

Tutorial on Argumentation Technology for Artificial Intelligence Part 4: Argumentation-based aggregation of evidence for decision support

Prof. Dr. Philipp Cimiano (Bielefeld University)

Prof. Dr. Benno Stein (Bauhaus-University Weimar)

Prof. Dr. Henning Wachsmuth (Paderborn University)



Bauhaus-Universität Weimar



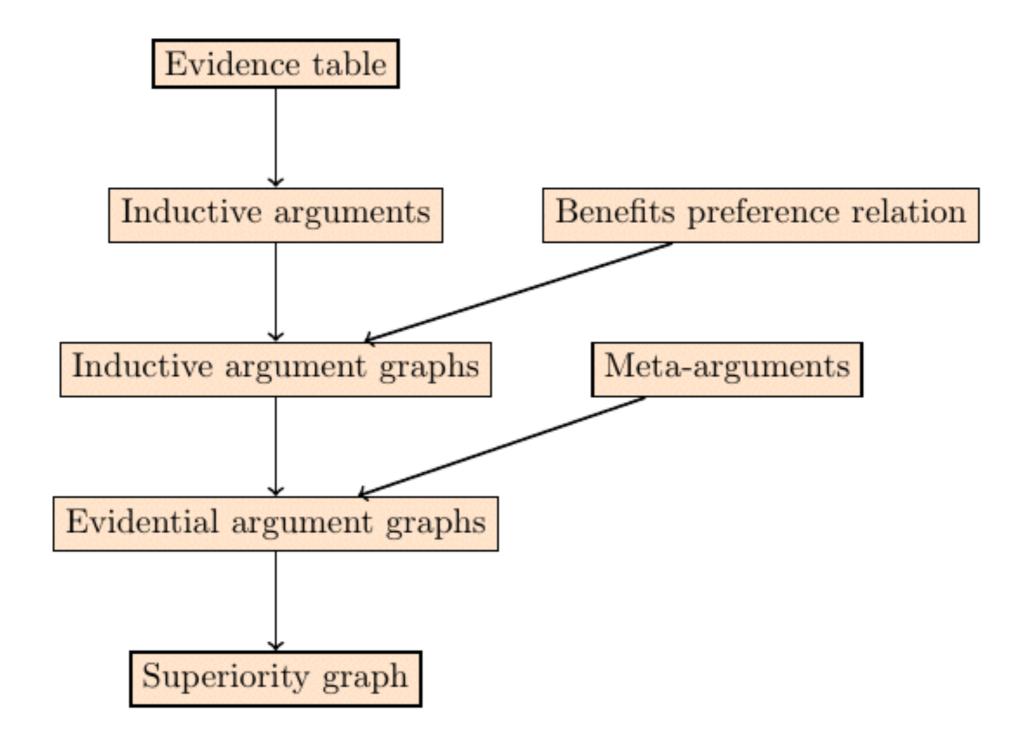
Argumentation-based aggregation of evidence for decision support

- In many domains, decision making is challenging due to heterogeneous pieces of evidence that need to be aggregated to reach an informed decision
- The challenge in aggregating evidence is characterized by the following issues: (Hunter and Williams 2015):
 - heterogeneous
 - uncertain
 - incomplete
 - inconsistent
- Following Hunter and Williams (2015), in this tutorial we consider the particular case of decision making in medicine.
- In medicine, there exist "published aggregates" in the form of systematic reviews, meta-analyses, guidelines etc.

Some problems with published aggregates

- According to Hunter and Williams (2015), published aggregates in medicine have the following issues:
 - expensive to produce
 - long time to produce
 - can become outdated quickly
 - consider a broad patient group
 - normally do not consider co-morbidities
 - decouple clinicians from the actual evidence and from being able to use own aggregation and weighting criteria
- Hunter and Williams conclude that there is a need for formal / computational tools to aggregate evidence.

Framework proposed by Hunter and Williams for aggregating clinical evidence



Evidence Table

ID	Left	Right	Indicator	Risk Ratio	Outcome	Р
e1	СР	NT	Pregnanc y	0.05	superior	0.01
e2	СР	NT	Ovarian Cancer	0.99	superior	0.07
e3	СР	NT	Brest Cancer	1.04	inferior	0.01
e4	СР	NT	DVT	1.02	inferior	0.05

CP denotes "contraceptive pill"

NT denotes "no treatment"

Risk ratio: prop. of people with indicator in left arm / prop. of people with indicator in right arm Thus:

RR > 1 iff people in the left arm tend to have the indicator more than people in the right arm
If indicator is positive, then left condition is better than right condition
If indicator is negative, then right condition is better than left condition

RR < 1 iff people in the left arm tend to have the indicator less than people in the

RR < 1 iff people in the left arm tend to have the indicator less than people in the right arm

If indicator is sth. positive, then right arm is better than left arm condition If indicator is sth. negative, then left arm is better than right arm condition

Generating Inductive Arguments

ID	Left	Right	Indicator	Risk Ratio	Outcome	Р
e1	СР	NT	Pregnanc y	0.05	superior	0.01
e2	СР	NT	Ovarian Cancer	0.99	superior	0.07
e3	СР	NT	Brest Cancer	1.04	inferior	0.01
e4	СР	NT	DVT	1.02	inferior	0.05

From the above evidence table, we can generate the following inductive arguments:

$$\langle \{e_1\}, CP > NT \rangle$$
 $\langle \{e_3\}, CP < NT \rangle$ $\langle \{e_2\}, CP > NT \rangle$ $\langle \{e_4\}, CP < NT \rangle$ $\langle \{e_1, e_2\}, CP > NT \rangle$ $\langle \{e_3, e_4\}, CP < NT \rangle$

Constructing an argument graph

$$\langle \{e_1\}, CP > NT \rangle$$
 $\langle \{e_3\}, CP < NT \rangle$
 $\langle \{e_2\}, CP > NT \rangle$ $\langle \{e_4\}, CP < NT \rangle$
 $\langle \{e_1, e_2\}, CP > NT \rangle$ $\langle \{e_3, e_4\}, CP < NT \rangle$

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Integrating Preferences

ID	Left	Right	Indicator	Risk Ratio	Outcome	Р
e1	СР	NT	Pregnanc y	0.05	superior	0.01
e2	СР	NT	Ovarian Cancer	0.99	superior	0.07
e3	СР	NT	Brest Cancer	1.04	inferior	0.01
e4	СР	NT	DVT	1.02	inferior	0.05

Substantial reduction in risk of pregnancy is *more preferred* to modest reduction in risk of either breast cancer or DVT.

Modest reduction in ovarian breast cancer is *equally preferred* to modest reduction in risk of either breast cancer or DVT.

Modest reduction in ovarian breast cancer is *less preferred* to modest reduction in breast cancer and DVT.

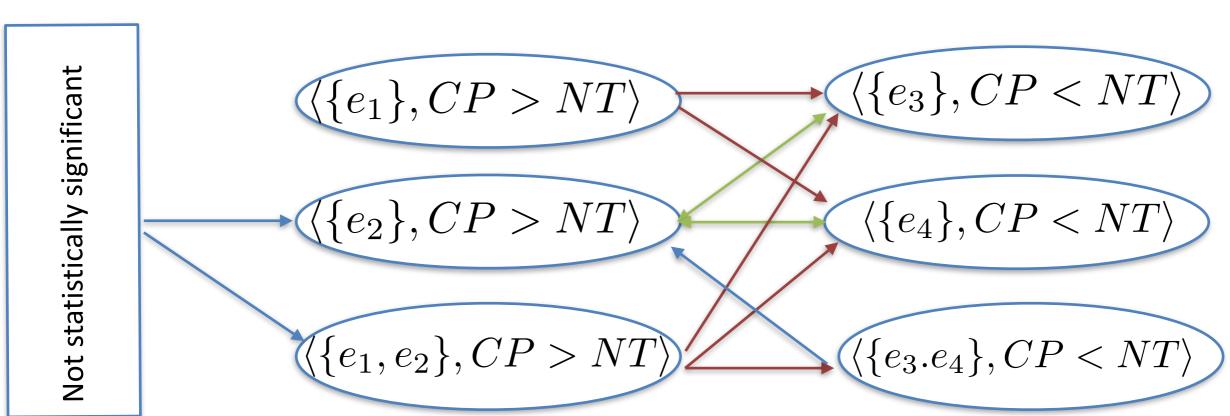
Integrating Preferences

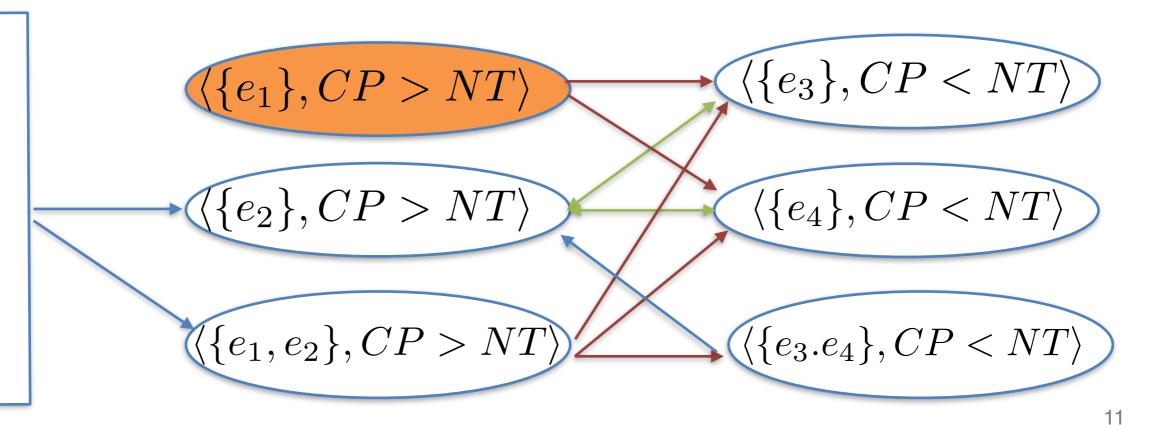
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$$\langle \{e_1\}, CP > NT \rangle$$
 $\langle \{e_3\}, CP < NT \rangle$ $\langle \{e_4\}, CP < NT \rangle$ $\langle \{e_1, e_2\}, CP > NT \rangle$ $\langle \{e_3, e_4\}, CP < NT \rangle$

Meta-arguments

ID	Left	Right	Indicator	Risk Ratio	Outcome	Р
e1	СР	NT	Pregnanc y	0.05	superior	0.01
e2	СР	NT	Ovarian Cancer	0.99	superior	0.07
e3	СР	NT	Brest Cancer	1.04	inferior	0.01
e4	СР	NT	DVT	1.02	inferior	0.05



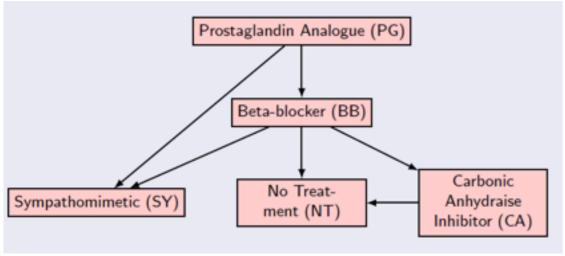


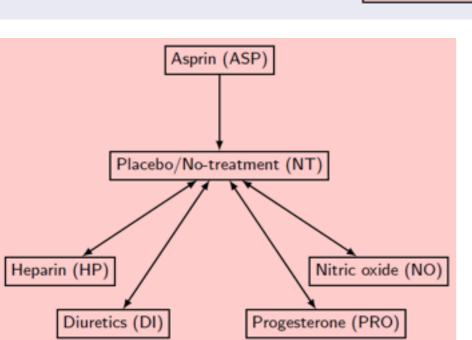
The winner is.... $\langle \{e_1\}, CP > NT \rangle$

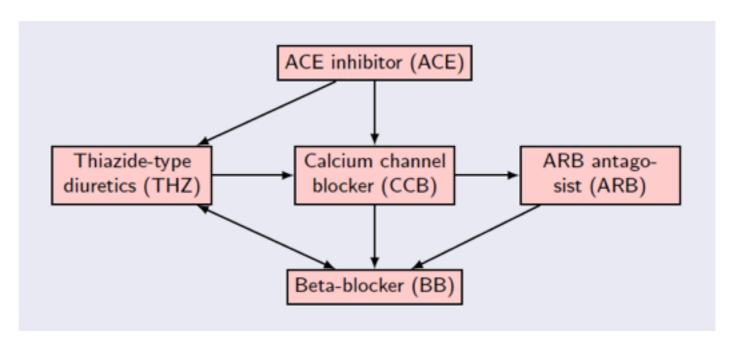
This is actually the grounded extension as defined by Dung (1995)

Case studies

- Reproducing the NICE Glaucoma Guideline
- Reproducing the NICE Hypertension Guideline
- Reproducing the NICE Pre-eclampsia guideline
- Case study in non-small lung cancer







Conclusion

- We can use argumentation technology to aggregate evidence to support informed decision making
- Framework proposed by Hunter and Williams (2015) relies on:
 - generating inductive arguments from evidence tables
 - incorporating preferences to eliminate attacks
 - incorporate meta-arguments
 - determine winning arguments according to some Dung semantics

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References

- A. Hunter and M. Williams (2012) Aggregating evidence about the positive and negative effects of treatments, AI in Medicine Journal, 56:173-190.
- A. Hunter and M. Williams (2015) Aggregation of Clinical Evidence using Argumentation: A Tutorial Introduction, Foundations of Biomedical Knowledge Representation, edited by Arjen Hommersom and Peter Lucas, LNCS volume 9521, Springer, pages 317–338.