

### Fueling a Cycle for Continuous Improvement in Discussion Based Learning

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# Outline

- Historical Overview: 18 years of work
- Technology Approach: Highlighting Chinese Discourse Analysis tools
- Recent Work on Advanced Discourse Analysis Techniques
- Conclusion

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# Why Computer-Supported Collaborative Learning?

Students learn significantly more when interactive directed lines of reasoning replace hints. (Rosé et al., 2001)



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**Tutor:** Let's think about the difference between speed and velocity. A closely related distinction is that of the difference between distance traveled and displacement from the origin. Take as an example a bee flying from point A to point B by means of a curvy path. If you draw a vector from point A to point B, you will have drawn the bee's displacement vector. What does that vector represent?

#### Student: The bee's distance?

**Tutor:** The displacement vector only represents the net change in position. So it does not tell you how far the bee traveled. If you want to know how far the bee traveled, what do you need to measure?

Student: the bee's path?

**Tutor:** Right. Now, the bee's displacement is a vector. Is the distance a vector or a scalar?

#### Student: Scalar.

**Tutor:** So then distance traveled is the scalar counterpart to displacement. Now thinking about our analogy, what is the difference between speed and velocity?:

**Student:** Speed is a scalar, and velocity is a vector.

# Insights towards an ongoing research focus...

- Human tutoring not always better than non-interactive support (VanLehn et al., 2007)
  - Focus shift to capturing what it is about interaction that is effective for instruction
- Effective human tutors guide students towards opportunities for reflection (Rosé & Torrey, 2004)
- Student interaction with dialogue agents lacks evidence of reflection (Rosé et al., 2003)
- Students expect to behave differently with agents than with humans (Rosé & Torrey, 2004)

### **SOCIAL Interaction as a Learning Resource**

- Students can benefit from working with another student, even in the absence of scaffolding (Gweon et al., 2006; Kumar et al., 2007)
- Students gain as much from a human partner as from a carefully crafted tutor agent (*Kumar et al., 2007*)
- Context sensitive support for collaboration is more effective than static support (*Kumar et al., 2007*)



### Conversational Agent Based Support in Computer Supported Collaborative Learning



Students learn 1.24 s.d. more when working with a partner and automated support than students working alone (Kumar et al., 2007)

### **Effective in Multiple Learning Contexts**

- A decade and a half of successful classroom studies
  - Middle school, High school, College level
  - Urban school districts
  - Top tier and second tier universities
  - Math, Science, Engineering, Social Sciences
- Massive Open Online Courses (MOOCs)
  - Demonstrates that success generalizes to massive scale

### **Empirical Support for Design Principles**

- *Personalized agents* increase supportiveness and help exchange between students (*Kumar et al., 2007*)
- 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., 2014)



### Effective Collaborative Learning is rare without support

### Technology Support for Collaborative Learning



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### From Data to Design



Data Infrastructure unifies social interaction into uniform interface



analyzes learning paths conditioned on social network





through discussions

# New Partnership CMU-BNU



AICFE

#### AICFE BNU

Advanced Innovation Center for Future Education Beijing Normal University 北京 海淀区 | 学术研究

目前就职	Beijing Advanced Innovation Center for Future Education
教育背景	Beijing Normal University
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As part of a broader effort to provide tools for enabling research and practice in the space of collaborative and Discussion based learning, DiscourseDB is an NSF funded data infrustructure project designed to bridge data sources from multiple platforms for hosting those learning experiences. Our vision is to provide a common data model designed to accommodate data from diverse sources including but not limited to Chat, Threaded Discussions, Blogs, Twitter, Wikis, and Text messaging.

We will make available analytics components related to constructs including **role taking**, **help exchange**, **collaborative knowledge construction**, **showing openness**, **taking an authoritative stance**, **attitudes**, **confusion**, **alliance and opposition**. In enabling application of such metrics across datasets from multiple platforms, research questions related to the mediating and moderating effect of these process and state measures on information transfer, learning, and attrition can be conducted, building on the earlier research of our team.

#### **Current Capabilities**

We have one publically available dataset, consisting of online discussion of bugs and features in a set of related open source software projects, OpenFL. Other datasets are available to researchers by request, subject to IRB approval.

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## Vision

Facilitate analysis of discussion data across multiple research sites and multiple platforms

(e.g., Knowledge Forum and Idea Thread Mapper, or Knowledge Forum and a Wiki)



## Data Analytics Pipeline



- Browse data in DiscourseDB
- Import/Export data



- View, manipulate, create Annotations
- <u>http://brat.nlplab.org</u>



- Use annotations on DiscourseDB data to train models.
- Use models to annotate DiscourseDB data
- <u>http://ankara.lti.cs.cmu.edu/side</u>

### **Chinese DiscourseDB**

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### Chinese LightSIDE

Extract Features Restructure Data Exclusions Explore Results Compare Models Predict Labels

Fold Assignment

L2 Regularization

L1 Regularization

O L2 Regularization (Dual)

Learning Plugin

Naive Bave:

O Logistic Regression

Decision Trees

Evaluation Options:

Weka (All)

Linear Regression

Support Vector Machines

Feature Tables

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Class: annotation Focus

Feature Table: 12grams\_nopunct\_2



### **Feature Engineering**

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### **Error Analysis**

### Error Analysis Process High Level Overview

=== Confusion Matrix ===



Goal: We want to discover how to rerepresent the data so that instances with the same class value look more similar to one another and instances with different class values look more different

- Identify large error cells
- Make comparisons
  - Ask yourself how it is similar to the instances that were correctly classified with the same class (vertical comparison)
  - How it is different from those it was incorrectly not classified as (horizontal comparison)

### **Stretchy Patterns**

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# **Configuring Stretchy Patterns**

#### Configure Stretchy Patterns

0 1 2 3 4 5 6 7 8 Pattern Length	1 2
Gap Length	3
log About Stretchy Patterns	
☑ Include surface words in patterns	
Include POS tags in patterns	•
Categories: Add	lear
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Require at least one category per pattern	U
<ul> <li>Require at least one category per pattern</li> <li>Don't include surface/POS form when a category matches</li> </ul>	6
<ul> <li>Require at least one category per pattern</li> <li>Don't include surface/POS form when a category matches</li> <li>Categories match against surface words</li> </ul>	6
<ul> <li>Require at least one category per pattern</li> <li>Don't include surface/POS form when a category matches</li> <li>Categories match against surface words</li> <li>Categories match against POS tags</li> </ul>	6
<ul> <li>Require at least one category per pattern</li> <li>Don't include surface/POS form when a category matches</li> <li>Categories match against surface words</li> <li>Categories match against POS tags</li> <li>Count pattern hits</li> </ul>	© (6) (7)

- Longer patterns and longer gaps lead to larger numbers of features
- Categories are useful both for abstraction and for

#### anchoring Catheie Mellon University

# Outline

- Historical Overview: 18 years of work
- Technology Approach: Highlighting Chinese Discourse Analysis tools
- Recent Work on Advanced Discourse Analysis Techniques
- Conclusion







# Building Blocks: Types of Nonlinear Transformation



### **XOR: Non Separable Function**



# Building Blocks: Types of Nonlinear Transformation

- Context and Co-occurrence
  - Common: PCA, LSA, LDA
  - Neural: Skip Gram models (Embeddings), Autoencoders
- Sequences
  - Common: HMMs, DBNs, Lag models, other time series models
  - Neural: Recurrent networks, LSTM, BiLSTM
- Filters
  - Common: SVM with nonlinear kernels, Filters and templates as feature extractors
  - Neural: Convolutional Networks, Additional fullyconnected (hidden) layers

### **Recent work on Transactivity Detection**

### **Building Reasoning Together**

# Transactivity

### Transactivity

**Transact**: elaborate, build upon, question, or argue against the ideas presented by his/her partners [Berkowitz & Gibbs, 1983]

*"I recommend nuclear energy for this city since it's very efficient."* 

Transactive:

*"Nuclear energy, as it is efficient, it is not sustainable. Also, think of the disaster probabilities."* 

Non-transactive:

"I agree that nuclear power would be the best solution."






### The Task Envisioned



# Building Blocks: Types of Nonlinear Transformation

- Context and Co-occurrence
  - Common: PCA. LSA. LDA
  - Neural Skip Gram models (Embeddings), Autoencoders
- Sequences
  - Common: HMMs, DBNs, Lag models, other time series models
  - Neural: Recurrent networks, LSTM, BiLSTM
- Filters
  - Common: SVM with nonlinear kernels, Filters and templates as feature extractors
  - Neural: Convolutional Networks, Additional fullyconnected (hidden) layers

### Task Challenges

Limited quantity of annotated data for transactivity.

Annotated data is in a single domain.

Proposed solution - using entailment:

 Use pre-trained semantic vector models from a large data set and, given a method of comparison between the vectors, determine if a text is transactive as compared to another

text.

# **Entailment: Wikipedia Definition**

• In semantics, entailments depend on the "dictionary definition" of the words in question.

### **Relevance and Necessity**

• To judge whether an entailment is true, one can ask, "Could it *ever* be the case that *B* isn't true while *A* is true?"

# Entailment: Example

• Example from M. Lynne Murphy's *Lexical Meaning* 

• "If it is a shoe, then it is made to be worn on a foot."





### Leveraging Entailment as a Pretraining Task

### **Transactivity**

Entailment

# Reframing the Task

- Learning inference (entailment, contradiction, neutral) with Stanford Natural Language Inference dataset.
- Starting with word embeddings.
  - GloVe embeddings
- Classification



### Foundation: Deep Learning for Entailment Detection Parikh et al. 2016



### Step 1: Attend



## Step 1: Attend

- For each pair of words in the two posts, determine some attention score via 2 layer dense feed-forward neural network.
- For each word in each post, average all the attention scores with relation to the other post.
- What you get:
  - Information that indicates how important each word in a given post is with respect to the other post.

### Step 2: Compare



# Step 2: Compare

- Using the representation from the attention step along with the corresponding vectorized input post, run though a 2 layer dense feedforward neural network.
- What you get:
  - Two sets of vectors for that contain information comparing the posts with respect to each other.

# Step 3: Aggregate



# Step 3: Aggregate

• Sum each set of comparison vectors into two one dimensional vectors.

• Each of these vectors is a representation of a given post in relation to the other.

### Step 4: Classify



# Step 4: Classify

• With the resulting vectors from the aggregation step, we concatenate them and run them through another 2 layer dense feedforward neural network with cross-entropy loss to classify the data.

### Experiment 1

1. Train Entailment task first

- 2.Use trained weights as initialization for Transactivity task
- 3. Train on Transactivity task

### **Entailment Dataset**

- Stanford Natural Language Inference Corpus, Bowman et al. 2015.
- Collection of 570,000 English sentence pairs labeled for balanced classification of entailment, contradiction, and neutral.
- Examples were generated by humans in response to sentences describing pictures from Flickr
- Example:
  - Sentencel: "A soccer game with multiple males playing."
  - Sentence2: "Some men are playing a sport."

# Transactivity Dataset

- Discussion data from online forum where students offered feedback to one another on their proposals for city power plans
- 476 human annotated posts.
- Example:
  - Sentence 1:

"But if the energy is saving them some money it could go towards the batteries. W hats

frustrating is that it doesn't really give us information regarding the costs of g enerating electricity currently."

- Sentence 2:

"But those batteries add even more cost, and for a city concerned with cost, that would be a

problem. Plus, without the batteries, it's not very reliable, and that's also a pr oblem for a touristry driven economy."

### Results, Part 1

Model	Accuracy	Cohen's Kappa
Logistic Regression with unigrams	0.795	0.510
Logistic Regression with embeddings	0.626	0.182
Neural model	0.848	0.542

### Experiment 2

- Transactivity prediction with in domain data vs. out of domain data
- Train the model as in experiment 1, however on each cross validation fold, evaluate the model on out of domain annotated transactivity data.
- Note that there is no point in which the model is trained on the out of domain data.

### Out of Domain Transactivity Dataset

• 57 human annotated transacts from an Massive Open Online Course (MOOC) in which students were asked to design their own superheroes and provide feedback on other students' designs.

### Results, Part 2

Model	Accuracy (in   out)	Cohen's Kappa (in   out)
Logistic Regression with unigrams	0.795   0.667	0.510   0.376
Logistic Regression with embeddings	0.626   0.635	0.182   0.195
Neural model	0.848   0.824	0.542   0.586

### Recent work on Rhetorical Structure Analysis

### **Rhetorical Structure in Student**

# Writing

#### **INTRODUCTION: Create A Research Space**

#### Move 1: Establishing a territory

Step: Claiming centrality Step: Providing general background Step: Reviewing previous research

#### Move 2: Identifying a niche

Step: Indicating a gap Step: Highlighting a problem Step: Raising general questions Step: Proposing general hypotheses Step: Presenting justification

#### Move 3: Addressing the niche

Step: Introducing present research descriptively Step: Announcing present research purposefully Step: Presenting research questions Step: Presenting research hypotheses Step: Clarifying definitions Step: Summarizing methods Step: Announcing principal outcomes Step: Stating the value of present research Step: Outlining the structure of the paper

### Dataset

- Research Writing Tutor Dataset (RWT) from Iowa State University
- 700-1000 documents for each Introduction, Methods, Results, and Discussion/Conclusion
- 120,000+ annotated sentences in a 90%/10% split

# Prior Results by Elena Cotos

- Models: Naive Bayes, SVM, and MaxEnt
- N-Grams on stemmed text
- N-Grams on part-of-speech tags
- Unigram, bigram, and trigram for each stemmed text and part-of-speech

#### Kappa classification agreement for Step Classification

	Unigrams	Bigrams	Trigrams
Stemmed text	0.32	0.24	0.17
Part-of-speech	0.26	0.28	0.28

### Sequence model

• Document-level Bi-LSTM-CRF (Huang et al. 2015; Song et al. 2017)



### Results



Overall

# Outline

- Historical Overview: 18 years of work
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- Recent Work on Advanced Discourse Analysis Techniques
- Conclusion

#### DANCE: Discussion Affordances for Natural Collaborative Exchange



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Co-Director: Sreecharan Sankaranarayanan Carnegie Mellon University sreechas@cs.cmu.edu

### JOIN MAILING LIST TALK SERIES RESOURCES DANCE SCHOLAR

#### About DANCE

Drawing from two decades of research in Computer Supported Collaborative Learning, we are working to design an extension of the edX platform to enhance instructionally beneficial discussion opportunities available to students. With this working group, we want to bring together people from academia and industry to build a common vision regarding what kinds of research would be valuable to the community once such a platform extension was in place to support it. Our work is initially focusing on the edX platform in particular, but in the long run we seek to provide these capabilities to Massive Open Online Courses and other online learning platforms more generally. In particular, this working group is partnering with edX as a satellite collaborative, seeking to involve researchers and developers from multiple universities, foundations, and industrial organizations.

### DANCE is a community of practice with many open source resources

# Our foundational work is beginning with specific interventions designed to offer synchronous collaboration activities supported by intelligent conversational agents and enhancements to threaded discussions to support more intensive help exchange by leveraging social recommendation technology. However, our goals are much broader than this, seeking to leverage insights and methodologies from the field of Human-Computer Interaction and encompassing both synchronous and asynchronous communication very broadly. Our vision includes text, speech, and video based interactions, instrumented with all sorts of intelligent support powered by state-of-the-art analytics and leveraging language technologies and artificial intelligence more broadly in order to offer contextually appropriate support. We will coordinate this effort with regular online meetings and occasional in-person workshops.



#### Thousands of visitors

Hundreds of return visitors each month

### Resources

#### Resources



DANCE Home

One goal of the DANCE initiative is to provide a community platform to help researchers in the MOOC/CSCL space interested in contributing to the OpenEdX platform. This page aggregates resources the came out of the DANCE effort as well as related third party tools and artifacts. It is our hope that this can inspire contributions by others and foster discussion among the community of CSCL researchers about possibilities for collaborative tools that can be deployed and tested on platforms such as OpenEdX.

#### DANCE XBlock Development

The DANCE discussion forum XBlock represents a first step towards improving scripted support for collaboration in MOOCs. The XBlock provides all basic features expected of a forum while augmenting the experience with social recommendation (that as an example recommendation application matches help seekers with help givers). It provides light social awareness and semisynchronous interaction through a Personal Messaging capability. It also provides the forum data in a source agnostic data infrastructure model using DiscourseDB (see below) that will allow the contextualization and comparison of discourse data from across platforms.

- The source code and documentation can be found on GitHub.
- A walkthrough of its functionality can be found here.
- The features currently on offer from the XBlock as well as planned additions can be found here.
- The design document detailing the overarching goals and guiding principles behind the development of the XBlock can be found here.

### DANCE Discussion Forum is compatible with Open edX

Includes hooks for interventions like Social Recommendation and Discussion Scaffolding

### Resources

### LightSIDE

#### LightSide

The open-source LightSide platform, including the machine-learning and feature-extraction core as well as the researcher's workbench UI, has been and continues to be funded in part through Carnegie Mellon University, in particular by grants from the National Science Foundation and the Office of Naval Research. See the full acknowledgements and grant details below!

We make the LightSide research platform freely available for research and education. In exchange, we ask that you provide us with basic information about who you are and how you're making use of LightSide's capabilities.

- · You can download the current LightSide binaries and the user manual here
- The source code is freely available on GitHub.

#### Social Recommendation

Massive Open Online Courses have experienced a recent boom in interest. Problems students struggle with in the discussion forums, such as difficultly in finding interesting discussion opportunities or attracting helpers to address posted problems, provide new opportunities for recommender systems.

We developed a social recommendation technology to support help seekers in MOOC discussion forums implemented using a context-aware Matrix Factorization model to predict students' preferences for answering a given question. This recommendation framework allows for this two-way recommendation. The source code is freely available on GitHub.

#### References:

- Yang, Diyi, Piergallini, Mario, Howley, Iris and Carolyn Penstein Rose. "Forum thread recommendation for massive open online courses." Educational Data Mining 2014. 2014.
- Yang, Diyi, David Adamson, and Carolyn Penstein Rose. "Question recommendation with constraints for massive open online courses." Proceedings of the 8th ACM Conference on Recommender systems. ACM, 2014.

### Text mining tool bench

Over 10,000 users have downloaded LightSIDE Automated collaborative process analysis Automated writing assessment/feedback generation

### **Social Recommendation**

deployed so far in one MOOC to support help exchange

### Resources

#### DiscourseDB

DiscourseDB is an NSF funded data infrustructure project designed to bridge data sources from multiple platforms for hosting those learning experiences. Our vision is to provide a common data model designed to accommodate data from diverse sources including but not limited to Chat, Threaded Discussions, Blogs, Twitter, Wikis, and Text messaging.

We will make available analytics components related to constructs including role taking, help exchange, collaborative knowledge construction, showing openness, taking an authoritative stance, attitudes, confusion, alliance and opposition. In enabling application of such metrics across datasets from multiple platforms, research questions related to the mediating and moderating effect of these process and state measures on information transfer, learning, and attrition can be conducted, building on the earlier research of our team.

- Source code and additional documentation on GitHub
- Instructional video explaining the foundations of DiscourseDB
- Slides of the 1/2016 DiscourseDB HackDay

#### Bazaar

Bazaar is a publicly available architecture for orchestrating conversational agent based support for group learning. It is a powerful tool for facilitating research in collaborative learning. It hosts a library of reusable behavioral components that each trigger a simple form of support. More complex supportive interventions are constructed by orchestrating multiple simple behaviors. Its flexibility and simplicity mean it can be used to very rapidly develop platforms for investigating a wide range of important questions within the design space of dynamic support for collaborative learning.

- The source code is freely available on GitHub.
- Slides and video recordings of a Bazaar tutorial (May 2016) can be found here
- · You can find additional documentation and links to relevant research papers here.

### **DiscourseDB:**

Data infrastructure to offer discourse data and analytic tools through LearnSphere

#### **Bazaar:**

Tutorial dialogue architecture Dialogue agents for individual or collaborative learning
## Conclusion

- Language Technologies like Text Classification and Dialogue Agents help make collaboration effective
- Some resources have already been ported to Chinese
- Join us: We are happy to extend our work to collaborate with you
  - Let me know if you would like to collaborate

