The Effects of Entrainment in a Tutoring Dialogue System

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Outline

- Introduction
- Corpus
- Post-Hoc Experiment
- Results
- Summary

Introduction

- Spoken dialogue systems can offer students one-on-one instruction from a computer tutor
- Student entrainment to computer tutor voice has been shown to correlate with learning gain (Ward and Litman, 2007; 2008)
- A system encouraging or responding to entrainment might lead to better student performance

Introduction

- The CMU Let's Go!! bus information system elicited user entrainment to improve speech recognition (Raux and Eskenazi, 2004)
- For tutoring systems, knowing which entrainment features are correlated with learning could inform this strategy
- We searched an existing intelligent tutoring dialogue system corpus to find such correlations

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Corpus

- Our data comes from a 2005 experiment with ITSPOKE
- Each student interacted with either a pre-recorded or synthesized tutor voice (Forbes-Riley et al., 2006)
- Students responded to tutor questions both verbally and with written essays for 5 problem dialogues

Corpus

- We omit Students who started but did not complete a problem in a past session
- This left us with 26 students
- Effects of tutor voice, but not entrainment, were examined in (Forbes-Riley et al., 2006)

Corpus and Motivations

- Student pre- and post-test scores, satisfaction evaluations of the system, ASR word-error rate per student, and other student metadata were available

- We investigate whether the level of student entrainment had any correlation with learning gain, user satisfaction, or word-error rate

Corpus and Motivations

- Whether student entrainment differed significantly between the pre-recorded and synthesized voices was also of interest

- Inspired by (Pardo, 2006), we were also interested the relationship between user gender and entrainment

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Hypotheses

1. a positive correlation between entrainment and learning gain
2. a positive correlation between entrainment and user satisfaction
3. a negative correlation between entrainment and word-error-rate
4. higher entrainment coefficients for students interacting with the pre-recorded tutor voice
5. higher entrainment coefficients for males

Entrainment Features

- Lexical and prosodic
- Lexical based on coarser-grained, free-form student essays
- Prosodic based on finer-grained, exchange-level student utterances
- All entrainment scores calculated on a per-problem basis, then averaged to obtain student entrainment value

Lexical Entrainment Features

- We take word repetition as primary measurement of entrainment
  - Not counting repeated words between turns
- ITSPOKE tutoring format:
  - Student reads the problem, writes initial essay

Reference essay

  - Computer tutor evaluates, guide to improve

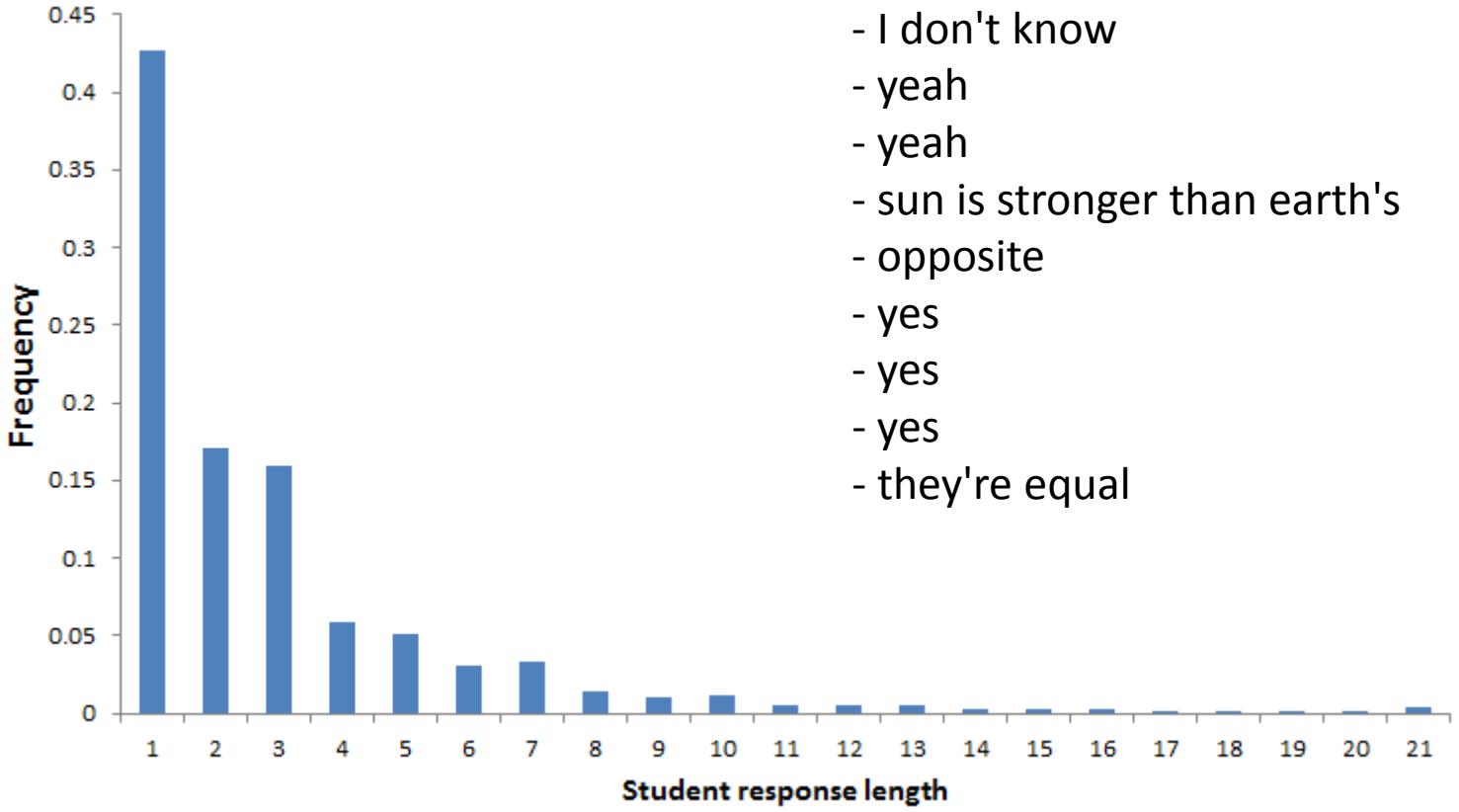
T-S conversation

  - Student re-writes the essay, submit again

Edited essay

Observation 1

- Students' answers are typically short



- I don't know
- yeah
- yeah
- sun is stronger than earth's
- opposite
- yes
- yes
- yes
- they're equal

Observation 2

- Learning evidence are shown by occurrence of new terms, and lost of other terms

Reference essay:

No the earth does not pull equally on the sun. The mass of the earth is much smaller than the sun. So it pulls with a smaller force. This is why the earth orbits the sun.

Edited essay:

No the earth does pull equally on the sun because of **Newton's Third Law**. The force is **gravitational**. It is **equal** and **opposite**.

Lexical entrainment as understanding to suggestions

- Knowledge entrainment through language
- Consider non-stop words
  - in tutor responses
  - appear in edited essay — New-word
  - but not in reference essay
- Also, non-stop words
  - appear in reference essay — Removed-word
  - but not in edited essay

Three metrics

1. new-word:

$$mean\left(\frac{\text{number of new words}}{\text{number of tutor responses}}\right)$$

2. new+removed-word:

$$mean\left(\frac{\text{number of new words + removed words}}{\text{number of tutor responses}}\right)$$

3. essay-length:

$$mean\left|\frac{\text{length(reference\_essay) - length(edited\_essay)}}{\text{number of tutor responses}}\right|$$

Prosodic Entrainment Features

- Our method is inspired by the metric used to find entrainment in (Ward and Litman, 2007)
  - Itself inspired by the method in (Reitter et al., 2006)

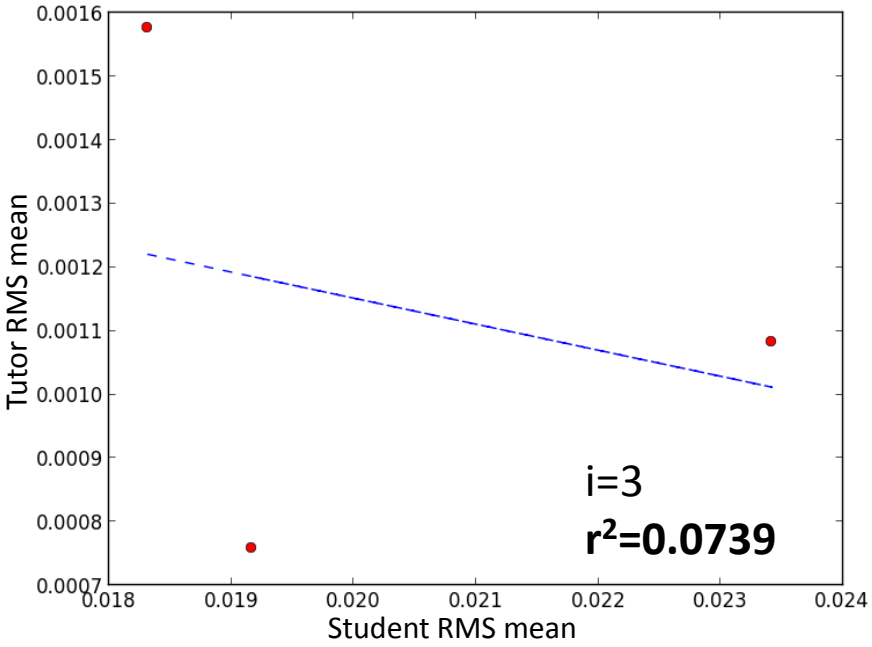
- openSMILE to get mean, min, max, and standard deviation of the energy (RMS) and pitch (F0) of every utterance

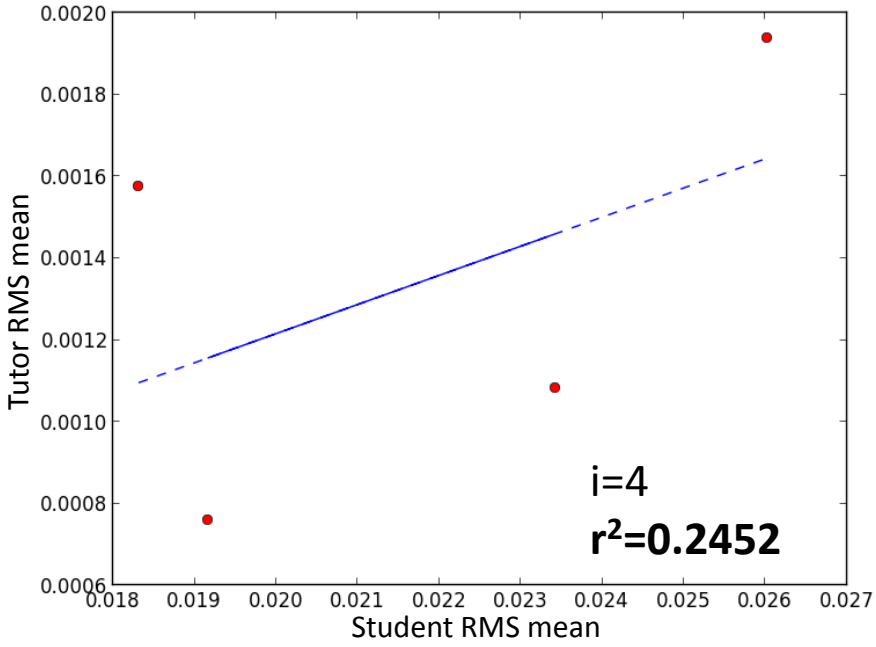
Prosodic Entrainment Features

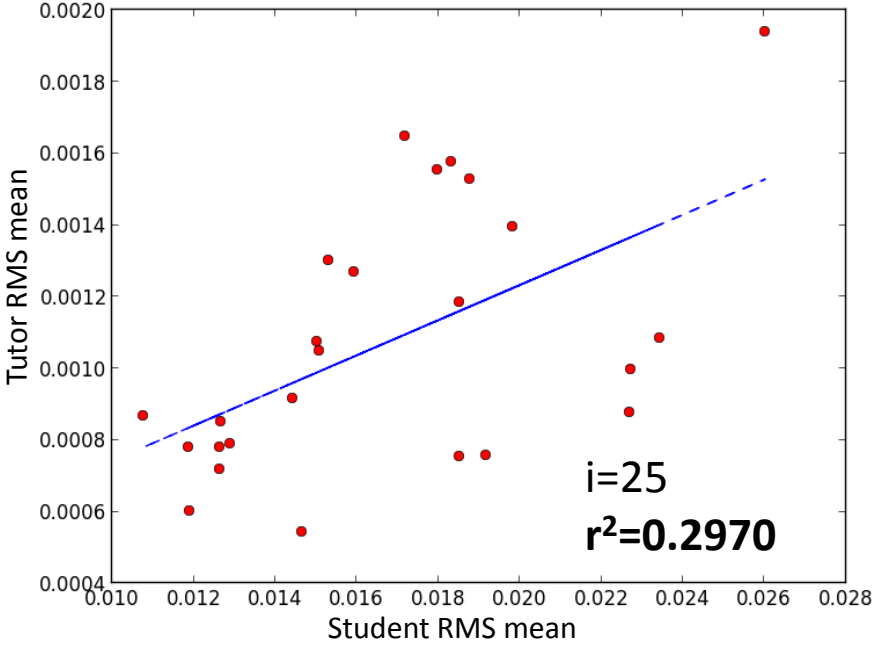
- Strict turn-taking offers verbal student responses to most tutor utterances
- We created progressive, exchange-level similarity scores between the student and tutor
- We used a linear regression to find the change in those similarity scores throughout each dialogue

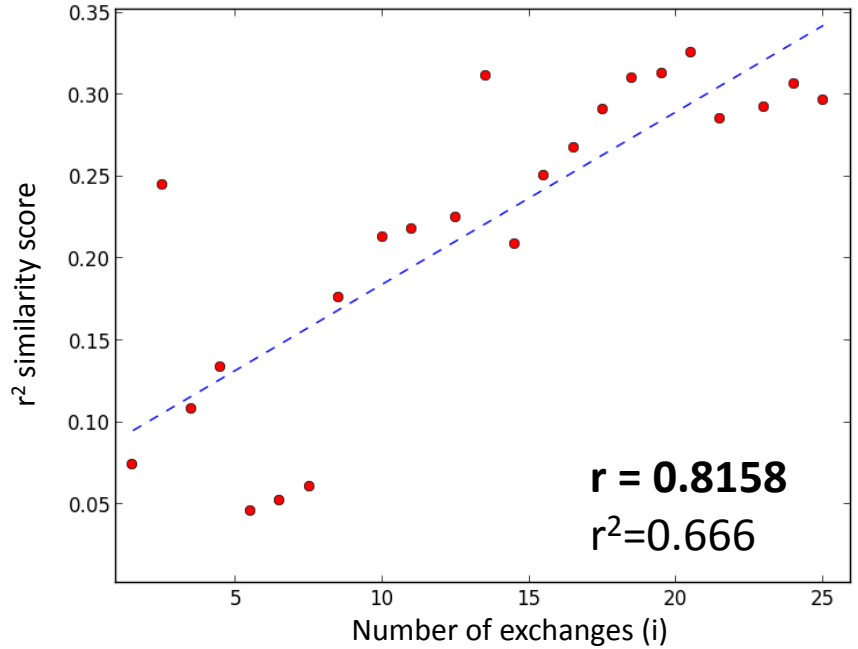
Prosodic Entrainment Features

- For each problem dialogue and raw prosodic feature, our algorithm is implemented as follows


Tutor RMS mean
Student RMS mean
i=3
r²=0.0739


Tutor RMS mean
Student RMS mean
i=4
r²=0.2452


Tutor RMS mean
Student RMS mean
i=25
r²=0.2970


r² similarity score
Number of exchanges (i)
r = 0.8158
r²=0.666

Experimental Methods

- We looked for significance in:
- Correlations entrainment scores and student properties relevant to hypotheses
- Those same correlations for low and high pre-testers (using a median split)
- Differences in mean between users' entrainment in the pre-recorded and synthesized voice conditions and between male and female entrainment to the system

Experimental Methods - Control

- Re-performed these tests on a randomized baseline corpus
- Tutor turns remained in place as student responses were randomly paired with tutor turns from which they did not originally follow
- No relationships which appeared significant in the original corpus appeared in the randomized corpus

Experimental Methods - Metrics

- For learning gain, we considered:
  - Standard Learning Gain (**SLG**)
    - *post* – *pre*
  - Normalized Learning Gain (**NLG**)
    - (*post* – *pre*) / (1 – *pre*)
- User satisfaction, **UsrSat**, based on sum of survey questions in (Forbes-Riley et al., 2006)

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Results and Discussion

- We denote:
- Significant ($p < 0.05$) results with $*$
- Highly significant ($p < 0.01$) results with $**$
- All other shown results are trending ($p < 0.1$)

- 12 Low pre-test student (under median)
- 10 High pre-test student (above media)

Support Hypothesis 1

- "a positive correlation between entrainment and learning gain"
- When considering all students, we found:

Student Data	Entrainment	(r-value)
SLG	new+removed–word	0.447*
SLG	essay–length	0.348
NLG	new+removed–word	0.382

- We note that prosodic features were not found indicative of learning gain

Support Hypothesis 2

- "a positive correlation between entrainment and user satisfaction"
- With respect to **UsrSat**, we found mostly positive correlations with prosodic features:

Group	Entrainment	(r-value)
ALL	RMS max	0.536**
Low pre-tester	F0 max	0.623*
Low pre-tester	RMS max	0.554
Low pre-tester	F0 mean	-0.533

Reject Hypothesis 3

- “a negative correlation between entrainment and word-error-rate ”
- WER often did not correlate at all
- When considering high pre-testers, we found:

Student Data	Entrainment	(r-value)
WER	RMS mean	0.771**
WER	RMS stddev	0.693*

Support Hypotheses 4,5

- "higher entrainment coefficients for students interacting with the pre-recorded tutor voice"
  - *RMS mean** and *RMS stddev* entrainment higher in the pre-recorded voice condition
- "higher entrainment coefficients for males"
  - *F0 min* entrainment higher among males

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Summary

1. a positive correlation between lexical entrainment and learning gain
2. a positive correlation between prosodic entrainment and user satisfaction
3. a negative correlation between prosodic entrainment and word-error-rate
4. higher prosodic entrainment for students interacting with the pre-recorded tutor voice
5. higher prosodic entrainment coefficients for males

Summary

- We support existing claims that:
  - entrainment may affect student performance in intelligent spoken tutor dialogue systems
  - tutor voice and gender both play roles in entrainment
- Our findings suggest that:
  - dialogue-level entrainment correlates with learning gain and trends against satisfaction
  - short-term, prosodic entrainment correlates with satisfaction
- Encouraging entrainment from their users may elicit higher learning gain and user satisfaction
  - the duration of that elicited entrainment must be considered

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All Correlations

Student Data	Entrainment	(r-value)
SLG	new+removed–word	0.447*
SLG	RMS min	-0.367
SLG	essay–length	0.348
NLG	RMS min	-0.558**
NLG	new+removed–word	0.382
UsrSat	RMS max	0.536**
UsrSat	new–word	-0.330

Student data correlated with entrainment features

Low pre-test correlation

Student Data	Entrainment	(r-value)
UsrSat	F0 max	0.623*
UsrSat	RMS max	0.554
UsrSat	F0 mean	-0.533

Low pre-test student (12 total) data correlated with entrainment features

High Pre-test Correlations

Student Data	Entrainment	(r-value)
SLG	RMS min	-0.708*
SLG	F0 stddev	0.582
NLG	RMS min	-0.720*
NLG	RMS mean	0.554
WER	RMS mean	0.771**
WER	RMS stddev	0.693*

High pre-test student (10 total) data correlated with entrainment features

Tutor Voice and Gender

- Voice: *RMS mean* $*$ and *RMS stddev* entrainment higher in the pre-recorded (12 students) than synthesized (14 students) condition
- Gender: *F0 min* entrainment higher among males (11 students) than females (15 students)