Roadmap for Persuasive Argumentation

Goals of persuasive argumentation:

1. Providing knowledge
2. Convincing
Goals of persuasive argumentation:

1) Providing knowledge
   - Argumentation structure
   - Causal relations

2) Convincing
   - Personal
   - Emotionally moving
Outline

1 Introduction

2 Persuasion

3 Causal Relations

4 Generation
Roadmap for Persuasive Argumentation

1. Persuasion
   1. What makes an argument more persuasive than a logical sequence of reasons?
   2. How are persuasive arguments structured?

2. Causal Relations

3. Generation
Roadmap for Persuasive Argumentation

1. Persuasion
2. Causal Relations
   1. How can we better represent and model causal relations?
   2. How can we model sequences of reasoning?
3. Generation
Roadmap for Persuasive Argumentation

1. Persuasion
2. Causal Relations
3. Generation
   1. How can we customize generation to emphasize persuasion?
   2. How can we generate goal-oriented and globally coherent arguments?
What makes an argument more persuasive than a logical sequence of reasons?

How are persuasive arguments structured?

### Social Media

- Tan et al. (2016)
- Habernal and Gurevych (2016)
- Das et al. (2016)
- Rosenthal et al. (2017)
- Walker et al. (2012)

### Persuasive Essays

- Peldszus and Stede (2015)
- Ghosh et al. (2016)
- Somasundaran et al. (2016)
- Forbes-Riley et al. (2016)
1. What makes an argument more persuasive than a logical sequence of reasons?

2. How are persuasive arguments structured?

Social Media

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Tan et al. (2016)

**Goal:** Predict persuasion

**Data:** Change My View

**Method:** Logistic Regression

**Features:** Sentiment, Style, Interplay

- (+) Naturally labeled open-domain data
- Balanced prediction controlled for topic but (-) assumes persuasion

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Winning Arguments: Interaction Dynamics and Persuasion Strategies in Good-faith Online Discussions
Tan et al. (2016)

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Winning Arguments: Interaction Dynamics and Persuasion Strategies in Good-faith Online Discussions
Persuasion → Social Media

**Tan et al. (2016)**

**Goal:** Personal persuasion
- (+) Naturally labeled open-domain data
- Balanced prediction controlled for topic but (-) assumes persuasion

**Habernal and Gurevych (2016)**

**Goal:** Ranking arguments
**Data:** CreateDebate and Procon
**Method:** SVM and LSTM
**Features:** Sentiment, Readability
- (+) Objective ranking for quality
- (-) May just reveal which arguments are bad

Which argument is more convincing? Analyzing and predicting convincingness of Web arguments using bidirectional LSTM
Persuasion → Social Media

Tan et al. (2016)

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Which argument is more convincing? Analyzing and predicting convincingness of Web arguments using bidirectional LSTM
### Tan et al. (2016)

**Goal:** *Personal* persuasion

### Habernal and Gurevych (2016)

**Goal:** *Objectively* ranking arguments

### Das et al., (2016)

**Goal:** Analyze intent in social networks  
**Data:** Manually generated and Twitter  
**Method:** Crowdsourcing and LDA

- (+/-) Measure persuasion by change in sentiment  
- (-) Controlled, artificial experiments

---

*Hyundai cars just suck.*  
*Mine broke down right after their guarantee period.*
Persuasion → Social Media → Influence

Tan et al. (2016)

Goal: Personal persuasion

Habernal and Gurevych (2016)

Goal: Objectively ranking arguments

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Hyundai cars just suck.
Mine broke down right after their guarantee period.
Das et al., (2016)

**Goal:** Analyze intent in social networks (*global influence*)

Rosenthal and McKeown (2017)

**Goal:** Predict *personal* influence

**Data:** LiveJournal, Wikipedia Talk, Twitter, CreateDebate

**Method:** Cascaded supervised system

**Features:** Persuasion, Argument, Sentiment, Dialog, Agreement

- (-) Evaluation assumes at least one influencer
- (+) Domain adaptation
Das et al., (2016)

**Goal**: Analyze intent in social networks (*global* influence)

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- (+) Domain adaptation
Das et al., (2016)

**Goal:** Analyze intent in social networks (*global* influence)

Rosenthal and McKeown (2017)

**Goal:** Predict *personal* influence

Walker et al. (2012)

**Goal:** Predict stance

**Data:** CreateDebate

**Method:** MaxCut, Logistic Regression

**Features:** Sentiment, Argumentation

- (+) Naturally-labeled data, (+) proxy for persuasion
- (+) Model social interaction, (-) limited set of topics
<table>
<thead>
<tr>
<th><strong>Persuasion → Social Media → Stance</strong></th>
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<td><strong>Das et al., (2016)</strong></td>
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**Stance Classification using Dialogic Properties of Persuasion**
What makes an argument more persuasive than a logical sequence of reasons?

- Social Interaction
  - Walker et al. (2012) - graph partitions
  - Das et al. (2016) - neighbor content similarity
  - Tan et al. (2016) - word overlap
  - Rosenthal and McKeown (2017) - dialog patterns

- Emotional Content

How are persuasive arguments structured?
1. What makes an argument more persuasive than a logical sequence of reasons?
   - Social Interaction
   - Emotional Content
     - Das et al. (2016) - emotion and logic depending on topic
     - Habernal and Gurevych (2016) - negative often less convincing
     - Tan et al. (2016) - presence of sentiment
     - Rosenthal and McKeown (2017) - sentiment for attempts to persuade
     - Walker et al. (2012) - sentiment for stance

2. How are persuasive arguments structured?
What makes an argument more persuasive than a logical sequence of reasons?

How are persuasive arguments structured?

Social Media

Tan et al. (2016)
Habernal and Gurevych (2016)
Das et al. (2016)
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Walker et al. (2012)

Persuasive Essays

Peldszus and Stede (2015)
Ghosh et al. (2016)
Somasundaran et al. (2016)
Forbes-Riley et al. (2016)
Peldszus and Stede (2015)

**Goal:** Argumentation parsing  
**Data:** Manually generated German and (-) translated English essays  
**Method:** Logistic regression, MST

- Claims/premises and support/attack relations  
- (+) Joint prediction, (-) but components modeled individually
Persuasion → Essays

Pelczszus and Stede (2015)

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Joint prediction in MST-style discourse parsing for argumentation mining
## Ghosh et al. (2016)

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<th>Goal: Persuasive essay scoring</th>
<th>Goal: Argumentation parsing</th>
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<tbody>
<tr>
<td>Data: TOEFL essays</td>
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<td>Method: Linear regression</td>
<td>Method: Logistic regression, MST</td>
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<td>(+/-) Coarse-grained claims/premises and support/attack relations</td>
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Somasundaran et al. (2016)

**Goal**: Automatic essay scoring

**Data**: GRE essays

**Methods**: Linear Regression

**Features**: PageRank and graph-based

- Model (+) *globally* as graphs with each word as a node
- (-) All nodes of the same word are collapsed
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Evaluating Argumentative and Narrative Essays using Graphs
Somasundaran et al. (2016)

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Forbes-Riley et al. (2016)

**Goal:** Analyze and predict Penn Discourse Tree bank relations

**Data:** AP English essays

**Methods:** Crowdsourcing and pre-trained discourse parser

- Mostly sequential *local* relations
- More Contingency relations, (-) missing Justification and Claim

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Extracting PDTB Discourse Relations from Student Essays
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Extracting PDTB Discourse Relations from Student Essays

Christopher Hidey
Candidacy Exam
April 21, 2017
1. What makes an argument more persuasive than a logical sequence of reasons?

2. *How are persuasive arguments structured?*
   - Ghosh et al. (2016) and Peldszus and Stede (2015) use tree structures
   - Somasundaran et al. (2016) study graphs of word interactions
   - Forbes-Riley et al. (2016) analyze local discourse relations
Goals of persuasive argumentation:

1) Providing knowledge
   - Structure
     - Causality

2) Convincing
   - Personal
   - Emotional

Persuasion

Influence

Stance
Causal Relations

Causal relations for persuasive argumentation:

1. Mining factual causal relations
2. Modeling causal relations in persuasive argumentation

Goals:

1. How can we better represent and model causal relations?
2. How can we model sequences of reasoning?
Causal Relations

Causal relations for persuasive argumentation:

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- Ji et al. (2016)
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- Riaz and Girju (2014)

**Distributional**

- Biran and McKeown (2013)
- Braud and Denis (2016)
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- Rocktaschel et al. (2015)
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**Ji et al (2016)**

**Goal:** Predict implicit discourse relations

*John was tired. He left early.*

**Data:** Wall Street Journal (PDTB)

**Model:** LSTM with discourse relation as latent variable

- (+) Discourse-aware language modeling
- (-) Implicit discourse relation detection still very difficult
- (-) No reporting of individual class performance
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**Prasad et al. (2010)**

**Goal:** Identify alternative discourse markers

GM appears to be stepping up the pace of its factory consolidation to get in shape for the 1990s. **One reason is** mounting competition.

**Data:** Wall Street Journal (PDTB)

**Model:** Paraphrases

- (+) Provides lexical signal, (+/-) open class of markers
- (-) Limited to intra-sentence relations
Causal Relations → Contextual Approaches

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**Goal:** Identify alternative discourse markers

Dunietz et al. (2017)

**Goal:** Predict causality and cause/effect spans

*For market discipline to work, banks cannot expect to be bailed out.*

**Data:** New York Times, Wall Street Journal, Dodd-Frank hearings

**Model:** Cascaded supervised system

**Features:** Lexical, Syntactic, Semantic

- (+) Contiguous and non-contiguous, but (-) no temporal
- (-) Closed class at prediction, (-) per-relation classifier

Automatically Tagging Constructions of Causation and Their Slot-Fillers
### Causal Relations → Contextual Approaches

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For market discipline to work, banks cannot expect to be bailed out.

- Lexical grounding

Riaz and Girju (2014)

Goal: Predict causality
At least 1,833 people died in the hurricane.

Data: FrameNet, WordNet, and GigaWord

Model: Semi-supervised ILP

- (+) Non-contiguous, (+) open class
- (+/-) Requires real-world definition of causality
- (-) Missing other causal constructions

In-depth Exploitation of Noun and Verb Semantics to Identify Causation in Verb-Noun Pairs
Causal Relations → Contextual Approaches

Dunietz et al. (2017)

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In-depth Exploitation of Noun and Verb Semantics to Identify Causation in Verb-Noun Pairs
How can we better represent and model causal relations?

- Dunietz et al. (2017)- expand to constructions like “so ... that”
- Prasad et al. (2010)- alternative lexicalizations, “The reason is”
- Riaz and Girju (2014)- verb-noun pairs such as “died/hurricane”
- Ji et al. (2016)- implicit discourse relations as latent variables

How can we model sequences of reasoning?
Causal Relations

1. How can we better represent and model causal relations?
2. How can we model sequences of reasoning?

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**Formal Logic**
- Rocktaschel et al. (2015)
- Das et al. (2017)
Biran and McKeown (2013)

**Goal:** Distributed representations for implicit discourse

**Method:** Calculate weighted word-pairs for each explicit connective

- (-) Unable to score unseen word pairs
- (+/-) Simple pre-processing, (-) no evaluation
Biran and McKeown (2013)

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Causal Relations → Distributional Approaches

**Goal:** Distributed representations for implicit discourse
TF-IDF and PMI-IDF, with IDF over connectives

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<td><strong>Method:</strong> Each word is a weighted d-dimensional vector</td>
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<td>(+) Evaluation of pre-processing</td>
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Learning Connective-based Word Representations for Implicit Discourse Relation Identification
Goal: Distributed representations for implicit discourse
TF-IDF and PMI-IDF, with IDF over connectives

Biran and McKeown (2013)
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Learning Connective-based Word Representations for Implicit Discourse Relation Identification
Biran and McKeown (2013), Braud and Denis (2016)

**Goal:** Distributed representations for implicit discourse

Sharp et al. (2016)

**Goal:** Distributed representations for causality

**Method:** skip-gram, word-context pairs are from causes and effects

- (-) Simple pre-processing, (+/-) some evaluation of span selection
- (+) Both intrinsic and extrinsic evaluation
# Causal Relations

1. How can we better represent and model causal relations?
2. *How can we model sequences of reasoning?*

### Contextual

- Ji et al. (2016)
- Prasad et al. (2010)
- Dunietz et al. (2017)
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### Distributional

- Biran and McKeown (2013)
- Braud and Denis (2016)
- Sharp et al. (2016)

### Formal Logic

- Rocktaschel et al. (2015)
- Das et al. (2017)
Rocktaschel et al. (2015)

**Goal:** Perform inductive reasoning on a knowledge base

**Data:** New York Times (train) and Freebase (train/test)

**Methods:** Matrix factorization and probabilistic logic rules

\[
    r_s(x, y) \implies r_t(x, y)
\]

\[
    [\mathcal{A} \implies \mathcal{B}] = [\mathcal{A}] ([\mathcal{B}] - 1) + 1
\]
**Goal:** Perform inductive reasoning on a knowledge base

**Rocktaschel et al. (2015)**

**Methods:** Matrix factorization and probabilistic logic rules

**Das et al. (2017)**

**Data:** Freebase

**Methods:** RNN over paths in a knowledge base

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Chains of Reasoning over Entities, Relations, and Text using Recurrent Neural Networks
Goal: Perform inductive reasoning on a knowledge base

<table>
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- (+) Open set of relations
- (-) Difficult to model confounding variables and other complex interactions
How can we better represent and model causal relations?
- Biran and McKeown (2013) - word pairs for explicit connectives
- Braud and Denis (2016) - word co-occurrence vectors
- Sharp et al. (2016) - skip-gram for cause/effect word pairs

How can we model sequences of reasoning?
Causal Relations → Distributional Approaches

1. How can we better represent and model causal relations?

2. *How can we model sequences of reasoning?*
   - Rocktaspel et al. (2015) - matrix factorization with injected logic
   - Das et al. (2017) - RNNs over paths in knowledge graph
Causal Relations

Goals of persuasive argumentation:

1) Providing knowledge
   - Structure
     - Causal relations
       - Contextual
         - Ji
         - Prasad
         - Dunietz
         - Riaz
         - PDTB
         - Alt. lex.
         - construction
         - verb-noun
       - Distributional
         - Biran
         - Braud
         - Sharp
         - Rocktaschel
         - Das
         - causal
         - logic
     - Personal
   - Emotional

2) Convincing
Natural language generation for persuasive argumentation:

1. Content-framed
2. Context-driven
3. Goal-oriented
4. Globally coherent

1. How can we customize generation to emphasize persuasion?
2. How can we generate goal-oriented and globally coherent arguments?
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**Persuasion**

- Ding and Pan (2016)
- Bilu and Slonim (2016)
- Li et al. (2016)
- Dodge et al. (2016)

**Other**

- Andreas and Klein (2016)
- Hu et al. (2017)
- Chen et al. (2009)
- Kiddon et al. (2016)
Generation

1. How can we customize generation to emphasize persuasion?
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**Framing**
- Ding and Pan (2016)
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**Goal-oriented**
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- Chen et al. (2009)
- Kiddon et al. (2016)
Bilu and Slonim (2016)

**Goal:** Generate valid claims (template-based)

**Data:** idebate

Banning violent video games is a violation of free speech
Censoring internet content is a violation of free speech

**Method:** Logistic regression

**Features:** similarity, relevance, fluency

- (+) Parameter sharing across topics
- (+/-) Text-to-text generation, (-) closed set
Bilu and Slonim (2016)

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### Bilu and Slonim (2016)

**Goal:** Generate valid claims

### Ding and Pan (2016)

**Goal:** Determine effects of personality on persuasion  
**Data:** Personality tests  
**Method:** Metric Pairwise Constrained K-Means  
**Features:** Big5, Schwartz

- (-) Domain-specific
- (-) No control for how personality affects generation decisions
### Bilu and Slonim (2016)

**Goal:** Generate valid claims

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- Andreas and Klein (2016)
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**Coherent**
- Chen et al. (2009)
- Kiddon et al. (2016)
Andreas and Klein (2016)

**Goal:** Generate reference text  
**Data:** Abstract Scenes Dataset 
**Method:** Referent ranker, text generator

- (+) Contextual, social interaction 
- (+) Agnostic to input representation 
- (-) Sampling instead of joint modeling

---

*the owl is sitting in the tree*
Considering Context

Andreas and Klein (2016)

Goal: Generate reference text
Data: Abstract Scenes Dataset
Method: Referent ranker, text generator
- (+) Contextual, social interaction
- (+) Agnostic to input representation
- (-) Sampling instead of joint modeling

the owl is sitting in the tree

Reasoning about Pragmatics with Neural Listeners and Speakers
Andreas and Klein (2016)

**Goal:** Generate reference text

Hu et al. (2017)

**Goal:** Generate controllable text

**Data:** IMDB, Stanford Sentiment Treebank-2, TimeBank

**Method:** Variational Auto-Encoder

*the film is strictly routine!*

*the film is full of imagination.*

- (+) Semi-supervised, requires little labeled data
- (-) Unclear how to extend to multi-dimensional attributes with complex interactions
Considering Context

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Generation

1. How can we customize generation to emphasize persuasion?

2. How can we generate goal-oriented and globally coherent arguments?

**Framing**

- Ding and Pan (2016)
- Bilu and Slonim (2016)

**Goal-oriented**

- Li et al. (2016)
- Dodge et al. (2016)

**Context-driven**

- Andreas and Klein (2016)
- Hu et al. (2017)

**Coherent**

- Chen et al. (2009)
- Kiddon et al. (2016)
Li et al. (2016)

**Goal:** Generate dialog for maximizing the length of the conversation

**Data:** OpenSubtitles

**Method:** Deep reinforcement learning

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<th>B: I’m going to the restroom.</th>
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- (+) Models both agents in dialog simultaneously
- (-) Preventing loops may contrast with other goals
### Li et al. (2016)

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Accomplishing Goals

Li et al. (2016)

**Goal:** Generate dialog likely to result in continued dialog

Dodge et al. (2016)

**Goal:** Generate dialog for question answering

**Data:** Online Movie Database, Reddit movies sub-reddit

**Method:** Memory network

---

A: I liked Tombstone and The Net. I’m looking for a Fantasy film.
B: Jumanji
A: Who directed that?
B: Joe Johnston
A: I like Tim Burton movies more...

- (+) Ability to store and query factual information
- (-) No shared representation between memory elements
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**Coherent**
- Chen et al. (2009)
- Kiddon et al. (2016)
Chen et al. (2009)

**Goal:** Model topic transitions  
**Data:** Wikipedia  
**Method:** Generalized Mallows Model

- (+) Works well for domain-specific modeling  
- (-) Bag-of-words generation
Modeling Coherence

Chen et al. (2009)

**Goal**: Model topic transitions

**Data**: Wikipedia

**Method**: Generalized Mallows Model

- (+) Works well for domain-specific modeling
- (-) Bag-of-words generation
### Chen et al. (2009)

**Goal:** Improve topic transitions by global constraints on ordering

### Kiddon et al. (2016)

**Goal:** Generate text from an agenda

**Data:** Recipes, Hotel dialogs

**Method:** Neural LM with soft checklist

- Sift *flour*, measure, and sift with *baking powder* and *salt*. Fold in stiffly beaten *egg whites*.

- Able to balance long-term goals with short-term word generation
1. **How can we customize generation to emphasize persuasion?**
   - **Framing**
     - Bilu and Slonim (2016) - template-based generation of claims
     - Ding and Pan (2016) - emphasis of attributes based on personality
   - **Context**

2. **How can we generate goal-oriented and globally coherent arguments?**
   - **Goals**
   - **Coherence**
1. *How can we customize generation to emphasize persuasion?*
   - Framing
   - *Context*
     - Andreas and Klein (2016) - pragmatic reasoning for descriptions
     - Hu et al. (2017) - text generation conditioned on attributes

2. *How can we generate goal-oriented and globally coherent arguments?*
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   - Coherence
1 How can we customize generation to emphasize persuasion?
   • Framing
   • Context

2 How can we generate goal-oriented and globally coherent arguments?
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     • Li et al. (2016) - maximizing conversation length for dialogue
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1. **How can we customize generation to emphasize persuasion?**
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   - Context

2. **How can we generate goal-oriented and globally coherent arguments?**
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   - Coherence
     - Chen et al. (2009) - topic modeling and ordering
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Goals of persuasive argumentation:

1) Providing knowledge
   - Structure
     - Causality
   - Personal
   - Emotional

2) Convincing
   - Coherence
     - Framing
     - Goals
     - Context
   - Chen Kiddon Bilu
   - Ding Li Dodge Andreas
   - Hu
Conclusion

Goals of persuasive argumentation:

1) Providing knowledge
   - Structure
   - Causality

2) Convincing
   - Personal
   - Emotional

Trees/Graphs
- Coherence
- Framing

Contextual
- Distributional
- Formal Logic

Social Interaction
- Framing
- Pragmatics

Sentiment
- Topic/Context