

Learning through Discussion: Foundations, Findings, and Future

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**Slides with full citations for all referenced work
will be available from my website!**

**Feel free to contact me to discuss further or
collaborate!!**

Carolyn Penstein Rosé

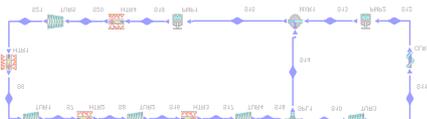
<http://www.cs.cmu.edu/~cprose>

cprose@cs.cmu.edu

Developing ***technology*** capable of shaping conversation and ***supporting effective participation in conversation*** to achieve positive impact on...

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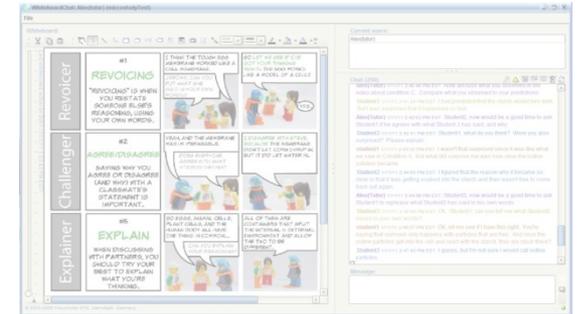
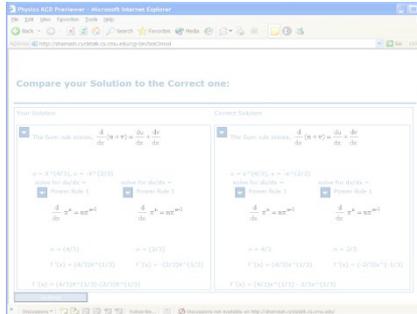
Human learning



Developing **technology** capable of shaping conversation and **supporting effective participation in conversation** to achieve positive impact on...



Human learning

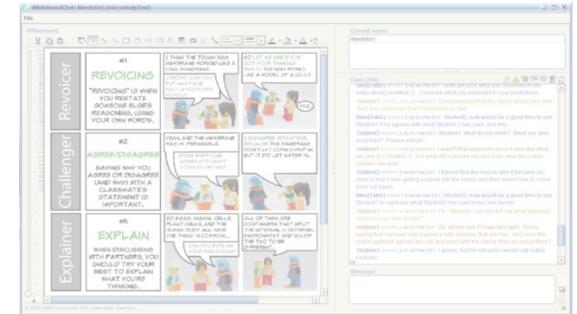
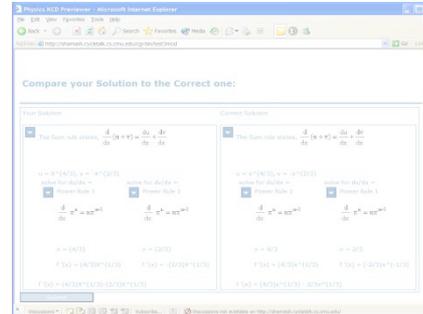


Health



Developing **technology** capable of shaping conversation and **supporting effective participation in conversation** to achieve positive impact on...

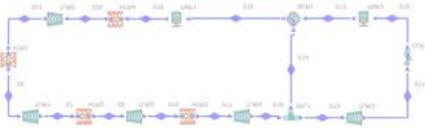
Human learning



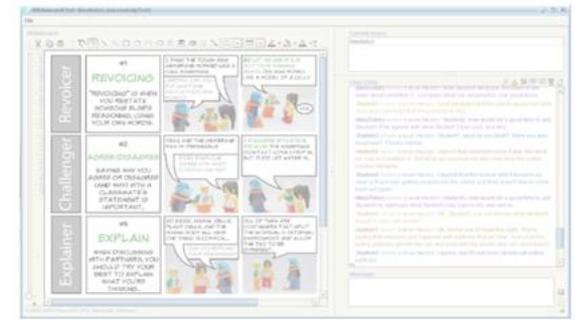
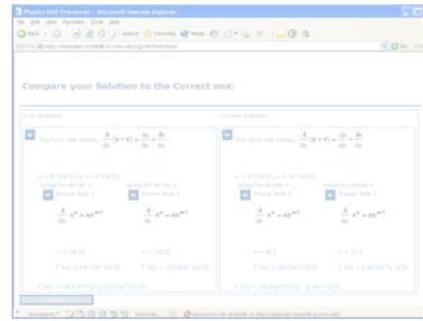
Health



Wellbeing



Human learning



Human learning

- Understand what properties of discussions have a positive effect on learning
- Computationally model those selected properties of conversation
 - Makes research more scalable/efficient
 - Enables real time monitoring and dynamic triggering of supportive interventions
- Deployment and evaluation of supportive interventions at scale

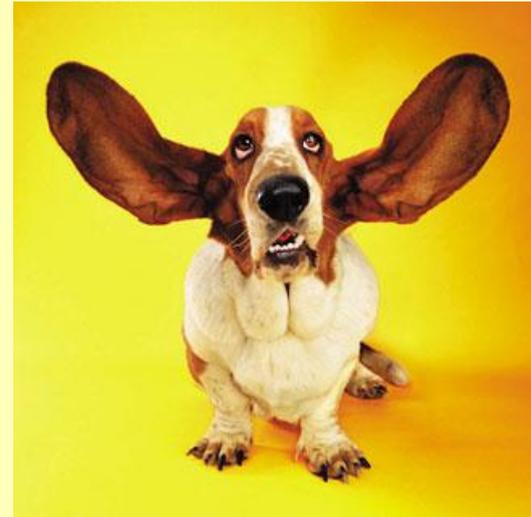
**Little known
fact
about me...**



Overview

- **Foundations**
 - Applied machine learning
 - Learning Sciences
- **Findings**
 - Pitfalls to Avoid
 - Patterns to Leverage
- **Future**
 - Working together!!

- Hmelo-Silver, C., Chinn, C., Chan, C., & O'Donnell, A. (2013). *The International Handbook of Collaborative Learning*, Routledge.
- Luckin, R., Puntambekar, S., Goodyear, P., Grabowski, B., Underwood, J., & Winters, N. (2013). *Handbook of Design in Educational Technology*, Routledge.
- Suthers, D., Lund, K., Rosé, C. P., Teplovs, C., Law, N. (2013). *Productive Multivocality in the Analysis of Group Interactions*, edited volume, Springer.
- *The International Journal of Computer Supported Collaborative Learning*, Springer.
- *The Journal of the Learning Sciences*, Taylor & Francis.



Recommended Reading

Tutorial Dialogue

Knowledge Construction Dialogues are simple directed lines of reasoning (Rosé et al., 2001a)

System: *Let's think about the motivation for Reheat. What process does the steam undergo in the Turbines ?*

Student: condensation

System: *Steam undergoes Isentropic Expansion in a turbines that converts the heat energy of the steam into work by rotating the blades. What happens to the Quality of steam during Expansion ?*

Student: I'm not sure

System: *As steam expands in a turbine, it's moisture level increases. Does this affect the extent to which the Quality is acceptable for use?*

Student: wtf!!!

System: *We should NOT use low quality steam in turbines as it condenses on the turbine blades and damages the turbine running at high speeds.*

Does this constrain the amount of work steam can do in turbines ?

Student: yes

System: *Good. Since quality of steam falls gradually in the turbines, we design turbines such that the quality remains above acceptable levels [0.85]. ...*

Computer Supported Collaborative Learning

(Kumar et al., 2007)

The screenshot displays a software interface titled "WhiteboardChat: St1BG (TeamB01)". The interface is divided into several sections:

- Whiteboard:** Contains two line graphs. The top-left graph plots "eta-therm [%]" on the y-axis (ranging from 2.67 to 21.48) against "T [°C]" on the x-axis (ranging from 338.9 to 490.7). The top-right graph plots "eta-therm [%]" on the y-axis (ranging from 2.67 to 25.78) against "T [°C]" on the x-axis (ranging from 330.0 to 488.2). The bottom-left graph plots "dot out [kW]" on the y-axis (ranging from -2.639 to -2.261) against "T [°C]" on the x-axis (ranging from 274.4 to 41). The bottom-right graph plots "Power out [kW]" on the y-axis (ranging from 1.023 to 1.144) against "T [°C]" on the x-axis (ranging from 274.4 to 486.9). A status bar at the bottom of the whiteboard area shows "T [°C]: 286.56336 eta-therm [%]: 22.4976".
- Current users:** A list box containing "St1 3BP", "St1BG", and "Tutor".
- Chat:** A text area showing a conversation. The chat history includes:
 - Tutor: 11/26/07 9:35:59 PM EST: Now might be a good time for some reflection.
 - Tutor: 11/26/07 9:36:04 PM EST: Consider the effect of increasing Q_{in} - which is heat input to a cycle. First, let's consider what happens to power out when Q_{in} is increased. What happens to power out when steam is cooled?
 - St13BP: 11/26/07 9:36:52 PM EST: well the idea is to increase the heat in
 - Tutor: 11/26/07 9:36:56 PM EST: Power is generated when steam is cooled. If there is more heat input, will there be more or less potential for cooling?
 - St13BP: 11/26/07 9:37:01 PM EST: because that increases power
 - Tutor: 11/26/07 9:37:04 PM EST: There will be more potential for cooling. If there is more potential for cooling, is there more or less potential for power generation?
 - St1BG: 11/26/07 9:37:19 PM EST: but not too much that it leaves too much thermal pollution
 - Tutor: 11/26/07 9:37:22 PM EST: There will be more potential for power generation. So the amount of power generated has the potential to increase, though it doesn't always. Where might the increased heat input go instead?
 - St13BP: 11/26/07 9:38:05 PM EST: right
 - Tutor: 11/26/07 9:38:07 PM EST: it makes the steam leaving the turbine better, to the
- Message:** An empty text input field at the bottom of the chat window.

Students & Tutor working on designing a power plant

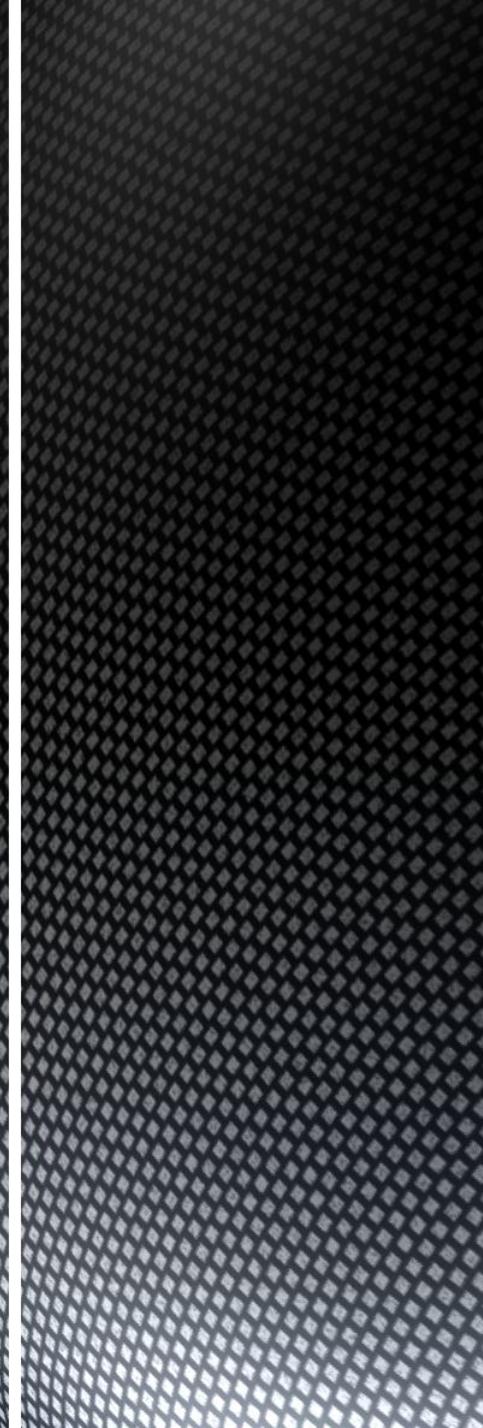
Tutor discusses thermodynamics concepts and makes arguments for design alternatives.

Students share results and ideas in a common workspace

**** Students learn up to 1.25 standard deviations more when interactive support is provided in the environment. (more than a full letter grade!)**



Foundations



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LightSIDE

CSV Files: sentiment_sentences DOCUMENT_LIST Documents: sentiment_sentences Class: <class> Text Fields: text

Feature Extractor Plugins: Basic Features Column Features Previous Label Features

Configure Basic Features

- Unigrams
- Bigrams
- Trigrams
- POS Bigrams
- Line Length
- Contains Non-Stopwords
- Binary N-grams?
- Include Punctuation?
- Remove Stopwords?
- Stem N-grams?
- Differentiate text columns?

Extract Name: Features Rare Threshold: 5

Feature Table

FEATURE TABLE	Features	Target
Documents: sentiment_sentences	Basic Table Statistics	
Feature Plugins	Recall	
Feature Table: Features	Target Hits	
	Precision	
	Total Hits	
	Correlation	
	F-Score	
	Accuracy	

Features in Table

Feature	Kappa	Target Hits
and	0.106	2,740
of	0.095	2,441
is	0.045	2,827
the	0.039	4,801
<COMMA>	0.035	3,181
in	0.035	710
with	0.034	829
to	0.033	1,512

CSV Files:

sentiment_sentences.csv

DOCUMENT_LIST

Documents: sentiment_sentences
Files:
Instances: 10662
Text Column: text

Class: class

Type: NOMINAL

Text Fields:

text

Differentiate Text Fields

Feature Extractor Plugins:

- Basic Features
- Character N-Grams
- Column Features
- Parse Features
- Regular Expressions
- Stretchy Patterns

Configure Basic Features

- Unigrams
- Bigrams
- Trigrams
- POS Bigrams
- POS Trigrams
- Word/POS Pairs
- Line Length
- Count Occurrences
- Normalize N-Gram Counts
- Include Punctuation
- Stem N-Grams

Extract

Name: 1grams_1

Rare Threshold: 5

Feature Table:

1grams

FEATURE_TABLE

Documents: sentiment_sentences.csv
Feature Plugins: basic
Feature Table: 1grams
4485 features
Class: class
Type: nominal

Evaluations to Display:

Target: neg

Basic Table Statistics

- Correlation
- F-Score
- Kappa
- Precision
- Recall
- Target Hits
- Total Hits

Features in Table:

Search:

Feature

'60s
'70s
'em
--
-lsb-
-rsb-
1
10
100
101

Feature Tables:

1grams

FEATURE_TABLE

- Documents: sentiment_sentences.csv
- Feature Plugins: basic
- Feature Table: 1grams
 - 4485 features
 - Class: class
 - Type: nominal

Learning Plugin:

- Naive Bayes
- Logistic Regression
- Linear Regression
- Support Vector Machines
- Decision Trees
- Weka (All)

Evaluation Options:

- Cross-Validation
- Supplied Test Set
- No Evaluation

Fold Assignment:

- Random
- By Annotation:

- By File

Number of Folds:

- Auto
- Manual: 10

2 5 10 Max

Configure Logistic Regression

- L2 Regularization
- L1 Regularization
- L2 Regularization (Dual)

Train

Name: logit_1grams_1

Feature Selection

Trained Models:

logit_1grams

TRAINED_MODEL

- Documents: sentiment_sentences
- Feature Plugins: basic
- Feature Table: 1grams
- Learning Plugin: Logistic Regress
- Validation: CV

Model Evaluation Metrics:

Metric	Value
Accuracy	0.7586
Kappa	0.5172

Model Confusion Matrix:

Act \ Pred	neg	pos
neg	4077	1254
pos	1320	4011

LightSide

Extract Features | Restructure Data | Build Models | Explore Results | Compare Models | Predict Labels

Highlight: **logit_1grams**

Cell Highlight:

Act \ Pred	neg	pos
neg	<input type="radio"/> 4077	<input checked="" type="radio"/> 1254
pos	<input type="radio"/> 1320	<input type="radio"/> 4011

Evaluations to Display:

- Horizontal Absolute Difference
- Horizontal Difference
- Normalized Bayes
- Vertical Absolute Difference
- Vertical Difference
- Model Analysis

Features in Table:

Search:

Feature	Frequency	Horizontal Absolute Difference	Feature Weight
<input type="radio"/> boring	2	0.0104	-2.2036
<input type="radio"/> bore	3	0.0006	-2.1322
<input type="radio"/> supposed	3	0.0025	-2.0136
<input type="radio"/> dull	1	0.0166	-1.9629
<input type="radio"/> fails	4	0.0064	-1.8998
<input type="radio"/> worst	2	0.0104	-1.8554
<input type="radio"/> flat	0	0.0091	-1.8355
<input type="radio"/> unless	2	0.0016	-1.7715
<input type="radio"/> badly	2	0.0036	-1.7447
<input type="radio"/> plodding	1	0.0021	-1.7333
<input type="radio"/> disappointment	1	0.0007	-1.7247
<input type="radio"/> mindless	4	0	-1.6985
<input type="radio"/> routine	1	0.0048	-1.6918
<input type="radio"/> unfunny	0	0.0064	-1.6832
<input type="radio"/> junk	3	0.0007	-1.6677
<input type="radio"/> neither	3	0.0067	-1.65

Trained Model: **logit_1grams**
Accuracy: 0.759
Kappa: 0.517

Exploration Plugin: **Documents Display**

Filter documents by selected feature
 Reverse document filter
 Documents from selected cell only

Instance	Predicted	Actual	Text
<input type="checkbox"/> 5	pos	neg	the story is also as...
<input checked="" type="checkbox"/> 6	pos	neg	about the only thin...
<input type="checkbox"/> 12	pos	neg	interesting , but no...
<input type="checkbox"/> 17	pos	neg	such master scree...
<input type="checkbox"/> 26	pos	neg	our culture is head...
<input type="checkbox"/> 32	pos	neg	payami tries to rais...
<input type="checkbox"/> 39	pos	neg	curling may be a u...
<input type="checkbox"/> 42	pos	neg	the effort is sincer...
<input type="checkbox"/> 55	pos	neg	an odd , haphazar...
<input type="checkbox"/> 56	pos	neg	though her fans wil...
<input type="checkbox"/> 57	pos	neg	pascale bailly's ro...
<input type="checkbox"/> 66	pos	neg	isn't as sharp as th...
<input type="checkbox"/> 79	pos	neg	takes one characte...
<input type="checkbox"/> 90	pos	neg	a portrait of alienat...
<input type="checkbox"/> 94	pos	neg	dignified ceo's mee...
<input type="checkbox"/> 97	pos	neg	beware the quirky ...
<input type="checkbox"/> 98	pos	neg	has its moments --...
<input type="checkbox"/> 100	pos	neg	completely awful ir...
<input type="checkbox"/> 105	pos	neg	there's no doubting...

Instance 5 (Predicted pos, Actual neg)
Highlighting and feature hits
the story is also as unoriginal as they come , already having been recycled more times than i'd care to count .

Instance 6 (Predicted pos, Actual neg)
Highlighting and feature hits
about the only thing to give the movie points for is bravado -- to take an entirely stale concept **and** push it through the audience's meat grinder one more time .

Report a Bug | Multithreaded | 0.2 GB used, 5.9 GB max

Highlight: logit_1grams

TRAINED_MODEL

- Documents: sentiment_sentences.csv
- Feature Plugins: basic
- Feature Table: 1grams
- Learning Plugin: Logistic Regression
- Validation: CV
- Trained Model: logit_1grams
 - Accuracy: 0.759
 - Kappa: 0.517

Cell Highlight:

Act \ Pred	neg	pos
neg	4077	1254
pos	1320	4011

Evaluations to Display:

- Horizontal Absolute Difference
- Horizontal Difference
- Normalized Bayes
- Vertical Absolute Difference
- Vertical Difference

Model Analysis

Features in Table:

Search:

Feature	Frequency	Horizontal Absolute Difference	Feature Weight
<COMMA>	776	0.0753	0.1661
's	403	0.0692	0.0755
and	572	0.0622	0.3515
movie	128	0.0571	-0.3714
of	555	0.0563	0.0634
a	659	0.0536	0.1344
too	20	0.0515	-1.6008
but	245	0.0489	-0.1922
film	201	0.045	0.2711
you	140	0.0449	0.5975
an	166	0.0426	0.2877
its	170	0.0411	0.2376
bad	7	0.0369	-1.35
it	364	0.0325	0.1119
with	182	0.0313	0.2867
n't	103	0.0297	-0.5698

Exploration Plugin: Documents Display

Filter documents by selected feature

Reverse document filter

Documents from selected cell only

Instance	Predicted	Actual	Text
<input checked="" type="checkbox"/> 94	pos	neg	dignified ceo's mee...
<input checked="" type="checkbox"/> 143	pos	neg	so genial is the con...
<input checked="" type="checkbox"/> 149	pos	neg	the four feathers is...
<input type="checkbox"/> 170	pos	neg	you might be shock...
<input type="checkbox"/> 193	pos	neg	if you go into the t...
<input type="checkbox"/> 197	pos	neg	what you end up g...
<input type="checkbox"/> 222	pos	neg	'you'll laugh for not...
<input type="checkbox"/> 234	pos	neg	watching austin po...
<input type="checkbox"/> 236	pos	neg	the film can depres...
<input type="checkbox"/> 244	pos	neg	an alternately rauc...
<input type="checkbox"/> 249	pos	neg	this is the kind of ...
<input type="checkbox"/> 284	pos	neg	die another day is ...
<input type="checkbox"/> 336	pos	neg	and if you apprecia...
<input type="checkbox"/> 338	pos	neg	it's a very tasteful r...
<input type="checkbox"/> 340	pos	neg	an infuriating film
<input type="checkbox"/> 380	pos	neg	adam sandler's eig...
<input type="checkbox"/> 430	pos	neg	do you say hi to y...
<input type="checkbox"/> 435	pos	neg	a wildly erratic dra...
<input type="checkbox"/> 444	pos	neg	if you think it's a ri...

Highlighting you feature hits

so genial is the conceit , this is one of those rare pictures that **you** root for throughout , dearly hoping that the rich promise of the script will be realized on the screen . it never is , not fully .

Instance 149 (Predicted pos, Actual neg)

Highlighting you feature hits

the four feathers is definitely horse feathers , but if **you** go in knowing that , **you** might have fun in this cinematic sand box .

What do we learn from this?

- It's easy to find low level, simple features that give us leverage for making a prediction
- Frequently, they correlate with the real factors of interest
- But their effect is very specific to the data that we have trained the model on
- The models will not generalize well!!

What do we learn from this?

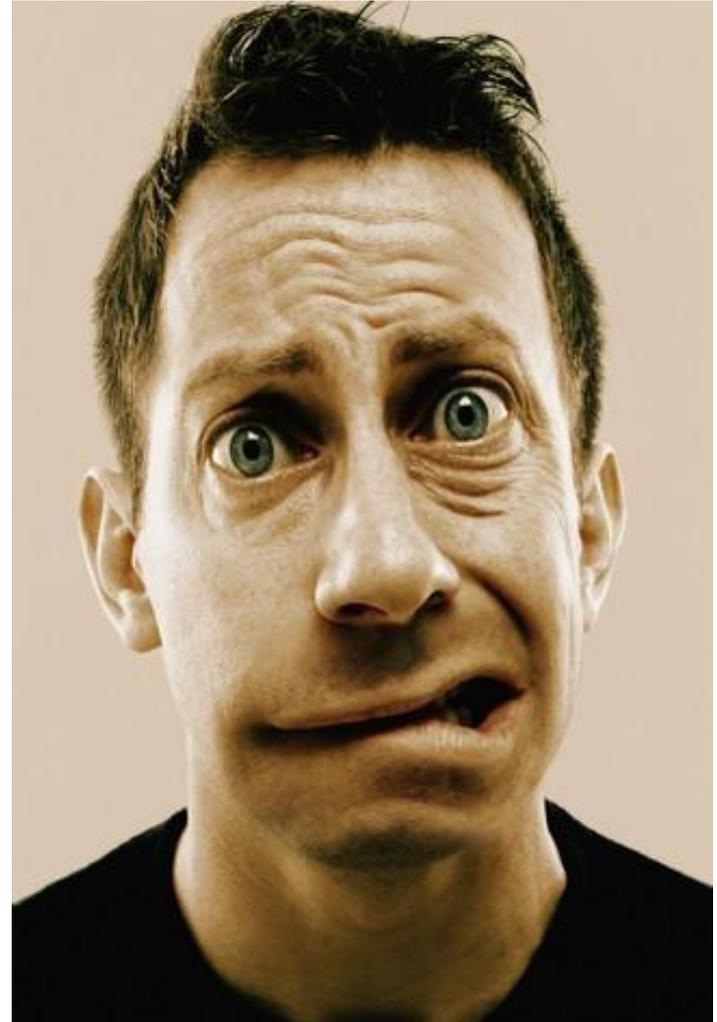
- It's easy to find low level, simple features that give us leverage for making a prediction
 - Frequently, they correlate with the real factors of interest
 - But their effect is very specific to the data that we have trained the model on
 - The models will not generalize well!!
-
- **We find the same thing in a learning context!!!!**

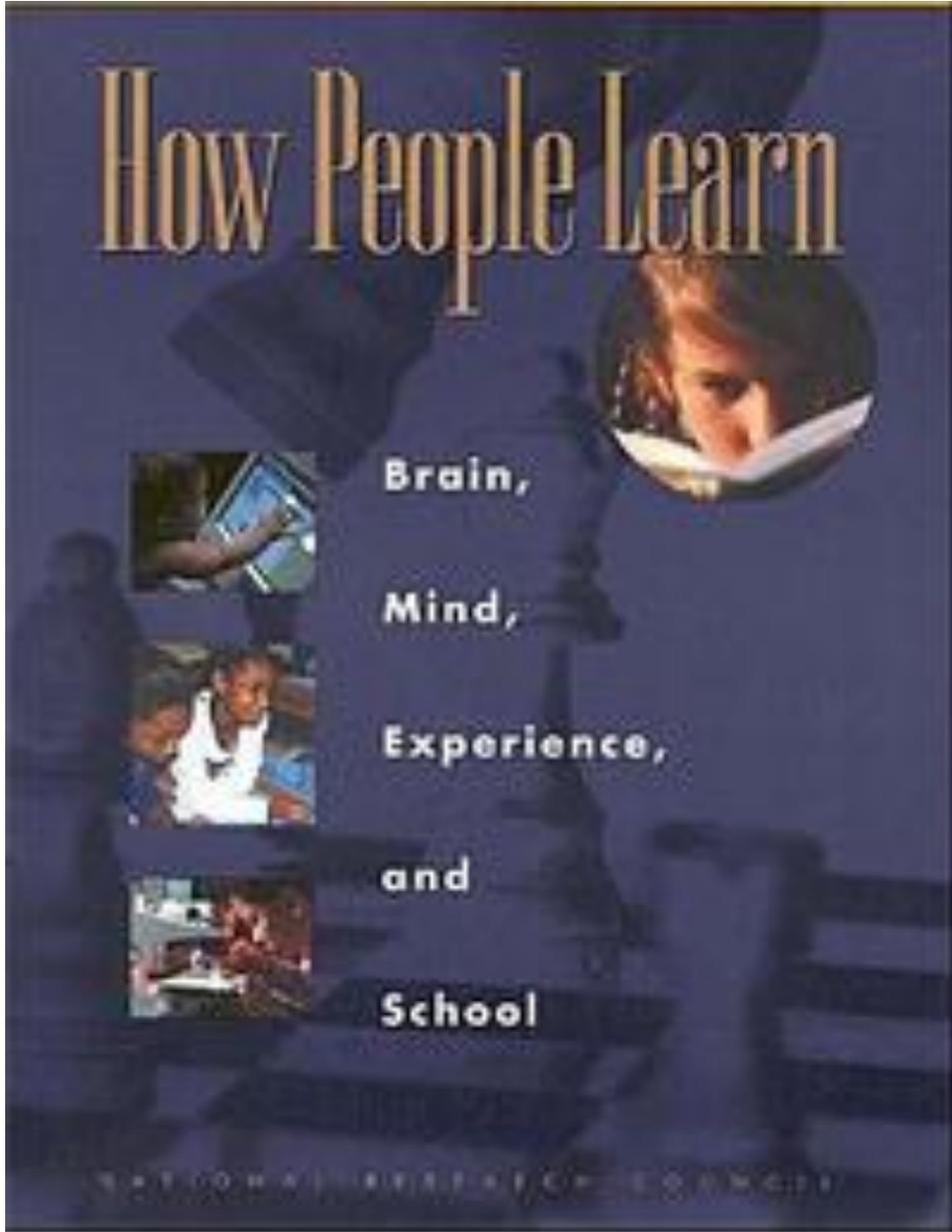
Low level features we used to believe in

- General indicators of interactivity
- Turn length
- Conversation length
- Number of student questions
- Student to tutor word ratio
- Student initiative

VanLehn, K., Graesser, A., Jackson, G. T., Jordan, P., Olney, A., Rosé, C. P., (2007). Natural Language Tutoring: A comparison of human tutors, computer tutors, and text. *Cognitive Science* 31(1), 3-52

Rosé, C. P., Wang, Y.C., Cui, Y., Arguello, J., Stegmann, K., Weinberger, A., Fischer, F., (2008). Analyzing Collaborative Learning Processes Automatically: Exploiting the Advances of Computational Linguistics in Computer-Supported Collaborative Learning, *International Journal of Computer Supported Collaborative Learning* 3(3), pp237-271.





So, what do we know about how people learn?

Learning about Learning by Listening to Learners



<http://www.slideshare.net/ALHalverson/the-think-aloud-ta-method>

- Think aloud protocols, verbal protocol analysis (Ericsson & Simon, 1993; van Someren et al., 1994; Chi, 1997)
 - Understanding problem solving processes
 - Assessing mental models
- Self-explanation studies (Chi et al., 1994)
 - Understanding sense making and learning processes of individuals
- Tutorial Dialogue (Graesser et al., 1998; Evens & Michael, 2003; Rosé et al., 2001b)
 - Understanding learning from human tutoring
- Collaborative Process Analysis (Berkowitz & Gibbs, 1983; Stahl, 2006; de Wever et al., 2006; van der Pol et al., 2006; Weinberger & Fischer, 2006; Rosé et al., 2008)
 - Understanding collaborative learning processes

What do we mean by learning?

■ Cognitive

- Individual is the unit of analysis
- The goal is for an individual to acquire concepts and skills
- Discussion provides stimulus for the individual's learning
- The focus of the work is to understand the psychological processes located within the individual's head

■ Cognitive Apprenticeship

- Individual is still the unit of analysis
- The goal is still for an individual to acquire concepts and skills
- Learning occurs through interaction
 - That could be phrased as "learning is inherently social"
- Discussion is one medium on interaction, especially when the interaction is between humans
- The focus of the work is to understand how scaffolding influences cognitive processes, especially acquisition of concepts and skills

■ Sociocultural

- The individual within a community is the focus
- The goal is for a student to learn to participate in the community, relationships are an important outcome
- Learning still occurs within interaction
- The focus of the work is to understand the paths of participation that lead from peripheral participation to core participation within the community

■ Communities of Practice

- The community itself is the unit of analysis (or an organization, or a small group)
- The goal is for the group to learn to function well together
- Learning still occurs within interaction, but the interaction now is an end, not just a means
- The focus is on understanding the processes that exemplify optimal group interactions

A Spectrum of Complexity

Individuals Pairs Small Groups Organizations Communities Nations

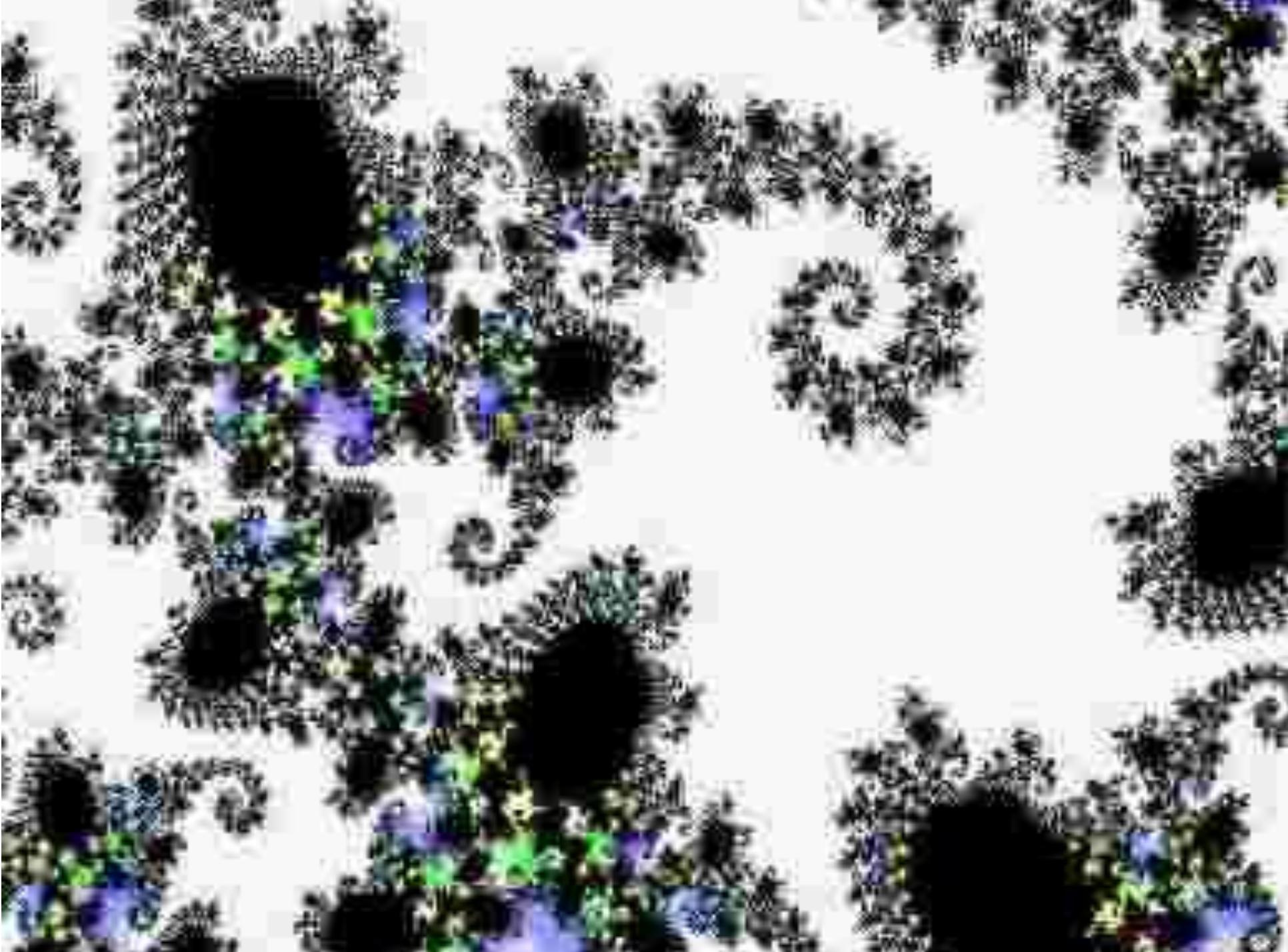
The essence of quantitative forms of science....

Causality

Hypothesis: If I manipulate variable A, it will have effect B on variable C.

How do we test this?





A Spectrum of Research Methodologies

**Simplification/
Abstraction**

**Preserving
Complexity**

Quantitative

Qualitative

Individuals

Pairs

Small Groups

Organizations

Communities

Nations

How can we use measures derived from process analysis?

- Assuming we are approaching our analysis quantitatively
 - Test for mediation vs moderation
 - Process variable correlates with dependent variable
 - Experimental manipulation has an effect on a process variable
 - Experimental manipulation has an effect on a dependent variable
 - If we add the process variable in as a covariate, and the effect of condition becomes non-significant, then the process variable mediates the effect of condition
 - Otherwise it is just a moderator

What if we don't agree on what learning is?

- Our definition of learning affects:
 - How we measure learning
 - What role discussion plays in learning
 - What about discussion is relevant for learning
 - What kinds of manipulations we are interested in
 - Whether we can even study learning experimentally
 - What we'll decide is conducive to learning

The think aloud method

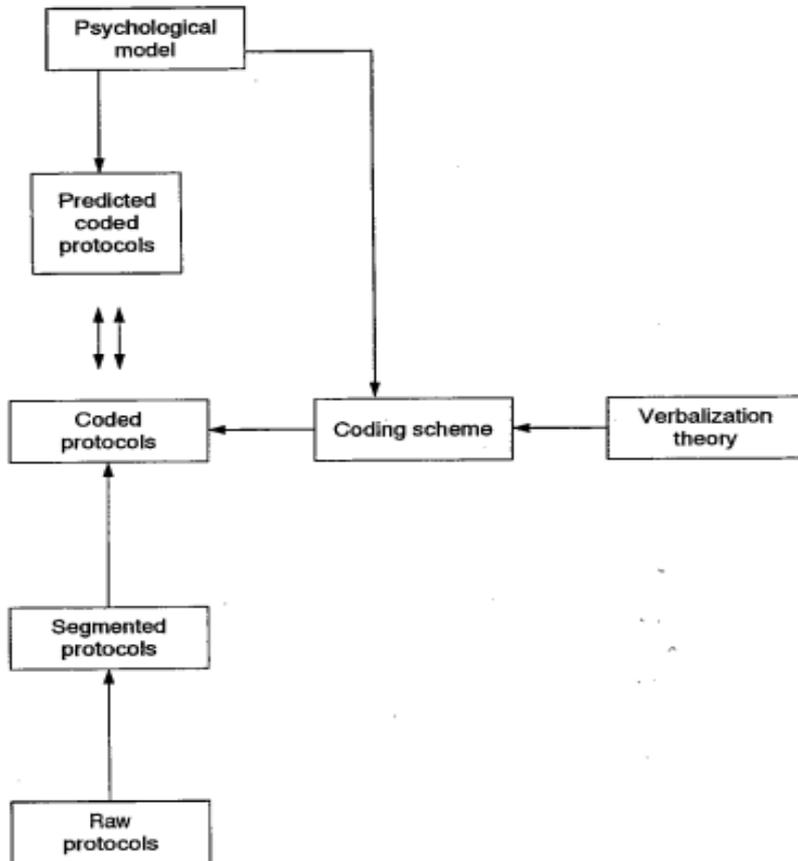


FIGURE 7.1: The analysis process

From van Someren et al., 1994





Caution!!!

Cognitive and
Social Processes
are Intertwined

Findings



Purpose of Interaction in Learning Contexts

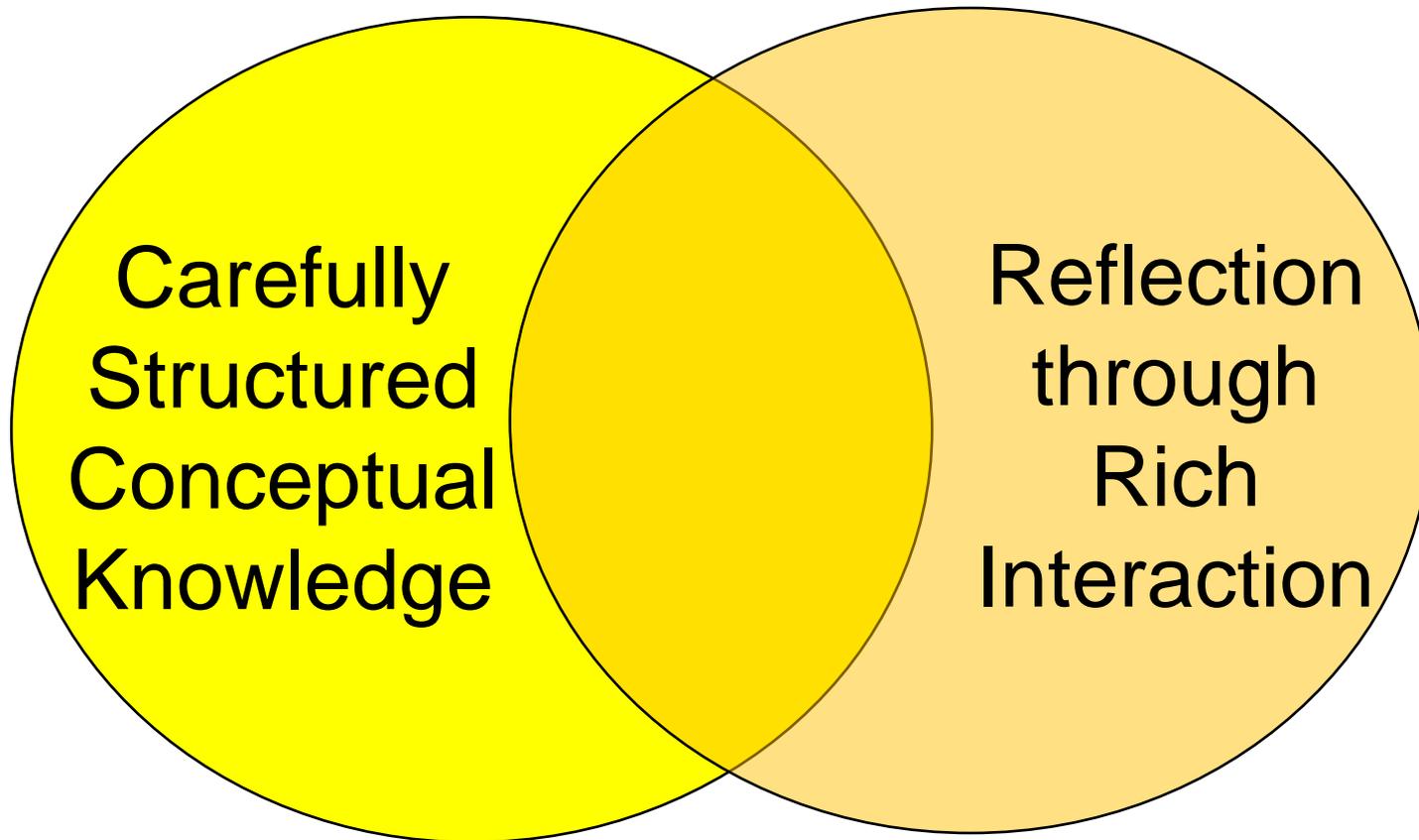


Take Home Message:

Introducing reflection points provides opportunities for students to take advantage of learning resources

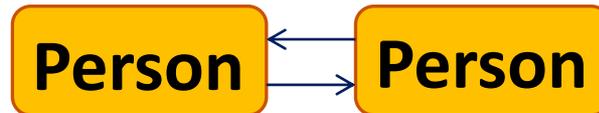
- Reward structures encourage students to focus on performance over learning
- Well crafted instruction provides opportunities for learning
- Opportunities only help if students take them

Important Ingredients for Learning



Souflé Framework

(Howley et al., 2013)

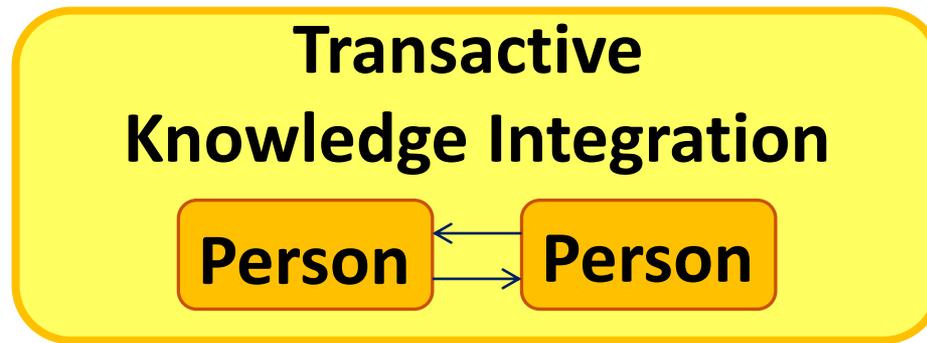


3 Dimensions:

- Transactivity
- Engagement
- Authoritativeness

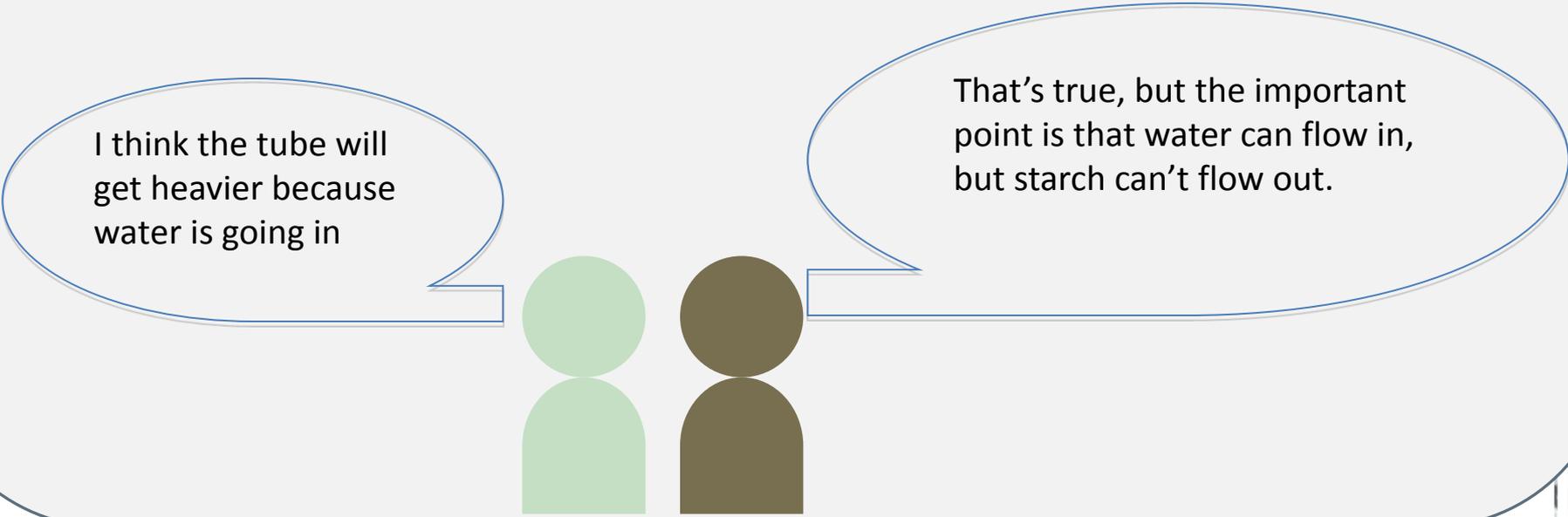
Souflé Framework

(Howley et al., 2013)



- **Definition of Transactivity**

- building on an idea expressed earlier in a conversation
- using a reasoning statement



I think the tube will get heavier because water is going in

That's true, but the important point is that water can flow in, but starch can't flow out.

Transactivity (Berkowitz & Gibbs, 1983)

■ Findings

- Moderating effect on learning (Joshi & Rosé, 2007; Russell, 2005; Kruger & Tomasello, 1986; Teasley, 1995)
- Moderating effect on knowledge sharing in working groups (Gweon et al., 2011)

■ Computational Work

- Can be automatically detected in:
 - Threaded group discussions (Kappa .69) (Rosé et al., 2008)
 - Transcribed classroom discussions (Kappa .69) (Ai et al., 2010)
 - Speech from dyadic discussions ($R = .37$) (Gweon et al., 2012)
 - Predictable from a measure of speech style accommodation computed by an unsupervised Dynamic Bayesian Network (Jain et al., 2012)

Accountable Talk (Resnick, Michaels & O’Connors, 2010)

		Utterance	
1	Teacher	OK, does anyone want to respond to that? Who wants to respond and can prove that explanation and can, kind of respond with their own ideas or can add another idea to	Add on
2	Frank	I um I agree with what you said because this for example like if you put-- if you had big um, can- like if you got a big cup of water and you put a- an eraser in there, like a- a ah, like the eraser over there, if you put something like that in a big cup of water, the water level would rise a lot, and, if you put in a copper cube, and it’s not even gonna- it’s not going to rise that much even though that copper cube will weigh more than a eraser.	
3	Teacher	Ahh ok, anyone agree with Frank’s idea? I like that he kind of, talked about another object and he chose an object that we know has a different volume than the copper of an object that has a much greater volume. And can someone explain what would happen if I put an object this big, in water? James, what he think would happen if I put big, into a cup of water?	Agree/Disagree Explain Other
4	James	He said that if you-- if you like a big- bur--like a big bottle of like water	
5	Teacher	Uh huh	
6	James	and you put the eraser in it, then it would probably like, rise a lot. Then--	
7	Teacher	Woah, woah, rephrase that – it has a what?	Press for Reasoning
8	James	a different vol-- a different volume...	
9	Teacher	And which has a greater volume?	Say More
10	James	The eraser.	
11	Teacher	The eraser. Which means it takes up more space. So if I were to put this into, a big container of water for example, if I were to put it into my little pitcher here, if I had this filled up and I poured it in, well, which direction would my water have to go?	Revoice

Empirical Support for Accountable Talk

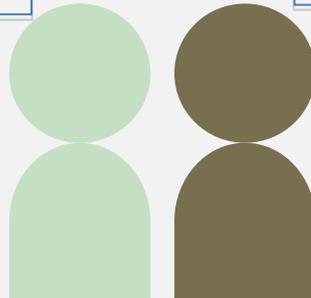
- When teachers of math, science, and reading use structured teacher-lead discussion methods...
 - steep changes in student **achievement** (Bill, Leer, Reams & Resnick, 1992; Chapin & O'Connor, 2004)
 - **Retention** for up to 3 years (Adey & Shayer, 1993, 2001; Shayer, 1999; Topping & Trickey, 2007a, 2007b)
 - **Transfer** across domains for up to 3 years (Bill, Leer, Reams & Resnick, 1992; Adey & Shayer, 1993, 2001; Shayer, 1999; Chapin & O'Connor, 2004)
 - Students perform better on **non-verbal reasoning** tests e.g. Ravens (Mercer, Wegerif & Dawes, 1999)
 - **Reasoning** itself improves (Kuhn & Zillmer, in press; Lin et al 2012)

- Definition of Transactivity

- building on an idea expressed earlier in a conversation
- using a reasoning statement

Homozygous for both.
One parent is orange
and the other is not.
Orange is dominant.

I agree because all the kids are
orange also.



Self-oriented vs other-oriented

Representational vs transformational

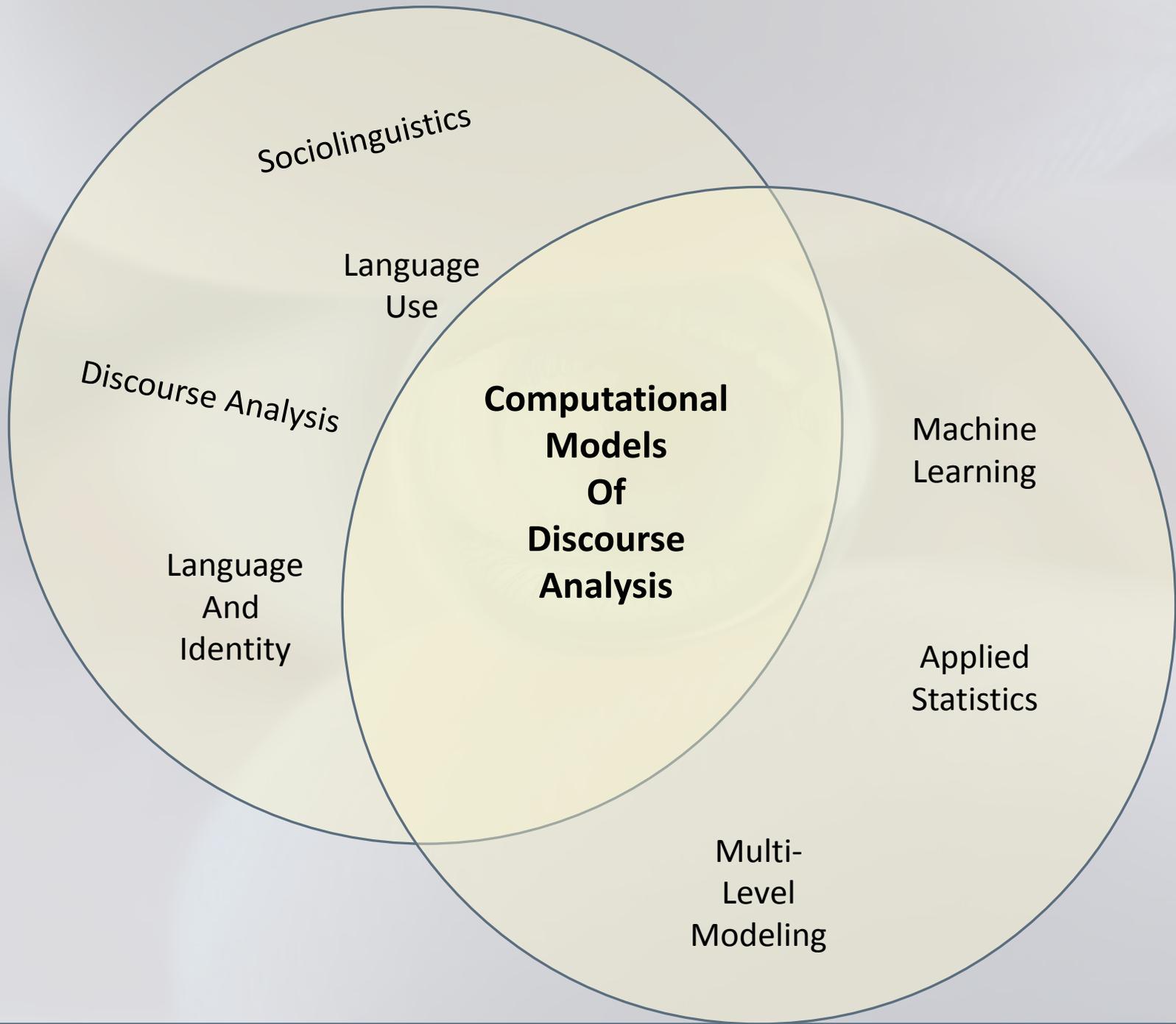
Consensus-oriented vs Conflict-oriented

Example Teacher Utterance	Accountable Talk Move	Transact Category
Explain your thinking.	SAY MORE	SELF ORIENTED, REPRESENTATIONAL, CONSENSUS ORIENTED
What's it prove? Put it into words.	PRESS FOR REASONING	SELF ORIENTED, REPRESENTATIONAL, CONSENSUS ORIENTED
Let me see if I understand correctly. Are you saying they were all adopted?	REVOICE	SELF ORIENTED, TRANSFORMATIONAL, CONSENSUS ORIENTED
If capital 'G's dominant, wouldn't all babies be orange?	CHALLENGE	SELF ORIENTED, TRANSFORMATIONAL, CONFLICT ORIENTED
Can you repeat what she said?	RESTATE	OTHER ORIENTED, REPRESENTATIONAL, CONSENSUS ORIENTED
Help him out Stephen. Can you add to what he said?	ADD MORE	OTHER ORIENTED, REPRESENTATIONAL, CONSENSUS ORIENTED
Kelly, are they right? Do you agree or disagree with what they said?	AGREE/DISAGREE	OTHER ORIENTED, REPRESENTATIONAL, CONFLICT ORIENTED
In your own words, explain why she's right or wrong.	EXPLAIN OTHER	OTHER ORIENTED, TRANSFORMATIONAL, CONFLICT ORIENTED

8 Years of Positive Results

- **Foundational study:** students work with a partner and dialogue agent for support Learn **1.24 s.d.** more than individuals without support (Kumar et al., 2007a)
- Results inform **iterative design** of agent behavior
 - **Personalized agents** increase supportiveness and help exchange between students (Kumar et al., 2007b)
 - Agents are more effective when **students have control** over timing of the interaction (Chaudhuri et al., 2008; Chaudhuri et al., 2009)
 - Agents that employ **Balesian social strategies** are more effective than those that do not (Kumar et al., 2010; Ai et al., 2010)
 - Students are sensitive to agent **rhetorical strategies** such as displayed bias (Ai et al., 2010), **displayed openness** to alternative perspectives (Kumar et al., 2011), and targeted elicitation (Howley et al., 2012)
 - **Accountable talk agents** (Dyke et al., 2013; Adamson et al., in press)
- **Bazaar architecture** enables efficient, principle based agent development (Kumar & Rosé, 2011; Adamson & Rosé, 2012)

Exploring the Connection between Cognitive and Social Processes



Sociolinguistics

Language
Use

Discourse Analysis

Language
And
Identity

**Computational
Models
Of
Discourse
Analysis**

Machine
Learning

Applied
Statistics

Multi-
Level
Modeling

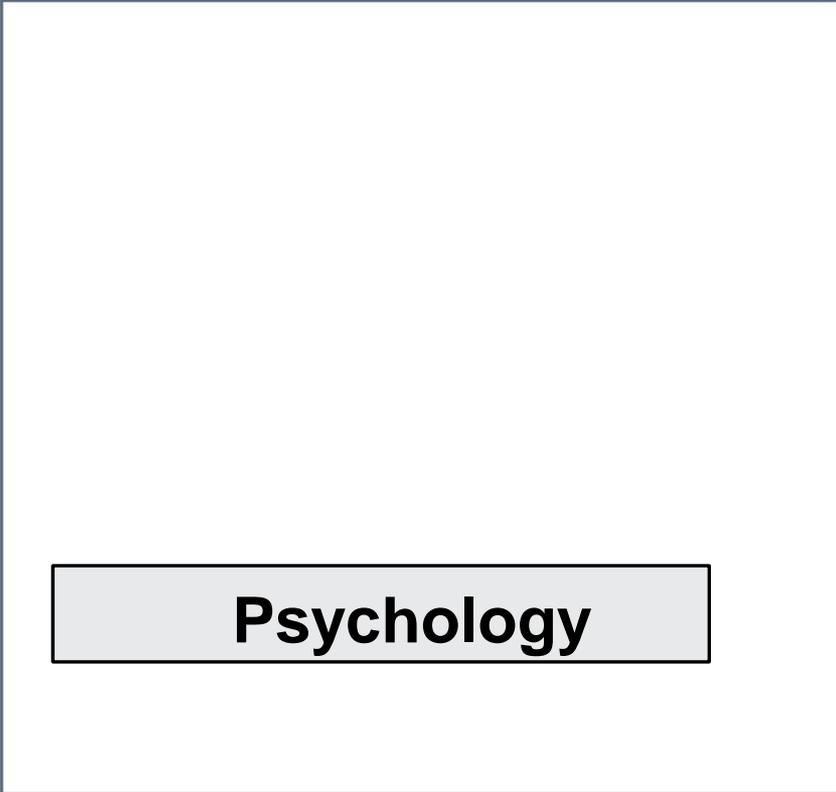
Theoretical Framework

- Basic concepts of power and social distance explain social processes operating in interactions



Theoretical Framework

- Basic concepts of power and social distance explain social processes operating in interactions



Psychology

Theoretical Framework

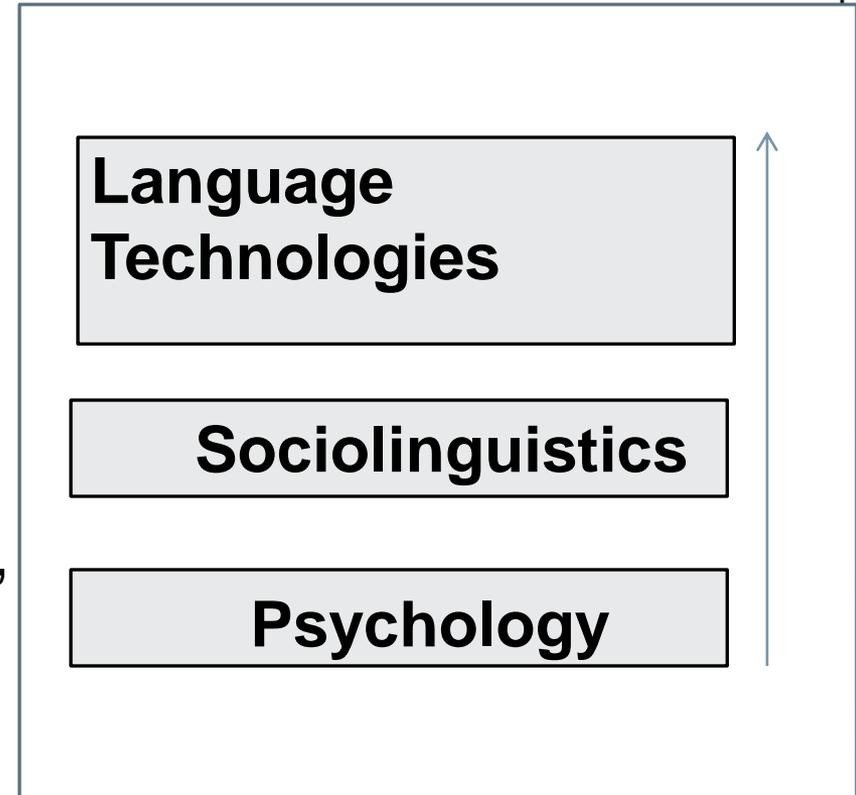
- Basic concepts of power and social distance explain social processes operating in interactions
- Social processes are reflected through patterns of language variation

Sociolinguistics

Psychology

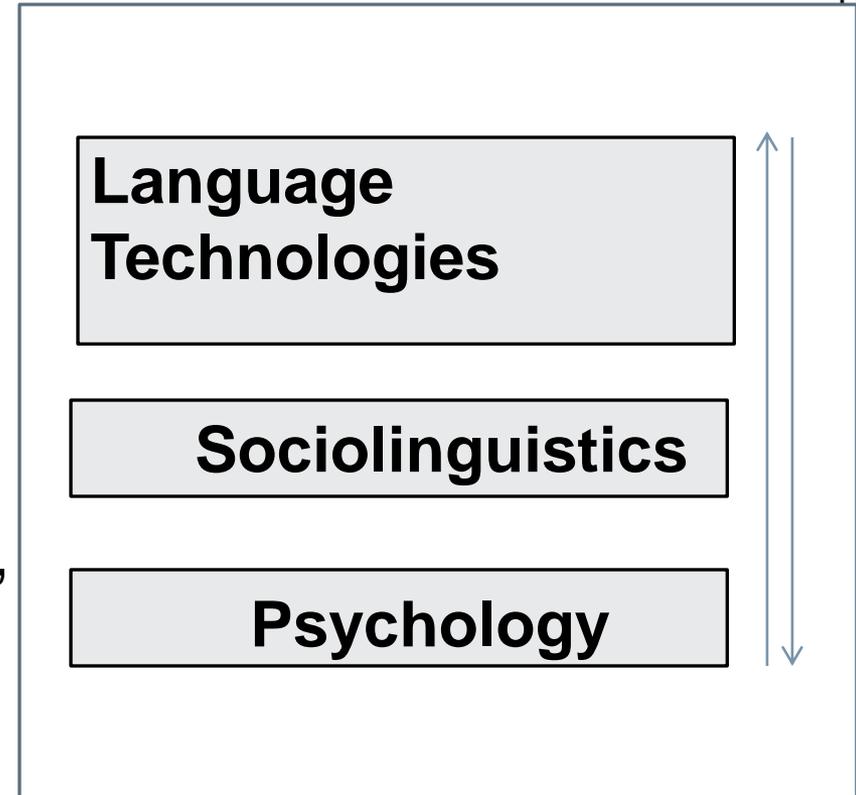
Theoretical Framework

- Basic concepts of power and social distance explain social processes operating in interactions
- Social processes are reflected through patterns of language variation
- If we understand this connection, we can model language more effectively



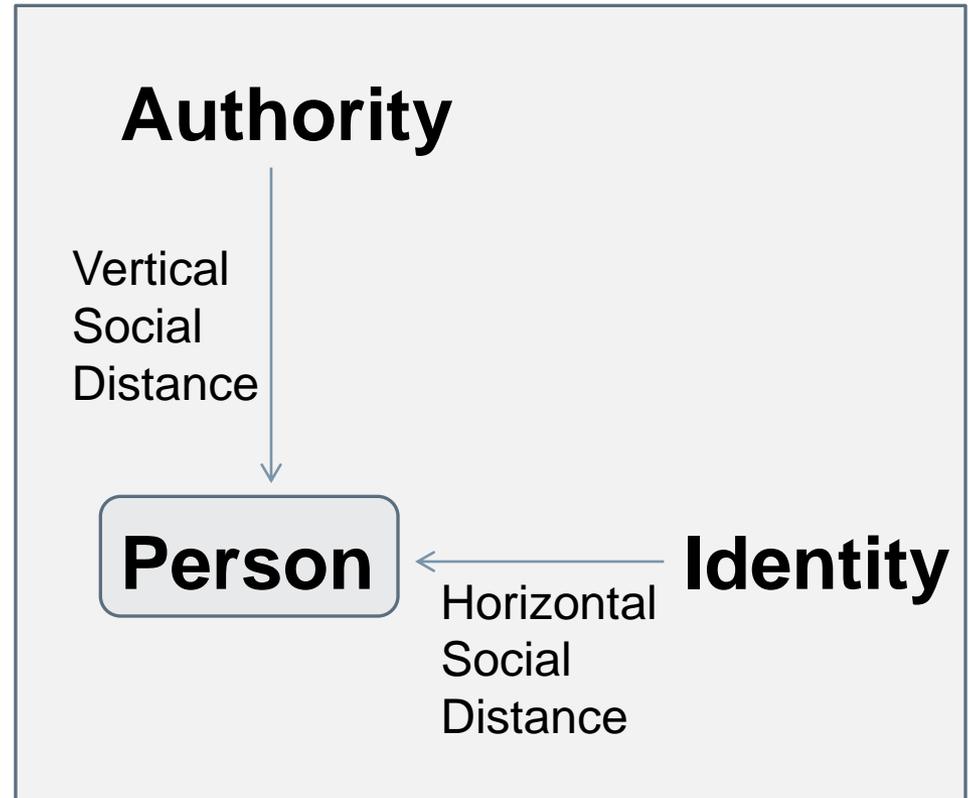
Theoretical Framework

- Basic concepts of power and social distance explain social processes operating in interactions
- Social processes are reflected through patterns of language variation
- If we understand this connection, we can model language more effectively
- Models that embody these structures will be able to predict social processes from interaction data



Theoretical Framework

- We gain influence in interaction through manipulation of horizontal and vertical social distance
- We manipulate distance through signaling



Power, Relationships, and Transactivity

Piaget

Berkowitz
& Gibbs

Kruger &
Tomasello

Azmitia
& Montgomery

Power,
Cognitive Conflict,
And Learning

Socio-
Cognitive
Conflict and
Transactivity

Power Balance
And
Transactivity

Friendship,
Transactivity,
And Learning

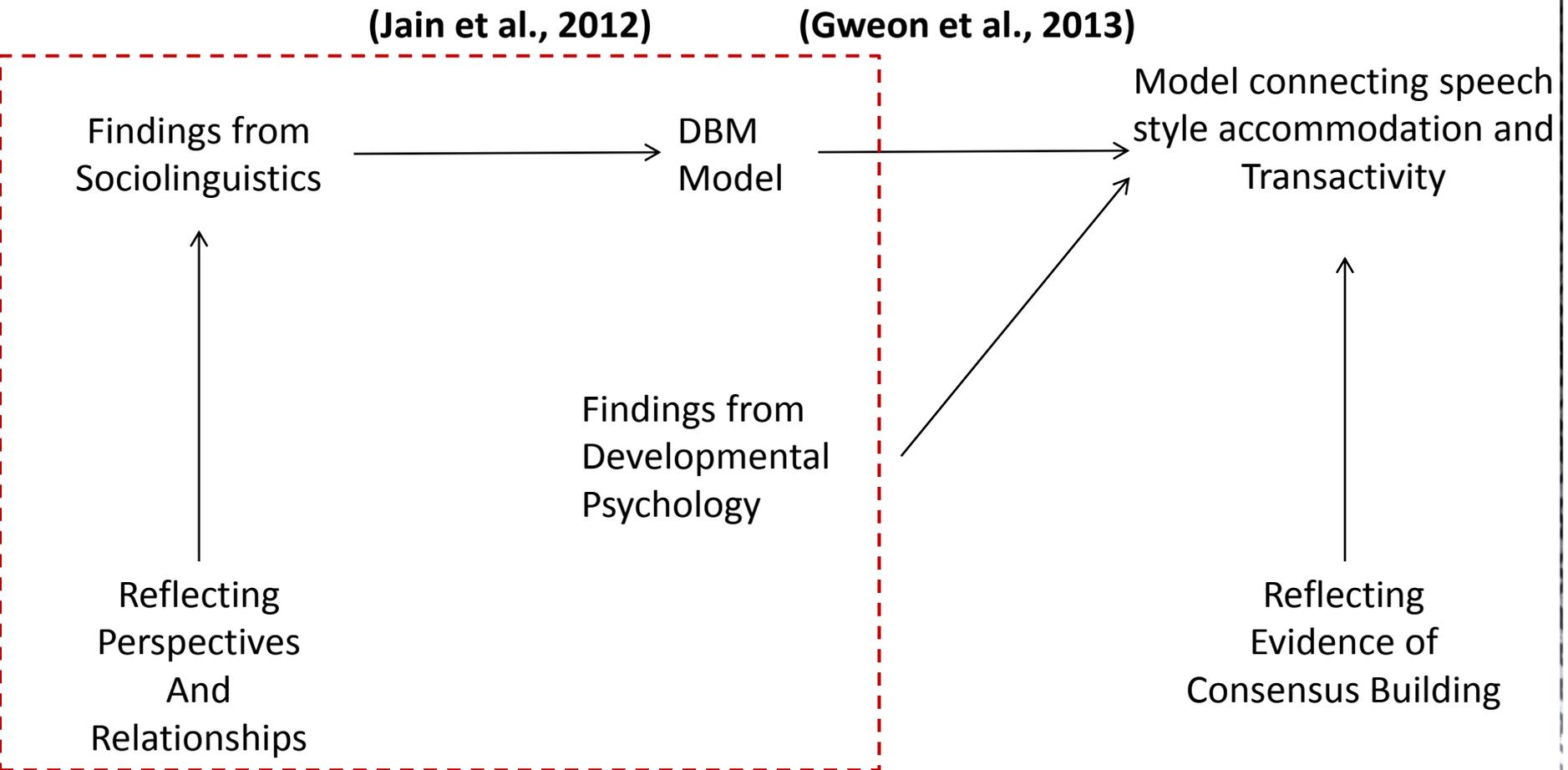
1963

1983

1986

1993

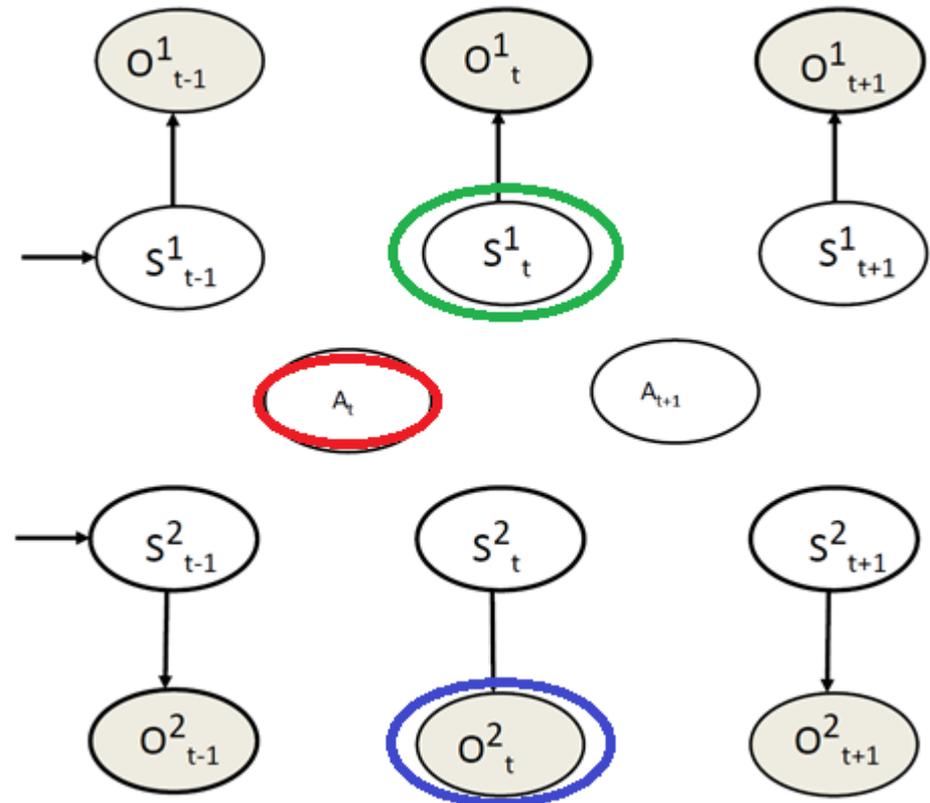
Modeling the Cognitive-Social Connection



Key insight: Accommodation occurs over time as a reflection of social processes that extend over time

Speech Observation(O): Obtained from speech feature such as pitch, loudness, voice probability, harmonic to noise ratio, voice quality. We used openSMILE(Eyben et al., 2010) to extract these features.

We use BNT(Murphy, 2001) to learn parameters for our DBN models.



Models

- Explore a space of model defined by two independent factors:

- Direct Links:** Direct influence of one speaker's style on another speaker's style (Prior work mostly focused on this aspects by findina similarity between speech of partners).

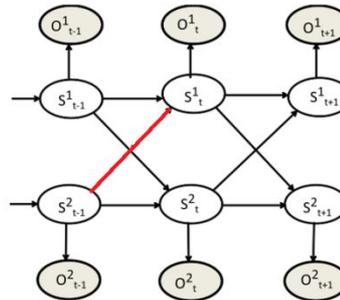


Figure 1

- Indirect Links:** The influence of the relational gestalt between the two speakers that motivates the stylistic accommodation.

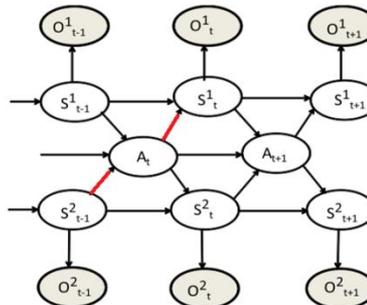
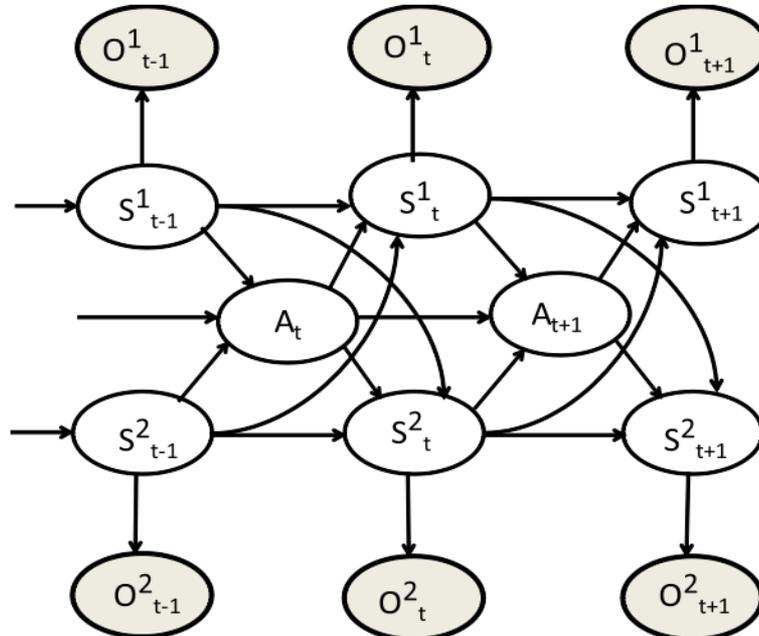


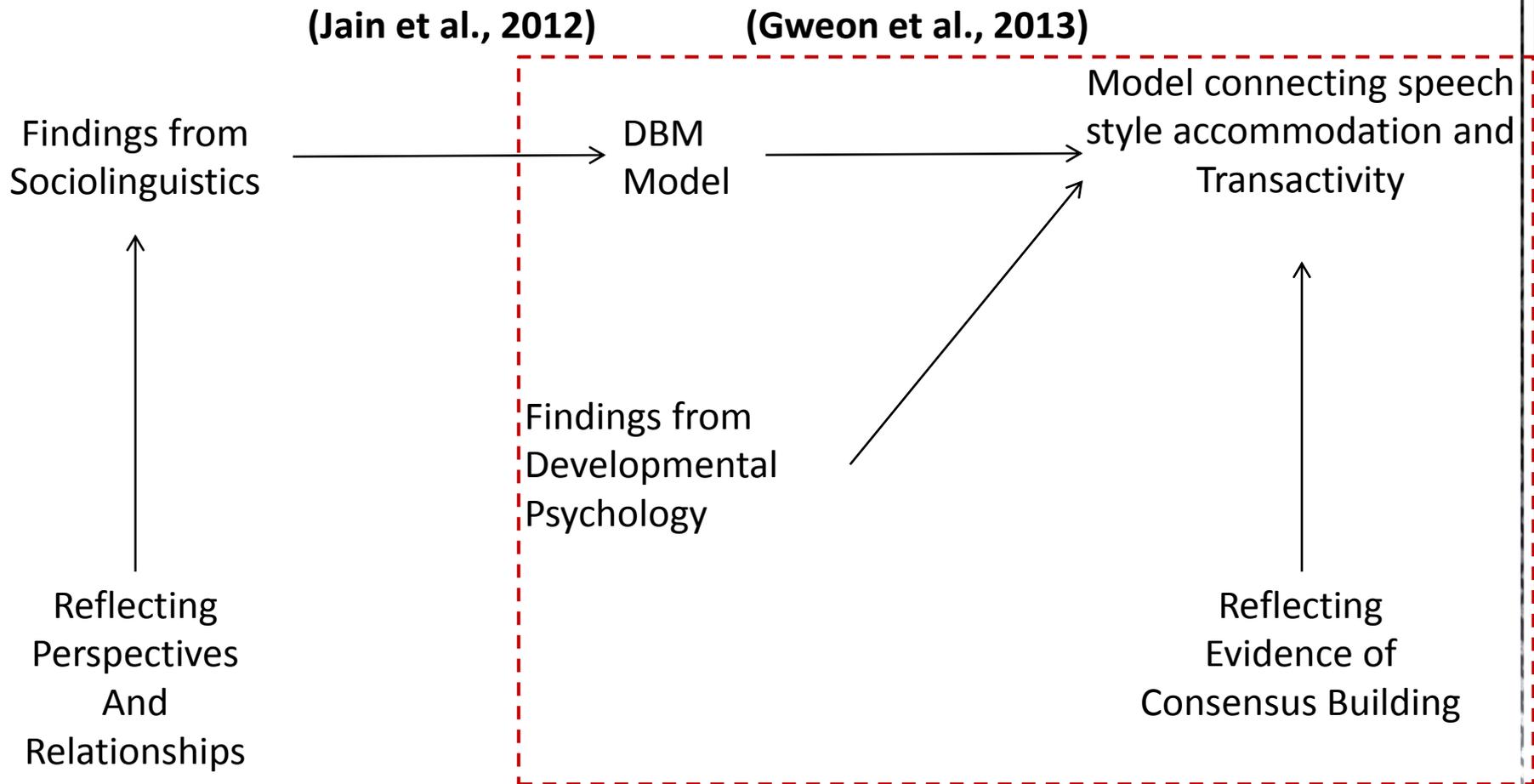
Figure 2

Evaluation

- SASDM Model that includes both symmetric IndirectInfluence and Direct influence links performs best

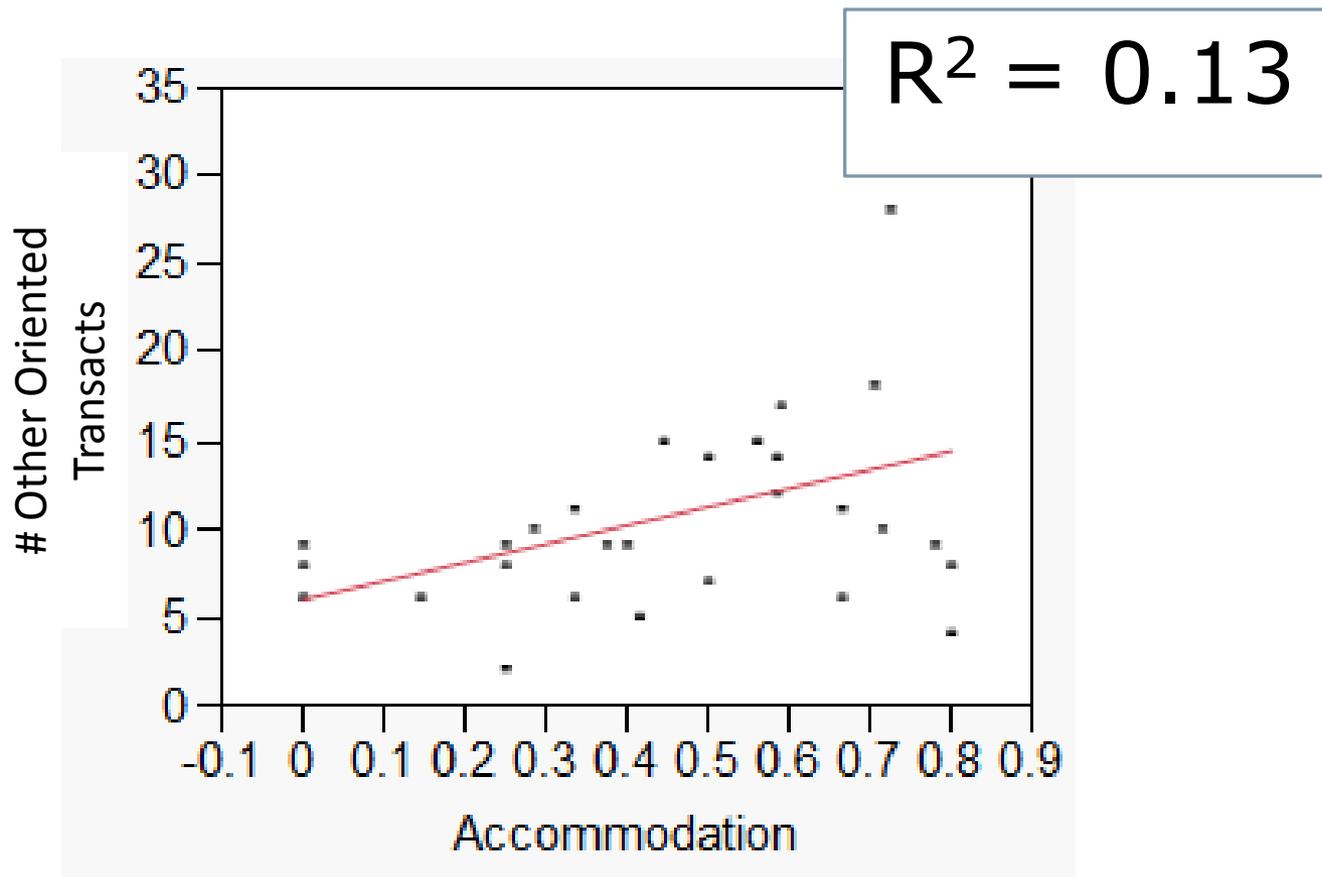


Modeling the Cognitive-Social Connection



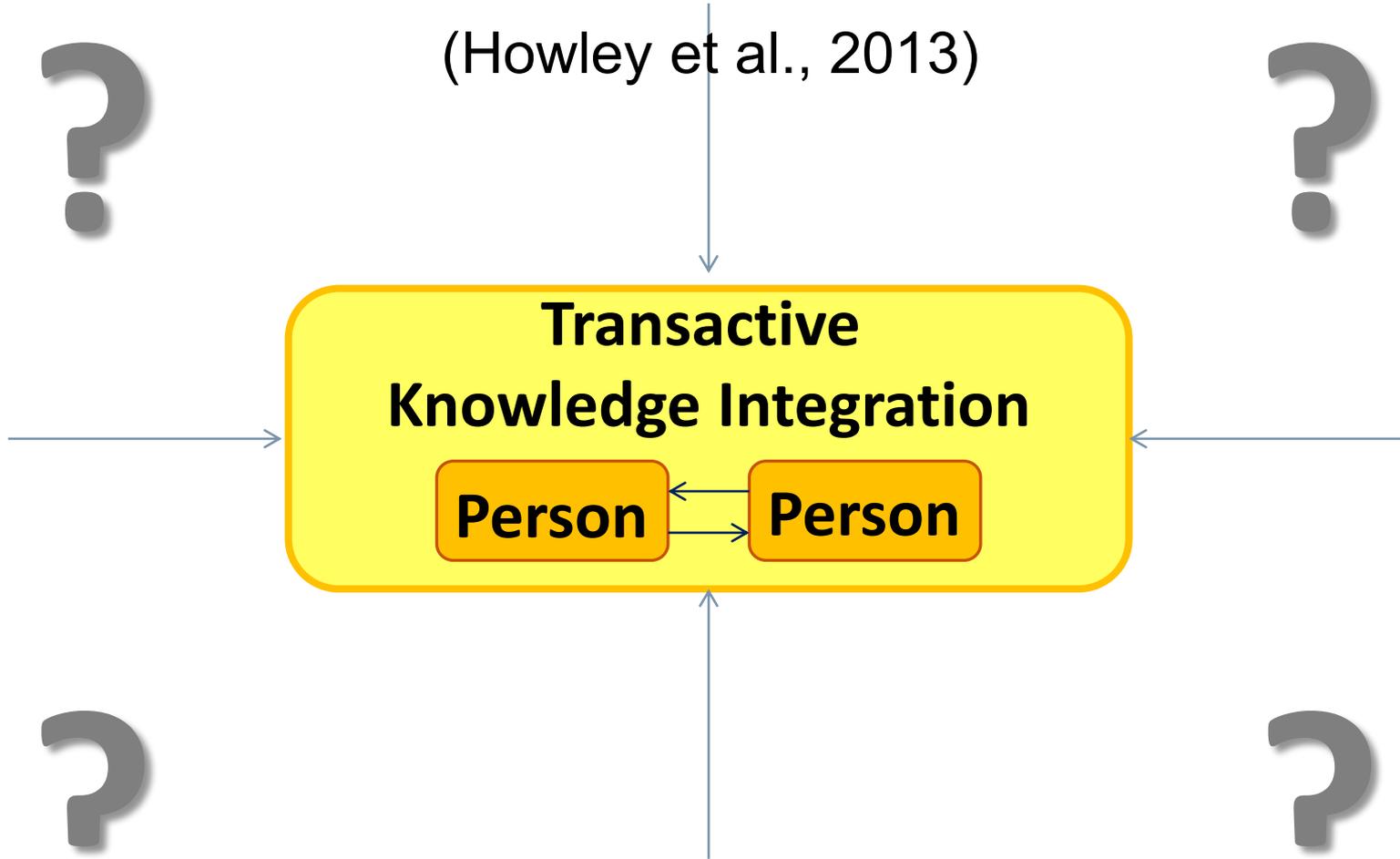
Correlation between Accommodation Score and Discussion Process Variables

Model #	Acc & Reas	Acc & Transactivity	Acc & Other Oriented Transactivity
1	0.15	0.11	0.36*
2	0.10	0.07	0.35*
3	0.12	0.07	0.30*
4	0.18	0.12	0.37*
5	0.18	0.13	0.36*
6	0.15	0.10	0.33*



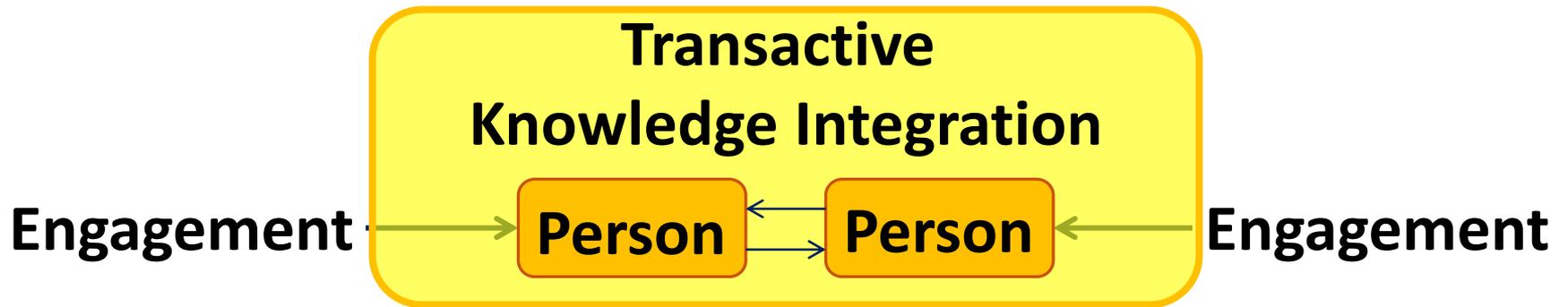
Souflé Framework

(Howley et al., 2013)



Souflé Framework

(Howley et al., 2013)



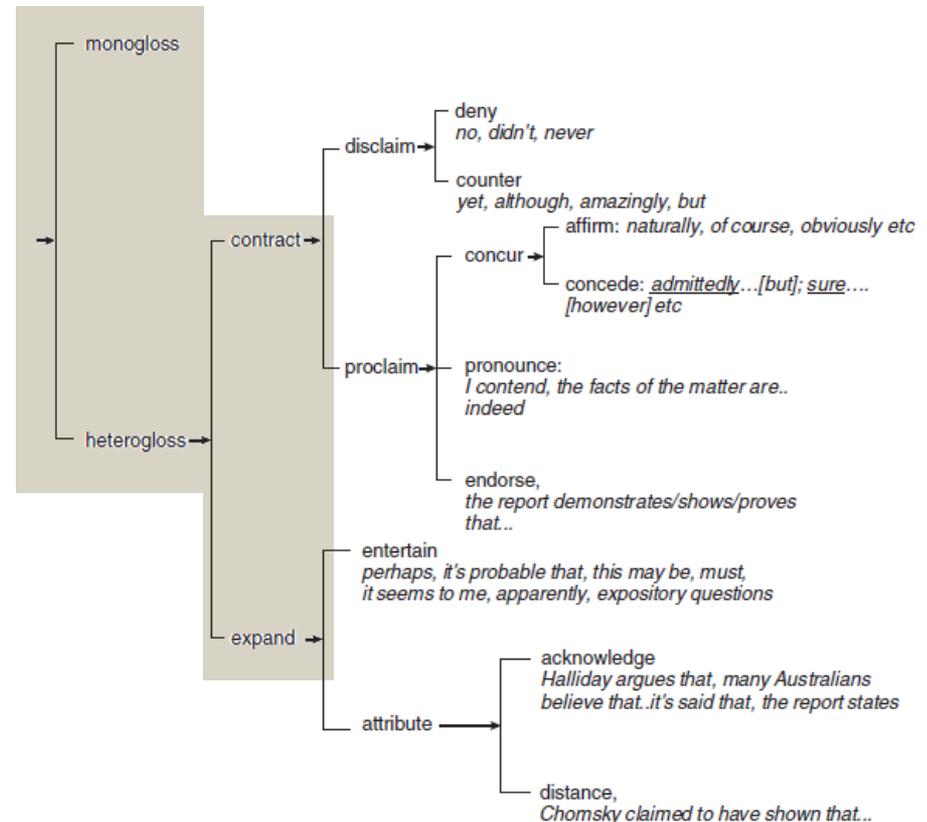
- System of Engagement
 - Showing openness to the existence of other perspectives
 - Less final / Invites more discussion

■ Example:

- **[M]** Nuclear is a good choice
- **[HE]** I consider nuclear to be a good choice
- **[HC]** There's no denying that nuclear is a superior choice
- **[NA]** Is nuclear a good choice?

Engagement

(Martin & White, 2005, p117)



Engagement (Martin & White, 2005)

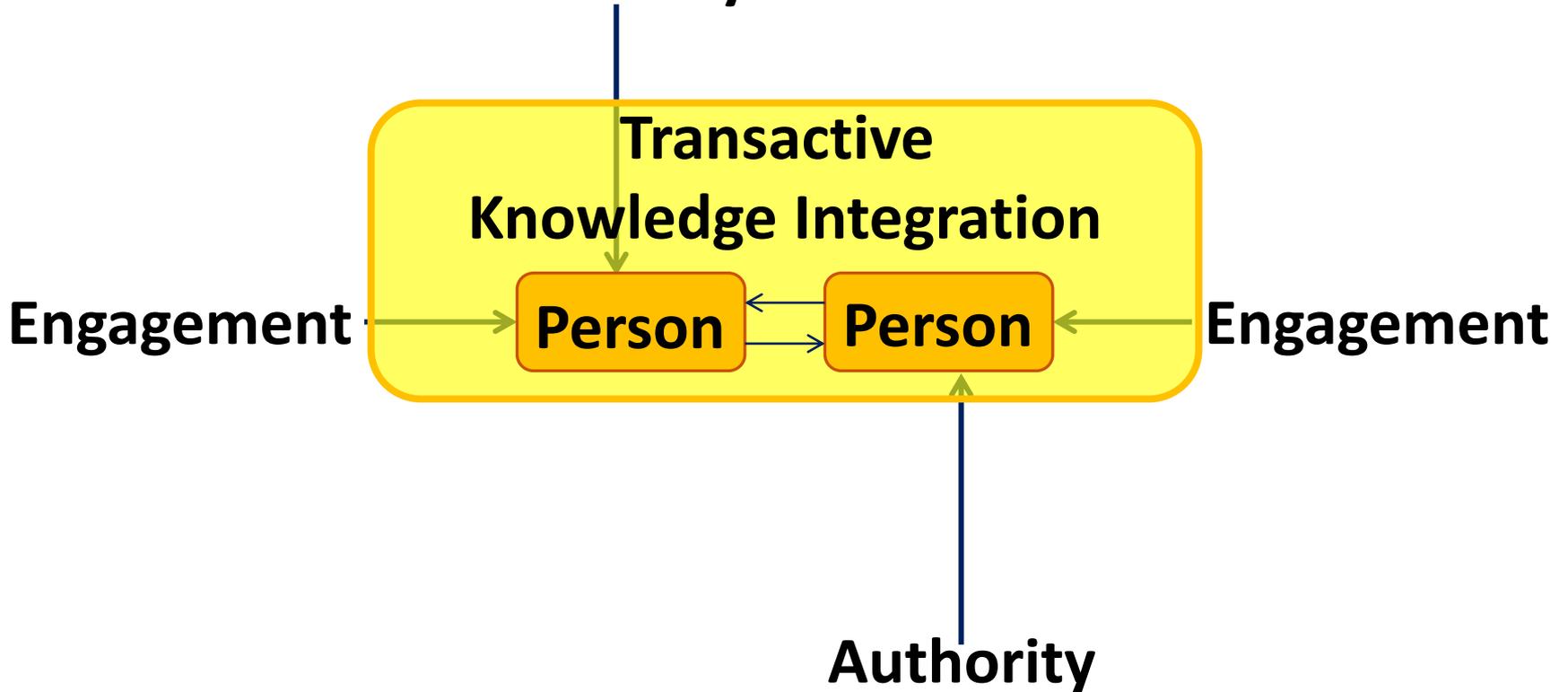
■ Findings

- *Correlational analysis*: Strong correlation between displayed openness of group members and articulation of reasoning ($R = .72$) (Dyke et al., in press)
- *Intervention study*: Causal effect on propensity to articulate ideas in group chats (effect size .6 standard deviations) (Kumar et al., 2011)
- Mediating effect of idea contribution on learning in scientific inquiry (Wang et al., 2011)

Souflé Framework

(Howley et al., in press)

Authority



Analysis of Authoritativeness



Water pipe analogy:

Water = Knowledge or Action

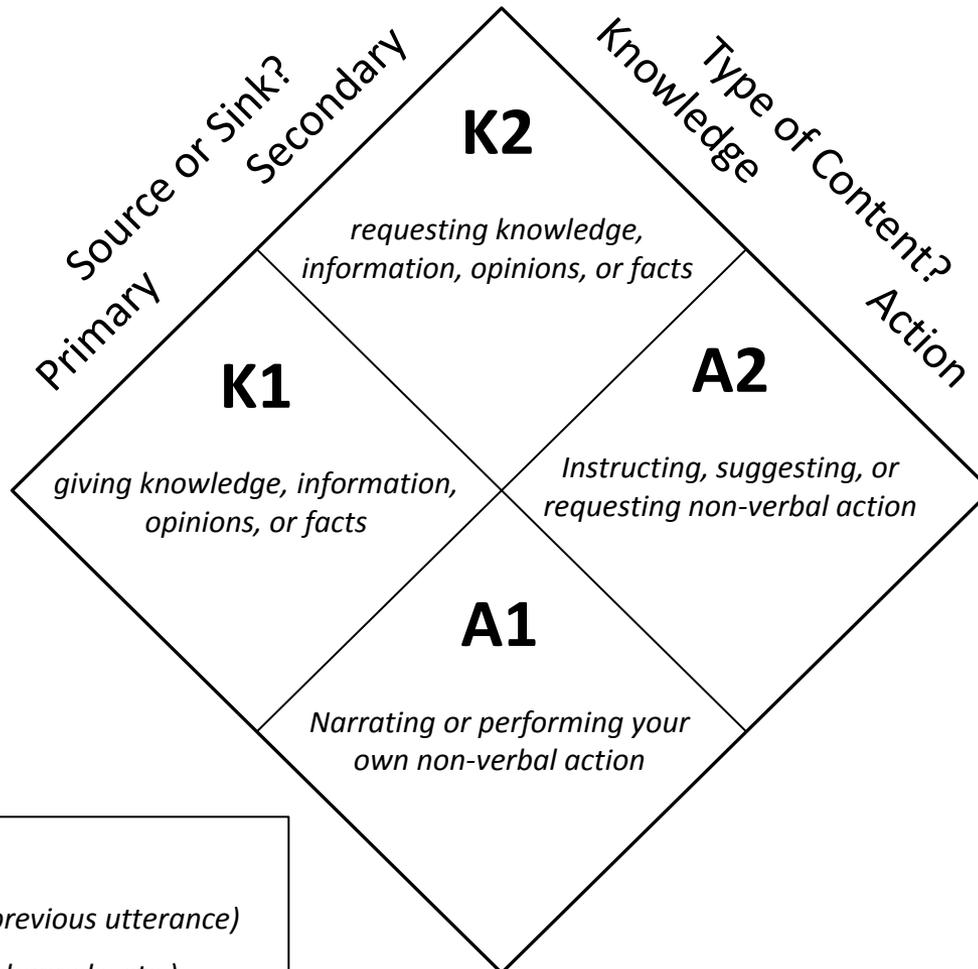
Source = Authoritative speaker

Sink = Non-authoritative Speaker

Authoritativeness Ratio = $\frac{\text{Source Actions}}{\text{Actions}}$

The Negotiation Framework

(Martin & Rose, 2003)



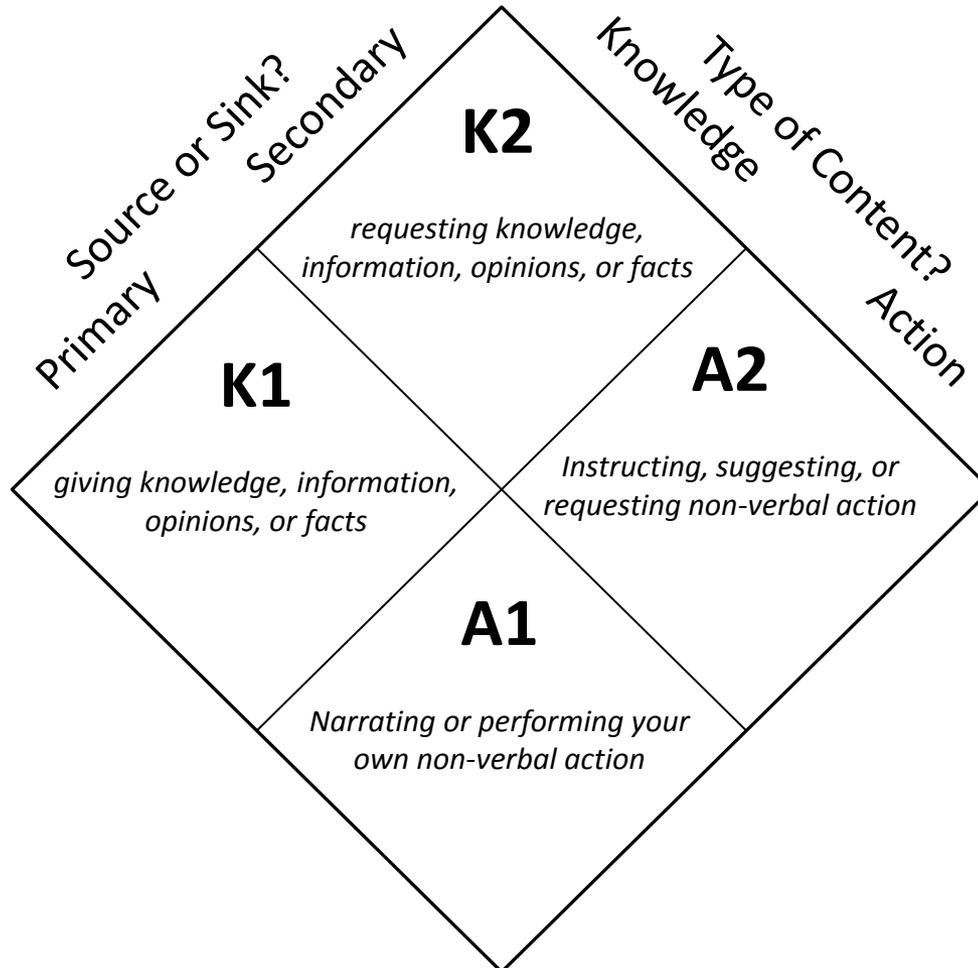
Additionally...

ch *(direct challenge to previous utterance)*

O *(all other moves, backchannels, etc.)*

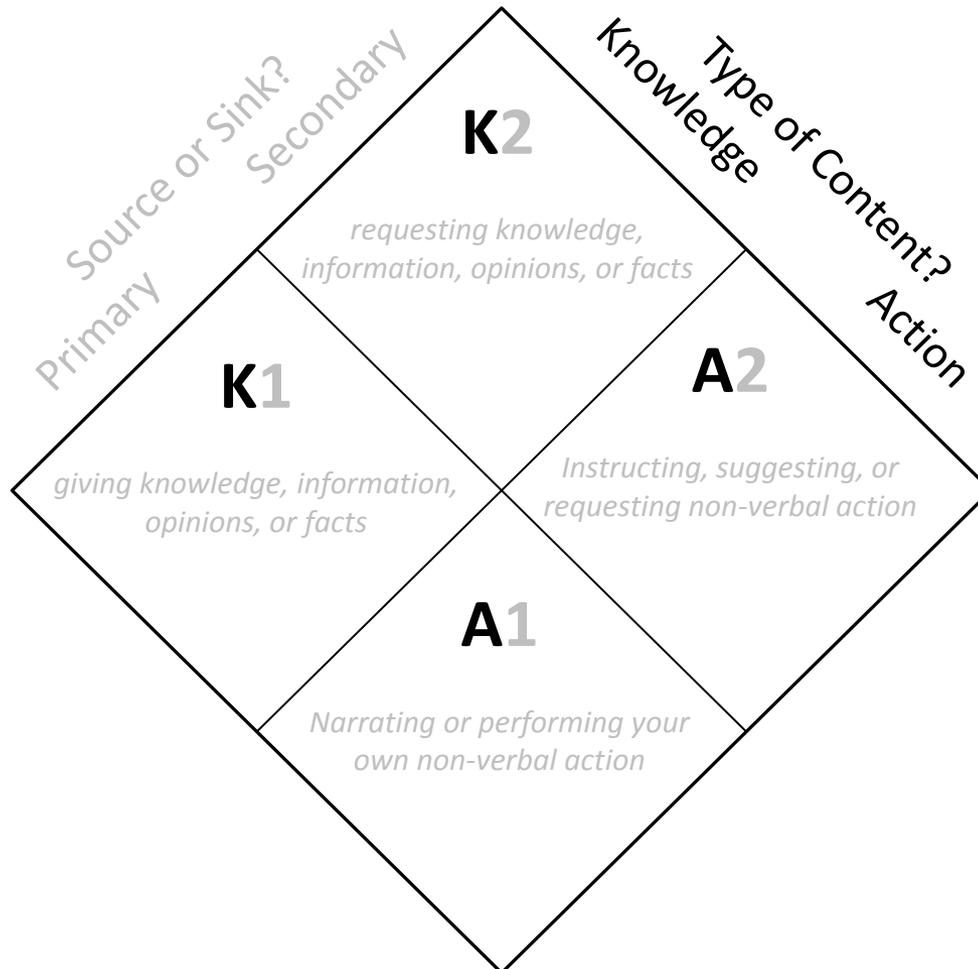
The Negotiation Framework

(Martin & Rose, 2003)



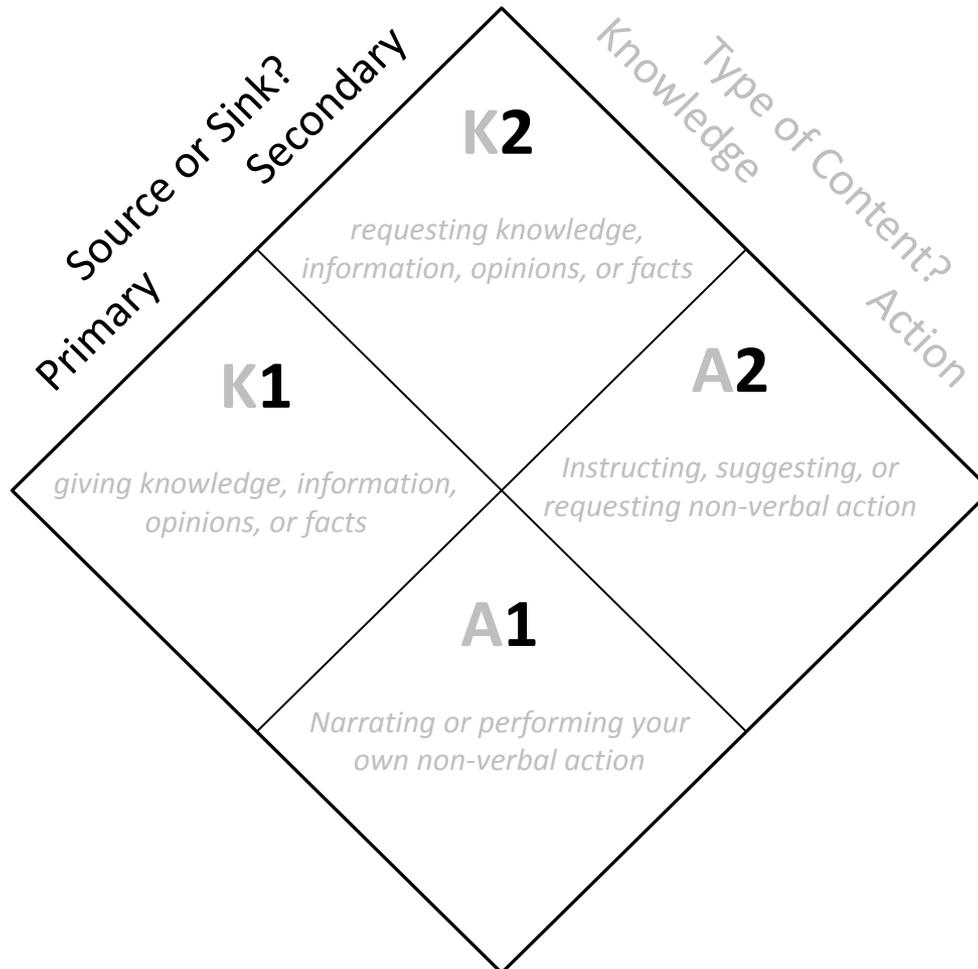
The Negotiation Framework

(Martin & Rose, 2003)



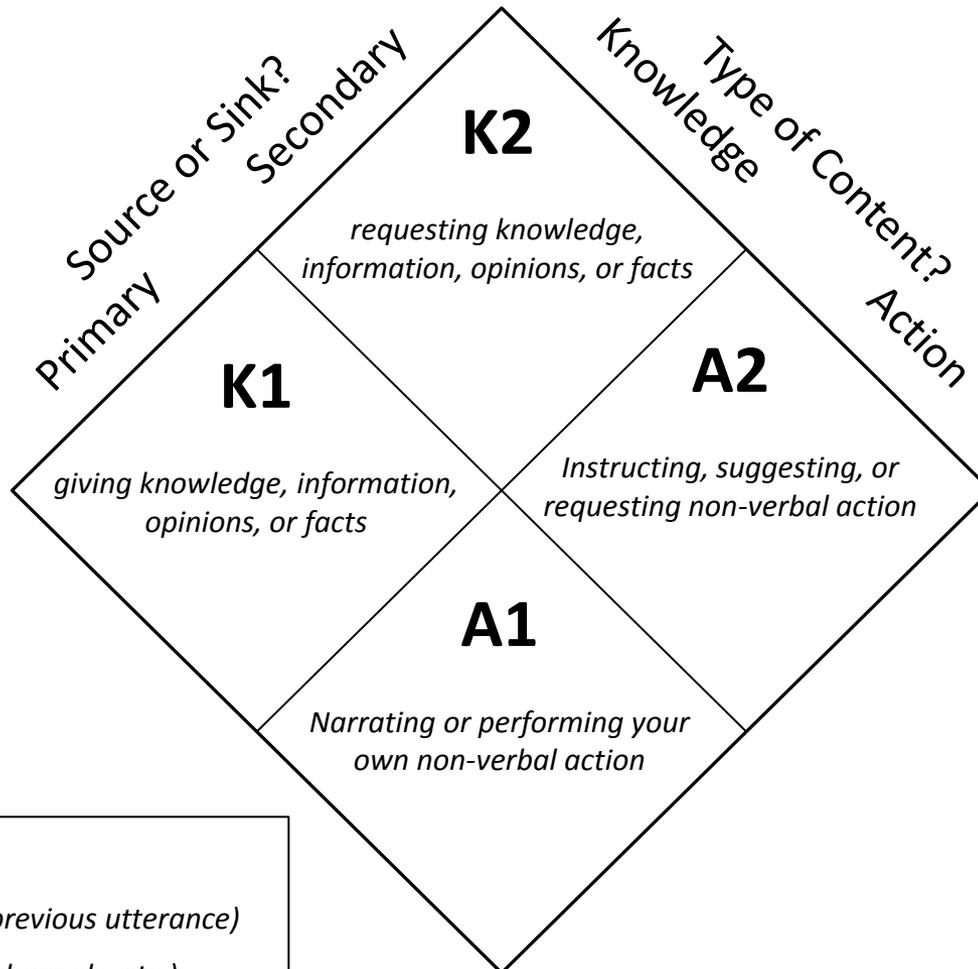
The Negotiation Framework

(Martin & Rose, 2003)



The Negotiation Framework

(Martin & Rose, 2003)



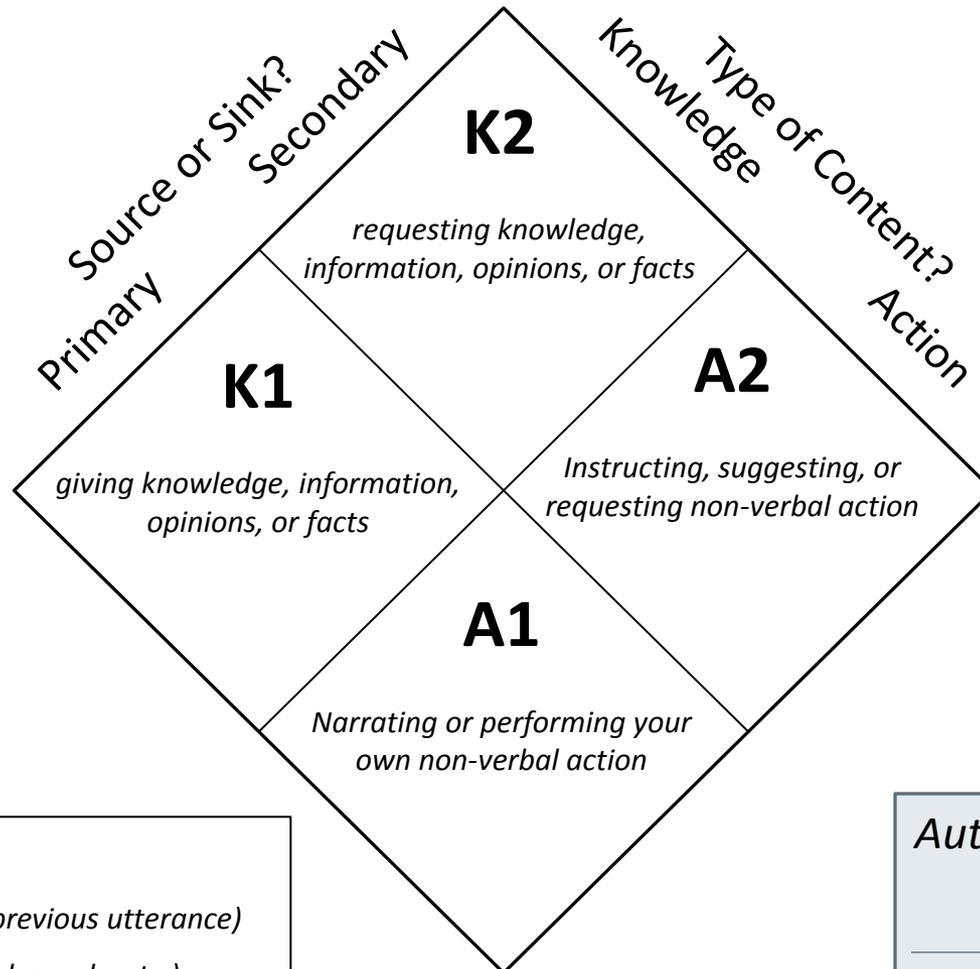
Additionally...

ch *(direct challenge to previous utterance)*

o *(all other moves, backchannels, etc.)*

The Negotiation Framework

(Martin & Rose, 2003)



Additionally...

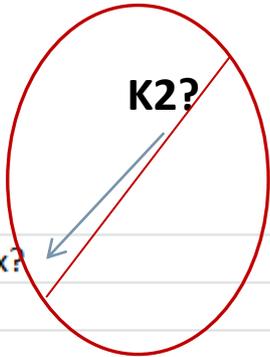
ch *(direct challenge to previous utterance)*

O *(all other moves, backchannels, etc.)*

Authoritativeness:

K1 + A2

K1 + K2 + A1 + A2



Doctor Bob	BTW: Is it safe to keep increasing Tmax?	05.12.17
sa08	no	05.12.33
Sa04	nope. you'll blow out your turbine	05.12.33
Doctor Bob	Good. Material properties constrain the maximum temperature we can use in a Cycle. For our cycle, Tmax cannot be more than 570C	05.12.39

Set up!

Doctor Bob		BTW: Is it safe to keep increasing Tmax?	05.12.17
sa08	K2	no	05.12.33
Sa04		nope. you'll blow out your turbine	05.12.33
Doctor Bob	K1	Good. Material properties constrain the maximum temperature we can use in a Cycle. For our cycle, Tmax cannot be more than 570C	05.12.39

Authoritativeness (Martin & Rose, 2003)

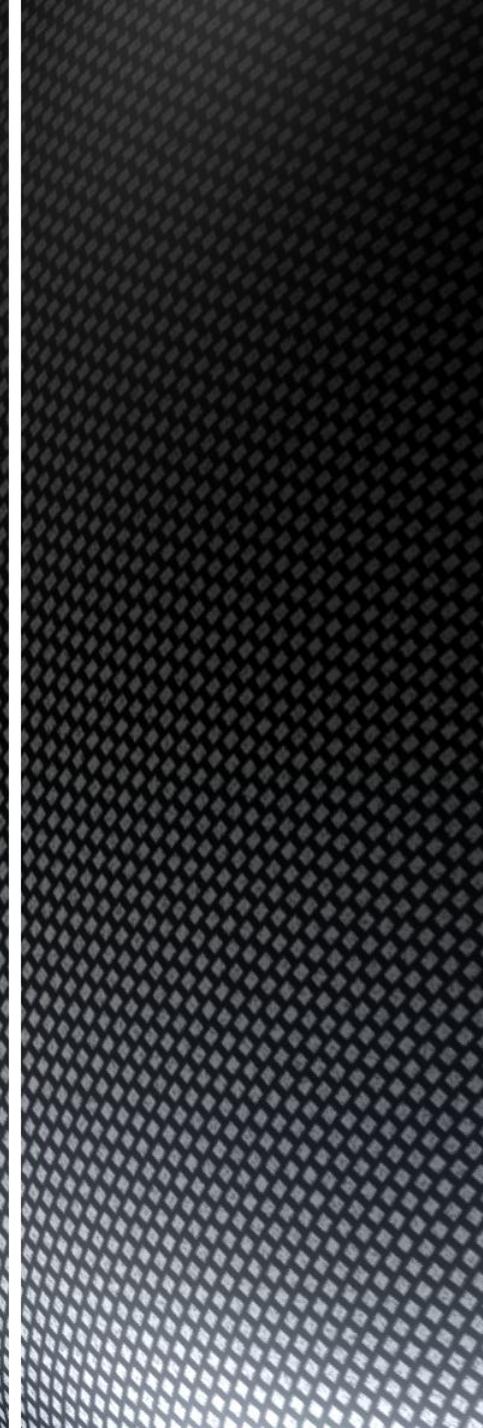
■ Findings

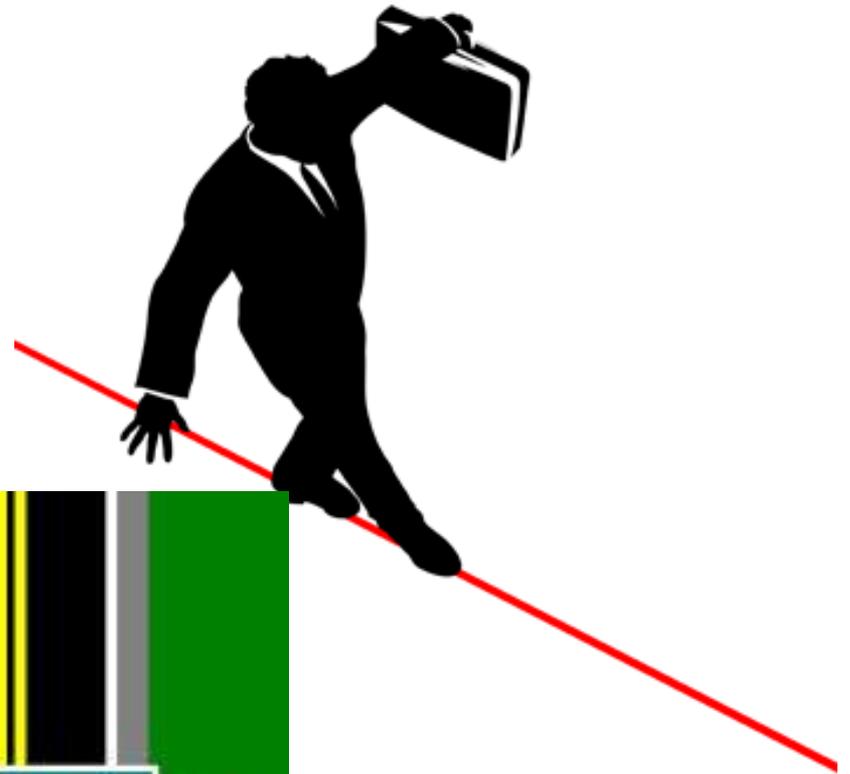
- Authoritativeness measures display how students respond to aggressive behavior in groups (Howley et al., in press)
- Authoritativeness predicts learning ($R = .64$) and self-efficacy ($R = .35$) (Howley et al., 2011)
- Authoritativeness predicts trust in doctor-patient interactions (R values between $.25$ and $.35$) (Mayfield et al., 2014)

■ Computational Work

- Detectable in collaborative learning chat logs ($R = .86$)
- Detectable in transcribed dyadic discussions in a knowledge sharing task ($R = .95$) (Mayfield & Rosé, 2011)
- Detectable in transcribed doctor-patient interactions ($R = .96$) (Mayfield et al., under review)

Future



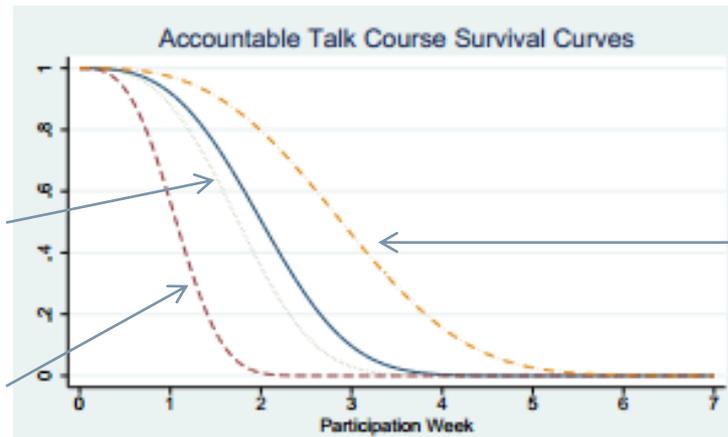




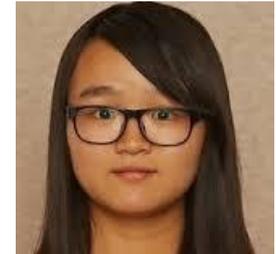
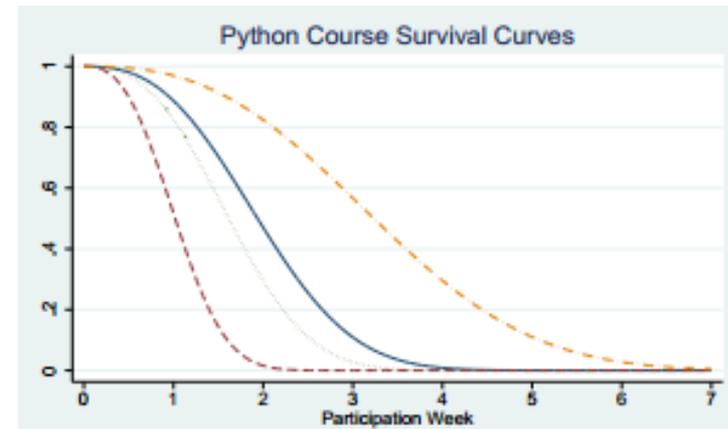
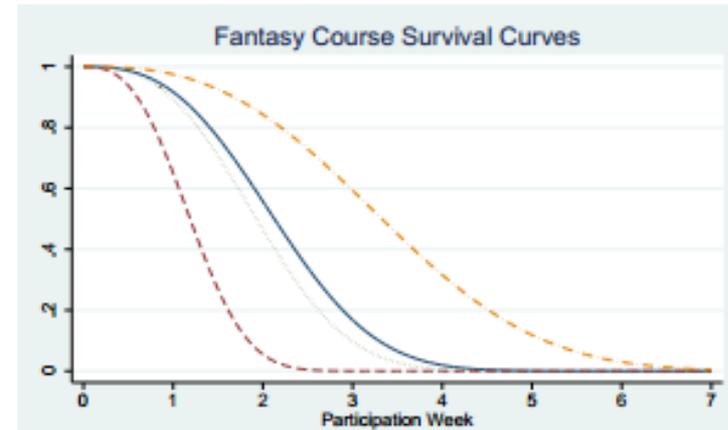
Researching Attrition in Massively Open Online Courses

Losing many acquaintances this week

Losing many acquaintances last week



Having many significant acquaintances





**What would
MOOC
training
wheels
look like?**

What will support look like in MOOCs?

- Challenges
 - Asynchronous
 - Split attention
 - Differing norms of participation
- Idea: Personal Mentoring Paradigm
 - Inspired by recommender systems





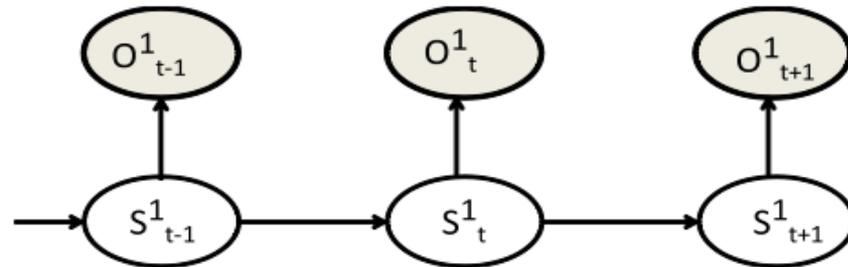
Thank You!

Questions?



Style based models: *The Independent Speaker Model*

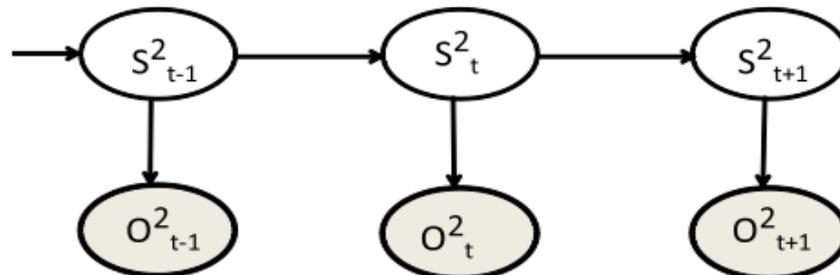
The dynamics of each speaker are independent of the other speaker



Model: ISM

Direct Link : NoDirect

InDirect Link: NoIndirect



ISM

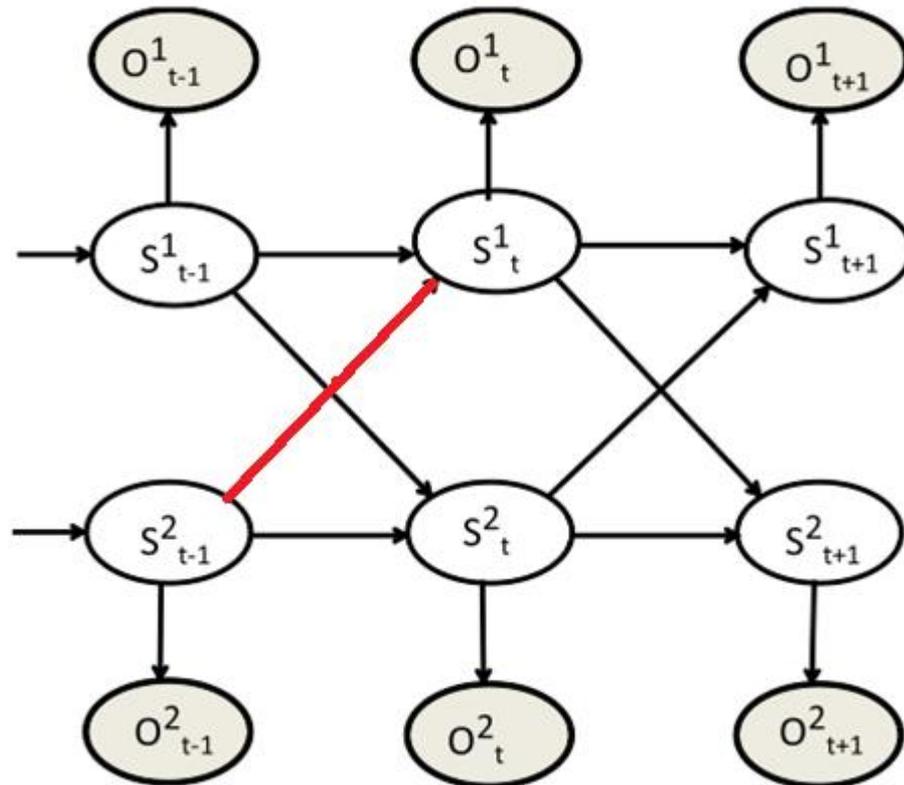
Style based models: *The Cross-speaker Dependence Model*

A speaker's style depends on their partner's style at the previous turn.

Model: CSDM

Direct Link : Direct

InDirect Link: NoIndirect



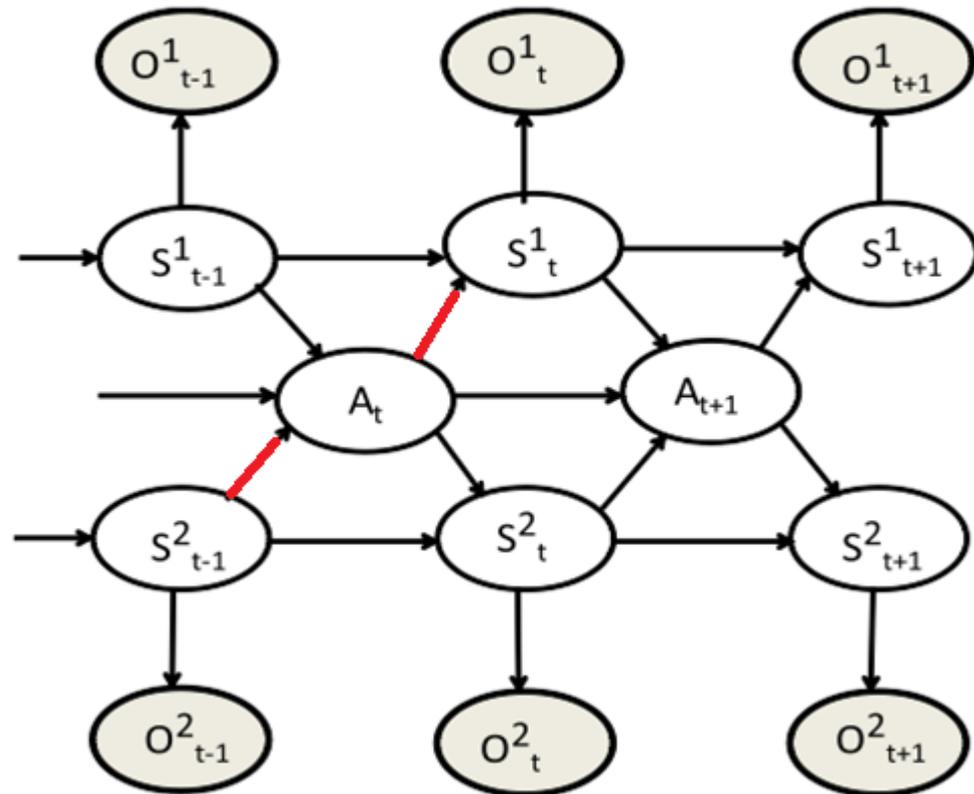
Accommodation state models: *The Symmetric Accommodation State Model*

Both partners styles depend on mutual accommodation to one another.

Mode: SASM

Direct Link : NoDirect

InDirect Link: Symetric



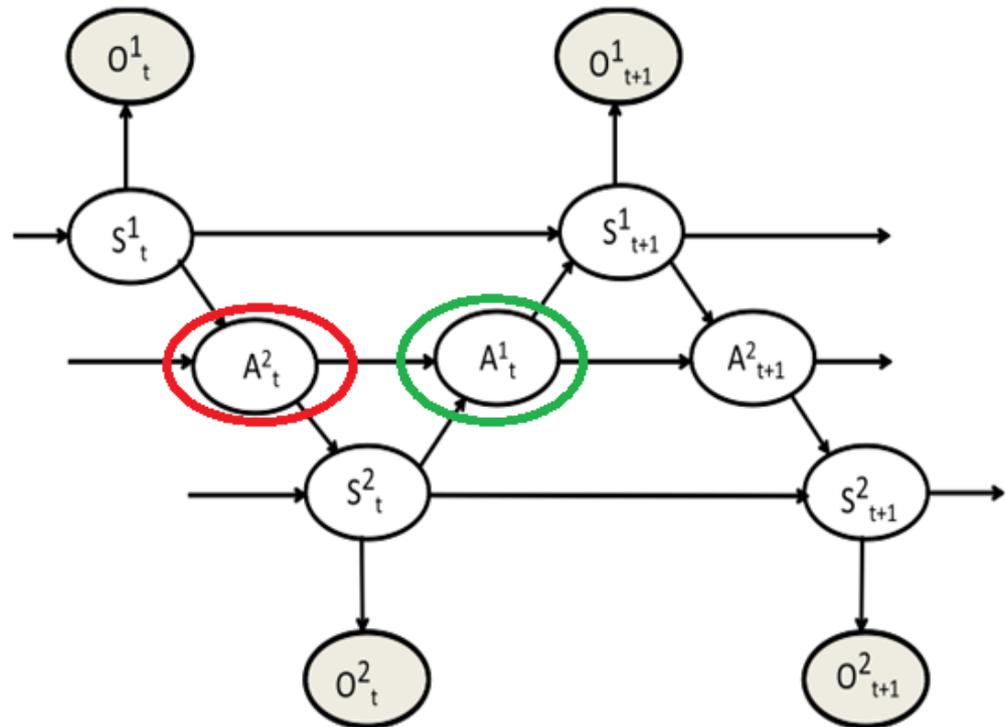
Accommodation state models: *The Asymmetric Accommodation State Model*

Accommodation state associated
with every speaker turn

Model: AASM

Direct Link : NoDirect

InDirect Link: Asymmetric



Accommodated style dependence models:

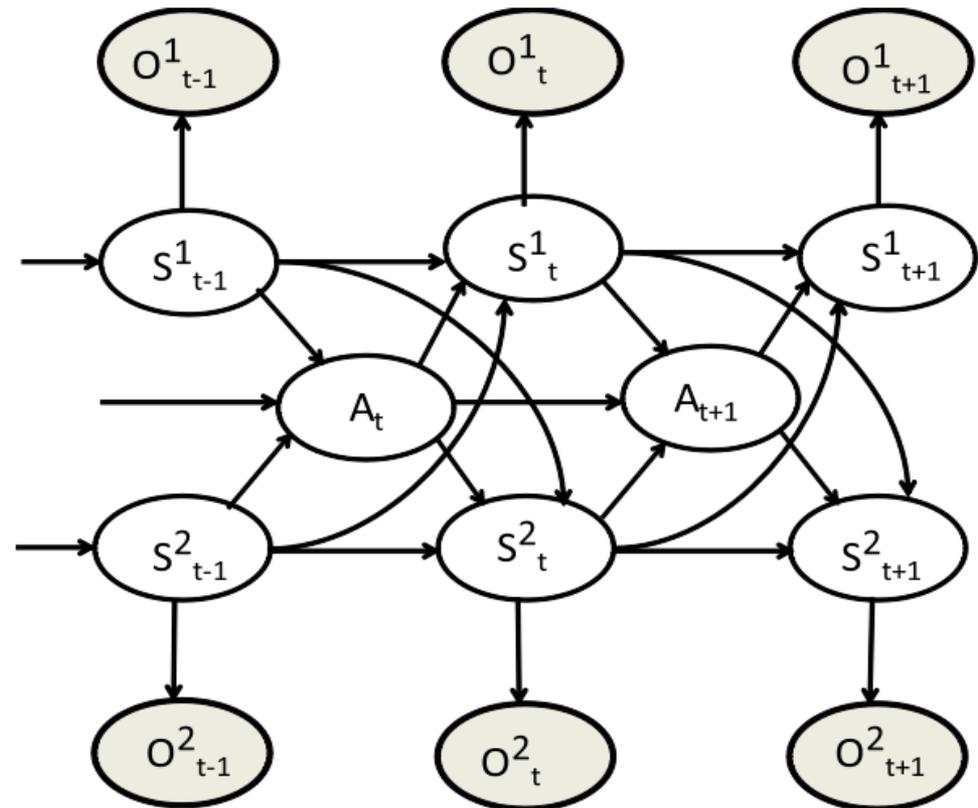
The Symmetric Accommodated Style Dependence Model

A speaker's style depends both on mutual accommodation and the partner's style in the previous turn.

Model: SASDM

Direct Link : Direct

InDirect Link: Symetric



Accommodated style dependence models:

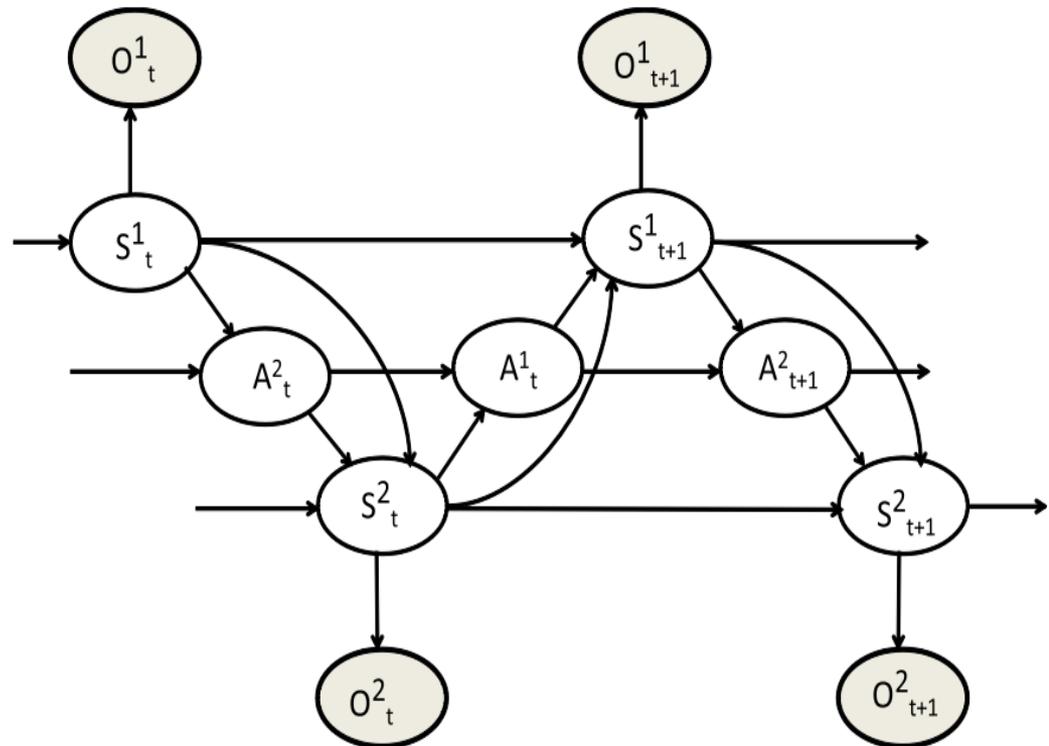
Asymmetric Accommodated Style Dependence Model

The accommodation state associated with every speaker and a speaker's style depends on the partner's style.

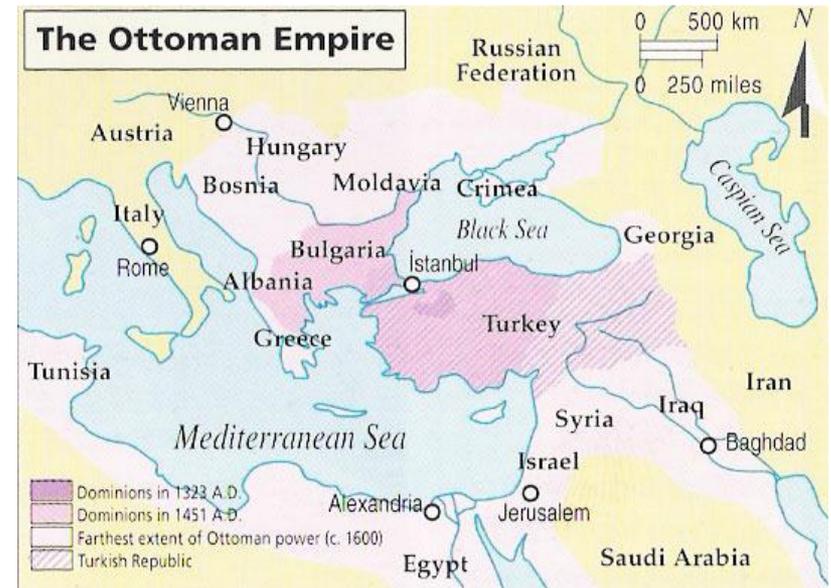
Model: AASDM

Direct Link : Direct

InDirect Link: Asymmetric



- Task: 2 students debating about the cause of the Ottoman Empire fall
- Participants: Male undergraduates between 18 and 25 years old
- Each student equipped with mic
- 8 min sessions, recorded and transcribed

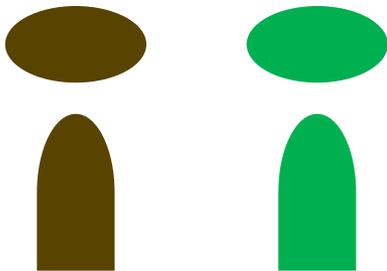


[Nokes, et al, 2010]

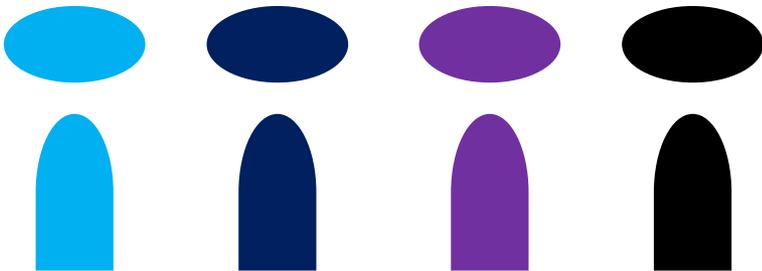
Evaluation

- Goal: evaluate style accommodation
 - Factor out lexical similarity that results from speaking on the same topic
 - Measure success by separating Real pairs and Constructed pairs
 - No gold standard labels needed
- For each Constructed pair
 - Start with a real pair
 - Select one speaker S
 - Replace each of S's turns with the most lexically similar turn from another conversation
- 3 fold cross validation
 - For each test conversation, compute an Accommodation score for the Real pair and each Constructed pair

Fake Partner Construction



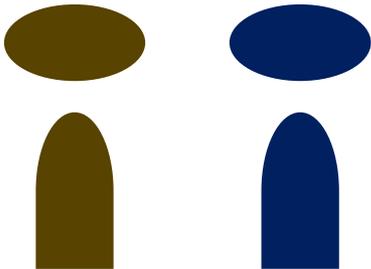
Real Partners (Speaker1 and Speaker2)



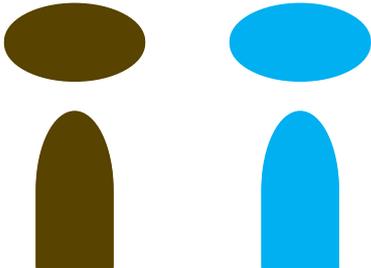
Speakers from other debates

Fake partner for speaker1

Turn1

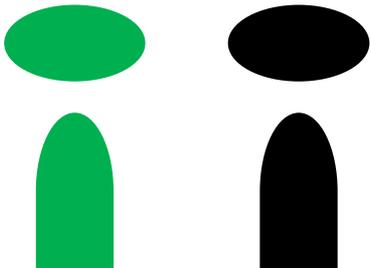


Turn2

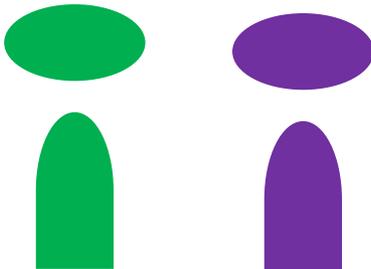


Fake partner for speaker2

Turn1



Turn2



Evaluation

- Goal: evaluate style accommodation
 - Factor out lexical similarity that results from speaking on the same topic
 - Measure success by separating Real pairs and Constructed pairs
 - No gold standard labels needed
- For each Constructed pair
 - Start with a real pair
 - Select one speaker S
 - Replace each of S's turns with the most lexically similar turn from another conversation
- 3 fold cross validation
 - For each test conversation, compute an Accommodation score for the Real pair and each Constructed pair

Evaluation

- Results evaluated with an ANOVA model
 - Dependent Variable: Accommodation Score
 - Independent Factors: RealVsConstructed, DirectLink, IndirectLink
- Significant main effect of the RealVsConstructed factor
 - $F(1,780) = 18.22, p < .0001$
 - Real pairs demonstrate higher Accommodation scores than Constructed pairs

Evaluation: Effect of Indirect Links

Model	Direct Link	Indirect Link	Real $\mu(\sigma)$	Constructed $\mu(\sigma)$
SASDM	Direct	Symmetric	.54(.23)	.44(.29)
SASM	NoDirect	Symmetric	.54(.23)	.44(.29)
AASM	NoDirect	Asymmetric	.6(.24)	.51(.3)
AASDM	Direct	Asymmetric	.61(.24)	.48(.3)
CSDM	Direct	NoInDirect	.6(.26)	.52(.3)
ISM	NoDirect	NoInDirect	.56(.25)	.51(.32)

- Posthoc comparison of interaction between IndirectLink and RealVsConstructed factors
 - Significant difference only when IndirectLinks are present (both Symetric and Asymetric)

Evaluation: Effect of Direct Links

Model	Direct Link	Indirect Link	Real $\mu(\sigma)$	Constructed $\mu(\sigma)$
SASDM	Direct	Symmetric	.54(.23)	.44(.29)
SASM	NoDirect	Symmetric	.54(.23)	.44(.29)
AASM	NoDirect	Asymmetric	.6(.24)	.51(.3)
AASDM	Direct	Asymmetric	.61(.24)	.48(.3)
CSDM	Direct	NoDirect	.6(.26)	.52(.3)
ISM	NoDirect	NoDirect	.56(.25)	.51(.32)

- Posthoc comparison of interaction between DirectLink and RealVsConstructed
 - Significant separation Irerespective of whether DirectLinks are present or not.