



# **Towards argument-based explanatory** dialogues: from argument mining to (explanatory) argument generation **Serena Villata**

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# High quality explanations for AI deliberations Challenges

- proper level of generality/specificity of the explanations
- reference to specific elements that have contributed to the deliberation
- analytic statements
- use of additional knowledge (common-sense knowledge, domain ontologies, knowledge bases, knowledge graphs, ...)
- use of examples (e.g., from the data the prediction is produced on)
- evidence supporting negative hypotheses

Formulate the explanation in a clearly interpretable, and possibly convincing, way



### Natural language explanations **Key features**

### **Argumentation theory**

### Task-oriented dialogues

### Natural language explanations

### Argument mining and generation



### Natural language explanations **Key features**

**Argumentation theory** 

### Task-oriented dialogues

### Natural language explanations

### Argument mining and generation



### Explanatory dialogues **Argumentation theory**

- Argumentation as reasoning-in-interaction
- Arguments need not only be rational, but "manifestly" rational (Johnson (2000))
- Arguers can see for themselves the rationale behind inferential steps taken
- In explanations
  - an agent accepts the conclusion but queries premises "OK that the diagnosis you proposed is D, but why?"
  - pragmatic goal is understanding, typically reached via causal reasoning

### **Explanatory argumentative dialogues** From argument mining to generation through extractive summaries

- The task of analysing discourse on the pragmatics level and applying a certain argumentation theory to model and automatically analyze the data at hand.
- Providing structured data for computational models of argument.
- Large resources of natural language texts: user-generated arguments on blogs, product reviews, newspapers,...
- Computational linguistics and machine learning advances.
- Argument mining IS NOT opinion mining.



Argument Mining



# Argument mining Twitter (LREC16, EMNLP17)

**Tasks**: argument detection (binary classification), factual vs. opinion classification, source identification.

**Data**: DART [Bosc et al., LREC2016], thread #Grexit (987 tweets) + 900 tweets from #Brexit. 2 annotators, IAA:  $\kappa$ =0.767 (1st task, 100 tweets),  $\kappa$ =0.727 (2nd task, 80), Dice=0.84 (3rd task, whole dataset)).

**FACT:** The Guardian: Greek crisis: European leaders scramble for response to referendum no vote. http://t.co/cUNiyLGfg3 **OPINION:** Trump is going to sell us back to England. #Brexit #RNCinCLE

### Method and results:

Task	Method	Features	Results
argument detection	LR	lex., Twitter, synt., sem., sent.	0.78
factual/opinion classification	LR	lex., Twitter, synt., sem., sent.	0.80
source identification	Matching $+$ heuristics		0.67



# Mining argumentative structures from clinical trials Al in Medicine 2021, ECAI20, COMMA2020, IJCAI19

**Task**: argument component detection (evidence, claims) and relation prediction (attack, support).

**Data**: 4073 argument components (2808 evidence, 1265 claims). IAA: 3 ann., 10 abs., Fleiss'  $\kappa = 0.72$  (arg. comp.) and  $\kappa = 0.68$  (c/e) – 2601 argument relations (2259 supports, 342 attacks). IAA: 3 ann., 30 abs., Fleiss'  $\kappa = 0.62$ . **Topics**: neoplasm, glaucoma, hepatitis, diabetes, hypertension.

[The diurnal intraocular pressure reduction was significant in both groups (P < 0.001)]<sub>1</sub>. [The mean intraocular pressure reduction from baseline was 32% for the latanoprost plus timolol group and 20% for the dorzolamide plus timolol group<sub>2</sub>. The least square estimate of the mean diurnal intraocular pressure reduction after 3 months was -7.06 mm Hg in the latanoprost plus timolol group and -4.44 mm Hg in the dorzolamide plus timolol group (P < 0.001)]<sub>3</sub>. This study clearly showed that [the additive diurnal intraocular] pressure-lowering effect of latanoprost is superior to that of dorzolamide in patients treated with timolol]<sub>1</sub>.

**Method**: Gated Recurrent Unit + Conditional Random Fields, sciBERT. **Results** : evidence (F1: **0.92**), claim (F1: **0.88**), arg. comp. (F1: **0.87**) – relation classification F1: .68.

Review > Infez Med. 2020 Ahead of print Jun 1;28(2):198-211.

#### Update on treatment of COVID-19: ongoing studies between promising and disappointing results

Silvano Esposito<sup>1</sup>, Silvana Noviello<sup>1</sup>, Pasquale Pagliano<sup>1</sup>

Affiliations + expand PMID: 32335561 Free article

#### Abstract

The COVID-19 pandemic represents the greatest global public health crisis since the pandemic influenza outbreak of 1918. We are facing a new virus, so several antiviral agents previously used to treat other coronavirus infections such as SARS and MERS are being considered as the first potential candidates to treat COVID-19. Thus, several agents have been used by the beginning of the current outbreak in China first and all over the word successively, as reported in several different guidelines and therapeutic recommendations. At the same time, a great number of clinical trials have been launched to investigate the potential efficacy therapies for COVID-19 highlighting the urgent need to get as quickly as possible high-quality evidence. Through PubMed, we explored the relevant articles published on treatment of COVID-19 and on trials ongoing up to April 15, 2020.

> **Collaborations**: INSERM, CHU Nice





# Mining argumentative structures from clinical trials Al in Medicine 2021, ECAI20, COMMA2020, IJCAI19



**Outcome Analysis** 

# ACTA

### **Argumentative Clinical Trial Analysis**

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superiority of th



### http://ns.inria.fr/acta/

Home About Contacts

Abstract: One attempt to improve long-term survival in patients wi advanced ovarian cancer was thought to be the addition non-cross-resistant drugs to platinum-paclitaxel combin regimens. Gemcitabine was among the candidates for a t We performed a prospective, randomized, phase III, interto compare carboplatin plus paclitaxel (TC; area under th [AUC] 5 and 175 mg/m(2), respectively) with the same combination and additional gemcitabine 800 mg/m(2) on and 8 (TCG) in previously untreated patients with advance epithelial ovarian cancer. TC was administered intravenou on day 1 every 21 days for a planned minimum of six cours Gemcitabine was administered by IV on days 1 and 8 of ea in the TCG arm. Between 2002 and 2004, 1,742 patients randomly assigned; 882 and 860 patients received TC an respectively. Grades 3 to 4 hematologic toxicity and fatig occurred more frequently in the TCG arm. Accordingly, qu life analysis during chemotherapy showed a disadvantage TCG arm. Although objective response was slightly highe TCG arm, this did not translate into improved progression <mark>survival</mark> (PFS) or <mark>overall survival</mark> (OS). Median PFS was 17 months for the TCG arm and 19.3 months for the TC arm ratio [HR], 1.18; 95% CI, 1.06 to 1.32; P = .0044). Median 49.5 for the TCG arm and 51.5 months for the TC arm (HI 95% CI, 0.91 to 1.20; P = .5106). The addition of gemcita carboplatin plus paclitaxel increased treatment burden, re PFS time, and did not improve OS in patients with advance epithelial ovarian cancer. Therefore, we recommend no a clinical use of TCG in this population.

Highlight Argumentative Components

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# Mining political arguments COLING20, IJCAI19 demo, ACL19 short, AAAI18

**Task:** argument component detection (claim, premises) and relation classification (attack, support).

Data: 29521 argument components (16087 claims and 13434 premises) and 25012 relations (3723 attacks and 21289 supports). IAA: 3 ann., moderate/faire agreement.

Method: LSTM + Fine tuned BERT

Results: evidence (F1: 0.72), claim (F1: 0.69), argument components (F1: 0.84), relation classification (F1: 0.68)



**Collaborations**: Univ. of Luxembourg





### Mining political arguments COLING20, IJCAI19 demo, ACL19 short, AAAI18





#### Premise4

We have thousands, equivalent of megaton, or million tons, of TNT warheads

**Collaborations**: Univ. of Luxembourg





# Disputol https://disputool.uni.lu/



Filter data **Based on Year:** 

#### 21 Oct 1960

#### Filter

Highlight Claims Hiahlight Pren

Based on NER Type:

Based on Speaker: 🗆 Barack H. Obama Donald J. Trump 🗆 George H. W. Bush 🗆 George W. Bush Geraldine A. Ferraro Henry Ross Perot Hillary D. R. Clinton James B. Stockdale James D. Quayle Jimmy E. Carter John B. Anderson John F. Kennedy □ Johnny(John) R. Edwards 🗆 Joseph I. Lieberman Joseph(Joe) R. Biden 🗆 Lloyd M. Bentsen Michael S. Dukakis Richard M. Nixon Richard(Dick) B. Cheney 🗆 Ronald W. Reagan Walter F. Mondale Willard(Mitt) M. Romney William(Bill) J. Clinton APPLY FILTER

Our policies are very different. Now I don't know what Senator Kennedy suggests when he says that we should help those who oppose the Castro regime, both in Cuba and without. But I do know this: that if know something else. Now, what can we do? Well



number one. Number two, and also the countries of Western Europe, Canada, Japan and the others. Number three, 🖸 only the beginning of our difficulties throughout Latin America. The big st nce is growing - mostly because thi ver have had Castro. Why didn't we?





# Explanatory arguments (and their further use in dialogues)

### **Argument-based explanation patterns** (Darpa XAI Program Update)

 analytic statements in NL that describe the elements and context that support a choice,  $\rightarrow$  the arguments (evidence, claim, warrant if any)

- **visualizations** that highlight portions of the raw data that support a choice,
- cases that invoke specific examples, and

hard, you need more than one case to support by examples the choice

rejections of alternative choices that argue against less preferred answers based on analytics, cases, and data.

hard, you need the arguments from the rejected options



# Use case example to build the dataset

A 37-year-old woman is brought to the emergency department because of intermittent chest pain for 3 days. The pain is worse with inspiration, and she feels she cannot take deep breaths. She has not had shortness of breath, palpitations, or nausea. She had an upper respiratory tract infection 10 days ago and took an over-the-counter cough suppressant and decongestant and acetaminophen. Her temperature is 37.2°C (98.9°F), pulse is 90/min, and blood pressure is 122/70 mm Hg. The lungs are clear to auscultation. S1 and S2 are normal. A rub is heard during systole. There is no peripheral edema. An ECG shows normal sinus rhythm and diffuse, upwardly concave ST-segment elevation and PR-segment depression in leads II, III, and a VF.

### Use case example Training residents to improve argument-based diagnosis

- Which of the following is the most likely diagnosis?
  - (A) Acute pericarditis
  - (B) Aortic dissection
  - (C) Gastroesophageal reflux disease
  - (D) Myocardial infarction
  - (E) Peptic ulcer disease
  - (F) Pulmonary embolism
  - (G) Unstable angina pectoris



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### Use case example Training residents to improve argument-based diagnosis

### Which of the following is the most likely diagnosis? (A) Acute pericarditis

### Why?

A friction rub and diffuse low-grade ST-segment elevation equals pericarditis.



# Use case example

- because of intermittent chest pain for 3 days. The pain is worse with a VF.
- and diffuse low-grade ST-segment elevation.

• <u>Clinical case</u>: a 37-year-old woman is brought to the emergency department inspiration, and she feels she cannot take deep breaths. She has not had shortness of breath, palpitations, or nausea. She had an upper respiratory tract infection 10 days ago and took an over-the-counter cough suppressant and decongestant and acetaminophen. Her temperature is 37.2°C (98.9°F), pulse is 90/min, and blood pressure is 122/70 mm Hg. The lungs are clear to auscultation. S1 and S2 are normal. A rub is heard during systole. There is no peripheral edema. An ECG shows normal sinus rhythm and diffuse, upwardly concave ST-segment elevation and PR-segment depression in leads II, III, and <u>Diagnosis</u>: the patient is showing a pericarditis because she has a friction rub

### First step: extractive explanatory argument generation

- because of intermittent chest pain for 3 days]. [The pain is worse with leads II, III, and a VF].
- systole] and the ECG shows [concave ST-segment elevation].

• <u>Clinical case</u>: [a 37-year-old woman is brought to the emergency department] inspiration], and she feels [she cannot take deep breaths]. [She has not had shortness of breath, palpitations, or nausea]. [She had an upper respiratory tract infection 10 days ago] and [took an over-the-counter cough suppressant] and decongestant and acetaminophen]. [Her temperature is 37.2°C (98.9°F)], [pulse is 90/min], and [blood pressure is 122/70 mm Hg]. [The lungs are clear to auscultation]. [S1 and S2 are normal]. [A rub is heard during systole]. [There is no peripheral edema]. [An ECG shows normal sinus rhythm and diffuse], [upwardly concave ST-segment elevation] and [PR-segment depression in

• <u>Diagnosis</u>: the patient is showing a pericarditis because [a rub is heard during]



# **Extractive explanatory argument generation Argument Mining + Knowledge graphs**

- has a friction rub and diffuse low-grade ST-segment elevation.
- **because** [a rub is heard during systole] and the ECG shows [concave ST-segment] elevation].
- What we have?
  - Premises extracted from description of the case, correct diagnosis.
- What we need further?
  - diagnosis -> knowledge graphs of clinical knowledge
  - What if the explanation is not "contained" in the evidence?

**Diagnosis with explanation by expert**: the patient is showing a pericarditis **because** she

**Diagnosis with extracted explanatory arguments**: the patient is showing a pericarditis

• Criteria to choose among the premises to pick the right ones, those which justify the

# **Explanatory dialogues Argument mining and generation**

- (Counter-)argument generation SoA (e.g., (Park et al., 2019, Hua et al., 2019)): mainly reformulation of arguments mined from Wikipedia and newspaper articles
- Insufficient to generate effective and interactive explanatory arguments
- **Extractive argument generation vs. abstractive argument generation**
- Large-scale unsupervised language models to generate arguments
- **Explanatory arguments meet high quality arguments:** 
  - quality (i.e., variability of the explanatory arguments, no repetitiveness)
  - quantity
  - standard evaluation metrics: BLEU and BertScore

# Main open challenges

- (Annotated) Data
- World knowledge and specific domain knowledge
  - To allow for generalisations, instantiations, inferences
- How to evaluate explanatory dialogues?
  - quality and quantity of the generated arguments
  - structural simplicity, coherence, minimality
  - what else?
- Are these explanations actually for humans? If so, human feedback required!





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# Thanks !

