LEARNING & CONTESTING ASSUMPTION-BASED ARGUMENTATION FRAMEWORKS

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ROADMAP

- Assumption-based Argumentation
  ABA frameworks
- Learning
  ABA frameworks
- Contesting
  argumentative claims
- Redressing
  as a way of learning

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- **Assumption-based Argumentation**
  ABA frameworks
- **Learning**
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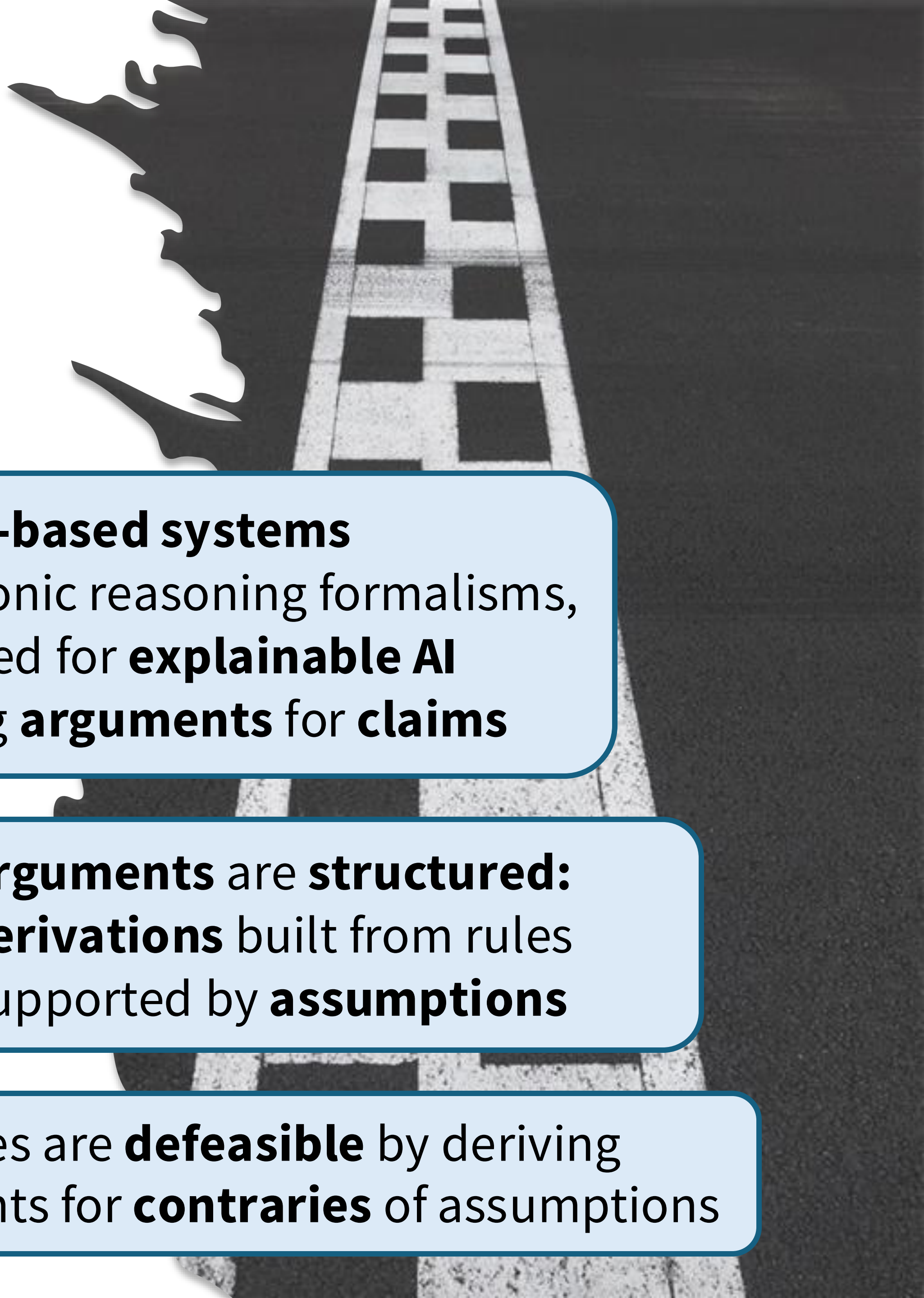
  as a way of learning

Rule-based systems
for non-monotonic reasoning formalisms,
can be used for **explainable AI**
by providing **arguments** for **claims**

Arguments are **structured:**
derivations built from rules
supported by **assumptions**

Rules are **defeasible** by deriving
arguments for **contraries** of assumptions



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- **Assumption-based Argumentation**
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- **Learning**
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  argumentative claims
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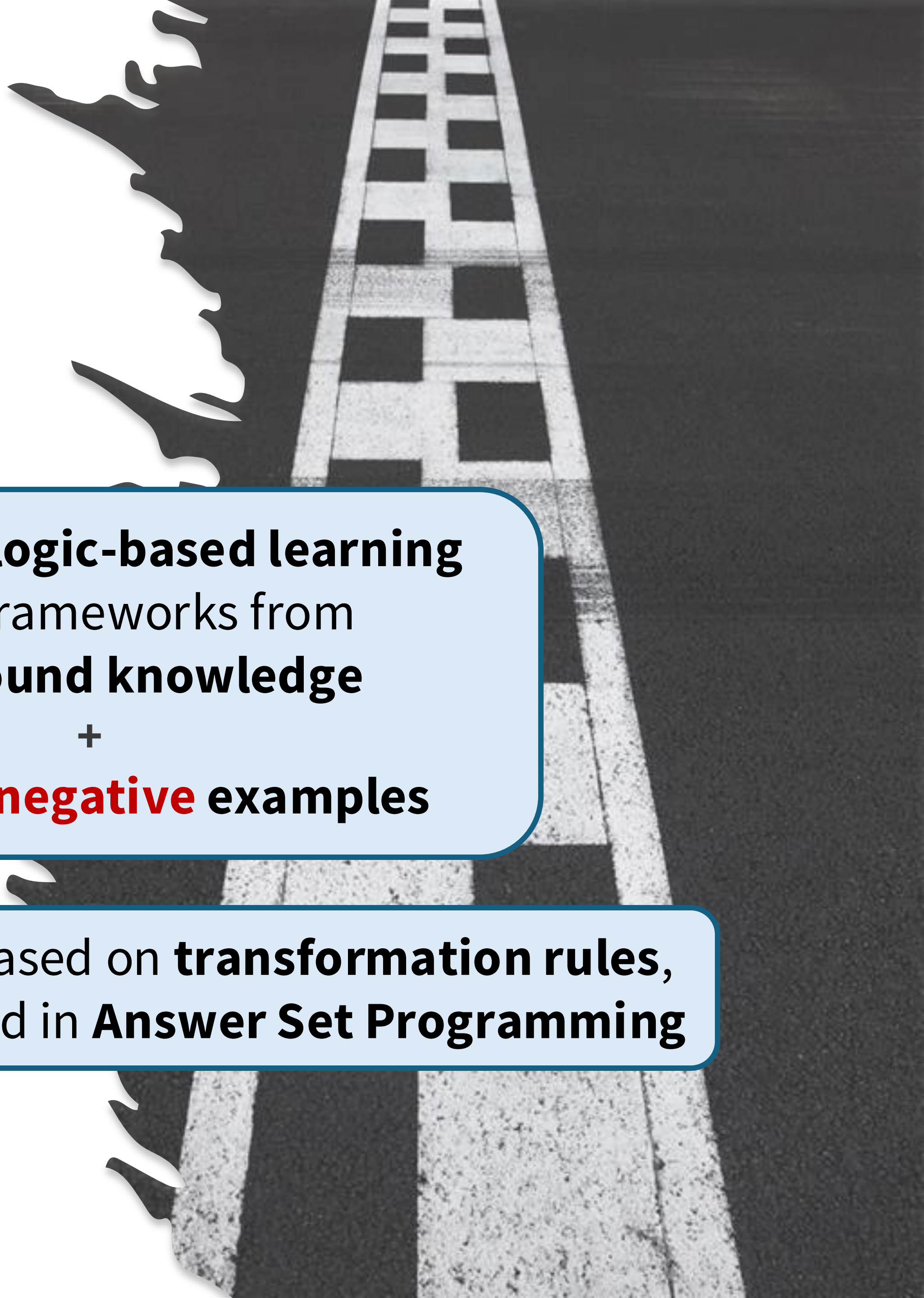
Automated logic-based learning
of ABA frameworks from
background knowledge
+
positive & **negative** **examples**

Algorithm based on **transformation rules**,
implemented in **Answer Set Programming**



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- **Assumption-based Argumentation**
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  argumentative claims
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highly desirable property
for **human-centric AI**

claims are subject to **contestation**:
- **rejected** claims may be **desirable**
- **accepted** claims may be **undesirable**

modify rules incrementally
to **reconcile** contestations

ABA FRAMEWORKS

Assumptions

Language
(set of sentences)

$$\langle \mathcal{L}, \mathcal{R}, \mathcal{A}, \overline{} \rangle$$

flat ABAFs
assumptions are
not heads of rules

Rules

$$\underbrace{h}_{\textbf{head}} \leftarrow \underbrace{s_1, \ldots, s_n}_{\textbf{body}}$$

if n=0, $h \leftarrow$ is called **fact**

total mapping from $\mathcal{A}$ into $\mathcal{L}$
$\bar{a}$ is the **Contrary** of a in $\mathcal{A}$

ABA FRAMEWORKS

an example ...

```
employed(jo) ←          onleave(jo) ←     maternity(jo) ←
employed(bob) ←         onleave(bob) ←    maternity(diana) ←
employed(claudia) ←
```

facts

```
loan(X) ← employed(X), nobreaks(X)
breaks(X) ← onleave(X)
```

rules

contrary of
nobreaks

assumption

nobreaks(X) renders the rule defeasible:
it can be applied only if **breaks**(X) cannot be derived

ABA FRAMEWORKS - SEMANTICS

"**acceptable**" extensions:
sets of **arguments** able to
"defend" themselves from "attacks"
(as determined by the chosen semantics)

- **Arguments** are **deductions** of claims using **rules** and supported by **assumptions**
- **Attacks** are directed at the assumptions in the support of arguments

```
employed(jo) ←          onleave(jo) ←       maternity(jo) ←
employed(bob) ←         onleave(bob) ←      maternity(diana) ←
employed(claudia) ←
loan(X) ← employed(X), nobreaks(X)
breaks(X) ← onleave(X)
```

{
~~arg1: { nobreaks(jo) } ⊢ loan(jo)~~
~~arg2: { nobreaks(bob) } ⊢ loan(bob)~~
arg3: { nobreaks(claudia) } ⊢ loan(claudia)
arg4: { } ⊢ breaks(jo)
arg5: { } ⊢ breaks(bob)
}

attacks

We focus on **stable extensions**

any set of arguments S that
1. do not attack each other (conflict-free)
2. S attacks all arguments it does not contain

Accepted claims: loan(claudia)

Rejected claims: loan(jo)
loan(bob)

BRAVE ABA LEARNING PROBLEM

Given

1. ABA framework **F** = $< \mathcal{L}, \mathcal{R}, \mathcal{A}, \overline{} >$ (**background knowledge**) with at least one stable extension
2. **Ep** = { **positive examples** }
3. **En** = { **negative examples** }
4. **T** = { **learnable predicates** }

find **F'** = $< \mathcal{L}', \mathcal{R}', \mathcal{A}', \overline{}' >$ with **a stable extension** S such that

i. **F** ⊆ **F'**
ii. **positive** are **covered**: every positive has an argument in S
iii. **negative** are **not covered**: no negative has an argument in S

F' is a **solution** to the brave ABA learning problem

CAUTIOUS ABA LEARNING PROBLEM

Given

1. ABA framework **F** = $< \mathcal{L}, \mathcal{R}, \mathcal{A}, \overline{} >$ (**background knowledge**) with at least one stable extension
2. **Ep** = { **positive examples** }
3. **En** = { **negative examples** }
4. **T** = { **learnable predicates** }

find **F'** = $< \mathcal{L}', \mathcal{R}', \mathcal{A}', \overline{}' >$ with **at least one stable extension**

i. **F** ⊆ **F'**

ii. **positive** are **covered**: every positive has an argument in C

iii. **negative** are **not covered**: no negative has an argument in C

$C = \bigcap_k^n S_i$

$S_1,\ldots,S_n$: stable extensions of **F'**

F' is a **solution** to the cautious ABA learning problem

ABA LEARNING
VIA TRANSFORMATION RULES

Learning ABA frameworks relies upon a set of **transformation rules**

$$\langle \mathcal{L}_1, \mathcal{R}_1, \mathcal{A}_1, \bar{\ }^{1} \rangle \longrightarrow \langle \mathcal{L}_2, \mathcal{R}_2, \mathcal{A}_2, \bar{\ }^{2} \rangle \longrightarrow \ldots \longrightarrow \langle \mathcal{L}_n, \mathcal{R}_n, \mathcal{A}_n, \bar{\ }^{n} \rangle$$

background knowledge **intensional solution**

learnt rules **do not** make explicit **reference** to specific values in the universe

$\longrightarrow$ ∈ { Rote Learning, Folding, Assumption Introduction, Subsumption }

A **strategy** controls the order of application of the transformation rules

ABA LEARNING at work

Language

{ employed(X)←, onleave(X)←,
maternity(X)←, loan(X)← }

Assumptions

{ nobreaks(X) }

Contraries

{ $\overline{\text{nobreaks(X)}} = \text{breaks(X)}$ }

1. Background Knowledge $\langle \mathcal{L}, \mathcal{R}, \mathcal{A}, \overline{} \rangle$

Rules

{ employed(jo)←, employed(bob)←, employed(claudia)←,
onleave(jo)←, onleave(bob)←,
maternity(jo)←, maternity(diana)← }

$X \in$ {claudia,jo,bob,diana}

2. Positive examples **Ep** = { loan(claudia) }
3. Negative examples **En** = { loan(bob) }
4. Learnable Predicates **T** = { loan }

TRANSFORMATION RULES at work
ROTE LEARNING

Add **facts**

- from **positive** examples
- for **contraries** of **assumptions**

to get a (**non-intensional**) **solution**

It's enough to learn

`loan(X) ← X=claudia` **Ep** = { `loan(claudia)` }

to get

$\mathcal{R}' = \mathcal{R} \cup \{$ `loan(X) ← X=claudia` $\}$

TRANSFORMATION RULES at work
FOLDING

Towards an **intensional** solution …

Generalise

```
loan(X) ← X=claudia
```

to

```
loan(X) ← employed(X)
```

by using

```
employed(X) ← X=claudia
```

WARNING

It also constructs an argument for a negative example: `loan(bob)`

ABA LEARNING is **parametric** w.r.t. the folding strategy

It includes a portfolio of strategies, sucha as “nondeterministic” and “greedy” folding

TRANSFORMATION RULES at work
ASSUMPTION INTRODUCTION

Repairing the ABA framework to get a solution …

Add an **assumption** to avoid

- **rejecting** a positive example
- **accepting** a negative example

```
loan(X) ← employed(X), nobreaks(X)
```

with contrary
`breaks(X)`

AND REPEAT!

Rote Learning breaks(X) ← X=bob

Folding breaks(X) ← onleave(X)

No more rules to learn:
LEARNING COMPLETED!

```
employed(jo) ←          onleave(jo) ←       maternity(jo) ←
employed(bob) ←         onleave(bob) ←      maternity(diana) ←
employed(claudia) ←
```

Rules in the Background Knowledge

```
loan(X) ← employed(X), nobreaks(X)
breaks(X) ← onleave(X)
```

Learnt rules

TRANSFORMATION RULES at work
ASSUMPTION INTRODUCTION

Repairing the ABA framework to get a solution …

Add an **assumption** to avoid

- **rejecting** a positive example
- **accepting** a negative example

`loan(X) ← employed(X), nobreaks(X)`

with contrary
`breaks(X)`

To get termination …

`p1(X) ← Q(X), asm_Q(X)`

reuse

…

`p2(X) ← Q(X), asm_Q(X)`

`asm_Q(X)`
is "relative to"
`Q(X)`

Algorithm 1: *RASP-ABAlearn*

Input: $(\langle \mathcal{R}_0, \mathcal{A}_0, \overline{}^0\rangle, \langle \mathcal{E}^+, \mathcal{E}^-\rangle, \langle \mathcal{E}^+_C, \mathcal{E}^-_C\rangle, \mathcal{T})$: redress problem
Output: $\langle \mathcal{R}, \mathcal{A}, \overline{}\rangle$: incremental redress relative to $\langle \mathcal{E}^+_C, \mathcal{E}^-_C\rangle$

$\mathcal{R} := \mathcal{R}_0$; $\mathcal{A} := \mathcal{A}_0$; $\overline{} := \overline{}^0$; $\mathcal{R}_l := \emptyset$;
RoLe(); *Gen*(); **return** $\langle \mathcal{R}, \mathcal{A}, \overline{}\rangle$;
Procedure *RoLe*()
  $P := ASP(\langle \mathcal{R}, \mathcal{A}, \overline{}\rangle, \langle \mathcal{E}^+, \mathcal{E}^-\rangle, \langle \mathcal{E}^+_C, \mathcal{E}^-_C\rangle, \mathcal{T})$;
  if $\neg sat(P)$ **then**
    fail;
  else
    $S := as(P)$;
    // R1. Rote Learning
    foreach newp(t) $\in S$ **do**
      $\mathcal{R}_l := \mathcal{R}_l \cup \{p(X) \leftarrow X = t\}$;
    end
  end
Procedure *Gen*()
  foreach $\rho : (p(X) \leftarrow X = t) \in \mathcal{R}_l$ **do**
    $\mathcal{R}_l := \mathcal{R}_l \setminus \{\rho\}$;
    // R4. Fact Subsumption
    if $\neg sat(ASP(\langle \mathcal{R} \cup \mathcal{R}_l, \mathcal{A}, \overline{}\rangle, \langle \mathcal{E}^+, \mathcal{E}^-\rangle, \langle \mathcal{E}^+_C, \mathcal{E}^-_C\rangle, \emptyset))$ **then**
      // R2 w/ R3. Folding with Assumption Introduction
      $\langle \rho_g, \alpha(X), C_\alpha\rangle := FoldingWAsmIntro(\rho)$;
      $\mathcal{R} := \mathcal{R} \cup \{\rho_g\}$;
      $\mathcal{A} := \mathcal{A} \cup \{\alpha(X)\}$;
      $\overline{\alpha(X)} := c\_\alpha(X)$;
      // R1. Rote Learning
      foreach c_α(t) $\in C_\alpha$ **do**
        $\mathcal{R}_l := \mathcal{R}_l \cup \{c\_\alpha(X) \leftarrow X = t\}$;
      end
    end
  end
Function *FoldingWAsmIntro*(ρ)
  // R2. Folding
  while $foldable(\rho, \mathcal{R})$ **do**
    $\rho := fold(\rho, \mathcal{R})$;
  end
  // R3. Assumption Introduction
  Let ρ be $H \leftarrow B$; $X := vars(B)$;
  if *there exists* $\alpha(X) \in \mathcal{A}$ *relative to* B **then**
    $\rho_g := H \leftarrow B, \alpha(X)$; $C_\alpha := \emptyset$;
    if $\neg sat(ASP(\langle \mathcal{R} \cup \{\rho\}, \mathcal{A}, \overline{}\rangle, \langle \mathcal{E}^+, \mathcal{E}^-\rangle, \langle \mathcal{E}^+_C, \mathcal{E}^-_C\rangle, \emptyset))$ **then**
      fail;
    end
  else // introduce an assumption $\alpha(X)$, with a new predicate α
    $\rho_g := H \leftarrow B, \alpha(X)$;
    $F := \langle \mathcal{R} \cup \{\rho\}, \mathcal{A} \cup \{\alpha(X)\}, \overline{} \cup \{\alpha(X) \mapsto c\_\alpha(X)\}\rangle$;
    $C_\alpha := \{c\_\alpha(X) \mid c\_\alpha(X) \in as(ASP(F, \langle \mathcal{E}^+, \mathcal{E}^-\rangle, \langle \mathcal{E}^+_C, \mathcal{E}^-_C\rangle, \{c\_\alpha\}))\}$;
  end
  return $\langle \rho_g, \alpha(X), C_\alpha\rangle$;

A GLIMPSE OF IMPLEMENTATION via ASP

- **ASP encoding**

```
loan(X) :- employed(X), nobreaks(X). …
nobreaks(X) :- employed(X), not breaks(X).
breaks(X) :- onleave(X).
```

```
{ breaksP(X) } :- onleave(X).
breaks(X) :- breaksP(X).
#minimize{1,X: breaksP(X)}.
:- not loan(claudia).
:- loan(bob).
```

learning facts
for contraries

- **Answer sets**

(1-to-1 correspondence with **Stable extensions**)

```
{ breaks(bob), … }, …
```

- **Rote learning**

```
braks(X) ←X=bob
```

SWI Prolog + **Clingo** (ASP)
Potassco

https://github.com/ABALearn/aba_asp

EXPERIMENTS

ASP-ABAlearnB

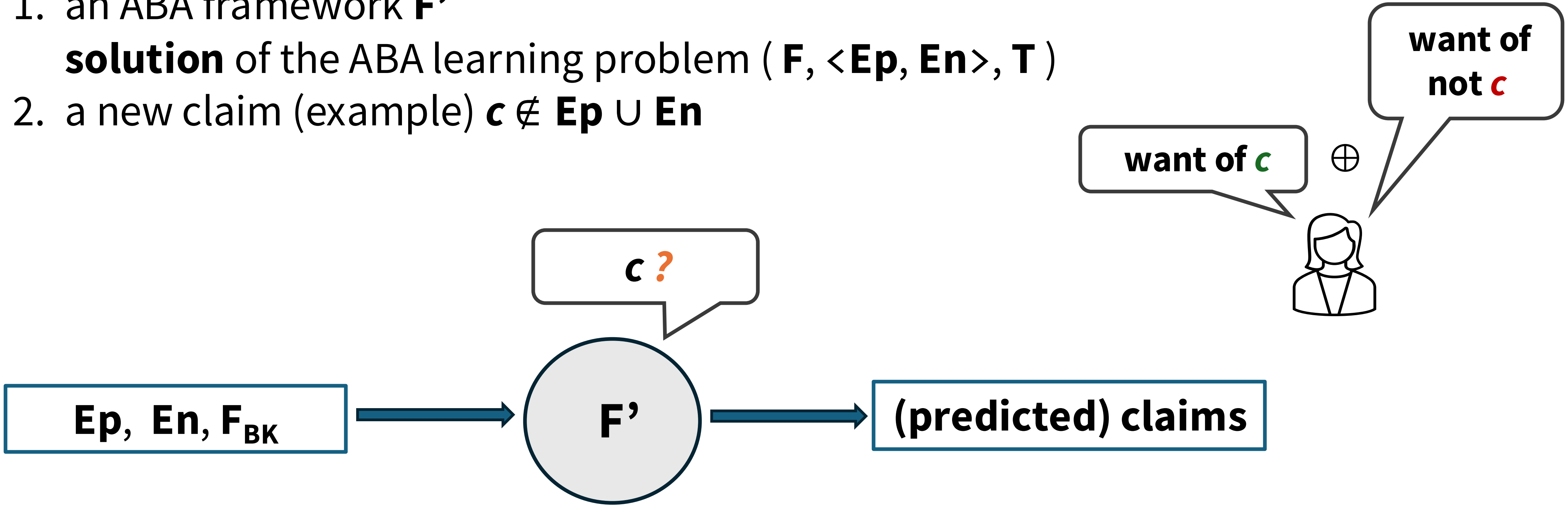
https://doi.org/10.5281/zenodo.13330013

Learning problem	BK	Ep	En	ASP-ABAlearnB	ILASP
Flies	8	4	2	0.01	0.09
Flies_bird&planes	10	5	2	0.02	0.25
Innocent	15	2	2	0.01	1.84
Nixon_diamond	6	1	1	0.01	unsat
Nixon_diamond_2	15	3	2	0.01	unsat
Tax_law	16	2	2	0.02	0.66
Tax_law_2	17	2	2	0.01	0.92
Acute	96	21	19	0.04	unsat
Autism	5716	189	515	23.43	timeout
Breast-w	6291	241	458	16.32	timeout

CONTESTATION

Given

1. an ABA framework **F'**
   solution of the ABA learning problem (**F**, <**Ep**, **En**>, **T**)
2. a new claim (example) $\boldsymbol{c} \notin$ **Ep** ∪ **En**



CONTESTATION

Given

1. an ABA framework **F'**
   solution of the ABA learning problem (F, <Ep, En>, T)
2. a new claim (example) ***c*** $\notin$ Ep $\cup$ En

F' is **contested** by

want of *c*	**want of *not c***

iff $\nexists$ stable extension S of **F'** s.t.

Ep $\cup$ { *c* } are **covered** in S & En are not covered in S	Ep are covered in S & En $\cup$ { *c* } are **not covered** in S

REDRESS

When a solution **F'** is **contested** by either ***want of c*** or ***want of not c***, **redressing** consists in deriving a **solution F''** of the ABA learning problem

- (**want of *c***) $(F, \langle \mathbf{Ep} \cup \{ c \}, En \rangle, T)$
- (**want of *not c***) $(F, \langle Ep, \mathbf{En} \cup \{ c \} \rangle, T)$

How to redress

from scratch

trivial form

1. forgetting F'
2. solving the original problem w/***c***
   either $(F, \langle \mathbf{Ep} \cup \{ c \}, En \rangle, T)$
   or $(F, \langle Ep, \mathbf{En} \cup \{ c \} \rangle, T)$

Incremental

modifies F' *as little as possible*

1. selecting some of the **learnt** rules & making them **defeasible** by assumption introduction, to get the new problem $(\mathbf{F'_{ai}}, \langle Ep, En \rangle, \mathbf{T'_{ai}})$
2. solving the new problem w/***c***
   either $(\mathbf{F'_{ai}}, \langle \mathbf{Ep} \cup \{ c \}, En \rangle, \mathbf{T'_{ai}})$
   or $(\mathbf{F'_{ai}}, \langle Ep, \mathbf{En} \cup \{ c \} \rangle, \mathbf{T'_{ai}})$

INCREMENTAL REDRESS **w/ABA Learning**

Suppose (the current solution) F’

```
employed(jo) ←         onleave(jo) ←     maternity(jo) ←
employed(bob) ←        onleave(bob) ←    maternity(diana) ←
employed(claudia) ←
loan(X) ← employed(X), nobreaks(X)
breaks(X) ← onleave(X)
```

is contested by the **want of** `loan(jo)`, which is not covered by any stable extension

We can **incrementally modify** F’ by applying the transformation rules

(0) Select the learnt rule to redress

`breaks(X) ← onleave(X), alpha(X)`	(1) by **assumption introduction** rule
`c_alpha(X) ← X=jo`	(2) by **rote learning** rule
`c_alpha(X) ← maternity(X)`	(3) by **folding** rule

to get a new solution **F’’** with at least one stable extension covering `loan(jo)`

EXPERIMENTS

RASP-ABAlearn

https://github.com/ABALearn/aba_asp

Problem		0	1	2	3	4	5	6	7	8	9	10
			+	−	−	−	−	+	−	+	+	+
acute	T_S	39	31	32	31	32	32	37	41	38	40	39
495	T_R	36	2	3	3	2	4	7	2	3	2	3
⟨54, 55⟩	S_S	501	501	501	501	501	501	503	503	503	503	503
	S_R	501	501	501	501	501	501	502	502	502	502	502
			+	+	+	−	+	−	−	−	−	+
autism	T_S	13524	14427	14552	15004	14985	15252	15048	15114	15246	15097	15329
6568	T_R	12741	970	905	999	44	1126	47	46	44	44	1144
⟨171, 464⟩	S_S	6953	6954	6955	6956	6956	6958	6958	6958	6958	6958	6961
	S_R	6953	6954	6955	6956	6956	6957	6957	6957	6957	6957	6958
			+	−	−	−	−	+	−	+	+	+
breastw	T_S	8371	8749	9061	9258	9208	9082	9039	9086	9061	9235	9318
6325	T_R	8482	36	430	35	36	36	36	35	35	37	418
⟨216, 400⟩	S_S	6519	6519	6520	6520	6520	6520	6520	6520	6520	6520	6521
	S_R	6519	6519	6520	6520	6520	6520	6520	6520	6520	6520	6521
			−	−	−	+	+	+	−	−	+	−
krkp	T_S	40595	42557	42250	42173	42357	41985	42417	42673	[illegible]	[illegible]	[illegible]
33210	T_R	40475	111	1711	106	106	108	106	1682	1189	[illegible]	[illegible]
⟨1503, 1374⟩	S_S	33409	33409	33410	33410	33410	33410	33410	33411	[illegible]	[illegible]	[illegible]
	S_R	33409	33409	33410	33410	33410	33410	33410	33411	[illegible]	[illegible]	[illegible]
			+	−	−	−	−	+	−	−	[illegible]	[illegible]
mushroom	T_S	555525	559972	471200	469676	474180	552260	552583	579530	[illegible]	[illegible]	[illegible]
33868	T_R	471191	300	11338	280	11680	11409	279	279	280	[illegible]	[illegible]
⟨214, 1587⟩	S_S	34762	34762	34763	34763	34764	34763	34763	34763	[illegible]	[illegible]	[illegible]
	S_R	34762	34762	34763	34763	34764	34765	34765	34765	[illegible]	[illegible]	[illegible]
			+	+	−	+	+	−	−	+	[illegible]	[illegible]
voting	T_S	663	663	675	670	669	705	707	664	664	[illegible]	[illegible]
2172	T_R	664	11	12	12	12	70	10	185	11	12	12
⟨98, 112⟩	S_S	2230	2230	2230	2230	2230	2233	2233	2229	2229	2229	2229
	S_R	2230	2230	2230	2230	2230	2231	2231	2234	2234	2234	2234

Learning problems

six standard datasets of the UCI ML Repo as ABA learning problems

Experimental processes

Redress from scratch (***S***) **vs.** Incremental redress (***R***)

11 runs of **RASP-ABALearn**:

0: run (*S*) and (*R*) using 90% of positive and negative examples

1-10: run (*S*) and (*R*) each using a randomly selected **new example** either **positive** or **negative**

			+	+	+	−	+	−	−	−	−	+
autism	T_S	13524	14427	14552	15004	14985	15252	15048	15114	15246	15097	15329
6568	T_R	12741	970	905	999	44	1126	47	46	44	44	1144
⟨171, 464⟩	S_S	6953	6954	6955	6956	6956	6958	6958	6958	6958	6958	6961
	S_R	6953	6954	6955	6956	6956	6957	6957	6957	6957	6957	6958

size of the background knowledge (# rules)

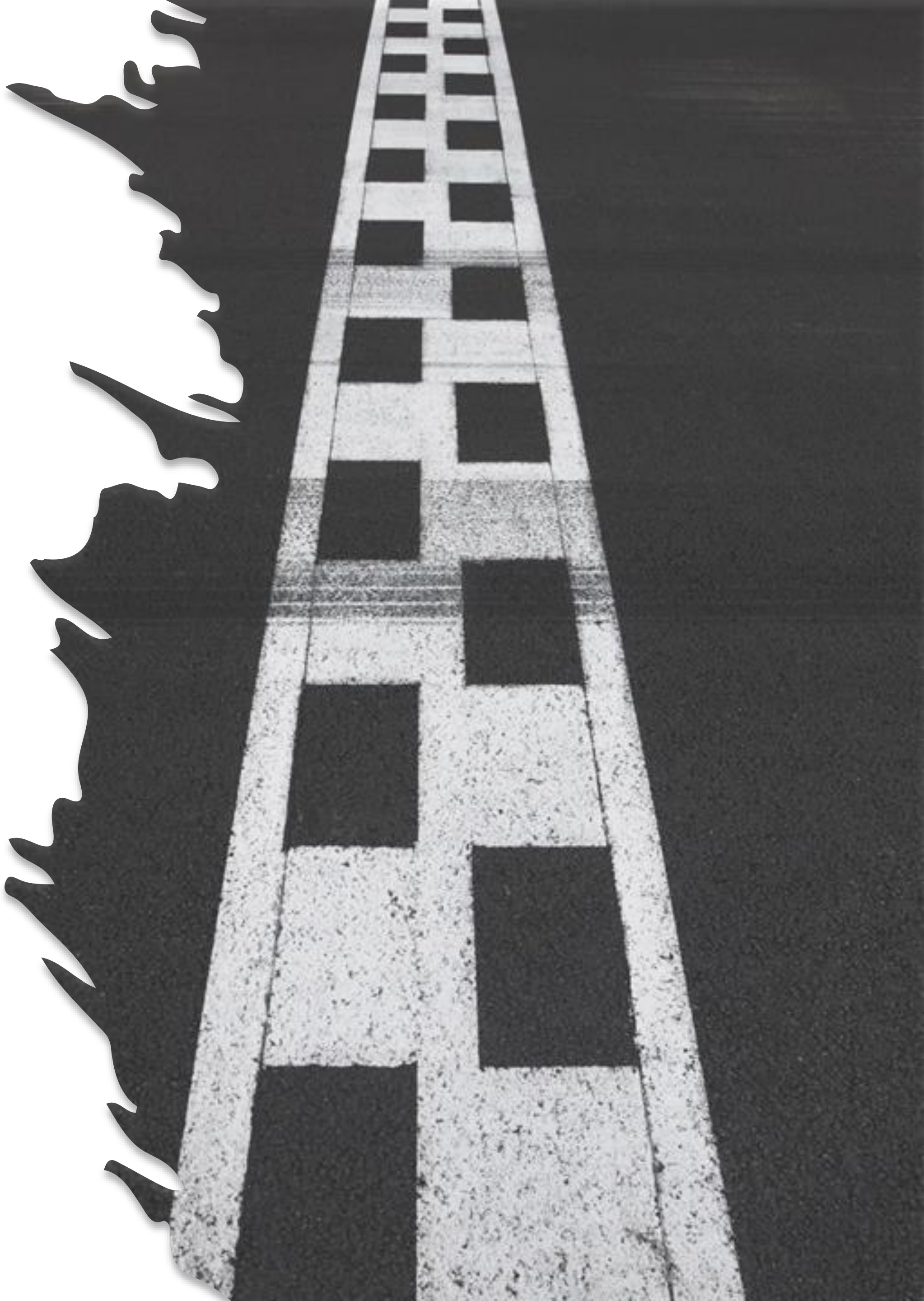
⟨ |Ep| , |En| ⟩

T_S T_R time in ms

S_S S_R # of learn rules

CONCLUSIONS

- **Automatic learning** of **ABA frameworks** from a background knowledge, and positive and negative examples
- **Contestability** for ABA frameworks
- **Redressing** as **a way of learning** from additional positive or negative examples
- Experiments show
  - **folding** & **assumption introduction** improve **effectiveness** in learning
  - **incremental redress** is more **efficient** than **re-learning from scratch**



AGENTIFIED ARGUMENTATIVE LEARNING

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from

ARGUMENTATIVE LEARNING (w/ABA Learning)

- learn ABAFs from (possibly) very few examples
  to make run-time inference about previously unseen examples
- learnt ABAFs may admit no or several extensions,
  failing to determine definite (non-)acceptance of unseen example

to

AGENTIFIED
ARGUMENTATIVE LEARNING (w/ABA Learning)

- **actions** : consulting an external source (human, agent or data repo)
- **observations** : learning the outcome of the consultation

NON-FLAT ABAFs w/ "actionable assumption"

NON-FLAT ABA FRAMEWORKS

a variant of the Nixon diamond problem

```
quaker(a) ←        quaker(b) ←        republican(c) ←
```

facts

```
voted(X,against_war) ← pacifist(X)
voted(X,pro_war) ← militarist(X)
```

rules

heads of the rules are **assumptions**

$\overline{\texttt{voted(X,against\_war)}} = \texttt{voted(X,pro\_war)}$

$\overline{\texttt{voted(X,pro\_war)}} = \texttt{voted(X,against\_war)}$

ARGUMENTATIVE LEARNING w/ABA Learning

$X \in \{a,b,c\}$

Language

{ quaker(X)←, republican(X)←, voted(X,pro_war)←,
voted(X,against_war)←, militarist(X)←, pacifist(X)← }

Assumptions

{ voted(X,pro_war),
voted(X,against_war) }

1. Background Knowledge $< \mathcal{L}, \mathcal{R}, \mathcal{A}, \overline{} >$

Rules

{ quaker(a)←, quaker(b)←, republican(c)←,
voted(X,against_war) ← pacifist(X),
voted(X,pro_war) ← militarist(X). }

Contraries

{ $\overline{\text{voted(X,against\_war)}}$ = voted(X,pro_war),
$\overline{\text{voted(X,pro\_war)}}$ = voted(X,against_war) }

2. Positive examples **Ep** = { pacifist(a), pacifist(b), militarist(c) }
3. Negative examples **En** = { militarist(a), militarist(b), pacifist(c) }
4. Learnable Predicates **T** = { pacifist, militarist }

ABA LEARNING at work

Rote Learning	pacifist(X) ← X=a	militarist(X) ← X=c
Folding	pacifist(X) ← quaker(X)	militarist(X) ← republican(X)

No more rules to learn:
LEARNING COMPLETED!

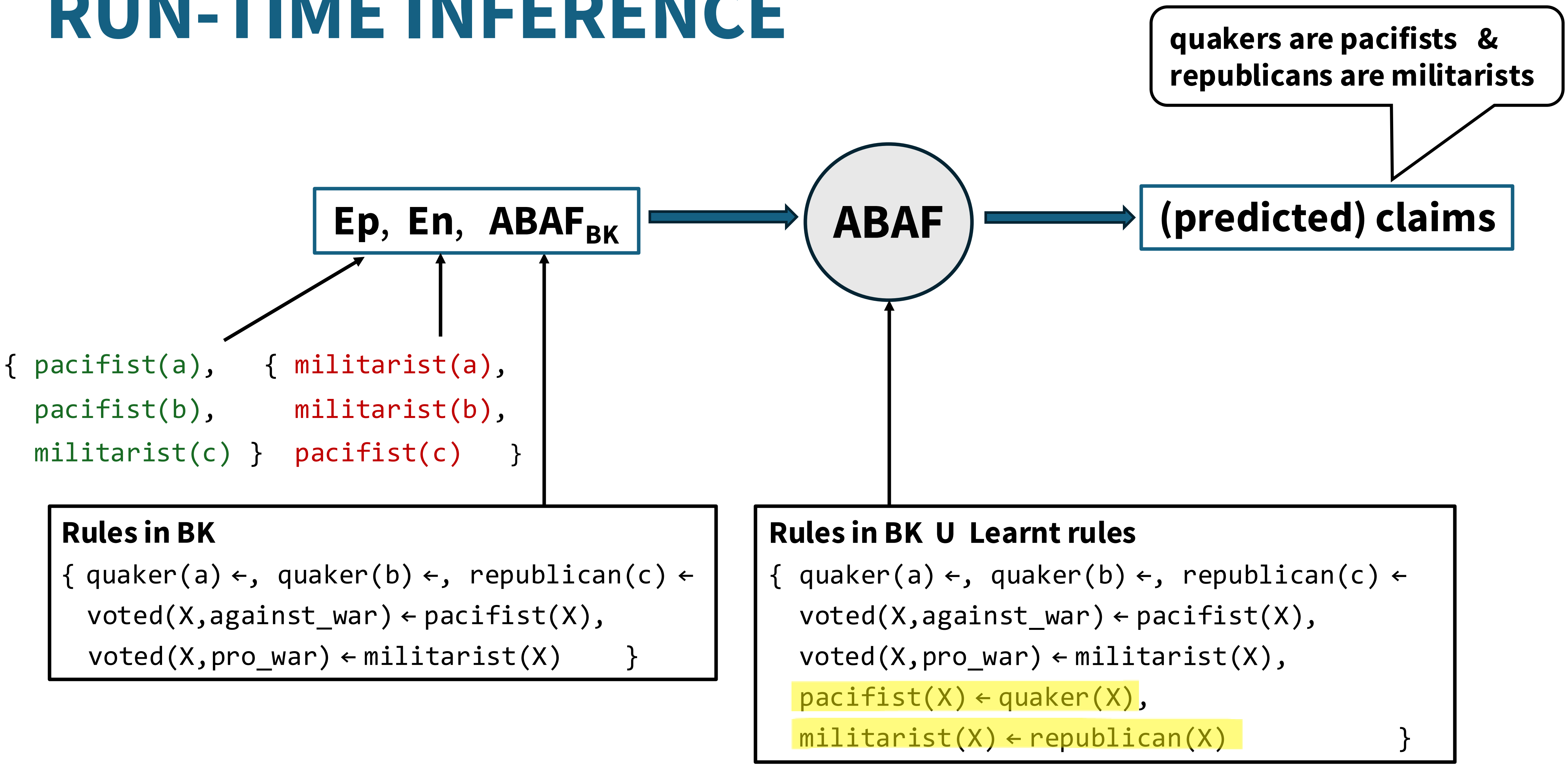
```
quaker(a) ←        quaker(b) ←        republican(c) ←
voted(X,against_war) ← pacifist(X)
voted(X,pro_war) ← militarist(X)
```

Rules in the Background Knowledge

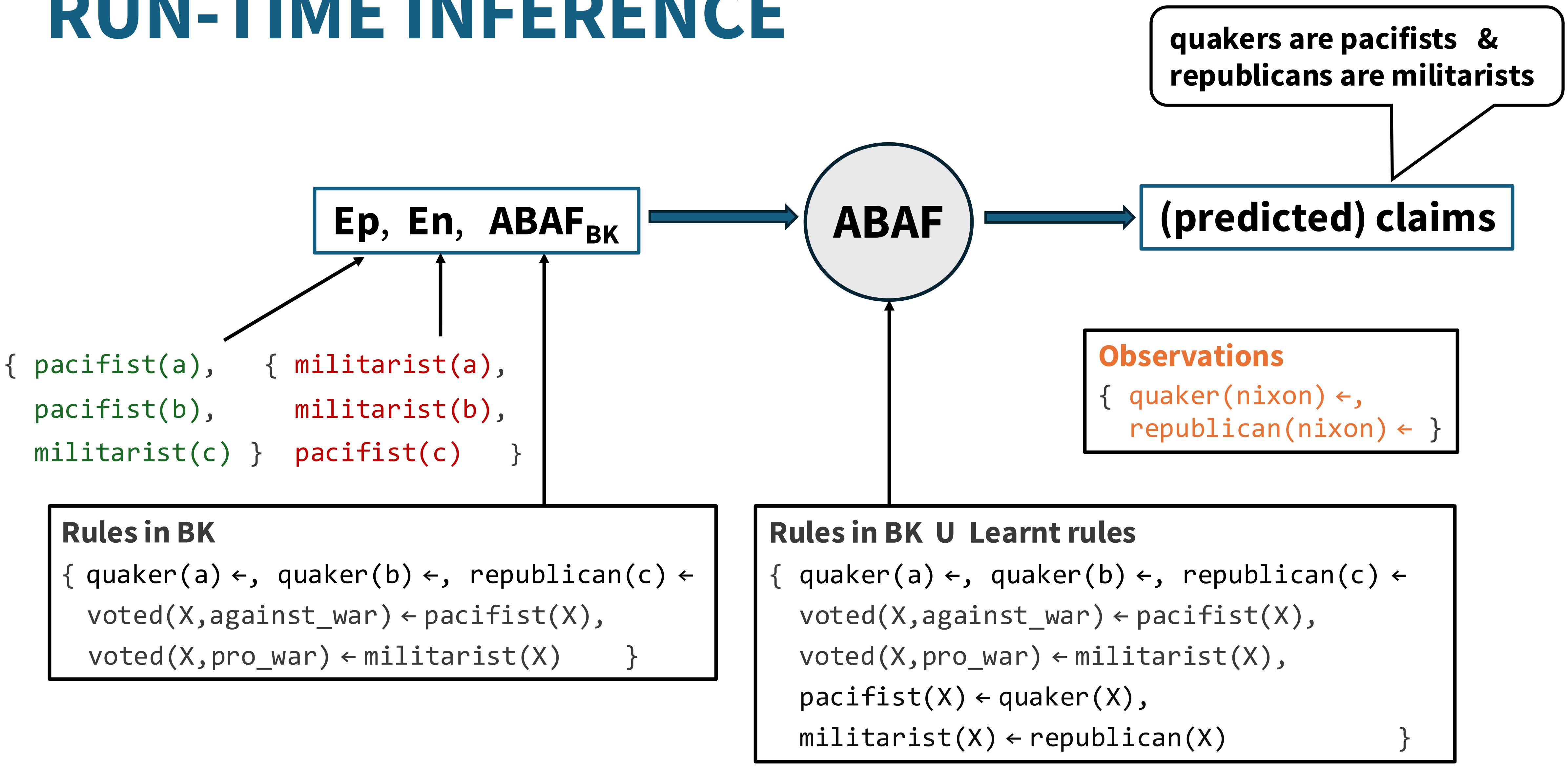
```
pacifist(X) ← quaker(X)
militarist(X) ← republican(X)
```

Learnt rules

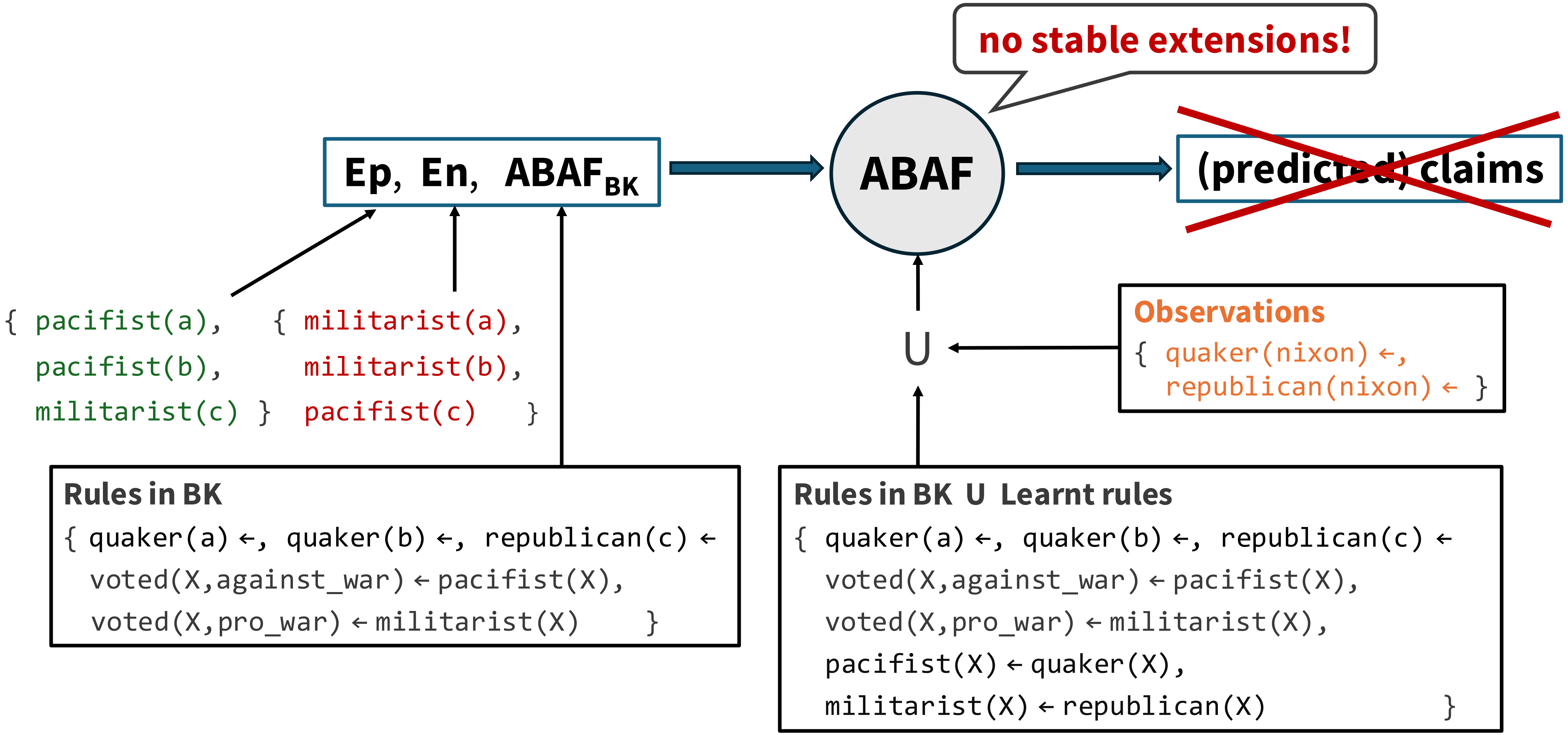
RUN-TIME INFERENCE



RUN-TIME INFERENCE



RUN-TIME INFERENCE



ABA LEARNING at work

quaker(a) ←   quaker(b) ←   republican(c) ←
voted(X,against_war) ← pacifist(X)
voted(X,pro_war) ← militarist(X)

Rules in BK

pacifist(X) ← quaker(X), **normal_quaker**(X)
militarist(X) ← republican(X), **normal_republican**(X)

Learnt rules

Learnt rules are rendered defeasible
by applying **assumption introduction**

pacifist(X) ← quaker(X), **normal_quaker**(X)
militarist(X) ← republican(X), **normal_republican**(X)

Learnt rules

$\overline{\texttt{normal\_quaker(X)}} = \texttt{abnormal\_quaker(X)}$
$\overline{\texttt{normal\_republican(X)}} = \texttt{abnormal\_republican(X)}$

ABA LEARNING at work

```
quaker(a) ←     quaker(b) ←     republican(c) ←
voted(X,against_war) ← pacifist(X)
voted(X,pro_war) ← militarist(X)
```

```
pacifist(X) ← quaker(X), normal_quaker(X)
militarist(X) ← republican(X), normal_republican(X)
```

Rote Learning

```
abnormal_quaker(X) ← X=nixon
```

Which **rule** should we **learn** ?

```
abnormal_republican(X) ← X=nixon
```

Folding

```
abnormal_quaker(X) ← republican(X)
```

```
abnormal_ republican(X) ← quaker(X)
```

Which **claim** should be **accepted** ?

```
militarist(nixon)
voted(nixon,pro_war)
```

```
pacifist(nixon)
voted(nixon,against_war)
```

AGENTIFIED ABA LEARNING at work

```
quaker(a) ←     quaker(b) ←     republican(c) ←
```

```
voted(X,against_war) ← pacifist(X)
voted(X,pro_war) ← militarist(X)
```

actionable assumption

```
pacifist(X) ← quaker(X), normal_quaker(X)
militarist(X) ← republican(X), normal_republican(X)
```

Rote Learning

```
abnormal_quaker(X) ← X=nixon
```

Which **rule** should we **learn** ?

```
abnormal_republican(X) ← X=nixon
```

Folding

```
abnormal_quaker(X) ← republican(X)
```

```
abnormal_ republican(X) ← quaker(X)
```

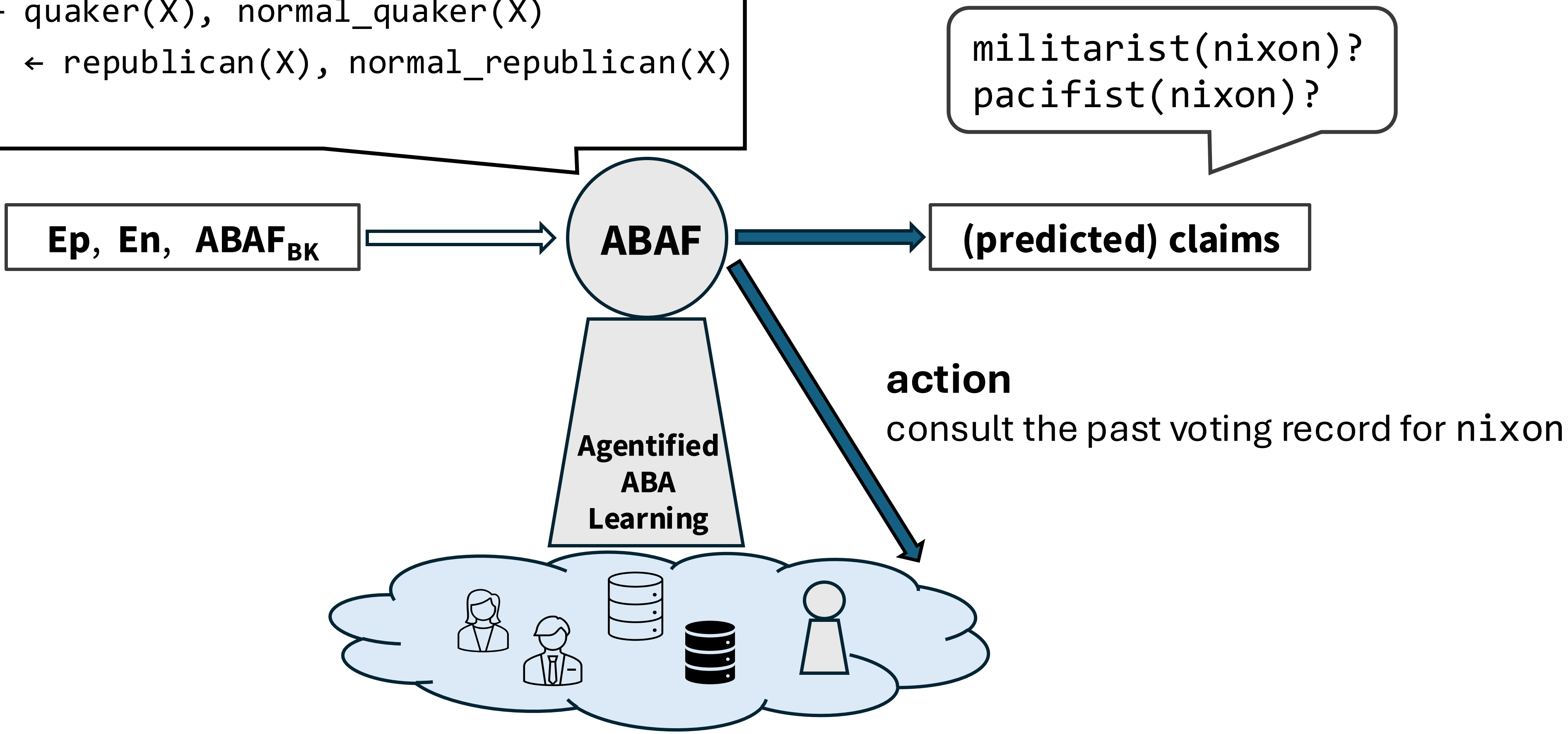
Which **claim** should be **accepted** ?

```
militarist(nixon)
voted(nixon,pro_war)
```

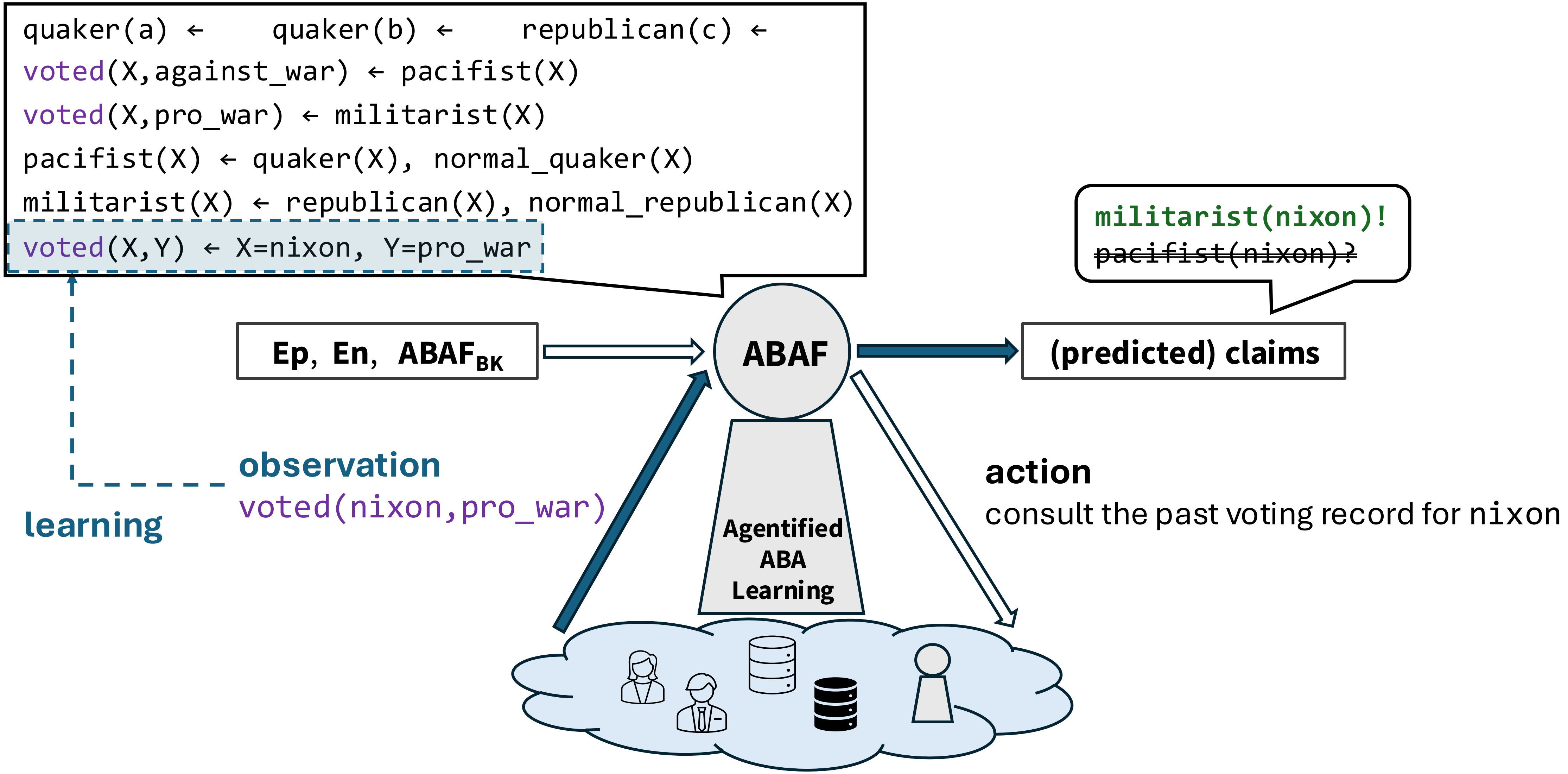
```
pacifist(nixon)
voted(nixon,against_war)
```

AGENTIFIED ABA LEARNING at work

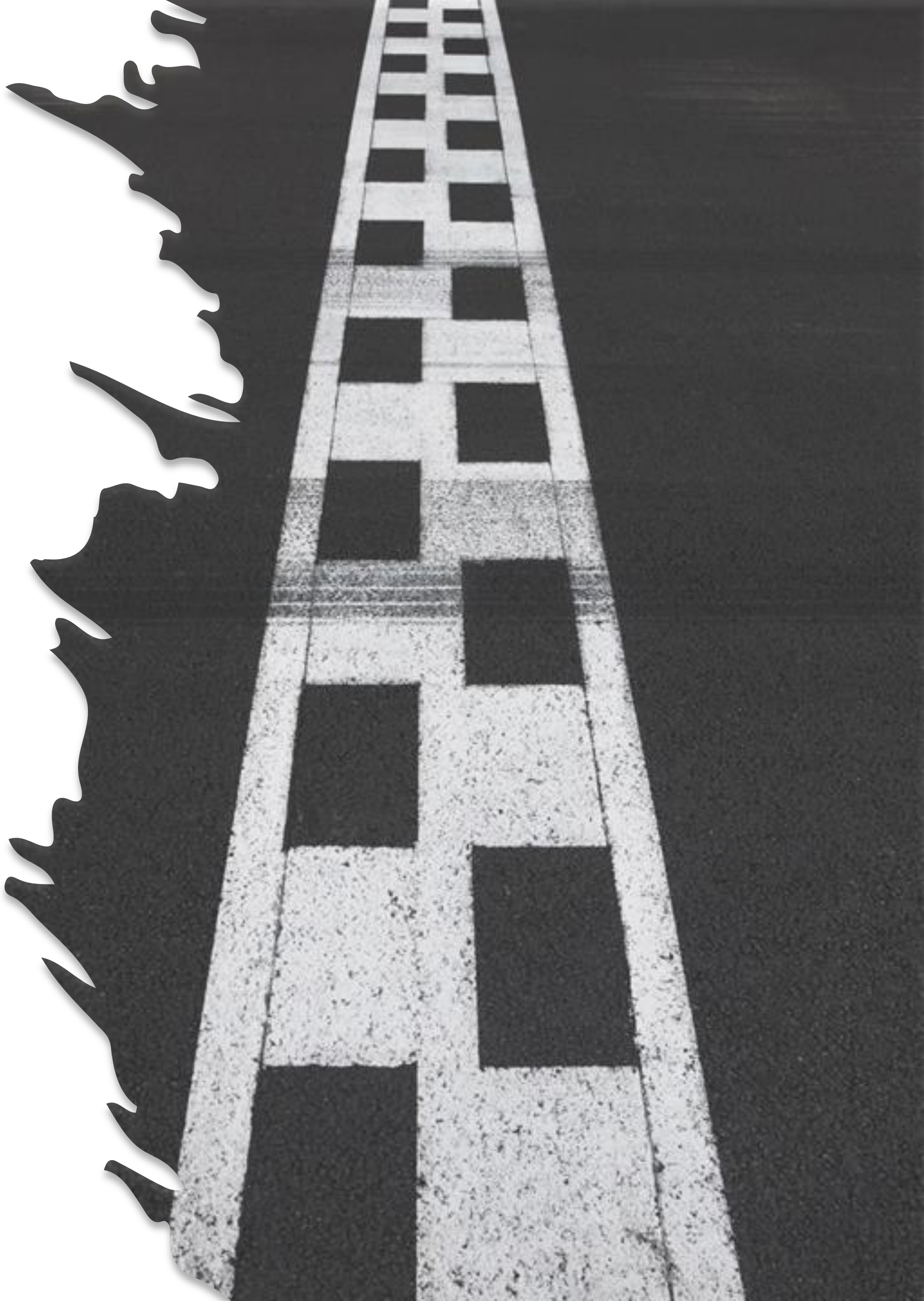
```
quaker(a) ←     quaker(b) ←     republican(c) ←
voted(X,against_war) ← pacifist(X)
voted(X,pro_war) ← militarist(X)
pacifist(X) ← quaker(X), normal_quaker(X)
militarist(X) ← republican(X), normal_republican(X)
```



AGENTIFIED ABA LEARNING at work



CONCLUSIONS



- **Novel vision** for **argumentative agents** learning from examples & performing actions to generate targeted expansions of their knowledge
- **Enhancement of ABA Learning** leveraging on non-flat ABAFs
- **TODO** turn the **vision** into an **algorithm**