Argument Mining using Argumentation Scheme Structures

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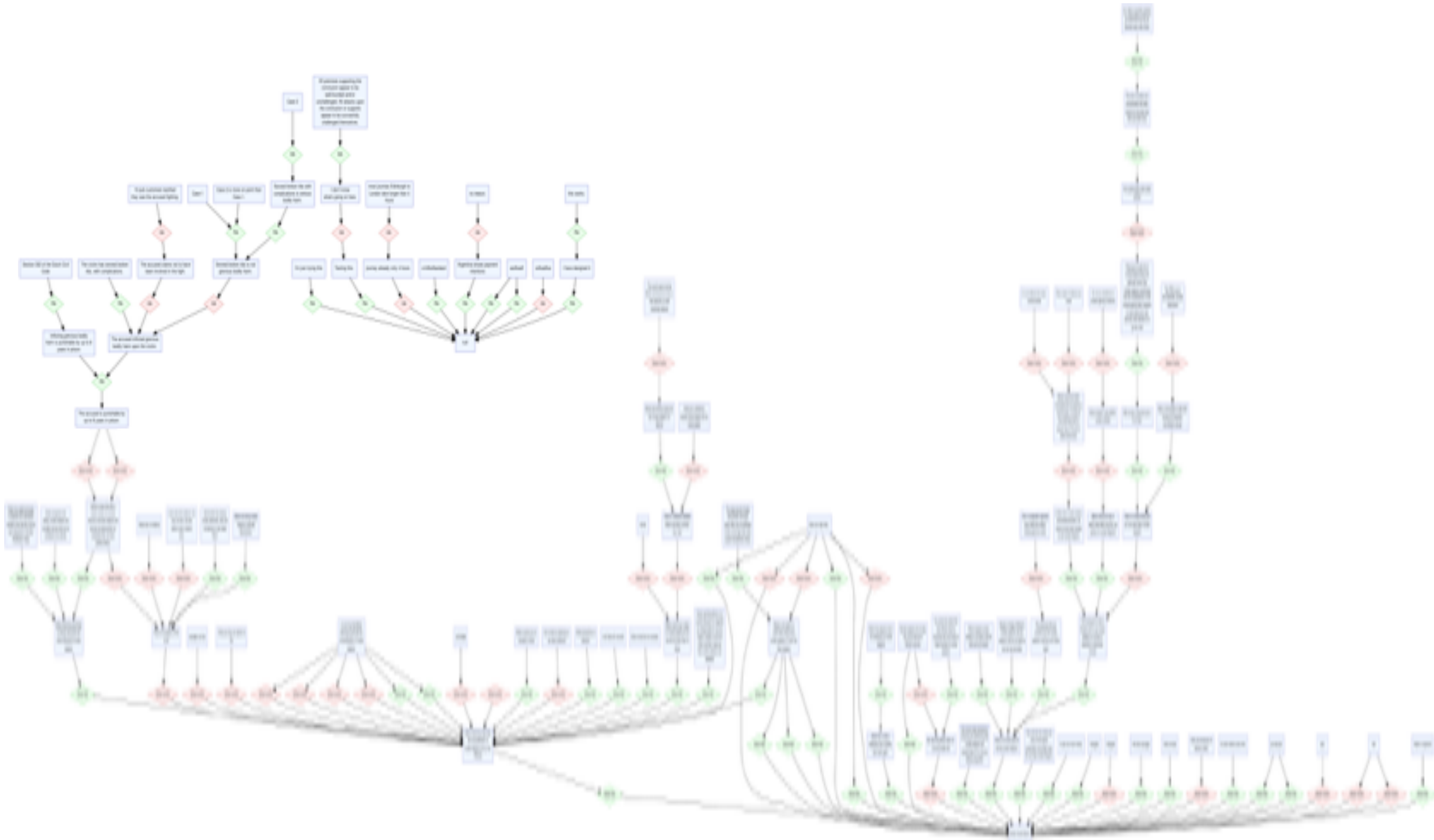
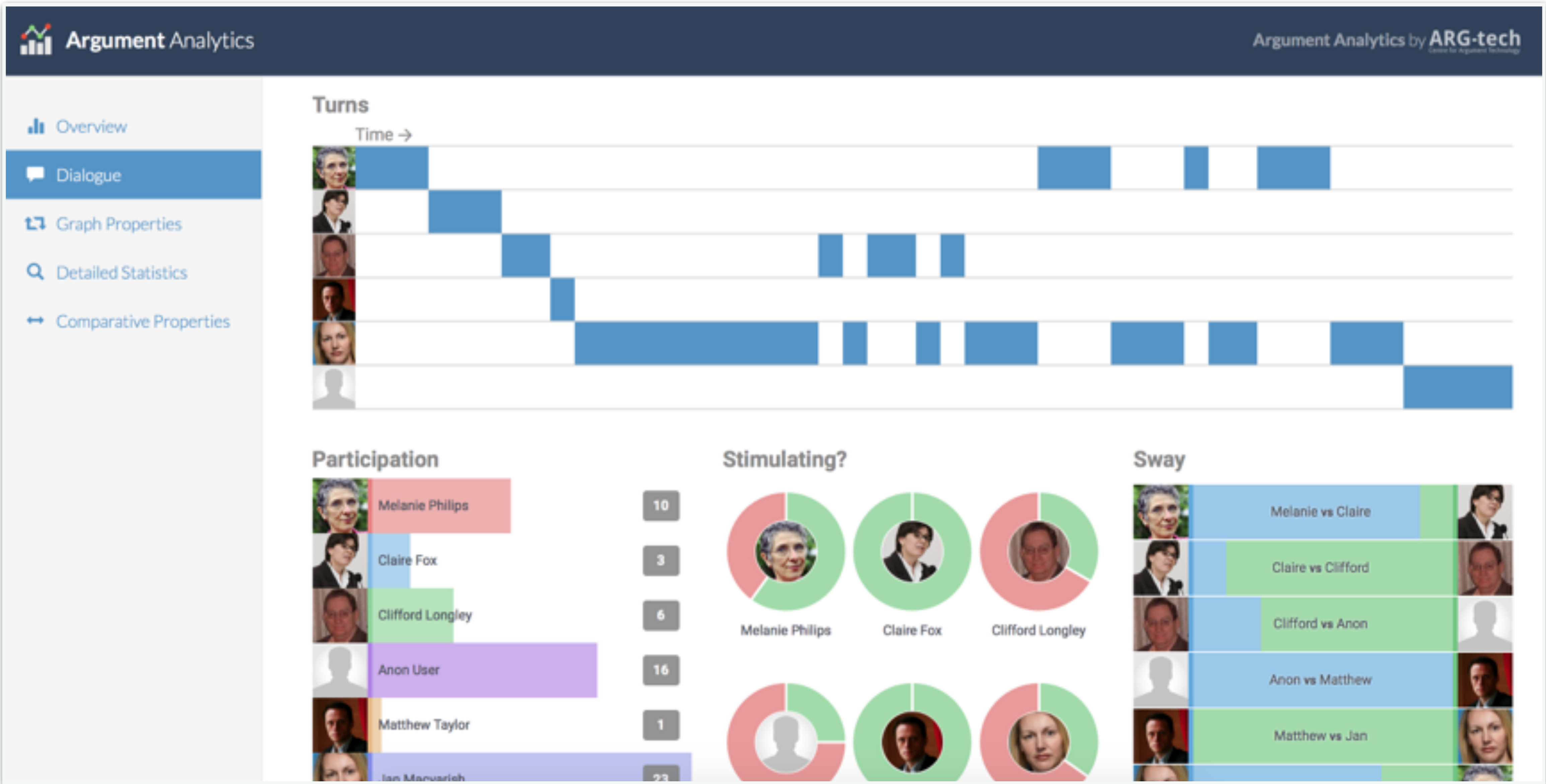
Argument Mining


ELECTION 2016
Election 2016
HollywoodLife.com
Click For More Pics Of Presidential Debate '16
Donald J. Trump @realDonaldTrump · 4h
"@FrankLuntz: I'm getting a lot of @MegynKelly hatemail tonight. #GOPDebate" She is totally overrated and angry. She really bombed tonite
Donald J. Trump @realDonaldTrump · 4h
.@FrankLuntz is a low class slob who came
CNN DEMOCRATIC PRESIDENTIAL DEBATE
TUESDAY 8:30 PM ET
THE DEMOCRATS
RUNNING
CHAFEE CLINTON LESSIG O'MALLEY SANDERS WEBB
EXPLORING
BIDEN
NOT RUNNING
WARREN
THE REPUBLICANS
RUNNING
BUSH CARSON CHRISTIE CRUZ FIORINA GILMORE GRAHAM HUCKABEE
JINDAL KASICH PATAKI PAUL RUBIO SANTORUM TRUMP
DROPPED OUT
PERRY WALKER
NOT RUNNING
ROMNEY





Argument Analytics

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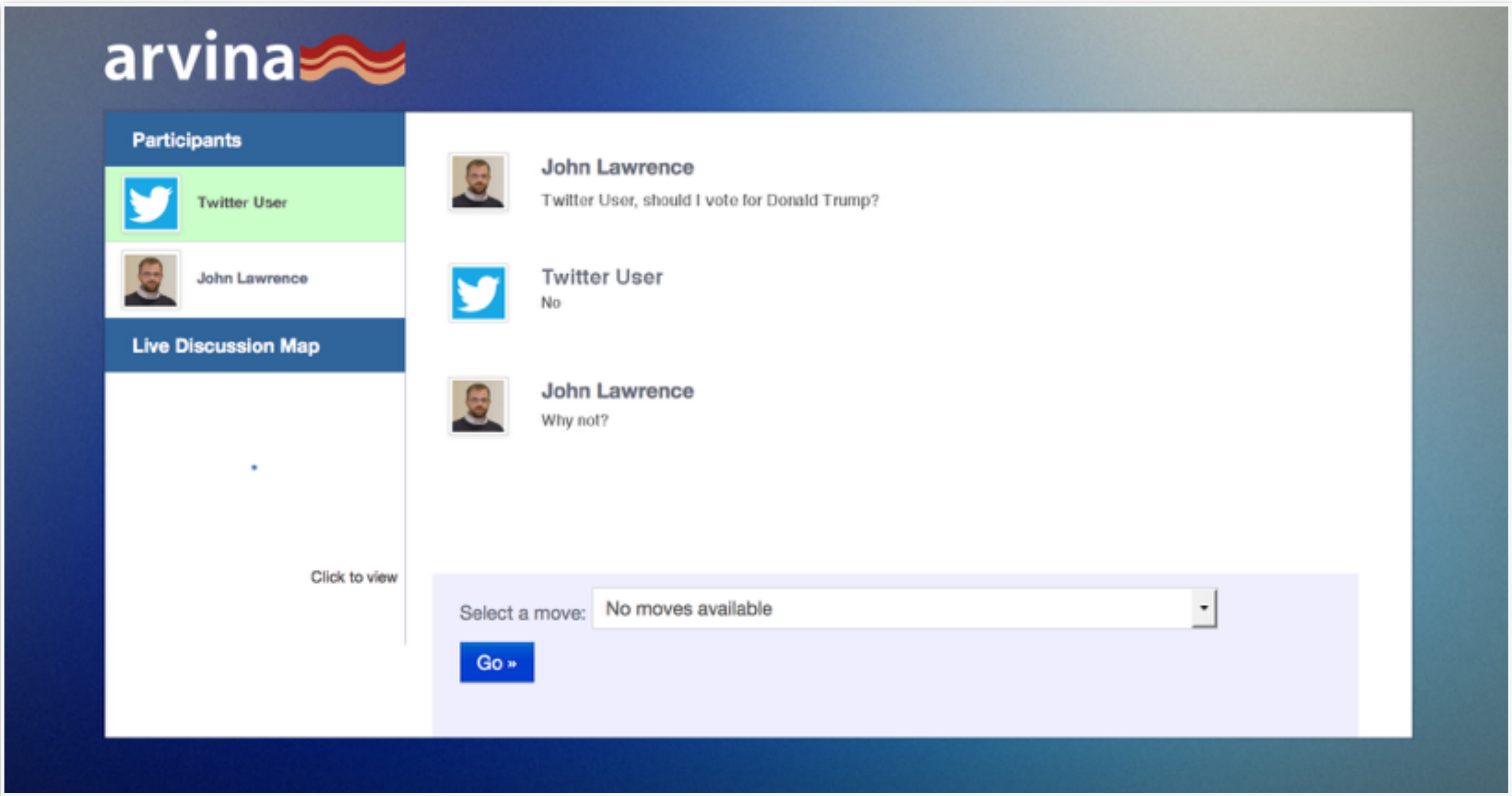
Argument Mining using Argumentation Scheme Structures

John Lawrence



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Human Annotation

Example

Trump's speech was poor. The speech was "lacking in policy prescriptions," and its "strident rhetoric masked a lack of depth," said Robert McFarlane, a former national security adviser. However, his popularity in the polls continues to rise, perhaps because of his recently self-declared high IQ.

Example

Trump's speech was poor. The speech was "lacking in policy prescriptions," and its "strident rhetoric masked a lack of depth," said Robert McFarlane, a former national security adviser. **However**, his popularity in the polls continues to rise, perhaps **because** of his recently self-declared high IQ.

Discourse Indicators ("However", "because")

Example

Trump's speech was poor. The speech was "lacking in policy prescriptions," and its "strident rhetoric masked a lack of depth," said Robert McFarlane, a former national security adviser.

....

However, his popularity in the polls continues to rise, perhaps because of his recently self-declared high IQ.

Topical Similarity

Example

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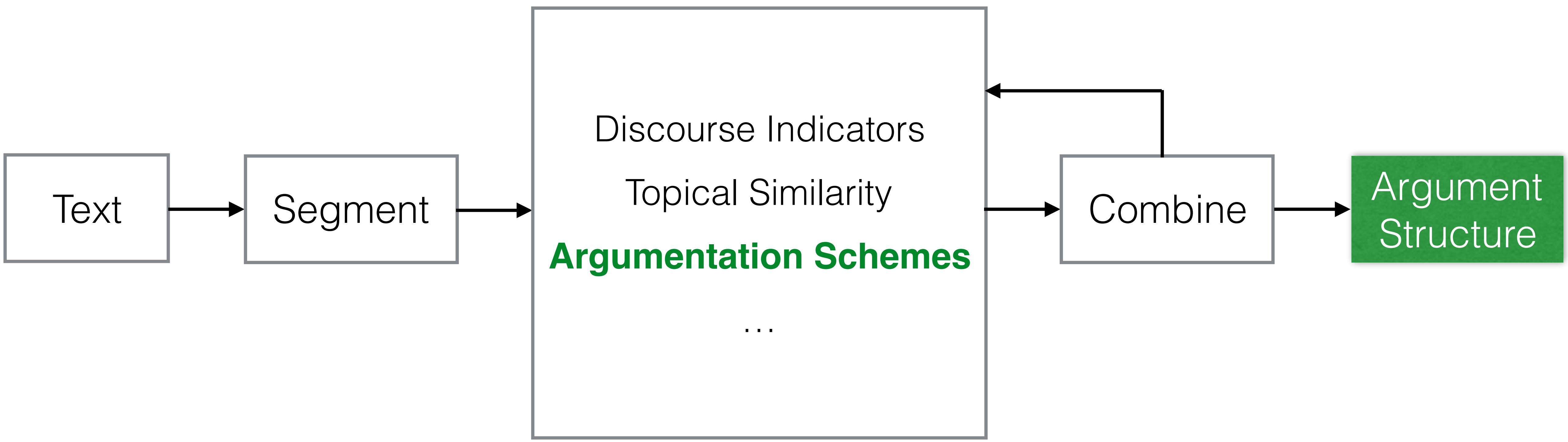
Argumentation Schemes
(Argument from expert opinion)


Text
Segment
Discourse Indicators
Topical Similarity
Argumentation Schemes
...
Combine
Argument Structure

Argumentation Scheme Structures

V. W. Feng and G. Hirst. Classifying arguments by scheme. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, pages 987–996. Association for Computational Linguistics (ACL), 2011*

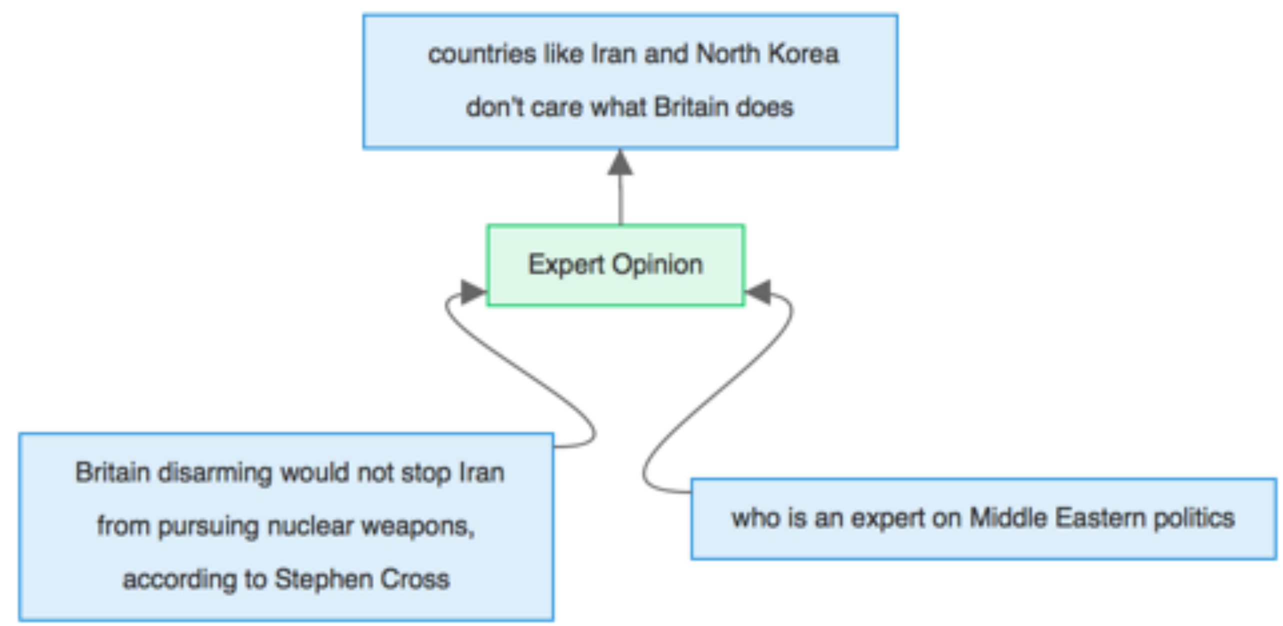
Aims to classify instances of schemes based on pre-identified structure

Identify segment as scheme **components**

Premise: Source E is an expert in subject domain S containing proposition A [FieldExpertise]

Premise: E asserts that proposition A is true (false) [KnowledgeAssertion]

Conclusion: A is true (false) [KnowledgePosition]



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Dataset

- Over 500 examples of schemes identified in AIFdb
- Limiting the data to those schemes with at least twenty instances that are fully defined:

Analogy (31 examples)

Cause To Effect (89 examples)

Practical Reasoning (68 examples)

Verbal Classification (38 examples)

Analogy (AN)

Premise [SimilarityOfCases]: Generally, case C1 is similar to case C2

Premise [Precedent]: A is true (false) in case C1

Conclusion: A is true (false) in case C2

CauseToEffect (CE)

Premise [Causal]: Generally, if A occurs, then B will (might) occur

Premise [Occurrence]: In this case, A occurs (might occur)

Conclusion: Therefore, in this case, B will (might) occur

PracticalReasoning (PR)

Premise [Goal]: I have a goal G

Premise [GoalPlan]: Carrying out this action A is a means to realise G

Conclusion: Therefore, I ought (practically speaking) to carry out this action A

VerbalClassification (VC)

Premise [ContainsProperty]: a has a property F

Premise [ClassificationProperty]: For all x, if x has a property F, then x can be classified as having a property G

Conclusion: a has property G

Classifiers for each **component**

Unigrams	Each word in the proposition
Bigrams	Each pair of successive words
Length	The number of words in the proposition
AvgWLength	The average length of words in the proposition
POS	The parts of speech contained in the proposition
Punctuation	The presence of certain punctuation characters, for example " " indicating a quote
Similarity	The maximum similarity of a word in the proposition to pre-defined words corresponding to each proposition type

Type	Keywords
AN Similar	similar, generally
AN Precedent	be (to be)
AN Conc	be (to be)
CE Causal	generally, occurs
CE Occurance	occurs
CE Conc	occurs
PR Goal	goal
PR GoalPlan	action
PR Conc	ought, perform
VC Property	be (to be)
VC Class	all, if
VC Conc	be (to be)

Results: One vs Others Classification

Type	Naïve Bayes			SVM			Decision Tree		
	p	r	f1	p	r	f1	p	r	f1
PR Goal	0.65	0.79	**0.71**	0.55	0.86	0.67	0.59	0.71	0.65
PR GoalPlan	0.65	0.93	0.76	0.76	0.93	**0.84**	0.75	0.86	0.80
PR Conc	0.90	0.64	0.75	0.55	0.43	0.48	0.76	0.93	**0.84**
CE Causal	0.57	0.89	0.70	0.58	0.61	0.59	0.94	0.89	**0.91**
CE Occurance	0.50	0.72	**0.59**	0.40	0.22	0.29	0.38	0.33	0.35
CE Conc	0.73	0.89	**0.80**	0.54	0.78	0.64	0.57	0.72	0.63
AN Similar	0.58	1.00	**0.74**	0.60	0.43	0.50	0.56	0.71	0.63
AN Precedent	0.64	1.00	**0.78**	0.75	0.43	0.55	0.29	0.29	0.29
AN Conc	1.00	0.29	0.44	0.38	0.43	0.40	0.57	0.57	**0.57**
VC Property	0.88	0.88	**0.88**	1.00	0.50	0.67	0.75	0.75	0.75
VC Class	0.58	0.88	0.70	0.67	0.75	0.71	0.75	0.75	**0.75**
VC Conc	1.00	0.50	**0.67**	0.62	0.62	0.62	1.00	0.38	0.55

Baseline = 0.5

Identifying Scheme Instances

Segments corresponding to (one or two) scheme components within a fixed window

Reduce the threshold for the other classifiers until we have matches for all components

Identifying Scheme Instances

Knowledge Assertion

Trump's speech was poor. **The speech was "lacking in policy prescriptions," and its "strident rhetoric masked a lack of depth," said Robert McFarlane**, a former national security adviser.

Threshold = 0.9

Identifying Scheme Instances

Trump's speech was poor. **The speech was "lacking in policy prescriptions," and its "strident rhetoric masked a lack of depth," said Robert McFarlane**, **a former national security adviser**.

Field Expertise

Threshold = 0.8

Identifying Scheme Instances

Trump's speech was poor. **The speech was "lacking in policy prescriptions," and its "strident rhetoric masked a lack of depth," said Robert McFarlane**, **a former national security adviser**.

Field Expertise

Threshold = 0.7

Identifying Scheme Instances

Knowledge Position

Trump's speech was poor. The speech was "lacking in policy prescriptions," and its "strident rhetoric masked a lack of depth," said Robert McFarlane, a former national security adviser.

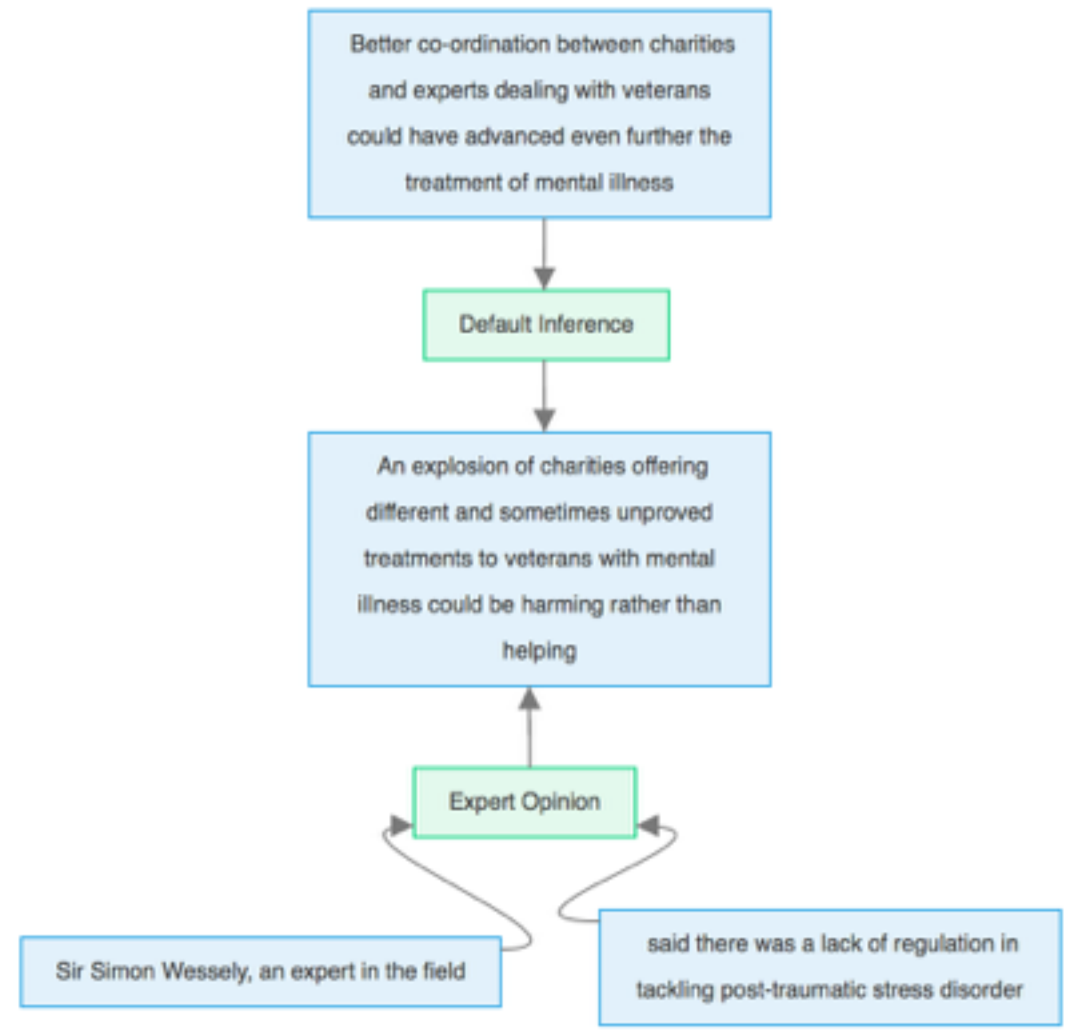
Field Expertise

Threshold = 0.6

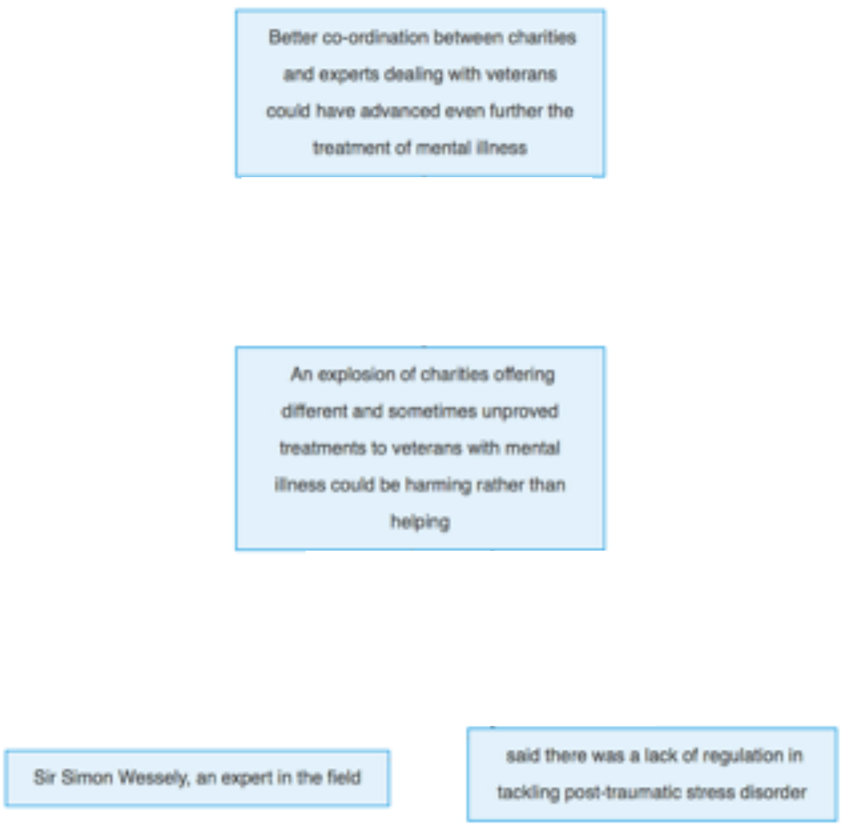
Combining Techniques

An explosion of charities offering different and sometimes unproved treatments to veterans with mental illness could be harming rather than helping, it was claimed last night.

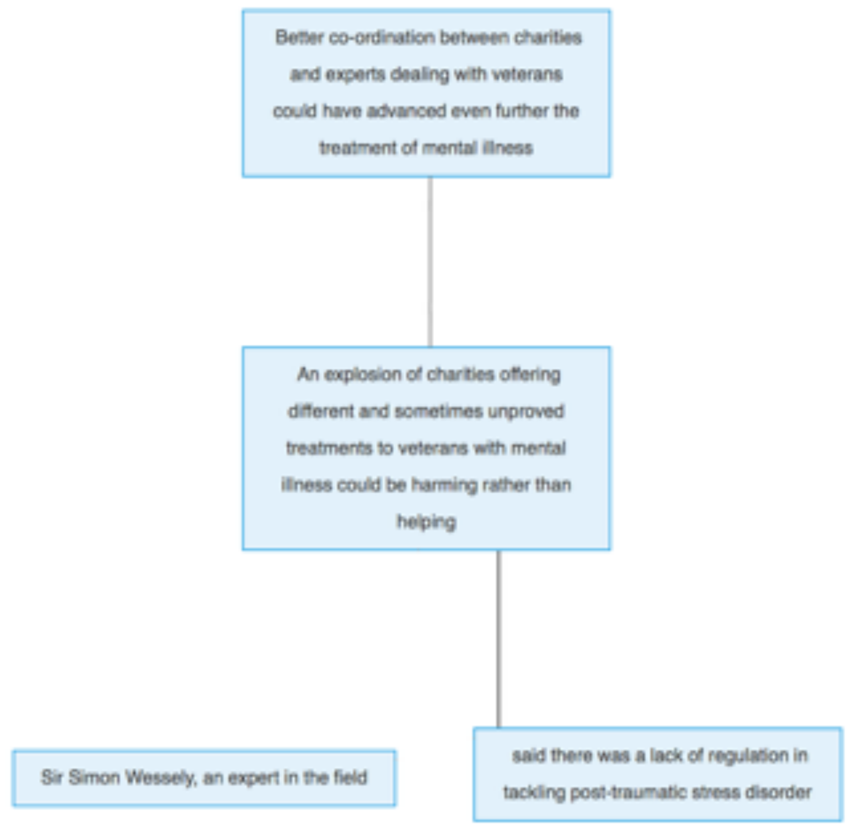
Sir Simon Wessely, an expert in the field said **there was a lack of regulation in tackling post-traumatic stress disorder**. **Better co-ordination between charities and experts dealing with veterans could have advanced even further the treatment of mental illness**



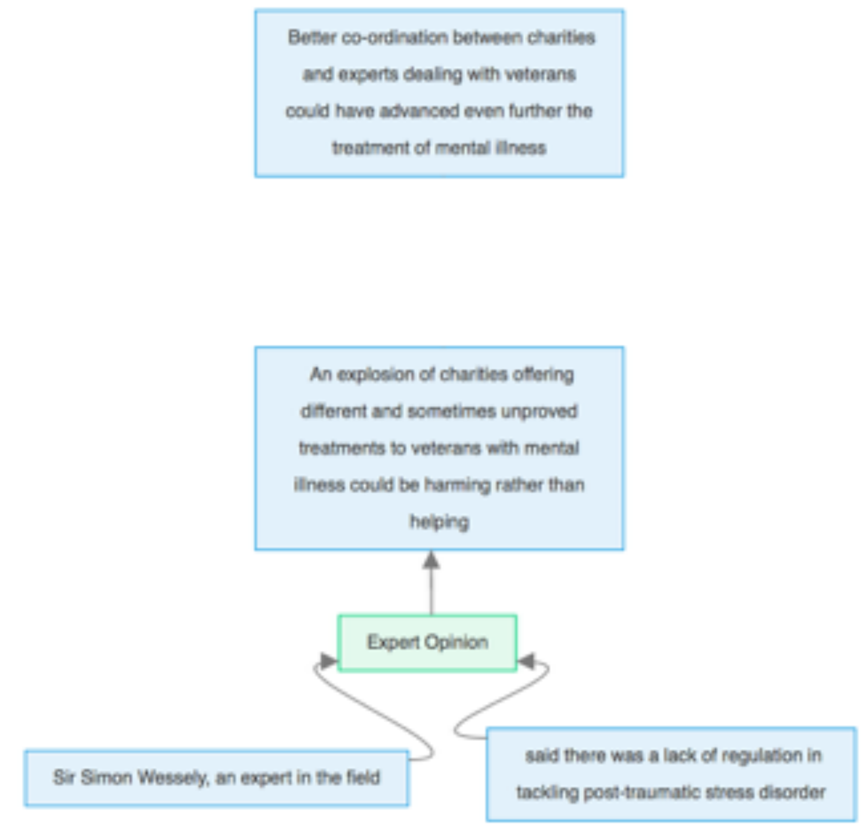
Manual Analysis



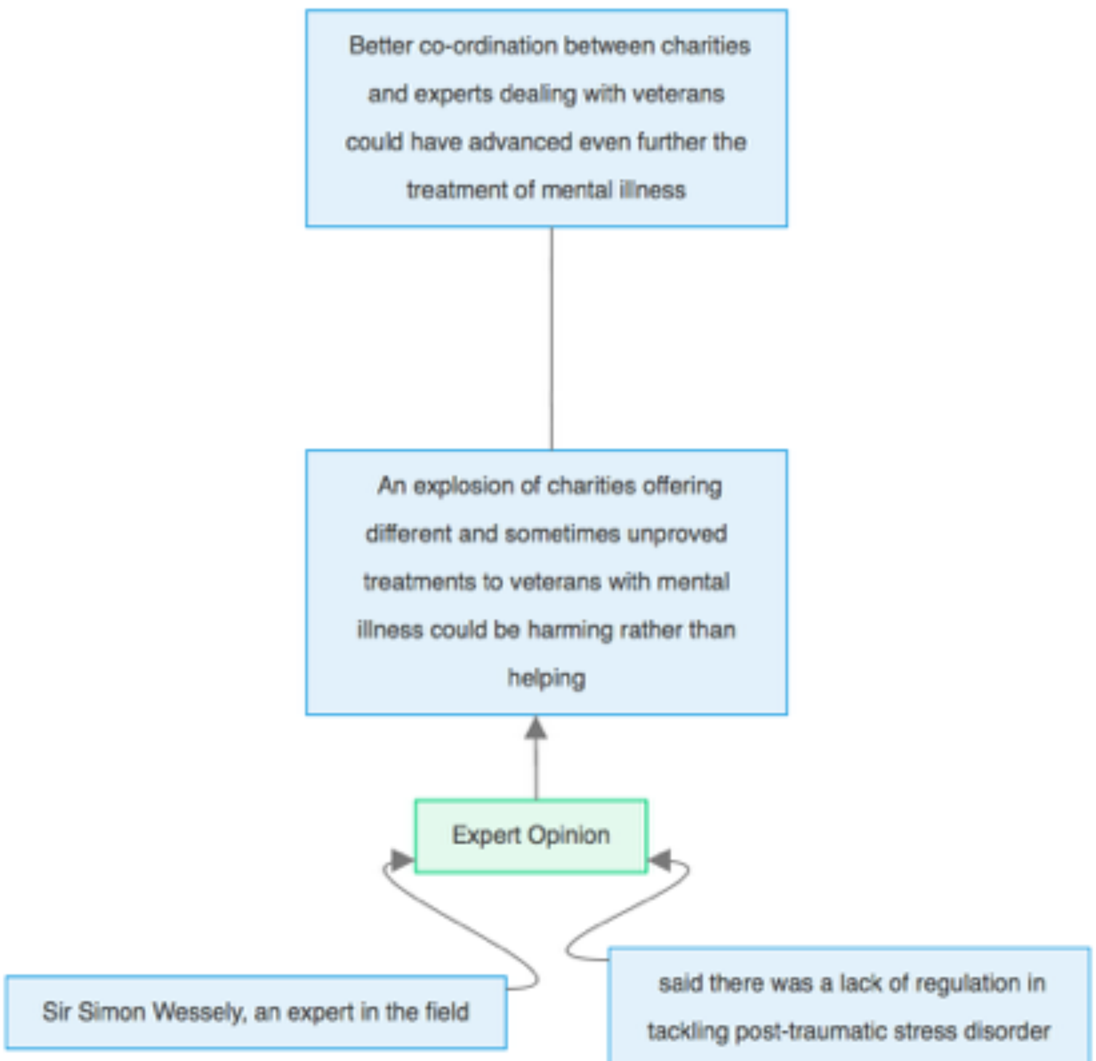
Discourse Indicators



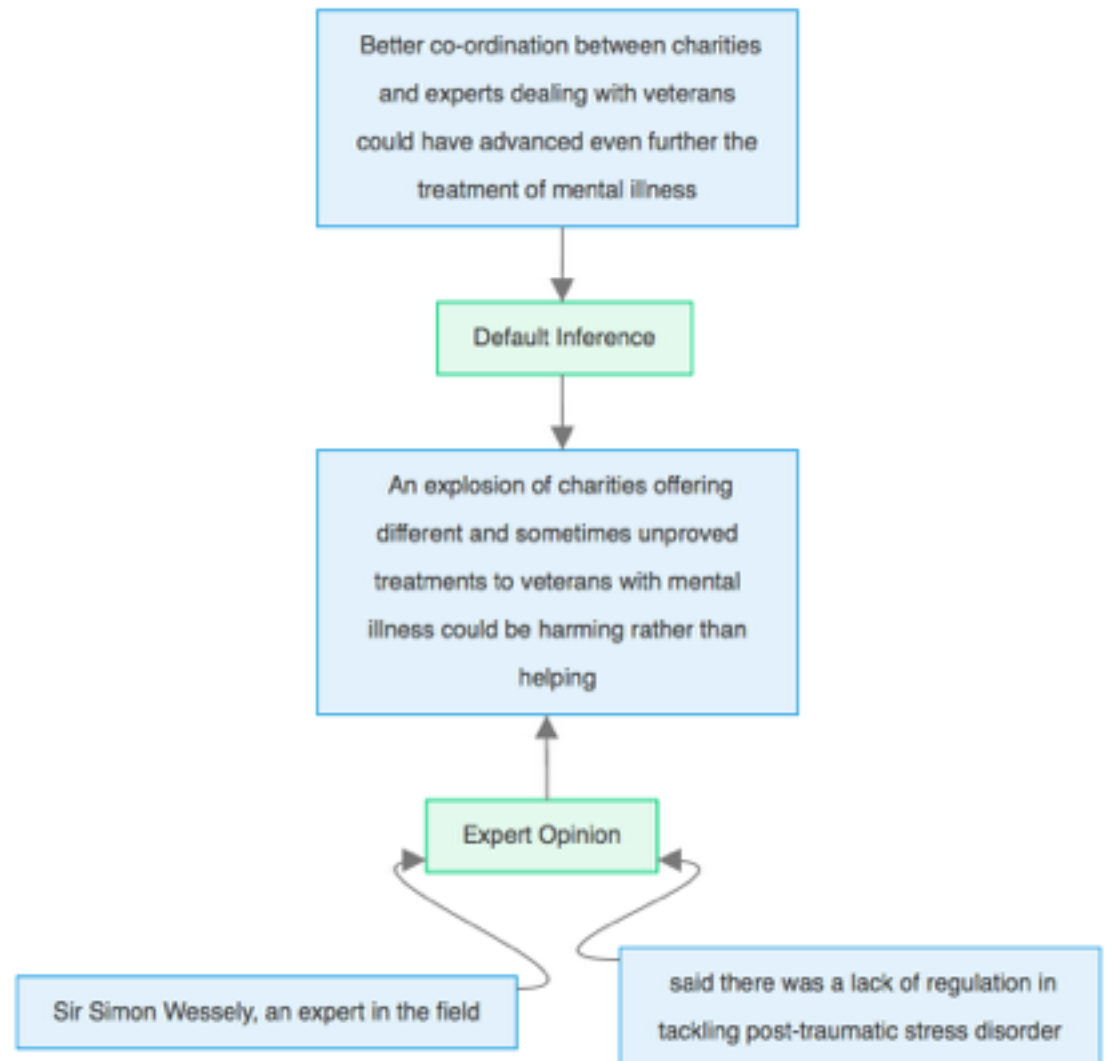
Topical Similarity



Scheme Structure



Combined Techniques



Manual Analysis