

Using Past Speaker Behavior to Better Predict Turn Transitions

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Outline

- 1 Motivation
- 2 Summary Features
- 3 Evaluation
- 4 Results and Discussion
- 5 Summary

Problem

- For a natural conversation between human and machine, we want to conform to human to human turn taking system (Sacks et al, 1978)
- In Human-Human conversations conversant predict (Sacks et al, 1978) or signal (Duncan 1972) each other on coming turn transition
- Timeouts leads to poor user interaction(Arsikere et al, 2015)
 - Not effective in noisy environment
 - too little - machine barge in during intra turn pause.
 - too much - user waiting for the machine.
- Turn transition prediction based on local features improve turn taking but still do not match human performance.
 - Syntactic (Sacks et al 1978,De Ruiter et al. 2006)
 - Prosodic (Ford 1996,Stolcke 2002,Ferrer 2003)
 - Pragmatic (Ford 2001)

Goal of the work

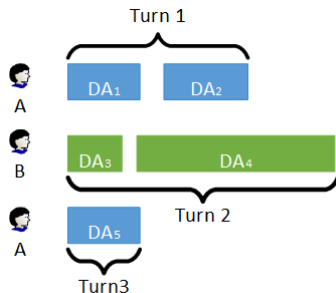
Conversant's past behavior can help predict turn transitions

Past behavior represented by Summary features

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Conversation



Conversation

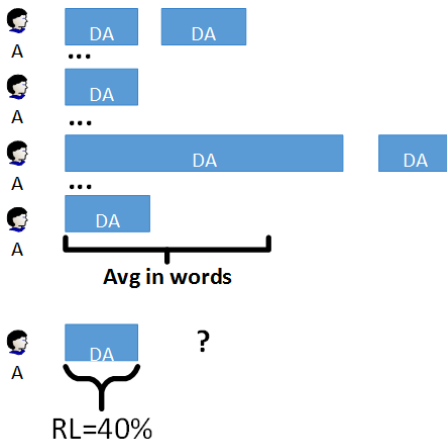
... A, DA₁, A, DA₂, B, DA₃, B, DA₄, A, DA₅ ...

Conversation with turn change

... DA₁, 0, DA₂, 1, DA₃, 0, DA₄, 1, DA₅ ...

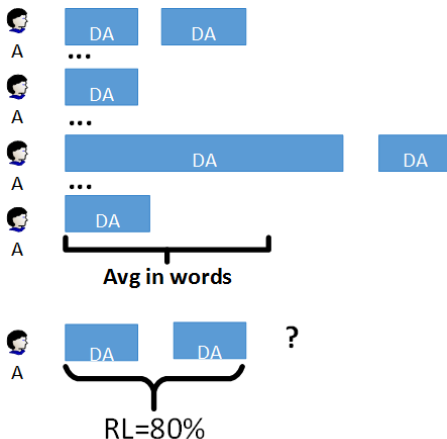
Relative Turn Length

Measure ratio of current turn length relative to average turn length.



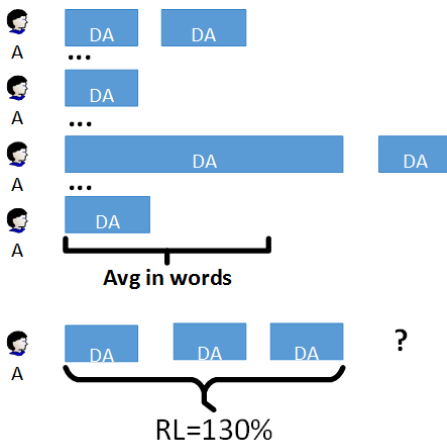
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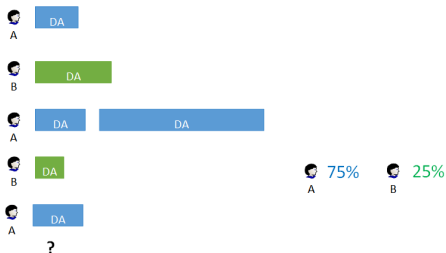
Relative Turn Length

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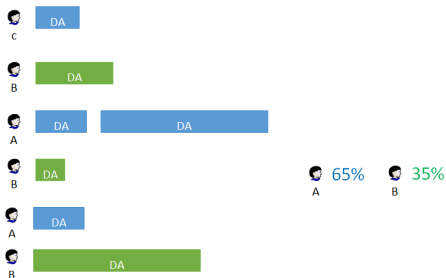
Relative Floor Control

Measure ratio that current speaker held the floor.
How dominate current speaker is.



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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 conversational 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,aa^	agree accept
%.%-,%@	abandon
b,bh	backchannel
qy,qo,qh	question
no,ny,ng,arp	answer
+	+
o@,+@	NA

ML 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 current and previous dialog acts.
- Evaluation was done using 10 fold cross validation.
- Run grid search to find the optimal hyper parameters.

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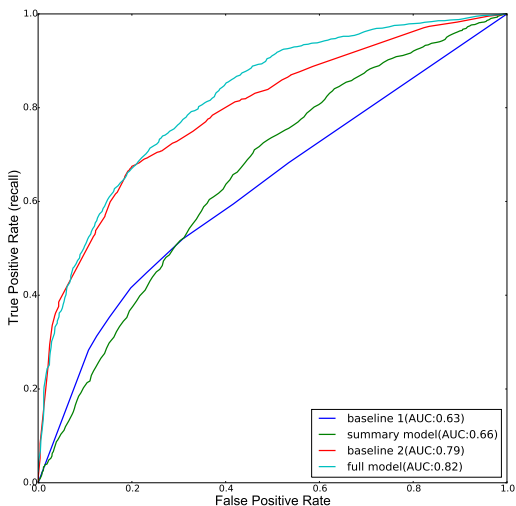
Accuracy

Model	Accuracy	AUC	hyper parameters
Baseline 1	60.26%	0.63	max_features=sqrt, max_depth=7
Baseline 2	74.43%	0.79	max_features=log2, max_depth=9
Summary	66.14%	0.65	max_features=sqrt, max_depth=5
Full	76.05%	0.82	max_features=10, max_depth=9

Table: Accuracy, Area under the curve

- The Summary model is more accurate than Baseline 1.
- The Full model is more accurate than Baseline 2.

ROC curves and AUC of the different models



Precision & Recall

Model	Precision	Recall	F1
Baseline 1	69.49%	45.52%	54.97%
Baseline 2	80.38%	68.80%	74.08%
Summary	64.55%	68.88%	66.42%
Full	76.17%	77.25%	74.87%

Table: Precision, recall and F1 results

- Summary model makes more mistakes vs Baseline 1, however it detects more turn transition.
- Summary model makes more mistakes vs Baseline 2
- Full model makes slightly more mistakes vs Baseline 2, however it detects more turn transitions.
Overall F1 is slightly better.

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Conclusion and Future Work

- Conclusion
 - Experiment proved that summary features improve turn transition prediction
- Future Work
 - Combine summary features with other local features: syntax, prosody.
 - Test simple moving average windows (5,10,20 turns)
 - Test exponential moving average.
 - Convert other local features to summary feature.