Enhancing Rules with Imperfection

Integration with Soft Computing

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Bologna/San Diego - April 19-23th, 2010

Outline

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What is Imperfection?

Imperfection

Imperfection, be it Imprecision or Uncertainty, pervades . . . systems that attempt to provide an accurate model of the real world

P.Smets, 1999

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Uncertainty

Uncertainty is a condition where Boolean truth values are unknown, unknowable, or inapplicable . . .

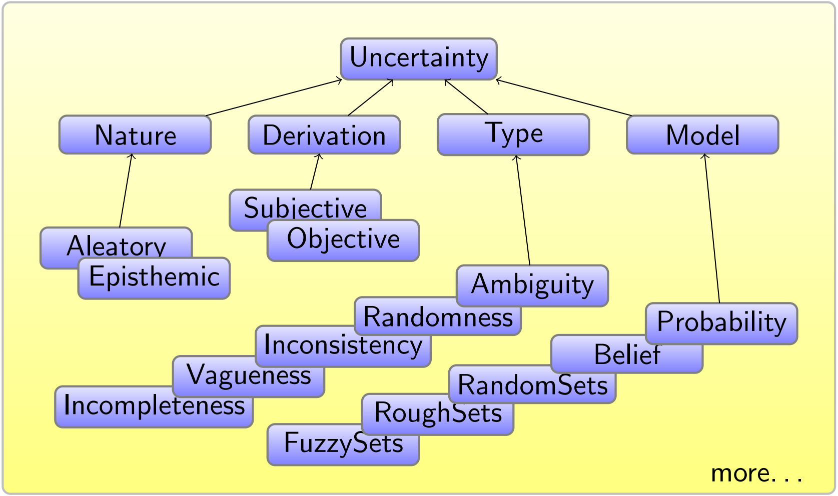
W3C Incubator Group on Uncertainty Reasoning for the Web, 2005

What is Imperfection?

Imperfection - a negative definition

Uncertainty/Imperfection is the opposite of preciseness and certainty, i.e. of what Boolean logic models

An Ontology for Imperfection



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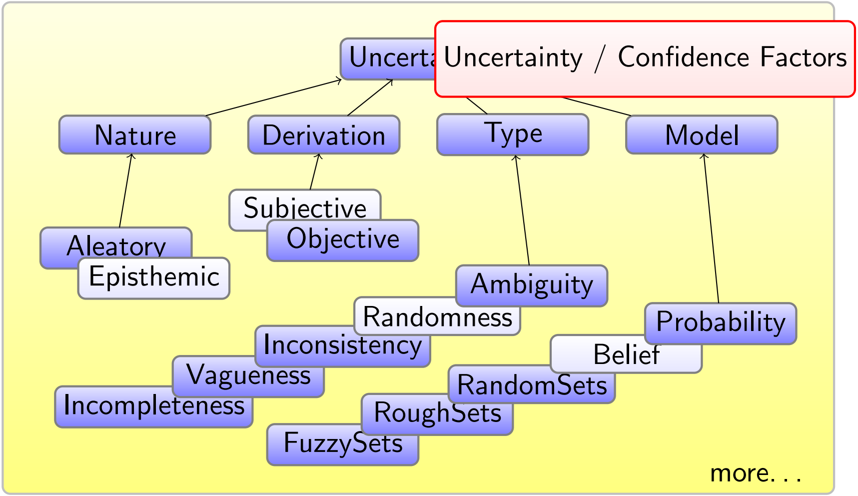

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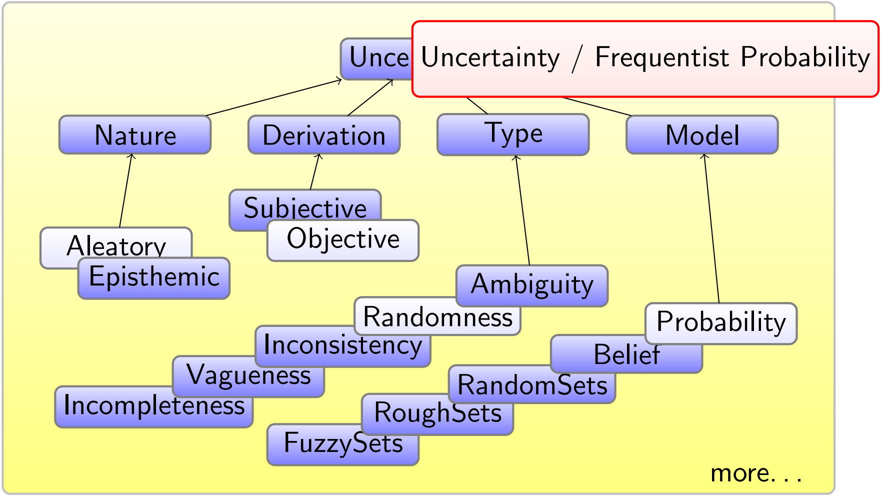

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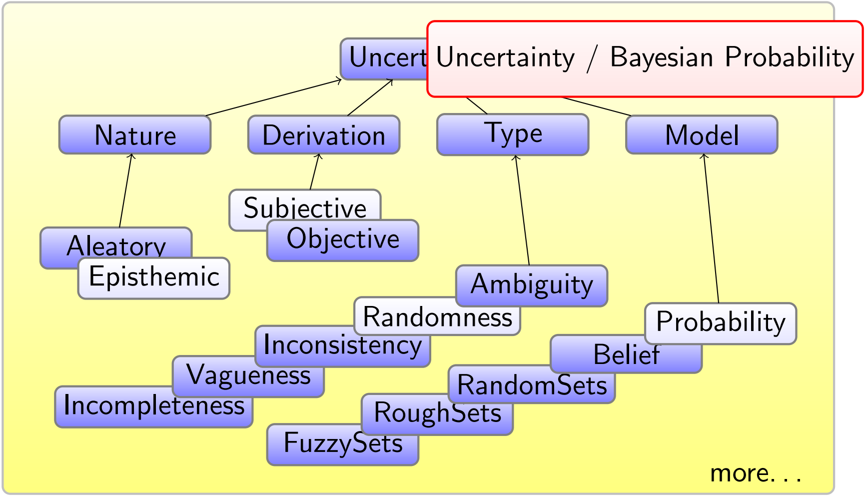

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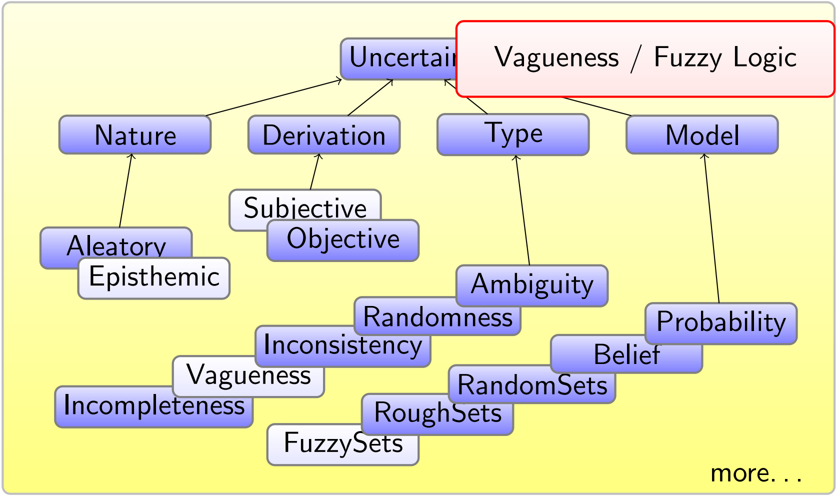

Possible Applications

- Information Processing
  - Clinical Procedures
  - Semantic Web

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Using Imperfection

Rules should handle uncertainty, not ignore it

Benefits

- Conciseness
- Robustness

Drawbacks

- Complexity
- Correctness and Coherence

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”**If** *you place your bet on an improbable number,*
and *it gets extracted on next round,*
then *expect an increase in your capital*”

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If bet(Sum,Number,T)
$\wedge$ improbable(Number)
$\wedge$extracted(Number,T+1)

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If bet(Sum,Number,T)
$\wedge$ improbable(Number)
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Then
eval(bet(Sum,Number,T),B)
eval$_F$(improbable(Number), D)
eval$_P$(extracted(Number), P)
eval$_\wedge$(B,D,P,Number,T,X)
eval$_\rightarrow$(X,Number,T)
print('Gain is',gain(Number,X))

Some Issues

If bet(Sum,Number,T)
$\wedge$ improbable(Number)
$\wedge$extracted(Number,T+1)

Then
eval(bet(Sum,Number,T),B)
eval_F(improbable(Number), D)
eval_P(extracted(Number), P)
$\text{eval}_\wedge$(B,D,P, X)
$\text{eval}_\rightarrow$(X)
print('Gain is',gain(Number,X))

- Truth-functionality
  - Simplifies computation
  - Not always possible (e.g. probability)

Some Issues

If bet(Sum,Number,T)
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Then

print('Gain is',gain(Number,X))

- Truth-functionality
  - Simplifies computation
  - Not always possible (e.g. probability)
- Transparency
  - Automatic computation
  - User should not be aware

Outline

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Generalized Inference

$$\frac{\langle P(x), P(X) \rightarrow C(Y) \rangle}{C(y)}$$

- Classic Modus Ponens
  - Premise and Implication entail Consequence

Example

$Rich(X) \wedge Healthy(X) \rightarrow Happy(X)$

Generalized Inference

$$\frac{\langle \Phi(\ldots, A_j(x)/\varepsilon_j, \ldots), P(X) \rightarrow C(Y) \rangle}{C(y)}$$

- Premise
  - Atomic constraints are evaluated
  - General, pluggable `Evaluators`
  - A `Degree` is returned

Example

$Rich(x)_{0.6} \wedge Healthy(x)_{0.8} \rightarrow Happy(X)$

Generalized Inference

$$\frac{\langle \Phi(\ldots, A_j(x)/\varepsilon_j, \ldots)/\varepsilon_P, P(X) \rightarrow C(Y)\rangle}{C(y)}$$

- Premise
  - Atomic constraints are evaluated
  - General, pluggable `Evaluators`
  - A `Degree` is returned

- Premise
  - Atoms are aggregated in formulas
  - using generalized logic Connectives
  - evaluated by `Operators`

Example

$Rich(x) \wedge_{0.6} Healthy(x) \rightarrow Happy(X)$

Generalized Inference

$$\frac{\langle P(x)/\varepsilon_P \;, \;\rightarrow(X,Y)/\varepsilon_{\rightarrow}\rangle}{C(y)}$$

- Implication
  - Implication has a Degree
  - often given *a priori*

Example

$Rich(x) \wedge Healthy(x) \rightarrow_{0.4} Happy(X)$

Generalized Inference

$$\frac{\langle P(x)/\varepsilon_P \; , \; \rightarrow(X,Y)/\varepsilon_{\rightarrow} \rangle}{C(y)/\varepsilon_C}$$

- Implication
  - Implication has a Degree
  - often given *a priori*

- Modus Ponens
  - MP computes the Degree of the Consequence

Example

$Rich(x) \wedge_{0.6} Healthy(x) \rightarrow_{0.4} Happy(x)_{0.4}$

Generalized Inference

$$\frac{\frac{\langle P_1, \rightarrow_1 \rangle}{C_1 / \varepsilon_{C_1}}, \ldots, \frac{\langle P_n, \rightarrow_n \rangle}{C_n / \varepsilon_{C_n}}}{C(y) / \varepsilon_C}$$

- Merging multiple sources
  - Multiple premises for the same conclusion
  - Solve conflicts
  - Handle missing values

Example

$Rich(x) \wedge Healthy(x) \rightarrow Happy(x)_{0.4 \cap 0.2 \cap 0.7}$

Outline

Language extensions : Example

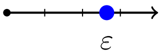
```
rule "Rule"
  // custom: implications and MP
  implication @[degree ="0.75"]
  deduction @[kind="min"]
when
    $o1 : Type( $f1 : field1
      /* custom: external evaluator */
      == @[id="i1", kind="external", params="..."]
    "val")
  or @[kind="max"]  // custom: operators
    $o2 : AnotherType(
      field3 == 0
      ^^ // custom: operators
      field3 == @[crisp] $f1 ) //custom: behaviour
then
  /* consequence degree */
  ... = drools.getConsequenceDegree();
```

Generalized Degrees

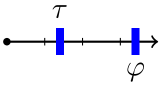
Degrees generalize the boolean `true/false`

- **truth**: compatibility with a prototype
- **probability**: ratio of relevant events over total
- **belief**: opinion in assuming a property to be true.
- **possibility**: disposition towards accepting a situation to be true.
- **confidence**: strength of an agent's belief in a statement.

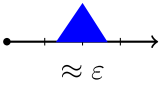
Different models, including:



Simple



Interval



Type-II degrees

Custom Evaluators

$$Object \times Object \mapsto Degree$$

```
when
   Patient( fever ~seems ''high'' )
then
   ...
```

- Wrap an external function
- Define (and evaluate) a property $p(L, R)$
- Return a *Degree*

Custom Operators

$\{(Tuple), Degree\}^n \mapsto Degree$

```
rule "Ops"
  implication
  deduction
when
  $p : Patient( temperature ~>= 38 ^^ ~<= 41 )
  and
  exists Medicine( this not ~allergenic $p )
then
  ...
```

- Aggregate evaluations
- Better if truth-functional
- Return a *Degree*
- Noteworthy : implication and modus-ponens

Configuration Attributes

Control the behaviour of the engine

- **id** : assign id to constraint/operator
- **kind** : choose evaluator/operator implementation
- **degree** : set “prior” degree
- **params** : additional initialization info
- **crisp** : cast to boolean
- **filter** : configure propagation strategy
- more...

Injection[1]

```
rule "Inject"
when
  $p : Patient( temperature ~>= 38 )
then
  inject(''idFever'',$p)
end

rule "Injected"
when
  $p Patient( fever ~seems @[id=''idFever''] ''high'' )
...
```

Chaining by evaluation: source conseguence degree sets the target's

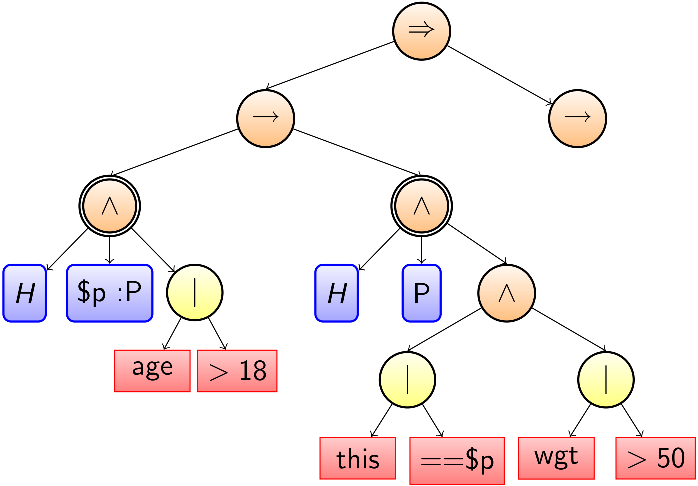
[1] Soon to be deprecated in form, but not in concept

Outline

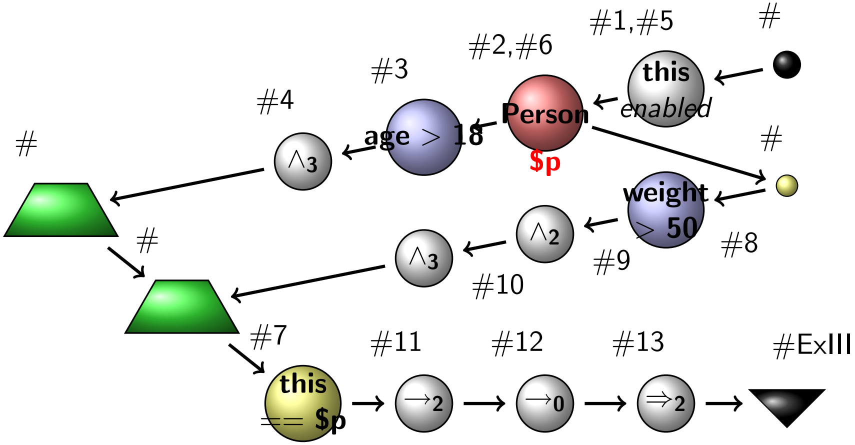
Refactored Rule Structure

```
when
   $p : Patient( age ~> 18 )
   implies
   Person( this == $p, weight ~> 50)
then
   ...
```

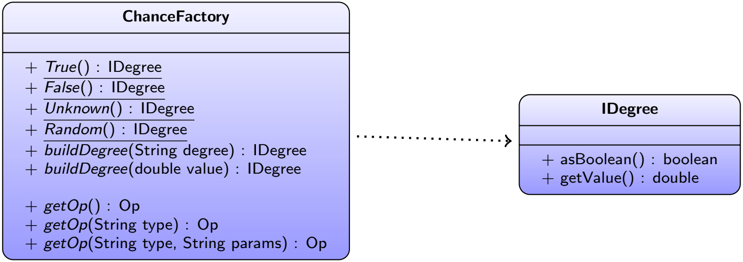
Refactored Rule Structure



Extended RETE



Factory



Factory controls the coherence

- Builds Degrees
- Builds Operators
- Attributes become params for the factory

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Applications

Pure Logic-Based Approaches

- Symbolic reasoning
- Rules are annotated with degrees
- Computation of facts and degrees according to inference rules

Hybrid Approaches

- Mixed Symbolic/Sub-Symbolic reasoning
- Rule delegate, embed or emulate SC techniques

Outline

Certainty Factors

```
rule "Mycin"
  implication @[ degree=''0.7'' ]
    when
      $s : Site( this ~sterile )
       Infection( cause ~== ''bacteremia'',
                  site == @[crisp] $s )
      ...
    then
       // Infection is bacteroid
  end
```

- Simple rule structure
- Evaluators return CF
- Rules have CF themselves

Bayesian Logic Programs

```
rule "BLP"
      //CPT here : p(m|S1,S2)
  implication @[ degree=‘‘...’’ ]
    when
      $s1 : Symptom1( ... )
       $s2 : Symptom2( ... )
    then
      // Illness is ...
     end
```

- Conditional probabilities over state of premises

Many-Valued (Fuzzy) Logic Programs

```
rule "MVL"
  implication @[ kind=''Lukas'' ]
    when
      Patient( pressure ~seems ''high''
                     || @[ kind=''max'' ]
               temperature ~seems ''high'' )
    then
      // ...
    end
```

- Variety of operators (families)
- Full fuzzy set chaining not complete (yet)

Possibilistic Logic Programs

- Degrees given by Necessity/Possiblity intervals
- Similar in form to a specific MVL
    - Specific operators
    - Specific semantics
    - Not gradual truth, nor probability!!
- ... but generalizes to fuzzy possibility easily

Hybrid Logic Programs

```
rule "Hybrid Imperfect"
  // probability
  implication @[ degree=''0.99'' ]
when
  // truth
  true @[ degree=''0.5,0.7''] (
    Patient( temperature ~seems ''high'' )
  )
then
// ...
end
```

- Uncertain/Vague Mix
- Consequence is given a specific probability...
- ... if and only if premise is true to a certain degree

Outline

Soft Computing

Alternative (?) to Rule-Based Systems

A vast family

Basically, everything that is not (purely) symbolic

- Fuzzy Logic
- Neural Networks
- Genetic Algorithms
- Bayesian Network
- Clustering

Outline

No Integration - External Call

```
rule "No integration"
when
   $s : SCModule(...)
then
   $s.invoke(...);
end
```

- Rules, at best, select the SC module
- SC module is invoked in RHS
- Compatible with boolean logic

Loose Integration - Wrapper

```
rule "Cytofluorimetry"
when
  // Using a neural classifier
  $c : Cell( $f : features ~isA ''red globule'' )
then
  ...
end
```

- SC module is embedded in a custom evaluator
- SC module must evaluate a predicate
- i.e. the return value must be a *Degree*
- Boolean return value would be a limitation

Strong Integration - Emulation

- SC module is implemented using (imperfect) rules
- Based on *Degree* manipulation - using operators

Outline

Induction

```
rule "Induction"
when
   forany ( $p : Patient( heart ~risk ''high'' )
               subject_to
                 Patient(this == $p,
                    weight ~seems ''heavy'' ))
then
   ...
```

- Generalized quantifier
- Accumulates quantitative degrees

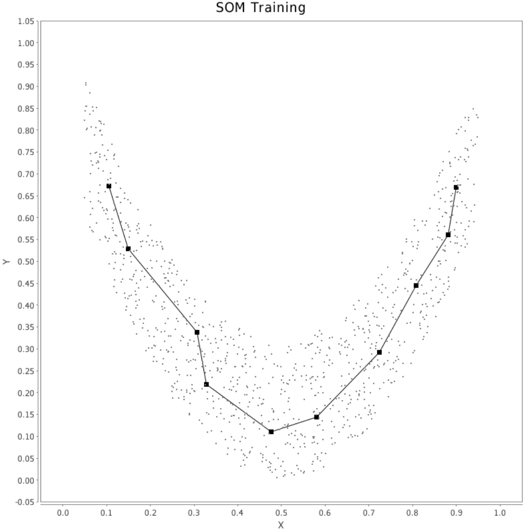
Self-Organizing Map

```
rule "Map Query"
when
  $x : Sample()
  exists Neuron( position ~close $x )
then
  // (Gradual) Recall...
```

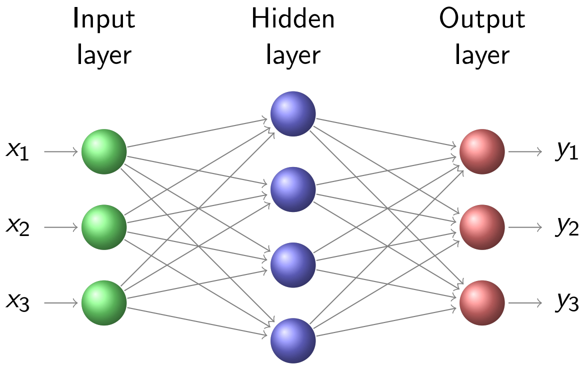
- Rule-based Training algorithm
- Rule-based querying

Self-Organizing Map

Example: 10 neurons in a 2D space:

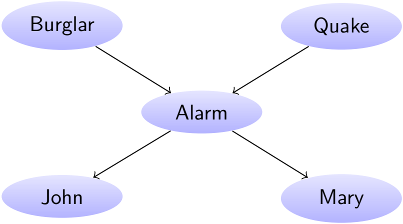


Feed-Forward Neural Network



- Function-Approximating Networks $\rightarrow$ Invoke
- Classification Networks $\rightarrow$ Wrap
- Emulation feasible, under development

Bayesian Network



- Wrappable for use in probabilistic logic
- Emulation is possible (still too verbose)

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- Uncertainty can be handled using other approaches:
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Conclusions

- Uncertainty exists in many forms

  $\longrightarrow$ Uncertainty should be embedded in rules

- Several Imperfect Logics do exist
- Uncertainty can be handled using other approaches:
  - Bayesian Networks, Neural Networks, Fuzzy Systems, ...
- Current Goal : Provide a unified and integrated framework