Argument Mining for MT

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Outline of my talk

"**Why do I search for someone like you, not working in the area of machine translation?** *The reason is that MT has seen an astonishing leap in translation quality and about four evaluations as of now has shown that MT has surpassed human translation quality for individual sentences. At the same time, the systems still totally lack any true understanding of the meaning of the sentence; no sanity checks or commonsense reasoning are involved. Given your work in argument mining, I think that you could provide a very useful* **high level picture of the current state of the art in processing of text meaning, esp. beyond the level of individual sentences**. *In short, I would like to learn* **what argument mining can offer to MT these days**."

[MTM2018 organisers' invitation email]

Argumentation: why is it important?

- A **reasoning framework** based on the need of **justifying**. Fundamental to decide, convince, explain, ...
- **Interdisciplinary topic**
  - Artificial Intelligence [Loui (1987), Pollock (1987)]
  - Philosophy [Aristotele, Toulmin (1958)]
  - Psychology [McGuire (1960)]
  - Linguistics [van Eemeren et al. (1996)]
- **Examples of Applications**
  - **Medical domain**: support systems for argumentative diagnosis
  - **Legal domain**: argumentative decisions based on laws
  - Online **debate platforms** (e.g., idebate.org, debategraph, ProCon.org)
  - Online systems for **conflicts resolution** (e.g., CyberSettle)

The dawning of argument mining

- Argument zoning in research articles [Teufel, 1999]
- "Argumentation Mining" first coined by Mochales and Moens in 2011
- Two events organized in 2014:
  - **Frontiers and Connections between Argumentation Theory and NLP** workshop in Bertinoro [Cabrio, Villata, Wyner]
  - 1st Workshop on Argumentation Mining @ACL 2014 in Baltimore [Green, Ashley, Litman, Reed, Walker]

What is Argument(ation) mining?

- Methods allowing for **the automatic identification and extraction of argument data from large resources of natural language texts** **to provide structured data for computational models of argument and reasoning engines.**
- Large resources of natural language texts: user-generated arguments on blogs, product reviews, newspapers,...
- Computational linguistics and machine learning advances (e.g., deep learning)

Argument mining vs opinion mining

- Goal of **opinion mining**: understand what people think about something
- Goal of **argument mining**: understand **why** people think X about something
  - Causes and reasons instead of opinion and sentiment

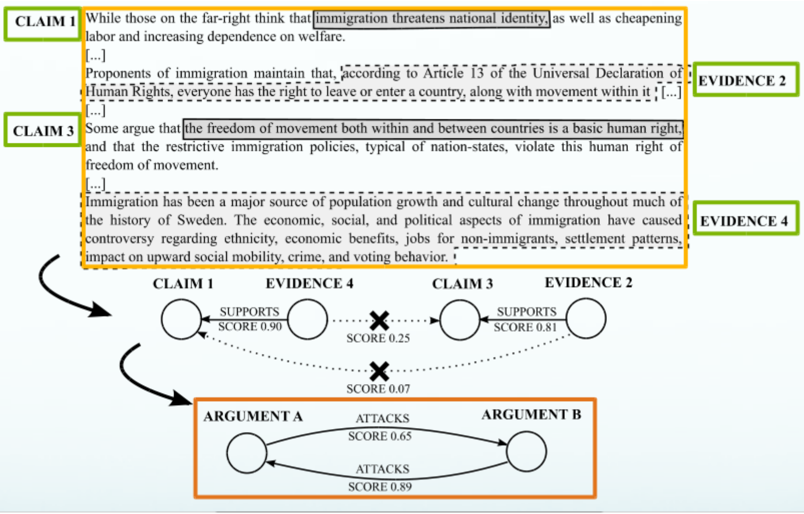
Moving from opinion analysis to the next step: analyse and understand the reasoning processes bringing humans to accept or reject an argument (or a theory or an opinion)

[Habernal, 2014]

Why is it a relevant topic?

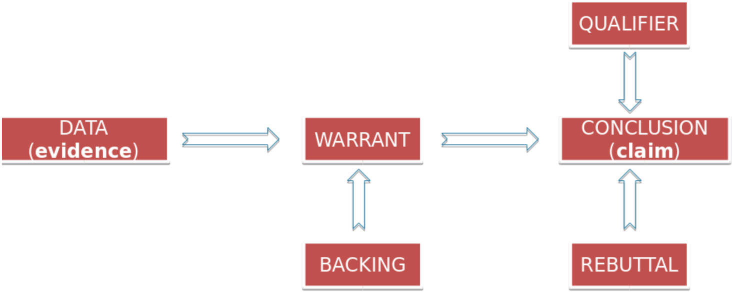
- Mining “arguments”: ability **to find, analyze and assess** arguments on large scale
  - Cognitive human task does not scale
  - Computational methods can process both **heterogeneous sources and big data**
- Analyzing complex lines of argumentation helps in **supporting decision making**
  - Argument maps from natural language texts
  - Structured summarization of huge texts
  - Contrasting viewpoints and recursive argumentative patterns

Example [Lippi, Torroni 2015]

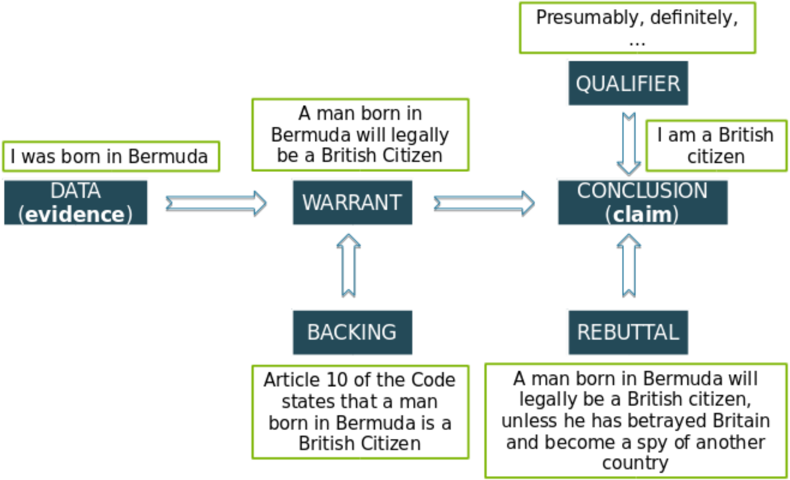


Argumentation models

- From dialectics and philosophy, to discover how:
  - statements and assertions are proposed and debated
  - conflicts between diverging opinions are resolved
- Toulmin model [1958]



Toulmin model - Example



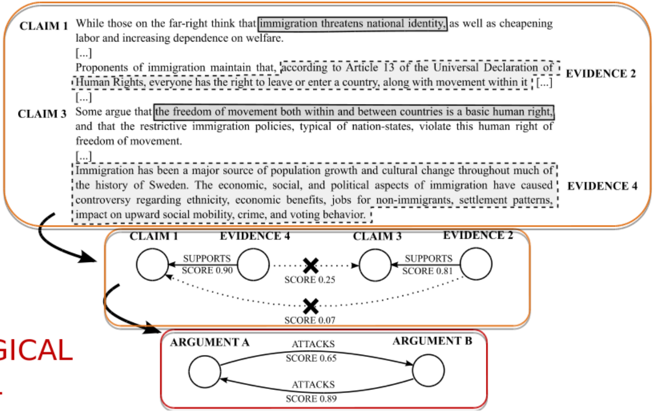
Argumentation models (cont.)

- Computational argumentation:
  - **Rhetorical models:** audience and persuasive intention
  - **Dialogical models:** how arguments are connected in dialogical structures
  - **Monological models:** structure of the arguments, relations between the different components of an argument
- Dynamics!

Argumentation models (cont.)

MONOLOGICAL MODELS

DIALOGICAL MODEL



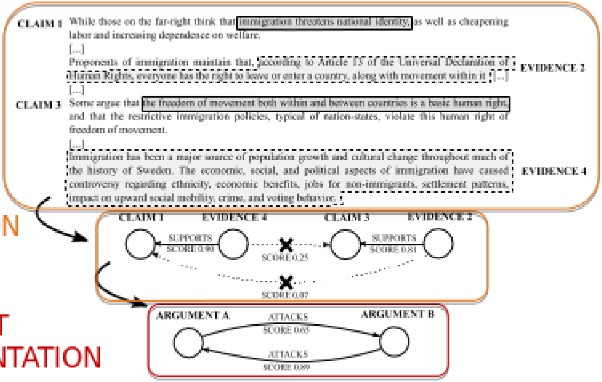
Argumentation models (cont.)

- **Structured argumentation**:
  - A set of premises, a conclusion, an inference from the premises to the conclusion [Walton, 2009]
  - Conclusion, claim
  - Premises, evidence, data, reasons
  - Inference, warrant, argument
  - Monological model
- **Abstract argumentation**:
  - Argument: atomic element without internal structure
  - Attacks between the arguments
  - Dialogical model

Argumentation models (cont.)

STRUCTURED ARGUMENTATION

ABSTRACT ARGUMENTATION



Argumentation models (cont.)

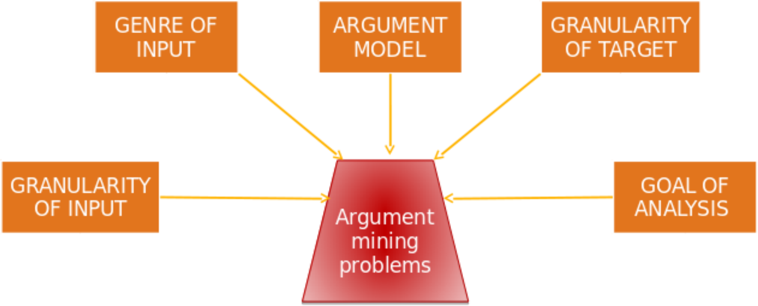
Argumentation schemes [Walton, Macagno, Reed, 2008]

- Informal argumentation
- Identify and prevent errors in reasoning (fallacies)
- 60 schemes
  - Argument from Expert Opinion
  - Argument from Analogy
  - Argument from Example
  - Argument from Position to Know
  - Argument from Ignorance
  - ...

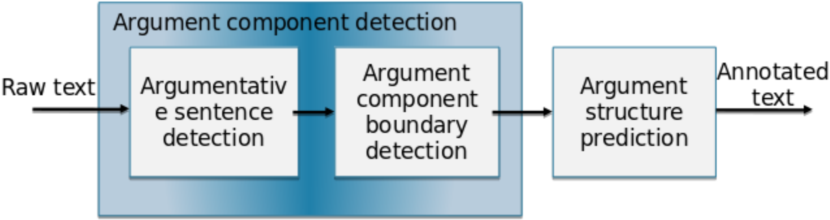
Argumentation models (wrapping up)

- **Micro-level**
  - Walton's schemes
  - Toulmin's model
  - Components and relations (claims, premises and support, attack)
- **Macro-level**
  - Dung's abstract framework and its extensions (graph based)
  - Pragma-dialectical theory

A taxonomy of problems



AM tasks


Argument component detection
Raw text
Argumentativ
e sentence
detection
Argument
component
boundary
detection
Argument
structure
prediction
Annotated
text

Datasets

	Datasets	Document source	Size	Component Detection		RP
				Sent. Clas.	BD	
Educ.	[Stab and Gurevych, 2017]	persuasive essays	402 essays	✓	✓	✓
	[Peldszus and Stede, 2015]	microtexts	112 short texts	✓		✓
Web-based content	[Bar-Haim *et al.*, 2017]	debate motions DB	55 topics	✓		
	[Rinott *et al.*, 2015]	Wikipedia, debate motions DB	58 topics, 547 articles	✓		
	[Bar-Haim *et al.*, 2017]	Wikipedia, debate motions DB	33 topics, 586 articles	✓		
	IAC	4forums.com	11,800 discussions			
	[Habernal and Gurevych, 2017]	comments, forum, blog posts	524 documents	✓		
	[Khatib *et al.*, 2016]	*i-debate*	445 documents		✓	
	NoDE	online debates	260 pairs			✓
	DART	Twitter	4,713 tweets		✓	✓
	Araucaria	newspapers, legal, debates	660 arguments	✓		
Legal	[Teruel *et al.*, 2018]	ECHR judgments	7 judgments	✓	✓	✓
	[Mochales and Moens, 2011]	ECHR judgments	47 judgments	✓	✓	✓
	[Niculae *et al.*, 2017]	eRule-making discussion forum	731 comments			✓
Politics	[Menini *et al.*, 2018]	Nixon-Kennedy Presid. campaign	5 topics (1,907 pairs)			✓
	[Lippi and Torroni, 2016a]	Sky News debate for UK elections	9,666 words	✓		
	[Duthie *et al.*, 2016]	UK parliamentary record	60 sessions	✓		
	[Naderi and Hirst, 2015]	speeches Canadian Parliament	34 sent., 123 paragr.			✓

Methods

Approaches	Component Detection		Relations prediction
	Sentence classification	**Boundaries Detection**	
SVM	[Mochales and Moens, 2011], [Duthie *et al.*, 2016] [Lippi and Torroni, 2016a; 2016c] [Habernal and Gurevych, 2017] [Bar-Haim *et al.*, 2017]	[Mochales and Moens, 2011] [Lippi and Torroni, 2016c]	[Naderi and Hirst, 2015] [Niculae *et al.*, 2017] [Stab and Gurevych, 2017] [Menini *et al.*, 2018]
P	[Villalba and Saint-Dizier, 2012] [Peldszus and Stede, 2015] [Eger *et al.*, 2017]	[Eger *et al.*, 2017]	[Villalba and Saint-Dizier, 2012] [Peldszus and Stede, 2015] [Eger *et al.*, 2017]
LR	[Levy *et al.*, 2014], [Rinott *et al.*, 2015] [Nguyen and Litman, 2018]	[Dusmanu *et al.*, 2017] [Ibeke *et al.*, 2017] [Nguyen and Litman, 2018]	[Nguyen and Litman, 2018]
RNN	[Eger *et al.*, 2017]	[Eger *et al.*, 2017]	[Niculae *et al.*, 2017] [Eger *et al.*, 2017]
ME	[Mochales and Moens, 2011], [Duthie *et al.*, 2016]	[Mochales and Moens, 2011]	
CRF	[Stab and Gurevych, 2017]		
NB	[Duthie *et al.*, 2016]		
RF		[Dusmanu *et al.*, 2017]	
TES			[Cabrio and Villata, 2013]
ML		[Levy *et al.*, 2014]	

The features most frequently computed for AM tasks

Features
1. Syntactic and Positional
2. Lexicon
3. Topic relatedness/ semantic similarity
4. Sentiment
5. Embeddings
6. Patterns (regex)
7. Discourse
8. Bag-of-words
9. Subjectivity classifier
10. NER
11. Vocal (speech)
12. Wikipedia-based
13. PMI
14. Emoticons

Ongoing activities

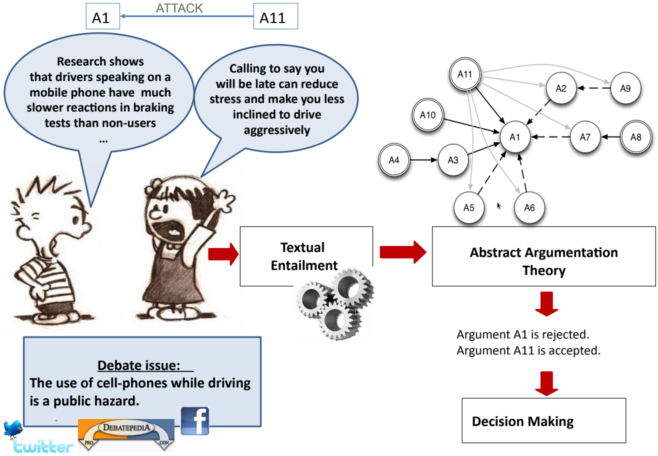
- Debating technologies - Dagstuhl seminar (December 2015)
- Natural Language Argumentation: Mining, Processing, and Reasoning over Textual Arguments - Dagstuhl seminar (April 2016)
- CMNA-2016 Workshop @IJCAI2016
- Argument Mining Workshop @ACL2016, @EMNLP2017
- Tutorial "Argument Mining" (K. Budzynska, S. Villata) @IJCAI2016
- Tutorial "NLP Approaches to Computational Argumentation" (N. Slonim, I. Gurevych, C. Reed, B. Stein) @ACL2016
- Conference COMMA
- Linguistic Features and Argumentation Workshop @COMMA
- 3 courses on Argument Mining at the ESSLLI 2017 Summer School
- Next Argument Mining Workshop @EMNLP2018

Overview papers

- **E. Cabrio and S. Villata: Five Years of Argument Mining: a Data-driven Analysis. In IJCAI, 2018**.
- K. Budzynska and S. Villata: Processing Natural Language Argumentation. In Handbook of Formal Argumentation, College Publications, 2018.
- M. Lippi, P. Torroni: Argumentation Mining: State of the Art and Emerging Trends. ACM Transactions on Internet Technology, 2016.
- Link to available resources for argumentation mining: `http://argumentationmining.disi.unibo.it/resources.html`
- A. Peldszus, M. Stede. From argument diagrams to argumentation mining in texts: a survey. Int'l Journal of Cognitive Informatics and Natural Intelligence (IJCINI) 7(1):1-31, 2013.

Argument Mining:
our story so far.

Argument Mining for Online Debates



[Arg.&Comp.2013, ECAI2012, ACL2012-short]

AM for Online Debates Platforms

Application: online debate platforms (Debatepedia, iDebate)
Task: relation prediction (support, attack) $\rightarrow$ Textual Entailment
Data: IAA: $\kappa = 0.74$.

Training set					Test set				
Topic	**#arg**	**#pairs**			**Topic**	**#arg**	**#pairs**		
		tot.	**yes**	**no**			**tot.**	**yes**	**no**
Violent games/aggress.	16	15	8	7	*Ground zero mosque*	9	8	3	5
China one-child policy	11	10	6	4	*Mandat. military service*	11	10	3	7
Coca as a narcotic	15	14	7	7	*No fly zone over Libya*	11	10	6	4
Child beauty contests	12	11	7	4	*Airport security profiling*	9	8	4	4
Arming Libyan rebels	10	9	4	5	*Solar energy*	16	15	11	4
Random alcohol tests	8	7	4	3	*Natural gas vehicles*	12	11	5	6
Osama death photo	11	10	5	5	*Cell phones while driving*	11	10	5	5
Private social security	11	10	5	5	*Marijuana legalization*	17	16	10	6
Internet as a right	15	14	9	5	*Gay marriage as a right*	7	6	4	2
					Vegetarianism	7	6	4	2
TOTAL	109	**100**	**55**	**45**	**TOTAL**	110	**100**	**55**	**45**

Method: Tree edit distance (EDITS – Edit Distance Textual Entailment Suite, `http://edits.fbk.eu/`)

Results: Pr: **0.74**, Rec: **0.76**, Acc.: **0.75**

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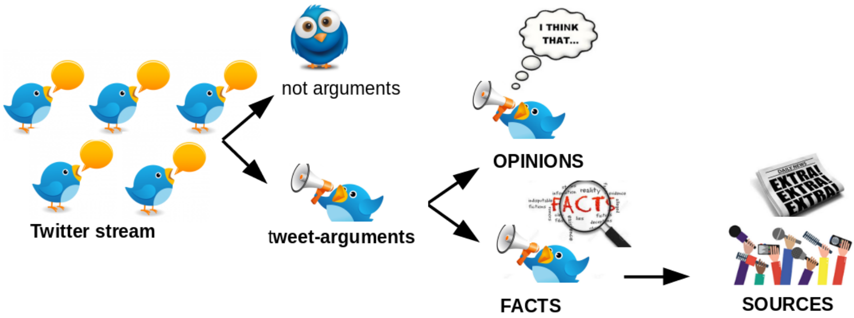
Argument mining on Twitter



[EMNLP2017, COMMA2016, LREC2016]

Argument mining on Twitter

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

Data: DART, thread *#Grexit* (987 tweets) + 900 from *#Brexit*. 2 annotators, IAA: κ=0.767 (1st task, 100 tweets), κ=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
argu. detection	LR	lex., Twitter, synt., sem., sent.	**0.78**
factual/opinion	LR	lex., Twitter, synt., sem., sent.	**0.80**
source identif.	Matching + heuristics		**0.67**

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Argument mining on political speeches

United States presidential election, 1960

- CUBA
- DISAMAMENT
- MINIMUM WAGE
- MEDICAL CARE
- UNEMPLOYMENT

relation prediction →

DIGITAL HUMANITIES

Supporting historians in their analysis, detection of inconsistencies, detection of fallacies, …

[AAAI2018]

Argument mining on political speeches

Tasks: relation prediction (attack, support).

Data: 881 documents, 1,907 pairs. IAA: 3 ann., 100 pairs, $\kappa = 0.63$.

Nixon: *Now, some people might say, Mr. Nixon, won't it be easier just to have the Federal Government take this thing over rather than to have a Federal-State program? Won't it be easier not to bother with private health insurance programs? Yes; it would be a lot simpler, but, my friends, you would destroy the standard of medical care.*

ATTACK

Kennedy: *I don't believe that the American people are going to give their endorsement to the leadership which believes that medical care for our older citizens, financed under social security, is extreme, and I quote Mr. Nixon accurately.*

Method and results:

Task	Method	Features	Results (avgF1)
related/unrelated	SVM (LIBSVM)	lex., topic pos., sim.	**0.65**
attack/support (gold data)	SVM (LIBSVM)	lex., neg., keyword emb., entail., sent.	**0.82**
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Argument Mining on Clinical Trials

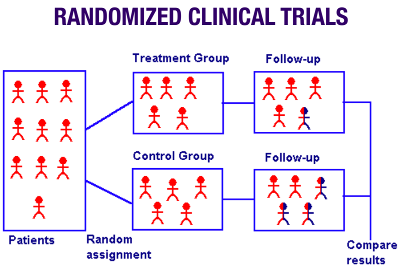
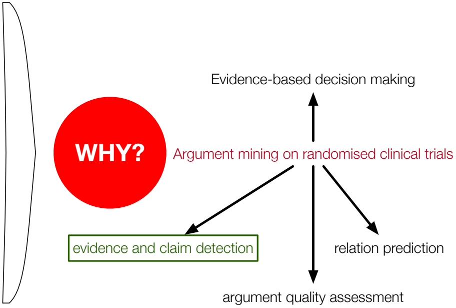


Image: SUNY downstate.



[COMMA2018, ArgMin2018]

Argument Mining on Clinical Trials

Task: argument component detection (evidences, claims).
Data: 976 components (697 evidences, 279 claims). IAA: 3 ann., 10 abstracts, Fleiss'κ=0.72 (arg. comp.), 0.68 (claim/evidence).
Topics: glaucoma, hepatitis, diabetes, hypertension.

[*The diurnal intraocular pressure reduction was significant in both groups ($P < 0.001$)*]$_1$. [*The mean intraocular pressure reduction from baseline was 32% for the latanoprost plus timolol group and 20% for the dorzolamide plus timolol group*]$_2$. [*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 ($P < 0.001$)*]$_3$. 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]$_1$**.

Method: Support Vector Machines with Subset Tree Kernel.
Results (F1): evidence (**0.80**), claim (**0.72**), arg. comp. (**0.78**).

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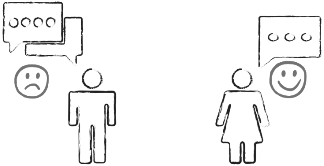
Argumentation and Emotions

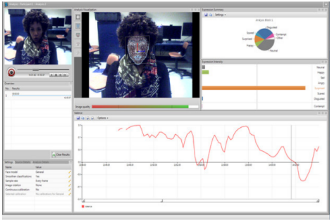
- **Connection between the arguments proposed by the participants of a debate and their emotional status?**
  - correlation of polarity of arguments and polarity of detected emotions?
  - relation between kinds and amount of arguments, and the engagement of participants?
  - How do personality traits and opinions affect participants' emotions during the debates?

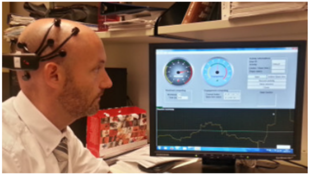


[IJCAI2015, Arg & Comp.2017, FLAIRS2018]

Emotion detection (Heron Lab, University of Montreal)

- webcams for facial expressions analysis [FACEREADER 6.0]
- physiological sensors (EEG) for cognitive states [Chaouachi et al., 2010]





Real-time engagement

- engagement index [Pope et al.,1995]
- EEG frequency bands

Real-time facial analysis

- classifying 500 key points in facial muscles
- neural network
  - happy, sad, angry, surprised, scared, disgusted.
  - valence, arousal
  - neutral probability.

Are there any meeting points?

MT for AM?

AM for MT?

AM and Multilinguality

- most of the available datasets are in English
- a bunch of small datasets on different languages:
  - German [Peldszus,Stede2015, Eckle-Kohler et al.2015, Liebeck et al.2016], Italian [Basile et al. 2016], Chinese [Li et al. 2017] and Greek [Sardianos et al. 2015]
- **a few recent works addressing some forms of cross-linguality**
  - [Aker and Zhand 2017]: argumentative sentences from English to Mandarin using MT on Wikipedia articles
  - [Sliwa et al. 2018]: corpora in Balkan languages and Arabic by labeling the English side of corresponding parallel corpora
  - [Eger et al. 2018]: annotation projection, bilingual word embeddings based direct transfer learning strategies for cross-lingual AM

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MT for AM

- acquiring (high quality) datasets for AM for new languages comes at a high cost
- machine translated parallel data
- annotation projection
- direct transfer (cross-lingual word embeddings)
- supervised multi-task learning
- ...

Cross-cultural differences in argumentation

- theorists insist upon taking seriously, in the evaluation of arguments, the features and perspectives – and in particular, the cultural locations – of the evaluators
- importance of cultural differences in argument appraisal: **the quality of an argument depends upon culturally-specific beliefs, values, and presuppositions (or not?)**.
- to which extent can MT address such issue?
  - corpora of translated arguments vs corpora of arguments uttered by people in their native language
  - (+ corpora in English uttered by not native English speakers...)

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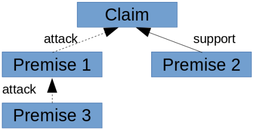
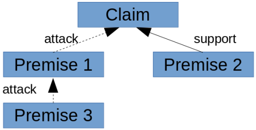
AM for MT

- **commonsense reasoning**
- **consistency check** of the argumentative structure in both languages

[Living and studying overseas is an irreplaceable experience when it comes to learn standing on your own feet].
[One who is living overseas will of course struggle with loneliness, living away from family and friends]$_1$ but [those difficulties will turn into valuable experiences in the following steps of life]$_2$.
Moreover, [the one will learn living without depending on anyone else]$_3$.



[Vivere e studiare all'estero è un'esperienza insostituibile quando si tratta di imparare a stare in piedi con le proprie gambe].
[Uno che vive all'estero, ovviamente, combatterà con la solitudine, vivendo lontano dalla famiglia e dagli amici]$_1$, ma [quelle difficoltà si trasformeranno in esperienze preziose nei seguenti passi della vita]$_2$.
Inoltre, [uno imparerà a vivere senza dipendere da nessun altro]$_3$.

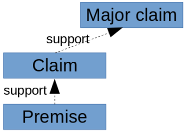


AM for MT

- **commonsense reasoning**
- **consistency check** of the argumentative structure in both languages

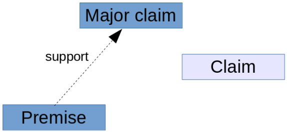
[Gun control push complicates Sanders's 2020 ambitions]

[**Hillary Clinton knows Bernie Sanders' gun control record is not his strong suit**]. ["<u>He has voted with the NRA, with the gun lobby numerous times,</u>"] Clinton said on stage in Charleston, South Carolina.



[La spinta del controllo delle armi complica le ambizioni 2020 di Sanders]

?[**Hillary Clinton sa che il record di controllo delle armi di Bernie Sanders non è il suo forte seme**]. [<u>"Ha votato con l'NRA, con la lobby delle armi numerose volte"</u>,] ha detto Clinton sul palco a Charleston, in South Carolina.



AM for MT

- **commonsense reasoning**
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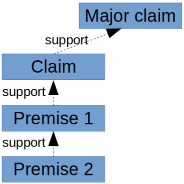
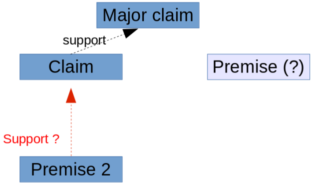
[Lotto, il prof Pazzaglia azzecca le previsioni]. [Siccome il 23 non usciva nella ruota di Napoli da ben 45 settimane]1, [il prof. Pazzaglia ha detto di scommettere sul 23 sulla ruota di Napoli]2. **[Previsione che si e' avverata]**.



[Loto, le professeur Pazzaglia devine les prévisions]. [Depuis 23 ans ne sont pas sortis au volant de Naples pendant 45 semaines], [prof. Pazzaglia a déclaré parier sur 23 au volant de Naples]2. **[Prévision qui s'est réalisée]**. ?



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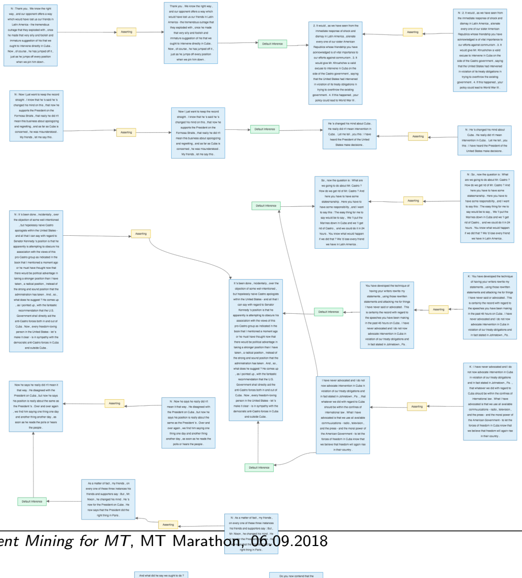
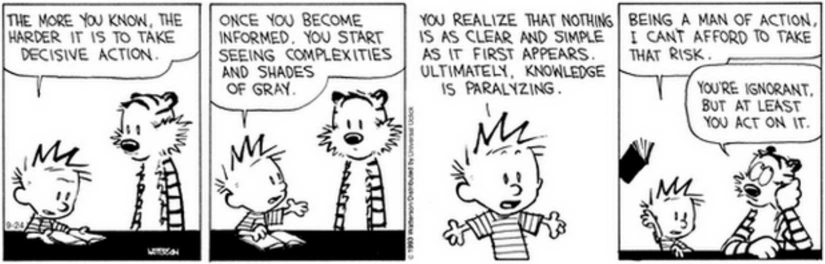


Thanks for your attention!



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