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Schemes for Legal Argumentation

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(some slides by Henry Prakken, Utrecht/Groeningen)

Defeasible and deductive arguments in the law

- A valid argument can be said to consist of three elements: a set of premises, a conclusion, and a support relation between premises and conclusion.
  - In a deductively valid argument, the premises provide conclusive support for the conclusion
  - In a defeasibly valid argument , the premises only provide presumptive support for the conclusion: if we accept the premises we should also accept the conclusion, but only so long as we do not have prevailing arguments to the contrary.
- In the law most arguments are defeasible

Argument(ation) schemes: general form

Douglas Walton

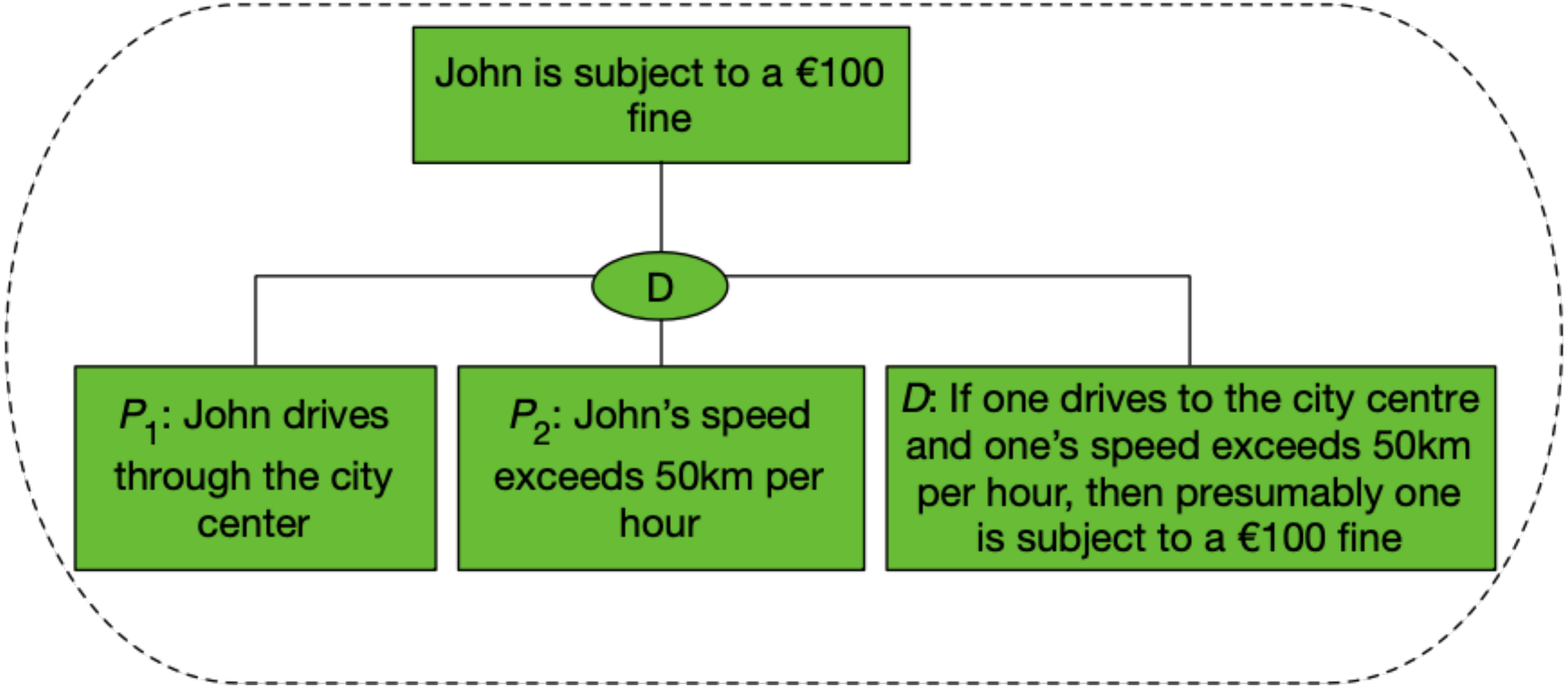
Premise 1,
… ,
<u>Premise n</u>
Therefore (presumably), conclusion

- But also critical questions

Linked arguments

- A linked argument includes, beside a conditional warrant, more than one premises.
- None of these premises is sufficient to trigger on its own the conjunctive antecedent of the conditional warrant.

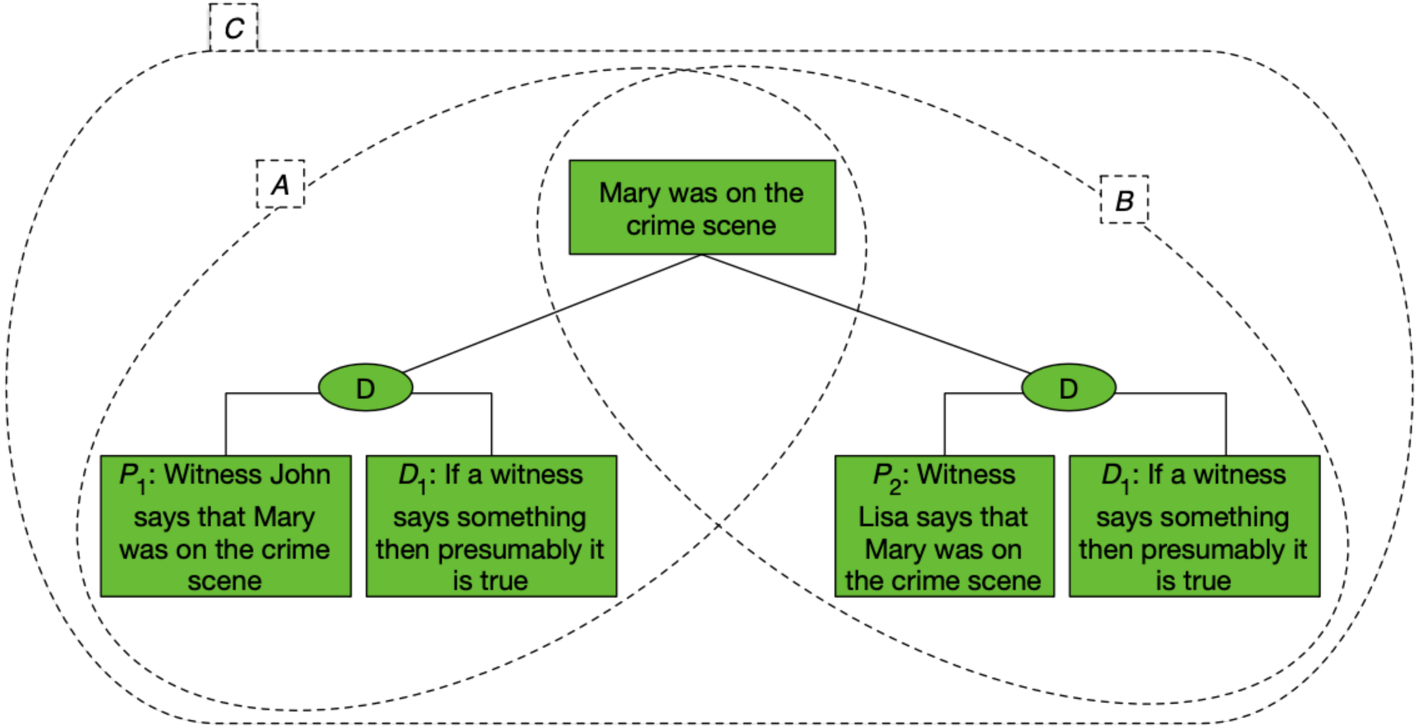
Linked argument



Convergent arguments

- A convergent argument structure is a combination of multiple arguments, each leading to the same conclusion.
- Often, but not always a convergent argument structure leads to accrual: the combined convergent arguments provide a stronger support to the common conclusion of its component arguments than each of these arguments would do in isolation.

Convergent argument



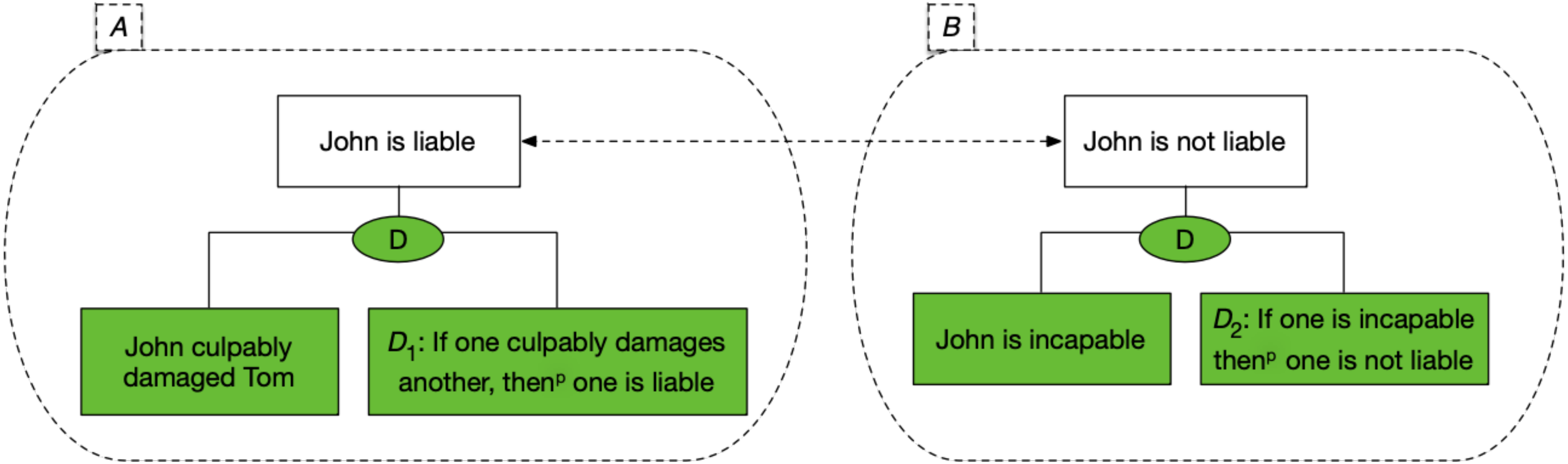
Attacks on arguments


An argument can be attacked in any of three ways:

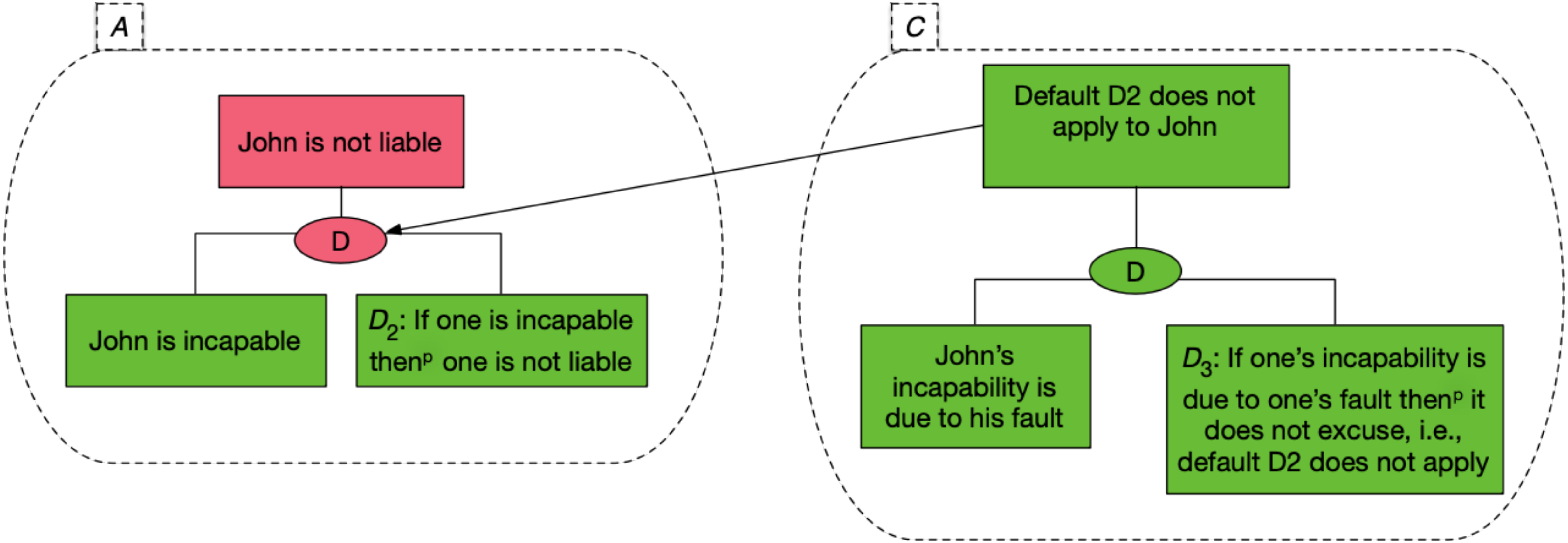
- by opposing one of its premises (undermining),
- by opposing one of its conclusions (rebutting),
- or by opposing the support relation between premises and conclusions (undercutting)

- Critical questions point to opportunities for attack

Rebutting attack



Undercutting attack



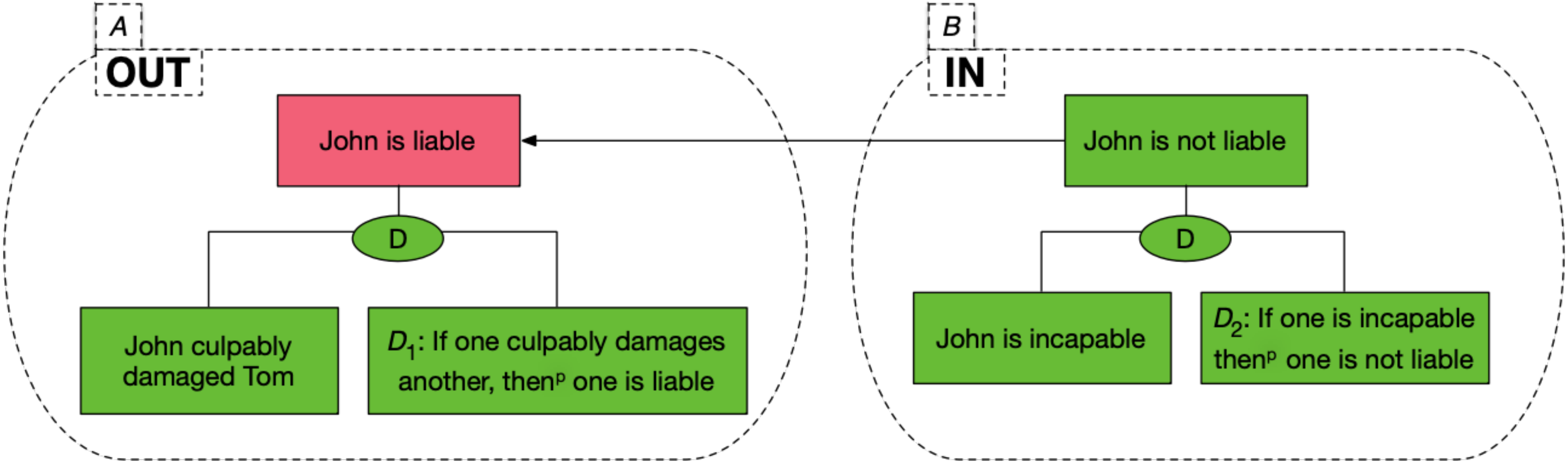
Defeat

- An argument is defeated iff:
  - its premises are attacked
  - it is rebutted by a stronger argument
  - it is undercut by an argument

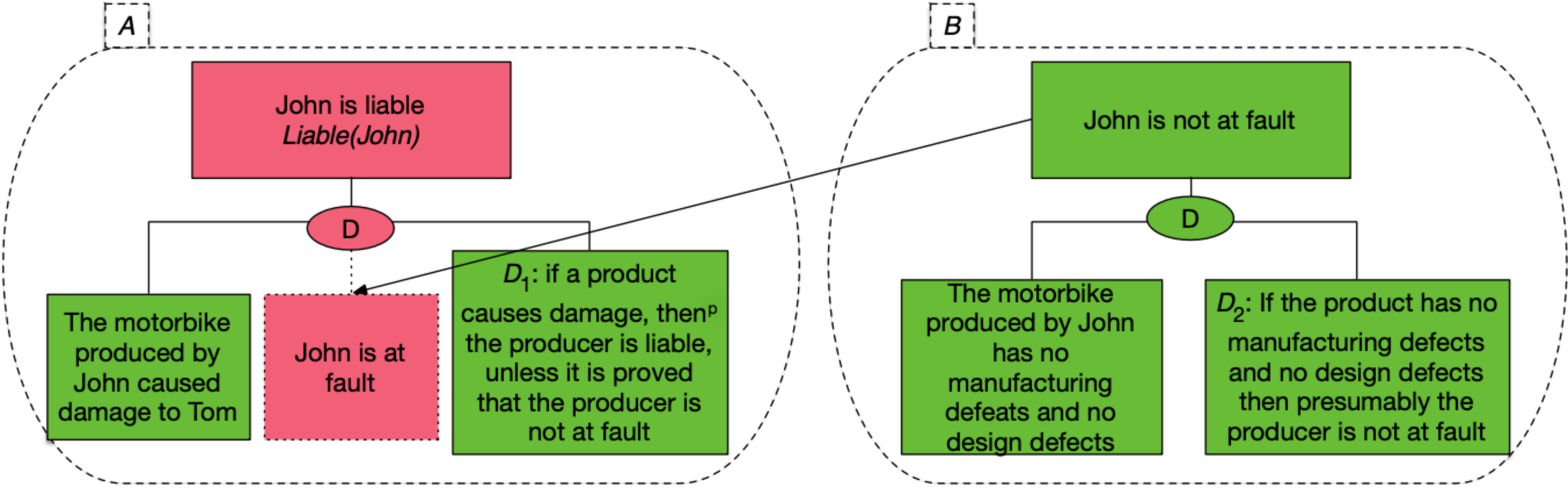
Defeat in the law

- Defeat in the law can result from different attacks
  - the conclusion of the argument is contradicted by a non-weaker arguments (rebuttal)
  - the default (rule) in the argument undercut by an exception
  - the default (rule) in the argument is undercut by establishing an impeditive fact (contradicting a presumption).

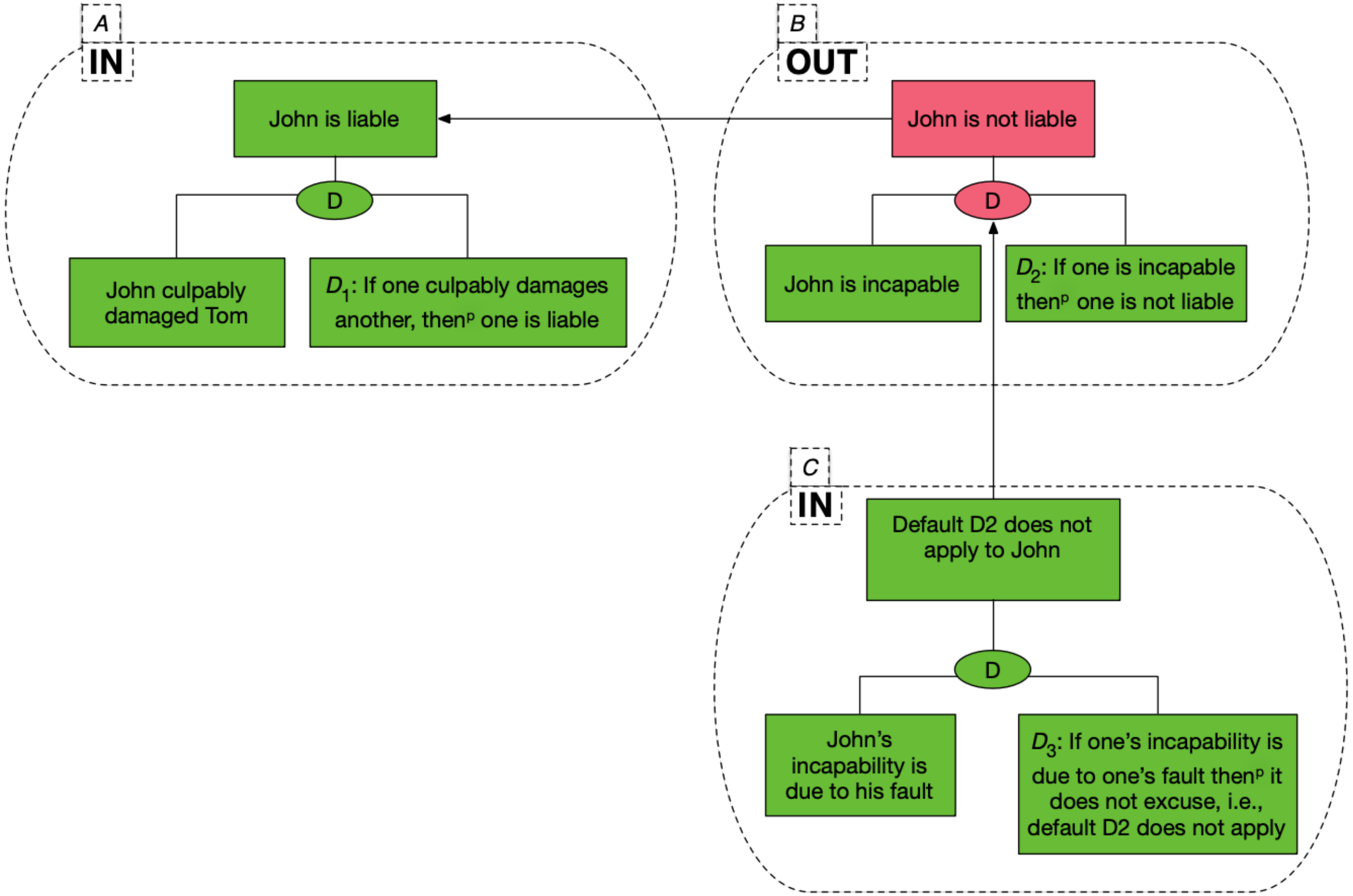
Defeat by rebutting



Defeat by undercutting



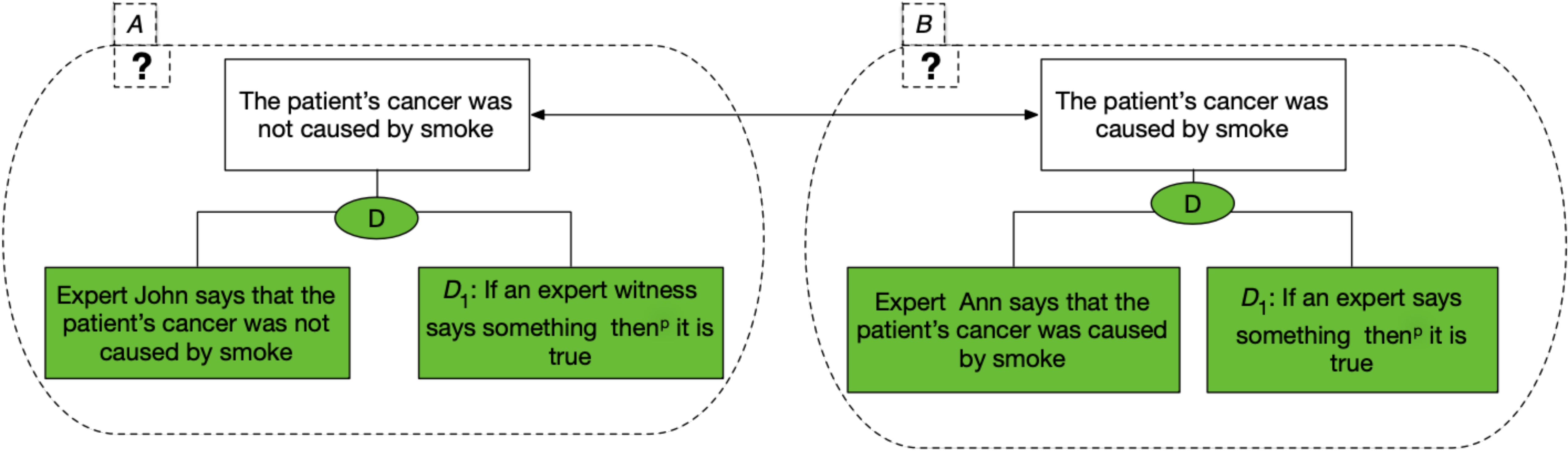
Reinstatement



Burden of proof

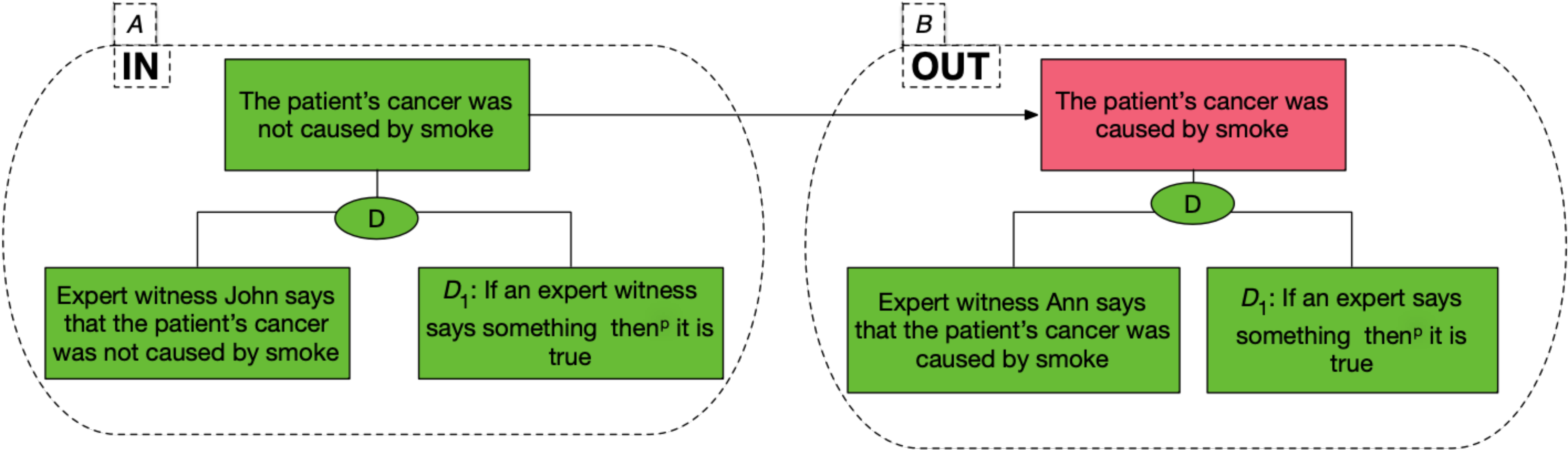
- The conflict between conflicting legal arguments may be decided according to the burden of proof.
  - The party (the argument) having the burden of proof looses (is defeated) if it does not meet the burden of persuasion, relatively to the argument to the contrary.
  - But if the defeating argument is out, the burden of proof is met.

Undecided argument conflict

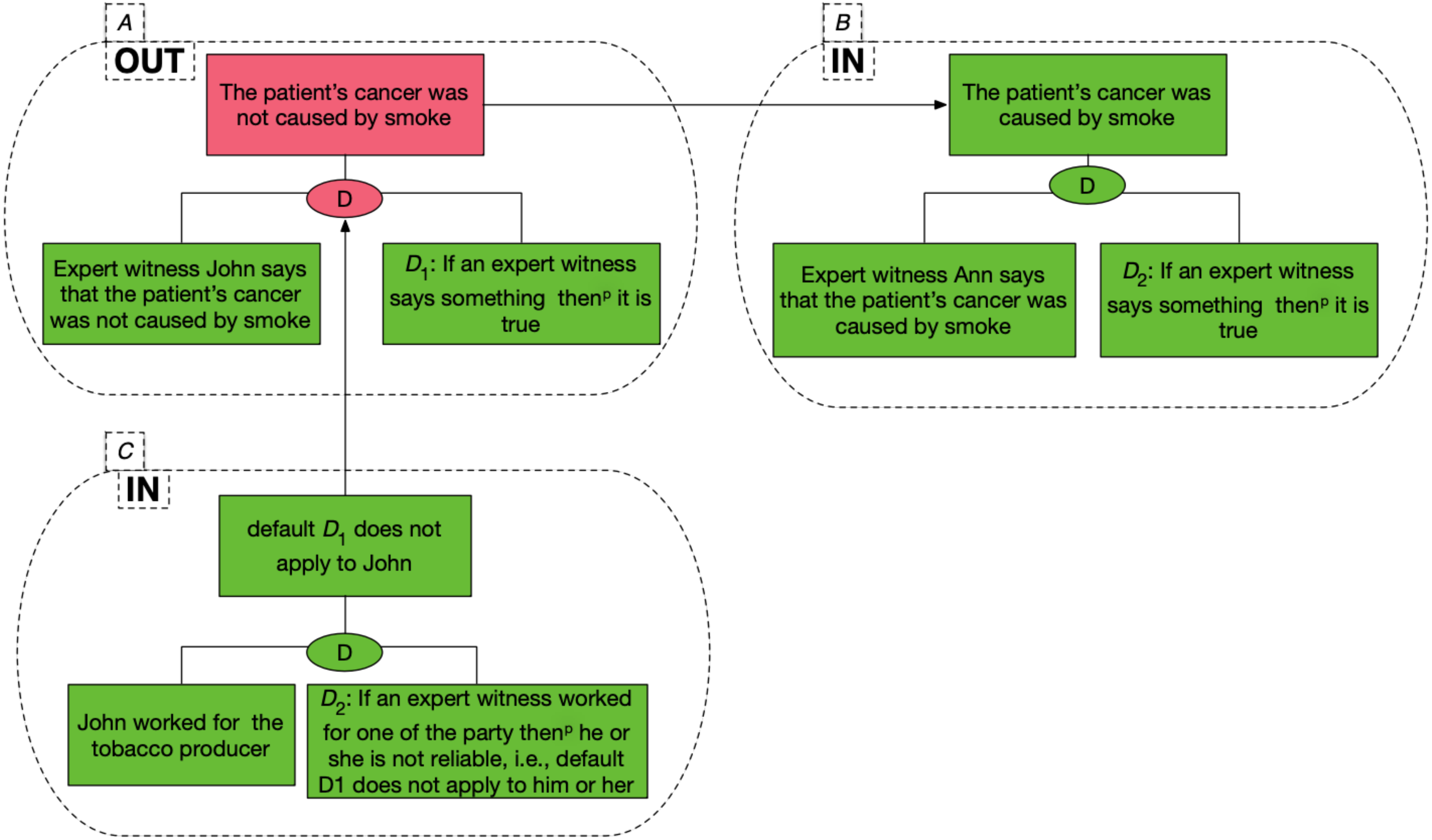


Arguments A and B defeat each other (and neither of them is OUT on other grounds), then the outcome is undecided: if we assume that A is IN then B will be OUT, and if we assume that B is IN, then A will b out

Resolution through burden of proof



Burden of proof and reinstatement

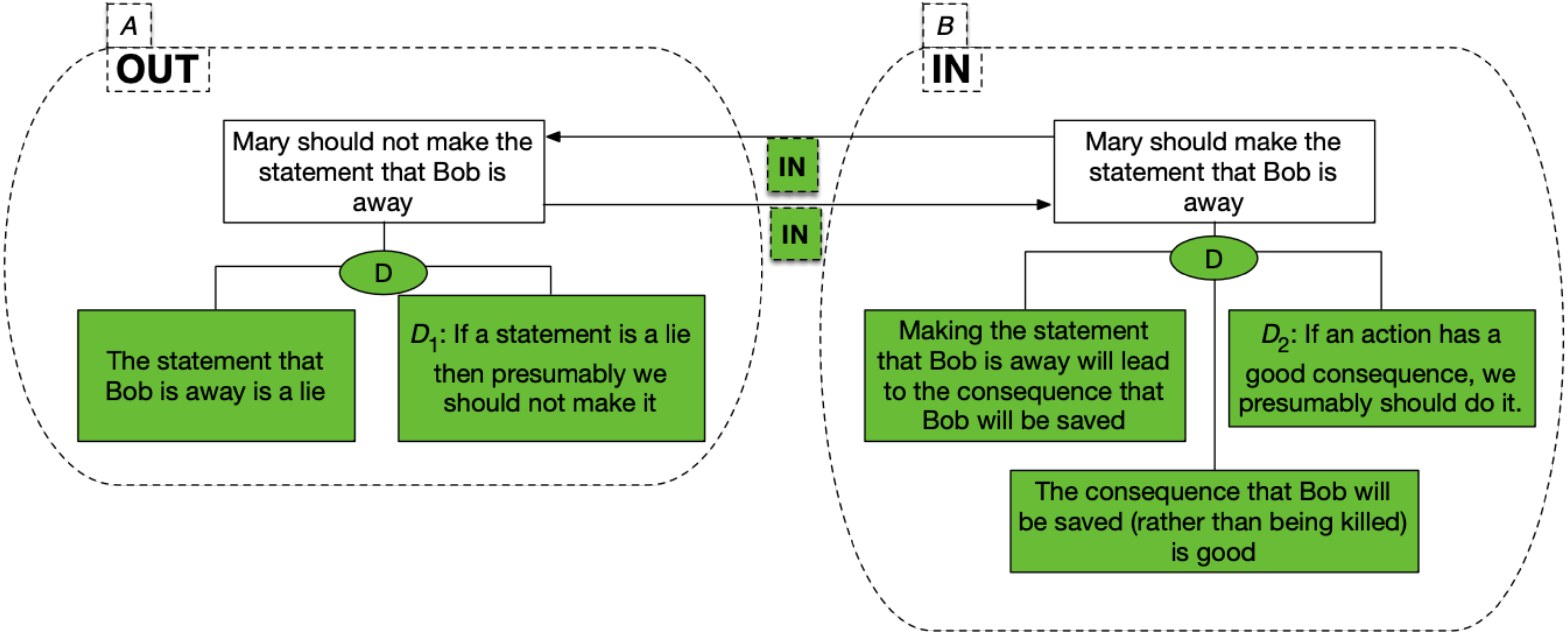


Dynamic priorities

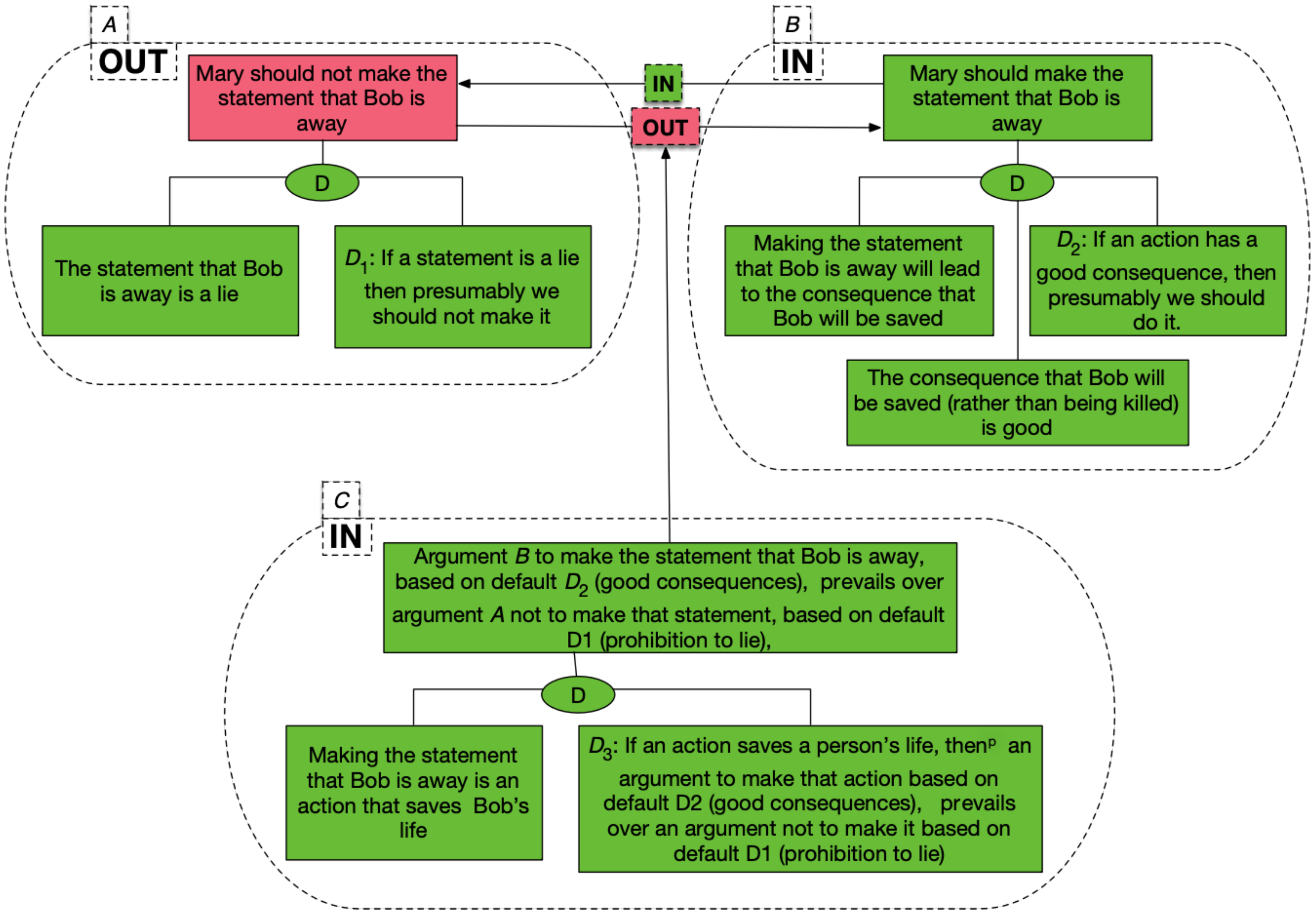
Priority argument establish the comparative strength of conflicting defaults. They may be based on:

- formal legal principles,,i.e., criteria which do not refer to the content of the norms at issue:
  - preference for more recent norms
  - preference for more specific norms
  - preference for norms issued by a higher authority
  - textual clues, e.g., norms having negative conclusions are usually meant to override previous norms having the corresponding positive conclusions.
- the substantive interests at stake, e.g., assigning priority to the norm that promotes the most important values (legally valuable interests) to a greater extent.

Priorities

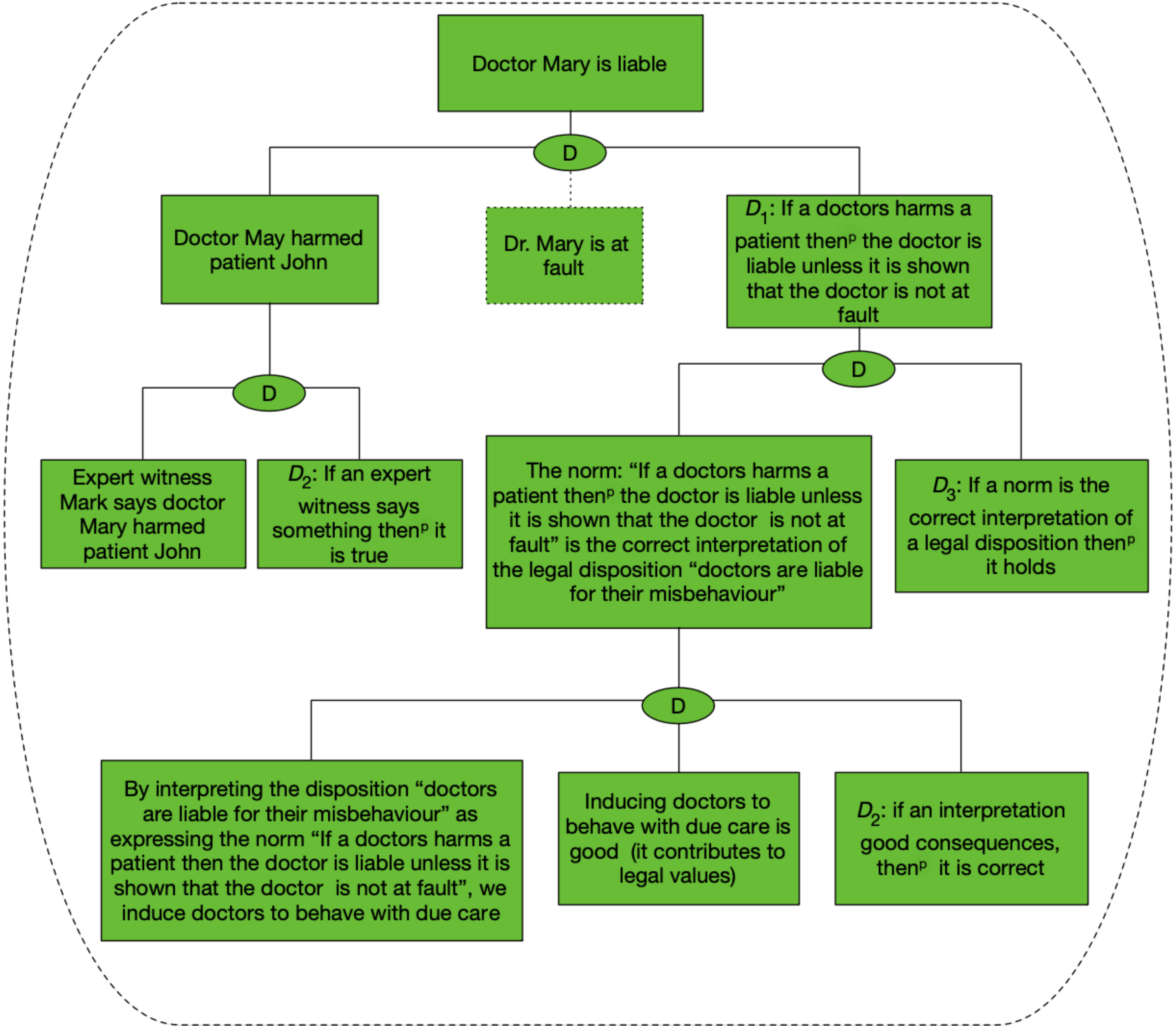

A
OUT
B
IN
Mary should not make the statement that Bob is away
Mary should make the statement that Bob is away
IN
IN
D
The statement that Bob is away is a lie
D1: If a statement is a lie then presumably we should not make it
D
Making the statement that Bob is away will lead to the consequence that Bob will be saved
D2: If an action has a good consequence, we presumably should do it.
The consequence that Bob will be saved (rather than being killed) is good

Attack on priorities



Multistep Arguments

- Legal arguments can include multiple steps:
  - the application of rules
  - item the interpretation of norms
  - item the determination of facts


Doctor Mary is liable
D
Doctor May harmed patient John
Dr. Mary is at fault
D_1: If a doctors harms a patient then^p the doctor is liable unless it is shown that the doctor is not at fault
D
Expert witness Mark says doctor Mary harmed patient John
D_2: If an expert witness says something then^p it is true
D
The norm: “If a doctors harms a patient then^p the doctor is liable unless it is shown that the doctor is not at fault” is the correct interpretation of the legal disposition “doctors are liable for their misbehaviour”
D_3: If a norm is the correct interpretation of a legal disposition then^p it holds
D
By interpreting the disposition “doctors are liable for their misbehaviour” as expressing the norm “If a doctors harms a patient then the doctor is liable unless it is shown that the doctor is not at fault”, we induce doctors to behave with due care
Inducing doctors to behave with due care is good (it contributes to legal values)
D_2: if an interpretation good consequences, then^p it is correct

Argument schemes in ASPIC+

- Argument schemes are defeasible inference rules
- Critical questions are pointers to counterarguments
  - Some point to undermining attacks
  - Some point to rebutting attacks
  - Some point to undercutting attacks

Eg: Attacks on expert testimony

- Is the expert really an expert in the domain at issue?
- Have other experts expressed opposed views?
- Is there any reason for its testimony not to be reliable (e.g. has he a connection to one of the parties)

Factor-based reasoning

- In legal classification and interpretation there are often no clear rules
- Often there only are factors: tentative reasons pro or con a conclusion
  - Often to different degrees
- Factors are weighed in cases, which become precedents
  - But how do judges weigh factors?
  - And what if a new case does not perfectly match a precedent?

HYPO

Ashley & Rissland 1987-1990

- Representation language:
  - Cases: decision (π or δ) + π-factors and δ-factors
  - Current Fact Situation: factors
- Arguments:
  - Citing (for its decision) a case on its similarities with CFS
  - Distinguishing a case on its differences with CFS
  - Taking into account which side is favoured by a factor

Running example factors: misuse of trade secrets

- Some factors pro misuse of trade secrets:
  - F2 Bribe-Employee
  - F4 Agreed-Not-To-Disclose
  - F6 Security-Measures
  - F15 Unique-Product
  - F18 Identical-Products
  - F21 Knew-Info-Confidential

- Some factors con misuse of trade secrets:
  - F1 Disclosure-In-Negotiations
  - F16 Info-Reverse-Engineerable
  - F23 Waiver-of-Confidentiality
  - F25 Info-Reverse-Engineered

HYPO
Ashley & Rissland
1985-1990

CATO
Aleven & Ashley
1991-1997

Citing precedent

- Mason v Jack Daniels Distillery (Mason) – undecided.
  - F1 Disclosure-In-Negotiations (d)
  - F6 Security-Measures (p)
  - F15 Unique-Product (p)
  - F16 Info-Reverse-Engineerable (d)
  - F21 Knew-Info-Confidential (p)

Plaintiff cites Bryce because of F6,F21

- Bryce and Associates v Gladstone (Bryce) – plaintiff
  - F1 Disclosure-In-Negotiations (d)
  - F4 Agreed-Not-To-Disclose (p)
  - F6 Security-Measures (p)
  - F18 Identical-Products (p)
  - F21 Knew-Info-Confidential (p)

Distinguishing precedent

- Mason v Jack Daniels Distillery (Mason) – undecided.
  - F1 Disclosure-In-Negotiations (d)
  - F6 Security-Measures (p)
  - F15 Unique-Product (p)
  - F16 Info-Reverse-Engineerable (d)
  - F21 Knew-Info-Confidential (p)

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  - F6 Security-Measures (p)
  - F18 Identical-Products (p)
  - F21 Knew-Info-Confidential (p)

Defendant distinguishes Bryce because of F4,F18 and F16

Counterexample

- Mason v Jack Daniels Distillery – undecided.
  - F1 Disclosure-In-Negotiations (d)
  - F6 Security-Measures (p)
  - F15 Unique-Product (p)
  - F16 Info-Reverse-Engineerable (d)
  - F21 Knew-Info-Confidential (p)

- Robinson v State of New Jersey – defendant.
  - F1 Disclosure-In-Negotiations (d)
  - F10 Secrets-Disclosed-Outsiders (d)
  - F18 Identical-Products (p)
  - F19 No-Security Measures (d)
  - F26 Deception (p)

Defendant cites Robinson because of F1

Distinguishing counterexample

- Mason v Jack Daniels Distillery – undecided.
  - F1 Disclosure-In-Negotiations (d)
  - F6 Security-Measures (p)
  - F15 Unique-Product (p)
  - F16 Info-Reverse-Engineerable (d)
  - F21 Knew-Info-Confidential (p)

Defendant cites Robinson because of F1

- Robinson v State of New Jersey – defendant.
  - F1 Disclosure-In-Negotiations (d)
  - F10 Secrets-Disclosed-Outsiders (d)
  - F18 Identical-Products (p)
  - F19 No-Security Measures (d)
  - F26 Deception (p)

Plaintiff distinguishes Robinson because of F6,F15,F21 and F10,F19

K.D. Ashley. Modeling Legal Argument: Reasoning with Cases and Hypotheticals. MIT Press, Cambridge, MA, 1990.

Plaintiff:
I should win because as in Bryce, which was won by plaintiff, I took security measures and defendant knew the info was confidential

Defendant:
Unlike in the present case, in Bryce defendant had agreed not to disclose and the products were identical

Defendant:
Unlike Bryce, in the present case the info is reverse engineerable

Defendant:
I should win because as in Robinson, which was won by defendant, plaintiff made disclosures during the negotiations

Plaintiff:
Unlike in Robinson, I took security measures, and defendant knew the info was confidential

Proportionality

- What if decisions A and B are such that that their affect differently different values
  - A is better than B if the extent to which A contributes more to values VA with regard to which it is better outweighs the extent to which B contributes more to the values VB in regard to which B is better
    - Prohibiting cannabis may be better the permitting it for health (is it true?) and security
    - Permitting cannabis is better than prohibiting it for freedom and control of criminality
  - A decision should be rejected if:
    - It causes unnecessary harm (there is a less harmful choice that produces as much good)
    - It causes more harm than good
  - Various heuristics: e.g., adopt the choice that is better with regard to more values, to more important values, etc.

Interpretive arguments

- *Argument from ordinary meaning* requires that a term should be interpreted according to the meaning that a native speaker would ascribe to it.
- *Argument from technical meaning* requires that a term having a technical meaning and occurring in a technical context should be interpreted in its technical meaning.
- *Argument from contextual harmonization* requires that a term included in a statute or set of statutes should be interpreted in line with whole statute or set.

- *Argument from precedent* requires that a term should be interpreted in a way that fits previous judicial interpretations.
- *Argument from statutory analogy* requires that a term should be interpreted in a way that preserves the similarity of meaning with similar provisions of other statutes.
- *Argument from a legal concept* requires that a term should be interpreted in line with the way it has been previously recognized and doctrinally elaborated in law.
- *Argument from general principles* requires that a term should be interpreted in a way that is most in conformity with general legal principles already established.

- *Argument from history* requires that a term should be interpreted in line with the historically evolved understanding of it.
- *Argument from purpose* requires that a term should be interpreted in a way that fits a purpose that can be ascribed to the statutory provision, or whole statute, in which the term occurs.
- *Argument from substantive reasons* requires that a term should be interpreted in line with a goal that is fundamentally important to the legal order.
- *Argument from intention* requires that a term should be interpreted in line with the intention of the legislative authority.

(MacCormick and Summers 1991)

The problem of the interpretation of “loss”

- An employee dismissal case (from MacCormick)
  - An employee claimed to have been unfairly dismissed, and as a result to have suffered humiliation, injury to feelings and distress (but no money loss)
  - The Employment law says: “If an employee is unfairly dismissed, the employee has the right to compensation for their loss”

Interpretive issue. Should “loss” be interpreted as including:

- Only money loss? If so no compensation!
- Also emotional loss (injury to feelings)?If so, compensation!

Possible arguments

- Loss in the Employment Relations Act should be interpreted as
  - not including injury to feelings according to ordinary language
  - including injury to feelings since otherwise provision redundant
  - not including injury to feelings, to discourage litigation
  - including injury to feelings, to discourage unfair dismissal
  - not including injury to feelings, for coherence with other uses of “loss”
  - Including injury to feelings, for coherence with constitutional favour for labour
  - not including injury to feelings since this was the intention of the legislator

Any criteria for preference for one of these argument over the competing ones

- Maybe ordinary language argument for exclusion should prevail, since in labour relations certainty is important and expectations should be upheld
- Maybe constitutional argument for inclusion should prevail, given that it supports more important values ….

Legal argumentation systems: the KA bottleneck

- Realistic models of legal reasoning
  - argumentation with rules, precedents, balancing reasons or values, …
- But hardly applied in practice:
  - Required knowledge is hard to manually acquire and code
- Is NLP the solution?
  - Learn everything from case law and law journals?
    - What arguments are included in legal documents (argument mining)?
    - What arguments scheme may be triggered by the facts of a particular case (argument generation)?

Mining and reasoning

We have seen examples of **argument schemes**

Is it possible to **mine** them and to **reason** with them?

Argumentation has **deep roots in logic** and philosophy, thus it deals with **symbolic reasoning**

We argue that novel methods are necessary, combining **symbolic** and **sub-symbolic** approaches

Caveat

This is a **recent exploratory study** in our research group, thus no experimental results will be shown!

Argument mining

Existing **state-of-the-art** approaches in argument mining are nowadays based on **neural** architectures

- LSTMs, CNNs, …
- Word and sentence embeddings
- Attention models
- Multi-task learning
- …

Symbolic vs. Sub-symbolic

How is knowledge represented in our mind?

Symbolic approaches

- Reasoning is the result of the formal manipulation of symbols (typically exploiting logic)

Sub-symbolic (or connectionist) approaches

- Reasoning is the result of processing of interconnected (networks of) simple units

Symbolic vs. Sub-symbolic

Symbolic approaches

- Founded on the principles of logic
- Highly interpretable

Sub-symbolic approaches

- Can easily deal with uncertain knowledge
- Can be easily distributed
- Often seen as black box (a.k.a. “dark magic”)

NeSy, SRL, etc.

In the research areas of artificial intelligence and machine learning, a **great effort** has recently been devoted to **combine** these two families of approaches

- Neural-symbolic learning and reasoning (NeSy)
- Statistical relational learning (SRL)
- Deep architectures for reasoning tasks

NeSy, SRL, etc.

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- Neural-symbolic learning and reasoning (NeSy)
- Statistical relational learning (SRL)
- **Deep architectures for reasoning tasks**

NOT COVERED IN THIS TALK

NeSy

Research area that aims at combining **neural** models and **symbolic** approaches for learning and reasoning

- Encode knowledge in the **architecture** of the network
- Use a **regularization** term to encode rules
- **Constrain** neural computations with rules

SRL

Research area that aims at combining first-order **logic** and **graphical models** for learning and reasoning

- Exploit the **expressive power** of first-order logic
- Handle **uncertainty** with graphical models
- Combine logic and probabilistic **inference**

Markov logic

An intuitive framework is that of Markov logic, where **probabilistic logic** is used to model knowledge

A Markov logic network consists of a set of **weighted** first-order logic rules and a set of **constants**

```
Person = {Alice, Bob, Carl}
Movie = {BladeRunner, TheMatrix}
2.3  LikesMovie(x,m) ^ Friends(x,y) => LikesMovie(y,m)
1.1  Friends(x,y) ^ Friends (y,z) => Friends(x,z)
```

THE HIGHER THE WEIGHT, THE MORE LIKELY IS A WORLD WHERE THE RULE IS TRUE, OTHER THINGS BEING EQUAL

Markov logic

Both weights and rules themselves can be **learned** from a collection of predicate observations.

Given a set of known facts, the weighted rules can be used to **infer** the truth value of other (query) facts.

```
LikesMovie(Alice,BladeRunner)

Friends(Alice,Bob)

!Friends(Alice,Carl)

LikesMovie(Carl,BladeRunner)???
```

Markov logic

The probability of a world/configuration depends on the **weights** (w_i) and the **number of groundings** (n_i) of each formula (F_i)

$$P(Y = y|X = x) = \frac{\exp\left(\sum_{F_i \in \mathcal{F}} w_i n_i(x, y)\right)}{Z_x}$$

$$P(X = x) = \frac{\exp\left(\sum_{F_i \in \mathcal{F}} w_i n_i(x)\right)}{Z}$$

Inference aims to find the **most probable** y given x

$$y^* = \mathrm{argmax}_y P(Y = y|X = x)$$

Markov logic

In [Lippi & Frasconi, 2009] we extended Markov Logic to **embed neural networks to compute weights**

```
w(s)    HasFeatures(s,$f) => Claim(s)
```

The **weight** `w(s)` is computed by a neural network using (any) set of features `$f` describing sentence `s`

These are named **Ground-Specific MLNs**

Markov logic

In this framework we could model argument **schemes**

```
w1(s)    HasFeatures(s,$f) => Claim(s)

w2(s)    HasFeatures(s,$f) => Premise(s)

w        Support(x,y) => Premise(x) ^ Claim(y)
```

All these rules can be seen as **defeasible rules**

Collective classification

This framework could be easily exploited to perform **collective classification** on a document.

Given a **set** of (possibly neural) rules, and a **collection** of constants/features representing the document, the **inference** algorithm computes the **most likely world**, or interpretation, thus assigning a truth value to each predicate in the document.

Collective classification

KNOWN FACTS

```
HasFeatures(X,$F1)
HasFeatures(Y,$F2)
```

```
 2.3   HasFeatures(X,$F1) => Claim(X)
-3.4   HasFeatures(X,$F1) => Premise(Y)
-0.9   HasFeatures(Y,$F2) => Claim(X)
-0.1   HasFeatures(Y,$F2) => Premise(Y)
1.5    HasFeatures(X,$F1) ^ HasFeatures(Y,$F2) => Support(Y,X)
+Inf   Support(X,Y) => Premise(X) ^ Claim(Y)
```

Markov logic

We can model more complex **hard** and **soft** rules

```
w1  Support(x,y1) ^ Support(x,y2) => !Attack(y1,y2)
   w2  Support(x,y) ^ Attack(z,x) => Defeat(z,y)
```

The first rule encodes **common sense knowledge**

The last rule encodes **undermining** scheme!

DeepProbLog

Problog is a **probabilistic extension** of Prolog where probabilities can be attached to ground facts or rules.

DeepProblog extends Problog by **computing** such probabilities with **neural networks**.

- Necessary to know Pro(b)log
- Cannot (yet) perform collective classification

Novelty

Many approaches in Argumentation Mining have tried to embed background knowledge in machine learning

- [Stab & Gurevych, 2016]: background knowledge is exploited **a priori** for link candidate extraction
- [Persing & Ng, 2016]: **pipeline** scheme that applies **constraints** to the results of a first detection stage
- [Niculae et al., 2017]: inter-dependencies between random variables are encoded in a **factor graph**

Novelty

- **Joint learning** of rule weights and neural networks
- **Interpretable** rules for background knowledge
- Argument **schemes** naturally **encoded** in rules
- **Collective classification** over documents

Looking to the future

- Are these solutions effective for **mining** arguments?
- How do these models **scale up** to large domains?
- Can these frameworks allow to perform **reasoning**?
- Is it possibile to **learn the rules**?

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Thanks for your attention

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