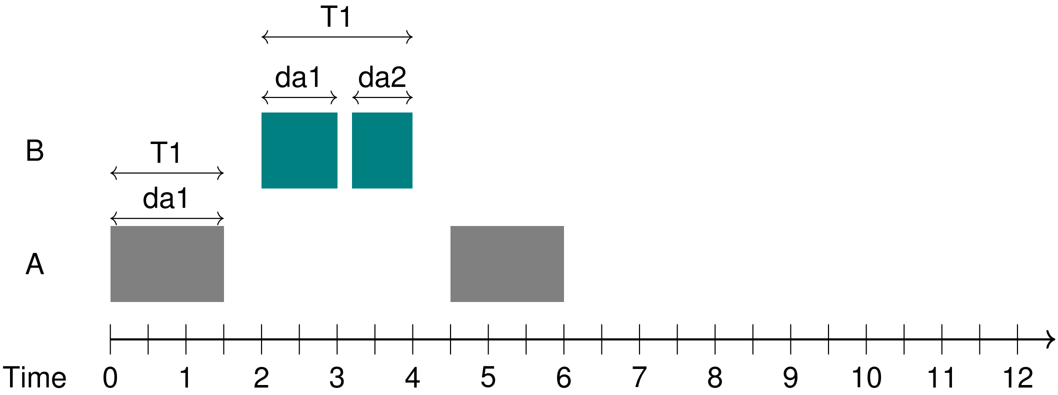

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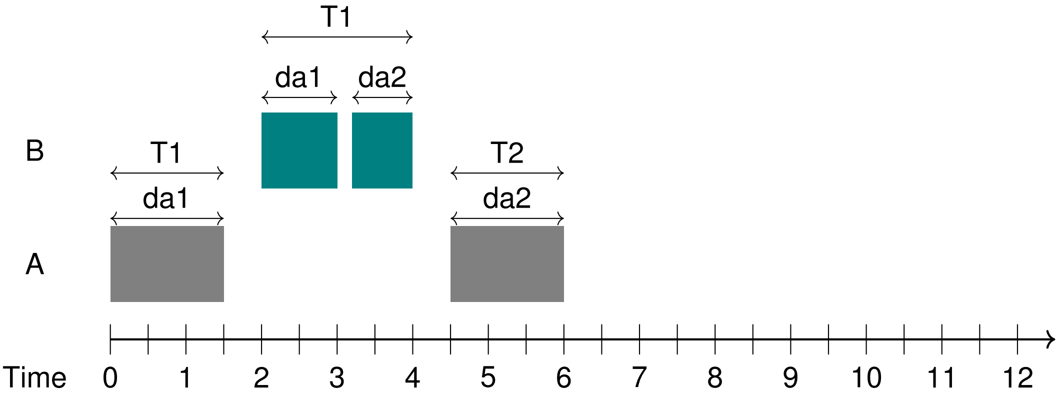

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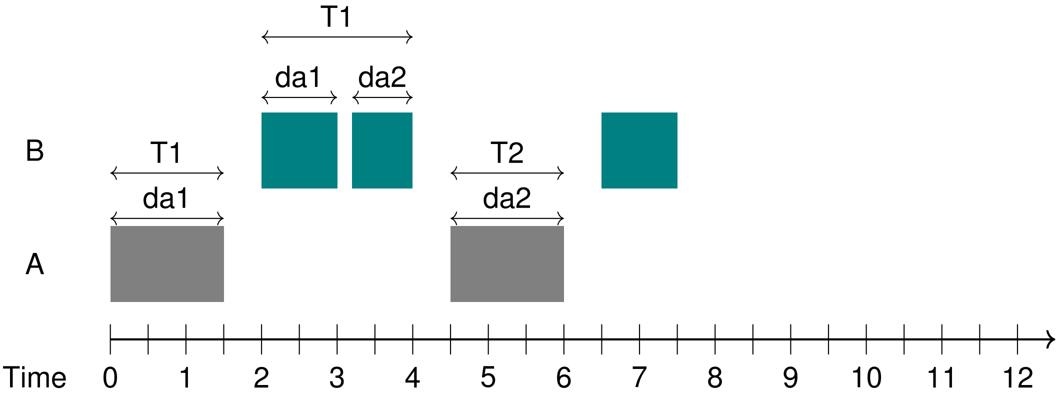

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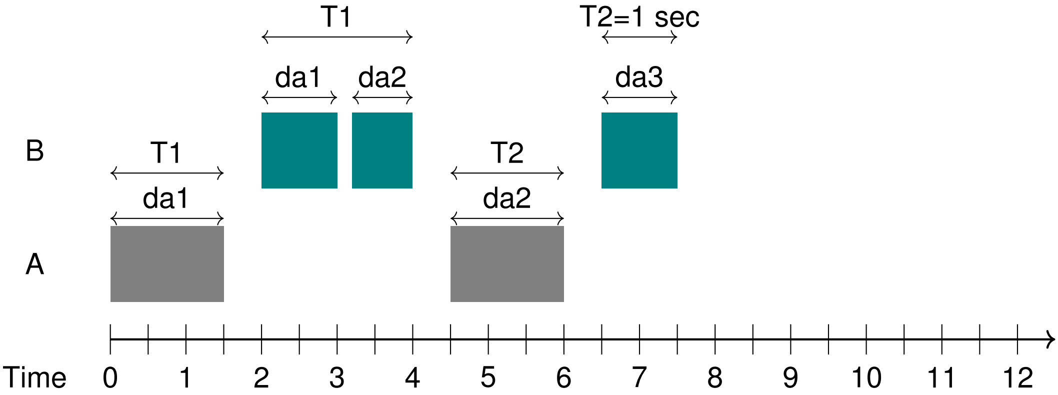

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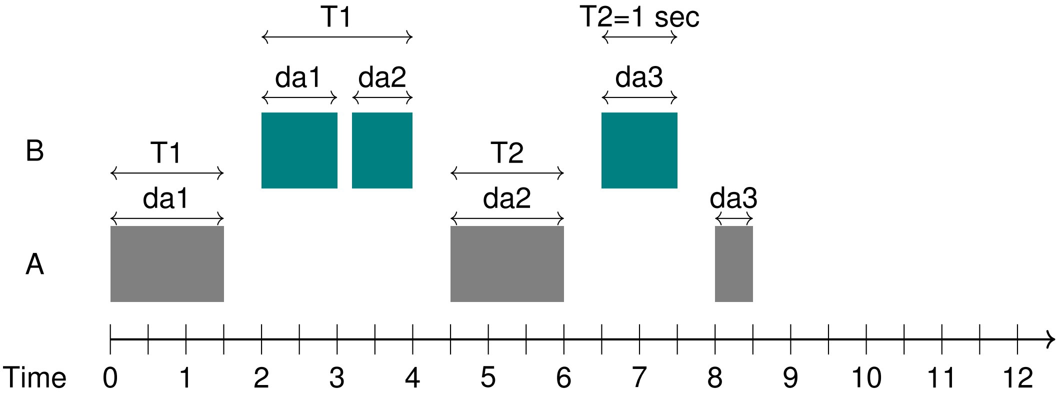

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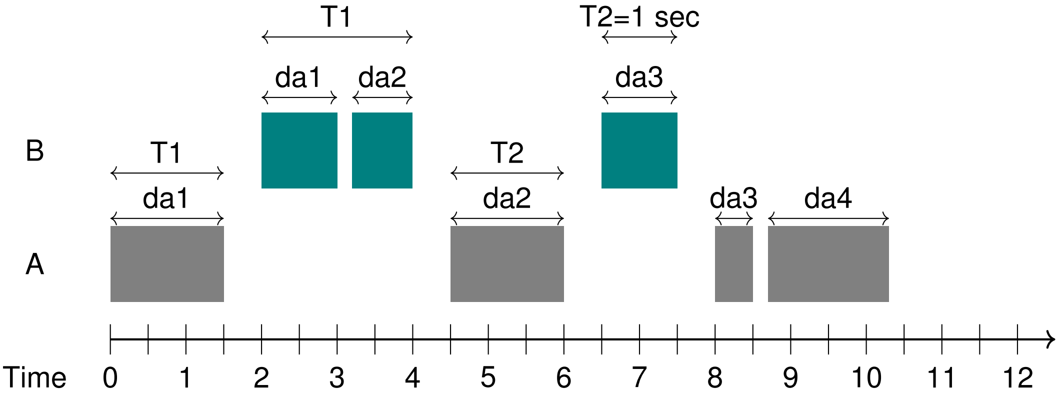

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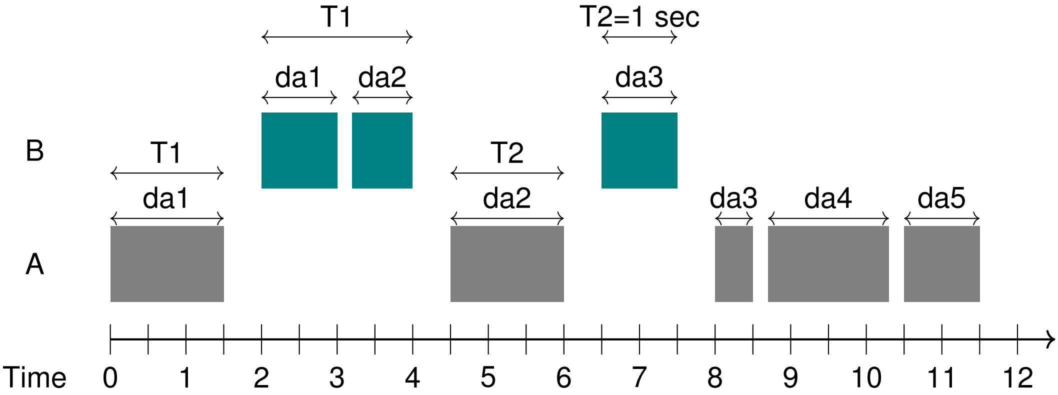

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   - Prosodic (Ford 1996,Stolcke 2002,Ferrer 2003)
   - Pragmatic (Ford 2001)

Goal of Work

Conversant's past behavior can help predict turn transitions
Past behavior represented by Summary features

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Section 2

Theoretical Model

Conversation

Conversation

$\ldots s_{i-2}, d_{i-2}, s_{i-1}, d_{i-1}, s_i, d_i \ldots$

Conversation with turn change

$\ldots d_{i-2}, y_{i-1}, d_{i-1}, y_i, d_i, y_{i+1} \ldots$

Relative Turn Length

Relative Floor Control

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Section 3

Data

Corpus

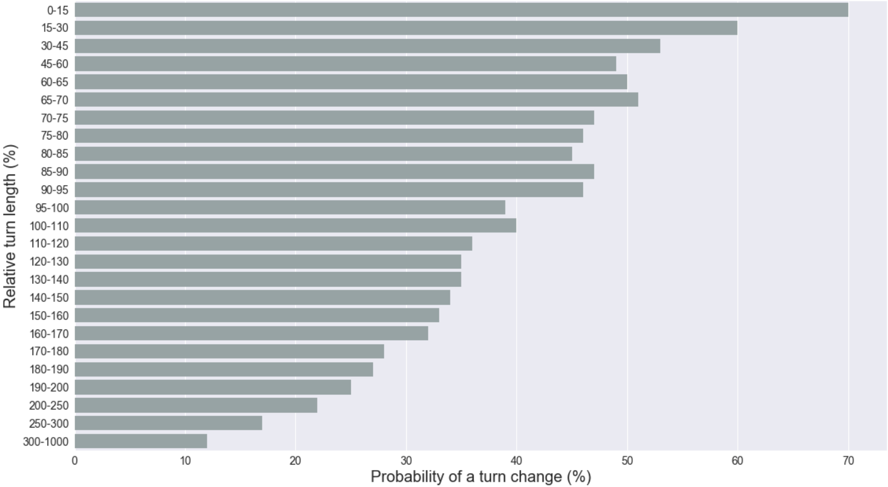
Preprocessing

- 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.

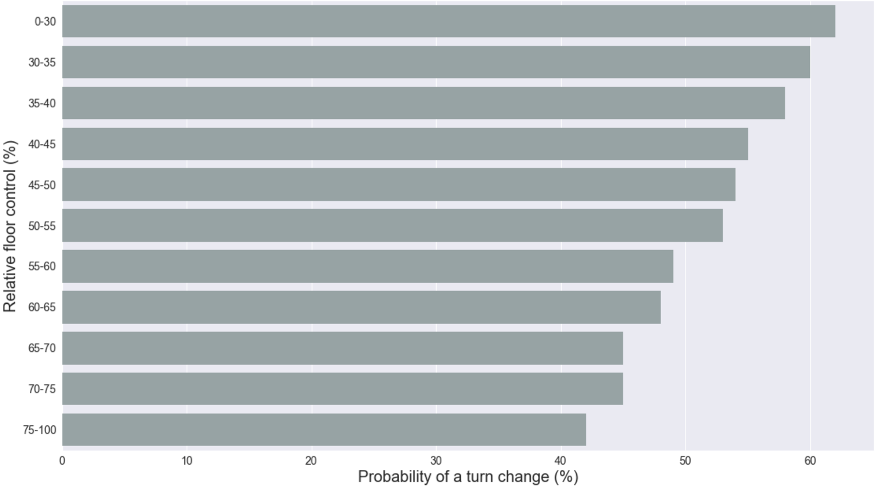
Switchboard dialog acts	Dialog act classes
sd,h,bf	statement
sv,ad,sv@	statement - opinion
aa,aar̂	agree accept
%.%-,%@	abandon
b,bh	backchannel
qy,qo,qh	question
no,ny,ng,arp	answer
+	+
o@,+@	NA

Table: Mapping from dialog act to dialog act class

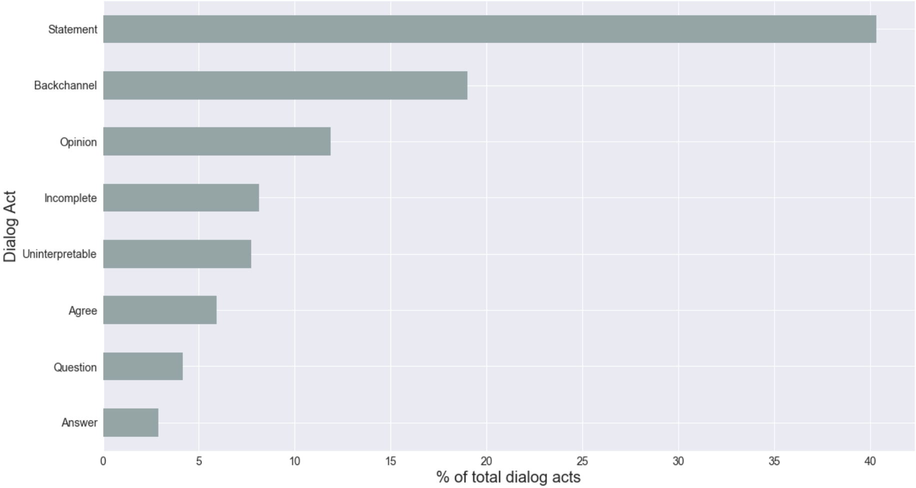
Relative floor control probability of turn change



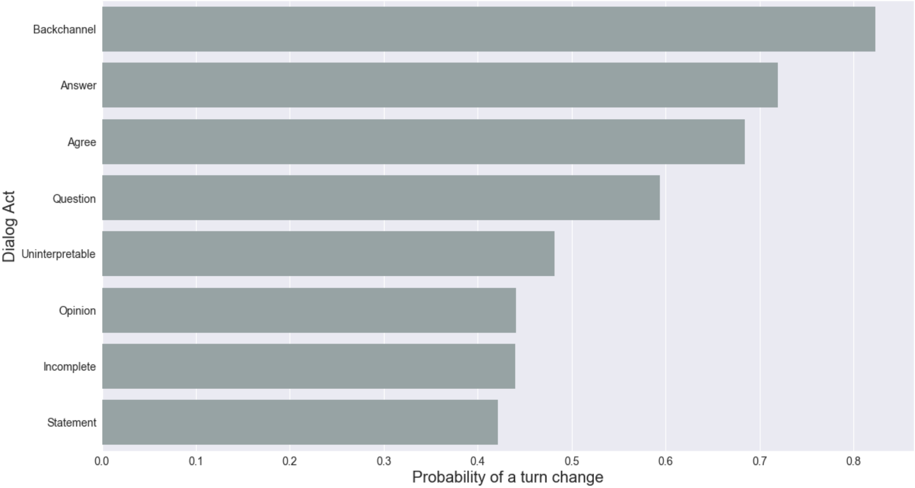
Relative turn length effect on probability of a turn change



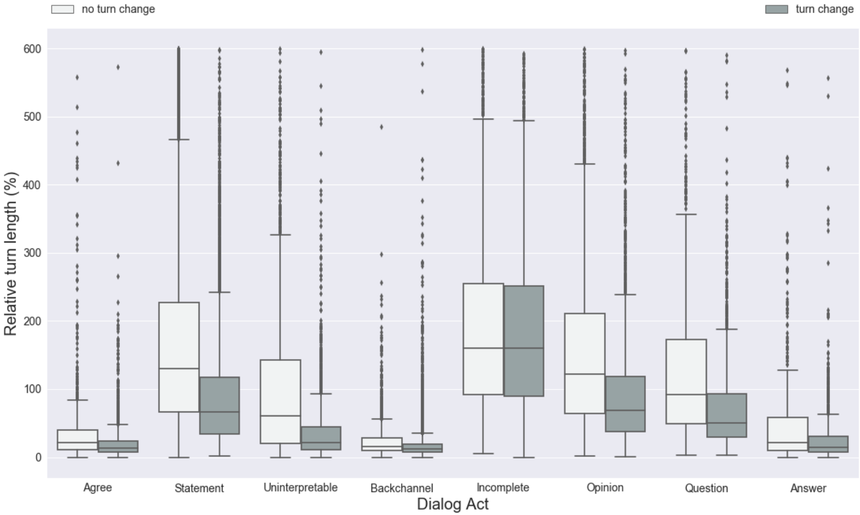
Dialog act relative count



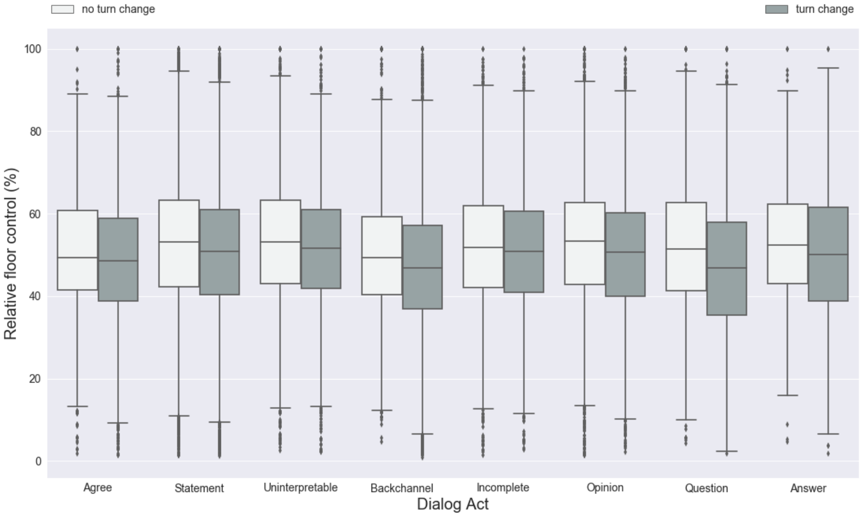
Dialog act probability of turn change



Relative turn length for dialog act type



Relative floor control by dialog act



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Section 4

Study

Classifiers

- Used random forests (N=200) 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%

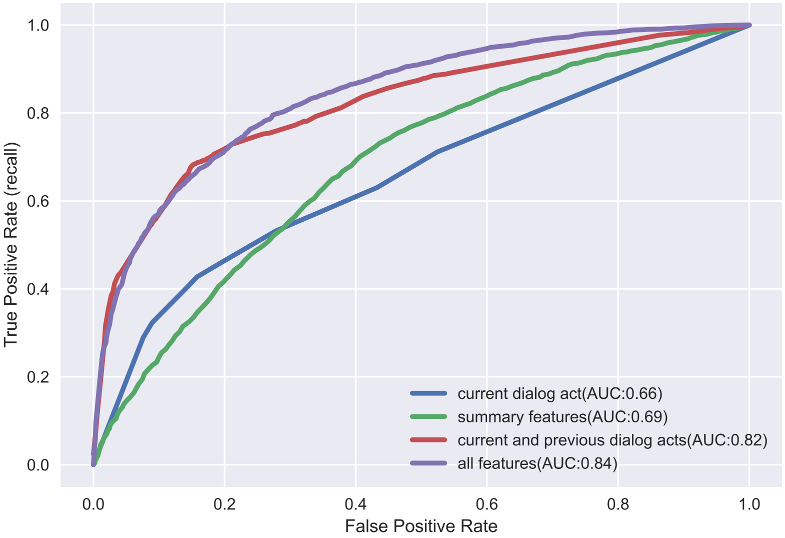
Table: Precision, recall and F1 results using Random Forests

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

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Section 5

Summary

Conclusion

Future work