

Learning Constraints for the Epistemic Graphs Approach to Argumentation

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Epistemic graphs: Introduction

Epistemic graphs are a generalization of the epistemic approach to probabilistic argumentation

Using constraints In the epistemic graphs approach, the argument graph is augmented with a set of constraints that can restrict the belief in arguments, and state how these influence each other.

Capturing relationships The graphs can model both **attack** and **support** as well as relations that are neither positive nor negative.

Key features of epistemic graphs

- 1** Quantify the effect of combinations of influence (e.g. attack plus support).
- 2** Model the attitude of different agents to a graph.
- 3** Model the attitude of an agent to different arguments but same topology.

A Hunter, S Polberg and M Thimm (2020) Epistemic Graphs for Representing and Reasoning with Positive and Negative Influences of Arguments, Artificial Intelligence, 281: 103236.

Epistemic graphs: Example

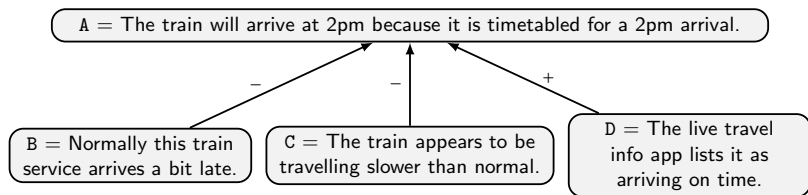


Figure: Example of an epistemic graph. The + (resp. -) label denote support (resp. attack) relations. These are specified via the following constraints.

- $\varphi_1 : (p(D) > 0.8 \wedge p(B \vee C) < 0.2) \rightarrow p(A) > 0.8$
- $\varphi_2 : (p(D) > 0.5 \wedge p(B \vee C) \leq 0.5) \rightarrow p(A) > 0.5$
- $\varphi_3 : p(B \wedge C) > 0.5 \rightarrow p(A) < 0.5$

Epistemic graphs: Advantages

- 1 Epistemic graphs allow us to both model the rationale behind the existing dialectical semantics as well as completely deviate from them when required.
 - There is some resemblance with variants of abstract argumentation such as ranking and weighted approaches, but the conceptual differences between epistemic probabilities and abstract weights/scores lead to significant differences in modelling.
- 2 Epistemic graphs are expressive and flexible for argumentation that supports
 - **Subjective reasoning** by allowing different agents to be modelled by a different set of constraints.
 - **Context-sensitive reasoning** by basing constraints on what arguments represent rather than the just the structure of graph.
- 3 Epistemic graphs also allow for better modelling of imperfect agents, which can be important in dialogical argumentation (e.g. persuasion, negotiation, etc.).

Learning process for epistemic constraints

- Data about participants attitudes to arguments
- Use a form of association rule learning
 - Format for the data
 - Format for influences
 - Format candidate rules
 - Quality measures from association rule learning
 - Select the good rules using quality measures
- Evaluate with two datasets

Data for training and evaluation

- In this paper, we consider data from two published studies.
 - **Spanish study** The appropriateness of Wikipedia in a Spanish higher education institute which was obtained from 901 individuals and involved 26 statements;
 - **Italian study** Views on political issues in Italy which was obtained from 774 individuals and involved 75 statements.
- The data from each study contains the answers from asking individuals a number of questions including their level of agreement with certain statements (e.g. Likert scale).
- Each statement can be regarded as an argument.
- Each row in the data concerns an individual.

- Pu3 = “Wikipedia is useful for teaching”,
- Qu1 = “Articles in Wikipedia are reliable”,
- Qu3 = “Articles in Wikipedia are comprehensive”,
- Enj1 = “Articles in Wikipedia stimulate curiosity”

	Pu3	Qu1	Qu3	Enj1
903	0.3	0.5	0.3	0.7
904	0.9	0.9	0.9	0.9
905	0.7	0.7	0.5	0.9
908	0.3	0.5	0.7	0.3
909	0.5	0.5	0.7	0.7

Table: Some rows and columns of data from the Spanish study (after mapping Likert values to our 11 point (probabilistic) scale).

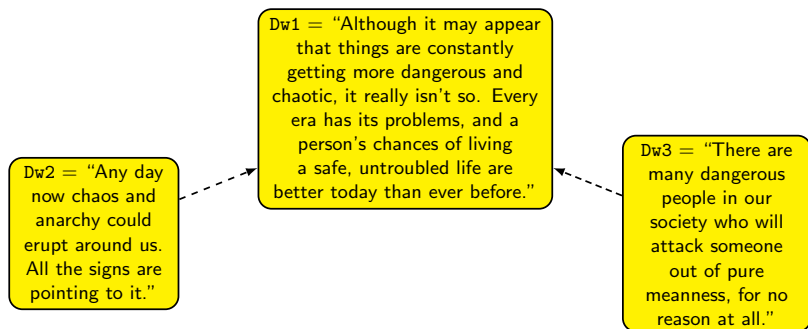


Figure: Arguments from the Italian study. The dashed arcs denote influences.

Influences

- For a pair of arguments α and β , we say that α **influences** β if a change in the belief in α will potentially result in the change in the belief in β .
- For instance, an argument influences another argument
 - if it appears to attack it (i.e. it could be regarded as a counterargument)
 - or if it appears to support it.
- **But relationships may be more subtle or mixed.**

Definition

An **influence tuple** is a tuple $(\{\alpha_1, \dots, \alpha_n\}, \beta)$, where

- $\{\alpha_1, \dots, \alpha_n\} \subseteq \text{Nodes}(\mathcal{G}) \setminus \{\beta\}$
- and $\beta \in \text{Nodes}(\mathcal{G})$
- and each α_i influences β .

We refer to each α_i as an **influencer** and β as an **influence target**.

Example

Let $I = (\{Qu1\}, Enj1)$ be an influence tuple and let $\Pi = \{0, 0.5, 1\}$. From this, the set of candidate rules $Rules(I, \Pi)$ is

$$p(Qu1) > 0.5 \rightarrow p(Enj1) > 0.5$$

$$p(Qu1) > 0.5 \rightarrow p(Enj1) \leq 0.5$$

$$p(Qu1) \leq 0.5 \rightarrow p(Enj1) > 0.5$$

$$p(Qu1) \leq 0.5 \rightarrow p(Enj1) \leq 0.5$$

Measures of rule quality

For a rule R , and a dataset D .

$$\text{Support}(R, D) = \frac{1}{|D|} \times |\{d \in D \mid R \text{ is fired by } d\}|$$

$$\text{Confidence}(R, D) = \frac{1}{|D|} \times |\{d \in D \mid R \text{ is correct w.r.t. } d\}|$$

$$\text{Lift}(R, D) = \frac{|\{d \in D \mid R \text{ is correct w.r.t. } d\}|}{|\{d \in D \mid R \text{ is fired by } d\}| \times |\{d \in D \mid R \text{ agrees with } d\}|}$$

Lift is a measure of how good a rule is at predicting a class divided by how often that class occurs.

Example

The following are some of the rules generated from the Spanish dataset, with influence tuple $(\{Qu1, Qu3, Enj1, Jr1, Jr2, Sa1\}, Pu3)$

- 1 $p(Qu3) > 0.5 \wedge p(Qu1) > 0.5 \rightarrow p(Pu3) > 0.5$
- 2 $p(Enj1) \leq 0.5 \wedge p(Qu1) \leq 0.5 \rightarrow p(Pu3) \leq 0.5$
- 3 $p(Jr2) \leq 0.5 \wedge p(Enj1) \leq 0.5 \rightarrow p(Pu3) \leq 0.5$

where

- $Pu3$ = “Wikipedia is useful for teaching”
- $Qu1$ = “Articles in Wikipedia are reliable”
- $Qu3$ = “Articles in Wikipedia are comprehensive”
- $Enj1$ = “Articles in Wikipedia stimulate curiosity”
- $Jr2$ = “My university considers the use of open collaborative environments in the Internet as a teaching merit”

Example

The following are some of the rules generated from the Italian dataset.

1 $p(\text{Sys7}) > 0.5 \rightarrow p(\text{Sys2}) \leq 0.5$

2 $p(\text{Sys8}) > 0.5 \rightarrow p(\text{Sys2}) \leq 0.5$

3 $p(\text{Sys7}) > 0.5 \rightarrow p(\text{Sys3}) > 0.5$

where

- Sys2 = “In general, the political system works as it should”,
- Sys3 = “The Italian society must be radically changed”,
- Sys7 = “Our society gets worse year by year”,
- Sys8 = “Our society is organized so that people generally get what they deserve”,

with the following influence tuples

- $(\{\text{Sys1}, \text{Sys3}, \text{Sys4}, \text{Sys5}, \text{Sys6}, \text{Sys7}, \text{Sys8}\}, \text{Sys2})$
- $(\{\text{Sys1}, \text{Sys2}, \text{Sys4}, \text{Sys5}, \text{Sys6}, \text{Sys7}, \text{Sys8}\}, \text{Sys3})$.

Study	Influence target	No. of influencers	No. of rules	Condi-tions	Support	Confidence	Lift	Time (sec)
Spain	Use2	19	11.3	1.0	0.68	0.95	1.04	192.34
Spain	Use3	19	14.0	1.69	0.60	0.84	1.16	178.36
Spain	Bi1	17	15.8	1.84	0.54	0.82	1.15	148.02
Spain	Bi2	17	12.7	2.1	0.51	0.80	1.20	140.98
Spain	Qu1	13	3.3	2.07	0.51	0.84	1.37	56.55
Spain	Qu3	13	4.2	1.68	0.58	0.88	1.17	48.66
Italy	Dw1	9	3.1	2.45	0.43	0.80	1.22	14.33
Italy	Dw3	9	4.0	1.0	0.75	0.84	1.15	15.39
Italy	Dw6	9	5.0	1.02	0.69	0.88	1.11	17.95
Italy	Dw8	9	4.2	1.7	0.67	0.83	1.22	16.65
Italy	Sys2	7	7.0	1.0	0.76	0.96	1.03	7.89
Italy	Sys3	7	1.6	1.48	0.52	0.82	1.22	8.21

Table: Results for the Spanish and Italian datasets with 10 repetitions. Column 3 is the number of influencers in the influence tuple. Column 5 is the average number of conditions per rule. For columns 4 to 9, the value is the average of the repetitions with $\tau_{\text{confidence}} = 0.8$ and $\tau_{\text{support}} = 0.4$.

Epistemic graphs offer a rich formalism for modelling argumentation.

- Epistemic graphs allow for modelling of
 - context-sensitivity.
 - multiple perspectives.
 - incomplete situations.
 - imperfect agents.
- Data about people's opinions on a set of related statements (arguments) is widely available (or can straightforwardly be obtained by crowdsourcing).
- Such data can be harnessed to learn constraints for epistemic graphs.
- This paper provides a simple form of association rule learning for a very restricted form of epistemic constraints.
- Future work includes developing methods for learning a wider range of epistemic constraints and for using alternative approaches to learning (e.g. supervised learning).