9-22-2016

Temporal Network Analysis of Small Group Discourse

Bernard P. Ricca
St. John Fisher College, bricca@sjfc.edu

Michelle Jordan
Arizona State University

Publication Information
Ricca, Bernard P. and Jordan, Michelle, "Temporal Network Analysis of Small Group Discourse" (2016). *Mathematical and Computing Sciences Faculty/Staff Publications.* Paper 14.
https://fisherpub.sjfc.edu/math_facpub/14

Temporal Network Analysis of Small Group Discourse

Abstract

The analysis of school-age children engaged in engineering projects has proceeded by examining the conversations that take place among those children. The analysis of classroom discourse often considers a conversational turn to be the unit of analysis. In this study, small-group conversations among students engaged in a robotics project are analyzed by forming a dynamic network with the students as nodes and the utterances of each turn as edges. The data collected for this project contained more than 1000 turns for each group, with each group consisting of 4 students (and the occasional inclusion of a teacher or other interloper). The conversational turns were coded according to their content to form edges that vary qualitatively, with the content codes taken from prior literature on small group discourse during engineering design projects, resulting in approximately 10 possible codes for each edge. Analyzed as a time sequence of networks, clusters across turns were created that allow for a larger unit of analysis than is usually used. These larger units of analysis are more fruitfully connected to the stages of engineering design. Furthermore, the patterns uncovered allow for hypotheses to be made about the dynamics of transition between these stages, and also allow for these hypotheses to be compared to expert consideration of the group's stage at various times. Although limited by noise and inter-group variation, the larger units allowed for greater insight into group processes during the engineering design cycle.

Disciplines

Mathematics

Comments

Presented at the Conference on Complex Systems in Amsterdam, Netherlands on September 22, 2016.

TEMPORAL NETWORK ANALYSIS OF SMALL GROUP DISCOURSE

Bernard Ricca

St. John Fisher College

Michelle Jordan

Arizona State University

Problem & Purpose

Problem: Traditional methods of analyzing classroom discourse are not sufficient to understand complex group dynamics. Instead, they focus on:

- the conversational turn as unit of analysis
- individual-student analysis
- content of interactions, and *not the dynamics*

Purpose: Explore small group discourse as a dynamic network with the students as nodes and the utterances of each turn as edges

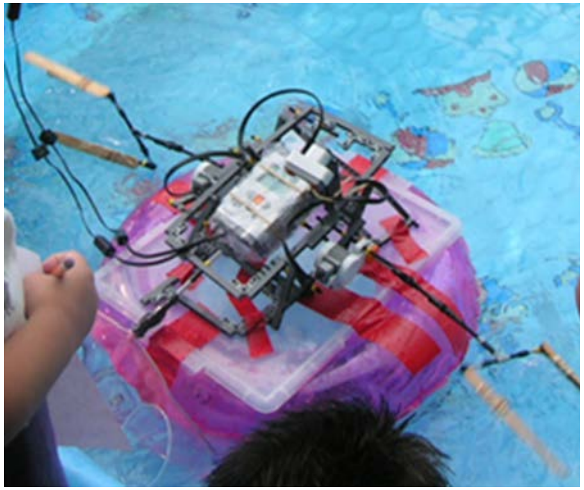
“Exploratory”

- There’s really no theory (yet) to drive this
  - Discourse theories aren’t of any help with the interpretations
  - Data are:
    - Not exactly a time series
    - Not exactly a multiplex
    - Not exactly a dynamic network
      - But this is close, at least…

The Context

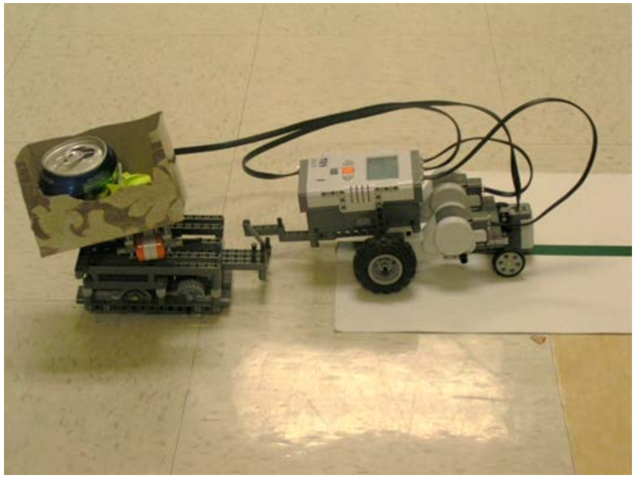
- Sustainability + Robots
- 3 Groups (see products below) – “am”, “ch”, & “shiv”
  - Four students each (3M,1F; 3F, 1M; 3F, 1M)
  - Fifth grade class of 24 students (3 groups not followed)
  - After introduction to programming, recorded 12 class meetings
    - 36 transcripts

Pollution pickup



Branch Rambler

Recycling Rover



Data Processing

- Transcripts were produced for each recorded session.
- Coding: Convert ~22000 utterances (1-5 seconds each) into more abstract codes:

Utterance	Code
SH: no, it has to be able to bend	EA (Evaluate Alternatives)
REB: Oh yeah	TP (Team Process)
K: xxx plastic	GO (Generate Options)
REB: aluminum foil xxx .	GO

- Codes based on team macrocognition processes (Fiore et al., 2010), which seeks sophisticated models to explain and predict complex cognitve processes

The Data

- Three streams (one for each small group) of time-ordered data:
  - Code (7+ levels)
  - Date
  - Speaker (4 levels/group)
  - Recipient
  - Coding agreement: % of coders who agreed (usually 100%)
  - Engineering Process (testing, problem scoping, etc. – 8 levels)
- Not a traditional (e.g., continuous, ordered dependent variable) time series
- >20k @ 4-node networks
  - Dynamic network: same nodes at almost all times, but links change (a lot)
  - Very sparse (<1.5 links/4 nodes)

Analysis (part I)

- Look in the data for patterns that repeat
- Individual patterns aren't dynamics
    - Well, not really…maybe…
    - It's a start
- Clusters don't quite work
    - Linking the nodes across time can overwhelm the clustering algorithms.
    - Weight those links, but then some links are weighted and some are categorical
        - There are ways to do that
    - Tuning the weights of links can produce almost anything one wants.
- ARIMA-type or Markov-type methods
    - ARIMA: Hard to subtract off the "average" or "trend"
    - Markov: End up with probabilities

Analysis (part II)

- Compare these patterns to random data with some of the same distributions of codes, etc.
  - Most patterns and transcripts are highly unlikely to be random
- Then, compare patterns…
  - Across groups
  - Across time
  - Across speakers
    - And with speakers considered interchangeable
- Less directly about dynamics, but differences do tell a story

Patterns

- Distribution of patterns are not random
  - E.g. In one transcript (1253 utterances), there are 37 repetitions of length 7 and there is a string of 9 utterances that repeats 3 times
    - There is also a string of 14 utterances that is found in 4 locations, but those strings were all off-task behavior.
  - A random distribution with the same probability of each code has
    - Approximately the same number of repeats
    - Much shorter strings on balance (only 2 @ length 7, and 0 length 9)
- A difficulty
  - Compare these two strings:
    - xx-IE-IE-IE-IE-TP-IE-IE-IE-IE-xx
    - xx-IE-IE-IE-IE-IE-TP-IE-IE-IE-xx
  - Are they the same in terms of dynamics or not?

Example Group Comparisons

- Groups are different from each other. For example
  - On most days, the am group has far fewer repeating patterns (about 1/3 as many, on average) than the ch group
  - But…a much higher percentage of them are “long” repetitions.
- Not surprisingly, when we consider the speakers & recipients to be interchangeable, there are many more repetitions
  - But…in the am group, this difference is much smaller than in the ch group, indicating a stronger set of roles in that group.

More Examples

- Getting closer to dynamics:
  - Comparing groups at different stages (e.g., problem scoping vs. building)
    - Early on: no patterns
    - Later, long stretches of information exchange (IE)…15-18 turns on several occasions
- Transitions?
  - One would hope to see more planning (Team Process) before changes in activities, but that doesn't happen significantly
    - Not really surprising
- Group Dynamics
  - 1 group has a very quiet person (who speaks only about 3% of the time)
  - No group seems to be dominated by a single person, though

Interpretation

- Mostly, to this point, description rather than dynamics
  - Result of the exploratory nature: How would we know what dynamics would look like in conversational patterns?
- Definite differences between groups
  - Nothing that a teacher wouldn't pick up when watching the video
  - But it is good when the process corresponds to the judgment of experts
- Some weak correlations between moving summaries and parts of the engineering process

Discussion

- Current discourse analysis done in classrooms is not that insightful because it doesn't allow us to identify dynamics of the system well
- Looking at groups (and comparing groups) can reveal group structure
- Looking for community structure in network to reveal dynamics
  - Not yet clear how to define the communities
  - Also not yet clear how to relate those to the dynamics of the situation

Ongoing Work

- Working to determine more precisely what the state of the group is
  - Additional coding
  - Additional features?
- Deeper machine learning
  - Don't exactly have a measure to optimize, though
- Looking for interpretations of the group dynamics via the judgment of teachers
  - These may indicate phases over longer time
  - These may also allow us to work with blocks, rather than just guessing/searching for those groupings
- Additional data

Acknowledgements

- A great “Thank-you!” to our intrepid coders and transcribers:

  - Luke Bottar (SJFC)
  - Sarah Morton (SJFC)
  - Camille Pensabene (SJFC)
  - Avinash Patel (ASU)

- Many thanks for the students who participated, their teacher, and their school for allowing us access.