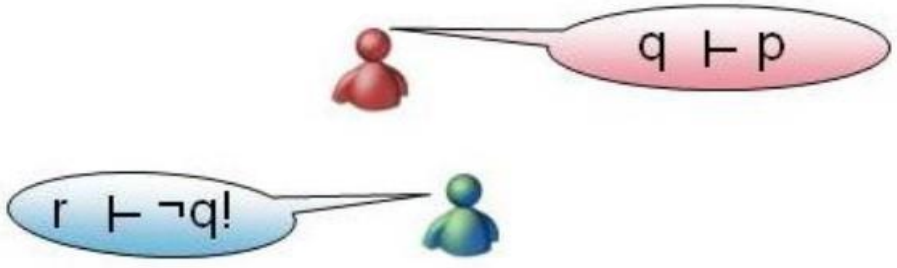
From data and rules to argumentation frameworks

Prof Francesca Toni

Computational Logic and Argumentation Group



Department of Computing

Imperial College London

FRANCESCA TONI
OANA COCARASCU
KRISTIJONAS ČYRAS
ANTONIO RAGO

MACHINE ARGUING

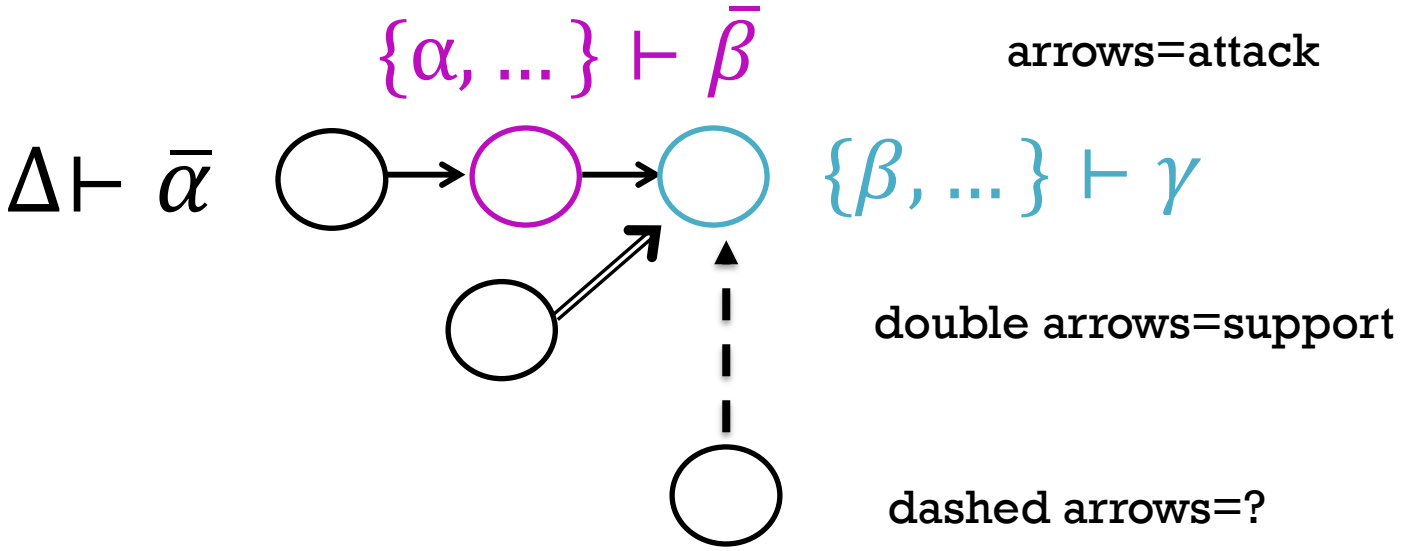
Design&build machines that **argue**:

- To resolve conflicts (within and across)
- To reason with incomplete information
- To explain outcomes

1. Argumentation frameworks
2. Dialectical/gradual semantics/algorithms/properties/systems
3. **Mining argumentation frameworks**

1. Argumentation frameworks

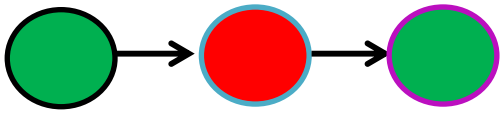
- **Abstract**
- **Structured (e.g. Assumption-based)**
- **Bipolar (e.g. Quantitative Debates)**
- **Tripolar**



2. Semantics/algorithms

– "Dialectical" semantics/algorithms, e.g.

- a set of arguments is **admissible** if it does not attack itself and *attacks every argument attacking it*



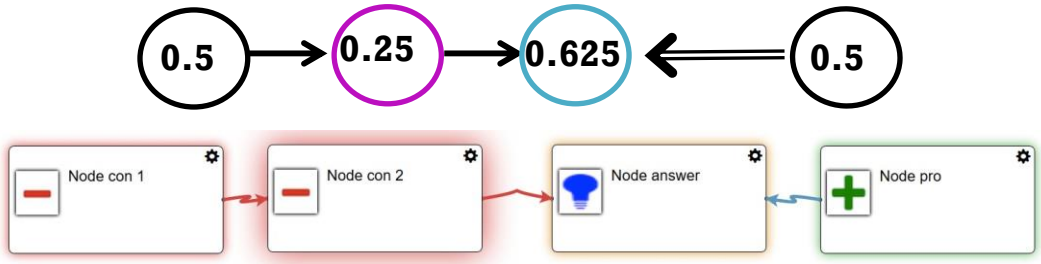
– Gradual semantics/algorithms, possibly (in Quantitative Debates) starting from a-priori strength (e.g. 0.5)

2. Systems

Arg & Dec

Argue and Decide

www.arganddec.com



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(with preferences, bottom-up)

X-dispute derivations (proxdd and abagraph)

(without preferences, top-down)

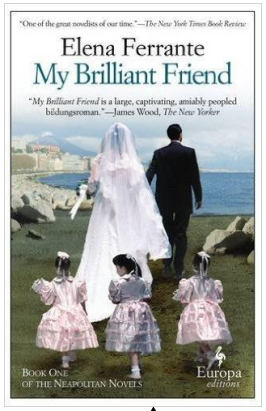
$$\Delta \vdash \bar{\alpha} \rightarrow \{\alpha, \ldots\} \vdash \bar{\beta} \rightarrow \{\beta, \ldots\} \vdash \gamma$$

3. Mining argumentation frameworks

- From text
- From other data (of various types)
- From rules

Integrating mined argumentation frameworks and "reasoning" with them can empower several applications, possibly in combination with other (AI) methods

Mining argumentation frameworks - from text -



This was a wonderful book and probably the best that I have read this year. Both the portrayal of the girls' friendship, and of the community they come from, are complex, detailed, realistic and

I really wanted to like this but I just can't. To my mind it just goes on and on into endless detail.

This book was an unexpected treat purchased as something light to read on the train I was immediately drawn in and impatient to get back to it. It is a tale of childhood, friendship, poverty overshadowed by post war paranoia. The friends are cleverly depicted. Lila the shoemaker's daughter is bright precocious a natural leader - even at 5 years of age, Lena the porter's daughter quiet studious well behaved is enthralled and frightened by her friend. There is an excellent cast of characters the brothers with a car who may have Mafia connections, the grocers children whose father may have collaborated with the nazis, the delusional neighbour obsessed with the local poet. It is a subtle book a lot is inferred but little is confirmed so I constantly felt I was missing something and flicking back. My only caveat is the names, there are a lot of similiar

Really struggled with this, found characters names confusing and the style very rambling.

Carstens, Toni 2015, 2017
Cocarascu, Toni 2017

Relation-based argument mining

Review 1: I recommend the hotel, it has nice rooms

Review 2: The room was very dusty

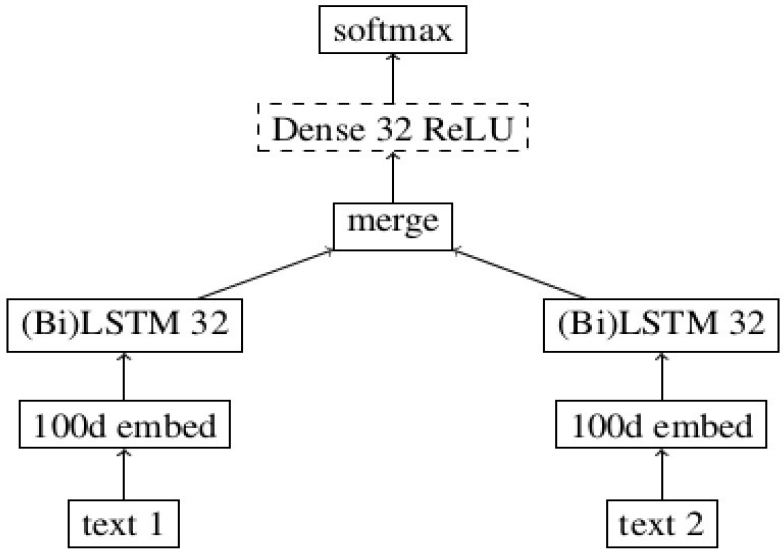
Bipolar argumentation framework

The hotel is recommended ⟸ The hotel has nice rooms ← The room was very dusty

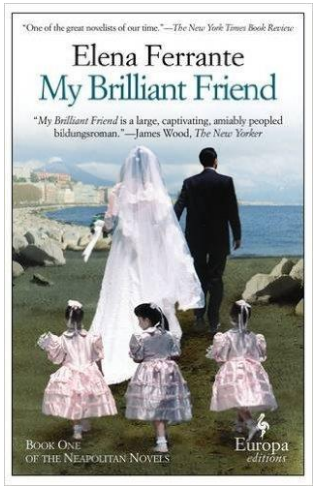
Dataset (movies, technology, politics):

- attack pairs (31%)
- support pairs (32%)
- neither pairs (37%)

Baseline LR (unigrams)	A%	P%	R%	F_1%						
	77.87	78.02	77.87	77.89						
Model / Merge / Dense	Non-trained embeddings				Trained embeddings					
	A%	P%	R%	F_1%	A%	P%	R%	F_1%	A std	F_1 std
BiLSTM / concat / True	60.72	64.36	52.64	57.36	70.66	73.18	62.96	66.93	2.06	4.60
LSTM / concat / False	68.25	72.39	59.07	64.38	**89.53**	**90.80**	**87.67**	**89.07**	**0.47**	**0.73**
LSTM / concat / True	68.68	72.77	58.21	63.49	90.02	90.89	88.26	89.41	2.09	2.92
LSTM / sum / True	64.21	69.18	51.07	57.09	84.84	86.75	79.98	82.35	5.02	9.26



Mining ⇒ Systems



Answer ranking

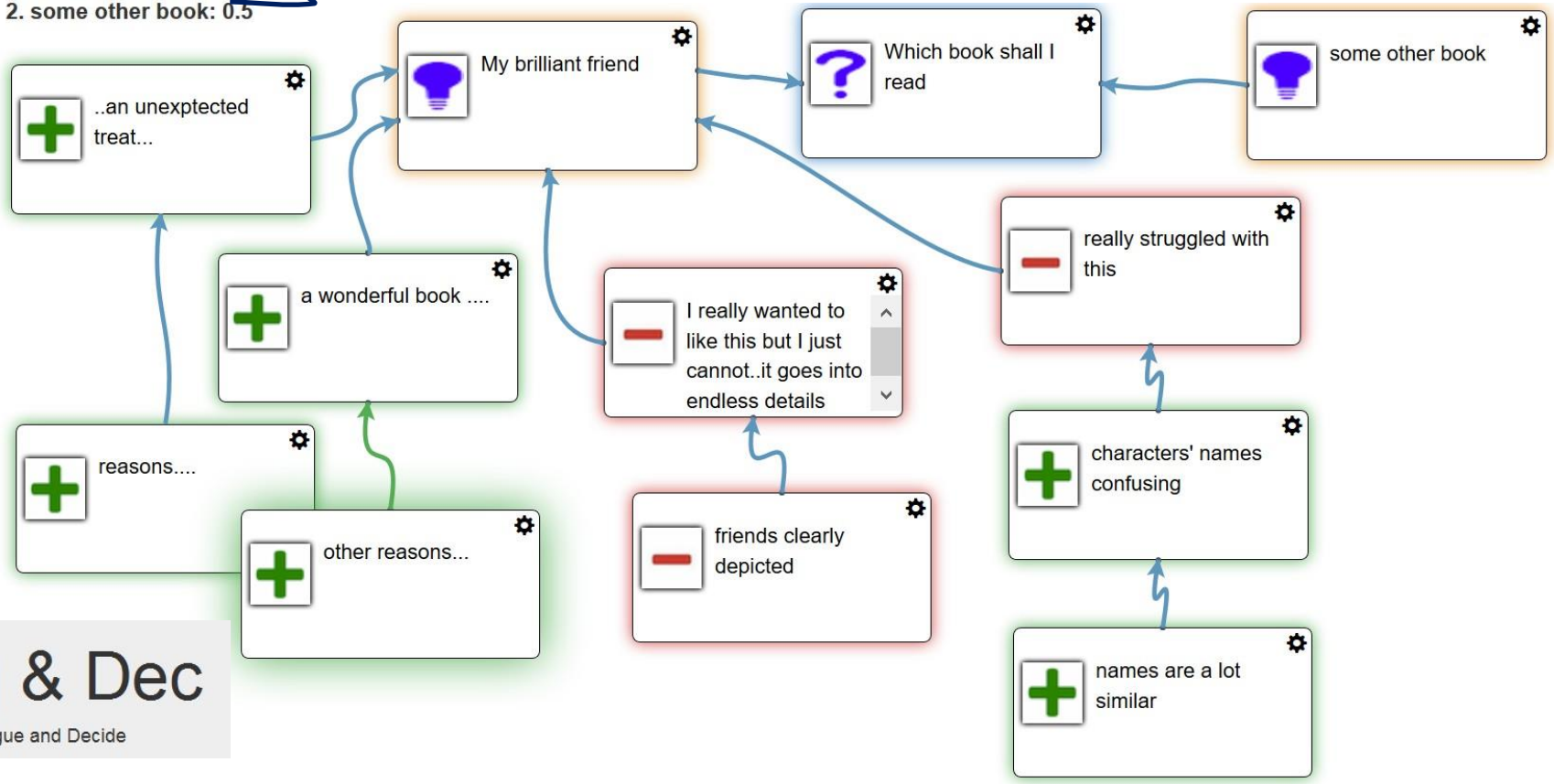
QUAD Algorithm

- **1. My brilliant friend: 0.548555**
- **2. some other book: 0.5**

DF-QUAD Algorithm

- **1. My brilliant friend: 0.905234**
- **2. some other book: 0.5**

Book is recommended!

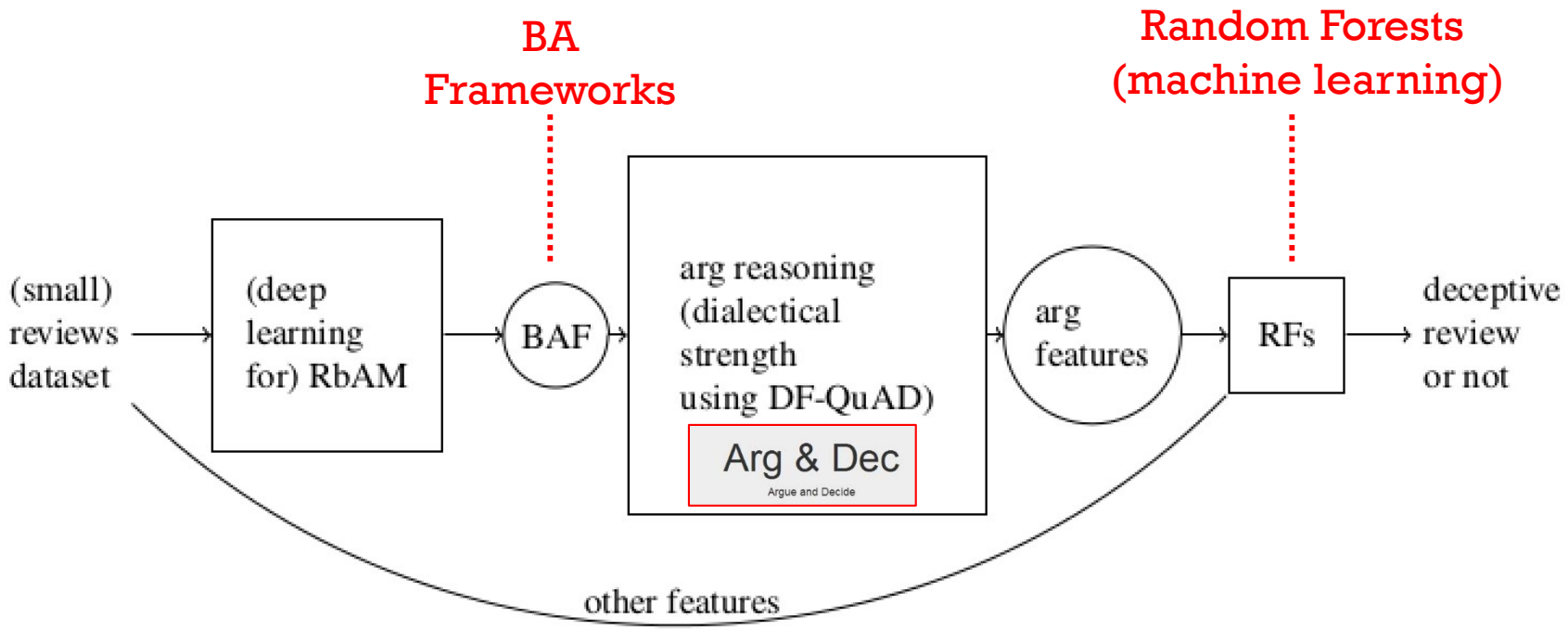


Arg & Dec

Argue and Decide

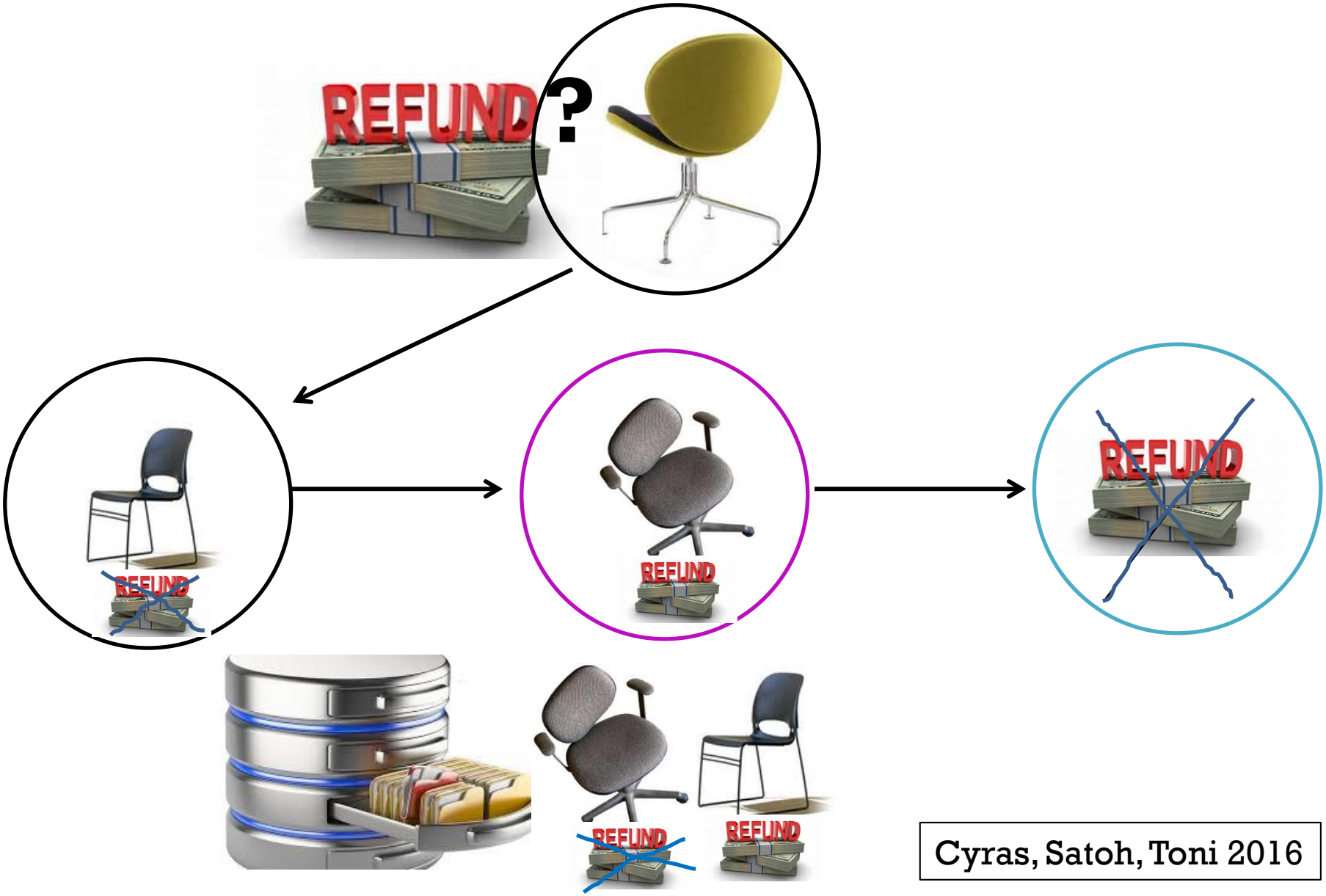
Mining → Systems → Other applications

Detecting deceptive reviews:



Cocarascu, Toni 2018

Mining argumentation frameworks – from other data –



Cyras, Satoh, Toni 2016

Mining ⇒ Systems

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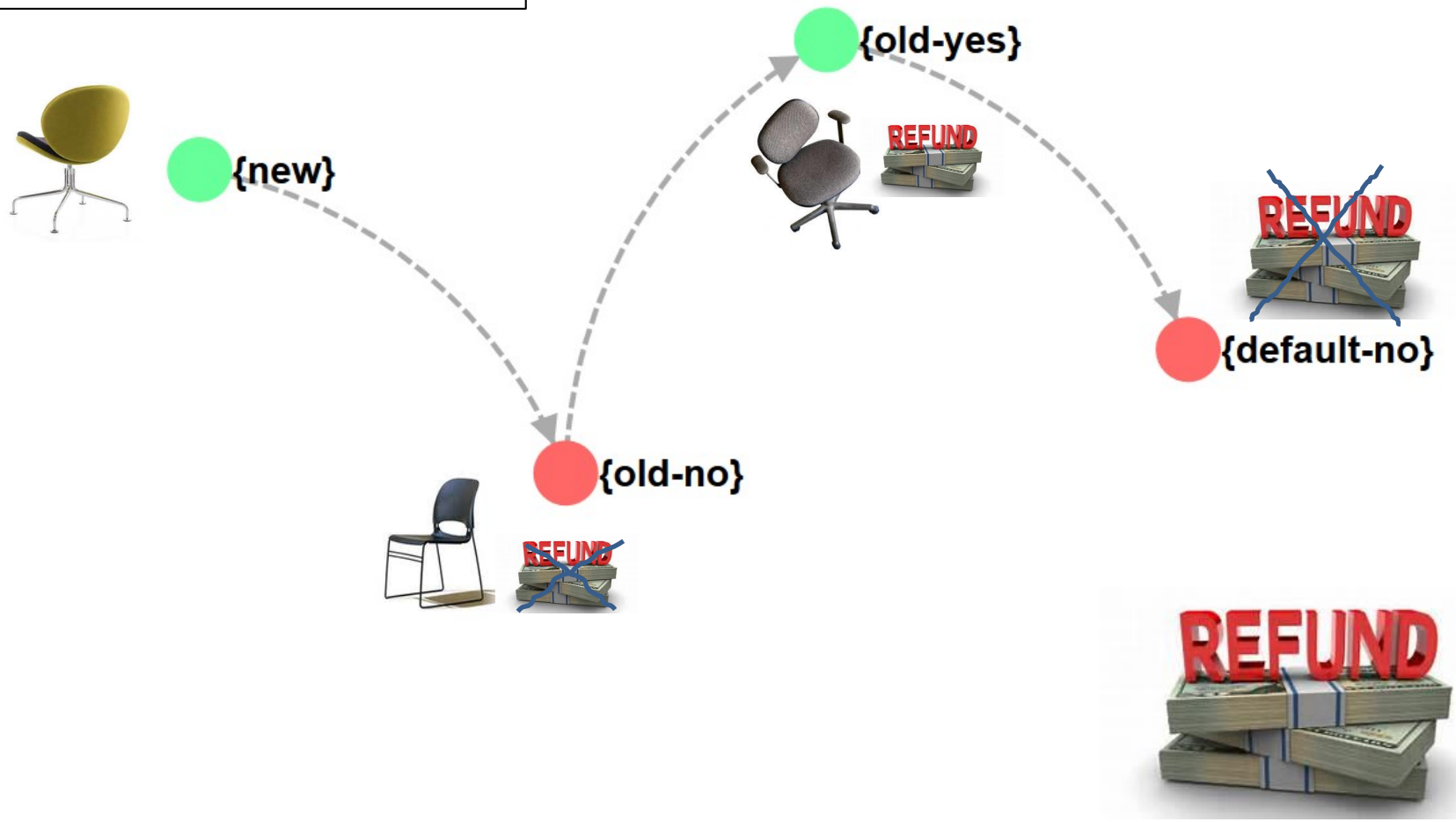


Data: Cases

- a *case* is a pair (X, o) with $X \subseteq \mathbb{F}$ and $o \in \mathbb{O}$;
- a *case base* is a finite set $CB \subseteq \wp(\mathbb{F}) \times \mathbb{O}$ that is *coherent*, i.e. for $(X, o_X), (Y, o_Y) \in CB$, if $X = Y$ then $o_X = o_Y$;
- a *new case* is a pair $(N, ?)$ with $N \subseteq \mathbb{F}$ and $?$ indicating that the outcome is yet unknown.

e.g. $CB = \{(\{\mathsf{a}\}, \overline{\delta}), (\{\mathsf{b}\}, \overline{\delta}), (\{\mathsf{a}, \mathsf{c}\}, \delta), (\{\mathsf{b}, \mathsf{d}\}, \overline{\delta})\}$

$(N, ?) = (\{\mathsf{a}, \mathsf{d}\}, ?)$

Cases ⇒ AA frameworks

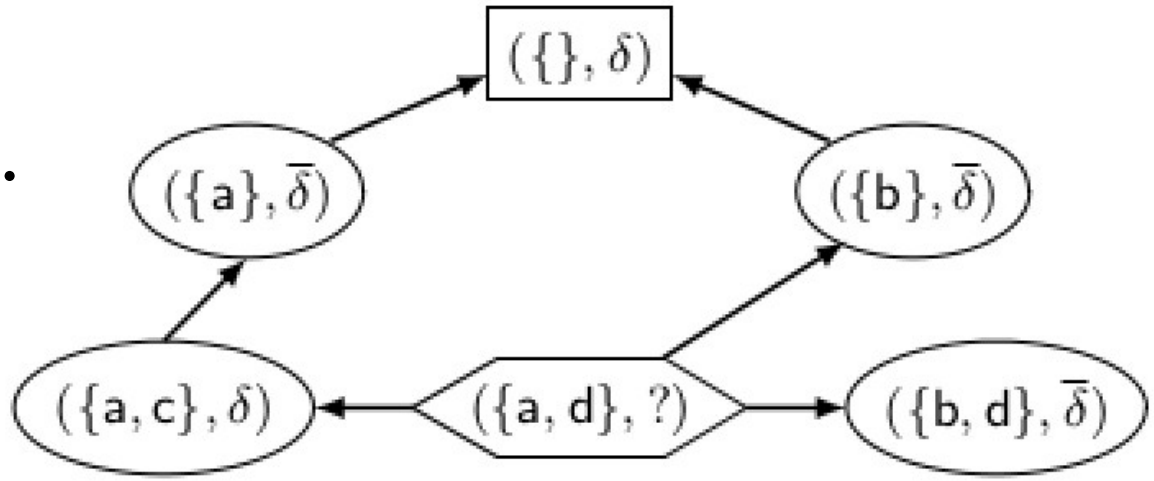
$(Args, \rightsquigarrow)$

- $Args = CB \cup \{(\{\}, \delta)\}$;
- for $(X, o_X), (Y, o_Y) \in CB \cup \{(\{\}, \delta)\}$ $(X, o_X) \rightsquigarrow (Y, o_Y)$ iff
  1. $o_X \neq o_Y$, and (different outcomes)
  2. $Y \subsetneq X$, and (specificity)
  3. $\nexists (Z, o_X) \in CB$ with $Y \subsetneq Z \subsetneq X$. (concision)

$(Args_N, \rightsquigarrow_N)$

- $Args_N = Args \cup \{(N, ?)\}$;
- $\rightsquigarrow_N = \rightsquigarrow \cup \{((N, ?), (Y, o_Y)) : (Y, o_Y) \in Args, Y \not\subseteq N\}$

e.g.

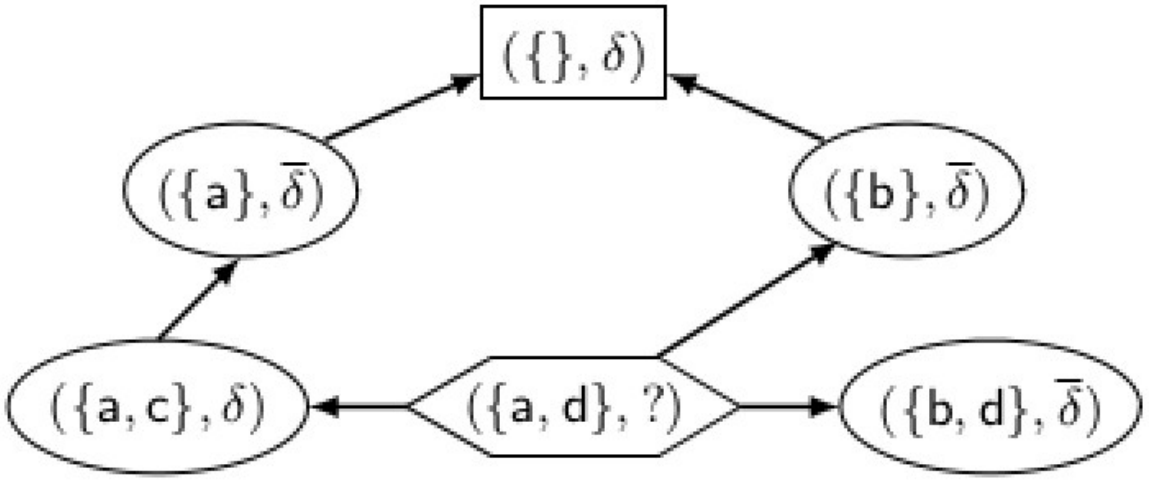


AA frameworks ⇒ Prediction

let $\mathbb{G}$ be the grounded extension of $(Args_N, \rightsquigarrow_N)$

then the *AA-CBR outcome* of $(N, ?)$ is
δ, if $(\{\}, \delta) \in \mathbb{G}$;
$\overline{\delta}$, otherwise, if $(\{\}, \delta) \notin \mathbb{G}$.

e.g.



$\mathbb{G} = \{(\{a, d\}, ?), (\{a\}, \overline{\delta})\}$, and $(\{\}, \delta) \notin \mathbb{G}$

Mining → Systems → Other applications

Cocarascu, Cyras, Toni 2018

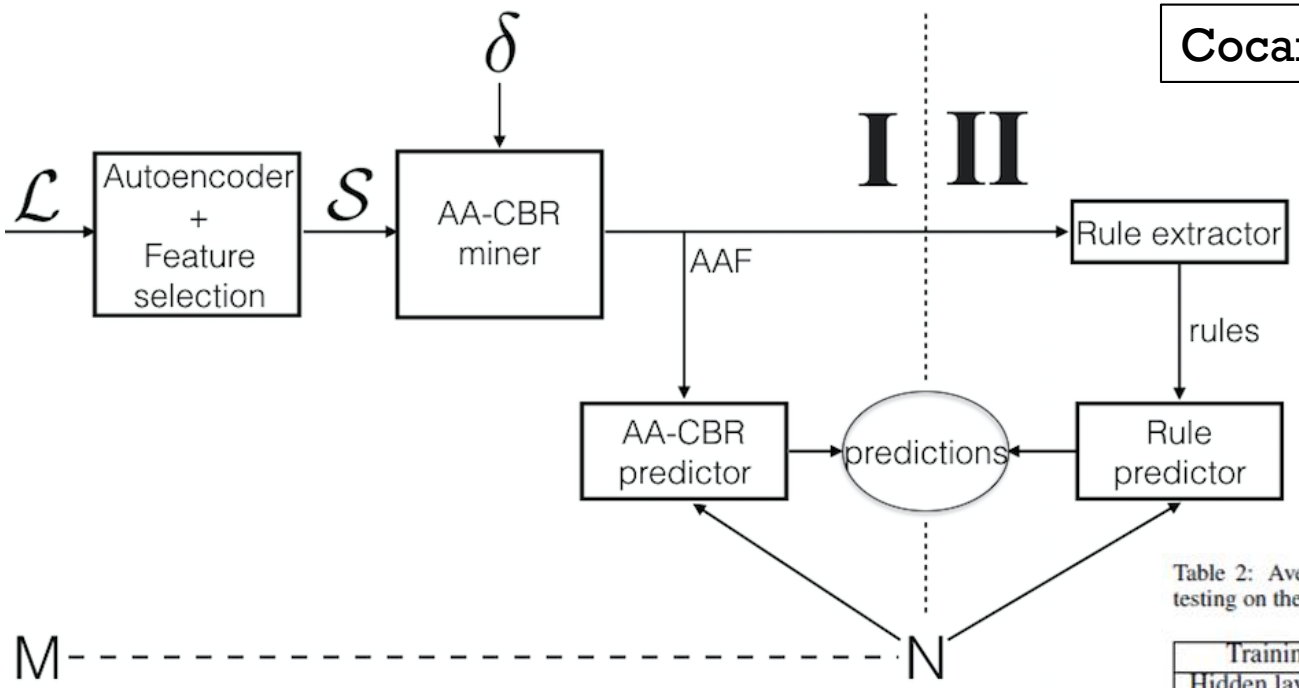


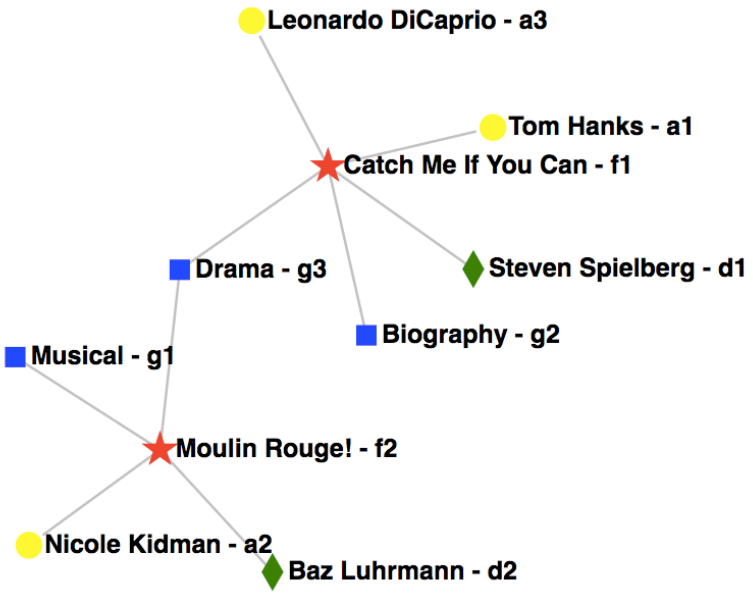
Table 1: 5-fold cross validation results

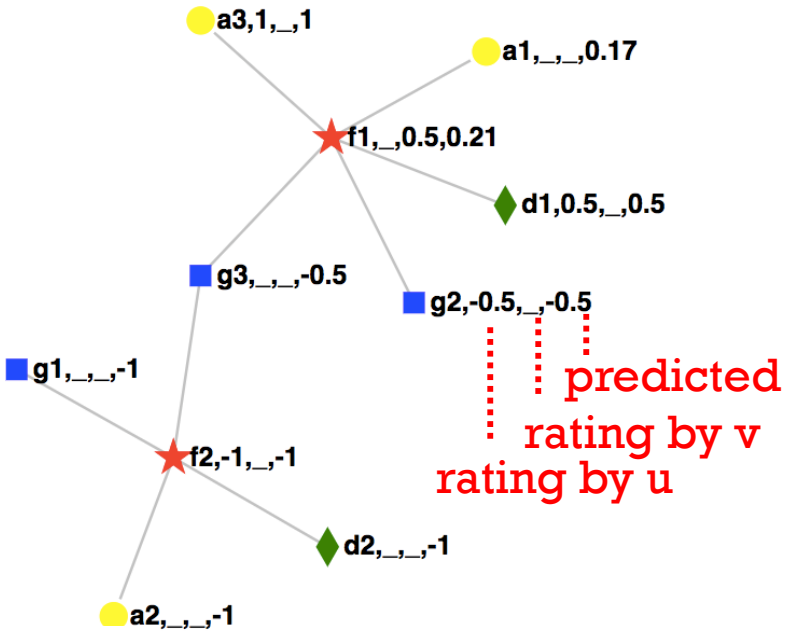
Hidden layer size 22	Precision	Recall	F_1
ANNA	**0.97**	**0.96**	**0.958**
Autoencoder + ANN	0.938	0.894	0.878
ANN	0.934	0.888	0.87
Hidden layer size 30			
ANNA	**0.97**	**0.962**	**0.962**
Autoencoder + ANN	0.932	0.886	0.86
ANN	0.936	0.896	0.88

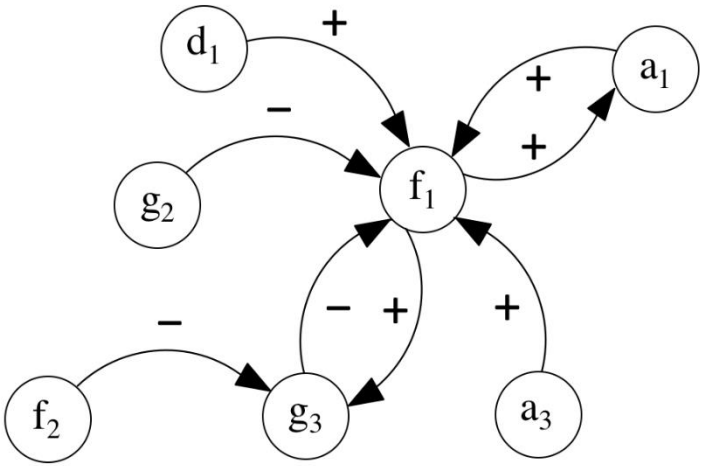
Table 2: Average of 5 runs of training on a reduced dataset and testing on the remaining examples.

Training set size: 6000, Testing set size: 2124			
Hidden layer size 22	**Precision**	**Recall**	F_1
ANNA	**0.978**	**0.976**	**0.976**
Autoencoder + ANN	0.802	0.642	0.61
Decision Tree (DT)	0.858	0.774	0.762
Hidden layer size 30			
ANNA	**0.966**	**0.964**	**0.966**
Autoencoder + ANN	0.802	0.638	0.604
Decision Tree (DT)	0.852	0.772	0.766
Training set size: 5000, Testing set size: 3124			
Hidden layer size 22	**Precision**	**Recall**	F_1
ANNA	**0.954**	**0.954**	**0.954**
Autoencoder + ANN	0.84	0.76	0.75
Decision Tree (DT)	0.876	0.828	0.826
Hidden layer size 30			
ANNA	**0.97**	**0.97**	**0.97**
Autoencoder + ANN	0.84	0.756	0.748
Decision Tree (DT)	0.886	0.844	0.844

Mining argumentation frameworks – from other data –

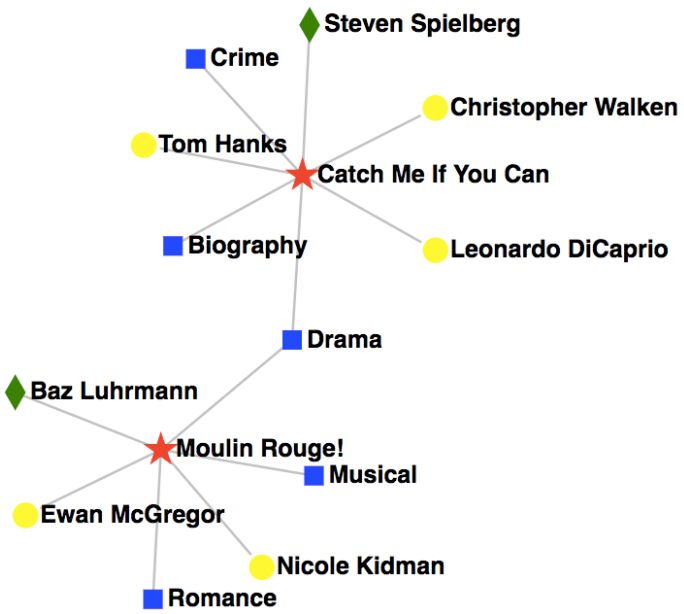


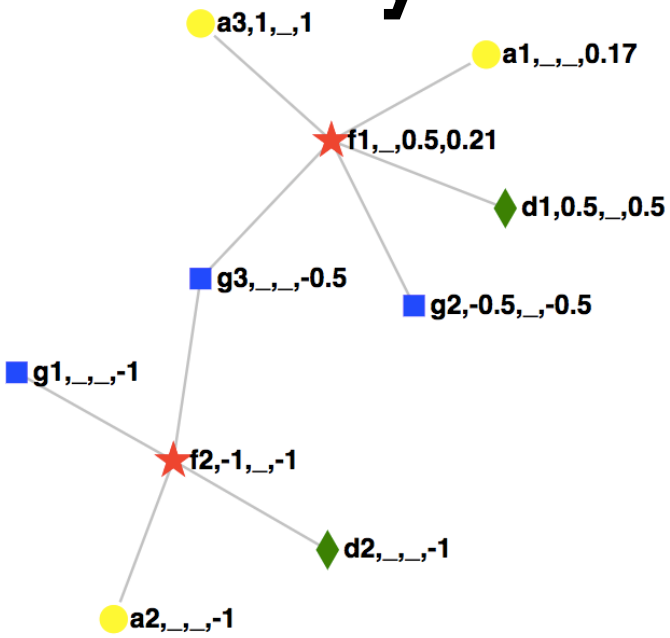


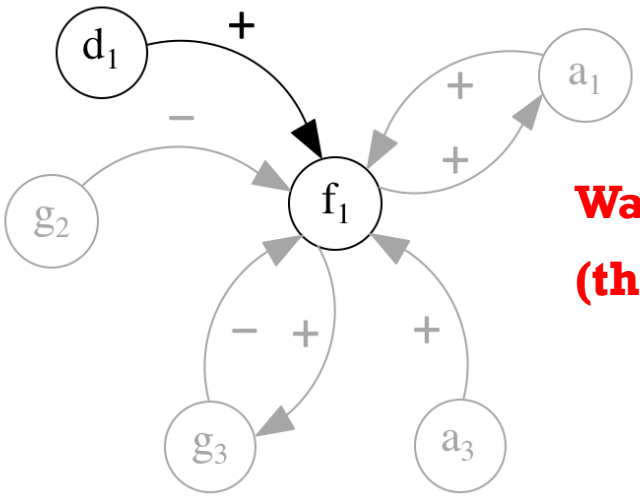


Rago, Cocarascu, Toni 2018

Mining “Explanation Systems”

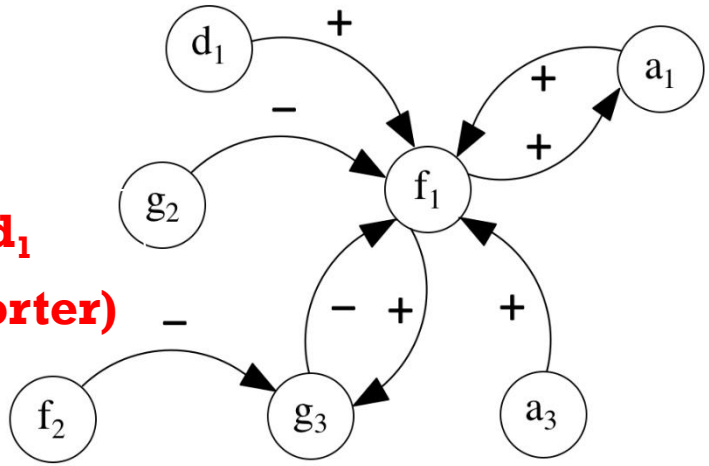






Watch f_1 because of d_1

(the strongest supporter)

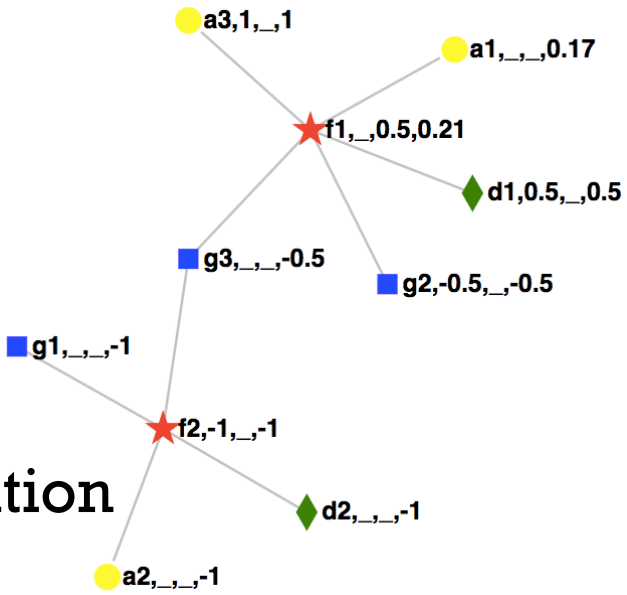


Rago, Cocarascu, Toni 2018

Data: Aspect-Item recommender system

$\langle \mathcal{I}, \mathcal{A}, \mathcal{T}, \mathcal{L}, \mathcal{U}, \mathcal{R} \rangle$ such that:

- $\mathcal{I}$ is a finite, non-empty set of *items*
- $\mathcal{A}$ is a finite, non-empty set of *aspects*
  $\mathcal{I}$ and $\mathcal{A}$ are pairwise disjoint
- $\mathcal{T}$ is a finite, non-empty set of *types*
  (each aspect has a unique type)
- $\mathcal{L} \subseteq (\mathcal{I} \times \mathcal{A})$ is a symmetrical binary relation
- $\mathcal{U}$ is a finite, non-empty set of *users*;
- $\mathcal{R} : \mathcal{U} \times \mathcal{X} \rightarrow [-1, 1]$ is a partial function of *ratings*.



Each item-aspect has a ***predicted rating***

Model	Min #movies training set/ #movies 'cold-start'			
	10/5	20/5	20/7	20/10
Co-clustering	83.4%	84.1%	85.1%	86.7%
KNN	85.5%	85.7%	85.9%	86.6%
KNN with z score	85.5%	85.3%	86.4%	87.5%
NMF	83.7%	84.2%	85.3%	86.1%
Slope one	86.2%	86.0%	87.2%	88.2%
SVD	85.9%	86.3%	87.3%	87.8%
A-I model	**94.9%**	**94.0%**	**93.3%**	**93.4%**

Data ⇒ Argumentation Framework

- Item-aspects are arguments (that the user (dis)likes that item-aspect).
- Argumentative relations depend on user ratings for direction $\mathcal{L}^u$ and (predicted) ratings for polarity:

let $r^u(i)$ be $\mathcal{R}(u,i)$ if defined,
else $\rho^u(i)$ if defined, and otherwise be undefined.

$$\langle \mathcal{X}, \mathcal{L}^-, \mathcal{L}^+, \mathcal{L}^0 \rangle$$

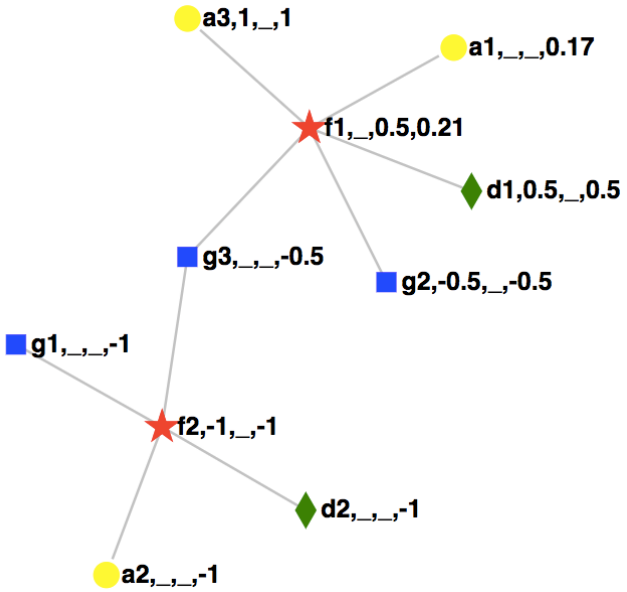
$\boldsymbol{\mathcal{X}} = \mathcal{I} \cup \mathcal{A}$

$$\mathcal{L}^- = \{(i,a) \in \mathcal{L}^u | r^u(i) < 0\} \cup \{(a,i) \in \mathcal{L}^u | \mathcal{P}^u_{\mathcal{A}}(a) < 0\}$$
$$\mathcal{L}^+ = \{(i,a) \in \mathcal{L}^u | r^u(i) > 0\} \cup \{(a,i) \in \mathcal{L}^u | \mathcal{P}^u_{\mathcal{A}}(a) > 0\}$$
$$\mathcal{L}^0 = \{(i,a) \in \mathcal{L}^u | r^u(i) = 0\} \cup \{(a,i) \in \mathcal{L}^u | \mathcal{P}^u_{\mathcal{A}}(a) = 0\}$$

TA framework ⇒ Explanation

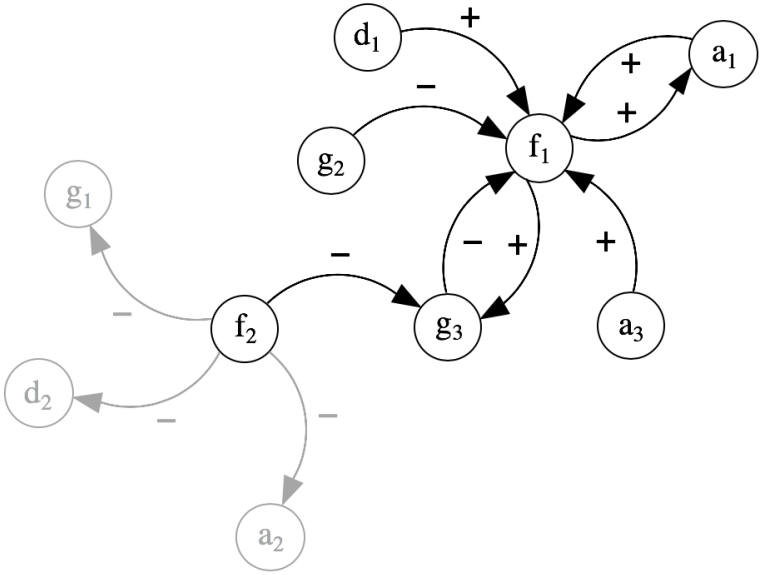
Aspect-Item recommender systems:

$\langle \mathcal{I}, \mathcal{A}, \mathcal{T}, \mathcal{L}, \mathcal{U}, \mathcal{R} \rangle$



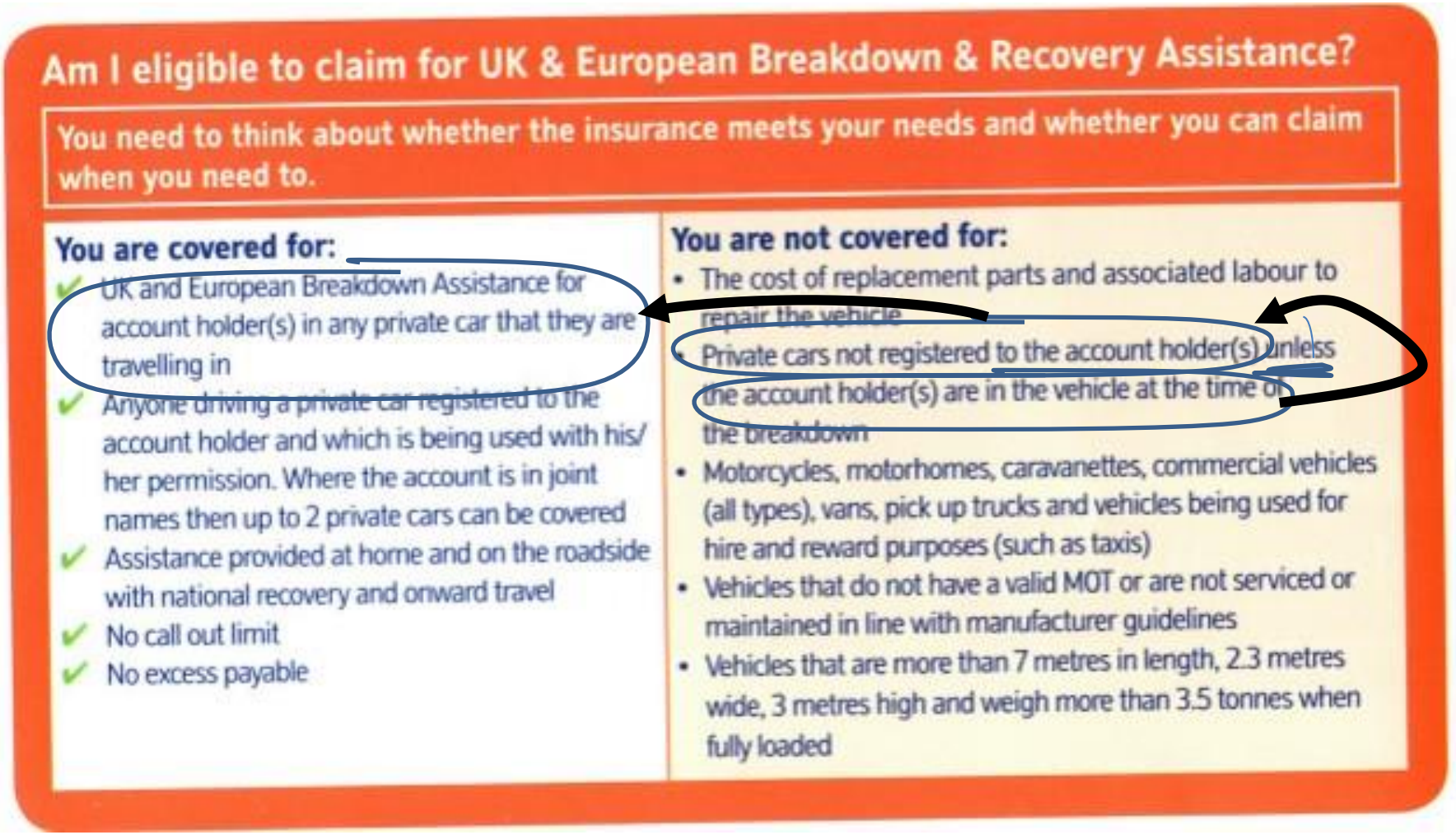
Tripolar argumentation frameworks:

$\langle \mathcal{X}, \mathcal{L}^-, \mathcal{L}^+, \mathcal{L}^0 \rangle$



The explanation for (recommending) f_1
is the subgraph in which all nodes have a path to f_1

Mining argumentation frameworks – from rules –



Am I eligible to claim for UK & European Breakdown & Recovery Assistance?

You need to think about whether the insurance meets your needs and whether you can claim when you need to.

You are covered for:

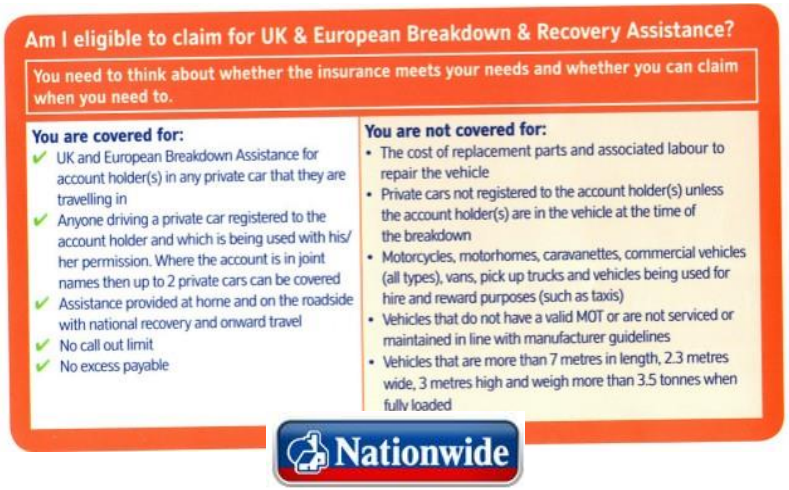
- ✔ UK and European Breakdown Assistance for account holder(s) in any private car that they are travelling in
- ✔ Anyone driving a private car registered to the account holder and which is being used with his/her permission. Where the account is in joint names then up to 2 private cars can be covered
- ✔ Assistance provided at home and on the roadside with national recovery and onward travel
- ✔ No call out limit
- ✔ No excess payable

You are not covered for:

- The cost of replacement parts and associated labour to repair the vehicle
- Private cars not registered to the account holder(s) unless the account holder(s) are in the vehicle at the time of the breakdown
- Motorcycles, motorhomes, caravanettes, commercial vehicles (all types), vans, pick up trucks and vehicles being used for hire and reward purposes (such as taxis)
- Vehicles that do not have a valid MOT or are not serviced or maintained in line with manufacturer guidelines
- Vehicles that are more than 7 metres in length, 2.3 metres wide, 3 metres high and weigh more than 3.5 tonnes when fully loaded

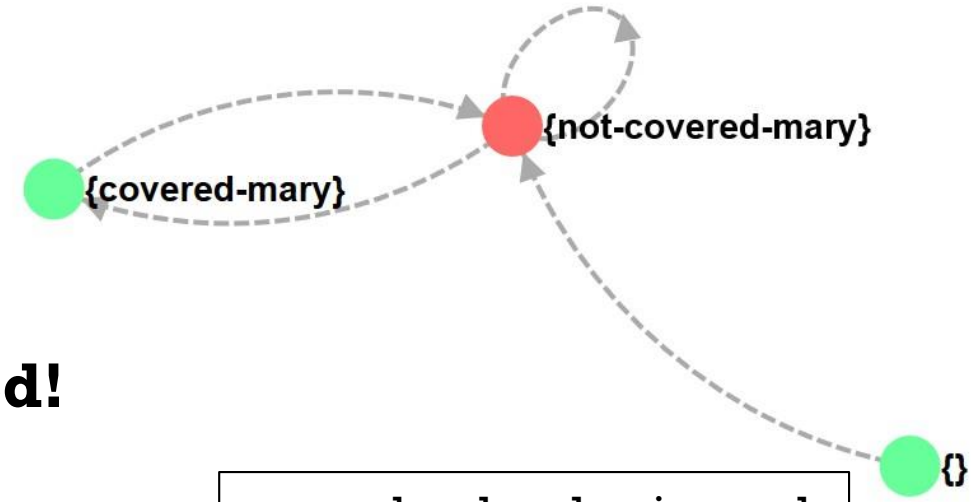
Nationwide

Mining → Systems



COVERED FOR: UK/EU Breakdown Assistance for account holder(s) in any private car they are travelling in
NOT COVERED FOR: private cars not registered to the account holder(s) unless in the vehicle at the time of the breakdown

Mary: account holder traveling in friend's car; car breaks down



Mary should be covered!

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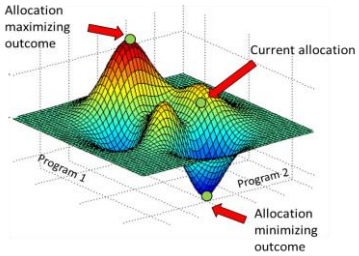
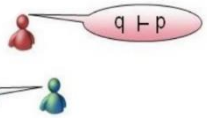
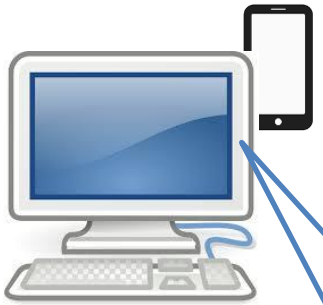
Healthcare (decision-support): ROAD2H

AA Frameworks

Decision, Explanation







Prescribe this treatment because…

Protocols/guidelines /…

EHRs

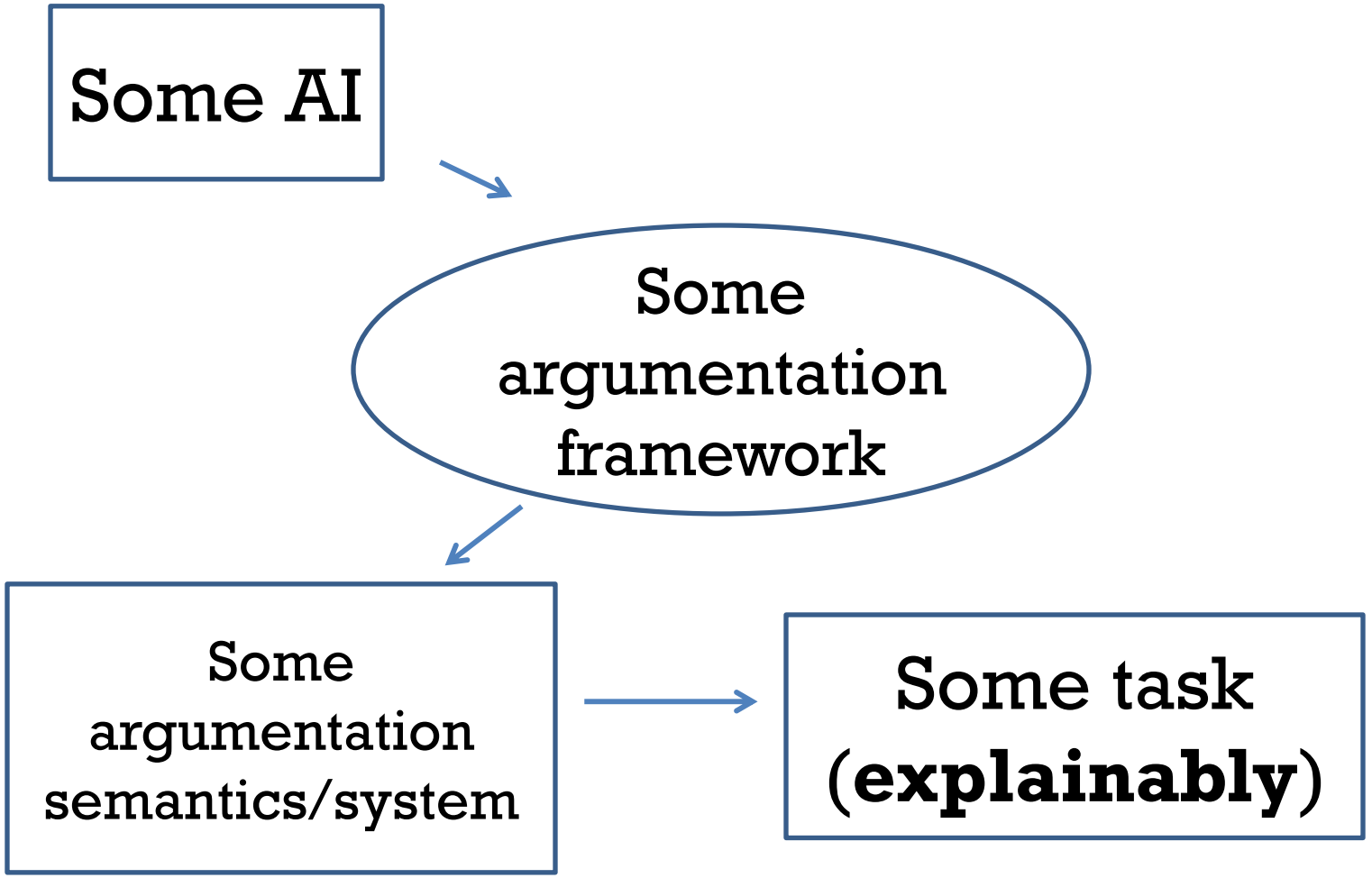
Electronic billing data

but …

(flat) ABA Frameworks

Standardised guidelines

In summary…


Some AI
Some argumentation framework
Some argumentation semantics/system
Some task (**explainably**)

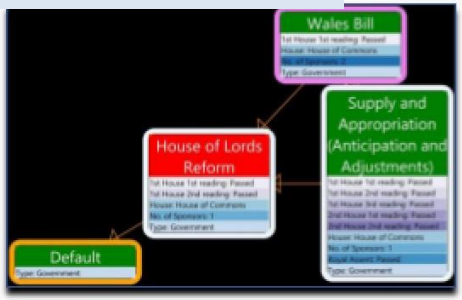
Conclusion

1. Argumentation frameworks
2. Semantics/systems
3. **Mining**

Healthcare (decision-support)

Deception detection (fake reviews)

Legal tech (explanations)



The future: machine arguing for explainable AI?

Questions?